

A Day-Ahead Stochastic Robust Dispatch Model Considering Demand Response

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Abstract. Increasing scale of wind power and electric vehicles connected to the power grid bring new challenges to the operation of power system. In this paper, probabilistic scenario is used to represent the uncertainty of wind power and robust theory is introduced to deal with the uncertainty of electric vehicles. Combined with the advantage of Demand response, a day-ahead stochastic robust dispatch model is established. The results of IEEE RTS-24 system demonstrate the validity of the model.

1. Introduction

In recent years, energy and environmental crisis have become increasingly prominent. Wind power as a clean and renewable energy has received extensive attention and is developing rapidly in the world. However, affected by the uncertainty of wind power, the integration of large-scale wind power will increase the dispatching pressure of the power system and cause serious problem such as wind power consumption. As a result, the adjustment ability of conventional units and traditional power grid dispatching mode has been unable to meet the large-scale wind power dispatching and consumptive demand [1]. At the same time, along with the wide application of electric vehicle (EV), EV is involved in the power grid dispatching as a new flexible load resource. But the disorderly charging of large-scale EVs is likely to cause negative effects such as increasing the peak load of the power system [2]. Therefore, the research on how to establish scientific EV charging and discharging strategy and arrange EVs to participate in wind power system reasonably is of great importance.

In the past few years, many researches have been worked on coordinated optimization of wind power and EV. In [3], a coordinated dispatching model of EV charging and wind power is established. In this model, the potential of EV to absorb excess wind power and reduce the startup cost of thermal units during valley load period is illustrated. In [4], the coordinated integration of EVs and wind energy in power system is studied by stochastic security-constrained unit commitment model which can effectively reduce the operating costs of the power system.

In the research above, EV is introduced into the wind power system and is controlled as energy storage device without considering the uncertainty of EVs and the convenience of users. With the popularity of EVs, the impact of the uncertainty of EV on the power system will become increasingly evident. With the continuous progress of smart grid construction, more two-way interactive demand side resources are involved in power grid operation and scheduling. Demand response (DR) as an important demand-side resource of smart grid architecture, which can smooth the load curve, quickly response to power demand and guide the users to change their habits through price signal.



In [5], the real-time electricity price is introduced into the unit commitment, and it has been proved that DR can reduce the operation cost caused by the randomness of the wind power. In [6], interruptible load (IL) is introduced to deal with the uncertainty of wind power in the day-ahead dispatch. And it is verified that IL can effectively reduce the operation cost of the system and improve the reliability of the power grid. In [7], a two-stage unit commitment model for high wind power penetration combined with price-based demand response (PDR) and incentive-based demand response (IDR) is established. And it is proved that coordinated optimization of PDR and IDR can effectively enhance the consumptive capacity of wind power.

In this paper, DR is introduced into a day-ahead dispatch model with high penetration of wind power and EVs. The model is established aiming at minimizing the operating cost of the system. The stochastic theory and the robust theory are used to deal with the uncertainty of wind power and electric vehicles. Results of IEEE RTS-96 system show effectiveness of the proposed model.

2. Day-Ahead Dispatch Model For The System With Wind Power And Electric Vehicle

2.1. Model of price-based demand response

By adjusting electricity price, PDR aims to guide users to adjust their own habits to use electricity in order to respond to changes in the power system. PDR mainly consists of time-of-use pricing (TOU), real-time-pricing (RTP) and critical peak pricing (CPP). As a static electricity price mode, by lowering the electricity price during valley load period and increasing the peak electricity price, TOU means to guide users to take a more economical and reasonable way of using electricity so as to realize peak load shifting and improve the consumptive capacity of wind power. TOU based on consumer psychology can be expressed as follow:

$$d(i) = d_0(i) + \varepsilon(i) \times \frac{d_0(i)}{p_0(i)} \times (p(i) - p_0(i)) + \sum_{\substack{j=1 \\ j \neq i}}^{24} \varepsilon(i, j) \times \frac{d_0(i)}{p_0(j)} \times (p(j) - p_0(j)), \quad i = 1, 2, \dots, 24 \quad (1)$$

Where $\varepsilon(i)$ represents self-elasticity coefficient in period i ; $\varepsilon(i, j)$ is the cross-elasticity coefficient between period i and period j ; $p_0(i)$ and $d_0(i)$ are initial price and demand in period i ; $p(i)$ and $d(i)$ are price and demand after TOU.

2.2. Model of interruptible load

Interruptible load is an important demand side resource based on incentive. After the dispatch center issuing load interrupt request during the peak load hours or equipment failure period, users signing interruptible load contract with the power grid use less electricity or stop using electricity and obtain the corresponding interruption compensation. Under the environment of power market, as a flexible DR resource, IL can indirectly increase the reserve of the power system, stabilize fluctuations caused by intermittent energy, reduce the peak load of the power and improve the economy and reliability of the system.

In this paper, IL is introduced into day-ahead dispatch as virtual units in order to analyse its influence on the dispatch of the power system. The model of IL can be established according to conventional units. Unlike conventional units, constraints on interruption times and advanced notification time before load interrupting restrict the participation of IL to the day-ahead dispatch of power grid. The specific constraints can be expressed as follows and is the total number of interrupt times to user j .

$$\sum_{t=1}^{N_T} (1 - v_{j,t-1}) v_{j,t} \leq N_j \quad (2)$$

2.3. Electric vehicle model for day-ahead dispatch

Different from the traditional demand side resources, EV can operate in charging and vehicle-to-grid (V2G) mode so as to achieve a two-way interaction with the power grid. In order to realize the unified dispatching of a large number of distributed EVs, the concept of "electric car sets" [8] is introduced in this paper which means EVs connected with the power grid are considered as a whole and is optimized with wind power and thermal power.

When the power load is small, Electric car sets work in charging mode. EVs which can be dispatched are partially in charging state so as to meet the daily running power demand of the EVs. When the power system load is large, EVs are in V2G mode. EV which is idle and maintains a certain amount of electricity is arranged to discharge electricity to the power grid in order to replace the part of conventional units with high emission. The specific EV model for day-ahead dispatch is as follows. Constraints (3) and (4) describe the charging and discharging power of EVs. Constraints (5) makes sure that EVs can only operate in charging state or V2G state during period t . Constraints (6) and (7) restrict the maximum charging and discharging power of EVs. Constraints (8) restrict the minimum and maximum power stored totally in batteries of EVs. The total power stored in EVs can be expressed as (9).

$$P_{t,s}^{ch} = N_{t,s}^{ch} P_{charge}^{av} \quad (3)$$

$$P_{t,s}^{dch} = N_{t,s}^{dch} P_{discharge}^{av} \quad (4)$$

$$P_{t,s}^{ch} P_{t,s}^{dch} = 0 \quad (5)$$

$$P_{t,s}^{ch} \leq (N_{EV} - N_{TR,t}) P_{charge}^{av} \tau \quad (6)$$

$$P_{t,s}^{dch} \leq (N_{EV} - N_{TR,t}) P_{discharge}^{av} \tau \quad (7)$$

$$E_{\min} N_{EV} \leq E_{s,t} \leq E_{\max} N_{EV} \quad (8)$$

$$E_{s,t} = -\frac{P_{t,s}^{dch}}{\eta_d} + \eta_c P_{t,s}^{ch} - \lambda D_{av} N_{EV} \frac{N_{TR,t}}{\sum_{t=1}^{24} N_{TR,t}} + E_{s,t-1} \quad (9)$$

Where $E_{s,t}$ is the total amount of electricity stored in EV in t period; η_c , η_d are the charging, discharging efficiency of EVs; P_{charge}^{av} , $P_{discharge}^{av}$ are the average charging, discharging power of EV; $N_{t,s}^{ch}$, $N_{t,s}^{dch}$ are the charging, discharging number of EVs in t period; $P_{t,s}^{ch}$, $P_{t,s}^{dch}$ are the charging, discharging power of EV in t period; $N_{TR,t}$ is the number of EVs in running state during t period; N_{EV} is the total number of EVs connected to the power grid; D_{av} is the daily average mileage of EVs; λ is the power consumption per unit mile of electric vehicle. E_{\max} , E_{\min} represent maximum, minimum energy stored in batteries of EV; τ is the availability of charging facilities.

2.4. Day-ahead dispatch mode for system considering demand response

In this paper, the problem of DR involved in the day-ahead dispatch of power system with wind power and EVs is constructed as a two-stage coordination optimization model. In this model, the uncertainty of wind power is represented by probabilistic scenarios. And robust theory is introduced into to deal with the uncertainty of EVs. The first-stage simulation of the model mainly includes the optimization of start-stop state of conventional units and charge-discharge state of EVs. At the same time, TOU with lower flexibility is introduced into the first-stage coordinated optimization in order to smooth the load curve. Based on the optimization result of the first-stage simulation, the real-time balancing process of the power grid under different wind power scenarios is simulated in the second-stage optimization. The adjustment of conventional unit output and charge-discharge power of EVs under different wind power scenarios is done in this process. For the reason that IL is more flexible than TOU in day-ahead dispatch, IL is introduced into the second-stage optimization to achieve flexible configuration so as to meet the need of different wind power scenarios.

3. Day-Ahead Dispatch Model of System Containing Wind Power And Electric Vehicles

3.1. Objective function

The objective function is given in (10) which is minimized throughout the dispatching periods.

$$F = \sum_{t=1}^{N_T} \sum_{g=1}^{N_G} S_{g,t}^{on} + \sum_{s=1}^{N_s} \rho_s \sum_{t=1}^{N_T} \left[\sum_{g=1}^{N_G} u_{g,t,s} f(P_{g,t,s}) + \sum_{w=1}^{N_w} C_w^{shed} P_{w,t,s}^{shed} + \sum_{j=1}^{N_{IL}} C_{IL,j} P_{IL,j,t} + C_{EV,t} P_{t,s}^{dch} \right] \quad (10)$$

Where N_T, N_G, N_w are the number of dispatching periods, conventional units, wind farms; N_s is the number of wind power scenarios; N_{IL} is the number of users signing interruptible load contracts; $S_{g,t}^{on}$ is the start-up cost of unit j in the t period; $f(\cdot)$ is the generating cost function of unit j ; C_w^{shed} is punishment cost for wind power curtailment; $P_{w,t,s}^{shed}$ refers to wind power curtailed; $u_{g,t,s}$ is a binary variable (1 if unit j is in a running state in t period and 0 otherwise). ρ_s is the probability of occurrence of wind power scenario s ; $P_{g,t,s}$ is the output of unit g during t period; $C_{IL,j}$ is the compensate price for interrupting load; $P_{IL,j,t}$ is the load interrupted by user j during period t ; $C_{EV,t}$ is the compensate cost for the electricity discharged by EVs during t period.

3.2. Constraints

The constraints for a two-stage unit commitment with wind power and EV is shown from (11) to (17). Constraints (11) guarantee power balance of the power system. Constraint (12) is the transmission capacity constraint. Constraint (13) restricts the maximum and minimum outputs of unit j during t period. Constraints (14) and (15) make sure that the output of unit j operates within the ramping rate limitation. Constraints (16) and (17) are the startup-shutdown constraints of unit j .

$$\sum_{g=1}^{N_G} P_{g,t,s} + \sum_{w=1}^{N_w} P_{w,t,s} + P_{t,s}^{dch} = \sum_{d=1}^{N_D} L_{d,t,s} - \sum_{j=1}^{N_{IL}} P_{ILj,t,s} + P_{t,s}^{ch} \quad (11)$$

$$\underline{\mathbf{F}} \leq \mathbf{T} \cdot \mathbf{P}_t^{inj} \leq \overline{\mathbf{F}} \quad (12)$$

$$P_g^{\min} \leq P_{g,t,s} \leq P_g^{\max} \quad (13)$$

$$u_{g,t,s} P_{g,t,s} - u_{g,t-1,s} P_{g,t-1,s} \leq r_{up,g} \quad (14)$$

$$u_{g,t-1,s} P_{g,t-1,s} - u_{g,t,s} P_{g,t,s} \leq r_{dn,g} \quad (15)$$

$$(u_{g,t} - u_{g,t-1}) t_g^{\text{on}} + \sum_{j=t-t_g^{\text{on}}}^{t-1} u_{g,j} \geq 0 \quad (16)$$

$$(u_{g,t-1} - u_{g,t}) t_g^{\text{off}} + \sum_{j=t-t_g^{\text{off}}}^{t-1} (1 - u_{g,j}) \geq 0 \quad (17)$$

$L_{d,t,s}$ Is the load predicted of load point d in the t period; $P_{w,t,s}$ is the output of wind farm w during period t . \mathbf{T} is the power transfer distribution coefficient matrix; $\mathbf{P}_t^{\text{inj}}$ is the injected power column vectors of the power system; $\bar{\mathbf{F}}$ and $\underline{\mathbf{F}}$ are column vectors for the upper and lower bounds of the line transmission capacity. P_g^{min} And P_g^{max} respectively are the lower and upper output limit of unit g ; t_g^{on} , t_g^{off} are the minimal start, off time of unit g ; $P_{w,t,\text{max}}$ is the maximal output predicted of wind farm w ; $r_{up,g}$, $r_{dn,g}$ are the upward, downward ramping rate of unit g .

3.3. Stochastic robust dispatch model

However, affected by the driving habits and driving demand of EV users, there are some uncertainties on the number of EVs on running states during different time of the day. In this paper, to deal with uncertain of the EVs, robust theory is introduced into the model. Suppose that the number of EV in running states during period t has the following fluctuation range as follow. Where $N_{TR,tm}$ and $N_{TR,m}$ respectively represent the upper and lower limit of the number of EV in running states during period t .

$$N_{TR,tm} \leq N_{TR,t} \leq N_{TR,m} \quad (18)$$

According to the central limit theorem, (18) can be transformed into the following uncertain set [9]:

$$\begin{cases} N = \{N_{TR,t} = N_{d,t} + z_t N_{f,t} \quad \forall t \in T, |z_t| \leq 1, |z_t| \leq \Gamma\} \\ N_{d,t} = 0.5(N_{EV,tm} + N_{EV,m}) \\ N_{f,t} = 0.5(N_{EV,tm} - N_{EV,m}) \\ \Gamma = J\mu + \phi^{-1}(\alpha)\sqrt{J}\sigma \end{cases} \quad (19)$$

Where $N_{d,t}$ the predicted value of EVs in running is state during t period; ϕ^{-1} is the inverse function of standard normal distribution cumulative distribution function; J is the number of variables in the constraint; α represents the confidence probability;

Based on the uncertain set above, when the uncertainty of EV is taken into consideration, the stochastic model above can be transferred into the following stochastic robust scheduling model:

$$\begin{cases}
F = \sum_{t=1}^{N_T} \sum_{g=1}^{N_G} S_{g,t}^{on} + \sum_{s=1}^{N_S} \rho_s \sum_{t=1}^{N_T} \left[\sum_{g=1}^{N_G} u_{g,t,s} f(P_{g,t,s}) + \sum_{w=1}^{N_w} C_w^{shed} P_{w,t,s}^{shed} + \sum_{j=1}^{N_{IL}} C_{IL,j} P_{ILj,t,s} + C_{EV,t} P_{t,s}^{dch} \right] \\
\Gamma N_{f,t} \geq X_{t,s} - H_{t,s} \\
\Gamma N_{f,t} \leq W_{t,s}^{ch} - N_{t,s}^{ch} \\
\Gamma N_{f,t} \leq W_{t,s}^{dch} - N_{t,s}^{dch} \\
0 \leq \Gamma \leq 1, H_{t,s} \geq 0 \\
X_{t,s}, W_{t,s}^{ch}, W_{t,s}^{dch} \geq 0
\end{cases} \quad (20)$$

Where $X_{t,s}$, $W_{t,s}^{ch}$, $W_{t,s}^{dch}$ and $H_{t,s}$ are the auxiliary decision variables introduced in the equivalence transformation with no specific physical meaning; Γ is the robust coefficient. When the robust coefficient equals to zero, this model is a deterministic model without considering the uncertainty of EVs. When the robust coefficient equals to one, this stochastic robust day-ahead scheduling model is in the most conservative form. By adjusting the robust coefficients, the conservative degree of the model can be adjusted.

4. Case study

4.1. Basic data

The performance of the model introduced in this paper is simulated using the IEEE RTS system [10]. Wind farm of 600MW is connected to bus 21. Maximum load of the system is 3250MW. Date of wind farm can be seen in [7]. Assuming that the number of EVs in the system is 50000, the relevant parameters of the EV can be seen in [11]. In calculation, the penalty fee for wind power curtailment is set as 150\$/MW·h. The maximum deviation of EVs in running state during calculation is 30% of its predicted value. The upper and lower spinning reserve is required no less than 10% of the load. All numerical simulations are coded in MATLAB on a 2.2 GHz Windows-based laptop with 4 GB of RAM.

4.2. Simulation scenario

In order to fully explain the influence of DR on the day-ahead dispatch of the power system with wind power and EVs, this paper choose the following four cases as analysis objects.

Case 1: In this scenario, the basic power system with wind power and EVs is simulated with different robust coefficient in order to analyze the influence of the uncertainty of EVs on the power grid without considering DR.

Case 2: Based on Case 1, this case mainly analyzes the influence of TOU on the power grid. The cross elasticity coefficient is set as 0.01 in this paper. And self-elasticity coefficient varies from 0 to -0.2 in this case. The paper divides one day into different periods representing different load levels which is shown in Table 2.

Case 3: Based on case 1, this case mainly analyzes the influence of IL on the power grid. The simulation is carried out based on different compensate price for IL.

Case 4: In this case, both TOU and IL are introduced into the day-ahead dispatch of the model containing wind power and EV. The cross-elasticity coefficient is set as 0.01 and the self-elasticity coefficient is set as -0.1 in this case. The compensate price is set according to Table 1.

Table 1. Parameters of IL

Access Nodes	$P_{ILj,t,s}$ (MW)	Compensate Price(\$/MW•h)	$t_{IL,j}^{on}$ (h)	$t_{IL,j}^{off}$ (h)
1	40	100	5	3
2	20	60	6	4
3	50	80	7	4
4	30	120	5	3

Table 2. Electricity Price With/Without PDR

	Period	Price(\$/MW•h)
Before DR	00:00-24:00	450
Peak	10:00-12:00, 16:00-22:00	600
Normal	08:00-10:00, 12:00-16:00, 22:00-24:00	450
Valley	00:00-08:00	350

4.3. Results

4.3.1. *Case 1.* According to Table 3, comparing the results of different robust coefficients, it can be concluded that with the increase of the robust coefficient, the operating cost of the system increases gradually. This is because when the coefficient of robustness increases, the difference between the actual value and the predicted value of the EV energy consumption increases. In order to ensure the power balance within the system, the scheduling decision tends to be conservative, and the corresponding daily operation cost increases.

Table 3. Results of day-ahead dispatch with different robust coefficient

Γ	0	0.2	0.4
Total Cost(10^3 \$)	14605.5	14670.3	14679.8
Generation Cost(10^3 \$)	14594.2	14660.9	14670.03
Start-up Cost(10^3 \$)	6.3	5.25	5.6
Wind Curtailment Cost(10^3 \$)	0	0	0
Cost for EV(10^3 \$)	4.670	4.1653	4.1654

4.3.2. *Case 2.* Fig.1 and Table 4 respectively show the influence of different self-elasticity coefficients on load curve and operating cost of the system. It can be seen from Fig.1 that when the self-elasticity coefficients varies from 0 to -0.2, the minimum load rises from 1917.5 MW to 2015.65 MW, and the maximum load drops from 3250 MW to 3105.7 MW. After introducing PDR into the system, the load curve is smoother and the effect of peak shaving and valley filling is more obvious. Fig.1 explains the reason for the change Table 4. When the price elasticity varies from 0 to -0.2, the operating cost of the system and discharge demand of EV obviously decrease. Due to the introduction of TOU, the load curve is smoother which may reduce the spinning reserve needed by the system during peak load period and reduce the operating cost of the system.

Table 4. Results of day-ahead dispatch with different self-elasticity coefficients considering TOU

ε	0	-0.1	-0.2
Total Cost(10^3 \$)	14605.5	14581.9	14441.9
Generation Cost(10^3 \$)	14594.5	14575.6	14435.65
Start-up Cost(10^3 \$)	6.3	6.3	5.25
Wind Curtailment Cost(10^3 \$)	0	0	0
Cost for EV(10^3 \$)	4.6708	0	0

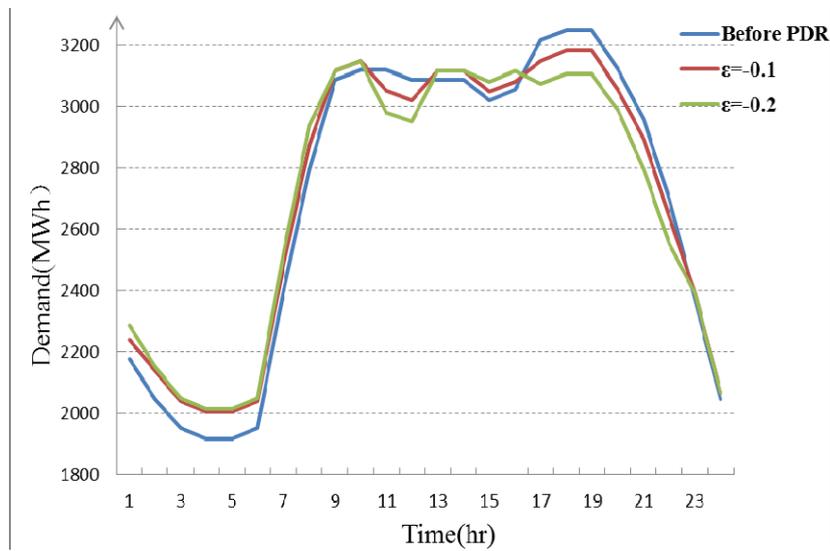


Figure 1. Load curve with different self elasticity coefficients

4.3.3. Case 3. This Case mainly analyses the impact of IL on the day-ahead dispatch. Table 1 shows the operating cost of the system with different compensate prices for load interruption which is represented by C_{IL} in Table 5. Compared to Table 3, when IL is introduced into the power system, the total operating cost of the system reduces obviously. From Table 5, it can be seen that total cost and generation cost rises as the compensate price for load interruption increases. When compensate price rises to $5C_{IL}$, the system stop dispatching IL for the reason that the cost for load interruption is higher than the cost for units output. According to Fig.2, it can be seen that the outputs of conventional units during peak hours reduce obviously when IL is introduced into the system. Compared to Case 2, we can see that IL can reduce the outputs of conventional units more effectively than TOU because IL is restricted by interruption times so the system choose to interrupt load in peak load period in order to maximize the profit brought by load curtailment.

4.3.4. Case 4. In this case, both TOU and IL are introduced into the system. Compared with Table 3, Table 6 makes it obvious that TOU and IL can effectively reduce the operating cost of the system. Also, compared with Table 3, it can be seen that when the robust coefficient changes from 0 to -0.1, the change of the total costs of the system is smaller which shows that the system containing both TOU and IL is more stable.

Table 5. Results of day-ahead dispatch with different self-elasticity coefficients considering IL

	C_{IL}	$3C_{IL}$	$5C_{IL}$
Total Cost(10^3 \$)	14373.6	14656.8	14762.9
Generation Cost(10^3 \$)	14299.8	14458.4	14753.48
Start-up Cost(10^3 \$)	6.65	5.25	5.25
Cost for IL(10^3 \$)	73.8	189	0
Cost for EV(10^3 \$)	4.1654	4.1674	4.1672

Table 6. Results of day-ahead dispatch with different robust coefficients considering TOU and IL.

Γ	0	0.2	0.4
Total Cost(10^3 \$)	14264.4	14292.3	14299.1
Generation Cost(10^3 \$)	14184.3	14212.2	14219
Start-up Cost(10^3 \$)	6.3	6.3	6.3
Cost for IL(10^3 \$)	73.8	73.8	73.8
Wind Curtailment Cost(10^3 \$)	0	0	0
Cost for EV(10^3 \$)	0	0	0

5. Conclusion

The increasing scale of wind power and EVs connected to the power grid bring more uncertainty to the power system and increase the operating cost of the power system. In order to reduce the impact of wind power and EVs, DR is introduced into the power system with wind power and EVs. A day-ahead stochastic robust dispatch model of EV and wind power system considering DR is established in this paper. Through the example analysis of IEEE RTS-96 system, it can be concluded that robust optimization results are affected by robust coefficients. When the robust coefficient increases, the difference between the actual value and the predicted value becomes larger and the system becomes more conservative which may cause the rise of the operating cost of the power system.

According to the simulation results from Case 1 to Case 4 it can be seen that the introduction of DR can smooth the load curve and reduce the operating cost of the system. TOU can guide users to change their power consumption mode. IL which is more flexible can reduce the output of conventional unit during peak hour and increase system reserve.

With the increase of the scale of grid connected EVs, as a demand side resource, EV can provide auxiliary services for peak shaving and frequency regulation. The introduction of EV into demand response, under the premise of considering user economy, can reasonably guide users to change their mode of using EV which will be our next research direction.

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