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REVIEW

A Critical Review of Active Distribution Network Reconfiguration: Concepts, Development, and Perspectives

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ABSTRACT

In recent years, the large-scale grid connection of various distributed power sources has made the planning and operation of distribution grids increasingly complex. Consequently, a large number of active distribution network reconfiguration techniques have emerged to reduce system losses, improve system safety, and enhance power quality via switching switches to change the system topology while ensuring the radial structure of the network. While scholars have previously reviewed these methods, they all have obvious shortcomings, such as a lack of systematic integration of methods, vague classification, lack of constructive suggestions for future study, etc. Therefore, this paper attempts to provide a comprehensive and profound review of 52 methods and applications of active distribution network reconfiguration through systematic method classification and enumeration. Specifically, these methods are classified into five categories, i.e., traditional methods, mathematical methods, meta-heuristic algorithms, machine learning methods, and hybrid methods. A thorough comparison of the various methods is also scored in terms of their practicality, complexity, number of switching actions, performance improvement, advantages, and disadvantages. Finally, four summaries and four future research prospects are presented. In summary, this paper aims to provide an up-to-date and well-rounded manual for subsequent researchers and scholars engaged in related fields.

KEYWORDS

Active distribution network; reconfiguration; meta-heuristic algorithm; machine learning

Nomenclature

ABC	Artificial bee colony
ACO	Ant colony optimization

ADN	Active distribution network
BA	Bat algorithm
BEM	Branch exchange method
CSA	Cuckoo search algorithm
DABC	Discrete artificial bee colony
DN	Distributed network
DG	Distributed generation
DL	Deep learning
DMA	Discrete monkey algorithm
ESS	Energy storage system
EOA	Equilibrium optimizer algorithm
FA	Firework algorithm
HAS	Harmony search algorithm
ICSA	Improve cuckoo search algorithm
IWO	Invasive weed optimization
IAICA	Improved adaptive imperialist competitive algorithm
ISFLA	Improved shuffled frog leaping algorithm
GA	Genetic algorithm
LCM	Loop cutting method
LRA	Lagrange relaxation approach
MABC	Multi-object artificial bee colony
MPGSA	Modified plant growth simulation algorithm
MWOA	Modified whale optimization algorithm
N.P.	No proposed
OPF	Optimal flow pattern
PDN	Passive distribution network
RL	Reinforcement learning
SMA	Slime mold algorithm
TSA	Tabu search algorithm
P_{loss}	Active power loss of the network, kW
l	Number of the branch
N_l	Total number of branches
R_l	Branch impedance, Ω
x_l	Opened and closed state of the branch
T_i	Average annual outage time of load node i, s
M_i	Number of users at load node i
L_i	Average load at load node i, kW
V_i	Actual values of distribution network node voltages, kV
G_{ij}	Conductance between nodes i and j, S
θ_{ij}	Phase angle difference between nodes i and j, °
P_{FL}	Flexible load, kW
V_{id}^k	Current velocity of the ith particle
P_l	Active power flowing through the branch l, kW
Q_l	Reactive power flowing through the branch l, kVar
U_l	Voltage at the end node of the branch l, kV
$S_{l,\max}$	Capacity of branch l, kW
N_{b}	Total number of nodes

U_p	Average voltage of all nodes, kV
K	Total number of line switches in the network
V_{iN}	Rated values of distribution network node voltages, kV
X_{id}^k	Current position of the ith particle in search space
W	Inertia weight
r_1, r_2	Two random numbers
λ_i	Average failure rate of load node i
C_1 C_2	Acceleration coefficients
L_d U_d	Upper and lower limits of the search space

1 Introduction

As the last link in the power supply system [1], the distribution network directly distributes electric energy to end-users to ensure a reliable power supply [2]. For the safety of the grid, the structure of distribution networks often is shifted from a mesh topology to a radial one [3]. Note that the planning of closed-loop distribution grids and the characteristics of open-loop operation provide the groundwork for such changes [4]. Furthermore, the maturation of power electronics [5], artificial intelligence [6], communication engineering [7], and other technologies, coupled with the widespread implementation of distributed power sources [8], energy storage [9], and demand-side response [10] accelerate the development of active distribution networks (ADN) but introduce increasing complexity to the network structure [11].

Active distribution network reconfiguration (ADNR), as a crucial technology for smart grid development [12], offers several benefits such as reducing network losses [13], eliminating overloads [14], improving power quality [15], and increasing the capacity for distributed generation (DG) grid connection [16]. It can be viewed as a multi-objective and multi-constraint problem. Currently, various methods for ADNR have been proposed. Merlin and Back first formulated the distributed system reconfiguration (DSR) method as a mixed-integer nonlinear optimization problem to minimize energy loss [17]. Based on the typical daily load and output prediction of DG, Reference [18] utilized an improved optimal fuzzy C-mean clustering method to address the dynamic reconfiguration problem for minimizing feeder losses. To enhance the security and cost-effectiveness of distribution network operations, another study [19] employed the limit scenario method to robustly optimize ADN and system reactive voltage, which resolved the volatility issues associated with integrating distributed energy sources. Meanwhile, more studies focus on ADNR models. Literature [20] proposed a robust model considering generation and load uncertainty, thus effectively incorporating uncertain load demand, and fluctuating generation of DG into the reconstruction framework, and enhancing the accuracy of the reconstruction model. The study [21] provided the radial constraints applicable to different reconstruction methods from the perspective of reconstruction model solution accuracy and solution speed.

In the past few decades, a large number of ADNR methods have been proposed. To provide a comprehensive overview of the existing research methods for ADNR, this paper undertook an overall statistic on relevant literatures published from 2013 to September 2023. Furthermore, Fig. 1 depicts the statistics results, which reveal an increasing research interest in ADNR, thus indicating its emergence as a prominent and popular research topic.

Figure 1: Statistic results of ADNR methods from 2013 to September 2023

Thus far, several reviews on ADNR have been published. However, they did not provide a comprehensive and systematic summary of modeling technology, constraint condition, test system, and evaluation criteria, especially the key indicators, discussion of the targeted application, and research recommendations for ADNR. Therefore, this paper aims to provide a fully comprehensive and integrated review of the various methods used in ADNR. Specifically, the paper seeks to systematically analyze and compare different methods and develop a detailed evaluation of each method to give a comprehensive reference guide for future in-depth research in related fields. Specifically, Table 1 demonstrates the highlights and limitations of existing reviews.

Table 1: Evaluation of several previous reviews

Literature/Year	Highlights	Limitations
Sultana et al. (2016) [22]	• Consider an islanding model	• No detailed description and evaluation of the study • Vague or incomplete classification
Mishra et al. (2017) [23]	• Detailed literature review is presented • Various objective functions are reviewed • Methods of PDNR are classified in chronological order	• Lack of systematic integration of methods • Lack of quantitative evaluation of methods

(Continued)

Table 1 (continued)

Literature/Year	Highlights	Limitations
Badran et al. (2017) [24]	• Focus on power distribution systems containing distributed power supplies • Review meta-heuristics, artificial intelligence methods	• Lack of specific parameters • Lack of discussion of targeted applications • Lack of recommendations for future research • Overlook some advanced methods
Guimaraes et al. (2021) [25]	• Consider distribution network reliability, network loss	• Lack of evaluation system
Mahdavi et al. (2021) [26]	• Highlight switch time, capacitor placement, electricity market, reliability • Consider the complete scope of DSR • Integrate various methods systematically	• Lack of visual evaluation • Insufficiently detailed vision of the future
Mahdavi et al. (2021) [27]	• A detailed overview of meta-heuristics is presented • The mechanism and application of the proposed algorithm are deeply analyzed • Propose a novel ADNR method and validate the feasibility	• Lack of quantitative evaluation of methods • Non-intuitive presentation of advantages and disadvantages of various methods • Incomplete overview of ADNR methods

For the sake of overcoming these gaps addressed in Table 1, this paper aims to provide a fully comprehensive and integrated review of the various methods used in ADNR. Specifically, each method will be systematically compared, analyzed, and evaluated to formulate a reliable reference guide for future in-depth research in related fields. Fig. 2 illustrates the tackled problems and main goals.

Therefore, this paper aims to provide a fully comprehensive and integrated review of the various methods used in ADNR. Specifically, the paper seeks to systematically analyze and compare different methods and develop a detailed evaluation of each method to provide a comprehensive reference guide for future in-depth research in related fields. The main contributions of this paper are as follows:

- A comprehensive review of existing algorithms for ADNR is given, which are classified into five categories, i.e., traditional, mathematical, meta-heuristic, machine learning based method, and hybrid algorithm. Besides, the specific optimization structures and strengths and weaknesses of each algorithm are detailly introduced and analyzed.
- A set of systematic scoring guidelines based on theoretical and practical aspects are developed to analyze and evaluate various methods profoundly and objectively. Which theoretical index

incorporates optimization objective algorithm structure, and hyperparameter while the practical one includes economic cost, power and voltage loss, and practical application.
- Insightful suggestions/recommendations are proposed for further improvements of ADNR from four different aspects, i.e., technology, constant, testing system, and network.

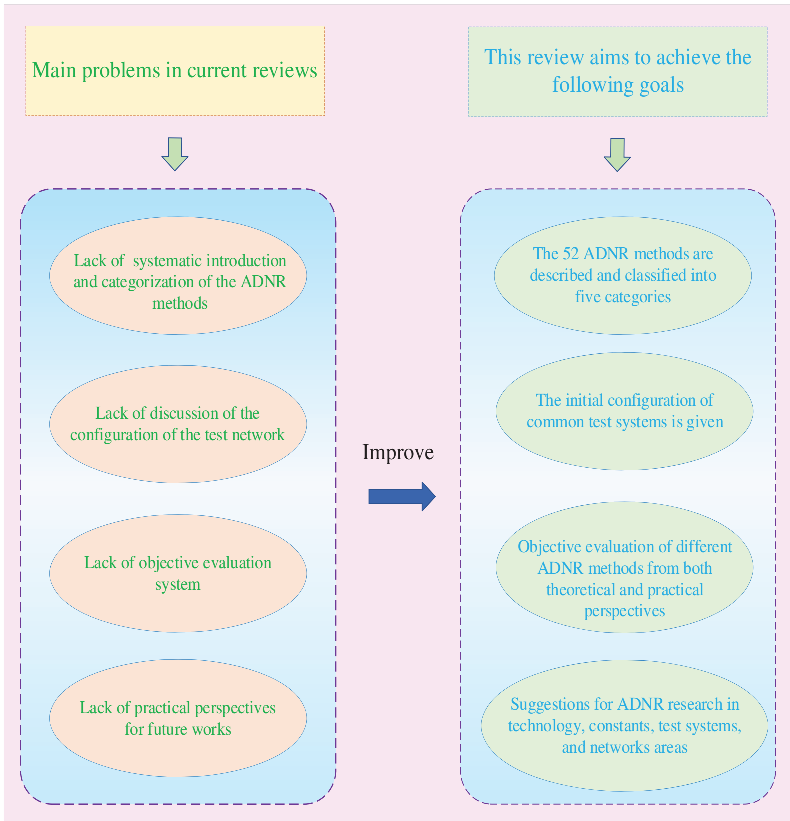


Figure 2: Tackled problems and main goals of this paper

The remainder of this paper is organized as follows: Section 2 provides the technical background of ADNR, summarizes the mathematical modeling of the ADNR process, provides detailed objective/constraint formulations, and summaries the initial state of the network configuration. Section 3 reviews 52 methods for ADNR, classified into five categories, and analyzes and compares the theoretical properties of each method, such as complexity, practicality, number of switching actions, and reconfiguration effectiveness. Section 4 provides a discussion of this literature. Finally, Section 5 offers a thorough analysis, summary, suggestions, and outlooks for future research in this area.

2 Active Distribution Network Reconfiguration

The ADN is designed as a closed-loop system with an open-loop operation, and it has a radial structure [28]. During normal operating conditions, the sectional switch is closed and the contact switch is disconnected, which allows the network to operate in a radial configuration [29]. In this state, network reconfiguration can be implemented to achieve load balancing, eliminate overloads, reduce network loss, improve voltage quality, and enhance the overall economic performance of the system.

2.1 Distribution Network

2.1.1 Passive Distribution Network

Due to the safe power supply development concept, the operation, control, and management modes of traditional distribution networks are passive, also referred to as passive distribution networks (PDNs) [30], as depicted in Fig. 3. Electric energy is primarily generated by large power plants, transmitted through the transmission grid, and ultimately distributed to consumers via the distribution network [31]. In PDNs, electric energy flows from the grid to the load, which leads to the consideration of one-way energy flow characteristics in various aspects such as line selection [32], equipment selection, relay protection, power flow control, and metering [33]. The natural distribution of load demand in PDNs cannot be automatically adjusted, and abnormal operating states and faults cannot be controlled in advance [34], making it difficult to ensure the quality of power supply in all directions and achieve optimal economic operation of the entire distribution system [35].

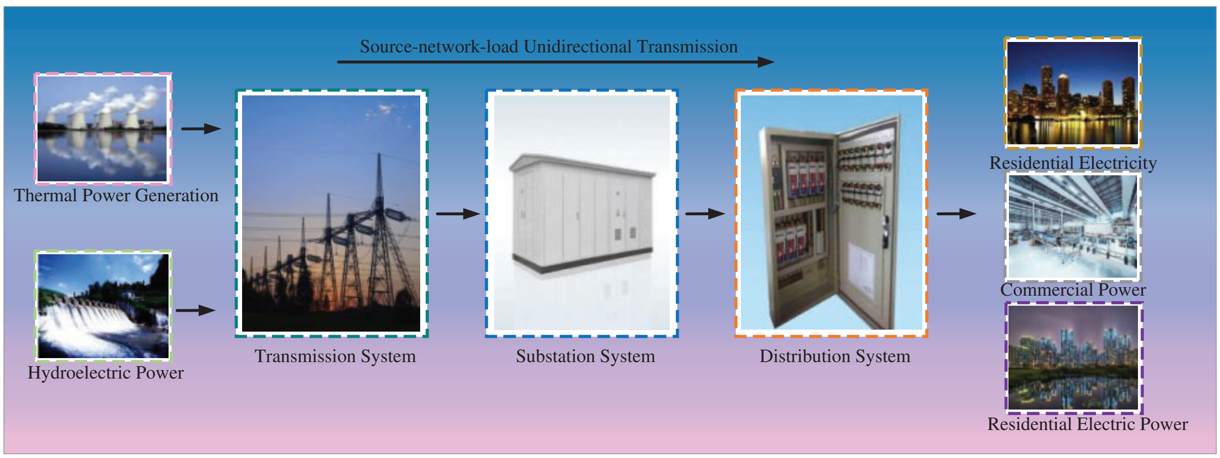


Figure 3: Passive distribution network architecture

The connection of DG to the distribution network will have a significant impact on power flow direction and magnitude [36], short-circuit current direction and magnitude [37], equipment capacity and selection [38], voltage and reactive power distribution [39], power factor and harmonics, protection coordination, and settings, automation settings and management, fault restoration, and other factors [40]. Therefore, to achieve the intelligent transformation of traditional distribution networks [41], it is crucial to establish an ADN with active control and management functions [42,43].

2.1.2 Active Distribution Network

ADN can actively control various DGs [44] via advanced technologies such as information [45], communication, and power electronics to manage power flow based on flexible network topology [46], as shown in Fig. 4. Its control purpose is to increase the capacity of acceptable renewable energy, enhance the utilization rate of distribution network assets, delay the investment in upgrading [47], and improve the quality and reliability of power supply for users [48].

Compared to the ADN, which actively controls and manages distributed energy devices in different areas through a flexible network topology [49], the traditional distribution network is based on the one-way power distribution network between grid power supply and user power consumption

[50,51]. The traditional distribution network does not participate in system frequency regulation, voltage, and reactive power control, and does not provide ancillary services to the system [52].

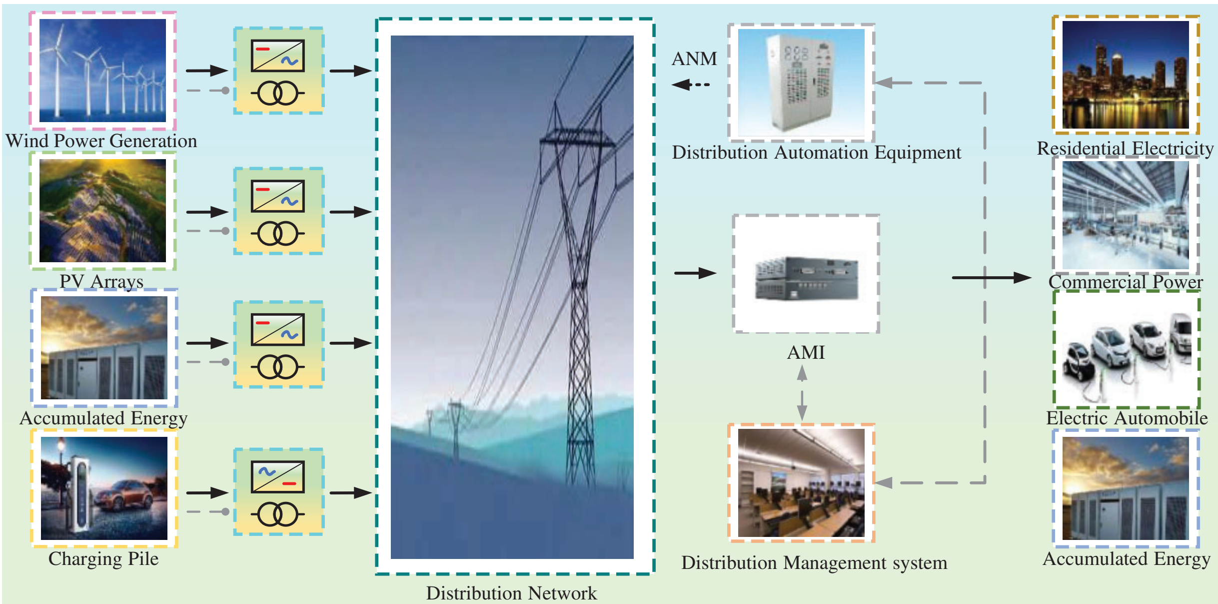


Figure 4: Distribution network architecture

2.2 Demand Response

The ADN is characterized by high penetration of distributed power sources [53] and flexible network topology [54]. These characteristics can have an impact on the magnitude of supply voltage, network loss [55], voltage distribution, and frequency range of unit operation in the power system [56]. As a result, the ADN requires cooperation with demand-side response, to enable the integration of distributed power, such as DG [57], ESS, and other distributed resources [58].

Demand-side response (DSR) is a strategy used to manage the balance between the supply and demand of the power system. When there is an imbalance between supply and demand [59], DSR involves customers taking an active role in adjusting their regular power consumption patterns in response to price incentives from the power company. This may involve reducing or shifting their load during a certain period to improve the operational efficiency of the power system [60]. DSR aims to improve the reliability and stability of the power system by matching supply and demand in real-time [61].

Demand-side response measures can be classified into two types: price-based demand-side response and incentive-based demand-side response [62]. Price-based demand-side response refers to customers arranging and adjusting their electricity consumption time [63] and mode based on targeted tariffs set by power supply companies [64,65]. Incentive-based demand-side [66] response means that power supply companies use economic incentives [67] or compensation mechanisms to motivate customers to adjust or cut their loads during peak hours based on load availability [68].

The price-based demand-side response includes three types of tariffs:

- Time-sharing tariff: This tariff divides electricity into three prices (peak, flat, and valley) based on the user's electricity consumption time.

- Real-time tariffs: This tariff fluctuates in real-time according to the cost of electricity purchased in the market and can effectively reflect the supply and demand of electricity.
- Peak tariff: This tariff sets a high price during emergencies to encourage users to use electricity at off-peak times or reduce consumption.

Moreover, the incentive-based demand-side response includes several measures:

- Direct load control: The power supply company adjusts or shuts down the customer's electricity consumption equipment remotely during peak or emergency times and compensates the customer.
- Interruptible load: After the customer signs a contract with the power supply company, the company informs the customer in advance of the outage time, capacity, and compensation method. If the customer defaults on the contract, they will be punished.
- Demand-side bidding: The customer participates in market bidding and, after a consensus is reached between supply and demand, cuts the load value.

Consequently, demand-side response can promote the transformation of traditional distribution networks while ensuring the safe and efficient operation of ADNs. It can also enable distributed power supply, achieve large-scale access to distributed power supply, and optimally allocate resources on both the supply and demand sides [69].

2.3 Distribution Network Switch

As a large number of distributed power sources and ESSs are put into operation, the distribution network experiences spatial and temporal differences in load [70], uneven distribution of tidal currents, and large network losses [71]. In such cases, the topology of the distribution network must be changed by altering the opening and closing states of switches [72]. Faulty branches can be isolated by closing some normally open switches [73], while faulty loads can be transferred to other feeders by breaking some normally closed switches [74]. Reconfiguration of the ADN is achieved by changing the topology of the network by switching the state of switches in the distribution network [75]. This balances the load [76], eliminates overload [77], balances current, and reduces network loss [78].

2.4 Reconfiguration Goals

(1) Reduction of power loss

Network loss reduction [79,80] is the most common objective of distribution network reconfiguration [81,82], and its objective function expression is as follows:

$$f(\mathbf{X}) = \sum\nolimits_{\forall i \in \psi^{\text{line}}} R_i \times |I_i|^2 \tag{1}$$

where the control vector $\mathbf{X}$ includes three parts. (i) Status of tie switch $\overline{\mathbf{T}}$, (ii) candidate sectionalizing switches $\overline{\mathbf{Sw}}$, and (iii) the power factor of DG units $\overline{\mathbf{Pf}}$.

$$\begin{cases} \mathbf{X} = [\overline{\mathbf{T}}, \overline{\mathbf{Sw}}, \overline{\mathbf{Pf}}] \\ \overline{\mathbf{T}} = \left[T_1, T_2, \ldots, T_{N_{\text{tie}}}\right] \\ \overline{\mathbf{Sw}} = \left[S\text{w}_1, S\text{w}_2, \ldots, S\text{w}_{N_{\text{tie}}}\right] \\ \overline{\mathbf{Pf}} = \left[P\text{f}_1, P\text{f}_2, \ldots, P\text{f}_{N_{\text{DG}}}\right] \end{cases} \tag{2}$$

(2) Balanced load

The more balanced the load is, the higher the stability margin of the distribution network is [83]. The index describing the degree of load balance is not unique [84], and the load balance coefficient [85] is usually used as the measurement standard:

$$\min L_{\mathrm{B}} = \sum_{l=1}^{N_l} \left| \frac{S_l}{S_{l,\max}} \right|^2 \tag{3}$$

where L_{B} is the equalization coefficient; S_l and $S_{l,\max}$ are the apparent power and capacity of branch l.

The formula that describes the balanced load by maximizing the minimum margin over all lines is as follows:

$$\min L_{\mathrm{B}} = \max[\min_l (S_{l,\max} - S_l)] \tag{4}$$

(3) Power distribution reliability

System reliability indicators [86] considered in distribution network reconfiguration mainly include the average number of system outages [87], system average outage duration, and customer average outage demand [88], etc.:

$$\mathrm{minSAIFI} = \frac{\text{Total number of customer outages}}{\text{Total number of users}} = \frac{\sum_{i\in R} \lambda_i M_i}{\sum_{i\in R} M_i} \tag{5}$$

$$\mathrm{minSAIDI} = \frac{\text{Total customer outage duration}}{\text{Total number of users}} = \frac{\sum_{i\in R} T_i M_i}{\sum_{i\in R} M_i} \tag{6}$$

$$\mathrm{minAENS} = \frac{\text{The total power of the system is low}}{\text{Total number of users}} = \frac{\sum_{i\in R} L_i T_i}{\sum_{i\in R} M_i} \tag{7}$$

where R is the set of load nodes; λ_i and T_i are the average failure rate and the average annual outage time of load node I; M_i is the number of users at load node i; and L_i is the average load at load node i.

(4) Voltage quality improvement

Usually, the range of node voltage fluctuation is one of the constraints of distribution network reconfiguration [89], and some studies also take it as the optimized objective of reconfiguration [90], expressed by:

$$\min U_{\mathrm{v}} = \sqrt{\frac{1}{N_{\mathrm{b}}} \sum_{i=1}^{N_{\mathrm{p}}} \left(U_i - U_{\mathrm{p}}\right)^2} \tag{8}$$

where N_{b} is the total number of nodes; U_i is the voltage amplitude of node i, and U_{p} is the average voltage of all nodes.

Similarly, the formula for measuring the range of node voltage fluctuation is not unique. The formula for calculating the range of node voltage fluctuation concerning the margins is as follows:

$$\min U_v = \max\{\min[\min_i (U_{\max} - U_i), \min_i (U_i - U_{\min})]\} \tag{9}$$

where $U_{\max}$ is the maximum voltages of all nodes; $U_{\min}$ is the minimum voltages of all nodes.

(5) Switch operation times

Frequent changes in the opening and closing state of the switch will reduce the service life of the switch. To extend the service life of the switch, the number of switch operations should be reduced as much as possible [91].

$$\min \sum_{i=1}^{K} |x_i - x_{i0}| \tag{10}$$

where K indicates the total number of line switches in the network; x_i, x_{i0} indicate the opening and closing state of line switch i before and after reconfiguration; disconnected and closed states are indicated by '0' and '1', respectively.

(6) Voltage offset index

Node voltage offset size is an important indicator to measure whether the voltage quality is qualified [92], and the minimum node voltage offset can ensure the safe and stable operation of the system [93].

$$\min \sum_{i=1}^{M} \frac{(V_i - V_{iN})^2}{{V_{iN}}^2} \tag{11}$$

where M is the number of distribution network nodes; V_i and V_{iN} are the actual and rated values of distribution network node voltages.

2.5 Reconfiguration Constraints

2.5.1 Continuity Constraints

(1) Node voltage constraints

$$U_{i\min} \le U_i \le U_{i\max} \tag{12}$$

where U_i, $U_{i\min}$ and $U_{i\max}$ are the actual voltage and its upper and lower limits of node i.

(2) Bus voltage constraints

$$V_{\min} \le V \le V_{\max} \tag{13}$$

(3) Considering the constraint of the power flow equation of distributed power supply

$$\begin{cases} Q_{\mathrm{DG}}^i + Q_{\mathrm{non-DG}}^i + Q_i - Q_{\mathrm{L}i} - U_i \sum_{j=1}^{N} U_j \left(G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}\right) = 0 \\ P_{\mathrm{DG}}^i + P_{\mathrm{non-DG}}^i + P_i - P_{\mathrm{L}i} - U_i \sum_{j=1}^{N} U_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right) = 0 \\ P_{\mathrm{L}i} = P_{\mathrm{FL}} + P_{\mathrm{FI}} \\ P_{\mathrm{FLmin}} \le P_{\mathrm{FL}} \le P_{\mathrm{FLmax}} \end{cases} \tag{14}$$

where P_i, Q_i are the active and reactive power of the input transmission line; P_{DG}^i and Q_{DG}^i are the active and reactive power of the DG connected with the ith node, respectively; $P_{\mathrm{non-DG}}^i$ and $Q_{\mathrm{non-DG}}^i$ are the active and reactive power of the non-DG connected with the ith node, respectively; $P_{\mathrm{L}i}$, $Q_{\mathrm{L}i}$ are the load active and load reactive power of the ith node; B_{ij}, θ_{ij} are the electric power and phase angle difference between the nodes i and j; U_i and U_j are the voltage amplitudes of node i and node j; N is the total number of nodes connected to node i; P_{FL}, P_{FI} are the flexible load and fixed load power; P_{FLmin} is the flexible load power lower limit; P_{FLmax} is the flexible load power top limit.

(4) Thermal capacity of distribution lines constraints

$$|p_i| \leq p_{i,\max} \quad \forall(i) \in \psi^{\text{line}} \tag{15}$$

where $p_{i,\max}$ is the maximize active power of the ith line.

(5) Active power outputs of DG units

$$P^d_{\text{DG,min}} \leq P^d_{\text{DG}} \leq P^d_{\text{DG,max}} \quad \forall(d) \in \psi^{\text{DG}} \tag{16}$$

where $P^d_{\text{DG,min}}$ is the minimum active power of the dth DG units, and $P^d_{\text{DG,max}}$ is the maximum power factor of the dth DG units.

(6) Power factors of DG units

$$P\text{f}^d_{\text{DG,min}} \leq P\text{f}^d_{\text{DG}} \leq P\text{f}^d_{\text{DG,max}} \quad \forall(d) \in \psi^{\text{DG}} \tag{17}$$

where $Pf^d_{\text{DG,min}}$ is the minimum power factor of the dth DG units, and $Pf^d_{\text{DG,max}}$ is the maximum power factor of the dth DG units.

2.5.2 Discreteness Constraints

(1) Network topology constraints

The topology of the distribution network in the reconfiguration process is radial and must not create loops or islands.

$$g_k \in G_k \,\&\, g_k \notin G_{\text{islanding}} \tag{18}$$

where G_k is the set of switch combinations of the effective radiation state network; $G_{\text{islanding}}$ is the set of switch combinations of networks with islands.

(2) Current safety constraints

$$\left|I_{ij}\right| \leqslant z_{ij} I_{ij,\max}, \forall ij \in \Phi_{\text{line}} \tag{19}$$

where $I_{ij,\max}$ is the upper limit of the branch current amplitude.

2.6 The Initial State of the Network Configuration

Most of the tests related to ADNR are based on the standard IEEE 33 bus and IEEE 69 bus systems, with flexible configurations for various hybrid energy sources such as wind, photovoltaic, fuel cells, and energy storage, depending on the research context. Additionally, a small number of studies have explored the feasibility of field testing methods. In this paper, we have selected systems with promising performance for illustration.

(1) Initial state of the standard IEEE33-bus radial distribution system:

The IEEE 33 bus radial distribution system comprises 33 buses with 32 lines and 5 interconnection switches that are normally open: 33, 34, 35, 36, and 37. The initial data for the 33-bus radial distribution system is provided in Table A1. In Reference [94], the initial total active power was set at 3715 kW, the total reactive power at 2300 kvar, and the total active losses were 202.676 kW. In comparison, in Reference [95], considering the presence of a comprehensive energy system, with the total active/reactive power of the system unchanged, the active power loss was 211 kW.

(2) Initial state of the standard IEEE69-bus radial distribution system:

The IEEE 69 bus radial distribution system consists of 69 buses with 68 lines and 5 interconnection switches that are normally open: 69, 70, 71, 72, and 73. The initial data for the 69-bus radial distribution system is provided in Table A2. In Reference [94] the system was set to have total power losses of 229.73 kW under rated load conditions. In the Reference [96], the system's total active load was set at 3802 kW, and total reactive load at 2694 kvar, with initial active losses of 225 kW, and reactive losses of 102.16 kvar.

(3) The initial state of the actual network test system:

Reference [97] conducted experiments on an actual 47-bus distribution network to validate the effectiveness of their proposed algorithm. This network comprised 47 buses and 42 branches, and received power from a 132 kV transmission system. Notably, four key substations were connected to Buses 2, 17, 34, and 39. Additionally, there were seven tie switches facilitating alterations to the system's configuration in response to unforeseen events or contingencies. For a comprehensive overview of the system's bus details, please refer to Table A3.

3 Research Methods and Evaluation

3.1 Methods Evaluation Criteria

This paper presents a comprehensive evaluation of each reconfiguration method, focusing on both theoretical and practical aspects. The theoretical evaluation mainly considers the complexity of reconfiguration methods, with a particular emphasis on the complexity of meta-heuristic algorithms, which is largely dependent on the algorithm design. The evaluation indicators used for this evaluation include (a) multi-objective optimization, (b) hyper-parameters, and (c) operational mechanism. The application evaluation aims to assess the testing process and practical effectiveness of the reconfiguration methods, which is scored based on three aspects: (a) test system, (b) optimization indicators, and (c) social indicators. The complexity and applicability of reconfiguration methods increase with the accumulation of the above evaluation indicators. Thus, the overall score of each ADNR method can be calculated by:

$$Q_r = \sum_{k=1}^{6} \omega_k f_k \tag{20}$$

where Q_r represents the overall score of the rth method, ($r = 1, 2, \ldots, 52$); ω_k is the percentage of each indicator. To equally showcase the performance of each method across the six evaluation indicators, the percentages of the six evaluation indicators are objectively divided equally ($\omega_1 = \omega_2 = \ldots = \omega_6 = 1/6$); f_k is the number of $*$ obtained (e.g., if $f_1 = 4$ means that the method of ADNR considers multi-objective function).

The proportions of each indicator and the detailed evaluation criteria are presented in Fig. 5.

3.2 Research Methods and Evaluation

Up to now, many researchers have conducted research on ADNR. In this chapter, we will divide the existing research methods into five categories: traditional methods, mathematical methods, meta-heuristic methods, machine learning methods, and hybrid methods. Next, a detailed introduction of each method will be offered.

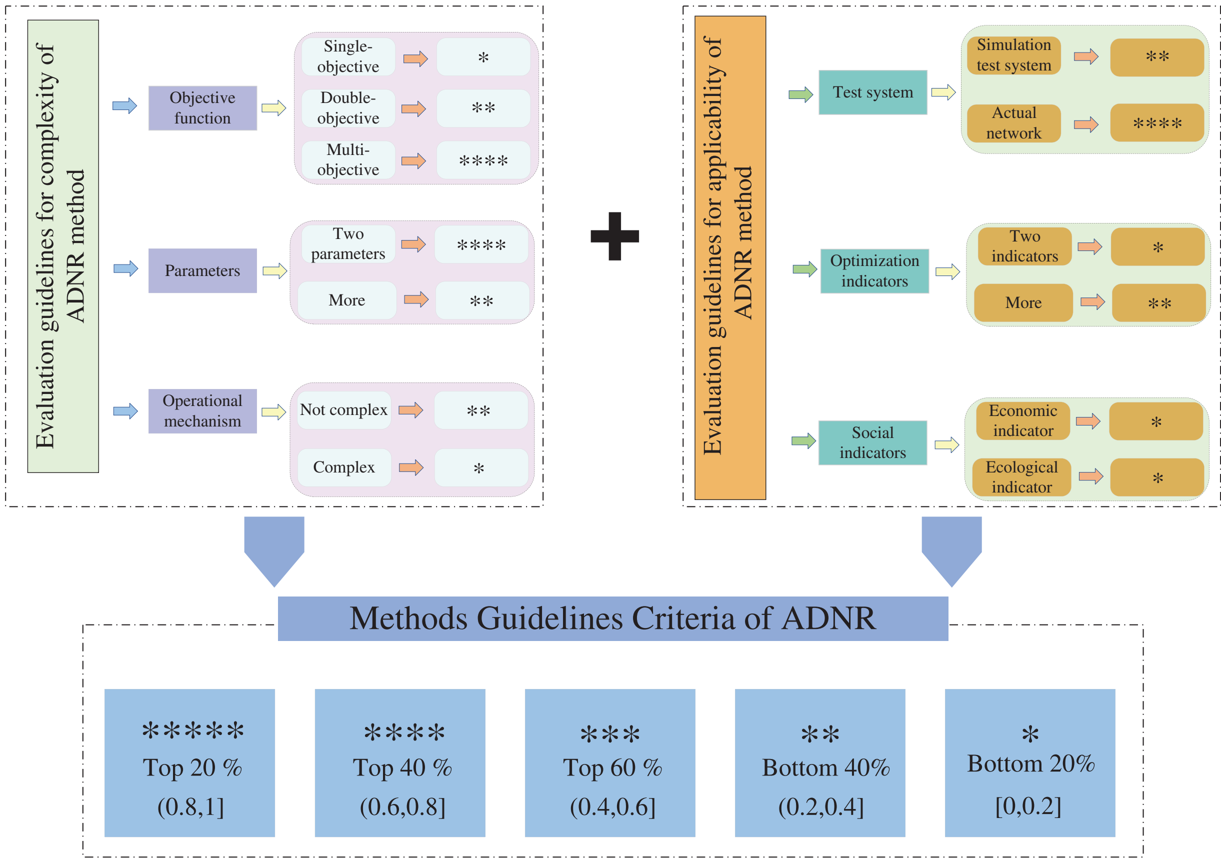


Figure 5: The methods evaluation criteria

3.2.1 Traditional Method

Loop Cutting Method

The LCM was proposed by Darish Shrimohammad in 1989 [98]. It created multiple loops by closing all the connection switches in the system and then switches the distribution network system to a weak grid state and ignoring the OFP of the system branch reactance calculation network [99]. Finally, the distribution system was restored to radial structure operation by turning on the switch with the minimum current under the optimal flow mode [100].

Although the LCM has low requirements on the network structure of the distribution system, its calculation efficiency is low, and it cannot be applied to medium and large network structures. Moreover, it is prone to producing the “island” effect in network reconfiguration [101].

Branch Exchange Method

Compared to the LCM, the BEM started from the radial distribution network and calculated the power flow distribution and network loss of the distribution network [102]. The distribution network formed a loop network by closing the connection switch. Therefore, another switch needed to be opened to restore the network to a radial structure, to balance the load and reduce the network loss. The process would stop when the system network loss couldn’t be further reduced [103]. The BEM had the advantage of fast solution speed, but it heavily depended on the initial network structure [104].

3.2.2 Mathematical Programming Method

Mathematical programming methods have not received much attention due to their complex operation mechanism. In this paper, we review the mathematical methods that have been proposed so far, the summary of mathematical programming methods is tabulated in Table 2.

Lagrange Relaxation Approach

The LRA is capable of transforming difficult constraints into a part of the objective function to maintain linearity. This method yields a superior lower bound and is equivalent to transforming the (0,1) integer variable into a continuous variable ranging from 0 to 1. The Lagrange multiplier, which reflects duality information, is obtained as a result of Lagrange relaxation, as illustrated in Fig. 6. The method further decomposes the coupled variables in the constraint and simplifies them into independent sub-problems [105].

In the Reference [106], the minimum active power loss of the network was taken as the objective function, and the distribution network reconfiguration was formulated as a mixed integer linear programming (MILP) problem. The Lagrange relaxation method was used for dynamic distribution network reconfiguration. The operational constraints were relaxed, and the Lagrange duality problem was subsequently decoupled into several independent sub-problems. The solution of the Lagrange dual problem was then used for heuristic search. The algorithm was tested using two examples, a 15-bus test benchmark and a 1021-bus real test system, and the results showed that the algorithm was robust and scalability, making it suitable for large-scale distribution networks.

Standard Newton Method

The Standard Newton method is an iterative derivative algorithm, that utilizes the first and second derivatives of the objective function at the current iteration point, x_k, to approximate the function and determine the minimum point of the quadratic model as the next iteration point. This process is repeated until the minimum value meets the required accuracy, and the method is known for its fast-solving speed and high precision.

In Reference [107], the Standard Newton method was applied to calculate the distribution of branch current in an integer search, which was then used to guide the status of switches in the distribution network to search for the global optimal value. While this approach can solve the power flow calculation with only one iteration, it may be susceptible to local minima.

Simplex Algorithm

The simplex method, proposed by George Dantzig in 1947, is an optimization method for multi-variable functions. It first finds a basic feasible solution and then determines whether it is the optimal solution. If not, it finds another solution and continues iterating until it either finds the optimal solution or determines that it is unbounded [108]. In Reference [109], an improved simplex algorithm for minimizing distribution network losses based on linear programming was proposed. This algorithm determined the infeasibility of a given problem during the initialization of the linear programming solution. By ignoring the voltage constraint and considering line capacity, this algorithm generated a radial system configuration that ensures the minimum system loss under the line capacity constraint.

Table 2: Summary of seven mathematical programming methods applied to ADNR

Literature/Year	Mathematical modeling	Purpose					Complexity index		Applicability index			Overall score
		Reduction of power loss	Balanced load	Voltage quality improvement	Switch operation	Others	Method complexity	Parameters	Test system	Indicator optimization	Number of switch actions	
Taylor et al. (2012) [110]	MISOCP	√	√	√	×	×	**	*	• IEEE 32/70/135/880 bus network	N.P.	IEEE 32 bus network: (7,8) (9,10) (14,15) (28,29) (32,33) IEEE70 bus network: (9,15) (21,27) (28,29) (37,38) (40,44) (49,50) (62,65) (67,15) IEEE 135/880bus network: N.P.	**
Jabr et al. (2012) [111]	MILP	√	×	×	×	×	**	*	• Distribution system of Taiwan and Brazilian power company	• Reduction of power loss: from 5.319 to 4.701 MW	(8,91) (22,105) (92,175) (106,189) (176,259) (190,273) (302,385)	***
Franco et al. (2013) [112]	MINLP	√	×	×	×	√	**	*	• IEEE 69/136/417 bus network	• Reduction of power loss: IEEE69: from 0.019 to 0.013 MW • IEEE136: from 0.274 to 0.162 MW • IEEE417: from 0.392 to 0.266 MW	IEEE69: (14,22) (15,16) (56,57) (62,63) (69,70)	***
Deese, et al. (2014) [113]	MINLP	√	×	×	×	×	*	*	• IEEE 118 bus network	N.P.	N.P.	*
Zhai et al. (2018) [114]	MILP	√	×	×	×	√	*	*	• IEEE 34 bus network	• Reduction of power loss: from 1.203 to 1.180 MW	(6,7) (6,10) (13,14) (29,31) (20,29)	**
Macedo et al. (2022) [115]	MISOCP	√	×	×	×	√	*	*	• IEEE 84 bus network	• Total annual cost of the energy losses: from \$93644.96 to \$92024.57 • Maximum short-circuits current deviation: from 25% to 25%	(12,13) (33,34) (38,39) (82,83) (5,55) (11,43) (14,18) (16,26)	***
Chen et al. (2022) [116]	MISOCP	√	×	×	√	√	*	*	• IEEE 33 bus network • Distribution system of Barry Island	N.P.	(5,6) (11,12) (13,14) (7,20) (9,15)	****

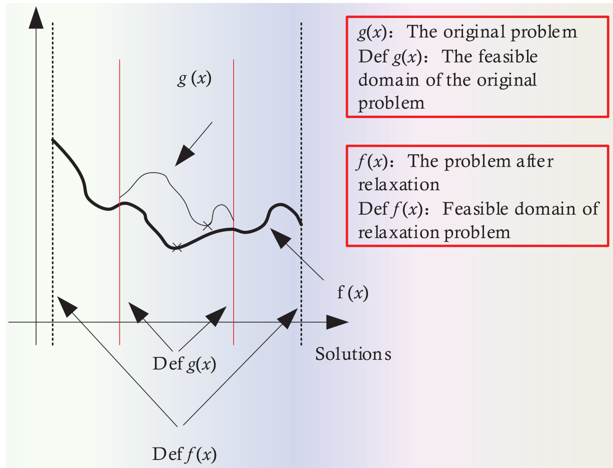


Figure 6: Schematic diagram of LRA

In recent years, the rapid development of bionics and computer technology has led to wide attention and application of meta-heuristic algorithms due to their high efficiency, accuracy, and relative simplicity. Meta-heuristic algorithms can effectively balance the exploration of the local and full-domain equilibrium when dealing with optimization problems, enabling them to quickly find the full-domain optimal solution. As a result, many meta-heuristic algorithms and their variants have been applied to ADNR.

3.2.3 Meta-Heuristic Algorithm

Simulated Annealing

Reference [117] employed the SA method to find the optimal switching strategy for DNR to minimize power losses and balance loads. However, this method is time-consuming due to the repeated power flow calculations during the solving process. To address this limitation, Reference [118] proposed a highly efficient and accurate approach for power flow solution. It ensures both high-speed and high-precision power flow solutions. By incorporating the network connectivity checking matrix and the criterion for imposing radiality constraint suggested by Lavorato et al., it utilizes the SA algorithm to determine the radial structure that reduces active power losses.

Tabu Search

Reference [119], to minimize power losses, applied the Tabu Search (TS) method to solve ADNR with distributed generation (DG). Despite demonstrating that the TS method has superior computational speed and solution accuracy compared to Simulated Annealing (SA), the global search capability of the TS algorithm heavily depends on the length of the tabu list. Reference [120] modified the size of the tabu list with an adaptive strategy. Additionally, it employed a 'random multiplicative move' to achieve a global optimum for ADNR. Reference [121] proposed an adaptive TS method. Compared to the traditional TS method, this method eliminated the concept of a list of prohibited attributes and aspiration criteria, and restarted the search from the existing solutions, avoiding the paths formed by revisiting candidate solutions. This method was tested on 33, 84, 118, and 136 nodes, and the test results verified its effectiveness.

Genetic Algorithm

In the Reference [122], the impact of DG and electric vehicle grid-connection's volatility and intermittence on the system was considered. A genetic algorithm was adopted to solve the network distribution network reconfiguration problem, using network loss, voltage deviation, and voltage stability as the objective function. To improve the PV carrying capacity (PVCC) of a distribution system with harmonic pollution, the Reference [123] proposed distribution network reconfiguration and employed the NSGA-II algorithm to find a Pareto-front candidate solution set for the grid-connection problem of many photovoltaic generating units. Reference [124] aimed to minimize the economic losses of operators under fault conditions. It used a combination of GA and mathematical optimization for a comprehensive analysis of the power system through nonlinear programming and discontinuous derivatives. The method was validated on IEEE 9 bus and 30 bus systems and was evaluated for its effectiveness in reducing network losses and economic losses. The flowchart of GA applied to ADNR is shown in Fig. 7.

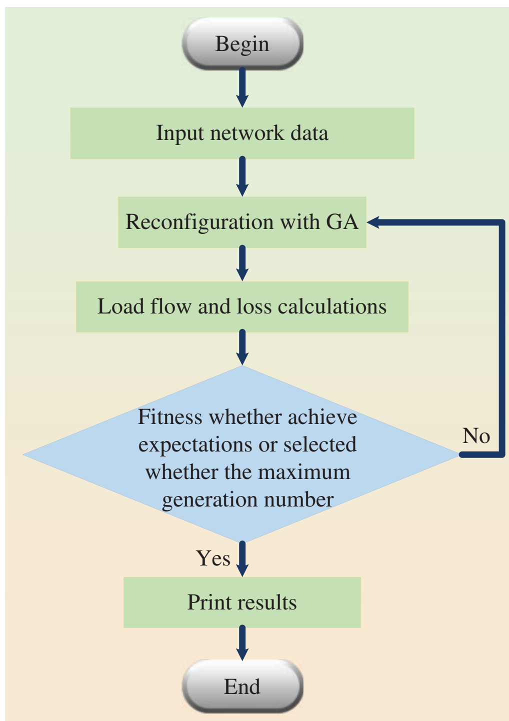


Figure 7: The flowchart of GA applied to ADNR

Ant Colony Optimization

Reference [125] established a dynamic reconfiguration model to minimize network losses and switch operations in the short term. They optimized the model using Ant Colony Optimization (ACO) and validated the feasibility of this method under the variable characteristics of DG output. The flowchart of ACO addressing ADNR with DGs is depicted in Fig. 8. The traditional ACO suffers from slow search speed, low flexibility, and a tendency to fall into local optima. Literature [126] addressed these shortcomings by proposing an improved differential evolution ACO. This novel approach integrated an enhanced differential evolution algorithm with linearly decreasing weight into the ACO for the reconfiguration of the IEEE 33 bus system with DGs. Simulation results demonstrated that this method not only achieved faster convergence and avoided local optima but also offered significantly higher flexibility.

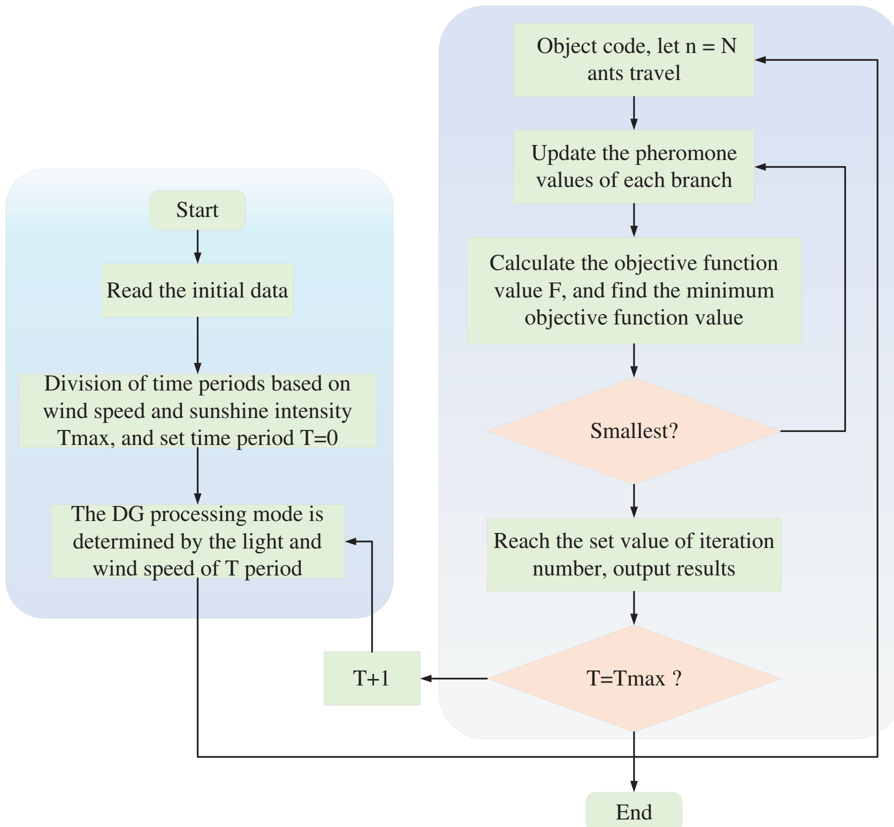


Figure 8: The flowchart of ACO addressing ADNR with DGs

Particle Swarm Optimization

Reference [127] achieved significant improvements in network losses and voltage distribution balance by simultaneously implementing hierarchical reconfiguration, DG integration, and low-voltage distribution allocation. This demonstrated that the Particle Swarm Optimization (PSO) algorithm can effectively provide solutions for segmenting switches and sizing DG units. However, the performance of the PSO algorithm largely depends on the initial data selection. Additionally, a considerable amount of parameter tuning is required during the reconfiguration process to achieve optimal results. The Hybrid Particle Swarm Optimization (HPSO) proposed in the Reference [128] improved the particle position update formula. By balancing local and global searches in later stages, the results tended towards the optimal particles in the population, ultimately converging to the global optimum particle. Compared to the approach in Reference [128], which only improved the particle position update formula, the Improved Particle Swarm Optimization Approach proposed in Reference [129] employed a chaos-oriented inertia weight and crossover operation mechanism. This method enhanced the particle velocity update, particle position update, and linearly varying inertia weight. It required fewer control parameters, needing only the inertia coefficient to be set, and its superiority was validated on the IEEE 69 bus system. Reference [94] introduced evolutionary particle swarm optimization, effectively addressing the problem of poor convergence caused by inaccurate parameter settings such as inertia weight (w), cognitive constant (c1), and social constant (c2). The process of applying PSO to ADNR is illustrated in Fig. 9, and the summary of PSO algorithms is tabulated in Table 3.

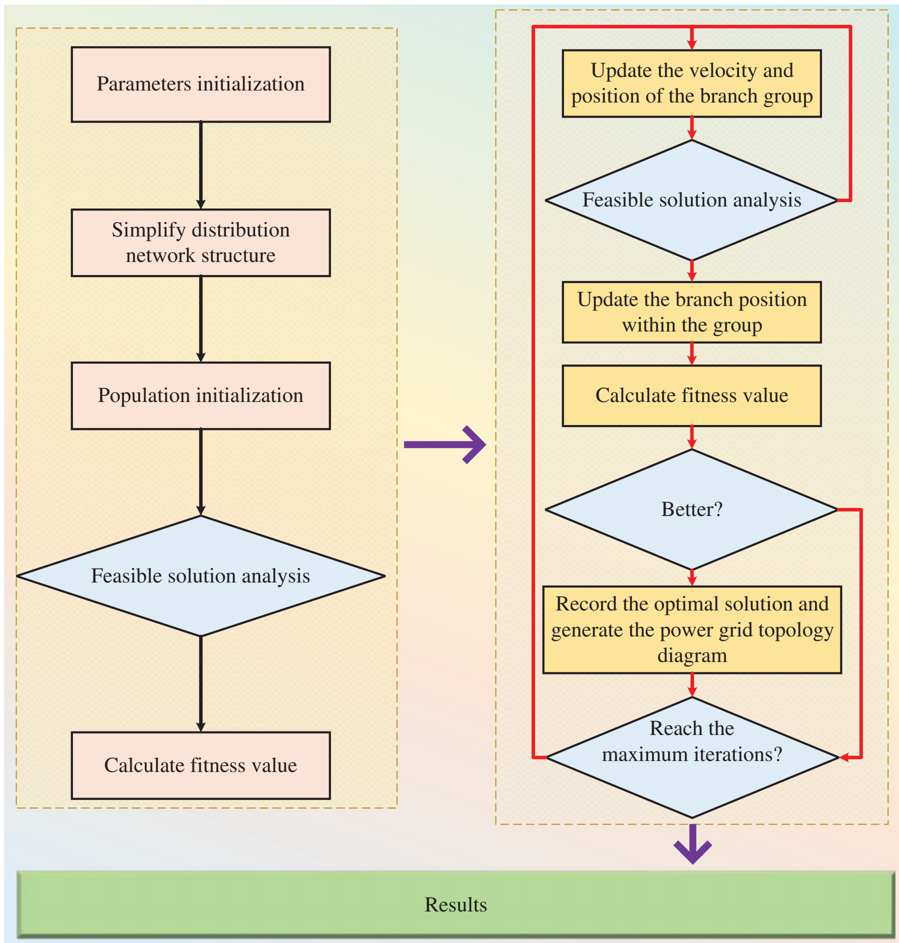


Figure 9: Flow chart of PSO applied to ADNR

Table 3: Summary of seven PSO algorithms applied on ADNR

Literature/ Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Li et al. (2012) [130]	NBPSO	• $F = a_1\left(\frac{1}{P_{L\Sigma}}\sum_{i=1}^{n} R_i\frac{P_i^2+Q_i^2}{V_i^2}\right) + a_2\left(\frac{1}{n_t}\sum_{j=1}^{n_1}\left\|\beta_j-\beta_{avc}\right\|\right)$	• Reduction of power loss • Balanced load	• Node voltage constraints • Network topology constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 33 bus network	• Reduction of power loss: from 0.647 to 0.619 MW	• IEEE 33 bus network: (6-7) (8-10) (9-11)	**
Zhao et al. (2016) [131]	PSO-BFO	• $\min f_1 = \min\sum_{t=1}^{T}\left(\sum_{z=1}^{z_L} G_{ij}\left(U_i^2+U_j^2-2U_i^2U_j^2\cos\theta_{ij}\right)\right)$ • $\min f_2 = \sum_{t=1}^{T}\left(\sum_{i=1}^{N}\left(\frac{U_i-U_i^*}{\Delta U_{i\max}}\right)^2\right)$ • $\min f_3 = \sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(\max\{P_{iAL,t}\}-\min\{P_{iAL,t}\}\right)\right)$	• Reduction of power loss • Voltage quality improvement	• Node voltage constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 33 bus network	• Reduction of power loss: from 5.371 to 5.008 MW • Voltage deviation: from 35.23 to 25.97 kV • Peak-valley load difference: from 7.01 to 5.69 MW	N.P.	***
Ma et al. (2017) [129]	HPSO	• $\min f = \sum_{i=1}^{N} K_iR_i\frac{P_i^2+Q_i^2}{U_i^2}$	• Reduction of power loss	• Node voltage constraints • Branch circuit capacity constraint • Network topology constraints • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 33 bus network	• Reduction of power loss: from 0.202 to 0.112 MW	• IEEE 33 bus network: (8,9) (8,21) (14,15) (28,29) (32,33)	***
Napis et al. (2018) [94]	IEPSO	• $P_{loss} = \sum_{i=1}^{nbr}\|I_i\|^2 \times R_i$	• Reduction of power loss • Voltage quality improvement	• Node voltage constraints • Network topology constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 33 bus network • IEEE 69 bus network	• Reduction of power loss: from 0.496 to 0.309 MW • Voltage stability index: from 0.863 to 0.715	• IEEE 33 bus network: 33, 13, 27, 7, 16 • IEEE 69 bus network: 9, 20, 53, 14, 41	***
Vasudevan et al. (2018) [132]	GA-PSO	• $\min P_{loss} = \sum_{i=1}^{m}\|I_i\|^2 r_i, \forall T$	• Reduction of power loss	• Node voltage constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 69 bus network	• Reduction of power loss: from 0.224 to 0.102 MW	• IEEE 69 bus network: (8–9) (52–69)	**

(Continued)

Table 3 (continued)

Literature/ Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Shafik et al. (2019) [133]	MPSO	• $F = \mathrm{Min}(P_{\mathrm{loss}} + w_1 * \sum_{i \in Nf} \lvert V_n - V_i \rvert + w_2 * Pl)$	• Reduction of power loss • Voltage quality improvement	• Node voltage constraints • Branch circuit capacity constraint • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 33 bus network	• Reduction of power loss: from 0.202 to 0.064 MW • Voltage stability index: from 5.15% to 1.30%	• IEEE 33 bus network: (2–3) (8–21)	**
Rezaee Jordehi (2020) [134]	PSO	• $P_{\mathrm{loss}} = \sum_{l=1}^{N_l} R_l \left(\frac{\lvert V_i - V_j \rvert^2}{R_l^2 + X_l^2} \right)$ • $P_{\mathrm{wholesale}} = P_{\mathrm{D}} + P_{\mathrm{loss}} - \sum_{p=1}^{p=\gamma} P_{\mathrm{DG}p} - P_{\mathrm{renew}}$	• Reduction of power loss	• Node voltage constraints • Network topology constraints • Current safety constraints	• IEEE 69 bus network	• Operation cost of distribution system: from 15,676.34 to 15,230.81 • Reduction of power loss: from 4.503 to 2.010 MW	• IEEE 69 bus network: (17,18) (41,42) (45,46) (57,58) (62,63)	**

Harmony Search Algorithm

In Reference [135], the Harmony Search Algorithm (HSA) was used to solve the distribution network reconfiguration problem. However, due to the large amount of data in the large-scale distribution network reconfiguration, the algorithm was prone to falling into the local minimum and unable to find the global optimal solution. Based on this, an improved HSA was proposed in Reference [96] to optimize the algorithm by enhancing the PAR and BW parameters in the iteration process of optimization. The process of solving ADNR with IHSA is illustrated in Fig. 10. Additionally, Reference [136] proposed a self-adaptive HSA that provides better accuracy and convergence. The performance of HSA for ADNR is shown in Table 4.

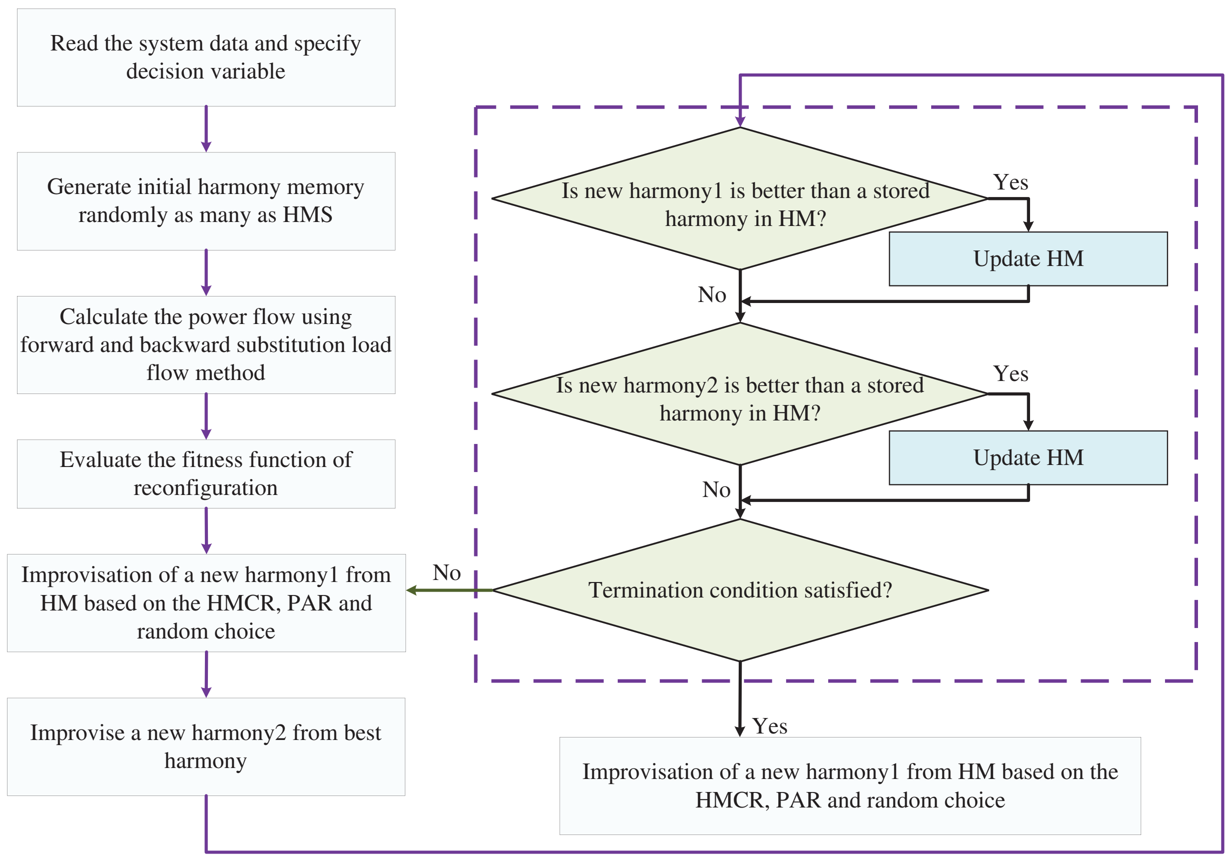


Figure 10: Flow chart of IHSA for solving ADNR

Artificial Bee Colony

To improve the convergence of the algorithm, the discrete artificial bee colony (DABC) [138] was proposed to continuously search for the new food source location in memory. Furthermore, Reference [95] proposed the multi-objective artificial bee colony (MABC) to enrich the search process for optimal solutions by using archived solutions. The specific evaluation is shown in Table 5. The flowchart of the artificial bee colony based ADNR is depicted in Fig. 11.

Table 4: Summary of four HSA algorithms applied on ADNR

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Shariatkhah et al. (2012) [135]	HAS-DPA	• $\min f(x) = \sum_{d=1}^{ND}\sum_{t=1}^{24}\sum_{l=1}^{N1} C_{\text{energy}}(d,t) R_l I_l^2(d,t) + \sum_{d=1}^{ND}\sum_{t=1}^{24}\sum_{l=1}^{N1} C_{\text{energy}}(d,t) R_l I_l^2(d,t)$	• Reduction of power loss • Balanced load • Switch operation	• Node voltage constraints • Current safety constraints	• IEEE 95 bus network	• Operation cost of distribution system: from $3,691,062 to $3,612,360 • Switching costs: from $31,059 to $4060	• IEEE 95 bus network: 15, 19, 30, 43, 55, 60, 77, 81, 82, 84, 87	**
Sudha et al. (2014) [96]	SAHSA	• $P_{\text{loss}} = \sum_{i=1}^{nl} I_i^2 R_i$ • $Q_{\text{loss}} = \sum_{i=1}^{nl} I_i^2 X_i$	• Reduction of power loss	• Node voltage constraints • Network topology constraints • Current safety constraints	• IEEE 33 bus network • IEEE 69 bus network	• IEEE 33 bus network: Active power loss: from 0.202 to 0.139 MW • Reactive power loss: from 0.135 to 0.102 MW • IEEE 69 bus network: Active power loss: from 0.225 to 0.098 MW • Reactive power loss: from 0.102 to 0.092 MW	• IEEE 33 bus network: 7, 9, 14, 32, 37 • IEEE 69 bus network: 14, 57, 61, 69, 70	****
Santos et al. (2020) [136]	IHSA	• $\min P_{\text{loss}}^{\text{total}} = \sum_{(k,m)\in\Omega_l}\left[x_{km}g_{km}\left(V_k^2 + V_m^2 - 2V_kV_m\cos\theta_{km}\right)\right]$	• Reduction of power loss	• Node voltage constraints • Branch circuit capacity constraint • Network topology constraints • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint	• IEEE 33 bus network • IEEE 84 bus network • IEEE 118 bus network	• IEEE 33 bus network: Active power loss: from 0.202 to 0.139 MW • IEEE 84 bus network: Active power loss: from 0.531 to 0.469 MW • IEEE 118 bus network: Active power loss: from 1.298 to 0.854 MW	• IEEE 33 bus network: 7, 9, 14, 32, 37 • IEEE 84 bus network: 7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92 • IEEE 118 bus network: 23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	****
Dias et al. (2022) [137]	IHSA	• $\min P_{\text{loss}}^{\text{total}} = \sum_{(i,j)\in\Omega_l}\left[\alpha_{ij}g_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right)\right]$	• Reduction of power loss	• Node voltage constraints • Network topology constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint	• IEEE 14 bus network • IEEE 33 bus network • IEEE 84 bus network • IEEE 119 bus network	• IEEE 14 bus network: from 0.511 to 0.466 MW • IEEE 33 bus network: from 0.202 to 0.139 MW • IEEE 84 bus network: from 0.531 to 0.469 MW • IEEE 119 bus network: from 1.298 to 0.854 MW	• IEEE 14 bus network: 7, 12, 16 • IEEE 33 bus network: 7, 9, 14, 32, 37 • IEEE 84 bus network: 7, 13, 34, 39, 55, 62 • IEEE 119 bus network: 23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	****

Table 5: Summary of three ABC algorithms applied on ADNR

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Nasiraghdam et al. (2012) [95]	MOABC	• $\mathrm{VSI}_j = V_i^4 - 4(P_{ij}X_{ij} - Q_{ij}R_{ij})^2 - 4(P_{ij}R_{ij} - Q_{ij}X_{ij})V_i^2$ • $\min f_2(\overline{X}) = \sum_{i=1}^{N_{\text{hid}}} \sum_{j\in \text{Tech}} C_{i,j} + C_{\text{pur}}$ • $\min f_3(\overline{X}) = \sum_{i=1}^{N_{k,b}} \sum_{j\in \text{Tech}} P_{i,j} \times ER_j \times CF_j \times 8760 + P_{\text{sub}} \times LF \times ER_{\text{grid}} \times 8760$	• Reduction of power loss • Balanced load	• Node voltage constraints • Branch circuit capacity constraint • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constrain	• IEEE 33 bus network	• Reduction of power loss: from 0.211 to 0.0827 MW • Maximizing the voltage stability index: from 0.66716 to 0.8762	37, 7, 11, 14, 31	***
Aman et al (2014) [138]	DABC	• $VDI = \sqrt{\frac{\sum_{i=1}^{NVB} (V_i - V_{\text{Limit}(i)})^2}{N}}$	• Reduction of power loss • Voltage quality improvement	• Node voltage constraints • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 33 bus network • IEEE 69 bus network	• IEEE 33 bus network: Reduction of power loss: from 0.211 to 0.129 MW • Voltage deviation index: from 0.0245 to 0.0013 • IEEE 69 bus network: Reduction of power loss: from 0.224 to 0.098 MW • Voltage deviation index: from 0.0119 to 0	• IEEE 33 bus network: 7, 9, 14, 32, 37 • IEEE 69 bus network: 10, 14, 32, 28, 06 **	****
Choton et al. (2018) [139]	ABC	• $F = \text{minimize} \left\{ \underbrace{(\gamma_{VD} \cdot C_{VD}^n + \gamma_{PL} \cdot C_{PL}^l + \gamma_{LL} \cdot C_{LL}^l)}_{C_{\text{performance}}} + (\gamma_{ESS} \cdot C_{ESS}^{UT}) \right\}$	• Reduction of power loss • Voltage quality improvement	• Node voltage constraints • Branch circuit capacity constraint • Considering the constraint of the power flow equation of distributed power supply	• IEEE 33 bus network	• Voltage deviation index: from 89.73%to 75.75% • Active power loss: from 0.11 to 0.09 MW • Reactive power loss: from 0.09 to 0.068 MW	N.P.	**

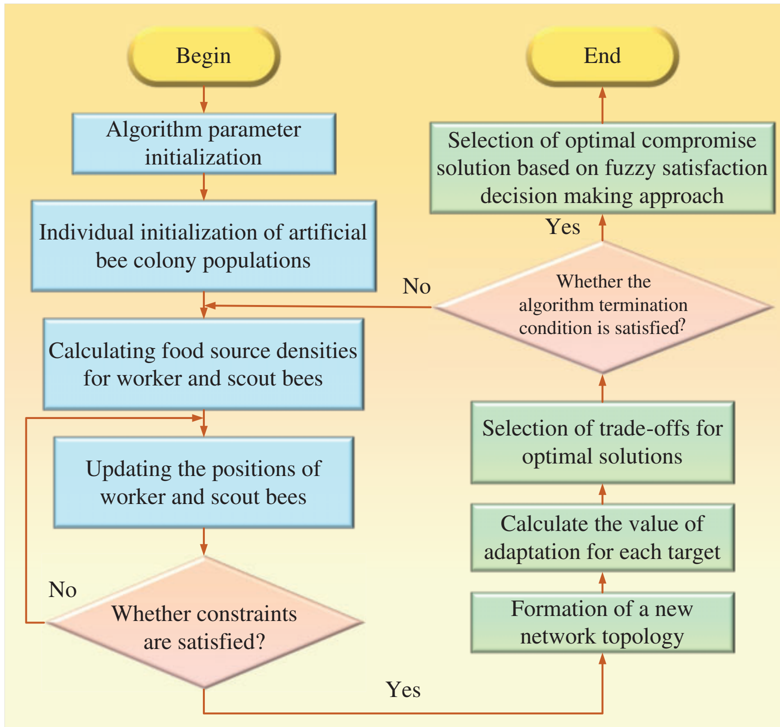


Figure 11: Principle of ABC applied to ADNR

Cuckoo Search Algorithm

The original cuckoo search algorithm (CSA) can only solve the simple continuous optimization problem. Therefore, Reference [140] introduced the variable radix operation and incorporated the concept of quantum bits to construct an improved CSA for ADNR. Additionally, the hybrid algorithm of CSA and simulated annealing was developed to effectively improve the convergence speed and solution quality of ADNR [117]. The specific performance of the above methods is tabulated in Table 6. The flowchart of CSA is given in Fig. 12.

Slime Mold Algorithm

Inspired by the diffusion and foraging behavior of slime molds, the SMA optimizes the changing process of vein morphology and systolic patterns during foraging. With the change of food odor concentration in the air, slime molds constantly change their movement position and speed [142].

Table 6: Summary of three CSA algorithms applied on ADNR

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Nguyen et al. (2015) [141]	CSA	• $\min F = \Delta P_{\text{loss}}^{R} + V_D\left(\Delta P_{\text{loss}}^{R} = \frac{P_{\text{loss}}^{\text{rec.}}}{P_{\text{loss}}^{0}}\right)$ • $\Delta V_D = \max\left(\frac{V_1 - V_i}{V_1}\right) \forall i = 1, 2, \ldots, N_{\text{bus}}$)	• Reduction of power loss • Voltage quality improvement	• Node voltage constraints • Network topology constraints • Current safety constraints • The network radiate has no island constraint • Distributed generation capacity limits	• IEEE 33 bus network • IEEE 69 bus network • IEEE 119 bus network	• IEEE 33 bus network: Reduction of power loss: from 0.202 to 0.053 MW • Voltage stability index: from 0.697 to 0.931 • IEEE 69 bus network: Reduction of power loss: from 0.224 to 0.037 MW • Voltage stability index: from 0.685 to 0.943 • IEEE 119 bus network: Reduction of power loss: from 0.224 to 0.037 MW • Voltage stability index: from 0.685 to 0.943	• IEEE 33 bus network: 33, 9, 8, 36, 27 • IEEE 69 bus network: 69, 70, 14, 58, 64 • IEEE 119 bus network: 42, 25, 21, 121, 122, 58, 39, 125, 70, 127, 128, 129, 85, 131, 33	****
Gao et al. (2020) [140]	ICSA	• $\min \sum_{h=1}^{H} \sum_{t=1}^{T} \sum_{\phi} \sum_{j \in N_t} \lambda_h P_{i,F,j}^{k,\phi,t} \Delta d_t$	• Reduction of power loss	• Node voltage constraints • Branch circuit capacity constraint • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint • Active and reactive power generation constraints of the distributed generators • Constraints of Three-Phase Voltage Unbalance	• Modified IEEE34-bus system	• IEEE 34 bus network: Reduction of power loss: from 2.163 to 1.179 MW	• IEEE 34 bus network: 6 9 13 30 38	**

(continued)

Table 6 (continued)

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Xiao et al. (2020) [117]	CSA-SA	• $\min f_1 = \sum_{i=1}^{n} \frac{P_i^2 + Q_i^2}{U_i^2} k_i R_i$ • $\min f_2 = \sum_{j=1}^{k} \frac{\left(U_{js} - U_{j\mathrm{N}}\right)^2}{U_{j\mathrm{N}}^2}$ • $\min f_3 = \sum_{j=1}^{m} \left(\frac{S_j}{S_{jmax}}\right)^2$	• Reduction of power loss • Voltage quality improvement • Balanced load	• Node voltage constraints • Branch circuit capacity constraint • Network topology constraints • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint • Reliability constraints of high-voltage power networks • Constraints on load rates of adjacent voltage levels	• IEEE 33 bus network	• Reduction of power loss: from 0.346 to 0.206 MW • Voltage deviation: from 0.045 to 0.015 • Degree of load balancing: from 1.136 to 0.635	• IEEE 33 bus network: 9, 11, 16, 17, 28, 31, 41, 49, 50, 54	***

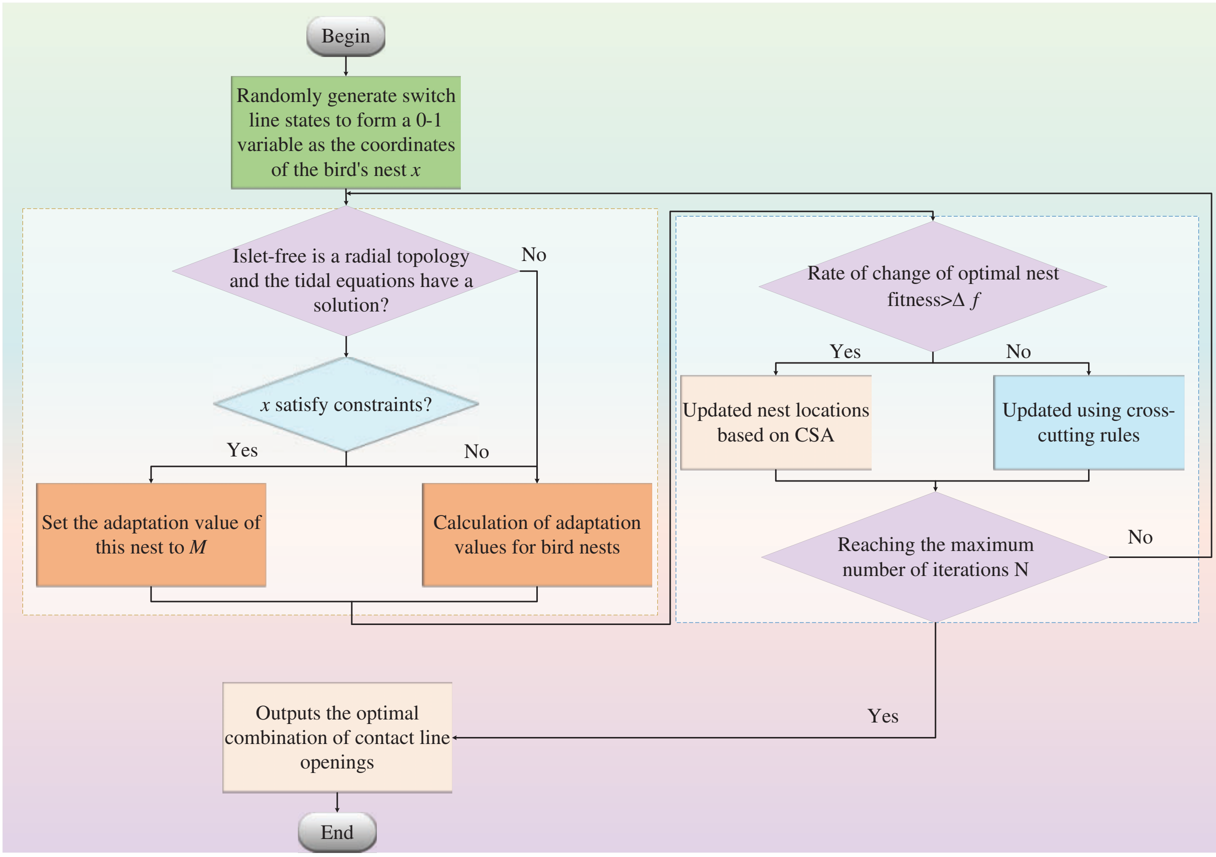


Figure 12: Flow chart of CSA

However, SMA is slow to converge, has low computational efficiency, and is prone to falling into local optima. In Reference [143], a parallel slime mold algorithm based on packet communication strategy and inertia weights was proposed to improve its convergence. Additionally, a multi-group flight slime mold algorithm based on packet communication and Levy flight was proposed in the Reference [144]. The flow chart of SMA to solve the problem of DNR with DG is shown in Fig. 13. Specific parameters are shown in Table 7.

$$X^{t+1} = \begin{cases} \text{round}\left(X_b^t + \mu \cdot v_b\left(W \cdot X_A^t - X_B^t\right)\right), r < p \\ \text{round}\left(\mu \cdot v_c \cdot X^t\right), r > p \\ \text{round}\left(\text{rand} \cdot (u_b - l_b) + l_b\right)\right), \ \text{rand} \ < z \end{cases} \tag{21}$$

Other Meta-Heuristic Methods

Overall, genetic algorithm (GA), particle swarm optimization (PSO), and Tabu search (TS) are the most commonly used meta-heuristic algorithms for ADNR. However, with the increasing scale of grid-connected distributed power supply and ESSs, as well as the demand for more intelligent and reliable power supply in the distribution network, the reconfiguration of ADN has become increasingly complex. As a result, meta-heuristic algorithms with stronger search capabilities and higher optimization efficiency are being increasingly applied in the reconfiguration of ADNs, summary of other meta-heuristic methods applications is demonstrated in Table 8.

3.2.4 Machine Learning Based Method

Machine learning exhibits powerful parallel information processing capabilities through self-adaptation and self-learning. Machine learning based ADNR methods are summarized in Table 9.

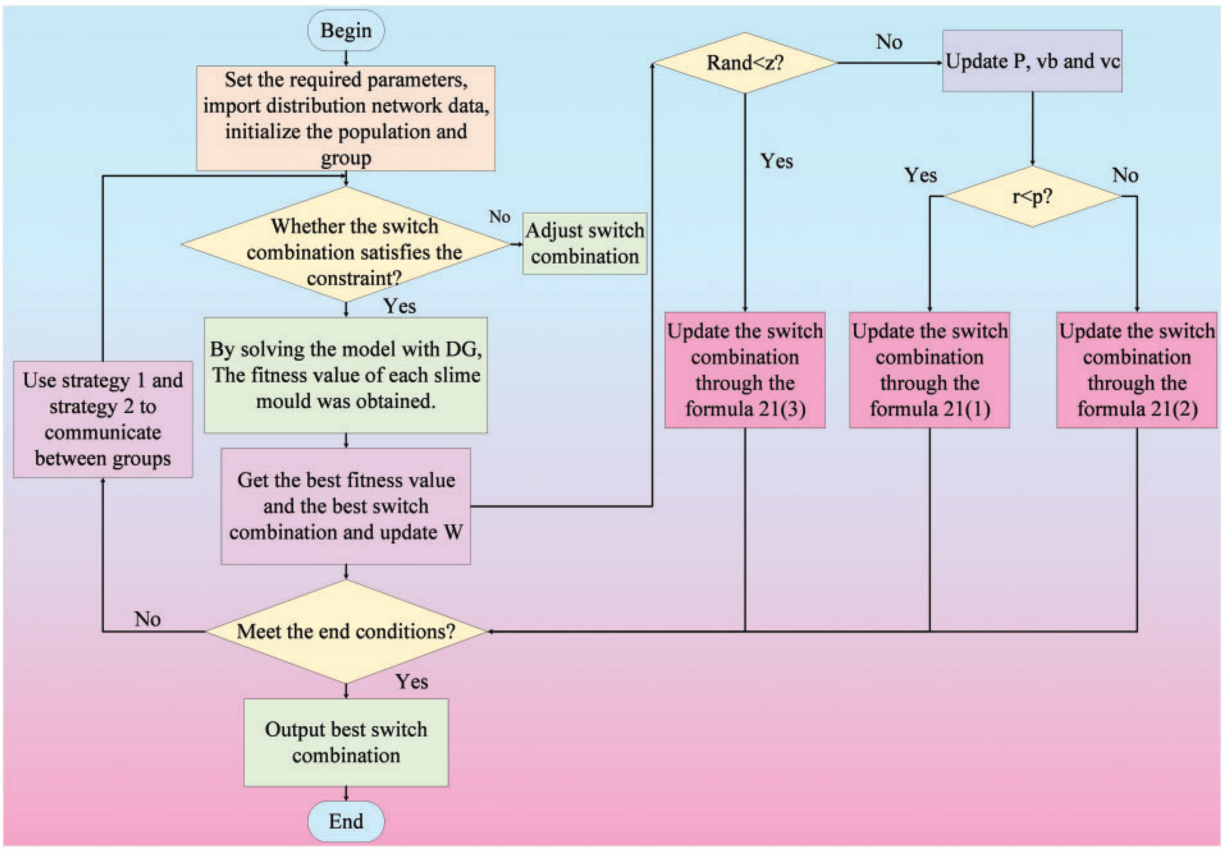


Figure 13: Flow chart of SMA applied to ADNR

Reinforcement Learning Approach

RL is a machine learning method where agents act based on feedback from environmental characteristics. By continuously observing the environment and through repeated trial-and-error, agents accumulate experience and ultimately achieve goal optimization. The principle of RL based ADNR is shown in Fig. 14. The model-free multi-agent deep reinforcement learning (MDRL) proposed by the Reference [157], used multi agents to control the operations of the branch switches in the network. Through centralized training and distributed execution, this training framework reconstructed the network. Reference [158] developed a data-driven batch-constrained reinforcement learning (RL) algorithm for the dynamic ADNR problem, which learned the network reconfiguration control policy from a finite historical operational dataset without interacting with the distribution network.

Table 7: Summary of SMA algorithms applied on ADNR

Literature/ Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Wang et al. (2022) [143]	PSMA	• $f_1 = \min P_{\text{loss}} = \min \sum_{i=1}^{B} S_i R_i \frac{P_i^2 + Q_i^2}{V_i^2}$ • $f_2 = \min\left[\max\left(VSI_1, VSI_2, \ldots, VSI_{N-1}, VSI_N\right)\right]$ • $f_3 = \min LBI = \min \sum_{l=1}^{B} \left(\frac{S_l}{S_{l\max}}\right)^2$ • $f_4 = \min \sum_{i=1}^{M} \lvert s_{it0} - s_{it} \rvert$	• Reduction of power loss • Voltage quality improvement • Balanced load • Switch operation	• Branch circuit capacity constraint • Network topology constraints • Considering the constraint of the power flow equation of distributed power supply • Active and reactive power generation constraints of the distributed generators	• IEEE 33 bus network	• IEEE 33 bus network Active power loss: from 0.135 to 0.093 MW • Load balance index: from 0.570 to 0.413	• IEEE 33 bus network: Five times	***
Pan et al. (2022) [144]	MFSMA	• $\min P_{\text{loss}} = \min \sum_{l=1}^{N_l} r_l \frac{P_l^2 + Q_l^2}{U_i^2}$ • $\min\left(\max\left(VSI_1\left(t_k\right), VSI_2\left(t_k\right), \ldots, VSI_n\left(t_k\right)\right)\right)$ • $\min \mathrm{VSI}\left(t_k\right) = \frac{4\left(\left(x_l Q_j^k + r_l P_j^k\right)\left(U_i^k\right)^2 + \left(x_l P_j^k + r_l Q_j^k\right)^2\right)}{\left(U_i^k\right)^4}$	• Reduction of power loss • Balanced load • Voltage quality improvement	• Node voltage constraints • Branch circuit capacity constraint • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint	• IEEE 33 bus network • IEEE 118 bus network	• IEEE 33 bus network: Active power loss: from 2.217 to 1.585 MW • Voltage stability index: from 0.0113 to 0.0104 • IEEE 118 bus network: Active power loss: from 6.809 to 4.971 MW • Voltage stability index: from 0.054 to 0.031	• IEEE 33 bus network: 33,34,10,32,28 • IEEE 118 bus network: 43, 26, 24, 52, 62, 37, 9, 96, 73, 88, 129, 130, 131, 110, 35	***

Table 8: Summary of other meta-heuristic methods applied on ADNR

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Kavousi-Fard et al. (2013) [145]	Improved Shuffled Frog Leaping Algorithm (ISFLA)	• $f_1(X) = P_{\text{loss}}(X) = \sum_{i=1}^{N_{br}} R_i \lvert I_i \rvert^2$ • $f_2(X) = \text{SAIFI} = \frac{\sum_{i=1}^{N_{\text{Cus}}} \lambda_i N_i}{\sum_{i=1}^{N_{\text{Cus}}} N_i}$ • $f_3(X) = \text{SAIDI} = \frac{\sum_{i=1}^{N_{\text{Cus}}} U_i N_i}{\sum_{i=1}^{N_{\text{Cus}}} N_i}$ • $f_4(X) = \text{AENS} = \frac{\sum_{i=1}^{N_{\text{Cus}}} \text{La}_i U_i}{\sum_{i=1}^{N_{\text{Cus}}} N_i}$	• Reduction of power loss	• Branch circuit capacity constraint • Bus voltage constraints: • Considering the constraint of the power flow equation of distributed power supply • Current safety constraints	• IEEE 32 bus network	• Active power loss: from 0.202 to 0.139MW • SAIFI: post-reconstruction: 1.1781 • SAIDI: post-reconstruction: 9.6422 • AENS: post-reconstruction: 1.9052	• IEEE 32 bus network: 7, 9, 14, 32, 37	***
Shareef et al. (2014) [97]	Quantum Firefly Algorithm (QFA)	• Fitness $= \min\left(\frac{N_{\text{sag}}}{N_{\text{sag\_max}}} + \frac{P_{\text{loss}}}{P_{\text{lass\_max}}}\right)$ • Fitness = min(ASIFI) • Fitness =min (MAIFI) • Fitness = min(SAIFI) • Fitness $= \min\left(N_{\text{sag}}\right)$	• Reduction of power loss	• Network topology constraints • Node voltage constraints • Power flow constraints	• Actual 47-bus test distribution system	• Reduction of power loss: from 2 to 2.33 MW • N_{sag} : from 11577 to 4752 • SARFI: post-reconstruction: 143.4% • SAIFI: from 18.88 to 17.45 • ASIFI: from 55.07 to 23.45 • MAIFI: from 4.33 to 2.32	• IEEE 33 bus network: (2–18), (3–4), (15–16), (17–33), (18–19), (20–23), (24–25), (24–29), (28–29)	***
Mirhoseini et al. (2014) [146]	Improved Adaptive Imperialist Competitive Algorithm (IAICA)	• $\min P_{\text{loss}} = \sum_{l=1}^{n_b} r_l \frac{P_l^2 + Q_l^2}{V_l^2}$	• Reduction of power loss	• Radial network constraint • Node voltage constraints • Branch current constraints • Isolation constraint	• IEEE 33 bus network • IEEE 69 bus network	• IEEE 33 bus network: Reduction of power loss: from 0.169 to 0.115 MW • IEEE 69 bus network: Reduction of power loss: from 0.152 to 0.067 MW	• IEEE 33 bus network: 7, 9, 14, 32, 37 • IEEE 69 bus network: 14, 57, 61, 69, 70	***
Kavousi-Fard et al. (2014) [147]	BA	• $g_1(X) = \text{AENS} = \frac{\sum_{i=1}^{N_{\text{Cus}}} \text{La}_i U_i}{\sum_{i=1}^{N_{\text{Cus}}} N_i}$ • $g_2(X) = \text{SAIFI} = \frac{\sum_{i=1}^{N_{\text{Cus}}} \lambda_i N_i}{\sum_{i=1}^{NN_{\text{Cus}}} N_i}$ • $g_3(X) = P_{\text{loss}}(X) = \sum_{i=1}^{N_{\text{br}}} R_i \times \lvert I_i \rvert^2$	• Reduction of power loss • Balanced load	• Branch circuit capacity constraint • Considering the constraint of the power flow equation of distributed power supply • Bus voltage constraints • Current safety constraints	• IEEE 32 bus network	• Reduction of power loss: from 0.202 to 0.139 MW	• IEEE 32 bus network: 7 9, 14, 32, 37	**

(Continued)

Table 8 (continued)

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Rajaram et al. (2015) [148]	Modified Plant Growth Simulation Algorithm (MPGSA)	• $\max f = \max\left(\Delta P_{\text{loss}}^{\text{R}} + \Delta P_{\text{loss}}^{\text{DG}}\right)$	• Reduction of power loss	• Network topology constraints	• IEEE 33 bus network	• Reduction of power loss: from 0.202 to 0.072 MW	• IEEE 33 bus network: 7, 10, 14, 28, 31	***
Rani et al. (2015) [73]	Invasive Weed Optimization (IWO)	• $f_1 = \min P_{\text{loss}} = \min \sum_{i=1}^{B} S_i R_i \frac{P_i^2 + Q_i^2}{V_i^2}$ • $f_2 = \min\left[\max\left(VSI_1, VSI_2, \ldots, VSI_{N-1}, VSI_N\right)\right]$ • $f_3 = \min LBI = \min \sum_{l=1}^{B} \left(\frac{S_l}{S_{l\max}}\right)^2$ • $f_4 = \min \sum_{i=1}^{M} \lvert s_{it0} - s_{it} \rvert$	• Reduction of power loss • Balanced load • Voltage quality improvement • Switch operation	• Bus voltage constraints • Branch circuit capacity constraint • Network topology constraints • The network radiate has no island constraint	• IEEE 33 bus network • 84 Bus Taiwan Power Company Practical Distribution Network	• IEEE 33 bus network: Reduction of power loss: from 0.202 to 0.144 MW • Maximum node voltage deviation: from 0.086 to 0.064 p.u. • Load balance index: from 0.077 to 0.038 • 84 Bus Taiwan Power Company Practical Distribution Network: • Reduction of power loss: from 0.526 to 0.474 MW • Maximum node voltage deviation: from 0.071 to 0.051 p.u. • Load balance index: from 0.057 to 0.058	N.P.	****
Naveen et al. (2015) [149]	Modified Bacterial Foraging Optimization Algorithm (MBFOA)	• $\Delta P = \text{Re}\left\{2\sum_{i=1}^{n} I_i \left(E_m - E_n\right) + R_{\text{line}} \sum_{i=1}^{n} \lvert I_i \rvert^2\right\}$	• Reduction of power loss	• Current safety constraints • Network topology constraints • Branch circuit capacity constraint • Voltage drop within limits	• IEEE 16 bus network • IEEE 33 bus network • IEEE 69 bus network	• IEEE 16 bus network: Reduction of power loss: from 0.511 to 0.424 MW • IEEE 33 bus network: Reduction of power loss: from 0.202 to 0.134 MW • IEEE 69 bus network: Reduction of power loss: from 0.225 to 0.098 MW	• IEEE 16 bus network: 5–11, 10–14, 7–16 • IEEE 33 bus network: 7, 10, 13, 14, 32 • IEEE 69 bus network: 19, 42, 55, 61, 63	***

(Continued)

Table 8 (continued)

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index: Test system	Applicability index: Indicator optimization	Applicability index: Number of switch actions	Overall score
Li et al. (2016) [150]	Minimum Spanning Tree Algorithm (MSTA)	• $\min P_{\text{loss}} = \sum_{k=1}^{n_b} R_k \frac{P_k^2 + Q_k^2}{V_k^2}$	• Reduction of power loss	• Network topology constraints • Node voltage constraints • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 33 bus network • IEEE 69 bus network • IEEE 210 bus network	• IEEE 33 bus network: Reduction of power loss: from 0.202 to 0.139 MW • IEEE 69 bus network: Reduction of power loss: from 0.226 to 0.099 MW • IEEE 210 bus network: Reduction of power loss: from 0.647 to 0.427 MW	• IEEE 33 bus network: 7, 9, 14, 32, 37 • IEEE 69 bus network: 15, 59, 62, 70, 71 • IEEE 210 bus network: 13, 34, 36, 55, 111, 118, 128, 133, 151, 157, 163, 197, 210, 218, 211	***
Uniyal et al. (2021) [151]	Modified Whale Optimization Algorithm (MWOA)	• $\min(\text{del} - \text{P}P_{\text{loss}} + \text{del} - \text{VSI})$ $del - P_{\text{loss}} = \frac{P_{\text{loss}}^{\text{cal}}}{P_{\text{loss}}^{\text{base}}}$ $del - VSI =$ $\max\{1 - VSI_{n+1}\} \forall n = 1, N - 1_{\text{bus}}$	• Reduction of power loss • Voltage quality improvement	• Network topology constraints • Node voltage constraints • Current safety constraints • DG capacity constraints	• IEEE 33 bus network • IEEE 69 bus network	• IEEE 33 bus network: Reduction of power loss: from 0.204 to 0.052 MW • Voltage stability index: from 0.6960 to 0.9047 p.u. • IEEE 69 bus network: Reduction of power loss: from 0.227 to 0.036 MW • Voltage stability index: from 0.6865 to 0.9372	• IEEE 33 bus network: 11, 28, 31, 33, 34 • IEEE 69 bus network: 71, 62, 57, 17, 8	***
Azad-Farsani et al. (2021) [152]	FA	• $f(\text{X}) = \sum_{\forall i \in \psi^{\text{line}}} R_i \times \lvert I_i \rvert^2$	• Reduction of power loss	• Bus voltage constraints • Active power outputs of DG units • Power factors of DG units. • Thermal capacity of distribution lines	• Single line diagram of TPC test network	Reduction of power loss: from 0.531 to 0.463 MW	• Single line diagram of TPC test network: 55, 7, 86, 72, 88, 14, 90, 83, 92, 39, 34, 41, 62	***
Anteneh et al. (2021) [153]	Modified Shark Smell Optimization (MSSO)	• $OF_1 = \min(SAIFI, SAIDI, EENS)$ • $OF_2 = \min(P_{\text{tlass}})$ • $OF_3 = \sum_{n=1}^{NL}\left(K_n R_n \left(\frac{P_n^2 * Q_n^2}{V_n^2}\right)\right)$	• Reduction of power loss • Voltage quality improvement	• Node voltage constraints • Feeder's capability constraints	• Initial reconfiguration of kombolcha distribution network	• Power loss reduction: from 0.430 to 0.170 MW • SAIFI: from 261 to 91 • SAIDI: from 423 to 150	• Initial reconfiguration of kombolcha distribution network: 6, 11, 24, 28, 36	*****

(Continued)

Table 8 (continued)

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index: Test system	Applicability index: Indicator optimization	Applicability index: Number of switch actions	Overall score
Li et al. (2022) [154]	Discrete Monkey Algorithm (DMA)	• $\min F = \sum_{t=1}^{T} \sum_{y=1}^{N_y} \Delta P_{y,t} C_{\mathrm{kWh}} + \sum_{t=1}^{T} N_{\mathrm{ch}} C_{\mathrm{ch}}$	• Reduction of power loss • Switch operation	• Node voltage constraints • The output numbers of shunt capacitor unit constraints • Controllable equipment operation frequency constraints	• Topology of IEEE 33-node DN system	Power loss reduction: from 1.04 to 0.24 MW	N.P.	****
Li et al. (2022) [155]	Multi-objective Sparrow Search Algorithm	• $F_1 = \sum_{t=1}^{T} \left(C_a \sum_{k=1}^{N_b} P_{t,loss}^{k} + C_b N_S^t + C_r^t \right)$ • $F_2 = \sum_{t=1}^{T} \sum_{k=1}^{N_b} R_k \frac{P_{t,k}^2 + Q_{t,k}^2}{U_{t,k}^2}$ • $F_3 = \sum_{t=1}^{T} \left(\frac{1}{N_n} \sum_{i=1}^{N_n} \lvert U_{ti}^2 - U_r^2 \rvert \right)$	• Reduction of power loss • Voltage quality improvement	• Considering the constraint of the power flow equation of distributed power supply • Node voltage constraints • Current safety constraints • SVC switching capacity constraint • Network topology constraints	• Improved IEEE 30 system topology diagram	• The total power loss: from 3.268 to 0.792 MW • Total voltage deviation: from 1.9776 to 0.5920 p.u.	4, 34, 35, 31, 28	*****
Cikan et al. (2022) [156]	Equilibrium Optimizer Algorithm (EOA)	• Fitness Function $= \min \left(\omega_1 \Delta P_{\mathrm{loss}}^{\mathrm{reduced}} + \omega_2 \Delta V_{\mathrm{D}} \right)$	• Reduction of power loss • Voltage quality improvement	• Node voltage constraints • Current safety constraints	• IEEE 16 bus network • IEEE 33 bus network • IEEE 69 bus network • IEEE 118 bus network	• IEEE 16 bus network: Power loss reduction:from 0.514 to 0.468 MW • IEEE 33 bus network: Power loss reduction: from 0.202 to 0.139 MW • IEEE 69 bus network: Power loss reduction: from 0.224 to 0.098 MW • IEEE 118 bus network Power loss reduction: from 1.297 to 0.853 MW	• IEEE 16 bus network: 7, 8, 16 • IEEE 33 bus network: 7, 9, 14, 32, 37 • IEEE 69 bus network: 14, 56, 61, 69, 70 • IEEE 118 bus network: 23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	****

Deep Learning Approach

Reference [159] proposed an ADNR method based on Efficient Deep Learning (EDL), which is based on deep convolutional neural network (CNN) to design the short-term voltage stability assessment network, and selected historical data to train it. The STVS platform calculated the indices under all topologies and gradually filters out the topologies that meet the requirements. The large number of computations leads to poor robustness of the algorithm, which is difficult to cope with the challenges of ADN. Reference [160] combined DL with robust optimization: based on deep neural networks adaptively constructing the uncertainty set of DG and load from the historical dataset of the distribution network, robust ADNR was considered as a two-stage mixed-integer quadratic programming problem, and solved the ADNR configuration by using column generation method and constraint generation method. The flowchart for solving ADNR by DL is shown in Fig. 15.

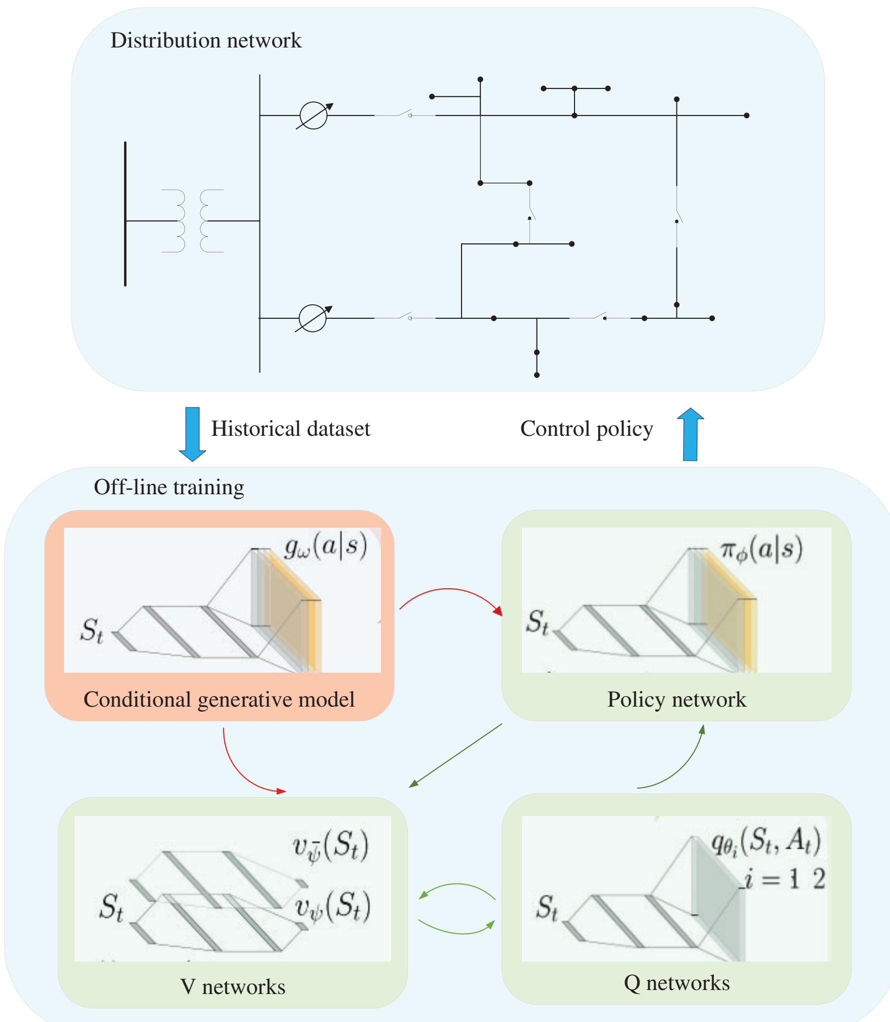


Figure 14: Reinforcement learning principles

Table 9: Summary of machine learning based method applied on ADNR

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Zheng et al. (2020) [160]	DL	• $P_{\text{loss}} = \sum_{b=1}^{E} \sum_{\phi=\{A,B,C\}} \left[\frac{\left(p_b^{\phi}\right)^2 + \left(q_b^{\phi}\right)^2}{v_i^{\phi}} R_b^{\phi\phi} \right]$ • $\text{LBI} = \sum_{b=1}^{E} \sum_{\phi=\{A,B,C\}} \left[\frac{\left(p_b^{\phi}\right)^2 + \left(q_b^{\phi}\right)^2}{\overline{S}_b^2} \right]$	• Reduction of power loss • Balanced load	• Branch circuit capacity constraint • Network topology constraints • Considering the constraint of the power flow equation of distributed power supply • Active and reactive power generation constraints of the distributed generators	• IEEE 123 bus network	N.P.	• IEEE 123 bus network: 42, 25, 21, 121, 122, 58, 39, 125, 70, 127, 128, 129, 85, 131, 33	****
Oh et al. (2020) [161]	RL-DQL	N.P.	• Voltage quality improvement • Balanced load	• Node voltage constraints • Branch circuit capacity constraint • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint	• Modified CIGRE 14-bus network • IEEE 123 bus system	• Modified CIGRE 14-bus network: Line capacity violation: from 2% to 2.5% • Bus voltage violation: from 13.50% to 1.25% • IEEE123-bus system: Line capacity violation: from 3.75% to 0 • Bus voltage violation: from 0.75% to 2%	N.P.	**

(Continued)

Table 9 (continued)

Literature/ Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Bui et al. (2022) [162]	RL-DQL	• $\min \left\{ \begin{matrix} \sum_{i \in I} \sum_{t \in T} \left(C_i^{\mathrm{DG}} \cdot P_{i,t}^{\mathrm{DG}} + y_{i,t} \cdot C_i^{SU} + z_{i,t} \cdot C_i^{SD} \right) \\ + \sum_{t \in T} \left(PR_t^{\mathrm{Buy}} \cdot P_t^{\mathrm{Buy}} \right) - \sum_{t \in T} \left(PR_t^{\mathrm{Sell}} \cdot P_t^{\mathrm{Sell}} \right) \end{matrix} \right\}$	• Reduction of power loss	• Node voltage constraints • Branch circuit capacity constraint • Network topology constraints • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint • Reliability constraints of high-voltage power networks • Constraints on load rates of adjacent voltage levels	• IEEE 33 bus network	N.P.	• IEEE 33 bus network: 7, 9, 14, 32, 37	***
Malekshah et al. (2022) [163]	RL-DQL	N.P.	• Voltage quality improvement • Balanced load	• Node voltage constraints • Branch circuit capacity constraint • Network topology constraints	• IEEE 33 bus network • IEEE 118 bus network	• IEEE 33 bus network Active power loss: from 0.202 to 0.130 MW • Min voltage: from 0.9131 to 0.9513 p.u.	• IEEE 33 bus network: 7, 9, 14, 32, 37	****

Table 10: Summary of hybrid algorithm applied on ADNR

Literature/Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Vasudevan et al. (2018) [132]	GA-PSO	• $\min P_{\text{loss}} = \sum_{i=1}^{m} \lvert I_i \rvert^2 r_i, \forall T$	• Reduction of power loss	• Node voltage constraints • Considering the constraint of the power flow equation of distributed power supply	• IEEE 69 bus network	• Reduction of power loss: from 0.224 to 0.102 MW	• IEEE 69 bus network: (8–9) (52–69)	**
Xu et al. (2020) [117]	CSA-SA	• $\min f_1 = \sum_{i=1}^{n} \frac{P_i^2 + Q_i^2}{U_i^2} k_i R_i$ • $\min f_2 = \sum_{j=1}^{k} \frac{(U_{js} - U_{j\text{N}})^2}{U_{j\text{N}}^2}$ • $\min f_3 = \sum_{j=1}^{m} \left(\frac{S_j}{S_{jmax}}\right)^2$	• Reduction of power loss • Voltage quality improvement • Balanced load	• Node voltage constraints • Branch circuit capacity constraint • Network topology constraints • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint • Reliability constraints of high-voltage power networks • Constraints on load rates of adjacent voltage levels	• IEEE 33 bus network	• Reduction of power loss: from 0.346 to 0.206 MW • Voltage deviation: from 0.045 to 0.015 • Degree of load balancing: from 1.136 to 0.635	• IEEE 33 bus network: 9, 11, 16, 17, 28, 31, 41, 49, 50, 54	***
Oh et al. (2020) [161]	RL-DQL	N.P.	• Voltage quality improvement • Balanced load	• Node voltage constraints • Branch circuit capacity constraint • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint	• Modified CIGRE 14-bus network • IEEE 123 bus system	• Modified CIGRE 14-bus network: Line capacity violation: from 2% to 2.5% • Bus voltage violation: from 13.50% to 1.25% • IEEE123−bus system: Line capacity violation: from 3.75% to 0 • Bus voltage violation: from 0.75% to 2%	N.P.	**

Table 10 (Continued)

Literature/ Year	Mathematical modeling	Objective function	Purpose	Reconfiguration constraints	Applicability index			Overall score
					Test system	Indicator optimization	Number of switch actions	
Bui et al. (2022) [162]	RL-DQL	• $\min\left\{\begin{array}{l}\sum_{i\in I}\sum_{t\in T}\left(C_i^{\mathrm{DG}}\cdot P_{i,t}^{\mathrm{DG}}+y_{i,t}\cdot C_i^{SU}+z_{i,t}\cdot C_i^{SD}\right)\\+\sum_{t\in T}\left(PR_t^{\mathrm{Buy}}\cdot P_t^{\mathrm{Buy}}\right)-\sum_{t\in T}\left(PR_t^{\mathrm{Sell}}\cdot P_t^{\mathrm{Sell}}\right)\end{array}\right\}$	• Reduction of power loss	• Node voltage constraints • Branch circuit capacity constraint • Network topology constraints • Current safety constraints • Considering the constraint of the power flow equation of distributed power supply • The network radiate has no island constraint • Reliability constraints of high-voltage power networks • Constraints on load rates of adjacent voltage levels	• IEEE 33 bus network	N.P.	• IEEE 33 bus network: 7, 9, 14, 32, 37	***
Malekshah et al. (2022) [163]	RL-DQL	N.P.	• Voltage quality improvement • Balanced load	• Node voltage constraints • Branch circuit capacity constraint • Network topology constraints	• IEEE 33 bus network • IEEE 118 bus network	• IEEE 33 bus network Active power loss: from 0.202 to 0.130 MW • Min voltage:from 0.9131 to 0.9513 p.u.	• IEEE 33 bus network: 7, 9, 14, 32, 37 **	****

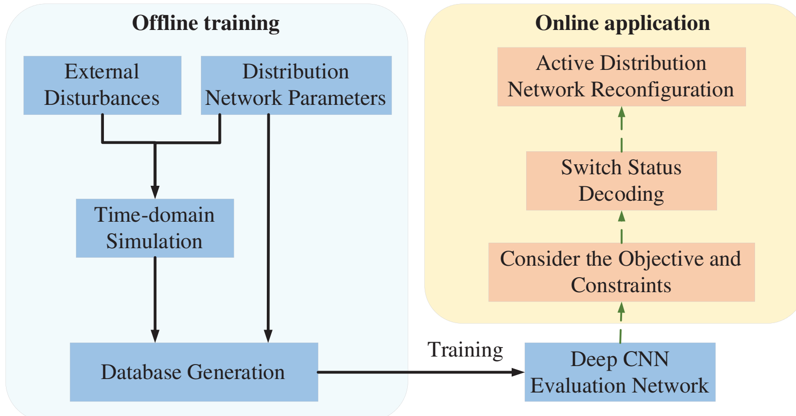


Figure 15: The flowchart for solving ADNR by DL

3.2.5 Hybrid Algorithm

As ESS and DG become more widely connected to the grid, DSR to incentive measures such as time-of-use and real-time pricing are causing tidal changes in the power system, resulting in voltage fluctuations, and increasing system complexity. Many scholars have attempted to mix meta-heuristic algorithms to ensure global optimal results, The summary of hybrid algorithm is shown in Table 10.

4 Summary and Discussion

The paper provides a comprehensive review of numerous existing methods for ADNR, which focuses on both theoretical and practical aspects, aiming to emphasize the operational mechanisms, testing systems, optimization objectives, complexities, strengths, weaknesses, and limitations of each method to facilitate a more comprehensive and practical comparison. Tables 2–10 offer detailed summaries of the 52 ADNR methods mentioned in this paper, categorized by application years, sub-methods, and experimental data.

Based on the recently proposed ADNR methods, two constructive discussions are conducted to illustrate the current research status and existing issues, as follows:

a) Photovoltaic, wind power and other renewable energy sources exhibit strong randomness and significant fluctuations. The integration of a large amount of renewable energy into the distribution network can lead to issues such as poor power quality, excessive voltage fluctuations, uneven load distribution, and high network losses. To address these difficult and complex issues, each type of method goes its way, as follows:

Mathematical programming methods (e.g., linear programming and nonlinear programming) mainly consider the impact of renewable energy sources on the power loss of the active distribution network. In particular, the Lagrange relaxation divides the network into smaller regions via dual decomposition, which converts this MINLP problem into a simpler MILP one. Then coordinating node solutions can be obtained to minimize overall network loss. The Standard Newton method transforms the objective into an unconstrained problem using Lagrange multipliers or penalty functions, making it ideal for large-scale reconfiguration under renewable energy integration. The Simplex algorithm, while ignoring the capacity limits of transmission lines, converts the minimum network loss problem into a linear programming problem. However, when a significant number of renewable energy sources are integrated into the system, it significantly increases the complexity and difficulty of computation. Therefore, the effectiveness of this method may decline substantially.

Unlike mathematical programming methods that only consider a single objective, i.e., power loss, and ignore mitigating the impact of renewable energy sources on the distribution network, Meta-heuristic algorithms effectively and flexibly handle large-scale nonlinear optimization problems e.g., minimizing power losses, maximizing renewable energy utilization, minimizing voltage fluctuations, etc. They enable decision-making on variables such as capacity, location, output power of renewable energy sources, and load adjustments, which exhibit good global exploration capabilities. Furthermore, their stochastic elements can effectively address the uncertainty of renewable energy sources.

By leveraging data-driven insights, Machine Learning methods establish models that accurately describe the operation status, load demands, and power quality of distribution networks containing renewable energy sources. Through training these models and addressing multi-objective optimization problems like minimizing power losses, maximizing renewable utilization, and minimizing voltage fluctuations, rational reconfiguration solutions are obtained. Subsequently, their adaptive learning capabilities are applied to adapt the reconfiguration strategies dynamically, aligning with the output stochastic nature of renewable energy sources. Moreover, Machine Learning methods can accurately predict the energy supply and demand relationship, effectively overcoming uncertainty and fluctuations in the distribution network.

b) The applicable electrical network scenarios of each ADNR method are different due to their mechanism differences, as follows:

The traditional method has the advantages of simple modeling and fast solving speed, but it is only suitable for small and medium-sized distribution networks. When facing more complex networks, it is unable to handle intricate typologies and multiple constraints, and may get stuck in local optimal solutions;

The Mathematical programming method can accurately establish mathematical models and is suitable for small and medium-sized distribution network reconfiguration. As the distribution network scales up, the Mathematical programming method needs to consider complex linear and nonlinear constraints, making the model establishment and solving process more complicated and resulting in longer reconfiguration times;

Meta-heuristic algorithms are currently widely applied in medium to large-scale active distribution network reconfiguration. By utilizing diverse searching strategies, they have the opportunity to find global optimal solutions. However, due to the need for multiple iterations and searches, as well as their susceptibility to initial solutions, they tend to have longer run times and may lead to sub-optimal reconfiguration results;

Machine learning based methods can leverage the advantages of data-driven approaches to adapt to the environment and requirements of distribution networks while possessing strong predictive and optimization capabilities. With the development of big data and artificial intelligence technologies, machine learning based methods are expected to gain even more applications in the future;

Hybrid algorithms make full use of the strengths of different methods, considering various problems and requirements, and utilize diverse and global search strategies to obtain more optimal solutions. However, when dealing with large-scale distribution network reconfiguration, the design and implementation of the algorithm can be more complex.

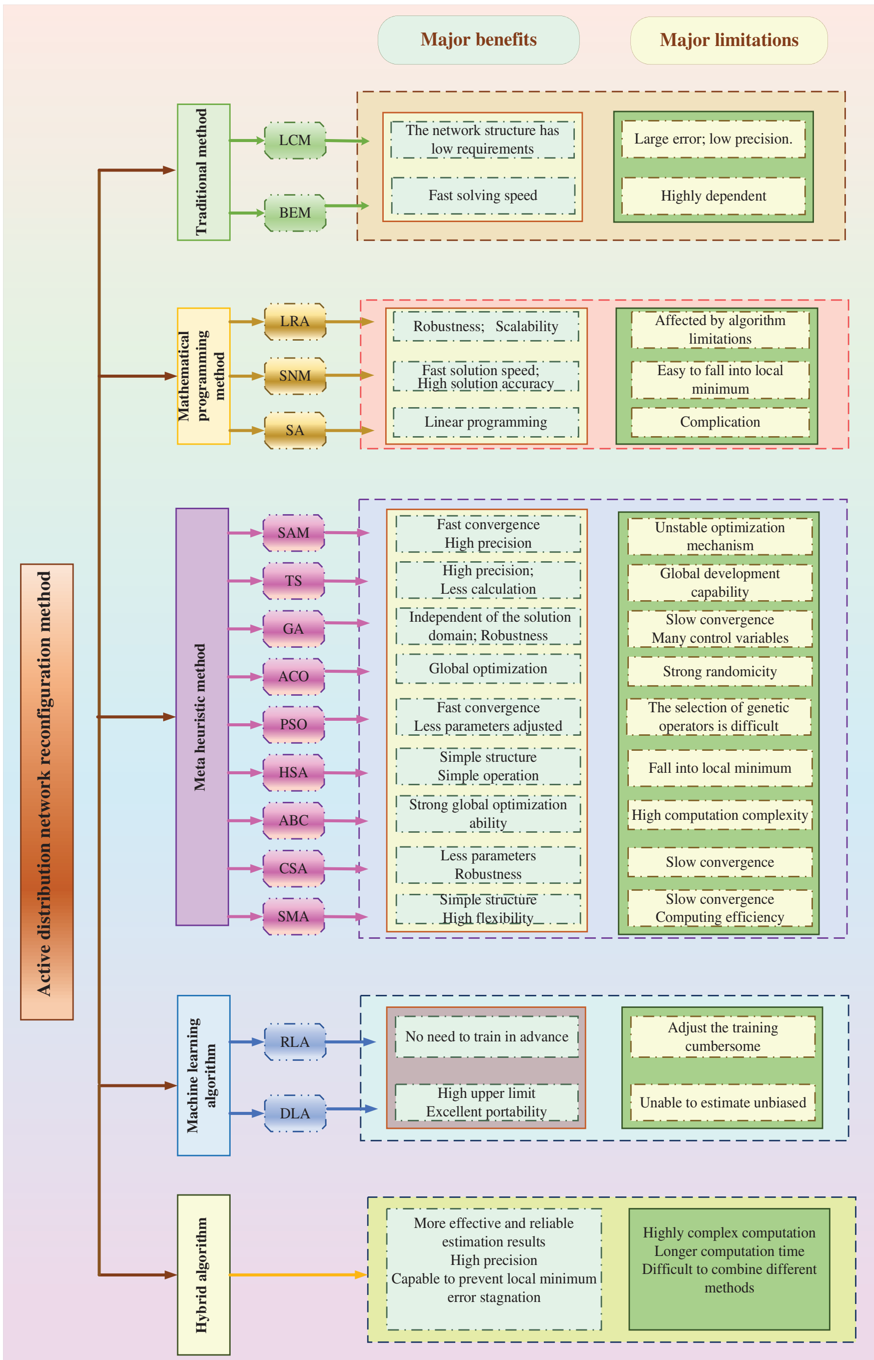
c) The distribution networks studied in this paper are all tree structures, so in most cases, there is no loop. Complex loop problems need to be unlooped and tested, and each node is verified to be out of bounds through simulation, which in turn calculates the loop.

Overall, Table 11 tabulates a comprehensive and systematic summary and analysis.

Table 11: Practical analysis of ADNR methods

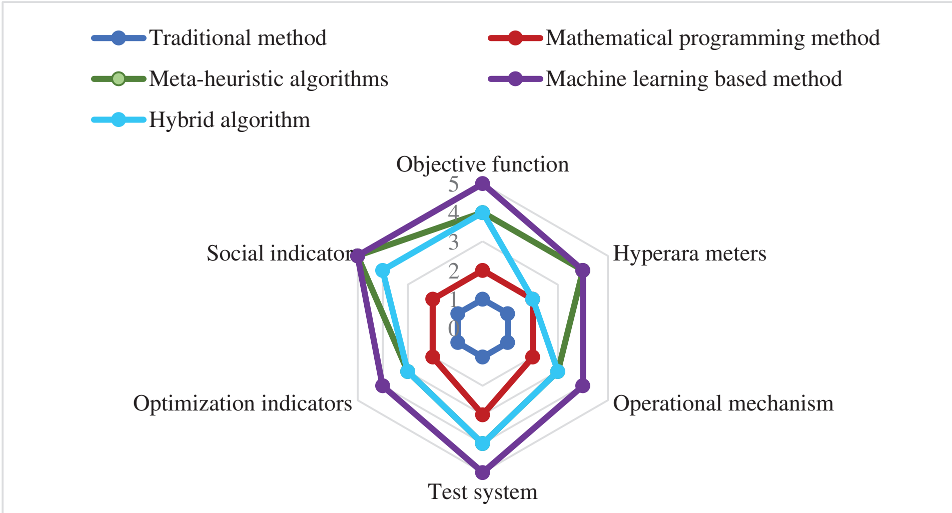
Method	Applicable systems	Reason
Traditional method	Small-scale virtual distribution networks	• Only address local issues and cannot obtain a global optimal solution • Face challenges in dealing with complex network topologies and frequent load variations
Mathematical programming method	Medium to small-scale virtual distribution networks (only LRA is feasible for medium-scale actual distribution networks)	• The algorithm's execution time is too long, making it difficult to apply in practical situations • Involves a substantial number of matrix computations, resulting in high memory requirements • Poor convergence makes it prone to getting trapped in local optima • LRA decomposes the large-scale formulated original problem into independent subproblems, enabling faster solution speeds
Meta-heuristic algorithms	Medium to large-scale actual distribution networks	• Involving extensive search and iteration processes, the running speed is slow • Complex ADNR may involve multiple locally optimal solutions • Difficult to effectively handle constraints, resulting solutions may not meet practical requirements • Poor scalability
Machine learning based method	Large-scale actual distribution networks	• Speeding up the training process through parallel computing • Possesses strong global search capabilities • Dynamically adjust decisions through adaptive learning • Using historical operational data and real-time monitoring data of the distribution network for modeling and optimization, adapting to real-world operating conditions
Hybrid algorithm	Medium to large-scale actual active distribution networks	• Fulfilling the strengths of various methods and compensating for their respective weaknesses • Strong adaptability • By combining multiple optimization methods, diverse searching strategies can be achieved

Lastly, Fig. 16a systematically summarizes the major benefits and limitations of each method. Based on the summary of the major benefits and limitations of each method in Fig. 16a, a 6-axis radar chart is used in Fig. 16b to visually compare the performance of five types of ADNR methods across six indicators: objective function, social indicator, hyperparameters, optimization indicators, operational mechanism, and test system. The scoring system used in the radar chart rates methods according to their relative performance: the best-performing method in each indicator receives 5 points, the second-best receives 4 points, the average method receives 3 points, and the worst receives 1 point.



(a)

Figure 16: (Continued)



(b)

Figure 16: Comprehensive evaluation of ADNR methods (a) Summary and comparison of all algorithms (b) Comprehensive comparison

5 Conclusions and Prospects

This paper profoundly summarizes and analyzes active distribution network reconfiguration methods, which endeavors to offer future researchers comprehensive and systematic references and guidelines. Here, several conclusions are stated as follows:

a) A total of 52 methods are summarized and counted in this paper, which are categorized into five major categories, i.e., traditional (2 methods), mathematics-based (3 methods), meta-heuristic (32 methods), hybrid (3 methods), and machine learning based (2 methods).

b) Given the uniqueness of ADNR methods and their impact on the network, a comprehensive evaluation system is carefully established considering complexity and applicability. Specifically, complexity is determined by three indicators: (a) multi-objective optimization, (b) hyperparameters, and (c) operational mechanism. Meanwhile, the applicability is scored according to three aspects: (a) test system, (b) optimization indicators, and (c) social indicators.

c) 32 meta-heuristic algorithms are widely used in ADNR thanks to their fast convergence speed and independence for models. However, due to their inherent randomness, it is challenging to balance the relationship between local and global optimization. Many scholars have attempted to mix meta-heuristic algorithms to ensure global optimal results.

On this basis, the paper provides the following recommendations for future research:

a) Reconfiguration technology improvement: Heuristic algorithms such as PSO [131,133], GA [132], and HSA [96,136] were heavily used in ADNR, and the feasibility of the algorithms was verified in small-scale simulation test networks, e.g., IEEE 33-bus system and IEEE 69-bus system. Compared with heuristic algorithms, machine learning algorithms such as DL [160], RL [162,163], etc., acquired more satisfactory performance on actual 123-node networks, Modified CIGRE 14-bus network actual networks. Hence, RL and DL with strong stability, adaptability, portability, and drivability seem to be promising tools for large-scale ADNR in the future.

b) Reconfiguration constraint improvement: The introduction of numerous ESSs, DGs, and DR complexifies the topology of the grid. Additionally, DRs based on incentives such as time-sharing tariffs and real-time tariffs can change power flow and cause voltage fluctuations. Unfortunately, DRs are usually ignored in ADNR, which contradicts reality and application. Thus, more complex constraints of flexible power sources and the influence of DRs ought to be covered when implementing ADNR.

c) Reconfiguration test system improvement: Test systems of ADNR are mainly small-scale, e.g., the IEEE 14 bus system [137], IEEE16 bus system [156], and IEEE32 bus system [145]. The small-scale test network cannot effectively reflect the real situation of power grids, especially integrated ESSs and DGs. Therefore, larger-scale systems with real nodes are recommended to validate the proposed ADNR methods.

d) Reconfiguration network improvement: More significant consideration should be given to the unified whole of the heat network, gas network, and grid, and the reconfiguration problem should be approached from the perspective of energy integration and synergy.

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Appendix A

Table A1 Practical analysis of ADNR methods

Branch		Branch impedance		Loads	
Rc.Nd.	Sn.Nd.	*r* (Ω)	*x* (Ω)	PL (kW)	QL (kvar)
1	2	0.0922	0.0477	100	60
2	3	0.493	0.2511	90	40
3	4	0.366	0.1864	120	80
4	5	0.3811	0.1941	60	30
5	6	0.819	0.707	60	20
6	7	0.1872	0.6188	200	100
7	8	1.7114	1.2351	200	100
8	9	1.03	0.74	60	20
9	10	1.04	0.74	60	20
10	11	0.1966	0.065	45	30
11	12	0.3744	0.1238	60	35
12	13	1.468	1.155	60	35
13	14	0.5416	0.7129	120	80
14	15	0.591	0.526	60	10
15	16	0.7463	0.545	60	20
16	17	1.289	1.721	60	20
17	18	0.732	0.574	90	40
2	19	0.164	0.1565	90	40
19	20	1.5042	1.3554	90	40
20	21	0.4095	0.4784	90	40
21	22	0.7089	0.9373	90	40
3	23	0.4512	0.3083	90	50
23	24	0.898	0.7091	420	200
24	25	0.896	0.7011	420	200
6	26	0.203	0.1034	60	25
26	27	0.2842	0.1447	60	25
27	28	1.059	0.9337	60	20
28	29	0.8042	0.7006	120	70
29	30	0.5075	0.2585	200	600
30	31	0.9744	0.963	150	70
31	32	0.3105	0.3619	210	100
32	33	0.341	0.5302	60	40
21	8	0	2	–	–
9	14	0	2	–	–
12	22	0	2	–	–
18	33	0	0.5	–	–
25	29	0	0.5	–	–

Table A2 Practical analysis of ADNR methods

Branch		Branch impedance		Loads	
Rc.Nd.	Sn.Nd.	r (Ω)	x (Ω)	PL (kW)	QL (kvar)
1	2	0.0005	0.0012	0	0
2	3	0.0005	0.0012	0	0
3	4	0.0015	0.0036	0	0
4	5	0.0251	0.0294	0	0
5	6	0.366	0.1863	2.6	2.2
6	7	0.381	0.1941	40.4	30
7	8	0.0922	0.047	75	54
8	9	0.0493	0.0251	30	22
9	10	0.819	0.2707	28	19
10	11	0.1872	0.0619	145	104
11	12	0.7114	0.2351	145	104
12	13	1.03	0.34	8	5
13	14	1.044	0.345	8	5.5
14	15	1.058	0.3496	0	0
15	16	0.1966	0.065	45.5	30
16	17	0.3744	0.1238	60	35
17	18	0.0047	0.0016	60	35
18	19	0.3276	0.1083	0	0
19	20	0.2106	0.069	1	0.6
20	21	0.3416	0.1129	114	81
21	22	0.014	0.0046	5	3.5
22	23	0.1591	0.0526	0	0
23	24	0.3463	0.1145	28	20
24	25	0.7488	0.2475	0	0
25	26	0.3089	0.1021	14	10
26	27	0.1732	0.0572	14	10
3	28	0.0044	0.0108	26	18.6
28	29	0.064	0.1565	26	18.6
29	30	0.3978	0.1315	0	0
30	31	0.0702	0.0232	0	0
31	32	0.351	0.116	0	0
32	33	0.839	0.2816	14	10
33	34	1.708	0.5646	19.5	14
34	35	1.474	0.4873	6	4
3	36	0.0044	0.0108	26	18.55
36	37	0.064	0.1565	26	18.55
37	38	0.1053	0.123	0	0
38	39	0.0304	0.0355	24	17
39	40	0.0018	0.0021	24	17
40	41	0.7283	0.8509	1.2	1

(Continued)

Table A2 (continued)

Branch		Branch impedance		Loads	
Rc.Nd.	Sn.Nd.	r (Ω)	x (Ω)	PL (kW)	QL (kvar)
41	42	0.31	0.3623	0	0
42	43	0.041	0.0478	6	4.3
43	44	0.0092	0.0116	0	0
44	45	0.1089	0.1373	39.22	26.3
45	46	0.0009	0.0012	39.22	26.3
4	47	0.0034	0.0084	0	0
47	48	0.0851	0.2083	79	56.4
48	49	0.2898	0.7091	384.7	274.5
49	50	0.0822	0.2011	384.7	274.5
8	51	0.0928	0.0473	40.5	28.3
51	52	0.3319	0.1114	3.6	2.7
9	53	0.174	0.0886	4.35	3.5
53	54	0.203	0.1034	26.4	19
54	55	0.2842	0.1447	24	17.2
55	56	0.2813	0.1433	0	0
56	57	1.59	0.5337	0	0
57	58	0.7837	0.263	0	0
58	59	0.3042	0.1006	100	72
59	60	0.3861	0.1172	0	0
60	61	0.5075	0.2585	1244	888
61	62	0.0974	0.0496	32	23
62	63	0.145	0.0738	0	0
63	64	0.7105	0.3619	227	162
64	65	1.041	0.5302	59	42
11	66	0.2012	0.0611	18	13
66	67	0.0047	0.0014	18	13
12	68	0.7394	0.2444	28	20
68	69	0.0047	0.0016	28	20
11	43	0.5	0.5		
13	21	0.5	0.5		
15	46	1	0.5		
50	59	2	1		
27	65	1	0.5		

Table A3 Practical analysis of ADNR methods

Branch number	kV	Load		Load type	No. of customers
		PL (kW)	QL (kvar)		
1	132	0	0	0	0
2	11	0	0	0	0
3	11	0.85	0.527	1	1
4	11	0.342	0.194	4	1
5	11	0.244	0.145	3	24
6	11	0.244	0.177	3	24
7	11	0	0	0	0
8	3.3	0	0	0	0
9	3.3	1.275	0.513	1	1
10	0.433	1.594	0.641	1	1
11	11	0.146	0.098	3	14
12	11	0.294	0.143	3	29
13	11	0.488	0.341	2	4
14	11	0.437	0.199	2	4
15	11	1.776	1.006	2	8
16	11	0.297	0.098	3	30
17	11	0	0	0	0
18	11	0.616	0.43	3	61
19	11	0.388	0.23	3	39
20	11	0.732	0.354	1	1
21	3.3	1.063	0.427	1	1
22	11	0.925	0.549	2	5
23	11	0.582	0.345	2	3
24	11	0.504	0.23	4	100
25	11	1.25	0.605	3	125
26	11	0.351	0.149	6	1
27	11	0.276	0.118	3	28
28	11	0.314	0.134	4	63
29	11	0.613	0.261	2	3
30	11	0.592	0.252	3	59
31	11	0	0	0	0
32	6.6	0	0	0	0
33	11	0.032	0.024	6	1
34	33	0	0	0	0
35	33	0	0	0	0
36	33	0	0	0	0
37	11	8	6	5	8
38	11	7.65	4.741	5	7
39	33	0	0	0	0
40	33	0	0	0	0
41	33	0	0	0	0

(Continued)

Table A3 (continued)

Branch number	kV	Load		Load type	No. of customers
		PL (kW)	QL (kvar)		
42	33	0	0	0	0
43	33	0	0	0	0
44	11	12.75	7.902	5	26
45	11	12.75	7.902	5	26
46	11	6.8	4.214	5	14
47	11	4.8	3.6	5	10