Bidding Strategy for Virtual Power Plant Considering the Large-scale Integrations of Electric Vehicles

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***Abstract*- In order to alleviate the energy crisis and environmental pollution, Electric Vehicles (EVs) have obtained the large-scale development in the exceptional period in the world. On the other hand, Virtual Power Plant (VPP), an aggregator involved in various renewable energies and diversified loads, is considered as the crucial measure to coordinate the EVs to participate in the power market. Obviously, the equivalent model of EV in the VPP is difficult to satisfy the need for large-scale development of EVs in the future. Therefore, it is of great significance to establish the detailed charging models of EVs and explore the influences on the operation of the VPP. First of all, the basic structure and operation feature of VPP considering four different kinds of EVs is introduced briefly. Moreover, in order to describe the bidding processing of VPP, the three stages of power market are introduced from the trading aspects. Then, the charging characteristics of four types EVs are analyzed from charging time, charging power and access probability. In addition, the bidding strategy models of VPP at three different stages are built and the improved Artificial Bee Colony algorithm is utilized to solve the optimal bidding strategies of the VPP. Finally, the performances of the bidding model of VPP are validated by the different scenarios which considered the multi-type EVs integrations, and the influences of the different scales of EVs on the bidding strategy of VPP are also analyzed.**

***Index terms*- virtual power plant; electric vehicle; artificial bee colony algorithm; step transactions cost; bidding strategy**

Nomenclature

Parameters

C_i	MT environmental penalty
k_{mt}	MT dynamic cost coefficient
$L_{load,da,t}$	Forecast load level of the day-ahead market
$L_{load,r,t}$	Forecast load level of real-time market
$L_{load,t}$	Actual load level
$L_{ev,t}$	EV load level
$P_{w,dap,t}$	WT forecast output in day-ahead market
$P_{pv,dap,t}$	PV forecast output in day-ahead market
$P_{w,rp,t}$	WT forecast output in real-time market
$P_{pv,rp,t}$	PV forecast output in real-time market
$P_{w,t}$	WT actual output
$P_{pv,t}$	PV actual output
$P_{\min,mt}$	MT minimum output
$P_{mt,\max}$	MT maximal output
Q_i	MT pollutant gas emission
$\lambda_{da,p,t}$	Forecast price of day-ahead market
$\lambda_{da,r,t}$	The day-ahead market-clearing price
$\lambda_{r,p,t}$	Forecast price of real-time market
$\lambda_{r,t}$:	Real-time market-clearing price
λ_{sd} :	MT start-up/shut-down costs
λ_{base}	MT fixed cost

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Variable

$C_{da,mt,t}$	MT output cost in the day-ahead market
$C_{da,rt,t}$	MT output cost in the real-time market
$\mathrm{C}_{da,m,t}$	Trading cost in the day-ahead market
$C_{r,m,t}$	Trading cost in the real-time market
$P_{w,da,t}$	WT bidding output in day-ahead market
$P_{w,rd,t}$	WT forecast bidding output in real-time market
$P_{w,r,t}$	WT bidding output in real-time market
$P_{pv,da,t}$	PV bidding output in the day-ahead market
$P_{pv,rd,t}$	PV forecast bidding output in the real-time market
$P_{pv,r,t}$	PV bidding output in the real-time market
$P_{mt,da,t}$	MT bidding output in the day-ahead market
$P_{mt,\mathrm{r},t}$	MT bidding output in the real-time market
$P_{da,m,t}$	Trading power of VPP and external markets in the previous market
$P_{rd,m,t}$	Trading power of VPP and external markets in the real-time market
$P_{balance,t}$	VPP trading power in balance market at time t
$P_{\theta,m,t}$	VPP trading power with the market at time t
$R_{w,da,t}$	WT forecast bidding revenue in day-ahead market
$R_{pv,da,t}$	PV forecast bidding revenue in day-ahead market
$R_{mt,da,t}$	MT forecast bidding revenue in day-ahead market
$R'_{w,da,t}$	WT actual bidding revenue in day-ahead market
$R'_{pv,da,t}$	PV actual bidding revenue in day-ahead market
$R'_{mt,da,t}$	MT actual bidding revenue in day-ahead market
$R_{w,rt,t}$	WT forecast bidding revenue in real-time market
$R_{pv,rt,t}$	PV forecast bidding revenue in real-time market
$R_{mt,rt,t}$	MT forecast bidding revenue in real-time market
$\mu_{sd,t}$	MT status coefficient

I. Introduction

Nowadays, shortages of fossil energy and environmental pollution problems are becoming more and more serious in the last few years. In order to alleviate the energy crisis and reduce pollutant emissions, the government has built a large number of renewable energy units and promoted the developments of electric vehicles (EVs) in urban. Relying on the development of the Virtual Power Plant (VPP), the distributed renewable energies, the EVs, the common loads can be aggregated to an entirety to participate in grid operation and bidding in the power market [1]. The integrations of EVs into the distribution system under the dispatching of the VPP can improve the absorption ability of renewable energy and alleviate the detrimental effects of random access [2]. As a kind of specific load in the power system [3], EV is not only utilized as the traditional load to consume the electricity but also can be considered as the controllable load to participate in the daily operation and dispatch of the distribution network [4]. At present, many studies have been completed on the EVs load calculated and the bidding strategy of the VPP. Until now, the existing researches on the VPP bidding strategy and on the EV operational features are summarized as follows:

1) *The Research Status of EV Operation*

Considering the massive penetration of plug-in hybrid vehicles into the electricity grid and widespread utilization of distributed energy resources in the future, the energy management model for VPPs was developed in [5-6]. In order to improve the ability of the power grid to absorb wind energy and balance the electric vehicle charging power, a multiple-goal hierarchical algorithm integrating plug-in EVs charging and wind energy scheduling was proposed in[7]. Large-scale integrations of EVs into the power grid posed a negative impact on the system operation, the impact of EVs on the power system and the optimal dispatching of EVs were analyzed in [8]. In [9], several types of EVs charging characteristics were studied. In addition, the probability model of different types of the EV charging profile was also proposed.

2) *The Research Status of VPP*

In [10], the industrial VPP model was built and the model was utilized to manage the renewable energies and the loads. Moreover, the cooperative VPPs using the distributed artificial intelligence and game theory were respectively proposed in [11-13] and these papers designed the payment mechanism to encourage the distributed energy resources to join the VPPs. On the other hand, Reference [14] developed a real-time algorithmic framework and established a system-theoretic foundation to realize the vision of distribution-level VPP. A bidding strategy of VPP in the joint market of energy and ancillary services market was proposed in [15-16], and the results were analyzed under the different scenarios.

In recent years, only a few papers have studied the cooperative bidding strategy of VPP by considering the integrations of EVs. However, the EV was disposed as a whole to participate in the power market and neglect the charging characteristics of different EVs. Therefore, four kinds of EVs (private car, business car, bus, taxi) are considered in the bidding model of VPP and the charging loads are calculated based on the integrating time and charging power of EVs.

The organization of this paper is organized as follows: Section II introduces the overall framework of VPP and the operational structure of power market is also proposed. The computation method of charging load by considering four kinds of EVs is presented in Section III. Section IV builds up of the three stages bidding model of VPP in power market, and the improved Artificial Bee Colony (ABC) algorithm is utilized to solve the built bidding model. Next, the bidding strategies of VPP in power market considering the influence of optimal dispatching of EVs based on the charging features and different scales are analyzed in Section V. Finally, the conclusions are summarized in Section VI.

II. The Comprehensive Bidding Model of VPP

1) *The Basic Structure of VPP*

Generally speaking, it is difficult to balance the distributed generations and loads due to the unstable and intermittent feature of the renewable energy, such as the Photovoltaic (PV) and Wind Turbine (WT). On the other hand, in order to alleviate the consumption of fossil energy, the development of EV is strongly encouraged. How to coordinate the renewable energies and EVs from the market aspects has been becoming a hot researching topic in the world. Under this circumstance, VPP is employed to implement the energy optimization. VPP can not only receive information about the current status of each unit, but it can also send the signals to control the objects.

Furthermore, VPP may enable itself to supply energy and ancillary services to the utility grid [17]. Fig.1 proposes the overall framework of VPP in this paper.

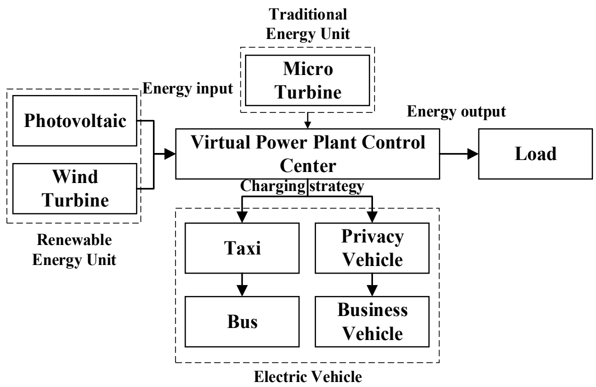

Fig.1 The Overall Framework of VPP

From the perspective of internal structure, Micro Turbine (MT), PV and WT are determined as the generating power units in VPP. All the physical units are connecting with the control center of VPP. The kernel of VPP is an energy management system (EMS) which coordinates the power flows coming from the generators to the loads. In the proposed framework, the output power of MT can be

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regulated according to the load level, the total cost of itself and the market price.

From the aspects of energy management, VPP can purchase the insufficient electricity and sell the surplus energy to the external gird based on the energy balance between the generation and consumption. Therefore, in VPP, the unstable power generation units (WT and PV) and the controllable load (EV) are considered as the key to optimize the energy and obtain the maximal revenue from the power market

2) Electricity Market Transaction Structure

In this paper, VPP is considered as the price taker. That means the bidding strategy of VPP has no effect on the market price. Furthermore, it should be noted that the power loss is neglected because the physical distance between each generation unit and load is assumed to be short. The power market operating mechanism is illustrated in Fig.2 based on the theory in [18][18]. It contains three stage from the time dimension.

Stage1: Day-ahead Market

In this stage, each unit should send the day-ahead forecast output information to VPP control center, and VPP makes the bidding output of each units participating in the day-ahead market and forecast each unit bidding output in the real-time market according to the market forecasting price. The day-ahead market is usually opened at 10:00 and closed at 13:00 on the day before the trading. After the day-ahead market closed, the market clears and VPP calculates the income and cost based on the day-ahead clearing market price.

Stage2: Real-time Market

On the trading day, the bidding in the real-time market is assumed to start every hour and the market is then clearly hourly. At this stage, the day-ahead bidding output of each unit is known, meanwhile, WT and PV forecast outputs are more accurate. VPP makes bidding decision in the real-time market based on the real-time market latest forecasting price. The real-time market will be closed an hour before the actual operating time. And the VPP calculates the revenue and cost according to the real-time market price.

Stage3: Balance Market

The balance market is opened after the real-time market closed, which is used to compensate the deviation of PV and MT output. At this stage, the total bidding output of each unit is known. When there is a deviation between the total bidding output and the actual output, VPP needs to purchase power at a price higher than the real-time market price and sell power at a price lower than the real-time market price.

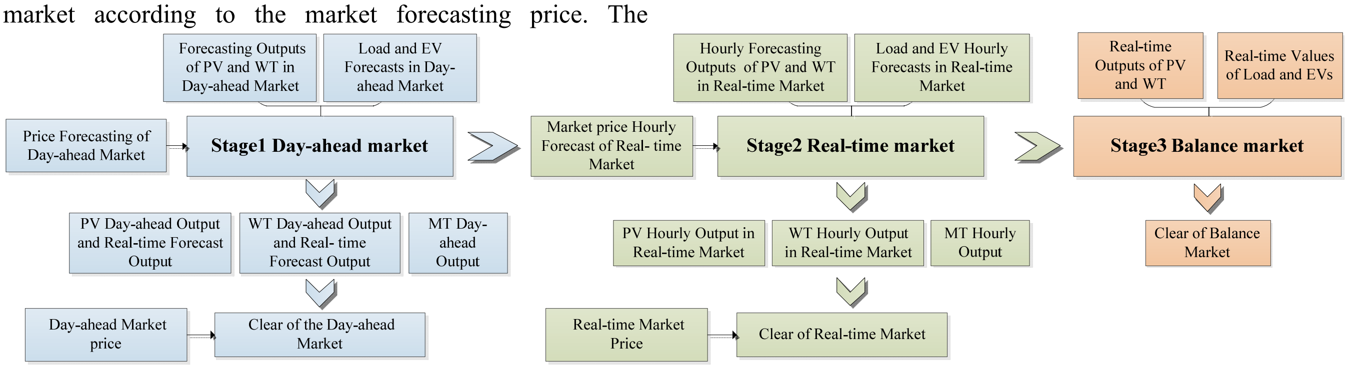

Fig.2 The Operating Mechanism of Power Market

III. Charging Load Computation of EVs

In modern power systems, EVs are becoming reliable and flexible resources for energy balancing under varying renewable energy supply and demand scenarios. In this paper, four types of EVs are considered: taxi, bus, private car and business car. Different kinds of EVs have different operating characteristics and the differences are expressed as the charging times, charging capacities, charging locations and the accessing probabilities [19-20]. Four types of EVs charging parameters and assumptions are shown in Table I.

According to the charging power, the charging styles of EVs can be classified into three kinds: fast charging, normal charging and slow charging. Next, the charging features of four types of EVs are analyzed in the following content.

(1) Electric Bus: the charging power of bus can be divided into 0.75C and 0.25C per hour comparing with the capacity of the battery (total capacity is 150kW). The charging time in one day are concentrating in two periods: 10:00-16:30 and 22:00-5:30. The access probability and SOC probability of bus in the former charging time obey the Bernoulli distribution and Normal distribution respectively. However, the values in later charging time are both distributed as the Normal distribution.

(2) Electric Business Car: in this paper, business cars are mainly used for business reception during the day. Therefore, the charging style is usually selected as the slow charging and the charging power is 0.25C per hour comparing with the capacity of the battery (total capacity is 45kW).

(3) Electric Taxi: as for the taxi, they are always working in the 24 hours. Obviously, the main charging period of taxi are concentrated on shifting and rest time. Moreover, the common charging style is fast charging in the station. The access probability and SOC probability obey to the Bernoulli distribution and Normal distribution respectively.

(4) Private Car: the charging characteristics of the private car is more complicated. In this paper, the charging features of private car divided into weekdays and weekends. On weekdays, private car is usually used for commuting and shopping and the working place with charging facilities can provide normal charging for EVs during working hours.

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Moreover, the customers have to charge their EVs at charging stations after working if the working places haven't charging facilities. Besides, private cars also can be charged during the shopping time. However, the users can charge their EVs at night by slow or normal charging when the private charging piles are installed. At weekends, the private car also can be charged at home, in charging station and shopping mall according to the living habits and driving styles.

TABLE.I THE CHARGING PARAMENTS FOR DIFFERENT TYPES OF EVS

EV type	Major Charging period	Charging Power	Charging time limit	Access probability	SOC probability	Charging location
Bus	10:00-16:30	112.5kW	\	Be (1.1,1.1)	N (0.4,0.1)	Charging station
	22:00-5:30	37.5kW	\	N (23,1)	N (0.4,0.1)	
Business Car	19:00-6:00	11.25kW	\	N (20,1.5)	N (0.5,0.1)	Charging station
Taxi	1:00-5:00	22.5kW	120min	Be (2,4)	N (0.3,0.1)	Charging station
	11:00-14:00	56.25kW	60min	Be (2,4)	N (0.3,0.1)	
Private Car (working day)	9:00-17:00	11.25kW	\	N (9,0.5)	N (0.5,0.1)	Company
	19:00-7:00	11.25kW	\	N (20,0.5)	N (0.5,0.1)	Home
	19:00-21:00	22.5kW	80min	U (19,21)	N (0.6,0.1)	Shopping Mall
	19:00-23:00	56.25kW	\	N (20,0.8)	N (0.3,0.1)	Charging Station
Private Car (weekend)	10:00-22:00	22.5kW	80min	N (15,1.5)	N (0.5,0.1)	Shopping Mall
	17:00-6:00	11.25kW	\	N (20,1.5)	N (0.5,0.1)	Home
	16:00-23:00	56.25kW	\	N (17,0.8)	N (0.3,0.1)	Charging Station

Aiming at analyzing the influence of the EVs on the bidding strategy of VPP, the scale and corresponding charging probability of each type of EVs are listed in Tab.II.

TABLE.II THE SCALES AND CHARGING PROBABILITIES OF DIFFERENT TYPE OF EVS

EV type	Number	Charging Period	Charging Probability
Bus	150	10:00-16:30	0.4
		22:00-5:30	0.6
Taxi	250	1:00-5:00	0.5
		11:00-14:00	0.5
Business Car	150	19:00-6:00	1
Private vehicle (working day)	550	9:00-17:00	0.2
		19:00-7:00	0.5
		19:00-21:00	0.1
		19:00-23:00	0.2
Private vehicle (weekend)		10:00-22:00	0.3
		17:00-6:00	0.4
		16:00-23:00	0.3

Then, the charging curves of EVs are drawn based on the Monte Carlo simulation and the results are compared in Fig.3.

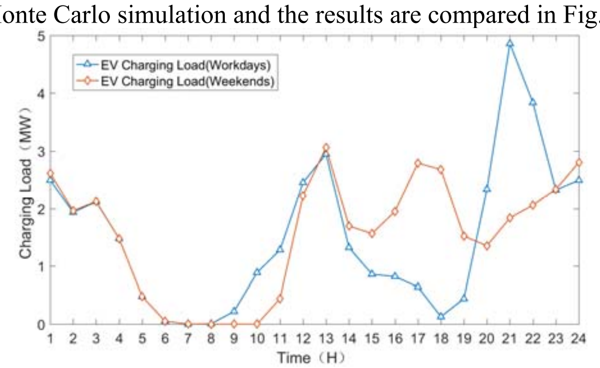

Fig.3 The Charging Load Curves of Private EVs

From Fig.3, it is clear that the charging load curves of weekday and weekend are obviously different. There are three load peaks occurring at 0:00, 12:00 and 21:00 in weekday while the load peaks occurring time on weekend changed into 0:00, 12:00 and 17:00. In order to analyze the impact of the EVs charging on the load demand, the total load curves which obtained by superimposing the ordinary load and charging load are shown in Fig.4. Apparently, the integrations of EVs change the peaking time of loads and increase the peak-valley difference. Generally speaking, EVs produce the negative impact on power system operation without the dispatching optimization and charging management.

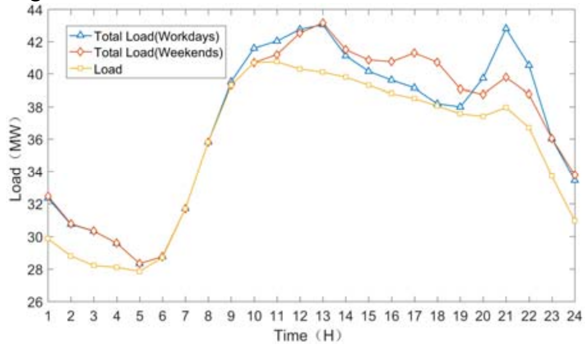

Fig.4 The Load Level Based on the Consideration of EVs

IV. THREE STAGES BIDDING MODELS OF VPP

The power market for the bidding strategy of VPP contains three stages according to the different time arrangement.

1) Stage1: Day-ahead Market Bidding Model

In the day-ahead market, the aim of VPP is to maximize the revenue by considering the integrations of different renewable energies and loads [21][21]. The detailed model of bidding strategy of VPP is presented as follows.

A. Objective Function

Generally speaking, the day-ahead market opens between 10:00 a.m. and 1:00 p.m. in the day prior to the day energy consumption. The goal of the day-ahead market bidding strategy is to maximize the revenue of VPP.

$$\max \sum_{t=1}^{24} (R_{w,da,t} + R_{pv,da,t} + R_{mt,da,t} \text{-}(C_{da,m,t} + C_{da,mt,t})) \tag{1}$$

$$R_{w,da,t} = P_{w,da,t}\lambda_{da,p,t} + P_{w,rd,t}\lambda_{r,p,t} \tag{2}$$

$$R_{pv,da,t} = P_{pv,da,t}\lambda_{da,p,t} + P_{pv,rd,t}\lambda_{r,p,t} \tag{3}$$

$$R_{mt,da,t} = P_{mt,da,t}\lambda_{da,p,t} \tag{4}$$

$$P_{market,t} = (L_{load,da,t} + L_{ev,t}) - (P_{w,da,t} + P_{w,rd,t} + P_{pv,da,t} + P_{pv,rd,t} + P_{mt,da,t}) \tag{5}$$

$$C_{da,m,t} = P_{da,m,t}\lambda_{da,p,t} + P_{rd,m,t}\lambda_{r,p,t} \tag{6}$$

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$$P_{da,m,t} + P_{rd,m,t} = P_{market,t} \tag{7}$$

$$\begin{aligned} C_{da,mt,t} &= ((\mu_{sd,t} - \mu_{sd,t-1})\lambda_{sd} + k_{mt,t}(P_{mt,da,t} - P_{\min,mt}) + \\ &\mu_{sd,t}\lambda_{base} + \sum_{i} P_{mt,da,t} Q_i C_i) \end{aligned} \tag{8}$$

Obviously, Formulation (1) denotes the objective function of the bidding model in the day-ahead market. Equation (2) and (3) represent the forecasting revenue of WT and PV respectively. Equation (4) explains the MT bidding revenue in the day-ahead market at time *t*. Equation (5) indicates the trading power of VPP in the day-ahead market and to ensure the power balance between the generation and consumption in the VPP. When the $P_{market,t}$ is positive, that means the output power from renewable energies in VPP can't meet the demand of the loads. Therefore, it is necessary to purchase additional power from the external market. Conversely, when the $P_{market,t}$ is negative, the generated power of VPP exceeds the load demand and the sufficient power can be sold to the external market. Equation (6) shows the VPP forecasting cost in the day-ahead market at time t (when $C_{da,m,t}$ is negative, it indicates the VPP forecasting revenue obtained from the day-ahead market). Equation (7) represents the sum of the electricity trading between the VPP and the external market in the day-ahead market and the estimated real-time market. Equation (8) indicates the MT operation cost at time *t*. Generally speaking, the MT operation cost consists four parts: the MT start-up/shut-down cost, the MT operating cost, the MT fix cost under operating condition and the MT environmental penalty. Furthermore, in equation (8), $\mu_{sd,t}$ is the operational state parameters of the MT. When $\mu_{sd,t}$=1, the MT is working. When $\mu_{sd,t}$ =0, MT is out of the service. Next, the technical parameters and the environmental penalty coefficient of MT are presented in Tab.III and Tab.IV respectively [20]. It should be noted that the C_i in Equation (8) equals to the sum of the E_{id} and P_i.

TABLE.III THE TECHNICAL PARAMETERS OF MT

Maximal power	Minimal power	K_{mt}	Start-up/ Shut-down cost	Fix cost	Ramping rate
5.67MW	2.5MW	6.31$/MW	30$	30$	3MW/H

TABLE.IV THE ENVIRONMENTAL PENALTY OF MT

Contaminants	NO_X	CO_2	CO	SO_2	
Emission (Q_i)	0.6188	184.0829	0.1702	0.000928	kg/MWh
Environmental value (E_{id})	1	0.002875	0.125	0.75	$/kg
Penalty (P_i)	0.25	0.0125	0.02	0.125	$/kg

B. Constraints

The constraints of each unit in the day-ahead market are listed as follows:

$$P_{w,da,t} + P_{w,rd,t} \le P_{w,dap,t} \tag{9}$$

$$P_{pv,da,t} + P_{pv,rd,t} \le P_{pv,dap,t} \tag{10}$$

$$P_{mt,da,t} \le P_{mt,\max} \tag{11}$$

$$P_{mt,da,t+1} - P_{mt,da,t} \le P_{c\lim b} \tag{12}$$

Equations (9)-(10) ensure that the bidding output powers of PV and WT are less than the day-ahead forecasting output respectively. Equation (11) limits the maximal output of MT and equation (12) limits the MT ramping rate.

2) Stage2: Real-time Market Bidding Model

Similarly, the objective in the real-time market is to maximize the revenue of VPP and to balance the mismatch between generation forecast and load prediction hourly. In this stage, the bidding outputs of PV, WT and MT in the day-ahead market are known. Therefore, VPP can updates the forecast output values of PV and WT. Obviously, the forecast results of PV and WT are more accurate and the price of real-time market are also more assured [22]. The bidding model of VPP in real-time market is described as follows:

A. Objective Function

$$\max \sum_{t=1}^{24} \begin{pmatrix} R'_{w,da,t} + R_{w,rt,t} + R'_{pv,da,t} + R_{pv,rt,t} + R'_{mt,da,t} + \\ R_{mt,r,t} - C_{r,m,t} - C_{da,mt,t} - C_{rt,mt,t} \end{pmatrix} \tag{13}$$

$$R'_{w,da,t} = P_{w,da,t}\lambda_{da,r,t} \tag{14}$$

$$R_{w,rt,t} = P_{w,r,t}\lambda_{r,p,t} \tag{15}$$

$$R'_{pv,da,t} = P_{pv,da,t}\lambda_{da,r,t} \tag{16}$$

$$R_{pv,r,t} = P_{pv,r,t}\lambda_{r,p,t} \tag{17}$$

$$R'_{mt,da,t} = P_{mt,da,t}\lambda_{da,r,t} \tag{18}$$

$$R_{mt,r,t} = P_{mt,r,t}\lambda_{r,p,t} \tag{19}$$

$$C_{r,m,t} = P_{da,m,t}\lambda_{da,r,t} + P_{r,m,t}\lambda_{r,p,t} \tag{20}$$

$$\begin{aligned} C_{da,mt,t} + C_{rt,mt,t} &= ((\mu_{sd,t} - \mu_{sd,t-1})\lambda_{sd} + k_{mt,t}(P_{mt,da,t} + \\ P_{mt,r,t} - P_{\min,mt}) &+ \mu_{sd,t}\lambda_{base} + \sum_{i}(P_{mt,da,t} + P_{mt,r,t})Q_i C_i) \end{aligned} \tag{21}$$

As the information in day-ahead market, Equation (13) is the bidding objective in the real-time market. Equations (14), (16) and (18) are the WT, PV and MT actual revenue in the day-ahead market. Under this condition, the market price has changed from the forecast price to the market-clearing price. Equations (15), (17) and (19) are the bidding outputs of WT, PV and MT in the real-time market respectively. Equation (20) denotes the VPP total trading cost in the real-time market. Equation (21) shows the MT total operational cost in both two-stage markets.

Different from the day-ahead market stage, the day-ahead clearing price is known at this stage. VPP determines the day-ahead revenue based on the day-ahead bidding output and day-ahead clearing price and calculates the real-time market bidding output based on the real-time market forecast price.

B. Constraints

The constraints of each unit in the real-time market are listed as follows.

$$P_{w,da,t} + P_{w,r,t} \le P_{w,rp,t} \tag{22}$$

$$P_{pv,da,t} + P_{pv,r,t} \le P_{pv,rp,t} \tag{23}$$

$$P_{mt,da,t} + P_{mt,r,t} \le P_{mt,\max} \tag{24}$$

$$\begin{aligned} &P_{da,m,t} + P_{r,m,t} + P_{w,da,t} + P_{w,rt,t} + P_{pv,da,t} + \\ &P_{pv,r,t} + P_{mt,da,t} + P_{mt,r,t} = L_{load,r,t} + L_{ev,t} \end{aligned} \tag{25}$$

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Equations (22)-(24) limit the maximal output power of WT, PV and MT in the real-time bidding model. Equation (25) ensures the power balance of the VPP.

3) Stage3: Balance Market Model

In this stage, the bidding output of each unit and the real-time market-clearing price are both known. Although the PV and MT forecast outputs in the real-time market are more accurate, the deviations are still unavoidable comparing with the actual output. In the balance market, the bidding model of VPP is calculated as follows:

$$P_{balance,t} = (L_{load,t} + L_{ev,t}) - (P_{w,t} + P_{pv,t} + P_{mt,da,t} + P_{mt,r,t} + P_{da,m,t} + P_{r,m,t}) \tag{26}$$

$$C_{balance} = \alpha P_{balance} \lambda_{r,t} \tag{27}$$

Equation (26) stands for the computation of the power in the balance market. In Equation (27), when $P_{balance} > 0$, α is set as 1.1[23]. Conversely, α is set as −0.9.

4) Step Transaction Cost

By convention, VPP is mostly considered as the price takers in the power market, indicating that all participants' actions in single VPP do not influence the price and do not influence other VPP's actions. In fact, VPP operates as a ''prosumer'' in power market and the trading capacity with power system is limited. In this paper, the step transaction cost is utilized to denote the limitation of the transaction power in the power market. Therefore, Equations (6) and (20) are modified as the following expressions respectively.

$$C_{da,m,t} = P_{da,m,t} \delta_{da} \lambda_{da,p,t} + P_{rd,m,t} \lambda_{r,p,t} \tag{28}$$

$$C_{r,m,t} = P_{da,m,t} \delta_{da} \lambda_{da,r,t} + P_{r,m,t} \delta_r \lambda_{r,p,t} \tag{29}$$

Obviously, δ_{da} , δ_r are the step transaction cost coefficients of the day-ahead market and real-time market respectively. The determinations of two parameters are shown in Equations (30) and (31). The values of δ_{da} and δ_r are set as the same for the convenient purpose.

$$\delta_{da} = \delta_r = 1 + \gamma, (P_{\theta,m,t} > 0) \tag{30}$$

$$\delta_{da} = \delta_r = -\gamma, (P_{\theta,m,t} < 0) \tag{31}$$

The penalty coefficient γ is listed in the Tab.V.

TABLE V. THE PENALTY COEFFICIENT OF STEP TRANSACTION COST

Transactions Power (MW)	γ
$\lvert P_{\theta,m,t} \rvert$<5	0
5<$\lvert P_{\theta,m,t} \rvert$<10	5%
10<$\lvert P_{\theta,m,t} \rvert$<15	10%
15<$\lvert P_{\theta,m,t} \rvert$<20	15%
$\lvert P_{\theta,m,t} \rvert$>20	20%

5) VPP Dispatch Cost

In VPP, the optimal dispatching of EVs can not only improve the benefits of the VPP but also reduce the peak-valley difference of the load. In this paper, the dispatching cost is proposed to indicate the expected charging deviations of the EVs and the calculating formula is shown in Equation (28).

$$C_{ev,trans} = \sum_{i=1}^{24} \beta P_{ev,t} \lambda_{da,r,t} \tag{28}$$

β is the subsidy coefficient, which is related to the difference between the expected charging time before and after dispatch. The value of β is set as 0.02/h.

6) The flowchart of the Proposed Algorithm

Recently, the Artificial Bee Colony (ABC) algorithm has been widely applied to solve the optimization problems in the power system [24-25]. Generally speaking, the ABC algorithm consists of four parts: hire bee, follow bee, detection bee, and source. Accordingly, application of ABC algorithm to solve the problem can be divided into the initialization stage, employment stage, following stage and detection stage.

In this paper, the ABC algorithm is employed to solve the objective functions of day-ahead market and real-time market. It should be noted that: the day-ahead and real-time market objective function can be regarded as honey source values. The feasible solution of each iteration can be regarded as the locations of honey sources. The optimal solution of each iteration will be recorded in the best source location matrix. In order to make the ABC algorithm more suitable for this model, the improvements of ABC algorithm are described as follows:

(1) A single source location can store as a set of solutions, that will greatly increase the storing capacity;

(2) The iteration is carried out in the feasible region, and the constraints are only considered in the initialization process;

(3) Optimize the locations of honey sources and select the necessary source location randomly.

Based on the mentioned modifications, the solving ability of ABC algorithm has been greatly improved. Obviously, the improved ABC algorithm can store more information in a single source and it is easier to calculate the matrix. In the process of iteration, no constraints need to be considered, which is more conducive to model expansion. The flow chart of the improved ABC algorithm is shown in Fig.5.

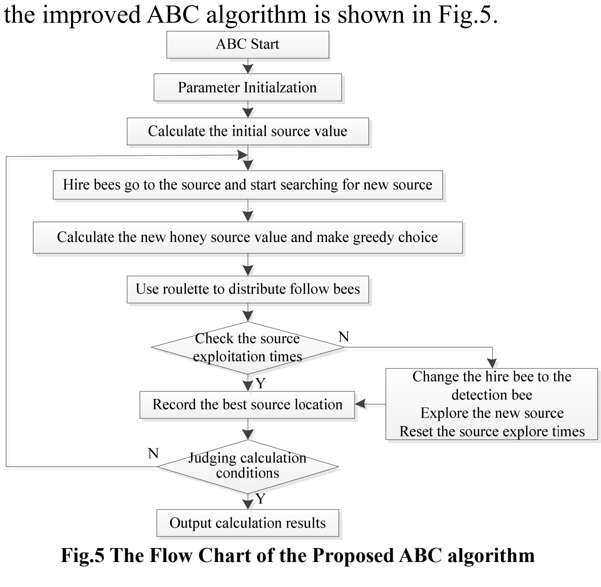

Fig.5 The Flow Chart of the Proposed ABC algorithm

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V. CASE STUDIES

In order to analyze the bidding strategies of VPP by considering the large-scale integrations of EVs, the corresponding parameters are proposed in this paper. First of all, the forecasting and actual prices of day-ahead and real-time market are compared in Fig.6. From the perspective of time, all the values are near the same from 0:00-10:00. However, the variations of these values are inestimable from 10:00-24:00.

The purpose of VPP is to achieve maximum benefits in the power market by scheduling the renewable energies and EVs. In this paper, the output powers of WT and PV in three stages of power market are from the Nordpool shown in Fig.7 and Fig.8 respectively.

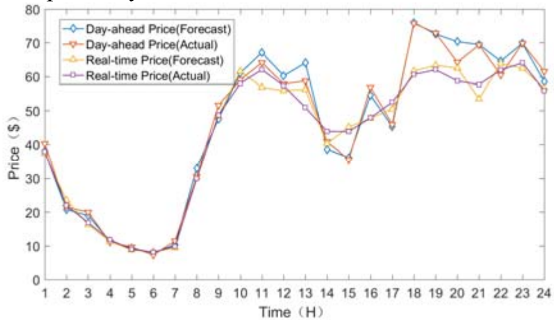

Fig.6 The Price Information in Day-ahead and Real-time Market

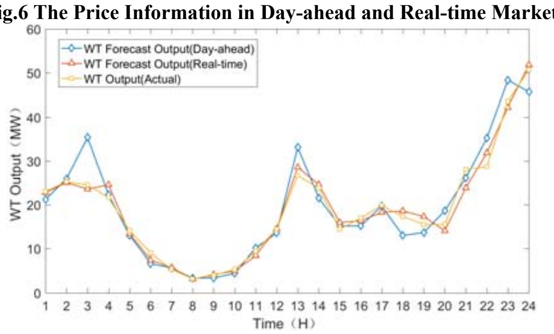

Fig.7 The Outputs of WT in the Bidding Model of VPP

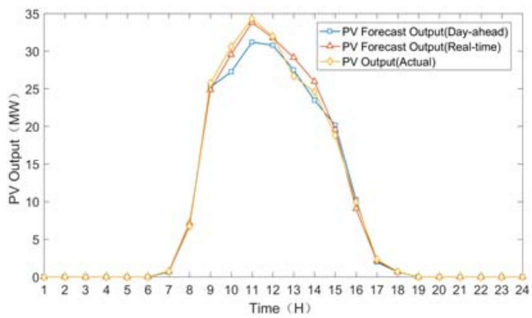

Fig.8 The Outputs of PV in the Bidding Model of VPP

A. *VPP Bidding Strategy in Day-ahead Market*

In this paragraph, the bidding strategy of VPP in day-head market are solved by the proposed ABC algorithm. In order to emphasize the influence of EVs on the bidding strategy of VPP, the bidding output power by the WT, PV, and MT are shown in Fig.9. Moreover, the actual output power of PV and WT are also added in the Fig.9. Traditionally, the output power of WT and PV in the day-ahead market should be consumed totally due to the lower marginal cost. The function of the MT is to compensate for the mismatch between short-term supply and demand in VPP. However, the output of the MT is affected by the forecasting price, the bidding output of WT and PV unit as well as the load.

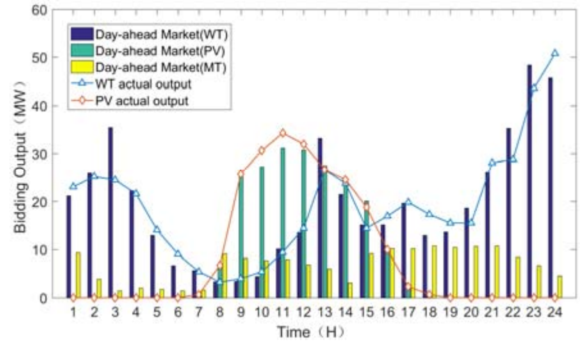

Fig.9 Bidding Strategy of VPP in Day-ahead Market (Without EVs)

In VPP, there are two different ways to dispose the power unbalance caused by PV and WT. One is to adjust the output of MT in the first step and then implement the energy exchange with the utility grid if the total generation is lower than the consumption of VPP. The other is direct to purchase or sell the electricity from or to the utility grid without considering the output of the MT. Under this condition, the trading power between the VPP and utility grid is determined by the install capacities of PV and WT of VPP. In order to evaluate the influence of the exchange power in the bidding model, the difference with and without consideration of the step transaction cost are compared in Fig.10.

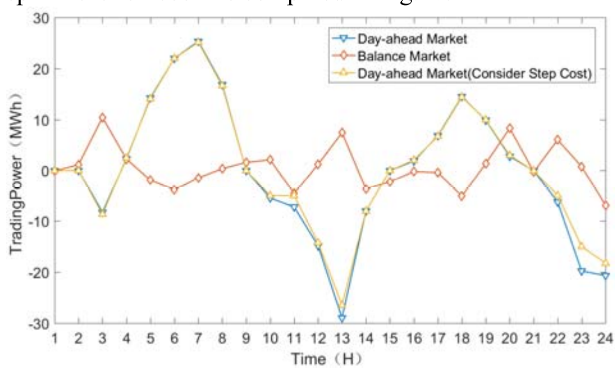

Fig.10 Trading Power of VPP in Day-ahead Market

After considering the step transaction cost, the transaction cost of the VPP is proportional to the transaction capacity. Obviously, the transaction power of the VPP decreases the bidding output of the units in the VPP. At this stage, the revenue of VPP is less affected by the predicting deviations from the unstable abilities of PV and WT. The VPP revenue increase from $29685 to $29814. Next, the influences of the EVs on the bidding strategy of VPP in Day-ahead market and Balance market are analyzed. The comparisons in the typical day are expressed in the Fig.11.

From the results in Fig.11, it is obvious that the integrations of EVs increase the load demand at the peak hour. That means the VPP should purchase more electricity from the utility gird and adjust the output of MT aiming at meeting the load demand. Under this circumstance, the revenue of VPP decreases from $29814 to $29250.

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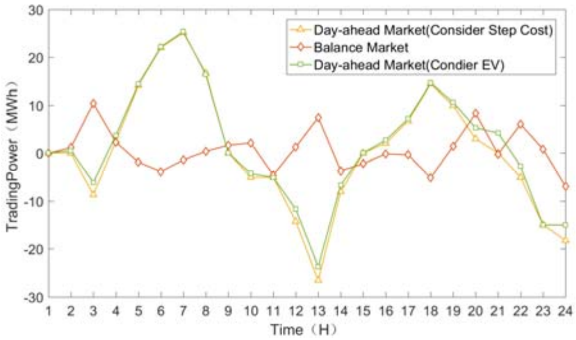

Fig.11 VPP Trading Power Considering the Integrations of EVs

B. VPP Bidding Strategy in Real-time Market

In the day-ahead market, PV, WT, and MT can only bid one time. The single bidding regulation will cause a large deviation between the bidding output and actual output. However, in the real-time market, VPP can adjust the bidding output and bid to times according to the information from the internal and external participants to obtain higher revenue. The bidding outputs of WT and PV are shown in Fig.12 and Fig.13.

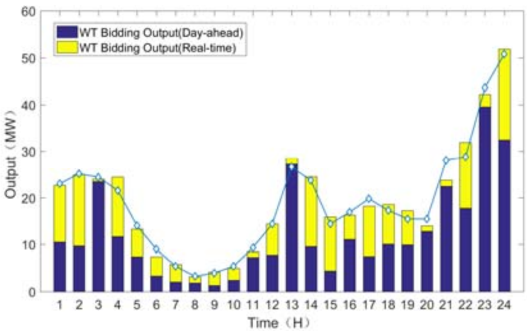

Fig.12 The Bidding Outputs of WT in Real-time Market

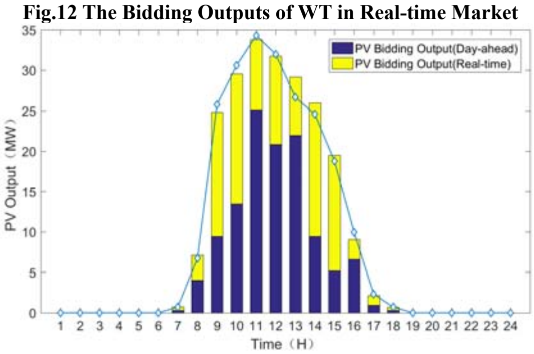

Fig.13 The Bidding Outputs of PV in Real-time Market

Comparing with the bidding output in day-head market, the values of the PV and WT in real-time market are closer to the actual output. The higher accuracy of the power output of PV and WT not only can optimize the power flows and improve the stable and economical operation of VPP, but also can increase the revenue of VPP from the electricity trading aspects. The total bidding revenue of VPP increased from $29250 to $35424 in the whole bidding process.

C. Influence of EVs on VPP's Bidding Strategy

In this paragraph, the influences of different scales of EVs on the bidding strategies are analyzed. In the first part, the number of the EV is gradually increasing according to the proportions in Tab II. Then, the values of VPP revenues considering different scales of EVs are presented in Tab.VI.

TABLE.VI REVENUE COMPARISONS OF VPP WIHT DIFFERENT EVS

Number of EV	0	1000	4000	6000	8000	10000
VPP Revenue($)	29814	29250	26524	24024	21057	17741

It is clear that the increasing integration of EVs will grossly reduce the revenue of the VPP duo to the huge electricity purchasing from the utility grid. Therefore, the management of VPP should comprehensively consider the magnitudes of the renewable energies and the load demands. Furthermore, the trading power in Day-head and Balance Market with the 10000 EVs integration are displayed in Fig.14.

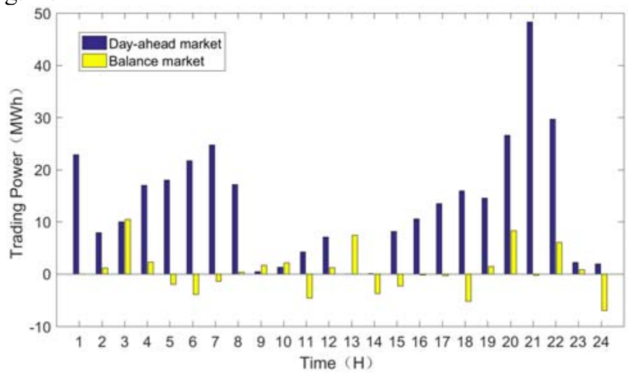

Fig.14 VPP Trading Power considering 10000EVs

Under this condition, it can be seen that the demands of EVs exceed the power supply from the values of trading power of VPP in Day-ahead market. Comparing with the values in Fig.11, the trading power of MTs are nearly the same. That means the outputs of MT have little change due to the multiple constraints.

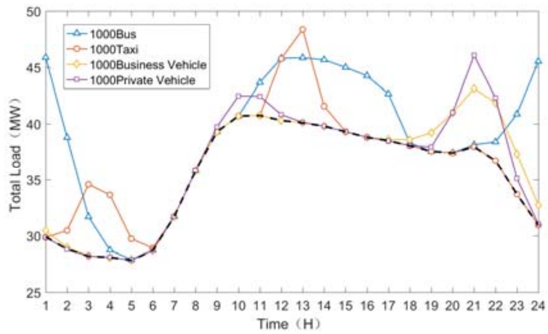

Fig.15 The Total Load Demands Considering Four Types of EVs

Due to the different charging characteristics of EVs, four types of EVs with the same scale (the integration number is 1000) are utilized to study the influences of the EVs on the bidding strategy. From the perspective of equivalent load, the total load demands by superposing the ordinary load and EVs are compared in Fig.15.The dashed black line stands for the original load curve.

Although the scales of the EVs are same, the equivalent load demands show obvious changes, especially in the charging periods. From the point of performances, all the kinds of EVs produce the different levels on the load peaking

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time and rush values. Furthermore, the influences of the different kinds of EVs on the bidding revenue of VPP are listed in Tab. VII.

TABLE.VII THE REVENUES OF VPP CONSIDERING FOUR TYPES OF EVS

Types of EVs	1000-bus	1000-taxi	1000-business	1000-private
Revenue ($)	28709	29908	29117	29015

Combing with the outputs of PV and WT and the equivalent load demands in Fig.16, it can be deduced that the bus charging load is mostly concentrated in the peak period and the charging power is relative higher, therefore, the total bidding revenue of VPP declines significantly. On the other hand, the charging power of taxi is smaller and most of the charging time are in the lower price periods as well the huge outputs of WT and PV, so the taxi has the least impact on the bidding revenue of VPP. In fact, the influences of the business car and private car also be analyzed similarly. In a word, the influences of EVs on the bidding revenue can be sorted as follows: bus, private car, business car and taxi. At this point, the optimal dispatching of bus and private car will obtain much benefits in the bidding strategy of VPP.

D. Dispatching Strategy of EVs in VPP

In general, the objective of the VPP when participating in the short-term electricity market is to maximize its expected profit from the trading energy in the whole bidding process. In order to reduce the impact of EVs and improve the benefits of VPPs, the dispatching strategies of EVs by considering the outputs of PV, WT and MT as well as the variations of power price are researched in this section. Frist of all, the comparisons of peak-valley differences, bidding revenues and charging costs before and after dispatching with the increasing scale of the EVs are listed in Tab.VIII.

TABLE.VIII VPP CHANGES BEFORE AND AFTER DISPATCHING

		Before Dispatch	After Dispatch	Comparison Results
1000 EVs	Peak-valley Difference	14.72MW	14.09MW	-0.63MW
	Bidding Revenue	$29250	$29532	+$282
	Charging Cost	$1774	$1615	-$159
4000 EVs	Peak-valley Difference	28.48MW	20.98MW	-7.5MW
	Bidding Revenue	$26524	$28081	+$1557
	Charging Cost	$7096	$6328	-$768
8000 EVs	Peak-valley Difference	47.71MW	28.94MW	-18.77MW
	Bidding Revenue	$21057	$25142	+$4085
	Charging Cost	$14193	$11394	-$2799

The conclusions contained in Tab VIII can be summarized as follows:

(1) With the increasing of EVs, the peak-valley difference is becoming bigger and bigger and the dispatch of the EV can obviously reduce the peak-valley difference by coordinating the renewable energies and load demands to guide the charging strategy at different time and locations. For example, the Peak-valley differences with or without dispatch is 7.5MW when the number of the EVs is 4000 while the value is 18.77MW when the number of EVs reaches to 8000.

(2) The bidding revenue of the VPP is reduced with the increasing number of the EVs. However, the optimal dispatch of EVs can improve the benefits of VPP. For example, although the number of EVs increases to 8000, the revenue decreases from $29532 to $25142 while this value is $21057 before the dispatch of the EVs.

(3) The dispatching of the EVs also can decrease the charging cost. The cost of charging will be deduced more obvious with the gradually increasing of EV's scale. Therefore, the dispatching of large-scale EVs will provide tremendous benefits to the VPP in the power market.

In order to explore the influences of EVs on the bidding strategy of VPP, the equivalent load demand before and after the dispatching of EVs (the scale of EVs is 4000) are compared in Fig.16.

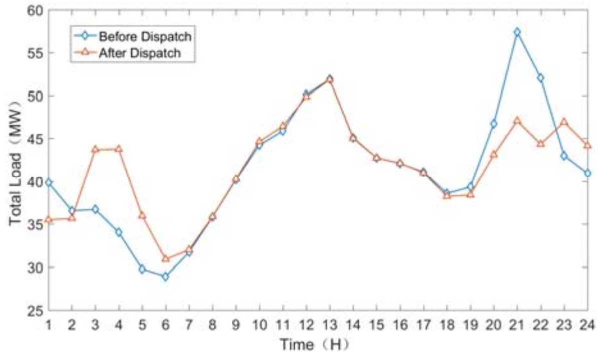

Fig.16 Comparison of Equivalent Load Demand Before and After Dispatching Considering the Integrations of EVs (4000)

From Fig.16, it is clear that the optimal dispatching of EVs can reshape the load demand of the power system to improve the bidding strategy of VPP. From that point of view, the scheduling strategy of VPP has direct relationship with the number of EVs. The integration of EVs not only improve the consumptive ability of renewable energy but also increase the benefit of the VPP by coordinating the generation and consumption over a longer time scale.

VI. CONCLUSION

In this paper, EV is utilized to improve the operation efficiency of VPP. The influences of EVs on the bidding strategies of VPP is also studied by considering different types and scales.

(1) From the perspective of type, electric bus and private car have the greater impact on the bidding strategy of VPP comparing with the business car and taxi.

(2) From the perspective of scale, the integrations of EVs should coordinate with the development of renewable energy in the VPP.

(3) From the perspective of management, the dispatching of EVs can improve the benefit of VPP by optimize the charging time and charging style.

For the future research works, the uncertainties of renewable energy and different kinds of EVs and their influences on the bidding strategies of VPP are still needed to further study in the next step. Furthermore, the performances of the bidding strategies of VPP should be evaluated in the practical power market by considering the actual integration of EVs.

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