Reliability-Oriented Optimal Planning of Charging Stations in Electricity-Transportation Coupled Networks

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Abstract: With the increasing application of electric vehicles (EVs), the deployment of charging stations is vital for supporting the charging and navigation for EVs, which also affects the reliability of the corresponding electricity network. To achieve a balanced reliability in both the electricity network and EV trips, an optimal planning method for charging stations in the electricity-transportation coupled networks is proposed. Firstly, an integrated management strategy of EVs is demonstrated to model the reliability enhancement of the two networks. Thereafter, a coupled network reliability assessment method based on the Quasi-sequential Monte Carlo simulation is proposed in this paper. This paper proposes a novel reliability-oriented multi-objective optimal planning model for charging stations planning problem, which is resolved by implementing the optimal planning scheme from the candidate nodes. Additionally, correlation analysis is performed to ensure that the proposed model can be solved quickly for large-scale electricity network with complex transportation flow input data. A test case is presented and simulated to validate the feasibility and effectiveness of the proposed method.

1. Introduction

With the rapid development of social economy, the consumption of fossil fuel grows dramatically. It brings some serious social problems, i.e., resource exhaustion, greenhouse effect, et al. **Electric vehicles (EVs)** have drawn more attentions in solving such problems. Nevertheless, the new transport brings extra challenges and threats to electricity network reliability, while benefiting the environment on the other hand [1], [2]. EVs can be regarded as both the energy storage devices and controllable loads to the power grid, which may bring more flexibility. However, they can also cause power reliability and power quality issues. When a large number of EVs are connected to the power grid, the interactions between the transportation network and the electricity network will be very complex, which needs to be studied in many aspects.

Since EVs need to be charged in the electricity network, a proper charging and discharging management strategy could help improve the reliability of the electricity network. A detailed analysis of the charging and discharging control modes of EVs could be found in [3]–[5]. A Spatial-Temporal model (STM) was developed in [3] based on the integration of both the electricity and transportation network analyses. As presented in [4], EVs could be considered as the intelligent interruptible loads and temporary virtual energy storage devices in charging and discharging modes respectively. In [5], the charging demand of charging infrastructures is integrated into a cost-based model to assess the economics of candidate plans. A bidirectional charging power control method, based on the time series model of EVs charging, is proposed in [6]. In order to understand the impacts of EV charging load, [7] proposes a methodology to integrate the modeling of the EV charger

within an electricity network. A bi-level optimal allocation model for allocating the fast charging stations is proposed in [8], which is able to coordinate both the objectives of interest and the optimization of the fast charging service efficiency at the same time. However, the above studies focus on the impact of EVs on electricity network reliability, but few discussions take EVs travelling reliability into account.

To study the reliability of the electricity-transportation coupled networks, reliability level of both networks should be considered comprehensively [9]–[11]. EVs play an important role in the interaction process of coupled networks. It was indicated that the time-space uncertain feature of EV charging loads will cause adverse effect on electricity network reliability, such as fluctuation of power load, insufficient peak power supply [12], [13]. However, as a type of interruptible loads, demand **response** could be performed on EVs to improve the overall reliability of the electricity network [14]. A method of combining the scale evolution model with charging demand model to detect the possible EVs evolution patterns and long-term charging demand profiles is proposed in [15]. In order to improve the reliability of radial distribution system, the demand response programs and smart charging and discharging of plug-in EVs are investigated in [16].

On the basis of coupled network modeling, the research on charging station planning is becoming more and more important. In the existing research, planning objectives are usually the minimization of the users' loss on the way to the charging station [17], the reliability of the distribution network incorporating EVs [18] or the maximization of economic and social benefits [19]. However, the above studies only focus on either the electricity network or transportation network and analyse the reliability

enhancement on a certain aspect. In reliability assessment of the electricity-transportation coupled networks, there is still a lack of quantitative reliability assessment approach. Additionally, the reliability-based planning method of the coupled networks is rarely mentioned. Thus, it is important to establish the suitable reliability indicators and assessment method for the coupled networks.

In order to solve the above problems, first of all, an electricity-transportation coupled networks model is established. The concepts of charging set and discharging set are introduced as the medium of the coupled networks, which comprehensively considers a balanced reliability plan of the coupled networks. Subsequently, a series of reliability indicators are introduced to assess the reliability of the coupled networks, and a quasi-sequential Monte Carlo simulation approach is proposed for the coupled networks. In order to solve the problem of the charging station planning with large-scale EVs, a reliability-oriented multi-objective planning model for coupled networks is built, and the two-stage planning framework is used to guide the selection of the candidate locations and solve the optimal planning scheme. Furthermore, a correlation analysis model based on multivariate regression is proposed to accelerate the planning model solving. The key contributions of this paper are summarized as follows:

- The novel concepts of EVs' charging set and discharging set are performed as the medium to establish the coupled network model of electricity network and transportation network.
- A quasi-sequential Monte Carlo simulation reliability assessment approach is proposed for the coupled networks, and an integrated management strategy of EVs for reliability enhancement is designed as well.
- A reliability-oriented multi-objective planning model for coupled networks is built to solve the optimal planning scheme, and an optimal planning model based on the simplified reliability correlation is established to speed up the calculation efficiency.

The rest of this paper is as follows: the interaction model between the transportation network and the electricity network is discussed in Section 2. The reliability assessment method is presented in Section 3. The planning model is established in Section 4, including a correlation analysis method. Case studies are demonstrated in Section 5 and conclusions are drawn in Section 6.

2. Electricity-transportation coupled networks modelling

The transportation network and the electricity network are tightly integrated due to the increasing penetration of EVs. For simplicity, it is assumed that charging stations for slow charging exist in residential and commercial areas with conventional load. This paper focuses on the optimal siting and sizing of charging stations with fast charging. Furthermore, the charging demand of EVs will bring additional loads to the distribution network. Thus, the planning for charging stations should be carried out by integrating both the electricity network and the transportation network, as shown in Fig. 1.

Let GE (BE, RE) denote the electricity network, where BE and RE are the sets of buses and branches, respectively. GT (NT, LT) denotes the transportation network in the same

urban area that shares geographic information with GE, where NT and LT are the sets of nodes and links, respectively. Assuming that travel demands originate from a set of origin nodes, and are destined for a set of destinations $D \in NT$, which are defined as OD pairs, charging stations are to be planned at the nodes of the transportation network and connected to the corresponding buses in the electricity network through special transformers and lines. Thus, it can be seen that a certain node in the transportation network may overlap with the corresponding bus in the electricity network, which is defined as a "node-bus" pair. Without losing generality, it is assumed that there is no more than one charging station at each node [20].

Fig. 1. Schematic diagram of coupled networks

From Fig. 1, it can be concluded that EVs play an essential role in the interaction between the two networks. The increasing penetration of EVs will bring in extra load demands, and may decrease the reliability of the electricity network. Thus, an integrated management strategy of EVs is designed for enhancing reliability, presented as follows.

2.1. Charging set and discharging set

Denote the total number of EVs as N_{EV} , then the EV set of the transportation network can be represented by $S_{EV} = \{V_1, V_2, \dots, V_{N_{EV}}\}$, where V_i refers to the i th EV. In order to indicate the charging states of EVs' batteries, we assign each EV a parameter called state of charge (SOC), which is defined as:

$$SOC_i = \frac{E_i}{E_{Ni}} \quad (1)$$

where E_{Ni} and E_i are the rated capacity and remaining capacity of the V_i , respectively.

The set of EVs charging in the grid is expressed as S_{Chg} .

$$S_{Chg} = \{V_i | SOC_i < 100\%, V_i \in S_{Cnct}\} \quad (2)$$

where S_{Cnct} is a set of EVs connected to the electricity network, and the number of them is n_{Cnct} .

The basic idea of the charging set is to disconnect several charging EVs from the grid, such that power supply shortage can be alleviated. Generally, in order to satisfy travelling demands of drivers, the charging set should not include EVs with low SOC. Therefore, a threshold δ_t is applied to obtain the maximum number of the charging set $S_{CHG,max}$, which is derived by

$$S_{CHG,max} = \{V_i | SOC_i > \delta_t, V_i \in S_{Chg}\} \quad (3)$$

Denote the power shortage as ΔP_G , which can be obtained by

$$\Delta P_G = \max \left(P_L + \sum_{V_i \in S_{Chg}} P_{C,i} + P_{LOSS} - P_G, 0 \right) \quad (4)$$

where P_G is the power supply capacity, P_L is the total electric load without EVs, $P_{C,i}$ is the charging power of EVs and P_{LOSS} is the network loss.

When $\Delta P_G > 0$, it indicates that the power supply is in shortage. In this case, the EVs in charging set should be disconnected from the grid to alleviate the power supply shortage. In the worst case, when all the EVs in $S_{CHG,max}$ are disconnected, the charging set reach reaches the maximum response power $P_{CHG,max}$, that is:

$$P_{CHG,max} = \sum_{V_i \in S_{CHG,max}} P_{C,i} \quad (5)$$

When the power shortage is too large for the $P_{CHG,max}$ to eliminate, the discharging set can be used as a complement. The discharging not only makes some EVs stop charging, but also makes them discharge power back to the grid, which usually known as the V2G technology (Vehicle-to-grid) [21]. As illustrated the V2G control possibility in the charging station by using synchronverter technology [22], Thus, the discharging mode would be considered for the management design. Different from the charging set, the discharging set could be performed on any connected EVs. However, due to the limitation of battery technology, the discharging would potentially cause the battery degradation of EVs. Hence it should be used as a supplementary measure of EVs' charging management in the reliability enhancement when the latter fail to fully compensate for the power supply shortage and the drivers should get some compensation. The maximum discharging set $S_{DSC,max}$ can be obtained by

$$S_{DSC,max} = \{V_i | SOC_i > \delta_i, V_i \in S_{Cnet}\} \quad (6)$$

The maximum response power $P_{DSC,max}$ for discharging is:

$$P_{DSC,max} = \sum_{V_i \in S_{DSC,max}} P_{D,i} \quad (7)$$

where $P_{D,i}$ is the discharging power of V_i .

2.2. Management strategy of EVs

The integrated management strategy of EVs significantly affects the reliability of coupled network, which can be divided into several steps. When the power supply shortage occurs, the charging management that minimizes the loss of EVs and effectively alleviates the power supply shortage should be implemented first. Secondly, if the power supply shortage cannot be addressed completely, the discharging should be carried out. In extreme cases, if neither the charging nor discharging management can fill the power supply shortage, a part of the power load must be cut off to maintain the security of the power grid. The specific management steps are as follows:

Step 1: It can be seen in (5), if $0 < \Delta P_G \leq P_{CHG,max}$, the power shortage can be completely eliminated by the charging set. Generally, EVs with higher SOC have priorities over those with lower SOC. Therefore, EVs in $S_{CHG,max}$ should be sorted in descending order by their SOC values. Then the charging set S_{CHG} can be obtained by

$$S_{CHG} = \{V_j | j \leq n_{CHG}, V_j \in S_{CHG,max}\} \quad (8)$$

where n_{CHG} is the number of EVs in the charging set.

Step 2: It can be seen in (7), When $P_{CHG,max} < \Delta P_G \leq P_{CHG,max} + P_{DSC,max}$, the charging set is not able to resolve the power shortage. Therefore, the discharging set should also be performed. In order to reduce the damage of V2G technology to EV batteries, EVs in $S_{DSC,max}$ should also be

sorted in descending order by their SOC. Then the discharging set S_{DSC} can be obtained by

$$S_{DSC} = \{V_j | j \leq n_{DSC}, V_j \in S_{DSC,max}\} \quad (9)$$

where n_{DSC} is the number of EVs with the discharging set.

Step 3: It is noticeable that when $\Delta P_G > P_{CHG,max} + P_{DSC,max}$, both the charging set and discharging set are not able to address the power shortage. In this case, load curtailment is inevitable to balance the power demand and supply. Denote it as P_C , which is defined as

$$P_C = \Delta P_G - P_{CHG,max} - P_{DSC,max} \quad (10)$$

In summary, the amount of power that participates in the charging and discharging management strategy P_{CS} is expressed by

$$P_{CS} = \begin{cases} \eta \sum_{j=1}^{n_{CHG}} [B_j (SOC_j - \delta_i)], & 0 < \Delta P_G \leq P_{CHG,max} \\ \eta P_{CHG,max} + \eta \sum_{j=1}^{n_{DSC}} [B_j (SOC_j - \delta_i)], & P_{CHG,max} < \Delta P_G \leq P_{CHG,max} + P_{DSC,max} \\ \eta P_{CHG,max} + \eta P_{DSC,max}, & \Delta P_G > P_{CHG,max} + P_{DSC,max} \end{cases} \quad (11)$$

where B_j is the battery capacity of EV V_i , η is EV charging and discharging efficiency.

Based on the EVs' management strategy, the power that participates in the charging and discharging management is calculated at this time. By feeding this power back to the system operator, the real-time power shortage will be updated to calculate the reliability level of the coupled network again, and the problem of power supply shortage will be solved quickly.

3. Reliability assessment

After integrating EVs into the electricity-transportation coupled networks, the extra load demands for the coupled networks caused by the increasing EV penetration must be considered. As demonstrated in the previous section, the power shortage can be relieved by applying the integrated management strategy. However, such technique will cause adverse effect to the battery life of EVs and may decrease their travelling distances. Therefore, it is necessary to establish a new approach to assess the reliability of the electricity-transportation coupled networks, incorporating the interaction between the two networks.

3.1. Reliability Indicators of Coupled Networks

Quantified indicators are the foundation of reliability assessment. For the electricity network, traditional generation adequacy indicators can be used to quantify its reliability:

Loss of Energy Expectation (LOEE, MWh/year) is the expected loss of energy caused by load curtailments.

$$LOEE = \frac{\int_0^{T_{MC}} P_{LC,t} dt}{T_{MC}} \quad (12)$$

where T_{MC} is the simulation time horizon of the Monte Carlo simulation (MC), measured by year; $P_{LC,t}$ is the load curtailment at time t .

For EV integrated transportation networks, new reliability indicators are developed. Because EVs must find the

charging stations for battery charging, extra time is required on additional driving distance and battery charging [23]. Two indicators are introduced to quantify the impact of this kind of situations on the EV travelling reliability, as follows:

Charging time expectation (CTE, h/year) is the expected total charging time of an EV in a year.

$$CTE = \frac{\sum_{i=1}^{N_{EV}} \sum_{j=1}^{N_{CHG}} (\Delta D_{i,j,CHG} / v_i + T_{i,j,CHG})}{N_{EV} T_{MC}} \quad (13)$$

where N_{EV} is the number of EVs; N_{CHG} is the total times for V_i to reach the charging stations; $\Delta D_{i,j,CHG}$ and $T_{i,j,CHG}$ are the additional required travelling distance and charging duration for V_i when reaching the optimal selected charging station at the j th time interval; v_i is the travelling speed of V_i ; T_{MC} is the simulation time horizon.

When EVs **run out of power**, drivers must call for help, costing plenty of extra time. An indicator is developed for this type of emergencies, as follows:

Battery exhaustion time expectation (BTE, h/year) is defined as the expected total battery exhaustion time of an EV in a year.

$$BTE = \frac{\sum_{i=1}^{N_{EV}} \sum_{j=1}^{N_{BE}} (T_{i,j,WAT} / v_i + T_{i,j,WAT})}{N_{EV} T_{MC}} \quad (14)$$

where N_{EV} is the number of EVs; N_{BE} is the number of V_i run out of power; $T_{i,j,WAT}$ and $T_{i,j,BE}$ are the waiting and charging duration time for V_i when it is exhausted at the j th time interval.

By adding up CTE and BTE, extra time expectation (ETE) can be obtained, as follow:

$$ETE = CTE + BTE \quad (15)$$

Two more indicators are developed to quantify how much battery capacity is participated in charging and discharging sets:

Charging set energy expectation (CSEE, MWh/year) is the expected energy that participates in the charging set.

$$CSEE = \frac{\int_0^{T_{MC}} \sum_{V_i \in S_{CHG,t}} P_{C,i,t} dt}{T_{MC}} \quad (16)$$

where $S_{CHG,t}$ is the charging set at time t and $P_{C,i,t}$ is the charging power of V_i ; T_{MC} is the simulation time scale.

Discharging set energy expectation (DSEE, MWh/year) is the expected energy that participates in the discharging set.

$$DSEE = \frac{\int_0^{T_{MC}} \sum_{V_i \in S_{DSC,t}} P_{D,i,t} dt}{T_{MC}} \quad (17)$$

where $S_{DSC,t}$ is the discharging set at time t and $P_{D,i,t}$ is the discharging power of V_i ; T_{MC} is the simulation time scale.

3.2. Reliability Assessment of Coupled Networks

In order to calculate the reliability indicators defined above, an appropriate assessment method must be developed for the coupled networks. In general, the up/down process of generating units can be simulated by sequential or nonsequential Monte Carlo method. However, because the driving behaviours of EVs are interrelated in the time domain, only sequential method can be applied to the coupled networks. Traditional sequential Monte Carlo simulation method necessarily requires long computational

time to sample and store the operation process of generating units and the driving behaviour of EVs, and hence to calculate the accurate indicators thereafter. Considering the large number of EVs and the long simulation time, this method is inefficient.

For the transportation network, because the travelling plans of EVs in different periods are usually independent from each other, the driving behaviours of EVs can therefore be sampled periodically on a daily basis, which greatly improves the simulation efficiency.

For the electricity network, the quasi sequential Monte Carlo simulation method can effectively simulate the state change of the generation units [24]. Up/Down processes of generation units can be sampled by calculating the state transit probability K_t for each generation unit, as follow:

$$K_t = 1 - e^{-\lambda_g \Delta t} \approx \lambda_g \Delta t \quad (18)$$

where Δt is the time interval. g refers to the g th generation unit. When g is Up, λ_g is the failure rate, otherwise, λ_g is the repair rate.

Suppose a random number $R_g \in [0, 1]$. Then operation state $S_{g,t}$ of g at time t is determined by

$$S_{g,t} = \begin{cases} S_{g,t-1}, & R_g \geq K_t \\ 1 - S_{g,t-1}, & R_g \leq K_t \end{cases} \quad (19)$$

where $S_{g,t-1}$ is the operation state of the previous moment; K_t is the state transit probability.

Thus, the total generation capacity P_G at time t is:

$$P_G = \sum_{g=1}^{N_g} P_g S_{g,t} \quad (20)$$

where P_g is the output power of the g th generation unit. N_g is the number of generation units; $S_{g,t}$ is the operation state of g at time t .

The power shortage ΔP_G can then be calculated by (4), and the charging management can be performed accordingly.

4. Reliability-oriented multi-objective optimal planning model

4.1. Multi-objective optimal model

After the reliability assessment model is established, because the reliability of two networks cannot be improved at the same time, the optimal solution can be obtained by multi-objective decision-making. A multi-objective planning model for electricity-transportation coupled networks is built. It captures the reliability indicators from both the electricity network and transportation network, which achieves a balanced trade-off between the two objectives.

The reliability of the electricity network R_{EN} is reflected by the loss of energy expectation in the target year; the average extra time expectation (ETE) indicates the reliability of the transportation network R_{TN} . Then the comprehensive objective is formulated as:

$$\begin{cases} \min R_{EN} = LOEE \\ \min R_{TN} = \sum_{i=1}^{n_{EV}} R_{EV_i} = \frac{\sum_{i=1}^{n_{EV}} ETE}{n_{EV}} \end{cases} \quad (21)$$

where n_{EV} is the number of EVs participating in the management strategy. R_{EV_i} is the average extra time expectation of V_i .

Constraints:

(1) Power balance equations:

$$P_L + \sum_{V_i \in S_{\text{Chg}}} P_{C,i} + P_{\text{LOSS}} = P_G + CSEE + DSEE + P_C \quad (22)$$

where P_L is the total electric load without EVs; S_{Chg} is the charging set; $P_{C,i}$ is the charging power of EVs; P_{LOSS} is the network loss; P_G is the power supply capacity; P_C is the load curtailment.

(2) SOC limitations:

$$SOC_{\min} \leq SOC_i \leq SOC_{\max} \quad (23)$$

where $SOC_{\min}$ and $SOC_{\max}$ are the minimum and maximum SOC for the EV batteries. Generally, if the SOC of the EV battery is less than 5%, the EV battery management system will start self-protection function to protect the battery. In addition, it will intelligently avoid overcharging. Once the EV battery is charged to an appropriate level, it will automatically cut off the power.

(3) Voltage magnitude limits:

$$V_{\min} < V_{i,t} < V_{\max} \quad (24)$$

where $V_{i,t}$ is the voltage magnitude at bus i at time t . In the power flow calculation, the voltage magnitude constraints $V_{\max}$ and $V_{\min}$ are determined by the voltage quality.

(4) Charging station capacity:

$$\sum_{i=1}^{N_{\text{EV}}} P_{C,i,k} \leq P_{\text{CS},k} \quad (25)$$

where N_{EV} is the number of EVs; $P_{C,i,k}$ is the charging power of i th EV at the k th charging station; $P_{\text{CS},k}$ refers to the k th charging station's capacity.

(5) The geographical distance between the charging stations:

$$D_{m-n} \leq D_{\max} \quad (26)$$

where $D_{m-n} = \zeta \sqrt{(X_m - X_n)^2 + (Y_m - Y_n)^2}$, X_m and Y_m respectively represent the horizontal and vertical coordinates of the charging station at node M in the transportation network, X_n and Y_n respectively represent the horizontal and vertical coordinates of the charging station at node N , which is the nearest to the charging station M . ζ is the distance modification coefficient. $D_{\max}$ is the longest distance between two charging stations, and it can be calculated by:

$D_{\max} = C_e \delta_e / 2A_e$, where C_e is EV's rated battery capacity; δ_e is SOC threshold for finding the charging station; A_e is the average power consumption of EVs.

(6) Economic constraints:

$$N_{\text{CPmin}} \leq N_{\text{CP}} \leq N_{\text{CPmax}} \quad (27)$$

where N_{CP} is the number of new charging piles; N_{CPmin} and N_{CPmax} are the minimum and maximum number of new charging piles. The number of planned charging piles should not be less than N_{CPmin} and should not be more than N_{CPmax} .

(7) Convergence condition:

$$\beta = \frac{S_{id}(\rho_{n\text{MC}})}{M_{\text{ean}}(\rho_{n\text{MC}})} \leq \varepsilon_c \quad (28)$$

where β is the coefficient of variation; S_{id} is the standard deviation function; M_{ean} is the mean value function; $\rho_{n\text{MC}}$ is reliability indicator after n_{MC} simulations; ε_c is convergence criterion of simulation.

4.2. Solving methodology

Step 1- Potential Candidate Locations Assessment:

Before the implementation of the planning schemes, because there are several candidate locations in the planned area, the distribution of EVs run out of power in the initial situation

can be obtained through the optimization method for further analysis of designing the transformation plan. On the basis of the original scheme without transformation, the reliability of the coupled network is assessed, and the locations where EVs are most likely to exhaust their power are considered as the potential candidate locations.

The conventional mathematical programming could not solve the proposed planning model easily. Besides, the calculation of the reliability, represented by the LOEE, integrates the network topology search, which is generally hard to be formulated as an explicit expression, so normally the analytical optimization algorithm could not work. But as an intelligent discrete optimization algorithm, Genetic Algorithm (GA) could be easier to be implemented and integrated with simulations to obtain the effective solution. Thus, an improved GA is adopted in this paper [25].

The adaptive strategies for computing the fitness function, crossover and mutation probability adjustments, and elite reserve strategies are introduced in the improved GA. It should be noted that the probability of crossover and mutation directly affects the operating efficiency and algorithm convergence. The probability adjustment strategy is formulated as:

$$p_{\text{jc}}(m) = \begin{cases} p_{\text{jc},0} & m=1 \\ p_{\text{jc}}(m-1) + k_{\text{jc}} & m>1 \end{cases} \quad (29)$$

$$p_{\text{by}}(m) = \begin{cases} p_{\text{by},0} & m=1 \\ p_{\text{by}}(m-1) + k_{\text{by}} & m>1 \end{cases} \quad (30)$$

where $p_{\text{by}}(m)$ is the probability of mutation, $p_{\text{by},0}$ is the initial value and k_{by} is the growth factor of probability, $p_{\text{jc}}(m)$ is the probability of crossover, where $p_{\text{jc},0}$ is the initial value and k_{jc} is the growth factor of probability.

Step 2- Correlation Analysis: In the process of calculating (21), it is difficult to solve the planning problem expressed by (12)-(17). Additionally, the relationship between transformation measures and reliability indicators cannot be obtained by formula. It is necessary to perform an explicit long-scale simulation on the operation state of the system and components, and then calculate the reliability indicators of the system according to the annual average. Therefore, in the process of using intelligent optimization algorithm to solve multi-objective optimal model, there will be a risk of low convergence speed, local convergence or even non-convergence. The simulation process consumes a large amount of calculation time, hence requires significant computational effort.

In order to improve the calculation efficiency and find the relationship between the data of EV input operating condition and reliability indicators, a correlation analysis method based on simplified reliability is established. The reliability prediction will be obtained through the analysis of the correlation rules between transformation measures and reliability indicators, and the correlation rules are used as constraints to replace the reliability assessment program in the multi-objective optimal planning model, which can effectively alleviate the difficulties in the process of solving the model. The correlation analysis method avoids the iterative calculation process of multiple reliability indicators in step 1, which effectively improves the calculation speed. The model of the correlation analysis based on multiple regression is as follows:

$$\Phi_i(N_{EV}, \delta_i, X_{Chg}, Y_{Chg}, N_{Chg}) = 0 \quad (31)$$

where Φ_i represents the implicit function of the correlation rules. The inputs contain EV penetration, SOC threshold δ_i of EV, location of charging station, number of charging piles, etc. The outputs are the predicted value of coupled networks reliability indicators under this specific input condition. The location and number of newly built or expanded charging stations and the expected reliability level can be accordingly derived.

To develop an efficient clustering-based optimal schemes selection approach, the most effective domain to perform clustering must be selected. The problem can be defined as follows [26]:

$$X = \{x_d, d = 1, \dots, D\} \in R^{(N_{EV}, \delta_i, X_{Chg}, Y_{Chg}, N_{Chg})} \quad (32)$$

where X is the input multivariate operating condition data of the multi-objective planning model, D is the total number of periods. The key challenge is to transform the data from the input domain into a more effective domain with a nonlinear mapping $f: X \rightarrow \Gamma$ such that the clusters $[X^1, \dots, X^K] \subset X$ constructed based on the cluster labels $y = \text{Clustering}(\Gamma)$ can finally result in the optimal planning scheme Γ^* by using the candidate locations X^* selected from $[X^1, \dots, X^K]$. Note that K and $\text{Clustering}(\cdot)$ are the number of clusters and the clustering procedure, respectively.

The input operating condition data is denoted by

$$X = [X_{EN}, X_{TN}] = \{x_d, d = 1, \dots, D\} \in R^{(N_{EV}, \delta_i, X_{Chg}, Y_{Chg}, N_{Chg})} \quad (33)$$

where X_{EN} , X_{TN} represent the reliability indicators datasets of electricity network and transportation network respectively. This step is to run optimal charging stations planning scheme for each individual day d . Note that day d is assumed the same over the whole simulation horizon. The output of this step is the dataset of optimal planning scheme results $\Gamma = [\Gamma_1, \dots, \Gamma_D]^T \in R^{(N_{EV}, \delta_i, X_{Chg}, Y_{Chg}, N_{Chg})}$, where $\Gamma_1, \dots, \Gamma_D$ represents the candidate locations of the newly built or expanded charging stations.

In this step, after establishing the correlation analysis model, the optimal planning scheme can be efficiently solved. The location and number of newly built or expanded charging stations and the expected reliability level can be accordingly derived. The overall methodology is presented in the flow chart as shown in Fig. 2.

Step 3- Two-stage Optimization: After obtaining the initial candidate locations in step 1, a two-stage planning framework is introduced to optimize the candidate locations and derive the optimal scheme, the process is presented as follows:

Stage-I: After obtaining the initial candidate locations, first the planning scheme should be determined according to the transformation measures of the candidate locations. According to the information of the initial topology and the candidate charging stations, the reliability indicators of the coupled network corresponding to the planning scheme can be obtained by using the GA introduced in the first step. In this way, the reliability improvement effect of the planning scheme corresponding to each individual transformation measure can be easily obtained.

Next, the candidate charging stations schemes are combined to obtain the “mixed” combination schemes. Then power flow calculation and constraints verification are implemented. If it failed to pass the verification, the scheme would be abandoned. Otherwise, the “effective” combination schemes would be filtered. Afterwards, the reliability level (objectives) corresponding to each “effective” scheme will be calculated based on the correlation rules in step 2, which will be applied for the next stage to select the optimal solution among all feasible schemes.

Fig. 2. Correlation analysis flowchart

Stage-II: Multi-objective decision is taken into consideration by the integrated objectives of the candidate planning schemes. Each objective has its own expected value and optimal trend. In the optimization problem, the minimum value of $F(x)$ is called the best value, which is denoted as $F(x^*)$ with x^* being the optimal solution [27]. Conversely, the worst value of $F(x)$ is the maximum value, defined as F^w . Then, the normalization is formulated in (34), which produces 0 as the minimum value and 1 as the maximum value:

$$F_{i,j}^N(x) = \frac{F_{i,j}(x) - F_i(x^*)}{F_i^w - F_i(x^*)} \quad (34)$$

where $F_{i,j}(x)$ is the value of the i th objective function in the j th candidate scheme.

In order to compare the relative efficiencies of various multi-objectives, a bargaining function is used to determine the optimal results, formulated as:

$$\text{Max } BI_j = \prod_{i=1}^R (1 - F_{i,j}^N(x))^{\tau_i} \quad j = 1, \dots, N_p \quad (35)$$

where N_p is the number of effective candidate schemes, R is the number of objectives, $BI_j(x)$ is the bargaining function describing the distance from the solution point to the worst value of the objectives. τ_i is the weight factor for the i th objective, if all objectives share the same weight, then $\tau_i = 1$.

In the multi-objective optimal problem shown in (21), it is considered that the reliability of electricity network and EV trips are equally important, so the two objectives share the

In this research, a reliability-oriented planning approach is proposed to transform the clustering domain from input variables to their optimal charging stations planning scheme at each simulation period of each location via running multi-objective optimal planning for each period. The overall solving methodology is presented in the flowchart as shown in Fig. 3.

Case studies are performed on an IEEE RTS system to examine the performance of the proposed approach. The IEEE RTS system is a composite electricity network with 24 buses, 32 generator units, 38 branches, 10 generation (PV) buses and 13 load (PQ) buses. The total generation capacity is 2999.3 MW. Its peak load is 2850 MW. Wind power generators are incorporated at bus 3. Reference [28] illustrates the system of IEEE RTS in detail, as depicted in Fig. 4. There are three customer types in this system, including residential, recreational and commercial. In addition, three charging stations are introduced into this network, locating at bus 9, 20 and 24. The electricity-

The commercial area represented by the blue points is equipped with slow charging piles. Yellow points indicate residential area and green points indicate recreational area. Some parameters are shown in Table 1.

The proposed approach is used to assess the reliability of this system. Results are shown in Table 2. Among all those indicators, LOEE is used to quantify the reliability of electricity network. CTE, BTE, and ETE are transportation network reliability indicators. The Monte Carlo simulation will terminate when the number of simulations reaches the maximum N_{MCmax} or the convergence criteria $\mathcal{E}c$ is satisfied $\mathcal{E}c < 0.01$.

Parameters	Value
Wind power penetration	15%
Number of EVs	30000
EV penetration	10%
SOC threshold for management strategy (δ_c)	60%
SOC threshold for finding charging station (δ_s)	20%
Convergence criterion of simulation ($\mathcal{E}_c$)	0.01
Simulation time interval (Δt , hour)	1/6
EV rated capacity (C_e , kWh)	U(30,50)
EV rated charging power (P_e , kW)	30
EV travelled speed (V_e , km/h)	U(20,50)
EV average power consumption (A_e , kWh/km)	0.15

When assessing the reliability of the coupled network, travelling behaviours of all EVs are simulated to calculate the transportation network reliability indicators. Therefore, the locations at which the EVs run out of power can be recorded for further analysis. In Fig. 6, the red point is used to indicate the locations that EVs run out of power, and the shade of color is used to indicate the frequency of the battery exhaustions. Such locations associated with the results shown in Table 2 are depicted in Fig. 6.

Fig. 6. Initial simulation results

Table 2 Assessment results of the initial scheme

Reliability indicators	Value
LOEE (MWh/y)	1339.4
CTE (h/y)	1.8027
BTE (h/y)	1.8157
ETE (h/y)	3.6184
CSEE (MWh/y)	13334
DSEE (MWh/y)	13257
Battery exhaustion times	428

The proposed approach can be used to analyse the interaction between the two networks in detail. In order to investigate the impact of different SOC thresholds, a series of test cases are performed by altering the value of δ_i . LOEE and ETE are used to quantify the reliabilities of the two networks, respectively. CSEE and DSEE are also calculated, as presented in Fig. 7.

Fig. 7. Impact of SOC Threshold

It can be seen from Fig. 7 that with the decrease of δ_i , LOEE decreases, while ETE, CSEE and DSEE increase. It is because that a higher δ_i leads to larger S_{CHGmax} and S_{DSCmax} , the implementation of EV charging and discharging management strategy benefits the reliability of the electricity network, but is disadvantageous to the transportation network. With the increase of SOC threshold δ_i from 0 to 100%, the transportation network reliability indicator ETE

will be reduced to 43.95% at most, while the electricity network reliability indicator LOEE will be increased to more than twice of the original value.

Hence if it is necessary to ensure a higher reliability level for the electricity network, we can consider choosing a lower threshold. On the contrary, if a higher reliability is required for the transportation network, the threshold should be relatively higher. It can be seen that the reliability of both networks will be affected by δ_i .

With the increasing penetration of EVs, additional charging stations are needed to maintain the sustainability of EVs. An intuitive idea is to construct new charging stations or expand the original charging stations at the place where EVs are most likely to exhaust their power. Such idea can be carried out with the proposed reliability assessment approach.

It can be seen in Fig. 6, for the places that are far away from charging stations or charging station capacity is insufficient to support all EVs, red points are densely distributed, which means numerous EVs run out of power at those places.

Table 3 Assessment results of the transformation scheme

Reliability indicators	Newly built	Extended
LOEE (MWh/y)	1222.8	1212.4
CTE (h/y)	2.0761	2.0441
BTE (h/y)	0.3597	0.3502
ETE (h/y)	2.4358	2.3943
CSEE (MWh/y)	12483	12304
DSEE (MWh/y)	12634	12487
Battery exhaustion times	114	78
Investment amount (Ten thousand yuan)	300	120

In order to reduce the number of red points, it is reasonable to construct new charging stations or expand the original charging stations at the locations with the densest red points. For this case, new charging stations are planned to location near Bus 5 and 15. Extended charging stations are sited at Bus 5, 15 and 24. Thereby, by applying the proposed approach to the newly planned network, battery exhaustion locations can be found in Fig. 8. It can be seen that with the newly built or extended charging stations, the total quantity of red points is remarkably reduced, indicating that fewer EVs have to face the battery exhaustion problem.

Fig. 8. Transformation simulation results

The reliability indicators of the planned network are presented in Table 3. Comparing with the results in Table 2, it can be concluded that **BTE** and ETE indicators are considerably decreased. In this case, under the two schemes of newly built or expanded charging stations, LOEE is reduced by 8.71% and 9.48%, respectively, ETE is reduced by 32.68% and 33.83% respectively. But at the same time CTE is slightly increased. This is because that the probability for EVs to find a reachable charging station is enhanced in the optimal planning network. In addition, according to the change of LOEE, the newly built or expanded charging stations have limited impact on the electricity network reliability.

Because the calculation of reliability program is very time-consuming, it is hoped that a correlation analysis model can be used to replace the reliability calculation in the planning process. Multiple regression method is used to construct the input variables of multiple regression with the location and capacity of each charging station, as well as the penetration level and SOC threshold of EV in the current network. The output variables are the reliability indicators of the coupled networks. Therefore, the reliability level of the networks and the current optimal planning scheme under a certain input condition can be predicted by correlation rules.

Table 4 Parameters of correlation analysis model

Parameters	Value
EV penetration	10%
SOC threshold for management strategy (δ_s)	60%
Location of expanded charging station	5, 15
Expansion investment	150

Table 4 shows the quantitative values of input variables under a certain practical condition. The investment cost constraints are taken as input samples to be entered into the trained reliability prediction correlation analysis model.

By substituting the data of input variables in Table 4 into the optimization algorithm, the reliability indicators of this case can be obtained.

Table 5 Assessment results of correlation analysis

Parameters	correlation analysis value	Reliability calculation value
LOEE (MWh/y)	1242.5	1212.4
CTE (h/y)	2.0523	2.0441
BTE (h/y)	0.3604	0.3502
ETE (h/y)	2.4127	2.3943
CSEE (MWh/y)	12586	12304
DSEE (MWh/y)	12835	12487
Calculation time(s)	2822	33582

With the application of the correlation analysis model, the optimal expansion scheme is derived as adding 7 charging piles at bus 5 and 18 charging piles at bus 15. The reliability indicators calculated by using the correlation analysis model is shown in Table 5. It indicates that the optimization results derived from the proposed correlation analysis method are similar to the results from the reliability assessment program with an error less than 5%. Therefore, the proposed method can appropriately assess the reliability of the coupled networks. At the same time, the average solving time is greatly reduced, which is less than 10% of the computational time of the reliability assessment program. This is because that the correlation analysis method avoids the iterative process of the optimization algorithm, and obtains the reliability prediction directly from the correlation rules. Thus, the proposed correlation analysis method could

significantly accelerate the speed of solving the optimal planning problem.

6. Conclusion

In order to solve the problem of charging stations planning with the access of large-scale EVs, a reliability-oriented multi-objective planning model for the coupled networks is proposed, subsequently, the correlation analysis is performed to ensure that the proposed model can be solved efficiently.

It turns out that the implementation of EV charging and discharging management strategy benefits the reliability of the electricity network, but goes against the transportation network. With the increase of SOC threshold δ_s , the transportation network reliability indicator ETE will decrease rapidly, while the electricity network reliability indicator LOEE will increase significantly.

With the increasing penetration of EVs, the proposed planning method may effectively solve the optimal planning scheme. Under the two schemes of newly built or expanded charging stations, LOEE is slightly reduced, and ETE can achieve significant reduction effect.

The proposed correlation analysis method could significantly accelerate the speed of solving the optimal planning problem, and reduces the average solving time for the optimization.

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8. References

- [1] Liu, C., Chau, K. T., Wu, D., et al.: 'Opportunities and challenges of vehicle-to-home, vehicle-to-vehicle, and vehicle-to-grid technologies', *Proceedings of the IEEE*, 2013, 101, (11), pp. 2409-2427.
- [2] Xiang, Y., Hu, S., Liu, Y., et al.: 'Electric vehicles in smart grid: a survey on charging load modelling', *IET Smart Grid*, 2019, 2, (1), pp. 25-33.
- [3] Mu, Y., Wu, J., Jenkins, N., et al.: 'A spatial-temporal model for grid impact analysis of plug-in electric vehicles', *Applied Energy*, 2014, 114, pp. 456-465.
- [4] Xiang, Y., Liu, J., Liu, Y.: 'Optimal active distribution system management considering aggregated plug-in electric vehicles', *Electric Power Systems Research*, 2016, 131, pp. 105-115.
- [5] Xiang, Y., Liu, J., Li, R., et al.: 'Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates', *Applied Energy*, 2016, 178, pp. 647-659.
- [6] Liu, Z., Wang, D., Jia, H., et al.: 'Aggregation and bidirectional charging power control of plug-in hybrid electric vehicles: Generation system adequacy analysis', *IEEE Transactions on Sustainable Energy*, 2014, 6, (2), pp. 325-335.
- [7] Haidar, A. M., Muttaqi, K. M.: 'Behavioral characterization of electric vehicle charging loads in a distribution power grid through modeling of battery chargers', *IEEE Transactions on Industry Applications*, 2015, 52, (1), pp. 483-492.
- [8] Liu, Y., Xiang, Y., Tan, Y., et al.: 'Optimal allocation model for EV charging stations coordinating investor and user benefits', *IEEE Access*, 2018, 6, pp. 36039-36049.
- [9] Xiang, Y., Liu, J., Li, F., et al.: 'Optimal active distribution network planning: a review', *Electric Power Components and Systems*, 2016, 44, (10), pp. 1075-1094.

- [10] Kavousi-Fard, A., Rostami, M. A., Niknam, T.: 'Reliability-oriented reconfiguration of vehicle-to-grid networks', *IEEE Transactions on Industrial Informatics*, 2015, 11, (3), pp. 682-691.
- [11] Quinn, C., Zimmerle, D., Bradley, T. H.: 'An evaluation of state-of-charge limitations and actuation signal energy content on plug-in hybrid electric vehicle, vehicle-to-grid reliability, and economics', *IEEE Transactions on Smart Grid*, 2012, 3, (1), pp. 483-491.
- [12] Farzin, H., Moeini-Aghaie, M., Fotuhi-Firuzabad, M.: 'Reliability studies of distribution systems integrated with electric vehicles under battery-exchange mode', *IEEE Transactions on Power Delivery*, 2015, 31, (6), pp. 2473-2482.
- [13] Xu, N. Z., Chung, C. Y.: 'Reliability evaluation of distribution systems including vehicle-to-home and vehicle-to-grid', *IEEE Transactions on Power Systems*, 2015, 31, (1), pp. 759-768.
- [14] Fotuhi-Firuzabad, M., Billinton, R.: 'Impact of load management on composite system reliability assessment short-term operating benefits', *IEEE Transactions on Power Systems*, 2000, 15, (2), pp. 858-864.
- [15] Yang, W., Xiang, Y., Liu, J., et al.: 'Agent-based modeling for scale evolution of plug-in electric vehicles and charging demand', *IEEE Transactions on Power Systems*, 2017, 33, (2), pp. 1915-1925.
- [16] SADEGHIAN, O., NAZARI-HERIS, M., ABAPOUR, M., et al.: 'Improving reliability of distribution networks using plug-in electric vehicles and demand response', *Journal of Modern Power Systems and Clean Energy*, 2019, pp. 1-11.
- [17] Ge, S., Feng, L., Liu, H.: 'The planning of electric vehicle charging station based on grid partition method', 2011 International Conference on Electrical and Control Engineering, IEEE, September 2011, pp. 2726-2730.
- [18] Zhang, Q., Zhu, Y., Wang, Z., et al.: 'Reliability assessment of distribution network and electric vehicle considering quasi-dynamic traffic flow and vehicle-to-grid', *IEEE Access*, 2019, 7, pp. 131201-131213.
- [19] Tang, S., Liu, J., Xiang, Y., et al.: 'Combined planning strategy for charging infrastructures and distribution network integrated with district information', IET International Conference on Intelligent and Connected Vehicles (ICV 2016), Chongqing, 2016, pp. 1-7.
- [20] Jiang, Z., Xiang, Y., Liu, J., et al.: 'Charging load modeling integrated with electric vehicle whole trajectory space and its impact on distribution network reliability', *Power System Technology*, 2019, 10, pp. 3789-3800.
- [21] Huang, Z., Fang, B., Deng, J.: 'Multi-objective optimization strategy for distribution network considering V2G enabled electric vehicles in building integrated energy system', *Protection and Control of Modern Power Systems*, 2020, 5, (1), pp. 48-55.
- [22] Liu, D., Zhong, Q., Wang, Y., et al.: 'Modeling and control of a V2G charging station based on synchronverter technology', *CSEE Journal of Power and Energy Systems*, 2018, 4, (3), pp. 326-338.
- [23] Hou, K., Xu, X., Jia, H., et al.: 'A reliability assessment approach for integrated transportation and electrical power systems incorporating electric vehicles', *IEEE Transactions on Smart Grid*, 2018, 9, (1), pp. 88-100.
- [24] da Silva, A. M. L., González-Fernández, R. A., Sales, W. S., et al.: 'Reliability assessment of time-dependent systems via quasi-sequential Monte Carlo simulation', 2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems, IEEE, June 2010, pp. 697-702.
- [25] Xiang, Y., Zhou, L., Su, Y., et al.: 'Coordinated DG-Tie planning in distribution networks based on temporal scenarios', *Energy*, 2018, 159, pp. 774-785.
- [26] Sun, M., Teng, F., Zhang, X., et al.: 'Data-driven representative day selection for investment decisions: A cost-oriented approach', *IEEE Transactions on Power Systems*, 2019, 34, (4), pp. 2925-2936.
- [27] Xiang, Y., Yang, W., Liu, J., et al.: 'Multi-objective distribution network expansion incorporating electric vehicle charging stations', *Energies*, 2016, 9, (11), pp. 909.
- [28] Subcommittee, P. M.: 'IEEE reliability test system', *IEEE Transactions on Power Apparatus and Systems*, 1979, PAS-98, (6), pp. 2047-2054.