

Article

Reliability Assessment Method for Urban Distribution Network Based on Lightning Search Algorithm

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Abstract

With the gradual improvement of residential electricity reliability, the lower design strength of the distribution network makes it more prone to large-scale power outages in resisting natural disasters. Among them, the cold load start-up effect will significantly prolong the recovery time and affect reliability indicators. Based on this, this article proposes a reliability evaluation method for urban distribution networks based on a lightning search algorithm, which is used for optimal recovery planning and reliability calculation of urban power systems with highly concentrated load under constant temperature control. Firstly, a delay index model is used to establish a time-sharing power demand calculation model for cold load start-up events, and an optimal recovery model with the goal of minimizing recovery time and its corresponding constraints are proposed. Then, the cold load start-up event is incorporated into the Monte Carlo simulation platform for reliability assessment, and the lightning search algorithm is used to develop the optimal recovery plan. The recovery time and sequence are determined based on the duration of the power outage and the electricity demand at the time of recovery. Finally, the test distribution system was used to verify that the optimal recovery plan considering cold load start events does not violate the constraint conditions, and the stability and convergence robustness of the lightning search algorithm are stronger than the current mainstream algorithms. It can effectively improve the reliability of the distribution grid when considering cold load start events.

Keywords: reliability assessment; cold load pick-up; optimal recovery planning; delay index model; lightning search algorithm



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1. Introduction

With the continuous pursuit of people's material needs, air conditioning, floor heating and other temperature-controlled appliances have become indispensable in people's lives, making it increasingly difficult for such temperature-controlled appliances to predict the load of urban residents [1–3]. Coupled with the complexity and diversity of global climate change, the frequent extreme weather in recent years has made the power distribution network more prone to power outages [4–6]. Based on the fault history and maintenance records of electrical components, the power grid company proposed various reliability indicators such as the average outage time and unsupplied power to accurately evaluate the reliability of the distribution system but failed to take cold load pick-up (CLPU) into account [7–10]. Therefore, it is urgent to find out the reliability indicators that are more

in line with the actual behavior of distribution networks, which is of great significance to guide the company's future infrastructure construction of distribution networks.

The occurrence of the CLPU phenomenon is due to the aggregation effect of constant-temperature control-type electricity consumption loads. After the power system experiences a long period of power outage, these loads will suddenly have a significant demand for electricity, and in most scenarios, it is impossible to complete the one-time power grid restoration operation. It may cause pressure on electrical equipment or violate system operation and protection limits, thereby delaying power user power supply recovery and shortening the service life of electrical components [11–13]. In [14], taking into account factors such as temperature control load ratio, power outage time, and ambient temperature, a single-node load recovery model was established based on the constraints of power grid frequency, node voltage, and generator output of the substation. The effectiveness of this method was verified by tidal current simulation calculation and transient energy analysis. Based on the CLPU characteristics and load function coupling relationship, a multi-threaded decision-making model for the restoration of distribution network load power supply considering intermittent power supply capacity is established in [15]. Ref. [16] establishes an air conditioning load aggregation power model considering the power failure time and determines the optimal scheme for air conditioning load recovery in distribution networks based on the amount of recovery that can be provided by the substation at a single time. Ref. [17] takes the spring and autumn loads as a reference; in-depth research discusses the relationship between the summer temperature control loads and the temperature, and the extraction results are more accurate and reliable. The Monte Carlo sampling method is used to analyze the effect of temperature and power failure time on the start of cold loads. The function simulation obtains relevant calculation formulas, which can be used for practical engineering guidance. The aforementioned literature only studies the start-up characteristics of cold loads and does not optimize the load recovery strategy. Ref. [18] models residential load points with high permeability, uses sequential Monte Carlo simulation to randomly simulate the temperature-controlled load operating state, and calculates the residential load demand and its impact on reliability based on the power outage duration. Based on the cold load start-up curve of power failure time and ambient temperature, the multi-objective function of improved weighted flow entropy minimization and load recovery maximization was established in the literature [19]. It was solved by the fast non-dominant sorting genetic algorithm, and the accuracy and calculation time of the simulation results were greatly improved. Ref. [20] established a cold load startup model related to the power failure time and linearized the power supply recovery model of distribution networks built with the maximum load recovery as the objective function, and the simulation verified the effectiveness of the proposed method. In [21], considering the CLPU and load-dependent user load decision-making, the load recovery curve is quantified by knowledge-driven and data-driven methods, which can avoid the problem of voltage and tidal current overrun in the process of load recovery. A comparative analysis of numerical examples shows that the solving time of the adaptive recovery model based on time series outperforms that of the double-layer load model. Ref. [22] proposes a load recovery strategy for damaged distribution networks based on mixed integer linear programming. According to the recovery of traditional feeder distribution and the island recovery of distributed power supply, the optimal switching action sequence is generated, respectively. The correctness of the method is verified by a multi-feed system simulation. Ref. [23] addressed the issue of power imbalance caused by the startup of cooling loads in the power restoration of isolated microgrids. By taking power balance and current imbalance degree as constraints, it established a solution model for the power restoration path and the sequence of load input in the distribution network. Ref. [24], based on the

three-phase unbalanced power flow algorithm using backward scanning and the elastic concept to handle the changes in the static load model, used the Monte Carlo method to calculate and determine the voltage amplitude and phase of the busbars in the microgrid. Ref. [25] introduced the power and quantity balance method of the fuzzy C-means average multi-point algorithm, considering the elastic characteristics of various loads, to achieve the optimization and efficient balance of power distribution in the distribution network, and has obvious advantages in terms of load prediction accuracy and power matching efficiency. Ref. [26] aimed to reduce the average absolute error of cooling loads and improve the overshoot suppression rate and adopted the time-varying QRNN control technology for cooling load startup to solve the dynamic response lag and instability problems of the elastic microgrid. Ref. [27] considers the impact of power outage duration and environmental temperature changes on the duration, power, and energy requirements of CLPU, establishes an adaptive CLPU model, and verifies the effectiveness of the method in maintaining the reliability of microgrids using a microgrid islanding operation scenario. Ref. [28] used a semi analytical element method to construct an optimization model for distribution network restoration that takes into account user interruption costs and CLPU but did not consider relevant reliability calculations. Ref. [29] proposed a sequential restoration model for distribution networks based on non-exponential time-varying CLPU characteristics and soft constant open point operation, verifying the superiority of traditional delay exponential models in handling non-exponential time-varying CLPU characteristics. Ref. [30] proposed a dynamic recovery strategy for cold load start-up by coordinating maintenance personnel scheduling and frequency constraints. Model predictive control was used to handle random maintenance time, and its effectiveness was verified on IEEE 33-node and actual 136-node systems. In contrast, the lightning search algorithm (LSA) is used in various applications of the literature [31,32] to solve the optimization problem, showing stronger robustness and shorter solving time. The aforementioned studies mostly regarded CLPU as an independent failure event, only affecting the SAIFI, but failed to incorporate its dynamic impact on the recovery duration (SAIDI, CAIDI, ENS) into the sequential Monte Carlo simulation framework, and lacked a system-level assessment of the coordinated optimization of the recovery sequence and the time-varying characteristics of CLPU under voltage and protection constraints.

In summary, this paper proposes a reliability evaluation method for an urban distribution network based on a lightning search algorithm. First, the delay index model is used to establish the time-sharing power demand calculation model for CLPU events, and the optimal recovery model with the shortest recovery time and its corresponding constraints are proposed. CLPU events are then incorporated into the Monte Carlo simulation platform for reliability assessment, using the LSA to develop an optimal recovery plan that determines the recovery time and order based on the duration of the outage and the power demand at the time of recovery. Finally, the test system is used to verify the optimal recovery planning of CLPU events, and the LSA and genetic algorithm are compared and analyzed.

This paper is the first to embed the CLPU delay index model based on power outage duration into the SMC simulation and aims to minimize the additional recovery time. It uses LSA to generate the optimal recovery plan that meets multiple constraints. The main innovations of this paper lie in: (1) proposing a mathematical expression for the correction of recovery time under CLPU events; (2) establishing a reliability assessment platform jointly using SMC and LSA and quantitatively revealing the impact degree of CLPU events on the SAIFI, SAIDI, CAIDI, and ENS indicators.

2. CLPU Modeling

2.1. Load Modeling

Based on the time-of-use electricity price variation curve, a random simulation analysis of residential electricity load in target cities can be conducted. Power consumption data are derived from actual measurements by smart meters and integrated with electricity usage statistics provided by power authorities. Residential electricity loads can be categorized into two main types: temperature-controlled loads (TCL) and non-temperature-controlled loads (NTCL). NTCLs exhibit little fluctuation in electricity demand before and after a power outage, whereas TCLs show significant changes in electricity consumption following power restoration—devices such as refrigerators, air conditioners, and electric heating systems fall into this category. The act of powering on these devices is defined as a cold-start load. Studies [33,34] demonstrated a significant statistical correlation between the probability of air conditioning activation and indoor temperature. The logistic regression model indicated that when the indoor temperature varied within the range of 22 to 36 °C, the probability of air conditioning activation increased significantly as the temperature rose. In the residential air conditioning usage condition probability model proposed in [35], the threshold for air conditioning state switching was directly determined by the indoor temperature parameter, and the parameters of this model were obtained through regression based on the actual measured data of the air conditioning operation status and temperature of the actual residents. Regarding the fundamental cause of the CLPU phenomenon, after a long power outage, the diversity of loads is lost, and the vast majority of temperature-controlled loads will inevitably be in operation due to the large difference between the ambient temperature and the set temperature of the thermostat. This qualitative conclusion fundamentally determines that the ambient temperature is the most crucial determinant of the peak load demand in CLPU events. Therefore, setting the urban ambient temperature will be the only factor considered in the TCL AC load usage probability curve, and the corresponding calculation relationship is shown in Equation (1).

$$S_{\text{TCL}} = \begin{cases} \text{Prob} > 0 & \text{if } T > T_{\text{max}} \text{ or } T < T_{\text{min}} \\ \text{Prob} = 0 & \text{otherwise} \end{cases} \quad (1)$$

where T_{max} represents the maximum temperature; T_{min} represents the minimum temperature. The value is related to the environmental temperature. The greater the difference between the environmental temperature and the set temperature range of the air conditioner thermostat, the higher the corresponding probability will be.

After establishing the time-of-use electricity price curves for various electrical devices, the correction of the load/demand factor is required. Based on the average power demand at each load node, the specific number of individual appliances can be estimated. The primary function of these two factors is to maintain a stable average power demand across all load nodes during designated time periods. When a cooling load activation event occurs, a delay index model is used to simulate the rapid increase in temperature-controlled loads, while other types of loads remain unchanged. The overall system power demand consists of the adjusted temperature-controlled load demand and the unadjusted non-temperature-controlled loads. The corresponding index models are shown in Figure 1. The corresponding delay index model shows that after a long power outage, TCL concentratedly resumed operation due to the loss of diversity, resulting in a three-stage change process of “instantaneous jump—exponential decay—return to normal” in load demand. The following specifically outlines this:

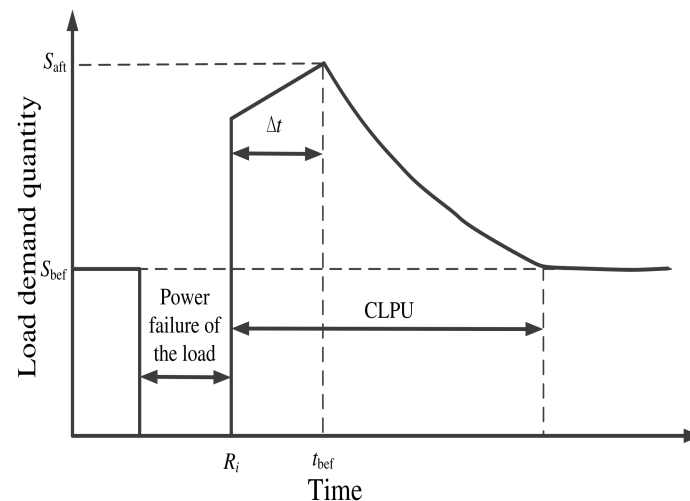


Figure 1. The delay index model of CLPU.

Stage 1 ($t = t_i$): At the moment of power restoration, the TCL load starts in an undiversified state, and the load demand jumps from the diversified value S_{bef} before the outage to the undiversified peak S_{aft} , corresponding to the “load peak” stage of cold load startup.

Stage 2 ($t_i \sim R_i$): As some TCLs reach the set temperature and automatically exit operation, the load demand decays exponentially according to the law, with the decay rate controlled by parameter α .

Stage 3 ($t \geq R_i$): The load demand returns to the normal diversified level S_{bef} , marking the end of the cold load startup process.

$$S(t) = S_{bef} + (S_{aft} - S_{bef})e^{-\alpha(t-t_bef)}u(t-t_bef) + S_{bef}[1 - u(t-t_bef)]u(t - (R_i - t_bef)) \quad (2)$$

where α represents the decay rate; S_{bef} represents the load power demand before the power failure, which will be used as the output of the random load model; S_{aft} represents to directly consider the power demand after the recovery of the CLPU affected by the TCL operation.

The relationship between S_{bef} and S_{aft} is as follows (3) [36]:

$$\begin{cases} S_{aft} = cS_{bef-TCL} + S_{bef-NTCL} \\ c = \frac{\ln(t_{outage}/0.107)}{1.101} \end{cases} \quad (3)$$

From Formula (3), it can be concluded that the longer the power outage lasts, the higher the power demand during the system’s power restoration stage. The underlying mechanism is that as the duration of the power outage increases, the temperature deviates from the set range, which in turn causes more temperature control loads to exit the shutdown range. Parameter c is used to characterize the relationship between the load peak and the duration of the power outage. This empirical formula is derived from the statistical analysis of cold load startup events in residential power distribution systems [36]. It establishes a logarithmic linear relationship between the duration of power outage and the undiversified load peak, with a range of 2 to 5 [37,38]. The duration for which the power demand S_{aft} is maintained is denoted as Δt . This duration also represents the continuous period of the cold load startup process, and its value is the difference between t_i and R_i . The specific relationship is shown in Figure 1.

2.2. Optimal Recovery Modeling

For this research question, the following model can be constructed: When formulating the optimal power supply restoration plan, the cold load startup process needs to be incorporated into the reliability assessment system of the distribution network. Within the selected assessment period, the optimal restoration strategy is adopted each time a power supply failure occurs, and the additional restoration time required for each faulty load node is calculated through the following objective function. The specific expression is shown in Equation (4):

$$\text{minimize} \left(\sum_{i=1}^k \overline{TTR}_i - \sum_{i=1}^k TTR_i \right) \quad (4)$$

where TTR_i is the recovery time of the i -th of the k failed load points.

Before restoring power supply to the affected load nodes, in addition to going through a specific waiting period, the corrected overall repair duration is the same as the initial duration without considering the cold load startup situation. These two durations satisfy the mathematical relationship $\sum_{i=1}^k \overline{TTR}_i = \sum_{i=1}^k TTR_i + t_{r1} + t_{r2} + \dots + t_{rk}$ [38]. In this formula, t_{rk} represents the additional repair duration for load node k after the power grid failure. Based on the above definition, the objective function can be further simplified to the form, as shown in Formula (5):

$$\text{minimize} (t_{r1} + t_{r2} + \dots + t_{rk}) \quad (5)$$

The indicators such as Unsupplied Energy (ENS), System Average Interruption Frequency Index (SAIFI), and System Average Interruption Duration Index (SAIDI) should be automatically optimized to reach the optimal level. Since the total number of faults remains unchanged, the SAIDI indicator will not change.

When formulating the optimal power supply restoration strategy, the following constraints need to be met:

- (1) Protection device constraint: The transformer operating load should not exceed 125% of the rated capacity, and the constraint relationship is $S_T \leq 1.25$ pu.
- (2) Operating state constraint: The voltage of each node should remain within the $\pm 5\%$ range of the rated value, and the constraint relationship is $0.95 \leq V_i \leq 1.05$, $i \in [1, M]$.
- (3) Grid topology constraint: In actual distribution networks, a radial structure is commonly adopted. The restoration operation must start from the power source point and proceed step by step along the main feeder to the downstream.
- (4) Charging time constraint for lines: The charging time for long lines or cables is relatively long, which will delay the power-on time of downstream nodes [23].
- (5) Black start capability of distributed power sources: The node where the black start power source is located can be restored step by step initially, while the non-black start power source needs to wait until the charging of the upstream lines is completed before it can be started.

Limiting the transformer load can effectively prevent the protection device from malfunctioning. The system also has other operational constraints, such as the downstream power supply area not completing the power restoration earlier than the upstream area. The selection of optimization variables involves the additional recovery duration required for the cold load startup process, denoted as $[t_{r1}, \dots, t_{ri}, \dots, t_{rk}]$. After each fault occurs during the evaluation period, the optimal recovery duration is solved using the objective

function, thereby correcting the repair time at each fault load point. Finally, the reliability indicators for the entire evaluation stage can be calculated using Equation (6).

$$\begin{cases} SAIFI = \frac{\sum M_i}{M_T} \\ SAIDI = \frac{\sum O_i M_i}{M_T} \\ CAIDI = \frac{SAIDI}{SAIFI} = \frac{\sum O_i M_i}{\sum M_i} \\ ENS = \sum P_i O_i \end{cases} \quad (6)$$

where M_T represents the total quantity of users corresponding to each load node; $\sum M_i$ represents the cumulative occurrence times of power outage events; P_i represents the average power supply load during the power outage stage; O_i represents the fault continuation time, and this value needs to be corrected based on the additional recovery duration measured during the CLPU event.

3. Model Solving

3.1. Monte Carlo Simulation

The flowchart of the solution is shown in Figure 2, and the main code is based on Sequential Monte Carlo (SMC) simulation to find reliability indicators. SMC simulation is essentially a process of component state timing sampling, and its computational complexity is linearly related to the system size, which can effectively avoid the problems of multiple components and complex system structure in large-scale power systems. It is suitable for the evaluation and calculation of large-scale distribution systems [39]. Underground cables, low-voltage circuit breakers, and transformers are reliability analysis projects considered in this study. The SMC algorithm can accurately obtain the relevant parameters of system reliability by processing and calculating the power data. At the initial moment of the evaluation cycle ($T = 0$), all electrical equipment is in a normal working state. Under the premise of knowing the equipment failure rate λ and repair rate r , combined with uniformly distributed random numbers U , the pre-failure duration and repair duration of each component can be respectively solved. The specific calculation formula is shown in Equation (7):

$$\begin{cases} TTF = \frac{-1}{\lambda} \ln(U) \\ TTR = \frac{-1}{r} \ln(U) \end{cases} \quad (7)$$

According to the literature [40,41], a 200-year evaluation period is set for sequential Monte Carlo simulation to assess the reliability of distribution networks. After the 200-year evaluation period, Equation (6) is used to solve the reliability index without considering CLPU events. Only the main components of the system will affect the analysis results. Each time the system fails, the program enters the second processing stage. This stage corrects the repair duration based on the cold load startup event and assumes that the power supply company implements the optimal power restoration strategy. Under the condition of meeting the operational restrictions, the power restoration time at the fault load point is shortened as much as possible. Therefore, all types of power restoration schemes need to be calculated through the LSA optimization module in this stage. The corrected repair duration will be fed back to the main program so that various reliability indicators can be statistically calculated at the end of the evaluation.

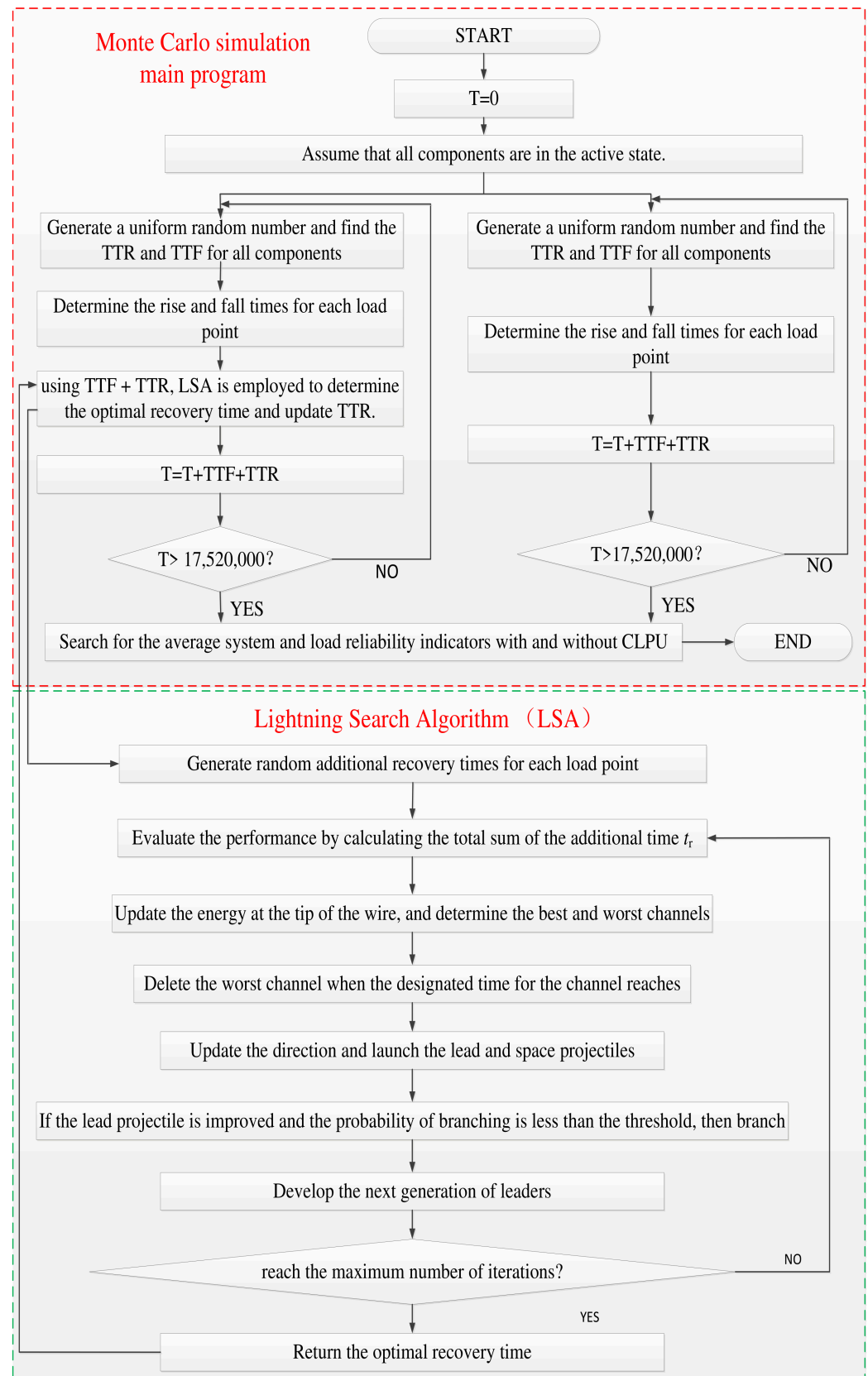


Figure 2. Algorithm flow based on SMC and LSA.

The total time complexity of SMC simulation is: $T_{SMC} = O(T_{sim} \cdot N_{comp} + N_{fault} \cdot N_{load})$. Among them, N_{comp} is the total number of system components, T_{sim} is the evaluation period, N_{fault} is the total number of faults, and N_{load} is the number of load nodes affected by

faults, where $T_{\text{sim}} \cdot N_{\text{comp}}$ is dominant [42]. The time complexity of LSA single optimization is $T_{\text{LSA}} = O(G \cdot N \cdot N_{\text{load}} \cdot C_{\text{eval}})$. Among them, N is the population size of LSA, G is the maximum iteration generation, and C_{eval} is the computational cost of a single fitness evaluation (including power flow calculation and constraint verification) [43]. The total time complexity of the SMC-LSA coupling framework is $T_{\text{total}} = T_{\text{SMC}} + N_{\text{CLPU}} \cdot T_{\text{LSA}}$. Among them, N_{CLPU} refers to the total number of times CLPU was triggered during the evaluation period. When the system scale expands, N_{load} does not increase linearly with the system scale, and the N_{CLPU} value does not increase significantly, thus ensuring that the LSA optimization module has good scalability.

3.2. LSA Optimization Platform

In large-scale systems, the impact range of CLPU events is usually local (limited to several nodes downstream of a certain feeder or distribution transformer), so the number of affected load points in a single optimization does not increase linearly with the scale of the entire network, and has good scalability, which can effectively handle large-scale distribution network optimization problems with far more nodes than the system tested in this paper [44]. Mixed integer linear programming requires both the objective function and constraints to be linear. For complex nonlinear problems such as the time-varying exponential model of cooling load start-up in this paper, precise linearization or cone relaxation is more difficult. The dynamic programming algorithm decomposes multi-stage decision problems into several sub problems and achieves efficient solutions through optimal substructure and overlapping sub problem properties. However, in this paper, voltage constraints and current imbalance constraints have temporal coupling characteristics, and the discretization of continuous variables such as voltage and power introduces accuracy loss, making it difficult to meet their usage conditions [45]. The branch and bound method prunes the search tree through branch and bound operations, but in this paper, the lower bound estimation is difficult, the exponential complexity is too high, and the non-linear constraint conditions are difficult to handle, resulting in high pruning and search difficulty for the branch and bound method. In practical applications, it is usually necessary to combine it with heuristic algorithms [46]. Heuristic optimization methods can provide suboptimal solutions that meet engineering accuracy requirements within minutes to tens of minutes, and the computational complexity does not accelerate with the problem being solved. They exhibit significant advantages in solving different types of optimization problems [47,48]. LSA is highly suitable for the optimal recovery model of cold load start-up due to its fast convergence speed, simple parameter tuning, and natural adaptation to continuous variable optimization problems [49]. The LSA simulates three types of projectiles during the formation process of natural lightning: transitional projectiles, spatial projectiles, and guiding projectiles [50].

- (1) Initialization (transitional projectiles): A random initial population is generated, and each individual corresponds to a set of possible additional recovery time combinations. At the same time, the “upstream load point restores first” order constraint is ensured, which stems from the radial topology characteristic of the distribution network, meaning that downstream nodes cannot restore power supply before upstream nodes.
- (2) Spatial projectile update: Corresponding to the one-dimensional exponential distribution perturbation in the main loop of the algorithm, it simulates the random bifurcation of the lightning channel in space. The reason for using an exponential distribution is that the step length of lightning follows a statistical characteristic of “short steps as the main, long steps occasionally appearing”, and the exponential distribution precisely conforms to this physical property, used for global exploration to avoid getting stuck in local optima.

- (3) Guiding projectile update: Only the current optimal solution is perturbed with a normal distribution, allowing the search to mainly focus on the small neighborhood around the current optimal solution, used for local exploration to refine the optimal solution.
- (4) Guiding projectile update: Only the current optimal solution is perturbed with a normal distribution. Every generation, the worst solution is replaced with the optimal solution with a crossover probability, which can effectively prevent the population from becoming too homogeneous too early and maintain the algorithm's vitality.

By applying the LSA as shown in Figure 2, the optimal re-energization sequence for each load point during a single power outage can be determined. The LSA first randomly generates an initial population, which is defined as a transition particle. Each transition particle corresponds to a set of feasible solutions, also known as step leaders (SL). The energy of an SL is composed of the corresponding objective function value and the penalty term for constraint violations [50]. A single SL consists of n step leader units, and its specific expression form is as shown in Equation (8):

$$SL_n = [t_{r1}, \dots, t_{ri}, \dots, t_{rk}] \quad (8)$$

All the transition impulses from t_{r1} to t_{rk} are within the search range of k load points (LP) affected by a single power outage and are uniformly distributed. For the power supply interruption of LP8, LP9 and LP10 caused by faults,. Each node has set the maximum re-energization duration T_M , which is in minutes. The generation of transition impulses follows the following sequence: t_{r8} is randomly determined within the interval $(0, T_M)$; t_{r9} completes random value selection within the interval (t_{r8}, T_M) ; and t_{r10} completes random selection within the interval (t_{r9}, T_M) . Based on the objective function, the performance of various transition impulses as the first-level leader is evaluated. Among them, the transition impulse with the lowest energy indicator is determined as the most preferred leading unit, and the SL with the best performance is stored in the external space. The algorithm sorts the energy of all SLs in each generation: the one with the lowest energy is the best channel, and the one with the highest energy is the worst channel. The best channel is used to guide the local fine search of the projectile and the inferior replacement in the bifurcation operation. For the N groups of SL ($SL_1, SL_2, SL_3, \dots, SL_N$) generated, through the exponential distribution mapping rule, the transition impulses complete corresponding matching with each SL, and the specific expression is as shown in Equation (9):

$$t_{ri}^{n+1} = t_{ri}^n \pm \exp rand(\mu) \quad (9)$$

where μ represents the shape coefficient of the exponential distribution, whose value is determined by the distance between the optimal step unit and the reference unit.

The optimization direction of the parameters is determined through small-scale experiments, and then the adjustment method to improve the step guidance effect is determined. Subsequently, the lead projectile is independently corrected using the normal distribution function. The corresponding calculation formula is shown in Equation (10):

$$t_{ri}^{n+1} = t_{ri}^n \pm \text{normrand}(\mu, \sigma) \quad (10)$$

where σ and μ are the scaling and shaping parameters of the normal distribution, respectively.

Finally, the secondary operation process of the LSA is carried out, namely the bifurcation operation. Bifurcation can re-plan the search path and generate more differentiated solutions within the feasible domain. The LSA achieves the bifurcation function through two approaches. The first approach is to start the counting device at a specified time, elimi-

nate the SL with lower performance, and replace it with the unit with the best performance. This method can increase the probability of obtaining a better solution near the optimal SL. The above counter is defined as channel time and needs to be set together with other parameters during the algorithm initialization stage. The second bifurcation method is to numerically correct the transition bullet with an extremely low probability, as shown in Equation (11):

$$\overline{t_{ri}} = a + b - t_{ri} \quad (11)$$

where a and b respectively represent the lowest and highest boundaries of the throw value. This boundary constraint applies to the first recovery node in the horizontal direction, as well as the recovery nodes with a value of 0 and T_M . The replacement operation can only be executed if the energy of the modified transition bomb is higher than that of the original transition bomb and can pass the verification with a probability of 5% or less.

4. Simulation Analysis

4.1. Test System Selection

Figure 3 shows the radial distribution test system adopted in this paper. This platform offers multiple power restoration methods: it can restore all loads at once, restore each single feeder one by one in sequence, or restore power to specific areas of multiple feeders according to constraint conditions in stages. Based on the calculation of the active and reactive power requirements during the system operation, within a 60 min period, the maximum apparent power requirement is 6.35 MVA. Therefore, a transformer with a rated capacity of 6.5 MVA was selected. The overload protection action value of this transformer is set at 1.25 times the rated current per unit. The calculation shows that the total electricity load at any time must be lower than 8.125 MVA. Once it exceeds this limit, the protection device will trigger a trip. All distribution lines are buried with underground cables. Under extreme operating conditions, the fluctuation amplitude of the line impedance is limited to within 5% of the rated value. The total length of the main feeder is set at 600 m. The lengths of the cables in Sections 1, 2, 3, 8, 9, and 10 are all 200 m, while the remaining sections uniformly use 300 m-long underground cables [42,51,52]. The implementation of the project relies on the following communication support: (1) The SCADA/AMI system provides fault location, real-time power load and switch status; (2) the meteorological monitoring station provides environmental temperature data (update cycle ≤ 30 min); (3) the DG controller provides black start capability and output limit values, and adopts a centralized communication architecture.

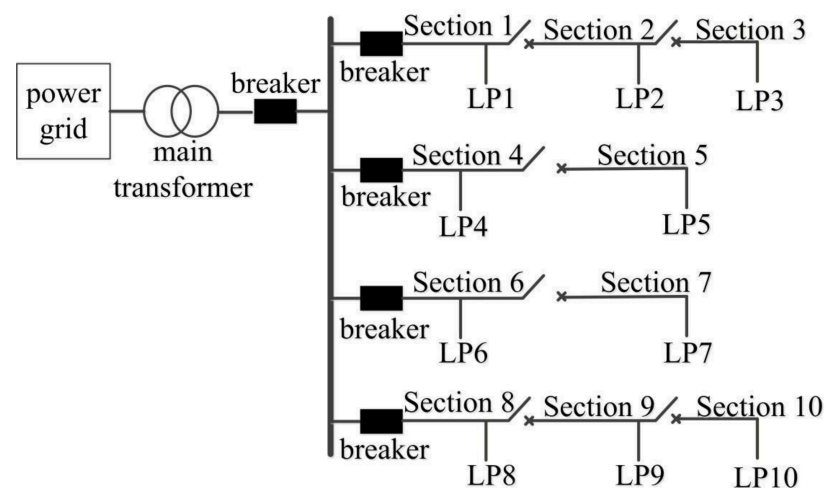


Figure 3. Experimental power distribution system.

4.2. Load Model Calculation

The time-of-use electricity consumption curve is obtained by multiplying the load coefficient with the demand coefficient. The upper and lower temperature boundaries for the temperature control load are set at 26 °C and 20 °C respectively. The time-of-use curves for various electrical appliances are summarized in Figure 4. This curve can be divided into temperature control electricity consumption types for winter and summer seasons, and the electricity consumption trends of other devices remain stable throughout the day.

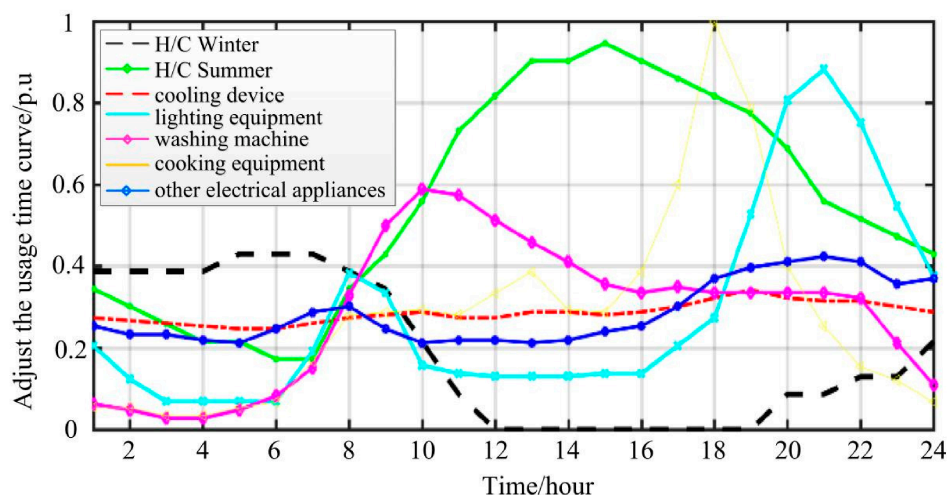


Figure 4. TOU curve of household appliances.

Based on the above curves, a random simulation model was constructed. The dates of 1 January and 1 July were selected as the representative dates for winter and summer respectively for calculation. The simulation results are shown in Figure 5. From this, the electricity consumption data of each load node can be obtained. The load values at each location fluctuate slightly around the initial system average. The parameter $\alpha = 0.5 \text{ h}^{-1}$ and $\Delta t = 30 \text{ min}$ were selected for the modeling analysis of the cold load startup [36]. The corresponding load change characteristics are shown in Figure 6. By comparing the data, it can be seen that the electricity consumption of the power restoration nodes is approximately twice the daily level, and it will also cause a sharp increase in the total load of the main transformer.

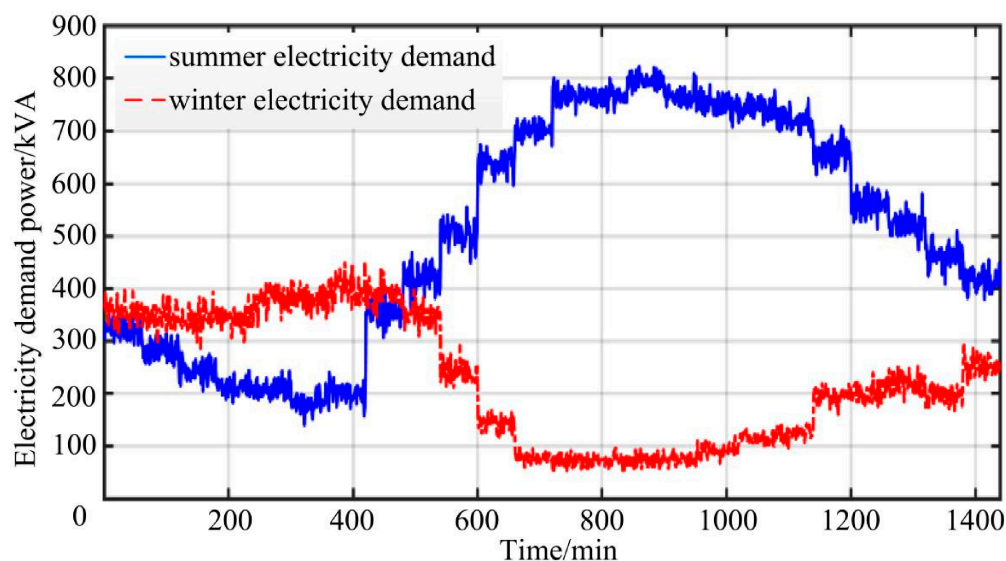


Figure 5. LP1 winter and summer random load mode.

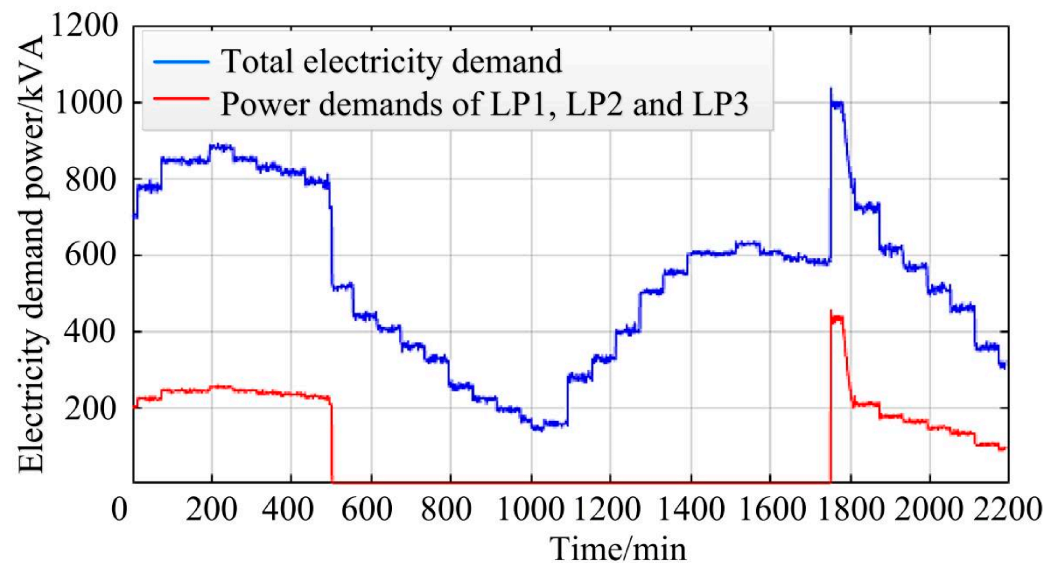


Figure 6. Cold load picking model.

4.3. Optimal Recovery Analysis

Not every power outage will trigger a peak load, thereby causing the protection or operational boundaries to be breached. However, after a prolonged power outage, the phenomenon of cold load startup is prone to occur, which will bring difficulties to the phased restoration of the power supply. A fault caused power outages at three load points: LP1, LP2, and LP3. The plan was to complete the restoration 482 min after the power outage, and this period was during the off-peak electricity consumption period. The proportion of the temperature control load was not high. Based on the cold load model calculation, the load during the restoration was approximately 6.9 MVA. The minimum voltage amplitude was 0.9721, and all constraints were not exceeded. This indicates that no cold load startup occurred, so the power supply restoration can be completed in a single step. This process has no impact on the reliability indicators, and the restoration result is shown in Figure 7. None of LP1, LP2, and LP3 generated additional restoration time.

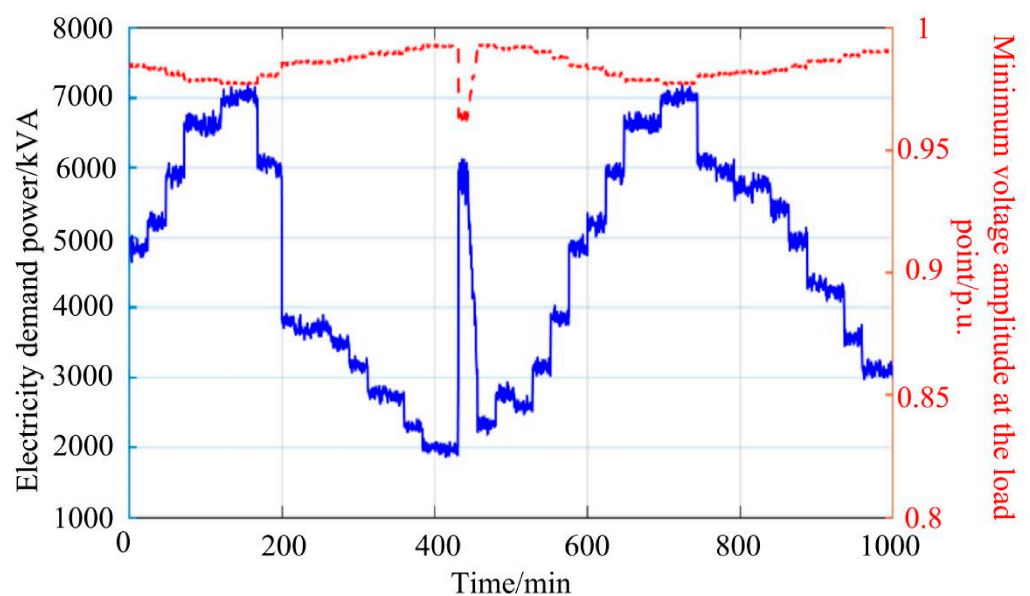


Figure 7. Long-term power outage recovery process under low TCL demand.

Another set of simulated faults affected LP8, LP9, and LP10. This fault was caused by damage to the 8th line and lasted for 321 min. If all load nodes are restored simultaneously, the peak load will reach 6213.35 kVA. Although this value does not exceed the limit set by the protection device, the voltage will drop to 0.9475, thus exceeding the operational constraints. In this case, the LSA needs to be used to enter the optimal recovery process. Even if direct restoration does not exceed the load limit, the voltage indicator will still exceed the standard. The specific recovery process is shown in Figure 8.

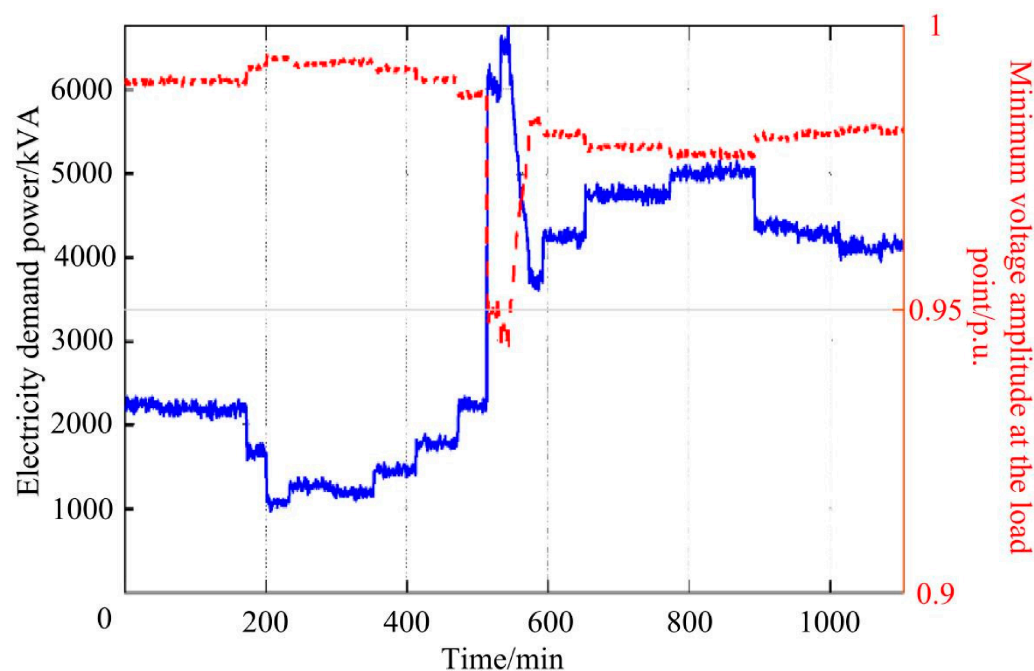


Figure 8. Power demand and bus voltage without optimization period.

For the optimal optimization program of LSA running 5 times during this power outage, the following LSA parameters were selected: code: 100, population size $N = 50$, maximum iteration number: 100, bifurcation probability: 0.01, channel time: 10, search space lower boundary $a = 0$, upper boundary $b = T_M = 500$ min [53,54]. The shape coefficient μ of the exponential distribution in Equation (9) is dynamically changing, and its value is the Euclidean distance between the current solution and the current optimal solution, which can adaptively reduce the search step size as it approaches the optimal solution. When the shape parameter of the normal distribution in Equation (10) is $\sigma = 0.3(b - a)$, the algorithm converges the fastest without sacrificing the quality of the solution [55]. After the algorithm is executed, the optimal re-powering schemes corresponding to each faulty load node are shown in Table 1 and Figure 9. Figure 9 presents the power demand and voltage distribution under the optimal scheme. The results show that the lowest voltage is 0.9511 pu and the highest power demand is 5.79 MVA. All the running parameters meet the constraint requirements.

Table 1. Optimal restoration plan for load points.

LP Number	Improve TTR/Min	Recovery Load/MVA	Coefficient K
LP8	321	1.08	3.54
LP9	321	1.56	3.54
LP10	363	1.38	3.65

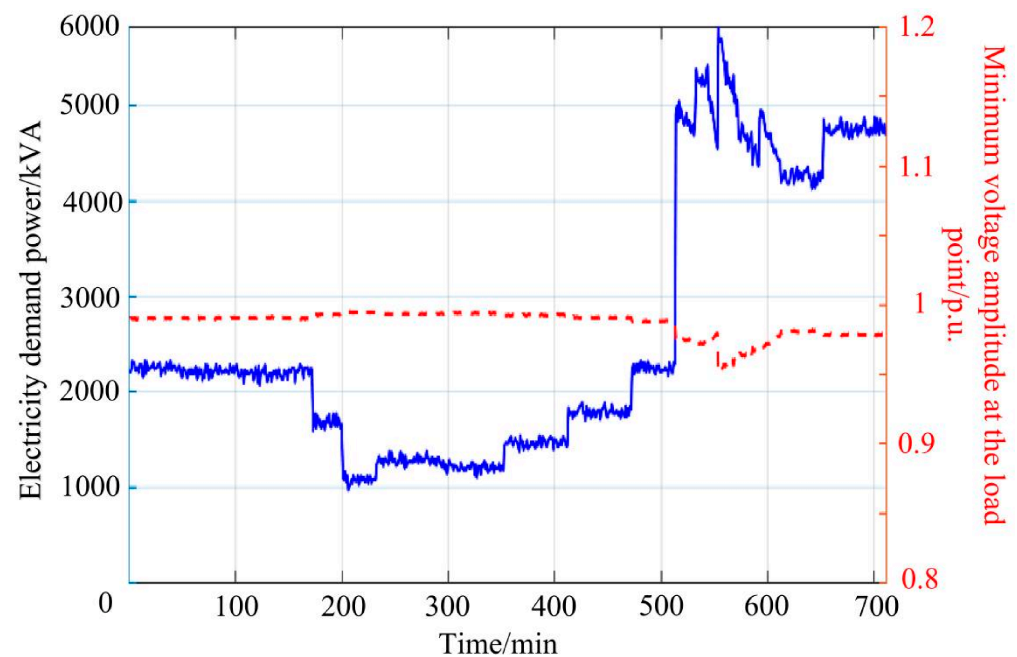


Figure 9. Power demand and minimum bus voltage during LSA optimization period.

4.4. Method Comparison

During the process of the system selecting the optimal recovery plan, the values of the two reliability indicators, ENS and SAIDI, will decrease. For the same power outage event, the genetic algorithm (GA), particle swarm optimization (PSO), grey wolf optimization (GWO), and Harris Hawks Optimization (HHO) were used for repeated analysis to evaluate and compare the LSA results, as shown in Table 2. The LSA iteration count was 15 times, which was the fastest among all the algorithms. Compared with the suboptimal GWO with 31 iterations, it improved by 51.6%, and compared with the worst GA with 56 iterations, it improved by 73.2%. In terms of stability, the unique optimal solution of LSA and GA (with a standard deviation of the objective function of 0) indicates that they can always converge to the best result stably, while the solutions of other algorithms have varying degrees of fluctuations. In terms of computational efficiency, the average running time of LSA of 360.71 s was also the best, which was 6.14% higher than the performance of suboptimal GWO (384.32 s), and had more significant advantages compared to GA (403.98 s), PSO (394.29 s), and HHO (425.47 s).

Table 2. Comparison of calculation results.

Test Standards	LSA	GA	PSO	GWO	HHO
Minimum objective function/min	43	43	43	43	43
Max. objective function/min	43	43	46	44	47
Average Objective Function/min	43	43	44.2	43.5	44.6
Objective function standard deviation	0	0	1.13	0.53	1.36
Optimization parameters/min	[1,1,41]	[1,1,41]	[1,1,41]	[1,1,41]	[1,1,41]
Average execution time/s	360.71	403.98	394.29	384.32	425.47
Iteration times/generation	15	56	43	31	42

While ensuring that the solution results always converge to the optimal solution, the best running results of the LSA optimization and GA optimization methods are shown in Figure 10. The initial population sizes of LSA optimization were set to 30, 50, 70, and 90 respectively for simulation analysis, and the results are shown in Figure 10. For the LSA, even if the initial population parameters are different, its final output results remain consistent, indicating that this algorithm has good stability. In addition, LSA outperforms the genetic algorithm in terms of convergence speed and average calculation time, which fully proves that it is more suitable for generating the optimal strategy in real-time scheduling scenarios. Subsequent research will continue to use the LSA to derive the optimal recovery scheduling plan for all CLPU failure events. When extended to the online restoration scenario of the distribution network, through parallel computing, the optimization time of a single LSA can be reduced from 360.71 s to less than 50 s.

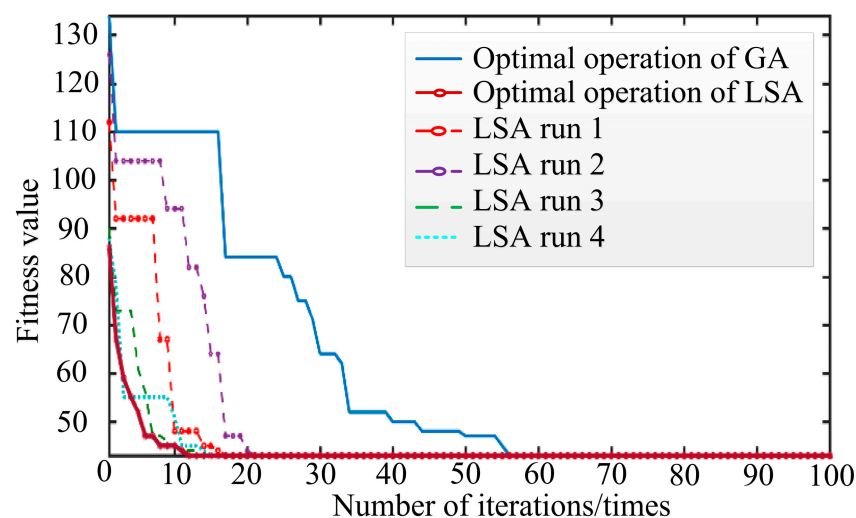


Figure 10. LSA and GA calculation results.

The proposed method was applied to all 7 fault scenarios triggering CLPU in a 200-year sequential Monte Carlo simulation, and the comparative calculation results are shown in Table 3. The results showed that, except for scenario 1 and scenario 4, LSA achieved better optimal target values than GA in scenarios 2, 3, 5, 6, and 7. This is because the optimal solutions for scenarios 1 and 4 are determined by explicit constraints such as voltage upper and lower limits, and the boundaries are relatively smooth. GA can stably converge to this boundary. The optimal solutions for scenarios 2, 3, 5, 6, and 7 are determined by implicit constraint boundaries such as nonlinear power flow coupling. The boundary shape is complex, and GA fails to converge to the global optimum within the specified maximum iteration times. However, LSA's guidance mechanism enables it to achieve better results in such scenarios. Regardless of the CLPU triggering scenario, LSA can consistently find the same optimal solution at an average speed much faster than GA's 72.5%, demonstrating performance advantages consistent with the main case in all scenarios.

When the simulation time is within the range of 4214 min to 5486 min, the operating conditions of the 10th load point are affected by the combined actions of the main transformer, main circuit breaker, feeder circuit breaker, and the 8th, 9th, and 10th transmission lines. Within this simulation period, a fault occurred in the 8th cable line, directly causing a power outage at the 10th load point. The study conducted SMC simulation analysis for this fault event to calculate the various average reliability parameters of the system. During this simulation test, the test system detected a total of 38 power outage failure events. The calculation of each reliability parameter is based on the premise that each load point only

connects to a single electricity user, and all index changes are triggered by the failure of power equipment components.

Table 3. Performance comparison between LSA and GA in multiple fault scenarios.

Fault Scenario	Affected Load Points	Average Objective Function/Min		Iteration Times/Generation	
		LSA	GA	LSA	GA
1	LP1, LP2, LP3	43	43	15	56
2	LP4, LP5	28	29	12	48
3	LP6, LP7	35	37	14	52
4	LP8, LP9, LP10	52	52	16	58
5	LP9, LP10	31	32	13	48
6	LP2, LP3	30	32	13	47
7	LP6, LP7, LP8, LP9, LP10	61	74	18	62

This study relies on the CLPU analysis method and applies the proposed optimal recovery strategy to the simulation analysis of 38 power outage scenarios. The statistical results show that only the 7th fault cannot be restored by a single-step operation. The other power outage events can be restored in a single step mainly because the duration of the fault is short or the TCL concentration at the time of the fault is low, and the overall power load of the grid is at a relatively low level. Affected by this special working condition, the three core reliability parameters SAIDI, CAIDI, and ENS corresponding to the 7th power outage fault all show a certain degree of increase, and the specific change values can be referred to in Table 4.

Table 4. Reliability index calculation result.

Reliability Metrics	No CLPU	Best Recovered CLPU
SAIDI (hours/household)	8.1126	8.1646
SAIFI (Times/household · Year)	0.1076	0.1076
CAIDI (hours/time)	76.0143	76.8622
ENS (MWh/year)	24.213	24.324

To further verify the optimization effect of the proposed optimal recovery strategy on the reliability of power supply for the power grid, this paper sets up a set of comparative simulation scenarios. Assuming that the power grid operation department performs load restoration operations at fixed time intervals after each power outage occurs, load restoration intervals of 20 min, 30 min, and 60 min are respectively set to avoid equipment overload issues and ensure that the power grid operation complies with the setting requirements of protection devices. Based on the reliability index data obtained from the above simulation assumptions, all of them are summarized in Table 5.

For larger-scale networks in the future, the method proposed in this paper can divide the system into independent recovery domains based on substations as boundaries. Within each domain, the number of affected nodes by CLPU is not higher than 20. At the substation level, MILP global coordination is adopted, while at the feeder level, LSA fine optimization is used [23]. Taking a distribution network with 12,110 kV substations, 9610 kV feeder lines, and 800 nodes in the core area of the city as an example, after partitioning, the single LSA optimization still remains within 500 s. The total evaluation time is approximately 8 h.

After parallel computing, it can be compressed to within 3 h, which verifies the engineering scalability of the method.

Table 5. Reliability index calculation results.

Reliability Metrics	Fixed Recovery Procedure		
	20 min	30 min	60 min
SAIDI (hours/household)	8.1427	8.1489	8.1671
SAIFI (Times/household · Year)	0.1076	0.1076	0.1076
CAIDI (hours/time)	75.3703	75.4333	75.6038
ENS (MWh/year)	24.256	24.3	24.343

4.5. Parameter Sensitivity Analysis

To evaluate the impact of four key parameters, namely power outage duration, TCL proportion, ambient temperature, and attenuation coefficient, on the reliability indicators of SAIDI, CAIDI, and ENS, SAIFI only depends on the number of power outages and is not affected by changes in CLPU parameters. Conduct sensitivity analysis using the single variable method. The calculation results of reliability indicators under different power outage durations are shown in Table 6. As the duration of the power outage extended from 60 min to 600 min, SAIDI increased by 1.31%, CAIDI increased by 1.31%, and ENS increased by 0.80%. Under long power outages (≥ 450 min), the CLPU effect is significantly enhanced, and the rate of deterioration of reliability indicators is accelerated.

Table 6. Reliability index calculation results under different power outage durations.

Reliability Metrics	60 min	180 min	311 min	600 min
SAIDI (hours/household)	8.0832	8.1047	8.1217	8.1894
CAIDI (hours/time)	75.544	75.745	75.903	76.537
ENS (MWh/year)	24.086	24.135	24.165	24.728

The calculation results of reliability indicators under different TCL ratios are shown in Table 7. When TCL's proportion increased from 30% to 60%, SAIDI increased by 0.45%, CAIDI increased by 0.45%, and ENS increased by 0.34%. When the proportion of TCL exceeds 45%, the deterioration rate of reliability indicators significantly accelerates, indicating that high TCL penetration areas are more sensitive to CLPU events.

Table 7. Reliability index calculation results under different TCL ratios.

Reliability Metrics	20%	30%	45%	60%
SAIDI (hours/household)	8.1115	8.1217	8.1368	8.1581
CAIDI (hours/time)	75.792	75.903	76.045	76.244
ENS (MWh/year)	24.137	24.165	24.201	24.247

The reliability index calculation results under different environmental temperatures are shown in Table 8. When the ambient temperature changes within the range of 20~30 °C, the amplitude of SAIDI change is less than 0.18%. But when the temperature exceeds 30 °C, SAIDI increases by 0.26% and ENS increases by 0.16%. The probability of TCL activation significantly increases under extreme high-temperature weather, and the CLPU effect is significantly enhanced.

Table 8. Reliability index calculation results under different environmental temperatures.

Reliability Metrics	20 °C	25 °C	30 °C	35 °C
SAIDI (hours/household)	8.1068	8.1145	8.1217	8.1426
CAIDI (hours/time)	75.765	75.837	75.903	76.099
ENS (MWh/year)	24.131	24.148	24.165	24.204

The calculation results of reliability indicators under different attenuation coefficients are shown in Table 9. When the attenuation coefficient α varies within the range of $0.3\sim 0.7\text{ h}^{-1}$, the relative changes in SAIDI and ENS are both less than 0.12%, and the changes in CAIDI are also very small. This indicates that the method proposed in this article is insensitive to the value of α , and the model has good robustness. This is because α mainly affects the power attenuation rate during the CLPU process, and the optimal recovery strategy in this paper avoids peak power exceeding the limit by adjusting the load operation timing, with a low dependence on the specific numerical value of the attenuation rate.

Table 9. Reliability index calculation results under different attenuation coefficients.

Reliability Metrics	0.3 h ⁻¹	0.4 h ⁻¹	0.5 h ⁻¹	0.6 h ⁻¹
SAIDI (hours/household)	8.1312	8.1263	8.1217	8.1172
CAIDI (hours/time)	75.993	75.947	75.903	75.862
ENS (MWh/year)	24.188	24.177	24.165	24.153

Overall, in practical engineering applications, it is important to focus on monitoring the duration of power outages and the proportion of TCL. In extreme hot weather conditions, the conservatism of recovery strategies can be appropriately increased.

5. Conclusions

To accurately evaluate the impact of CLPU events on the power supply restoration of distribution networks, this paper proposes an urban distribution network reliability evaluation method based on a lightning search algorithm. By introducing a delay index model to model CLPU events and using LSA to develop an optimal restoration program, it can be used for optimal restoration planning and reliability calculation of urban power systems with highly concentrated loads under constant temperature control.

- (1) Introducing a random load model to simulate accurate power demand considering factors such as environmental temperature and random customer behavior, using a delay index model to establish a time-sharing power demand calculation model for cold load start-up events, and proposing an optimal recovery model with the goal of minimizing recovery time and corresponding constraints. Incorporate the cold load start-up event into the Monte Carlo simulation platform for reliability assessment, use LSA to develop the optimal recovery plan, and determine the recovery time and sequence based on the duration of the power outage and the electricity demand during recovery.
- (2) The case analysis shows that compared with the fixed 60 min interval recovery strategy, the optimal recovery method based on LSA proposed in this paper reduces SAIDI from 8.1671 h/household to 8.1646 h/household, a decrease of 0.03%, and ENS from 24.343 MWh/year to 24.324 MWh/year, a decrease of 0.08%. The power supply recovery time is significantly shortened, and LSA can converge to the global optimal solution within 15 generations. The convergence speed is 51.6% faster than the 31st generation of the suboptimal GWO, and the average execution time is only 360.71 s,

which is 6.14% faster than the 384.32 s of the suboptimal GWO, showing excellent robustness and engineering applicability.

- (3) Future studies may incorporate impacts such as customer behavior, demand response, house insulation, and holidays into CLPU modeling, or consider load requirements under different voltage conditions and ambient temperature dynamics, which can further enhance grid equipment modeling. And expand research on the applicability of more optimization recovery methods in large-scale CLPU-aware load recovery problems to overcome the computational scalability challenges associated with centralized optimization methods.

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References

1. Lei, Y.; Sun, Y.; Hou, K.; Zhang, P.; Zhu, L.; Yang, X.; Liu, X. Impact increment based hybrid reliability assessment method for transmission systems. *CSEE J. Power Energy Syst.* **2022**, *8*, 317–328. [\[CrossRef\]](#)
2. Huang, C.; Bu, S.; Fei, C.-W.; Lee, N.; Kong, S.W. Reliability Assessment for Aeroengine Blisks Under Low Cycle Fatigue with Ensemble Generalized Constraint Neural Network. *IEEE Trans. Reliab.* **2024**, *73*, 922–936. [\[CrossRef\]](#)
3. Wang, L.; Zhao, W.; Liu, B.; Li, Y.-F. Reliability Assessment for Partially Monitored Systems Based on Degradation Hidden Markov Models With Time-Varying Parameters. *IEEE Trans. Reliab.* **2025**, *74*, 5272–5286. [\[CrossRef\]](#)
4. Sun, B.; Wu, Z.; Feng, Q.; Wang, Z.; Ren, Y.; Yang, D.; Xia, Q. Small Sample Reliability Assessment with Online Time-Series Data Based on a Worm Wasserstein Generative Adversarial Network Learning Method. *IEEE Trans. Ind. Inform.* **2023**, *19*, 1207–1216. [\[CrossRef\]](#)
5. Zhang, Q.; Liu, Y.; Xing, L.; Huang, H.-Z. Reliability Modeling and Assessment of Internet-of-Things in Smart Manufacturing Systems: A Modular Petri Net Approach. *IEEE Trans. Reliab.* **2025**, *74*, 4791–4805. [\[CrossRef\]](#)
6. Yarramsetty, C.; Moger, T.; Jena, D.; Rao, V.S. Advances in Composite Power System Reliability Assessment: Trends and Machine Learning Role. *IEEE Access* **2025**, *13*, 80871–80888. [\[CrossRef\]](#)
7. Ma, J.; Wang, Y.; Li, R.; Kang, R. Belief Connection Reliability Algorithm for Networks with Epistemic Uncertainty. *IEEE Trans. Reliab.* **2025**, *74*, 2955–2967. [\[CrossRef\]](#)
8. Trivedi, K. Reliability and Availability Assessment. *IEEE Trans. Reliab.* **2024**, *73*, 17–18. [\[CrossRef\]](#)
9. Nikmehr, N.; Zhang, P. Quantum-Inspired Power System Reliability Assessment. *IEEE Trans. Power Syst.* **2023**, *38*, 3476–3490. [\[CrossRef\]](#)
10. Tang, S.-W.; Zhou, Z.-J.; Hu, C.-H.; Zhao, F.-J.; Cao, Y. A New Evidential Reasoning Rule-Based Safety Assessment Method with Sensor Reliability for Complex Systems. *IEEE Trans. Cybern.* **2022**, *52*, 4027–4038. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Hamoud, G.A. Reliability Assessment of Distribution Stations Considering Spare Transformer Sharing. *IEEE Trans. Power Syst.* **2024**, *39*, 2264–2270. [\[CrossRef\]](#)
12. Gao, Y.; Sun, K.; Qiu, W.; Li, Y.; Li, M.; Sun, Y. Data-Driven Multidimensional Analysis of Data Reliability’s Impact on Power Supply Reliability. *IEEE Trans. Ind. Inform.* **2024**, *20*, 13240–13250. [\[CrossRef\]](#)
13. Xiahou, T.; Zeng, Z.; Liu, Y.; Huang, H.-Z. Measuring Conflicts of Multisource Imprecise Information in Multistate System Reliability Assessment. *IEEE Trans. Reliab.* **2022**, *71*, 1417–1434. [\[CrossRef\]](#)
14. Zhang, B.; Liu, Y.; Zheng, Y.-X. Dynamic Reliability Assessment of Hierarchical Multistate Systems with Sensors’ Degradation. *IEEE Trans. Reliab.* **2025**, *74*, 3784–3798. [\[CrossRef\]](#)
15. Hosseinpour, H.; Benidris, M.; Mitra, J. Enhancing Distribution System Reliability via Volt/VAr Regulation and Stability-Constrained Adaptive Inverter Control. *IEEE Trans. Power Syst.* **2026**, *41*, 337–353. [\[CrossRef\]](#)
16. Hamoud, G.A. Reliability Assessment of Distribution Power Transformers Considering Load Transfer Capability. *IEEE Trans. Power Syst.* **2023**, *38*, 1655–1662. [\[CrossRef\]](#)

17. Wen, J.; Bu, S.; Li, F. Two-Level Ensemble Methods for Efficient Assessment and Region Visualization of Maximal Frequency Deviation Risk. *IEEE Trans. Power Syst.* **2023**, *38*, 643–655. [\[CrossRef\]](#)
18. Zhu, Y.; Singh, C. Assessing Bulk Power System Reliability by End-to-End Line Maintenance-Aware Learning. *IEEE Access* **2023**, *11*, 49639–49649. [\[CrossRef\]](#)
19. Xiahou, T.; Zeng, Z.; Liu, Y.; Huang, H.-Z. Fusing Conflicting Multisource Imprecise Information for Reliability Assessment of Multistate Systems: A Two-Stage Optimization Approach. *IEEE Trans. Reliab.* **2023**, *72*, 90–105. [\[CrossRef\]](#)
20. Zhao, Y.; Sun, H.; Wang, Q.; Jiang, L.; Xie, K.; Tang, J. Speeding Up Composite Power System Reliability Evaluation via Efficient Random Line Importance Sampling Combined with Cross-Entropy Method. *IEEE Trans. Power Syst.* **2026**, *41*, 1094–1108. [\[CrossRef\]](#)
21. He, R.; Liang, H.; Wu, J.; Xie, H.; Shahidehpour, M. Reliability Assessment of Cyber-Physical Distribution System Using Multi-Dimensional Information Network Model. *IEEE Trans. Smart Grid* **2023**, *14*, 4683–4692. [\[CrossRef\]](#)
22. Li, J.; Dong, Z.; Zhang, X.; Xu, M.; Cao, L. An Extended Kriging Model-Based Method for Efficient Reliability Analysis Under Parametric Variation of Probability Distribution. *IEEE Trans. Reliab.* **2026**, *75*, 765–778. [\[CrossRef\]](#)
23. Cai, S.; Xu, Z.; Xie, Y.; Ding, B.; Zhang, M. A service restoration method for resilient distribution systems considering time-varying characteristic of cold load pickup. *Trans. China Electrotech. Soc.* **2025**, *40*, 139–151. [\[CrossRef\]](#)
24. Li, J.; Xiao, J.; Zhao, W.; Li, W.; Zhao, Y.; Li, Y.; Liu, Y.; Yan, L. Load elasticity analysis of high-penetration micro photovoltaic distribution network based on three-phase unbalanced power flow. *J. Electr. Power Sci. Technol.* **2025**, *40*, 71–81. [\[CrossRef\]](#)
25. Shu, D.; Yang, J.; Zhao, H.; Li, Y.; Xu, J.; Shao, F.; Zheng, J. The Application of Intelligent Algorithm in the Power Balance Method of Power Distribution Network. In Proceedings of the 2024 IEEE 6th International Conference on Civil Aviation Safety and Information Technology (ICCASIT), Hangzhou, China, 23–25 October 2024; pp. 247–252. [\[CrossRef\]](#)
26. Baixi, R. Variable QRNN control technology for cold load start-up in elastic distribution network. *Electron. Des. Eng.* **2025**, *33*, 69–73. [\[CrossRef\]](#)
27. Hu, R.; Shirsat, A.; Muthukaruppan, V.; Li, Y.; Zhang, S.; Tang, W.; Baran, M.; Lu, N. Adaptive cold-load pickup considerations in 2-stage microgrid unit commitment for enhancing microgrid resilience. *Appl. Energy* **2024**, *356*, 122424. [\[CrossRef\]](#)
28. Wang, W.; Chen, M.; Wang, H.; Peng, G.; Chen, H. Optimal Distribution System Restoration via Tractable Modeling of Decision-Dependent Interruption Cost and Cold Load Pickup. *arXiv* **2024**, arXiv:2411.12353.
29. Wang, Y.; Su, X.; Song, M.; Jiang, W.; Shahidehpour, M.; Xu, Q. Sequential Load Restoration with Soft Open Points and Time-Dependent Cold Load Pickup for Resilient Distribution Systems. *IEEE Trans. Smart Grid* **2023**, *14*, 3427–3438. [\[CrossRef\]](#)
30. Pang, K.; Wang, C.; Hatziargyriou, N.D.; Wen, F. Dynamic Restoration of Active Distribution Networks by Coordinated Repair Crew Dispatch and Cold Load Pickup. *IEEE Trans. Power Syst.* **2024**, *39*, 4699–4713. [\[CrossRef\]](#)
31. Hannan, M.A.; Ali, J.A.; Hussain, A.; Hasim, F.H.; Amirulddin, U.A.U.; Uddin, M.N.; Blaabjerg, F. A Quantum Lightning Search Algorithm-Based Fuzzy Speed Controller for Induction Motor Drive. *IEEE Access* **2018**, *6*, 1214–1223. [\[CrossRef\]](#)
32. Hamanah, W.M. A Lightning Search Algorithm for Optimal Planning of Power Systems with Short/Long-Term Storage. *IEEE Access* **2024**, *12*, 16682–16695. [\[CrossRef\]](#)
33. Yu, J.; Liao, S.; Ke, D.; Zhang, J. Heterogeneity Modeling and Low-Dimensional Broadcast Cooperative Control of Air Conditioning Load for Power Grid Demand Response. *Electr. Power* **2025**, *58*, 14–26.
34. Du, C.; Yu, W.; Li, B.; Ma, Y.; Ming, R.; Yao, R. Evaluation of Occupant Behavior on Annual Air Conditioning Use in Residential Buildings in Chongqing. *Build. Sci.* **2020**, *36*, 12–19. [\[CrossRef\]](#)
35. Ren, X.; Yan, D.; Wang, C. Air-conditioning usage conditional probability model for residential buildings. *Build. Environ.* **2014**, *81*, 172–182. [\[CrossRef\]](#)
36. Rodriguez Medina, D.; Rappold, E.; Sanchez, O.; Luo, X.; Rodriguez, S.R.R.; Wu, D.; Jiang, J.N. Fast Assessment of Frequency Response of Cold Load Pickup in Power System Restoration. *IEEE Trans. Power Syst.* **2016**, *31*, 3249–3256. [\[CrossRef\]](#)
37. Gilvanejad, M.; Askarian Abyaneh, H.; Mazlumi, K. Estimation of Cold-Load Pickup Occurrence Rate in Distribution Systems. *IEEE Trans. Power Deliv.* **2013**, *28*, 1138–1147. [\[CrossRef\]](#)
38. Ucak, C.; Pahwa, A. An analytical approach for step-by-step restoration of distribution systems following extended outages. *IEEE Trans. Power Deliv.* **1994**, *9*, 1717–1723. [\[CrossRef\]](#)
39. Maytham, A.; Azah, M.; Raad, H. Hybrid LSA-ANN Based Home Energy Management Scheduling Controller for Residential Demand Response Strategy. *Energies* **2016**, *9*, 716. [\[CrossRef\]](#)
40. Li, Y.; Sun, W.; Yin, W.; Lei, S.; Hou, Y. Restoration Strategy for Active Distribution Systems Considering Endogenous Uncertainty in Cold Load Pickup. *IEEE Trans. Smart Grid* **2022**, *13*, 2690–2702. [\[CrossRef\]](#)
41. Torquato, R.; Shi, Q.; Xu, W.; Freitas, W. A Monte Carlo Simulation Platform for Studying Low Voltage Residential Networks. *IEEE Trans. Smart Grid* **2014**, *5*, 2766–2776. [\[CrossRef\]](#)
42. IEEE Std 493-2007; IEEE Recommended Practice for the Design of Reliable Industrial and Commercial Power Systems—Redline. Revision of IEEE Std 493-1997—Redline; IEEE: Piscataway, NJ, USA, 2007; pp. 1–426.

43. Huda, A.S.N.; Živanović, R. Distribution system reliability assessment using sequential multilevel Monte Carlo method. In Proceedings of the 2016 IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia), Melbourne, VIC, Australia, 28 November–1 December 2016; pp. 867–872. [\[CrossRef\]](#)
44. Lu, Y.; Zhou, Y.; Wu, X. A Hybrid Lightning Search Algorithm-Simplex Method for Global Optimization. *Discret. Dyn. Nat. Soc.* **2017**, *2017*, 1–23. [\[CrossRef\]](#)
45. Yusoff, W.Y.W. Distribution Network Expansion Planning and Integration of Distributed Energy Resources Considering Massive Penetration of Electric Vehicle Charging Stations in Malaysia. *J. Adv. Res. Des.* **2025**, *130*, 113–125. [\[CrossRef\]](#)
46. Gu, T.; Tian, Y.; Shi, K.; Liu, Z.; Pan, J. A Distribution Network-Microgrid Coordinated Optimization Method Based on Dynamic Networking and Electricity Price Incentives. In Proceedings of the 2025 International Conference on New Power System Technology (PowerCon), Hefei, China, 24–25 September 2025; pp. 1–6. [\[CrossRef\]](#)
47. Jiang, W.; Wu, J.; Qi, H.; Feng, W.; Duan, X. An Optimization Method for Evaluation and Decision-Making of Distribution Network Planned Projects Based on Branch and Bound Algorithm. In Proceedings of the 2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2), Beijing, China, 20–22 October 2018; pp. 1–9. [\[CrossRef\]](#)
48. Shu, L.; Lang, L.; Shuxin, T.; Yang, F.; Shurong, W.; Xiangjing, S. A Robust Dynamic Islanding Restoration for active distribution network considering load control. In Proceedings of the 2020 International Conference on Smart Grids and Energy Systems (SGES), Perth, Australia, 23–26 November 2020; pp. 612–617. [\[CrossRef\]](#)
49. Mori, H.; Muroi, T. Application of probabilistic Tabu Search to distribution system service restoration. In Proceedings of the 2011 IEEE International Symposium of Circuits and Systems (ISCAS), Rio de Janeiro, Brazil, 15–18 May 2011; pp. 1037–1040. [\[CrossRef\]](#)
50. Bao, Y.; Wang, C.; Zeng, X.; Wei, H. Prediction method for daily water demand in water management based on improved chaotic lightning search algorithm. *Foreign Electron. Meas. Technol.* **2025**, *44*, 232–237. [\[CrossRef\]](#)
51. Chavali, S.; Pahwa, A.; Das, S. A genetic algorithm approach for optimal distribution feeder restoration during cold load pickup. In Proceedings of the 2002 Congress on Evolutionary Computation, CEC'02 (Cat. No.02TH8600), Honolulu, HI, USA, 12–17 May 2002; IEEE: Piscataway, NJ, USA, 2002; Volume 2, pp. 1816–1819. [\[CrossRef\]](#)
52. Schneider, K.P.; Sortomme, E.; Venkata, S.S.; Miller, M.T.; Ponder, L. Evaluating the magnitude and duration of cold load pick-up on residential distribution using multi-state load models. *IEEE Trans. Power Syst.* **2016**, *31*, 3765–3774. [\[CrossRef\]](#)
53. Shareef, H.; Ibrahim, A.A.; Mutlag, A.H. Lightning search algorithm. *Appl. Soft Comput.* **2015**, *36*, 315–333. [\[CrossRef\]](#)
54. Shareef, H.; Mutlag, A.H.; Mohamed, A. A novel approach for fuzzy logic PV inverter controller optimization using lightning search algorithm. *Neurocomputing* **2015**, *168*, 435–453. [\[CrossRef\]](#)
55. Cai, S.; Xie, Y.; Zhang, M.; Jin, X.; Wu, Q.; Guo, J. A Stochastic Sequential Service Restoration Model for Distribution Systems Considering Microgrid Interconnection. *IEEE Trans. Smart Grid* **2024**, *15*, 2396–2409. [\[CrossRef\]](#)

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