Decision Aid Model for Private-owned Electric Vehicles Participating in Frequency Regulation Ancillary Service Market

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***Abstract*—To reduce the difficulty and enhance the enthusiasm of private-owned electric vehicles (EVs) to participate in frequency regulation ancillary service market (FRASM), a decision aid model (DAM) is proposed. This paper presents three options for EV participating in FRASM, i. e., the base mode (BM), unidirectional charging mode (UCM), and bidirectional charging/discharging mode (BCDM), based on a reasonable simplification of users' participating willingness. In BM, individual EVs will not be involved in FRASM, and DAM will assist users to set the optimal charging schemes based on travel plans under the time-of-use (TOU) price. UCM and BCDM are two modes in which EVs can take part in FRASM. DAM can assist EV users to create their quotation plan, which includes hourly upper and lower reserve capabilities and regulation market mileage prices. In UCM and BCDM, the difference is that only the charging rate can be adjusted in the UCM, and the EVs in BCDM can not only charge but also discharge if necessary. DAM can estimate the expected revenue of all three modes, and EV users can make the final decision based on their preferences. Simulation results indicate that all the three modes of DAM can reduce the cost, while BCDM can get the maximum expected revenue.**

***Index Terms*—Electric vehicle (EV), frequency regulation, decision aid model (DAM), utility maximization, battery wear cost.**

NOMENCLATURE

A. Parameters and Variables

$\rho^{\min}$	The minimum performance score requirement
γ	Relative regulation capacity in hours
η	Battery charging/discharging efficiency
β	Coefficient of battery wear model
$\theta_{t,j}$	Clearing probability of $w_{t,j}^{\mathrm{M,rep}}$
μ_t^{sig}	Average value of historical frequency regulation signal in hour t
$\mu_t^{\mathrm{R}}, \mu_t^{\mathrm{M}}$	Average values of historical regulation market capability clearing price (RMCCP) and historical regulation market performance clearing price (RMPCP) in hour t
$C_t^{\mathrm{up}}, C_t^{\mathrm{dn}}$	Upper and lower reserve capacities in hour t (MW)
$C_{i,t}^{\mathrm{ch,exp}}$	Expected charging cost of mode i in hour t
$C_{i,t}^{\mathrm{age,exp}}$	Expected battery wear cost of mode i in hour t
$d_{t,j}, s_{t,j}$	Upper and lower boundaries of index j during isometric intervals
e_t^0	Battery energy at the start of hour t (MWh)
$e_{i,t}$	Battery energy of mode i in hour t (MWh)
E	Battery energy storage capacity (MWh)
$\overline{E}, \underline{E}$	Upper and lower energy limits for battery energy (MWh)
i	Index of regulation modes, $i=1,2,3$
j	Index of regulation market mileage quotation
k	Index of regulation signal interval
$M_{t,k}^{\mathrm{up}}, M_{t,k}^{\mathrm{dn}}$	Upper and lower mileages
N	Number of isometric intervals
$P^{\max}$	The maximum charging/discharging power
P_t^{base}	Base power in hour t (MW)
R	Battery cell replacement price (¥)
SoC^{start}	Initial state of charge (SoC)
SoC^{off}	Expected SoC by users
$sig_{t,k}^{\mathrm{up}}, sig_{t,k}^{\mathrm{dn}}$	Upper and lower frequency regulation signals
$sig_{t,k}^{\mathrm{up,his}}, sig_{t,k}^{\mathrm{dn,his}}$	Historical upper and lower frequency regulation signals in interval k of hour t
t	Index of time (hour)
$t^{\mathrm{start}}, t^{\mathrm{off}}$	On-grid and off-grid time of electric vehicle (EV)
Δt	Time scale of submission scheme (1 hour)
T	Total time spent online (hour), $T=t^{\mathrm{off}}-t^{\mathrm{start}}$
u_t	Battery cycle depth in hour t
u_t^*	Optimal battery cycle depth in hour t
$U_{i,m}^{\max,\exp}$, $U_{i,m+1}^{\max,\exp}$	The maximum expected revenue of mode i when iterating m and $m+1$ times

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w_t^{R} RMCCP in hour t (¥/MWh)
w_t^{M} RMPCP in hour t (¥/MWh)
w_t^{TOU} Time-of-use (TOU) price in hour t (¥/MWh)
$w_{t,j}^{M,rep}$ Mileage quotation of index j in hour t
$Y_{i,t}^{R,exp}$ Expected RMCCP credit of mode i in hour t
$Y_{i,t,j}^{M,exp}$ Expected RMPCP credit of mode i in hour t

B. Functions

$f(\cdot)$ Probability density function of RMPCP
$\phi(\cdot)$ Battery wear cost function
$\varphi(\cdot)$ Derivative of $\phi(\cdot)$

I. Introduction

THE large-scale integration of renewable energy brings more challenges in power system frequency regulation [1], and new regulation resources are urgently needed for the operation of a modern electricity network [2]. With the increase of the ownership of pure electric vehicles (EVs) and more advanced vehicle-to-grid (V2G) technology [3], [4], EVs can provide peak shaving and frequency regulation ancillary services [5], [6], supply reactive power compensation [7], improve the consumption capacity of renewable energy, and reduce power grid investment, operation, and maintenance costs [8], [9], which have broad applications. EV users can make an extra profit by providing frequency regulation services [10]-[13]. According to the performance-based regulation mechanism, [14] proposed a charging scheduling model for EVs to participate in the frequency regulation ancillary service market (FRASM), and a mixed-integer linear programming (MILP) model was established to guarantee economic revenue for users. Reference [15] proposed non-cooperative and cooperative game theoretic approaches to encourage EV users to provide frequency regulation ancillary services. It focused on the interaction of EVs and EV aggregators and it was more practical. Reference [16] proposed an EV aggregator model and an individual EV model. It used the state-space method to simplify EV aggregator model and reduced the communication requirement in the individual EV model. It could improve the efficiency of EV aggregators in managing multiple EVs. Reference [17] established an EV aggregator model to evaluate reserve capacity and implement optimal power control for EVs. Reference [18] proposed the frequency regulation policy for decentralized V2G, which not only considered the charging demands of EV users but also presented two kinds of participating patterns.

While the rapid and flexible response capacity makes EVs a good candidate to smooth frequency variations [10], frequent charging or discharging can lead to battery failure [19]. Reference [20] designed an operation and economic model based on reinforcement learning algorithm for battery swap stations, which could provide a high-quality solution to the economic analysis considering the battery degradation. Reference [21] proposed a grouping-converting strategy to avoid frequent charging and discharging. Based on ambient temperature, cycle index, current, and charging/discharging depth, [22] proposed a cycle life model of EV batteries. It was concluded that the frequency stability of the power grid could be improved when EVs and generator sets cooperated. According to the Australian National Electricity Market, [23] proposed a battery market operation model of EVs and established a battery wear cost estimator to maximize the revenue.

Private EV owners are more interested in the benefits of participating in FRASM and the additional battery degradation while following the frequency regulation signals. They may not react fully to respond to frequency regulation signals to obtain more revenue [24]. Therefore, there are two major problems for EVs to participate in FRASM. First, the quotation mechanism for expressing the users' preferences is not friendly to EV users. They are difficult to accomplish quotation independently. Second, the private EV owners should take into account the cost of the batteries. They lack the professional knowledge and skills to make a good estimate of possible revenue and cost.

This paper proposes a decision aid model (DAM), which can facilitate private EV owners to participate in FRASM. EV users' participating preferences are simplified to three options: ① not participating, i.e., base mode (BM); ② only charging, but the charging rate can be adjusted according to frequency regulation signals, i.e., unidirectional charging mode (UCM); ③ not only charging but also discharging if necessary, i.e., bidirectional charging/discharging mode (BCDM). An optimal charging scheme will be generated based on EV user's departure hour and state of charge (SoC) requirement for the next journey in all three modes. DAM will assist EV users to generate hourly upper and lower reserve capabilities and regulation market mileage prices for UCM and BCDM only. Battery wear cost is considered in both UCM and BCDM. DAM can estimate the expected revenue of all three modes, and EV users can make a final decision based on their preferences. By making a choice among different participating modes, they can easily participate in FRASM.

The main contributions of this paper are as follows.

1) DAM is proposed in this paper. By setting simple participating modes, the users' preferences are taken into account. It will facilitate the participation of private EV users in FRASM.

2) An optimal bidding method is proposed in this paper, which can achieve the maximum expected revenue based on historical information in each participating mode.

The rest of this paper is organized as follows. Section II describes the frame of FRASM with the participating process of EV. Section III introduces DAM with its construction. Section IV describes and discusses the simulation results. Section V concludes this paper.

II. Frame of FRASM

Based on mainstream domestic and international FRASMs [25]-[31], the basic process of EV participating in FRASM through providing secondary control is illustrated in Fig. 1.

On day-ahead quotation day (day $D-1$), the dispatching center firstly issues market-related information, including the lower and upper limits of regulation market mileage price, i.e., $w^{M,min}=6$ ¥/MWh, $w^{M,max}=15$ ¥/MWh, respectively. EV users will submit their hourly upper and lower reserve capacities and regulation market mileage price of the next day with the assistance of DAM. DAM will estimate the expected revenue of three participating modes for users to select, along with the corresponding submission schemes. The dispatching center converts the submitted regulation market mileage price into mileage ranking price, and the trading center completes the pre-clearing.

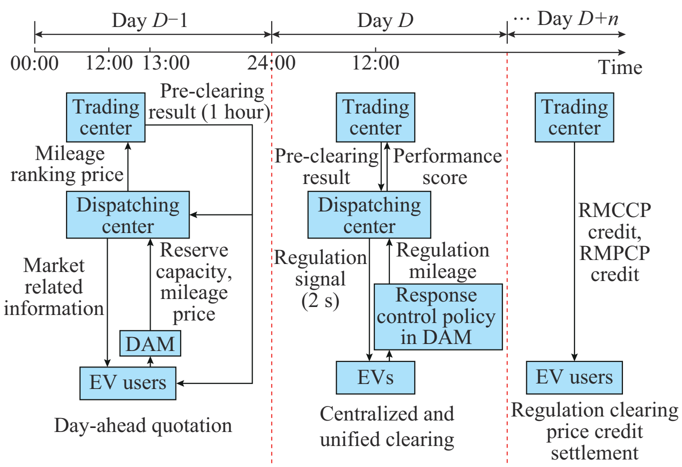

Fig. 1. Basic process of EV participating in FRASM.

On centralized and unified clearing day (day D), the dispatching center issues frequency regulation signals according to the pre-clearing result and frequency regulation requirement, where the resolution of the frequency regulation signal is 2 s. EVs adjust their power rates according to the received frequency regulation signals and the adopted response control policy in DAM. EVs do not always respond to 100% of the received frequency regulation signals, and the provided regulation mileage may be less than the required one.

On regulation clearing price credit settlement day (day $D+n$), the bid-winning EV users can get regulation market capability clearing price (RMCCP) credit and regulation market performance clearing price (RMPCP) credit based on clearing result and their performances. The RMCCP credit is calculated using RMCCP, which is determined by the trading center, and the formula is expressed as:

$$\sum_t w_t^{\mathrm{R}}(C_t^{\mathrm{up}}+C_t^{\mathrm{dn}}) \tag{1}$$

Each EV should perform well when providing frequency regulation ancillary services; otherwise, RMPCP credit will be reduced, or the eligibility of participating in FRASM will be lost. ρ_t is the performance score of EV in hour t, which is used to evaluate its performance. The calculation method is expressed as:

$$\rho_t=\frac{\sum_{k=1}^{\mathrm{K}}(M_{t,k}^{\mathrm{up}}+M_{t,k}^{\mathrm{dn}})}{C_t^{\mathrm{up}}\sum_{k=1}^{\mathrm{K}}\left|sig_{t,k}^{\mathrm{up}}\right|+C_t^{\mathrm{dn}}\sum_{k=1}^{K}\left|sig_{t,k}^{\mathrm{dn}}\right|} \tag{2}$$

For any EV, its RMPCP credit settlement formula is:

$$\sum_t\left[\frac{w_t^{\mathrm{M}}}{K}\rho_t\sum_{k=1}^{K}(M_{t,k}^{\mathrm{up}}+M_{t,k}^{\mathrm{dn}})\right] \tag{3}$$

where $sig_{t,k}^{\mathrm{up}}\in[-1,0]$, $sig_{t,k}^{\mathrm{dn}}\in[0,1]$, and they cannot be non-zero concurrently; $1\le k\le K$, and $K=1800$; and $\rho^{\min}\le\rho_t\le 1$ and FRASM generally uses $\rho^{\min}=0.7$.

III. DAM

A. DAM Framework

The structure of DAM is shown in Fig. 2. When EVs are connected to the grid, users are required to input their next departure time and the necessary SoC level of the battery.

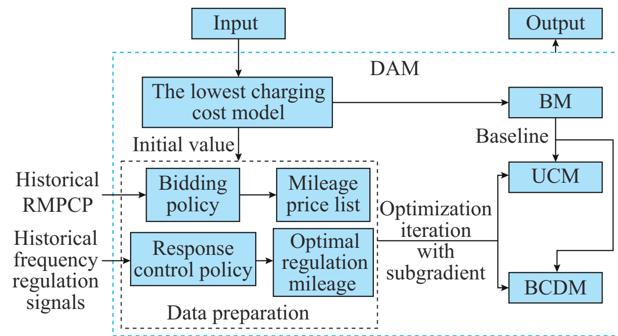

Fig. 2. Structure of DAM.

DAM firstly calculates base power with the lowest charging cost based on time-of-use (TOU) price and input. The base power is used as the charging scheme of BM, and also as the initial value of UCM and BCDM. Then, DAM calculates the submission schemes of UCM and BCDM. DAM determines regulation market mileage price list based on historical RMPCP and bidding policy, and estimates the optimal regulation mileage of EV based on historical frequency regulation signals and response control policy. The subgradient method is employed to iteratively optimize the base power over time until convergence is satisfied. Finally, DAM outputs the charging scheme of BM and the maximum expected revenues together with respective hourly upper and lower reserve capabilities and regulation market mileage prices of UCM and BCDM. DAM is applicable to all types of private EVs, and is located at the EV owner end.

B. Three Participating Modes

To make it easier for EV users to participate in FRASM, this paper simplifies three possible participating modes according to the electric energy flow direction and the preference of EV users.

1) BM

In this mode, EV will not respond to the frequency regulation signals from the dispatching center, and DAM will generate a charging scheme with the lowest cost based on TOU price and input. The charging scheme is represented by the base power of each hour $P_{1,t}^{\mathrm{base}}$, where “1” represents that the frequency regulation participating mode is BM. $P_{1,t}^{\mathrm{base}}$ will also be used as the initial values for the following modes, whose physical meaning is the baseline for power adjustment.

2) UCM

In this mode, EV will be partially involved in FRASM by modifying its charging power rate to respond to the upper and lower frequency regulation signals. DAM will generate a submission scheme with the maximum expected revenue based on the TOU price, input, and historical information of FRASM. The submission scheme will be obtained based on iterative optimization of the base power in BM.

3) BCDM

In this mode, EVs can provide a larger reserve capacity by discharging if necessary. DAM will produce a submission scheme of BCDM with the maximum expected revenue using the same approach and steps as UCM.

Table I lists the range of the upper and lower reserve capacities of a single EV in hour t in three modes.

TABLE I
RANGE OF UPPER AND LOWER RESERVE CAPACITIES OF A SINGLE EV IN HOUR t IN THREE MODES

Mode	Upper reserve capacity C_t^{up} (MW)	Lower reserve capacity C_t^{dn} (MW)
BM ($i=1$)	0	0
UCM ($i=2$)	$\min\left\{P_{i,t}^{base}, \dfrac{\overline{E}-e_{i,t}^0}{\gamma}\right\}$	$\min\left\{P^{max}-P_{i,t}^{base}, \dfrac{\overline{E}-e_{i,t}^0}{\gamma}\right\}$
BCDM ($i=3$)	$\min\left\{P^{max}+P_{i,t}^{base}, \dfrac{\overline{E}-\underline{E}}{\gamma}\right\}$	$\min\left\{P^{max}-P_{i,t}^{base}, \dfrac{\overline{E}-e_{i,t}^0}{\gamma}\right\}$

Note: when $\rho^{min}=0.7$, $\gamma=0.08$ [32].

C. Optimization Model

1) The Lowest Charging Cost Model

In BM, EVs do not participate in FRASM, and the objective function only includes the charging cost. Users expect to keep the cost of charging as low as possible, denoted as U_1^{min}. The expression is as follows and its decision variables are base power for T hours.

$$U_1^{min}=\min\sum_t w_t^{TOU}P_{1,t}^{base}\Delta t \tag{4}$$

To complete the next travel schedule, the base power should meet the charging demand constraint, which is shown as:

$$\sum_{t=t^{start}}^{t^{off}-1}\frac{P_{1,t}^{base}\eta\Delta t}{E}\geq SoC^{off}-SoC^{start} \tag{5}$$

The upper and lower limits of the base power are expressed as:

$$0\leq P_{1,t}^{base}\leq P^{max}\quad \forall t \tag{6}$$

The change constraint of the battery energy in BM is shown as:

$$e_{1,t}=e_{1,t-1}+P_{1,t}^{base}\eta\Delta t \tag{7}$$

where $e_{1,t^{start}}=SoC^{start}\cdot E$.

And the upper and lower limits of the battery energy storage are expressed as:

$$\overline{E}\leq e_{1,t}\leq \underline{E}\quad \forall t \tag{8}$$

The optimization formula of BM is expressed as:

$$\begin{cases}U_1^{min}=\min\sum_t w_t^{TOU}P_{1,t}^{base}\Delta t\\ \text{s.t. } (5)\text{-}(8)\end{cases} \tag{9}$$

Formula (9) is a constrained linear programming (LP) problem, which can be solved directly by Gurobi optimization software. Optimized $P_{1,t}^{base}$ for T hours will be the charging scheme of BM and also be used as the initial value of UCM and BCDM.

2) Data Preparation of UCM and BCDM

When calculating the expected revenue of EV participating in FRASM, we need to know the RMPCP, response costs, and the performance of participating period.

RMPCP can only be predicted, and whether the quotation can be cleared will depend on the actual situation of day D. DAM can only predict RMPCP of day D with historical data. So, we adopt the bidding policy to firstly split $[w^{M,min}, w^{M,max}]$ and estimate the clearing probability of each segment. All quotations and their clearing probabilities form the regulation market mileage price list.

The bidding policy considers that RMPCP of day D is subject to normal distribution. The historical RMPCP of the same period (PCP_t) is the mean value. The interval $[w^{M,min}, w^{M,max}]$ is divided into N isometric intervals, and N can be determined by the users. The geometric mean $w_{t,j}^{M,rep}$ of each interval is selected as the regulation market mileage quotation. The solution diagram of the regulation market mileage quotation is shown in Fig. 3 and the calculation is expressed as:

$$w_{t,j}^{M,rep}=f^{-1}\left(\frac{\int_{s_{t,j}}^{d_{t,j}}f(x)\mathrm{d}x}{d_{t,j}-s_{t,j}}\right) \tag{10}$$

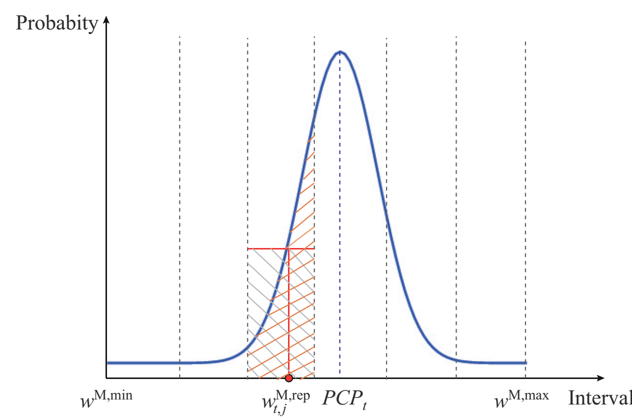

Fig.3. Solution diagram of regulation market mileage quotation.

Concurrently, the clearing probability $\theta_{t,j}$ of $w_{t,j}^{M,rep}$ is:

$$\theta_{t,j}=1-\frac{\int_{w^{M,min}}^{w_{t,j}^{M,rep}}f(x)\mathrm{d}x}{\int_{w^{M,min}}^{w^{M,max}}f(x)\mathrm{d}x} \tag{11}$$

where $f(x)=\dfrac{1}{\sqrt{2\pi}\,\sigma}\mathrm{e}^{-\frac{(x-PCP_t)^2}{2\sigma}}$, and $\sigma=\sqrt{\dfrac{w^{M,max}-w^{M,min}}{6}}$.

When calculating the expected revenue at a given price, the regulation clearing price credits (RMCCP credit and RMPCP credit), charging cost, and battery wear cost should be considered simultaneously. The full response is not always able to obtain the maximum expected revenue. When we know the regulation market mileage price list, we should also know the best mileage under each quotation. In this paper, the optimal mileage at every moment is determined by response control policy. $M_{i,t,k}^{\text{up}}$ and $M_{i,t,k}^{\text{dn}}$ at each regulation interval are described by base power $P_{i,t}^{\text{base}}$. The response control policy obtains the optimal battery cycle depth u^* by balancing the regulation clearing price credit and battery wear cost and limits the power adjustment range of the EV.

Frequent charging/discharging will accelerate the aging of EV battery, shorten its service life, and damage the profit of users. The battery wear cost of the EV is related to battery cycle depth u_t caused by frequent charging/discharging per hour. The deeper the cycle depth, the shorter the life, and the higher the cost of the battery [32]. In this paper, the cost of battery aging caused by the battery cycle depth is approximately expressed as (12) [33], which enables this electrochemically accurate model to be used in various battery optimization problems and guarantees the solution quality.

$$\sum_t ER\beta u_t^2 \tag{12}$$

where $R=¥21000$; and $\beta=0.097$.

According to [32], the regulation clearing price credit per hour is a linear incremental function of the battery cycle depth. According to (12), the battery wear cost is a non-linear incremental function of u_t. The distributions of u are shown in Fig. 4. The abscissa corresponding to the maximum difference between regulation clearing price credit and battery wear cost is u^*. When $u<u^*$, the difference increases with the increase of u; when $u>u^*$, the difference decreases with the increase of u. Therefore, when $u=u^*$, the difference is the largest.

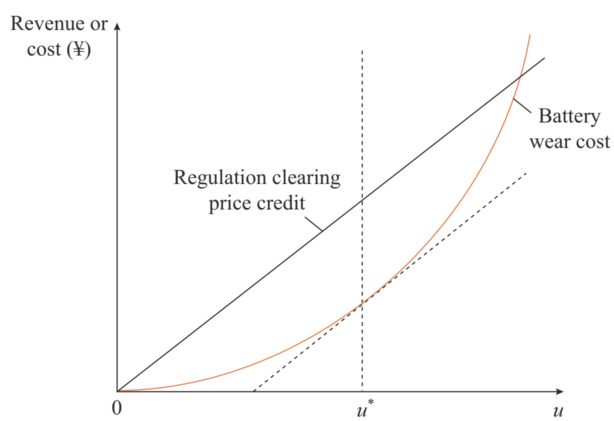

Fig. 4. Illustration of optimal cycle depth.

To determine the optimal mileage range of each regulation interval in hour t, u_t^* should be calculated. According to the geometrical relation in Fig. 4, when the tangent line of the curve is parallel to the line, the difference between the vertical coordinate of the line and the curve is the largest. Therefore, u_t^* is solved as:

$$u_t^*=\varphi^{-1}(\lambda_t) \tag{13}$$

$$\varphi(\mu_t^{\text{u}})=\frac{\mathrm{d}\phi(\mu_t^{\text{u}})}{\mathrm{d}\mu_t^{\text{u}}}=\lambda_t \tag{14}$$

where $\phi(\mu_t^{\text{u}})=\beta(\mu_t^{\text{u}})^2$; and $\lambda_t=\dfrac{\eta^2+1}{\eta R\Delta t}\dfrac{2\mu_t^{\text{R}}+\mu_t^{\text{M}}\mu_t^{\text{sig}}}{\mu_t^{\text{sig}}}$. Because the FRASM of day D is unknown, this problem is solved with historical data.

The upper and lower energy limits are enforced by the response control policy in interval k of hour t as:

$$\begin{cases} \overline{E}_{i,t,k}^{\text{g}}=\min\{\overline{E},\min\{e_{i,t,k-1}^{\min},e_{i,t,k}\}+u_t^*E/K\} \\ \underline{E}_{i,t,k}^{\text{g}}=\min\{\underline{E},\max\{e_{i,t,k-1}^{\max},e_{i,t,k}\}-u_t^*E/K\} \\ e_{i,t,k}^{\max}=\max\{e_{i,t,k-1}^{\max},e_{i,t,k}\} \\ e_{i,t,k}^{\min}=\min\{e_{i,t,k-1}^{\min},e_{i,t,k}\} \end{cases} \tag{15}$$

The regulation mileage of EVs in the lower frequency regulation section, the upper frequency regulation section with reducing charging rate, and the upper frequency regulation with increasing discharging rate section are calculated as:

$$M_{i,t,k}^{\text{dn}}=\min\left\{\frac{1}{\eta\Delta k}(\overline{E}_{i,t,k-1}^{\text{g}}-e_{i,t,k-1})-P_{i,t}^{\text{base}},C_{i,t}^{\text{dn}}\cdot sig_{t,k}^{\text{his}}\right\} \tag{16}$$

$$M_{i,t,k}^{\text{up}}=\min\left\{\frac{1}{\eta\Delta k}(\overline{E}_{i,t,k-1}^{\text{g}}-e_{i,t,k-1})-P_{i,t}^{\text{base}},C_{i,t}^{\text{up}}\cdot sig_{t,k}^{\text{his}}\right\} \tag{17}$$

$$M_{i,t,k}^{\text{up}}=\min\left\{P_{i,t}^{\text{base}}-\frac{\eta}{\Delta k}(\underline{E}_{i,t,k-1}^{\text{g}}-e_{i,t,k-1}),-C_{i,t}^{\text{up}}\cdot sig_{t,k}^{\text{his}}\right\} \tag{18}$$

where the initial value of the energy storage limit is $e_{i,t^{\text{start}},1}^{\max}=e_{i,t^{\text{start}},1}^{\min}=SoC^{\text{start}}\cdot E$; and $sig_{t,k}^{\text{his}}=sig_{t,k}^{\text{up,his}}+sig_{t,k}^{\text{dn,his}}$.

3) Construction of UCM and BCDM

The objective function in UCM or BCDM consists of RMCCP credit, RMPCP credit, charging cost, and battery wear cost caused by participating in FRASM.

Since the market situation of day D is not known, this paper calculates the expected revenue by using historical data. The objective function is the maximum expected revenue, expressed as:

$$U_i^{\max,\exp}=\sum_t \max_j\,(Y_{i,t}^{\text{R,exp}}+Y_{i,t,j}^{\text{M,exp}}-C_{i,t}^{\text{ch,exp}}-C_{i,t}^{\text{age,exp}}) \tag{19}$$

$$Y_{i,t}^{\text{R,exp}}=w_t^{\text{R}}(C_{i,t}^{\text{up}}+C_{i,t}^{\text{dn}}) \tag{20}$$

$$Y_{i,t,j}^{\text{M,exp}}=\frac{w_{t,j}^{\text{M,rep}}\theta_{t,j}\left[\sum_{k=1}^{K}(M_{i,t,k}^{\text{up}}+M_{i,t,k}^{\text{dn}})\right]^2}{C_{i,t}^{\text{up}}\sum_{k=1}^{K}\left|sig_{t,k}^{\text{up,his}}\right|+C_{i,t}^{\text{dn}}\sum_{k=1}^{K}\left|sig_{t,k}^{\text{dn,his}}\right|} \tag{21}$$

$$C_{i,t}^{\text{ch,exp}}=w_t^{\text{TOU}}P_{i,t}^{\text{base}}\Delta t \tag{22}$$

$$C_{i,t}^{\text{age,exp}}=ER\beta\left(\sum_{k=1}^{K}u_{i,t,k}\right)^2 \tag{23}$$

$$u_{i,t,k}=\begin{cases}(M_{i,t,k}^{\text{dn}}+M_{i,t,k}^{\text{up}})\eta\Delta k/E & M_{i,t,k}^{\text{up}}\le P_{i,t}^{\text{base}} \\ (M_{i,t,k}^{\text{dn}}+M_{i,t,k}^{\text{up}})\Delta k/\eta/E & M_{i,t,k}^{\text{up}}>P_{i,t}^{\text{base}}\end{cases} \tag{24}$$

To satisfy the travel demand, the UCM and BCDM should satisfy the charging demand constraints too. We assume that frequency regulation signals are energy zero-mean (including efficiency losses). The changes of the amount of battery created by the upper and lower frequency regulation signals can counteract each other over an extended time. Therefore, the

UCM and BCDM only need to consider the changes of the amount of battery created by base power. It can be expressed as:

$$\sum_{t=t^{\text{start}}}^{t^{\text{off}}-1}\frac{P_{i,t}^{\text{base}}\eta\Delta t}{E}\geq SoC^{\text{off}}-SoC^{\text{start}}\quad i=2,3 \tag{25}$$

The upper and lower limits of the charging base power in the UCM and BCDM are expressed as:

$$0\leq P_{i,t}^{\text{base}}\leq P^{\max}\quad i=2,3,\forall t \tag{26}$$

The change constraint of the battery energy in UCM is:

$$e_{2,t,k}=e_{2,t,k-1}+(P_{2,t}^{\text{base}}+M_{2,t,k}^{\text{dn}}-M_{2,t,k}^{\text{up}})\eta\Delta k \tag{27}$$

And the upper and lower limits of the battery energy storage in UCM are illustrated as:

$$\underline{E}\leq e_{2,t,k}\leq\overline{E}\quad \forall t,\forall k \tag{28}$$

In BCDM, the change constraint of the battery energy should be differentiated between charging and discharging intervals. Equations (29) and (30) represent the change constraints in the charging and discharging intervals, respectively.

$$e_{3,t,k}=e_{3,t,k-1}+(P_{3,t}^{\text{base}}+M_{3,t,k}^{\text{dn}}-M_{3,t,k}^{\text{up}})\eta\Delta k \tag{29}$$

$$e_{3,t,k}=e_{3,t,k-1}+(P_{3,t}^{\text{base}}+M_{3,t,k}^{\text{dn}}-M_{3,t,k}^{\text{up}})\Delta k/\eta \tag{30}$$

And the upper and lower limits of the battery energy storage in BCDM are expressed as:

$$\underline{E}\leq e_{3,t,k}\leq\overline{E}\quad \forall t,\forall k \tag{31}$$

where $\Delta k=2$ s; and the initial battery energy of the EV is $e_{2,t^{\text{start}},1}=e_{3,t^{\text{start}},1}=SoC^{\text{start}}\cdot E$.

The optimization formula of UCM is expressed as:

$$\begin{cases}U_2^{\max,\exp}=\sum_t\max_j\,(Y_{2,t}^{\text{R},\exp}+Y_{2,t,j}^{\text{M},\exp}-C_{2,t}^{\text{ch},\exp}-C_{2,t}^{\text{age},\exp})\\ \text{s.t.}\;\;(25)\text{-}(28)\end{cases} \tag{32}$$

The optimization formula of BCDM is expressed as:

$$\begin{cases}U_3^{\max,\exp}=\sum_t\max_j\,(Y_{3,t}^{\text{R},\exp}+Y_{3,t,j}^{\text{M},\exp}-C_{3,t}^{\text{ch},\exp}-C_{3,t}^{\text{age},\exp})\\ \text{s.t.}\;\;(25),(26),(29)\text{-}(31)\end{cases} \tag{33}$$

In UCM and BCDM, the objective function and the constraint expression are identical, so the solution method and the step are identical. As listed in Table I, $C_{i,t}^{\text{up}}$ and $C_{i,t}^{\text{dn}}$ are the functions of $P_{i,t}^{\text{base}}$. The optimization formula of UCM or BCDM is the function of $P_{i,t}^{\text{base}}$, $M_{i,t,k}^{\text{up}}$, and $M_{i,t,k}^{\text{dn}}$. After adopting response control policy, $M_{i,t,k}^{\text{up}}$ and $M_{i,t,k}^{\text{dn}}$ can be described by $P_{i,t}^{\text{base}}$. At this time, the objective function and constraint expressions of UCM or BCDM become the non-linear function of only $P_{i,t}^{\text{base}}$. $P_{i,t}^{\text{base}}$ exists many times in the optimization formula of UCM or BCDM, and its objective function is non-linear, so it is difficult to solve directly.

To solve $P_{i,t}^{\text{base}}$ in UCM or BCDM, the subgradient method is adopted to iteratively update $P_{i,t}^{\text{base}}$ and traverse regulation market mileage price list until the convergence condition is satisfied. The flow chart of DAM solving in UCM or BCDM is shown in Fig. 5. The convergence condition is as follows:

$$\frac{U_{i,m+1}^{\max,\exp}-U_{i,m}^{\max,\exp}}{U_{i,m}^{\max,\exp}}<1\times 10^{-4} \tag{34}$$

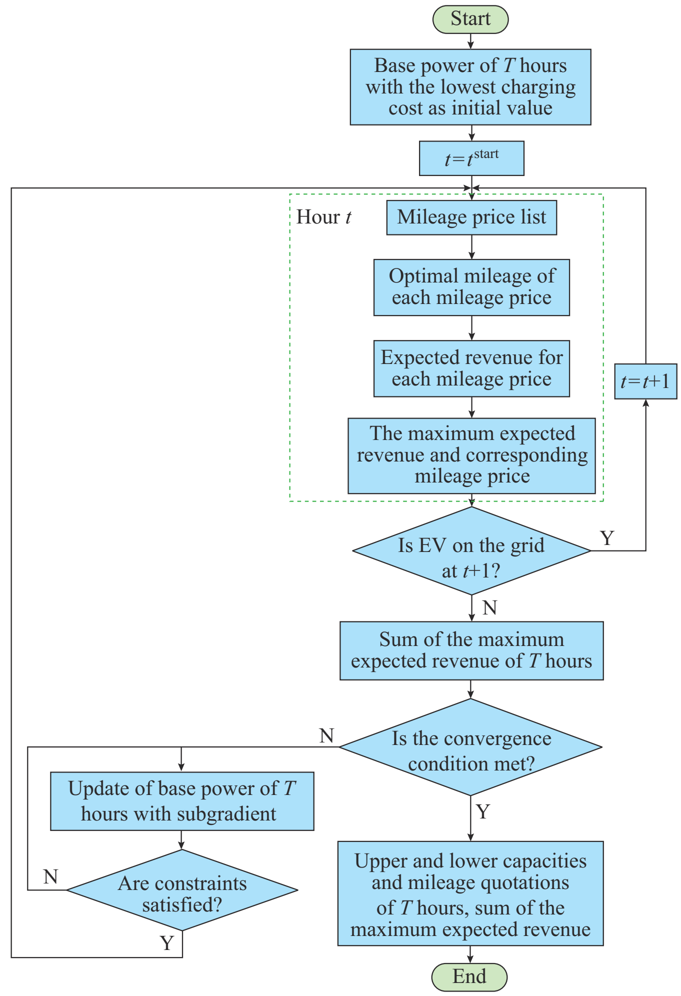

Fig. 5. Flow chart of DAM solving in UCM or BCDM.

IV. SIMULATION

A. Data and Setting

The effectiveness of the DAM and the superiority of the control policy will be analyzed by taking EV participating in FRASM as an example. In this case study, the TOU price, RMCCP, and RMPCP refer to the data of the energy market and FRASM in Guangdong Province. The form of frequency regulation signals adopted in China is similar to PJM. Because there is a lack of public data in China, frequency regulation signals come from PJM in the case examples. Different types of EVs may have slightly different parameters, which can be initialized manually when the user first uses DAM. In simulations, the following parameters shall be used for EVs: $P^{\max}=0.007$, $E=0.03$, $\overline{E}=0.95E$, $\underline{E}=0.15E$, and $\eta=0.92$ [34]. Among input data, t^{start} and SoC^{start} are automatically identified by the DAM, and t^{off} and SoC^{off} are input by users according to their travel plans.

B. Case Study

Based on the above research, case studies will be carried out. It is assumed that the EV participating in FRASM will not affect the regulation signals, the RMCCPs, or the TOU prices.

1) Simulation Results in Three Modes

The input of the DAM is $t^{\text{start}}=13$, $t^{\text{off}}=18$, $SoC^{\text{start}}=0.35$, $SoC^{\text{off}}=0.75$, and $N=6$. In BM, EV does not participate in FRASM, and the upper and lower reserve capacities are always 0. The regulation market mileage prices are always $w^{\text{M,max}}$ for T hours. The lowest charging cost for BM is ¥5.93. The SoC level of the battery is 0.75 when EV is off the grid.

Figure 6 shows the submission schemes for hours 13-17 in UCM and BCDM generated by DAM.

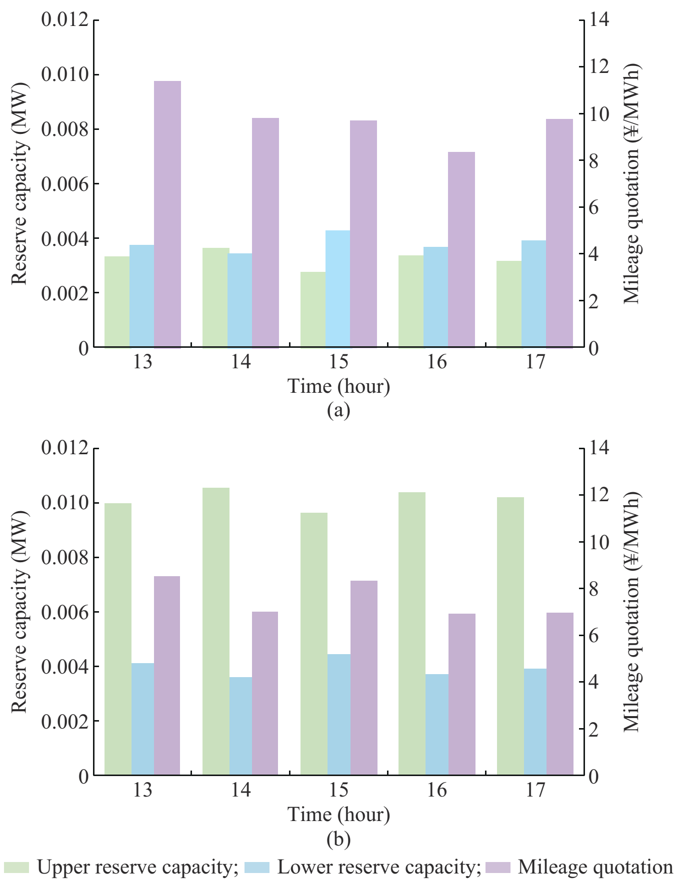

Fig. 6. Submission schemes in UCM and BCDM generated by DAM. (a) UCM. (b) BCDM.

The maximum net revenues of UCM and BCDM are ¥0.98 and ¥1.57, respectively. The off-grid SoC of UCM and BCDM are 0.825 and 0.785, respectively. BCDM has a larger reserve capacity and a smaller mileage quotation, and its clearing probability is higher. It can be observed that EV users who choose BCDM are more willing to participate in FRASM, which is in line with the actual situation of users. The model proposed in this paper is an aid model, which aims to reduce the workload of users and enhance their participating enthusiasm. Users will be able to determine which one is the most suitable for their actual situations.

Table II shows the input data for two different typical scenarios. Table III shows the net revenue and SoC that can be obtained in three modes and the above two scenarios when EV is off the grid. In Scenario I, the SoC requirement for the next travel is small and the TOU price is low. Moreover, the lower frequency regulation signals are more in the early morning. In this scenario, the majority of users will opt for BCDM. They can obtain more net revenue by meeting the charging demand. In Scenario II, BCDM may fail to satisfy the SoC requirement due to the presence of more upper frequency regulation signals. Users who are eager to travel or pay more attention to SoC tend to choose UCM. Therefore, when the same user faces different scenarios, the choice is not constant. However, users who do not rush to travel or pay more attention to revenue tend to choose BCDM. Although SoC is not as good as expected, it does not have much impact on users. Therefore, different users might make different choices when dealing with the same scenario.

TABLE II
INPUT DATA FOR TWO DIFFERENT TYPICAL SCENARIOS

Scenario	$[t^{\text{start}}, t^{\text{off}}]$ (hour)	$[SoC^{\text{start}}, SoC^{\text{off}}]$
I	[0, 6]	[0.35, 0.75]
II	[13, 18]	[0.35, 0.85]

TABLE III
NET REVENUE AND SOC IN THREE MODES UNDER TWO SCENARIOS

Scenario	BM		UCM		BCDM	
	Net revenue (¥)	Off-grid SoC	Net revenue (¥)	Off-grid SoC	Net revenue (¥)	Off-grid SoC
I	–3.89	0.75	1.54	0.867	1.930	1.130
II	–7.41	0.85	0.65	0.923	0.802	0.844

2) Verification of Submission Scheme

To verify the effectiveness of the DAM, we use the frequency regulation signals of the same time on day D to calculate the revenue and cost. The comparison results of days D and D–1 are shown in Fig. 7. Net income for both days is about the same. Therefore, the proposed DAM in this paper is feasible.

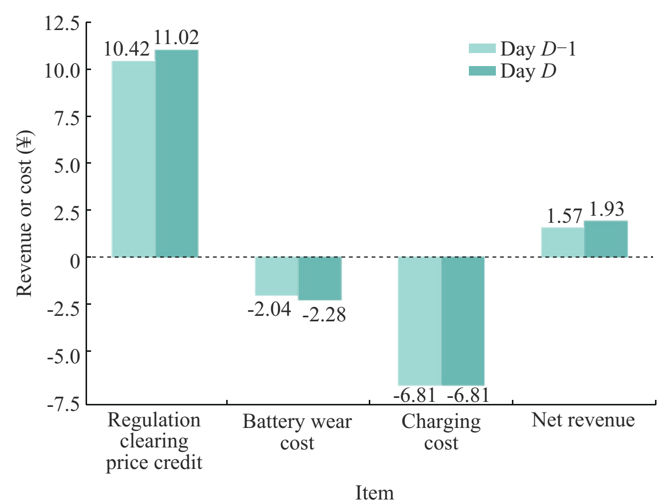

Fig. 7. Comparison results of days D and D–1.

To verify the optimality of the response control policy, using the data of day D, response control policy, and simple policy (actual regulation mileages are always equal to the requirements) are used to calculate and compare revenue and cost.

As listed in Table IV, EV users using the response control policy may receive a higher net income compared to those using the simple policy when submitting the same scheme. Figure 8 shows that the SoC fluctuation is more moderate with response control policy than that with simple policy. Simple policy schedules the whole battery to fully respond to frequency regulation signals, and the performance score is always 1. This is despite the fact that the simple policy provides a regulation clearing price credit that is 11.98% higher than that of the response control policy. However, the downside is that the battery cycle is deeper, resulting in 62.28% higher battery wear costs. Therefore, the net revenue is 7.64% less. Response control policy in FRASM can improve the net revenue for EV users.

TABLE IV
COMPARISON OF RESPONSE CONTROL AND SIMPLE POLICIES

Policy	Regulation clearing price credit (¥)	Battery wear cost (¥)	Charging cost (¥)	Net revenue (¥)
Response control	11.02	2.28	6.81	1.57
Response simple	12.34	3.70	7.19	1.45

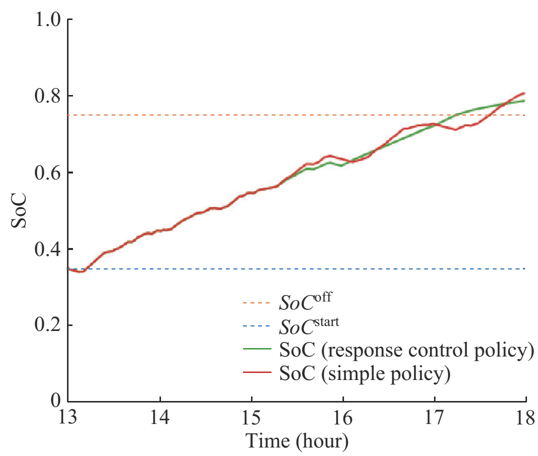

Fig. 8. Comparison of SoC between two policies.

V. CONCLUSION

EVs can be flexible resources that are urgently needed by the modern power grid. With the proposed DAM, private EV owners can participate in FRASM by inputting basic travel information. The following conclusions can be drawn.

1) With the assistance of DAM, including an optimal charging scheme, bidding policy, and response control policy, EVs can make an extra profit for their owners even battery wear cost is considered.

2) When the travel mileage is relatively low, which is very common for commuters, EV owners can make more extra profits by choosing a more aggressive participating mode, i.e., BCDM. In most cases, participating in FRASM will not affect planned trips since the mean value of regulation signals is statistically significant zero.

The proposed DAM fully depends on the operation rules of FRASM. For example, the TOU price is assumed fixed in this study. If the integration EV number is large enough to affect the energy market, real-time electricity price might be adopted, so DAM must be modified accordingly. However, we believe users' preference and if it is ease to use (user-friendly) are still two key issues when building DAM no matter what kind of market it is.

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