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Decision-Making of Determining the Start Time of Charging / Discharging of Electrical Vehicle Based on Prospect Theory

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Abstract — The moment when Electrical Vehicle (EV) starts charging or discharging is one of the most important parameters in estimating the impact of EV load on the grid. In this paper, a decision-making problem of determining the start time of charging and discharging during allowed period is proposed and studied under the uncertainty of real-time price. Prospect theory is utilized in the decision-making problem of this paper for it describes a kind of decision making behaviors under uncertainty. The case study uses the parameters of Springo SGM7001EV and adopts the historical real-time locational marginal pricing (LMP) data of PJM market for scenario reduction. Prospect values are calculated for every possible start time in the allowed charging or discharging period. By comparing the calculated prospect values, the optimal decisions are obtained accordingly and the results are compared with those based on Expected Utility Theory. Results show that with different initial State-of-Charge (SoC_0) and different reference points, the optimal start time of charging can be the one between 12 a.m. to 3 a.m. and optimal discharging starts at 2 p.m. or 3p.m. Moreover, the decision results of Prospect Theory may differ from that of the Expected Utility Theory with the reference points changing.

Keywords: Electrical vehicle (EV), Prospect theory, Expected utility theory, Reference price, Decision-making

Nomenclature

A. Index

i	Index of scenarios
t	Index of times

B. Parameters and constants

μ	Mean of the trip length (km)
σ	Variance of the trip length (km)
E_{total}	Total energy of the batteries in a single EV (kwh)
p_c , p_d	Charging/discharging power of EV (kw)
η_c , η_d	Efficiency of charging/discharging
R	Maximal mile range of an EV (km)
P_{ai}	Probability of resulting in x_i of strategy a
α , β	Parameter in the value function that indicating risk attitude
λ	Parameter in the value function that indicating loss aversion
γ , δ	Parameter in the weighting function
$T_{S,C}$, $T_{E,C}$	The starting / ending time of the allowed charging period
P_i	Probability of scenario i
S	Number of scenarios
$price_{i,t_0}$	The real-time price of time t_0 under scenario i (\$/Mwh)
$[T_c]$	Rounds T_c to the nearest integer towards zero
ΔT	Unit time slot (1 hour)
RP_c , RP_d	Reference price for charging /discharging
Ref_c , Ref_d	Reference point for evaluating the value for charging/discharging

C. Variables and functions

m_0	Trip length for a commute private vehicle (km)
m	Daily travel length for a commute private vehicle (km)
T_c	Charging duration (h)
T_d	Discharging duration (h)
E_c	Energy that needs to charge (kwh)
E_d	Energy that plans to discharge (kwh)
SoC_0	SoC at the time which charge starts
$u(x)$	Utility function
$v(x)$	Value function
$\pi(P)$	Weighting function
x_i	Possible result that brought by a behavior
x_{ref}	A certain reference point
Δx_i	Deviation value of x_i compared to x_{ref}
U_{i,t_0}	Utility of starting to charge/discharge at t_0 under scenario i (\$)

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v_{i,t_0} Value of starting to charge/discharge at t_0 under scenario i ($)

1. Introduction

The market for plug-in electric vehicle (EV) has grown rapidly in the last two years, reaching more than 120,000 unit sales worldwide in 2012 [1]. Big cities of China like Beijing and Shanghai are also facing booming sales of private EV. In order to increase the penetration rate of EV and make it more convenient for the EV to connect to the grid, a large number of charging facilities are being built worldwide. In 2012, there are almost 45,000 public charging stations installed globally [2]. As far as the city of Beijing is concerned, there are already 61 charging stations and 1,080 charging facilities so far. It is no doubt that the development of EV cannot be separated from the support of the power grid.V2G has already become one of the most hot topics in the research field of smart grid which describes a new mode of interaction between vehicles and the grid. FERC has also emphasized the urgent need to accomplish this integration for the future health of the system [3]. EV is a kind of special load which has the same behavior as the usual load when charging its batteries, in some cases, it can discharge to the grid as a storage device, realizing the interaction between the batteries and the grid under control [4]. By charging EV when electricity price is low (off-peak hours) and selling energy back to the grid when the price is high (peak hours), namely buying low and selling high, EV users will make a profit. Grid Company, meanwhile, will face less pressure to meet the power demand of growing number of EV.

There are many researches concerning the estimation of EV load demand (including the possible discharging load under incentive policies) and charging strategy of the EV. Works on these topics usually estimated the number of EV in the first step then estimated their electricity demand and the new peak load and base load [5-7]. The power demand of EV relates to many different factors like battery, charging facility and user habits etc. Ref. [8] analyzed various factors related to the power demand of EV and established a statistical model of the power demand. Ref. [9] raised a model to reflect the charge-discharge characteristics of EV and finally obtained the average charging and discharging power in a single day. Research on the charging strategy of EV mainly aims to exploit V2G to optimize residential energy consumption and minimize the electricity payment etc., such as [10, 11]. In estimating daily load of EV and optimizing the charging strategy, one of the most important parameters is the time at which the EV user plug-in their vehicles and start charging. Lots of works proposed off-peak charging strategy. For example, in the “delayed charging” scenario, all EVs start charging at 10p.m. [12]. And there are also the “night charging” strategy which suggests half of the EVs start charging at 10 p.m. and the other half start to charge one hour later [13] and the “delayed night charging” strategy [14] which limits the charging behavior between 12 a.m. to 6 a.m. [15]. Further, other works also take the real travel pattern into consideration to make charging allowed every time during 10 p.m. to 7 a.m.. However, paper [10] points out that though the aforementioned off-peak charging strategies may to some extend lower the electricity cost compared to uncontrolled charging, the electricity cost could be further reduced by shifting the EV load to the period with lowest LMP. Nevertheless, the LMP used in [10] was a given day-ahead price. The uncertainty of the real-time price was not considered.

As a kind of vehicle, EV should first satisfy their users' travel demand. On the other hand, when being idle, it can be plugged-into the grid for bi-directionally exchanging energy with the grid. Under appropriate charging and discharging strategy, EV users can make profit. So far, for EVs are still not widely used, most EV users make their own decisions autonomously rather than scheduled by the ISO or an aggregator. Under real-time price scenario, the prices cannot be accurately forecasted, which is an uncertain factor. When determining the moment to start charging, the users tend to choose the time period that with the lowest electricity cost. When making discharging decision, they would like to choose a period with high prices for making a profit. In brief, the EV users want to maximize their economic benefit. However, people are not fully rational and thus the decision-making not always aims at the optimal absolute advantage but the relative advantage compared to a reference point. Prospect theory [16-18] is widely used for describing the psychology of decision maker under uncertain condition. It gives the prospect values of different strategies by analyzing people's reaction towards the probability of the events and the potential benefit compared to a reference point. In this paper, Prospect Theory is adopted to obtain the optimal start time of charging and discharging and the results are compared with those obtained by Expected Utility Theory. In the final case study, the parameters of Springo SGM7001EV are used and several typical price scenarios are selected from the historical real-time data of PJM market.

The rest of the paper is organized as follow: Section 2 is the related concept of the Prospect Theory; Section 3 first outlines some assumptions concerning EV users' behaviors used in this paper then explains the application of Prospect Theory in the decision-making problem of determining the start time for charging and discharging. In Section 4, a case study is given. Finally, Section 5 concludes the paper.

2. Some Concepts About Prospect Theory

Under real-time price scenario, electricity price vary randomly and cannot be accurately forecasted. For this reason, selecting different times to plug-in and start charging or discharging will result in different charging cost or profit made by selling energy. Thus, deciding start time is a typical decision-making problem under risk.

2.1 Proposition of prospect theory

The decision-making under risk had been dominated by Expected Utility Theory for a long time. The basic connotations of Expected Utility Theory are: rational expectation, risk aversion and utility maximization. However, facts show that this theory does not always apply. Though people try to maximize their benefit, they usually follow the "satisfaction principle" rather than the "utility maximization principle" due to their bounded rationality. Considering the bounded rationality of the decision makers, prospect theory is widely used and verified in this kind of decision-making problem.

The Prospect Theory, also called the Expectation Theory, was proposed by Kahneman and Tversky, which is developed form the Expected Utility Theory and is a descriptive model of decision-making under uncertainty. The theory provides a new insight into solving decision-making problem by introducing psychology into decision-making problem and it well explained the observed departures from expected utility theory. Comparing with expected utility theory, it can better model people's decision-making problem because it has considered people's irrational side.

2.2 Model of the prospect theory

Before introducing the model of the Prospect Theory, the model of the Expected Utility Theory should be mentioned first. In Expected Utility Theory, the decision maker should first estimate the probability of the events. Then the second step is to anticipate the results of different strategies. Finally, the decision maker comes to a decision by analyzing all the available information. It assumes that every decision maker has a utility function $u(x)$ which changes with the possible result that brought by a certain condition. The independent variables have i possible values: $x_1, x_2 ... x_i$. Suppose there are two strategies ***a*** and ***b*** for the decision maker to choose and in strategy ***a***, the probability of resulting in x_i is P_{ai} and in strategy ***b***, the probability is P_{bi}. In this way, the expected utility of strategy ***a*** is $\sum_i P_{ai} u(x_i)$ and that of strategy ***b*** is $\sum_i P_{bi} u(x_i)$. The decision maker chooses strategy ***a*** rather than ***b*** only when:

$$\sum_i P_{ai} u(x_i) > \sum_i P_{bi} u(x_i) \tag{1}$$

In Prospect Theory, value function and weighting function are used for replacing the utility function and the subject probability respectively. Prospect theory distinguishes two phases in the choice process: framing and valuation. In the framing phase, the decision maker constructs a representation of the acts, contingencies, reference point and outcomes that are relevant to the decision. In the evaluation phase, the decision maker assesses the value of each prospect and chooses accordingly. The decision maker tends to choose strategy ***a*** rather ***b*** when:

$$\sum_i \pi(P_{ai}) v(\Delta x_i) > \sum_i \pi(P_{bi}) v(\Delta x_i) \tag{2}$$

where $\Delta x_i = x_i - x_{ref}$ or $x_{ref} - x_i$.

It is obvious that in Prospect Theory the decision-making process is influenced by the subjective value, namely the value function, and the decision maker's perceived probability, that is the weighting function.

2.3 Important details in the prospect theory

1) *The Reference point*：According to Prospect Theory, the decision maker does not care the absolute value of the economic benefit but the relative value compared to a reference point. Different decision makers can have different reference points which can be the initial or the expected economic benefit etc. Variation of the reference points may explain why different decision makers may choose different strategies when facing the same situation. In this paper, the concept of reference price [21] is introduced when choose reference point. The theory of reference price is a combination of social psychology and economics. Long-term studies have shown that when purchasing, consumers use a certain standard of price to evaluate the selling price of the commodities. That is to say, when judging the attraction of a certain commodity, consumers tend to compare the actual selling price with the reference standard in their mind rather than only focusing on the absolute price. Result of the comparison determines the level of the perceived price, and thus affects the consumers' price standard for decision-making. This standard is called Reference Price (RP).
2) *The value function* $v(x)$: The value function appears to be an S-shape. And the independent variable of the value function is the deviation of the economic benefit from the reference point. The three characteristics of the value functions are: When there is a gain, most people show risk aversion and; when there is a loss, most people have risk preference and; the sense of the pain for the loss is more intense than the pleasure for the same amount of gain.

$$v(x) = \begin{cases} x^{\alpha} & x \ge 0 \\ -\lambda \cdot (-x)^{\alpha} & x < 0 \end{cases} \tag{3}$$

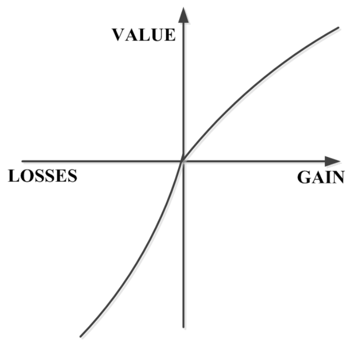

Fig. 1. Plot of value function

3) *The weighting function* $\pi(p)$: It is a transformation of the subject probability in the Expected Utility Theory:

$$\pi(p)=\begin{cases}\dfrac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{\frac{1}{\gamma}}}, \text{ when there is a gain}\\ \dfrac{p^{\delta}}{(p^{\delta}+(1-p)^{\delta})^{\frac{1}{\delta}}}, \text{ when there is a loss}\end{cases} \tag{4}$$

$\pi(p)$ is monotonically increasing in the defined domain $p\in(0,1)$. There is no value for $p=0$ and $p=1$.

The transformation of the probability makes the small probability event have a slightly larger weight and it also lowers the weight of high probability event, which is to simulate the psychology of human beings of overweighting small probabilities and underweights moderate and high probabilities.

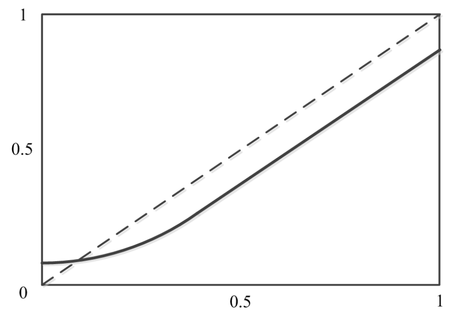

Fig. 2. Plot of weighting function

3. Application of Prospect Theory on Determining the Start Time of Charging and Discharging

3.1 Assumptions on the charging and discharging behaviors

When analyzing EV's charging behaviors, the allowed period for charging, the mileage distribution and the limitation of charging duration should first be outlined. In this paper, the discharging behavior is also included.

Assumption 1: An EV only charges -or discharges in the corresponding allowed time periods daily. And both charging and discharging only happen once respectively every day.

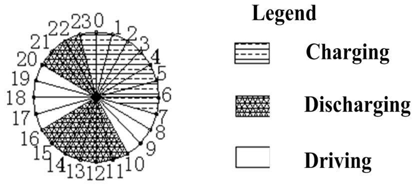

Fig. 3. Allowed charging and discharging period

Assumption 2: EV has similar daily mileage to the gasoline-powered vehicles. We can roughly estimate the energy consumption by the mileage data and then estimate the required power energy to fully charge the EV. The mileage data can be obtained from NHTS2009 [19]. Taking a commute private vehicle as an example, a commute vehicle travel twice a day, the average trip length is listed below in Table 1:

Table 1. The mileage data of a commute private EV

Average Commute Trip Length (miles)	95%CI (miles)
12.09	[11.84, 12.34]

Suppose the trip length m_0 is normally distributed, then

$$f(m_0)=\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(m_0-\mu)^2}{2\sigma^2}\right) \tag{5}$$

$$\text{and} \quad m=2m_0 \tag{6}$$

where $\mu=19.4570, \sigma=0.2012$ when calculated in km.

Assumption 3: There is no limitation on the charging duration and EV won't stop charging until their SoC equal to 100%. We suppose that an EV user can set his/her own $SoC_0(\geq 0.2)$ which is the user's expected SoC value when the day ends and charging starts. An EV user can either use the EV to travel or to discharge before the SoC decreases to SoC_0 . Thus, the duration of charging and discharging can be calculated by:

$$T_c=\frac{E_c}{p_c\bullet\eta_c}=\frac{E_{total}(1-m/R)-E_d}{p_c\bullet\eta_c} \tag{7}$$

$$Td=\frac{E_d}{p_d/\eta_d}=\frac{(1-SoC_0-m/R)\cdot E_{total}}{p_d/\eta_d} \tag{8}$$

3.2 LMP Scenario Simulation

Real-time LMP changes hour to hour, so the cost/profit differs with the start time of charging and discharging changing. Through Backward Scenario Reduction technique, it is feasible to obtain some typical real-time LMP scenarios and their corresponding probability from

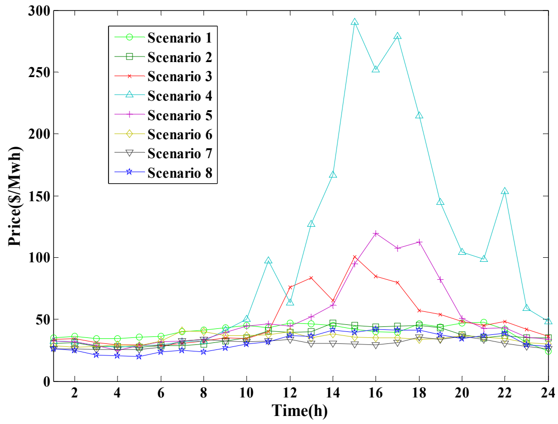

Fig. 4. Eight typical real-time LMP scenarios obtained from the historical data of PJM

Table 2. Probabilities of the typical LMP scenarios

Scenario	1	2	3	4
Probability	0.18202	0.13268	0.0636	0.00768
Scenario	5	6	7	8
Probability	0.03180	0.13158	0.35965	0.09101

historical data. As shown in Fig. 4, the eight typical real-time LMP scenarios are obtained by using historical data of PJM [20] from January 2011 to June 2013. Table 2 shows the corresponding probability of the eight scenarios.

As seen in Fig. 4, the peak and valley of LMP curve could be easily observed. In most cases, LMP is below 50$/MWh. Probabilities of the scenarios with extremely high peak price are very low. In Table 2, Scenario 7 represents the most common LMP curve.

3.3 Calculations by using prospect theory and expected utility theory

The calculation of expected utility and prospect value for the decision-making problem of the start time proposed in this paper can be drawn as follows:

3.3.1 Expected utility

Taking EV's charging as an example, if the allowed plug-in time period is $[T_{S,C}, T_{E,C}]$, taking the charging duration into account, EV users should decide when to start charging during $[T_{S,C}, T_{E,C}-T_c]$. The expected utility of starting charging at t_0 and lasting for T_c can be calculated using Eq. (9)

$$\begin{aligned}\sum_{i=1}^{S} P_i \cdot U_{i,t_0} &= \sum_{i=1}^{S} P_i \cdot U_{i,t_0}(price_{i,t_0} ... price_{i,t_0+T_c}, p_c, T_c) \\ &= \sum_{i=1}^{S} P_i \cdot [(\sum_{t=t_0}^{[t_0+T_c]} price_{i,t} \cdot p_c \cdot \Delta T) \\ &+ (T_c - [T_c]) \cdot price_{i,[t_0+T_c]} \cdot p_c \cdot \Delta T] \\ &\forall t_0 \in [T_{S,C}, T_{E,C} - T_c]\end{aligned} \quad (9)$$

3.3.2 Prospect value

To calculate the prospect value, RP_c is needed. Then Ref_c for a charging duration of T_c is:

$$Ref_c = RP_c \cdot T_c \cdot p_c \cdot \Delta T \quad (10)$$

Prospect value of starting charging at t_0 and lasting for T_c can be calculated using Eq. (11, 12)

$$\sum_{i=1}^{S} \pi(P_i) \cdot v_{i,t_0} \quad (11)$$

$$v_{i,t_0} = \begin{cases} (Ref_c - U_{i,t_0})^{\alpha}, & \text{when } Ref_c \geq U_{i,t_0} \\ \lambda \cdot (U_{i,t_0} - Ref_c)^{\alpha}, & \text{when } Ref_c < U_{i,t_0} \end{cases} \quad (12)$$

The calculation of expected utility and prospect value of discharging that starts in the allowed discharging period and lasts for T_d is similar to that of charging. Therefore, no more details are shown here.

4. Test Case Study

To verify the proposed method, a test case is built based on actual EV parameters and historical price data. Results based on Expected Utility Theory and Prospect Theory are both calculated.

4.1 Test case data and parameters

The following data and parameters are used in the test case.

1) *EV data*: Now there are mainly three types of EV in Shanghai. In this case, Springo SGM7001EV data is adopted.

Table 3. Parameters of Springo SGM7001EV

Type	Product	Rated mileage (km)	Battery capacity (kWh)
Springo	SGM7001EV	160	21.4kWh

2) *Charge/Discharge Power*: Normally, EV is charged or discharged under 220V/15A in constant-current mode. For simplicity, it is assumed that charge/discharge power is a constant of which is approximately 3kW during the charge/discharge process. Set both charge/discharge efficiency equals to 0.85.
3) Set $SoC_0 = 0.35$. *This* is reasonable and acceptable.
4) The trip length of EV is sampled using NHTS2009 data, assuming it is a commute private vehicle.

Table 4. Sampled trip length using NHTS2009 data

Per trip (km)	Total (km)
19.4155	38.831

For the parameters in the Prospect Theory, Kahneman et al. gave the estimates value by experiments in paper [17]:

$$\alpha = 0.88, \lambda = 2.25, \gamma = 0.61, \ \ \delta = 0.69$$

4.2 Expected utility and prospect value results

According to the setting1) to 4) in Section 4.1 and Eq. (7) and (8), the duration of charge and discharge are obtained as follows:

$$T_c\text{=5.45h}, \ \ T_d = 2.47\text{h} \tag{13}$$

Thus, the start time for EV charging is 23p.m to 2a.m. and that for discharging is 10a.m. to 16p.m. and 20p.m. (Assuming that discharging starts at 15p.m .or 16p.m. can continue to discharge when discharging period 20-22 p.m. begins). Expected utility has no relationship with reference point. Results based on Expected Utility Theory are presented in Table 5 and Table 6. The highlighted number is the time with optimal expected utility

Prospect value for charging and discharging is calculated under different reference points, which is shown in Table 7 and Table 8. The highlighted number is the time with the largest prospect value.

From Table 5 to Table 8, following conclusions can be drawn:

1) *Using Expected Utility Theory*, As seen in Table 5-6, the optimal start time for charging is 1a.m and for discharging is 15p.m. Though starting charging in 1a.m. is not an optimal choice under any scenario, the user chooses it because the expectation of the charging expense is the minimum, which shows that the EV user is perfectly rational.
2) *Using Prospect Theory*, the optimal start time differs from that of Using Expected Utility Theory in some cases. It is observed that when the reference price (RP) of charging or discharging is high or low, the optimal start time is the same as that of Expected Utility Theory. However, when the RP is moderate, the optimal start time changes, as seen in Table 7-8. When RP is too low or too high with respect to LMP, the optimal start time under Prospect Theory and Expected Utility Theory is close, because the value function is pretty much linear when the value is far from reference point. However, if RP is near LMP, the

Table 5. Expected Utility for charging

Start time	Utility($)								
Scenario	1	2	3	4	5	6	7	8	Expected utility
Probability	0.18202	0.13268	0.0636	0.00768	0.0318	0.13158	0.35965	0.09101	
23	0.531907	0.517391	0.572483	0.636902	0.520554	0.477874	0.43227	0.417401	0.479641
24	0.542168	0.496385	0.534214	0.543748	0.493449	0.471347	0.424931	0.389656	0.468688
1	0.575624	0.476305	0.513653	0.486689	0.48227	0.472131	0.425819	0.370255	0.468670
2	0.583387	0.470709	0.501257	0.480601	0.481565	0.493491	0.435223	0.363804	0.474088
MIN	**0.531907**	**0.470709**	**0.501257**	**0.480601**	**0.481565**	**0.471347**	**0.424931**	**0.363804**	**0.468670**

Table 6. Expected utility for discharging

Start time	Utility($)								
Scenario	1	2	3	4	5	6	7	8	Expected utility
Probability	0.18202	0.13268	0.0636	0.00768	0.0318	0.13158	0.35965	0.09101	
10	0.331389	0.283507	0.331824	0.530835	0.334087	0.279493	0.240886	0.237179	0.278729
11	0.335782	0.297344	0.466467	0.660376	0.344778	0.281637	0.242231	0.257913	0.293914
12	0.343152	0.30488	0.570695	0.80567	0.376281	0.27852	0.236866	0.278163	0.304504
13	0.334226	0.324821	0.588184	1.290638	0.474377	0.26969	0.225684	0.28931	0.30931
14	0.31753	0.337476	0.616985	1.726684	0.636719	0.270667	0.222309	0.301665	0.31833
15	0.311585	0.317893	0.623865	1.77395	0.713511	0.264875	0.228001	0.292605	0.318352
16	0.327812	0.291954	0.463331	1.207734	0.570069	0.267075	0.243543	0.281273	0.303596
20	0.343471	0.268365	0.347347	0.824876	0.340507	0.266191	0.252013	0.267887	0.287413
MAX	**0.343471**	**0.337476**	**0.623865**	**1.77395**	**0.713511**	**0.281637**	**0.252013**	**0.301665**	**0.318352**

Table 7. Prospect value for charging under different reference points

Start time	Expectation	Prospect value				
		RP_c (\$/MWh)/ Ref_c (\$)				
		15/0.2453	25/0.4088	34/0.5559	45/0.7358	55/0.8992
23	0.47964	-0.91832	-0.33534	0.121307	0.433829	0.682488
24	0.46869	-0.87001	-0.2817	0.158982	0.458836	0.705875
1	0.46867	-0.85958	-0.27359	0.153608	0.464536	0.711397
2	0.47409	-0.87261	-0.29116	0.143967	0.459044	0.706258
MIN	**0.46867**	**-0.85958**	**-0.27359**	**0.158982**	**0.464536**	**0.711397**

Table 8. Prospect value for discharging under different reference points

Start time	Expectation	Prospect value				
		RP_d (\$/MWh)/ Ref_d (\$)				
		30/0.2223	40/ 0.2964	55/ 0.4076	75/0.5557	95/0.7040
10	0.27873	0.139127	-0.07694	-0.49061	-0.99744	-1.4728
11	0.29391	0.179418	-0.0218	-0.41863	-0.92391	-1.40196
12	0.3045	0.210571	0.012798	-0.37564	-0.86227	-1.34334
13	0.30931	0.241292	0.040515	-0.33799	-0.82049	-1.29993
14	0.31833	0.279128	0.081831	-0.29789	-0.76578	-1.2385
15	0.31835	0.283347	0.082667	-0.30265	-0.76758	-1.22812
16	0.3036	0.225917	0.0248	-0.36153	-0.85249	-1.33149
20	0.28741	0.164613	-0.04749	-0.45329	-0.95912	-1.43004
MAX	**0.3184**	**0.28335**	**0.08267**	**-0.2979**	**-0.7658**	**-1.2281**

Table 9. Optimal strategies under different SoC_0

SoC_0	T_c (h)	Decision making result for start time of charging		T_d (h)	Decision making result for start time of discharging	
		Expected Utility Theory	Prospect Theory (As RP increasing)		Expected Utility Theory	Prospect Theory (As RP increasing)
0.3	5.875	24	1->24->1	2.773	14	14
0.35	5.455	1	1->24->1	2.470	15	15->14->15
0.4	5.035	1	2->1->2->24->2->1->2	2.166	15	15
0.45	4.616	2	2	1.863	15	15
0.5	4.196	2	2	1.56	15	15
0.55	3.776	3	2	1.257	15	15
0.6	3.357	3	2	0.954	15	15

results can be tricky. The Optimal start time under Prospect Theory differs from that of Expected Utility Theory. EV user tends to start charging and discharging when LMP volatility is high. It can be seen in Fig. 1 that value function is very steep near 0.

4.3 Effects of Changing SoC_0

Set value of SoC_0 has an effect on the duration of charging and discharging and thus it may influence the optimal start time. In this subsection, optimal results under different SoC_0 are calculated under both Expected Utility Theory and Prospect Theory, see Table 9.

Note that the optimal start time under Prospect Theory is calculated with the RP_c changing from 10 to 100\$/MWh and RP_d changing from 20 to 250\$/MWh with a step of 1\$/MWh. The notation

1->24>1 in Table 9 means that in the process of RP increasing, the optimal start time changes from 1a.m. to 12a.m then back to 1 a.m. The results in the Table 9 actually tend to show two phenomena. First, in every row, the results were obtained under a certain SoC_0. It shows that the Expected Utility Theory only gives one rational decision according to the absolute utility while the results obtained from the Prospect Theory varies with the subjective RP in PEV users' mind. Another thing shown in this table is that the setting of SoC_0 also affects the decision result by affecting the charging/discharging durations. By looking at just one column and comparing each row, it can be seen how SoC_0 affect the results.

5. Conclusions

The time at which EV plugs-in and starts charging or discharging is an important parameter in EV load estimation. It is influenced by both user habit and electricity price. In this paper, decision making of determining the start time of charging and discharging is proposed and solved by Prospect Theory under assumption that EV users are bounded rational. Calculated results under Prospect Theory are also compared with that of Expected Utility Theory. The proposed method is tested on an example case based on actual data. Obtained results show that EV users may have two different optimal strategies with the two theories respectively. Under Expected Utility Theory, EV users will choose to start charging at the time with the lowest expected cost. However, the optimal start time may change when adopt Prospect Theory with different choice of reference points. SoC_0 has an effect on the duration of charging and discharging and thus influence the optimal start time. When the duration gets shorter and shorter with the increasing value of SoC_0, the decision result of Prospect Theory gradually became stable and remained the same with the results of Expected Utility Theory. The calculated prospect value by Prospect Theory can provide the EV users with guidance for deciding what time to charge or to discharge.

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