1 Introduction

Electric vehicles (EVs) have long been considered as one of the potential alternative technologies for fossil fuel-based vehicles in order to alleviate the energy efficiency and environmental concerns. Relatively high oil prices caused by the depletion of oil reserve and large greenhouse emissions have been strong impetus for the widespread penetration of EVs. However, relatively short driving distances and long battery charging time in battery charging stations hinder the widespread use of EVs. EVs still have a number of disadvantages which hinder their further prevalence. A well-known shortcoming of EVs is their short driving range and long battery charging time, which can greatly affect the driving experience. AC Level 1 and AC Level 2 charging as commonly seen in EV charging stations can add around 2–5 and 10–20 miles of driving range per hour of charging [1], respectively, which are far more time consuming than refuelling a car using gasoline. Even the state-of-the-art DC Level 2 fast charging technology can achieve 75% of the state-of-charge (SoC) of the batteries for replacement may take more than ten minutes slower than adding the same driving range to a conventional car with a gas pump. A new business model of building a network of fast battery swapping station (BSS) has been proposed to address this challenge and is supported by major EV manufacturers such as Tesla [2], Mitsubishi [3], and so on. In a BSS, depleted or partially depleted batteries can be easily replaced by fully or partially charged batteries [4, 5]. Drivers only need to wait for a short period of time for dismounting and loading batteries. By adopting the battery swapping strategy, customers are released from the time- and energy-consuming recharging operations and the maintenance of batteries, which are frequently implemented in the BSS. Charging scheduling of batteries is managed by the operator of the BSS, targeting maximisation of the energy cost and satisfying customer demands at the same time, with the potential of enhancing grid stability by properly responding to the dynamic energy pricing policies [6, 7].

Different from the traditional ‘park and charge’ scenario, the battery swapping concept is a relatively new idea with only a history of a few research investigations. Zheng et al. [8] and Yang and Hao [9] focused on the optimal installation location problems of BSS. In [8], the battery charging/swapping station models are developed to compare the revenue of rapid-charging stations and BSSs using life-cycle cost analysis. Yang and Hao [9] proposed a heuristic to determine the location strategy of BSS and the routing plan for a fleet of EVs under battery driving range limitation. Sun et al. [10] formulated the battery charging scheduling problem in a BSS as a stochastic control problem using the queueing network model, and derived the optimal solution using dynamic programming. In [11], Yang et al. compared the BSS and the traditional battery charging stations and analysed the market strategy of BSS to increase the profit from the energy price fluctuation, but only fully charged batteries could be swapped in their model, which is not practical. These previous works are based on stationary models and have not effectively integrated battery charging scheduling with the time-varying EV arrival rate, the dynamic energy price fluctuation, which limits their practicality in actual implementations. EVs may arrive at the BSS requesting for swapping service with different rates at different times-of-day, and the state-of-charges (SoCs) of the battery for replacement may also vary. The BSS operator needs to make online adaptive decisions about the charging scheduling of (partially) depleted batteries based on the battery SoCs, the dynamic energy pricing policy, and estimated EV arrival rates.

Different from the aforementioned works, we consider a realistic BSS framework in which EVs can arrive at BSS with time-of-day dependent rates having different battery state-of-charges. They investigate the battery charging scheduling problem in the BSS under a dynamic energy pricing strategy. They solve (i) an online optimal BSS control problem to minimise the energy cost with a quality-of-service (QoS) guarantee, and (ii) an offline optimal BSS design problem to determine the optimal number of stored batteries so as to achieve a desirable tradeoff between flexibility in charging and amortised battery costs. The experimental results show that the total charging energy cost can be reduced significantly under different traffic scenarios.
which manufactures, capabilities, and other battery metrics are included. (ii) We jointly consider online BSS control problem and offline BSS design problem in our framework.

The rest of paper is organised as follows. The detailed system model and problem formulation are described in Section 2. Section 3 presents the solution methods of both BSS control problem and BSS design problem. Experimental results are followed in Section 4.

2 Problem formulation

2.1 BSS system model

The general BSS system multilevel design architecture is proposed in Fig. 1. The swapping centre at the bottom level is the interface for delivering swapping services to the incoming EV traffic. The battery coordinator manages all stored batteries inside the BSS and has the ability to set target SOCs and appropriate charging deadlines for batteries based on a probabilistic prediction of the near future EV traffic. A target QoS must be provided. The battery charging scheduler aims at deriving optimal charging rates for batteries in response to energy price fluctuations, and meeting constraints, such as battery characteristics, desired QoS levels.

In order to fulfil the swapping requests from the incoming EV traffic, the BSS should be equipped with a sufficient number of batteries. Let $N$ denote the total number of batteries in the BSS of interest, and let $T = 24$ h denote the optimisation time horizon of the BSS management problem. Obviously, the number $N$, which is the count of batteries stored in the BSS at any time $t$, will remain fixed during the whole day. In a realistic BSS system, each battery + could be either fully charged or (partially) depleted, i.e. its charging demand $D_j \geq 0$ can be an arbitrary value according to the target SOC for that battery. Finally, the number of batteries $N$ in the BSS needs to be optimised since storing more batteries than needed will incur a more significant capital cost and battery maintenance cost.

Suppose the $i$th EV arrives at time $t$ with the battery state-of-charge $SoC_i$, the battery nominal capacity $C_i$, the maximum battery charging rate $V_o$, and the requested battery SOCrj. If there is a stored battery with a SOC at least SOCrj, the battery on the EV will be replaced by the stored battery $j$ (SOCrj $\geq$ SOCrj) in the BSS based on a swapping policy, supposing that each stored battery in the BSS has a unique index (ID) $j \in \{1, 2, \ldots, N\}$. The information of stored battery $j$ should be updated with the dismounted battery, i.e. the starting time $t' = t$, SoCrj, and $R_j$. With the updated information of all stored batteries, the battery coordinator determines target SOCrj and charging deadlines $t'j$ for all batteries $j \in \{1, 2, \ldots, N\}$ according to a prediction of future traffic and a desirable QoS level. At the battery charging scheduler level, optimal charging rates $s_j$ for the $j$th battery at time $t$ can be determined so as to minimise charging costs while considering battery characteristics and charging deadlines.

Similar to previous works [10, 12], the instantaneous power consumption of BSS satisfies a general quadratic function of the total charging rate of batteries at time $t$, i.e.

$$S_t = \alpha(\sum_{j \in J} s_j) + \beta(\sum_{j \in J} s_j)^2,$$

where $J$ is the set of batteries being charged in the BSS at time $t$, $\alpha$ and $\beta$ are parameters accounting for various aspects of energy loss such as the battery's rate capacity effect, the loss inside batteries, the energy loss in DC–DC converters and other conversion circuitry, and so on [13, 14]. We derive $\alpha$ and $\beta$ parameters from our actual measurement results for a number of different batteries and the requisite conversion circuitry. In our BSS charging scheduling model, the dynamic energy pricing scheme from the utility grid is considered. Dynamic energy pricing programs allow customers to pay a temporally fluctuating market rate for their electricity [15–17]. Price is higher during the peak hours than off-peak periods, encouraging users to shift loads to off-peak hours to lower their electric energy cost, thereby relieving the stress on the utility grid [18]. Let $\xi(t)$ denote the energy price at time $t$.

2.2 Battery charging scheduler

Based on the above definitions and system modelling accounting for the energy price fluctuation, the static version of the battery charging problem at the battery charging scheduler level for energy cost minimisation is described as follows.

**Static version of battery charging problem for energy cost minimisation.**

**Given:** the charging starting time $t_j$, deadline $t'_j$, maximum charging rate $R_j$, charging target SOCrj and current SOCjr for each battery $j$ at time $t$, $1 \leq j \leq N$.

**Find:** the optimal charging rate $s_j$ for each battery at time $t$.

**Minimise:**

$$\int_{t_j}^{t'_j} \xi(t) \times \left(\sum_{j \in J} s_j \right)^2 \, dt$$

**Subject to:**

$$\int_{t_j}^{t'_j} s_j \, dt \geq D_j, \quad \forall j \in \{1, 2, \ldots, N\}$$

$$0 \leq s_j \leq R_j, \quad \forall j \in \{1, 2, \ldots, N\}$$

$$D_j = \max \{0, \text{SOCrj} - \text{SOCjr}\}$$

where constraint (1b) ensures that the charging demands of all batteries are satisfied during the time interval between the starting time and the deadline. Constraint (1c) ensures that the charging rate cannot be negative or exceed the maximum charging rate for each battery. The charging demand is zero if target SOCrj $\leq$ SOCjr, which is described by constraint (1d).

For the static version with charging demands, $(t'_j, \xi(t), D_j, R_j)$ of all batteries are given to the BSS battery charging scheduler. The problem is thus a convex optimisation problem with a convex objective function and linear constraints, and therefore can be solved optimally with a polynomial time complexity [19]. However, in reality, the BSS management problem is essentially an online adaptive problem, in that EVs can arrive at the BSS at random times during a day, and a dismounted battery along with all other stored batteries can have arbitrary charging demands and deadlines that are determined by the BSS battery coordinator. Therefore, the BSS battery coordinator should adaptively provide appropriate inputs to the battery charging scheduler based on the current status and prediction of future arrival of EVs, in order to satisfy the QoS constraint. Details of the BSS battery coordinator are described in the next subsection.

2.3 Battery coordinator

In our proposed multilevel architecture, the objective of battery coordinator is to determine the charging target SOC and deadlines for a batch of batteries in the BSS with the guarantee of QoS levels based on the EV traffic prediction.

2.3.1 QoS guarantee: The swapping service request of an EV can only be fulfilled if the BSS has at least one battery at the
requests at time \( t \) the probability of \( k \) EVs arriving during time interval \([t, t + \Delta t]\) is given by

\[
P_L^k \Delta t(k) = \frac{\lambda_L(t) \Delta t}{k!} e^{-\lambda_L(t) \Delta t} \tag{2}
\]

At time \( t + \Delta t \), the number of quality level \( L \) batteries is \( N_{L+}^{\Delta t} \) and thus a total number of \( \sum L N_{L+}^{\Delta t} \) EVs can be served, where \( m \) is the discrete quality level index. From (2), the probability that the quality level \( L \) requirement of EVs can be satisfied is given by

\[
P_{\text{RSS}}^{\Delta t} = \sum_{k=0}^{N_{L+}^{\Delta t}} P_L^k \Delta t(k) \tag{3}
\]

which equals the probability that no more than \( N_{L+}^{\Delta t} \) EVs will arrive in the prediction sliding time window \([t, t + \Delta t]\). Let \( \rho \) denote the QoS tolerance level for the BSS, then \( P_{\text{RSS}}^{\Delta t} \) should satisfy the constraint \( P_{\text{RSS}}^{\Delta t} \geq \rho \).

### 2.3.2 Battery coordination

Given the time window \([t, t + \Delta t]\), predicted arrival rates \( \lambda_L(t) \) and QoS tolerance value \( \rho \), we can calculate the least number \( N_{L+}^{\Delta t} \) of level \( L \) batteries which should be ready for swapping at time \( t + \Delta t \), i.e. the charging deadlines. The prediction time window should be varied in an appropriate range, which should consider both the short term and relatively long term. The short-term prediction can help determine more precise deadlines, however, it cannot deploy batteries effectively and would suffer from the short horizon. The long-term prediction would neglect the bursting traffic, which may result in the failure to serve swapping requests.

Among all stored batteries, the BSS battery coordinator should select which batteries are swapping candidates for quality level \( L \) requests at time \( t + \Delta t \), aiming at satisfying QoS and minimising the total charging energy. Let the binary variable \( x_{jm} \in [0, 1] \) denote whether the battery coordinator sets the charging target of the battery \( j \) as \( L_m \) (1) or not (0). In our work, the quality level \( L_m \) belongs to a discrete set, for \( m \in [0, M] \).

Based on the above description, we formulate the BSS battery coordinating problem as follows.

**Given**: the QoS tolerance \( \rho \), the prediction time window \([t, t + \Delta t]\), the arriving rate \( \lambda_L(t) \), stored batteries \( SOC_j \), charging target \( SOC_{L_m} \), maximum charging rate \( R_j \).

**Find**: the optimal mapping of a battery \( j \) to a charging target \( SOC_{L_m} \), which is denoted as the value of \( x_{jm} \), \( j \in [0, N], m \in [0, M] \).

**Minimise**:

\[
\sum_{j=0}^{N} \sum_{m=0}^{M} x_{jm} \times D_{jm} \tag{4a}
\]

**Subject to**:

\[
x_{jm} \in \{0, 1\} \tag{4b}
\]

In the objective function (4a), \( D_{jm} \) is the charging demand by setting the target of battery \( j \) as \( L_m \). The BSS battery coordinator tries to minimise the total charging demand for all batteries.

Constraint (4b) captures the fact that the \( x_{jm} \) is a binary variable.

Constraint (4c) ensures that a battery can be assigned only one target level. Constraint (4d) captures the relation that the number of batteries at level \( L_m \) should be at least \( N_{L+}^{\Delta t} \) in order to satisfy swapping requests at time \( t + \Delta t \). Constraint (4e) is the charging demand for \( SOC_j \) targeting at \( SOC_{L_m} \). Constraint (4f) ensures that the charging demand is feasible considering the maximum charging rate. Constraint (4g) ensures that the QoS is guaranteed.

Based on the above description and formulation, the minimum number of \( L_m \) batteries at time \( t + \Delta t \), \( N_{L+}^{\Delta t} \) can be calculated by (3). Therefore, the BSS battery coordination problem is an integer linear programming (ILP) problem, which can be solved in standard solvers.

### 2.4 Online optimal BSS control problem

Based on the discussion before, we describe the online optimal BSS control problem for energy cost minimisation. Given the total number of batteries \( N \) of the offline design problem and battery information, the BSS battery coordinator and battery charging scheduler adaptively make deployment decisions and set charging schedules when each EV arrives considering the dynamic energy pricing.

An example of the online BSS control problem is illustrated in Fig. 2. The hourly dynamic energy prices are denoted by \( \xi(1), \xi(2), \ldots, \xi(24) \) for the price during each hour \([00:00, 01:00), [01:00, 02:00), \ldots, [23:00, 24:00) \). At time \( t = \delta_1 \), only the profiles \( t_1, t_1', t_1'' \) of first and second battery are given or decided by the BSS charging scheduler. Let the set of time epochs represent the union set of integer time points (hours), and starting times and deadlines of battery charging. A time interval is defined as the time period between two adjacent time epochs. At time \( t \), let \( K(t, j) \) denote the index set of time intervals for \( j \)th battery, and let \( \delta(k) \) denote the duration of \( k \)th interval. For example, at time \( t = \delta_2 \), the duration of time intervals are given by \( \{\delta(1), \delta(2), \ldots, \delta(k)\} \). We use \( J(t, k) \) to denote the set of batteries being charged at the \( k \)th interval, based on the charge scheduling determined at time \( t \).

The online BSS control problem is described as follows.
Online BSS control problem for energy cost minimisation at time $t$.

**Given:** Stored batteries information $\text{SOC}_j$, the maximum charging rate $R_j$, the battery nominal capacity $C_j$, and the QoS tolerance $\rho$, the prediction time window $[t, t + \Delta t]$, the predicted arrival rate $\lambda_\text{in}(t)$, $m \in [0, M]$. 

**Find:** The optimal charging rate $s_j(k)$ for $j \in J(t, k)$ at $k$th time interval, $k \in K(t)$, which is the union of all $K(t, j)$ for all $j \in J(t, k)$, given the number of batteries $N$. 

**Minimise:** 

$$\sum_{k \in K(t)} \xi(k) \left( \alpha \left( \sum_{j \in J(t, k)} s_j(k) \right)^2 + \beta \left( \sum_{j \in J(t, k)} s_j(k) \right) \right) \times \delta(k)$$  

(5a)

**Subject to:** 

$$\sum_{k \in K(t, j)} s_j(k) \times \delta(k) \geq D_j(t), j \in J(t, k)$$  

(5b)

$$0 \leq s_j(k) \leq R_j, \quad j \in J(t, k)$$  

(5c)

$$s_j(k) = 0, \quad k \in K(t) \setminus K(t, j)$$  

(5d)

$$P_\text{BSS, in} \geq \rho$$  

(5e)

where this online BSS control problem is a discrete-time-based optimisation problem. When a new EV comes and the battery is swapped at time $t$, the sets $K(t, j)$, $J(t, k)$, and $D_j(t)$ are updated. $D_j$ is the charging demand for $j$ at time $t$. The battery coordinator first maps batteries to the target SOC and sets the charging deadlines by solving charging levels in (4). Then, the new charging schedules will be decided by the BSS battery charging scheduler solving (5). Note that the problem described in (1) is a static version of battery charging problem for energy cost minimisation and the charging deadlines of all EVs' batteries are prior known to BSS in (1). The problem of (1) can be optimally solved using convex optimisation but it is not a realistic setting. Here, the problem described in (5) is an online problem involving battery swapping and has QoS constraint. Note that the owners of BSSs can be a third-party company which provides battery swapping service or EV manufacturers aiming to improve QoS and concerning about the operation costs. In this case, the formulation would be still reasonable. In Section 3, we will present details of proposed solutions to this problem.

2.5 Offline optimal BSS design problem

For a profitable BSS, the infrastructure must be provided at a low cost. In the BSS business model, batteries are owned by BSS instead of EV drivers. It is critical for the BSS to determine an appropriate number of batteries in circulation because the equipment purchasing, maintenance cost, and amortised battery degradation cost will increase when more batteries are in store. The optimal number of batteries is influenced by several key factors, such as the EV traffic, charging demands, and charging rates. A low number of batteries at the BSS can reduce the battery degradation and maintenance cost, but will restrict the freedom of BSS scheduler on charging scheduling exploiting the energy price fluctuation. The optimal number of stored batteries should be derived to achieve a desirable trade-off of the above two factors.

Let $\gamma$ denote the cost per stored battery in a unit time, which includes the maintenance cost and the amortised degradation cost, i.e. the state-of-health degradation. Let $\Gamma$ denote the capital cost per stored battery. For simplicity, we assume that $\gamma$ will be constant during a day. Therefore, the fixed cost associated with $N$ batteries during time $\Delta t$ is $N \cdot \gamma \cdot \Delta t$. Given the traffic data for a whole day, the offline BSS design aims at finding the optimal number of stored batteries and charging policies for minimising the total cost.

**Offline BSS design problem.**

**Given:** The EV traffic information within a day.

**Find:** the optimal number of batteries $N$ at the design time.

**Minimise:** 

$$\sum_{k \in K(t)} \xi(k) \left( \alpha \left( \sum_{j \in J(t, k)} s_j(k) \right)^2 + \beta \left( \sum_{j \in J(t, k)} s_j(k) \right) \right) \times \delta(k)$$  

(6a)

**Subject to:** 

$$P_\text{BSS, in} \geq \rho$$  

(6b)

The EV traffic information should be given to the BSS, and the optimal number of stored batteries can be found by a local search procedure. The state of all stored batteries could be initialised based on a proportional rule in the offline design problem to reflect the adjustment of battery number. However, in the online control problem, the initial batteries could be in random states. Notice that the offline BSS design problem requires the solution of the BSS control problem, i.e. the BSS control problem must be solved and the optimal $s_j(k)$ profile derived for each possible $N$ value.

3 Solution method

Based on the aforementioned formulation, a framework for solving the online BSS control and offline BSS design problem, named the battery swapping charging algorithm (BSCA), is proposed in this section to effectively minimise the overall cost. The BSCA algorithm comprises of two parts: (i) solution to the online optimal BSS control for optimal battery coordinating and charging policies in order to minimise the energy cost with QoS guarantee, (ii) offline BSS design for searching the optimal number of stored batteries.

3.1 Online optimal BSS control

In the online optimal BSS control problem, the number of batteries $N$ is given by the offline design. At each time $t$ with an EV arriving, a battery having finished its charging process or the dynamic energy price period changing, the stored battery information is updated. Then, charging deadlines and charging SOC targets for all stored batteries are calculated by the BSS battery coordinator with the QoS guarantee.

As described in Section 2, the future arrival of EVs is assumed to follow a time-varying Poisson process. Based on the key prediction parameter, the future arrival rate $\lambda_\text{in}(t)$ at time $t$, the minimum number of batteries $N_\text{min}$ that should be at SOC $\text{C}_j$ at time $t$ is calculated by using (2) and (3) satisfying the QoS tolerance$. The optimal mapping of the current stored batteries to charging targets SOC $\text{C}_j$ at time $t + \Delta t$ is calculated by solving (4). We find the appropriate deadline $T_j^t$ by searching the prediction time window $[t, t + \Delta t]$ with increasing $\Delta t$ at each prediction step. The described problem can be solved using a kernel ILP solver within a loop which increases the prediction window at each iteration.

After determining appropriate deadlines and SOC target levels, information about all batteries $B_{\text{BSS}}$ is updated, and the optimal charging rates of all batteries that minimise the energy cost are derived by solving (5). A package for specifying and solving convex programs, such as CVX [22], or the fmincon function in Matlab, is used in this paper.

3.2 Offline BSS design

The offline BSS design problem is solved by a local search method, where searching range is specified as $[N_{\text{min}}, N_{\text{max}}]$. For each number in the searching range, the starting time $T_j^t$, deadlines $T_j^t$ and target SOC levels of all stored batteries and the batteries that can be swapped in the future are calculated by solving (4). Next, the minimum total cost is obtained by solving (6). Using the EV traffic information offline, the optimal number of stored batteries satisfying the QoS constraint is found.
The pseudo-code of proposed online BSCA is provided in Algorithm 1 (see Fig. 3). The input data include the initial $N$ batteries information $B_{init}$ consisting of the battery profiles $(V_j, t_j^f, SoC_j, C_j)$, predicted EV arriving rate $\lambda_{ev}(t)$, and QoS tolerance level $\rho$. The output data include the optimal mapping of batteries to certain target SOCs and deadlines, charging rates profile for all batteries.

The algorithm is executed when an EV arrives, a battery has finished its charging process or the dynamic energy price period changes. When a swapping service is requested, the algorithm checks if the BSS has batteries at least at the requested level. The battery can be swapped only if batteries above the requested are available and the stored battery information $B_{old}$ is updated. Given each $\Delta t$ within the prediction time window (here, 2 h is default), (2)–(4) are solved for obtaining the optimal mapping of batteries to target SOC levels and deadlines at time $t + \Delta t$ satisfying the $P_{soc}$ constraint. The battery coordinator updates the battery mapping results and sends them to the battery charging scheduler for calculating optimal charging rates achieving the energy minimisation under dynamic energy prices. At each decision time epoch, $B_{old}$ is updated based on previous charging rate profiles. In addition, the real-time energy cost from the last decision time epoch until the current time is calculated. Finally, the overall cost for the whole time horizon is calculated.

### Algorithm 1: BSCA

| Data: $B_{init}$, $\lambda_{ev}(t)$, $\rho$, $N$ | Result: $s_j(k), E_{j,im}, C_j$ for each battery $j$ |
|------------------------------------------------|--------------------------------------------------|
| initialization $B_{init} = B_{init}$ | while an EV arrives or a battery has finished its charging process or the dynamic energy price period changes do |
| Record current time $t$ | if swapping is requested then |
| Update the $B_{init}$ | if the BSS has at least one battery at or above the requested SOC level then |
| Swap the battery | Update the $B_{init}$ |
| else | $s_j(k) = 0$, $E_{j,im} = 0$, $C_j = 0$ for each battery $j$ |
| Record the swapping failure | end |
| for $\Delta t = [0, 2h]$ do | The battery coordinator solves Eqn. (2)–(4) for the optimal mapping of batteries to target SOC levels and deadlines at time $t + \Delta t$. |
| Update the charging demands $D_{j,im}$ and deadlines $t_{j}^f$ of batteries according to the mapping results. | if at least one battery needs to be charged then |
| The battery charging scheduler solves Eqn. (5) for optimal charging rates $s_j(k)$. |
| end |

![Fig. 3](image)

Algorithm 1: BSCA

![Fig. 4](image)

Off-line design tradeoff with the battery number

The cumulative charging costs using the BSCA, A1, A2, and A3 are plotted in Fig. 5: light traffic (Fig. 5a), moderate traffic (Fig. 5b), heavy traffic (Fig. 5c). Only the charging costs are considered for comparison. As shown in Table 1, charging costs can be reduced by 45, 92, and 90%, respectively, comparing with A1, A2, and A3 methods under the heavy traffic scenario. By comparing the (A2, A3) or (A1, BSCA), in which charging rates are determined by an identical policy, we can see that the battery coordinator can reduce the charging cost. The reason of the battery charging scheduler in BSCA reducing a significant amount of charging cost is that the charging is shifted to 'off peak' hours when energy prices are lower. This shifting can reduce total charging costs at the end of a day. For the moderate and the heavy traffic scenario, the charging costs is closed to the BSCA because charging some batteries at lower SOC at the ‘off peak’ will have the chance to save costs in the future under the condition that the charging rates are optimised as the BSCA. However, this is not guaranteed.

Implementing the proposed BSCA in multi design levels in the BSS reduces the charging cost significantly.

### 4 Experimental results

In this section, we evaluate the proposed BSCA in real-time scenarios. Typical market prices are obtained by averaging day-ahead LMP prices from the period August 2015 in the PJM market [23]. The coefficients of the charging cost function are set to $\alpha = 0.225/kW$ and $\beta = 0.13$. The battery cost $\gamma = 1.75$/h, $\Gamma = 3000$. According to state-of-art battery charging parameters [24], the requested levels battery swapping can be divided into four groups [25, 50, 75, 100] kWh. For QoS tolerance probability, $\rho$ is set to 95%.

Three scenarios are simulated: (i) light traffic, (ii) moderate traffic, (iii) heavy traffic. First, the offline design problem for the moderate traffic is shown in Fig. 4. From the result, we know that increasing the total number of batteries will gain more flexibility result in reducing the charging cost at the expense of increasing the amortised and capital cost. In order to maximise the avenue of BSS, a carefully offline design is needed considering possible economical parameters.

Three baselines are developed for the comparison of charging cost: (A1) the battery coordinator satisfies the larger target SoC first by randomly choosing feasible batteries, while the deadlines and charging rates are decided the same as the BCSA; (A2) the battery coordinator randomly chooses batteries for charging at an average rate $D_j/(t_j^f - t_j)$; (A3) the battery manager follow the same policy as the BSCA, but charges the battery at average rates. For all baselines, a same QoS is ensured.

The BSS strategy is promising for meeting fast recharging demands in the future. In this work, the battery charging scheduling and design problem are investigated under dynamic energy pricing. An online QoS-aware algorithm, BSCA, is proposed to minimise the charging energy costs and to satisfy swapping requests with a service tolerance probability at the same time. In addition, an offline optimal BSS design problem is solved to find the optimal number of batteries. Realistic EVs swapping and charging experiments are implemented to evaluate the performance of proposed BSCA under three traffic scenarios. The results show that the charging energy costs can be reduced significantly comparing with three other baselines.

### 5 Conclusion

The BSS strategy is promising for meeting fast recharging demands in the future. In this work, the battery charging scheduling and design problem are investigated under dynamic energy pricing. An online QoS-aware algorithm, BSCA, is proposed to minimise the charging energy costs and to satisfy swapping requests with a service tolerance probability at the same time. In addition, an offline optimal BSS design problem is solved to find the optimal number of batteries. Realistic EVs swapping and charging experiments are implemented to evaluate the performance of proposed BSCA under three traffic scenarios. The results show that the charging energy costs can be reduced significantly comparing with three other baselines.
Fig. 5  Experimental results for three different scenarios: light, moderate, heavy traffic
(a), (b), (c) Cumulative charging cost comparisons for these three scenarios using the proposed algorithm and baselines, respectively

| Table 1 | Total charging costs comparison with baselines |
|------------------|------------------|
| **Charging costs reduction percentage** | A1, % | A2, % | A3, % |
| light | 5 | 80 | 74 |
| moderate | 26 | 86 | 82 |
| heavy | 45 | 92 | 90 |

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