Optimal charging strategy for intercity travels of battery electric vehicles

Yongxing Wang [1], Jun Bi [2,3,*], Wei Guan [2,3], Chaoru Lu [4], Dongfan Xie [2,3]

[1]*Department of Civil and Environmental Engineering, Norwegian University of Science and Technology, Trondheim, 7033, Norway*
[2]*School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China*
[3]*Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Beijing Jiaotong University, Beijing 100044, China*
[4]*Department of Civil Engineering and Energy Technology, Oslo Metropolitan University, Oslo, 0166, Norway*

A B S T R A C T

Limited driving range, long charging time and high charging costs affect the use of battery electric vehicles (BEVs) for intercity travels and often compel drivers to charge their vehicles more than once. This study proposes a multistage optimisation model to provide BEV drivers with a charging strategy for intercity travel. This model aims to jointly minimise travel time and charging cost and to determine the optimal amount of charged energy in each charging station located along the available routes. A dynamic programming method for solving this model is also designed. The feasibility and effectiveness of the proposed model and solution method are verified through the numerical example and simulations. The results indicate that the trade-offs between travel time and charging cost significantly influence the proposed solution, and the residual energy at the destination affects the availability of routes. The policy implications for the BEV-based intercity travels are discussed.

Keywords:
Battery electric vehicles
Charging behaviour
Multicriteria charging strategy
Multistage optimisation model
Dynamic programming

1. Introduction

Petroleum dependence and environmental issues have directed much attention towards the use of vehicles that consume alternative sources of energy. Battery electric vehicles (BEVs) have been long regarded as a promising solution to these problems (Riemann et al., 2015). With the recent advances in battery technologies and the support of the government, BEVs have enjoyed increasing adoption in recent years (Sun et al., 2017). However, BEVs have a shorter driving range compared with internal

[*] Corresponding author. Address: Beijing Jiaotong University, School of Traffic and Transportation, NO.3 Shangyuancun Street, Beijing 100044, China. Tel.:+86 134 8881 2321
E-mail addresses: bilinghc@163.com (J. Bi), yongxing.wang@ntnu.no (Y. Wang), weig@bjtu.edu.cn (W. Guan), chaorulu@oslomet.no (C. Lu), dfxie@bjtu.edu.cn (D. Xie)

combustion engine vehicles (ICEVs) and often need to be charged during trips. Therefore, BEVs are often regarded as travel tools for short-distance travels and are not widely used for long-distance travels, such as intercity travels (Wang et al., 2015). Considering the serious environmental and energy problems being faced across the world, ICEVs are predicted to be replaced by BEVs in the future (Plötz et al., 2014). Therefore, how to use BEVs for intercity travels presents a critical issue for drivers.

Drivers of BEVs need to search for and select suitable charging stations along their routes given that these stations are much less common than gas stations. As the penetration of BEVs in urban transportation systems is predicted to reach high levels in the future, drivers of BEVs need to develop a charging strategy. However, previous studies have mostly focused on short-distance BEV travels as will be discussed in Section 2. Unlike short-distance travels, intercity travels require BEV drivers to stop at more than one charging station along their route. Moreover, charging a BEV is relatively time consuming and thereby significantly extend the travel time of drivers. Another important concern is that charging BEVs costs money. All of these factors introduce complexities in making decisions related to BEV intercity travels. In other words, drivers should consider different travel cost components, such as travel time and charging cost, when formulating a charging strategy for intercity travels. Travel time often comprises driving time and charging time for a BEV trip, and both charging time and cost are influenced by the amount of charged during charging events. In previous studies, the fully charged assumption is widely used to simplify the problem formulation. This assumption has limited effects on travel costs for short-distance travels as drivers only need to charge their vehicles for a few times yet has a significant influence on intercity travels. Therefore, the charging strategy for intercity travels should take into account multiple traveling cost components, including driving time, charging time and charging cost.

In this study, we focus on the problem with regards to the charging strategy for BEV intercity travels. The problem statement is given as follows: a BEV with a certain level of initial battery energy takes a trip between two different cities with long distance. In the road network, there exist a fixed number of charging stations that can be used to recharge the vehicle, and different charging stations may have different charging power and service cost. In order to realise the intercity travel, the first task is to search the available routes from origin to destination. An available route often traverses multiple charging stations to ensure that the BEV can be charged multiple times and then reaches its destination. As the set of available routes is determined, we aim to devise a multistage optimisation model to provide BEV drivers with an optimal charging strategy. In general, drivers tend to choose those routes with the shortest travel time to ensure that they would reach their destinations on time (Dell'Orco et al., 2016). For ICEVs, the total travel time can be approximatively equivalent to the driving time from the origin to the destination, whereas the refuelling time is often ignored as it is significantly shorter than the driving time. By contrast, the total travel time of BEVs includes driving and charging times. Moreover, BEV drivers also spend a considerable amount to charge their vehicles and hence want to reduce the charging cost during charging events. Therefore, in the proposed model, both travel time and charging cost are treated as optimisation objectives, and a dynamic programming method is designed to solve this model. The solution includes the location of recommended charging stations, the amount of charged energy in each charging station and the corresponding travel route. The methods developed in this study may help BEV drivers determine the optimal charging strategy for intercity travels and provide decision support to city planners when designing public charging infrastructure by taking into account the demands of BEV drivers for intercity travels.

The contributions of this study are as follows. Firstly, this work proposes an available route searching method to determine the available routes for BEVs in a road network. These available routes ensure that the BEVs reach their destinations in consideration of the limited driving range and number of charging stations. In the previous studies, the available routes were often predetermined and the conditions for them were not discussed. For BEV-oriented intercity travels, it is an especially important issue to search available routes. This is because the multiple charging events are often required during the intercity travels, whereas the charging stations for BEVs are much less popular than gas stations. Secondly, this work proposes a multistage optimisation model to provide drivers with the optimal charging strategy for each available route. This model aims to minimise the generalised cost, which is formulated as the weighted sum of travel time and charging cost. The amount of charged energy in each charging station along the optimal route can also be calculated by using this model, which in turn is solved by applying a dynamic programming method that can effectively integrate the interaction effects between different charging actions into the solution. In the exiting literature, most of the related methods focused on the short-distance travel problems for BEVs while neglected the characteristics of intercity travels, which are consistent in the current development situation of BEV adoption to a certain extent. However, as the increasing adoption of BEVs in the future, they will eventually be used to undertake intercity travels. In addition, the preferences of the driver for travel cost components are also considered in the proposed model, whereas less attention has been focused on the impacts of BEV driver's preferences on the charging strategy in the previous studies, especially for the intercity travels. Thirdly, a numerical example and simulations with six available routes are conducted to demonstrate the feasibility of the proposed model and the solution method. The results of this work are expected to provide valuable references for BEV drivers engaging in intercity travel. In addition, the research results also have the contribution to the BEV-based intercity travel policy proposal, and some of the related policy implications are discussed.

The rest of this paper is organised as follows. Section 2 reviews the literature. Section 3 presents the characteristics of available routes for BEVs and discusses the proposed available routes searching method. Section 4 constructs the charging optimization model and introduces the solution method. Section 5 conducts the numerical example and simulations to demonstrate the feasibility of the charging optimization model and solution method. Section 6 concludes the paper and presents directions for future research.

2. Literature review

Previous studies on travel problems have mainly focused on conventional ICEVs (i.e. Li et al., 2009; Pillac et al., 2013; Kovacs et al., 2014), and only few works have examined alternative energy vehicles, such as BEVs. Compared with ICEVs, BEVs have a shorter driving range and often need to be charged during trips. Accordingly, the traditional methods proposed in the ICEV-based literature should be adjusted to realise BEV trips. To this end, a considerable amount of research has attempted to investigate the travel and charging problems for BEVs. For example, Eisner et al. (2011) adopted the Dijkstra algorithm to solve the travel route optimisation problem for BEVs in a large network and regarded energy consumption as a link cost. Erdoğan and Miller–Hooks (2012) developed a mixed integer linear programme to formulate the routing problem of BEVs in consideration of limited driving range and insufficient charging stations. Wang et al. (2018a) examined the impacts of driving direction on charging station selection and proposed an algorithm to guide BEV routing and charging. They used total driving distance as a metric to evaluate the algorithm yet completely ignored the amount of charged energy and its effects on travel time. Said et al. (2013) adopted queuing theory to formulate a mathematical model for the BEV routing problem that aims to minimise charging time. Kobayashi et al.

(2011) designed a route search method for BEVs that considers both limited driving range and locations of charging stations. Charging behaviour was also considered in this method based on the assumption that BEVs need to be fully charged upon arriving at charging stations. Under the similar assumption, Shao et al. (2017) utilised a mixed integer linear programme to formulate a routing problem for BEVs and represented travel time in the model by using a piecewise function. Yang et al. (2015) integrated the charging actions of BEV drivers into a traveling salesman problem and designed a learnable partheno-genetic algorithm to solve this model. Based on network equilibrium theory, several studies have explored the travel route problem of BEVs from the perspective of a macroscopic transportation network (i.e. Jiang and Xie, 2013; He et al., 2014; Jiang et al., 2014). For instance, Qin and Zhang (2011) and Johnson et al. (2013) attempted to improve the travel efficiency of BEVs by alleviating the negative impacts of charging behaviour and thereby formulated charging strategies with minimal time spent in charging actions. Wang et al. (2020) conducted a simulation analysis to explore the impacts of charging events on the operational efficiency of charging stations. Based on this consideration, heuristic-based route guidance strategies have been proposed to formulate charging station suggestions for BEV drivers with charging demands. Travel distance minimisation is treated as a metric in selecting charging stations from the aspect of the travel cost of individual drivers. The travel cost components of BEV trips have multidimensional features due to the costs from charging actions coupled with the costs of driving processes. However, the aforementioned studies have mainly focused on BEV travel problems with a single objective, such as charging time, travel distance and charging cost minimisation, and failed to establish highly comprehensive travel and charging schemes by considering multiple travel cost components simultaneously. BEV drivers tend to select routes and charging stations whilst taking into account several cost-related factors, and, most importantly, each driver may show unique preferences for travel cost components. Therefore, integrating multidimensional travel cost components into BEV travel problems can effectively improve the performance and acceptability of the solution in actual scenarios.

To formulate highly comprehensive and acceptable travel and charging schemes, several studies have taken into account multiple objectives in BEV trip optimisation. For instance, Sweda and Klabjan (2012) built an optimisation model to determine the travel routes for a BEV by considering energy consumption and charging cost. Alizadeh et al. (2014) proposed a route optimisation model for BEVs and considered travel time and charging cost as the objectives. Given their limited battery capacity and potential long charging time, some studies have focused on BEV travel problems whilst taking charging time and energy consumption into consideration and also proposed some heuristic algorithms to solve the models (Wang et al., 2013; Demir et al., 2014; Alesiani and Maslekar, 2014). Sun and Zhou (2016) investigated the impacts of monetary and time factors on BEV trip plans and proposed a guidance strategy to realise an intelligent routing design whilst considering travel time and charging cost. Yagcitekin and Uzunoglu (2016) proposed a double-layer smart charging strategy in consideration of routing and charge scheduling and used travel time and charging cost as metrics to evaluate the solution. Wang et al. (2018b) proposed a multi-objective optimisation model to formulate the traveling and charging problems of BEVs. The objectives considered in the model include charging cost, energy consumption and travel time. Charging event was considered in the model based on the assumption that drivers can charge their vehicles only once between their departure points and destinations. Yang et al. (2017) integrated time-varying charging cost into the BEV travel and charging problem and formulated a crowdsensing-based charging guidance strategy that aims to minimise both trip time and charging cost. Although several works have investigated BEV travel problems in consideration of multiple travel-cost-related factors, only few studies have considered intercity travels. For these travels, BEVs often need to be charged multiple times because of the long distance from the origin to the destination and the limited driving range of these vehicles. More importantly, different charging actions show a definite relationship during intercity travel. In other words, the amount of charged energy in a specific charging action can significantly affect the subsequent ones and further influences the charging time and cost spent in each charging event and the travel cost for the entire trip. Accordingly, the intercity-travel-oriented BEV travel problem is more complex than those problems concerning short distance travels. Yi and Shirk (2018) then introduced an optimal model for charging-related decision making whilst taking into account situations that involve long travel distance travel. Nevertheless, this model only considers monetary and energy costs and ignores travel, driving and charging times during a trip. Moreover, the charging strategies in this model are based on itinerary data collected from the US, and hence the conditions for the availability of travel routes are not discussed. In some areas, several candidate routes may be available, and the available routes should be determined by considering the features of vehicle operation, location of charging stations and structure of road networks. To the best of our knowledge, only few studies have examined the BEV travel and charging problem from the perspective of intercity travels whilst considering multiple travel cost components.

Overall, whilst previous studies have shown some achievements in BEV travel and charging optimization, they still show some limitations as outlined above. In view of these limitations, we develop an intercity travel oriented optimisation model with multiple criteria to formulate an optimal charging strategy coupled with the travel route for a BEV trip. Unlike most of existing studies, this model allows drivers to select several charging stations along their route instead of charging at only a single station. The optimal amount of charged energy for each charging action is also explored to jointly minimise travel time and charging cost.

3. Available route searching method

In a road network, some routes from the origin to the destination may not be used by BEVs due to their limited driving range and lack of charging infrastructures. For example, drivers of ICEVs tend to choose those routes with the shortest distances as their trip routes. However, unlike ICEVs, for BEVs, the route with the shortest distance may be unavailable because the driving range of these vehicles does not cover the distance of the route and charging stations may be unavailable along this route. Fig. 1 presents the available and unavailable routes for BEVs.

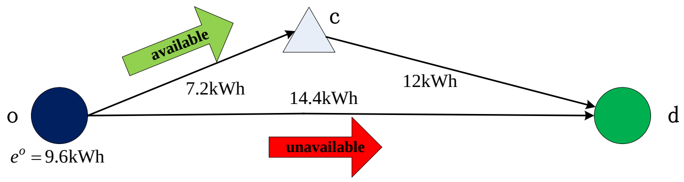


Fig. 1. Available and unavailable routes in a road network

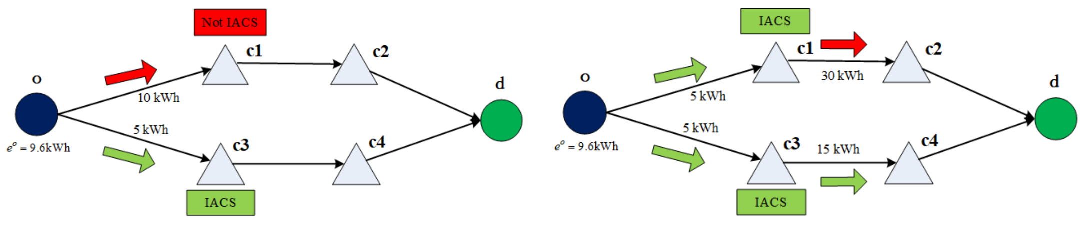
As shown in Fig. 1, the origin–destination (O–D) pair, i.e. nodes o and d, is connected by two routes. The number near the lines in the figure denotes the energy consumed when traversing the routes. One of these routes has a charging station (node c), whereas the other lacks a charging station. The nominal capacity of a battery is assumed to be equal to 24 kWh, whereas the initial energy of a BEV is equal to 9.6 kWh. The route without a charging station can then be easily determined as unavailable because 9.6 kWh is less than 14.4 kWh even though the distance of this route is shorter than that of another route. Moreover, a route with a charging station is available because the BEV can reach this charging station (node c) to charge its battery and then arrive at its destination (node d). Therefore, before determining the optimal charging strategy for a BEV, one should search for the available routes from the departure point to the destination.

An available route searching method is proposed in this paper to determine the available routes for BEVs. Assume that a road network has n charging stations. A BEV driver can select no less than one charging station to charge his/her vehicle. The available routes consist of charging station(s) and the corresponding travel paths. Let E denote the nominal capacity of a BEV, and let e^o be the initial energy when the BEV driver has a charging demand. Given the limited driving range and lack of charging infrastructures, an available route from the origin to the destination should meet the following conditions. Meanwhile, to better illustrate the conditions required for the availability of the routes, Fig. 2 is introduced to show an example of the conditions. Similar with Fig.1, we also assume that the nominal capacity of a battery equals to 24 kWh, whereas the initial energy is equal to 9.6 kWh.

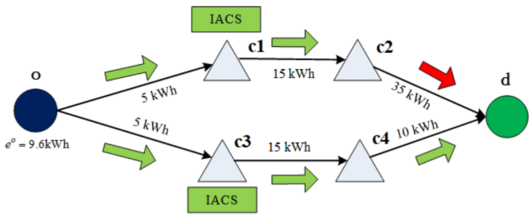
(1) The BEV can reach the nearest charging station along an available route by using its initial energy e^o. As shown in the case (1) of Fig.2, the route connecting c3 to c4 has the chance to become an available route because the BEV from the origin can reach c3 through its initial energy e^o, and the charging station located in node c3 is regarded as the initial accessible charging station (IACS) in this study. By contrast, since the energy consumed from the origin to c1 exceeds the initial energy of the BEV, the route connecting c1 to c2 has no chance to become an available route.

(2) Along an available route, the energy consumed to traverse the routes between any two adjacent charging stations needs to be less than the nominal capacity E. As shown in the case (2) of Fig. 2, if both the charging station from the nodes c1 and c3 are IACSs, we need to further check the energy consumption on the routes between two adjacent charging stations located in the corresponding paths. In this case, the route connecting c3 to c4 has the chance to become an available route because the energy consumed from c3 to c4 is less than the nominal capacity E of the BEV. On the contrary, the route connecting c1 to c2 has no chance to become an available route because the energy consumption on the routes between c1 and c2 exceeds the nominal capacity E of the BEV.

(3) For an available route, the total energy consumed from the origin to the destination should be less than the maximum energy that a BEV can use along the route. As shown in the case (3) of Fig. 2, the route connecting c3 to c4 is an available route, because the maximum energy that the BEV can use, which includes the initial energy e^o, energy charged in c3 and energy charged in c4, exceeds the total energy consumed from the origin to the destination. In contrast, the route connecting c1 to c2 is an unavailable route. This is because the energy consumption on the route from c2 to the destination exceeds the nominal capacity E of the BEV, which indicates that the total energy consumed from the origin to the destination is larger than the maximum energy that the BEV can use.



(1) Condition (1) (2) Condition (2)



(3) Condition (3)

Fig. 2. Illustration of the conditions for available routes

The available route searching method is designed based on the above conditions. Let R' denote the set of candidate routes between the O–D pair, including the available and unavailable routes, which can be obtained by using existing path navigation devices and built-in navigation systems. Correspondingly, let $c^{r'}$ be the number of charging stations along the route r', where $r' \in R'$. Therefore, according to the condition (3) as mentioned above, the maximum energy that a BEV can use along the route r' is

$$E^{r'} = e^{o} + E \times c^{r'} \tag{1}$$

where $E^{r'}$ is the maximum energy that a BEV can use in the route r'. Eq. (1) indicates that $E^{r'}$ consists of the maximum energy that can be charged along the route and the initial energy of the BEV.

The purpose of the proposed method is to search and select the available routes from candidate ones in consideration of the limited driving range and charging stations; therefore, those methods related to enumerating candidate routes are not the focus of this study. Several studies have discussed route searching methods based on different objectives (i.e. Santos et al., 2007; Fan and Liu, 2010; Chen et al., 2017). Let R denote the set of available routes, and $R \subseteq R'$. The available route searching method aims to generate R by finding out the available routes from R'. The detailed steps of this method are outlined as follows:

Algorithm 1 Available route searching

Step 1: Search for the IACSs for the routes from R'.

Step 1.1: Determine the initial energy e^{o} of the BEV.

Step 1.2: Determine the energy consumed to reach the nearest charging stations along the candidate routes from R'.

Step 1.3: Compare the initial energy e^{o} of the BEV with the energy consumed from the origin to the nearest charging station for each route from R':

Step 1.3.1: If the initial usable energy e^{o} is less than the energy consumed to reach the nearest charging station for the route r', remove the route from R'.

Step 1.3.2: If the initial usable energy e^{o} is no less than the energy consumed to reach the nearest charging station for the route r', retain the route from R' and treat the charging station as an IACS.

Step 2: Investigate the energy consumed to traverse the routes between any two adjacent charging stations.

Step 2.1: Check the total number of charging stations along the routes from R':

Step 2.1.1: If only one charging station (IACS) is present along the route r', retain the route from R'.

Step 2.1.2: If more than one charging stations are present along the route r', go to Step 2.2.

Step 2.2: Compare the nominal capacity E of the BEV with the energy consumed between any two adjacent charging stations located in the routes from R':

Step 2.2.1: If the nominal capacity E of the BEV is no less than the energy consumed between any two adjacent charging stations along the route r', retain the route from R'.

Step 2.2.2: If the nominal capacity E of the BEV is less than the energy consumed between any two adjacent charging stations along the route r', remove the route from R'.

Step 3: Calculate the maximum energy that a BEV can use along the routes from R' and determine the available routes.

Step 3.1: Calculate the maximum energy that a BEV can use along each route from R' by using Eq. (1).

Step 3.2: Determine the total energy consumed to traverse each route from R'.

Step 3.3: For each route r', compare the usable maximum energy $E^{r'}$ with the total energy consumed to traverse the route:

Step 3.3.1: If the usable maximum energy $E^{r'}$ is no less than the total energy consumed to traverse the route r', collect the route into R.

Step 3.3.2: If the usable maximum energy $E^{r'}$ is less than the total energy consumed to traverse the route r', remove the route.

Step 4: Output the available routes and generate R.

Note that, in this section, the minimum required residual energy after each arrival at the charging stations is not considered to simplify the algorithm description. It is straightforward to add such a factor into the route searching process in the practical application.

4. Charging optimisation model with multiple criteria

An optimal charging strategy is then developed by taking into account the available routes obtained by the available route searching method. Given that a BEV may be charged more than once during intracity travel, we establish a multistage optimisation model to abstract the connected charging events. This model aims to obtain the optimal amount of charged energy in each charging station along the available routes. Afterwards, the route with the minimum weighted sum of charging cost and travel time is selected as the optimal route.

4.1. Basic assumption

To facilitate the model construction, the following assumptions are made:

Assumption 1: To guarantee the availability of the charging optimisation model, we assume that at least one available route exists along the road network for a BEV. This is because the existence of available route is the precondition for the application of the proposed model.

Assumption 2: To realise multistage optimisation modelling, we assume that the energy consumption and amount of charged energy are both discretised; accordingly, their values are set as an integer in this study.

Assumption 3: To reduce model complexity, we assume that the energy consumed to traverse each link in the road network is constant. The relationship between energy consumption and its influencing factors with time-varying characteristics, such as driving speed (Bi et al., 2018), is outside the scope of this work and is therefore not discussed.

Assumption 4: To reduce model complexity, we assume that the driving time to traverse each link in the road network is constant. This assumption is tenable if the traffic condition in the road network is stable, i.e. during off-peak hours (Gendreau et al., 2015). The situation with a time-varying road network is not the focus in this study and is therefore not considered in the model.

4.2. Modelling

When obtaining a set of available routes R, an optimal charging strategy for each available route needs to be determined. Multiple charging stations are often available along the available routes in intercity travel, and a BEV may need to be charged more than once during a trip. Let c^r denote the number of charging stations along the available route *r*, where $r \in R$. The charging optimisation problem for the BEV operating in the available route *r* can be divided into c^r optimisation stages. Specifically, one of these optimisation stages, i.e. the *k*th stage $(k = 1, \cdots, c^r)$, starts when the BEV arrives at the *k*th charging station along the route and ends when the BEV reaches the $k+1$th charging station or destination (if $k = c^r$). Let t_k^l denote the driving time when the BEV travels from the *k*th charging station to the $k+1$th charging station, let τ_k be the charging time spent on per unit amount of charged energy in the *k*th charging station and let x_k be the amount of charged energy in the *k*th charging station. Fig. 3 presents the overall process for a BEV operating during the *k*th period.

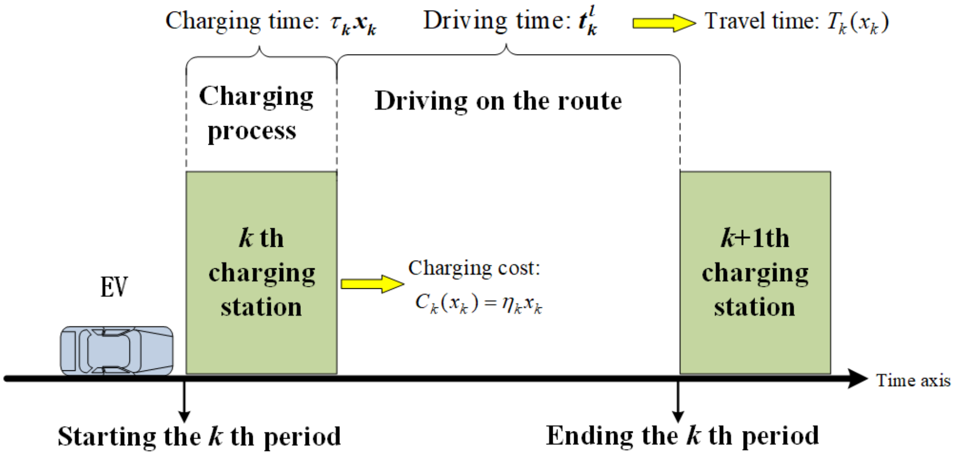


Fig. 3. Overall process for a BEV operating during the *k*th stage.

As shown in Fig. 3, the operating process of a BEV during the *k*th stage includes the charging action in the *k*th charging station and the driving process on the route between the *k*th and *k*+1th charging stations. The travel time spent on the *k*th stage consists of the charging time in the *k*th charging station $\tau_k x_k$ and the driving time from the *k*th charging station to the $k+1$th charging station t_k^l.

Let $T_k(x_k)$ denote the travel time during the kth stage with energy amount x_k, and this parameter can be calculated as

$$T_k(x_k) = t_k^l + \tau_k x_k \tag{2}$$

Furthermore, let $C_k(x_k)$ denote the charging cost in the kth stage with energy amount x_k. This parameter can be calculated as

$$C_k(x_k) = \eta_k x_k \tag{3}$$

where η_k represents the charging cost spent on per unit amount of charged energy in the k th period. In real-word situations, the charging cost comprises electricity and service costs, which often have different pricing policies. Take China for example, where the charging stations located in different cities may have a similar pricing for electricity cost and may have significantly different pricing for service cost. To conform to such pricing policies, we define the unit charging cost η_k as the sum of unit electricity and unit service costs as shown in Fig. (4);

$$\eta_k = \eta_k^e + \eta_k^s \tag{4}$$

where η_k^e and η_k^s are the electricity price and service cost spent on per unit amount of charged energy in the kth charging station, respectively.

Eqs. (2) and (3) indicate that x_k is a decision variable that is used to determine the amount of charged energy; accordingly, the travel time and charging cost during the kth stage are obtained. Let h_k denote the residual energy as the BEV arrives at the kth charging station. For the available route r, the multistage charging optimisation model with multicriteria is constructed as

$$\min \sum_{k=1}^{c^r} (C_k(x_k) + a_t T_k(x_k)) + a_t t_0^l \tag{5}$$

s.t.

$$h_k = \begin{cases} e^o - \delta_0 \geq 0.2E, & k = 1 \\ e^o - \delta_0 + \sum_{j=1}^{k-1} (x_j - \delta_j) \geq 0.2E, & k = 2, \cdots, c^r \end{cases} \tag{6}$$

$$h_{c^r} + x_{c^r} - \delta_{c^r} = e^d \tag{7}$$

$$0 \leq x_k \leq (E - h_k) \qquad (k = 1, 2, \cdots, c^r) \tag{8}$$

$$x_k \in \mathrm{Z} \tag{9}$$

In the model, objective (5) is formulated as weighted sum of the travel time and charging cost accumulated as a BEV travels on the available route with serial number r. In this equation, a_t (in yuan/minute) represents value of time, whereas t_0^l denotes the driving time from the origin to the IACS along the route. a_t can also be used to indicate the preferences of the driver for travel cost components. The trade-off between travel time and charging cost is embodied by translating travel time into monetary cost. The baseline of parameter a_t can be determined by referring to both electricity price and charging rate based on an assumption that the baseline for the value of time mainly depends on the unit electricity price and unit charging time. Constraint (6), which is a piecewise equation, indicates that the residual energy when the BEV reaches any charging station should not be less than the minimum required residual energy, i.e. 20% of the nominal capacity E (Bi et al., 2018). In this equation, δ_0 represents the energy consumption from the origin to IACS, and δ_j $(j \geq 1)$ is the energy consumption in the jth stage. Constraint (7) denotes the residual energy as the BEV reaches its destination, where the value of e^d can be determined according to the driver's trip purpose or other factors. Constraint (8) represents the upper and lower bounds of the amount of charged energy in the kth charging station, whereas constraint (9) ensures that the charged energy amount x_k belongs to the integer.

4.3. Dynamic programming for optimal charging strategies

The multistage charging optimisation model can be regarded as a multi-period decision-making problem that can be effectively solved by using the dynamic programming method (Tian, 2015). Different periods are not independent of one another in the proposed model, that is, the previous stage can influence the subsequent stage, and the task is to obtain a sequence of charged energy amounts during each stage with the optimisation goal of minimising the overall generalised cost. In other words, for an intercity travel with multiple charging events, the previous charging process can influence the subsequent one, and then affect the overall optimal charging strategy. Confronted with such a problem, the conventional global optimisation methods are not adequately efficient to explore the insightful solution, as compared to the dynamic programming method. As a matter of fact, the previous studies often aim to optimise the BEV travel path and thus simplify the charging behaviour to a certain extent (i.e. Erdoğan and Miller-Hooks, 2012; Shao et al., 2017; Wang et al., 2018b). By this way, the corresponding problems can be solved by the global optimisation algorithms. Unlike the previous literature, this study aims to optimise the charging strategy for BEV-oriented intercity travels by considering the interaction effects between different charging actions. Fortunately, the dynamic programming method can deal with the interrelation amongst different stages, store the solution in each stage and avoid repetitiously solving the same sub-problem, thereby increasing the solving efficiency. Therefore, the dynamic programming method shows significant advantages in solving the proposed model compared with other approaches, such as the divide-and-conquer method (Liao et al., 2016). In view of these advantages, this paper uses the dynamic programming method to solve the charging optimisation model. Based on the architecture of the proposed model, the dynamic programming method transforms the original problem into several interrelated sub-problems. Afterwards, the sub-problems are solved one by one before arriving to a solution to the multi-period decision-making optimisation problem. The dynamic programming method does not have a standard mathematical expression or an explicitly defined regulation. Each problem may correspond to a unique architecture of the dynamic programming method. Therefore, a targeted dynamic programming method must be designed for the charging optimisation model. The critical points for the dynamic programming method are to define the states, the decision variable and the state variable and to determine the state transition equation and optimal value function (Pang and Liu, 2013). Considering the characteristics of the problem, a stage in the model is regarded as a period in the dynamic programming method. Meanwhile, x_k and h_k in the model are regarded as the decision and state variables in the dynamic programming method, respectively. Based on these settings, the state transition equation is formulated as

$$h_{k+1} = h_k + x_k - \delta_k \tag{10}$$

which highlights the interrelation between the state in the kth stage and the subsequent stage (i.e. $k+1$th stage). This equation includes the decision variable x_k of the model.

To design the optimal value function of the dynamic programming method, the objective function of the proposed model should be transformed, and the structure of the objective function after transformation includes the optimal value function. Considering the characteristics of the model, a reverse solution method is adopted to design the optimal value function. Let $f_k(h_k)$ denote the minimum total generalized cost from the kth charging station to the destination with the value of h_k. The optimal value function is

$$f_k(h_k) = \min_{\max(0,\delta_k - h_k) \le x_k \le (E_i - h_k)} [C_k(x_k) + a_t T_k(x_k) + f_{k+1}(h_k + x_k - \delta_k)] \quad (k=1,\cdots,c^r) \tag{11}$$

For the proposed model, the boundary condition of the optimal value function is

$$f_{c^r+1}(h_{c^r+1}) = C_{c^r}(e^d) + a_t T_{c^r}(e^d) \tag{12}$$

Therefore, based on the optimal value function, as shown in Eq. (11), the objective function of the model can be transformed as

$$\min \sum_{k=1}^{c^r} (C_k(x_k) + a_t T_k(x_k)) + a_t t_0^l = f_1(h_1) + a_t t_0^l \tag{13}$$

The architecture of the objective function after transformation, as shown in Eq. (13), is different from that in the original model, as shown in Eq. (5). However, both functions have the same optimal objective values.

5. Numerical example and simulations

5.1. Example scenario description

This section presents a numerical example to demonstrate the feasibility of the proposed model. Specifically, this model is applied to solve a multistage charging optimisation problem for a BEV trip in the road network with 17 charging stations, as shown in Fig. 4. In the figure, the nodes are denoted by two colours, with the red nodes representing the origin and destination, and the yellow nodes representing the charging stations. The directed links that connect the nodes are used to abstract the road segments between a charging station and an O–D node or two charging stations. The figure also presents the detailed information on the energy consumption and travel time for each road segment, which are assumed by reference to the map information of the highway network.

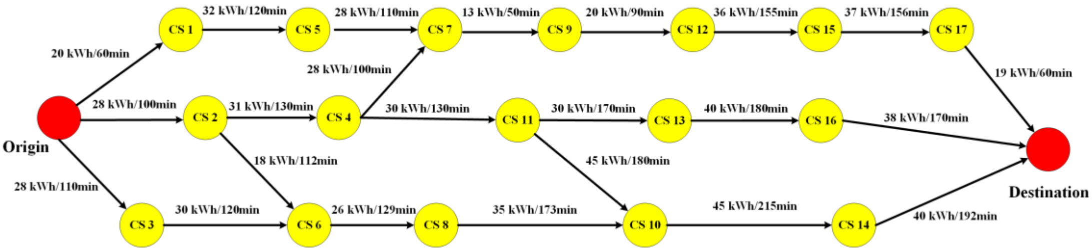


Fig. 4. Road network with energy consumption and driving time in the numerical example.

Referring to the existing BEV models, such as the BYD e6, we assume that the nominal capacity E of a battery is equal to 60 kWh and that the BEV has a full battery as it starts to leave the origin. Based on the charging station locations coupled with the road structure, the available routes that can be used for intercity travel are determined by using the available route searching method, and all the available routes need to meet the conditions required for the availability of the routes, as mentioned in Section 3. Accordingly, six available routes are identified between origin and destination, as listed in Table 1, and these routes are denoted by available routes 1-6. In this example, the residual energy at destination e^d is set to 20% of the nominal capacity, i.e. 12 kWh. Those other cases with different values of e^d are discussed in Section 5.3.

Table 1

Available routes deriving from the numerical example.

Available route	Charging stations along the available route
Available route 1	Origin→CS 1→CS 5→CS 7→CS 9→CS 12→CS 15→CS 17→Destination
Available route 2	Origin→CS 2→CS 4→CS 7→CS 9→CS 12→CS 15→CS 17→Destination
Available route 3	Origin→CS 2→CS 4→CS 11→CS 13→CS 16→Destination
Available route 4	Origin→CS 2→CS 6→CS 8→CS 10→CS 14→Destination
Available route 5	Origin→CS 2→CS 4→CS 11→CS 10→CS 14→Destination
Available route 6	Origin→CS 3→CS 6→CS 8→CS 10→CS 14→Destination

Apart from driving time, BEV drivers should also consider the time and monetary costs in charging their vehicles during trips. In the numerical example, the unit charging time for each charging station is determined by referring to the related information for the charging infrastructure of China. Meanwhile, the service cost for each charging station is obtained by referring to the price standards issued by Chinese local governments. Table 2 presents information on the charging stations in the numerical example, including unit charging time τ_k (min/kWh) and unit service cost η_k^s (yuan/kWh).

Table 2

Unit charging time τ_k and unit service cost η_k^s of charging stations.

Charging stations	Unit charging time (min/kWh)	Unit service cost (yuan/kWh)	Charging station	Unit charging time (min/kWh)	Unit service cost (yuan/kWh)
CS 1	0.75	1.00	CS 10	0.60	0.65
CS 2	0.75	1.00	CS 11	1.00	0.65
CS 3	0.75	1.00	CS 12	0.60	2.04
CS 4	1.00	0.60	CS 13	0.75	1.68
CS 5	1.00	0.60	CS 14	0.50	1.68
CS 6	1.00	0.65	CS 15	0.75	1.68
CS 7	1.00	0.65	CS 16	0.50	2.04
CS 8	1.00	0.65	CS 17	0.50	2.04
CS 9	0.75	0.65			

In contrast to service cost, electricity price often follows a relatively uniform price standard in some countries, such as China. Therefore, we suppose that the charging stations located in the road network have the same electricity price η_k^e and set 1.00 yuan/kWh as the unit electricity price based on actual information about the electricity price standard in China. The unit electricity price coupled with unit charging time is also used to determine the baseline for the value of time a_t (yuan/min) when drivers have equal preferences for travel time and charging cost. In the numerical example, without loss of generality, the most common value of unit charging time (1 min/kWh as shown in Table 2) is selected, and accordingly, the baseline for the value of time a_t is computed as $\frac{\eta_k^e}{\tau_k} = 1.00 \text{ yuan/min}$.

Note that, the different drivers' preferences for the travel cost components may have the significant difference. For example, some drivers tend to complete their trips with the travel time as less as possible, whereas other drivers desire to spend less monetary cost for charging events to finish their travels. In view of this, to analyse the influence of various trade-offs between travel time and charging cost on the optimisation results, five conditions regarding the value of time a_t are considered in the numerical example, namely, a_t =0.2, 0.5, 1.00, 1.5 and 5.0 yuan/min. In this way, a larger value of a_t indicates the greater importance of travel time with consideration of the baseline. Specifically, the condition with a_t=0.2 indicates that the travel time is extremely more unimportant than charging cost; the condition with a_t=0.5 represents that the travel time is more unimportant than charging cost; the condition with a_t=1 indicates that the travel time has equal importance to charging cost; the condition with a_t=1.5 represents that the travel time is more important than charging cost; the condition with a_t=5 indicates that the travel time is extremely more important in comparison to charging cost.

5.2. Optimal results and analysis

As shown in Table 1, there are seven charging stations (CS 1, CS 5, CS 7, CS 9, CS 12, CS15, CS 17) along the available route 1 and thus the charging optimisation problem on this route is considered a problem under seven stages based on the model. The optimal amount of charged energy in each charging station under different conditions is listed in Table 3.

Table 3

Optimal amount of charged energy in each charging station along available route 1.

Conditions	CS 1	CS 5	CS 7	CS 9	CS 12	CS 15	CS 17
a_t=0.2	4 kWh	46 kWh	0 kWh	43 kWh	8 kWh	48 kWh	8 kWh
a_t=0.5	4 kWh	41 kWh	0 kWh	48 kWh	8 kWh	48 kWh	8 kWh
a_t=1.0	4 kWh	41 kWh	0 kWh	48 kWh	8 kWh	48 kWh	8 kWh
a_t=1.5	4 kWh	41 kWh	0 kWh	48 kWh	8 kWh	37 kWh	19 kWh
a_t=5.0	20 kWh	25 kWh	0 kWh	48 kWh	20 kWh	25 kWh	19 kWh

For available route 2, the BEV passes through seven charging stations (CS 2, CS 4, CS 7, CS 9, CS 12, CS 15, CS 17). Therefore, the charging optimisation problem on the available route 2 is considered a problem under seven stages. Table 4 presents the optimal amount of charged energy in each charging station along available route 2.

Table 4

Optimal amount of charged energy in each charging station along available route 2.

Conditions	CS 2	CS 4	CS 7	CS 9	CS 12	CS 15	CS 17
a_t=0.2	11 kWh	46 kWh	0 kWh	43 kWh	8 kWh	48 kWh	8 kWh
a_t=0.5	11 kWh	41 kWh	0 kWh	48 kWh	8 kWh	48 kWh	8 kWh
a_t=1.0	11 kWh	41 kWh	0 kWh	48 kWh	8 kWh	48 kWh	8 kWh
a_t=1.5	11 kWh	41 kWh	0 kWh	48 kWh	8 kWh	37 kWh	19 kWh
a_t=5.0	28 kWh	24 kWh	0 kWh	48 kWh	20 kWh	25 kWh	19 kWh

For available route 3, there are five charging stations (CS 2, CS 4, CS 11, CS 13, CS 16) along the route and thus the charging optimisation problem on this route is considered a problem under five stages. The optimal amount of charged energy in each charging station along available route 3 is presented in Table 5.

Table 5

Optimal amount of charged energy in each charging station along available route 3.

Conditions	CS 2	CS 4	CS 11	CS 13	CS 16
a_t=0.2	11 kWh	48 kWh	12 kWh	48 kWh	30 kWh
a_t=0.5	11 kWh	48 kWh	12 kWh	48 kWh	30 kWh
a_t=1.0	11 kWh	48 kWh	12 kWh	48 kWh	30 kWh

a_t=1.5	11 kWh	48 kWh	12 kWh	48 kWh	30 kWh
a_t=5.0	28 kWh	31 kWh	12 kWh	48 kWh	30 kWh

For available route 4, the BEV passes through five charging stations (CS 2, CS 6, CS 8, CS 10, CS 14). Therefore, the charging optimisation problem on the available route 4 is considered a problem under five stages. Table 6 presents the optimal amount of charged energy in each charging station along available route 4.

Table 6

Optimal amount of charged energy in each charging station along available route 4.

Conditions	CS 2	CS 6	CS 8	CS 10	CS 14
a_t=0.2	0 kWh	46 kWh	13 kWh	48 kWh	37 kWh
a_t=0.5	0 kWh	43 kWh	16 kWh	48 kWh	37 kWh
a_t=1.0	0 kWh	44 kWh	15 kWh	48 kWh	37 kWh
a_t=1.5	28 kWh	18 kWh	13 kWh	48 kWh	37 kWh
a_t=5.0	28 kWh	18 kWh	13 kWh	58 kWh	37 kWh

For available route 5, there are five charging stations (CS 2, CS 4, CS 11, CS 10, CS 14) along the route and thus the charging optimisation problem on this route is considered a problem under five stages. The optimal amount of charged energy in each charging station along available route 5 is presented in Table 7.

Table 7

Optimal amount of charged energy in each charging station along available route 5.

Conditions	CS 2	CS 4	CS 11	CS 10	CS 14
a_t=0.2	11 kWh	43 kWh	22 kWh	48 kWh	37 kWh
a_t=0.5	11 kWh	43 kWh	22 kWh	48 kWh	37 kWh
a_t=1.0	11 kWh	43 kWh	22 kWh	48 kWh	37 kWh
a_t=1.5	11 kWh	43 kWh	22 kWh	48 kWh	37 kWh
a_t=5.0	28 kWh	26 kWh	22 kWh	48 kWh	37 kWh

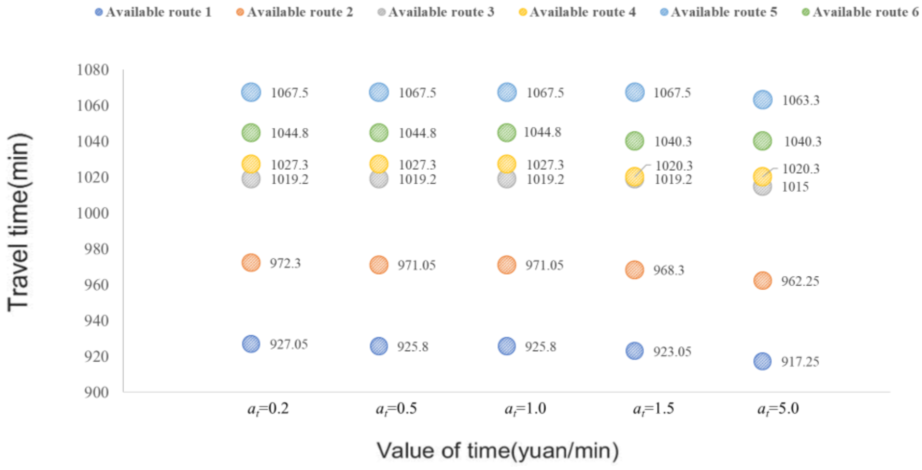
For available route 6, the BEV passes through five charging stations (CS 3, CS 6, CS 8, CS 10, CS 14). Therefore, the charging optimisation problem on the available route 6 is considered a problem under five stages. The optimal amount of charged energy in each charging station under different conditions is listed in Table 8.

Table 8

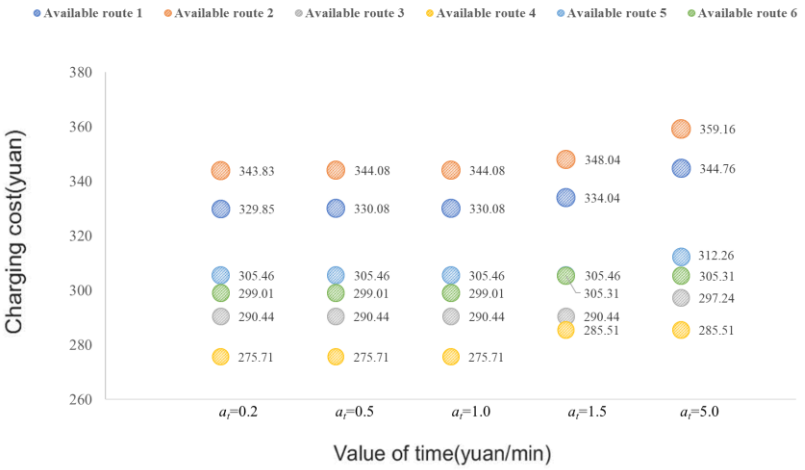
Optimal amount of charged energy in each charging station along available route 6.

Conditions	CS 3	CS 6	CS 8	CS 10	CS 14
a_t=0.2	10 kWh	46 kWh	15 kWh	48 kWh	37 kWh
a_t=0.5	10 kWh	46 kWh	15 kWh	48 kWh	37 kWh
a_t=1.0	10 kWh	46 kWh	15 kWh	48 kWh	37 kWh
a_t=1.5	28 kWh	30 kWh	13 kWh	48 kWh	37 kWh
a_t=5.0	18 kWh	26 kWh	17 kWh	48 kWh	37 kWh

Fig. 5 presents the optimal travel cost components, including travel time and charging cost, for the six available routes under different conditions. Cases (1) and (2) respectively present the travel time and charging cost from the solution under different conditions. The travel time for available route 5 is longer than that for the other available routes, whilst available route 1 has the shortest travel time under all situations with different values of time a_t. In addition, available route 4 has the lowest charging cost, whereas available route 2 has the highest charging cost under all conditions. These results suggest that these available routes show significant differences in their travel cost components. Moreover, for a specific available route, different travel cost components may have different optimality. Therefore, how to determine an optimal route by considering the trade-offs amongst various travel cost components presents a critical issue.



(1) Travel time



(2) Charging cost

Fig. 5. Optimal travel cost components for the six available routes under different conditions

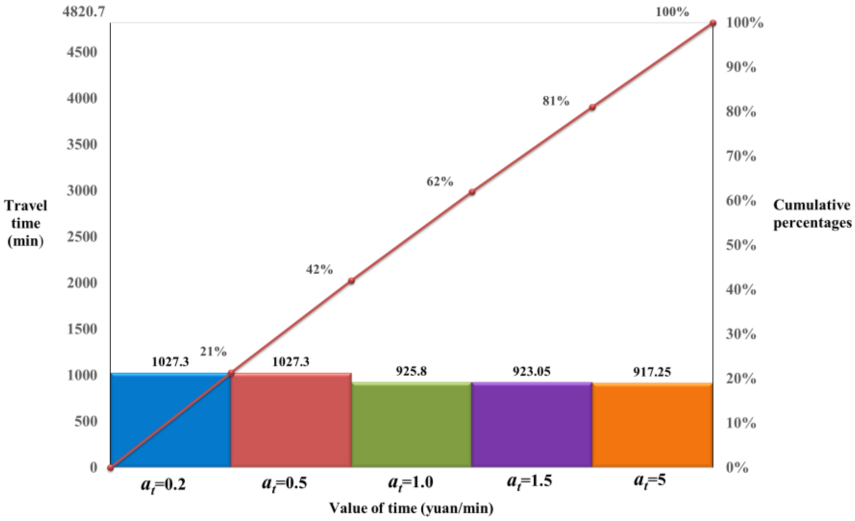
To determine the optimal routes, the generalised cost is considered in the multistage charging optimisation model as mentioned in Section 4.2. The generalised cost derived from the solution for each available route under different conditions is listed in Table 9. The optimal routes for those conditions with different values of time a_t are also presented and marked in bold in the table. Available route 1 is selected as the optimal route for the condition a_t=1, which suggests that travel time and charging cost have equal importance, because this route has the lowest generalised cost amongst all routes. Meanwhile, available route 4 is deemed the optimal route for the a_t=0.2 and 0.5 conditions. This result is consistent with those presented in Fig. 5 because both values of a_t indicate that travel time is less important than charging cost and that available route 4 has the lowest charging cost amongst all routes. Available route 1 is considered the optimal route for the conditions with a_t=1.5 and 5 because both values of a_t indicate that travel time is more important than charging cost, and available route 1 has the shortest travel time amongst all routes.

Table 9

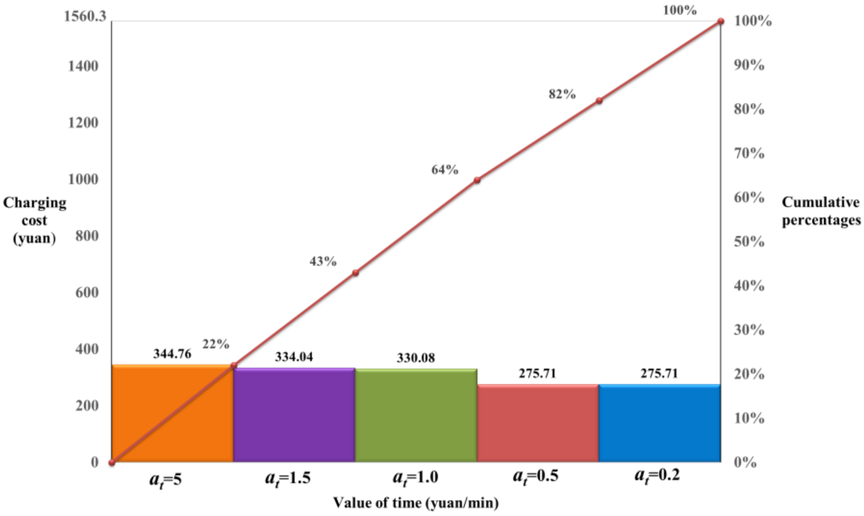
Optimal routes for each value of time a_t

Conditions	Available routes	Generalized cost (yuan)
a_t=0.2	Available route 1	515.24
	Available route 2	538.29
	Available route 3	494.29
	Available route 4	**481.17**
	Available route 5	518.97
	Available route 6	507.97
a_t=0.5	Available route 1	792.98
	Available route 2	829.61
	Available route 3	800.065
	Available route 4	**789.36**
	Available route 5	839.24
	Available route 6	821.41
a_t=1	**Available route 1**	**1255.9**
	Available route 2	1315.1
	Available route 3	1309.7
	Available route 4	1303.0
	Available route 5	1373.0
	Available route 6	1343.8
a_t=1.5	**Available route 1**	**1718.6**
	Available route 2	1800.5
	Available route 3	1819.3
	Available route 4	1816.0
	Available route 5	1906.8
	Available route 6	1865.8
a_t=5	**Available route 1**	**4931.0**
	Available route 2	5170.4
	Available route 3	5372.2
	Available route 4	5387.0
	Available route 5	5628.8
	Available route 6	5506.8

As shown in Table 9, the value of time a_t significantly affects route choice because the preferences of drivers regarding the travel cost components will affect the cost structure of optimal routes. To further explore the impacts of the value of time a_t on the travel cost components obtained from the solution, we use Pareto curves to illustrate the travel time and charging cost of the optimal routes and the corresponding cumulative percentages under each condition as shown in Fig. 6.



(1) Pareto curve of travel time



(2) Pareto curve of charging cost

Fig. 6. Pareto curves of travel cost components under five conditions with different values of time a_t.

In Fig. 6, case (1) compares the travel time of the optimal routes for the numerical example under conditions with different values of time a_t. Travel time generally demonstrates a downward trend as the value of time a_t increases, and the conditions with a_t=0.2 and 0.5 report an equivalent travel time. The gap between the minimum and maximum values of travel time under these conditions is equal to 110.05 min. The cumulative percentages indicate that the travel time under the five conditions exhibits moderate changes. Meanwhile, case (2) presents the charging cost of the optimal routes under conditions with different values of a_t. Charging cost generally shows a downward trend as the value of time a_t decreases, whilst the conditions with a_t=0.2 and 0.5 report an equivalent charging cost. The gap between the minimum and maximum values of charging cost under these conditions is equal to 69.05 yuan. The cumulative percentages indicate that charging cost shows moderate changes except for a relatively sharp change between the adjacent conditions with a_t=0.5 and 1.0.

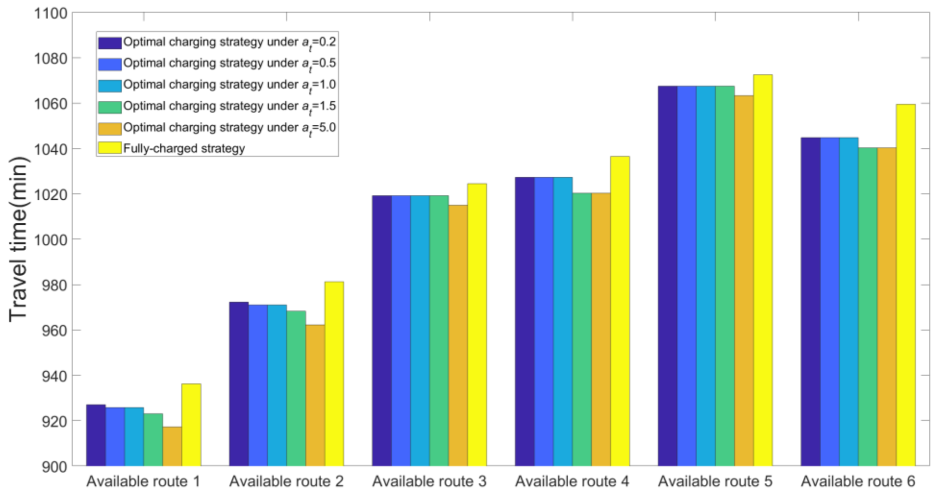
Notably, in the previous studies and practical travel experiences, a commonly-used charging strategy is to fully charge the battery after the BEV's arrival at the charging station, namely, the fully-charged strategy, and accordingly the corresponding BEV travel problems are solved by the conventional global optimisation algorithms (i.e. Kobayashi et al., 2011; Sun and Zhou, 2016; Shao et al., 2017). For the fully-charged strategy, it is often assumed that the charging actions take place as the residual energy is lower than a certain battery level and the battery is full after charging. To further verify the multistage optimisation model, the fully-charged strategy is performed on the numerical example for the purpose of comparison. Likewise, in this experiment, we also assume that the minimum required residual energy before arriving at each charging station is equal to 20% of the nominal capacity *E*. In other words, if the current residual energy cannot support the BEV to reach the next charging station while the residual energy is no less than 20% of the nominal capacity *E* before arrival, the BEV is charged in the current charging station; otherwise, the BEV is not charged in the current charging station. Based on such a strategy, the amount of charged energy in each charging station and corresponding travel cost components for each available route are obtained, as listed in Table 10. Note that, the amount of charged energy driving from the fully-charged strategy is unaffected by the driver's preferences for travel cost components, namely, the value of time a_t. Nevertheless, the driver's preferences still have the impacts on the route choice, because the generalized cost would change with the different value of time a_t.

Table 10

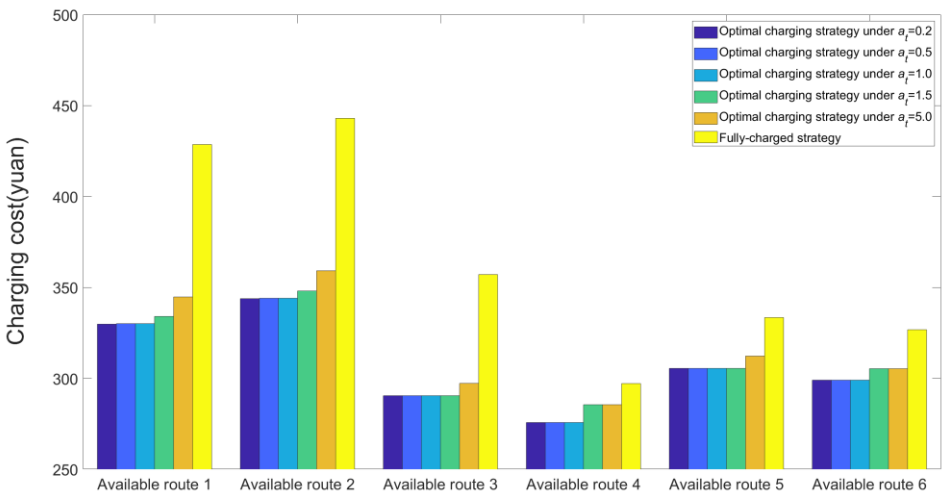
Amount of charged energy and travel cost components deriving from the fully-charged strategy.

Available route	**Amount of charged energy in each charging station**	**Travel time (min)**	**Charging cost (yuan)**
Available route 1	20 kWh (CS 1)→32 kWh (CS 5)→0 kWh (CS 7)→41 kWh (CS 9)→20 kWh (CS 12)→36 kWh (CS 15)→37 kWh (CS 17)	936.25	428.61
Available route 2	28 kWh (CS 2)→31 kWh (CS 4)→0 kWh (CS 7)→41 kWh (CS 9)→20 kWh (CS 12)→36 kWh (CS 15)→37 kWh (CS 17)	981.25	443.01
Available route 3	28 kWh (CS 2)→31 kWh (CS 4)→30 kWh (CS 11)→30 kWh (CS 13)→40 kWh (CS 16)	1024.50	357.10
Available route 4	0 kWh (CS 2)→46 kWh (CS 6)→26 kWh (CS 8)→35kWh (CS 10)→45 kWh (CS 14)	1036.50	297.15
Available route 5	28 kWh (CS 2)→31 kWh (CS 4)→30 kWh (CS 11)→35 kWh (CS 10)→45 kWh (CS 14)	1072.50	333.45
Available route 6	28 kWh (CS 3)→30 kWh (CS 6)→26 kWh (CS 8)→35kWh (CS 10)→ 45 kWh (CS 14)	1059.50	326.75

To have a better comparison, the optimal travel cost components obtained from the fully-charged strategy and proposed optimal charging strategy are presented in Fig. 7. As can be seen from the figure, the travel time from the fully-charged strategy is longer than that from the proposed charging strategy. Meanwhile, the charging cost from the fully-charged strategy is significantly higher than that from the proposed optimal charging strategy. The comparison results indicate that the multistage optimal charging strategy has a better ability to reduce the travel costs for BEV-based intercity travels, including both travel time and charging cost, as compared to the conventional fully-charged strategy.



(1) Travel time



(2) Charging cost

Fig. 7. Optimal travel cost components obtained from the fully-charged strategy and proposed optimal charging strategy

According to the travel cost components derived from the fully-charged strategy, the corresponding generalized costs under the five conditions with different value of time a_t are obtained, as shown in Table 11. The optimal routes for those conditions are presented and marked in bold in the table. Obviously, the optimal generalized costs under all the conditions from the fully-charged strategy are higher than that from the proposed optimal charging strategy (listed in Table 9). The fully-charged strategy results in an average increase of 4.10 % in the optimal generalized costs compared with the multistage optimal charging strategy. The results further indicate that the proposed optimal charging strategy can improve the travel efficiency for BEV-based intercity trips.

Table 11

Optimal routes and generalized costs based on the fully-charged strategy.

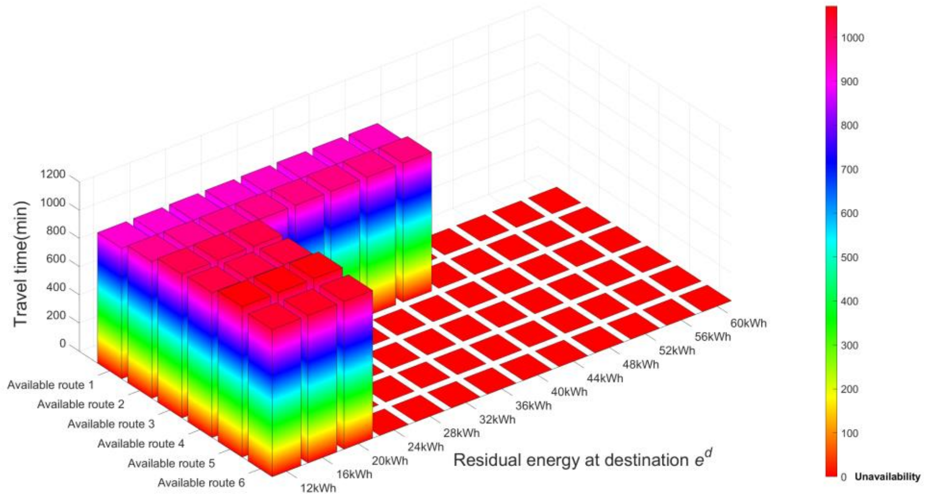
Conditions	Available routes	Generalized cost (yuan)

a_t=0.2	Available route 1	615.86
	Available route 2	639.26
	Available route 3	562.00
	Available route 4	**504.45**
	Available route 5	547.95
	Available route 6	538.65
a_t=0.5	Available route 1	896.74
	Available route 2	933.64
	Available route 3	869.35
	Available route 4	**815.40**
	Available route 5	869.70
	Available route 6	856.50
a_t=1	Available route 1	1364.86
	Available route 2	1424.26
	Available route 3	1381.60
	Available route 4	**1333.65**
	Available route 5	1405.95
	Available route 6	1386.25
a_t=1.5	**Available route 1**	**1832.99**
	Available route 2	1914.89
	Available route 3	1893.85
	Available route 4	1851.90
	Available route 5	1942.20
	Available route 6	1916.00
a_t=5	**Available route 1**	**5109.86**
	Available route 2	5349.26
	Available route 3	5479.60
	Available route 4	5479.65
	Available route 5	5695.95
	Available route 6	5624.25

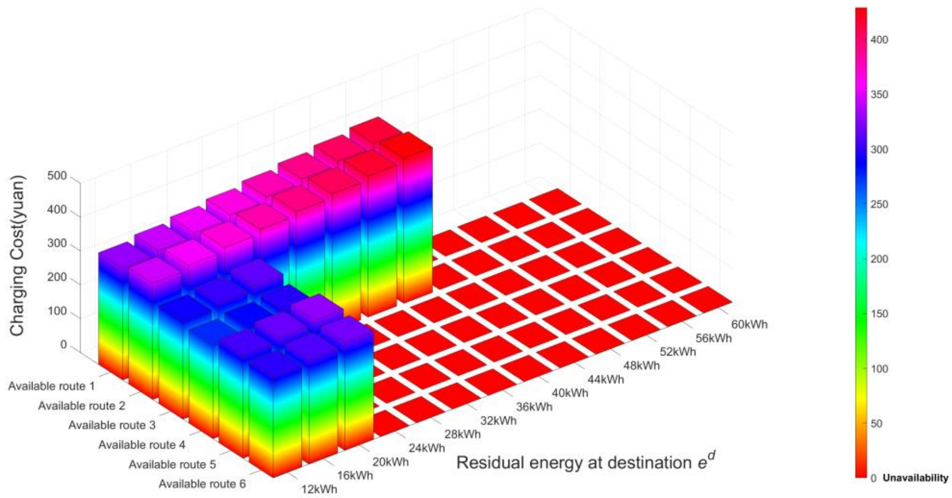
5.3. Impact analysis of residual energy at destination

In the numerical example, the residual energy at destination e^d is set to 12 kWh, which equals to the 20% of the nominal capacity of the BEV battery. Without loss of generality, we consider the 20% of the nominal capacity as the minimum requirement for the residual energy at destination e^d. However, some BEV drivers may tend to reserve more battery energy upon reaching their destinations (Bi et al., 2015; Bi et al., 2019). The travel cost components increase along with e^d due to the additional charging time and charging cost resulting from e^d. The availability of routes also changes as the value of e^d increases because the additional energy resulting from e^d increases the required amount of energy to traverse the routes, and such energy requirements may exceed the maximum energy that a BEV can use when traveling along these routes. Therefore, the residual energy at destination e^d can affect the travel cost and even the travel safety of BEVs.

With regard to the impact of the residual energy at destination e^d on the travel cost components, we conduct several simulations to explore the trends of travel time and charging cost with different values of e^d for each available route based on the example scenario. Specifically, the residual energy at destination e^d is set to different values between 12 kWh and 60 kWh at 4 kWh intervals. Fig. 8 presents the optimal travel time and charging cost under different e^d values for each available route. For those situations where the available route becomes unavailable, the corresponding travel time and charging cost are equal to 0.



(1) Optimal travel time



(2) Optimal charging cost

Fig. 8. Optimal travel cost components under different values of e^d for each available route.

In Fig. 8, cases (1) and (2) indicate the optimal travel time and charging cost under different values of e^d for each available route. In case (1), the optimal travel time for each available route demonstrates an upward trend as the value of e^d increases. Case (2) also exhibits a rising trend in charging cost along with an increasing value of e^d. Both cases (1) and (2) show that as the value of e^d increases to 24 kWh, the available routes 3-6 becomes unavailable, whereas the other two available routes still be used. However, when e^d reaches 44 kWh, available routes 1 and 2 also become unavailable, thereby leaving no available route in the network. Therefore, the residual energy at the destination significantly influences the travel cost components and the availability of routes in a road network. Given that the residual energy at the destination is one of the most important travel demand components for BEV drivers, such energy should be considered when formulating charging strategies.

6. Conclusions and policy implications

This study investigates the charging and traveling problem of BEVs in intercity travels. A multistage optimisation model that considers multiple charging events during a trip is proposed to explore this problem. Before modelling, an available route searching method is designed to determine those routes that can be used by a BEV to reach its destination in the road network. This method considers the impacts of charging station locations and limited driving range and obtains a set of available routes that can be regarded as candidate routes for the intercity travels of BEVs. A multistage optimisation model is also developed to determine the optimal charging strategy for each available route. In this model, the number of optimisation stages depends on the number of charging stations along the route. This model jointly minimises travel time and charging cost by introducing generalised cost. A dynamic programming method is also designed to obtain the optimal solution by considering the characteristics of the proposed model, which provides the optimal amount of charged energy in each charging station.

A numerical example is performed to demonstrate the feasibility of the proposed model and solution method, where 17 charging stations and six available routes are considered. The optimal amount of charged energy on each charging station along the available routes and the corresponding travel cost components are obtained in consideration of five conditions, and then the charging strategy with the lowest generalised cost amongst all available routes is selected as the optimal solution for a specified condition. The numerical example demonstrates that the proposed charging optimisation model can help BEV drivers complete their intercity travels and reduce their travel costs regardless of their preferences. The effects of residual energy at the destination on the charging strategy for intercity travels are also explored by performing several simulations, which results indicate that the residual energy at the destination significantly influences the travel cost components and the availability of routes in a road network. Based on these findings, BEV drivers should reserve a safety margin of battery energy to avoid situations where no available routes can be used for intercity travels. Moreover, the research results can also contribute to the BEV-based intercity travel policy proposal to attract more drivers with different preferences to utilize BEVs. Some of the policy implications are drawn as follows:

(1) The results from the study indicate that the charging time accounts for 10.32%-13.48% of the travel time. In general, it is difficult to reconstruct the highway network to decrease the driving time for intercity travels. Therefore, this is necessary to reduce the charging time by adopting high power chargers along highways to improve the travel efficiency and then attract more drivers, especially the drivers with relatively high value of time, to complete intercity travels using BEVs.

(2) As the primary monetary cost for BEV-based intercity travels, the charging cost has significant impacts on the drivers' acceptance for BEVs. The results from the study implies that the service cost accounts for 47.77%-54.46% of the charging cost. Thus, reducing reasonably the unit service cost is an effective means to improve the attraction of BEVs for intercity travels, especially for the drivers with relatively low value of time. Moreover, by adjusting the unit service cost, BEV drivers can be guided to choose suitable routes, and meanwhile the traffic equilibrium on highway networks would be realized, which is a critical issue when large-scale BEVs are adopted for intercity travels. Such a problem will be explored in our future work.

(3) Considering the conservative drivers who tend to reserve relatively high level of residual energy at destinations, additional charging stations should be constructed along highways to attract

these drivers to utilize BEVs for intercity travels. Meanwhile, this is essential to take the BEV driving range into account when determining the location of charging stations. In this way, more available routes would be generated and then more drivers would be attracted to use BEVs.

The energy consumption and driving time spent to traverse each link are assumed as constants in this study. Such assumption can reduce the model complexity yet leaves out the potential effects of traffic conditions on the operating state of vehicles. Traffic conditions may show time-varying characteristics, which may lead to similar energy consumption and driving time characteristics. Therefore, built upon the multistage optimisation model, BEV intercity travels should be examined in future research whilst taking time-varying characteristics into account. In addition, the road grade has impacts on the required energy. In the future work, we will adopt data-driven methods to investigate the relationship between road grade and required energy. The optimal charging strategy is projected to become increasingly accurate and practical by considering these factors.

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Appendix. Notation

Sets	
R'	Set of the candidate routes between the O-D pair, $r' \in R'$
R	Set of the available routes between the O-D pair and $R \subseteq R'$, $r \in R$
Parameters	
E	Nominal capacity of the BEV
$E^{r'}$	Maximum energy that the BEV can use in the route r', $r' \in R'$
e^o	Initial energy when the BEV has a charging demand.
$c^{r'}$	Number of the charging stations along the candidate route r', $r' \in R'$
c^r	Number of the charging stations along the available route r, $r \in R$
t_k^l	Driving time from *k*th charging station to the *k*+1 th charging station
τ_k	Charging time spent on per unit amount of charged energy in the *k*th charging station
η_k	Charging cost spent on per unit amount of charged energy in the *k*th charging station
η_k^e	Electricity price spent on per unit amount of charged energy in the *k*th charging station
η_k^s	Service cost spent on per unit amount of charged energy in the *k*th charging station

h_k	Residual energy as the BEV arrives at the *k*th charging station, *k*=1
a_t	Value of time
t_0^l	Driving time from the origin to the IACS
δ_0	Energy consumption from the origin to the IACS
δ_j	Energy consumption during the *j*th stage, $j > 1$
e^d	Residual energy as the BEV reaches its destination
Variables	
x_k	Decision variable, amount of charged energy in the *k*th charging station
h_k	Residual energy as the BEV arrives at the *k*th charging station, $k > 1$
Functions	
$T_k(x_k)$	Travel time during the *k*th stage with respect to the charging amount x_k
$C_k(x_k)$	Charging cost in the *k*th charging station with respect to the charging amount x_k
$f_k(h_k)$	Minimum generalized cost from the *k*th charging station to the destination with the value of h_k

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