Optimization Strategy for Improving Power Supply Capacity in Distribution Networks with Electric Vehicle Integration

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Abstract. In order to alleviate the heavy air pollution problem in China in recent years, power energy alternative loads, such as electric vehicles, are widely integrated into distribution networks, which has a significant impact on power supply capability of distribution networks. In this paper, considering the randomness of electric vehicles, probabilistic multiple scenarios generation method is proposed based on Latin hypercube sampling method, Cholesky decomposition and synchronous back-off reduction, realizing the quick scenario generation with the balance of scenario number and precision. Based on probabilistic multi-scene, taking the power supply ability of distribution network as the main objective, a robust operation optimization model of distribution network containing electric vehicles is established in order to optimize the opening and closing status of the switches. Ant colony algorithm based on the Pareto optimal is adopted to solve the model. A modified IEEE 33 node system is used to verify the effectiveness of the model and algorithm, and simulation results show that the proposed method can effectively promote the power supply ability of distribution networks, and can greatly improve the computational efficiency of the model in the case that lots of uncertain parameters exist due to large-scale integration of electric vehicles.

1. Introduction
In recent years, China has been continuously plagued by air pollution problems, in particular, the continuous occurrence of heavy and high peak haze weather in the heating season. The air pollution problem represented by smog has a serious impact on air quality and has aroused widespread concern in the social. From the composition of air pollutants, vehicle exhaust is the main reason for the occurrence of hazy weather [1-2]. Electricity is clean, safe and convenient. In the stage of energy consumption, direct consumption of electric energy replacing for fossil fuels such as coal, oil and natural gas, and increasing the proportion of electric energy in terminal energy consumption are of great significance for alleviating severe haze weather.

At present, electricity alternative facilities such as electric vehicles [3-4] are in a rapid development stage, and local distribution networks will have to bear the rapidly growing electric vehicle load. However, the electric vehicle load has the characteristics of strong randomness and time concentration, and the disorder integration of electric vehicle load will bring unprecedented challenges to the efficient operation of distribution network. For electric vehicle charging facilities, residents’ charging peak overlaps with the existing peak load, and the charging time and power have greater uncertainty, which will have a significant impact on the load characteristics of the distribution network, thus affecting the security and stability of distribution network operation.
At present, for the distribution network with electric vehicle integration, the current literatures studied separately from the aspects of impact analysis, planning and operation optimization and so on. Reference [5] discussed the status quo of electric vehicle’s access into the grid from three main aspects: the electric vehicle charging load modelling and simulation calculations, the influence of electric vehicle’s access to the power system, the electric vehicle’s charging and discharging control and utilization. Reference [6] established the daily electrical changing demand model for electric vehicles according to the probability distribution of the daily driving distances of various types of electric vehicles in the planning area. Based on a comprehensive consideration of user's charging demand and the grid load level and targeting at peak cutting and valley filling, the study in [7] used heuristic algorithm to dynamically solve the price-time period of electric vehicles in the charging stations, which is responsive by the users to achieve the orderly charging of electric vehicles in charging stations.

From the research above, we can find that: due to the obvious sequential and stochastic characteristics of electric vehicles, the peak-valley difference of distribution system is aggravated, which has a significant impact on the power supply capability of distribution networks [8]. In the traditional distribution network, the load between lines is generally balanced by network reconfiguration, which is achieved by changing the status of switches, thus realizing the economical and safe operation of distribution networks [9]. Considering electric vehicle integration, the reconfiguration methods of traditional distribution network need to be improved, and the focus should be transformed from a single-goal of economic benefits into a multi-objective optimization, focusing mainly on improving the power supply capacity. On the other hand, the sequential and stochastic characteristics of electric vehicle load should be fully considered, and a typical application scenario of electric vehicle load should be established.

In this paper, the distribution network with large-scale electricity vehicles is taken as the research object, and the main goal is to improve the power supply capacity of distribution networks. A robust operation optimization model of distribution network with electric vehicles is established to optimize the status of switches. Considering the sequential and stochastic characteristics of electric vehicle load, we used the combination of Latin hypercube sampling [10], Cholesky decomposition [11] and synchronous back-off reduction [12] to achieve the rapid generation of probabilistic multi-scenario and the reduction of the scenarios when meeting the accuracy requirements. The method proposed in this paper improves the optimization efficiency and provides a theoretical and technical reference in the distribution network with large-scale electric vehicle integration.

2. Probabilistic scenarios generation method based on Latin hypercube sampling
Considering the timeliness of global optimization of distribution network and the technical limitations of information processing and communication system, this paper uses the combination of scenario analysis and robust optimization to optimize the power supply capability of distribution network. In order to improve the efficiency of optimization, Latin hypercube sampling method is applied to generate scenarios in the robust operation optimization, which can improve sampling precision and scene generation efficiency. The scenario generation method requires the predicted output values of electric vehicles as well as their error probability distributions, and therefore, we first generate the probability distribution of variables according to the data collected and predicted, and then use Latin hypercube sampling to generate the scene so that the sampling points cover the entire distribution interval. Then, according to the correlation coefficient matrix in different scenarios, reorder the elements sampled by uncertain parameters by using Cholesky decomposition method, to reduce the correlation between the scenes. Finally, reduce the scene by synchronous back-off reduction to improve the optimization of robust operation efficiency.

2.1. Probabilistic distribution generation method of random variables
The predicted value of each load and its error probability distribution are the necessary conditions for the Latin hypercube sampling. According to the historical load data in the short-term period, the
probability distribution of random variables can be obtained by means of probability estimation, fitting and testing. The closer the probability distribution of random variables to the distribution of the actual operation, the more reasonable the solution of robust operation optimization model in multi-scenario, the robustness and economy of the model can also be reflected.

The historical data of load and energy output are analyzed using the nuclear density estimation. The specific steps are as follows:

(1) Density function estimation. Take the historical data within a short time period, using (1) to calculate the value of the predicted error density function \( f_n(x) \) at each time point and draw the curve

\[
1 \leq k \leq n, K(x_i) = \int K(x) \, dx
\]

where \( K(*) \) is a kernel function in \( \mathbb{R} \), \((x_1, x_2, ..., x_n)\) is a simple subsample of the parent \( X \), and \( f_n(x) \) is an estimation of the probability density function \( f(X) \) of the parent \( X \);

(2) Normal fit of density function. The shape of the curve is basically close to the normal distribution curve, which indicated that the prediction error basically obeys the normal distribution. The normal curve can be used to fit \( f_n(x) \) to estimate the variance coefficient of the normal distribution.

(3) Statistical test. Judging whether the fitted normal distribution function is acceptable, usually using the Pearson's theorem in the \( x^2 \) test.

2.2. Latin hypercube sampling based on probability distribution of random variables
The essence of Latin hypercube sampling is stratified sampling based on inverse function transformation, which is different from the probability distribution discretization of scene tree sampling.

Without changing the original density function, the range of distribution function is divided into \( N \) non-overlapping equal-interval range.

The sample values in the subinterval are then inverse function transformed based on the probability density function, the sampling result obtained can not only meet the probability distribution characteristics but also cover the entire distribution interval, and the sampling efficiency is high. Figure 1 showed the sampling process, the steps are as follows:

(1) Assuming that there are a total number of \( K \) uncertain parameters, the number of samples required to be sampled for each parameter is \( N \), then forming a sample matrix \( X_{kn} \) of \( K \) rows and \( N \) columns:

\[
X_{kn} = \begin{bmatrix}
  x_1^1 & x_1^2 & \cdots & x_1^N \\
  x_2^1 & x_2^2 & \cdots & x_2^N \\
  \vdots & \vdots & \ddots & \vdots \\
  x_K^1 & x_K^2 & \cdots & x_K^N 
\end{bmatrix}
\]  

(2) Suppose the sampling result of the \( m \)th uncertain parameter is \( X_m = [x_m^1, x_m^2, ..., x_m^k, ..., x_m^N] \) and \( F(X_m^k) \) is the normal distribution function of \( X_m^k \). In order to facilitate the inverse function, \( F(X_m^k) \) is taken halfway from the median and then the left and right halves are sampled separately.

(3) Assuming that the range of the normal distribution function is \([0, R]\), the interval is equally divided into \( N \) non-overlapping sub-intervals. Each interval is randomly sampled to obtain a sampling value \( Y_m^k \):

\[
Y_m^k = R \frac{U(0,1)}{N}, k = 1, 2, ..., N
\]

(4) Take the inverse function of the probability distribution function to get the actual sampling value of \( X_m^k \):

\[
X_m^k = F^{-1}(Y_m^k)
\]

(5) Continue sampling from the remaining sub-interval, and repeating the steps above until the end of sampling.
2.3. The reorder of the scene based on Cholesky decomposition

The accuracy of scene generation is related not only to the sample values, but also to the correlation between the samples of each uncertain parameter. In general, the smaller the correlation is, the higher the accuracy will be.

The purpose of Cholesky decomposition is to reduce relevance between scenes. According to the correlation coefficient matrix between different scenes, an approximately orthogonal arrangement matrix \( L_{KN} \) is constructed, the positions of the elements in the sampling matrix \( X_{KN} \) are reordered to reduce their correlation, and the size of each element is not changed.

The steps of Cholesky decomposition are as follows:

1. Randomly generate a matrix \( L_{KN} \) of \( K \) rows and \( N \) columns. The \( k^{th} \) row vector in the matrix \( L_{KN} \) is randomly arranged by integers 1, 2, ..., \( N \), and its element value indicates the position where the \( k^{th} \) row vector in the matrix \( X_{KN} \) should be arranged.

2. Calculate the correlation coefficient matrix \( \rho_L \), which is between the lines of the matrix \( L_{KN} \). \( \rho_L \) is a positive definite symmetric matrix, which can be decomposed into a non-singular lower triangular matrix \( D \):

\[
\rho_{ij} = \frac{\text{cov}(L_i, L_j)}{\sqrt{\text{cov}(L_i, L_i) \text{cov}(L_j, L_j)}}, \quad i, j = 1, 2, ..., N \tag{5}
\]

\[
\rho_L = DD^T \tag{6}
\]

3. Calculate matrix \( G_{KN} \) of \( K \) rows and \( N \) columns:

\[
G_{KN} = D^{-1} L \tag{7}
\]

4. The elements of each row in the matrix \( L_{KN} \) are sorted according to the element sizes of the corresponding positions in the matrix \( G_{KN} \) to construct an approximately orthogonal arrangement matrix.

5. The elements of each row in the matrix \( X_{KN} \) are reordered according to the positions indicated by the corresponding elements in the updated alignment matrix \( L_{KN} \).

Since the rows of the matrix \( G_{KN} \) are uncorrelated, the correlation between the rows is weakened after the elements in each row of the matrix \( L_{KN} \) and \( X_{KN} \) is rearranged according to the corresponding row of the matrix \( G_{KN} \).

2.4. Scene reduction based on the simultaneous back reduction

In order to meet the accuracy requirements of Latin hypercube sampling, the total number of the scenarios generated should be large enough that the population of samples can be closer to the probability density distribution of uncertain parameters. However, if all the generated scenarios are used in the robust optimization model, the efficiency of optimization is weakened, which is not conducive to the practical application of the model. The purpose of synchronous back-off reduction is to improve the efficiency of robust operation optimization. By iterative reduction, the nearest scenario of "norm distance" can be reduced until the number of scenes is adequate. The reduced sample population still meets the probability distribution.
n represents the number of variables contained in a scene, N represents the number of the original scene, the scene \( \omega(i) \) is defined as a sequence:

\[
\omega(i) = (\lambda_1^{(i)}, \lambda_2^{(i)}, \ldots, \lambda_n^{(i)}) \quad i = 1, 2, \ldots, N;
\]

where \( \lambda_s^{(i)} \) represents the value of the \( s \)-th variable in scene \( i \);

\( \pi(i) \) represents the probability that scene \( i \) will occur. Since the Latin hypercube samples are evenly sampled over the range of values, the probability of the sampled values is the same, that is, \( \pi(i) = 1/N \), satisfying the property \( \sum \pi(i) = 1 \);

The "norm distance" of the scene \( \omega(i) \) and the scene \( \omega(j) \) is:

\[
d(\omega(i), \omega(j)) = \sqrt{\sum_{s=1}^{n} (\lambda_s^{(i)} - \lambda_s^{(j)})^2}
\]

The steps to synchronize back reduction method are as follows:

1. Determine the scene to be cut, then remove the scene \( \omega(s) \), \( s \in \{1, \ldots, n\} \) that satisfies the following conditions:

\[
\pi(s) \min_{s \neq i} d(\omega(s), \omega(i)) = \min_{i \in \{1, \ldots, n\}} \min_{j \in \{1, \ldots, n\}} \pi(i) d(\omega(i), \omega(j))
\]

This heuristic approach takes into account the distance and probability between scenes so that those close, small-probability, and unrepresentative scenes are more easily rejected.

2. Change the total number of scenes: \( N = N-1 \), change the probability of the scene closest to remove the scene \( \omega(s) \), and ensure that the sum of the remaining scene probabilities is 1;

\[
\pi(i) = \pi(i) + \pi(s)
\]

3. If the total number of scenes after reduction \( N \) is still greater than the total number of scenes required, repeat the steps 1-2.

**3. Optimal Robust Control Model of Switches and Algorithm Based on Scenario Analysis**

In distribution networks, in order to meet node voltage constraint under the worst case of uncertain parameter, robust optimization needs to sacrifice certain running economy. Especially when more uncertain parameters exist, the economy deteriorates further. In this paper, the robust optimization and scenario analysis method are combined to establish an optimal robust control model of switches, with multiple scenarios system expected minimum network loss and unbalanced load degree expected minimum as multi-objectives and robust constraints, which realizes the best balance of the power supply capacity and economy.

**3.1. Objective function**

For the typical areas integrated with electric vehicle loads, a dynamic reconfiguration model is built considering the load variety during the optimization period, to reduce network losses, improve the quality of voltage, balance the loads between lines and alleviate the negative impact of the integration of electrical energy alternative load. By collecting load data, combining with the fluctuation in the short period of history, the probability multi-scene is formed, and the day-ahead switching action plan is set up to realize the optimal operation in multi-scene system. The optimization objective function can be described as:

\[
\begin{align*}
\min f_1 &= \sum_{i=1}^{N} p_i \left( \sum_{t=1}^{T} c_{tp}^i \Delta t + \sum_{j=1}^{M} \sum_{t=1}^{T} c_{swi} \left| s_{pi} - s_{j(i-1)} \right| \right) \\
\min f_2 &= \sum_{i=1}^{N} p_i \left( \sum_{t=1}^{T} \sum_{j=1}^{N} \left| S_j^i \right| S_{j_max} \right)
\end{align*}
\]
where $c_{ep}^t$ is the electricity price of time $t$; $P_{loss}^t$ is the power loss of time $t$; $T$, $M$ is the period number before and after periods are divided; $N$, $K$ is the total number of branches and nodes; $c_{swi}$ is the switching action price; $s_{ji}$ is the state of the switch, and $s_{ji} = 0$ means open, $s_{ji} = 1$ means closed; $S_{ji}^t$ is the apparent power of branch $j$ at time $t$; $S_{j\text{max}}^t$ is the maximum power of branch $j$; $p_s$ is the probability of scenario $s$; $N_r$ is the scenario number after reduced.

3.2. Constraints

1) Constraint of active and reactive power balance

\[
P_i^t - U_i \sum_{j=1}^{n} U_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) = 0
\]
\[
Q_i^t - U_i \sum_{j=1}^{n} U_j (G_{ij} \sin \delta_{ij} + B_{ij} \cos \delta_{ij}) = 0
\]

where $P_i, Q_i$ are active and reactive power injection of bus $i$; $U_i$ and $U_j$ are voltages of $i$ and $j$; $G_{ij}$ and $B_{ij}$ are real part and imaginary part of admittance matrix; $\delta_{ij}$ is phase angle difference between $i$ and $j$.

2) Constraint of branch power

\[
0 \leq I_{ij}^2 \leq (I_{ij}^{\text{max}})^2
\]
\[
I_{ij} = \frac{P_{ij}^2 + Q_{ij}^2}{U_{ij}}
\]

where $I_{ij}$ is the current of branch $ij$; $U_{ij}$ is the voltage difference between $i$ and $j$; $P_{ij}$ and $Q_{ij}$ is the active and reactive power of branch $ij$.

3) Constraint of node voltage

\[
U_i^{\text{min}} \leq U_i \leq U_i^{\text{max}}
\]

4) Constraint of network topology

After reconfiguration, the network is still connected radially without the presence of the islanding.

5) Constraint of the maximum number of switching actions

\[
\sum_{i=1}^{M} |s_{ji} - s_{j(i-1)}| \leq W_{j\text{max}}
\]
\[
\sum_{j=1}^{N} \sum_{i=1}^{M} |s_{ji} - s_{j(i-1)}| \leq W_{\text{max}}
\]

Where $W_{j\text{max}}$ is the maximum number of single switching action; $W_{\text{max}}$ is the maximum number of total switching actions.

3.3. Optimization method

The only global optimal solution usually does not exist in multi-objective optimization problems, and the solution a set which is made up of multiple optimal solutions. Compared with the weighted and transformation methods, Pareto optimal multi-objective transformation method can evaluate multi-objective solution vector based on set theory, which can avoid the subjectivity of weight selection in weighted method and can be more scientific. In this paper, a Pareto optimal method based on non-dominant solution set [13] is adopted to optimize the multi-objective problem.
According to the radiation characteristics of distribution network, ant colony algorithm [14] is used to solve the problem of network reconfiguration in distribution network. One journey of ants can acquire a spanning with some random strategy (a new reconfiguration scheme satisfying the radial and connectivity constraint), so that the network topology in each scheme are radiant, which can avoid the radiant inspection process and increase the number of feasible solutions and the algorithm efficiency.

The specific process of the algorithm is shown in figure 2:

![Algorithm flowchart](image)

**Figure 2.** Algorithm flowchart

4. Case study

4.1. Test System Specifications

Footnotes should be avoided whenever possible. If required they should be used only for brief notes that do not fit conveniently into the text.

An IEEE 33 node system is used to verify the feasibility of the model and algorithm. The wiring diagram of the distribution network shows as Fig. 3. The voltage level is 12.66kV, with 1 power source, 33 nodes and 3 branches, and the tie lines are 7-20, 8-14, 11-21, 17-32, 24-28, and the rest is the section switch. Electric vehicle charging stations are installed at nodes 7, 13, 23 and 30.
Load variety range is set to ±10%, and the error probability distribution is normal distribution. The number of scenarios generated by Latin hypercube sampling is set to 1000, and after reduction the number of scenarios is set to 50, which has the close precision compared with the scenario generation method based on scenario tree sampling. The hardware environment of the test system is Intel quad-core i5-3230m CPU 2.60 GHz, with an 8GB of memory, and the operating system is WIN 10 64bit, and the development environment is MATLAB R2016a.

4.2. The simulation result analysis
Sections should be numbered with a dot following the number and then separated by a single space. Through probability scenario analysis and robust optimization, the final optimized reconstruction results are shown in table 1.

### Table 1. The Solution of Robust Operation Optimization Model

| Scheme                  | Time    | The open branch |
|-------------------------|---------|-----------------|
| Before control          | All day | 7-20, 8-14, 11-21, 17-32, 24-28 |
|                         |         | 0-7, 16-17, 13-14, 7-20, 8-9, 24-28 |
| The optimal control     | 8-14    | 15-16, 13-14, 7-20, 7-8, 24-28 |
| scheme                  |         | 16-23, 13-14, 12-13, 7-20, 5-6, 24-28 |

In order to fully analyze the influence of power energy alternative for the power supply capacity of distribution network and verify the effect of the proposed method for improving the capacity of power supply, four indexes are put forward to evaluate circuit of power supply capacity, which are 10 kV line power loss, 10 kV line power factor qualified rate, the qualified rate of 10 kV line load rate and the qualified rate of 10 kV contact line load transfer. The satisfaction evaluation function of the evaluation index is established to calculate the power supply capacity of 10kV line. Entropy weight method [15] is used to calculate the weight of each evaluation index. The evaluation model of power supply capacity of 10kV line is established, taking the maximum weighted sum of the index satisfaction of each operation state as objective function.

$$\max f = \sum_{i=0}^{m} W_i F_i$$  \hspace{1cm} (20)

where $W_i$ is the index weight of the $i$th evaluation index; $F_i$ is the satisfaction degree of the $i$th evaluation index; $m$ is the number of evaluation index.

The power supply capacity is evaluated before power energy alternative integrated, after power energy alternative integrated and after optimization with power energy alternative integrated, respectively. The evaluation results are shown in Table 2.
Table 2. The evaluation results

| Power energy alternative scenario                                      | Evaluation score of power supply ability |
|------------------------------------------------------------------------|------------------------------------------|
| Before power energy alternative integrated                             | 0.85                                     |
| Without switch control after power energy alternative integrated      | 0.63                                     |
| With switch control after power energy alternative integrated         | 0.83                                     |

According to the data obtained from Table 2, it can be seen that the power supply capacity of the distribution network is greatly affected by power energy alternative load. Network reconfiguration based on switch control can effectively promote the power supply ability of distribution circuits, which proves the correctness and validity of the power supply capacity optimization method in this paper.

4.3. Probabilistic statistical analysis of the effect of robust control model

In order to further analyze the overall effect of robust control model under different operating scenarios based on probabilistic multi-scene, deterministic operation optimization model is compared with the traditional robust control model [16], and Monte Carlo method is used for validation. With the system parameters unchanged, 2000 samples are selected randomly based on the normal distribution function of uncertainty parameters, and then the solution of the optimization model can be plugged into the sample scenario and the power flow can be calculated. Finally, the scenario number of out-of-voltage can be counted and the expected power losses can be achieve, which are shown in Table 3.

Table 3. The number of voltage limits, the proportion and the expected value of network loss in each model

|                                | The scenario number of out-of-voltage | The scenario ratio of out-of-voltage | The expected power losses/MW |
|--------------------------------|--------------------------------------|-------------------------------------|-------------------------------|
| Determinate control model      | 373                                  | 18.65%                              | 0.4411                        |
| Conventional robust control model | 0                                     | 0                                   | 0.4864                        |
| Robust control model based on probabilistic multi-scenario | 0                                     | 0                                   | 0.4773                        |

The table above shows that 18.65% of the scenarios occur out-of-voltage with the deterministic operation optimization model, while out-of-voltage doesn’t happen in any scenarios with the model proposed in this paper, showing good robustness. In this paper, system network losses are 0.4773 MW, lying between 0.4411 MW and 0.4864 MW, which is superior to the traditional robust optimization model. The above results show that the model in this paper can well realize the balance of economy and safety, with ensuring the security of node voltage.

5. Conclusion

For the distribution networks with large scale integration of power energy alternatives, this paper considers the effects of electric vehicles for the power supply capacity, and a scenario generation method is proposed based on Latin hypercube sampling method, which improves the efficiency of the model. Based on the probabilistic multi-scene, an optimal robust control model is established, which can well realize the balance of economy and safety, with ensuring the security of node voltage in distribution networks.

Numerical example results show that network reconfiguration based on switch control can effectively promote the power supply ability of distribution circuits. Meanwhile, the proposed approach can greatly improve the computational efficiency of the model in the case that lots of
uncertain parameters exist due to large scale integration of power energy alternatives. Therefore, the model has good practicability, which can effectively cope with the time-sequenced and randomness characteristics of electric vehicles. Deficiency is that the short-term probability density function of load error draws lessons from other literature data, which is rough, and subsequently further modeling need to be researched based on the collection and probabilistic statistics of prediction data.

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