Robust Pricing Strategy with EV Retailers Considering the Uncertainty of EVs and Electricity Market

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Abstract: In the context of high penetration of electric vehicles (EVs) in the distribution network, the electricity consumption behaviour of EVs and the real-time electricity market exhibit high uncertainty. EV retailers need to establish reasonable retail pricing to reduce market risks, while ensuring their own profitability and the benefits of EV users. This paper proposes a two-stage robust pricing strategy for EV retailers based on the Stackelberg game, which considers various uncertain factors in the distribution network and satisfies the benefits of both EV users and EV retailers. First, a robust optimization model is established for EV retailers' day-ahead planning and real-time dispatch, considering the uncertainty of EVs and the real-time electricity market. Then, the robust optimization model is divided into a master problem and a sub-problem for two-stage optimization, which is solved iteratively using the Stackelberg game model and the column and constraint generation (CC&G) algorithm. Finally, simulations and verifications based on the IEEE33 benchmark model are conducted to demonstrate the effectiveness of the proposed strategy in the electricity market.

Keywords: Electric Vehicle (EV), retail price, robust optimization, electric market, distribution network

1. Introduction

At present, the uncertainty of the electricity market and the large-scale EVs access lead to fluctuations in retail electricity prices, which will in turn affect the co-economic objectives of EV users and EV retailers. The operational profits of retailers and the benefits for EV users are crucial indicators reflecting the vibrancy of the electricity market. Therefore, an available retail electricity pricing strategy that considers the interests of different stakeholders within the coverage of distribution network under high EV penetration is necessary.

In the retail pricing strategy of EV retailers, EV retailers are characterized as "representing all EVs participating in day-ahead and real-time electricity market transactions, trading with EV users at retail prices, earning profit from price differences, and avoiding market risks [1, 2] ". However, the retail price of EV retailers is influenced by uncertain factors such as the high penetration of EVs distribution and day-ahead and real-time electricity markets [3, 4]. Ref. [5] considers the uncertainty of distribution locational marginal price (DLMP) [6] and obtains the best power purchase plan for retailers based on a two-stage robust optimization model. Ref. [7] investigates the impact of demand-side uncertainty on the bidding decisions of load retailers and develops optimal bidding strategies for retailers. Ref. [8] proposes a detailed robust pricing strategy for power retailers. Meanwhile, since the relationship between retailers and customers constitutes a non-cooperative game, existing research typically employs a Stackelberg game model to describe their interaction [9]. Ref. [10] proposes an intelligent community agent pricing strategy based on the Stackelberg game. Ref. [11] represents an optimal dispatch and bidding strategy of a virtual power plant based on a Stackelberg game. However, existing literature overlooks the uncertainty of EV retail users and the real-time electricity market, which cannot fully coordinate the profits of EV retailers with EV users in the context of high EV penetration.

Based on the analysis above, an EV retailer pricing strategy that considers the uncertainty of EVs and real-time electricity markets, based on Stackelberg game and robust optimization is proposed. Firstly, the uncertainty of EVs and real-time electricity markets are described based on the ideas of distributed robust optimization and stochastic optimization respectively. Then, the objective function of the EV retailer is divided into two stages: day-ahead and real-time electricity market optimization, and a two-stage robust optimization model for the EV retailer is established. Considering the game relationship between EV users and EV retailers, a Stackelberg game pricing model for both parties' objective functions is established. Finally, the CC&G algorithm [12] and the Stackelberg model are used for solution, and the effectiveness of the proposed strategy is verified through IEEE33-node distribution network.

2. Operation Mode of Retailers

The EV retailers link the electricity market with the retail market through the operation mode depicted in Fig. 1.

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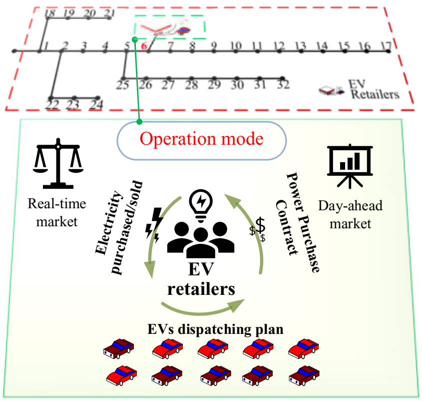

Fig. 1. Operation strategy of EV retailers (node 6).

The EV retailers typically equip themselves with energy storage devices to participate in electricity trading in day-ahead and real-time markets. Retailers purchase electricity from the power market at the clearing price and sell it at the retail price in the real-time market, with their economic benefits reflected in the difference between the purchase and sale prices of electricity. EV users determine their charging and discharging behaviour based on the retailer's published retail price and can also maximize their own utility by participating in grid demand response (DR) through vehicle-to-grid (V2G). The clearing price is calculated based on the DLMP of the distribution network node where the EV retailer is located.

The EV retailers' robust pricing strategy in the electricity market process is shown in Fig. 2.

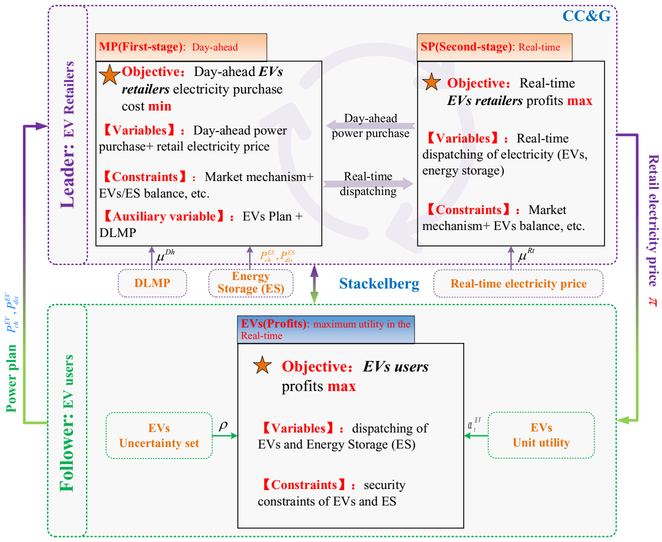

Fig. 2. Process of robust pricing strategy.

As shown in Fig. 2, the EV retailer pricing model based on the Stackelberg game and two-stage robust optimization ensures the maximization of profits for both the EV retailer and the EV during the game. The EV retailer's decision involves two stages of electricity procurement, namely day-ahead and real-time, with the corresponding objectives of maximizing the profit from day-ahead procurement decisions (master problem, MP) and minimizing the purchase cost for real-time scheduling (sub-problem, SP). The EV user's decision is based on the retail electricity price set by the EV retailer for the day-ahead stage and their own utility, controlling the charging and discharging behaviour of the EV, with the objective of maximizing their own utility. The optimization process for the EV retailer requires the use of the clearing price in the day-ahead electricity market and the wholesale price in the real-time electricity market, which are obtained through DLMP and prior knowledge, respectively. To account for the uncertainty in EVs, this paper adopts the idea of robust optimization with multiple discrete scenario distributions, which are described under clustering. The CC&G algorithm and Stackelberg game model are used to solve the strategies proposed in this paper.

3. Mode of EV Retailer Robust Pricing Strategy

3.1. EV Retailers' Profits

3.1.1 Objective Function:

In the day-ahead stage, EV retailers need to make decisions on the amount of electricity they purchase from the day-ahead power market and publish their retail prices to maximize their profits. In the real-time stage, EV retailers will optimize the electric energy plan according to the actual EV charging and discharging capacity, including the charging and discharging capacity of the ESS and the purchase and sale energy from the real-time power market. The real-time expected revenue of EV retailers includes the payment fee of EVs, the real-time power purchase cost and the real-time power sales income. Therefore, their objective function is described by equation (1), which includes the cost of day-ahead power purchase and the expected income of real-time operation.

$$max\Big(-\sum_{t\in T}\mu_t^{Da}P_{b,t}^{Da}+\min_{\{\mathcal{N}^{EV}\in\mathbb{E}(DR_n^{EV})\}}\max\{\sum_{t\in T}\sum_{n\in\mathcal{N}^{EV}}\left(\pi_t p_{ch,n,t}^{EV}-\pi_t p_{dis,n,t}^{EV}\right)+\sum_{t\in T}\left(\mu_t^{Re}P_{s,t}^{Re}-\mu_t^{Re}P_{b,t}^{Re}\right)\}\Big) \tag{1}$$

where, μ_t^{Da} embodies the Day-ahead clearing price (DLMP) at time t, $P_{\mathrm{b},t}^{\mathrm{Da}}$ represents the day-a-day electricity purchased by the operator at time t, π_t denotes the retail electricity price at time t, $\mathcal{N}^{\mathrm{EV}}$ indicates the collection of EVs, $\mathbb{E}(DR_n^{EV})$ represents the expected value of EV users DR profits; $p_{\mathrm{ch},n,t}^{\mathrm{EV}}$ and $p_{\mathrm{dis},n,t}^{\mathrm{EV}}$ represent the charge and discharge amount of EV_n at time t, which is determined by EV users DR profits function (equation (11)).

3.1.2 Constraints:

$$0\le P_{b,t}^{Da}\le P_{b,max}^{Da},\forall t\in T \tag{2}$$

$$\begin{cases}0\le P_{b,t}^{Re}\le P_{b,max}^{Re},\forall t\in T\\ 0\le P_{s,t}^{Re}\le P_{s,max}^{Re},\forall t\in T\end{cases} \tag{3}$$

$$\begin{cases}\pi_{t,min}\le\pi_t\le\pi_{t,max},\forall t\in T\\ \displaystyle\sum_{t\in T}\pi_t/T\le\pi_{av}\end{cases} \tag{4}$$

$$\mu_t^{Da}=\varphi_t\big(P_{b,t}^{Da}\big),\forall t\in T \tag{5}$$

$$P_{b,t}^{Da}+P_{b,t}^{Re}+P_{dis,t}^{ESS}+\sum_{n\in\mathcal{N}^{EV}}p_{dis,n,t}^{EV}=P_{s,t}^{Re}+P_{ch,t}^{ESS}+\sum_{n\in\mathcal{N}^{EV}}p_{ch,n,t}^{EV},\forall t\in T \tag{6}$$

$$\begin{cases}0\le P_{ch,t}^{ESS}\le P_{ch,max}^{ESS},\forall t\in T\\ 0\le P_{dis,t}^{ESS}\le P_{dis,max}^{ESS},\forall t\in T\end{cases} \tag{7}$$

$$\begin{cases} S_t^{ESS} = S_{t-1}^{ESS} + \eta_{ch}^{ESS} P_{ch,t}^{ESS} - \dfrac{P_{dis,t}^{ESS}}{\eta_{dis}^{ESS}}, \forall t \in T \\ S_{min}^{ESS} \le S_t^{ESS} \le S_{max}^{ESS}, \forall t \in T \\ S_1^{ESS} = S_T^{ESS} = S_0^{ESS} \end{cases} \tag{8}$$

$$P_{dis,t}^{ESS} \cdot P_{ch,t}^{ESS} = 0, \forall t \in T \tag{9}$$

$$P_{b,t}^{Re} \cdot P_{s,t}^{Re} = 0, \forall t \in T \tag{10}$$

where, $P_{\mathrm{b},t}^{\mathrm{Re}}$ and $P_{\mathrm{s},t}^{\mathrm{Re}}$ convey the EV retailers real-time electricity purchase and sales under the maximum profit of EVs at time t, respectively; $P_{\mathrm{ch},t}^{\mathrm{ESS}}$ and $P_{\mathrm{dis},t}^{\mathrm{ESS}}$ display the charging/discharging amount of the energy storage system at time t, respectively; S_t^{ESS} refers to the battery power of the energy storage system at time t; μ_t^{Re} involves the real-time DLMP at time t; $P_{\mathrm{b,max}}^{\mathrm{Da}}$ represents the maximum daily electricity purchase; $\pi_{t,\max}$ and $\pi_{t,\min}$ represents the upper and lower limits of retail electricity price; T represents the number of scheduling periods; π_{av} represents the average retail electricity price allowed by the market regulatory authority; λ_t^{Da} denotes the Day-ahead market electricity price; $P_{\mathrm{ch,max}}^{\mathrm{ESS}}$ and $P_{\mathrm{dis,max}}^{\mathrm{ESS}}$ are the maximum charge and discharge capacity of the ESS; $\eta_{\mathrm{ch}}^{\mathrm{ESS}}$ and $\eta_{\mathrm{dis}}^{\mathrm{ESS}}$ represent the charge and discharge efficiency of the energy storage system, $S_{\mathrm{min}}^{\mathrm{ESS}}$ and $S_{\mathrm{max}}^{\mathrm{ESS}}$ represents the safety boundary of the battery capacity of the energy storage system, S_1^{ESS} represents the battery capacity of the energy storage system after the completion of the first scheduling period, $S_{\mathrm{T}}^{\mathrm{ESS}}$ represents the battery capacity of the ESS after the completion of the last scheduling period, S_0^{ESS} represents the initial battery capacity of the energy storage system; $P_{\mathrm{b,max}}^{\mathrm{Re}}$ and $P_{\mathrm{s,max}}^{\mathrm{Re}}$ represent the maximum power purchase and sales in the real-time market, respectively.

Equation (2) restricts the Day-ahead power purchase of EVs retailers. Equation (3) represents the restriction of EV retailers' real-time purchase and sale power. Equation (4) represents the limitation of the market supervision department on the retail price. Equation (5) represents the DLMP of the grid at time t, and it can be solved through the optimal power flow problem of the distribution network [13]. Equation (6) denotes the balance of active power, equation (7) ensures the safety constraint of the energy storage. Equation (8) is the energy storage charging and discharging safety capacity constraint. Equation (9) ensures the uniqueness of the energy storage charge and discharge status. Equation (10) ensures the uniqueness of the purchase and sale status.

Regarding the bilinear term $\mu_t^{Da} P_{b,t}^{Da}$ in the objective, a general solution method has been proposed in [14]. However, considering the complexity of the computation, this paper adopted a different approach (as shown in Fig. 3, the DLMP at a fixed time is roughly proportional to the purchased power): $\mu_t^{Da} = a_t^{\mathrm{Da}} P_{\mathrm{b},t}^{\mathrm{Da}} + b_t^{\mathrm{Da}}$, the coefficients a_t^{Da} and b_t^{Da} in the equation were obtained by the least-squares method.

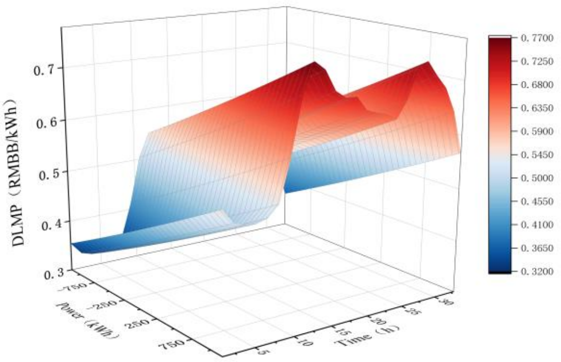

Fig. 3. *Relationship between node 6's DLMP and injection power.*

3.2. EV Retailers' Profits

The EV users determine their charging and discharging behaviour based on the retailer's published retail price. The objective of the EV users is to maximize their utility by DR.

3.2.1 Objective Function:

In the day-ahead stage, EV retailers need to make decisions on the amount of electricity they purchase from the day-ahead power market and publish their retail prices to maximize their profits. In the real-time stage, EV retailers will optimize the electric energy plan according to the actual EV charging and discharging capacity, including the charging and discharging capacity of the ESS and the purchase and sale energy from the real-time power market. The real-time expected revenue of EV retailers includes the payment fee of EVs, the real-time power purchase cost and the real-time power sales income. Therefore, their objective function is described by equation (1), which includes the cost of day-ahead power purchase and the expected income of real-time operation.

$$\max_{\{p_{ch,n,t}^{EV}, p_{dis,n,t}^{EV}, s_{n,t}^{EV}, \pi_t, N^{EV}\}} \mathbb{E}(DR_n^{EV}) = \sum_{t \in T_n^{EV}} [\alpha_{n,t}^{EV}(\eta_{ch}^{EV} p_{ch,n,t}^{EV} - \frac{p_{dis,n,t}^{EV}}{\eta_{dis}^{EV}}) - \pi_t(p_{ch,n,t}^{EV} - p_{dis,n,t}^{EV})] \tag{11}$$

where, $s_{n,t}^{\mathrm{EV}}$ denotes the amount of electricity consumed by EV_n during time t, T_n^{EV} represents the set of dispatch time periods for EV_n, $\eta_{\mathrm{ch}}^{\mathrm{EV}}$ and $\eta_{\mathrm{dis}}^{\mathrm{EV}}$ denote the charging and discharging efficiencies of EVs, and $\alpha_{n,t}^{\mathrm{EV}}$ denotes the unit utility of EV_n during time t; $\mathbb{E}\{\cdot\}$ is the expected value of EVs profits DR.

3.2.2 Constraints:

$$\begin{cases} 0 \le p_{ch,n,t}^{EV} \le p_{ch,max}^{EV}, \forall t \in T_n^{EV} \\ 0 \le p_{dis,n,t}^{EV} \le p_{dis,max}^{EV}, \forall t \in T_n^{EV} \end{cases} \tag{12}$$

$$p_{ch,n,t}^{EV} \cdot p_{di,n,t}^{EV} = 0, \forall t \in T_n^{EV} \tag{13}$$

$$p_{ch,n,t}^{EV} = p_{dis,n,t}^{EV} = 0, \forall t \notin T_n^{EV} \tag{14}$$

$$\begin{cases} s_{n,t}^{EV} = s_{n,t-1}^{EV} + \eta_{ch}^{EV} p_{ch,n,t}^{EV} - \dfrac{p_{dis,n,t}^{EV}}{\eta_{dis}^{EV}}, \forall t \in T_n^{EV} \\ s_{min}^{EV} \le s_{n,t}^{EV} \le s_{max}^{EV}, \forall t \in T_n^{EV} \\ s_{n,1}^{EV} = s_{n,0}^{EV} = s_{n,T}^{EV} \end{cases} \tag{15}$$

$$
\begin{cases}
\sum\limits_{n\in\mathcal{N}^{EV}} p_{ch,n,t}^{EV} \triangleq N_{EV} \sum\limits_{n\in\mathcal{N}^{EV}} \rho_n p_{ch,n,t}^{EV} \\
\sum\limits_{n\in\mathcal{N}^{EV}} p_{dis,n,t}^{EV} \triangleq N_{EV} \sum\limits_{n\in\mathcal{N}_1^{EV}} \rho_n p_{dis,n,t}^{EV}
\end{cases} \tag{16}
$$

where, $p_{\mathrm{ch,max}}^{\mathrm{EV}}$ and $p_{\mathrm{dis,max}}^{\mathrm{EV}}$ denote the maximum charging and discharging amounts of the EVs, respectively; $s_{\mathrm{min}}^{\mathrm{EV}}$ and $s_{\mathrm{max}}^{\mathrm{EV}}$ determine the limits of the battery levels of the EVs, $s_{n,1}^{\mathrm{EV}}$ represents the battery level of EV_n before the first scheduling period, $s_{n,0}^{\mathrm{EV}}$ represents the initial battery level of EV_n , $s_{n,\mathrm{T}}^{\mathrm{EV}}$ represents the battery level of EV_n after the completion of the last scheduling period, N_{EV} is the average number of EVs served by the operator in a day, $\mathcal{N}^{EV}$ is a type set of EVs, which contains N_{type} elements, ρ_n is the proportion of EV_n.

Equation (12) represents the constraint of the safety capacity of EVs. Equation (13) ensures the physical constraints on charging and discharging of EV. Equation (14) declares the charging and discharging capacity of EVs during non-scheduled periods. Equation (15) is the constraint on the battery capacity of EVs, and equation (16) represent the scene constraints of EVs.

For the uncertainty of EVs, this paper describes the uncertain as [15]:

$$
\mathcal{R} = \begin{cases}
\|\boldsymbol{\rho} - \boldsymbol{\rho}_0\|_1 \le \theta_1 \\
\|\boldsymbol{\rho} - \boldsymbol{\rho}_0\|_\infty \le \theta_\infty, \boldsymbol{\rho} \in \mathbb{R}_{N_{type}} \\
\| \boldsymbol{\rho} \|_1 = 1
\end{cases} \tag{17}
$$

where, $\mathcal{R}$ represents an uncertain set, $\boldsymbol{\rho}$ is a vector composed of the distribution of uncertain variables, i.e $\boldsymbol{\rho} = \{\rho_n, \forall n \in \mathcal{N}^{EV}\}$, which represents the proportion of EV_n, ρ_0 is the original distribution of uncertain variables obtained by historical data clustering. θ denotes the moment boundaries of $\mathcal{R}$.

4. Two-Stage Robust Optimization Strategy Based on Stackelberg and CC&G

It is evident that the profits of EV users and EV retailers constitute a classic Stackelberg game model. Thus, integrating the two benefit functions into a concise objective function becomes apparent. The compact form of EV retailers robust pricing strategy model as shown in equation (18):

$$
\begin{cases}
\max\limits_{\{x,\pi\}} \boldsymbol{a}^T\boldsymbol{x} + \min\limits_{\{\rho\in\mathcal{R},\boldsymbol{y}_o\in Y,\forall o\in\mathcal{O}\}} \max \left(\sum_{o\in\mathcal{O}} \boldsymbol{v}_o \boldsymbol{b}_o^T \boldsymbol{y}_o + N_{EV} \boldsymbol{z}\boldsymbol{\rho}[\boldsymbol{\pi}_{ch}^T - \boldsymbol{\pi}_{dis}^T]\right) \\
\text{s.t. } \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y}_o + \boldsymbol{C}\boldsymbol{z}\boldsymbol{\rho} = \boldsymbol{0},\ \forall \boldsymbol{o} \in \mathcal{O} \\
\max\limits_{z_n=\{p_{\mathrm{ch},n,t}^{\mathrm{EV}}, p_{\mathrm{dis},n,t}^{\mathrm{EV}}, \forall t\in\mathrm{T}\}} \mathbb{E}(\boldsymbol{DR}_n^{EV}) = \sum_{t\in T_n^{EV}} [\boldsymbol{\alpha}_{n,t}^{\mathrm{EV}}(\boldsymbol{\eta}_{\mathrm{ch}}^{\mathrm{EV}} \boldsymbol{p}_{\mathrm{ch},n,t}^{\mathrm{EV}} - \frac{\boldsymbol{p}_{\mathrm{dis},n,t}^{\mathrm{EV}}}{\boldsymbol{\eta}_{\mathrm{dis}}^{\mathrm{EV}}}) \\
\qquad -\boldsymbol{\pi}_t(\boldsymbol{p}_{\mathrm{ch},n,t}^{\mathrm{EV}} - \boldsymbol{p}_{\mathrm{dis},n,t}^{\mathrm{EV}})],\ \forall \boldsymbol{n} \in \mathcal{N}^{EV}
\end{cases} \tag{18}
$$

where, $\boldsymbol{x}$ and $\boldsymbol{\pi}$ are the decision variables of the first stage, and $\boldsymbol{x} = \{P_{\mathrm{b},t}^{\mathrm{Da}}, \forall t \in \mathrm{T}\}, \boldsymbol{\pi} = \{\pi_t, \forall t \in \mathrm{T}\}$, $\boldsymbol{y}_o$ is the second stage decision variable corresponding to scenario o, and $\boldsymbol{y}_o = \{P_{\mathrm{b},t,o}^{\mathrm{Re}}, P_{\mathrm{s},t,o}^{\mathrm{Re}}, P_{\mathrm{ch},t,o}^{\mathrm{ESS}}, P_{\mathrm{dis},t,o}^{\mathrm{ESS}}, S_{t,o}^{\mathrm{ESS}}, \forall t \in \mathrm{T}\}$; $\mathcal{R}$, $\boldsymbol{Y}$, and $\mathcal{O}$ respectively represent the set to which the corresponding variables $\boldsymbol{\rho}$, $\boldsymbol{y}_o$, and o belong; $\mathcal{O}$ is the real-time DLMP set; v_o represents the probability of scenario o ; b_o is the coefficient vector corresponding to scenario o; z_n represents the energy plan of EV_n; $\boldsymbol{a}$、 $\boldsymbol{A}$、 $\boldsymbol{B}$ and $\boldsymbol{C}$ are coefficient vectors and matrices.

The above model is a two-stage robust optimal problem based on Stackelberg and can be directly solved through CC&G, KKT, and Strong duality. The flowchart for solving the above model by CC&G are shown in Fig. 4. It should be noted that the case studied in this paper assumes that the retailer's energy storage system has sufficient capacity and there is no situation where real-time energy demand cannot be met. Therefore, the infeasibility of SP and MP cannot be considered.

5. Case Study

The distribution network topology is shown in Fig. 1,

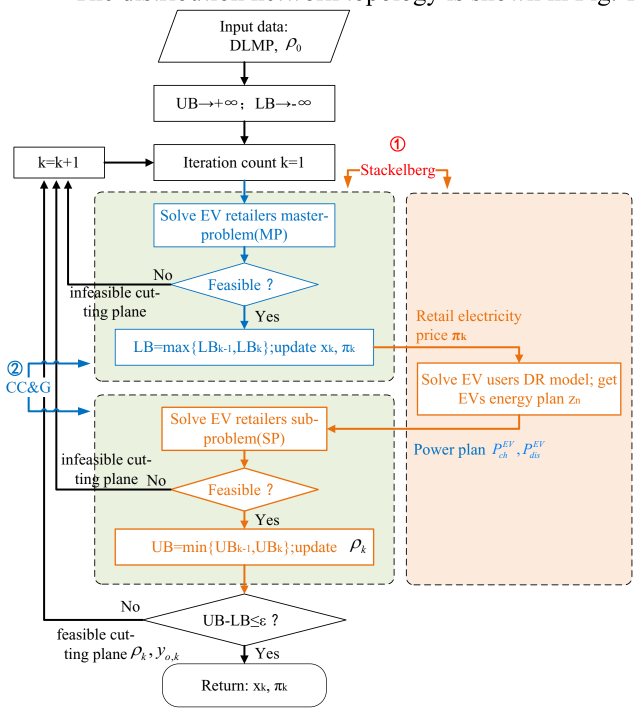

Fig. 4. Flowchart of solving the proposed robust pricing strategy.

which is taken from the authoritative literature on the IEEE 33 model [16,17]. To simplify the calculation, the total number of EVs covered by EV retailers is set to 60. Node 0 in the IEEE 33 bus system served as the slack bus on the low-voltage side of the transformer. EV retailers are located at node 6. All calculations were performed on a computer with an Intel(R) Core (TM) i7-2500 3.9 GHz CPU, 8 GB RAM, Windows 11, and GUROBI 10.0 optimization platform. The simulation period is conducted as 24-hour.

This article clustered 1000 historical EVs data into 10 categories, as shown in Fig. 5. As can be seen from Fig. 6, the charging and discharging of EVs occurred during low electricity demand periods and high electricity demand periods, respectively. Real-time electricity purchase and sale by power retailers followed a profit-making pattern of buying electricity during low-price periods and selling during high-price periods. Energy storage serves as a flexible unit for power retailers, and its charging and discharging status is consistent with that of the power retailers. The real-time buying and selling curves of the retailers under the other 9 different real-time DLMP curve scenarios all follow the rule of "charging during low electricity demand periods and discharging during high electricity demand periods".

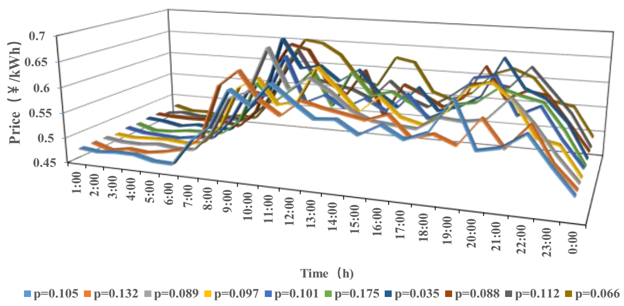

Fig. 5. *DLMP data of different types of EVs in real-time phase.*

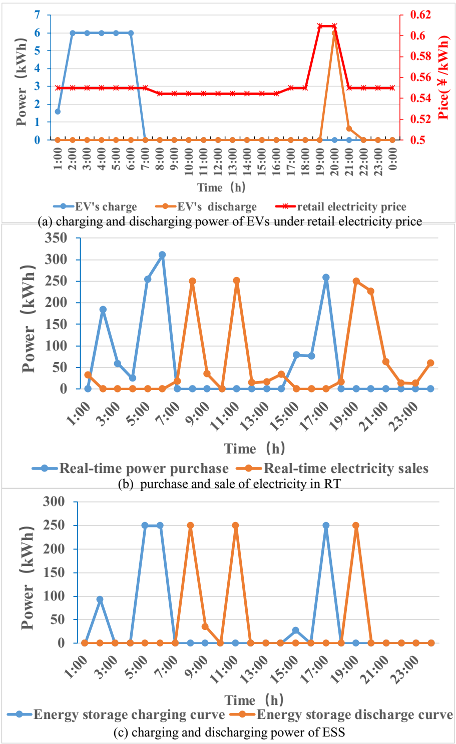

Fig. 6. *Curve of power in Real-time(p=0.105).*

5.1. EV retailers' two-stage robust pricing strategy

The EV users determine their charging and discharging behaviour based on the retailer's published retail price. The objective of the EV users is to maximize their utility by DR.

The iterative solution process of the CC&G algorithm for the EV retailers' two-stage robust pricing strategy is presented in Fig. 7. As the iterations of the MP and SP proceed, the upper and lower bounds approach each other, and convergence is achieved after 3 iterations.

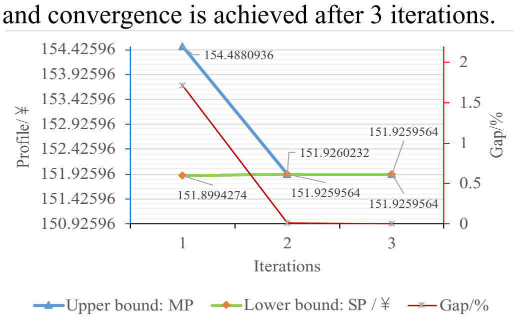

Fig. 7. *Iterative results of CC&G.*

Besides, to demonstrate the effectiveness of the robust pricing strategy, this paper considers the experience distribution obtained by clustering as the true distribution and uses it as a control experiment. The proportion of different types of EVs is shown in Fig. 8. It can be seen that the worst distribution obtained by robust optimization is not significantly different from the empirical distribution obtained by clustering. This is because the number of clustering samples used in this study is sufficient, resulting in a small moment distance between the actual distribution and the empirical distribution. It demonstrates that the distribution robust optimization proposed in this paper is driven by actual data and considers both the optimality and conservatism of the optimization strategy.

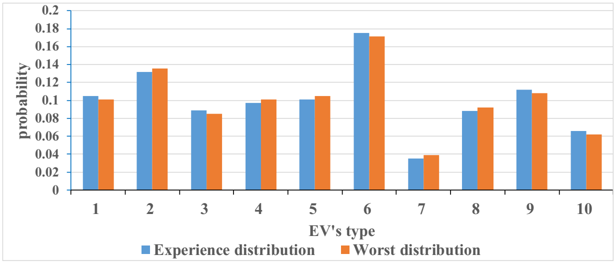

Fig. 8. *Proportion of 10 types of EVs under two distributions.*

The pricing curves and revenue under the determined distribution and worst-case distribution from robust optimization are shown in Fig. 9, respectively. The results show that the proposed robust pricing strategy can effectively reduce the fluctuation range of the retailer's revenue while maintaining a higher average revenue compared to the deterministic optimization strategy. This indicates that the proposed robust optimization strategy fully considers the deviation between the actual distribution and empirical distribution, broadens the search range of the retailer's strategy, and is more universally applicable. From a long-term operational perspective, the results obtained from robust optimization can adapt to more practical scenarios and improve the retailer's expected revenue.

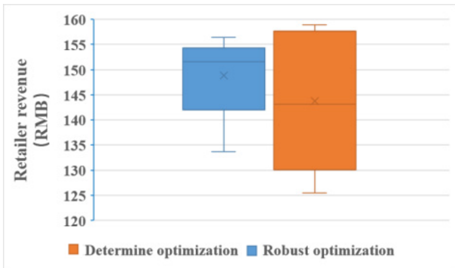

Fig. 9. *Boxplot of benefit in different models.*

5.2. EV Users' Profits

To illustrate the impact of the EV utility function on retail pricing, this paper introduces the concept of EV user electricity satisfaction. Considering the normal demand of EV users to charge as quickly as possible, the unit efficiency αn of the EV decreases with time. As shown in Fig. 10, changes in EV electricity satisfaction lead to changes in the EV charging plan (compared to Fig. 6 (a)), with the goal of maximizing its own benefits through fast charging. Based on the idea of Stackelberg game theory, retailers also adjust the retail electricity price curve to track changes in EV users' utility, in order to obtain greater profits from EV users. Table 1 shows that, with consideration of the changes in the EV utility function, the profits of EV users will increase, while the profits of the EV retailer will decrease, due to the fact that the electricity plan formulated by the EV as a follower directly affects the market behavior of the retailer, reflecting the Stackelberg game between the EV and the EV retailer.

Table 1 EV and EV retailers' profits under the EV utility function.

EV Utility	EV retailers' profits /¥	EVs' profits /¥
Consider	151.9260	10.7094
No consider	128.3869	10.9125

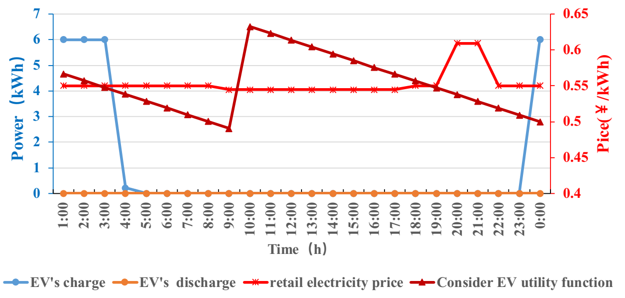

Fig. 10. EVs Power plan and retail electricity price considering EV utility.

6. Conclusion

To address the high uncertainty in EV electricity usage behavior and real-time electricity markets in distribution networks with high EV penetration, this paper proposes a robust pricing strategy for EV retailers based on robust optimization and a Stackelberg game to simultaneously satisfy the profits of both EV retailers and EV users. A two-stage robust optimization model based on the Stackelberg game is established. Some conclusions are drawn as follows:

1) Both EV and EV retailers can obtain satisfactory profits from the pricing strategy, where EV retailers can exhibit market behavior of "hedging" and EV users can attain appropriate profit from V2G.

2) The strategy fully considers the uncertainty of real-time electricity markets and EV user electricity usage behavior, and the data-driven two-stage robust optimization method can balance the optimality and conservatism of the strategy.

3) The Stackelberg game model of robust pricing for EV retailers considers the response of EV utility functions to prices, which can reduce the cost of EV users, achieve a game and win-win situation between EV retailers and EV users.

In the future, research on shared energy storage mechanisms between EV retailers can be further explored.

7. Acknowledgments

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