Research on Charging and Discharging Dispatching Strategy for Electric Vehicles

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Abstract: The popularity of electric vehicles may lead to negative effects on the power system if the charging procedures of plug-in electric vehicles (PEVs) are uncoordinated. In order to solve the problem, the hierarchical and zonal dispatching architecture and a new bi-level optimization model are respectively presented for the charging/discharging schedules of the PEVs. The upper level model is devoted to minimizing the system load variance so as to implement peak load shifting by optimizing the dispatching plan of all periods for each electric vehicle aggregator (EVA), and the lower one is aimed at tracing the dispatching scheme determined by the upper decision-maker through presenting an optimal schedule of charging and discharging for electric vehicles in the charging areas. Two highly efficient commercial solvers, AMPL/IPOPT and AMPL/CPLEX respectively, are employed to solve the developed optimization problem. Finally, the testing IEEE system consisting of 5 agents and 30 nodes is adopted to illustrate the characteristics of the model and solving method presented in this paper.

Keywords: Charging and discharging strategy, electric vehicle, hierarchical and zonal dispatching, optimization.

1. INTRODUCTION

Electric vehicle (EV) has wide prospects as an effective way for solving problems of environment pollution and global warming. However, the wide use of electric vehicles (EVs) could produce significant negative impacts on the secure and economic operation of the power system concerned, if the charging procedures of PEVs are uncoordinated [1]-[4].

Electric vehicle is different from other normal load by its energy storage characteristic, which EVs can both consume power as loads and release power to grids through V2G [5]. Coordinating the charging and discharging process can reduce the negative effect on the power system which produced by the extensive integration of numerous plug-in electric vehicles (PEVs). At the same time, it can also reduce the total charging cost and power network losses so as to implement peak load shifting [6]. There are some researches in this aspect. In [7], it presented the dispatching method in the electric market, which it can minimize the total charging cost by choosing the suitable time whether to charge or to provide the ancillary service. In [8], it built the random economic dispatching model considered the electrical vehicles and uncertainty of wind turbines. In [9], it built the optimal charging strategy model for electrical vehicles to achieve the aim of minimizing the distribution system losses and the voltage deviation, which verified that it can improve the power quality by controlling electric vehicles' behaviors. In [10], it presented the concentrated charging mechanism of

plug-in hybrid electric vehicle (PHEV) based on the demand response, and it can both save the users' costs and decrease the peak-valley difference to achieve win-win between users and suppliers. In [11], it built the mathematical model based on multiple time scale coordination scheduling and analyzed the feasibility of decreasing load fluctuation and utilizing the redundant wind electricity in the night.

So far, the research on the electrical vehicles' coordinate dispatching almost related to the charging process, while there are little research on the storage characteristic and V2G. However, the drivers' demand should be placed in the first place to achieve the optimal management on electrical vehicles behaviors, and the electricity price should also be considered to serve the system.

Given this, a charging and discharging dispatching strategy for electric vehicles based on bi-level optimization is presented in this paper. The model has two layers. The decision-maker of the upper level is dispatching institution that can determine the schedules of EVAs in the lower level to minimize the system load variance and implement peak load shifting [12]. The decision-maker of the lower level are aggregator that can dispatch the charging and discharging period so as to trace the upper plan. The upper model is a nonlinear programming problem which can be solved by primal-dual interior-point algorithm in this paper, while the lower model is the large-scale integer planning problem solved by the branch-and-bound method. Finally, the characteristic of the model is shown by the IEEE test system consisted of 30 nodes and 5 aggregators.

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2. THE RESEARCH ON EVS CHARGING AND DISCHARGING OPTIMAL ARCHITECTURE

2.1. The Hierarchical and Zonal Dispatching Mode

It is unrealistic that the dispatching institution can control every EV directly because of the huge scale of electrical vehicles. Moreover, the communication channel need to be built between dispatching institution and EV for centralized dispatching, which can be used for collecting information and sending out instructions conveniently. It throws out the challenge to the reliability of the communication network and the bandwidth. So, there is a feasible scheme about the hierarchical and zonal dispatching [13].

The main idea of the hierarchical and zonal dispatching is that the power system is layered according to the voltage grade, dividing the distribution system layers into the many areas rely on terrain. In each area, the electrical vehicles' coordinate dispatching is charged by distribution system dispatching institution or aggregators. The framework is shown in Fig. (**1**).

2.2. Dispatching Issues and Interactive Mechanism

2.2.1. Day-Ahead Declaration Mechanism

In order to make reasonable decision for both upper and lower dispatching institution, it presents the mechanism that drivers need to update information for its aggregator about the EV usage situation of the next day, consisting of the accessing period and the expected SOC at the leaving moment. It assumes that the average charging power, discharging power and capacity of the batteries are all the same, while it can be solved by means of declaration in case of the unequal conditions. Moreover, the electricity price

incentive mechanism is also needed in order to simulate the drivers' motive of providing ancillary services on condition that it satisfies its own request first.

2.2.2. The Data Packet Technology Based on the Similar Combination

Although the number of the electrical vehicle has decreased, it can also reach the scales of thousands of electrical vehicles. It is necessary for drivers to packet the declaration information to minimize the scale when using the hierarchical and zonal dispatching mode.

Agents can take charge of the electrical vehicles in their areas according to the declaration information of drivers provided. The similar information can be packet to one group, which is defined as a set of electric vehicle that are controlled by an agent. The dimension of lower layer can be decreased because of the data packet technology based on the similar combination. When the scale of electrical vehicle reaches to a certain extent, the increasing velocity of EV number will slow down obviously, decreasing the solving scale and difficulty largely.

2.3. Information Communication Mechanism

Both the reasonable electricity price simulating mechanism and related technology of smart grid are needed in order to achieve the optimal dispatching of EV charging and discharging behaviors. The combination of wired communication and wireless communication promote the process of recognizing the EV identity, transmitting the day-ahead information transmission and publishing the dispatching order. The technology can support the optimal dispatching of electrical vehicle, which is rather mature. The concrete steps are shown as follows.
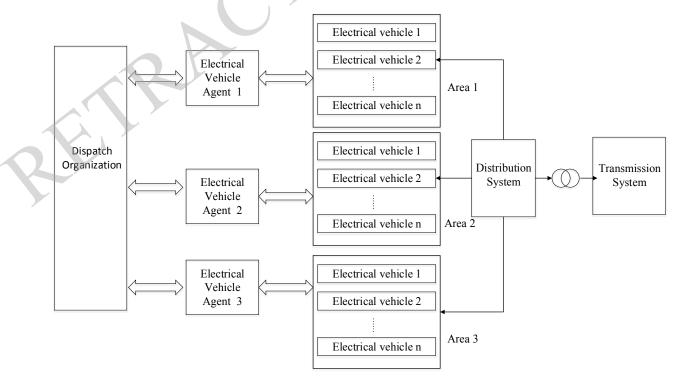

Fig. (1). Hierarchical and zonal architecture for dispatching electric vehicles.

1. Drivers provide the next day driving plan to its aggregator in advance.

2. Electric vehicle aggregator summaries the declaration information and divide the electric vehicles into based on the data packet technology based on the similar combination, after which EVA provide the dispatching capacity of all periods to system dispatching institution.

3. According to the declaration information of electric vehicle aggregator system institution make plans for all EVAs of every period and transmit the system load variance to system dispatching institution, resorting to the specific aim such as peak load shifting and so on.

4. According to the declaration information of drivers, EVAs optimize the charging and discharging time of all electric vehicles and transmit the system load variance to system dispatching institution, aiming at minimize the deviation between real dispatching results and plans.

5. Taking dispatching aim and variance of EVAs into account, system dispatching institution regulates the dispatching strategy resorting to the specific rule and transmit the result to the electric vehicle aggregator. Repeat step 4 and 5 until it can satisfy the condition of convergence.

3. A CHARGING AND DISCHARGING DISPATCHING MODEL FOR ELECTRIC VEHICLES BASED ON BI-LEVEL OPTIMIZATION

3.1. The Certain Model of Bi-Level Optimization

Bracken J and McGill J have presented the conception of multilevel programming to solve the optimal problems in 1973[14]. Bi-level programming is an exception of multilevel programming. As the name shows that the bi-level has two levels. The aim of upper level will influence the lower levels' and the lower level's decision will react to the upper levels'. There are researching reports in the areas of transmission system [15], reactive power optimization [16] and so on. The bi-level programming can be described as follows [17].

$$\begin{cases} J = \max F(x, y_1, y_2, \cdots, y_n) \\ s\,t.G(x) \le 0 \end{cases} \tag{1}$$

$$\begin{cases} J_i = \max_{y_i} f_i(x, y_1, y_2, \cdots, y_n) \\ s\,t.g_i(x, y_1, y_2, \cdots, y_n) \le 0 \end{cases} \tag{2}$$

where,

$F(\cdot)$ --- the objective function of the upper level decision maker.

X --- the decision vector of the upper level decision maker. $G(\cdot)$ --- the constraint condition of the upper level decision maker.

$f_i(x)$ --- the objective function of the lower level decision maker, i.

$Y(i)$ ---the decision vector of the lower level decision maker, i.

$g_i(x)$ --- the constraint condition of the lower level decision maker, i.

3.2. The Charging and Discharging Dispatching Model for Electric Vehicles Based on Bi-Level Optimization

3.2.1. Upper Optimal Model

The optimal scheduling architecture presented in this paper consists of 2 layers, which is shown as the Fig. (**1**). The upper decision maker make charging and discharging strategies for all EVAs to minimize the sum of variance between the real scheduling results and scheduling plans, implementing peak load shifting.

The first part of the upper objective function is the variance of system load and the second part is the deviation between the real scheduling results of EVAs and scheduling plans of system dispatching institution. The optimal function is shown as follows.

$$\min_x F = \frac{1}{T-1} \sum_{t=1}^{T} (P_{d,t} + \sum_{k=1}^{N_0} x_{k,t} - \overline{P_d})^2 + \alpha \sum_{k=1}^{N_0} f_k(X_k, Y_k) \tag{3}$$

$$\overline{P_d} = \frac{1}{T} \sum_{t=1}^{T} (P_{d,t} + \sum_{k=1} x_{k,t}) \tag{4}$$

$$Y_k = \begin{pmatrix} y_{k,1,1} & \cdots & y_{k,1,T} \\ \vdots & \ddots & \vdots \\ y_{k,n_k,1} & \cdots & y_{k,n_k,T} \end{pmatrix} \tag{5}$$

where,

T --- the number of periods that a scheduling cycle have.

$P_{d,t}$ --- the load level except the charging and discharging load of electric vehicles.

$\overline{P_d}$ --- the system average load of T periods.

$x_{k,t} > 0$ --- the charging state of EVA k in period t.

$x_{k,t} < 0$ --- the discharging state of EVA k in period t.

N_0 --- the number of EVA in the researching system.

A --- the penalty coefficient, represent the penalty force to deviation between the real scheduling results of lower level EVAs and upper level scheduling plans of system dispatching institution.

$X = [X_1, X_2, ... \blacklozenge X_{N_0}]$ --- the decision matrix made by dispatching institution for electric vehicles.

$X_k = [X_{k1}, X_{k2}, ... \blacklozenge X_{kT}]$ --- the dispatching plan of all periods mad by the system dispatching institution for EVA k. Y_k ---

the charging and discharging strategy of EVA k. $y_{k,m,t}$ --- the No m EV's charging and discharging state of EVA k at the moment t.

$y_{k,m,t}=1$ --- the charging state

$y_{k,m,t}=-1$ --- the discharging state

$y_{k,m,t}=0$ --- the state without electricity interaction.

n_k --- the number of electric vehicles.

1) Multi-period Power Flow Equality Constraints

$$\begin{cases} P_{Gi,t\partial} = P_{Di,t}+P_{Ei,t}+U_{i,t}\sum_{j=1}^{N}U_{j,t}(G_{ij}\cos\theta_{ij,t}+B_{ij}\sin\theta_{ij,t}) \\ Q_{Gi,t} = Q_{Di,t}+U_{i,t}\sum_{j=1}^{N}U_{j,t}(G_{ij}\sin\theta_{ij,t}-B_{ij}\cos\theta_{ij,t}) \end{cases} \quad (6)$$

where,

$P_{gi,t}$ --- the active power of generator i at moment t.

$Q_{gi,t}$ --- the reactive power of generator i at moment t.

$P_{Di,t}$ --- the active load of generator i at moment t.

$Q_{gi,t}$ --- the reactive load of generator i at moment t.

$P_{Ei,t}$ --- the scheduling plan of node i at moment t.

$U_{i,t}$ --- the voltage value of node i at moment t.

N --- the number of node

G_{ij} --- the real part of node admittance matrix.

B_{ij} --- the imaginary part of node admittance matrix.

θ_{ij} --- the phase angle difference of branch i and j.

2) The upper and lower bound constraints of generators

$$\begin{cases} P_{Gi}^{\min}\leq P_{Gi,t}\leq P_{Gi}^{\max} \\ Q_{Gi}^{\min}\leq Q_{Gi,t}\leq Q_{Gi}^{\max} \end{cases} \quad (7)$$

where,

$P_{Gi}^{\max}$ --- the upper bound constraints of active power.

$P_{Gi}^{\min}$ --- the lower bound constraints of active power.

$Q_{Gi}^{\max}$ --- the upper bound constraints of active power.

$Q_{Gi}^{\min}$ --- the lower bound constraints of active power.

3) Voltage Constraints

$$U_i^{\min}\leq U_{i,t}\leq U_i^{\max} \quad (8)$$

where,

$U_i^{\max}$ --- the upper bound constraints of voltage.

$U_i^{\min}$ --- the lower bound constraints of voltage.

4) Transmission power Constraints

$$|P_{l,t}|\leq P_l^{\max}\quad\forall t\in[1,T] \quad (9)$$

where,

$P_{i,t}$ --- the transmission power of line l at time t.

$P_{i,t}^{\max}$ --- the upper bound of transmission power at time t.

5) Dispatching Constraints

$$-\sum_{m=1}^{n_k}P_{k,m,dch}A\leq x_{k,t}\leq\sum_{m=1}^{n_k}P_{k,m,ch}A \quad (10)$$

where,

$P_{k,m,ch}$ --- the average charging power of EV m.

$P_{k,m,dch}$ --- the average discharging power of EVA k.

A -- $A=I_{k,m,t}k_{avail}$.

$I_{k,m,t}$ --- the connected state between EV m and system of EVA k at time t.

$I_{k,m,t}=1$ --- the connected state.

$I_{k,m,t}=1$ --- the unconnected state.

k_{avail} --- the available coefficient which is focused on the multiple results of average power and accessing EV's number.

3.2.2. Lower Optimal Model

In the lower model, EVS control the charging and discharging state of every period to minimize the deviation between the real loads and dispatching plan.

The objective function of aggregator is shown as follows.

$$\min_{Y_k} f_k(X_k,Y_k)=\sum_{t=1}^{T}(\sum_{m=1}^{n_k}P_{k,m,t}-x_{k,t})^2 \quad (11)$$

$$P_{k,m,t}=\begin{cases} P_{k,m,ch} & y_{k,m,t}=1 \\ 0 & y_{k,m,t}=0 \\ -P_{k,m,dch} & y_{k,m,t}=-1 \end{cases} \quad (12)$$

where,

$P_{k,m,t}$ --- the real dispatching result of EV m and EVA k.

1) Charging and discharging equality constraints

$$S_{k,m,t+1}=\begin{cases} S_{k,m,t}+\dfrac{\eta_{ch}P_{k,m,ch}\Delta t}{\beta_{k,m}}(y_{k,m,t}=1) \\ S_{k,m,t}(y_{k,m,t}=0) \\ S_{k,m,t}-\dfrac{P_{k,m,ch}\Delta t}{\beta_{k,m}\eta_{ch}}(y_{k,m,t}=-1) \end{cases} \quad (13)$$

where,

$S_{k,m,t}$ --- the SOC of EV m and EVA k at time t.

η_{ch} --- the charging efficiency.

η_{dch} --- the discharging efficiency.

$\beta_{k,m}$ --- the battery capacity of EV m and EVA k.

Δt --- the time period.

There is no consideration on self-discharge rate in formula 13.

2) Battery Safety Constraints

$$S_{\min} \leq S_{k,m,t} \leq S_{\max} \tag{14}$$

where,

$S_{\max}$ --- the upper bound of battery's SOC.

$S_{\min}$ --- the lower bound of battery's SOC.

3) Non-schedulable Period Constraints

$$y_{k,m,t} = 0 (t < t_{k,m,s}) \tag{15}$$

where,

$t_{k,m,s}$ --- the moment of accessing system of m_{th} EV and EVA k.

$t_{k,m,e}$ --- the moment of leaving system of m_{th} EV and EVA k.

4) The next-day driving demand constraints

$$S_{k,m,t_{k,m,e}} \geq S_{k,m} \tag{16}$$

where,

$S_{k,m,t_{k,m,e}}$ --- the real SOC of m_{th} EV.

$S_{k,m}$ --- the required SOC of m_{th} EV of EVA k when it leaves system.

4. THE SOLVING METHOD AND PROCESS OF THE MODEL

AMPL [18] is the language for modelling to describe and solve the large-scale problem. It finds the optimal result by extra solving device such as CPLEX, IPOPT and so on. AMPL suits for the complex questions consisting of on-line and discrete problems, having the most obvious characteristic that the defined language of the model is similar with the algebraic expression as usual.

In this paper, the IPOPT 3.8.0 [19] is adopted to solve the non-line programming problems and the CPLEX 12.2 based on the AMPL is used to solve the large-scale integer programming problem of lower layer. The concrete steps are shown in Fig. (2). At the beginning of the program, the deviation between the lower layer real load and upper layer dispatching plan is not taken into the consideration at the
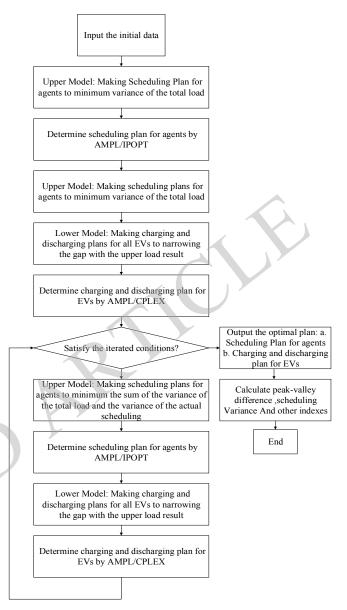

Fig. (2). Flow chart for solving bi-level optimal dispatching model with electric vehicles.

time calculating the function value of objective function in the first iteration because the real dispatching result of EVA is not known.

5. ANALYSIS OF EXAMPLES

5.1. Evaluate Indexes of Results

The variance of the total load and deviation of the agents are used to evaluate the result. They are defined respectively as follows.

$$\begin{cases} f_1 = \dfrac{1}{T-1}\sum_{t=1}^{T}(P_{d,t} + \sum_{k=1}^{N_0} y_{k,t} - \overline{P_d})^2 \\ \\ f_2 = \sum_{k=1}^{N_0}\sum_{t=1}^{T}(\sum_{m=1}^{n_k} P_{k,m,t} - x_{k,t})^2 \end{cases} \tag{17}$$

where,

$y_{k,t}$ ---the real dispatching result of agents at time t, which is got by solving the lower layer model.

f_1 --- the peak load shifting effect by the optimization regulation of charging and discharging behavior.

f_2 --- the performance degrees to upper layer scheduling plan, which made by all the agents.

5.2. The Testing System Consisting of 5 Agents and 30 IEEE Nodes

The testing system [20] consisting of 5 agents and 30 IEEE nodes is adopted to illustrate the feasible and effective of the model and solving method presented in this paper. The dispatching period is set between 12 am and 12 am the next day, considering the custom that the EV is charging at night. The dispatching period is set apart by hours. The 5 agents is set at node 6, 9, 22, 25 and 28[21].

US Department of Transportation did the survey on the trips of electric vehicles and published the results [22]. The analysis is conduct based on the method presented in [23]. The distributions of the beginning time of the first trip and the ending time of the last trip are the normal distribution functions approximately. The distribution of the daily driving distance is lognormal distribution approximately. The probability density function of these variables can be got by function fitting. The results are shown as follows.

$$\begin{cases} \frac{1}{\sqrt{2\pi}\delta_s}\exp\left(-\frac{(x-\mu_s)^2}{2\sigma_s^2}\right)(0 < x \leq \mu_s+12) \\ \frac{1}{\sqrt{2\pi}\delta_s}\exp\left(-\frac{(x-24-\mu_s)^2}{2\sigma_s^2}\right)(\mu_s+12 < x \leq 24) \end{cases} \quad (18)$$

where, $\mu_s = 8.92$; $\delta_s = 3.24$;

$$f_e(x) = \begin{cases} \frac{1}{\sqrt{2\pi}\delta_e}\exp(-\frac{(x+24-\mu_e)^2}{2\delta_e^2})(0 < x \leq \mu_e-12) \\ \frac{1}{\sqrt{2\pi}\delta_e}\exp(-\frac{(x-\mu_e)^2}{2\delta_e^2})(\mu_e-12 < x \leq 24) \end{cases}$$

(19)

where, $\mu_e = 17.47$; $\delta_e = 3.41$;

$$f_m(x) = \frac{1}{\sqrt{2\pi}\delta_m x}\exp(-\frac{(\ln x - \mu_m)^2}{2\delta_m^2}) \quad (20)$$

where, $\mu_m = 2.98$; $\delta_m = 1.14$;

There are 20 thousands EVs in the system in assumption. The owner can declare the information according to the service condition of EVs. The analyzing example makes a sample the probability distribution of the beginning time, ending time and daily driving distance, so as to simulate the SOC when the EV access to the system and leave the system. The SOC of leaving moment is set as 90% as usual.

In order to improve the searching ability of the bi-level optimal model, the deviation falls down quickly in the late period of the iteration. The punished coefficient α is set and the regular change is shown as follows.

$$\alpha = \exp(\frac{n-10}{3}) \quad (21)$$

where,

n --- the iteration times.

5.3. The Comparison Between Free Charging Model and Optimal Charging Model

The comparison is conduct between free charging model and optimal charging model, which result is shown as follows.

Table 1.   Comparisons of system load level indexes.

Punishment Coefficient	500	600
$\alpha = 1$	265.43	18.09
$\alpha = 1000$	280.60	0.14
$\alpha = \exp(\frac{n-10}{3})$	265.76	0.17

What can be got in Table **1** that the peak-valley difference increases obviously because of the free charging model. Optimal charging and discharging model can both decrease and peak load and improve the valley load level, which is benefit for decreasing the starting and stalling times to improve the safety and economy of the system.

5.4. The Comparison Between Free Charging Model and Optimal Charging Model

In the process of the bi-level optimization, the decision maker of the lower layer has the right to decide the dispatching aim, which has influence on the upper decision. The dispatching deviation of the lower layer for agents is added to the objective function in the bi-level optimal model, and the value of the punishing coefficient needs to make a sensitivity analysis. Three results of different types of punishing coefficient are shown as Table **2**.

Table 2.   Comparisons of each evaluation index under three penalty coefficients.

Mode	Peak Load /MW	Valley Load/MW	The Peak-Valley Difference/MW
Initial load	284.4	179.9	104.5
Free charging	291.0	180.8	110.2
Optimal mode	269.3	218.9	50.4

What can be seen from the Table **2** is that the searching ability is better when $\alpha = 1$ as well as the better effect of peak load shifting. But the deviation between real load of lower layer agents and a scheduling plan made in the upper

layer is too big to achieve the plan made by the upper layer. When, $\alpha = 1000$, the real load of lower layer is according with the scheduling plan made by the scheduling institution of upper layer, taking losing the ability of peak load shifting as cost.

When the punishing coefficient is adopted in index change, it has the better ability of global searching at early iteration stage and rapid decrease of the agents' dispatching deviation at the late iteration stage, which is benefit for the implement of the upper layer's dispatching plan.

CONCLUSION

The popularity of electric vehicles can pose threat to the safety and economy of the power system without the charging regulation. And the storage characteristics of electric vehicles batteries can improve the power system's performance. Therefore, how to make a dispatching optimization of charging and discharging is a vital problem to be researched for developing its advantages and avoid the disadvantages. Give its background, the hierarchical and zonal dispatching architecture and bi-level optimal model of charging and discharging is presented in this paper. The AMPL/IPOPT and AMPL/CPLEX are respectively used to solve the iteration problems in the upper layer and lower layer. The interaction of the two effective solver can develop the advantage of initial primal-dual interior-point algorithm and branch-and-bound method. At last, the testing system consisting of 5 agents and 30 IEEE nodes is adopted to illustrate the feasible and effective of the model and solving method presented in this paper. The issue, making the proper price incentive mechanism for guiding the frequency regulation and spinning reserve service, needs a further research.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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