Multi-objective Distribution Network Reconfiguration Optimization Considering Space Allocation of Electric Vehicles

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Abstract. This paper explores the space allocation method and fuzzy C cluster processing method of electric vehicles, establishes a multi-objective distribution network model, solves the calculation process of the model, and verifies the feasibility of this research through simulation analysis method, thus providing help for orderly charging of electric vehicles and reducing line loss.

1. Introduction
During the operation of the power distribution system, the topology structure can be adjusted by adjusting the network switch, thus eventually reducing the loss and ensuring the stability of the system operation. Distribution network reconfiguration, as a method to improve system safety and economic benefits, should be given sufficient attention. The large increase of EV makes the distribution network face challenges. The charging behavior of electric vehicles is random, and the distribution network transits from unidirectional radiation to multi-terminal network. The traditional reconfiguration model cannot meet the needs of the development of the times. The influence scope of electric vehicle access on distribution network reconfiguration is continuously expanding. Therefore, researchers have conducted more in-depth research on electric vehicle charging load. In this study, a multi-objective distribution network reconfiguration optimization method considering electric vehicle space allocation is explored, and simulation analysis is combined to prove the feasibility of the model.

2. Space Allocation of Electric Vehicles and Fuzzy C Cluster

2.1. Space Allocation of Electric Vehicles
If there is a Q-seat charging station in the power grid within a certain range and n electric vehicles are charged, the position of the p-th electric vehicle can be expressed by the following formula:

\[ L_p = (l_{p1}, l_{p2}, \cdots, l_{pQ}) p = 1, 2, \cdots, n \quad (1) \].

In this formula, \( l_{pk} \) represents the distance of the p-th electric vehicle at different charging stations, so the concept of electric vehicle utility can be introduced first. Utility degree of electric vehicle is the comprehensive coefficient of electric vehicle power station charging, and charging distance and time are the factors that affect users. Therefore, the utility degree that the p-th electric vehicle reaches the k charging station can be obtained:

\[ S_{pk} = \frac{t_{pk}}{N_1} + \frac{l_{pk}}{N_2} \quad (2) \].

In this formula, \( t_{pk} \) and \( l_{pk} \) are respectively the time and distance corresponding to the k charging station of the p-th electric vehicle. \( N_1 \) represents the minimum charging time, \( N_2 \) represents the minimum charging distance, and the utility index is smaller and better. Assume the
charging time and distance. First, the charging method. The charging power of the p-th electric vehicle is related to the charging method, and the total charging power of the k-th electric vehicle station is $P_k$. Secondly, charging decision variables. Assuming that the number of electric vehicles in the kk-th charging station is $S_k$, the total charging power $P_k$ and $S_k$ of the k-th charging station can be calculated.

$$S_k = \sum_{p=1}^{n} x_{pk}k = 1,2,\cdots, Q$$

(3) $$P_k = \sum_{p=1}^{n} x_{pk}k = 1,2,\cdots, Q$$

(4). In this formula $x_{pk}$ represents the decision coefficient. If $x_{pk}=0$, it can be observed that the p-th electric vehicle is not charged in the k power station. Finally, the charging distance and time. If the p electric vehicle enters the k charging station, the charging time is calculated during the queuing process: $t_{pk} = t_1 + t_2 + t_3$. In this formula, $t_1$, $t_2$ and $t_3$ respectively represent queuing time, charging time and driving time. The queue time and the construction scale of charging stations are related to the number of charging electric vehicles.

$$t_1 = a_kS_k$$

(6) $$t_3 = \frac{t_{pk}}{v_j}$$

(7). In the above formula, $a_k$ represents the proportional coefficient of queuing time. If the proportional coefficient is small, it means that the charging station has a larger scale. Large-scale charging stations can shorten the queuing time of the same number of electric vehicles. The charging time is related to the charging mode of the electric vehicle. In order to control the calculation process, the charging time in the electric vehicle station is set to be consistent. The electric vehicle adopts a slow charging method, and the average speed of the vehicle is $V_i$, thus obtaining the driving time (7).

2.2. Fuzzy C-Means Clustering

Fuzzy C-means clustering is an improved clustering method. According to different clustering methods, data points are planned, and the method of clustering division is adopted to reduce the difference of the same type of data, and the difference of different types of data is increased as much as possible to obtain a smaller number of clusters. In the process of this study, electric vehicles were carried out intensively according to the space position, so as to avoid the influence of large number of electric vehicles on charging flow. The spatial distribution of similar electric vehicles is similar. If the decision variables of similar electric vehicles are assumed to be the same, the utility degree $s_k$ of I cluster electric vehicles is the sum of the utility degrees of electric vehicles. The method can solve the problem that the scale of the increase in the number of electric vehicles is too large. The N vectors $x_j$ ($J=1,2,\cdots,n$) are divided into different clusters by fuzzy C-means clustering method. In the calculation process, the random number of [0,1] is used to initialize the matrix to meet the constraint conditions of formula $\sum_{l=1}^{c} u_{lj} = 1, \forall J = 1,2,\cdots,n$ (8). According to $c_1 = \frac{\sum_{j=1}^{n} u_{1lj}}{\sum_{j=1}^{n} u_{lj}^m}$ (9), c clustering centers $c_i$ are calculated. According to $J(c_1,\cdots,c_c) = \sum_{l=1}^{c} J_j = \sum_{l=1}^{c} \sum_{j=1}^{n} u_{lj}^m u_{lj}^m d_{lj}^2$ (10), in this formula, $C_1$ and $u_{lj}$ represent I cluster center and membership degree, $u_{lj} \in [0,1],d_{lj}$ is the distance between j data points and cluster center. $M$ represents a weighting coefficient, $m \in [1, +\infty]$. According to $u_{lj} = \frac{1}{\sum_{w=1}^{c} [d_{lj}]^{2m(n-1)}}$ (11), the membership matrix is updated and returned to (9) for calculation.

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3. Multi-objective Distribution Network Model Based on Electric Vehicle Space Allocation

3.1. Build a Model

In this study, the objective function is constructed according to the distribution network loss and voltage offset level: 
\[ \min F = \lambda_1 \sum_{i=1}^{N_b} k_i R_i \frac{P_i^2 + Q_i^2}{V_i^2} + \lambda_2 \frac{V_N - V_{low}}{V_N} + \beta \left[ \sum_{k=1}^{M} \sum_{i=1}^{N} (x_{ik} S_{ik}) - a \right] \] (12). In this formula, the line loss, voltage offset level and utility penalty term are reflected. \( N_b \) is the number of branches of the system, \( k_i \) is the switching condition of I branch, 1 indicates closed, 0 indicates open, \( R_i \) indicates resistance, \( P, Q, V, \) etc. indicate the power and node voltage conditions on the branch, etc. \( V_N \) represents the rated voltage of the fixed node. \( V_{low} \) represents the minimum voltage value, \( x_{ik} \) represents the decision variable of \( k \) charging station, and \( S_{ik} \) is the charging utility, \( \lambda_1 + \lambda_2 = 1 \) is the network loss and voltage offset horizontal coefficient of \( \omega_1 \) and \( \omega_2 \). \( \lambda \) represents the basic index of utility degree, \( \beta \) represents the punishment index of electric vehicle utility degree, and \( \alpha \) values are higher than \( \lambda_1 \) and \( \lambda_2 \). The model will also generate certain constraints during the design process, for example, inequality constraints, the constraint power of the electric vehicle charging station is \( P_{EVI} \leq P_{station} \) (13), the branch constraint power is \( |P_{line}^{\text{upper}}| < P_{line}^{\text{max}} \) (14). In this formula, the maximum power, branch power and maximum power of electric vehicle charging station are respectively expressed. In the constraint of network structure, the reconstructed distribution network will take on radiation form to avoid the problem of information island. In terms of distribution constraints, each electric vehicle can only enter one charging station under special circumstances. The subjective awareness of electric vehicle users will also affect the selection of electric vehicle charging stations. In order to prevent electric vehicles from entering charging stations far away, the upper limit of the route should also be set. The utility penalty function of electric vehicles will include an objective function, so users can select charging stations that are close to each other, thus spending less time on charging.

2.2. Solution Process

The comprehensive optimization model optimizes the variables and adopts the network switch state and electric vehicle space allocation scheme. Chromosome pop is composed of sub-chain A and sub-chain B of network topology structure, which respectively indicate the switching state of power distribution. In this study, 1 indicates the closed state, 0 indicates the open state, which meets the relevant conditions of network constraints. Clustering in chromosome pop can indicate the load distribution method of electric vehicles, 1 indicates that electric vehicles enter the corresponding charging station for charging, and 0 indicates that electric vehicles are not full after charging and also meet the distribution conditions. GA fitness is generally used to solve non-negative problems. In this paper, the minimum optimization problem is solved by combining the following functions:

\[ f(x) = \frac{1}{1 + e^{c + F(x)}} \quad c \geq 0, c + F(x) \geq 0 \] (15). In this formula, \( c \) represents the evaluation value of \( F(x) \). According to the distribution constraints, the binary coding method is used to complete the distribution through gene block crossover and mutation operations. In the charging distance constraint condition, the penalty function is used to adjust the relevant elements of the matrix to meet the goal of maximum positive number. After the corresponding electric vehicle is allocated to the relevant charging station, the fitness is appropriately increased, and the chromosome eliminated in the optimization process is processed.

4. Simulation

In this study, IEEE33 nodes were adopted and a single line diagram was obtained. The system has 32 branches and 5 switching branches, the reference voltage is 12.66kv, the standard index of three-phase
power is 10MVA, and the overall load is expressed by 3715+j2300KVA. If Q=4 charging stations exist in the system, it is located at 4 nodes: 6, 11, 13 and 22. The system supplies and connects 100 electric vehicles, and the charging distance is 15km. Relevant research points out that the service range of electric vehicles can reach 10,000 m. Taking this as the maximum distance, the queuing time index is expressed by $a_1=1$ and $a_2=1$, $a_3=2$, $a_4=1$. If the number of selected populations in the algorithm is 1000, the maximum number of iterations is 60, and the cross coefficient and coefficient of variation are 0.9 and 0.05 respectively. 10 good individuals are retained after each evolution. The objective function is $1=0.5$, $2=0.5$. The coefficients 1 and 2 select the minimum value of initial network loss and voltage cheap level. Alpha and beta are selected according to the simulation index. Alpha is the overall index of electric vehicle charging in the charging station, with a value of 280, beta of 5 and electric vehicle charging power of 7kw. The clustering algorithm selects the index with small division in the process of fuzzy division. Too many clusters will increase the calculation scale and too few clusters will affect the optimization accuracy. The clustering coefficient is between 2 and 10, and the Xie-Beni index can be calculated. The minimum value is the best clustering number. If the optimal cluster number for this example is 5 and the Xie-Beni index is 1.254, see Table 1.

| Cluster | Number of Clusters | Cluster Center (L1, L2, L3, L4) /km |
|---------|-------------------|------------------------------------|
| 1       | 15                | 8.851,11.702,4.701,9.201           |
| 2       | 15                | 6.221,8.951,11.554,9.515           |
| 3       | 20                | 5.154,4.125,5.304,7.541            |
| 4       | 19                | 4.954,8.512,6.952,3.596            |
| 5       | 22                | 9.925,4.785,8.485,4.914            |

In order to explore the effectiveness of FCM in simplifying the algorithm, genetic calculation is carried out on the model that is not calculated by clustering algorithm. It can be observed that the convergence of the algorithm is unstable and the causes of poor convergence are related to FCM clustering in the network. As the number of electric vehicles increases, the difficulty of mathematical solution will increase. Chromosome dimensions continue to increase, and genetic algorithm crossover and mutation cannot be effectively operated, which proves the effectiveness of this operation. In order to effectively assume this model scenario, different cluster electric vehicles are randomly charged under the scenario, and the scenario calculation results are compared with the optimization results, as shown in Table 2.

| Project         | Before Optimization | After Optimization |
|----------------|---------------------|-------------------|
| Open Switch Set | 7-18,8-14,11-22     | 6-8, 9-11, 13-15  |
| EV Cluster 1    | M3                  | M3                |
| EV Cluster 2    | M2                  | M1                |
| EV Cluster 3    | M4                  | M2                |
| EV Cluster 4    | M2                  | M1                |
| EV Cluster 5    | M1                  | M4                |
| Net Damage      | 281.25kw            | 171.05kw          |
| Total Utility   | 398.25              | 274.45            |
| Minimum Voltage | 0.8541              | 0.9251            |
| Objective Function | 2.5111           | 0.4532            |

The network loss after optimization is obviously less than that before optimization, and the utility degree synthesis is also greatly reduced after optimization compared with that before optimization. According to the voltage distribution of system nodes under different conditions, it is observed that under the same network topology, the electric vehicle access network reduces the overall voltage level and adversely affects the safe operation of the power grid. The optimized method can eliminate
potential safety hazards in power grid operation and effectively improve the voltage level under the conditions of switch action and reasonable distribution of electric vehicle charging load.

5. Summary
This paper analyzes the trend of electric vehicles entering the network and explores the clustering method of electric vehicles' spatial positions, thus reducing the difficulty of interpretation of the model. Through the multi-objective comprehensive optimization method, the utility constraint conditions of the electric vehicle are brought in, and the branch switch state and the electric vehicle distribution method are processed. The formula and results prove the feasibility of the model, which can guide the spatial distribution of electric vehicles, avoid the influence of disorderly charging on the power grid, reduce the power grid loss, improve the reliability of power grid operation, and shorten the charging distance and time of users.

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