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Optimal parking lot retrofit planning for electric vehicle charging station during prolonged load shedding

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ABSTRACT

The rapidly increasing demand for electric vehicle (EV) charging drives the transition from conventional parking lots into charging stations. This transition, however, faces challenges in countries of Africa, Asia, and South America, where prolonged load shedding results in an unreliable power supply. This study addresses the optimal parking lot retrofit planning for EV charging stations, aiming to determine an ideal number of charging poles to be deployed within parking lots under prolonged load shedding. A multi-objective optimization approach is introduced to balance financial return and user satisfaction, generating Pareto-optimal solutions for charging stations. The impact of load shedding on the optimal retrofit planning is analyzed. Post-outage demand peaks substantially increase the maximum demand costs. The proposed charging scheduling method achieves a 14% reduction in maximum demand costs. The proposed parking lot retrofit planning approach improves weekly profit by 19% and user satisfaction by 14% compared to the existing planning approach. Additionally, this study investigates the implications of load shedding uncertainty, EV penetration rate, charging pole type, and time-of-use pricing on the optimal retrofit planning.

1. Introduction

With the global rise in charging demand, conventional parking lots are transitioning to electric vehicle (EV) charging stations [1]. The transition offers convenient charging services for EVs while opening up new revenue streams for parking lots [2,3]. In countries like Norway, the Netherlands, and Germany, the regulation mandates the installation of charging stations within parking lots [4]. To successfully retrofit parking lots into charging stations, charging poles should be integrated into existing parking bays [5]. Service providers, such as company EVCSGO, offer turnkey solutions for converting parking bays into charging stations [6]. The key challenge for parking lot owners lies in determining the number of charging poles within parking lots, which is defined as the optimal parking lot retrofit planning in this study. Parking lot owners and EV drivers have differing expectations regarding the optimal number of charging poles. Due to the uneven distribution of charging demand across different periods, deploying as many charging poles within parking lots can maximize charging convenience for drivers. However, charging stations are capital-intensive investments, and over-deployment risks undermining financial viability. Conversely, an insufficient number of charging poles can lead to user dissatisfaction, ultimately reducing customer retention [7,8]. Therefore, determining the optimal number of charging poles requires a careful balance between profitability and user satisfaction.

This study considers the optimal parking lot retrofit planning for charging stations in countries affected by prolonged load shedding. Unlike temporary load shedding implemented as a short-term response to natural disasters or power system failures [9], prolonged load shedding is more extensive and persistent, often caused by insufficient generation and transmission capacity. South Africa endured over 7431 cumulative hours of power outages between 2016 and 2023 [10], while Nepal faced severe electricity shortages resulting in up to 14 h of daily load shedding between 2007 and 2017 [11]. Due to high and volatile energy prices, Finland considers to implement load shedding during cold winter peak times [12]. Load shedding further exacerbates the challenges of retrofitting parking lots into charging stations. During power outages, charging stations are unable to provide services, resulting in a low utilization rate of charging poles and increased range anxiety for EV drivers. During power restoration periods, EV drivers may cluster at charging stations. The congestion declines the quality of service and increases the electricity cost of the charging stations during peak periods [13]. In addition, the unpredictable nature and varying duration of load shedding further complicate the determination of the optimal number of charging stations. To address these challenges, this study proposes an optimal parking lot retrofit planning approach under prolonged load shedding. The approach includes a charging

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management strategy to handle charging requests during load shedding and a multi-objective framework to determine the optimal number of charging poles. This ensures that the transition from parking lots to charging stations is both financially sustainable for operators and capable of meeting EV drivers' satisfaction.

The percentage-based approach, queuing theory-based approach, and optimization-based approach are generally employed to determine the required number of charging poles within parking lots. The percentage-based approach determines the number of charging poles based on a fixed percentage of the total parking bays [14]. Parking lot owners can get the recommended percentage values from local governments or industry associations for different types of parking lots [15–17]. Due to the uneven distribution of charging demand, the percentage-based approach is generally suboptimal for the overall efficiency of each parking lot. Queuing theory models the process of EV charging waiting to predict queue lengths and waiting times with given numbers of charging poles. In queuing models, the EV arrival pattern and charging service time are generally expressed as the stochastic process such as the widely applied multi-server queue model with Poisson arrivals, exponential service times, and multiple charging poles [18–20]. In [21], a non-stationary Poisson process and time-varying parameter queuing theory model is proposed to determine the ideal number of chargers for parking lot retrofitting. 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 a payback period of 1.78 to 2.40 years. For charging stations retrofitted from parking lots, some charging requests are schedulable, as their parking duration may exceed the time needed for charging. However, first-come, first-served (FCFS) mechanisms in queuing models fail to account for the flexibility of these charging requests, leading to an inaccurate estimation of the required capacity for parking lot charging stations.

This study adopts the optimization-based approach to determine the number of charging poles. The approach optimizes specific objectives, such as investment and operation costs, and service levels, within given constraints to find the optimal number of charging poles. These optimization problems are typically formulated as mixed-integer linear programming [22,23], stochastic programming [24], and robust programming [25]. When the solution space is vast or highly complex, heuristic methods such as genetic algorithms [26] and machine learning methods such as reinforcement learning [27] are often employed to solve the formulated optimization problem. In [14], an agent-based simulation is developed to model the charging behavior in a mixed scenario of EVs and internal combustion engine vehicles (ICEVs). Using a genetic algorithm, a charging station configuration optimization model for central business district parking lots is proposed to optimize the number and types of charging poles. Compared to deploying charging poles with fixed proportions, the proposed method reduces the total travel time cost for both EVs and ICEVs by 17.1%. In [24], the authors investigate 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-minimization problem with chance constraints. Ref. [28] uses a genetic algorithm to optimize the number of charging poles in office building parking lots, aiming to balance the average utilization rate of charging facilities and the average satisfaction rate of charging demand. The proposed method achieves an average utilization rate of 28.94% and a satisfaction rate of 97.48% for charging demand over a 10-year design period. The optimal parking lot retrofit planning investigated in [24,28,29] assumes a stable grid power supply. These frameworks lack integration of charging scheduling strategies under load shedding and do not examine the impact of prolonged load shedding on determining the optimal number of charging poles. Consequently, the optimal parking lot retrofit planning for charging stations during prolonged load shedding remains unaddressed.

The contributions of this study are summarized as follows: we develop an optimal parking lot retrofit planning model for EV charging stations under prolonged load shedding. A real-time charging scheduling strategy is proposed to optimally respond to electricity prices during load shedding. The proposed real-time scheduling strategy outperforms the FCFS approach in managing maximum demand, achieving a 14% reduction in maximum demand costs. A multi-objective optimization framework is established to determine the optimal number of charging poles, balancing profitability and user satisfaction. The proposed approach improves weekly profit by 19% and user satisfaction by 14% compared to the utilization rate user satisfaction (URUS) method.

The rest of this study is organized as follows. Section 2 states the research problem. Section 3 proposes the charging demand model, charging scheduling strategy, and multi-objective retrofit planning approach. Section 4 offers a case study. Section 5 concludes this study.

2. Problem statement

This study investigates the optimal parking lot retrofit planning for charging stations under prolonged load shedding. For a parking lot incorporating EV charging infrastructure, a designated charging area, comprising parking bays equipped with charging poles, is set up within the parking lot. A charging management system is integrated into the existing parking management system to coordinate the charging processes. When an EV arrives at the charging station, it submits a charging request to the charging management system, including arrival time, parking duration, and current battery state of charge (SOC). The charging management system then checks the availability of charging poles within the EV's parking duration. If there are charging poles available, the charging management system directs the EV to the charging area to charge or the non-charging area to wait. Otherwise, the request is not accepted. The driver can move the EV to the charging area, either personally or using the lot's valet service. Transfer costs are not considered as they are typically minimal. The charging start and end times are determined by the proposed scheduling strategy and communicated to drivers. Upon charging completion, drivers are expected to remove their EVs from the charging area. To discourage overstaying, a penalty policy may be implemented, similar to Tesla's policy [30]. In the planning stage, we assume all EVs are transferred after completing charging.

This study considers the South African load-shedding scheme. The load-shedding schemes in Pakistan and Nepal can be viewed as simplified versions of the South African load-shedding scheme [31]. The load-shedding schedule is divided into eight stages. As the stage level increases, both the frequency and duration of power outages rise. The load-shedding schedule is preannounced and can be accessed from [32]. During power outages, the charging station cannot provide charging service. Eskom, the largest electricity producer in South Africa, continuously monitors the national load and available power supply and announces new load shedding stages. Historical load-shedding stage records can be accessed from [33]. The parking lot retrofit planning is formulated as a two-stage optimization. At the investment stage, the optimization focuses on determining the optimal number of charging poles to strike a balance between profitability and user satisfaction. The primary decision variable is the number of charging poles equipped with a single charger. Note that the results can also be easily converted to charging poles with multiple chargers. For instance, if the optimization suggests installing two single-charger poles, the owner has the flexibility to install either two single-charger poles or one dual-charger pole. At the operational stage, the optimization aims to develop an efficient charging scheduling strategy that manages the charging process with a fixed number of charging poles, while responding to electricity tariffs and load shedding. The key decision variables at this level include the start time of charging, the assignment of charging poles, and the charging power.

3. Problem formulation

This section introduces the parking lot charging demand modeling method, charging scheduling strategy, and optimal parking lot retrofit planning framework.

3.1. Charging demand modeling

The number of charging poles required for the parking lot is determined by the charging demand, which is generally estimated according to historical charging records [34]. The historical charging record is unavailable in the planning stage, thus we suggest estimating the future charging demand according to the historical parking records, which are usually available in the parking lot's parking ticket database. We first model the requested charging demand, which is defined as the sum of all EVs' maximum chargeable energy. The requested charging demand may have peaks and valleys due to drivers' natural charging behaviors. With a limited number of charging poles and the application of charging scheduling strategies, the requested charging demand curve can be reshaped. The reshaped charging demand is defined as the rescheduled charging demand in this study.

Given that vehicle flows on different days exhibit distinct patterns in terms of arrival and parking times, we model the charging demand on a daily basis. The scheduling horizon is set to 24 h, discretized into K time intervals for convenience. The length of each time interval is Δk. Let the daily number of vehicles parking in the lot be denoted as J. Given that historical parking records might not specify vehicle types (EV or ICEV), this study assumes that both EVs and ICEVs have the same parking behaviors. Then, the daily number of EVs parking at the charging station is estimated as αJ, where α is the EV penetration rate in the area. The EV penetration rate is available from local vehicle management government institutions [35]. In our study, we uniformly sample EV parking records from the parking dataset with a sampling rate equal to the EV penetration rate. According to the arrival time t_i^{arr} and parking time t_i^{dep}, the available park-starting and park-ending time intervals of EV i are discretized as

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

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

where I represents the set of EVs, ceiling(·) and floor(·) are the round-down and roundup functions, respectively. The total number of parking time intervals that are available for charging is calculated as $\bar{t}_i^d - \bar{t}_i^a + 1$. Let $E_i^{arr} = SOC_i C_i$ be the remaining energy of the EV battery when arriving at the charging station. SOC_i is the state of charge (SOC) of EV i's battery when arriving at the charging station, C_i is the battery capacity of EV i. Then, the requested charging demand of EV i is

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

In the planning stage, the arrival SOC of EVs and battery capacity are unknown. The arrival SOC is assumed to follow a beta distribution as in [36], or a uniform distribution as in [37]. In [38,39], the arrival SOC is derived from travel chains, which calculate the SOC by considering the remaining energy from the previous destination and the energy consumed during the journey to the next destination. While this method accounts for the travel distance of EVs, it also introduces additional assumptions, such as the initial SOC and the travel distance between destinations. In practice, based on the functionalities of parking lots, such as those in shopping malls, office buildings, and hospitals, we can utilize SOC statistics from built charging stations at these locations. The average battery capacity of EVs can be estimated using data from available EV models on the market.

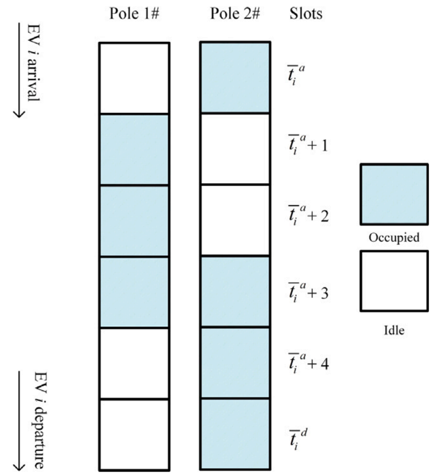

Fig. 1. Charging process of EV i.

Let m be the total number of charging poles to be deployed. Considering the limited parking time and amount of charging poles, the rescheduled charging demand of EV i is

$$E_i^{res} = \min\left\{g_i p^{rat} \Delta t, E_i^{req}\right\}, \tag{4}$$

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

To define g_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 interval 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 g_i by $g_i = \max\{H \mid \sum_{h=0}^{H} x_{ij}^{r+h} = 0, \forall j \in J, \bar{t}_i^a \le r, r+h \le \bar{t}_i^d\} + 1$. Note that $g_i = 0$ indicates that there is no available charging pole for EV i within the parking duration, thus $E_i^{res} = 0$.

3.2. Charging scheduling strategy

This section presents a real-time scheduling strategy for charging stations in response to the electricity tariffs and load shedding. We first model the grid electricity tariffs and EV charging service fees. Compared with [21], a more general grid electricity tariff consisting of time-of-use and maximum demand tariff is considered. The time-of-use tariff is

$$b_k^{tou} = \begin{cases} b^p, & \text{peak period,} \\ b^s, & \text{standard period,} \\ b^o, & \text{off-peak period.} \end{cases} \tag{5}$$

The maximum demand cost is based on the daily maximum power consumed in any half-hour interval within the demand window. The maximum demand tariff is defined as b^{md}/kVA and the demand window is represented by $[t_s^{md}, t_e^{md})$. t_s^{md} and t_e^{md} are the start and end times of the demand window, respectively. The charging service fee uses a fixed rate b^e \$/kWh.

It is expected that time-of-use and maximum demand tariffs will incentivize a shift in charging demand to non-peak periods and non-demand window periods, respectively. Additionally, the maximum demand tariff further encourages charging station operators to reduce peak demand during the demand window. This allows charging station owners to apply scheduling strategies to lower overall charging costs by appropriately shifting charging demand. The scheduling strategy proposed in this study seeks to maximize the daily profit of the charging service, which is calculated based on both revenue and cost considerations. When the ith EV arrives at the charging station, the following optimization problem is solved to allocate a charging pole and determine the charging start time interval t_i^s and charging power p_i^k for EV i.

$$\max_{t_i^s, p_i^k} D_i^n = \sum_{k=1}^{K} (b^e - b_k^{tou})(p_{load}^k + p_i^k)\Delta t - b^{md} \max_{t_s^{md} \le k < t_e^{md}} \left\{ p_{load}^k + p_i^k \right\}, \tag{6}$$

subject to

$$\bar{t}_i^a \le t_i^s, t_i^s + g_i - 1 \le \bar{t}_i^d, \tag{7}$$

$$p_i^k \le y_k p^{rat}, \ \forall t_i^s \le k \le t_i^s + g_i - 1, \tag{8}$$

$$p_i^k = 0, \ \forall k < t_i^s, k > t_i^s + g_i - 1, \tag{9}$$

$$E_i^k = E_i^{k-1} + p_i^k \Delta t, \ \forall k \in K, \tag{10}$$

$$E_i^k = E_i^{res}, \ k = t_i^s + g_i, \tag{11}$$

where $p_{load} = (p_{load}^1, \ldots, p_{load}^K)$ is the total rescheduled charging demand profile of EVs arriving before EV i. Constraint (7) ensures that the actual charging start and end times are within the parking duration. Constraints (8) and (9) are the power limits of charging poles. y_k is a binary indicator

$$y_k = \begin{cases} 0, & \text{if there is no power outage in time interval } k, \\ 1, & \text{if there is a power outage in time interval } k. \end{cases} \tag{12}$$

According to the load shedding schedule and stage record at time interval k, $y_k = 1$ if time interval k is designated as a power outage period in the load shedding schedule for stage s and stage s is active at time interval k. Constraint (10) is the energy balance of EV batteries. Constraint (11) ensures that the EV's rescheduled charging demand is fully satisfied when disconnecting from the charging pole. Note that there is a nonlinear term in the objective function (6), by introducing a new continuous decision variable y, the equivalent linear form is obtained in (13)

$$\max_{t_i^s, p_i^k} D_i^n = \sum_{k=1}^{K} (b^e - b_k^{tou})(p_{load}^k + p_i^k)\Delta t - b^{md} y, \tag{13}$$

and z satisfies

$$y \ge p_{load}^k + p_i^k, \ \forall k \in [t_s^{md}, \ t_e^{md}). \tag{14}$$

The proposed scheduling algorithm is detailed in Algorithm 1. When EV i arrives at the charging station, it submits a charging request (t_i^a, t_i^d, E_i^{arr}) to the charging management system. The selection of charging start times for EV i is influenced by arrival time, parking duration, and the proposed scheduling strategy, which prioritizes meeting requested charging demand to the greatest extent for each EV and then assigning the feasible charging slots to minimize drivers' charging costs. Specifically, the charging management system reads the current charging station status including p_{load} and x_{ij}^k. Then, the charging management system calculates g_i and E_i^{res}. The charging request is rejected if all charging poles are fully occupied during the parking time of EV i, that is, $g_i = 0$. Otherwise, the charging management system finds the optimal charging start time interval t_i^s, charging pole j^*, and charging power p_i^k for EV i by solving the optimization problem (13). By enumerating all available charging poles and time intervals, 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. After finishing all charging requests, the algorithm outputs the daily profit of charging service $D_{|I|}^n$ and load profile p_{load}.

Algorithm 1: Proposed real-time scheduling algorithm for n^{th} day.

Input: t_i^a, t_i^d, E_i^{arr}
Output: t_i^s, j^*, p_i^k, p_{load}, and $D_{|I|}^n$
Initialize D_i^n, p_{load} and x_{ij}^k
for $i = 1 : |I|$ **do**
  Calculate $\bar{t}_i^a$ and $\bar{t}_i^d$
  Calculate g_i and E_i^{res}
  if $g_i = 0$ **then**
    Reject charging request
  end
  Initialize matrix $cm = zeros(K, m)$
  for $k = \bar{t}_i^a : \bar{t}_i^d - g_i$ **do**
    for $j = 1 : m$ **do**
      Solve optimization problem (13) with constraints (7)-(11)(14)
      $cm[k, j] = D_i^*$
    end
  end
  Find minimum k^* such that $cm[k^*, j] = \max cm[k, j]$
  Find minimum j^* such that $cm[k^*, j^*] = \max cm[k, j]$
  $t_i^s = k^*$
  return t_i^s, j^*, and p_i^k
  Update x_{ij}^k, $p_{load}^k = p_{load}^k + p_i^k$, and $D_i^n = D_i^*$
end
return p_{load}, $D_{|I|}^n$

3.3. Multi-objective optimal retrofit planning

This section formulates a multi-objective optimization problem to find the optimal number of charging poles to be deployed to optimize the profit of the charging station investment and user satisfaction. The first objective is to maximize the profit of the charging station.

$$\max_m \mathcal{O}_1(m) = -\beta c^{inv} m + \sum_{n=1}^{N} D_{|I|}^n, \tag{15}$$

where $\beta = \frac{r}{1 - -(1+r)^{-s}}$ is the capital recovery factor. r is the discount rate and s is the lifetime of charging poles. c^{inv} is the cost of upgrading one parking bay into a charging station, including the purchase and installation costs of one charging pole and the corresponding transformer cost. $D_{|I|}^n$ is the optimal daily profit calculated by Algorithm 1, N is the number of days counted. The profit function can be decomposed into four components: energy cost, maximum demand cost, charging revenue, and capital cost. The energy cost includes costs arising from time-of-use tariffs. The maximum demand cost refers to the cost incurred from the maximum demand tariff. The charging revenue is the income generated by selling electricity to EV drivers. The capital cost represents the discounted capital cost based on the number of days counted.

The second objective is to maximize user satisfaction, which is defined as the extent to which the requested charging demand is met.

$$\max_m \mathcal{O}_2(m) = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum_{k=1}^{K} p_{load}^{k,n} \Delta t}{E_{req}^n}, \tag{16}$$

where E_{req}^n represent the requested charging demand of nth day.

The objection function is expressed as follows

$$\max_m w_1 \frac{\mathcal{O}_1(m)}{\max \mathcal{O}_1(m)} + w_2 \frac{\mathcal{O}_2(m)}{\max \mathcal{O}_2(m)}, \tag{17}$$

where $0 \le w_1, w_2 \le 1$ are weights for two objects and satisfy $w_1 + w_2 = 1$. Since the number of charging poles is limited, the optimization problem (17) can be solved by exhaustively searching all feasible values

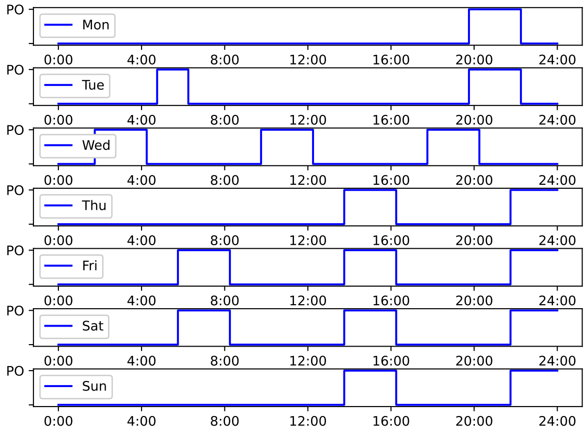

Fig. 2. Power outages (PO) in Hatfield, Pretoria, South Africa from Monday, July 13, 2023, to Sunday, July 20, 2023.

Table 1
Parameter setting.

Parameters	Value	Unit
Charging station open time	[9, 22)	h
Time interval Δt	30	min
Rated charging power p^{rat}	19.2 [42]	kW
Charging pole cost c_1	3,450 [42]	$/pole
Lifetime of charging pole s	9	years
EV penetration α	0.2	
Average EV battery capacity	72 [45]	kWh
Discount rate r	10%	
Peak period	[14, 20)	h
Standard period	[7, 14), [20, 22)	h
Off-peak period	[0, 7), [22, 24)	h
Demand window $[t_s^d, t_e^d)$	[14, 20)	h
Peak price b^p	0.1981	$/kWh
Standard price b^s	0.1578	$/kWh
Off-peak price b^o	0.1242	$/kWh
Maximum demand charge b^{md}	0.3574	$/kVA
Charging price b^e	0.3	$/kWh

of m. For cases where m has a large feasible region, it is recommended to use heuristic algorithms, such as the genetic algorithm, to accelerate the solving process [40].

4. Case study

This section presents a case study of a retrofit planning for a shopping mall parking lot in Hatfield, Pretoria, South Africa, with a simulation duration of one week. Extending the simulation duration to cover additional weeks can help handle uncertainties on requested charging demand, utilizing the Sample Average Approximation approach, as demonstrated in [41]. According to the load shedding schedule for Hatfield given in Table A.1 and historical load shedding record [33], the detailed power outage start and end times are plotted in Fig. 2, where each square represents the duration of a power outage. The simulation parameters are given by Table 1. This study selects the AC Level 2 charging poles for the charging station because Level 2 charging is the most widely applied in commercial charging stations [42]. The arrival SOC follows the Weibull distribution with scale parameter $\lambda = 0.8$ and shape parameter $c = 10$ according to [43]. The numerical simulation is performed by Gurobi solver [44], on an Intel Core i9-12900 CPU @3.20 GHz, 32 GB RAM.

The requested charging demand for a week is estimated in Fig. 3. Since the charging station at the shopping mall operates from 9:00 to 22:00, it only covers the standard and peak periods with respect to the grid time-of-use tariff. Therefore, the off-peak period is not shown in Fig. 3. The requested charging demand fluctuates throughout the week, with noticeable daily peaks. The weekday and Sunday peaks occur within the standard period. Saturday's peak falls within the peak period. The requested charging demand during the weekend is significantly higher than on weekdays, with Saturday experiencing the highest demand of 697 kW.

Fig. 4 illustrates the performance of the proposed scheduling strategy in weekly profit and user satisfaction, with and without load shedding, as the number of installed charging poles increases from 1 to 41. As the number of poles increases, profit initially rises and then gradually decreases in both scenarios. User satisfaction increases monotonically, tending to plateau as the number of charging poles increases. However, load shedding prevents some charging requests from being fully met, reducing profitability and limiting maximum user satisfaction below 1. The highest achievable profit is $ 683 with 19 charging poles and $ 430 with 14 charging poles, with and without load shedding, respectively. User satisfaction peaks at 83.39% when 41 charging poles are installed under load shedding. Notably, the increase in profit is not strictly monotonic before reaching its maximum. This is attributed to variations in the components of profit, which include charging incomes, energy costs, maximum demand costs, and capital costs. While charging incomes, energy costs, and capital costs all increase consistently with the number of poles, the maximum demand cost fluctuates. Increasing the number of charging poles can lead to a higher maximum demand cost, as it allows more EVs to charge simultaneously during the demand window. However, in some cases, adding more charging poles can reduce the maximum demand cost by preventing EVs that arrive before the peak period from being delayed into the peak period due to limited pole availability. In the requested charging demand shown in Fig. 3, the charging demand at most days' demand peaks occurs in the standard period before the peak period, thus this observation is important in reducing charging costs for charging station owners.

Table 2
Pareto solutions of the retrofit plan ($w_2 = 1 - w_1$).

w_1	Number of charging poles	Weekly profit ($)	User satisfaction (%)	DPP (years)
$[0, 0.02)$	41	159	83.39	4.89
$[0.02, 0.04)$	37	223	83.26	4.25
$[0.04, 0.06)$	35	257	83.11	3.86
$[0.06, 0.08)$	34	262	83.05	3.78
$[0.08, 0.1)$	33	270	82.93	3.68
$[0.1, 0.14)$	29	321	81.91	3.19
$[0.14, 0.18)$	26	351	80.98	2.79
$[0.18, 0.2)$	25	364	80.51	2.67
$[0.2, 0.42)$	20	412	78.24	2.15
$[0.42, 0.56)$	19	417	77.61	2.05
$[0.56, 0.7)$	17	424	70.07	1.81
$[0.7, 1]$	14	430	73.20	1.54

4.1. Optimal retrofit plan under load shedding

Table 2 presents the Pareto solutions for the retrofit plan, showing how different weightings of two objectives impact the number of charging poles, weekly profit, user satisfaction, and the discounted payback period (DPP). The results indicate that higher values of w_1 lead to fewer charging poles and lower user satisfaction but maximize profitability. The planning results with fewer charging poles have shorter DPPs due to lower capital costs.

Fig. 5 is plotted to answer whether parking lot owners would choose to install more or fewer charging poles under load shedding, compared to the no load shedding case. The answer depends on the parking lot owner's preference between the two objectives. When the preference weights are uniform ($w_1 = w_2 = 0.5$), the optimal number of charging poles under load shedding is 19 fewer than in the no load shedding case, where 20 poles are installed.

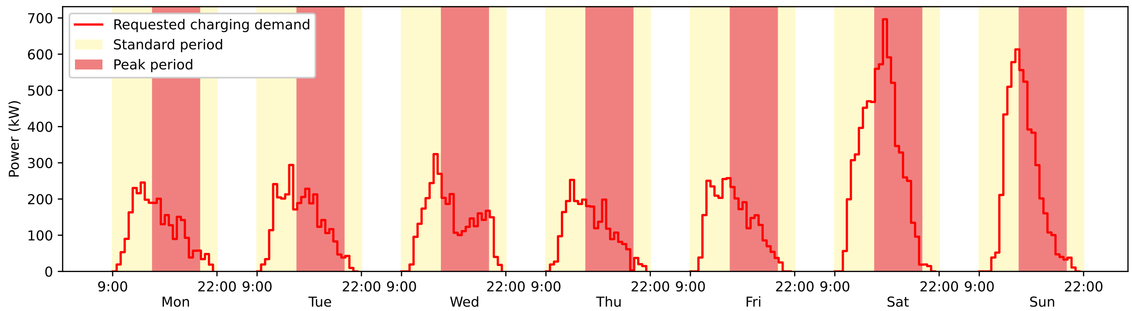

Fig. 3. Requested charging demand.

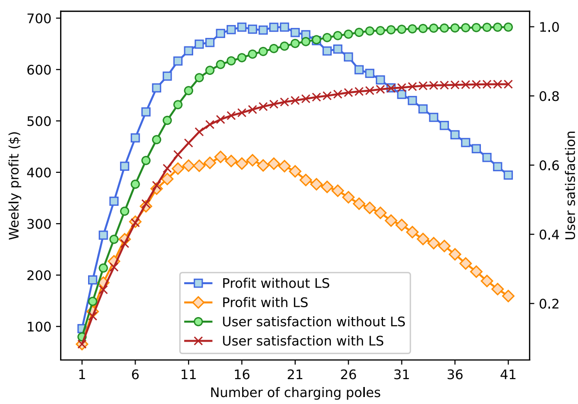

Fig. 4. Weekly profit and user satisfaction.

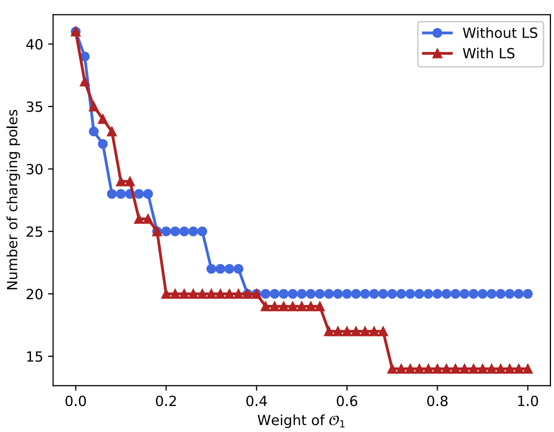

Fig. 5. Optimal number of charging poles with and without load shedding.

Table 3
Comparison between proposed scheduling and FCFS strategies with 19 charging poles under load shedding.

Scenario	Weekly profit ($)	User satisfaction (%)	Charging income ($)	Energy cost ($)	Maximum demand cost ($)
Proposed	417	77.61	3,787	2,254	614
FCFS	285	77.05	3,030	1,783	713

Table 3 compares the performance between the proposed scheduling strategy and the FCFS strategy [21]. Key performance metrics include weekly profit, user satisfaction, charging income, energy cost, and maximum demand cost. The proposed method demonstrates a substantial improvement in weekly profit, increasing it by 46%, along with a modest improvement in user satisfaction by 0.72%. The limited improvement in user satisfaction can be attributed to the constraints imposed by load shedding, with the satisfaction level already approaching its theoretical maximum of 83%. Additionally, the proposed method achieves a 14% reduction in the maximum demand cost. Fig. 6 visualizes the rescheduled charging demands for both scheduling strategies. The results indicate that the proposed scheduling strategy effectively reduces the maximum demand compared to FCFS on most days. However, a slight increase in maximum demand occurs on Tuesday. This may be due to the proposed strategy initially shifting charging requests to later periods, while EVs with non-shiftable demand arriving during that window, cause an increase in maximum demand. A potential improvement to the scheduling approach could involve incorporating predictive algorithms, such as model predictive control [46].

Table 4
Daily performance metrics of the proposed scheduling method with 19 charging poles.

Day	Energy (kWh)	Daily profit ($)	Daily Energy cost ($)	Maximum demand cost ($)	User satisfaction (%)
Mon	1,418	73	253	65	96.57
Tue	1,586	73	284	84	98.37
Wed	1,286	42	230	80	74.46
Thu	1,111	46	191	63	80.65
Fri	1,286	49	220	83	79.75
Sat	2,046	101	358	121	57.80
Sun	1,481	32	260	119	55.65

Table 4 presents the daily energy consumption, profit, energy cost, maximum demand cost, and user satisfaction. The proposed method is a real-time scheduling approach, sequentially scheduling EVs based on their arrival order to maximize profit. While variations in the load profile do not affect the optimality of individual scheduling decisions, fluctuations in load and the impact of load shedding lead to differences in overall performance across days. For instance, although weekday load profiles are similar, the daily profit on Wednesday is the lowest among weekdays due to the longest power outage duration.

Load shedding decreases both profit and user satisfaction, as charging station owners lose the opportunity to service charging requests during power outages. However, if an EV's charging request is schedulable, meaning the departure time is after the outage ends, part or all of the charging demand can be fulfilled once power is restored. This creates a peak demand immediately after the outage. If the peak demand occurs during the standard period, the charging cost remains largely unaffected. However, if the peak demand falls into the peak period, it significantly increases both energy costs and maximum demand costs. From the grid's perspective, this post-outage demand peak not only adds stress but also undermines the purpose of load shedding. During rolling power outages, power is typically restored in one area while another area experiences an outage to maintain grid balance. The post-outage peak disrupts this balance, reducing the effectiveness of load shedding. The proposed scheduling strategy mitigates peak demand during the post-outage period, benefiting both the charging station and the grid.

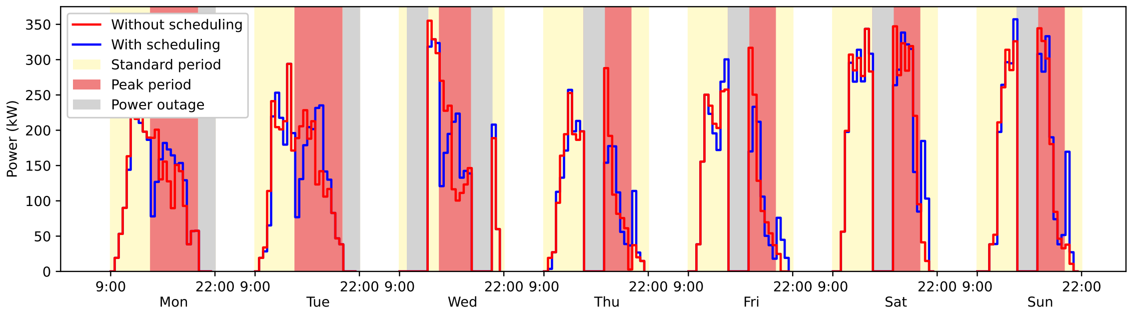

Fig. 6. Rescheduled charging demand under the proposed scheduling strategy, with and without load shedding.

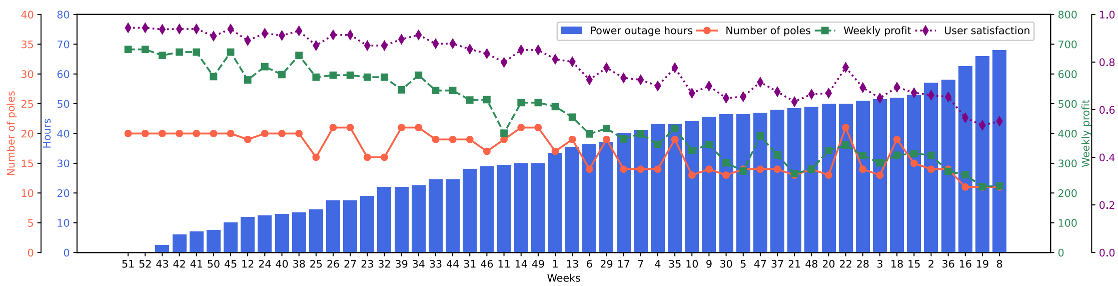

Fig. 7. Optimal parking lot retrofit plans for charging stations based on 52 weeks of load shedding stage data, ordered by weekly power outage duration.

Table 5
Comparison between the proposed and the URUS method.

Method	Weekly profit ($)	User satisfaction (%)
Proposed	417	77.61
URUS	350	68.10

Table 6
Statistical analysis of optimal retrofit plans for 52 weeks.

Items	Max	Min	Mean
Power outage hours (h)	68	0	66
Optimal number of poles	21	11	16
Weekly profit ($)	670	209	449
User satisfaction (%)	94	53	78

Table 5 compares the proposed planning method with another method modified from [28]. For simplicity, we refer to this as the utilization rate user satisfaction (URUS) method. The URUS method optimizes both the charging pole utilization rate and user satisfaction to determine the optimal number of charging poles. The utilization rate with m charging poles is defined by

$$\mathcal{O}_3(m) = \frac{1}{Nh} \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{\eta_k^n}{m}, \tag{18}$$

where η_k is the number of EVs charged at time interval k on day n, and h is the opening hours of the charging station. We modify the URUS method by considering load shedding in the scheduling process. According to the results in Table 5, the proposed approach improves weekly profit by 19% and user satisfaction by 14% compared to the URUS method. There are two reasons for this. First, due to the pyramid shape of the charging demand curve, optimizing for high utilization often results in fewer charging poles being installed. In extreme cases, installing only one charging pole might yield the highest utilization, but this would lead to lower weekly profits and user satisfaction, which could jeopardize the sustainability of the system. Second, our model considers electricity prices, meaning that simultaneously optimizing for user satisfaction and utilization rate does not necessarily reduce charging costs. Charging during peak hours and standard hours can yield the same levels of user satisfaction and utilization rate, but it is obviously more cost-effective to charge during standard hours when electricity costs are lower.

Fig. 7 presents the optimal number of charging poles, weekly profits, and user satisfaction levels, calculated using the 2023 load-shedding stage data (spanning 52 weeks). The results are ordered by the weekly power outage hours. Table 6 provides statistical analysis for the results given in Fig. 7. Weekly power outage hours, ranging from 0 to 168 h, are used as an indicator of load-shedding severity. Notably, scenarios with identical outage hours may yield different optimal charging pole numbers due to variations in the specific timing of outages. It can be seen a strong linear negative correlation exists between both weekly profit and user satisfaction and the weekly outage hours, with each additional hour of weekly outage leading to an estimated reduction in weekly profit by $ 3.74 and user satisfaction by 0.32%. The optimal number of charging poles does not exhibit as strong a linear negative correlation with power outage hours. This is likely because the determination of the optimal number of poles depends on multiple factors including user demand variability, and profit and satisfaction trade-offs, beyond just the total outage hours.

Fig. 8 shows the optimal number of charging poles, weekly profit, and user satisfaction under different load shedding stages. The number of poles decreases as the stage increases, reaching a minimum around stage 6, followed by a slight rise at stage 8. The weekly profit and user satisfaction show a decreasing trend as load shedding stages increase, which matches the results in Fig. 7. At stage 8, user satisfaction slightly increases due to more charging poles deployed.

Table 7 presents the optimal number of charging poles, capital cost, user satisfaction, weekly profit, profit to capital cost ratio, and user satisfaction to capital cost ratio when using different rated power levels of charging poles. The capital cost of the charging poles normalized into one week. The impact of the rated power of charging poles on charging scheduling is analyzed as follows. A higher-rated power allows EVs to charge more quickly, enhancing flexibility to avoid charging during power outages and thereby satisfying more charging demand and increasing charging incomes. However, higher-rated power also leads to an increase in maximum demand, particularly peak demand following power outages, which can increase maximum demand costs.

Table 7
Optimal retrofit planning with different charging poles.

p^{rat} (kW)	Optimal number of poles	Capital cost ($)	Weekly profit ($)	User satisfaction (%)	Weekly profit to capital cost ratio ($/$)	User satisfaction to capital cost ratio (%/$)
9.2	21	125	355	56.23	2.84	0.158
14.2	24	221	400	71.95	1.80	0.180
19.2	19	236	417	77.61	1.76	0.186

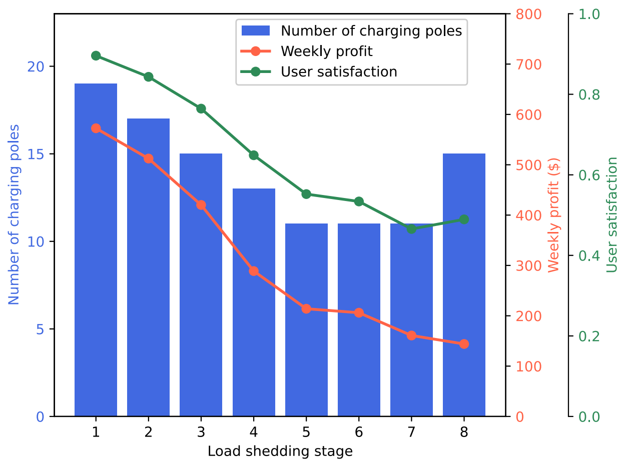

Fig. 8. Optimal number of charging poles with different load shedding stages.

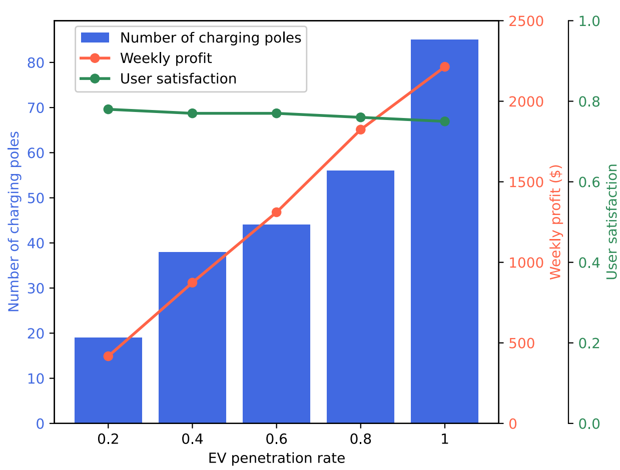

Fig. 9. Optimal number of charging poles with different EV penetration rates.

From Table 7, although weekly profit increases, the profit per unit capital cost decreases as power rating increases. Higher-rated power poles provide greater user satisfaction per unit capital cost. The optimal number of charging poles does not necessarily decrease as the rated power increases, as it is determined by the trade-off between profit and user satisfaction.

Fig. 9 illustrates the optimal number of charging poles for various EV penetration rates. On average, for every 0.2 increment in the EV penetration rate, the optimal number of charging poles increases by 19. Meanwhile, the average weekly profit rises by $ 443, with user satisfaction remaining largely unchanged.

Fig. 10 compares the scheduling results under the fixed and time-of-use charging service fees when installing 19 charging poles. The time-of-use charging service fee is $b^{tou} + \Delta b$, where b^{tou} represents the grid time-of-use tariff and Δb is a fixed value. Selecting an appropriate Δb to ensure direct comparability between the time-of-use and fixed-rate charging service fees is challenging. However, the scheduling results indicate that the rescheduled charging demand under the time-of-use charging service fee is independent of Δb, allowing for a fair comparison based on electricity costs. The results show that the energy costs under the time-of-use and fixed-rate tariffs are $ 1,794 and $ 1,795, respectively, with total energy served at 10,215 kWh and 10,144 kWh, respectively. However, the maximum demand cost under the time-of-use charging service fee is $ 626, exceeding the $ 616 observed under the fixed-rate charging service fee. These findings suggest that while both pricing schemes deliver a similar amount of energy, the fixed charging service fee leads to lower overall charging costs and higher user satisfaction within the proposed framework.

5. Conclusions

This study presents an optimal retrofit planning framework for transitioning parking lots into EV charging stations under prolonged load shedding. The proposed multi-objective approach determines the ideal number of charging poles by balancing financial viability and user satisfaction, yielding Pareto-optimal solutions for the number of charging poles. Depending on the owner's preference between the two objectives, the optimal number of charging poles may increase, decrease, or remain unchanged compared to scenarios without load shedding. The analysis highlights that post-outage demand peaks significantly elevate the maximum demand costs for charging stations. However, the proposed scheduling approach reduces maximum demand costs by 14%, offering benefits to both parking lot owners and the power grid. Through an evaluation of 52-week load shedding scenarios, a strong negative correlation emerges between weekly profit, user satisfaction, and outage hours, with each additional hour of load shedding reducing weekly profit by $3.74 and user satisfaction by 0.32%. Furthermore, for every 0.2 increment in EV penetration rates, the optimal number of charging poles increases by 19. Compared to URUS methods, the proposed parking lot retrofit planning approach improves weekly profit by 19% and enhances user satisfaction by 14%. These findings provide valuable insights and actionable recommendations for stakeholders in the development and optimization of EV charging infrastructure. Future work will focus on developing mitigation strategies to mitigate the impact of load shedding on charging stations.

CRediT authorship contribution statement

Gang Yu: Writing – original draft, Methodology. **Xianming Ye:** Writing – review & editing, Supervision, 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.

Appendix. Load shedding schedule

Table A.1 gives the load shedding schedule in Hatfield, Pretoria, South Africa.

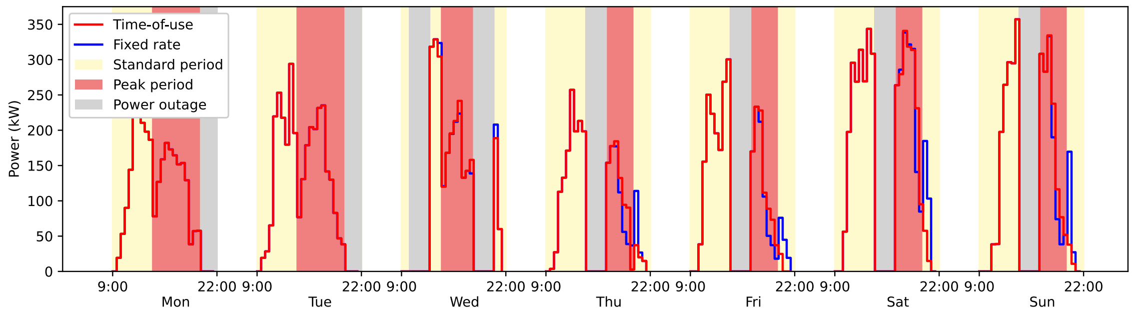

Fig. 10. Rescheduled charging demand under the fixed and time-of-use charging service fee with 19 charging poles.

Table A.1
Load shedding schedule in Hatfield, Pretoria, South Africa.

Stage	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	–	4:00–6:30	10:00–12:30	–	6:00–8:30	14:00–16:30	22:00–24:00
2	20:00–22:30	4:00–6:30	2:00–4:30 10:00–12:30	22:00–24:00	6:00–8:30	6:00–8:30 14:00–16:30	14:00–16:30 22:00–24:00
3	12:00–14:30 20:00–22:30	4:00–6:30 20:00–22:30	2:00–4:30 10:00–12:30	14:00–16:30 22:00–24:00	6:00–8:30 22:00–24:00	6:00–8:30 14:00–16:30	6:00–8:30 14:00–16:30 22:00–24:00
4	4:00–6:30 12:00–14:30 20:00–22:30	4:00–6:30 12:00–14:30 20:00–22:30	2:00–4:30 10:00–12:30 18:00–20:30	6:00–8:30 14:00–16:30 22:00–24:00	6:00–8:30 14:00–16:30 22:00–24:00	6:00–8:30 14:00–16:30 22:00–24:00	6:00–8:30 14:00–16:30 22:00–24:00
5	0:00–2:30 4:00–6:30 12:00–14:30 20:00–22:30	4:00–8:30 12:00–14:30 20:00–22:30	2:00–4:30 10:00–14:30 18:00–20:30	6:00–8:30 14:00–16:30 22:00–24:00	6:00–10:30 14:00–16:30 22:00–24:00	6:00–8:30 14:00–18:30 22:00–24:00	6:00–8:30 14:00–16:30 22:00–24:00
6	0:00–2:30 4:00–6:30 12:00–14:30 20:00–24:00	4:00–8:30 12:00–14:30 20:00–22:30	2:00–6:30 10:00–14:30 18:00–20:30	6:00–8:30 14:00–16:30 22:00–24:00	0:00–2:30 6:00–10:30 14:00–16:30 22:00–24:00	6:00–10:30 14:00–18:30 22:00–24:00	6:00–8:30 14:00–18:30 22:00–24:00
7	0:00–2:30 4:00–6:30 12:00–14:30 20:00–24:00	4:00–8:30 12:00–16:30 20:00–22:30	2:00–6:30 10:00–14:30 18:00–22:30	6:00–8:30 14:00–18:30 22:00–24:00	0:00–2:30 6:00–10:30 14:00–16:30 22:00–24:00	0:00–2:30 6:00–10:30 14:00–18:30 22:00–24:00	2:00–4:30 6:00–8:30 14:00–18:30 22:00–24:00
8	0:00–4:30 4:00–6:30 12:00–14:30 20:00–24:00	4:00–8:30 12:00–16:30 20:00–24:00	2:00–6:30 10:00–14:30 18:00–22:30	0:00–2:30 6:00–8:30 14:00–18:30 22:00–24:00	0:00–2:30 6:00–10:30 14:00–18:30 22:00–24:00	0:00–2:30 6:00–10:30 14:00–18:30 22:00–24:00	2:00–4:30 6:00–10:30 14:00–18:30 22:00–24:00

Data availability

Data will be made available on request.

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