Bidding Agent for Electric Vehicles in Peer-to-Peer Electricity Trading Market considering uncertainty

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***Abstract*—It is a problem that as the spread of solar power generation expands, the net power demand sharply fluctuates between day and night. The P2P (Peer to Peer) Electricity Market is expected to be a solution when accumulator-users play an important role. In such background, widespread EVs are expected to participate in the P2P market and utilize the battery storage. However, in previous research, only simulation and effect verification under an ideal condition were conducted and no EV bidding agent which works in the real situation was proposed. Therefore, in this paper, a whole system of a robust automatic bidding agent of EV which works in the real situation is proposed, and case studies based on the actual EV driving data were conducted. The results show that even EVs are running irregularly, proposed EV bidding agent was able to realize benefits for EV-users and leveling effect of the power demand through the day.**

***Index Terms*—Peer-to-Peer electricity trading market, electric vehicle, bidding strategy, multi-agent system**

I. INTRODUCTION

In recent years, there is an urgent need to convert from fossil fuels to renewable energy (RE) to reduce the bad effects on the earth's environment, and solar power generation is one of the important energy resources. On the other hand, it has been pointed out that, as the spread of solar power generation expands, the net load sharply fluctuates between day and night and the management costs of power generation will increase. This problem is generally called 'duck curve' [1].

The P2P (Peer to Peer) Electricity Market is considered to be one of the solutions of the duck curve. The P2P electricity trading market is a distributed electricity network realized by block-chain technology [2], and it is thought that a distributed electricity network will be suitable when the energy resources become distributed, instead of the centralized power system. And it is expected that when accumulator users participated in the P2P electricity trading market, surplus power will be optimally distributed by market principle and the duck curve will be leveled. Therefore, attention is being focused on utilizing the widely spread electric vehicles (EV) as storage batteries in the P2P power market. In [3], a localized Peer-to-Peer (P2P) electricity trading model for locally buying and selling electricity among Plug-in Hybrid Electric Vehicles (PHEVs) in smart grids was proposed.

However, as far as I know, there is no paper that designed the EV bidding agent, that works on the actual situation. In [4], simulation of the P2P electricity trading market including EV bidding agent was conducted and it was confirmed that power demand through the day can be leveled by EV's storage battery. However, in the paper, the condition in the simulation is not realistic at all because the running patterns of EVs are fixed and also it was assumed that the future power demand and supply amount are known. Therefore, the realistic leveling effect of electricity demand when EV-users entered the P2P electricity trading market has not been verified and incentives for EV-users are not guaranteed at all.

Therefore, in this paper, a whole system of a robust automatic bidding agent of EV which works in a real situation that the future is not known is proposed. In order to verify whether it works, we constructed a P2P market simulator and conducted some case studies using actual driving data of 446 of EVs.

In the case study, it was shown that considering future driving probability in the bid optimization phase is effective. Also, it was shown that combining the concept of "optimal bidding" and "robust bidding" (explained below) is effective for the EVs which are difficult to predict future driving time due to the variance of driving pattern. Also, it was indicated that even in actual situation assuming that the future driving is unknown, there are be incentives for all types of EVs to participate in the P2P electricity trading market.

II. P2P ELECTRICITY TRADING MARKET SIMULATOR

A. Designing Market System

The market of the P2P electricity trading market simulator deals with the futures market. Each future market deals with the electricity of 30 minutes, and the market is opened for 24 hours until the electricity transmission begins. In addition, it is thought that a market with high liquidity by continuous trading is suitable for optimal distribution of electric power, so the continuous double auction method is implemented.

The market accepts bids from the automatic bidding agents and executes the contract sequentially. Each contract result is notified to the automatic bidding agents.

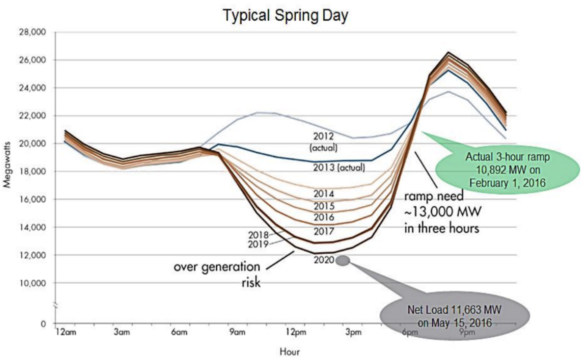

Fig. 1. Duck curve [1]

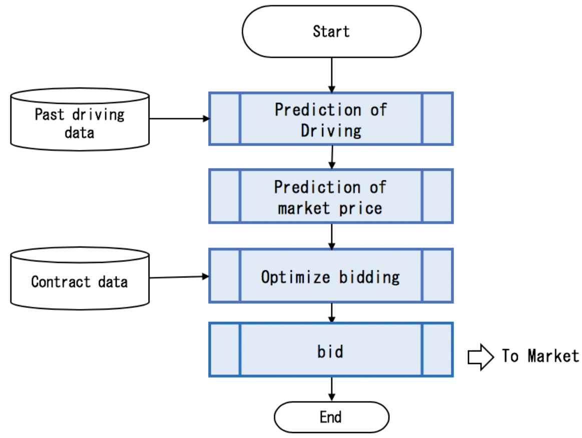

Fig. 2. Flow chart of EV automatic bidding agent

B. Designing Automatic Bidding Agent

The automatic bidding agent can bid simultaneously on all open markets (48 markets). The role of the automatic bidding agent is to determine the bidding price and quantity for each market in order to maximize the utility of the user. The automatic bidding agent obtains various data for each bidding opportunity, forecasts future power supply and demand of users, forecasts the market prices, and optimizes bid volumes and prices based on the users' needs.

III. Automatic Bidding Agent for Electric Vehicle

A. requirement definition

There are three factors for maximizing the utility of EV users: "Purchase electricity when it is cheap and sell it when it is expensive", "do not hinder driving", and "do not hold power trading during driving hours". In other words, it is necessary to not only maximize the "benefit" of power trading but also consider the "risk" of running out of power required for driving and the loss by trading electricity during driving timezone (When a transaction can't be realized because of driving, EV user will have to pay for a penalty). This is a different point from previous papers because previous papers have not considered those risks, rather they only focused on optimizing benefits under an ideal condition.

B. Required Functions and Overall Flow

Figure 2 shows the functional flow of the EV agent. First, driving at a future time is predicted from the past driving data. Next, the market price is predicted from the past result. Then, based on the values calculated in the driving prediction phase and the market price prediction phase, the prices and amounts of the bids are optimized and the bids will be passed to the market.

C. Prediction of Future Driving

In the phase of prediction of future driving, the driving time zone and the power consumption are predicted, and also the driving probability distribution of each timezone is predicted. The prediction of the driving time zone and the power consumption is conducted by clustering past driving data by the number of average driving times per day, and then use the median value in each cluster. The driving probability distribution is predicted by Kernel density estimation (KDE) using past driving data. An example of the prediction result of future driving is shown in Fig. 3. Also, an example of a prediction result of driving probability through the day is shown in Fig. 4.

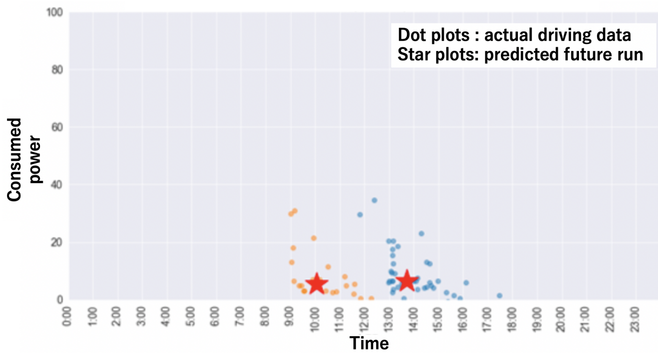

Fig. 3. Example of prediction of future driving

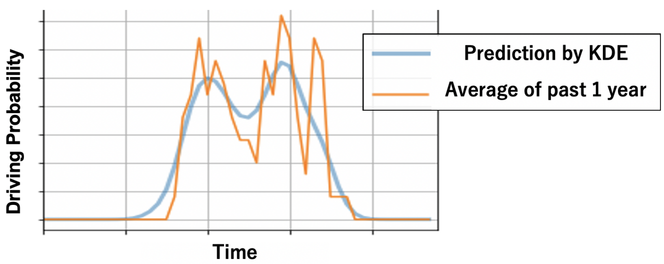

Fig. 4. Example of prediction of driving probability through the day

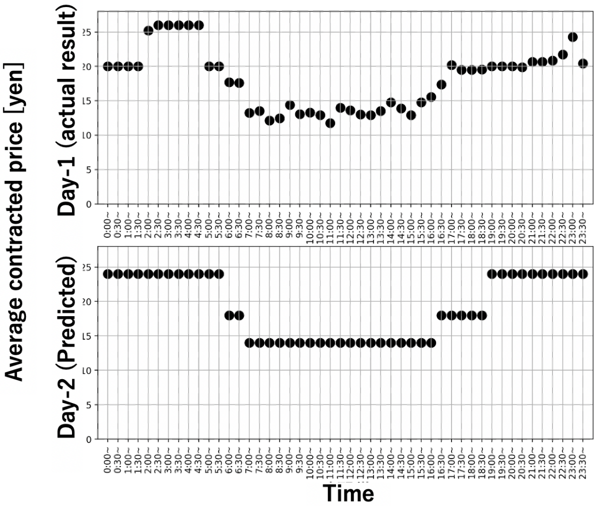

Fig. 5. Example of prediction of future driving

D. Prediction of Market Price

EV automatic bidding agent gets profits by purchasing cheap surplus power in the daytime and sell those power at a higher cost at night. As described in I, in a situation that the solar panels spread widely, the net power demand will be low during the daytime and high during the night. So there is no need for predicting the market price value accurately, rather, the important point is to predict global market price fluctuations throughout the day. Therefore, in prediction, EV agents use the market prices of yesterday for input and then apply the step function to level the outliers. By this method, EV agents could be able to predict global market price fluctuations throughout the day. An example of the prediction result is shown in Fig. 5.

E. Optimizing Bids

In the optimization phase, the EV agent solves the following linear minimization problem with linear programming. By this optimization, the optimal amount of buy or sell bids to each future market(i) is calculated.

Minimize.

$$\sum_{i=mn}^{mn+48} [\ \{Buy_i - Sell_i\} * PredPrice_i \tag{1}$$

$$+ C * \{Buy_i + Sell_i\} * \{RunProb_i + \epsilon\}\ ] \tag{2}$$

Subject to.

$$Buy_i,\ Sell_i \geqq 0$$
$$Buy_i + Contracted_i \leqq 3(kWh)$$
$$Sell_i - Contracted_i \leqq 3(kWh)$$
$$Buy_i,\ Sell_i = 0\ \ (if\ PredRun_i = True)$$
$$SOC_i \geqq SocLowerLimit$$
$$SOC_i \leqq SocHigherLimit$$

$$SOC_{i+1} = \begin{cases} (if\ PredRun_i = False) \\ SOC_i + Contracted_i + Buy_i - Sell_i \\ \\ (elif\ PredRun_i = True) \\ SOC_i - PredCons_i \end{cases}$$

Variables.

$Buy_i =$ Amount of buy bid to market(i)
$Sell_i =$ Amount of sell bid to market(i)
$SOC_i =$ State of charge at the beginning of market(i)
$PredPrice_i =$ Predicted price of market(i)
$RunProb_i =$ Predicted driving probability in timezone(i)
$PredCons_i =$ Predicted power consumption in timezone(i)
$PredRun_i =$ Whether the EV is running in timezone(i) $(boolean)$
$Contracted_i =$ power already contracted in market(i) $(positive : buy, negative : sell)$
$SocLowerLimit =$ SOC lower limit
$SocHigherLimit =$ SOC higher limit
$C =$ defines the balance between item(1) and item(2)

The first item of the objective function (item(1)) represents the value of expenditure, and the second item of formula (item(2)) represents the penalty to the bids during the timezone of high driving probability. Minimizing the item (1) means that EV's profits will be maximized. Minimizing the item (1) means that the risk of contracting while driving will be minimized. So, by minimizing this formula, the EV agent will try not only to maximize their profits but also to prevent the contract while driving. And the balance between maximization of the profits and minimization of the risk is defined by the constant value of C. In the following case studies, C was fixed at 1. The example of how the optimization works is shown in Fig. 6.

F. Bidding Strategy

There are two types of bidding; "optimal bidding" which is a bid that the amount and price are determined from the output of bidding optimization, and "robust bidding" which is a bid that amount and price are determined regardless of the optimization result. For "optimal bidding", the EV agent

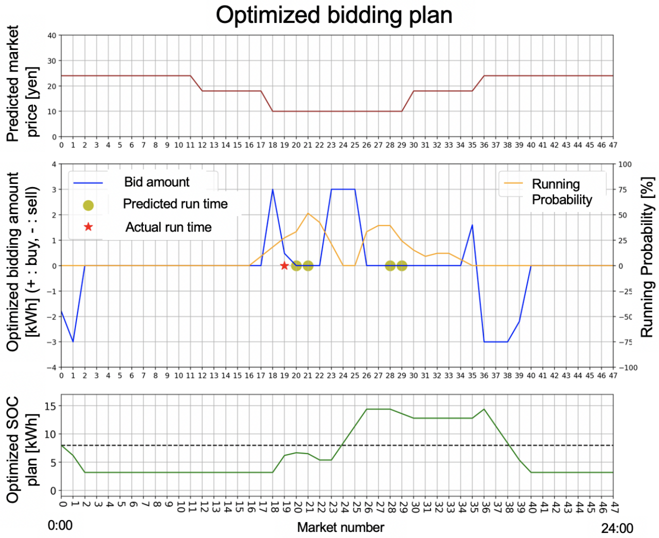

Fig. 6. Example of the result of bidding optimization

$T[min]$	0〜30	30〜60	60〜90	90〜120	120〜150	150〜
$Ratio(T)$	0.8	0.4	0.3	0.2	0.1	0
$C(T)$	0	0	1	1	2	–

Fig. 7. Robust bidding strategy

	span	House Agent	PV Agent	Total demand [kWh/day]	Total supply [kWh/day]	Electric power system	EV	EV/Surplus Ratio	Item(2) of the minimization formula
Case 1	7days	2	2	720	720	1	27	100%	x
									○
Case 2	7days	10	10	550	530	1	①20	100%	○
				615	615		②20		
				530	530		③20		
				576	576		④20		
				533	533		⑤20		
				526	526		⑥20		
				546	546		⑦20		
				550	550		⑧20		
				499	499		⑨20		
Case 3	7days	4	4	1299	1299	1	27	55%	○
				1157	1157			62%	
				1015	1015			71%	
				873	873			83%	
				731	731			100%	
				588	588			125%	
				446	446			166%	
				303	303			250%	
				159	159			500%	

Fig. 8. The scenarios of case studies

will make a buy or sell bid around the predicted market price with an optimized amount in optimized timezone, in order to realize their optimized EV's charging-discharging plan. On the other hand, for "robust bidding", the EV agent will bid at a low price for buying and bid at a high price for selling in all timezone, in order to buy electricity at a low price or sell electricity at a high price whenever if it's possible. The "robust bidding" works when the optimization result turned out to be wrong and there exists an opportunity to execute under good conditions even it's not the optimized timezone for bidding. Both the "optimal bidding" and "robust bidding" are important for EV-users profits when the uncertainty of future driving is considered. The strategy is formulated below.

Optimimal Bidding.

$$BidAmount_i = \begin{cases} OptBuy_i & (if\ Buy) \\ OptSell_i & (elif\ Sell) \end{cases}$$

$$BidPrice_i = \begin{cases} PredPrice_i - \beta + PassedTime_i * \alpha \\ (if\ Buy) \\ PredPrice_i + \beta - PassedTime_i * \alpha \\ (elif\ Sell) \end{cases}$$

Robust Bidding.

$$BidAmount_i = \begin{cases} CanBuy_i * Ratio(T_i) & (if\ Buy) \\ CanSell_i * Ratio(T_i) & (elif\ Sell) \end{cases}$$

$$CanBuy_i = SocHigherLimit - SocPlan_{i+1}$$

$$CanSell_i = SocPLan_{i+1} - SocLowerLimit$$

$$BidPrice = \begin{cases} BasePrice_{buy} - C(T_i) & (if\ Buy) \\ BasePrice_{sell} + C(T_i) & (elif\ Sell) \end{cases}$$

$$T_i = \text{rest of time until the market(i) opens [min]}$$

IV. Case Studies by Multi-Agent Simulation

The purpose of the case studies is to verify the effectiveness of the proposed EV bidding agent above. In the case studies, solar power generation agent, house agent, electric vehicle agent, electric power system agent participated in the P2P electricity trading market. For each agent, the actual data of electricity demand and supply was used. The EV running data used in the following case studies is composed of 446 EVs, and there are SOC(State of Charge) values of each one second for about 1-year span.

House and solar power generation agent bids for the actual amount of power demand or supply based on the actual data. The agents change the bidding price (i) linearly as the time gets closer to the timezone of the market(i). This is because as the time gets closer to the timezone of the market(i), the uncertainty of the amount of their power demand or supply at the timezone and market price decreases so that agents can bid more aggressively.

The electric power system agent bids at a fixed price and enough amount of power. The electric power system agent sells power at a high price and buys power at a low price, so it will work when there is no agent to absorb surplus power or there is no agent to sell power even if demand still exists.

In the case studies, several scenarios were conducted in order to evaluate how the proposed EV agent works. The scenarios of case studies are shown in Fig. 8.

A. Case 1

In case 1, it is evaluated that how the second item of minimization formula, which represents the penalty of bidding while high driving probability, works. In case 1, the total surplus power of solar power generation during daytime and the total storage capacity of all EVs are adjusted to be equal. In

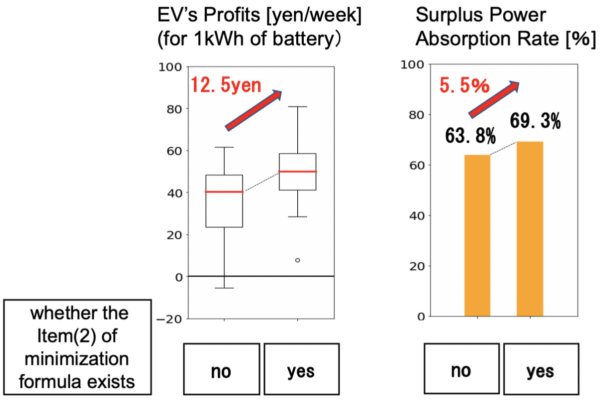

Fig. 9. difference between considering driving probability or not

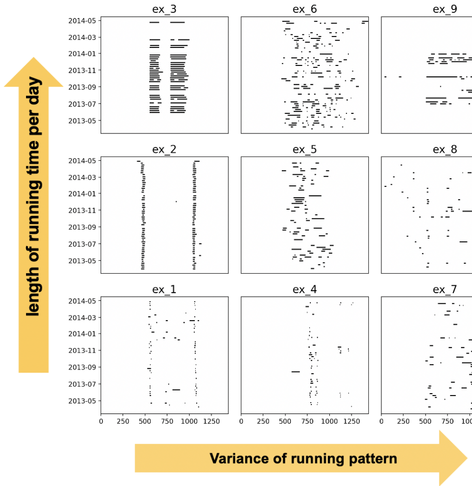

Fig. 10. Examples of classified EVs for each driving type.For each graph, the X axis represents the time through the day and the Y axis represents the date, and the black line represents each of the actual running.

other words, the ideal Surplus Power Absorption Rate realized by the P2P electricity trading market is 100% (it is realized when all EVs could charge all the surplus solar power).

The result (Fig. 9) shows that both EVs profit and Surplus Power Absorption Rate improved by considering driving probability when optimizing the bids. This is because it was more successful to prevent contracts while running time when considering driving probability.

B. Case 2

In case 2, 9 cases of simulations were conducted in order to see how the proposed EV bidding agent works for different driving patterns. In each case, running data of different EVs of the different driving patterns were used. EVs are classified into 9 classes by the length of running time per day and the variance of driving pattern. The examples of classified EVs are shown in Fig. 10. The EVs of short driving time per day are supposed to earn more money than the EVs of long driving time because more opportunity exists for trading power, and also the EVs of a low variance of the driving pattern are supposed to earn more money than EVs of high variance of the driving pattern because the future run is more predictable so that there is a smaller risk of contracting while running. In case 2, the total surplus power of solar power generation during daytime and the total storage capacity of all EVs are adjusted to be equal so that the ideal Surplus Power Absorption Rate realized by the P2P electricity trading market is 100% (same as case 1).

The result (Fig. 11) shows that except for cases where the driving time is 65 minutes or more, about the same profit and Surplus Power Absorption Ratio was achieved even the variance of driving pattern differs compared in the same length of driving time per day. Therefore it can be said that combining "optimal bidding" and "robust bidding" is effective for the EVs which are difficult to predict future driving time.

Also, it is indicated that even the EVs of the large variance of the driving pattern can realize nearly the same Surplus Power Absorption Ratio and about the same profit

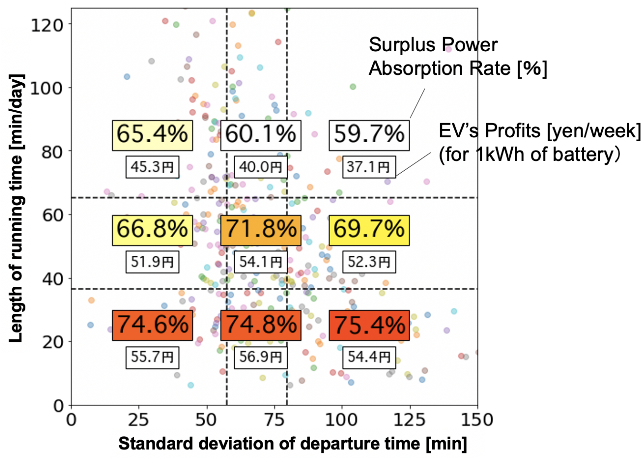

Fig. 11. Case2 result: comparison between different EV's running pattern

as EVs of the small variance of driving pattern. So it can be said that there should be incentives for various running patterns of EVs to participate in P2P electricity trading market.

C. Case 3

In case 3, different ratios of the total amount of battery capacity of all EVs to total surplus power of solar power generation (EV/Surplus Ratio) are compared. In each scenario, the total surplus power of solar power generation and the total demand of house and EVs is adjusted to the specified EV/Surplus Ratio.

The result (Fig. 12) shows that when the total EV storage battery and the total surplus power is equal (when EV/Surplus Ratio is 100%), 71.2% of total EVs' storage battery was able to utilize even the EVs were running.

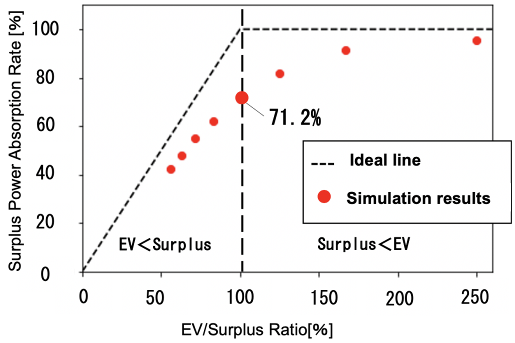

Fig. 12. case3 results: compared by EV/Surplus Ratio.

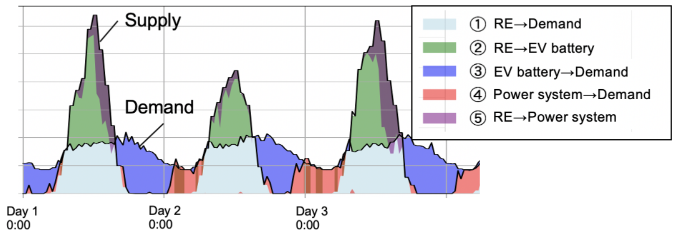

Fig. 13. Supply and demand curve and how the power has moved : First 3 days of scenario of EV/Surplus-Ratio=100%.

The example graph of supply and demand curve and how the power has moved during the simulation span is shown in Fig. 13. You can see that most of the surplus power during the daytime are absorbed by EV battery and soled to the household's demand during the night.

V. Conclusion

In previous research, only the virtual effects of EV agents in the P2P electricity trading market is evaluated, assuming the ideal situation that driving pattern is fixed and future supply and demand are known. In this paper, the EV automatic bidding agent was designed considering uncertainties of the future running, market price, and electric demand and supply. In all phases of driving prediction, market prediction, optimization, and bidding strategy, the future has to be predicted.

The case studies show the effect of the proposed EV bidding agent. In case 1, it is indicated that considering driving probability in the bid optimization phase is effective. In case 2, it is indicated that combining "optimal bidding" and "robust bidding" is effective for the EVs which are difficult to predict future driving time due to the variance of driving pattern. In case 3, it is indicated that the proposed EV bidding agent works well in the actual situation and when the total EV storage battery and the total surplus power is equal (when EV/Surplus Ratio is 100%), 71.2% of total EVs' storage battery was able to utilize even each EV was running.

Also, it is indicated that even in actual situations assuming the future is unknown, there should be incentives for all types of EVs to participate in the P2P electricity trading market. It is an important suggestion because the past research only discussed the ideal effect and incentives of EVs' participating in the P2P electricity trading market.

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