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Stochastic planning for transition from shopping mall parking lots to electric vehicle charging stations

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ABSTRACT

Shopping mall parking lots are promising and popular sites across nations to be transitioned into charging stations due to the nature of land availability and attractiveness to people. Sufficient charging poles contribute to satisfactory user experience, but excessive charging poles jeopardise the financial feasibility. In this study, an optimal transition planning strategy is proposed that carefully balances the number of charging poles to maximise financial returns while ensuring user convenience. For this purpose, a charging demand model at shopping malls is obtained from historical parking records. A real-time parking bay allocation strategy is obtained according to the charging requests against the available charging poles with the consideration of the maximum demand tariff. To handle the inherent uncertainty of charging demand, we formulate the optimal transition planning problem into a stochastic programming framework. In the case study, we investigate the optimal transition plan for a shopping mall parking lot in the United Kingdom. The optimal results show the transition planning method increases the annual profit by 34% and user satisfaction by 37% compared to the baseline method. The insights for the transition plans that accommodate varying factors including EV penetration, types of charging poles, and charging prices are provided.

1. Introduction

The green transition of the transportation sector requires a shift from traditional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs). Numerous countries worldwide set ambitious targets for EV sales [1] and establish timelines to phase out the sale of fossil fuel-powered cars [2]. According to forecasts by the International Energy Agency (IEA), the global EV market share is expected to reach 20% by 2030 [3].

The fast adoption of EVs drives the need for widespread deployment of charging infrastructures [4]. As a result, many studies focus on the layout and capacity design of charging station networks [5–7]. However, the option of upgrading existing infrastructure, such as parking lots and petrol stations, into charging facilities receives less attention in the literature. Building brand-new charging stations generally offers more design flexibility, as they do not have to accommodate existing structures, but this comes with higher upfront costs, including expenses for site selection and land acquisition. Consequently, upgrading existing infrastructure is often a simpler and more cost-effective approach for charging service providers [8]. This study addresses the transformation of existing shopping mall parking lots into EV charging stations. For mall parking lot owners, this transition enables them to make profits by offering charging services. From the EV drivers' perspective, shopping malls are ideal locations to provide convenient charging services while drivers shop. On the one hand, it is anticipated that EV drivers would prefer to get the vehicle charged whenever parking or idling, as charging typically takes longer than refuelling a conventional vehicle at a petrol station. The average parking durations at shopping malls range from 1.5 to 3.36 h, according to studies [9–11], while current commercial charging technologies can deliver a range of 180 to 240 miles with just one hour of charging [8]. On the other hand, shopping is the second most common daily travel purpose, following trips to home, according to the National Household Travel Survey in the United States [12]. Multiple surveys reveal that EV drivers have high expectations for the availability of charging services during shopping [13,14]. For example, a survey in Virginia finds that up to 64% of drivers expect to charge their EVs at stores when needing to charge outside the home [13]. From a regulatory perspective, the transition complies with evolving regulatory standards. In countries like Norway, the Netherlands, and Germany, regulations mandate the installation of charging stations in new or renovated parking facilities [15,16].

To successfully transition parking lots into EV charging stations, parking lot owners must upgrade existing bays by installing vertical or

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wall-mounted charging poles, transformers, and completing the necessary civil and electrical work [8]. While most parking lot owners may not be experts in constructing charging stations, service providers like EVCSGO in the USA offer turnkey solutions for converting parking bays into charging stations [17]. Therefore, the key challenge for parking lot owners during this transition lies in the optimal deployment of charging infrastructure. While transforming the entire shopping mall parking lot into charging stations can offer maximum convenience for EV drivers, it disrupts the parking of traditional ICEVs and is not cost-effective due to the limited penetration rate of EVs and the high capital costs of charging poles [18]. However, an insufficient number of charging poles can harm user satisfaction, leading to lower customer retention [19]. Therefore, both over- and under-deployment of charging poles can jeopardise the sustainability of this transition. This study defines the problem as the optimal transition plan for parking lots, aiming to determine the ideal number of charging poles to deploy to maximise financial returns while ensuring user convenience. Since historical charging data are not available during the planning stage, an appropriate approach to estimate the future charging demand in the charging station should be explored. It is predictable that there are peak and off-peak periods of charging demand in shopping malls. Peak periods of shopping malls often coincide with visitors' convenience time before or after work or school [20]. The number of charging poles should be determined carefully to ensure user convenience during peak times while avoiding unnecessary oversupply during off-peak hours. At the same time, implementing charging management strategies can effectively adapt to grid electricity tariffs while maintaining user convenience, which contributes to reducing the number of charging poles needed. In addition, the charging demand exhibits uncertainties on different days in the number of EV arrivals, arrival times, duration of parking, and requested energy. Weekends, public holidays, and special events such as promotions significantly increase the number of consumers, leading to fluctuation in charging demand [21]. Deterministic planning methods to find the optimal number of charging poles relying on a typical charging demand profile would lead to inaccuracies in this dynamic context. Therefore, a new approach for the optimal transition planning for shopping mall parking lots needs to be developed.

2. Literature review on shopping mall charging station

Understanding the expected demand for EV charging stations is essential for the design of charging stations. Generally speaking, the charging demand can be obtained by aggregating all charging requests consisting of arrival time, parking time, and requested energy, of EV drivers. If the historical charging record is available, the shopping mall charging demand can be easily modelled. A shopping mall charging demand model provided in [20] based on historical charging data reveals there are two peak times within a day, occurring at 12:00 and 18:00, respectively. However, the charging data is simply unavailable at the planning stage. This requires us to analyse the shopping mall charging demand according to other data, such as activity data [22,23] and Google Popular Times data [24]. Activity data, which records drivers' travel activities including trip start/end time, trip propose, trip distance, and trip tool, are usually accessible from travel surveys [25]. In [22], spatial and temporal charging demand models for the Atlanta metropolitan area are developed by integrating the activity data and user charging choice model. The resulting model provides an average charging demand profile for shopping areas in 24 h, revealing a clear peak period between 10:00 and 22:00. However, variations in charging demand between different days, particularly on weekdays and weekends, are not modelled. Moreover, limited by the sample amount, the activity data-based charging demand models can only reflect part of the charging demand of all shopping areas. In [24], a charging demand simulation tool is developed for shopping mall charging stations, where the Google Popular Times data is adopted to simulate the arrival rate of EVs. The Google Popular Times data reveals the degree of busyness of the shopping mall during different times of the day, but it lacks details of the arrival hours of each vehicle. In addition, the tool relies on assumptions about EVs' parking behaviour and requested energy. This study suggests modelling shopping mall charging demand using historical parking data, which comes with several advantages. Accessing parking data is straightforward as it is available from the parking ticket system of shopping mall parking lots. This data accurately and comprehensively mirrors the quantity and trends of vehicle parkings within the shopping mall on different days. It provides details information on actual patterns of vehicle arrivals and parking durations, offering an authentic representation of driver behaviour.

The optimal transition problem aims to determine the optimal number of charging poles to be deployed in a parking lot to maximise the interests of investors. The queuing theory model, as a classical approach, is good at the congestion analysis of charging stations and finding the optimal balance between waiting time and the quantity of charging poles [26,27]. In [26], the ideal number of chargers for parking lot retrofitting is estimated based on the queuing theory model. A non-stationary Poisson process and time-varying parameter exponential distribution are used to describe arrival and parking duration, respectively, which improves the assumption that parking lots have constant arrival and service rates. The developed method is applied on Docklands' parking lot in Melbourne and suggests that under 30% EV penetration rate, the optimal strategy is to place chargers in 9% to 13% of the total number of parking spots, with payback period of 1.78 to 2.40 years. However, the proposed queuing model is based on the first come first served charging strategy, which ignores the fact that the charging request can be scheduled if the parking time is longer than the required charging time. As revealed in [28], 43% of charging requests in large retail are schedulable, failing to consider the flexibility offered by schedulable charging requests results in an overestimation of the required capacity for shopping mall charging stations. At the same time, charging demand uncertainty is not considered in [26]. To overcome the shortcomings of queuing theory models, we suggested a stochastic optimisation framework for our optimal transition problem of shopping mall parking lots. Stochastic programming is widely applied in the charging station capacity planning problem [29–31]. In [30] investigates the optimal sizing of charging stations considering the quality of service. The quality of service is defined according to the probability that an EV will suffer a delay in the completion of its charging task. The sizing problem is formulated as a cost-minimisation problem with chance constraints. In [31], it proposes a two-stage stochastic framework for the single output multiple cables charging station planning, where the first stage obtains an optimal configuration of the charging station to minimise the station's equivalent annual investment costs. The second stage simulates the coordinated charging process to minimise the expectation of operation cost including electricity cost and penalty of unfulfilled energy. The stochastic programming approach is also applicable to the optimal transition problem since the shopping mall charging demand exhibits uncertainties on different days in the number of EV parkings, arrival times, duration of parking, and requested energy. It is predictable that the shopping mall charging demand will increase on weekends, public holidays, and special events due to the significant increase in the number of consumers [21].

The charging scheduling strategy is a prioritised vehicle charging management plan that determines the charging order, allocates charging poles, and controls the charging power of EVs to maximise charging station investors' interests. In shopping mall charging stations, shopping mall charging station owners need to formulate proper charging scheduling strategies in response to electricity tariffs. Maximum demand charges tariffs are widely applied to business consumers, which significantly increase the energy costs of shopping mall charging station owners [32,33]. Ref. [32] concludes that EV charging at retail buildings significantly increases the demand charge of the annual electricity bill, especially in cold-climate areas, where the increase is as high as 88%.

It should be noted that the concepts of peak demand and maximum demand are different because the maximum demand is only recorded in specific demand windows [34]. In [28], a demand-charge-reducing approach that combines a real-time water-filling algorithm and active demand response and load control is proposed. The proposed method shows that the maximum demand in large retail caused by EV charging can be reduced by 40% under the 30% EV penetration rate. However, the proposed strategies require EVs' long-term occupation of charging poles, thus decreasing the utilisation rate of charging poles. In [35,36], improved charging strategies are used, which allow EVs to connect to charging poles and complete charging in a specific duration during parking time. For example, in [35], the uninterrupted battery charging management strategy for battery swapping stations is investigated, where the charging start time and charging power of batteries are optimised to maximise the total profit. Such a problem is formulated as a two-dimensional-rectangle packing problem and solved by the mixed-integer linear program. In [36], an uninterrupted charging scheduling approach is proposed to smooth the aggregated load profile and reduce peak demand. The proposed algorithm is designed as a decentralised framework and eliminates the need for heavy computations and extensive bi-directional communications, which makes the developed approach particularly suitable for real-time implementation. Refs. [28, 35–37] do not consider the limit of the number of charging poles. This simplification is reasonable only in a few cases, i.e., the number of charging poles is significantly more than the number of EVs [38]. Such a problem cannot be simplified when considering the optimal design of shopping mall charging stations because the number of charging poles directly affects the investment cost of charging station owners. Recognising these challenges and limitations, this study introduces a real-time parking bay allocation strategy. This strategy is aimed at determining the optimal charging start times for EVs, considering both the need to reduce maximum demand and the constraints imposed by the limited number of charging poles.

Our work is closely related to the aforementioned research but significantly differs from them. The primary focus lies in promoting the transition from existing infrastructure such as shopping mall parking lots to charging stations, as opposed to the construction of brand-new charging stations as studied in [6,7]. Our objective is to stimulate interest from potential investors and municipalities towards the development of shopping mall charging stations. To achieve this, we offer an optimal transition planning strategy designed to determine the ideal number of charging poles for installation. On the technical aspect, the literature review of existing studies highlights several technical challenges that have not been adequately addressed, particularly in the domains of shopping mall charging demand modelling, charging scheduling strategies, and capacity planning. Considering the unavailability of charging demand data in the planning phase, we develop a shopping mall charging demand modelling approach based on historical parking data. The method prioritises data accessibility and reliability of shopping mall parking lots and is able to comprehensively mirror the trends of charging demand within the shopping mall on different days. It can be independently applied to various parking lots. Furthermore, the characteristic of schedulable of shopping mall charging demand promotes us to formulate a charging management strategy to allocate charging requests to available charging poles. This strategy takes into account commonly used maximum demand tariffs in commercial areas. Compared with maximum demand reduction strategies studied in [28,35–37], the developed strategy operates taking the limited number of charging poles into consideration and operates in real-time, enhancing its realism and applicability. Additionally, compared with the approach proposed in [26], we frame the planning problem within a stochastic programming framework, taking the inherent uncertainty associated with shopping mall charging demand into account.

3. Problem statement

EVs are widely recognised for their environmental friendliness compared to ICE vehicles. However, the disadvantage of driving an EV is ensuring timely access to charging facilities to alleviate range anxiety. The National Household Travel Survey from the United States shows that the top 3 people's daily travel purposes are home (34.3%), shopping (19.5%), and work (16.6%) [12]. Therefore, convenient access to EV charging at these locations, such as homes, shopping malls, and workplaces, across the country or region is essential for EV adoption. Upgrading the shopping mall parking lot into EV charging stations is a viable solution as it enhances the shopping experience for EV drivers and attracts more of them to shopping malls. One of the key challenges of transforming a parking lot into a charging station is to ensure users' convenience whilst demonstrating financial viability. The user convenience mainly links to the number of available charging poles in shopping mall charging stations. Intuitively, the more charging poles, the higher user convenience. However, excessive charging poles may jeopardise the financial feasibility of such a transition. To address this challenge, we propose an optimal transition planning strategy to determine the optimal number of charging poles for installation. The unknown shopping mall charging demand model brings challenges to the transition planning strategy problem. Since the historical charging demand data is unavailable, a charging demand model derived from historical parking data is proposed. Based on the established demand model, the optimal number of charging poles needs to be carefully determined to ensure user convenience during peak times while avoiding unnecessary oversupply during off-peak hours. At the same time, the application of charging management strategies helps smooth charging demand and maximise charging profit with the limited number of charging poles needed. Charging demand changes on different days in terms of volumes of EVs, arrival times, and parking times, particularly on weekends, public holidays, and promotion days, with notable increases in charging demand. To overcome the variations of charging demand, our study introduces a two-stage stochastic optimisation problem including both investment and operation stages for the optimal transition plan problem. The decision variables include the number of charging poles at the investment level the charging start time and the charging power of EVs at the operational level. At the investment level, the problem is constrained by the capacity of the shopping mall parking lot. At the operation level, constraints on the rated power of charging poles, the maximum demand, the parking time, and the number of charging poles to be installed take effect. Several vital energy and price models are developed to enable the problem formulation, which are introduced in the following sections.

4. Charging demand modelling

Intuitively, the number of charging poles required for the design of the shopping mall charging station is determined by the actual charging demand from the EVs. Therefore, the identification of the charging demand is crucial. To start with, we define several key charging demand profiles, including requested charging demand, rescheduled charging demand, and actual charging demand, as illustrated in Fig. 1. The requested charging demand is defined as the sum of EVs' maximum chargeable energy. The requested charging demand curve may have peaks and valleys due to drivers' natural charging behaviours [39]. Restricting the number of charging poles installed and implementing demand-side management techniques can reshape the requested charging demand curve, resulting in a rescheduled charging demand [28]. The trend of the rescheduled charging demand curve can be various, determined by the charging station owner's interest. In Fig. 1, we use a flat curve as an example, representing that the charging station owner aims to flatten the peak–valley difference. The rescheduled charging demand serves as a reference power level to guide the charging stations in managing EV charging. The actual charging demand is the real

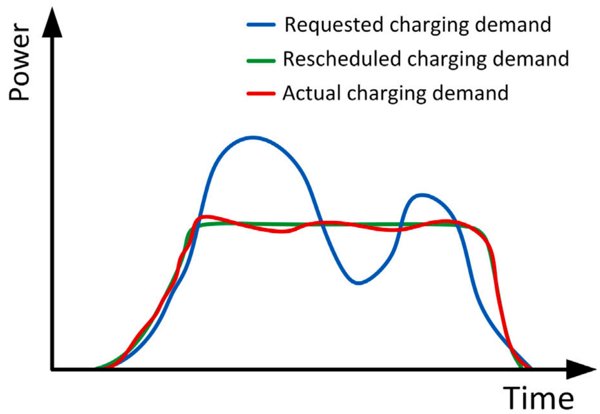

Fig. 1. The requested charging demand, rescheduled charging demand, and actual charging demand.

charging power offered by the charging station to the EV drivers, only available after the shopping mall charging station is open for use. Due to the power supply uncertainties, or sudden changes in drivers' charging requests, the actual charging demand may also deviate from the rescheduled charging demand. In the planning stage, it is assumed that the actual charging demand equals the rescheduled charging demand. This assumption holds when the grid power supply is reliable and no EV drivers would change their charging request after submission.

Without loss of generality, we try to model the requested charging demand profile on a daily basis based on the historical parking data. Since the requested charging demand is not measurable, we have to obtain it by the analytical method. The requested charging demand profile is determined by the integration of all charging demand requests. Key determinants for the daily requested charging demand profile are (1) the number of EVs that will park at the parking lot; (2) the EV arrival time; (3) the EV departure time; and (4) the maximum chargeable energy of each EV.

Let the daily number of vehicles parking at the shopping mall parking lot be denoted as G, encompassing both EV and ICEV are included. Considering that the historical parking records might lack specific features on vehicle type (EV or ICEV), the daily number of EVs parking at the shopping mall charging station is calculated based on the EV penetration rate α in the area of interest, which can be sourced from statistics from local governments and institutions such as [40]. This study assumes that both ICEV and EV drivers have similar travel patterns and parking habits when engaging in shopping activities. Then, the daily number of EV parkings at the shopping mall charging station is αG. Since vehicle flows on different days show differentiated features in terms of arrival time and parking time, the arrival time t_i^{arr} and parking time t_i^{dep} follow different distributions in different days. The arrival and parking time records can be obtained from the parking ticket system at the shopping mall. The scheduling horizon is set as 24 h and is divided into K time slots. The length of a time slot is Δt. Assume the charging state of each EV remains unchanged during a time slot. The available park-starting and park-ending time slots of EV i are calculated by

$$\bar{t}_i^a = \text{ceiling}\left(\frac{t_i^{arr}}{\Delta t}\right), i \in I, \tag{1}$$

$$\bar{t}_i^d = \text{floor}\left(\frac{t_i^{dep}}{\Delta t}\right) - 1, i \in I, \tag{2}$$

where I is the set of EVs, ceiling$(\cdot)$ is the roundup function, floor$(\cdot)$ is the rounddown function. When $\bar{t}_i^d < \bar{t}_i^a$, it means no available parking time slot exists after time discretisation. When $\bar{t}_i^d \geq \bar{t}_i^a$, the total number of parking time slots that is available for charging can be calculated as $\bar{t}_i^d - \bar{t}_i^a + 1$. Let SOC_i represent the SOC of EV i's battery when it arrives at the charging station and C_i represent the battery capacity of EV i. The requested charging demand of EV i is

$$E_i^{req} = (1 - SOC_i)C_i. \tag{3}$$

Limited by the availability of charging poles, it is possible that the requested charging demand may not be fully satisfied. Let J be the set of candidate charging poles to be installed and $m = |J| \leq \bar{m}$ be the total number of charging poles to be installed, where $\bar{m}$ is the number of parking bays in the shopping mall parking lot. Considering the limited parking time and amount of charging poles, the requested charging demand of EV i is rescheduled as

$$E_i^{res} = \min\left\{\left(\bar{t}_i^d - \bar{t}_i^a + 1\right) p^{\max}\Delta t, d_i p^{\max}\Delta t, E_i^{req}\right\}, \tag{4}$$

where $p^{\max}$ represents the rated power of charging poles to be installed and d_i is the maximum available number of continuous time slots within the parking duration of EV i. Fig. 2 is provided to illustrate how to obtain d_i. It displays the occupation status of the charging poles when EV i arrives (only two charging poles in the example). According to Fig. 2, the available continuous time slots provided by charging stations are (1) time slots k, (2) times slots $k+1$ and $k+2$, and (3) times slots $k+4$ and $k+5$, thus the maximum available number of continuous-time slots d_i is 2.

To define d_i mathematically, we first define the charging pole occupation state variable x_{ij}^k, which is a binary variable. $x_{ij}^k = 1$ represents that the charging pole j is occupied by EV i at time slot k. When EV i arrives at the charging station, according to x_{ij}^k, $\bar{t}_i^a$, and $\bar{t}_i^d$, the charging management system can calculate d_i by $d_i = \max\{H | \sum_{h=0}^{H} x_{ij}^{r+h} = 0, \forall j \in J, \bar{t}_i^a \leq r, r+h \leq \bar{t}_i^d\} + 1$. Note that $d_i = 0$ indicates that there is no available charging pole for EV i within the parking duration, thus $E_i^{res} = 0$.

The input parameters of the proposed charging demand model include the arrival time and parking time, the EV battery capacity, the arrival SOC, and the maximum power of charging poles. The statistical features of arrival time and parking time are available from the parking ticket system of the parking lot. The average battery capacity of EVs can be estimated using data from available EV models on the market. For the SOC, it is assumed to follow a beta distribution in [24] and follow a uniform distribution within the interval [0, 1] in [41]. In [22,23,42], the arrival SOC is obtained based on travel chains, which calculates the arrival SOC by considering the remaining energy of the EV from its previous destination and the energy consumption during the journey to the next destination. However, it introduces more assumptions on the initial SOC of EVs and the travel distance between two destinations. In practice, to avoid too many assumptions, the arrival SOC uses the Weibull distribution with scale parameter $\lambda = 0.8$ and shape parameter $c = 10$. This choice is based on the work in [20]. Their model is derived from real charging data collected from existing shopping mall charging stations. The requested charging demand is only determined by the states of arriving EV batteries, which is the maximum energy that can be charged. The rescheduled charging demand is determined by the rated power of installed charging poles, available charging time slots, and parking time. The rescheduled charging demand of one EV cannot exceed its requested charging demand.

5. Charging station operation

5.1. Electricity tariffs

This section gives the grid electricity tariffs and EV charging service fees. Compared with [26], a more general grid electricity tariff structure consisting of time-of-use (TOU) and maximum demand (MD) tariff is considered. The time-of-use tariff is given by

$$c_k^{tou} = \begin{cases} c^p, & \text{Peak period}, \\ c^s, & \text{Standard period}, \\ c^o, & \text{Off-peak period}. \end{cases} \tag{5}$$

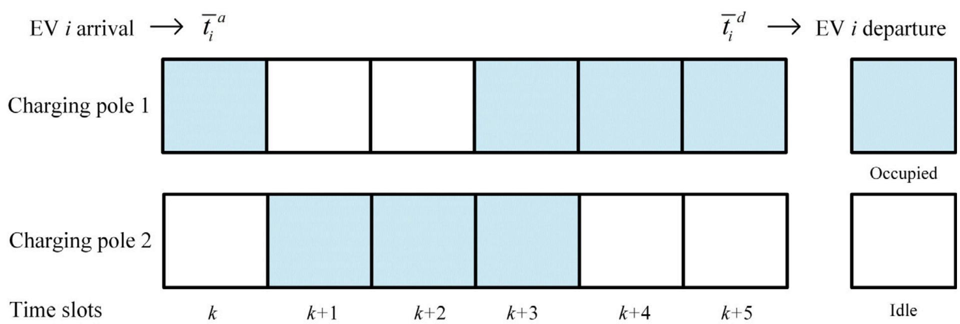

Fig. 2. Charging process of EV i.

The maximum demand charge is calculated based on the highest half-hourly electricity consumption within the demand window on any given day. The maximum demand tariff is defined as c^{md}/kVA and the demand window is defined by $[t_s^d, t_e^d)$. t_s^d and t_e^d are the start time and end time of the demand window, respectively. The time-of-use and maximum demand tariffs promote the charging demand shifting to the non-peak and non-demand window periods, respectively. The maximum demand tariff further encourages the charging station owner to reduce peak demand during the demand window. Since the design of the charging pricing exceeds the scope of this study, a fixed charging service fee of c^c per kWh is adopted.

5.2. Shopping mall charging station operation mode

The parking lot is divided into charging and non-charging areas. A charging management system will be integrated into the existing parking management system, forming a shopping mall vehicle management system to handle both parking and charging operations. Vehicles without charging requests are directed to the non-charging area, while those with charging requests are managed according to a predefined scheduling mechanism. Upon departure from the mall, vehicles are charged parking fees, with additional charging service fees applied if charging services are used. Specifically, when an EV arrives at the shopping mall charging station, it submits a charging request to the vehicle management system, including details such as arrival time, parking duration, and requested energy. The system checks the availability of charging poles, rejecting the request if no poles are available within the parking duration. If idle poles are available during the EV's parking period, the system guides the EV to the non-charging area to wait and assigns it a charging pole at the appropriate time. EV drivers can move their vehicles to the charging area themselves or use valet parking services. The charging start time and end time are determined by the proposed scheduling algorithm and will inform the drivers. Once the charging is over, drivers are required to transfer their EVs to the non-charging area. Charging station owners can implement a penalty policy to disincentivize the overstaying issue, like Tesla [43]. In the planning stage, we assume that all EV drivers will transfer their EVs in time after completing charging.

5.3. Charging without scheduling

This section describes the charging process without scheduling. It is regarded as a baseline model for the proposed charging strategy, suggested in [26,44]. The charging process without optimal scheduling is described as follows. EVs occupy parking bays with installed charging poles according to the first come first served principle and are charged at the maximum power until the battery is fully charged. The charging request will be declined if there is no available charging pole during the parking duration. Let t_i^s be the IDs of the charging start time slot of EV i, $t_i^s \geq \bar{t}_i^a$. The total energy that EV i obtained from the charging station at the beginning of time slot k is derived as

$$E_i^k = \begin{cases} 0, \text{ if } k < t_i^s, \\ \min\{E_i^{res}, E_i^{k-1} + p^{\max}\Delta t\}, \text{if } k \geq t_i^s, \end{cases} \tag{6}$$

$E_i^k = 0$ before EV i connects to one charging pole. After EV i connects to one charging pole, it will be charged at the maximum power $p^{\max}$ until the requested energy E_i^{res} is satisfied.

5.4. Proposed parking bay allocation strategy

In this study, a real-time parking bay allocation strategy is proposed. When ith EV arrives at the charging station the following optimisation problem is solved to allocate a parking bay with an installed charging pole and determine the charging start time slot t_i^s and charging power p_i^k for EV i. The goal of the strategy is to maximise the daily profit D_i of the charging station, which is calculated based on the charging revenue and costs.

$$\max_{t_i^s, p_i^k} D_i = \sum_{k=1}^{K} (c^c - c_k^{tou})(p_{load}^k + p_i^k)\Delta t - c^{md} \max_{t_s^d \leq k < t_e^d} \left\{p_{load}^k + p_i^k\right\}, \tag{7}$$

subject to

$$\bar{t}_i^a \leq t_i^s < t_i^s + d_i \leq \bar{t}_i^d, \tag{8}$$

$$p_i^k \leq p^{\max}, \ \forall k \in [t_i^s, t_i^e), \tag{9}$$

$$p_i^k = 0, \ k < t_i^s, k \geq t_i^s + d_i, \tag{10}$$

$$E_i^k = E_i^{k-1} + p_i^k \Delta t, \ \forall k \in K, \tag{11}$$

$$E_i^k = E_i^{res}, \ k = t_i^e, \tag{12}$$

where $p_{load} = (p_{load}^1, \dots, p_{load}^K)$ is the total rescheduled charging demand profile of EVs arriving before EV i. Constraint (8) ensures that the actual charging start and end times are within the parking duration. Constraints (9) and (10) are the power limits of charging poles. Constraint (11) is the energy balance equation of EV batteries. Constraint (12) ensures that the EV's charging request is fully satisfied when it is disconnected from the charging pole. By introducing a new decision variable z, we have the following equivalent linear form of (7),

$$\max_{t_i^s, p_i^k} D_i = \sum_{k=1}^{K} (c^c - c_k^{tou})(p_{load}^k + p_i^k)\Delta t - c^{md} z, \tag{13}$$

and z satisfies

$$z \geq p_{load}^k + p_i^k, \ \forall k \in [t_s^d, \ t_e^d). \tag{14}$$

The pseudo-code of the proposed real-time parking bay allocation algorithm is given in Algorithm 1. When EV i arrives at the charging station, it submits a charging request $(t_i^a, t_i^d, E_i^{req})$. The charging management system reads the current charging station status including p_{load} and x_{ij}^k. Then, the charging management system calculates d_i and E_i^{res}. The charging request is rejected if all charging poles are fully occupied during the parking time of EV i ($d_i = 0$). Otherwise, the charging management system finds the optimal charging start time slot t_i^s, charging pole j^*, and charging power p_i^k for EV i by solving the optimisation problem (13). By enumerating all available charging poles and time slots, the solution with the maximum profit is adopted as the charging instruction for EV i. If there are multiple solutions with the same maximum profit, the solution with the earliest start time and the minimum charging pole ID number will be assigned to EV i. According to the solution, the charging management system updates p_{load} and x_{ij}^k, outputs the charging instruction to EV i, and then waits for the next EV.

Algorithm 1: The real-time parking bay allocation algorithm for EV i.

Input: charging request (t_i^a, t_i^d, E_i^{arr}) of EV i
Read current charging pole occupancy state x_{ij}^k and charging load p_{load}^k
Calculate reschedule charging demand E_i^{res} and d_i according to (4)
Reject charging request i if $d_i = 0$
Solve optimisation problem (13) with constraints (8)-(12), and (14) to find charging start time t_i^s, allocated charging pole j^*, and charging power p_i^k
Update charging pole occupancy state x_{ij}^k
Update charging load $p_{load}^k = p_{load}^k + p_i^k$
return charging start time t_i^s, allocated charging pole j^*, and charging power p_i^k for EV i

6. Optimisation problem formulation

In this section, an optimisation problem is formulated to find the optimal number of charging poles for the shopping mall charging station to maximise the NPV of the investment of a shopping mall charging station. Considering the randomness of charging demand, this problem is formulated as stochastic programming. The objective function that aims to maximise the N-year NPV of the charging pole investment is formulated as follows:

$$\begin{aligned} &\max_m \mathrm{NPV} = -C_I + \textstyle\sum_{n=1}^{N} \frac{1}{(1+r)^n} \left(\mathbb{E}[C_P] - C_M\right), \\ &C_I = c_1 m, \\ &C_P = 365 D_{|I|}, \\ &C_M = c_2 m, \end{aligned} \tag{15}$$

where C_I is the total investment cost, c_1 is the investment cost of the unit charging station including the purchase cost of one charging pole and retrofitting cost for one parking bay. C_P is the annual profit by providing charging service. Considering the uncertainty of charging demand, we use the expectation of C_P. C_M is the annual management and maintenance cost, and c_2 is the annual management and maintenance cost per charging pole. r is the discount rate and N is the service life of charging poles.

The stochastic problem is solved by the sample average approximation (SAA) [45], where we sample different problem instances from the probability distribution of parameters $\bar{t}_i^a, \bar{t}_i^d$ and E_i^{req} and obtain an estimation of $\mathbb{E}[C_P]$. In particular, we create a set S of problem scenarios, where in each scenario a set $I^{(s)}$ with parameters $\bar{t}_i^{a,(s)}, \bar{t}_i^{d,(s)}$ and $E_i^{req,(s)}$ is created to represent the EV fleet. Then

$$\mathbb{E}[C_P] = 365 \frac{1}{|S|} \sum_{s=1}^{|S|} \gamma^{(s)} D_{|I|}^{(s)}, \tag{16}$$

where $\gamma^{(s)}$ is the probability of scenario s. $\mathbb{E}[C_P]$ is obtained after all scenarios are evaluated, then, the N-year NPV can be calculated.

7. Case study

This section provides a case study to illustrate the effectiveness of the proposed approach. We start with the analysis of vehicle parking patterns in the shopping mall parking lot.

Table 1
Vehicle parking statistics.

Number of vehicle parkings	Day(s)			
	Weekday	Saturday	Sunday	Total
0–500	1	0	1	2
500–1000	190	1	14	205
1000–1500	44	19	26	89
1500–2000	24	22	7	53
2000–2500	2	2	3	7
2500–3000	0	5	1	6
3000–3500	0	2	0	2
3500–4000	0	1	0	1
Total	261	52	52	365

7.1. Vehicle parking pattern analysis in the shopping mall parking lot

The vehicle parking pattern analysis of the shopping mall parking lot is based on data from 1 Oct 2018 to 30 Sep 2019 of Grafton East car park, which is a parking lot located at the Grafton shopping centre with 769 parking spaces [46]. We divide the dataset into two parts: 80% of the data used for modelling and 20% of the data used for validation. The parking statistics during the time period of Grafton East car park are shown in Fig. 3. The vehicle parking statistics are summarised in Table 1. The distributions of arrival time and parking time of each day are shown in Fig. 4. For parking records, we have the following observations:

- The number of visits per week is periodic. The number of visits on weekdays is lower than the number of visits on weekends, where the Saturday visits are more than the Sunday visits.
- The maximum and the minimum number of visits on weekdays are 2107 vehicles on 29th May and 512 vehicles on 17 September, respectively. There are 234 days with the number of visits between 500 and 1500, accounting for 91% of the weekdays. The average number of visits on weekdays is 885 vehicles.
- The maximum and the minimum number of visits on Saturday are 3650 vehicles on 3rd November and 1177 vehicles on 20th April, respectively. There are 41 days with the number of visits between 1000 and 2000 vehicles, accounting for 79% of the total number of Saturdays. The average number of visits on weekdays is 1748, which is twice the amount on weekdays.
- The maximum and the minimum number of visits on Sunday are 2512 vehicles on 7th November and 273 vehicles on 21st April. There are 40 days with the number of visits between 1000 and 2000 vehicles, accounting for 77% of the total number of Saturdays. The average number of visits on weekdays is 1245 vehicles.
- The distribution of arrival time from 16:00 to 20:00 on Wednesday is slightly different from other weekdays. The distributions of arrival times on weekdays, Saturdays, and Sundays are obviously different. On weekends, the vehicles arrive at the shopping mall earlier than on weekdays, especially on Sundays. The distributions of parking time for each day are roughly the same.

According to the above observations, the number of vehicles and arrival time distribution vary between weekdays, Saturdays, and Sundays, thus we select weekdays, Saturdays, and Sundays as typical days to generate charging demand scenarios. The arrival time distributions $f^{arr}(k)$, and the parking time distributions $f^{par}(k)$ of weekday, Saturday, and Sunday are shown in 5. Drivers' parking time is slightly longer on weekends than on weekdays. Let subscripts X_{pre} and X_{rea} represent the prediction value and real value, respectively. The following error functions are presented.

The prediction error of the number of vehicles

$$e_{veh} = |n_{pre} - n_{real}|/n_{pre}. \tag{17}$$

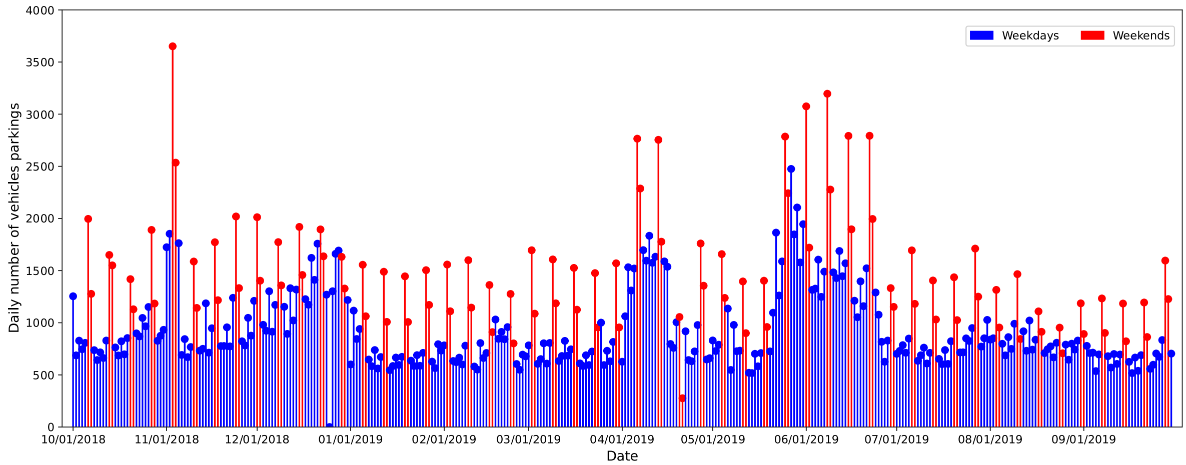

Fig. 3. Parking statistics from 1 Oct 2018 to 30 Sep 2019.

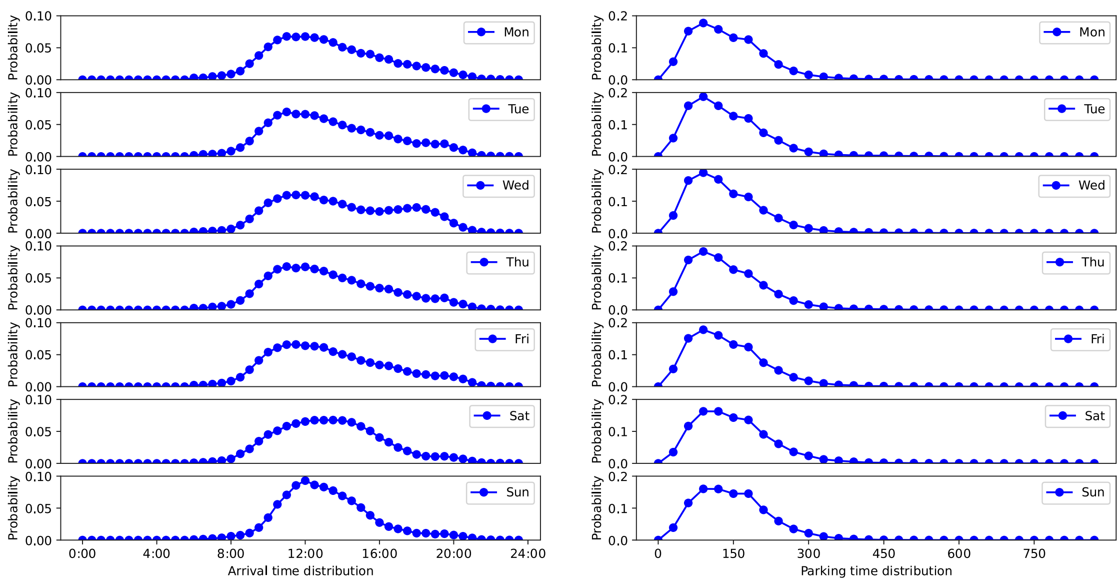

Fig. 4. Distributions of arrival time and parking time of each day.

Table 2
Model validation results.

Error	Weekday	Saturday	Sunday
e_{vhe}	3.90%	8.95%	4.73%
e_{arr}	2.42%	3.49%	7.84%
e_{par}	1.68%	2.74%	3.46%

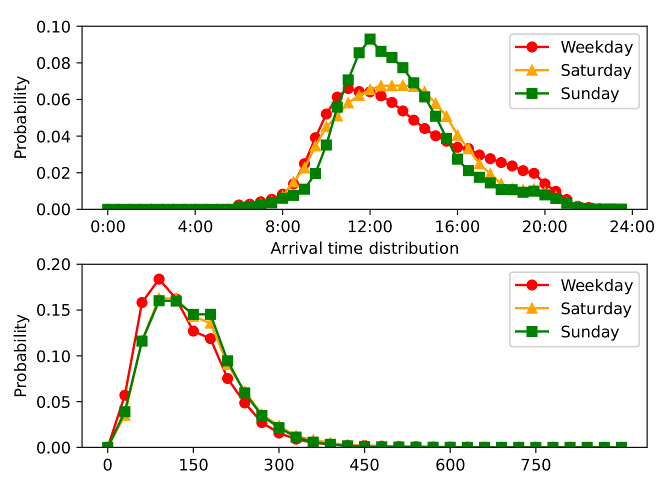

Fig. 5. Arrival time and parking time distributions.

The prediction error of the arrival time distribution

$$e_{arr} = \sum_{k=1}^{K} |f_{pre}^{arr}(k) - f_{rea}^{arr}(k)| / \sum_{k=1}^{K} f_{pre}^{arr}(k). \tag{18}$$

The prediction error of the parking time distribution

$$e_{par} = \sum_{k=1}^{K} |f_{pre}^{par}(k) - f_{rea}^{par}(k)| / \sum_{k=1}^{K} f_{pre}^{par}(k). \tag{19}$$

Based on the remaining 20% of data, the validation results are summarised in Table 2.

Table 3
Parameter settings.

Parameters	Value	Unit
Charging station open time	6:00–24:00	
Time interval Δt	30	min
Charging pole price c_1	3450 [49]	\$/pole
Rated power of charging poles $p^{\max}$	19.2 [49]	kW
Lifetime of charging pole N	9	year
Maintenance fee c_2	2%c_1 [50]	\$/pole
Charging service fee c^c	0.3	\$/kWh
EV penetration α	0.1	
Average EV battery capacity	72 [51]	kWh
Discount rate r	10%	

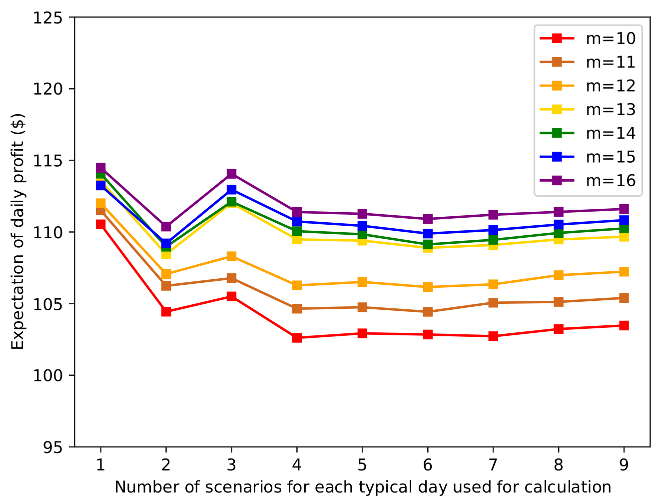

Fig. 6. The results stability of the sample average approximation method with respect to the number of scenarios and the number of charging poles m.

7.2. Simulations and results

The numerical simulation is performed by using Gurobi solver [47], on an Intel Core i9-12900 CPU @3.20 GHz, 32 GB RAM. The parameters used in the simulation are given by Table 3. The time-of-use tariff is given by

$$c_t^{tou} = \begin{cases} 0.1242 \text{ \$/kWh}, & t \in [0,7), [22,24), \\ 0.1578 \text{ \$/kWh}, & t \in [7,14), [20,22), \\ 0.1981 \text{ \$/kWh}, & t \in [14,20). \end{cases}$$

The maximum demand tariff is $c^{md} = 0.3574$ \$/kVA per day and the demand window is from 14:00 to 20:00 [48].

According to the analysis in Section 7.1, scenarios are generated to simulate requested charging demand profiles on weekdays, Saturdays, and Sundays. Each scenario contains four key parameters: (1) The number of EVs at the parking lot; (2) the EV arrival time; (3) the EV departure time; and (4) the arrival SOC of each EV. The daily number of EV parkings at the parking lot is determined by the average number of vehicles parkings on weekdays, Saturdays, and Sundays obtained in Section 7.1. The EV arrival time and parking time are generated from distributions given in Fig. 5. The arrival SOC of each EV is generated according to the Weibull distribution with scale parameter $\lambda = 0.8$ and shape parameter $c = 10$ as discussed in Section 4. In addition, the number of scenarios is critical in the sample average approximation approach. The optimal solution converges to the expectation as the number of scenarios approaches infinite. However, too many scenarios increase the computational complexity. To balance the accuracy and computing complexity, the relationship between the expectation of daily profit and the number of scenarios is tested under different numbers of charging poles m. The results are shown in Fig. 6. It can be seen that the number of charging poles has no significant impact on the optimal number of scenarios. The expectation of daily profit is stable when the amount of samples of each typical day is greater than or equal to 4. To balance the computational burden and accuracy, we chose 6 samples for each typical day (18 scenarios in total). According to the given parameters, the average requested charging demand profiles of weekdays, Saturdays, and Sundays, and weighted average requested charging demand are drawn in Fig. 7. It can be seen that the requested charging demand on Saturday is the highest and the charging demand on weekdays is the lowest. The peak demand occurs at 12:30 on weekdays and Sundays, while on Saturdays it peaks at 14:00.

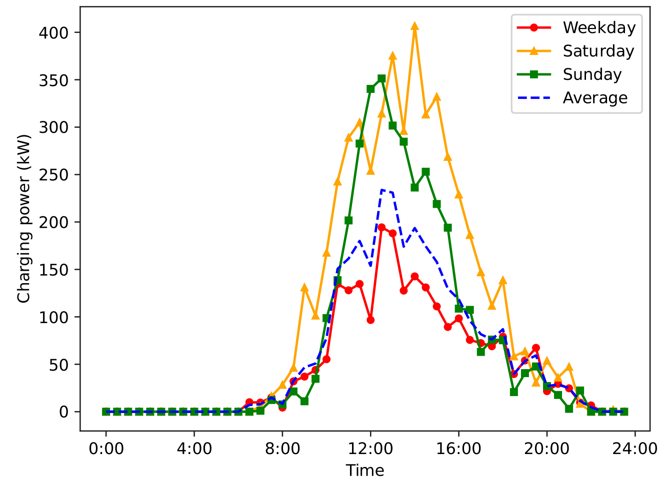

Fig. 7. Requested charging demands on different days.

7.3. Optimal number of charging poles and NPV

For the designed shopping mall charging station, the following indicators are used for performance evaluation. Since we categorise the scenarios into weekdays, Saturdays, and Sundays, the average values of each scenario and weighted values of all scenarios of these indicators are calculated. The weighted values for these three scenarios are derived based on the frequency of each day type in a typical year. The weights assigned to the scenarios are 261/365 for weekdays, and 52/365 for both Saturdays and Sundays, respectively.

(1) Energy consumption and maximum demand

The energy consumption is calculated by

$$\phi^{en,(s)} = \sum_{k=1}^{K} \sum_{i=1}^{I^{(s)}} p_i^{k,(s)}, \tag{20}$$

The maximum demand $\phi^{md,(s)}$ is z kVA.

(2) Electricity cost and profit

The energy cost is calculated by

$$\phi^{ec,(s)} = \sum_{k=1}^{K} \sum_{i=1}^{I^{(s)}} c_k^{tou} p_i^{k,(s)}, \tag{21}$$

The maximum demand charge $\phi^{md,(s)}$ is calculated by $c^{md} z$. The profit $\phi^{pr,(s)} = c^c \phi^{en,(s)} - \phi^{ec,(s)} - \phi^{md,(s)}$.

(3) Utilisation rate of charging poles

The hourly utilisation rate of the charging pole at the time interval k in scenario s is calculated by

$$\phi_k^{ur,(s)} = \frac{\text{Number of EVs charged at time interval } k \text{ in scenario } s \ (p_i^{k,(s)} > 0)}{\text{Number of charging poles}}. \tag{22}$$

Table 4
Optimal results with $m^* = 13$.

Day	Energy (kWh)	Maximum demand (kVA)	Energy cost ($)	Demand charge ($)	Profit ($)	Utilisation rate	User satisfaction
Weekday	1166	140	202	50	98	43%	100%
Saturday	2043	220	356	79	174	75%	82%
Sunday	1589	220	281	79	117	58%	88%
Average	1351	163	236	58	130	50%	96%

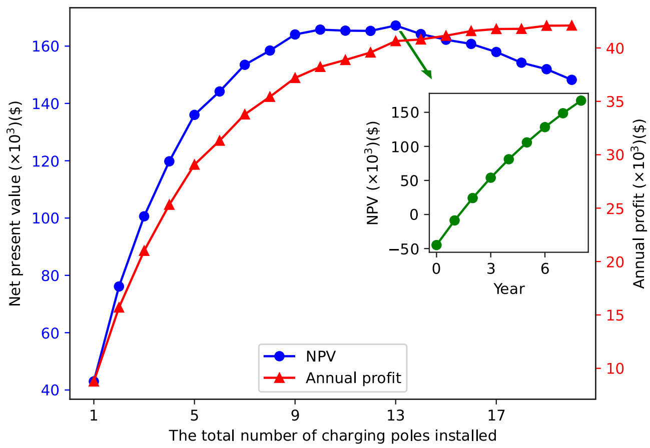

Fig. 8. NPV and annual profit under different number of charging poles installed.

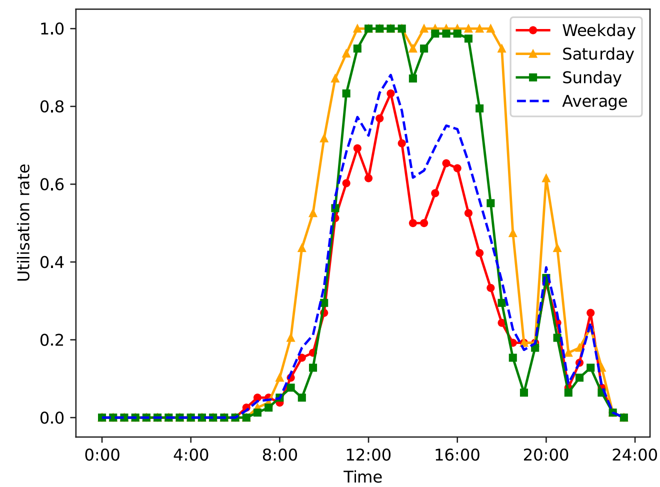

Fig. 9. Charging pole utilisation rate with $m^* = 13$.

The daily average utilisation rate is calculated by

$$\phi_d^{ur,(s)} = \frac{\sum_{k=1}^{K} \phi_k^{ur,(s)}}{\text{Charging station opening hours } / \Delta t}. \tag{23}$$

(4) User satisfaction

User satisfaction in scenario s is defined as

$$\phi^{us,(s)} = \frac{\text{Rescheduled charging demand in scenario } s}{\text{Requested charging demand in scenario } s}. \tag{24}$$

The relationship between the number of charging poles to be installed and NPV is shown in Fig. 8. The maximum NPV $ 167 190 is achieved when $m^* = 13$ and the corresponding annual profit is $ 41 643. The energy consumption, maximum demand, energy cost, demand charge, profit, utilisation rate, and user satisfaction are calculated in Table 4. The hourly utilisation rates of charging poles on different days are shown in Fig. 9. It can be observed that the highest charging demand on Saturday yields the highest energy consumption, maximum demand, energy cost, demand charge, profit, and utilisation rate between three days. However, user satisfaction on Saturday is the lowest due to the limited number of charging poles. Fig. 10 shows that user satisfaction increases as the number of charging poles increases. User satisfaction first reaches 100% on weekdays because the number of EVs visiting the shopping mall on weekdays is the least. Continuing to increase the charging pole contributes to increasing user satisfaction, but economically suboptimal. When the number of charging poles increases from 13 to 20, user satisfaction rises by 4%, but the NPV drops by 11%. It is important to note that this study focuses on single-objective optimisation for the design problem. If multiple objectives, such as NPV and user satisfaction, are considered simultaneously, the optimal number of charging poles may differ. The proposed planning method can easily be adapted to a multi-objective framework, depending on investors' attention to different objects.

Based on the optimal results, the potential of demand-side management is explored. The constraint (12) is relaxed to $E_i^k <= E_i^{res}, k = t_i^s + d_i$, which implies that the charging station can curtail the required energy of EVs through demand-side management. Since this study does not involve specific demand-side management strategies, we only show the potential of demand-side management in improving the investment of charging poles. Similar to the method adopted in [52], a weight factor η is assigned to the maximum demand charge item $c^{md}z$ in (13). The real-time scheduling algorithm tends to charge less electricity for EVs within the demand window as the increase of weight factor. According to the testing, the real-time scheduling algorithm shows the best performance when $\eta = 0.2$. The numerical results are compared in Table 5. Compared to the results of $E_i^k = E_i^{res}$, it is observed that partially satisfying the rescheduled charging demand can lead to higher annual profit and NPV. While the energy cost decreases by only 7%, the maximum demand charge is reduced by 28%, highlighting the value

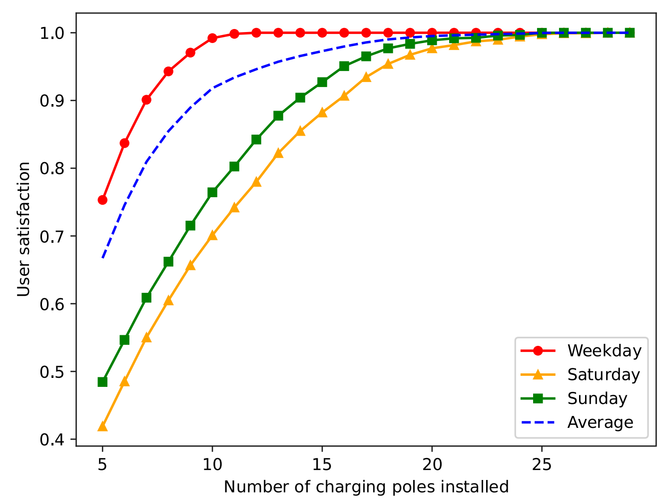

Fig. 10. User satisfaction with different numbers of charging poles.

Table 5
Comparison between the real-time parking bay allocation strategies with $E_i^k = E_i^{res}$ and $E_i^k \leq E_i^{res}$.

Case	NPV ($)	Annual profit ($)	Energy (kWh)	Energy cost ($)	Demand charge ($)	User satisfaction
$E_i^k = E_i^{res}$	167 190	41 643	1 351	236	58	96%
$E_i^k \leq E_i^{res}$	181 551	43 334	1 264	218	42	89%

Table 6
Comparison of transition plans with and without scheduling methods.

	m^*	NPV* ($)	Annual profit ($)	Payback period (years)	User satisfaction
Without charging scheduling	8	138 499	31 134	0.88	70%
Proposed method	13	167 190	41 643	1.2	96%
Proposed method with $m = 8$	8	158 459	35 428	0.79	85%

of demand-side management, especially in reducing the maximum demand for shopping mall charging stations.

7.4. Transition planning results under different scheduling strategies

Table 6 shows the comparisons of the transition planning results with and without the proposed real-time parking bay allocation strategy, including optimal numbers of charging poles to be installed, NPVs, annual profits, payback period, and user satisfaction. For the baseline case (transition planning without scheduling strategy), the optimal number of charging poles is 8 and the optimal NPV is $ 138 499. The proposed transition planning method can increase the annual profit by 34% and user satisfaction by 37%. The results indicate the proposed planning method can achieve higher annual profits and user satisfaction but a longer payback period because more charging poles are suggested to be installed. The performance of two operational strategies with the same number of charging poles (8 charging poles) are compared. It can be observed that all performance indicators listed in Table 6 of the proposed real-time parking bay allocation strategy are better than those without scheduling. The normalised annual profits (annual profit divided by the number of charging poles) of two cases with respect to the number of installed charging poles are shown in Fig. 11. The normalised annual profit decreases as the number of charging poles increase. When installing a small amount of charging poles, the normalised annual profits of the two cases are not significantly different. However, as the number of charging poles increases, the proposed method brings higher and higher normalised annual profit. Fig. 12 shows the maximum demand of two cases as the number of installed charging poles increases. When there are few charging poles in the charging station, although EV's charging requests are shiftable, the charging station lacks the capability to shift them because all the charging poles are fully occupied. With the increase in the number of charging poles, the charging station's capability of demand shifting improves (The decrease in the utilisation rate shown in Table 6 proves this point), which enables the implementation of the charging scheduling strategy to reduce maximum demand. When $m = 13$, the proposed strategy shows good performance in reducing the maximum demand, and the maximum demand is reduced by 26%.

7.5. Impact of EV penetration

With the increase in EV penetration, the charging station owner can obtain a larger NPV by deploying more charging poles in the charging station. Fig. 13 shows that the optimal number of charging poles and the corresponding NPV are positively related to the EV penetration rate. The optimal number of charging poles to be installed should be increased by an average of 11 to obtain the optimal NPV, whenever the EV penetration rate increases by 0.1.

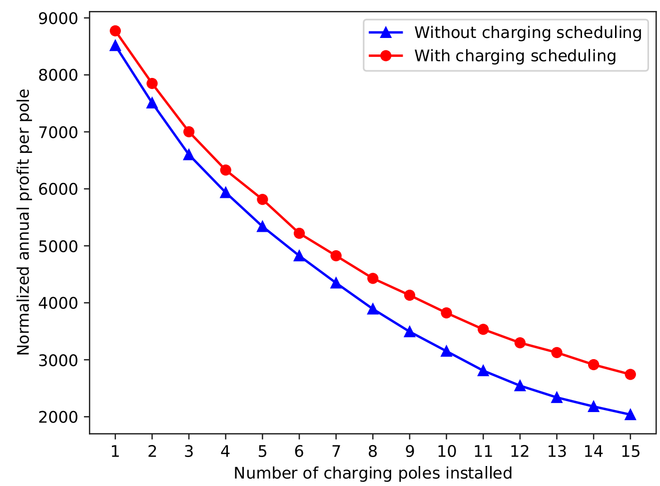

Fig. 11. Normalised annual profit of two operational strategies under different numbers of charging poles installed.

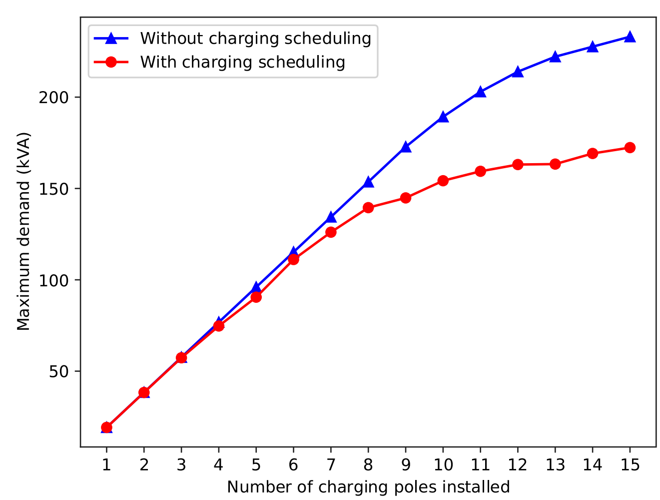

Fig. 12. Maximum demand of two operational strategies under different numbers of charging poles installed.

7.6. Impact of charging proce

Fig. 14 shows the relationship between the charging price and payback period. When $c^c = 0.3$ $/kWh, the discounted payback period

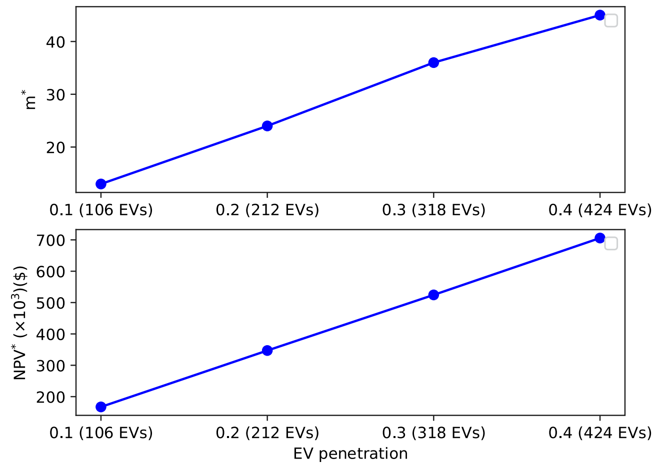

Fig. 13. Optimal number of charging poles and NPV as the increasing of EV penetrations.

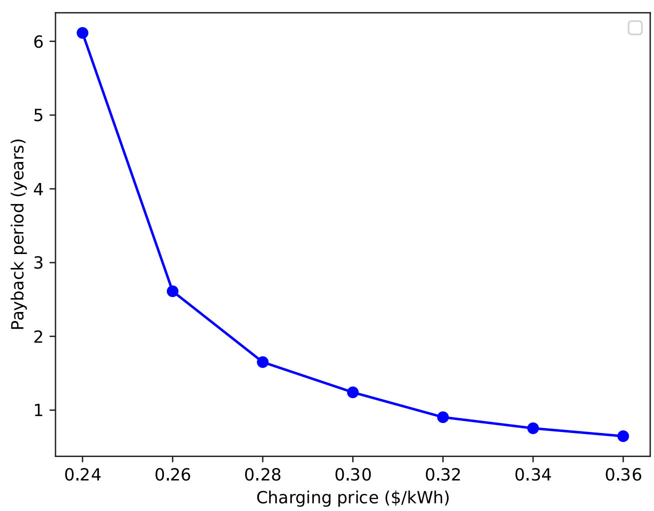

Fig. 14. Profit vs payback period with $m = 13$.

is 1.2 years. The payback period is larger than 8 years if the charging price is less than 0.24 $/kWh. The increase in profit decreases the payback period and brings higher NPV of the designed shopping mall charging station, but it will increase the charging cost of EV drivers, which may decrease drivers' willingness to charge EVs at the shopping mall charging station. The relationship between charging price and EV charging demand exceeds the research scope of this research. Interested readers can read [53,54] for more details.

7.7. Impact of the charging power of charging poles

This section considers the impact of the rated power of charging poles. According to the proposed charging demand model, charging poles with higher charging power can complete the EVs' charging task faster and satisfy more initial charging demand of EVs. However, the purchase and installation costs of the charging pole dramatically increase as the rated power of the charging pole increases. Here, we consider three levels of charging poles, alternating current (AC) Level 1, AC Level 2, and direct current (DC) fast charging. Their rated power outputs are 1.9 kW, 19.2 kW, and 50 kW, respectively, with purchase and installation costs of $ 900, $ 3 450, and $ 25 000, respectively [49]. The simulation results of three levels of charging poles are given in Table 7. According to the results, the AC level 2 charging pole is the most suitable choice for shopping mall charging stations, which has the highest NPV, profit, and user satisfaction. When the rated power of charging poles is small (Level 1), only a small part of the initial charging demand is satisfied, thus leading to the lowest user satisfaction rate. Since the unit price (Unit cost/power) of Level 1 charging poles is less than Level 2 charging poles, the optimisation problem prefers to install more Level 2 charging poles rather than Level 1 charging poles. In addition, the high initial cost hinders the application of direct current fast charging. Compared with the Level 2 charging, the higher utilisation rate and lower user satisfaction of DC fast charging indicate that the number of fast charging poles is too small such that many EVs cannot be connected to the fast charging stations.

8. Conclusions

In this study, we delve into the optimal transition planning for shopping mall parking lots to stimulate interest from potential investors and municipalities towards the development of shopping mall charging stations. Our approach involves modelling the charging demand specific to shopping malls, drawing from historical parking data while meticulously accounting for data reliability and availability. To efficiently manage the limited number of charging poles and reduce maximum demand, we propose a real-time parking bay allocation strategy to determine the optimal charging start time and charging power for each EV. Moreover, in light of the inherent uncertainty associated with drivers' parking behaviours, we propose a two-stage stochastic optimisation framework to determine the optimal number of charging poles to be deployed within shopping mall parking lots, maximising the NPV of the charging station investment. The optimal solution is analysed from the perspective of charging station owners and explores the impact of several sensitive factors, including rated power of poles, EV penetration rate, and charging price. The optimal results show the proposed planning method increases the annual profit by 34% and user satisfaction by 37% compared to the baseline method. There are significant disparities in the requested charging demand at shopping malls between weekdays, Saturdays, and Sundays. The performance of the proposed scheduling strategy in terms of profitability and maximum demand reduction is contingent on the number of charging poles to be installed. Specifically, with a limited number of charging poles, the profitability difference between employing the scheduling strategy and not doing so is negligible. However, as the number of charging poles increases, the proposed charging scheduling method becomes increasingly lucrative, resulting in higher normalised annual profits and greater maximum demand reduction. Additionally, our research suggests that the transition may not be sustainable in the financial return if the charging price is less than 0.24 $/kWh. Presently, AC level 2 charging is the most suitable option for shopping mall charging stations. While DC fast charging may seem appealing for EVs with high initial charging demand and short parking durations, its prohibitive purchase and installation costs present a significant hurdle. Consequently, reducing the expenses associated with fast-charging pole installation is pivotal for promoting the expansion of fast-charging networks in the future.

During the implementation stage, parking lot owners may face the selection of different types of charging poles, such as charging poles with varying power ratings or charging poles with multiple ports. The proposed solution can also be used to guide the selection. For instance, if the planning stage recommends installing 3 charging poles, the owner can choose to install either 3 individual poles or 1 multi-port pole with 3 ports. For charging poles with different rated powers. Our results give the number of charging poles and the minimum rated power that should be selected.

Table 7
Comparison between different charging power levels.

Charging power (kW)	m^*	NPV* ($)	Investment cost ($)	Energy (kWh)	Energy cost ($)	Demand charge ($)	Daily profit ($)	Utilisation rate	User satisfaction
1.9	11	21 512	9900	198	35	7	18	87%	12%
19.2	13	167 190	44 850	1351	236	58	130	50%	96%
50	4	87 178	100 000	1231	215	53	108	84%	69%

CRediT authorship contribution statement

Gang Yu: Writing – original draft, Software, Methodology, Conceptualization. **Xianming Ye:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Dunwei Gong:** Writing – review & editing, Funding acquisition. **Xiaohua Xia:** 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.

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Data availability

Data will be made available on request.

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