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Research on computationally optimized distribution network topology reconfiguration method combining Levy flight and electric eel foraging algorithm

Na Yan[1,✉], Jian Zeng[1], Hui Wang[1], Yunzhang Yang[1], Shuzhong Li[2]

[1] State Grid Shaanxi Electric Power Company Limited Research Institute, Xi'an, Shaanxi, 710065, China

[2] WLSL ELectric Energy Star, Inc Electric Energy Star Co., Ltd. (Chongqing), Chongqing, 400039, China

ABSTRACT

Energy level fluctuations in Distributed Generation (DG) systems and Electric Vehicles (EVs) sometimes exceed the carrying capacity of typical distribution network topologies, which may lead to inefficiencies and lack of reliability. Based on this, this paper introduces a new Levy flight-electric eel foraging optimization (LF-EEFO) method for adapting network topology reconfiguration for new power systems. The DG output power, EV charging power, distribution network loss power, and switch lifetime cost cost are taken as the objectives, and the tidal current, voltage, branch power, network topology, and switching action are set as the constraints, in order to construct a multi-objective optimization model for distribution network topology reconfiguration. In the optimization phase, a Levy flight strategy is used to optimize the local search capability of the EEFO algorithm to obtain the optimal solution of the multi-objective optimization model for distribution network topology reconfiguration. In order to ensure the efficiency of the LF-EFO algorithm in optimizing the distribution network topology reconstruction model, an IEEE-33 node test system was established for simulation analysis. The results show that this research can significantly reduce the operating cost and improve the operational reliability of distribution networks, while promoting the development of electric vehicles.

Keywords: distributed generation; electric vehicle; Levy flight; electric eel foraging algorithm; LF-EEFO algorithm; distribution network topology reconstruction

1. Introduction

A power system is a complex system consisting of a variety of power equipment connected together, including generators, substations, transmission lines and distribution transformers [1-2]. In the power

✉ Corresponding author.
E-mail address: liSZ0304@163.com (N. Yan).

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system, the grid topology is the way and form that represents the interconnection between various power equipments, including the layout of the grid and the power transmission path between equipments. Reasonable design and optimization of the grid topology can improve the reliability and economy of the power system [3-6].

Grid topology reconfiguration refers to the transformation, upgrading and optimization of the topology of the grid according to the actual needs of the power system [7-8]. Specifically, grid topology reconfiguration can achieve the following goals: improve the reliability and security of power transmission. By optimizing the grid topology, the crossing of transmission lines is reduced, and the line failures caused by bad weather and other factors are reduced. This reduces the outage time and improves the reliability and security of power transmission [9-12]. Improve the economic efficiency of the power system. Through grid topology reconstruction, the layout of the power system can be rationalized, the topology of the grid can be optimized, the utilization rate of transmission lines can be improved, and the power loss and cost can be reduced, so as to improve the economic efficiency of the power system [13-16]. Adapt to the development trend of new energy. With the continuous development and promotion of new energy, the topology of the power system needs to be changed accordingly to adapt to the access and development of new energy [17-19]. Through grid topology reconfiguration, the topology of the grid can be adjusted according to the actual demand for new energy, increasing the access to new energy and improving the sustainable development of the power system [20-21].

Traditional distribution network reconfiguration methods are often based on experience and rules, and cannot adapt to the complex and changing power demand. The method combining Levy flight and electric eel foraging algorithm can achieve the optimal reconfiguration decision through learning and optimization according to the real-time power demand and network state [22-25].

The large-scale application and promotion of distributed power generation and electric vehicles is an important focus for realizing the goal of "dual-carbon", but the integration of the two will increase the volatility of the distribution network, which makes the original static reconfiguration scheme unsatisfactory for the time-varying network. Based on this, this paper proposes a topology reconfiguration scheme solution method combining Levy flight and electric eel foraging algorithms for distribution networks. First, the variables of distribution network loss, DG generation power, EV charging cost and switch lifetime are taken as objective functions, and the corresponding constraints are set to construct the topology reconfiguration model of distribution network with DG and EV. Then, based on the electric eel foraging optimization algorithm, the Levy flight strategy is introduced to optimize its stochastic operator to improve the local search capability of the EEFO algorithm. Finally, a simulation example is set up based on the IEEE-33 node system, and the superiority of the distribution network topology reconfiguration scheme obtained by the LF-EEFO algorithm is explored through the example.

2. Topology reconfiguration model of distribution network with DG and EV

Distribution network is the final link in the power system from the issuance of electric energy to its use by users, and it has the most direct impact on the reliability and quality of power supply. As an important measure to optimize the network trend, distribution network reconfiguration can achieve safe, stable and economic operation of the system by flexibly adjusting the network topology without increasing additional construction costs. In recent years, with the progress of social economy and the growth of energy demand, distributed generation technology and electric vehicles are booming, which bring both opportunities and challenges for distribution networks, and the traditional distribution network reconfiguration strategy is increasingly difficult to meet the operational requirements of active distribution networks. Therefore, it is of great significance to study the topology reconfiguration problem of distribution networks containing DG and EV.

2.1. Distributed Power and Electric Vehicle Modeling

2.1.1. Stochastic Modeling of Distributed Power Supplies:

1) Node types of DG. According to the different ways of DG operation and control, its mathematical model can be divided into four node types: the PQ node, the PQ(V) node, the PV node and the PI node [26].

PQ nodes. This type of DG can be regarded as a “negative load”, whose active and reactive power are known, such as doubly-fed induction wind turbines, whose mathematical model is:

$$\begin{cases} P_{\mathrm{i}} = -P_s \\ Q_{\mathrm{i}} = -Q_s \end{cases} \tag{1}$$

PQ(V) node. The active power output of such DGs is known and the reactive power varies with the node voltage, as in the case of cage-type induction wind turbine, which is mathematically modeled as:

$$\begin{cases} P_i = -P_s \\ Q_i^{i+1} = -f(U^i) \end{cases} \tag{2}$$

where U is the voltage after t iterations and Q^{i+1} is the reactive power after $t+1$ deliveries.

PV node. The output active power and voltage of such DGs are known and are operated on the grid through constant voltage control strategy, such as permanent magnet synchronous direct-drive wind power systems and solar power systems connected to the grid through voltage-controlled inverters, which are mathematically modeled as:

$$\begin{cases} P_i = -P_s \\ U_i = U_s \end{cases} \tag{3}$$

This type of DG requires constant iterative correction of reactive power and must ensure that the reactive power must not cross the limit.

PI node. This type of DG provides constant active power and injects a constant current into the grid, and is generally operated in grid-connected mode through a current-controlled inverter, which is mathematically modeled as:

$$\begin{cases} P_i = -P_s \\ I_i = I_s \end{cases} \tag{4}$$

Different types of DGs are transformed into corresponding node types for modeling in the tidal current calculation, and all of them can eventually be transformed into PQ models for calculation by Eq.

2) Stochastic model of DG. It is simple and convenient to establish a deterministic model of DGs by considering them as nodes with constant output power. However, in practical situations, DG output power is stochastic and intermittent. After statistical studies, a two-parameter Weibull distribution is often used to fit the wind speed variation, so the probability density function of wind power active output is:

$$f(P_w) = \frac{k}{k_1 c}\left(\frac{P_w - k_2}{k_1 c}\right)^{k-1} \exp\left[-\left(\frac{P_w - k_2}{k_1 c}\right)^{k}\right] \tag{5}$$

The output power of the photoelectric mainly depends on the light intensity, after a large number of data statistics found that it can be used to fit the Beta distribution, the probability density function of the photoelectric active output power is:

$$f(P_M)=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{P_M}{R_M}\right)^{\alpha-1}\left(1-\frac{P_M}{R_M}\right)^{\beta-1} \tag{6}$$

In practice, similar locations within the same geographic area have some correlation between wind speeds and light intensity due to the same climatic zone.

2.1.2. Mathematical modeling of electric vehicles. The flexible load of EV has a high penetration rate, and the utilization of EV is regarded as an important technological way to reduce carbon emissions and combat haze. At present, EVs are mainly categorized into pure electric vehicles, hybrid vehicles and fuel cell vehicles. According to the EV charging sequence, EV charging strategies can be categorized into disorderly charging and intelligent charging (orderly charging). Under the disorderly charging mode, EV owners mainly complete charging according to their own travel wishes, and the charging mode is not regulated by the relevant departments, with strong randomness, and the charging characteristics of EVs show the disorderly charging behavior of "charging on arrival". Under the intelligent charging mode, EV owners have to obey the control of the technicians, and make reasonable arrangements for the charging behavior of private car owners on the next day through the scheduling center days ago, which requires EV owners to be constrained by the power grid company, and they cannot randomly choose the charging time [27].

The charging power probability model of EV for 1 day is constructed based on the existing literature, and the following mathematical model represents two kinds of smart charging and disordered charging in two ways.

1) EV travel probability model. It is shown that if the last arrival moment of EV is taken as the starting moment of charging, the probability density function of the starting moment of EV charging approximately satisfies the normal distribution. Then:

$$f_s(x)=\begin{cases}\dfrac{1}{\sigma_s\sqrt{2\pi}}\exp[-\dfrac{(x-\mu_s)^2}{2\sigma_s^2}],(\mu_s-12)<x\le 24\\ \dfrac{1}{\sigma_s\sqrt{2\pi}}\exp[-\dfrac{(x+24-\mu_s)^2}{2\sigma_s^2}],0<x\le(\mu_s-12)\end{cases} \tag{7}$$

Where $\sigma_s=3.4,\mu_5=17.6$, x is the charging moment.

The daily driving range of electric vehicles generally satisfies the lognormal distribution, which can be expressed by the following equation:

$$f(d)=\frac{1}{\sigma_d d\sqrt{2\pi}}\exp[-\frac{(\ln d-\mu_d)^2}{2\sigma_d^2}] \tag{8}$$

Eq. $\sigma_d=0.88;\mu_d=3.2$.

2) EV disordered charging model. EV counting from the moment of starting charging, the charging power of different types of electric vehicles meets the condition of uniform distribution between 2~3kW, so this range is used to analyze the probability distribution of charging time. Then:

$$f_\tau(t)=\frac{1}{1.61\times 0.15}\int_2^3\frac{1}{\sigma_d t\sqrt{2\pi}}\cdot\exp[-\frac{(\ln t-\ln 0.15-\ln 1.61+\ln p-\mu_d)^2}{2\sigma_d^2}]dp \tag{9}$$

A time period of 1 day is proposed to study the charging behavior of EVs, and in this paper, it is assumed that the random variable γ is 0 when the EV has not started charging or has finished charging, and γ is 1 when it is charging, and its probability function is:

$$\begin{cases} P(\gamma_{t_0}=0)=f_{st}(s>t_0,s+t\le t_0+24)+f_{st}(s+t\le t_0) \\ P(\gamma_{t_0}=1)=1-P(\gamma_{t_0}=0) \end{cases} \tag{10}$$

Where: f_{zt} represents the probability density distribution of EV charging moment and time length, where the probability distribution functions of $f_{zt}=f_z f_t$, f_z and f_t are consistent with those in the EV travel probability model.

When EV is charging in a disorderly manner, private car owners mainly complete charging according to their own travel wishes, and the charging mode is not regulated by the relevant departments and is highly stochastic. According to the method of the relevant literature, it is assumed that the power demand of EV at a certain moment t_0 is expressed as $P_{t_0}=\gamma_{t_0}P_c$, so the probability density distribution function of P_{t_0} can be expressed as:

$$\begin{cases} P(P_{t_0}=0)=P(\gamma_{t_0}=0) \\ P(0<P_{t_0}\le P_0)=P(\gamma_{t_0}=1)\cdot P(0<P_c\le P_0) \end{cases} \tag{11}$$

where P_c is the EV charging power, and γ_{t_0} is 0 or 1, indicating that the EV charging is complete or is charging, respectively.

3) EV smart charging model. Intelligent charging is that EV owners have to obey the regulation and control, through the scheduling center a few days ago to the charging behavior of the private car owners on the next day to make reasonable arrangements to achieve the reliable operation of the power grid [28]. When charging, 1 day is first divided into multiple time slots, and then the EVs charging at the beginning of each time slot are intelligently assigned spatially in accordance with the ratio of the regular load of that time slot to the total load of all time slots:

$$E_i=\frac{P_{l,i}}{\sum_{i=1} P_{l,i}}\cdot E \tag{12}$$

Where E_i is the calculated number of EVs allocated, proportional to the load at each moment, E is the total number of EVs, and $P_{l.i}$ is the load value at moment i.

2.2. Distribution network topology reconfiguration model construction

2.2.1. Objective function. Taking one day as a cycle, the economic globally optimal reconfiguration scheme is solved from the perspective of the distribution network considering the cost of DG generation represented by wind and PV, the cost of random EV charging, the cost of network losses, and the cost of switch lifetime losses under the constraints of node currents and voltages, branch circuit capacities, and spoke operation. The mathematical model for constructing the topology reconfiguration of the distribution network can be expressed as:

$$minF=\sum_{t=1}^{T}\left(P_{DG}^{'}\omega_d^{'}+P_{EV}^{'}\omega_e^{t}+P_{loss}^{t}\omega_{loss}^{t}+L_{Swiching}\right) \tag{13}$$

Where, $P_{DG}^{'}$ is the output power of wind and PV power generation, $P_{EV}^{'}$ is the EV charging power, $P_{lost}^{'}$ is the distribution network loss power, $L_{Swichin}$ is the switch life cost cost due to switching action, and $\omega_d^t,\omega_e^t,\omega_{loss}^t$ is the unit price of DG generation cost, EV charging cost, and network loss cost, respectively.

The integrated cost of distribution network consists of four parts. The first part of the objective function represents the generation cost of distributed power DG, then:

$$P_{DG}^{'}=\sum_{i=1}^{N_1}P_{i,DG}\cdot\Delta t_t \tag{14}$$

where N_I is the number of distributed power supply DGs, $P_{i,DG}$ is the output power of the i rd distributed power supply, and Δt_t is the length of distributed power supply operation.

The second part considers the cost of EV charging, then:

$$P_{EV}^{'} = \sum_{j=1}^{N_2} P_{j,EV}^{in} \cdot \Delta t_t^{in} - \sum_{j=1}^{N_3} P_{j,EV}^{out} \cdot \Delta t_t^{out} \tag{15}$$

Where, N_2 is the total number of EVs in each category, $P_{j,EV}^{in}$ is the charging power of the j rd EV, N_3 is the number of EVs in motion, $P_{j,EV}^{out}$ is the power of the j th EV, Δu_i^m is the charging time of the EV, and Δt_i^{out} is the driving time of the EV.

The third part represents the network loss in the operating state of the active distribution network, then:

$$P_{loss}^{'} = \sum_{i \grave{o} N} P_{i,loss} = \sum_{i \grave{o} N} \frac{P_i^2 + Q_i^2}{U_i^2} \cdot R_i \cdot L \tag{16}$$

where N is the set of distribution network branches, R_i is the resistance of the i rd branch, L is the distribution network topology connection matrix, P_{ilas} is the active power loss of the i th branch, P_i, Q_i is the active and reactive power flowing through the end of the line in a certain state of the line, and u_i is the value of the node voltage at the end of the branch i in a certain state.

The fourth part of the objective function is the switch lifetime cost due to switching action, then:

$$L_{Switching} = \sum_{i=1}^{N_5} N_{i,S} \omega_S = \sum_{i=1}^{N_5} \sum_{j=1}^{M} \omega_S \mid S_{j,i} - S_{j,i-1} \mid \tag{17}$$

Where, $N_{i,s}$ is the state of the i nd active to the distribution network, N_s is the number of active distribution network states, M is the number of switches with state changes, ω_s is the cost required to operate a switch action, $S_{j,t}$ is the state of switch j at i, and the value of switch j is 0 when it is open, and the value of switch j is 1 when it is closed.

It is worth noting that the open and closed states of the switches in each time slot division of the active distribution network are represented by vector X_t^i, i.e.:

$$X_i^{'} = \left[S_1^{'}, S_2^{'}, S_3^{'}, \ldots, S_{N_s}^{'} \right] \tag{18}$$

2.2.2. Constraints. The distribution network topology reconfiguration should satisfy the following constraints:

1) Tidal flow constraints, i.e:

$$\begin{cases} P_i = U_i \sum_{j=1}^{n} U_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \\ Q_i = U_i \sum_{j=1}^{n} U_j (G_{ij} \cos\theta_{ij} - B_{ij} \sin\theta_{ij}) \end{cases} \tag{19}$$

where P_i and Q_i are the active and reactive power injections at node i, respectively, U_i and U_j are the magnitudes at node i and node j, respectively, θ_{ij} is the phase difference between node i and node j, and G_{ij} and B_{ij} are the conductance and conductivity of the corresponding elements in the node conductance matrix, respectively.

2) Voltage constraints, i.e:

$$U_{i\min} \le U_i \le U_{i\max} \tag{20}$$

Where: $U_{i\max}$ and $U_{i\min}$ are the upper and lower lines of node i voltage.

3) The branch power constraint, i.e:

$$S_i \le S_{i\max} \tag{21}$$

4) Network topology constraints, i.e., the system is a connected topology without loops and islands.

5) Switching constraints

In dynamic reconfiguration, while the above conditions are satisfied, the switching lifetime constraints must also be satisfied, which include individual switching lifetime constraints and overall switching lifetime constraints, as reflected in the number of switching operations. Namely:

$$\begin{cases} \sum_{i=1}^{M} | S_{j,i} - S_{j,i-1} | \le S_{j\max} \\ \sum_{j=1}^{N} \sum_{i=1}^{M} | S_{j,i} - S_{j,i-1} | \le S_{\max} \end{cases} \tag{22}$$

where $S_{f\max}$ is the maximum number of operations corresponding to a switch that can be allowed in the distribution network, and $S_{\max}$ is the maximum number of operations that the overall switch life in the distribution network can withstand.

3. Optimization solution method for topology reconfiguration model of distribution network

The increasing demand for electrical energy has led to a series of problems such as feeder overloads and voltage overruns occurring with increasing frequency. Moreover, the high penetration of distributed power sources and the popularity of electric vehicles make it necessary to consider the impact of these factors when performing distribution network topology reconfiguration. Traditional reconfiguration methods are generally divided into centralized and decentralized control, where centralized control uses one or more control centers to develop a globally optimal reconfiguration scheme. Decentralized control, on the other hand, has no control centers, so it is difficult to achieve the global optimal processing, but its robustness is very good. Under the traditional localized control method, the integration of DG units in distribution networks can seriously affect the system voltage level, resulting in over-voltage or under-voltage, leading to an increase in system losses, as well as affecting the on-load regulator transformers and shunt capacitors. Based on this, this paper proposes a distribution network topology reconfiguration model solution method that combines Levy flight and electric eel foraging algorithms, in order to obtain the optimal distribution network topology reconfiguration strategy and realize the effective balancing of distributed power generation and electric vehicle charging and discharging.

3.1. Electric eel foraging with Levy flight algorithm

3.1.1. Electric eel foraging optimization algorithm. The electric eel foraging optimization algorithm (EEFO) is a novel bionic meta-heuristic algorithm inspired by the group foraging behavior of electric eels in nature, which solves the optimization problem to be solved by mathematically modeling four foraging behaviors, namely, interacting, resting, hunting, and migrating of electric eels [29].

1) Initialization. Initialize the spatial location of the electric eel, then:

$$x_i = Low + \eta_1 \times (Up - Low), i = 1, 2, \ldots, N \tag{23}$$

where x_i is the position of the i nd electric eel, Up, Low is the search space limit, r_1 is the random number in the range of [0, 1], and N is the electric eel scale.

2) Interaction behavior. In EEFO, electric eels use the information of all electric eel positions in the population to interact with the information of randomly selected electric eel positions in the population, and determine the updated position of the electric eel by comparing the difference between the position of the randomly selected electric eel and the position of the center of the population, and this interaction behavior makes the electric eel move in different directions in the search space to explore a larger search space, and this behavior is considered to be the EEFO global exploration phase. To wit:

$$\begin{cases} \begin{cases} x_i(t+1) = x_j(t) + C \times (\bar{x}(t) - x_i(t)) & p_1 > 0.5 \\ x_i(t+1) = x_j(t) + C \times (x_r(t) - x_i(t)) & p_1 \leq 0.5 \end{cases} fit(x_j(t)) < fit(x_i(t)) \\ \begin{cases} x_i(t+1) = x_i(t) + C \times (\bar{x}(t) - x_j(t)) & p_2 > 0.5 \\ x_i(t+1) = x_i(t) + C \times (x_r(t) - x_j(t)) & p_2 \leq 0.5 \end{cases} fit(x_j(t)) \geq fit(x_i(t)) \end{cases} \tag{24}$$

where $x_i(t+1)$ is the $t+1$ rd iteration position of the i nd electric eel, $x_j(t)$ is the current randomly selected position of electric eel j, $x_i(t)$ is the current iteration position of the i th electric eel, $\bar{x}(t)$ is the average position of all electric eels, p_1, p_2 is a random number in the range of [0,1], C is the electric eel churning coefficient, $C = n_1 \times B$, n_1 is the normal distribution obeying the mean value of 0 and the standard deviation of 1, $x_r = Low + r \times (Up - Low)$, r is a random number in the range of [0,1], $fit(x_j(t))$, $fit(x_i(t))$ is the the fitness value of the current position of the i th and j th electric eels.

3) Resting Behavior: In EEFO, electric eels will establish a resting area before entering the resting state. When rest is established, the electric eel will update its position to move toward the resting area according to the resting area position. Then:

$$x_i(t+1) = R_i(t+1) + n_i \times (R_i(t+1) round(rand) \times x_i(t)) \tag{25}$$

where $R(t+1)$ is the resting position of the i nd electric eel, n_1 follows a normal distribution with mean 0 and standard deviation 1, $roumd()$ is a rounding operator function, and $rand$ is a random number in the range [0,1].

4) Hunting behavior. When electric eels hunt, they tend to swim in concert and form a large electrically charged circle of water surrounding the prey. In EEFO, this large electrically charged circle of water is the hunting area. When hunting, electric eels will quickly locate the new position of the prey and swim in a spiral pattern within the hunting zone to hunt. Then:

$$x_i(t+1) = H_{pery}(t+1) + \eta \times (H_{pery}(t+1) - round(rand) \times x_i(t)) \tag{26}$$

where, $H_{prey}(r+1)$ is the location of the gray area in the hunting area, η is the spiral swimming factor $\eta = e \dfrac{r_3(1-t)}{T} \times \cos(2\pi r_3)$, r_3 is a random number in the range of (0, 1], and t, T is the current iteration number and the maximum iteration number.

5) Migration behavior. In EEFO, when electric eels find prey, they will migrate from resting area to hunting area. Then:

$$x_i(t+1) = -r_4 \times R_i(t+1) + r_5 \times H_r(t+1) - L \times (H_r(t+1) - x_i(t)) \tag{27}$$

where r_4, r_5 is a random number in the range (0,1), $H_r(t+1)$ is any position in the hunting area, $H_r(t+1) = x_{prey}(t) + \beta \times |\bar{x}(t) - x_{prey}(t)|$, $x_{prg}(t)$ is the current prey position, $\bar{x}(t)$ is the current average position of the electric eel, β is the size of the hunting area, and L is the Levy flight function.
6) Energy factor. In EEFO, the search behavior is determined by the energy factor E, which can effectively balance the transition between exploration and exploitation to improve the optimization performance of the algorithm. Then:

$$E(t) = 4 \times \sin(1 - \frac{t}{T}) \times \ln \frac{1}{r_6} \tag{28}$$

where $E(t)$ is the energy factor, which decreases with the number of iterations, and when $E(t)$ is greater than 1, the electric eel conducts global search in the whole search space through interaction behavior and enters the exploration phase. When the energy factor and is less than or equal to 1, the electric eel conducts local search in the promising subregion through migration, resting, or hunting behaviors, and enters the exploitation phase, and r_6 is a random number in the range of (0,1).

3.1.2. Levy flight strategy. Levy flight strategy it is a non-Gaussian stochastic transformation process [30]. Levy flight strategy its frequent small distance transformations and occasional long distance jumps with respect to time follows the characteristics mentioned in the relevant literature, these characteristics are simplified and Fourier transformed to obtain its expression as:

$$\begin{gathered} levy \sim \mu = t^{-\lambda} \\ 1 < \lambda < 3 \end{gathered} \tag{29}$$

After research, it was found that the above equation is difficult to implement it in a programming language, but this does not affect the strong robustness and researchability of the Levy flight strategy, some scholars and experts continue to study it until the following proposed by Mantegna, a researcher of the Levy flight strategy, to simulate the Levy flight trajectory. To wit:

$$\begin{gathered} s = \frac{\mu}{|v|^{-\beta}} \\ 0 < \beta < 2 \end{gathered} \tag{30}$$

where s is the Levy flight step $L(\lambda), \beta = 1.5$, μ and v are two random variables in the Levy flight strategy. μ and v are two random variables conforming to the distribution, viz:

$$\begin{cases} \mu = N(0, \sigma_\mu^2) \\ v = N(0, \sigma_v^2) \end{cases} \tag{31}$$

where $\sigma_\mu \sigma_v$ is obtained from the following equation, viz:

$$\begin{cases} \sigma_\mu = \left\{ \dfrac{\Gamma(1+B) + Sin(\pi^{*\beta} /_2)}{\Gamma[(1+\beta /_2)]^* \beta^* 2^{(\beta-1)/_2}} \right\}^{\frac{1}{\beta}} \\ \sigma_v = 1 \end{cases} \tag{32}$$

where Γ is a gama distribution function and $\beta = 1.5$.

3.2. Distribution network topology reconfiguration model solution

3.2.1. Levy flight optimized electric eel foraging algorithm. The electric eel foraging algorithm is a stochastic search by simulating the four basic behaviors of electric eel foraging. The EEFO algorithm is characterized by a simple principle, easy to set the objective function, low requirements for initial values and parameters, excellent parallelism characteristics, fast convergence speed and strong global search capability. With the continuous deepening of the research and application of the EEFO algorithm, researchers have found that there are many problems in the EEFO algorithm, for example, as the number of electric eels continues to increase, it will lead to a sharp increase in the computational volume of the algorithm, which in turn occupies a larger storage space. The stochastic nature of the algorithm makes it only converge to the neighborhood of the global extremes, and when the search region is relatively large, or in the change of the flat region, the algorithm's convergence speed is slow and the search efficiency is low. The algorithm converges slowly and easily to local extremes in the later stages of the search. These problems show that the EEFO algorithm has a large optimization space.

Aiming at the deficiencies in the EEFO algorithm, this paper introduces the Levy flight strategy into the stochastic operator, and proposes a LF-EFO algorithm based on the Levy flight and the EEFO algorithm. The Levy flight is a stochastic wandering model, which is characterized by a short-range in-depth local search interspersed with an occasional longer-range walk. Therefore, introducing Levy flight into the stochastic operator can enhance the local search ability of the EEFO algorithm and expand the search range of the EEFO algorithm so that it can jump out of the local optimum more easily.

Let the current position of electric eel i be X_i. Levy flight is used to update the current position of electric eel i. The position update method can be expressed as follows:

$$X_i^{t+1} = X_i^t + k\frac{u}{|v|^{1/\beta}}(X_i^t - Gbest^t) \tag{33}$$

Where $X_i^{'}$ is the position of electric eel i at the t rd search, $Gbest^{'}$ indicates the position of the optimal electric eel in the current population, u and v obey normal distribution, β is generally taken as a constant of 1.5, and k is the step size control factor.

The implementation steps of the LF-EEFO algorithm are as follows:

Step1 Initialize the parameters of electric eel foraging, total number of electric eels, step length, number of attempts, field of view, maximum number of swimming steps, Levy in-flight step control factor, etc.

Step2 Calculate the initial adaptation value corresponding to each electric eel, and assign the state of the optimal electric eel and its corresponding adaptation value to the bulletin board.

Step3 Judge whether each electric eel satisfies the clustering condition, and execute the interaction operator if it satisfies, otherwise execute the rest operator. In the rest operator, when the adaptation value of the electric eel is not improved after the number of attempts, the position of the electric eel is updated by Levy flight.

Step4 Judge whether each electric eel meets the hunting condition, if it meets, execute the hunting operator, otherwise execute the rest operator. In the rest operator, when the adaptation value of the electric eel is not improved after the number of attempts, the position of the electric eel will be updated by Levy flight.

Step5 Compare the adaptation values obtained by each electric eel in Step3 and Step4, and take the state corresponding to the better adaptation value as the current state of the electric eel.

Step6 Compare the current fitness value of each electric eel, if the current optimal fitness value is better than the fitness in the bulletin board, then write the current optimal value into the bulletin board.

Step7 Judge whether the algorithm reaches the end condition, if so output the corresponding result. Instead go to Step3.

3.2.2. Distribution network topology reconfiguration model solution process. After the dynamic reconfiguration time period is divided into multiple segments, the connection between segments cannot be cut off to consider only the system state in a single segment for the reconfiguration solution, and the optimal network structure cannot be solved by reconfiguration in each segment only, while ignoring other suboptimal solutions. Because the reconstruction result of the previous segment will affect the reconstruction solution of the next segment, which may lead to the reconstruction result of the previous segment is better and the reconstruction result of the next segment is worse, or lead to the reconstruction result of the previous segment is worse and the reconstruction result of the next segment is better, and the full-time reconstruction results of the last two cases are similar. In many cases, the reconstruction results need to satisfy not only the requirements of full-time reconstruction, but also the requirements of individual segments. This requires that the chosen dynamic reconstruction scheme ultimately solves a set of alternative solution sets rather than a single solution. Combining the distribution network topology reconstruction model with DG and EV given in the previous section and the LF-EEFO algorithm, then the distribution network topology reconstruction process is as follows:

1) Simulate the DG output and EV charging load in each time period, and superimpose the original network node load data in each time period to form the equivalent node load curve in each time period.

2) The amplitude and morphological similarity between node load curves are used as the basis for dividing the time periods, the objective function is constructed, and the segmentation scheme that minimizes the objective function (the location of the segmentation point) is identified as the optimal scheme under the segmentation under each number of segments.

3) After determining the segmentation points and the number of segments, the average load within each segment is taken as the equivalent load of each segment.

4) Multi-objective reconfiguration is solved within each segment using the LF-EFO algorithm, where the search space dimension of each electric eel is the number of basic loops when all switches of the system network are closed.

5) A set of Pareto solution sets is solved after the reconstruction within each segment, and since each segment of static reconstruction is based on the reconstruction results of the previous segment, the Pareto solution set solved in the last segment contains all the cases of the previous segments. The judgment of dominant and non-dominant relationship is performed on this solution set, and all the non-dominant solutions obtained are the multi-objective dynamic reconstruction solution set of the distribution network topology.

6) The obtained solution set is evaluated and ranked by the ideal solution method based on entropy weight, the solution with the highest evaluation is selected, and it is judged whether the solution satisfies the constraints, if yes, the result is outputted, otherwise the suboptimal solution is selected.

4. Example validation analysis of distribution network topology reconfiguration models

With the increasing penetration of distributed generation (DG) and electric vehicles (EVs) in the distribution network, the volatility and uncertainty of DG output and the disordered charging of EVs have brought about a greater impact on the reconfiguration of the grid topology and normal operation. In order to realize the dual-carbon goal and establish a new type of power system, DG plays an important role in the power system. However, the uncertainty of intermittent DG output brings great challenges to the secure operation of the power system. In addition, the rapid popularity of EVs in recent years has made traveling more environmentally friendly, but their disorderly charging and discharging also bring certain impacts to the power grid, which can easily lead to voltage deviation, over-voltage, and network loss increase in the distribution system. Coordination between EVs and DGs is needed to ensure the safe and reliable operation of the distribution system.

4.1. Algorithm Validation Analysis

4.1.1. IEEE-33 node system setup. The IEEE-33 node system used in this paper is shown in Fig. 1, which is utilized for the arithmetic analysis of topology reconfiguration of the distribution network.

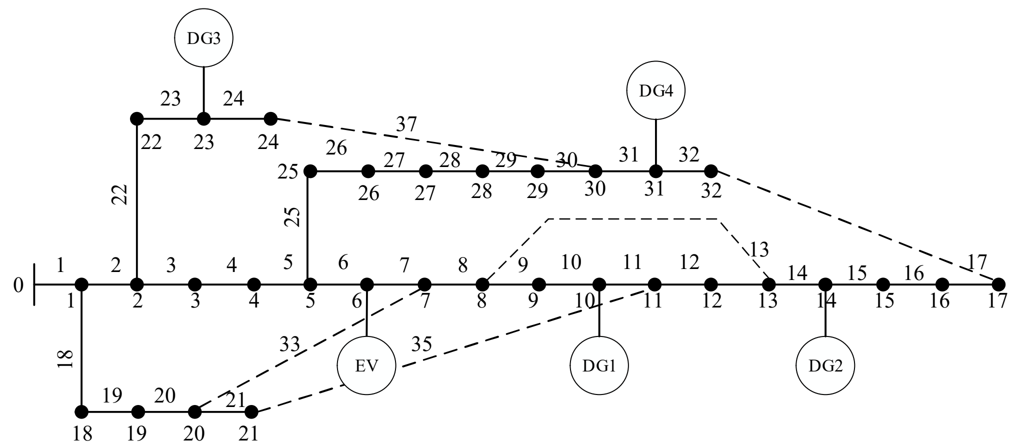

Fig. 1. IEEE-33 node system

The system consists of 33 nodes and 37 branches, 5 contact switches, each branch is equipped with sectional switches, the base voltage is 12.67kV, the base power is 110MV-A, and the total load is 2802kW+j2400kVar. DGs numbered 1-4 are connected to nodes 10, 14, 23, and 31, and the outputs are respectively DG1 active output 0.25MW, DG2 active output 0.32MW, DG3 active output 0.31MW, reactive output 0.16MVar, and DG4 active output 0.16MW. 400 electric vehicles are connected at node 6, each with a capacity of 27.05kW-h, and the average power consumption of the electric vehicles is 016kW -h/km, and the maximum charging power is 3.5 KW.In the LF-EFO algorithm, the electric eel population size is set to 60, the number of iterations is set to 200, and the learning factor is 2.5.

4.1.2. Distribution network topology reconfiguration without DG access. In order to prove that the LF-EFO algorithm has the advantages of fastness and high accuracy in the topology reconfiguration solving process of distribution networks, it is compared and analyzed with the traditional AFSA, Binary Particle Swarm Algorithm (BPSO), and Genetic Algorithm (GA) applied to the reconfiguration optimization of the topology reconfiguration test system for distribution networks without access to DG, respectively. The population size is set to be 40, the maximum number of iterations is 100, and the relevant parameters of the LF-EEFO algorithm are consistent as in the previous section. The comparison results of switch change, network loss and its load balance before and after reconfiguration are shown in Table 1, and the convergence characteristic curve of each algorithm is shown in Fig. 2.

From Table 1 and Fig. 2, it can be seen that the LF-EEFO algorithm and other algorithms can be applied to network reconfiguration optimization solving and get the same optimal solution. And to a certain extent, it has the effect of reducing the network loss and load balancing degree, so that the network is more economical, stable and reliable. The effect of LF-EEFO algorithm is more obvious compared with other algorithms, and the lowest node voltage is improved from 0.915p.u. of the initial network to about 0.942p.u., and the loss of the network is reduced by about 31.86% relative to the pre-reconfiguration period, and in addition, the load balancing degree is reduced by 0.191. In addition, the LF-EEFO algorithm has fast optimization characteristics in the optimization solving of distribution network topology network reconfiguration, the number of iterations can obtain the optimal value in about 70 times, which is obviously faster than other algorithms, and it can be seen from the figure that after falling into the local optimal solution can be jumped out right away, and the time of falling into the local optimum is reduced, so the effect of optimization search is better.

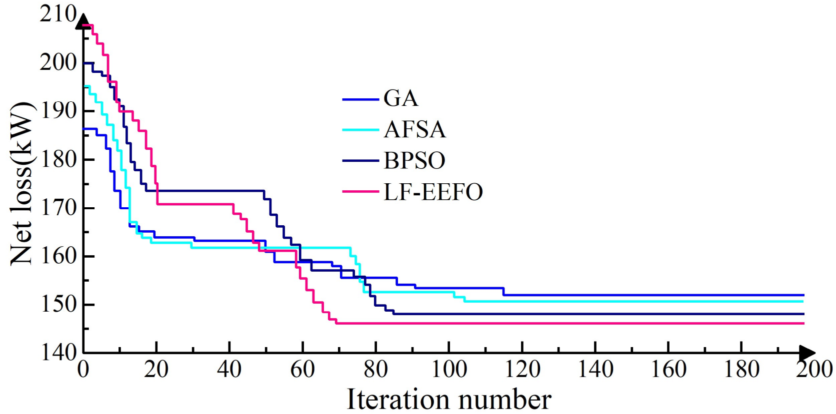

Fig. 2. The convergence characteristic curve of each algorithm

Table 1. Results before and after reconfiguration of distribution network without DG

Algorithm	Net loss/kW	Min node voltage/p.u.
Before	203.68	0.915
GA	145.27	0.931
AFSA	141.38	0.934
BPSO	138.52	0.938
LF-EEFO	138.79	0.942
Algorithm	Load equalization	Disconnect switch
Before	1.674	33, 34, 35. 36, 37
GA	1.648	7, 14, 9, 32, 29
AFSA	1.635	7, 14, 9,31, 28
BPSO	1.528	7, 14, 10, 31, 28
LF-EEFO	1.483	7, 14, 9, 31, 36

In order to verify that the LF-EFO algorithm can be generally applicable to the optimization of topology reconfiguration solution for distribution networks with better stability, the results of each algorithm running for 50 times are taken for comparative analysis, and the results of the analysis are shown in Table 2. The results are shown in Table 2, where AIT represents the average number of iterations, the minimum number of iterations (MIT) is the value of the minimum number of iterations for the algorithm to converge to the optimal solution, and the optimization rate (OR) is the ratio of the number of experimental runs for the algorithm to converge to the optimal solution to the total number of experimental runs.

As can be seen from the table, the average number of times that the LF-EFO algorithm converges to the optimal solution is similar to that of BPSO, stabilized at about 37.51 times, which is obviously smaller than that of the other two algorithms, but compared with the BPSO's running time of 18.42s, the algorithm of this paper only used 13.26s, which is obviously better, and the optimality rate of the LF-EFO algorithm can reach up to 100%, which is higher than that of the other algorithms, and basically, it can converge in 30 runs. Basically, it can converge to the optimal solution in 30 runs. Therefore, the combination of Levy flight and electric eel foraging algorithm in this paper can be effectively applied to the optimization calculation of distribution network topology reconstruction, and has the characteristics of fast convergence to the optimal solution and high computational efficiency.

Table 2. Performance comparison analysis results of algorithm

Algorithm	MIT	AIT	Mean time/s	OR/%
GA	34	52.38	26.38	68.42
AFSA	31	46.42	20.51	83.57
BPSO	23	37.65	18.42	97.69
LF-EEFO	28	39.51	13.26	100.00

4.1.3. Distribution network topology reconfiguration with DG access. The reconfiguration of the topology of the distribution network with DG access causes significant changes in the distribution network, and the LF-EEFO algorithm designed in this paper is utilized to solve the topology reconfiguration schemes of the distribution network with different types of access to DG. Figure 3 shows the distribution of voltage at each node of the distribution network with access to DG, and Table 3 shows the topology reconfiguration scheme of the distribution network with access to DG.

From the table, it can be seen that the network loss of the system decreases from 203.68 kW to 171.69 kW after adding distributed power supply, which is an overall decrease of 15.71%, and the network loss rate decreases by 1.18%, and the minimum voltage of the node is improved from 0.915

p.u. to 0.919 p.u. It shows that the reasonable inclusion of DG in the distribution network can reduce the loss of the network and the network line loss rate, and can also improve the power supply quality of the distribution network. Optimal reconfiguration of distribution network using the improved method of this paper can obtain nine distribution network topology reconfiguration schemes, which can be flexibly selected by decision makers according to their own criteria or actual situation. If the decision maker focuses on reducing the network loss, he/she can choose Scheme 1, in which the network loss in the line is reduced from 171.69kW to 114.37kW, which is 33.39% lower, and the network loss rate is reduced by 1.57%. If the decision maker needs to consider the number of switch operations and network loss in a comprehensive way, then option 9 can be chosen, which can reduce the network loss to 126.62kW by operating only three switches, reducing the network loss by 26.25% and the network loss rate by 0.94%. From the voltage distribution of the distribution network topology before reconfiguration and reconfiguration scheme 1 with access to the DG, the voltage after reconfiguration is significantly improved, and the minimum voltage of the distribution network is increased from 0.919 p.u. to 0.948 p.u., which is improved by 3.16%. In summary, the multi-objective optimal reconfiguration of distribution network topology using the LF-EEFO algorithm of this paper can obtain a set of Pareto optimal solution set schemes, in which the decision makers can choose according to their own criteria or the actual situation at that time, and select the satisfactory optimal decision-making scheme. Meanwhile, it can also be seen from the above results that the reconstructed Pareto optimal solution set also contains the optimal solution of static reconstruction for a single objective. Therefore, the multi-objective optimal reconstruction of distribution network topology using the LF-EEFO algorithm in this paper can provide more choices for decision makers on the one hand, and on the other hand, ensure that these optimal solutions contain optimal states under different operational requirements.

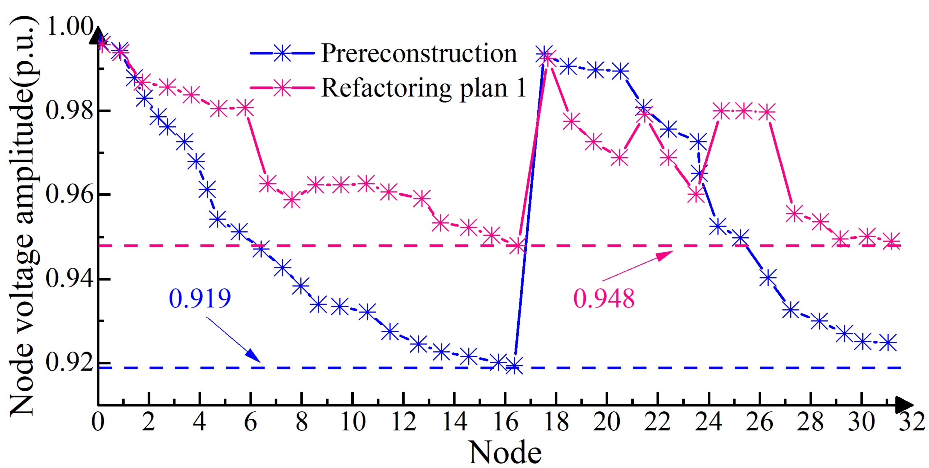

Fig. 3. Each node voltage of the distribution network of DG

Table 3. Access to DG's distribution network topology reconstruction scheme

Scheme	Disconnect switch	Net loss/kW	Min node voltage/p.u.	Load equalization	Switch operation times
Before	7,8,14,17,24,28,32	171.69	0.919	1.685	0
1	8,9,12,15,16,27,28	114.37	0.948	1.472	12
2	6,7,8,13,14,27,28	115.68	0.945	1.469	10
3	8,9,13,14,20,27,28	117.26	0.946	1.461	10
4	10,11,14,15,20,27,28	117.49	0.948	1.463	8
5	10,11,14,20,27,28,32	118.75	0.944	1.458	6
6	7,8,9,10,20,27,28	118.93	0.944	1.452	5
7	8,9,14,20,27,28,32	119.45	0.945	1.449	5
8	7,8,14,20,27,28,32	120.88	0.945	1.443	5
9	7,8,14,24,28,29,32	126.62	0.931	1.438	3

4.2. Comparison of different reconfiguration schemes

4.2.1. Topology Reconfiguration of Distribution Networks with DG and EVs. In order to verify the effectiveness of the proposed analysis method containing EV reconfiguration, this paper chooses to take the IEEE-33 node system as an example, and selects the node 6, which is more densely loaded in the system, to access the EV charging station, which provides charging and discharging services for 400 EVs, as shown in Fig. 1 in Section 4.1. In the example analysis, it is assumed that the daily driving distance of EVs is fixed, the average value of charging power is expected to be 450 kW, and the average value of discharging power is expected to be 250 kW. The distributed EV charging power daily load curve is used to simulate the load power curve of the accessed charging station. At the same time, it is set that the charging station injects power into the distribution network from 09:00 to 00:00, and absorbs power from the distribution network for charging from 00:01 to 08:59.

According to the time period division, combined with the distribution of electric vehicle charging power daily load curve, the charging power expectation during the two time periods is 475.32MW and 62.56MW respectively, which will be uniformly distributed on the selected access load nodes as the specific power values consumed by the charging station, then the charging power expectation of the charging station at a single location is 475.32kW and 62.56kW respectively. According to the time period division, the The total power consumed by the charging station in the first time period is about 450kW, and the total power injected into the distribution network in the second time period is 250kW, and the maximum capacity is directly substituted into the calculation in the analysis of the example. For the analysis of the example, the model is solved using the LF-EFO algorithm, and the results of the topology reconstruction of the distribution network with access to EV are shown in Table 4. In the table, Ⅰ, Ⅱ and Ⅲ are the reconfiguration results for the first time slot, the second time slot and the integrated time slot of the access EV, respectively.

From the results in the table, for the distribution network topology reconfiguration results carried out within time period I the system network loss is 183.43 kW and the lowest node voltage is 0.936 p.u., while the distribution network reconfiguration results carried out within the second time period the system network loss is 145.26 kW and the lowest node voltage is 0.948 p.u.. The main consideration is that EVs absorb power from the distribution grid as a consuming load during time period one and inject power into the system during time period two, and throughout this process, the loads in the arithmetic system are basically treated as static loads due to the fact that there is not much change in the loads in the arithmetic system. Through the charging and discharging regulation of the system by the EV charging station, the active loss during the peak load period of the system shows a lower state, thus obviously providing the system with the driving effect of peak shaving and valley filling, so as to achieve the purpose of optimizing the operation of the distribution network.

Table 4. Refactored the distribution network topology of the EV

Content	Before	I	II	III
Contact switch set	9~20	6~8	6~8	6~8
	8~16	8~16	13~16	13~16
	13~21	8~11	13~21	13~21
	19~32	30~32	29~31	30~32
	26~30	27~28	27~28	26~30
Net loss/kW	203.27	183.43	145.26	160.18
Min node voltage/p.u.	0.916	0.936	0.948	0.937

In the case of distributed power supply and electric vehicles accessing the distribution network at the same time, it is necessary to comprehensively consider the complementary role of distributed power supply to the distribution network trend and the charging and discharging control optimization of electric vehicles formed on the system in time periods, that is, combining the charging and discharging optimization of distributed power supply outlets and electric vehicle charging stations at the same time, to jointly provide support for the uniform trend of the distribution network. Combining the examples of reconfiguration with distributed power supply and reconfiguration with electric vehicle carried out separately in the previous paper, the specific parameters of electric vehicle charging station and distributed power supply are the same as those analyzed in the above paper. Using the LF-EEFO algorithm constructed in this paper, the relevant power inputs for the reconfiguration optimization of the distribution network topology containing DG and EV are obtained as shown in Table 5.

The finally obtained reconfiguration optimized distribution network topology is contact switch collection 6-8, 15-16, 13-21, 30-32, 27-29, and the system network loss is only 98.41 kW, the lowest node voltage is 0.964, and the load balancing degree is reduced to 1.276. Meanwhile, comparing the results of the reconfiguration of the topology of the distribution network that contains the distributed power source and the EV charging station, respectively, it can be seen that for the It can be seen that the integrated optimal scheduling control of the two can get lower system loss and achieve more obvious economic operation effect.

Table 5. The power optimization results of DG and EV

Content	Access load node	Capacity	Optimized result
DG output	10	60	60
	14	120	110
	23	240	220
	31	120	100
EV discharge power	6	400	300

4.2.2. Comparison of dynamic reconfiguration schemes for distribution network topology. In order to further validate the effectiveness of the distribution network topology reconstruction scheme containing DG and EV obtained by the LF-EFO algorithm, the reconstruction scheme in this paper is compared with the data obtained by the Multi-intelligent Genetic Algorithm (MAGA), the Harmonic Search Algorithm (HSA), the Variable Neighborhood Search Algorithm (VNS), and the Improved ABC algorithm for the reconstruction of the distribution network topology. The comparison results of different dynamic reconfiguration schemes are shown in Table 6.

The comparison shows that the number of switching actions obtained by the distribution network topology reconfiguration using the LF-EFO algorithm in this paper is only 10 times, which relatively reduces the network loss rate to 51.68%, and the total economic loss is only $915.8, and the overall economic savings rate reaches 30.78%. Therefore, the dynamic reconfiguration of the distribution network topology with DG and EV can be realized by the LF-EEFO algorithm based on the consideration of different output and absorbed power of distributed generation and EV. In addition, the reconfiguration scheme obtained in this paper based on the LF-EEFO algorithm performs well in terms of loss reduction, cost saving and voltage quality improvement, which proves the superiority of the topology reconfiguration strategy of the distribution network in this paper by comparing the results with other reconfiguration schemes.

Table 6. The dynamic reconstruction scheme compares the results

Scheme	MAGA	HSA	VNS	ABC	LF-EEFO
Time period	09:00~00:00 00:01~08:59	09:00~00:00 00:01~08:59	09:00~00:00 00:01~08:59	09:00~00:00 00:01~08:59	09:00~00:00 00:01~08:59
Refactorable frequency	6	6	6	6	6
Switch action	23	18	20	14	10
Net loss-before/kW	1264.58	894.37	516.85	357.92	203.68
Net loss-After/kW	1043.79	808.46	483.27	316.63	98.41
Loss rate/%	17.46	9.61	6.50	11.54	51.68
Total economic loss/yuan	1306.7	1372.5	1142.3	1054.7	915.8
Economy rate/%	12.68	5.74	2.62	9.71	30.78

5. Conclusion

In order to realize the topology reconfiguration of the distribution network with access to distributed generation and electric vehicles, this paper proposes a model solving method for topology reconfiguration of the distribution network combining Levy flight and electric eel foraging algorithms, and carries out simulation verification and analysis based on the IEEE-33 node system. In the distribution network topology reconfiguration considering access to DG, the network loss is reduced from 203.68 kW before reconfiguration to 171.69 kW after reconfiguration, the network loss rate is reduced by 1.18%, and the minimum voltage at the node is improved from 0.915 p.u. to 0.919 p.u.. When considering the reconfiguration of the distribution network topology with access to EV, the network loss is reduced to 160.18 and the node minimum voltage is improved to 0.937p.u. under the integrated time period. The network of the distribution network topology reconfiguration result after simultaneous access to DG and EV is reduced to 98.41 kW and the minimum node voltage is 0.964. The simultaneous access of distributed generation and EV to the distribution network can better achieve the effective utilization and optimal scheduling of distributed power sources, and realize the economic operation of the distribution network.

References

[1] Soares, J., Pinto, T., Lezama, F., & Morais, H. (2018). Survey on complex optimization and simulation for the new power systems paradigm. Complexity, 2018(1), 2340628.

[2] Machowski, J., Lubosny, Z., Bialek, J. W., & Bumby, J. R. (2020). Power system dynamics: stability and control. John Wiley & Sons.

[3] Xiao, R., Xiang, Y., Wang, L., & Xie, K. (2018). Power system reliability evaluation incorporating dynamic thermal rating and network topology optimization. IEEE Transactions on Power Systems, 33(6), 6000-6012.

[4] Da Silva, N. S., Costa, A. S., Clements, K. A., & Andreoli, E. (2016). Simultaneous estimation of state variables and network topology for power system real-time modeling. Electric Power Systems Research, 133, 338-

346.

[5] Cavraro, G., & Arghandeh, R. (2017). Power distribution network topology detection with time-series signature verification method. IEEE Transactions on Power Systems, 33(4), 3500-3509.

[6] Madurasinghe, D., & Venayagamoorthy, G. K. (2023). An efficient and reliable electric power transmission network topology processing. IEEE access, 11, 127956-127973.

[7] Pandey, P. K., & Badarla, V. (2018). Reconstruction of network topology using status-time-series data. Physica A: Statistical Mechanics and its Applications, 490, 573-583.

[8] Dai, J., Huang, K., Liu, Y., Yang, C., & Wang, Z. (2020). Global reconstruction of complex network topology via structured compressive sensing. IEEE Systems Journal, 15(2), 1959-1969

[9] Fan, B., Shu, N., Li, Z., & Li, F. (2022). Critical nodes identification for power grid based on electrical topology and power flow distribution. IEEE Systems Journal, 17(3), 4874-4884.

[10] Akhavein, A., & Porkar, B. (2017). A composite generation and transmission reliability test system for research purposes. Renewable and Sustainable Energy Reviews, 75, 331-337.

[11] Tavakoli, M., & Nafar, M. (2020). Human reliability analysis in maintenance team of power transmission system protection. Protection and Control of Modern Power Systems, 5(4), 1-13.

[12] Rasmussen, T. E., Sørensen, S., Pisinger, D., Jørgensen, T. M., & Baum, A. (2024). Topology reconstruction in telecommunication networks: Embedding operations research within deep learning. Computers & Operations Research, 106960.

[13] Aziz, T., Lin, Z., Waseem, M., & Liu, S. (2021). Review on optimization methodologies in transmission network reconfiguration of power systems for grid resilience. International Transactions on Electrical Energy Systems, 31(3), e12704.

[14] Wang, J., Pan, B., Rong, L., Sun, C., & Qi, C. (2024). Topology reconstruction of the district heating network for maximizing comprehensive benefits of thermal storage. Energy, 313, 134065.

[15] Patil, H., & Kalkhambkar, V. N. (2020). Grid integration of electric vehicles for economic benefits: A review. Journal of Modern Power Systems and Clean Energy, 9(1), 13-26.

[16] Liu, Y., Fan, R., & Terzija, V. (2016). Power system restoration: a literature review from 2006 to 2016. Journal of Modern Power Systems and Clean Energy, 4(3), 332-341.

[17] Petrenko, L. D. (2021). Green trend in global energy development: Tendencies and opportunities. International Journal of Energy Economics and Policy, 11(5), 1-7.

[18] Zou, C., & Zou, C. (2020). Trend of Energy Development. New Energy, 51-67.

[19] Qin, L., Yu, X., Gui, H., Wu, L., & Ou, S. (2022). Super resolution distribution network measurement considering distribution network topology reconstruction. Energy Reports, 8, 313-320.

[20] Zou, Y., Wang, R., & Gao, Z. (2020). Improve synchronizability of a power grid through power allocation and topology adjustment. Physica A: Statistical Mechanics and its Applications, 548, 122956.

[21] Alhazmi, M., Dehghanian, P., Wang, S., & Shinde, B. (2019). Power grid optimal topology control considering correlations of system uncertainties. IEEE Transactions on Industry Applications, 55(6), 5594-5604.

[22] Mishra, S., Das, D., & Paul, S. (2017). A comprehensive review on power distribution network reconfiguration. Energy Systems, 8, 227-284.

[23] Liu, K. Y., Sheng, W., Liu, Y., & Meng, X. (2017). A network reconfiguration method considering data uncertainties in smart distribution networks. Energies, 10(5), 618.

[24] Kamaruzaman, A. F., Zain, A. M., Yusuf, S. M., & Udin, A. (2013). Levy flight algorithm for optimization problems-a literature review. Applied mechanics and materials, 421, 496-501.

[25] Maurya, P., Tiwari, P., & Pratap, A. (2024). Electric eel foraging optimization algorithm for distribution network reconfiguration with distributed generation for power system performance enhancement considerations different load models. Computers and Electrical Engineering, 119, 109531.

[26] Alejandro Valencia Díaz,Ricardo A. Hincapié & Ramón A. Gallego. (2024). Optimal Placement and Sizing of Distributed Generation in Electrical DC Distribution Networks Using a Stochastic Mixed-Integer LP Model. Arabian Journal for Science and Engineering(prepublish),1-17.

[27] Yuki Nakajima & Hiroshi Shimamoto. (2024). Mathematical Model to Evaluate the Impact of Power Supply Constraint for Electric Vehicles on Transportation Network. International Journal of Intelligent Transportation Systems Research(prepublish),1-13.

[28] Ruixi Wu. (2024). Research on the Development Trend of New Energy Electric Vehicles in China based on Mathematical Model. Scientific Journal of Economics and Management Research(10),26-33.

[29] Priyanka Maurya,Prabhakar Tiwari & Arvind Pratap. (2024). Electric eel foraging optimization algorithm for distribution network reconfiguration with distributed generation for power system performance enhancement considerations different load models. Computers and Electrical Engineering(PB),109531-109531.

[30] Wangzhou Luo,Hailong Wu & Jiegang Peng. (2024). Improvement of Electric Fish Optimization Algorithm for Standstill Label Combined with Levy Flight Strategy. Biomimetics(11),677-677.