Based on regional integrated energy automatic demand response optimization scheduling of electric vehicle

Fangsheng Wang¹, Tao Zheng¹, Bowen Sun¹, Jianwei Gao² and Yu Yang²,³

¹ East Inner Mongolia Electric Power Company Limited, Hohhot 010010, Inner Mongolia, China;
² School of Economics and Management, North China Electric Power University,
Changping, Beijing, 102206
³ Email: yang_yang_yu_yu@163.com

Abstract. Regional integrated energy system research is the current trend of energy development. Electric vehicle is an important part of the integrated energy system. Electric vehicle can realize the optimal allocation of energy by participating in automatic demand response (ADR). Therefore, this paper proposes based on regional integrated energy automatic demand response optimization scheduling of electric vehicle with based on the conditional value at risk with the utility function (UCVaR-based) electric vehicle response intention decision model under integrated energy system. Primarily, given both the electric vehicle's advantage and the network load fluctuation, a based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model is proposed. The price-based DR stage aims to minimize the charge/discharge cost. Minimizing the gap at the incentive-based demand response stage between the peak and valley load. Then, to quantify the risk attitude of an EV group, the UCVaR-based EV owner response willingness decision model is adopted. Specifically, prospect theory is used to calculate the utility value of electric vehicle owners. Finally, to check the feasibility of the proposed process, a case study is given. Results show that compared to the price-based demand response model, the model, which is proposed in this paper, decreased the average charging expense of electric vehicles by 49 percent and raised the gain by 19 percent.

1. Introduction
Coordination between electric vehicles and the energy grid is gaining interest as a decarbonization tool and ancillary service provider [1]. A transition from traditional petrol cars to electric Mobility is A direction to reduce carbon emissions, realize energy conversion and increase the use of renewable energy [2]. Literature [3] shows through practical cases the effects of the gradual penetration of electric vehicles into the fleet of private cars and hydrogen trucks into light-duty vehicles. None of these papers has built the optimization model of EV participating dispatching.

[4] Presents an economic optimization algorithm for a laboratory microgrid. A hybrid storage system consisting of a battery bank and a hydrogen storage system is integrated into the microgrid and has a connection to the external electrical network and an EV charging station. EV participates in the scheduling optimization of micro intelligent network with EV charging stations. However, this paper does not propose a targeted optimization scheduling strategy for electric vehicles.

To achieve mutual benefits for EV owners and power providers, the energy exchange between a large fleet of EVs and the power grid is controlled by vehicle-to-grid technology. This paper provides...
an efficient vehicle-to-grid scheduling to minimize the variance of power grid load variance using the genetic algorithm [5]. On this basis, [6] a centralized smart charge/discharge scheduling algorithm is presented in order to optimize the charge/discharge of PEVs with the goal of achieving peak shaving and valley filling of the grid load profile subject to different power grid and PEV constraints. Using a method of particle swarm optimization (PSO), the solution to the optimization problem is realized. In [7], a new issue is proposed to research the complex economic/mission dispatch, including PEVs for peak shaving and valley filling, and to examine the impact on DEED induced by various vehicle-to-grid (V2G) and grid-to-vehicle (G2V) loads. The above optimization algorithms are complex and not easy to calculate. In [8], a load-based mechanism for ES is proposed to facilitate peak shaving, complex model construction and calculation are avoided.

None of the above literatures considers the participation willingness of EV owners. Literature [9] considered the satisfaction of EV owners, and this paper proposed Novel charging model for EV. The model deals with the following aspects, including optimal power flow (OPF), EV statistical attributes, the degree of satisfaction of EV owners (DoS), and the cost of the power grid. However, the paper did not conduct an in-depth study on the participation intention of electric vehicles. In [10] the GGluEvAr theory is applied to build a GGluevar-based consumer decision willingness model, which can be used to measure the participation willingness of an EV group. These two references only consider the willingness of consumers to participate driven by income value, but fail to consider the utility value and bounded rationality of consumers. Literature [11] used the value function of prospect theory to calculate the benefit utility of wind turbine. In this paper, UCVaR theory [12] is used in this paper to measure the willingness of electric vehicles to take part in. The utility value in UCVaR is calculated by using the utility function of prospect theory, and the limited rationality of electric vehicles is considered as well as the different risk preferences of electric vehicles.

The paper that remains is structured as follows. The model system and the relevant data structure which electric vehicles need is specified in Section II to provide when entering the network. The based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model, is introduced in Section III. Section IV suggests a technique of electric vehicle willingness decision based on the principle of UCVaR and prospect theory. This technique will choose electric vehicles who are able to engage in optimization while other owners of electric vehicles are involved in charging disorders. The charging/discharging phase of each vehicle will be optimized, after via the above model to achieve optimal impact. To verify the feasibility of the proposed process, Section V offers a case study. Section VI includes the concluding remarks.

2. Modeling
As the electric vehicle is linked to the grid, it will provide the network system operator with details about the electric vehicles. The electric vehicle will then enter into the two-stage automatic optimization of demand response after the operation.

The first phase optimization adopts a charging/discharging strategy for electric vehicles, which minimizes the cost of electric vehicle charging/discharging. The minimum charging/discharging cost of a single electric vehicle is taken as the objective feature in the first phase optimization model, and the normal driving habits of electric vehicles are needless to modify.

The optimization of the second phase is incentive-based. As the objective feature, the total load variance for the electric vehicle fleet needs to be reduced and the charging needs of each EV owner must be met without impacting their daily driving habits. Meanwhile the model requires that there is no rise in the charging expense borne by the owner of the EV. Thus, after the second stage of optimization, the reward helps EV owners to offset the rise in charge and discharge costs.

The willingness decision method of the UCVaR EV owner considers EV's benefit as the selected condition to choose owners of EVs who are willing to engage in optimization. Because the risk attitude of owners of EVs is distinct, this paper adopts the value function of prospect theory and UCVaR theory, which is used to calculate the ability of EV owners to engage in two-stage automatic optimization of demand response. The average degree of load and cumulative cost of charge and
discharge of the EV category was analyzed over a period of time. The basic model structure and composition will be presented in this article below.

In this article, the continuous time is split into $J$ periods in which the duration of each period is $\Delta t$, the overall duration of the scheduling time of the study is $T$ then:

$$ J \times \Delta t = T $$

(1)

The network system operator must obtain the appropriate parameters for each EV when the observed vehicle fleet is linked to the network. The EV’s related parameters are assumed as follows:

$$ \mathbf{V}_l = \{T_{m,j}, T_{o,j}, S_{e,j}, Q_l, P_{c,j}, P_{d,j}\} $$

(2)

Where, $T_{m,j}$ is initial time of EV $l$ to connect to the grid; $T_{o,j}$ is the expected leave time of EV from grid; $S_{e,j}$ is the initial state of charge (SOC) of the EV’s power battery; $S_{e,j}$ is the expected SOC for the EV $l$ when leaving the network; $Q_l$ is EV $l$ ‘s the battery capacity; $P_{c,j}$ and $P_{d,j}$ are the rated charging/discharging power for the EV $l$ respectively.

3. The optimization model

3.1. Optimization of the first stage: price-based response model for demand

On the basis of satisfying the travel needs of EV owners, the price-based demand response minimizes the consumption of EV owners through the charging/discharging strategy.

One of the key steps to adjust the load and optimize the mode of electricity use in demand-side management is the Time-of-Use. The aim of the first stage is to minimize charging/discharging costs for EVs. Meanwhile the charging needs of the EV should be met.

3.1.1. Objective function

The objective function that determines the price-based demand response optimization, and $C_{l}$ is the relevant charge and discharge cost; $e_{l}$ is the battery loss cost of EV $l$; $I_{l}$ represents the charging or discharging state of EV $l$; $\rho(k)$ represents the electricity prices at the time $k$; $I_{l}$ is an indicator function, $I_{0} = 1$, $I_{-1} = -1$ indicates charging and discharging respectively, $I_{0} = 0$ indicates idle; $\omega_{l}$ is the maneuverability of the vehicle battery.

$$ C_{l} = \sum_{k} \sum_{l} \left[ P_{c,j}(k) + P_{d,j}(k) \right] \cdot I_{l}(k) \cdot \rho(k) \cdot \Delta t + \sum_{k} e_{l} $$

(3)

$$ I_{l}(k) = \omega_{l}(k)I_{0} $$

(4)

$$ I_{0} \in \{+1, -1, 0\} $$

(5)

$$ \omega_{l}(k) = \begin{cases} 1, & k \in T_{m,l} \\ 0, & \text{otherwise} \end{cases} $$

(6)

Where, $k \in T_{m,l}$ means that the vehicle $l$ is connected to the power network. $T_{m,l}$ is the time frame when EV $l$ connect to the grid; $u_{l}$ is the EV $l$ optimization strategy of the price-based demand response optimization.

$$ e_{l} = [P_{c,j}(k) + P_{d,j}(k)] \cdot I_{l}(k) \cdot \varepsilon $$

(7)

where $\varepsilon$ means the battery loss factor; $P_{c,j}(k)$ and $P_{d,j}(k)$ are the rated charging/discharging power for the EV $l$ during the time period $k$ respectively.

3.1.2. Constraints

Since overcharging and discharging will shorten the service time of the EV battery, as shown in equation (8)-(10) below, it is important to limit the battery's charge/discharging state:

$$ S_{l}(k) = S_{l}(k-1) + \left[ P_{c,j}(k) \xi_{c,j} + P_{d,j}(k) / \xi_{d,j} \right] I_{l}(k) \Delta t / Q_l $$

(8)

$$ P_{c,j}(k)P_{d,j}(k) = 0 $$

(9)

$$ S_{min} \leq S_{l}(k) \leq S_{max} $$

(10)
where $S_i(k)$ is the SOC of the vehicle $l$ that can be scheduled during the period $k$; $\xi$ and $\bar{\xi}$ are the charging/discharging efficiency of the EV battery respectively; $S_{\min}$ is the minimum of the allowable SOC; $S_{\max}$ is the maximum allowable SOC.

$$S_{0,i} + \sum_{k=S_{0,i}}^\infty \Delta t \left[ \frac{P_{c,i}(k)\xi + P_{d,i}(k) / \bar{\xi}}{Q_i} \right] \geq S_{E,i}$$

(11)

where, $S_{0,i}$ is the initial SOC of the EV power battery; $S_{E,i}$ is the expected SOC of the EV $l$ when it is off the network, $0 \leq S_{0,i} \leq 1$, $0 \leq S_{E,i} \leq 1$.

$$T_{pe,i} > T_{e,i}, \quad l = 1, 2, ..., n$$

(12)

$$T_{e,i} = (S_{E,i} - S_{0,i})Q_i / P_{c,i}\bar{\xi}$$

(13)

where $T_{e,i}$ is the charging time required for EV $l$ to meet travel needs; $n$ is the EVs number.

The model above represents that EV may take part in the automatic demand response process only if the period of access to the power grid by the EV is longer than the shortest time needed for charging to the planned amount. If not, it will be in a disordered charging state.

3.2. Optimization of the second stage: incentive-based response model for demand

While the first stage model will reduce the cost of charging EVs, EVs would still tend to charge during the valley time and discharge during the peak period. It will also pose new challenges to the capability of the transformer and the stable operation of the network. To solve the problem, the second stage proposes an incentive-based demand response model. The goal of the second phase is to minimize the difference between the load of the peak and the valley.

The incentive model of the response to demand based on simulation is shown as follows:

$$D_{u'}(l) = K_1 Q_{u'}(l) + K_2 Q_{u'}(l)$$

(14)

where, $u'$ is the second-stage optimization strategy; $D_{u'}(l)$ represents the incentive compensation cost under the charging/discharging strategy $u'$; $Q_{u'}(l)$ is the load transfer generated by the EV $l$ under the strategy $u'$; $K_1$ and $K_2$ are the coefficient incentive-based demand response incentive.

The subject of the second stage optimization model is to monitor the load fluctuation of the network based on guaranteeing the benefit of EVs for charging/discharging.

3.2.1. Objective function

The optimization target of the second stage as follows:

$$\min V = Var(L_{c'}(k)), k = 1, 2, ..., J$$

(15)

where $Var(*)$ means variance of load; $V$ represents the load fluctuation of the EV fleet; $L_{c'}(k)$ is the load at $k$ period under the strategy $u'$ of the EV fleet. The formula (15) aims to minimum the load fluctuation of the EV fleet to reduce the impact on the distribution network.

3.2.2. Constraints

The benefit from the EV in the second stage model should be no less than the profit from the EV in the first stage model. The EV benefit restriction of the EV $l$ is as follows in the second stage model.

$$D_{u'}(l) - \Delta D_i \geq 0$$

(16)

Under the second stage strategy $u'$, the incentive compensation cost reflects the $D_{u'}(l)$; $\Delta D_i$ represents the cost increase of the second stage optimization strategy $u'$ compared with the first stage $u_{i,j}$.

$$S_{0,i} + \sum_{k=S_{0,i}}^\infty \Delta t \left[ \frac{P_{c,i}(k)\xi + P_{d,i}(k) / \bar{\xi}}{Q_i} \right] \geq S_{E,i}$$

(17)
where, \( 0 \leq S_{0,j} \leq 1, 0 \leq S_{E,j} \leq 1 \); Under the strategy \( u' \) of the second optimization process, the real charging/discharging state of the EV \( l \) is the \( I_{x',j}(k) \).

4. Consumer willingness decision model

4.1. UCVaR

Human activity is one factor affecting the responsivity of the EV owner. Psychological variables such as personality and risk preference may affect the conduct of EV owners engaged in DR. The EVs have a complex risk response[13]. The basic method of risk assessment can therefore not accurately calculate the complex risk preferences of owners of EVs. This paper puts forward an EV owner's willingness decision model based on the UCVaR to solve this problem. This paper proposes the application of the prospect theory value function based on the utility function curve improvement to distinguish the risk attitude of EV owners while considering their imperfect decision-making rationality. Then, the conditional value at risk with the utility function(UCVaR), which takes into account the risk preferences of EV owners, is calculated. The following content describes UCVaR in detail.

**Definition 1**: UVaR refers to the maximum potential loss of investors' risk preference in a certain investment portfolio within a certain holding period under a given confidence degree \( \gamma \). Usually expressed as the following formula [12]:

\[
U\text{VaR}(x) = \min \{ U\text{VaR} \in R : \Pr(U(f(x,y)) > U\text{VaR}) < 1 - \gamma \} \tag{18}
\]

**Definition 2**: UCVaR refers to the average loss when the potential decline of an investment portfolio is higher than the VaR value at a given confidence level under the condition of considering investors' risk preference under a given confidence level \( \gamma \). Usually expressed as the following formula [12]:

\[
U\text{CVaR}(x) = \frac{1}{1-\gamma} \int_{U(f(x,y))U\text{VaR}} U(f(x,y)) \rho(y) dy \tag{19}
\]

Where, \( f(x,y) \) is loss function; \( U[f(x,y)] \) means the utility value of the loss to the investor; \( x \) is a certain portfolio of assets; \( y \) stands for uncertainty that may arise due to market changes; \( \rho(y) \) is a probability density function of \( y \).

Kahneman and Tversky proposed the value function of prospect theory to characterize the psychological influence [14]:

\[
v(\Delta x) = \begin{cases} 
(\Delta x)^{\beta}, & \Delta x \geq 0 \\
-\theta(\Delta x)^{\alpha}, & \Delta x < 0 
\end{cases} \tag{20}
\]

Where \( \Delta x \) is the change of the decision scheme relative to the reference point; if \( \Delta x \) is positive, it means gain, and if \( \Delta x \) is negative, it means loss. \( \beta \) and \( \alpha \) are risk attitude coefficient, \( 0 < \alpha, \beta < 1 \); the greater the value of \( \beta \) and \( \alpha \), the greater the risk of decision makers, when \( \alpha = \beta =1 \), the decision maker maintains a neutral attitude towards risk; \( \theta \) is loss avoidance coefficient, \( \theta >1 \) indicates that decision makers are more sensitive to changes in loss gains.

4.2. Value function of prospect theory

The value function has a feature where the utility curve is concave for relative benefit, and the attitude of the consumer towards such gains is risk-averse. If the relative loss curve is convex, their response to such loss is risk-seeking (Figure 1).
4.3. UCVaR-based EV owner willingness decision model

The final result of the scheduling execution is influenced by the response willingness of EV owners to engage in two-stage automated demand response optimization scheduling. Pursuant to the relation reference, EVs in an area can on objective or subjective grounds, present different risk preferences. To better assess the complex risk priorities of the area's EV owners and the effect on the intention to participate. In this paper, according to the different risk preferences of EV owners, the utility function of prospect theory is applied to calculate the psychological utility value of EV owners. After that, put the utility value into the UCVaR function and build UCVaR-based willingness decision model, shown as Figure 2.

The UCVaR-based EV owner willingness decision model is depicted in the following figure.

The actual benefit of EVs taking part in the automatic response to demand is described as bellow:

$$\pi(l) = D_u(l) + f_{0,l} - C_{2,l}$$  \hspace{1cm} (21)

where, $$\pi(l)$$ is the actual profit of the vehicle $$l$$ when it participates in the two-stage automated demand response optimization scheduling; $$C_{2,l}$$ is the actual charging/discharge cost of the EV $$l$$ when he takes part in the ADR; $$f_{0,l}$$ is the disorderly charge cost of EV $$l$$.

The utility value of the value function based on the prospect theory of EV owners is:

$$v(\pi(l)) = \begin{cases} (\pi(l))^\alpha, & \Delta x \geq 0 \\ -\theta(-\pi(l))^\beta, & \Delta x < 0 \end{cases}$$  \hspace{1cm} (22)

Among them, the parameters of the value function are different according to different risk preference attributes of electric vehicles. According to literature [13], EV owners are divided into two categories: conservative and adventurous.

UVar measurement and UCVaR measurement for EV owners are shown below:

$$U_{\text{UVar}}(l) = \min \{U_{\text{Ref}} : \Pr(v(\pi(l)) > U_{\text{Ref}}) < 1 - \gamma\}$$  \hspace{1cm} (23)

$$U_{\text{UCVar}}(l) = \frac{1}{1 - \gamma} \int_{v(\pi(l)) < U_{\text{Ref}}(l)} v(\pi(l)) \rho(y) dy$$  \hspace{1cm} (24)

$$U_{\text{UCVar}}(l)$$ measurement criterion for electric vehicles' various risk attitudes and response intentions in the field.

$$\pi(l) \geq U_{\text{UCVar}}(l)$$  \hspace{1cm} (25)

For each EV, The electric vehicle is considered to be able to respond to the project, if the benefit meets the equation (32). If the conditions is not met, it will reach the disorderly charging point.

The two-stage optimization model's flow chart is shown in Figure 3.
5. Case

5.1. Case parameter

300 electric vehicles were selected for an empirical study of based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model based on the regular load of the IEEE-RTS79 system in the field.

As shown in Table 1, there are 300 electric vehicles in the area. Three types of EV batteries shown as [15], in this paper, which are highly representative of the market place, are chosen as illustrative examples to estimate the impact of the battery charging load on the load profile of the device.

As shown in Table 2, according to reference [13], the risk attitudes of electric vehicles can be inferred. The data in comparison depicts the risk attitude of electric vehicles, collected in Beijing, China. This paper divides electric vehicles based on their varying risk behaviors into two groups.

Table 1. Types of EV batteries

| Classification | Proportion (%) | Battery capacity (kwh) | Power (kW) |
|----------------|----------------|------------------------|------------|
| 1              | 40             | 24                     | 3.3        |
| 2              | 40             | 30                     | 4          |
| 3              | 20             | 53                     | 7          |

Table 2. The risk attitude

| Classification | Risk seeking | Risk averse |
|----------------|--------------|-------------|
| proportion     | 70%          | 30%         |

Among the utility value of the value function based on the prospect theory of EV owners; when EV owners are at risk seeking: $\alpha = \beta = 0.88$, $\theta = 2.25$; when EV owners are at risk averse: $\alpha = \beta = 1.21$, $\theta = 2.25$ [16]; in $U_{CVaR}(l)$ , $\gamma=0.9$. 
Charging initial time and daily mileage are based on the travel patterns and driving characteristics of the EV fleet. The probability density function of the electric vehicle access time can be obtained on the basis of the data given by reference[7] as follows, if the charging time is assumed to be the return time of the last trip:

\[
f_{i}(x) = \begin{cases} 
\frac{1}{\sigma_{i}\sqrt{2\pi}} \exp\left[-\frac{(x-\mu_{i})^{2}}{2\sigma_{i}^{2}}\right], & (\mu_{i}-12) < x \leq 24 \\
\frac{1}{\sigma_{i}\sqrt{2\pi}} \exp\left[-\frac{(x+24-\mu_{i})^{2}}{2\sigma_{i}^{2}}\right], & 0 < x \leq (\mu_{i}-12)
\end{cases}
\]

where \( \mu_{i} = 17.6 \), \( \sigma_{i} = 3.4 \). The initial SOC of an EV is simulated according to the vehicle's daily mileage and battery capacity. A vehicle's daily mileage obeys the logarithmic normal distribution, which probability density function is:

\[
f_{m} = \frac{1}{x\sigma_{m}\sqrt{2\pi}} \exp\left[-\frac{(\ln x-\mu_{m})^{2}}{2\sigma_{m}^{2}}\right]
\]

where \( \mu_{m} = 3.2 \), \( \sigma_{m} = 0.88 \). The Monte Carlo simulation system is used electric vehicles with the time of entry and daily travel distance to simulate the entry time of EV fleet.

The amount of time measured is 48 hours in this case. In Figure 4, the price of electricity is shown. When the electric vehicle connects to the network, the anticipated SOC is complete. The minimum SOC value is set as 0.1 during the charging/discharging cycle of the electric vehicle, and the electric vehicle's charging/discharging power is 0.92.7 yuan/(kW•h) and 630 yuan/(kW•h), respectively.

5.2. Case result analysis

5.2.1. Scene description Three scenarios are set for comparison with the calculation results of the based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model. The comparison shows that there is an important, optimistic and detailed effect on this model.

The first scenario is that all the electric vehicles take part in disorderly charge. When the electric vehicle is linked to the grid, it will be charged immediately and disrupted when the electric vehicle, with the exception of the SOC, reaches its destination. At the same time the discharge is not carried out by the electric vehicle.

The second scenario is that electric vehicles would be split into two groups, in accordance with the UCVaR-based decision model of willingness. In the first stage: price-based demand response part, electric vehicles whose benefit matches the formula (32) will participate, which means that electric vehicles will only participate in the first stage of the based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model. The rest will participate in a disorderly charge.
The third scenario is that the electric vehicles would also be divided into two groups, in accordance with the UCVaR-based readiness decision model. In the base on regional integrated energy automatic demand response optimization scheduling of electric vehicle model, electric vehicles whose benefit meets the formula (32) will participate. The rest will participate in a disorderly charge. The following outcomes can be achieved according to the estimate.

5.2.2. Two days load The load of the electric vehicle community in three separate scenarios and the baseload of the IEEE-RTS79 device over two days, reduced to 1/1000 of the original, are shown in Figure 5. This article pursues that electric vehicles linked to the grid can have as little effect as possible on the distribution network's original base load. Based on this reason, we seek to minimize the total load of the distribution network after the grid-connected electric vehicles minus the original base load of the distribution network when evaluating two days of load according to formula (15). As follow:

$$\min V = Var(L(k)) = \begin{cases} Var(ADR Load(k) - Basis Load(k)) \\ Var(First Stage Load(k) - Basis Load(k)) \end{cases}, k = 1, 2, ..., J \quad (28)$$

In the first scenario, as can be seen from figure 5, all electric vehicles involved in the disorderly charge contribute to the highest load peak and the most prominent load fluctuation in the network, seriously impacting the network's safe and stable service.

In the second scenario, some electric vehicles choose to engage in an optimization model of price-based demand response, and others participate in a disorderly fee. As in Figure 5, as shown. The load profile of the second scenario is lower at peak time than that of the first scenario and is higher at valley time than that of all other scenarios. This phenomenon of peak-valley inversion would also seriously impact the network's safety and reliability.

In the third scenario is the based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model. The profile of its peak load is lower than that of disorderly charging. The load profile of the valley is higher than that of disorderly charging, but lower than that of the second example. The load profile is comparatively smooth, and there is no phenomenon of peak and valley inversion. It means that the based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model, which is proposed in this article, will greatly reduce the effect of electric vehicles that are simultaneously connected to the network, and the electricity consumption patterns and demand of the electric vehicles remain unchanged.

The optimized standard deviation of electric vehicles load charging/discharging in the model area is 74.67 kW, as shown in Table 3, and the optimized standard deviation of electric vehicles load charging/discharging in the first stage of the optimization model is 144.43 kW, which is far higher than that of the model. The model can also reduce the effect of the electric which connect to grid on the area's networks.

| Two days load | (first stage-basis )load | (ADR-basis )load |
|---------------|-------------------------|-----------------|
| Average(kW)   | 56.26041667             | 56.26041667     |
| variance(kW^2)| 21163.7901              | 5967.818613     |
| standard deviation(kW) | 145.4777993 | 77.25165767 |

5.2.3. Electric vehicle average cost Figure 6 indicates the real cost of charge/discharge in three different scenarios for each electric vehicles. Divide the three hundred electric vehicles into 10 groups, or thirty groups in all. Calculate each group's average expense.

In the first scenario, both electric vehicles are involved in disorder charging activities. As Figure 6 shows, the cost of electric vehicles' charging/discharging is higher than any other scenarios.
In the second scenario, the cost of charging/discharging shows a large trend that is decreasing. The cost curve of the second scenario is smaller than that of disorderly charging, but is still greater than that of the third scenario.

In the third scenario, the cost profile for charging/discharging is lower than in any other scenarios. Since the optimization of the incentive-based demand response gives electric vehicles plenty of space to compensate for load transfer, compared to the price-based demand response scenario, the second scenario, this can offset the loss of the electric vehicles caused by load transfer.

![Figure 6](image1.png)

![Figure 7](image2.png)

**Table 4.** Average cost.

| Vehicle number/average cost | First: disorderly charging cost (yuan/unit) | Second: first stage cost (yuan/unit) | Third: ADR cost (yuan/unit) |
|-----------------------------|---------------------------------------------|--------------------------------------|----------------------------|
| 1 to 75                     | 12.36786                                    | 7.553304                             | 6.773334                   |
| 76 to 150                   | 12.2552                                     | 7.068805                             | 5.94783                    |
| 151 to 225                  | 12.4414                                     | 7.334688                             | 6.246544                   |
| 226 to 300                  | 20.52934                                    | 11.98694                             | 10.3924                    |
| Total average cost          | 14.3984                                     | 8.48594                              | 7.34003                    |

In disorderly charging, which is the first scenario, electric vehicles have the highest average cost, as shown in Table 4. In the second scenario, the overall average cost for electric vehicles is reduced to 5,91246(yuan/unit) from 14,3984(yuan/unit) in the first scenario. Electric vehicles have the lowest overall average cost of 7,34003 (yuan/unit) in the third scenario, that is the model proposed in this article. The third scenario addresses the evolving needs of electric vehicles at the same time and preserves the benefit of electric vehicles.

**5.2.4. Electric vehicle average profit** In the second and third cases, Figure 7 shows the benefit from charging/discharging of each EV owner. Divide the three hundred electric vehicles into 10 groups, or thirty groups in all. Calculate each group's average benefit. The advantage is that the cost of the fee is saved compared to the unordered charge. The lower the cost of the fee, the higher the gain. As shown in Figure 7, in the third scenario, for every electric vehicle, the electric vehicle’s profit is always higher than the profit in the second scenario. Meanwhile, for the second and third scenarios, the
benefit of EV owners is always positive, implying that in these two scenarios the charging/discharging cost of EV is always lower than in the first scenario. Table 5 indicates the average benefit for an electric vehicle.

Table 5. Electric vehicle average profit.

| Vehicle number/ average profit | Second: the first stage(yuan/unit) | Third: ADR(yuan/unit) |
|--------------------------------|------------------------------------|-----------------------|
| 1 to 75                        | 4.814559                           | 5.59453               |
| 76 to 150                      | 5.186392                           | 6.307367              |
| 151 to 225                     | 5.106709                           | 6.194853              |
| 226 to 300                     | 8.542397                           | 10.13694              |
| total average profit           | 5.91251                            | 7.05842               |

To conclude, it can smooth the load curve of the power load, decrease the peak and valley difference load, and decrease the charging/discharging costs of electric vehicles by encouraging electric vehicles to participate in the based on regional integrated energy automatic demand response optimization scheduling.

6. Conclusions

This article provided a based on regional integrated energy automatic demand response optimization scheduling of electric vehicle with consider a decision model of UCVaR-based EV owner willingness. At first section, the EV ADR optimization model have two stage: first stage is price-based demand response, which regards the minimization of charge/discharge costs of EVs as the optimization target; the second stage is incentive-based demand response, the optimization of the charging/discharging strategy is designed to minimize the load fluctuation of the EV community on the assumption that the interests of EV owners are guaranteed. Maximizing EV owner benefit and stabilizing load fluctuation can be achieved after the EV ADR optimization model. In addition, as a decision model to calculate the response willingness of EV owners, this paper innovatively introduced the conditional value at risk with the utility function (UCVaR) model.

Case study shows that UCVaR-based involvement of EVs in ADR for a two-stage scheduling model will reduce the effect of charging of the EVs on the load profile of the proposed region compared to the price-based demand response. For electric vehicles, the model will lower the average cost and increase the profit of electric vehicles. The proposed based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model, as seen in the case study, decreased the average electric vehicle charging cost by 49 percent and increased the profit resulting from DR by 19 percent compared to the price-based demand response.

The case study therefore shows that the based on regional integrated energy automatic demand response optimization scheduling of electric vehicle model can guide the charging of electric vehicles, decrease the charging/discharging costs of electric vehicles, and optimize the power system load profile.

Acknowledgments

This work was supported in part by Beijing Natural Science Foundation under Grant No. 9202017.

References

[1] Solanke TU, Ramachandaramurthy VK, Yong JY, Pasupuleti J, Kasinathan P, Rajagopalan A 2020 A review of strategic charging--discharging control of grid-connected electric vehicles J Energy Storage 28

[2] Giulio Vialetto, Marco Noro, Masoud Rokni 2015 Thermodynamic Investigation of a Shared Cogeneration System with Electrical Cars for Northern Europe Climate[J] Journal of Sustainable Development of Energy, Water and Environment Systems 5(4) 590-607

[3] Belloccchi S, Guidi G, Iulio R D, et al. 2020 Analysis of smart energy system approach in local alpine regions - A case study in Northern Italy[J] Energy 117748
[4] Mendes PRC, Isorna LV, Bordons C, Normey-Rico JE 2016 Energy management of an experimental microgrid coupled to a V2G system J Power Sources 327 702-713
[5] Tan KM, Ramachandaramurthy VK, Yong JY, Padmanabhan S, Mihet-Popa L, Blaabjerg F 2017 Minimization of load variance in power grids-investigation on optimal vehicle-to-grid scheduling Energies 10 1-21
[6] Ramadan H, Ali A, Nour M, Farkas C 2019 Smart Charging and Discharging of Plug-in Electric Vehicles for Peak Shaving and Valley Filling of the Grid Power 2018 20th Int Middle East Power Syst Conf MEPCON 2018 – Proc 735-739
[7] Liang H, Liu Y, Li F, Shen Y 2019 Dynamic Economic/Emission Dispatch Including PEVs for Peak Shaving and Valley Filling IEEE Trans Ind Electron 66 2880-2890
[8] Mao T, Xu Q, Zhou B, Zhang R, Wang J 2019 A Load-based Mechanism Supporting Peak Shaving for Energy Storage (ES): An Adaptive Method. ISPEC 2019 - 2019 IEEE Sustain Power Energy Conf Grid Mod Energy Revolution, Proc 1648-1652
[9] Yang J, He L, Fu S 2014 An improved PSO-based charging strategy of electric vehicles in electrical distribution grid Appl Energy 128 82-92.
[10] Gao Jianwei, Yang Yu, Ma Zeyang, Gao Fangjie 2020 GGlueVaR-based participation of electric vehicles in automatic demand response for two-stage scheduling[J] International Journal of Energy Research DOI: 10.1002/er.5846
[11] Gao Jianwei, Ma Zeyang, Guo Fengjia 2019 The influence of demand response on wind-integrated power system considering participation of the demand side[J] Energy 178 723-738
[12] Gao Jianwei, Lang Yutong, Gao Fangjie, Guo Guiyu, Liang Pengcheng 2020 Time Planning for Investment of Wind Farm Clusters According to Copula-UCVaR Risk Measurement[J] Electric Power Construction 41(8) 78-86
[13] L Pan, E J Yao and D MacKenzie 2019 Modeling EV charging choice considering risk attitudes and attribute non-attendance Transportation Research Part C-Emerging Technologies 102 60-72
[14] Xiao L, Mandayam NB, Poor HV 2015 Prospect Theoretic Analysis of Energy Exchange Among Microgrids IEEE T Smart Grid 6(1) 63-72
[15] K Qian, C Zhou, M Allan and Y Yuan 2011 Modeling of Load Demand Due to EV Battery Charging in Distribution Systems IEEE Transactions on Power Systems 26(2) 802-810
[16] Ma Jian, Sun Xiuxia 2011 Modified value function in prospect theory based on utility curve[J] Information and Control 40(4) 501-506