Electrical Power and Energy Systems 119 (2020) 105952

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Charging demand analysis framework for electric vehicles considering the bounded rationality behavior of users

Jun Yang[a,*], Fuzhang Wu[a], Jun Yan[b], Yangjia Lin[a], Xiangpeng Zhan[a], Lei Chen[a], Siyang Liao[a], Jian Xu[a], Yuanzhang Sun[a]

[a] School of Electrical Engineering and Automation, Wuhan University, Wuhan 430072, China
[b] Concordia Institute for Information Systems Engineering, Concordia University, Montreal, Quebec H3G 1M8, Canada

ARTICLE INFO

Keywords:
Charging demand of electric vehicles
Activity-based method
Bounded rationality
Cumulative prospect theory
Dynamic traffic assignment model

ABSTRACT

A novel analytic framework is proposed for the charging demand of electric vehicles (EVs), which considers charging demand is primarily determined by the travel behavior. And the bounded rationality of the EV users in travel choices is focused in this paper. The activity-based analysis is expanded to divide the travel behavior of users into the transfer relationship between activity chains and the time-space transfer rule for each activity chain. The transfer relationship between different activity chains is established by the Bayesian method. Based on the cumulative prospect theory, we prioritize the bounded rationality of users in the selection of the travel mode, the departure time and the travel path. And the time-space transfer rule and the charging demand of EVs on each activity chain are described by combining the dynamic traffic assignment model. On this basis, the daily charging demand rule for EVs is revealed. Finally, a test traffic network and a real urban traffic network are used to study the travel behavior and daily charging demand of EVs. The simulation results show that the proposed method can effectively describe dynamic changes in the charging demands of EVs. In addition, the charging demand of EVs will be affected by the ownership rate of EVs, the service capacity of charging stations and the degree of the bounded rationality of users.

1. Introduction

As increasing car ownership brings serious energy challenges and environmental problems, electric vehicles (EVs), as a kind of green transportation, have attracted growing attention and may replace fossil fuel-powered vehicles in the future [1]. However, the large-scale charging of EVs will bring great challenges to the development of electrical power grids [2–4]. Widespread adoption of EVs would significantly increase the overall electrical load demand in power distribution networks. By 2019, the number of EVs in Beijing is 400,000, accounting for only 6% of the total vehicles. In 2019, the city's peak load and valley load are 20 million kW and 13 million kW respectively. The peak of EV charging load has reached 1.3 million kW, accounting for 6.5% and 10% of the peak and valley loads, respectively, according to the data from Beijing electric power company. And, the goal of China's automotive development is to use EVs to completely replace all the fuel-powered vehicles. Under this trend, the power distribution network in Beijing will not be able to meet the demand for residential electricity and EV charging. Hence, there is a need for comprehensive planning and optimal operation of charging infrastructure in order to prevent power failures or scenarios which will result in a considerable demand–supply mismatch. Specifically, on one hand, an important factor considered in the charging station planning is whether their configuration can meet the EVs' charging demand or the traffic flow. It is necessary to give priority to the analysis of traffic flow and charging demand [5–7]. On the other hand, with the large-scale application of EVs in the future, the time-space change of charging load will bring great influence on the safe and economic operation of power grid. How to construct the distribution network reasonably and optimize the operation of distribution network according to the characteristics of charging load is also an important issue to be studied. For example, the economics under the demand of EVs' charging constraints is studied in the planning of distribution network in [5,6]. Thus, accurate prediction about the realistic charging demand of EVs is an essential part of the infrastructure planning and operation.

In the current studies of the charging station and distribution

* Corresponding author.
E-mail addresses: JYang@whu.edu.cn (J. Yang), wfzhang@whu.edu.cn (F. Wu), jun.yan@concordia.ca (J. Yan), linyj@whu.edu.cn (Y. Lin), xiangpengzhan@whu.edu.cn (X. Zhan), chen_lei@whu.edu.cn (L. Chen), liaosiyang@whu.edu.cn (S. Liao), xujian@whu.edu.cn (J. Xu), yzsun@mail.tsinghua.edu.cn (Y. Sun).

https://doi.org/10.1016/j.ijepes.2020.105952
Received 7 September 2019; Received in revised form 3 January 2020; Accepted 17 February 2020
Available online 27 February 2020
0142-0615/

network planning, the traffic flow is usually obtained first by means of calculation or statistics. The charging station location is often determined with the goal of maximizing the traffic flow served by the charging station, and the capacity of the charging station is optimized considering the construction economy of the charging station and distribution network. The methods only take the influence of traffic flow and charging demand on the location and capacity of charging station into consideration, while the location and capacity of charging station will actually influence the driving characteristics and charging demand of EVs. Therefore, in the planning of charging stations and the analysis of the economic operation of the power grid, the mutual influence between the two aspects should be considered.

In the studies of optimal operation of distribution network and charging infrastructure, previous researches focused on statistical models, simulation analyses and the method of utility maximization, especially statistical models. There are some unreasonable assumptions in statistical models. Since large-scale driving data for EVs in urban transportation is not presently available, it is assumed in [8,9] that the driving behavior of the drivers and their lifestyle remain largely unaffected by electrification of their vehicles. In reality, the charging time of EVs is relatively long, which has become an important factor for drivers to consider when making driving choices. Therefore, the electrification of vehicles may greatly change driving behaviors. Several researchers believe that the EVs have a fixed charging frequency, such as the assumptions of personal EVs are charged once every other day in [10] and once per day in [11], and adopt normal distributions to fit the important parameters of EVs including daily driving distance, starting time of charging and initial state of charge (SOC), to obtain the charging demand of EVs. The uncertainties of these parameters have been modeled by empirical cumulative distribution functions (CDF) without taking their mutual correlations into account. Fixed charging locations and predetermined charging periods are respectively assumed in studies of [12] and [13] to generate system-wide EV charging demands, in which the randomness of charging period and charging location is ignored. The actual traffic data in some areas may be widely used in the formulation of regulation measures for the participation of EVs in the power grid, such as the NHTS data is used to generate charging demand scenarios by [14–16]. Due to the constraints of economy, infrastructure and other factors, EV charging behavior in different regions will vary greatly, so the conclusions drawn may not be universally applicable. There are also some literature divide travelers' destinations into work, home and other according to the statistics of travel characteristics, establish the travel mode of EV by travel chain [17] and transition matrix [18], and use Markov model [19,20] to calculate the transition probability of EVs between different destinations, so as to obtain the driving behavior and charging demand of EVs. These methods to obtain the transition probability of EVs are based on an assumption that the transfer of the current state of EVs is only related to the previous state and has nothing to do with the historical ones. However, the transfer process of EVs is continuous in time and space, and it is inevitably affected by the historical states. In simulation analyses, dynamic evolution models of EV charging demand based on the fuzzy reasoning method and agent-based modeling are proposed in [21,22], respectively, and the driving behavior and path planning of EVs are simulated. Nevertheless, they also require a large amount of operation data to extract the characteristics of EVs' travel and charging. In the method of utility maximization, [23] proposed a decision-making model of EV charging consumption based on the principle of utility maximization to simulate the charging selection process of EVs. Many research fields have proved that utility maximization does not conform to the law of human decision-making.

Charging demand is the result of travel energy consumption and primarily determined by the travel behavior that consists of travel decision and driving characteristics of vehicles. While the travel decision of EVs is influenced by several factors, such as driving habit, location of charging stations, electricity pricing, etc. The indicators that affect users' travel choices are ultimately time cost and travel expense. Refs. [24–27] discussed the influence of charging price on EV travel and charging. However, many scholars believe that time cost is the main factor influencing the travel choice of travelers, as shown in [28,29]. Moreover, layout of roads and traffic patterns influence not only the travel decision but also vehicular energy consumption, which contributes to timing and distribution of charging demand. So, in order to accurately analyze the charging demand of EVs, it is necessary to combine traffic engineering and electric power systems.

Studies on users' travel behavior in traffic engineering have moved from statistical models to disaggregate models. The statistical models are difficult to analyze the real reasons behind a user's travel choices [30]. Beginning in the 1960s, disaggregate models have been applied to research users' travel behavior, and the main focus has been on the building of mathematical models. The multinomial Logit model for analyzing the decision-making behavior of users and the mixed Logit model are established in [31,32]. Smirnov [33] and Wan [34] proved that the travel behavior of users is greatly influenced by the social environment, urban planning and economic foundations by combining the maximum utility in economics and psychology. The above disaggregate models all follow the principle of utility maximization. While, the theory of utility maximization is based on the assumption that human beings are completely rational. In reality, people often do not act according to the predictions of the theory of utility maximization. The Allais paradox, the Ellsberg paradox, the ultimatum game [35–37] and other behavioral economics problems have all questioned the completely rational assumption of human beings. Theories that consider the bounded rationality decision-making process of humans, such as regret theory, have been applied to relevant studies of the path selection and departure time selection by users and have well explained some phenomena that cannot be explained by utility maximization theory [38].

By combining researches on travel behavior in the fields of traffic engineering and electric power systems, it can be concluded that the statistical models applied in the studies of EVs are difficult to implement and not universal because EVs are not widely used. It is also difficult to explore the internal causes of the charging behavior of EVs to develop corresponding measures for effective management. For instance, how the configuration change of charging stations affect the charging demand of EVs. In addition, the charging choices of EV users based on utility maximization theory does not conform to the bounded rationality of actual people, and may be considerably different from practical situations.

In this paper, an analytical framework for the charging demand of EVs that emphasizes the bounded rationality of users in travel choices of EVs is proposed. We divide the travel of vehicles into two parts: travel choice and driving characteristics. And this paper mainly considers the impact of time cost in users' travel choices. Firstly, the decision-making process of travel mode, travel path and departure time for travelers including EV users is analyzed. Then considering the actual situation of the traffic network, the driving process of vehicles in the traffic network is studied. Finally, charging demand of EVs is obtained by combining the travel mileage and vehicle power consumption rate. The proposed method can not only be applied to the analysis of different scenarios in the planning stage of charging infrastructure and distribution network without a large amount of operation data, but also reasonably predict the charging demand of EVs in actual operation. The main contributions of this paper are as follows.

- The idea of activity-based analysis of time geography is expanded to model the daily travel activities of EV users in three-dimensional space and to understand the daily travel frequencies of users. The transfer relationship between different activity chains is analyzed by categorizing the daily activities of users and judging their occurrence conditions. The activity-based analysis not only considers the influence of current state on travel transition, but also the historical ones.

- The three reference points of EV users' perceived satisfaction in the travel choice process are established by considering the bounded rationality of users and the correlation among user's departure time, travel mode and travel path. These reference points are used to create a travel choice probability model based on cumulative prospect theory to study the choices of EV travel and charging on each activity chain.
- The time-space transfer rule and the charging demand of EVs on each activity chain are illustrated by a dynamic traffic assignment model that considers the travel choice probability of users and the charging characteristics of EVs. The daily charging demand of EVs is revealed by combining the daily travel frequencies of users and the charging demand of each activity chain.

The remainder of this paper is organized as follows. Section 2 analyzes the transfer relationship between the different activity chains of users in a day. Section 3 establishes the travel choice probability model on each activity chain by considering the bounded rationality of users. Section 4 presents the time-space transfer rule of EVs in a traffic network and the dynamic change rule of the charging demand of EVs on each activity chain. Simulations and conclusions are presented in Section 5 and Section 6, respectively.

2. The time-space transfer relationship between the activity chains of users

This section analyzes the time-space transfer relationship between the different travel chains of users by expanding the activity-based analysis method, which lays a foundation for analyzing the daily travel frequencies of EVs.

2.1. Time-space modeling of user behavior based on activity-based analysis

Here, activity represents the total actions taken by someone to achieve her or his aims, such as travel to work and shopping. It is composed of purpose, motivation and action. The combination of actions for the purpose of the activity is called the activity chain. The activity-based analysis method uses the daily activity chains to connect the daily round trips of individuals, which reflects the internal connection between travel activity participation and travel schedule. And it describes the interdependent relationship between all individual trips and the time-space constraints of activity travel. As an example, Fig. 1 shows the spatiotemporal expression of a user's activities during the day.

It can be seen that the daily activities of the user are consist of many activity chains, and the transfer behavior of the user is divided into the transfer relationship between activity chains and the time-space transfer rule on each activity chain. The user's daily activity behavior is continuous in time and space. The starting point and activity time of each activity chain must be influenced by historical activity chains. For each traveler in the transportation system, the daily activities can be described by the activity attributes including the number of activities, activity type, activity location, departure time, duration of activity, travel time and travel mode. If the number of activities arranged by an individual i in a day is n, the activity-travel mode is expressed as ATP_i:

$$ATP_i = f_{i,n} = (g_{i1}, g_{i2}, ..., g_{in}) \tag{1}$$

where g_{ij} is the j-th set of activity attributes for the i-th user, and $f_{i,n}$ is the activity-travel mode in a day.

2.2. Analysis of the transfer relationship between different activity chains based on the Bayesian method

According to the analyses of human activity needs by [39] and [40],

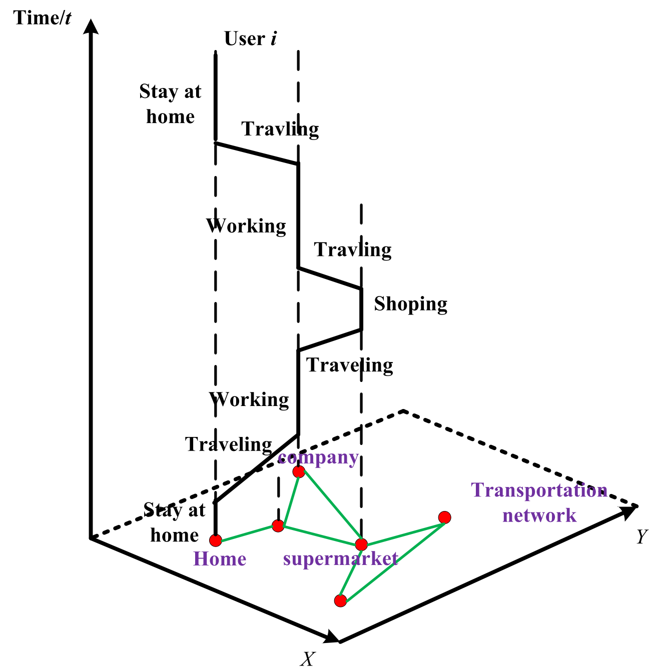


Fig. 1. Three-dimensional space-time representation of activity behavior.

individual activities can be divided into three categories: livelihood activities, maintenance activities and entertainment/leisure activities. Of these activities, the first type is necessary, and the others are flexible. For example, the business activities related to work are necessary, while shopping is a flexible activity.

Considering that a user's ATP changes every day and various patterns can occur with a certain probability, we propose that the probability of each activity's occurrence is equal to the conditional probability of all the historical activities. If the j-th activity of the user is necessary, the probability of the activity's occurrence can be denoted as:

$$P(g_{ij} | f_{i,j-1}) = 1 \tag{2}$$

If the j-th activity of the user is flexible, suppose that the upper limit of the acceptable time for arrival of the user i is T_j, the number of travel modes available to the user i is m, and the earliest arrival time for the user and the upper confidence limit of α of the earliest arrival time are T_{jk} and $T_{jk\alpha}$, respectively, when the k-th travel mode is selected.

$$P(T_{jk} \leqslant T_{jk\alpha}) = \alpha \tag{3}$$

The minimum arrival time of the earliest travel time of all the travel modes is $T_{j\min}$, $T_{j\min} = \min\{ T_{jk\alpha}, k \in m\}$. Thus, the occurrence probability of this activity is

$$P(g_{ij} | f_{i,j-1}) = \begin{cases} p_{ij} & T_{j\min} \leqslant T_j \\ 0 & T_{j\min} > T_j \end{cases} \tag{4}$$

where p_{ij} ($0 \le p_{ij} \le 1$) denotes the probability of user i to travel when they have enough travel time for flexible activity j. As residents' trips are affected by the transportation facilities, economic environment and other factors, the value of p_{ij} should be obtained by local statistical data.

According to the Bayes theory and Eqs. (2)–(4), the probability of a user's participation in the j-th activity is:

$$P(g_{ij}) = P(f_{i,j-1}) \cdot P(g_{ij} | f_{i,j-1}) \tag{5}$$

3. Travel choice on each activity chain considering the bounded rationality of users

This section establishes the travel choice probability model of the bounded rationality of users considering the correlation among travel mode, travel path and departure time on each activity chain. First, the perception utility of a user's bounded rational decision-making is analyzed. Second, the travel choice probability model is structured according to the perception utility.

3.1. Modeling of perception utility based on cumulative prospect theory

The time-space transfer rule of users on an activity chain depends on their choice of travel mode, departure time and travel path. Bounded rationality refers to the limited cognition and computing abilities of human beings. It is impossible for decision makers to master all the information and know the detailed rules needed for decision-making. Decision makers can only perceive results based on the information mastered, and they tend to pursue "satisfaction" criteria rather than "optimal" criteria in their decision-making.

In cumulative prospect theory, the decision-making behaviors of users are divided into two stages: editing and evaluation [41]. In the editing stage, users will compile their cognition of current traffic information, set the reference point of travel by combining all constraints, define the different choices as gains and losses relative to the reference point, and form subjective probability weights (or decision weights) of the gains and losses. In the evaluation stage, decision makers combine the gains and losses with the subjective probability weights to form the prospect or perceived utility for different choices. This process represents the first aspect of a user's bounded rationality.

Suppose that the probability of the result x_i appearing in a selected prospect P is p_i, and the probability of the reference point x_0 formulated by the user is p_0. If all possible results x_i are arranged in ascending order $x_{-m} \le \ldots \le x_{-1} \le x_0 \le x_1 \le \ldots \le x_n$, then the model of accumulative prospect theory can be expressed as:

$$V_P = \sum_{i=1}^{n} (w^+(p_i + \ldots + p_n) - w^+(p_{i+1} + \ldots + p_n)) g(x_i) + \sum_{j=-1}^{-m} (w^-(p_{-m} + \ldots + p_j) - w^-(p_{-m} + \ldots + p_{j-1})) g(x_j) \tag{6}$$

In the Eq. (6), V_P is the perceived utility of the user; $g(x_i)$ is the value function of the result x_i, which reflects the gain and loss; $w^+(\cdot)$ and $w^-(\cdot)$ are the subjective probability weight functions of gains and losses, respectively.

Considering the continuity of the occurrence probability of the result x_i, the probability distribution function of the selection result is introduced into Eq. (6). The perceived utility of the user, namely, the cumulative prospect, is denoted in Eq. (7). The detailed derivation is shown in Appendix A.

$$V_P = \int_{-\infty}^{x_0} \frac{dw^-(F(x))}{dx} g(x) dx + \int_{x_0}^{\infty} -\frac{dw^+(1-F(x))}{dx} g(x) dx \tag{7}$$

According to [42] study on value functions and decision weight functions that analyzes the choice behavior of a large number of people, risk preference will be reversed near the reference point, and people will tend to risk aversion in the face of gains and risk pursuit in the face of losses. In the face of the same amount of gains and losses, the degree of loss aversion is greater than the degree of preference for gains. As the distance from the reference point increases, the psychological impact of marginal changes in gains or losses decreases. Meanwhile, people tend to overestimate the low-probability events and underestimate the high-probability events. Ref. [42] proposed the "S" type value function and the inverted "S" type subjective probability weight function based on their research, as shown in Fig. 2.

The value function and the weight function can be expressed as:

$$g(x) = \begin{cases} (x - x_0)^{\alpha}, & x \geqslant x_0 \\ -\lambda (x_0 - x)^{\beta}, & x < x_0 \end{cases} \tag{8}$$

$$w^+(p_{ob}) = \frac{p_{ob}^{\zeta}}{[p_{ob}^{\zeta} + (1-p_{ob})^{\zeta}]^{\frac{1}{\zeta}}} \quad w^-(p_{ob}) = \frac{p_{ob}^{\delta}}{[p_{ob}^{\delta} + (1-p_{ob})^{\delta}]^{\frac{1}{\delta}}} \tag{9}$$

In Eqs. (8) and (9), α, β $(0 < \alpha, \beta < 1)$ and λ $(\lambda \ge 1)$ reflect the user's preference level for risk. As the value increases, the degree of diminishing sensitivity of the decision maker to risks (gains or losses) decreases, and the sensitivity of the decision maker to risks increases. The parameters ζ and δ determine the bending degree of the inverted "S" type subjective probability weight function. And p_{ob} is the objective probability of result occurrence.

The perceived utility of a decision maker for a choice can be described by Eqs. (6)–(9).

3.2. Reference point setting considering the multiple constraints of travel mode, departure time and travel path

The choices of travel mode, departure time and travel path affect and restrict each other. Therefore, the influence of the three factors must be considered in the selection of reference points. Jou [43] proposed the "acceptable earliest arrival time T_E" and the "activity starting time T_W" as two value function reference points for departure time selection based on prospect theory and survey data, as shown in Fig. 3. Travelers arriving between these two reference points will receive gains; otherwise, they will receive losses. Between the two reference points, there exists a "best expected arrival time T_O", and travelers obtain the greatest gain from arrival at T_O. Arrival before T_O is referred to as "early", and arrival after this time is referred to as "late".

Based on the description of the two reference points proposed in [43], the rule of three reference points is established in this paper to describe the user's behavior in selecting reference points for the travel mode, departure time and travel path simultaneously. T_E and T_W can be used as reference points for departure time selection, and T_O can be used as the reference point for path selection. Meanwhile, according to [44], the most important criterion of travel choice for travelers is travel time for a travel mode. Therefore, the travel time budget can be set as a reference point for the travel mode:

$$P\{T_{p,k}^{w}(t) \leqslant b_{p,k}^{w} = \tau_{p,k}^{w}(t) + \mu \sigma_{p,k}^{w}(t)\} = \rho \tag{10}$$

$$\mu_{0,p,k}^{w}(t) = \min\{b_{p,k}^{w}(t)\} \tag{11}$$

where $T_{p,k}^{w}(t)$, $b_{p,k}^{w}(t)$ and $\mu_{0,p,k}^{w}(t)$ represent the travel time, travel time budget and travel time reference point of the k-th travel mode on the path p at time t, respectively; $\tau_{p,k}^{w}(t)$ and $\sigma_{p,k}^{w}(t)$ are the expectation and standard deviation of $T_{p,k}^{w}(t)$, respectively; the transportation requirement is modeled by origin–destination (OD) demand pairs; w represents the set of all OD pairs in the traffic network; ρ is a confidence coefficient; and μ reflects the traveler's risk preference.

3.3. The model of travel choice probability on an activity chain

Define $v_{p,k}^{w}(t)$ as the prospect of path p of the k-th travel mode at time t, namely, the path prospect. $\psi_{p,k,E}^{w}(t)$ is the prospect of early arrival of the k-th travel mode when the path p is selected at time t, which is the prospect of early arrival. $\psi_{p,k,L}^{w}(t)$ refers to the prospect of late arrival for the k-th travel mode when the path p is selected at time t, this is the prospect of late arrival. $\psi_{p,k,E}^{w}(t)$ and $\psi_{p,k,L}^{w}(t)$ are collectively the prospect of arrival. $\varphi_{p,k}^{w}(t)$ is the prospect of the k-th travel mode at time t, which is the travel mode prospect. They can be obtained by substituting the three reference points into Eq. (7).

In the travel process, the traveler will make choices according to the prospects of the travel mode, departure time and travel path. $\gamma_k^{w}(t)$, $\eta_p^{w}(t)$ and $\mu^{w}(t)$ are the probability that the k-th travel mode, the path p and the time t, respectively, are selected. Then, the traveler's choice

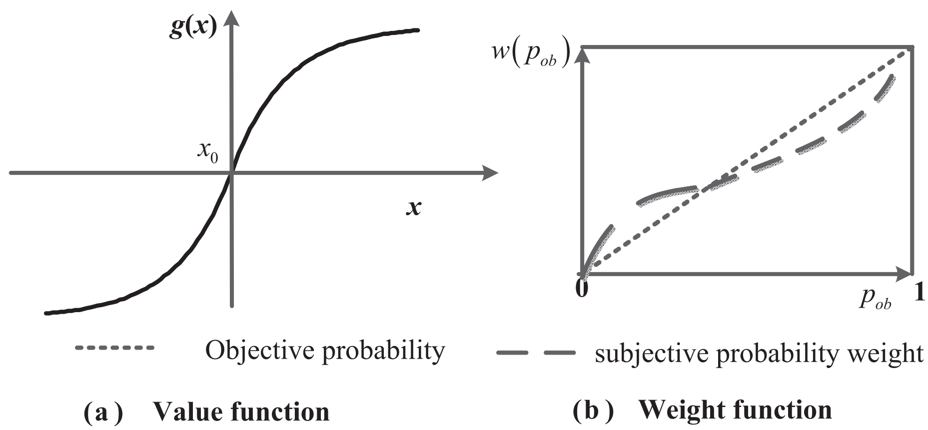


Fig. 2. The value function and the subjective probability weight function of users.

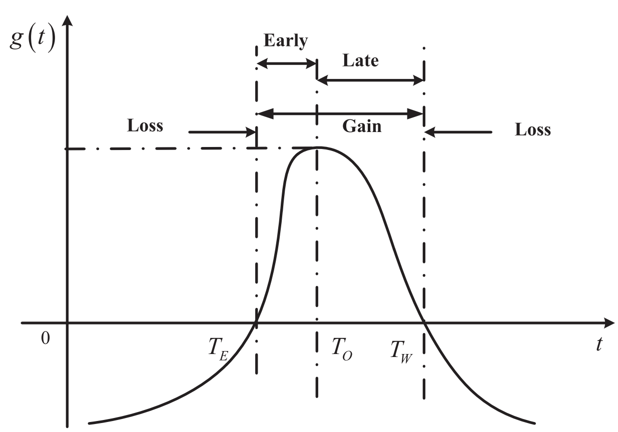


Fig. 3. Value function of arrival time.

probability model can be expressed as:

$$\gamma_k^w(t) = \exp(\varphi_{p,k}^w(t)) \Big/ \sum_{x \in m} \exp(\varphi_{p,x}^w(t)) \tag{12}$$

$$\eta_k^w(t) = \exp(v_{p,k}^w(t)) \Big/ \sum_{x \in R_w} \exp(v_{x,k}^w(t)) \tag{13}$$

$$\mu^w(t) = \exp(\psi_{p,k}^w(t)) \Big/ \int_0^{+\infty} \exp(\psi_{p,k}^w(s)) ds \tag{14}$$

Eqs. (12)–(14) embody the second aspect of a user's bounded rationality.

4. The time-space transfer and charging rule of EVs on an activity chain based on the dynamic traffic assignment model

The travel choice probability model analysis under the three reference points shows that the user's choice probability depends on the travel time which is affected by the traffic flow and the time spent at charging station. In this section, the dynamic traffic assignment model is applied to describe the time-space transfer rule of travelers on an activity chain considering the charging characteristics of EVs, and then solve for the travel time. The charging demand of EVs in the process of travel can be obtained later in this study.

4.1. Construction of the model

4.1.1. Travel time calculation

Private fuel vehicles, private EVs and public transport are defined as the first, second and third modes of travel, respectively. Considering that public transportation has special access in the actual traffic system,

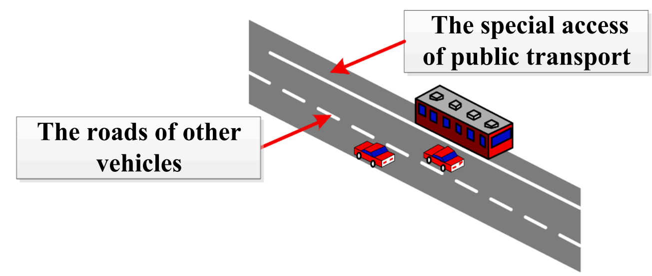


Fig. 4. The road structure of public transportation and private cars.

the assignment of private cars and public transportation can be separated in calculations, as shown in Fig. 4.

Because the driving paths of public transportation are fixed and their traffic flows are small, the expected travel time of public transportation $\tau_{p,3}^w(t)$ can be calculated based on distance and average speed. The variance of travel time is described by the variation coefficient.

Fuel oil gasoline stations are widely distributed among traffic, and the refueling time of fuel vehicles is short. Therefore, all simple paths of fuel vehicles can be considered as available paths. Because of the limits of the service capability of charging station and the range of EVs, the available paths of an EV can be defined as follows: if an EV chooses a simple path and can get to its destination without charging or by charging halfway, that path is available.

For private cars, the link's driving time is denoted as:

$$T_{ad,k}(t) = t_a^0 \left[1 + 0.15 \left(\frac{x_a(t)}{C_a} \right)^4 \right] \quad k = 1, 2 \tag{15}$$

where $T_{ad,k}(t)$ is the driving time of private cars on link a; $k = 1$ and $k = 2$ represent fuel vehicles and EVs, respectively; t_a^0, C_a and $x_a(t)$ reflect the free flow time, traffic capacity and traffic flow of link a, respectively.

The path travel time of private cars includes driving time and the time spent at charging station, and can be denoted as (16). The fuel private cars need not be charged, so $\zeta_{e,i,p}^w(t) = 0$ in Eq. (16).

$$\begin{aligned} T_{p,k}^w(t) &= T_{pd,k}^w(t) + \sum_i \zeta_{e,i,p}^w(t) T_{e,i,p}^w(t) \\ &= \sum_{a \in p} T_{ad,k}(t) + \sum_i \zeta_{e,i,p}^w(t) T_{e,i,p,total}^w(t) \end{aligned} \tag{16}$$

where $T_{pd,k}^w(t)$ is the driving time of path p; the charging of EV e on node i of the path p of OD pair w at time t is denoted as $\zeta_{e,i,p}^w(t) = 1$, otherwise, $\zeta_{e,i,p}^w(t) = 0$; $T_{e,i,p,total}^w(t)$ represents the time spent at charging station if the EV e is charged on node i. Similarly, the expectation and variance of path travel time can be expressed by the expectation and variance of driving time and the time spent at charging station, respectively.

The time spent at charging station consists of two parts: charging time and queuing time. The former depends on the charging energy and rated power of the charger. For a charging station i with $N_{cs,i}$ charging piles, its service capacity is $C_{cs,\ i}$ ($C_{cs,\ i} \gg N_{cs,i}$). When the number of vehicles in the charging station is less than $N_{cs,i}$, there is no need to wait for charging. In this case, the time spent at the charging station is the charging time. When the number of EVs to be charged is greater than the service capacity of the charging station, they will not be queued at the charging station. If the number of vehicles in the charging station is greater than $N_{cs,i}$ but does not reach the service capacity of the charging station, EVs need to wait to be recharged. The Davidson function which is developed in [45] based on the queuing theory is adopted to fit the consumption time of EVs at the charging station, as expressed as:

$$T^w_{e,i,p,total}(t) = T^w_{e,i,p}(t)\left(1 + J\frac{N^w_{cs,i}(t)}{C_{cs,i} - N^w_{cs,i}(t)}\right) \tag{17}$$

where, $T^w_{e,i,p}(t)$ represents the charging time if the EV e is charged at charging station i; the number of EVs that need to be charged at the charging station at node i at time t is $N^w_{e,i,p}(t)$; and parameter J related to the queuing mode and the service mode of the charging station, controls the shape of the function.

Generally, EVs will be charged in only two situations: if their SOC cannot meet the demand of the remaining travel during the trip or if their SOC is below a threshold which is set at 0.3 in this paper, when they reach the activity location. In addition, EVs can be assumed to be fully charged after coming home from the last activity in a day. If EVs are charged during their trips, the charging only needs to meet the remaining travel. When EVs are charged at the activity location, they will try to be fully charged.

The SOC of EV e before and after charging are $SOC^w_{e0,i,p}(t)$ and $SOC^w_{e1,i,p}(t)$, respectively, and the battery energy of EV e is C_e. The charging characteristics of an EV's battery can be approximated by the constant power model, which regards the charging power rate as a constant value P_e [46]. Thus, the expected charging time of EV e on node i at time t during a trip is:

$$E(T^w_{e,i,p}(t)) = \tau^w_{e,i,p}(t) = (SOC^w_{e1,i,p}(t) - SOC^w_{e0,i,p}(t))\cdot C_e/P_e \tag{18}$$

Because the battery capacity of EVs is limited and the charging time is relatively long, EV users will have anxiety when the SOC is lower than a certain value. The anxiety mileage of EV e can be denoted as m^e. The energy consumption rate of EV is c_e. The endpoint of the next charging node or path adjacent to node i on path p is j, and the distance between the two nodes is $d_{i,j}$. Then, the EV SOC after charging should meet Eq. (19) at each charging node i.

$$SOC^w_{e1,i,p}(t) - d_{ij}c_e \geqslant m^e c_e \tag{19}$$

Meanwhile, the number of EVs need to be charged simultaneously on node i should not be greater than the service capacity $C_{cs,\ i}$.

$$\sum_w \sum_p \sum_{e\in f^w_p(t)} \zeta^w_{e,i,p}(t) \leqslant C_{cs,i} \tag{20}$$

4.1.2. The dynamic traffic assignment model with fuel vehicles and EVs considering the charging characteristic of EVs

From Eq. (16), the driving time is a function of the traffic flow, so the traffic assignment should be studied. A dynamic traffic assignment model is established:

$$f^w_p(t) = D^w(\gamma^w_1(t) + \gamma^w_2(t))\eta^w_k(t)\mu^w(t) \tag{21}$$

where $f^w_p(t)$ is the traffic flow of available path p, and $_D{}^w$ is the travel demand.

Eq. (21) needs to meet the traffic flow conservation and nonnegative constraint conditions.

$$x_a(t) = \sum_{a\in p} f^w_p(t) \tag{22}$$

$$x_a(t) \geqslant 0, f^w_p(t) \geqslant 0 \tag{23}$$

From Eqs. (12)–(23), the time-space transfer rule and charging demand of EVs on each activity chain and at each activity location considering the bounded rationality of the users are established. Then, the total charging load of the charging station at each moment is the sum of the charging load of all EVs charged at the charging station at that moment.

4.2. The existence of model solutions

Considering the coupling between a user's selection and the traffic flow, and the asymmetry of the dynamic traffic assignment problem, a mathematical model corresponding to Eq. (21) cannot be found. By the method of variational inequality, Eq. (21) is transformed into its equivalent model, which is equivalent to the path flow $f^{w^*}_p(t)$ at any time that satisfies Eq. (24).

$$\sum_t \sum_w \sum_p [f^{w^*}_p(t) - D^w(\gamma^w_1(t) + \gamma^w_2(t))\eta^w_k(t)\mu^w(t)]\cdot(f^w_p(t) - f^{w^*}_p(t)) \geqslant 0 \tag{24}$$

The feasible set of Eq. (21) is Ω_w.

$$F(f^w_p(t)) = f^w_p(t) - D^w(\gamma^w_1(t) + \gamma^w_2(t))\eta^w_k(t)\mu^w(t) \tag{25}$$

The actual travel demand D^w has upper bounds, and $F(f^w_p(t))$ is a continuous function on Ω_w, so there exist solutions of Eq. (24).

4.3. Solutions of the model

Eq. (21) is equivalent to seeking $f^{w^*}_p(t) \in \Omega_w$ to satisfy Eqs. (26)–(28):

$$[f^{w^*}_p(t) - D^w(\gamma^w_1(t) + \gamma^w_2(t))\eta^w_k(t)\mu^w(t)]f^{w^*}_p(t) = 0 \tag{26}$$

$$f^{w^*}_p(t) - D^w(\gamma^w_1(t) + \gamma^w_2(t))\eta^w_k(t)\mu^w(t) \geqslant 0 \tag{27}$$

$$f^{w^*}_p(t) \geqslant 0 \tag{28}$$

First, all the unloop paths are set as the initial available path set R^*_w based on path search technology, and the discretization method is adopted to solve the problem. The method of successive average (MSA) is designed to solve the dynamic traffic assignment model. The specific steps are shown in the flowchart of Fig. 5.

5. Simulation analysis and discussion

Sections 2, 3 and 4 construct the charging demand analysis framework of EVs, which is generalized in Fig. 6.

To obtain the charging demand of EVs, the Nguyen-Dupius network is studied, and the network structure is shown in Fig. 7. The relevant parameters of the Nguyen-Dupius network are presented in attached Table A1. According to research by [42] and [47], the parameters of the value function and weight function can be set as $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\zeta = 0.61$ and $\delta = 0.69$. The iterative convergence condition is set as $\varepsilon = 0.01$, and the charging variation coefficient of the charging station is set as 0.3. Taking a Nissan Leaf as an example, the battery energy is 24 kW·h, the power consumption per 100 km is 15 kW·h [48,49], and the charge rate is 7.3 kW. The user's anxiety mileage is set as 20 km. The activity starting time namely the upper limit arrival time is defined as T_w, $T_O = T_w$–15 min is the best expected arrival time, and the acceptable earliest arrival time is $T_E = T_w$–30 min. The average speed of public transportation is required to be 35 km/h.

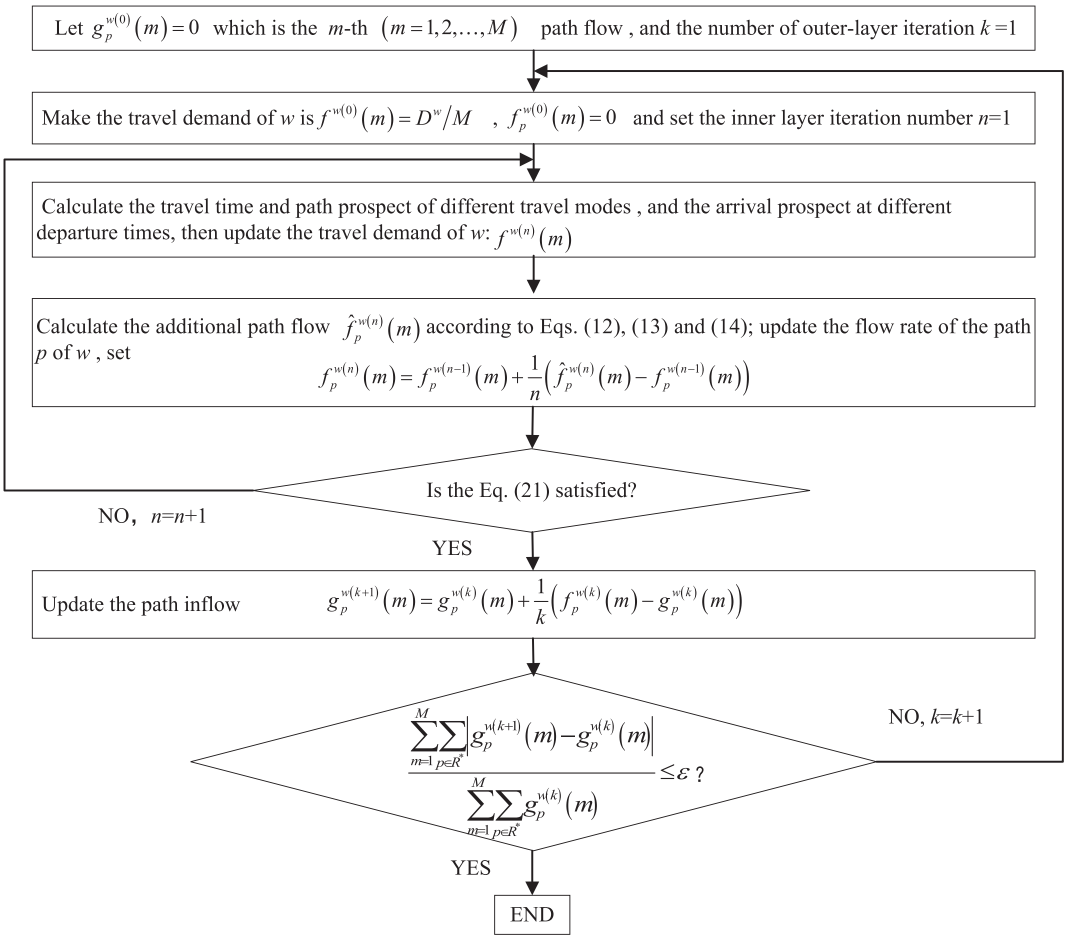


Fig. 5. Solutions of the model.

5.1. Analysis of the time-space transfer rule and charging demand on an activity chain for EVs

To study the travel mode, travel path and departure time choice behaviors of users of EVs under the constraints of different EV ownership rates and charging service capacities of charging stations, a travel case of a necessary activity is structured. The case conditions are shown in Table 1. The public transport paths are fixed at 1-4-11-15-18 and 3-10-17-19. The available paths for private cars are given in Table 2, and EVs on paths 2 and 5 need to be charged at node 11 and

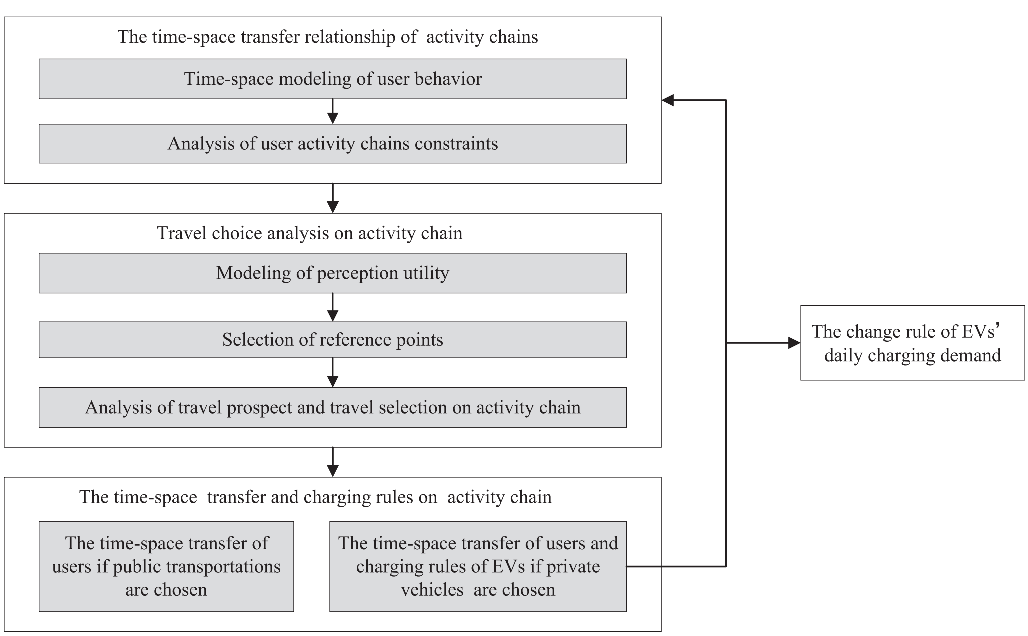


Fig. 6. The framework of the charging demand analysis for EVs.

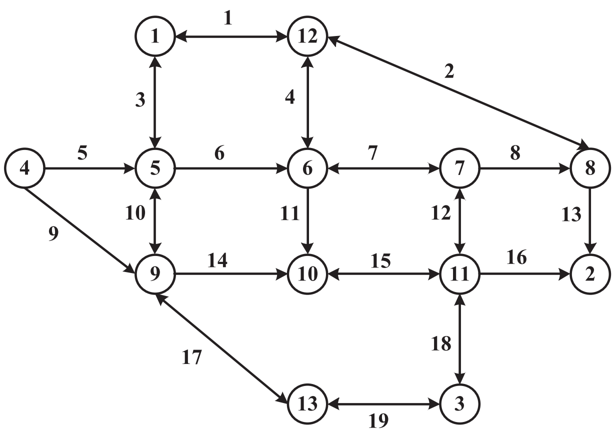


Fig. 7. Topology of Nguyen-Dupius network.

Table 1
The conditions of the first type of activity.

Starting point	Endpoint	T_w	Travel demand
Node 1	Node 3	9:00 a.m.	10,000

Table 2
The available paths of private cars.

Path	1	2	3	4	5	6
Links	1-4-7-12-18	1-4-11-15-18	3-6-7-12-18	3-6-11-15-18	3-10-14-15-18	3-10-17-19

node 9, respectively.

5.1.1. Analysis of the time-space transfer rule and charging demand on an activity chain under different EV ownership rates

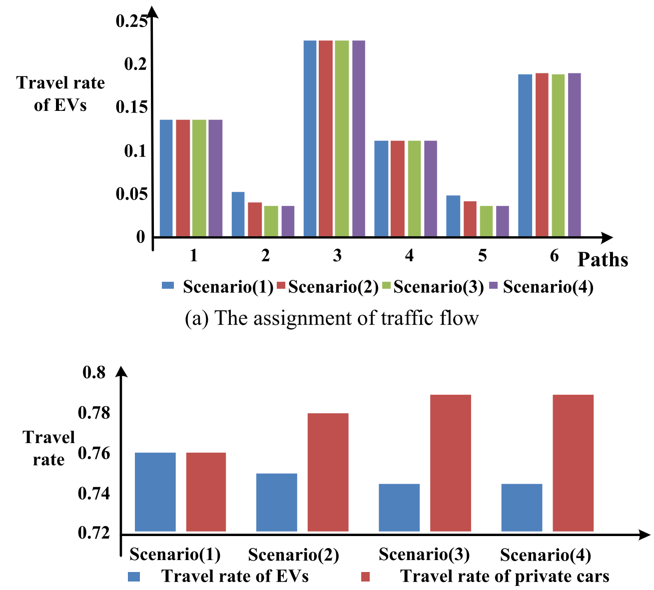
Scenarios (1) to (4) correspond to situations in which all private cars are EVs, and the ownership ratios of EVs to fuel vehicles are 3:1, 2:1 and 1:1, respectively. The charging station limitation is not considered, that is, all the charging stations have sufficient charging piles.

Fig. 8 shows the traffic flow assignment of fuel vehicles and EVs in scenarios (1) to (4). And the following conclusions can be drawn:

(1) The traffic flow and the travel rate of EVs on paths for which EVs are required to charge halfway (e.g., paths 2 and 5) will decrease as the ownership rate of fuel cars increases. The main reason is that fuel cars do not need to consider charging time. When fuel car ownership increases, users are more willing to choose fuel vehicles to travel. This will increase the traffic flow and travel time correspondingly, thus resulting in a decrease in the willingness of EV users to travel.
(2) For the paths for which EVs do not need to charge halfway (such as paths 1, 3, 4 and 6), the behavior of EVs is similar to that of fuel vehicles, and the path traffic flow as well as the travel rate of EVs are not affected by the ownership rate of fuel vehicles.
(3) The overall travel rate of EVs decreases with the increase of the ownership rate of fuel cars.

In scenarios (1) to (4), the EV users choose their departure time on different paths. As examples, Fig. 9 shows the departure time of EVs along paths 1 and 2. In Fig. 9, the departure time curves of EVs on path 1 in the four scenarios overlap, as well as the departure time curves of EVs on path 2 in scenarios (3) and (4). The following conclusions can be drawn:

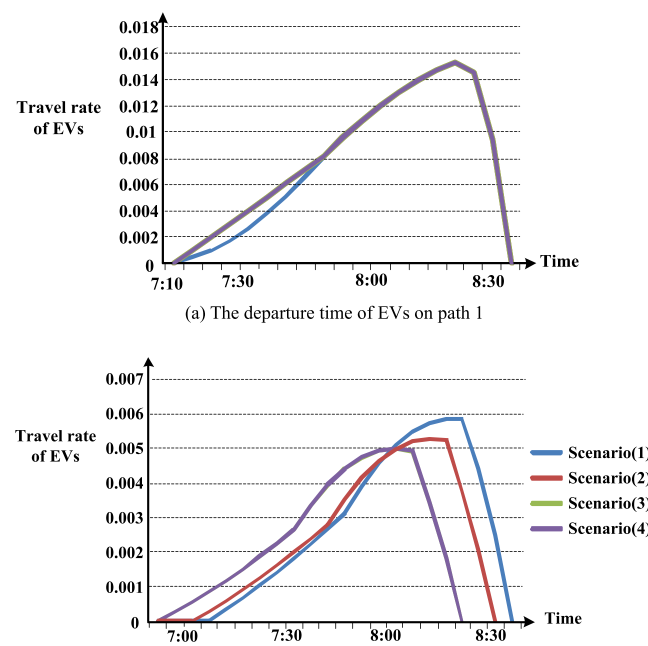
(1) EV ownership rate does not affect the departure time of EVs on the paths for which EVs are not required to charge halfway. The reason is that the increase of fuel vehicle ownership has no effect on their traffic flows.
(2) The rising rate of fuel vehicles will lead to traffic flow increases on the paths for which EVs are required to charge halfway, which increases the travel time of EVs. Therefore, as fuel vehicle ownership increases, the departure times of EVs on these paths will be earlier to avoid congestion.



(a) The assignment of traffic flow

(b) Travel rate of EVs and private cars

Fig. 8. The traffic assignment and the travelling rate of EVs in scenarios (1) to (4).



(a) The departure time of EVs on path 1

(b) The departure time of EVs on path 2

Fig. 9. Departure time of EVs in scenarios (1) to (4).

By analyzing the travel path selection and departure time of EVs, the time-space transfer rule of EVs can be obtained. An example of the time-space distribution of EVs in scenario (1) at 8:10 is displayed in Fig. 10. The load of charging stations is calculated, and Fig. 11 presents the charging load at node 11 from 5:00 a.m. to 9:00 a.m. in scenarios (1) to

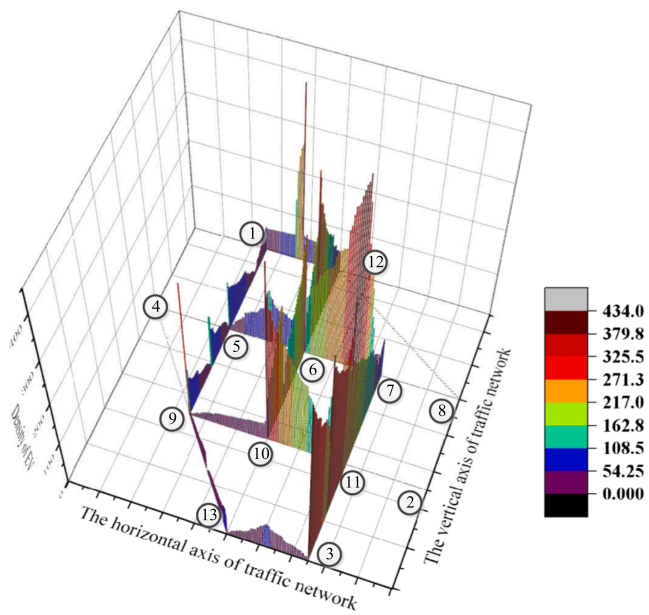


Fig. 10. The distribution of EVs in the traffic network under scenario (1) at 8:10.

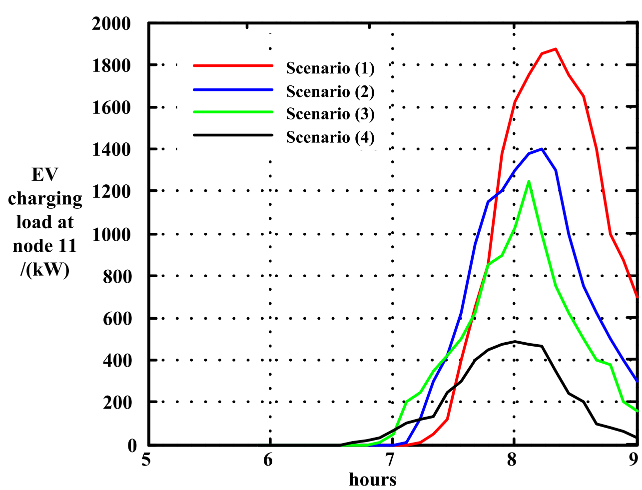


Fig. 11. Load of charging station at node 11 from 5:00 a.m. to 9:00 a.m. in scenarios (1) to (4).

(4).

5.1.2. Analysis of the time-space transfer rule and charging demand on an activity chain for EVs considering the service capacities of charging stations

It can be seen that EVs do not need to charge on paths 1, 3, 4 and 6, but they do need to do so on node 11 of path 2 and node 9 of path 5 in scenarios (1) to (4). Considering the limitation of charging service capacity, the following scenarios are set on the basis of scenario (1): the service capacities on node 11 and node 9 are 200%, 70%, 30%, and 20% of the maximum number of EVs need to charge at the same time, which corresponds to scenarios (5) to (8). Fig. 12 shows the traffic flow assignment of EVs on each available path in scenarios (1) and (5) to (8).

Fig. 12 indicates that under the number of EV charging service capacity in scenario (5), the traffic assignment is the same as that under no constraints. As the service capacities of the charging stations gradually decline, the travel rate of EVs on the paths requiring halfway charging will decrease, and some trips are transferred to the paths without halfway charging. However, the overall travel rate of EVs decreases with the declines of the service capacity of charging stations.

Taking paths 1 and 2 as examples, the departure time of EVs is

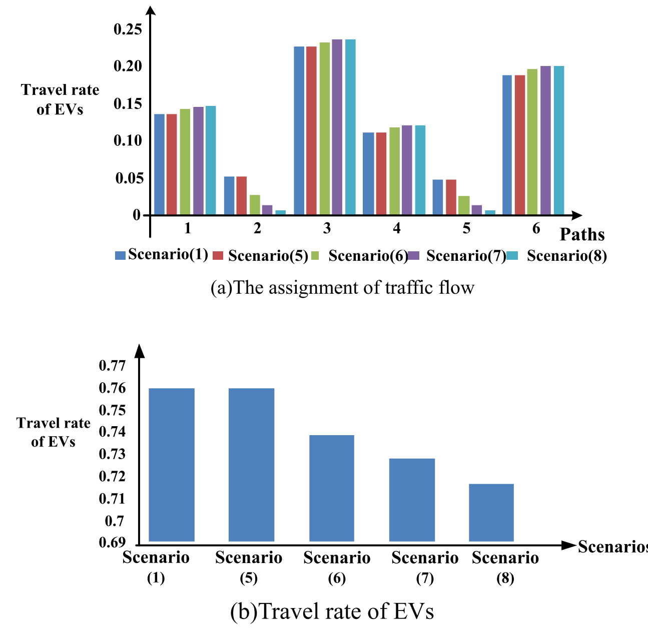


Fig. 12. The traffic assignment and the travelling rate of EVs in scenarios (5) to (8).

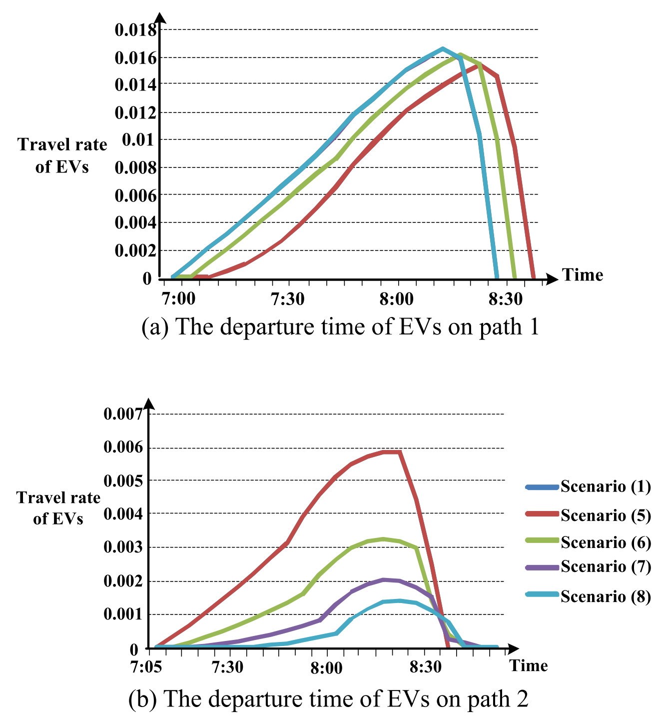


Fig. 13. Departure time of EVs in scenarios (5) to (8).

shown in Fig. 13. The departure time curves of EVs on both paths 1 and 2 in scenarios (1) and (5) overlap, as well as the departure time curves of EVs on paths 1 in scenarios (7) and (8). The following conclusions can be drawn from Fig. 13:

(1) When the service capacities of the charging stations decrease within a certain range, the charging demands of EVs with a higher travel demand can still be met.
(2) As the service capacities of the charging stations decline, the traffic flow and travel time of a path will decrease, and the departure time of the EVs on the paths for which EVs need to charge halfway will be delayed greatly.

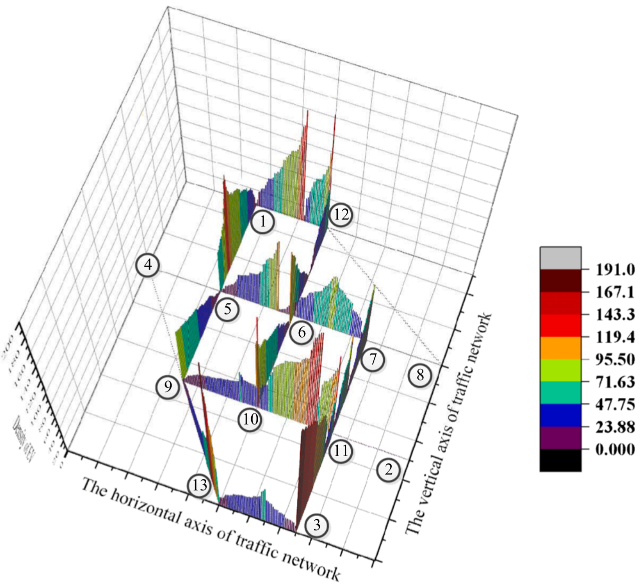


Fig. 14. The distribution of EVs in the traffic network in scenario (8) at 8:10.

(3) Since part of the transfer of EVs to the paths for which they do not need to charge halfway, the travel time of those paths will increase, which makes the EV users move their departure time to be earlier.

The time-space transfer rule of EVs and the load of each charging station can also be obtained. The distribution of EVs in the traffic network in scenario (8) at 8:10 is shown in Fig. 14, and Fig. 15 presents the charging load at node 11 from 5:00 a.m. to 9:00 a.m. in scenarios (5) to (8).

5.2. Analysis of the change rule for the daily charging demand of EVs

Based on the analysis of the daily travel frequencies and the charging rule on each EV activity chain, the daily charging demand can be described accurately. The daily activities of residents are taken as the research scope, and the daily typical travel activities, including travel for work, shopping, social activities, and returning home are considered. Different EV ownership rates and service capacities of charging stations are selected to study the daily charging demand rule of EVs. The daily activity attributes of users are listed in Table 3.

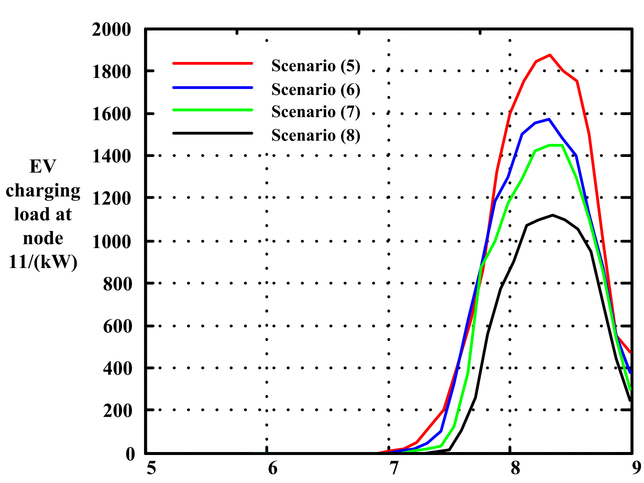


Fig. 15. Load of charging station at node 11 from 5:00 a.m. to 9:00 a.m. in scenarios (5) to (6).

5.2.1. The daily charging demand of EVs under different EV ownership rates

Under the conditions of scenarios (1) to (4), a traffic flow assignment analysis is carried out on the travel demands of daily activities, and the daily travel and charging frequencies of EVs under different EV ownership rates are obtained, as shown in Fig. 16.

It can be seen from Fig. 16 that the EV ownership rate has a significant impact on the daily travel and charging frequencies of EVs. As the EV ownership rate decreases, the average travel and charging frequencies of EVs will decrease because an increase in the fuel vehicle ownership rate does not affect the behavior of EVs on the paths for which EVs do not need to charge halfway, whereas this increase adds travel time to the EVs on those paths, which leads to a decrease in the travel rate of EVs and a corresponding decrease in the daily charging frequencies of EVs.

The daily charging demands of the EVs in scenarios (1) to (4) are shown in Fig. 17. It shows that the charging starting time and the maximum charging power time of EVs at different periods will be earlier as the EV ownership rate decreases. The maximum charging power for the day appears in the commute because it is a necessary activity for individuals.

5.2.2. The daily charging demand of EVs under different charging service capacities of charging stations

Under the conditions of scenarios (5) to (8), the daily travel and charging frequencies of EVs under different service capacities of charging stations are shown in Fig. 18.

As the service capacities of the charging stations decrease, the average daily travel frequencies of EVs will decrease, while the average daily charging frequencies of EVs will increase. Fig. 12 reveals that the traffic flow of the paths for which EVs need to charge halfway will decrease and transfer to the paths for which EVs do not need to charge, with the service capacities of the charging stations decreasing. This increases the travel time of EVs and makes the overall travel rate of users decrease, thereby reducing the daily average travel frequencies of EVs. Due to the limitation of the service capacities of charging stations, many EVs change their path selection plans, which results in the power consumption of EVs increasing, thus increases the average daily charging frequencies of EVs.

Fig. 19 provides the daily charging demand of the EVs in scenarios (5) to (8). The charging starting time and the maximum charging power time of EVs at different periods will be delayed as the service capacities of charging stations decrease.

5.3. Sensitivity analysis

Considering that the daily charging demand of EVs is also affected by many other factors, such as EV model, charge rate and degree of the bounded rationality of users, the sensitivity analysis of the daily charging demand of EVs to different parameters is studied based on scenario (1).

5.3.1. Sensitivity analysis of the daily charging demand of EVs to the degree of the bounded rationality of users

Many researchers, such as [50], have suggested that for decision makers, local economic level, transportation infrastructure and the crowd structure and other multiple factors influence the parameters of the value function and weight function, which may deviate from the values studied by [42]. The influence of the degree of bounded rationality of users on the daily charging demand of EVs is studied, and many cases are presented in the following studies:

Cases 1 to 4: the parameters of ζ and δ are set as 0.55, 0.60, 0.70, and 0.75.
Cases 5 to 8: the value of λ is assigned as 1.5, 2.0, 2.5 and 3.0.
Cases 9 to 12: the value of the parameters α and β are set as 0.65,

Table 3
The daily activity attributes of users.

Home point	Node 1	The upper limit arrival time for getting home	10:30 p.m.
Workplace	Node 3	Shopping location	Node 10
Morning working time	9:00 a.m.	The upper limit arrival time of shopping	12:00 a.m.
Noon off working time	11:00 a.m.	The place of dating activity after working	Node 7
Afternoon working time	2:00 p.m.	The upper limit arrival time of dating activity	5:45 p.m.
Working end time	5:00 p.m.		

0.75, 0.85 and 0.95.

The charging demands of EVs in cases 1 to 12 are shown in Figs. 21, 23 and 25, Figs. 20, 22 and 24 give the value functions and weight functions in cases 1 to 12 respectively.

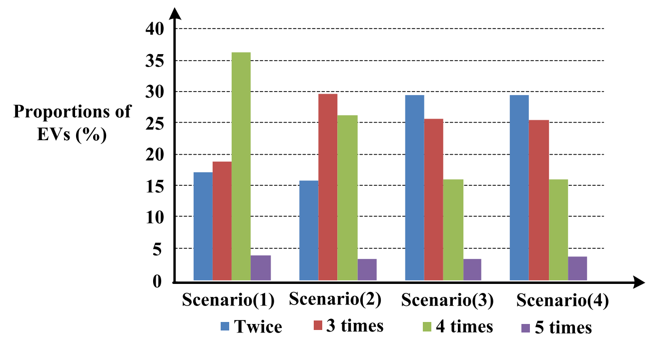
Under the assumption of complete rationality, the value function of the decision maker is the real benefit, namely, $g(x) = x\text{-}x_0$, and their perceived probability is the objective probability. When these parameters increase, the value function or weight function is closer to the completely rational hypothesis. Therefore, it can be concluded that with the increase of a user's rationality, the charging starting time and maximum charging power time of EVs will be delayed, and the daily charging demand will decrease.

5.3.2. Sensitivity analysis of the daily charging demand of EVs to the charge rate

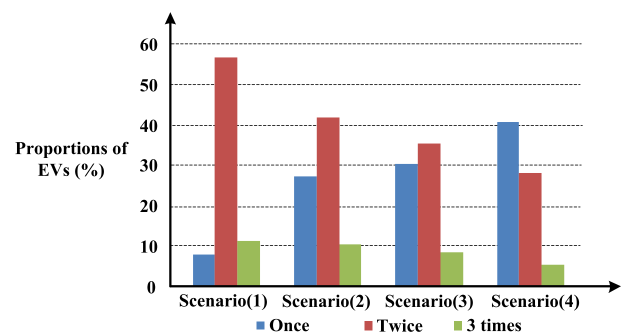
The charging time and the travel behavior of EVs will be affected by charge rate, thus resulting in different charging demands. The charging mode of EVs is set as fast charging modes whose charge rate are 30 kW, 45 kW and 60 kW, respectively corresponding to cases 13, 14 and 15. The application of fast charging mode effectively reduces the charging time of EVs and further makes the path travel time decrease. It is can be concluded from Fig. 26 that with the increase of charge rate, the charging starting time and the maximum charging power at different periods will be delayed. The increase of the charge rate will also cause greater peak-valley load difference.

5.3.3. Sensitivity analysis of the daily charging demand of EVs to the EV model

Tesla model S [49,51] is used in the charging demand analysis in case 16. Fig. 27 compares the charging demands of Tesla model S and Nissan Leaf under the same conditions. Due to the large longer range, Tesla model S can meet the daytime driving demands without recharging during its trips or at activity locations. Therefore, the charging demand of Tesla model S is concentrated after the evening rush hour. In addition, Tesla model S does not need to consider the charging time in daytime driving, and its driving characteristics are similar to those of fuel vehicles. In this case, users are more willing to choose EVs as their travel modes, resulting in an increase in the average range of EVs during the day. Thus more charging power and longer charging time are needed.



(a) Daily travel frequencies of EVs



(b) Daily charging frequencies of EVs

Fig. 16. The daily travel and charging frequencies of EVs in scenarios (1) to (4).

5.4. Daily charging demand analysis of EVs in a real urban traffic network

A new type of urban area in China is used for experimental analysis. The urban traffic network is shown in Fig. 28, and the residential, commercial and work nodes are labeled by red, green and blue, respectively. The main vehicles in the region are pure EVs, and there are 50,000 of them. The parameters of the weight function and value function fitted by statistics data are adopted to carry out the simulation on the daily activity travel selection of EVs in this region, and the daily charging demand of EVs is calculated in Fig. 29. At the same time, the actual charging load curve is obtained by the historical data of EV

Table A1
Traffic network parameters of Nguyen-Dupius.

Sections	Nodes' order	t_a^0/min	C_a/veh	Distance/km	$\varphi_{a,1,2}$	$\varphi_{a,3}$	Sections	Nodes' order	t_a^0/min	C_a/veh	Distance/km	$\varphi_{a,1,2}$	$\varphi_{a,3}$
1	1 ↔ 12	12	4000	13.6	0.4	0.1	11	6 ↔ 10	12	4000	20.8	0.4	0.1
2	12 ↔ 8	36	3500	22.4	0.4	0.1	12	7 ↔ 11	12	2500	14.4	0.4	0.1
3	1 ↔ 5	12	4000	11.2	0.3	0.07	13	8 → 2	12	3000	14.4	0.05	0.02
4	12 ↔ 6	12	4000	11.2	0.2	0.05	14	9 → 10	45	6000	64	0.3	0.07
5	4 → 5	12	4000	14.4	0.3	0.07	15	10 ↔ 11	10	5000	10	0.3	0.07
6	5 → 6	12	2500	4.8	0.2	0.05	16	11 → 2	12	3000	14.4	0.4	0.1
7	6 ↔ 7	12	3000	8	0.2	0.05	17	9 ↔ 13	24	3000	14.4	0.4	0.1
8	7 → 8	12	3000	8	0.4	0.1	18	11 ↔ 3	12	4000	12.8	0.2	0.05
9	4 → 9	24	4000	19.2	0.2	0.05	19	13 ↔ 3	12	4000	17.6	0.2	0.05
10	5 ↔ 9	12	4000	14.4	0.2	0.05							

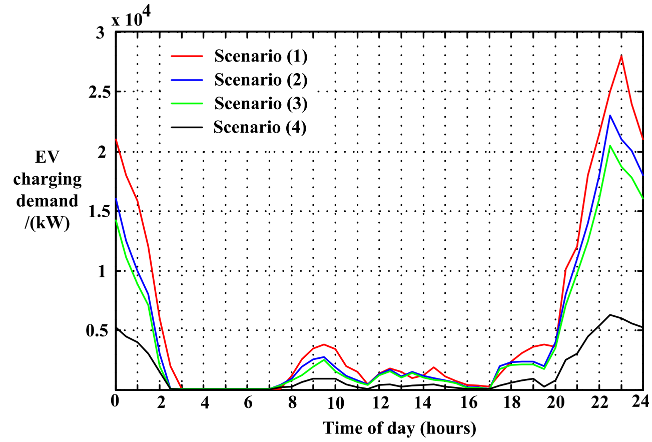
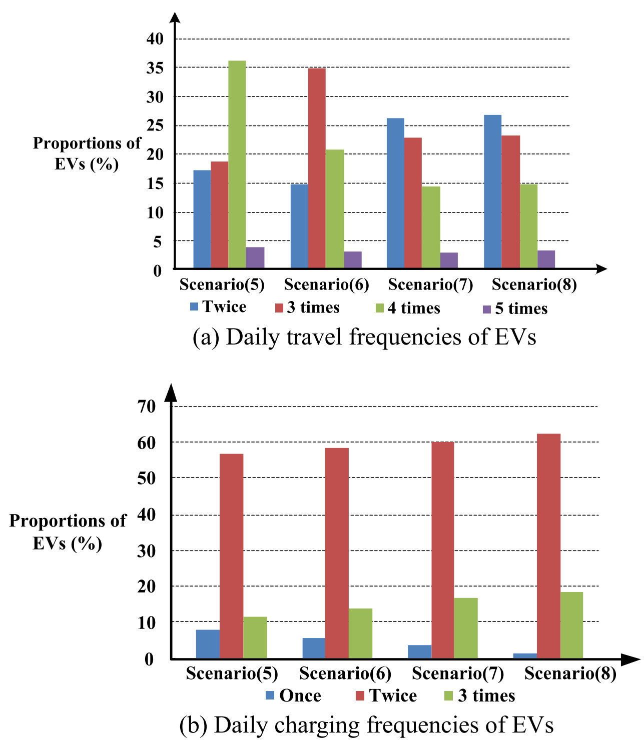


Fig. 17. The daily charging demands of EVs in scenarios (1) to (4).



(a) Daily travel frequencies of EVs

(b) Daily charging frequencies of EVs

Fig. 18. The daily travel and charging frequencies of EVs in scenarios (5) to (8).

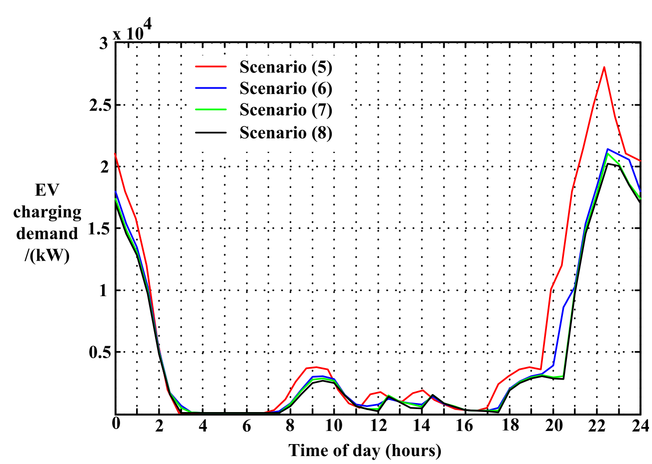


Fig. 19. The daily charging demand of EVs in scenarios (5) to (8).

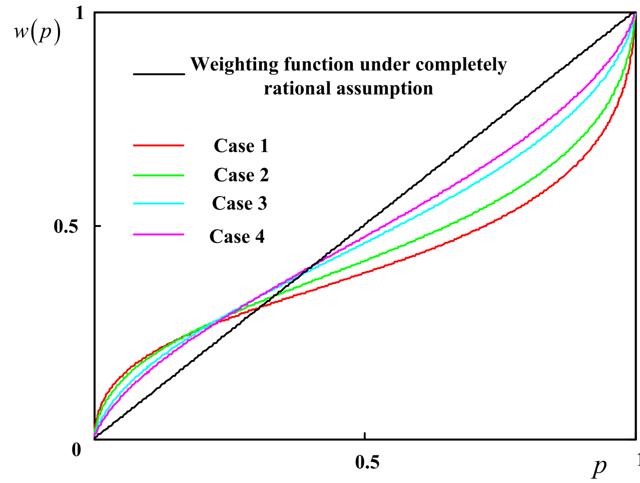


Fig. 20. The weight functions in cases 1 to 4.

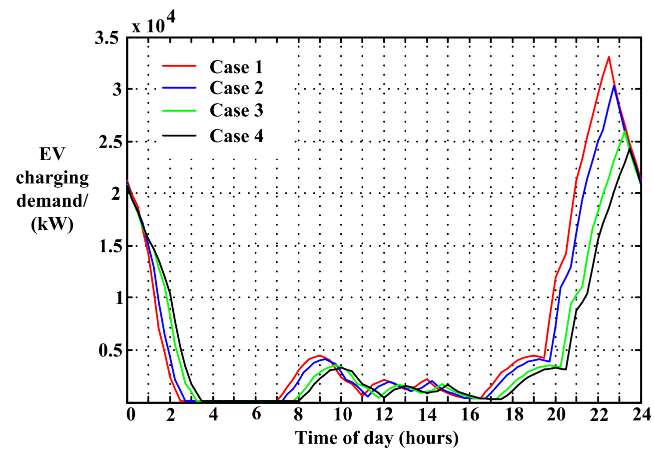


Fig. 21. The daily charging demand of EVs in cases 1 to 4.

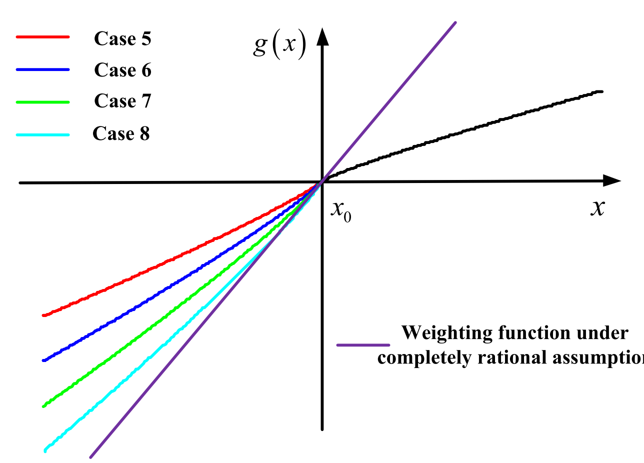


Fig. 22. The value functions in cases 5 to 8.

charging in this region.

The comparison between the calculated value of EV charging demand and the historical data shows that there are errors in the calculation results. Three main reasons result in the errors. Firstly, in the analysis of users' travel choices, the users are considered to have similar reference point selection criteria, that is, users have homogeneity. It is one of the reasons for the errors of this study. Secondly, the charging power rate of EVs is regarded as a constant value in the model. The charging of EV battery includes two processes: constant voltage and

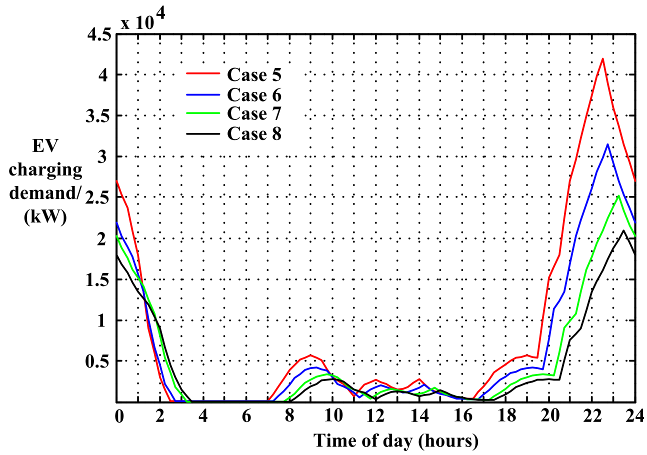


Fig. 23. The daily charging demand of EVs in cases 5 to 8.

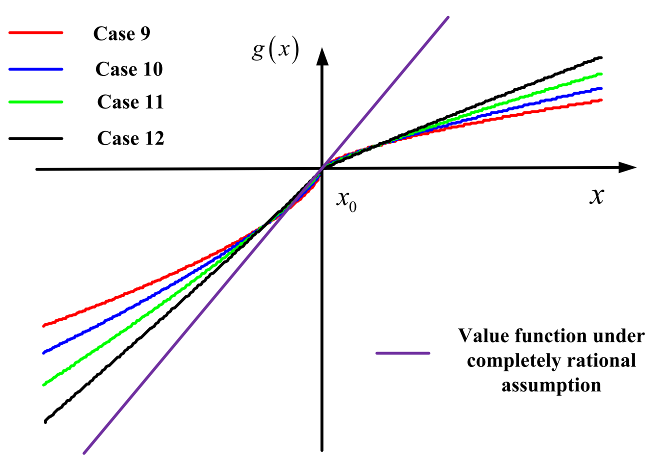


Fig. 24. The value functions in cases 9 to 12.

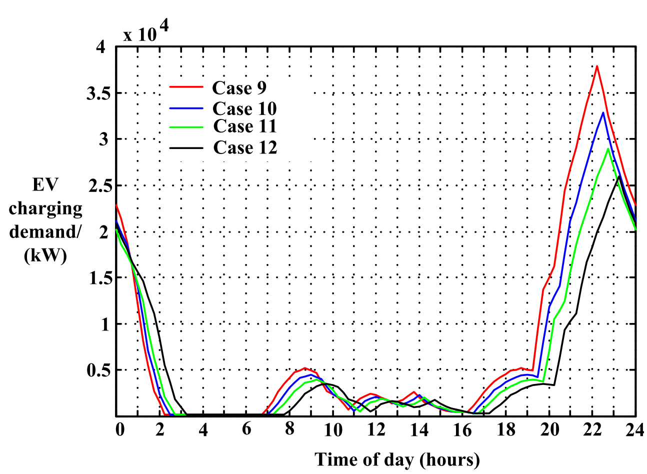


Fig. 25. The daily charging demand of EVs in cases 9 to 12.

constant current. The constant voltage stage has short duration and low current, and the variation range of voltage at constant current stage is small. Although, the charging characteristics of EV's battery can be approximated by constant power model, the charging power error is introduced. Last, the power consumption per 100 km is adopted to deal with the power loss of EVs in the simulation. As a matter of facts, the driving speed is also an important factor that needs to be considered. Considering that the main research object of this work is not the micro analysis of electric power loss in the driving process of EVs, and the electric power loss value per kilometer adopted by the authors is the average value obtained by current researches through a large number of statistical data. However, the calculation errors in Fig. 29 are within the allowable range, so the method proposed in this paper has sufficient accuracy.

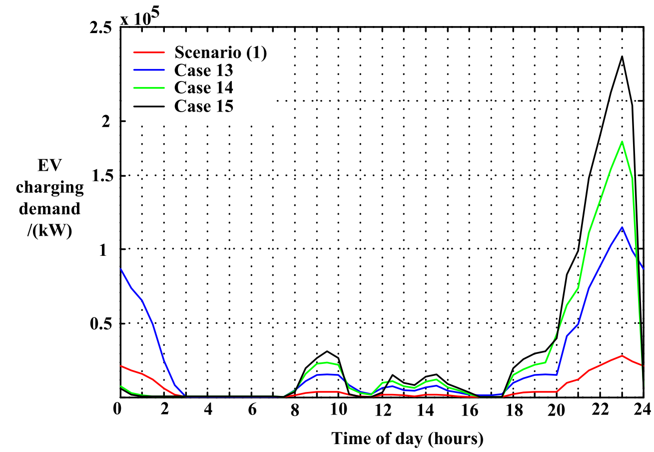


Fig. 26. The daily charging demand of EVs in cases 13 to 15.

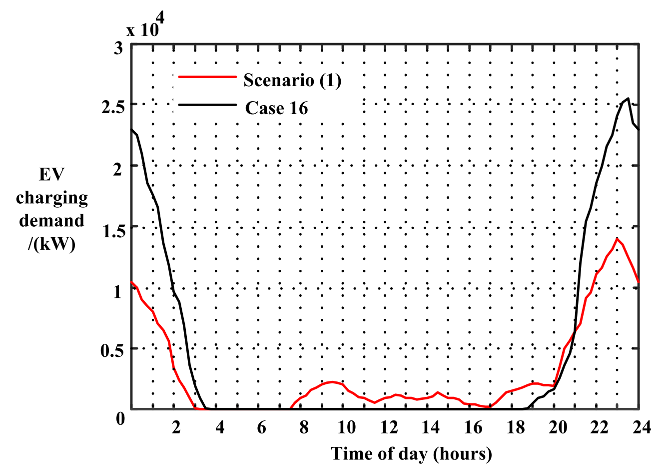


Fig. 27. The daily charging demand of EVs in case 16.

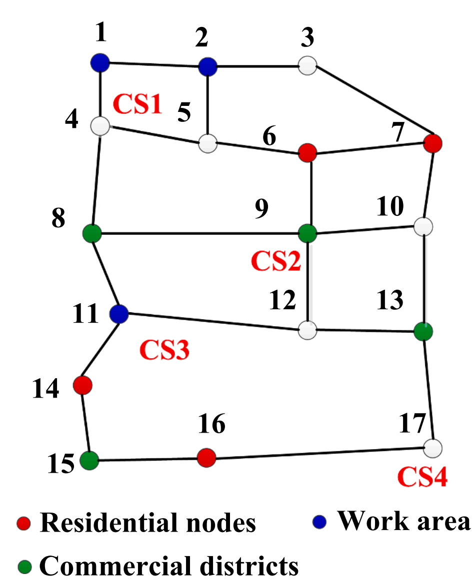


Fig. 28. Traffic network topology of the urban area.

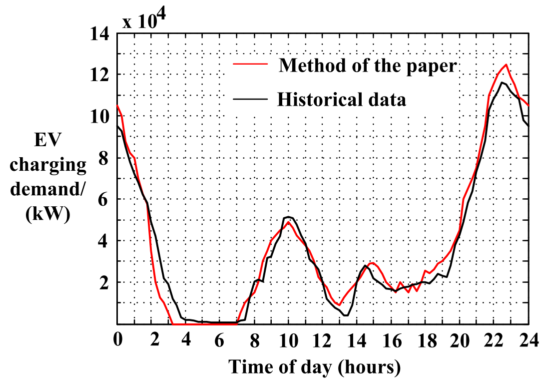


Fig. 29. EV charging demand for the urban area.

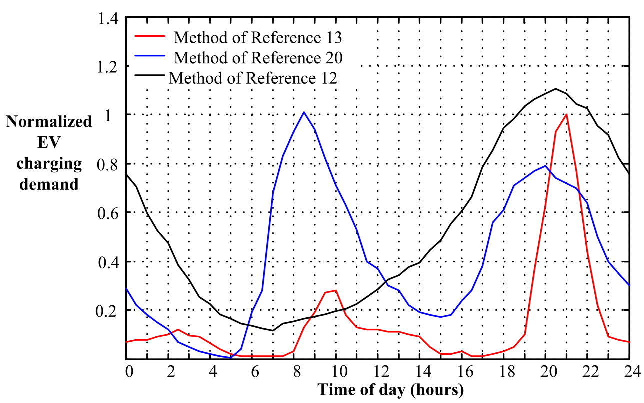


Fig. 30. The normalized EV charging demands obtained by different methods.

5.5. Comparative studies

The normalized EV charging demands obtained by [12,13] and [20] are shown in Fig. 30. It shows that a higher peak of EV charging demand in the evening is formed when only home charging is considered, as in [12]. Charging halfway or at an activity location may significantly reduce the EV charging demand in the evening. Ref. [13] limits the charging time to predetermined time periods. This assumption may not fully reflect the temporal randomness of EV charging. The trip chain and Markov decision process are utilized in [20], and the randomness of EV charging in time and space is considered. However, Markov decision theory assumes that each state transition is only related to the state of the previous and has nothing to do with the historical ones. Moreover, the influence of travel purpose (activity) on travel and charging selection cannot be explained, as evidenced by the unrealistic peak demands at early travel time points in Fig. 30. In practice, EV travel is related to the type of activity the user is participating in. Different activity types have different constraints on travel behavior selection, and the daily activity chains of users are continuous in time and space. The starting point of each activity chain and the travel time of an activity will be influenced by the history activity chains. In addition, a large number of statistical data have been applied in other existing methods. The internal factors affecting the distribution of charging power cannot be explained, so it is hard to formulate effective regulatory measures to guide orderly EV charging and discharging. With the utilization of an activity-based method, bounded rationality, and a dynamic traffic assignment model, the proposed method enables the stochastic modeling of moving EV loads considering randomness with varying spaces and times. Moreover, this method can analyze the internal factors that influence the charging demand of EVs. The influence of various factors such as the ownership rate of EVs, the service capacity of charging stations, the charging power rate, and the degree of the bounded rationality of users on the charging demand can be revealed in this paper.

6. Conclusion

This paper proposes an analytic framework for the charging demand of EVs, which emphasizes that charging demand is primarily determined by the travel behavior and the bounded rationality behavior of users in travel choices. The authors analyze the change rule of the charging demand of EVs by describing the decision-making process of users and the driving characteristics of vehicles in the time-space transfer. Studies on the charging demand of EVs can provide data to support charging facilities planning, power grid load optimization, safe and stable operation of power system. The following conclusions can be drawn from this paper:

(1) The behavior characteristics and charging demand of EVs are affected by multiple factors, and there will be great differences under various conditions.
(2) The travel rate, daily charging frequencies and charging demand of EVs will decrease, and the charging starting time and the maximum charging power of EVs at different times will be earlier as the EV ownership rate decreases.
(3) As the service capacities of the charging stations decrease, the travel rate and charging demand of EVs will decrease, but the daily charging frequencies of EVs will increase. Meanwhile, the charging starting time and the maximum charging power of EVs at different times will be delayed.
(4) As the rationality degrees of users increase, the charging starting time and the maximum charging power time of EVs will be delayed and the daily charging demand will decrease.

In this paper, the users are considered to have similar reference point selection criteria, namely the homogenization of users, which is a deficiency of this paper. Additionally, time cost is considered to be the main factor influencing users' travel decisions, and the impact of travel expense is not directly analyzed. Future work will focus on the influences of user heterogeneity and travel expense on the charging demand of EVs.

Funding

This work was funded by Humanities and Social Sciences Fund of Ministry of Education of China [grant number 17YJCZH212] and National Natural Science Foundation of China [grant number 51977154].

CRediT authorship contribution statement

Jun Yang: Conceptualization, Methodology. **Fuzhang Wu:** Data curation, Investigation, Writing - review & editing. **Jun Yan:** Writing - original draft. **Yangjia Lin:** Writing - original draft. **Xiangpeng Zhan:** Resources. **Lei Chen:** Validation. **Siyang Liao:** Formal analysis. **Jian Xu:** Funding acquisition. **Yuanzhang Sun:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. The user's perceived utility considering the continuity of the selection results' occurrence probabilities

Suppose that the cumulative subjective probability weight of user to result x_i can be expressed as $\pi^+(p)$ and $\pi^-(p)$:

$$\begin{cases}\pi^+(p_i) = w^+(p_i+...+p_n) - w^+(p_{i+1}+...+p_n),\ 0 \leqslant i < n \\ \pi^+(p_n) = w^+(p_n)\end{cases} \tag{A1}$$

$$\begin{cases}\pi^-(p_j) = w^-(p_{-m}+...+p_j) - w^-(p_{-m}+...+p_{j-1}),\ -m < j \leqslant 0 \\ \pi^-(p_{-m}) = w^-(p_{-m})\end{cases} \tag{A2}$$

According to Eq. (6), the perceived utility of user to a selection is:

$$V_p = \sum_{i=1}^{n} \pi^+(p_i)g(x_i) + \sum_{j=-1}^{-m} \pi^-(p_j)g(x_j) \tag{A3}$$

Taking into account the continuity of the occurrence probability of the result x_i, the probability distribution function $F(x)$ is introduced into the Eq. (A3). The probability accumulation formula in Eqs. (A1) and (A2) can be written as:

$$\begin{cases}p_i+...+p_n = 1-(p_{-m}+...+p_{i-1}) = 1-F(x_{i-1}) \\ p_{-m}+...+p_i = F(x_i)\end{cases} \tag{A4}$$

Then the cumulative subjective probability weight can be expressed as:

$$\pi^+(p_i) = w^+(1-F(x_i)) - w^+(1-F(x_{i-1})) = \frac{w^+(1-F(x_i)) - w^+(1-F(x_{i-1}))}{x_i - x_{i-1}}\cdot(x_i - x_{i-1}) \tag{A5}$$

$$\pi^-(p_i) = w^-(F(x_i)) - w^-(F(x_{i-1})) = \frac{w^-(F(x_i)) - w^-(F(x_{i-1}))}{x_i - x_{i-1}}\cdot(x_i - x_{i-1}) \tag{A6}$$

Considering that when the utility function is continuous random distribution, $(x_i\text{-}x_{i\text{-}1}) \to 0$, it can be obtained that:

$$\lim_{(x_i-x_{i-1})\to 0} (x_i - x_{i-1}) = dx \tag{A7}$$

In addition, both $F(x)$ and $w^+(x)$ are continuous and differentiable functions in the effective interval, so:

$$\lim_{(x_i-x_{i-1})\to 0} (w^+(1-F(x_i)) - w^+(1-F(x_{i-1}))) = -dw^+(1-F(x)) \tag{A8}$$

Thus the Eq. (A9) can be obtained:

$$\pi_i^+ = -\frac{dw^+(1-F(x))}{dx}dx \tag{A9}$$

Similarly,

$$\pi_i^- = \frac{dw^-(F(x))}{dx}dx \tag{A10}$$

According to Eqs. (A3), (A9) and (A10), the perceived utility of the user considering the continuity of the selection results' occurrence probabilities is denoted as:

$$\begin{aligned}V_p =& \int_{-\infty}^{x_0} \frac{dw^-(F(x))}{dx}g(x)dx \\ &+ \int_{x_0}^{\infty} -\frac{dw^+(1-F(x))}{dx}g(x)dx\end{aligned} \tag{A11}$$

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijepes.2020.105952.

References

[1] Luo Y, Zhu T, Wan S, et al. Optimal charging scheduling for large-scale EV (electric vehicle) deployment based on the interaction of the smart-grid and intelligent-transport systems. Energy 2016;97(4):359–68.

[2] Zhang L, Hu X, Wang Z, et al. Multi-objective optimal sizing of hybrid energy storage system for electric vehicles. IEEE Trans Veh Technol 2018;67(2):1027–35.

[3] De Hoog J, Alpcan T, Brazil M, et al. Optimal charging of electric vehicles taking distribution network constraints into account. IEEE Trans Power Syst 2015;30(1):365–75.

[4] Islam MS, Mithulananthan N, Hung DQ. A day-ahead forecasting model for probabilistic EV charging loads at business premises. IEEE Trans Sustain Energy 2018;9(2):741–53.

[5] Wang S, Dong Z, Luo F, Meng K, Zhang Y. Stochastic collaborative planning of electric vehicle charging stations and power distribution system. IEEE Trans Ind Informat 2018;14(1):321–31.

[6] Wang X, Shahidehpour M, Jiang C, et al. Coordinated planning strategy for electric vehicle charging stations and coupled traffic-electric networks. IEEE Trans Power Syst 2019;1(34):268–79.

[7] Xiang Y, Liu J, Li R, et al. Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates. Appl. Energy 2016;178:647–59.

[8] Shahidinejad S, Filizadeh S, Bibeau E. Profile of charging load on the grid due to plug-in vehicles. IEEE Trans Smart Grid 2012;3(1):135–41.

[9] Ghiasnezhad ON, Filizadeh S. Location-based forecasting of vehicular charging load on the distribution system. IEEE Trans Smart Grid 2014;5(2):632–41.

[10] Qian K, Zhou C, Allan M, et al. Modeling of load demand due to EV battery charging in distribution systems. IEEE Trans Power Syst 2011;26(2):802–10.

[11] Cao Y, Tang S, Li C, et al. An optimized EV charging model considering TOU price and SOC curve. IEEE Trans Smart Grid 2012;3(1):388–93.

[12] Darabi Z, Ferdowsi M. Impact of plug-in hybrid electric vehicles on electricity demand profile. IEEE Trans Power Syst 2012;2(4):501–8.

[13] Luo Z, Hu Z, Song Y, Xu Z, Lu H. Optimal coordination of plug-in electric vehicles in

power grids with cost-benefit analysis - Part II: A case study in China. IEEE Trans Power Syst 2013;28(4):3556–65.
[14] Zhang H, Hu Z, Xu Z, Song Y. Optimal planning of PEV charging station with single output multiple cables charging spots. IEEE Trans Smart Grid 2017;8(5):2119–28.
[15] Tehrani H, Wang P. Probabilistic estimation of plug-in electric vehicles charging load profile. Electr Power Syst Res 2015;124:133–43.
[16] Hao Xu, Fan Ouyang, Haifeng Liu, et al. A probability load modeling method for the charging demand of large-scale PEVs accounting users' charging willingness. Int J Electr Power Energy Syst 2016;82:331–8.
[17] Wang D, Gao J, Li P, et al. Modeling of plug-in electric vehicle travel patterns and charging load based on trip chain generation. J Power Sour 2017;359:468–79.
[18] Zhan K, Hu Z, Song Y, et al. A probability transition matrix based decentralized electric vehicle charging method for load valley filling. Electr Power Syst Res 2015;125:1–7.
[19] Mahmoud S, Joakim M. Spatial Markov chain model for electric vehicle charging in cities using geographical information system (GIS) data. Appl Energy 2018;231:1089–99.
[20] Tang D, Wang P. Probabilistic modeling of nodal charging demand based on spatial-temporal dynamics of moving electric vehicles. IEEE Trans. Smart Grid 2016;7(2):627–36.
[21] Omran NG, Filizadeh S. Location-based forecasting of vehicular charging load on the distribution system. IEEE Trans Smart Grid 2014;5(2):632–41.
[22] Yang W, Xiang Y, Liu J, et al. Agent-based modeling for scale evolution of plug-in electric vehicles and charging demand. IEEE Trans Power Syst 2018;33(2):1915–25.
[23] Weckx S, D'Hulst R, Claessens B, et al. Multiagent charging of electric vehicles respecting distribution transformer loading and voltage limits. IEEE Trans Smart Grid 2014;5(6):2857–67.
[24] Clairand J-M, Rodríguez-García J, et al. Smart charging for electric vehicle aggregators considering users' preferences. IEEE Access 2018;6:54624–35.
[25] Ensslen A, Ringler P, Dörr L, et al. Incentivizing smart charging: modeling charging tariffs for electric vehicles in German and French electricity markets. Energy Res Soc Sci 2018;42:112–26.
[26] Wang S, Bi S, Zhang YJ, et al. Electrical vehicle charging station profit maximization: Admission, pricing, and online scheduling. IEEE Trans Sustain Energy 2018;9(4):1722–31.
[27] Chung H, Li W, Yuen C, et al. Electric vehicle charge scheduling mechanism to maximize cost efficiency and user convenience. IEEE Trans Smart Grid 2019;10(3):3020–30.
[28] Leng JQ, Zhai J, Li QW, et al. Construction of road network vulnerability evaluation index based on general travel cost. Phys A 2017;493:421–9.
[29] Engelson L, Fosgerau M. The cost of travel time variability: three measures with properties. Transp Res Part B 2018;91:555–64.
[30] Ben-Akiva M, Bottom J, Gao S, et al. Towards disaggregate dynamic travel forecasting models. Tsinghua Sci Technol 2017;12(2):115–30.
[31] Chen Z, Fan W. A multinomial logit model of pedestrian-vehicle crash severity in North Carolina. Int J Transp Sci Technol 2018;8(1):43–52.
[32] Weng J, Du G, Li D, et al. Time-varying mixed logit model for vehicle merging behavior in work zone merging areas. Accid Anal Prev 2018;117(3):328–39.
[33] Smirnov OA. Spatial econometrics approach to integration of behavioral biases in travel demand analysis. Transp Res Rec J Transp Res Board 2010;21(57):1–10.
[34] Xia W, Wei W, Jun C, et al. Research on dynamic model of within-day travel mode choice of residents. China J Highway Transp 2012;25(2):121–6.
[35] Lester BY. An exploratory analysis of composite choices: Weighing rationality versus irrationality. J Socio Econ 2011;40(6):949–58.
[36] Eichberger J, Pirner HJ. Decision theory with a state of mind represented by an element of a Hilbert space: The Ellsberg paradox. J Math Econ 2018;78(15):131–41.
[37] Kloosterman A, Paul S. Ultimatum game bargaining in a partially directed search market. J. Econ. Behav. Organ. 2018;154(16):60–74.
[38] Chorus CG, Arentze TA, Timmermans HJP. A Random Regret-Minimization model of travel choice. Transp Res Part B Methodol 2018;42(1):0–18.
[39] Bekhor S, Ben-Akiva ME, Ramming MS. Estimating route choice models for large urban networks. the 9th World Conference on Transport Research. 2001. Seoul, Korea. 2001.
[40] Kahneman D, Tversky A. Prospect theory: an analysis of decision under risk. Econometrica 2012;47(2):263–92.
[41] Yunna Wu, Ke Yiming, Chuanbo Xu, et al. An integrated decision-making model for sustainable photovoltaic module supplier selection based on combined weight and cumulative prospect theory. Energy 2019;181(15):1235–51.
[42] Hackel B, Pfosser S, Trankler T. Explaining the energy efficiency gap-expected utility theory versus cumulative prospect theory. Energy Policy 2017;111:414–26.
[43] Jou RC, Kitamura R, Weng MC, et al. Dynamic commuter departure time choice under uncertainty. Transp Res Part A Policy Pract 2013;42(5):774–83.
[44] Rasouli S, Timmermans H. Activity-based models of travel demand: Promises, progress and prospects. Int J Urban Sci 2014;18(1):31–60.
[45] Wei W, Wu L, Wang J, et al. Network equilibrium of coupled transportation and power distribution systems. IEEE Trans Smart Grid 2018;9(6):6764–79.
[46] Hu Z, Zhan K, Zhang H, et al. Pricing mechanisms design for guiding electric vehicle charging to fill load valley. Appl Energy 2016;178:155–63.
[47] Weijun Xu, Huang Shaoying, Li Jia. A novel consensus reaching framework for heterogeneous group decision making based on cumulative prospect theory. Comput Ind Eng 2019;2(128):325–35.
[48] Li Mengyu, Lenzen Manfred. How many electric vehicles can the current Australian electricity grid support? Int J Electr Power Energ Syst 2020;117:105586.
[49] Hoehne Christopher G, Chester Mikhail V. Optimizing plug-in electric vehicle and vehicle-to-grid charge scheduling to minimize carbon emissions. Energy 2016;115:646–57.
[50] Schwanen T, Ettema D. Coping with unreliable transportation when collecting children: examining parents' behavior with cumulative prospect theory. Transp. Res. Part A Policy Pract. 2018;43(5):511–25.
[51] Li Linzhou, Tan Yitong, Liu Xinxin, et al. A cost-benefit analysis of V2G electric vehicles supporting peak shaving in Shanghai. Electr Power Syst Res 2020;179:106058.