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Considering The User Satisfaction of Electric Vehicles Double - layer Multi-objective Optimization Scheduling

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Abstract: In order to solve the problem of load peak increase caused by disorderly charging of large-scale electric vehicles (EV) connected to micro-grid, a double-layer multi-objective optimal scheduling scheme considering user satisfaction is proposed. The day ahead optimal scheduling process of micro-grid is divided into distribution system layer and load layer. The distribution system layer formulates the electric vehicle aggregator (EVA) scheduling strategy with the goal of minimizing the daily load variance and the lowest system operation and maintenance cost. The load layer formulates the charging strategy of each electric vehicle, and maximizes the comprehensive satisfaction of users under the dispatching plan of EVA following the distribution system layer. NSGA-II algorithm is used to calculate the multi-objective model of distribution system layer, and Yalmip is used to call CPLEX to solve the integer programming problem of load layer. Through the comparative analysis of multiple scenarios of the improved IEEE33 node example, the results show that the proposed optimization model can not only ensure the safe operation of the distribution system, but also reduce the daily load variance and improve the system economy.

Keywords: Electric vehicle, Charging scheduling, Two-layer optimization, Comprehensive customer satisfaction, The NSGA - II algorithm.

1. Introduction

With the increasing shortage of Energy and the widespread application of electric vehicles in our daily life, the large-scale Distributed Energy Storage (DES) of electric vehicles has become a key research object in the optimization scheduling of power system[1][2]. However, when EV is connected to micro-grid with high permeability, disordered charging and discharging behavior will bring great threat to micro-grid[3], and adopting efficient control strategy is the key to solve the problem [4].

At present, domestic and foreign studies on the optimal scheduling of micro-grid including electric vehicles mainly focus on reducing the operating cost of micro-grid, increasing the absorption rate of renewable energy, and reducing the peak-valley gap. Literature [5] proposed a multi-objective optimization charging strategy for electric vehicles based on TOU electricity price to solve the new peak problem caused by disordered electric vehicle loads. Literature [6] puts forward a two-layer scheduling strategy, which further improves the ability of regulating load peak-valley difference. Literature[7] established a multi-objective real-time charging and discharging scheduling system coordinated by power grid and electrical changing station. Literature[8] points out that user satisfaction has a certain impact on optimal scheduling. When user satisfaction is lower than the threshold value, the actual load curve will be offset.

Research on user satisfaction has now yielded some results. Literature[9] proposed a group scheduling strategy for ELECTRIC vehicles considering user satisfaction, and user satisfaction was taken into account when optimizing scheduling. Literature[10] established a user satisfaction model and quantitatively calculated comprehensive user satisfaction. Literature[11] considers the charging and discharging strategy of electric vehicle smart grid with wind power and satisfaction. However, the above literature only refers to the overall user satisfaction and does not consider the satisfaction of individual EV users.

Because there are many factors affecting user satisfaction, directly considering the influence of user satisfaction in the process of optimal scheduling will make the model extremely complicated and difficult to solve. Therefore, based on the model framework of "distribution grid-EV Aggregator (EVA) -EV user", this paper proposes a two-layer multi-objective optimal scheduling scheme considering user satisfaction. The upper layer formulates EVA charging plans through the dispatching center to reduce load fluctuation and system operation and maintenance costs. At the lower level, the user's personalized needs are considered, and the charging strategy of users is determined with the highest comprehensive satisfaction of users as the goal. At the same time, the upper and lower scheduling deviation is considered to achieve the overall optimal strategy.

2. Modeling of Ev Charging and User Evaluation

2.1 Optimization Model Architecture

As the intermediary between distribution network and EV user, EV aggregator is responsible for the distributed control of EV Cluster (EVC)[12]. The system contains wind power, photovoltaic, EVC and micro-combustion units. By coordinating the comprehensive satisfaction of users, EVA can charge EVC under the common guidance of the dispatching plan of the distribution network dispatching center. Each EVA performs independent optimization scheduling for the EVC under its jurisdiction. The simplified structure of the optimization scheduling model is shown in Fig. 1

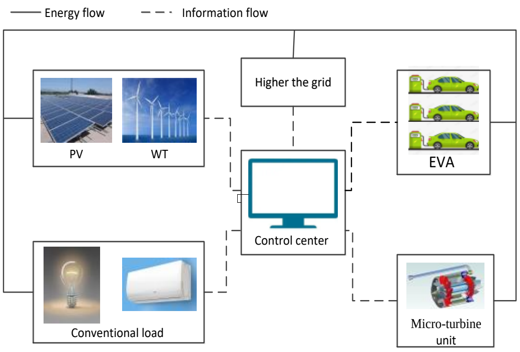

Fig.1 Structure diagram of two-layer optimal scheduling model

2.2 Related Models Of EV

(1)EV Travel Regularity Model

The study of EVs' departure rules is the basis of their participation in optimal scheduling. According to the National Household Travel Survey (NHTS), 14 per cent of vehicles are idle in a given day, 43.5 per cent drive less than 32km and 83.7 per cent drive less than 97km[13]. Based on the maximum likelihood estimation method, the corresponding probability density function is approximately lognormal distribution[14]. Its probability density function is:

$$f_D(x) = \frac{1}{x\sigma_D\sqrt{2\pi}} \exp[-\frac{(\ln x - \mu_D)^2}{2\sigma_D{}^2}] \tag{1}$$

$$\mu_D = 3.2, \quad \sigma_D = 0.88$$

Under normal circumstances, the owner will charge EV conventionally after the last return trip, and the last return trip time t_{in} obeys normal distribution. The probability density function is:

$$\begin{cases} \frac{1}{\sigma_{in}\sqrt{2\pi}} \exp(-\frac{(t_{in} - (\mu_{in} - 24))^2}{2\sigma_{in}^2}), & 0 < t_{in} < \mu_{in} - 12 \\ \frac{1}{\sigma_{in}\sqrt{2\pi}} \exp(-\frac{(t_{in} - \mu_{in})^2}{2\sigma_{in}^2}), & \mu_{in} - 12 < t_{in} \le 24 \end{cases} \tag{2}$$

$\mu_{in} = 18.47$， $\sigma_{in} = 3.41$。

The start time of travel t_{out} also approximately obeys normal distribution, and the probability density function is:

$$\begin{cases} \frac{1}{\sigma_{out}\sqrt{2\pi}} \exp(-\frac{(t_{out} - \mu_{out})^2}{2\sigma_{out}^2}), & 0 < t_{out} \le \mu_{out} + 12 \\ \frac{1}{\sigma_{out}\sqrt{2\pi}} \exp(-\frac{(t_{out} - (24 + \mu_{out}))^2}{2\sigma_{out}^2}), & \mu_{out} + 12 < t_{out} \le 24 \end{cases} \tag{3}$$

$\mu_{out} = 7.54$， $\sigma_{out} = 2.63$。

(2)Modeling Of EV Storage Capacity

The state of charging (SOC)[15]:

$$S_i(t) = S_{0,i} + \frac{P_i(t) \cdot \eta_i \cdot \Delta t}{E_{s,i}}, \ S_{dthr,i} \le S_i(t) \le S_{ex,i} \quad (4)$$

Where, $S_i(t)$ and $S_{0,i}$ is the charged state of the vehicle i at the t time period and the initial moment; $P_i(t)$ is the charging power of the vehicle i during the period t; η_i is conversion efficiency; $E_{s,i}$ is energy storage battery capacity; Δt is charging time; $S_{dthr,i}$ is the threshold value of SOC when discharging, $S_{dthr,i} = E_{dthr,i} / E_{s,i}$,which ensures that the energy storage battery can not be lower than $E_{dthr,i}$ in the use of EV; $S_{ex,i}$ is off-grid expected SOC.

(3)Off-Grid Expected SOC Constraints:

$$S_{ex,i} \le S_{de,i} \le 1 \quad (5)$$

Where, $S_{de,i}$ is the off-grid SOC of the vehicle i .

(4)EV Charging Power Constraints:

$$P_i(t) \le \frac{P_{c,N}}{\eta_i} \quad (6)$$

Where, $P_{c,N}$ is the rated charging power.

2.3 Constraints on Micro-grid System

(1)Constraints On Power Balance Of Micro-grid System：

$$P_{RES}(t) + P_{pc}(t) + \sum_{l}^{L} P_{MT,l}(t) = P_{LB}(t) + P_{loss}(t) + P_{sub}(t) + \sum_{j=1}^{K} P_{c,j}(t) \quad (7)$$

Where $P_{RES}(t) = P_{PV}(t) + P_{WT}(t)$ is the sum of photovoltaic output and fan output during the period of t time; $P_{pc}(t)$, $P_{sub}(t)$ is the purchasing power and selling power to the higher level for the micro-grid; $P_{c,j}(t)$ is the charging power in period t of EVA j ; K is the number of EVA; $P_{MT,l}(t)$ is the output in period t of the l micro-turbine unit; L is the number of micro-turbine units; $P_{LB}(t)$ is conventional load; $P_{loss}(t)$ is network loss.

(2)Climbing Constraints Of Micro-turbine Units

$$-r_{MT,l}\Delta t \le P_{MT,l}(t) - P_{MT,l}(t-1) \le r_{MT,l}\Delta t \quad (8)$$

Where, $r_{MT,l}$ is the climbing rate of the micro-turbine unit.

(3)Constraints On System Reserve Capacity:

$$P_{RES}(t) + \sum_{l}^{L} P_{MT,l}^{\max}(t) \ge P_{LB}(t)(1+\varphi_t) \quad (9)$$

Where, φ_t is the reserve rate.

(4)Network Node Voltage Constraint[16]:

$$U_m^{\min} \le U_m(t) \le U_m^{\max} \tag{10}$$

Where, $U_m^{\min}$, $U_m^{\max}$ are the lower limit and upper limit of the allowable operating voltage amplitude of node m respectively.

(5)Constraints on branch transmission power:

$$S_{mn}^{\min} \le S_{mn} \le S_{mn}^{\max} \tag{11}$$

Where, $S_{mn}^{\min}$ and $S_{mn}^{\max}$ are the lower limit and upper limit of the allowed transmission power between node m and node n respectively.

2.4 EV User Comprehensive Satisfaction Model

(1)Travel Satisfaction:

$$\vartheta_{tr,i}^{j} = \begin{cases} 0,\ 0 \le S_{de,i}^{j} < S_{dthr,i}^{j} \\ \delta_i^j,\ S_{dthr,i}^{j} \le S_{de,i}^{j} < S_{ex,i}^{j} \\ 1,\ S_{de,i}^{j} \ge S_{ex,i}^{j} \end{cases} \tag{12}$$

Where, $\vartheta_{tr,i}^{j}$ is the travel satisfaction of EV user i in the j EVA, $\delta_i^j = \dfrac{S_{de,i}^{j}}{S_{ex,i}^{j}}$.

(2)Cost Satisfaction

$$\vartheta_{co,i}^{j} = 1 - \frac{\left(\sum_{t=1}^{T} c(t) \cdot P_{c,i}^{j}(t)\right) - C_{i,\min}^{j}}{C_{i,\max}^{j} - C_{i,\min}^{j}} \tag{13}$$

Where, $\vartheta_{co,i}^{j}$ is the cost satisfaction of EV user i in the j EVA; $c(t)$ is the charging price of vehicle i in period t; $C_{i,\max}^{j}$ and $C_{i,\min}^{j}$ are the highest and lowest charging costs of vehicle i respectively. T is the total time 24 hours.

(3)Overall Satisfaction

$$\vartheta_j = \frac{\sum_{i=1}^{N(t)} (\vartheta_{tr,i}^{j} + \vartheta_{co,i}^{j})}{2} \tag{14}$$

Where, ϑ_j is the comprehensive satisfaction of the j EVA; $N(t)$ is the number of schedulable EVs of the j EVA.

3. Optimal Scheduling Scheme

3.1 Upper Level Scheduling Scheme

The upper layer of the optimization model in this paper is to optimize EVA scheduling by scheduling center, and the corresponding scheduling strategy is given. The objective function is to minimize the load variance and the total operating cost of the micro-grid system. The multi-objective optimization model is constructed, and the expression is as follows:

$$F = \min[F_1, F_2] \tag{15}$$

The first objective function is to minimize the variance of net load of micro-grid. The objective function is as follows:

$$\min F_1 = \frac{1}{T}\sum_{t=1}^{T}\left(P_{LB}(t) - \sum_{l=1}^{L}P_{MT,l}(t) + \sum_{j=1}^{K}P_{c,j}(t) - P_{avg}\right)^2 \tag{16}$$

Where, P_{avg} is the average load, and the distributed power mainly comes from the centralized discharge power of micro-gas turbine and EVA.

The second objective is to minimize the total operation and maintenance cost of micro-grid system as the objective function[17]. The objective function is as follows[18]:

$$F_2 = \min\left\{\sum_{t=1}^{T}\left[C_{op}(t) + C_{MT}(t) + C_{pc}(t) + C_{loss}(t) - C_{sub}(t) + \sum_{j=1}^{K}C_{c,j}(t)\right]\right\} \tag{17}$$

$$C_{op}(t) = P_W(t)\cdot c_w(t) + P_{PV}(t)\cdot c_{PV}(t) \tag{18}$$

$$C_{MT}(t) = \sum_{l=1}^{L}P_{MT,l}(t)\cdot c_{MT}(t) \tag{19}$$

$$C_{Loss}(t) = P_{loss}(t)\cdot c(t) \tag{20}$$

$$C_{sub}(t) = P_{sub}(t)\cdot R_{sub}(t) \tag{21}$$

$$C_{c,i}(t) = P_{c,i}(t)\cdot c(t) \tag{22}$$

Where: $C_{op}(t)$ is the operation and maintenance cost of wind power generation in the system; $C_{pc}(t)$ and $C_{sub}(t)$ are the cost of purchasing and selling electricity; $C_{MT}(t)$ is the operation and maintenance cost of micro-turbine unit; $c_W(t)$, $c_{PV}(t)$ and $c_{MT}(t)$ are the operation and maintenance cost standards of wind power, photovoltaic power generation and micro-turbine units respectively. $C_{Loss}(t)$ is system network loss cost; R_{sub} is the price of electricity sold by the system to the superior; $C_{c,i}(t)$ is the charging cost of EVA to the first EV user.

3.2 Lower Level Scheduling Scheme

The lower layer formulates the charging strategy for each EVA to its schedulable EVs. A two-stage optimization scheme is adopted in this layer. Firstly, according to the charging plan given by the upper dispatching center for each EVA, EV charging demand constraints are considered, and the charging plan of each EV is formulated with the goal of minimizing the scheduling deviation of the two layers. In the second stage, aiming at the highest comprehensive satisfaction of users, the scheduling deviation between the two layers is equal to the minimum scheduling deviation of the first stage as the constraint condition, and the charging plan of users is determined again.

(1)Stage 1 Optimization:

Taking the j charging station as an example, the optimization objective function is as follows:

$$\min\ f_j^1 = \sum_{t=1}^{T}\left|P_{c,j}(t) - \sum_{i=1}^{N(t)} P_i(t)\right| \tag{23}$$

(2)Stage 2 optimization:

According to Equation (12)-(14), it can be obtained:

$$\max\ f^2 = \sum_{j}^{K}\sum_{i=1}^{N(t)}(\vartheta_{tr,i}^{j} + \vartheta_{co,i}^{j})/2 \tag{24}$$

The lower layer receives charging plan feedback to the scheduling center through second-stage optimization calculation, and performs secondary optimization on the scheduling plan to realize information interaction between the upper and lower layers.

4. Optimization Model Solution Method

Since it is difficult to determine the appropriate weight between the upper objective functions to transform the multi-objective problem into a single objective problem, this paper uses the multi-objective algorithm to solve the objective function. For multi-objective function solving problem, the uniquely determined optimal solution can not be found, only a set composed of non-dominant solutions can be solved, which is called Pareto optimal set.

In this paper, an improved non-inferior sorting multi-objective genetic algorithm (NSGA-II) with elite reservation strategy is adopted to solve the model[19]. In this algorithm, non-dominated sorting is adopted as the main mechanism and the crowding degree is considered to ensure that the non-dominated solutions are distributed more evenly in the target space and improve the diversity of the population. Meanwhile, the elite retention strategy avoids the loss of excellent individuals and speeds up the execution speed of the genetic algorithm.

After Pareto solution set is obtained, fuzzy theory is used to obtain the optimal compromise solution[20].The single objective function value of each individual is fuzzified as follows:

$$\varepsilon_{\omega} = \begin{cases} 1, & F_{\omega}^{w} \le F_{\omega}^{\min} \\ \dfrac{F_{\omega}^{\max} - F_{\omega}^{w}}{F_{\omega}^{\max} - F_{\omega}^{\min}}, & F_{\omega}^{\min} \le F_{\omega}^{w} \le F_{\omega}^{\max} \\ 0, & F_{\omega}^{w} \ge F_{\omega}^{\max} \end{cases} \tag{25}$$

Where, F_{ω}^{w} is the wth frontier solution of the objective function ω, $F_{\omega}^{\max}$ and $F_{\omega}^{\min}$ are the maximum and minimum values of the frontier solution set of the objective function ω respectively.

The weighted average of the fuzzy objective function solutions is carried out, and the solutions are sorted to obtain the optimal compromise solution of multi-objective function.

$$\varepsilon^w = \frac{\sum_{\omega=1}^{m} \beta_\omega \varepsilon_\omega^w}{\sum_{w=1}^{W} \sum_{\omega=1}^{m} \beta_\omega \varepsilon_\omega^w} \tag{26}$$

Where, β_ω is the weight coefficient of objective function ω; m is the number of optimization targets; W is the number of leading edge solutions corresponding to each target.

At the lower level, the scheduling plan for EV in EVA is formulated according to the scheduling plan of the upper dispatching center. This problem is a large - scale optimization problem with constraints. This paper uses YALMIP to call commercial optimization software CPLEX to solve the model[21]. See Fig. 3 for the layered multi-objective solution process.

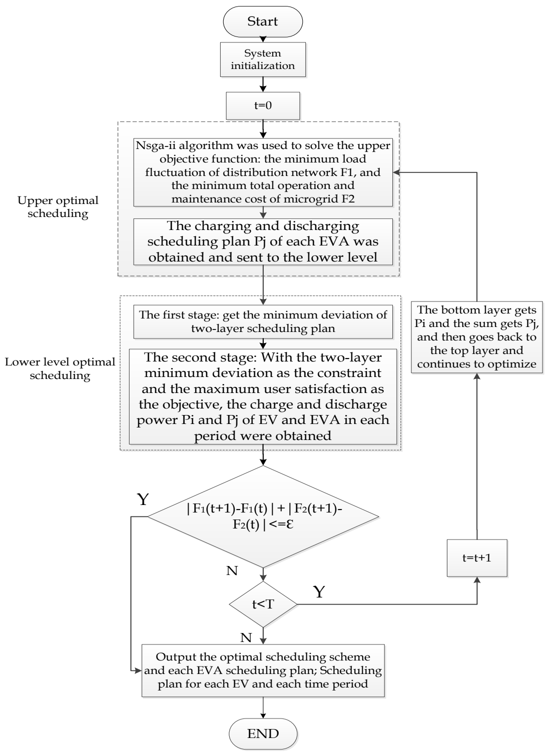

Fig. 2 Solving process of hierarchical multi-objective optimization

5. The Example Analysis

5.1 Example System Description

In this paper, the improved IEEE33 node system is selected as a test example. The installed capacity of fan (WT) is 1500kW and photovoltaic (PV) is 2000kW, which are respectively connected to node 16 and 23. Four EVAs are arranged in node 16, 20, 23 and 31, and two MT are arranged in node 9 and 20, as shown in Fig. 3

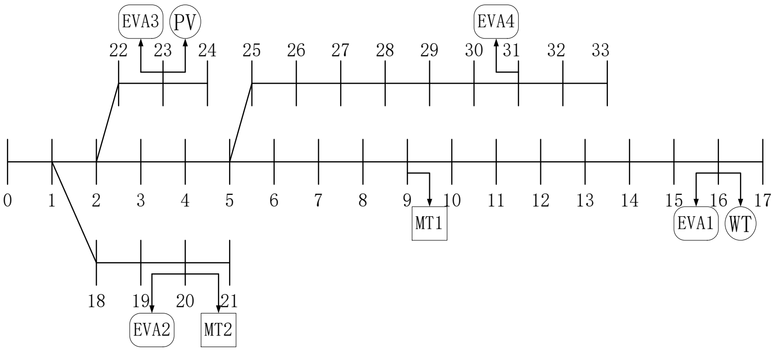

Fig. 3 Modified IEEE 33-bus system

5.2 System Parameter Setting

Combined with relevant content in I.B.1, it can be seen that the characteristics of large-scale EV charging can be approximated to a specific probability model. Therefore, Monte Carlo random sampling method is adopted in this paper to simulate the total charging demand of large-scale EV connected to micro-grid[22].

It is assumed that all EVs in the system are of the same type, the power consumption is 15$kW\cdot h$ per 100kmdriving, and the charge-discharge power is 5kW. Combined with the probability density function of travel start time, return time and daily mileage, Monte Carlo was used for sampling analysis to obtain the total charging demand of EV connected to micro-grid. The EV scale is assumed to be 600 units.

Other parameter Settings: $S_{ex,i}$ =0.85; $S_{dthr,i}$ =0.15; η_i =0.9; φ_t =0.4; $c_W(t)=c_{PV}(t)=0.03¥/(\mathrm{kW\cdot h})$; $c_{MT}(t)=0.085¥/(\mathrm{kW\cdot h})$; $R_{sub}=0.5¥/(\mathrm{kW\cdot h})$;Crossover probability and mutation probability were 0.9 and 0.1, respectively. Population size was set to 100; The maximum iteration number is 150. The market TOU price is shown in Table 1，Parameters of micro-turbine unit are shown in Table 2.

Table 1 Time-of-use electricity price of power distribution online shopping

Period of time	Time-sharing electricity/(¥·$(kW\cdot h)^{-1}$)
00：00-05：00，21：00-24：00	0.200
05：00-07：00，09：00-11:00 14：00-21：00	0.500
07：00-09：00，11：00-14：00	0.800

Table 2 Operation and maintenance parameters of micro-turbine unit

The unit	$c^1_{MT,l}$(¥/MW^2)	$c^2_{MT,l}$(¥/MW)	$c^3_{MT,l}$(¥)	upper limit(kW)	lower limit(kW)
1	0.0145	150	55	500	50
2	0.007	175	50	600	100

5.3 Analysis of Simulation Results

To illustrate the effectiveness of the proposed scheme, the following three scenarios are selected for testing and comparison:

Case 1:600 electric vehicles are evenly distributed to four EVA nodes in the system, and the charging and discharging process is not controlled.

Case 2:600 electric vehicles are evenly distributed among the 4 EVA nodes in the system, with no consideration of the optimal scheduling scheme of user satisfaction.

Case 3:600 electric vehicles are evenly distributed to 4 EVA nodes in the system, and the two-layer multi-objective optimal scheduling system described in this paper is adopted to optimize the scheduling.

Linear algorithm, single NSGA-II algorithm and double-layer optimization algorithm in this paper are respectively used to solve the three scenarios. Pareto front of case 3 is processed with fuzzy processing to obtain the optimal compromise solution, as shown in Fig. 4

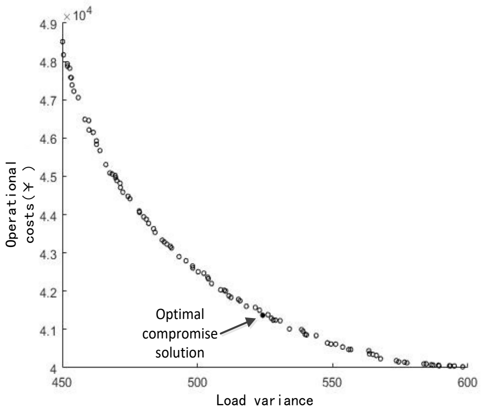

Fig. 4 Pareto frontier of two-layer multi-objective optimal scheduling

The generation plan of each unit in case 3 is shown in Figure 5. During the load trough periods of 1:00-5:00 and 21:00-24:00, the cost of purchasing power from the main network is far less than the generation cost of micro-turbine set, so the power shortage of distribution network mainly comes from purchasing power from the main network. During 7:00 to 14:00, the price of online power distribution is relatively high.

At this time, the output of the micro-combustion unit is increased, and the system does not purchase power from the superior grid. The optimization scheme improves the economy of the whole system.

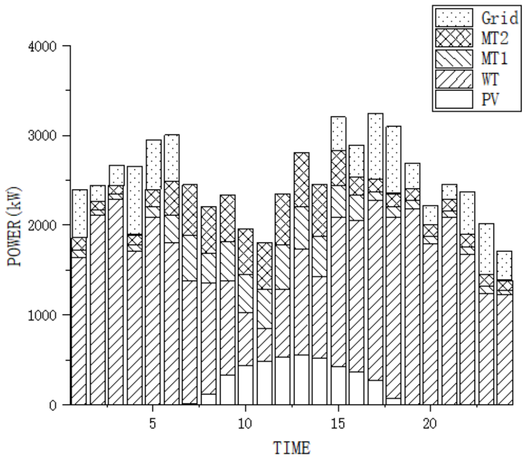

Fig. 5 Output distribution in case 3

Distribution network load curves under the three scenarios are shown in Fig 6. In case 1, the disordered charging and discharging of EV leads to the addition of peak on peak, while the load at the bottom is less and the load fluctuation is intensified. In the case of case 2, a large number of charging plans are arranged during the load trough periods of 1:00-5:00 and 21:00-24:00, and charging rarely occurs during the original load peak period, so the load is significantly reduced from 7:00-9:00 and 11:00-14:00. In the case 3, comprehensive user satisfaction is taken into account. Compared with case 2, charging load is lower in the periods of 7:00-9:00 and 11:00-14:00 when the electricity price is higher. More charging plans are arranged in the periods of lower electricity price, and users' cost satisfaction is improved. Part 00 EV users need to charge, and the charging load is slightly higher than case 2, so as to ensure the travel satisfaction of users.

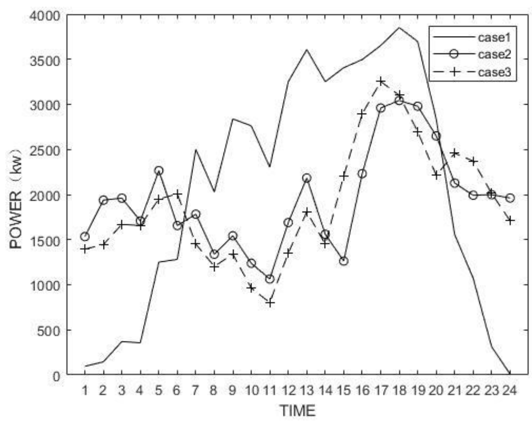

Fig. 6 Distribution network load distribution in each case

Table 3 compares distribution network data indicators in the three scenarios. The analysis shows that, without considering user satisfaction, EV users have greater flexibility because only the distribution network end is considered, so the daily load variance and system operation and maintenance cost of case 2 are minimal. When considering user satisfaction, due to the incentive effect of cost satisfaction, EV users are more inclined to charge in the period when the electricity price is low. However, due to the incentive mechanism, the operation and maintenance cost of distribution network in case 3 is high. At the same time, it can be seen that the active power loss of the distribution network is reduced in the optimization scheme of scenario 2 and case 3, which is of certain significance for energy saving and emission reduction.

Table 3 Optimization analysis results of each scenario

case	The peak valley difference(kW)	Variance of load	cost (￥)	Active loss($kW \cdot h$)
case1	3843.64	1359.7350	47453.45	3172.45
case2	1979.24	442.8325	39453.84	2984.55
case3	2449.74	526.7990	41371.33	2875.78

Fig. 7 shows the comparison of EV users' comprehensive satisfaction in the distribution network under three scenarios. According to the data in the figure, in case 1 of disordered charging and discharging, EV users have higher travel satisfaction, but lower cost satisfaction. When user satisfaction is not taken into account, the travel satisfaction of EV users in case 2 is significantly reduced, while the cost satisfaction is improved. In case 3, which considers user satisfaction, travel satisfaction is guaranteed to a certain extent and cost satisfaction is also improved to a certain extent, with the highest comprehensive satisfaction.

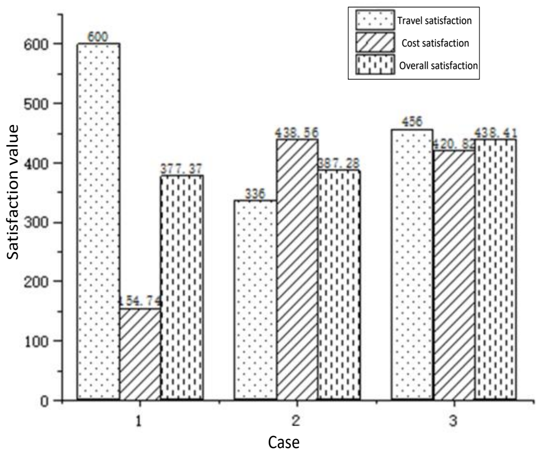

Fig. 7 Comparison of EV users' comprehensive satisfaction

Fig. 8 shows the comparison of charging distribution of single EV in a certain EVA before and after. The analysis shows that the two optimization schemes are greatly different from disordered charging. For case 1, users' travel satisfaction is 1 and cost satisfaction is 0.34. In case 2, charging is obviously concentrated in the periods of 1:00-4:00 and 22:00-24:00 when the electricity price is low, and no charging plan is arranged in the periods of 7:00-9:00 and 11:00-14:00 when the electricity price is high, so travel satisfaction decreases to 0.56 and cost satisfaction increases by 0.73. For case 3, charging plan is arranged between 15:00 and 16:00, and user travel satisfaction is guaranteed and increased to 0.76, cost satisfaction is 0.70, and comprehensive satisfaction is improved.

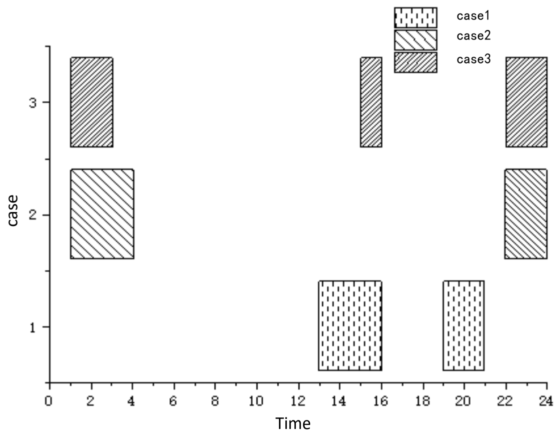

Fig. 8 Before-and-after comparison of various scenarios for charging a certain EV

6. Conclusion

In this paper, a two-layer multi-objective charging optimization strategy considering customer satisfaction is proposed for micro-grid systems with high EV permeability. Through the interactive relationship between distribution network-EV aggregator -EV users, a charging scheme taking into account the safe and economic operation of distribution network and user satisfaction is developed.

Through the coordinated scheduling of EV charging and micro-combustion unit output by the dispatching center, this model plays a good role in smoothing load fluctuation, reducing the operation and maintenance cost of micro-grid and reducing network loss, and improves the economics and security of micro-grid operation. In addition, on the premise of ensuring travel satisfaction, the comprehensive user satisfaction proposed in this paper reduces user charging costs and enhances EV's ability to participate in micro-grid scheduling. The win-win situation of distribution network and users has been realized.

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