Multi-Objective collaborative planning for distribution networks considering electric vehicle charging stations and distributed generation

Yunfei Zheng¹, ², Zixia Sang², Yingxiang Wang², Xiang Li¹, ³, Rian Wang¹, Shunfei Kong¹ and Zhijian Hu¹

¹ School of Electrical Engineering and Automation, Wuhan University, Wuhan, China
² Economic Research Institute, State Grid Hubei Electric Power Company Limited, Wuhan, China
³ E-mail: lixan12@163.com

Abstract. The large investment of electric vehicles and distributed generation has affected the stable operation of distribution network. At the same time, the construction of charging station of electric vehicles not only causes the burden of electric power network, but also the burden of transportation network. How to ensure the stability and economics of distribution network has become an urgent problem. Based on this background, this paper proposes a multi-objective collaborative planning method for distribution network, which considers the charging station of electric vehicle and the distributed generation. In order to find the optimal planning scheme, we use an improved NSGA-II algorithm. Finally, the simulation analysis of the case of IEEE 33-bus shows that the proposed planning method not only ensures the stability and economics of distribution network, but also fully saves the average waiting time of charging users of electric vehicles and improves the traffic satisfaction.

1. Introduction

With the development of smart grid, distributed generation (DG) and electric vehicle (EV) have attracted the attention of many countries because of their clean and environmentally friendly characteristics [1]. The low degree of automation and backward dispatching mode of traditional distribution network seriously restrict the development of DG and EV [2-4]. Therefore, it is of great significance to carry out integrated and coordinated planning of EV charging station, distribution network and distribution network structure.

The main problem of DG and EV access to power grid is that both of them have great uncertainties. So maintaining the dynamic balance of distribution network becomes the challenge of distribution network planning field [5]. Scholars at home and abroad have also done relevant research. Some scholars used two-step screening method considering geographical factors and service radius to determine the candidate site of charging station [6]. Based on the node charging requirements, some scholars gave the planning strategy of distributed charging piles and used a traffic distribution model to analyze the interception ability of fast charging stations [7]. In addition, some scholars used an electric renewable hybrid system, composed by photovoltaic and wind systems with a battery storage, to produce the electric energy for powering the heat pump, an EV charging station and building electric devices [8]. Recently, an in-depth analysis is developed regarding the energy reliability, economic rentability and emission abatement achievable by combining a PV-battery system with the
nocturnal EV charging in a residential user [9]. With the continuous maturity and popularization of EV technology, the distribution side directly becomes the boundary between the power system and the transportation system [10-12].

This paper establishes a mathematic model of EV transportation network based on the traffic network situation, and calculates the traffic economic benefit value and the charging equipment capacity of each station. The distribution network is coupled with the traffic network, and the uncertainties of the DG are considered to establish a multi-scenario DG and load model. In the plan, the distributed power supply and electric vehicle charging station location and capacity are comprehensively considered, with the goal of planning the lowest total cost and the optimal voltage quality of the network node. Through an improved NSGA-II algorithm, the Pareto solution set satisfying the constraints is obtained, and the optimal solution of the multi-objective function is obtained by the TOPSIS method. Finally, the model is verified by IEEE 33-node example.

2. Mathematical model of EV transportation network

The travel time and proportion of EV have obvious regularity. There are great differences in charging demand between different time and place. The location of charging station should take full account of the load growth, the convenience of charging users and traffic satisfaction. This paper calculates traffic flow based on gravity space interaction model and uses M/M/s queueing model to minimize average waiting time of charging users.

2.1. Economic benefit value of traffic flow

If EV is regarded as the charging demand flowing in the road, the charging station should be built in the traffic network to intercept the node location with more traffic flow, so that most charging users can charge nearby. In this paper, the gravity space interaction model is used to calculate the annual intercepted traffic flow of each node in the traffic network. The traffic flow of the shortest path \( k \) is related to the traffic flow and distance between nodes in time \( t \). If the shortest path \( k \) passes through the unit \( i \) and the unit \( j \) has a fast charging station, the unit \( i \) can intercept the traffic flow of path \( k \), as shown in Formula (1) and Formula (2).

\[
f_{k,t}^{load} = \frac{W_{O}W_{d}d_{k}}{s_{k}}s_{i}, k \in \Omega_{od}
\]

\[
f_{i,t}^{qc} = \sum_{k \in \Omega_{od}} f_{k,t}^{load} x_{k,t}^{qc}, i \in \Omega, t \in T
\]

Where \( \Omega_{od} \) is the set of the shortest path between any two nodes in the network. \( W_{O} \) and \( W_{d} \) are the weights of the starting point \( O \) and the ending point \( d \) of the path \( k \), respectively, to indicate the busyness of each traffic node; \( d_{k} \) is the standard value of the path \( k \) length; \( s_{k} \) and \( s_{i} \) are the travel ratios of the electric vehicle users during the time period \( t \) and the peak hours respectively; \( f_{k,t}^{load} \) is the traffic flow intercepted by the fast charging station at the unit \( i \) at the time \( t \); \( x_{k,t}^{qc} \) is the 0-1 variable indicating whether the path \( k \) passes the unit \( i \); \( x_{k,t}^{qc} \) is the 0-1 variable of the fast charge station at unit \( i \).

The more traffic flow intercepted by the fast charging station, the more charging users can get the charging service nearby. In addition, the busy node is often the node with large electric load. If the charging station is located in such kind of nodes will increase the burden of traffic and electricity. Therefore, this paper introduces the traffic flow discount coefficient so that the charging station avoids excessively falling on busy traffic sections, as shown in Formula (3).

\[
\omega_{k}^{load} = \frac{1}{d_{k}^{m}}
\]
Where $a$ is the busy discount of the traffic node; $m$ means that the shortest path $k$ contains $m$ busy paths, the busy path means that the first and last nodes of the path are the top $n$ nodes with the highest weight among all network nodes.

The economic benefit value of traffic flow $F_e$ is determined by the traffic flow and its economic benefit conversion coefficient and the discount factor, as shown in Formula (4)

$$F_{qe} = \omega_q \cdot 365 \cdot \sum_{i} \sum_{k \in \Omega} f_{k,i}^{|\text{load}} \cdot x_{k,i}^{|\text{load}} \cdot \alpha_{k,i}^{|\text{load}}$$

(4)

Where $x_{k,i}^{|\text{load}}$ is the 0-1 variable indicating whether the traffic on the path $k$ can be intercepted by the fast charging station; $\alpha_{k,i}^{|\text{load}}$ is the economic benefit conversion coefficient of the intercepted traffic flow.

2.2. Volume-setting method of fast charging station based on M/M/s queuing model

According to the queuing theory proposed by the British mathematician D. G. Kendall, the electric vehicle charging service queuing law is expressed by the M/M/s queuing model. The interval time between electric vehicles arriving at charging stations and charging service time satisfy Poisson distribution and negative exponential distribution [13], and each fast charging station will set different quantities of charging devices according to the busyness. The queue model type selection is shown in Figure 1.

![Figure 1. Queuing model selection process.](image_url)

The arrival rate of EV obeys Poisson distribution

Standard form

(Unlimited queueing of vehicles)

Charging service time obeys exponential distribution

Multi-stations queueing model

(M/M/s)

The arrival rate of the vehicles to be charged in the unit $i$ at the time $t$ and the peak traffic time, respectively. That is, the reciprocal of the average time interval of the electric vehicle user arriving at the charging station; $C_{qe}$ is the total frequency of the system's fast charging. $W$ is the average waiting time for receiving charging service during peak traffic hours, and $W_{ms}$ is the maximum allowable waiting time. $z_{e}^{|\text{load}}$ is the number of equipments at the fast charging station.
station at unit \(i\); \(p_{0i}\) is the average usage rate of the fast charging station at the peak traffic time of the unit \(i\); \(p_c\) is the probability that all the fast charging stations of the unit \(i\) are idle; \(\mu\) is the average service rate of a fast charge equipment, that is, the reciprocal of the average time for fast charge.

3. DG power output based on multi-scene technology

3.1. Time series model of DG

The power output of wind power and photovoltaic power generation is mainly determined by geographical location and climate. Its power scale has obvious time-varying characteristics, which is difficult to determine to a certain degree. It is generally assumed that the DG power output obeys a certain probability distribution model. We can represent its uncertainty by sampling method. However, this does not reflect the change in DG power output and power load with seasons and power supply periods. Therefore, this paper uses the timing characteristics of different seasons to describe the DG output and load power.

According to the meteorological data, the wind speed curve and the light intensity curved shape of different seasons are obtained, and the time series curved shape of wind power, photovoltaic power and load power are derived, as shown in Figure 2. Among them, the photovoltaic output curve in spring coincides with the output curve in autumn.

![Figure 2. (a)Wind power timing output model and (b)Photovoltaic power generation timing output model](image)

3.2. Multi-scene processing technology and Chance constrained planning

The basic principle of multi-scene technology is to identify and analyse uncertain factors, obtain their possible values, and then combine these possible values into multiple scenarios to simulate the impact of uncertain factors. The advantages of multi-scene technology: Using multiple deterministic combination scenarios to simulate the effects of uncertainties can reduce the complexity of mathematical models. It reduces the difficulty of modelling and solving problems with uncertainties. The difficulty of multi-scene technology lies in the analysis of uncertain factors and the division of scenes. Commonly used multi-scene technologies include multi-scene preference techniques and multi-scene probability methods.

Simulation of 96 distribution network operation scenarios according to DG timing characteristics (e.g. 4 seasons, 24 power supply periods per season) is carried out. Because the raw data used for planning is not inherently accurate, it is not very practical that all the scenarios are required to strictly
meet the constraints. In order to reduce the impact of extreme scenes, this paper introduces the chance-constraint programming method. It is mainly for random variables in constraints. Decisions must be made before the implementation of random variables is observed. The decision is allowed to satisfy the constraint to a certain extent, but the probability that the constraint is established under the decision is not less than a certain confidence level (e.g. 90%). Traditional static security constraints (node voltage, branch power, and barred power constraints) are treated as probabilistic constraints in this paper.

4. Collaborative programming model and Model solution

4.1. Collaborative planning for distribution networks and traffic network

The key to the collaborative planning of the transportation network and the power grid is that transforming single power grid into a system in which electricity and transportation are interconnected. We need to take into account the interests of both parties and achieve a win-win result.

In this paper, the traffic network and the power network are simply coupled, and the fast charging station is regarded as the power load. According to the charging requirements of different stations, the charging power of the fast charging station in each period is determined by its proportion of charging time, as shown in Formula (10).

\[ P_{i,t}^{\text{fc}} = \lambda_i \cdot \mu \cdot p_{q,e}, i \in \Omega, t \in T \]  \hspace{1cm} (10)

Where \( P_{i,t}^{\text{fc}} \) is the charging power of the fast charging station at unit \( i \) at time \( t \); \( p_{q,e} \) is the charging power of a single fast charging device; \( \mu \) is the average service rate of a single fast charge device, it is the reciprocal of the average time for fast charging.

The equivalent load of node \( i \) at time \( t \) is \( P_{\text{eq}}(t) \), as shown in Equation (11).

\[ P_{\text{eq}}(t) = P_{i,t}(t) + P_{i,t}^{\text{w}} - P_{\text{DG}}(t) \]  \hspace{1cm} (11)

Where \( P_{i,t}(t) \) and \( P_{\text{eq}}(t) \) represent the load value of node \( i \) at time \( t \) and the DG power output value, respectively.

4.2. Objective function

In this paper, after converting traffic flow into economic benefit value and coupling power of fast charging station into grid load, the objective function is to minimize the total cost of the system and to optimize the quality of node voltage, as shown in Formula (12).

\[
\begin{align*}
\text{min} & \quad \{ f_1 = \alpha C_{\text{inv}} + C_{\text{ope}} - F_{q,e} \\
& \quad \text{subject to} \quad f_2 = U_{\text{level}} \}
\end{align*}
\]  \hspace{1cm} (12)

Where \( C_{\text{inv}}, C_{\text{ope}}, \) and \( C_{q,e} \) are investment cost, operation and maintenance cost, and electricity purchase cost respectively; \( \alpha \) is the equal annual value coefficient; \( U_{\text{level}} \) is the node voltage quality evaluation function value.

Investment costs include line investment costs, DG investment costs, and charging station investment costs.

The smaller the \( U_{\text{level}} \), the better the voltage quality of the distribution network node. Its calculation formula is as shown in Equations (13)-(14).
Where $U_{level,i}$ is the voltage quality evaluation value of the $i$ node; $V_i$ is the voltage amplitude of node $i$; $V_{min}$ and $V_{max}$ are the allowable upper and lower limit values of the node voltage, respectively.

4.3. Constraints

(1)Flow constraints

$$
\begin{align*}
& P_{eqi} = U_i \sum_{j=1}^{n} U_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\
& Q_{eqi} = U_i \sum_{j=1}^{n} U_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij})
\end{align*}
$$

(15)

(2)Chance constraints

$$
P_t \left( V_{min} \leq V_i \leq V_{max}, P_i \leq P_{ij\max}, P_{DG} \leq P_{ij\max} \right) = \frac{K}{96} \geq \gamma
$$

(16)

(3)DG installation capacity constraint

$$
\begin{align*}
& 0 \leq P_{DG,i} \leq P_{DG\max} \\
& \sum_{i=1}^{n} P_{DG,i} \leq \eta \sum_{i=1}^{n} P_{DG,i}
\end{align*}
$$

(17)

Where $P_{eq}$ and $Q_{eq}$ are the injected active and reactive power of node $i$ respectively; $U_i$ and $U_j$ are the voltage amplitudes of nodes $i$ and $j$ respectively; $G_{ij}$ and $B_{ij}$ are network admittances respectively; $\theta_{ij}$ is the voltage phase angle difference of nodes $i$ and $j$; $P_i$ and $P_{max}$ are the power and power limits through which line $ij$ flows, respectively; $P_{DG}$ and $P_{DG\max}$ are the total DG power output and power load under the scene $s$; $K$ is the number of scenes that satisfy the opportunity constraint; $\gamma$ is a confidence level and its value is 0.9; $W_a$ is the maximum demand for EV daily charging; $\eta$ is the maximum penetration rate of DG access.

4.4. Model solution

This paper uses an improved NSGA-II algorithm to solve the problem [14]. Using elite strategy to select population and introducing the idea of crowding degree can effectively prevent the loss of the optimal solution obtained. On the basis of the original algorithm, this paper introduces the idea of normal distribution to carry out crossover calculation, and establishes NDX crossover operator to avoid local optimum, which greatly speeds up population evolution.

Firstly, we input the planning data to generate the initial population, and use the minimum spanning tree method based on Kruskal to obtain the grid structure and then calculate the power flow. For the population satisfying the chance constraints, we calculate its objective function and sort the
population by fast non-dominated sorting. Then, we select the parent according to the degree of congestion and perform genetic operation, and start iterating until convergence. Finally, the best compromise scheme is determined by TOPSIS method.

5. Case analysis
The simulation system adopts an IEEE 33-node system. The topology diagram of the power system and the topology map of the traffic network, as shown in Figure 3.

![Figure 3. Power and transportation network topology.](image)

In this case, the single charge per electric vehicle is 30 kWh. The charging power of a single charging device is 60 kW. The number of locations for charging stations is limited to 8. The improved NSGA-II algorithm has a maximum iteration number of 40, a population size of 50, a crossover rate of 0.9, a mutation rate of 0.1, and a polynomial variation index of 20. The traffic weights of the traffic nodes and the travel ratios of the EVs are given by the traffic department.

The Pareto solution set is obtained through simulation. Take out all the scenarios and their optimization results for a list. The Pareto solution set is processed by the TOPSIS method as shown in Figure 4. If we assume that the weight values of the indicators are equal, the multi-objective collaborative planning results are shown in Table 1, and the optimal compromise solution is the solution 10.

| Scheme number | Economic cost/10^4RMB | Voltage quality/pu | Scheme number | Economic cost/10^4RMB | Voltage quality/pu |
|---------------|-----------------------|--------------------|---------------|-----------------------|--------------------|
| 1             | 6340.34               | 0.1364             | 7             | 6577.75               | 0.1310             |
| 2             | 6845.92               | 0.1272             | 8             | 6586.04               | 0.1313             |
| 3             | 6008.93               | 0.2251             | 9             | 6339.00               | 0.1393             |
| 4             | 6549.30               | 0.1363             | 10            | 6064.42               | 0.1906             |
| 5             | 6813.85               | 0.1283             | 11            | 6186.84               | 0.1561             |
| 6             | 5967.44               | 0.5663             | 12            | 6242.18               | 0.1456             |

Table 1. Multi-objective collaborative planning results.

Taking the original average load of each node in 96 scenarios to compare with the electric load where the EV charging stations are built, we can find that the construction of the electric vehicle charging station make the original power load increase obviously, as shown in Figure 5.

After comparing the original load curve with the curve of load and photovoltaic power superimposed curve, it can be seen that the distributed power source can play the role of peak clipping and valley filling, as shown in Figure 6.
Figure 4. Pareto solution set in two-dimensional plane.

Figure 5. Comparison chart of primary average load and power load after considering EV charging station.

Figure 6. Comparison chart of the original load curve with the curve of load and photovoltaic power superimposed curve.

This example uses the gravity space interaction model to calculate traffic flow. The traffic flow has obvious time variation characteristics. After calculating, the traffic flow values at various times of the 24-hour of path 1-2 is extracted, as shown in Table 2.
Table 2. Corresponding traffic flow at different times.

| Time | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Flow | 0.078 | 0.037 | 0.019 | 0.012 | 0.033 | 0.142 | 0.445 | 1.075 | 1.348 | 0.983 | 1.131 | 1.152 |

The traffic flow has increased significantly after considering the traffic flow discount coefficient and the traffic flow discount coefficient, which results in a change in the node selection of the fast charging station. The specific location results are shown in Table 3. The location maps before and after optimization are shown in Figure 7.

Table 3. Fast charging station location before and after optimization.

|                   | Before |       |       |       |       |       |       |       |       |       |       |       |
|-------------------|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|                   | 3      | 5     | 6     | 7     | 9     | 24    | 26    | 29    |       |       |       |       |
| After             | 1      | 4     | 17    | 19    | 26    | 27    | 28    | 31    |       |       |       |       |

![Location maps before and after optimization](image)

Figure 7. (a) Pre-optimization and (b) Post-optimization.

After comparing the final site selection of pre-optimization and post-optimization, it can be seen that the node selection is mostly close to the busy node before the optimization. There is a greater probability that a node with a larger traffic weight or more connected traffic lines will be selected. After optimizing, the location of the fast charging station basically does not select the busy node, and...
it is still close to the busy node. It can not only achieve the initial purpose of intercepting more traffic flow, but also avoid traffic jams. The overall effect is achieved.

6. Conclusions
This paper combines traffic flow model and distributed power timing model to provide a reliable data basis for final decision making. Based on economic indicators and voltage quality indicators, an optimal planning program is finally decided. At the same time, the improved IEEE 33-node example is used to simulate the validity of the theory. The main conclusions are as follows:

1) When determining the location of charging station for EV, the traffic flow mathematical model is taken into account. The satisfaction degree of the whole EV users is measured by judging the intercepted traffic flow, so that the traffic flow prediction is more practical.

2) We have increased the judgment of road congestion, avoided increasing the burden of traffic network and power network at the same time by discounting traffic flow, and reduced the average waiting time of charging users of electric vehicles, which is more in line with users' wishes.

3) Considering the coupling of traffic network and distribution network can provide ideas for power system planning, and has more practical research value.

4) This paper provides a new idea for the planning of DG and EV charging stations, which can effectively improve the comprehensive benefits of the planning scheme. It reasonably evaluates the impact of DG and EV charging station access on power grid, provides effective measures to improve the economy, reliability and power quality of power grid operation.

Acknowledgment
This work was supported by State Grid Hubei Electric Power Company’s Limited (SGHBJY00PSJS1800033).

References
[1] Zhang Shenxi, Cheng Haozhong, Xing Haijun,Yao Liangzhong and Zhang Yi 2016 Electric Power Automation Equipment 36(08) 1-9
[2] Cai Jiaming, Lin Qiyou and Liu Yong 2018 Electrical Measurement & Instrumentation 55(07) 53-61
[3] Shen Xinwei, Zhu Shouzhen, Zheng Jinghong, Han Yingduo, Li Qingsheng and Nong Jing 2015 Power System Technology 39(07) 1913-1920
[4] Liu Bo, He Min and Tan Dan 2018 Electrical Measurement & Instrumentation 55(06) 47-51
[5] Liu Xueping, Liu Tianqi and Wang Jian 2010 Power System Technology 34(10) 126-130
[6] Liu Zhipeng, Wen Fushuan, Xue Yusheng and Xin Jianbo 2012 Automation of Electric Power Systems 36(3) 54-59
[7] Yao Weifeng 2014 Zhejiang University
[8] Domenico Mazzeo 2018 Energy 168 (2019) 310-331
[9] Domenico Mazzeo 2018 Journal of Cleaner Production 213 (2019) 1228e1250
[10] Tian Yuanyuan, Liao Qingfen, Liu Dichen, Zhi Zhenshan, Peng Sicheng and Xu Yutian 2016 Power Grid Technology 40(10) 2924-2934
[11] Liu Dichen, Peng Sicheng, Liao Qingfen Tang Fei,Chen Wei and Chen Yi 2015 Power System Technology 39(11) 3023-3034
[12] Liu Bailiang, Huang Xueliang, Li Jun, Qian Xin and Cheng Jun 2015 Power Grid Technology 39(02) 450-456
[13] Bae S and Kwasinski A 2012 IEEE Transactions on Smart Grid 3(1) 394-403
[14] JIANG Huilan, AN Xing, WANG Yawei, Qing Jingzhong and Qian Guangchao 2015 Proceedings of the CSEE 35(21) 5405-5411