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An Equivalent-Perceptional Intertemporal Choice Heuristics Model for Electric Operation Vehicle Charging Behavior

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Abstract: The inherent stochasticity of electric operation vehicle (EOV) charging poses challenges to the stability and efficiency of regional power distribution networks. Existing charging behavior decision-making models often prioritize revenue considerations, neglecting the influence of multi-time-span characteristics and the potential irrationality of EOV owners. To address these limitations, this study proposes a comprehensive framework encompassing three aspects. First, operational data are statistically analyzed to reconstruct EOV operation scenarios, establishing a dynamic charging scheme tailored to multi-time-span characteristics. Second, an improved ITCH model is developed using operational equivalent change to incorporate both gains and losses. Third, a WFL framework is employed to integrate the perceptual attenuation of revenue into the ITCH model. Simulation results show that decision-makers (DMs) demonstrate a preference for charging schemes with high equivalent perceived revenues and low time costs. Moreover, when the charging price is doubled, revenue perception attenuation leads decision-makers to postpone their charging behavior. Compared to other models, the equivalent perception intertemporal choice heuristics (EP-ITCH) charging model results in reduced load peaks, valleys, and variances on the grid side. This study highlights the model's effectiveness and accuracy in optimizing EOV charging infrastructure.

Keywords: intertemporal choice heuristics model; Weber–Fechner law; charging behavior analysis; irrationality; perceptual attenuation; multi-time-span characteristics

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1. Introduction

In recent years, electric vehicles (EVs) have become highly regarded for their characteristics such as "electricity instead of fuel", environmental cleanliness, low emissions, and high efficiency. However, the increasing penetration rate of EVs brings enormous panoramic situational awareness data, which poses new challenges for power grid planning and scheduling, stability control, and operation [1–4]. The large-scale integration of EVs will lead to an increase in peak-to-valley differences in electricity demand, affecting the stable operation of networks [5–7]. In addition, the chaotic charging behavior of EV owners, which form charging clusters, can result in the irrational allocation of electric power resources. Clusters of electric operation vehicles (EOVs) exhibit characteristics such as greater charging frequencies and charging power compared to conventional EV clusters. They have a more significant impact on the stable operation of power grids, making the study of charging-related issues for EOVs of great significance.

In the research on EV charging schemes, Chen et al. and Wang et al. simulated EV charging schemes using the Monte Carlo method [8,9]. However, due to the lack of modeling based on real operational data, the schemes and the charging strategies still need further validation. H. Al-Alwash et al. considered user preferences in waiting time and charging prices and established a real-time interaction model based on software-defined networking and cloud computing [10]; however, the issue of operational losses for EV owners was neglected. Feng et al. constructed charging schemes by considering both arrival times and left-over battery charge [11]; however, the research failed to organically integrate charging schemes and the value function of charging behaviors.

In terms of modeling charging decisions, Chakraborty A. points out that exponential discounting is widely used in economics to balance alternative scenarios obtained at different time points [12]. However, discounting models are rooted in economic theory and cannot fully explain the psychological principles and cognitive processes that influence intertemporal decision making. Feng et al. introduced the cumulative prospect theory, which considers the heterogeneity of the reference point that describes the irrational factors of charging decisions [11]. However, the theory only considers the impact of revenues and losses on decision making, while charging decisions are influenced by both time and revenue. J M. Clairand et al. took the impact of charging prices on EV charging into account and argued that the time cost is the primary factor influencing the travel choices of EV owners [13–18]. Marzilli Ericson et al. introduced the time factor into the conventional value function model and established the intertemporal choice heuristics model (ITCH model), which balances the influences of time and revenue by setting different weight coefficients [19].

In the research on psychological perception, the smart grid features comprehensive panoramic situational awareness; thus, when EV clusters integrate into the smart grid, they require access to real-time operational data. Using these data and considering their operational demands, EOV operators make decisions that are congruent with their psychological perceptions. As these data are not directly accessible, they significantly influence the operation and charging decisions of EOV owners [20]. Arslan et al. extended the conventional VIKOR method using the Weber–Fechner Law (WFL) [21], which is applicable for the quantification of subjective perceptual attenuation by DMs. This provides an opportunity for behavioral psychology to become a decision-making tool. Hou et al. introduced the WFL to quantify the psychological effects of EV owners' concerns about the inability to travel [22]. However, the model only treated this as a constraint condition in the mathematical model without delving into the irrational aspects of the owners' psychology. Long et al. introduced the regret theory to establish a value function, providing a theoretical basis for owners to choose charging stations [23,24]. However, they did not consider the issue of psychological perception attenuation that owners may experience when choosing charging stations. Li et al. established a user responsiveness model based on the WFL, demonstrating owners' responses to state of charge (SOC) and electricity prices [25]. Nevertheless, the EOV owners were not considered. The advantages and disadvantages of the above research are summarized in Table 1.

Table 1. Existing literature comparison.

Category	Approach	Advantage	Disadvantage
Charging schemes	[8,9]	Monte Carlo simulation	Lacks actual operational data
	[10,11]	Real-time interactive model considering arrival time and remaining battery level	The model lacks consideration of operational losses for the vehicle owner and does not integrate charging schemes with charging behavior
Charging decision model	[12]	Discounting models are widely used in the field of economics	It cannot effectively explain the psychological principles and cognitive processes of multi-time-scale decision making
	[11]	Improving cumulative prospect theory	Does not consider the impact of the timing of returns on scheme selection

Table 1. *Cont.*

Category	Approach	Advantage	Disadvantage
Psychological Perception Research	[13–18]	Established an optimization function with the objective of maximizing the benefits for the vehicle owner	
	[21]	Extended the traditional VILOR method using Weber–Fechner law	Lacks verification of subjects' JNDs variations in multiple different environments
	[22]	Used the Weber–Fechner law to evaluate the psychological impact on vehicle owners.	The Weber–Fechner law is used just as a constraint condition
	[23,24]	Used regret theory to establish a value function	Does not take into account the perceptual attenuation issue of vehicle owners
	[25]	Established a user response model using the Weber–Fechner law	Does not consider vehicle owners' irrational decision making

The existing research on EV charging schemes, modeling charging decisions, and psychological perceptions has several limitations:

1. Oversimplified assumptions

Most existing research on EV charging behavior modeling relies on oversimplified assumptions. These include the lack of real operational data, the neglect of operational losses, and the failure to integrate charging schemes with a broader value function encompassing the overall travel needs of vehicle owners.

2. Prioritizing Revenue over Time Considerations

Existing models often prioritize the impact of revenue on decision making while neglecting the equally important influence of time considerations on charging choices.

3. Insufficient Focus on Psychological Factors

Research has inadequately addressed the psychological perception attenuation of vehicle owners and their responsiveness to factors such as SOC (state of charge) and electricity prices, limiting the ability to accurately predict charging behavior.

This paper addresses the shortcomings of prior research on EV charging behavior as follows:

1. To overcome the oversimplified assumptions that most studies hold, we developed a novel multi-time-scale EOV scenarios model and charging scheme sets. This approach captures the key characteristics of EV operation and charging behavior, offering a more comprehensive and realistic framework for analysis.

2. We propose an innovative equivalent perception intertemporal decision-making charging model. This model overcomes limitations in existing approaches by incorporating time cost, accounting for owners' perception attenuation, and simultaneously considering both benefits and losses within the decision-making process.

This paper unfolds as follows. In Section 2, the framework of this article is delineated. In Section 3, a characteristic analysis is conducted on the operational revenue data of EOVs. Revenue characteristics for operational events are extracted, and on this basis, a revenue framework for the operational scenarios of EOVs is reconstructed. In Section 4, utilizing the WFL, a psychological scale is constructed to describe EOVs owners' perceptual attenuation to operational revenue. An ITCH model with equivalent perception is also established, which refines the application of the WFL. Section 5 presents an empirical evaluation of the proposed model by analyzing the charging behaviors of EOV owners in a southern Chinese city. The efficaciousness and validity of the model are corroborated by findings that demonstrate its capability to accurately depict owners' charging behaviors, thereby offering valuable decision-making insights for the operation of power grids. The meanings of all symbols in this article can be found in the Appendix A.

2. Materials and Methods

The structure of the equivalent perception intertemporal choice heuristics (EP-ITCH) charging model based on the WFL is shown in Figure 1.

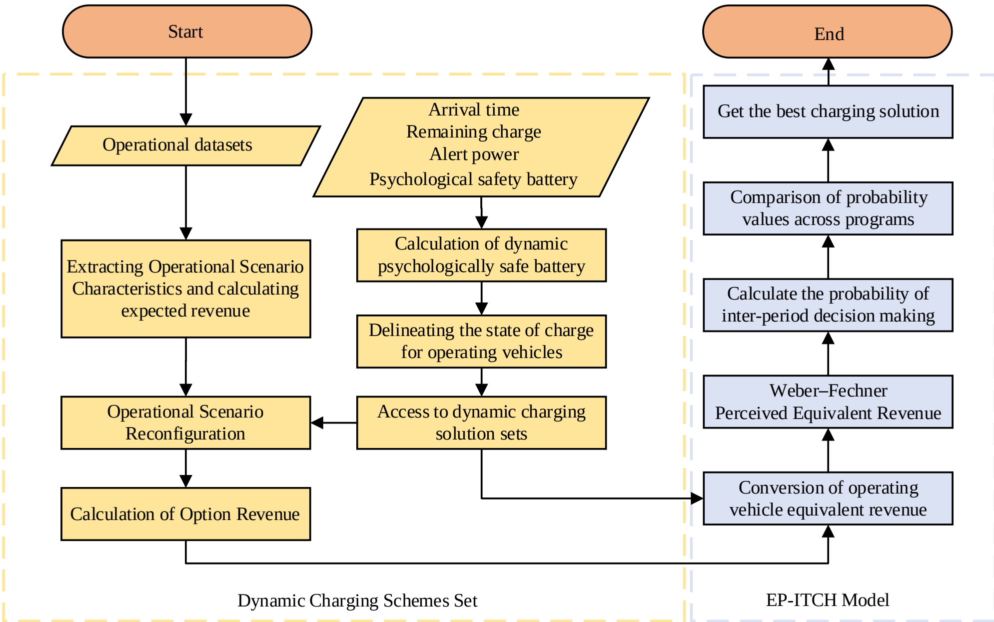


Figure 1. EP-ITCH charging model based on WFL.

(1) Construction of Dynamic Solution Sets and Calculation of EOVs Revenue

Combining the processing and analysis of the typical daily operating EOV owner income data set, we model the operating process of EOVs, extract and quantify the operating characteristics of EOVs, and construct a revenue framework for the operating scenarios of EOVs.

Considering the factors such as arrival time, remaining power, and alert power threshold, the dynamic psychological safety power is calculated to divide the charging demand of operational vehicles under different peak and off-peak electricity pricing; then, we can calculate the revenue of different scenarios under the revenue framework of operation scenarios, and the dynamic charging scheme set is constructed.

(2) An EP-ITCH Charging Model for EOVs

To comprehensively measure the relationship between the dynamic charging scheme revenue and charging time, we consider the phenomenon that EOV owners have a perceptual attenuation of the operational revenue in their daily operation. We construct a psychological scale based on the WFL and establish an EP-ITCH charging model.

3. Construction of Dynamic Charging Scheme Set for EOVs

3.1. Preprocessing the Historical Data

To extract the operational features of the historical data, the whole day is segmented into time slices with intervals of ε duration (in particular, ε = 10 min in this study), and the frequencies of all the operational events occurring in the corresponding time period for each slice in the historical data are counted. Thus, a typical-day historical passenger order frequency table can be constructed. Then, we can reformulate the operational process using the frequency table and the operational events. The frequency and corresponding features are defined below.

We define the frequency of the operational event $m_{\mathrm{w,h,i}}$ as $f_{\mathrm{w,h,i}}$, where $f_{\mathrm{w,h,i}}$ is derived from the typical daily operational events table $F_{\mathrm{w \times h \times i}}$ extracted from historical data. w ($w \in \{1, \ldots, \zeta\}$) is the index of current slicing interval; h is the event type, which, in this study, was defined as the duration of the event; here, set $H = \{1, 2, \ldots, \mathrm{k}\}$ (the duration each element in the set H can be calculated as k $\times$ 10 min, and particularly for the simplicity of the problem, $k = 6$ in this study), $h \in H$; $i \in \{0,1\}$, in which 0 and 1 denote without/with a passenger, respectively, e.g., $f_{2,3,1}$ represents the frequency of a passenger-carrying event lasting 30 min that occurred during the second time slice.

3.2. Reconstruct the Operational Scenarios Revenue Framework

In charging decision making, the EOV owner faces a dilemma between two symmetrical schemes: (1) charging immediately at time t_1 to obtain the revenue of an equivalent charging duration T_c at a future time t_2; or (2) charging at a future time t_2 to obtain the revenue of an equivalent charging duration T_c immediately at time t_1.

The first scheme reduces concerns regarding battery depletion by promptly initiating the charging process. However, it does carry the potential risk of revenue loss due to the uncertainty surrounding future revenue. On the other hand, the alternative scheme poses the risk of future battery depletion in exchange for immediate revenue retrieval. To make informed decisions, decision-makers (DMs) must first reconstruct the operational scenarios. This involves evaluating the equivalent operational revenue associated with two charging moments, t_1 and t_2, as well as the charging time T_c.

The operational time T_c can be segmented into several scenarios, each consisting of a unique combination of operational events $m_{w,h,i}$. To reconstruct the operational scenarios and calculate the expected revenue J within the operational duration, three features are required: (1) the frequency of events occurring in each scenario; (2) the probability of each operational scenario; and (3) the average revenue of each operational event. The following provides detailed steps as shown in Figure 2.

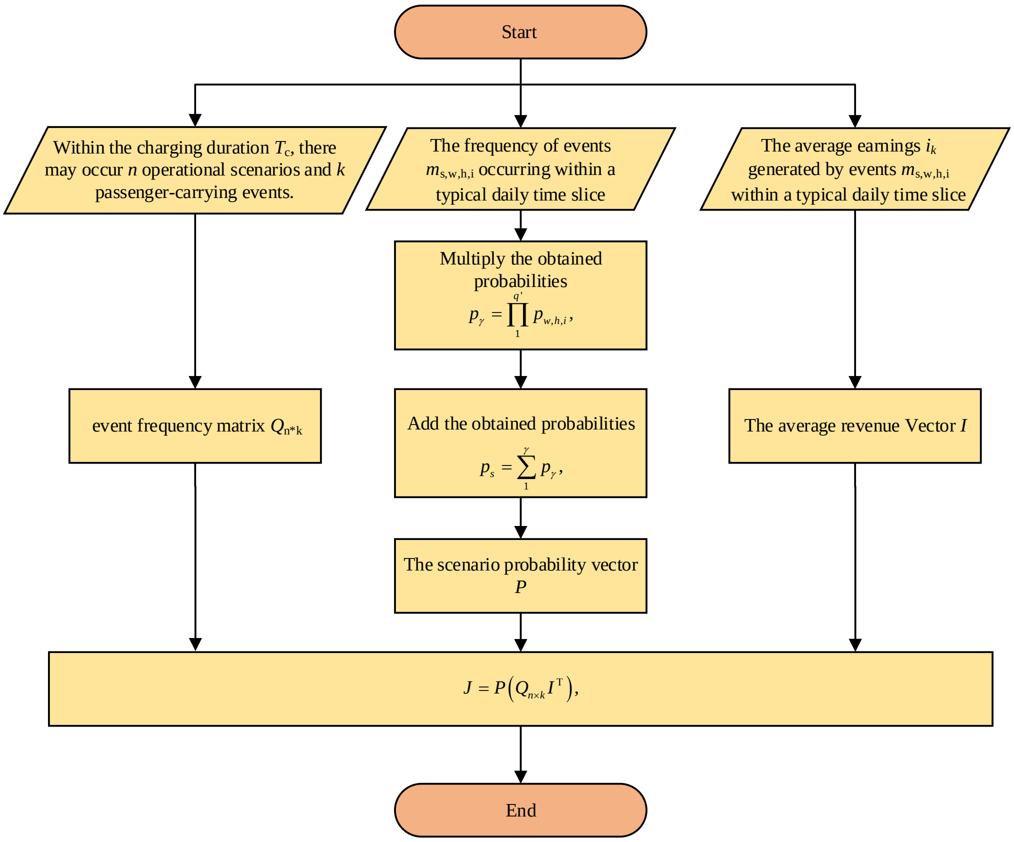


Figure 2. Scenarios revenue framework.

Step 1. The event frequency matrix $Q_{n\times k}$ within the operational duration

The operational scenarios s (where $s \in S$, $S = \{1, \ldots, n\}$) can be decoupled into several repeatable permutations of independent events $m_{s,w,h,i}$. The sum Σh of the durations h of all independent events in s scenarios equals the operational scenario duration. Therefore, the event frequency matrix $Q_{n\times k}$ is arrived at, consisting of k passenger-carrying events for each one in n scenarios. $Q_{n\times k}$ can be expressed as follows:

$$Q_{\mathrm{n\times k}} = \begin{pmatrix} q_{1,1} & \dots & q_{1,\mathrm{k}} \\ \vdots & & \vdots \\ q_{\mathrm{n},1} & \dots & q_{\mathrm{n,k}} \end{pmatrix} \quad (1)$$

where $q_{\mathrm{n,k}}$ denotes the frequency of the k_{th} passenger-carrying event in the s_{th} scenario.

Step 2. The scenario probability vector P

To calculate the possibilities of each event $m_{\mathrm{s,w,h,i}}$ in operational scenario s, the frequency $f_{\mathrm{w,h,i}}$ of the historical event is concerned.

Given the charging arrival time T_{a} and charging duration T_{c}, the time slices when charging starts and ends can be obtained from the table $F_{\mathrm{w\times h\times i}}$, which contains ζ slices.

$$p_{\mathrm{w,h,i}} = \frac{m_{\mathrm{w,h,i}}}{f_{\mathrm{w}}} \quad (2)$$

where $p_{\mathrm{w,h,i}}$ is the possibility of $m_{\mathrm{w,h,i}}$ and f_{w} is the total occurrences of all events that may possibly occur within the remaining operational time.

Knowing the types and the occurrences q' (total occurrences of all the events in current scenario) of events $m_{\mathrm{s,w,h,i}}$ under corresponding scenarios of the charging time T_{c}, these independent operational events can be modeled as the irretrievable "fetching-ball experiment" procedure. For each experiment, the balls are taken out one by one (an operational event happens), and the sequence of the balls is recorded (the sequence $\prod_1^{q'} p_{\mathrm{w,h,i}}$ of operational events is recorded). When all of the balls (events) are taken out (all events happen), the experiment completes (a possible combination of the events under one scenario). The "fetching-ball experiment" is repeated until no new sequences (γ) are generated. Thus, the probabilities of each operational scenario under all possible combinations (P_{s}) are recorded and calculated.

$$p_{\gamma} = \prod_{1}^{q'} p_{\mathrm{w,h,i}} \quad (3)$$

$$p_{\mathrm{s}} = \sum_{1}^{\gamma} p_{\gamma} \quad (4)$$

Then, the scenario probability vector P is shown below:

$$P = \begin{pmatrix} p_1 & \cdots & p_{\mathrm{s}} \end{pmatrix} \quad (5)$$

Step 3. The average revenue vector I is shown below:

$$I = \begin{pmatrix} i_1 & \cdots & i_{\mathrm{k}} \end{pmatrix} \quad (6)$$

where i_k is the average revenue generated by the k_{th} passenger-carrying event during the T_c time period, as obtained from historical data.

Step 4. The expected return J is shown below:

$$J = P\left(Q_{\mathrm{n\times k}} I^T\right) \quad (7)$$

The expected revenue J is reconstructed by combining the three features extracted from the historical operational data, which represent the operational behavior for time duration T_{c}.

3.3. Charging State Analysis of EOVs

Since EOVs are usually operated by both day-shift drivers and night-shift drivers, and the capacity of the vehicle batteries is limited, charging usually occurs several times in a day. Given that night-shift drivers typically charge their vehicles after their shifts end in the early morning, this study focuses on the EV charging during daytime hours.

The EV charging hours T_{c} are usually defined as follows:

$$T_{\mathrm{c}} = \frac{W \times (B_{\mathrm{lea}} - B_{\mathrm{N}})}{P_{\mathrm{EV}} \times \theta_{\mathrm{c}}} \tag{8}$$

where W is the rated capacity of the vehicle battery; B_N is the initial battery state of charge (i.e., remaining charge) when arriving at the station; B_{lea} is the battery state of charge upon completion of charging; P_{EV} is the EV charging power; and θ_{c} is the EV charging efficiency [26].

Assuming that B_{saf} is the dynamic psychological safety battery of each EOV owner for its remaining charge, and B_{min} is the alert power threshold at which the vehicle battery must be charged immediately, when the remaining charge B_{N} upon arrival is larger than B_{saf}, the owner chooses not to charge. When it is lower than B_{saf}, the owner chooses to charge to a value state that ensures the charge at turnaround time is greater than B_{min}. B_{saf} varies with the time period during the owner's daily operation. The computation of B_{saf} is established as follows.

$$B_{\mathrm{saf}} = B_{\mathrm{N}} + T_{\mathrm{c}} \times V_{\mathrm{c}} \tag{9}$$

where Vc is the average charging speed.

For charging demand, the charging time can be expressed as follows:

$$T_{\mathrm{c}} = \frac{(T_{\mathrm{d}} - T_{\mathrm{a}}) \times V_{\mathrm{r}} + W \times B_{\mathrm{min}} - B_{\mathrm{N}}}{V_{\mathrm{c}} + V_{\mathrm{r}}} \tag{10}$$

where T_{d} is the number of minutes from the start of operation to the end of the shift on the current day; T_{a} is the time of the owner's arrival at the charging station; V_{r} is the average discharge rate; and W is the capacity of the vehicle battery. It is necessary to ensure that the remaining charge at the end of charging is not less than B_{saf}.

The charging duration is related to the charging start moment, the remaining charge, and B_{saf}. While different DMs prefer different values of B_{saf}, different charging durations are derived from Equation (9). Additionally, the peak and off-peak pricing electricity prices are also important influencing factors. The whole day is divided into multiple charging decision intervals based on the peak and off-peak pricing periods (in the following text, the peak electricity price periods will be referred to as peak periods, and the flat electricity price periods will be referred to as flat periods). When $B_{\mathrm{N}} < B_{\mathrm{saf}}$, the EOV owners contemplate charging. At this point, the charging schemes that EOV owners can choose form a dynamic set, as the number of schemes in the set varies due to the different time points at which each owner generates charging ideas; In addition, the charging scheme is influenced by various factors, including $\{B_{\mathrm{saf}}, T_{\mathrm{a}}, B_{\mathrm{N}}, T_{\mathrm{c}}, J, D\}$, where J represents the expected benefit calculated based on T_{c} and D represents the charging cost calculated based on T_{c}. These schemes, influenced by changes in B_{saf}, constitute the set of dynamic charging schemes for EOVs. The dynamic charging scheme set is established as follows.

Scheme 1 is defined as charging immediately upon contemplating the need to charge. Some EOV owners may prefer to first accrue operational revenue before considering charging; thus, Scheme 2 involves waiting until the next charging decision interval to initiate charging. Instances where charging is postponed based on the owner's preferences constitute the scenario of first obtaining operational revenue before charging. Scheme 3 involves waiting until the subsequent charging decision interval, and this pattern continues to generate multiple alternative schemes. When the shift time falls within a specific charging decision interval, where B_{N} approaches B_{min}, the EOV owners must execute a charging operation. Therefore, the scheme corresponding to this decision interval becomes the final scheme.

4. EP-ITCH Model

4.1. ITCH Model for Charging EOVs

The ITCH model refers to the process of weighing the costs and revenue of values at different moments, and then making a choice. For EOV owners, immediate charging reduces range anxiety but risks losing current revenue, while symmetrically delayed charging risks running out of battery power to gain potentially greater revenue. Therefore, this is a typical ITCH problem.

As shown in Figure 3, we defined two alternative charging intervals, u and v, in which $t_v > t_u$ and $x_v > x_u$. If while charging at the time of t_u, a gain of x_u is obtained, then charging at the time of t_v helps us earn x_v. The different choices fall into symmetrical operational behaviors. Therefore, DM faces the dilemma problem of choosing to charge now and obtain revenue later, or to obtain revenue now but charge later.

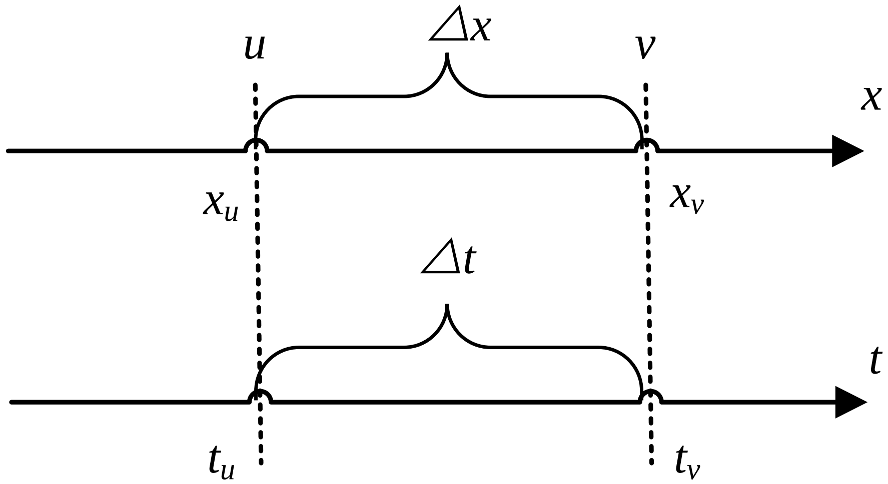


Figure 3. ITCH charging dilemma problem for EOV owners.

From the perspective of the two symmetry schemes for the DM, revenue x_u is expressed as the sum of the order revenue J_v obtained in interval v and the avoidable charging cost D_v in interval v. Then, the revenue x_u and x_v are given by the following:

$$x_u = J_v + D_v \tag{11}$$

$$x_v = J_u + D_u \tag{12}$$

$$D = T_c \times E_c \tag{13}$$

where J_u and J_v denote the expectancy order revenues in interval u and interval v, respectively; D_u and D_v denote the charging costs in interval u and interval v, respectively; and E_c represents the electricity price for the corresponding time period.

Let us define the inter-period probability P(LL) of the owner's charging choice as follows:

$$P(LL) = L\left(\beta_1 + \beta_{xA}(x_v - x_u) + \beta_{xR}\frac{x_v - x_u}{x^*} + \beta_{tA}(t_v - t_u) + \beta_{tR}\frac{t_v - t_u}{t^*}\right) \tag{14}$$

where $x^* = (x_u + x_v)/2$, $t^* = (t_u + t_v)/2$, and $L(\bullet) = 1/(1 + e^{-\bullet})$ is the cumulative distribution function of the logistic distribution with mean 0 and variance 1, and β_1, β_{xA}, β_{xB}, β_{tA}, and β_{tR} are the weights. When the value of $P(LL)$ is greater than σ, the option with a larger revenue at a later moment is selected. Otherwise, the option with lower revenue at an earlier moment is selected.

4.2. WFL of Perception

The WFL is a law that indicates the relationship between psychological and physical quantities and can characterize the nonlinear perceptions of DMs. For moderate stimuli, the response level η of the human body is proportional to the logarithm of the objective stimuli φ and is expressed as follows:

$$\eta = \frac{1}{\lg(1+c)} \lg \frac{\varphi_{\eta}}{\varphi_0} \tag{15}$$

where η denotes a natural number such that $\eta = 0, \ldots, \alpha$, with α representing the maximum response level on the psychological scale. The term φ_{η} is defined as the psychological scale threshold corresponding to the physical intensity threshold that is perceived at a response level of η, where c is the constant of proportionality, and φ_0 is the smallest physical intensity that can be felt.

Given a response level of η, it follows from the above equation that φ_η is given by the following:

$$\varphi_\eta = (1+\mathrm{c})^\eta \varphi_0 \tag{16}$$

By substituting all values of η, one can obtain the psychological scale that manifests the intensity of an individual's psychological response.

In this study, the passenger-carrying events with the lowest and the highest revenue per passenger are defined as $i_{\min}$ and $i_{\max}$, respectively, corresponding to the minimum physical intensity φ_0 and the psychological scale threshold φ_{a} in Equation (15), respectively. From this, the psychological scale of the EOV owner's perception of revenue can be established.

Furthermore, to account for the variability in DMs' sensitivity to revenue, psychological scales reflective of their heterogeneous sensitivity can be constructed by choosing different response levels η.

4.3. EP-ITCH Charging Model

Due to an owner's perceptual attenuation of operational revenue, the owner's revenue x for their charging decision can be processed using the psychological scale thresholds as boundaries for segmented perception. The flowchart of the EP-ITCH charging model is shown in Figure 4. The two charging schemes involved in each decision include two elements, which are time and revenues.

We define the Weber–Fechner operator for computing the perceived revenue X as follows:

$$X = A[x] = \varphi_\eta \left(\varphi_\eta < x < \varphi_{\eta+1} \right) \tag{17}$$

where x represents the revenue within the charging duration T_{c}.

By substituting the results of the operator calculations into Equation (12), it yields the following:

$$P(LL) = L\left(\beta_1 + \beta_{\mathrm{xA}}(A[x_{\mathrm{v}}] - A[x_{\mathrm{u}}]) + \beta_{\mathrm{xR}} \frac{A[x_{\mathrm{v}}] - A[x_{\mathrm{u}}]}{A^*} + \beta_{\mathrm{tA}}(t_{\mathrm{v}} - t_{\mathrm{u}}) + \beta_{\mathrm{tR}} \frac{t_{\mathrm{v}} - t_{\mathrm{u}}}{t^*} \right) \tag{18}$$

with

$$A^* = (A[x_{\mathrm{u}}] + A[x_{\mathrm{v}}])/2 \tag{19}$$

$$t^* = (t_{\mathrm{u}} + t_{\mathrm{v}})/2 \tag{20}$$

where $P(LL)$ represents the probability of opting for "the smaller, closer option". By default, when the value of $P(LL)$ exceeds σ, the choice of the DM falls on charging in interval u; conversely, when the value of $P(LL)$ is less than σ, charging in interval v is selected.

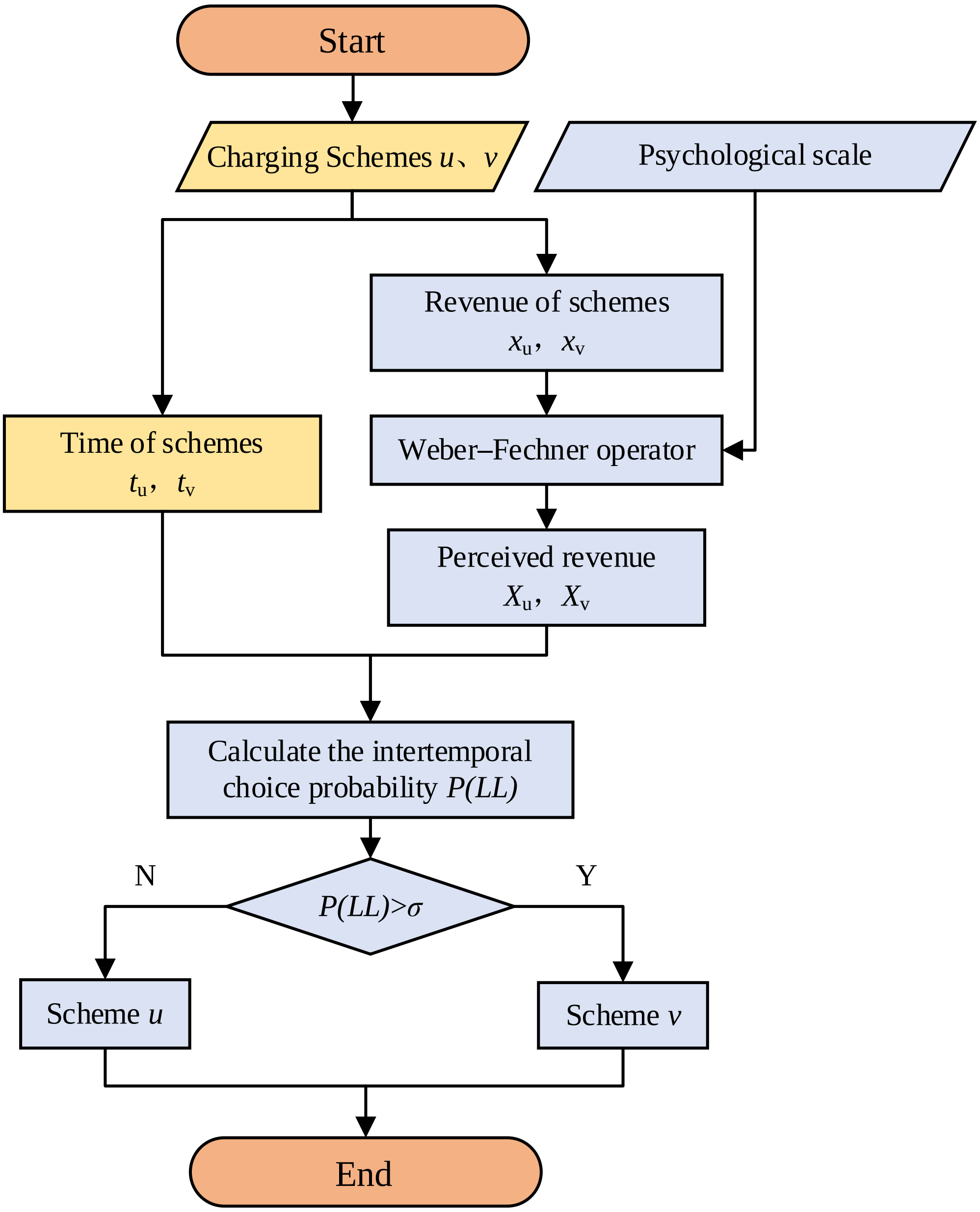


Figure 4. Flowchart of the Weber–Fechner-based EP-ITCH charging model.

5. Case Study

5.1. Data Preparation

The time periods in this case were divided with reference to the peak and off-peak electricity pricing in a certain city in southern China. We set the study time as 9:00–16:00. The time segments were defined as follows: 9:00–10:00 as the flat period T_1, 10:00–12:00 as the peak period T_2, 12:00–14:00 as the flat period T_3, and 14:00–16:00 as the peak period T_4. The charging schemes available to the owners were divided as shown in Table 2. In addition, the parameter settings for the different time periods in this study are shown in Table 3.

According to the research, the BYD E6 EV is a widely used EOV in the city, with a battery capacity of 45 kWh [27]; the charging stations in the city have a charging power of 35 kW [28], with a charging efficiency of θ_c of 0.95 [29].

Table 2. Charging schemes table.

Situation	Time	B_{saf}	Charging Schemes
1	9:00–9:59	0.5	Scheme 1: Charging in T_1 or charging from T_1–T_2 across time Scheme 2: Charging in T_2 or from T_2–T_3 across time Scheme 3: Charging in T_3
2	10:00–11:59	0.6	Scheme 1: Charging in T_2 or from T_2–T_3 across time Scheme 2: Charging in T_3 or from T_3–T_4 Scheme 3: Charging in T_4
3	12:00–13:59	0.35	Scheme 1: Charging in T_3 or from T_3–T_4 Scheme 2: Charging in T_4

Table 3. Parameterization.

	9:00–10:00	10:00–12:00	12:00–14:00	14:00–16:00
Electricity price/[CNY•(kw•h)$^{-1}$]	1	1.3553	1	1.3553
Power consumption rate/kw•h•(min)$^{-1}$			0.093066	

For the starting time of charging T_a, we fit a distribution based on the vehicle quantity curve in the commercial scenario described in reference [30]. We obtained an extension of the normal distribution known as the epsilon-skew normal distribution, which includes an additional parameter to control its skewness. The epsilon-skew normal distribution function is used as the probability density function for the starting time of charging for EOVs.

$$f(p_t|22.7879, 5.66158, 0.855894) = \frac{2}{5.66158}\varphi_t\left(\frac{9-22.7879}{5.66158}\right)\Phi_t\left(0.855894 \times \frac{9-22.7879}{5.66158}\right) \quad (21)$$

where φ_t and Φ_t are the probability density function and cumulative distribution function of the standard normal distribution, respectively.

For the power data, to ensure that the situation in the scheme exists, there are upper and lower limits on the residual power B_N, which are taken uniformly within the power limit and are recorded in fractional form. That is, 0.5 represents 50 percent of the charge.

When using psychological scales, we defaulted to a psychological scale with $\alpha = 7$ (Figure 4), with a maximum guest revenue of 134.7 and a minimum guest revenue of 10.

According to [18], in the ITCH model, the default parameters are set to $\beta_1 = 0$, $\beta_{xA} = 0.1$, $\beta_{xB} = 0.1$, $\beta_{tA} = -0.1$, $\beta_{tR} = -0.1$, and $\sigma = 0.5$.

For calculating the passenger revenue of EOVs according to the EOVs charge standard of a city in the south, the billing formula can be obtained as follows:

$$R_{price} = \begin{cases} 10, & 0 \le G < 2000 \\ \left(10 + \frac{G-2000}{1000}\right) \times 2.7, & 2000 \le G < 25{,}000 \\ \left(10 + \frac{G-2000}{1000}\right) \times 2.7 \times 1.3, & 25{,}000 \le G < 50{,}000 \end{cases} \quad (22)$$

where R_{price} is the cost of the passenger order, G is the actual mileage driven by the passenger order, the unit of revenue of the passenger order is CNY, and the unit of operating mileage is meters.

5.2. Case Design

The dataset used in this study consists of over 40,000,000 rows of historical operational data of over 1800 EOVs in a southern city in China, including car ID, time, latitudinal and longitudinal coordinates, and with/without passenger status. The coordinates were recorded using the WGS84 coordinate system.

The effectiveness of the proposed model in solving the multi-time-span decision-making problem was verified by horizontally comparing the charging decision-making results of the expected utility theory (EUT), the ITCH model, and the EP-ITCH model.

The effectiveness of the proposed model in quantifying the influence of irrational and objective factors was verified by vertically comparing the charging decision results of different psychological scales in the EP-ITCH model and under different electricity prices.

We completed the feature extraction of the frequency operational events, the probability of each operational scenario, and the average revenue of each operational event mentioned in Section 3. This was achieved by writing SQL programs in ClickHouse. In Section 4, we established the EP-ITCH model by writing macro programs in Excel, along with conducting the necessary calculations and analysis. Finally, all of the plotting was completed using Origin.

The structure of the case design is shown in Table 4.

Table 4. Case structure.

Cases	Issues Discussed	Approach	Psychological Scales	Electricity Price
I	With/without considering EP factor in ITCH model	[11]/[19]/EP-ITCH	$\alpha = 7$	1-fold
II	Influence on decision-making for DM with different sensitivities	Establishing psychological scales at different levels	$\alpha = 6$ $\alpha = 9$	1-fold 1-fold
III	Different Electricity prices influence on charging decision analysis and power shift	[19]/EP-ITCH	$\alpha = 7$	1-fold/2-fold

Case I: Charging decision analysis under three different models.

Besides the conventional EUT model [11], the ITCH [19] and EP-ITCH models were employed to model and analyze the charging problem of EOVs. A comparative analysis was conducted on the final charging schemes chosen by EVO owners under the three models, as illustrated in Figure 5.

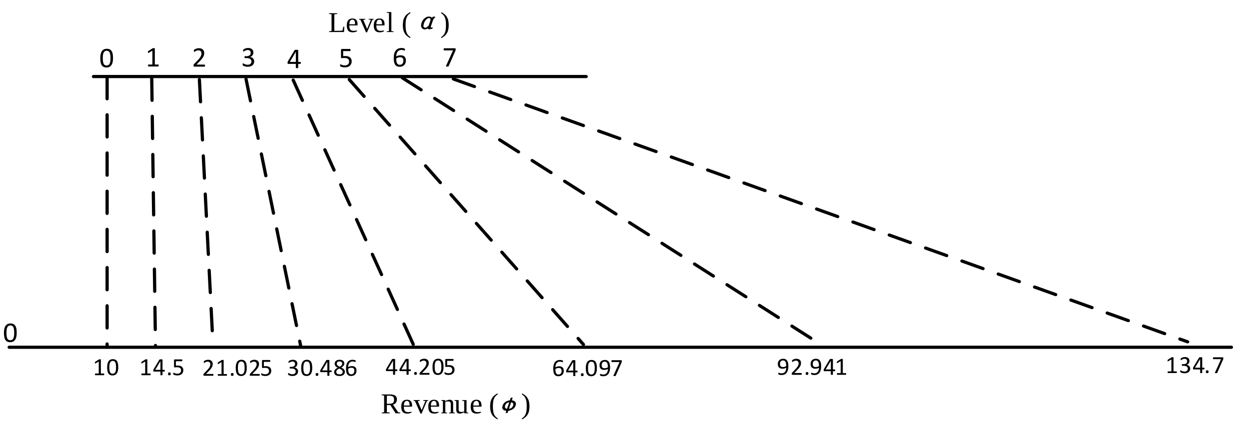


Figure 5. Psychological scale with $\alpha = 7$.

In Situation 1 (Figure 6), the fully rational owner under the EUT model will choose the scheme with the largest revenue, prioritizing Scheme 3 > Scheme 2 > Scheme 1. The growth of the remaining power B_N has a limited impact on this choice.

On the other hand, the ITCH model introduces weight parameters to model the value of the impact of revenue and time, which provides a tool for modeling irrational decision-making behavior [19]. By default, the ITCH model shows that a DM will be more inclined to choose the charging scheme with larger revenues and lower time costs. Since Scheme 1 has the lowest time cost, it becomes increasingly likely to be chosen. This effect becomes even more pronounced as the remaining power B_N increases.

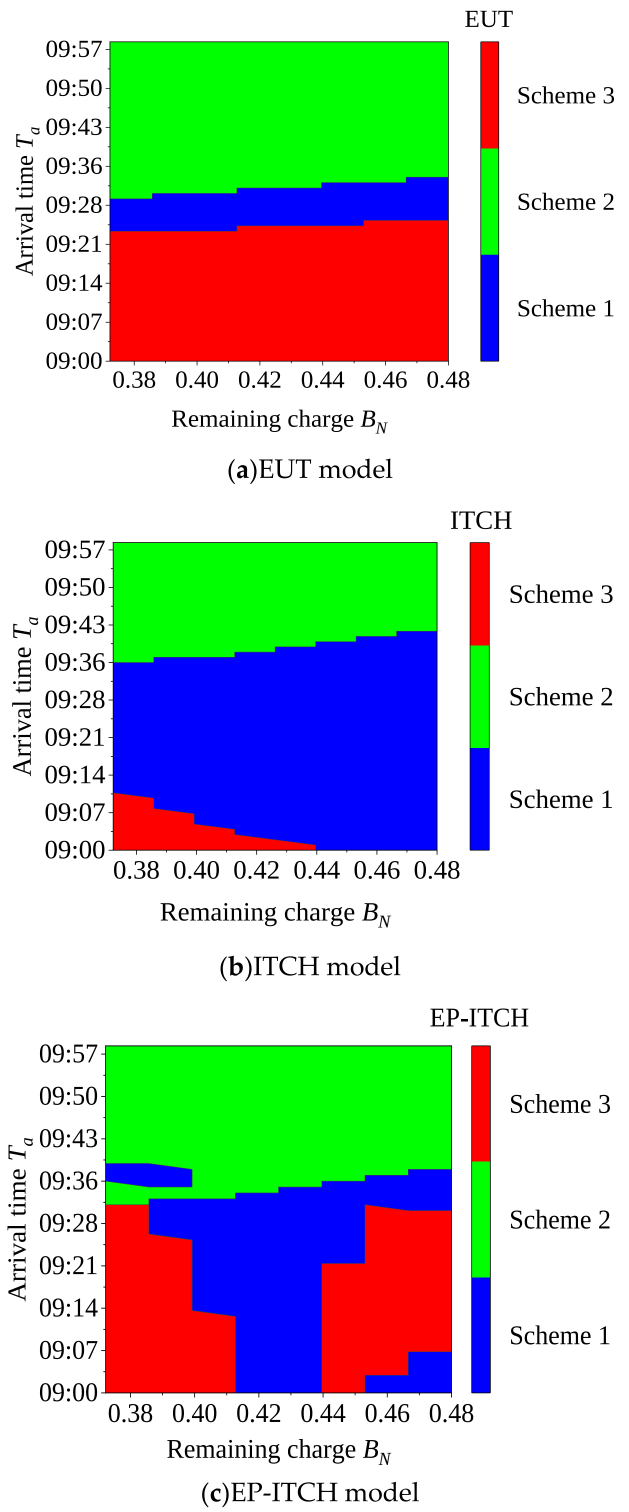


Figure 6. Schematic comparison of charging decision results under the three models for Situation 1.

The Weber–Fechner operator in the EP-ITCH model grades the difference between expected returns, leading to two phenomena:

1. When the perceived expected benefits exceed the perceived threshold, the disparity in benefits increases, which raises the probability of choosing the first charging option.

2. When the perceived expected returns are similar, differences in the expected returns are smoothed out, highlighting the impact of electricity costs on decision making.

Compared to the ITCH model without considering perceptual attenuation, a DM under the EP-ITCH model tends to choose charging schemes with lower average electricity prices and larger equivalent perceived revenues. The differences in the choices of the EP-ITCH model are because EP-ITCH introduces the Weber–Fechner operator to describe the perceptual attenuation in decision making, which leads to irrational factors in decision making. Therefore, it can capture irrational behaviors in decision making more accurately.

In Situation 2 and Situation 3, since the revenue decreases significantly with increased time, a DM will undoubtedly choose to charge immediately with Scheme 1, which comes with larger revenues and earlier times, and there is no difference in the owner's decision under the three models.

To sum up, the fully rational owner under the EUT will directly choose the charging scheme with larger revenues, and the growth of the remaining power B_{N} has little effect on the choice. Partially rational owners under the ITCH model will hesitate under the two options of "smaller revenue and earlier time" and "larger revenue and later time", because of immediate gratification. Compared with the EUT, the ITCH model takes into account the problem of time cost between the time spans of the different schemes, so that EOV owners are more inclined to choose the charging scheme with higher gains and smaller time costs, and the weakening effect of the instantaneous effect will gradually become obvious with the growth of the B_{N}. The EP-ITCH model describes the phenomenon that the owner has an attenuated grading of the subjective perception of revenue, and EOV owners will be more inclined to choose the charging scheme with a lower average electricity price and higher equivalent perceptual revenue.

Case II: Analysis of different psychological scales on EOV owners' charging decisions

To compare the differences in charging decisions of owners with varying perceptual acuity, the psychological scales of low acuity ($\alpha = 6$) and high acuity ($\alpha = 9$) were incorporated herein. The operational time remained 9:00–16:00 h to obtain the charging decisions of owners with three different psychological scales. Since it is known in Case I that in Situation 2 and Situation 3, all of them will choose Scheme 1, which has larger revenue at an earlier time; only the change in the psychological scales under Situation 1 was discussed in Case II.

In the EP-ITCH model, the decision is determined by time and revenue, and the revenue consists of expected returns and average electricity costs. Since the psychological scale grades the expected return, changes in the expected return under Situation 1 are analyzed first. According to the typical data analysis, the expected return is in the range of CNY 30–50 and decreases gradually with the growth of T_{a} and B_{N}.

The expected returns with the same threshold in psychological scale were transformed into perceived expected return through the Weber–Fechner operator, which are perceived as the same perceived expected return. When we focus on the change in average electricity cost in Situation 1, several conclusions can be drawn.

When we focus on the arrival time T_{a}, the trend in electricity fee variation is illustrated in Figure 7.

When T_{a} is small, Scheme 2 will charge during peak hours or start from peak hours and end in flat hours. Thus, Scheme 3 is chosen, because its average electricity cost is initially lower than that of Schemes 1 and 2.

When the charging decision time T_{a} is postponed, the peak-to-flat ratio of the average electricity cost calculation changes, resulting in an increase in the peak period ratio of Scheme 1, and the electricity cost gradually exceeds that of Scheme 2. The relationship between the average electricity costs of the schemes becomes Scheme 1 > Scheme 2 > Scheme 3.

When T_{a} increases to a certain value, one needs to charge for extra time to reach the dynamic psychological safety battery B_{saf}, which supports the operation of the vehicle until handover time. Therefore, Scheme 3 will experience extended charging time, and its charging time Tc will increase, as well as the electricity cost, when the electricity cost of Scheme 3 exceeds that of Scheme 2 and Scheme 1. The final relationship between the average electricity costs of the schemes becomes Scheme 1 > Scheme 3 > Scheme 2.

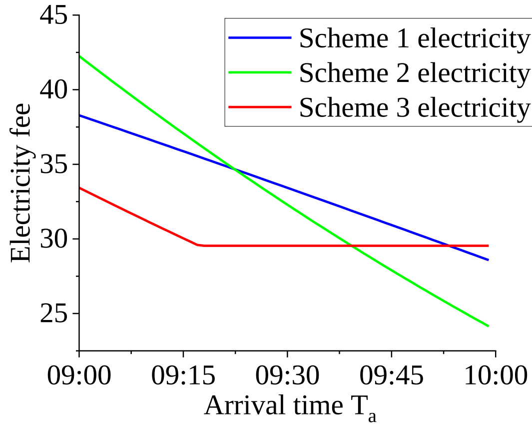


Figure 7. B_N = 0.37227, the trend in electricity fee varies with T_a.

When we focus on the remaining battery power B_N, the trend in electricity fee variation is illustrated in Figure 8.

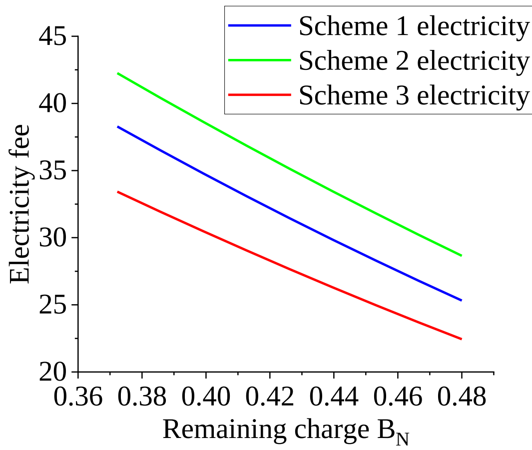


Figure 8. T_a = 9:00, the trend in electricity fee varies with B_N.

When B_N increases, T_c becomes shorter, and the difference in the average cost of electricity between the schemes decreases.

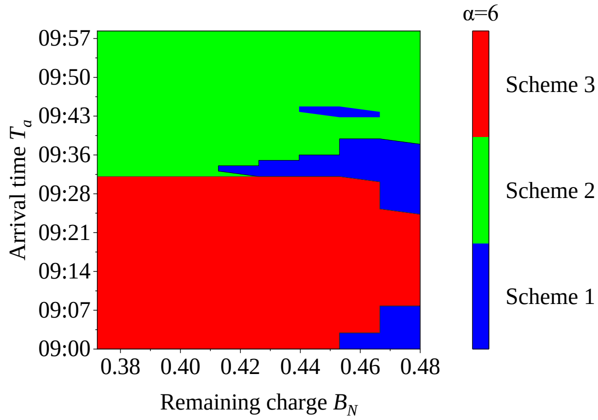
When $\alpha = 6$ (Figure 9a), the EOV owner's sensitivity to the expected return is lowest compared with the case where α is greater than 6.

In this case, the weight of the electricity cost is much greater than that of the revenue. When T_a and B_N are smaller, T_c is longer because of a smaller B_N, resulting in a large gap between the revenue of each scheme. Compared to the revenue, the influence of the time cost can be ignored; Scheme 3, which has low electricity costs and large revenues is the best option.

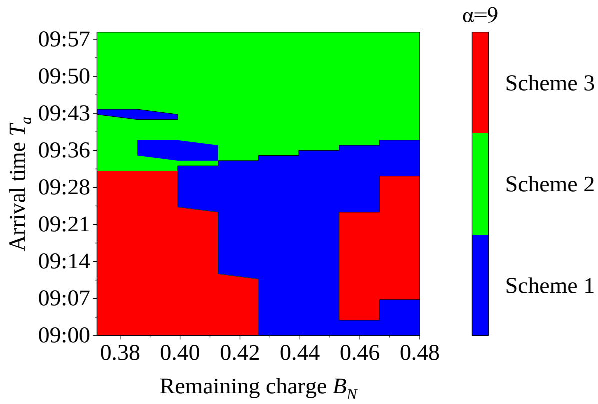
When B_N is fixed and T_a increases, decision making will prioritize Scheme 2 due to its lower electricity costs.

When T_a is fixed and B_N increases, the probability of choosing Scheme 1 increases due to the reduced difference in electricity costs and the impact of time costs.

When $\alpha = 7$ (Figure 6), the owner's sensitivity to revenue increases, and the effect of the psychological scale thresholds on the expected return gradually emerges. When T_a is in the 9:00–9:30 time period and B_N is in the 0.38–0.46 battery power interval, the expected return of different schemes will locate between two different levels of 3 (30.486–44.205) and 4 (44.205–64.097) in the $\alpha = 7$ psychological scale, which widens the gap of the revenue between the schemes, at which point the time cost effect is insufficient to compensate for the gap between the revenues, and the probability of choosing Scheme 1 with the largest perceived revenues increases.



(**a**) Decision result at α=6



(**b**) Decision result at α=9

Figure 9. EP-ITCH results under different psychological scales for Situation 1.

When α = 9 (Figure 9b), the larger revenue difference between the schemes makes the time cost impact insufficient to compensate for it. Thus, the decision tends to favor the scheme with the highest perceived revenue. For example, when T_{a} is in the 9:00–9:30 time period and B_{N} is in the 0.39–0.48 range, the expected return of the different schemes will be in the α = 9 psychological scale between the two different levels of 4 (32.24–43.2) and 5 (43.2–57.89). In this case, Scheme 1 comes with the greatest revenue; therefore, Scheme 1 is chosen over the other two options.

The results show that in Situation 1, as the level of the psychological scale increments, the more the expected return is graded by the psychological scale, the higher the probability that the scheme of charging first and obtaining later is selected. The results show that decision making is influenced by the thresholds of perception, which exhibit significant irrational characteristics. Different psychological scales that represent different sensibilities result in different irrational decision-making options.

Case III: Charging decision analysis and power shift of EOV owners subject to different electricity prices

As it is known from previous cases that the price of electricity influences decision making, it is valuable to discuss the differences in charging decisions under different electricity prices. The operational time was kept at 9:00–16:00, in order to obtain the charging decisions of owners under different electricity prices, and the change in average electricity cost in Situation 1 was analyzed, as shown in Case II.

In Figure 10, we can see that the probability of choosing Scheme 2 under electricity at twice the price increases when T_{a} is in the 9:30–9:59 time period compared to the original price, which is consistent with the trend that the prices of Scheme 2 are eventually become lower than the other schemes when T_{a} is delayed; the probability of choosing Scheme 3 under electricity at twice the price increases when T_a is in the 9:00–9:40 time period, and B_N is in the ranges of 0.38–0.43 and 0.44–0.48 compared to the original price. The probability of Scheme 3 increases, which is consistent with the pattern that was discussed in Case II.

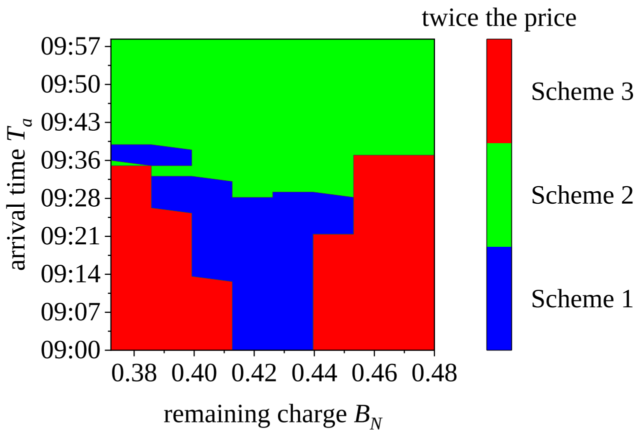


Figure 10. EP-ITCH results under different electricity prices for Situation 1.

In Situation 1, with the increase in electricity prices, the difference in revenue becomes larger. However, compared with the significant changes in electricity costs, the time cost change remains constant, and its impact on decision making is greatly reduced. Therefore, the probability of choosing the scheme with the lowest average electricity cost increases.

To better observe the impact of differentiated electricity price settings on the charging behavior of EOV owners and the impact of the settings on the power grid, we plotted the cumulative charging load curves (Figure 11) of EOV clusters under different electricity price settings.

Under the EP-ITCH model, compared with the original electricity price, the load transfer at double the electricity price is shown in Table 5. The load demands in the two time periods of 9:00–10:47 and 12:57–17:00 are transferred to 10:48–12:56. Under the ITCH model, compared with the original electricity price, the load transfer at double the electricity price is shown in Table 6. The load demands in the two time periods of 9:00–10:47 and 12:58–17:00 are transferred to 10:48–12:57.

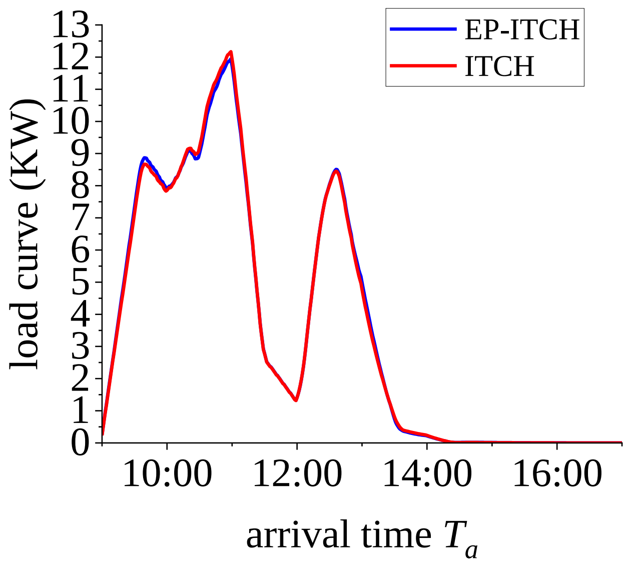
Table 5. EP-ITCH modeling load shifting volume.

Time Period	Load Shift (KW)
9:00–10:47	−1.30
10:48–12:56	1.46
12:57–17:00	−0.16

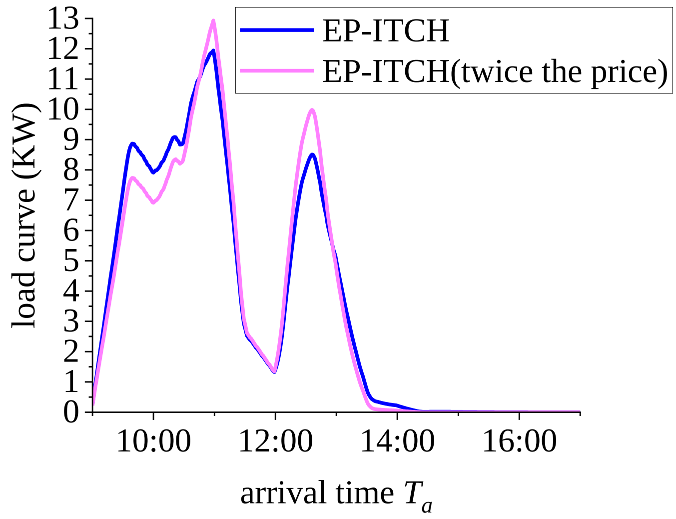
Table 6. ITCH modeling load shifting volume.

Time Period	Load Shift (KW)
9:00–10:47	−1.37
10:48–12:57	1.48
12:58–17:00	−0.11

From the load curve, compared to the ITCH model, the load under the EP-ITCH model is shifted from the peak hours to the flat hours. It can be seen from the amount of load transfer that, due to the increase in the gap between the revenues of higher electricity prices, the objective factor of time cost reduces the charging cost impact on the owner, and the owner is more inclined to obtain revenues first and then charge, so the load demand is shifted backward. The load reaches a peak at 11:00, which is in line with the law of electricity consumption during peak hours, but due to the impact of peak hours electricity prices, the load demand growth is not large; due to the price of electricity entering into the usual section at 12:00, and considering the increased possibility of EOV owners obtaining revenue first and charging later, compared with the original price, the load demand of the 2-fold price rises sharply around 12:40.



(**a**)



(**b**)

Figure 11. Load profiles under different tariffs in the ITCH model and the EP-ITCH model. (**a**) The comparison of load curves between EP-ITCH model and ITCH model under default the prices. (**b**) The comparison of the load curves of the EP-ITCH model under default the prices and double the prices.

From Tables 7 and 8, it is evident that with the same model, an increase in electricity price exacerbates grid fluctuations. When electricity prices are the same, compared to the ITCH model, the EP-ITCH model exhibits smaller peak–valley differences and grid fluctuation variances. Therefore, the charging decision model proposed in this study results in smaller fluctuations for the grid and has less of an impact on grid stability.

The results show that compared with the use of the ITCH model, the EP-ITCH model can, to a certain extent, help EOV owners avoid peak electricity consumption, improve their economic revenue, promote the rational utilization of charging equipment and electric power resources, and attenuate the impacts of large-scale EOV grid connections on the network. At the same time, in the EP-ITCH model, through the reasonable regulation of price changes, the load side of the regulation and scheduling can be realized.

Table 7. The load peak–valley difference under different electricity prices for the ITCH and EP-ITCH models.

Model	The Peak–Valley Difference in Load Demand under the Original Electricity Price (KW)	The Peak–Valley Difference in Load Demand under Twice the Electricity Price (KW)
ITCH	12.16994067	13.09297166
EP-ITCH	11.94369675	12.93333621

Table 8. The load fluctuation variance under different electricity prices for the ITCH and EP-ITCH models.

Model	The Load Fluctuation Variance under the Original Electricity Price	The Load Fluctuation Variance under Twice the Electricity Price
ITCH	15.11410719	15.62816677
EP-ITCH	14.97649603	15.48112037

6. Conclusions

By combining objective constraints on charging behavior decisions across multiple time spans with the subjective perception of vehicle owners, this study comprehensively assessed the relationship between revenues and time costs. It established an EOV equivalent perception intertemporal decision-making charging model based on WFL. Validation through simulations was conducted using transportation data from a southern city in China, leading to the following conclusions:

(1) Charging Scheme Selection Analysis:

Unlike the EUT model, which only considers revenues, the ITCH model incorporates both revenues and time costs. Within this framework, decision-makers are more inclined to choose charging schemes that offer higher revenues and lower time costs. Thus, EOV owners are more likely to select Scheme 1, which has the lowest time costs, especially when the remaining battery level (B_{N}) increases.

The EP-ITCH model integrates the WFL method to account for irrational factors in decision making, explaining the DMs' perception attenuation of revenue. This model makes DMs more likely to choose schemes with lower average electricity prices and higher perceived revenues.

(2) Decision-Influencing Factor Analysis:

In the EP-ITCH model, the influence proportions of expected revenue and average electricity price exhibit irrational characteristics with changes in the psychological scale level. Different psychological scales represent EOV owner groups with different sensitivities to income changes.

When the income is the same, EOV owners who are more sensitive to income changes are more influenced by the expected revenue in their decision making, and they tend to choose to charge first, then obtain revenue.

If EOV owners are not sensitive to income changes, the average electricity price and time significantly affect their decision making, and they prefer to charge during periods with lower electricity prices and the lowest time cost.

(3) Impact Analysis of different Electricity Prices:

After a price increase, the influence of revenue on decision making increases, and DMs are more inclined to obtain revenue first, then charge.

It can be seen from the analysis of load demand under different models and different electricity prices that the EP-ITCH model has smaller load peak–valley differences and load fluctuation variances, indicating that the charging decisions made by the model are more conducive to stable operation of the power grid, which demonstrates the superiority of the model.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to multiple authors and the confidentiality requirements of the authors' organizations.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. The related definition of symbols.

Notation	Parameters	Unit
Index of current slicing interval	w	minute
The duration of the operational event	h	minute
Without/with passenger	i	
Operational scenarios	s	
Number of scenarios	n	
passenger-carrying events	k	
Events sequences	γ	
Time slices	ε	minute
Operational event	m	
Frequency of operational events	f	
Charging time	T_c	minute
Expected revenue	J	yuan
Event frequency matrix	$Q_{n\times k}$	
The scenario probability vector	P	
Probability of operational scenarios	P_s	
Average revenue Vector	I	yuan
Rated capacity of vehicle battery	W	kW·h
Remaining charge	B_N	kW·h
Charge completed battery level	B_{lea}	kW·h
Charging power of EVs	P_{EV}	kW
Charging efficiency of EVs	θ_c	
Dynamic psychological safety battery	B_{saf}	kW·h
Alert power threshold	B_{min}	kW·h
average charging speed	V_c	kW·h/min
Full day operation time	T_d	minute
Arrival time at charging station	T_a	minute
average discharge rate	V_r	kW·h/min
Charging cost	D	yuan
Charging period v	t_v	minute
Charging period u	t_u	minute
Expected revenue v	x_v	yuan
Expected revenue u	x_u	yuan
Order revenue v	J_v	yuan
Order revenue u	J_u	yuan
Charging costs in period v	D_v	yuan
Charging costs in period u	D_u	yuan
Inter-period probability	P(LL)	
Average revenue	x^*	yuan

Table A1. *Cont.*

Notation	Parameters	Unit
Average time	t^*	minute
Intercept	β_1	
The weight of absolute returns	β_{xA}	
Weight on relative returns	β_{xB}	
The weight of absolute time	β_{tA}	
Weight on relative time	β_{tR}	
Logical distribution function	L	
Discriminant threshold	σ	
Response level	η	
The psychological scale threshold Corresponding to level η	φ_η	
Smallest physical intensity	φ_0	
Constant of proportionality	c	
WFL operator	X	
Average equivalent perceived revenue	A^*	yuan

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