An Optimization Model for Electric Vehicle Battery Charging at a Battery Swapping Station

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Abstract— **A new model for a viable battery swapping station (BSS) is proposed to minimize its cost by determining the optimized charging schedule for swapped EV batteries. The aim is to minimize an objective function considering three factors: the number of batteries taken from stock to serve all the swapping orders from incoming EVs, potential charging damage with the use of high-rate chargers, and electricity cost for different time period of the day. A mathematical model is formulated for the charging process following the constant-current /constant-current charging strategy. An integrated algorithm (IA) is proposed to determine an optimal charging schedule, which is inspired by genetic algorithm (GA), differential evolution (DE) and particle swarm optimization (PSO). A series of simulation studies are executed to assess the feasibility of the proposed model and compare the performance between IA and the typical evolutionary algorithms.**

Index Terms—**Battery swapping stations, electric vehicles, battery charging, optimization algorithms.**

I. Introduction

Electric vehicles (EVs) are now being widely adopted, not only to reduce the amount of fossil fuels used, but also out of consideration for greenhouse gas emissions and environmental protection. However, many car owners are still willing to buy traditional vehicles due to certain well-known drawbacks of EVs, such as long charging time, short battery life, limited travel distance per charge and expensive EV batteries. The introduction of the battery swapping station (BSS) would reduce range anxiety and provide access to fully-charged batteries for EV owners. When the battery of a vehicle is running low, an EV driver can drive to the nearest battery swapping station and swap to a recharged battery within two minutes.

Electric vehicle technology has been applied in many countries all over the world, and many different kinds of vehicles, such as private cars, taxicabs, buses and trucks have gone electric [1]. However, battery limitation remains the chief drawback to the development of EV technology. Firstly, the battery is deemed to be an expensive component of an electric vehicle, considering its initial purchase cost related to the life of the battery. Secondly, the travel range per charge mainly depends on the chemistry of the battery. The most commonly used battery on EVs is the lithium-ion battery, which can provide a travel range from 320 to 480 km per charge [2]. Yet, the range is still too short for some travelers who need to travel long distances within a day. Thirdly, charging time varies depending on different types of charging technology and equipment [3]. In this case, the battery swapping station model has been proposed as the alternative way for overcoming the drawback of EV batteries and charging technologies.

In the past decades, there are already loads of studies in the field of battery swapping station models. Some previous research [4] - [8] has focuses on maximizing the BSS's revenue by applying renewable energy resource, selling electricity back to grid and building centralized charging stations. In [4] and [5], a BSS model was proposed as a mediator between power system and EV order. It aimed to meet swapping demand and maximize its profits by buying electricity during low-price periods and selling electricity during high-price periods. However, the profits obtained by reselling electricity from batteries are unreal since they did not consider the batteries' degradation due to the frequent recharging cycles. In [6], an intelligent battery information management system was designed to eliminate the limitations of the long charging process and huge infrastructure cost. The idea was to charge swapped batteries in a management hub and then deliver them to a switching station via an optimized route with minimal supply chain costs. Nevertheless, the model assumes that all battery charging takes place only at the hub, which would result in many shipments of batteries. However, the challenge of the model is its difficulty to deliver the massive and heavy EV battery pack along with the potential damage during the delivery process. An economic dispatch model considering wind power for an EV battery swapping station was proposed in [7], and its results showed that a BSS operated on wind power can be profitable. In [8], a BSS distribution and power distribution model was established based on the energy exchanges in the battery swapping system. However, these studies are simplified since they didn't consider the possibility and complexity for building the renewable energy infrastructure in an urban area.

Other researchers [9] – [12] have worked to determine the location and distribution of battery swapping stations with the objective of maximizing its revenue, and decide on the charging schedule for electric buses. In [9], a distribution model of the BSSs in a particular area was proposed to optimize the cost-benefit and enhance safety. The life cycle cost criterion was used to specify the objective combining the cost of investment, operation, maintenance, failure and disposal. This model also considers the fluctuation of electricity prices during the day, and then adjust the charging strategies based on the electricity price. In [10], a decision model was proposed to choose the location of a battery swapping station serving EVs on freeways. The operation policy of the charging service provider was determined with the aim of preparing sufficient stock batteries for incoming swapping demand. However, the operation models with more than one battery swapping station has not been fully verified yet. Also, it is predictable that the investment for establishing a BSS distribution system is huge and the profit is not yet certain. Another BSS model was designed for the bus terminal at the Hong Kong International Airport in [11], which serves the electric bus routes in the airport. The BSS model aimed to optimize the battery charging methods to maximize the number of batteries in stock. However, the target of the model was only for the airport bus terminal serving electric buses. Also, the mathematical formulation was over simplified, and did not sufficiently consider the conditions of the charging stations and the batteries. An optimal charging schedule model for electric buses was proposed in [12] by determining the charging power of all the charging boxes over all time slots. The objective of the model was to minimize the cost combining the electricity cost, battery degradation and low battery utilization. However, the charging strategy did not follow the typical constant-current/constant-voltage strategy. Also, the arrival time of EVs considered in this paper is less predictable than electric buses.

Most of the research in the field of scheduling and decision making have focused on studying optimization algorithms, including heuristic, robust and evolutionary algorithms and policy definition. [4] and [5] used a mixed-integer linear programming model to solve the optimization problem. [8] proposed a "feed-in shift" method to realize the optimal configuration of wind, solar and hydro power. A robust optimization model was used for battery swapping infrastructure in [10]. Two particular policies, first-in first-out and highest State-of-Charge first, were compared in order to operate the swapping station with different numbers of batteries in stock. However, when the charging speed was improved to an acceptable level, the battery life factor becomes very important. Both the optimization software and robust models are not intelligent for exploring the optimal solution. A particle swarm optimization method was proposed in [6] to solve the multi-objective problem. The proposed model in [9] was a multistage, nonlinear, constrained mixed-integer optimization problem. A heuristic optimization technique was used to obtain a solution by determining the location, size, and strategy of the charging station based on the fixed demand of electric vehicles. [11] proposed a basic version of the genetic algorithm to obtain an optimal solution for determining the charging schedule for the airport buses. [12] proposed a direct projection method for solving the scheduling problem, which is more rapid than the generic algorithm. However, these research using optimization algorithms only implemented the basic program for solving a particular problem. Furthermore, they did not compare the performances using different algorithms for solving their problems.

Besides the operation model and optimization algorithms, the property of EV batteries play an important role in the proposed BSS model. Many factors, such as power and energy density, charging cycle life, calendar life, weight, and environmental friendliness, affect the development of battery technologies. Compared with lead acid, nickel-metal hydride and sodium batteries, the lithium-ion battery is regarded as the best type of battery for use in EVs ([13] - [16]). It has been widely reported that the battery's charging strategy is related to its charging rate, cycle life, temperature and safety ([17] - [19]). The constant-current (CC)/constant-voltage (CV) charging strategy [20] is the common standard for charging lithium-ion batteries. As a typical charging operation would take much longer than refilling a vehicle with gasoline, fast- and ultra-fast charging technologies were proposed [21] to improve the charging efficiency. However, these fast-charging schedules require certain conditions. First, the battery must be designed to be charged with a high current. Secondly, fast charging only applies to the first stage of charging, which is typically the constant-current stage. Thirdly, the high current should be reduced after the battery is around 70 percent charged, in order to protect the circuit and prolong the battery life. Lastly, fast charging can only be used in an environment in which a certain temperature can be maintained. Therefore, in this paper, we introduce a two-stage charging strategy (constant-current /constant-voltage) in Section II.

Cycle life is considered as one of the most important characteristics of EV batteries. There have been many experiments and studies that have focused on factors related to battery cycle life, such as material type, environmental temperatures, and charging depth [22] - [26]. After a battery has reached a long cycle life, the available electricity capacity is usually lower. Hence, the state of health (SOH) is used to indicate the battery's health condition in this paper. The cycle life of a battery is also related to the charging rate. When the SOH drops to a disposal threshold, it may indicate the retirement condition of the batter. The cycle life of a battery charged using 1C, 2C and 3C is around 500, 300, and 100 cycles respectively [21]. Hence, the damage to a battery charged using an ultra-fast charger is considerably increased. The cost of using fast chargers would be higher than that of using normal or slow chargers.

In this paper, based on the review of previous work, we assume that the BSS swaps and recharges batteries at the same location. The BSS does not aim to make profits by selling electricity back to the grid, considering that each discharging process would reduce the battery's lifecycle and increase the potential expense. Also, we have formulated a mathematical model for the constant-current/constant-voltage charging strategy in the optimization model. Three optimization algorithms are used and compared to solve the proposed model, and a new integrated algorithm is designed for improving the performance.

The main contribution of this paper is to develop a new battery swapping station model for determining a near-optimal schedule for recharging batteries at a battery swapping station, aimed at minimizing its operation cost. Previous research in [4] – [12] focused on making a profit by using a renewable energy source, optimizing the location of BSSs, and selling electricity back to the grid. Hence, the model and algorithms developed in this paper are inherently different from previous works. Based on the studies on battery technology in [13] - [26], this paper also formulates the battery's charging power function along with the charging time and charging power estimation model.

TABLE I
NOTATION OF VARIABLES

Variables	Descriptions
T	Set of time with index t.
S	Set of decision at time t.
E	Set of EV orders with index i.
B	Set of batteries with index j.
C	Set of charging methods with index k.
$sol(j)$	Assigned charging method to battery j.
$NumB$	Number of battery in a decision.
$NumE$	Number of EV orders.
P_{bat}	Normalized purchase price of a battery ($).
$dm(k)$	Normalized charging damage using charging method k ($).
$E(t)$	Electricity price at time t ($).
$P_j(t)$	Charging power to battery j at time t (kW).
T_j^S	Battery j's start charging time (HH:MM).
T_j^E	Battery j's end charging time (HH:MM).
$BT(t)$	Number of batteries taken from stock at time t.
$BC(t)$	Number of fully-recharged batteries at time t.
$BS(t)$	Number of batteries in stock at time t.
BT^{max}	Maximum number of batteries taken from stock.
$P_k(t)$	Charging power using method k at time t (kW).
P_k^{cc}	Power at constant-current stage of method k (kW).
P_{max}	Maximum power of a BSS (kW).
t_k^{cc}	Time for switching from constant-current to constant-voltage stage using method k.
t_k^{CV}	Time that finish charging using method k.
a_k	Parameter corresponding to charging method k.
η	State of health threshold switching from CC to CV state (%).
$SOH_j(t)$	State of health of battery j at time t (%).
$RCap_j$	Rated capacity of battery j (kWh).
$Cap_j(t)$	Available capacity of battery j at time t (kWh).
SOH_{min}	Disposal threshold state of health (kWh).
T_j	Time to recharge battery j from its current capacity to fully-charged.
$SOC_j(t)$	State of charge of battery j at time t (%).
$E_{off\text{-}peak}$	Electricity price in off-peak period ($).
$E_{mid\text{-}peak}$	Electricity price in mid-peak period ($).
$E_{on\text{-}peak}$	Electricity price in on-peak period ($).

This paper is organized as follows. Section II describes the operation model and the mathematical formulations. Section III introduces the optimization algorithms and a new integrated algorithm. A series of case studies are presented and discussed in Section IV. Finally, Section V gives the conclusions and describes the contribution of the paper.

II. Problem Formulation

In this model, the EV drivers are suggested to send an advanced notice to the BSS if they need to swap a battery. The advanced notice should include a forecast of arrival time, remaining capacity and state of health of the battery. In order to entice the EV drivers to send notices before arrival, the BSS may provide some price discount for the swapping service.

TABLE II
EXAMPLE WITH 16 ORDERS

Order index	Arrival Time	Remaining Capacity	SOH	**Charging method** [a]	Finishing time of recharging
1	9:04	30%	98%	**2**	11:16
2	9:17	13%	98%	**2**	11:29
3	9:43	26%	82%	**1**	10:57
4	9:55	17%	91%	**2**	11:57
5	10:03	34%	99%	**1**	11:32
6	10:26	14%	99%	**1**	11:55
7	10:44	34%	90%	**1**	12:05
8	10:53	30%	83%	**2**	12:45
9	11:00	21%	98%	**4**	15:23
10	11:26	30%	99%	**4**	15:52
11	11:36	26%	81%	**4**	15:13
12	11:54	31%	99%	**4**	16:20
13	12:14	27%	95%	**4**	16:29
14	12:22	29%	88%	**4**	16:18
15	12:32	26%	83%	**4**	16:15
16	13:00	28%	81%	**4**	16:37

a Notation of charging methods: 1-super charger; 2-fast charger; 3-normal charger; 4- slow charger.

From the BSS's perspective, the BSS aims to obtain an optimal charging schedule for all the known batteries. There are different strategies to enable a battery swapping station to minimize its operation cost.

1) Given a set of swapping orders with advanced notice from incoming EVs, the BSS should use the minimum number of batteries taken from the stock to serve the orders. This would allow the BSS to have more reserve to handle other EVs that arrive without appointment. With the use of the optimization strategy, the BSS can plan for a lower number of initial stock batteries in operation.
2) The BSS should aim to recharge swapped batteries with slow chargers, knowing that a fast charging schedule using high current/voltage would degrade the battery life cycle and hence increase the BSS's potential cost.
3) Due to the variability of electricity price during the day, the BSS should recharge the batteries when the electricity price is low.

Therefore, the proposed BSS model intends to find a balance to satisfy the above conditions.

A. Notation

The notation of variables used in this model is shown in Table I.

B. Decision Solution

From the battery swapping station's viewpoint, the aim is to minimize an objective function value which depends on the number of batteries needed from stock to serve all the orders, the potential charging damage with the use of different types of chargers and the electricity energy cost. Given a set of EV orders, with predicted arrival time, remaining capacity and SOH, the decision solution S is given as

$$S = \{sol(1), sol(2), ..., sol(j), ..., sol(NumE)\} \quad (1)$$

Here, $sol(j) = k$ means that charging method k is assigned to recharge the battery of EV order j in this solution, and $NumE$ is the number of EV orders/batteries needed for recharging.

Table II gives an illustration of the importance of determining an optimal schedule for simple 16-order case with arrival time between 9:00 and 13:00. The remaining capacity and state of health (SOH) of each incoming battery is assumed to be known. In this example, this information (column 3 and 4) is randomly assigned. A decision solution is shown below:

$S = \{2, 2, 1, 2, 1, 1, 1, 2, 4, 4, 4, 4, 4, 4, 4, 4\}$

as in column 5, and the finishing time of recharging is shown in column 6. Note that 1, 2, 3 and 4 denote super, fast, normal and slow charger respectively. For example, order index 3 arrives at 9:43, and a super charger (denoted by 1) is assigned to recharge the swapped battery. Then, the battery will be fully-recharged at 10:57 and it can be swapped to an order that comes after 10:57.

In this case, the eight batteries from order 1 to 8 have been assigned to use the super and fast chargers, so that they can be swapped to the subsequent orders. The other eight batteries from order 9 to 16 have been assigned for the slow chargers so that the charging damage can be minimal due to the use of low currents. This is as expected as they are the last batch of orders. With the use of the above solution, only 8 batteries would be taken from stock to serve the 16 swapping orders. Suppose the charger type for orders 1 to 8 are randomly assigned to super, fast, normal chargers, and orders 9 to 16 are assigned to slow chargers, our simulation results with 100 random solutions show that the average number of batteries taken from stock is over 10. In the next section, we will discuss that the key issue is on intelligent assignment of chargers for all the orders so as to balance between the number of batteries needed from stock, and the damage incurred to the batteries if super or fast chargers are used.

C. Objective Function

In order to determine an optimal solution for our problem, the objective function is formulated in terms of a monetary value. Here, it is defined as the average cost for serving the EV swapping orders as follows:

$$\text{minimize} \quad \frac{1}{NumB}[P_{bat} \cdot BT^{\max} + \sum_{j\in B} dm(sol(j)) + \sum_{j\in B} \int_{T_j^S}^{T_j^E} P_j(t)E(t)dt] \quad (2)$$

Here, the charger assigned for battery j is defined as $sol(j)$. The objective function consisted of three components. The first part,

$$P_{bat} \cdot BT^{\max} \quad (3)$$

refers to the need to use BT^{max} number of batteries taken from stock to serve all the orders, where P_{bat} is the normalized price of a battery.

The second part,

$$\sum_{j\in B} dm(sol(j)) \quad (4)$$

is the total charging damage by summing up the charging damage to each battery. $dm(sol(j))$ denotes the normalized charging damage using charger $sol(j)$. Details on their calculations are given in Section IV.

The third part,

$$\sum_{j\in B} \int_{T_j^S}^{T_j^E} P_j(t)E(t)dt \quad (5)$$

is the total electricity cost on recharging all the batteries. Here, j is the battery index for the battery. $P_j(t)$ is the charging power of battery j at time t, and $E(t)$ is the electricity price at time t. Considering the variation of electricity price, the electricity cost for each battery is obtained by integrating the product of charging power and electricity price within its charging period from T_j^S to T_j^E. The total electricity cost is the sum of individual cost spent on recharging the swapped batteries.

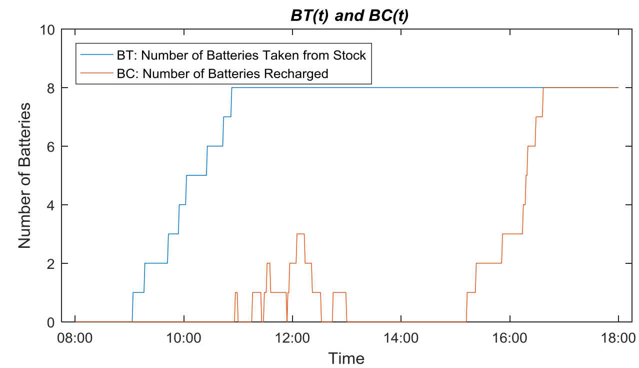

Fig. 1. *BT(t)* and *BC(t)* in the Example with 16 Orders.

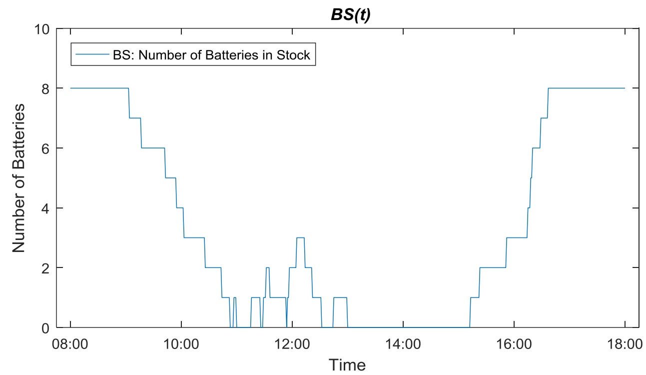

Fig. 2. *BS(t)* in the Example with 16 Orders.

D. Battery Stock Condition

Next, we define some features of BSS. $BT(t)$ is the number of batteries taken from stock at time t, and $BC(t)$ is the number of batteries that have been recharged and are available at time t. When an EV comes for a swap, if $BC(t)$ is not zero, the BSS would swap a recharged battery to the EV. Otherwise, the BSS would use a stock battery for swapping. That is, when an EV arrives at time t, $BT(t)$ and $BC(t)$ are updated as follows:

If $BC(t-1) > 0$,

$$BC(t) = BC(t-1) - 1 \quad (6)$$

, otherwise

$$BT(t) = BT(t-1) + 1. \quad (7)$$

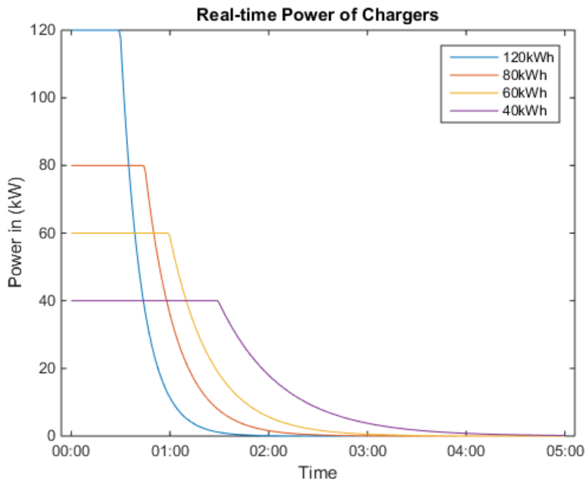

Fig. 3. Charging curve of different charging methods

When a battery becomes fully-charged at time *t*, *BC(t)* is updated as follows:

$$BC(t) = BC(t-1) + 1 \tag{8}$$

BT^{max} is the number of stock batteries taken to serve all the orders and it is defined as:

$$BT^{\max} = \max(BT(T)). \tag{9}$$

Here, *BT(T)* is the number of batteries taken from stock during the time period *T*.

In order to record the BSS's stock condition, *BS(t)* is defined as the number of batteries in stock at time *t*, which is derived based on

$$BS(t) = BT^{\max} + BC(t) - BT(t). \tag{10}$$

Fig. 1 shows the graph of *BT(t)* and *BC(t)* corresponding to the example in Section B. In the period from 9:00 to 10:56, the *BT(t)* increases at the time of a new order, and *BC(t)* is stable at zero. Refer to Table II, the battery swapped from order 3 is fully recharged at 10:57, so that *BC(t)* increases at 10:57 in Fig.1. When the next order comes at 11:00, there is a fully recharged battery in stock (*BC(t)>0*), then the BSS would swap this recharged battery to the EV rather than using a battery from stock. Hence, the *BC(t)* decreases while *BT(t)* remains stable at 11:00. At the end, both *BT(t)* and *BC(t)* would reach 8, which means that the number of batteries taken from stock is 8.

If the BSS starts with 8 batteries, the number of batteries in stock (*BS(t)*) is shown in Fig. 2. It is clear that the stock battery level can be split into three periods. In the first period (09:00 – 10:56), the stock level drops seriously because the stock batteries are swapped to the EVs and no swapped batteries are recharged yet. During the second period (10:57 -13:00), the stock level is stable around zero because the number of swapping demands and recharged batteries are more or less balanced. In the third period, the stock level increases because the swapped batteries have been recharged but the swapping demand is low in that period.

E. Charging Power Estimation Model

In order to simulate the characteristic of constant-current/constant-voltage charging strategy, we formulate the relationship between charging power and time in (11)

$$P_k(t) = \begin{cases} P_k^{cc} & ,0 < t < t_k^{cc} \\ P_k^{cc}\exp(-a_k(t - t_k^{cc})) & ,t_k^{cc} < t < t_k^{cv} \end{cases} \tag{11}$$

where $P_k(t)$ represents the output power of charging method *k* at time *t*, *t* is the time lapse since recharging from empty capacity, P_k^{cc} is the method *k*'s power at constant-current stage, t_k^{cc} represents the time for switching from constant-current to constant-voltage stage, t_k^{cv} represents the time that finish charging, and a_k is a parameter corresponding to charging method *k*.

As shown in Fig. 3, four types of chargers with different charging powers and charging curves are used. At the first stage of constant-current (CC), the charger would use a constant-power to recharge the battery from empty to a threshold η, which denotes a SOC of the battery. At the second stage of constant-voltage (CV), the charger's power would decrease gradually until the battery is fully charged.

F. Charging Time Estimation Model

Considering the degradation of lithium-ion battery, the state of health (*SOH*) of battery *j* at time *t* is defined as

$$SOH_j(t) = \frac{Cap_j(t)}{RCap_j} \cdot 100\% \tag{12}$$

such that

$$SOH_{\min} \le SOH_j(t) \le 100 \quad \forall j \in B \quad \forall t \in T \tag{13}$$

where *t* is the time when the battery is fully recharged, $RCap_j$ is the rated capacity of battery *j*, $SOH_j(t)$ is defined as the state of health of the battery *j* at time *t*, and SOH_{min} indicates the disposal threshold *SOH*. When the *SOH* of battery *j* degrades below SOH_{min}, the battery can no longer be used for recharging.

When an EV *i* comes to a BSS, one type of charger from the optimal schedule will be assigned for its swapped battery. Then, the BSS would calculate the time T_j needed to recharge the swapped battery *j* from its remaining capacity to full charge in (14).

If $SOC_j(t_0) < \eta$:

$$T_j = t_k^{cv} - \frac{SOC_j(t_0) \cdot Cap_j(t_0)}{P_k^{cc}} \tag{14a}$$

If $SOC_j(t_0) \ge \eta$:

$$T_j = t_k^{cv} - t_k^{cc} + \frac{1}{a_k}\ln[1 - \frac{a_k}{P_k^{cc}}(SOC_j(t_0) \cdot Cap_j(t_0) - P_k^{cc} \cdot t_k^{cc})] \tag{14b}$$

such that

$$0 \le SOC_j(t) \le 100 \quad \forall j \in B \quad \forall t \in T \tag{15}$$

Here, η is the threshold indicating the SOC that the charger need to switch from CC to CV mode, P_k^{cc} is the power at constant-current mode of charger *k*, $SoC_j(t)$ is the state of charge of the battery *j* at time *t*, Cap_j is the available capacity of battery *j* at time *t*.

Hence, we also denote T_j^S as the start charging time of battery *j*, which is the same as the arrival time of EV *i*. Then, the end charging time of battery *j* is

$$T_j^E = T_j^S + T_j \tag{16}$$

where T_j is the charging time obtained in (14).

G. Real-time Charging Power Estimation Model

The real-time charging power to battery *j* is shown below.

If $t < t_k^{cc} - \frac{SOC_j(t_0) \cdot Cap_j(t)}{P_k^{cc}}$:

$$P_j(t) = P_k^{cc} \tag{17a}$$

, otherwise:

$$P_j(k) = P_k^{cc} \cdot \exp(-a_k \cdot (t - \frac{1}{a_k}\ln(1 - \frac{a_k \cdot (SOC_j(t_0) \cdot Cap_j(t) - P_k^{cc} \cdot t_k^{cc})}{P_k^{cc}}))) \tag{17b}$$

such that

$$\sum_{j \in B} P_j(t) < P_{\max} \quad \forall t \in T \tag{18}$$

where *t* is the time since the battery starts charging, P_{max} is the maximum power that a BSS can reach at any time.

H. Electricity Price Model

A Time-of-Use (TOU) price model is used as the electricity price in this problem [32]. Three TOU periods, off-peak, mid-peak and on-peak, are assigned to different electricity price

$$E(t) = \begin{cases} E_{off-peak} & , t \text{ is in off - peak period} \\ E_{mid-peak} & , t \text{ is in mid - peak period} \\ E_{on-peak} & , t \text{ is in on - peak period} \end{cases} \cdot \tag{19}$$

III. Methodology

The objective of this paper is to determine an optimal charging schedule for the incoming EVs in order to minimize the cost for the BSS. Assuming that there are *N* incoming batteries and *K* types of charging methods, the solution is an array with *N* elements. In this model, the total number of possible solutions is K^N.

Accordingly, the solution of the model is a discrete array with exponential dependence of the number of batteries. As a result, the defined model is a non-deterministic polynomial-time hard (NP-hard) problem with high computational complexity [22].

Optimization algorithms are regarded as acceptable methods to solve the problem. Three well-known optimization algorithms genetic algorithm (GA), particle swarm optimization (PSO) algorithm, and differential evolution (DE) algorithm, are adapted to obtain a solution of the model. After studying the performances with previous algorithms, we propose an Integrated Algorithms (IA) by combining GA and PSO algorithms for solving the problem.

A. Genetic Algorithm

In order to obtain an optimized solution for the BSS based on the use of different charging methods, Genetic Algorithm (GA) is considered as an efficient and powerful method for NP-hard problems with high computational complexity. GA is a powerful metaheuristic algorithm proposed by Holland in 1970s [23] and has been applied in many areas for solving optimization problems.

Algorithm 1 in the Appendix presents the implementation of the adapted GA algorithms in this paper. Firstly, a set of initial parents are randomly generated at the beginning of the optimization. For each parent, crossover and mutation operations are used to work out some chromosomes as the children of this iteration in Line 5 - 14. After gathering up these children and parents, the scores of these candidates are calculated according to the multi-objective functions. Next, candidates with higher scores are selected as the parents in the next iteration. After iterations, the candidate with the best objective score is identified.

B. Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is a computational algorithm inspired by the social behaviors in the artificial life [24]. PSO is also a powerful method for solving the optimization problem by exploring the particles. In each iteration, the particles would be updated to a better position according to the particles' position and velocity.

Algorithm 2 (see Appendix) shows the detailed procedure of the PSO algorithm, which is initialized with a group of random particles. Each particle has a corresponding fitness value which is evaluated by the observation model, and has a relevant velocity which directs the movement of the particle. In each iteration, the particle moves with the adaptable velocity, which is a function of the best state found by that particle (for individual best), and of the best state found so far among all particles (for global best). In this paper, three versions of PSO algorithms, the original PSO [25], the PSO-In [26] and the PSO-Co [27], are implemented in lines 9 – 17.

C. Differential Evolution Algorithm

Differential Evolution (DE), proposed by Price and Storn in 1995 [28], is also a typical evolutionary computation algorithm to obtain an optimized solution for non-linear optimization problems. The basic idea of DE is to maintain a population of candidates, and then use the DE formulas to create new candidates by combining the existing solutions. After generating new solutions, the candidate with the best objective value would be stored.

Algorithm 3 (see Appendix) presents the pseudo-code of the differential evolution algorithm adapted in the BSS model. Assuming that a candidate solution is a permutation in the vector $\boldsymbol{X}$, each individual in the vector is indexed by *i*, and each generation is indexed by *g*. For the initial generation, the elements in parent $\boldsymbol{P}$ are generated randomly. The next populations will be created from the previous generation, as in line 2 – 20. After each generation, the best solution $\boldsymbol{X^P}$ would be updated.

D. Integrated Algorithm

After comparing the performances using the above three algorithms, we found that the PSO algorithms perform significantly better than GA and DE within the first few iterations. However, GA always explores for better solution with more iterations than PSOs and DE. Hence, an integrated algorithm (IA) is proposed to solve the optimization problem by combining the GA and PSO algorithm.

The steps of the proposed IA are as follows:

1) Set the total number of generations as *NumGen* and the

TABLE III
TOU PRICES - WINTER

Time of the day	TOU Period	Price in CAD per kWh	Price in USD per kWh
7:00 a.m. to 11:00 a.m.	On-peak	\$0.180	\$0.13
11:00 a.m. to 5:00 p.m.	Mid-peak	\$0.132	\$0.10
5:00 p.m. to 7:00 p.m.	On-peak	\$0.180	\$0.13
7:00 p.m. to 7:00 a.m.	Off-peak	\$0.087	\$0.0.06

number of generations for PSO as *NumGenPSO*. Set *NumP* as the number of parent in the IA process.

2) From the 1st generation to the *NumGenPSO-th* generation, execute the PSO, PSO-In and PSO-Co algorithms respectively in Algorithm 2.
3) Evaluate the objective values of the solutions at the *NumGenPSO-th* generation and choose the *NumP* solutions with the highest scores as new parents ***P***.
4) From the *NumGenPSO-th* generation to the *NumGen-th* generation, set the updated ***P*** as the new parents of GA and then execute the GA process introduced in Algorithm 1.
5) At the *NumGen-th* generation, the solution with best objective is assigned as the optimal solution.

In the next section, the simulation studies are shown and compared.

IV. CASE STUDY

The proposed model has been applied to a series of case studies. A type of lithium-ion battery pack is used with a rated capacity of 85 kWh, which is the typical battery on Tesla Model S [29]. Four types of EV battery chargers, super-charger, fast-charger, normal-charger and slow-charger, are used with different charging rate and different potential charging damages to batteries.

Some discussions on the cost calculation on the objective function are given below:

1) Cost 1: number of batteries taken from stock

We would like to minimize the use of batteries taken from stock, so that they can be reserved for the swapping orders that come without advanced notice. In the cost calculation, the number of batteries is multiplied by the battery's purchase price as a component in the objective function.

Nykvist et.al. [30] has analysed over 80 different reports from 2007 to 2014 to trace the costs of Li-ion battery packs for electric vehicles. They showed that the industry-wide cost has declined from above US\$ 1,000 per kWh to around US\$410 per kWh, and the cost of battery packs used by market-leading BEV manufacturers was even lower at US\$300 per kWh. They also concluded it is possible that economies of scale would continue to push cost towards US\$200 per kWh in the near future. The battery considered in the case study is an 85kWh battery pack for Tesla Model S, and the price is around \$250 per kWh. Hence, the initial purchase price for a battery pack is estimated to be \$21,000. Some studies showed that a lithium-ion battery's cycle life is from 600 to 1200 charging cycles depending on the charging rates [31].

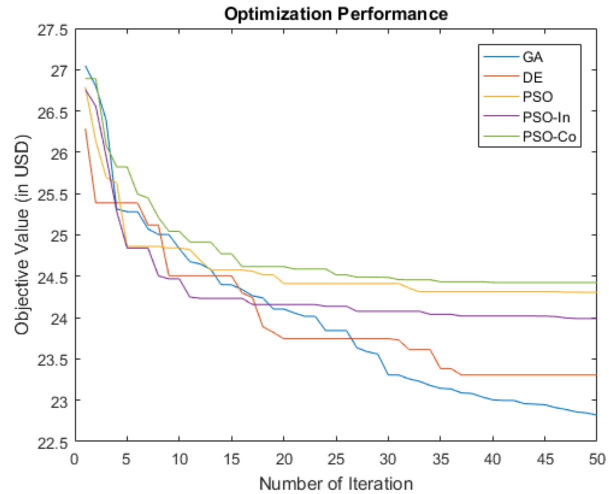

Fig. 4. Optimization performance of Case 1.

Assuming that the average life of the battery is 1000 charging cycles and the purchase price is \$21,000, the average cost for each charging is \$21. Hence, in this simulation study, the normalized purchase price of a battery P_{bat} is set to \$21 in (3).

2) Cost 2: charging damage due to different charging rates

Rezvanizaniani et.al. [31] has summarized the lithium-ion battery life for different charging rates. At a temperature of 30 ℃, the battery's cycle life is 1200, 1100 and 800 corresponding to the charging rate of 1C, 2C and 3C. In the case study, we use four types of chargers with power of 120kW, 80kW, 60kW and 40kW, and the charging curves are shown in Fig. 3.

As shown in [31], the use of fast chargers would decrease the life cycles of a battery. Suppose the life cycles of the four types of chargers are 800, 1100, 1150 and 1200, with the battery price of \$21,000, the normalized damages are worked out as US\$26.25, US\$21, US\$18.2 and US\$17.5. Suppose the slow charger (40kW) is used as a reference, the additional cost of using super-charger, fast-charger and normal charger are \$8.75, \$3.50 and \$0.70. Hence, the normalized charging damage using the four charging methods, *dm(1), dm(2), dm(3)* and *dm(4)*, are set to \$8.75, \$3.50, \$0.70 and \$0 respectively.

3) Cost 3: electricity cost for different time period of the day

In this paper, we refer to the Pricing and Schedules provided by Power Stream in Canada [32]. The TOU prices subject to winter in Table III.

The simulation results are computed by MATLAB R2016b on a PC with Intel Core i5-4570 CPU @3.20GHZ 3.20GHz, 8GB RAM and 64-bit Windows 10 Enterprise.

A. Case 1: Comparison Between an Optimal Schedule and a Random Schedule

This case assesses the feasibility of the proposed model and algorithms. The results with an optimal schedule and a random schedule are compared.

1) Initialization

This case simulates 100 EVs arrive between 09:00 to 13:00, and the arrival times are distributed evenly in this period. The remaining capacities of the swapped batteries are randomly set

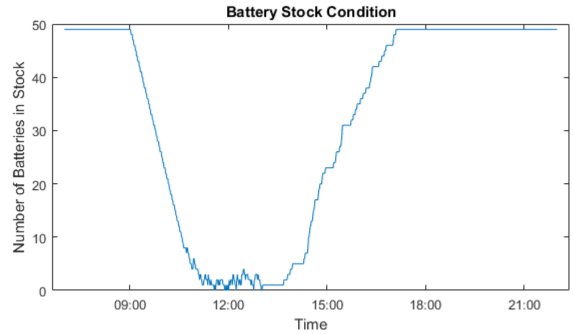

Fig. 5. Battery stock condition of Case 1 using optimal schedule.

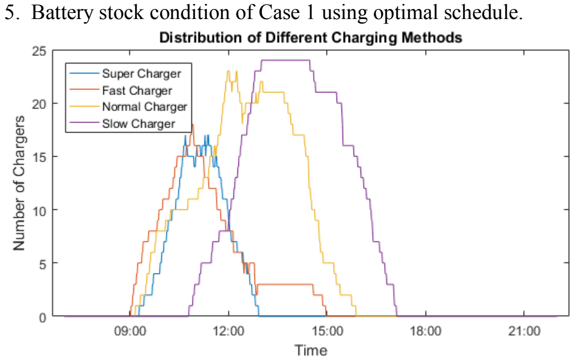

Fig. 6. Distribution of different charging methods of Case 1 using optimal schedule.

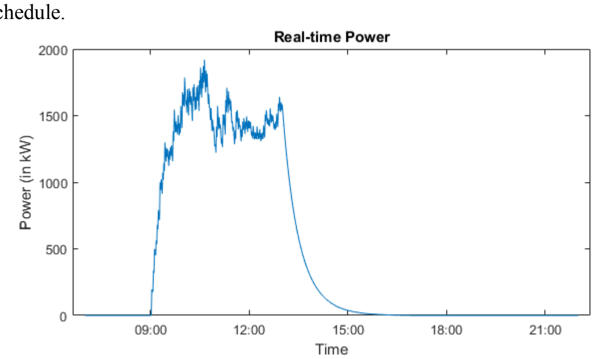

Fig. 7. Real-time power of Case 1 using optimal schedule.

between 10% and 35%, and the SOHs are randomly set between 100% and 80%.

Genetic algorithm (GA), differential evolution (DE), and three versions of particle swarm optimization (PSO) are implemented to solve the case. The basic parameters are identical. Both the number of parents and number of iterations are set to 50. In DE, the two adjustment parameters λ and μ are 0.9 and 0.8 respectively. The acceleration coefficients c_1 and c_2 are both set to 2. To the PSO with the inertia weight (PSO-In) algorithm, the weight w is varied linearly from 0.9 to 0.4 depending on the generation variable. The program would terminate when it reaches the maximum number of iterations, and the solution with the lowest objective value is chosen as the optimal solution.

2) Results using Optimal Schedule

Fig. 4 shows the optimization performances of the five algorithms. Within the first ten iterations, the performances of the algorithms are comparable, while GA obtains a better solution than others with more iterations. It is clear that the PSO algorithms cannot explore more significant solutions after the 15th iteration.

Initially, the PSO algorithms are more efficient than GA and

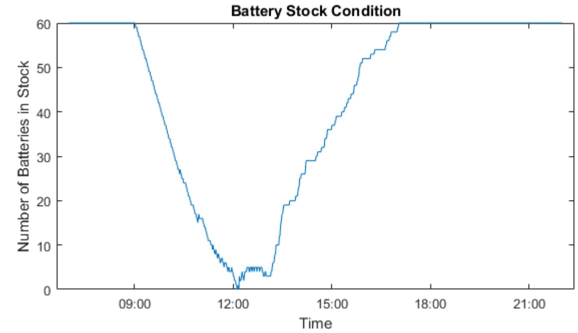

Fig. 8. Battery stock condition of Case 1 using random schedule.

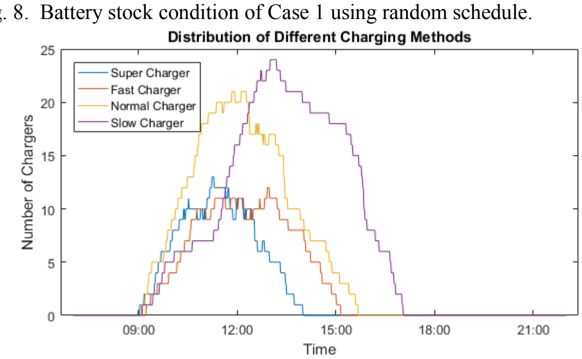

Fig. 9. Distribution of different charging methods of Case 1 using random schedule.

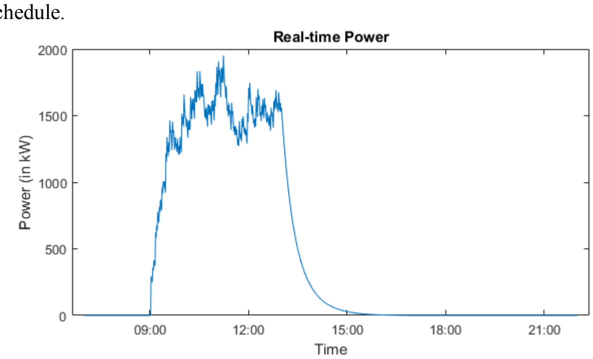

Fig. 10. Real-time power of Case 1 using random schedule.

DE. Particularly, the running times of the PSO, PSO-In and PSO-Co are 11.34s,11.24s and 11.15s respectively, while the running times of GA and DE are 38.25s and 44.28s, which are obviously longer than the PSO algorithms.

The GA obtains the optimal solution rather than the DE and PSOs. The objective value of the optimal charging schedule is $22.82, which indicates the average cost for serving a swapping EV.

Fig. 5 shows the battery stock condition during the day. With a number of initial stock battery of 49, the stock battery level drops when batteries are swapped to EVs, and the stock battery level increases when a battery has been recharged. It is clear that the stock battery level can be split into three periods. In the first period (09:00 – 11:00), the stock level drops seriously because the stock batteries are swapped to EVs but no swapped batteries are recharged yet. During the second period (11:00 -13:00), the stock level is stable around zero because the number of swapping demands and recharged batteries are more or less balanced. In the third period, the stock level increases because the swapped batteries have been recharged but the swapping demand is low in that period.

Fig. 6 shows the distribution of different charging methods.

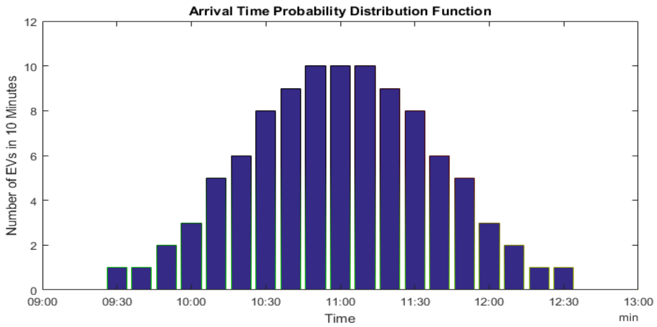

Fig. 11. Arrival time probability distribution function of Case 2.

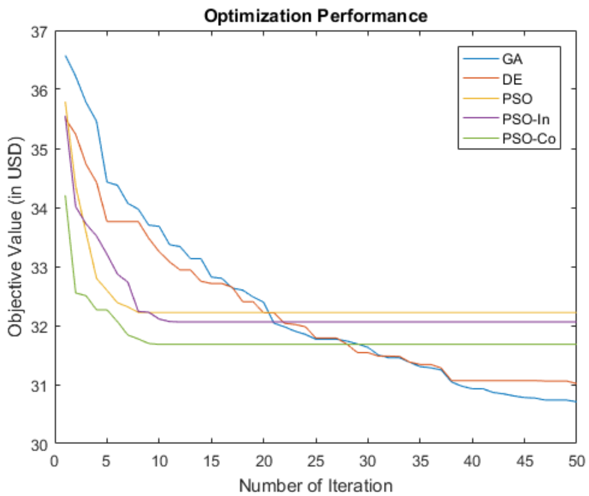

Fig. 12. Optimization performance of Case 2.

It is notable that the slow chargers are more frequently-used than other chargers, while the numbers of super chargers, fast chargers and normal chargers required are similar. Fig. 7 shows the real-time power requirement during the day. It is clear that the power reaches the peak power in the first period (09:00 – 11:00) for satisfying the initial demands.

3) Results using Random Schedule

This case generates a random schedule and the result is compared with an optimal schedule. We generate a solution by randomly assigning one type of charging method to each incoming battery. The procedure is repeated 100 times and the solution with the best objective value is chosen.

The objective value of the 100 random solutions has a range from 27.44 to 34.04. The mean of the values is 29.44 and the standard deviation is 1.19. Here, the solution with the lowest objective value is chosen for comparison.

The objective value of the random solution is 27.44, while the objective value of the optimal solution is 22.62. It means that the optimal solution saves $4.82 per battery than the random solution. Hence, for serving the 100 EVs, the BSS saves $482.00 in total. In the random solution, the number of batteries using super charger, fast charger, normal charger and slow charger are 26, 21, 28 and 25 respectively.

Fig. 8 shows the battery stock condition of the random solution. Compared with Fig. 5, the BSS needs to prepare eleven more batteries than the optimal solution. Fig. 9 shows the distribution of different charging methods using the random solution. In the first period (09:00 – 11:00), there is no significant difference for the four types for chargers. Fig. 10

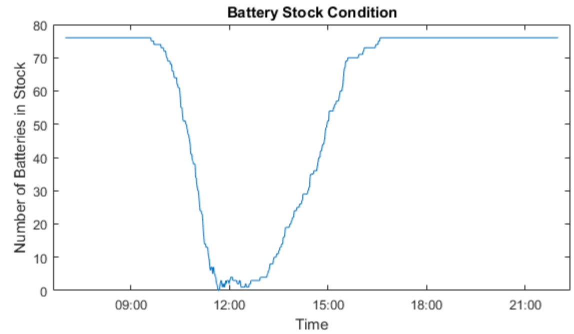

Fig. 13. Battery stock condition of Case 2.

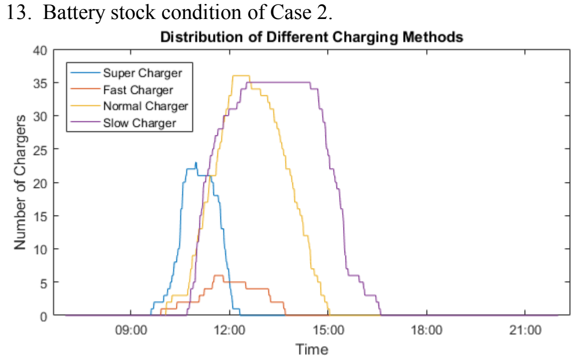

Fig. 14. Distribution of different charging methods of Case 2.

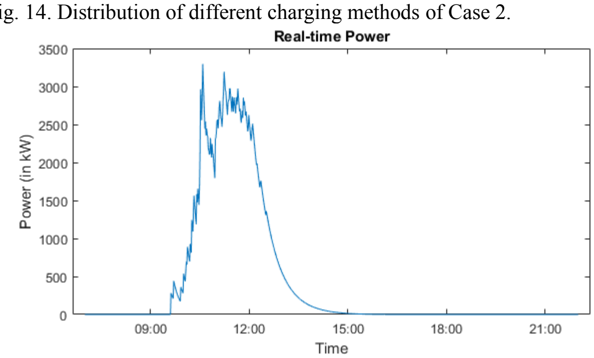

Fig. 15. Real-time power of Case 2.

and Fig. 7 indicate the real-time power requirement of the random solution and optimal solution are comparable.

Compared with the results using optimal schedule, it is obvious that the proposed optimization algorithms would help the BSS to obtain an optimal schedule with lower cost than a random assignment method.

B. Case 2: Comparison of Algorithms

This case compares the performance of the algorithms with an alternate arrival time pattern which follows a normal distribution function.

1) Initialization

We simulate 100 EVs come to the BSS for swapping batteries between 09:00 and 13:00. The arrival times of the EV orders follow the probability distribution function (PDF) in Fig. 11, which is a normal function with the peak at 11:00. The remaining capacities of the swapped batteries are randomly set between 10% and 35%, and the SOHs are randomly set between 100% and 80%.

Same as Case 1, the GA, DE and three versions of PSO are implemented to solve the case. The number of parents and number of iterations are both 50. In DE, the two adjustment parameters λ and μ are 0.9 and 0.8 respectively. The

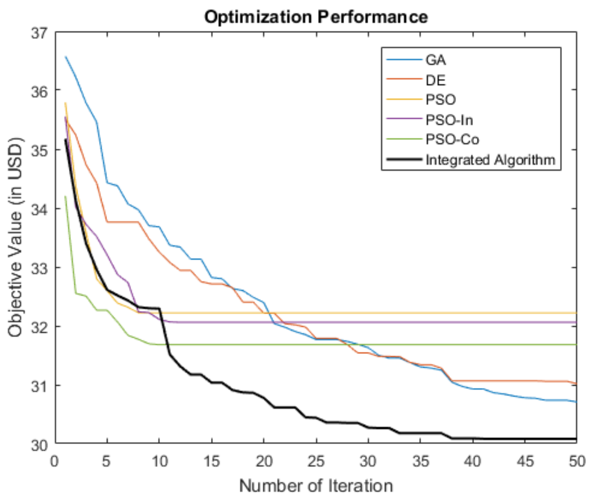

Fig. 16. Optimization performance of Case 3.

acceleration coefficients c_1 and c_2 are both set to 2. The weight w of PSO-In is varied linearly from 0.9 to 0.4 depending on the generation variable. The program would terminate when it reaches the maximum number of iterations, and the solution with the minimum objective value is chosen as the optimal solution.

2) Results

Fig. 12 shows the optimization performance of the five algorithms. At the first ten iterations, the PSO algorithms obtain more optimal solutions than GA and PSO, while the PSO algorithms cannot explore more significant solutions after the tenth iteration. However, the GA and PSO obtain optimal solutions with more iterations. At the 50^{th} iteration, the GA obtains the most optimal solution with objective value of $30.71.

The computational time in this case is comparable with Case 1. The PSO algorithms perform faster than GA and DE. Particularly, the running times of the PSO, PSO-In and PSO-Co are 10.88s,10.68s and 10.71s respectively, while the running times of GA and DE are 40.23s and 44.06s.

3) Optimal Schedule

The GA obtains the optimal solution with an objective value of the optimal charging schedule being $30.71, which indicates the average cost for serving a swapping EV.

Fig. 13 shows the battery stock condition during the day. The initial number of stock battery is 76. It is clear that the stock battery level can be split into three periods. In the first period (09:00 – 11:30), the stock level drops seriously because the stock batteries are swapped to EVs but there are no recharged batteries. In the second period (11:30 -13:00), the stock level is stable around zero because the number of swapping demands and recharged batteries are balanced. In the third period, the stock level increases because some swapped batteries have been recharged but there is less swapping demand in that period.

Fig. 14 shows the distribution of different charging methods. It is notable that the slow and normal chargers are more frequently-used than the fast and super chargers. To be specific, the number of batteries using super charger, fast charger, normal charger and slow charger are 23, 6, 36 and 35 respectively. Fig. 15 shows the real-time power requirement during the day. It is clear that the power reaches the peak power in the first period (09:00 – 11:30) for satisfying the initial demands.

TABLE IV
SIMULATION RESULTS

Item		IA	GA	DE	PSO	PSO-In	PSO-Co
Objective Value ($)	Best	**30.02**	30.38	30.24	31.33	31.40	31.38
	Worst	**30.21**	31.53	31.51	33.39	33.42	33.48
	Median	**30.09**	30.88	30.70	32.19	32.20	32.11
	Mean	**30.09**	30.93	30.75	32.22	32.26	32.14
	Std.	**0.05**	0.27	0.28	0.45	0.47	0.43
Cost 1 ($)	Best	**15.12**	15.33	**15.12**	**15.12**	**15.12**	**15.12**
	Worst	**15.33**	16.80	20.58	15.75	15.75	15.75
	Median	**15.12**	15.85	19.74	15.54	15.43	15.33
	Mean	**15.15**	15.87	15.89	15.43	15.45	15.41
	Std.	**0.074**	0.353	2.131	0.221	0.199	0.199
Cost 2 ($)	Best	2.278	1.921	**0.462**	3.062	2.894	2.975
	Worst	**2.576**	2.807	8.750	4.645	4.819	4.287
	Median	2.457	2.520	**1.061**	3.736	3.763	3.598
	Mean	**2.443**	2.493	2.935	3.779	3.765	3.623
	Std.	**0.068**	0.214	3.254	0.362	0.394	0.305
Cost 3 ($)	Best	12.49	**12.46**	12.50	12.49	12.49	12.49
	Worst	**12.50**	13.27	20.78	14.17	13.95	14.30
	Median	**12.50**	**12.50**	19.24	12.90	12.92	13.04
	Mean	**12.50**	12.57	17.75	13.01	13.05	13.10
	Std.	**0.002**	0.18	3.09	0.39	0.40	0.44
Time (s)	Best	32.54	35.04	40.27	10.22	10.24	**10.21**
	Worst	36.81	39.19	48.23	12.00	11.83	**11.81**
	Median	33.75	36.54	41.78	10.53	**10.48**	10.59
	Mean	33.97	36.63	41.99	10.69	**10.65**	10.66
	Std.	1.00	1.04	1.41	0.42	0.38	**0.37**

C. Case 3: Results from Integrated Algorithm

This case evaluates the proposed Integrated Algorithm (IA) with an EV order set following a normal distribution function.

1) Initialization

We use the same EV order set of Case 2. The number of batteries is 100, and the arrival times are between 09:00 and 13:00 following a normal distribution function.

In the proposed IA, we use the PSO, PSO-In and PSO-Co algorithms from the 1^{st} to 10^{th} iteration, and then use the GA from the 11^{th} to 50^{th} iteration. The number of parent and iteration are both 50, which are the same as Case 2.

2) Results and Comparison

As shown in Fig. 16, a better objective value is obtained by the IA, and the performance has been remarkable improved compared to the GA, DE and PSOs. The objective value obtain by IA is $30.08, which is $0.62 less than the solution by GA. Hence, the BSS would save $62.00 for serving the 100 swapping orders by the IA schedule.

In this case, the computational time of IA is 34.08s, which is shorter than GA (40.23s) and DE (44.06s) but longer than the PSO (10.88s), PSO-In (10.68s) and PSO-Co (10.71s).

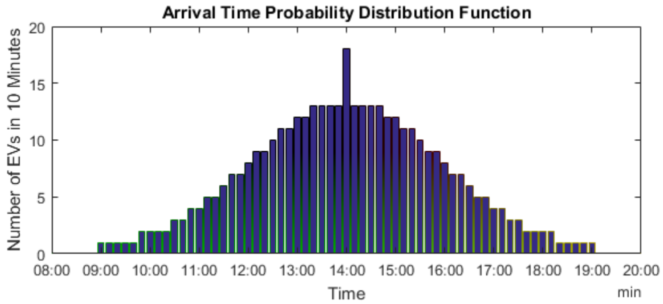

Fig. 17. Arrival time probability distribution function of Case 4.

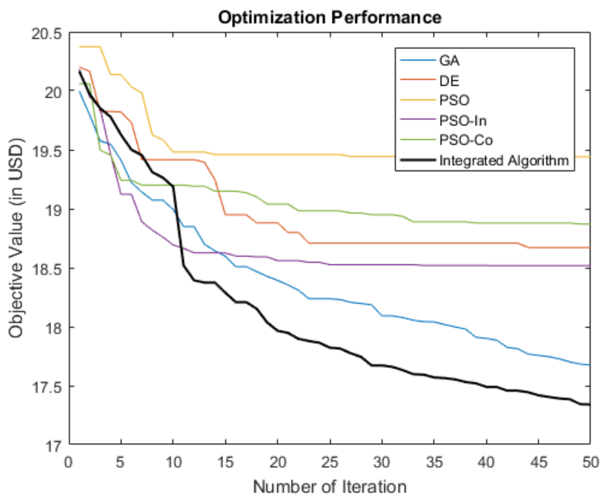

Fig. 18. Optimization performance of Case 4.

3) Results with More Evaluations

In order to evaluate the performance of the proposed algorithms, we repeat the above program for 50 times independently with the same set of EV orders. The detailed results including the objective value, separate costs and computational times are presented in Table IV.

In terms of the objective value, the proposed IA has significantly better performance than the other algorithms referring to all the metrics. The performance of the GA and DE are comparable, while the three version of PSO algorithms perform worse than IA, GA and DE. In terms of the three separated costs, Cost 1 and Cost 3 are the two major costs contributing to the objective value, because the impact of battery stock number and electricity cost play more important roles than the potential cost of different charging methods. The performance of IA is the best in both Cost 1 and Cost 3, and is comparable with DE in Cost 2.

It is important to note that the standard deviation of IA is significantly smaller than the other algorithms, which indicates that the proposed IA is the most reliable algorithm for solving the problem.

The computational time of IA is shorter than GA and DE but longer than PSO, PSO-In and PSO-Co. However, according to the optimization performance in Fig. 16 and the summarized results in Table IV, the performance of PSO algorithms is not acceptable for obtaining an optimal solution.

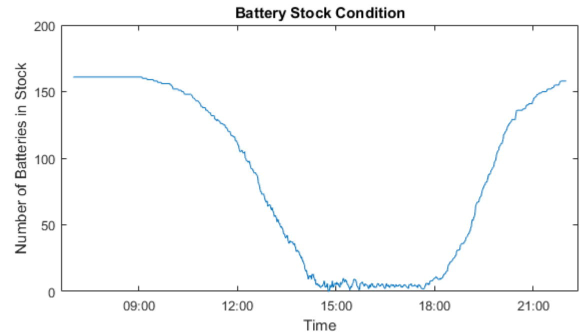

Fig. 19. Battery stock condition of Case 4.

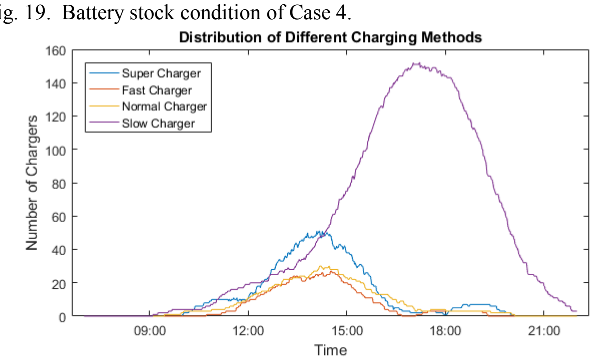

Fig. 20. Distribution of different charging methods of Case 4.

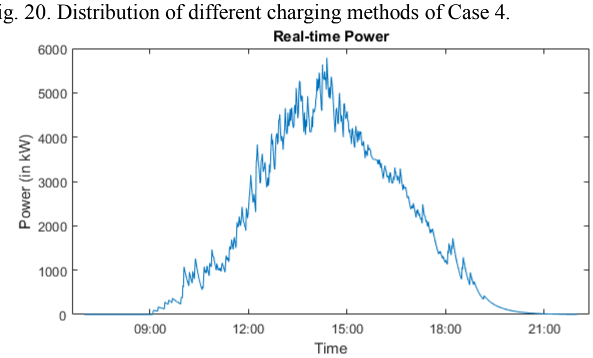

Fig. 21. Real-time power of Case 4.

D. Case 4: Extensive Evaluation on Integrated Algorithm

This case evaluates the proposed Integrated Algorithm (IA) by a massive EV order set following a normal distribution function.

1) Initialization

In this case, we simulate 400 EVs coming to the BSS for swapping batteries between 08:00 and 20:00. The pattern of arrival times follows a normal distribution in Fig. 17 with the peak at 14:00. The number of parents is set to 100. Other parameters are the same as Case 3.

2) Results and Comparison

As shown in Fig. 18, from the 1st to 10th iteration, the performances of GA, DE, PSO-In, PSO-Co and IA are comparable, but the performance of PSO is worse than others. After the 25th iteration, the PSO, DE, PSO-In and PSO-Co cannot explore for a better solution significantly. Only the performances of GA and IA are improved continuously. It is obvious that the proposed IA always performs better than GA after the 10th iteration.

3) Optimal Schedule

In this case, the IA obtains the optimal solution than GA, DE and PSOs. The objective value of the optimal charging schedule is \$17.34, which indicates the average cost for serving a swapping EV.

Fig. 19 shows the battery stock condition during the day. The initial number of stock battery is 161. The pattern is similar to the previous cases.

Fig. 20 shows the distribution of different charging methods. The number of batteries using super charger, fast charger, normal charger and slow charger are 125, 42, 42 and 191 respectively. Fig. 21 shows the real-time power requirement during the day. It is clear that the power reaches the peak power around 14:00 when the arrival peak comes.

V. Conclusion

In this paper, an optimization model has been established for EV battery charging in a battery swapping station. This model aims to optimize the operation of a BSS by assigning an optimized charging schedule for each incoming battery. This paper proposed a new integrated algorithm (IA) after studying and comparing the genetic algorithm (GA), differential evolution (DE) and particle swarm optimization (PSO). A series of simulation studies are executed to assess the feasibility of the proposed model and compare the performance between IA and the typical evolutionary algorithms.

The contributions are summarized as follows. This paper has proposed a new operation model for the operation of a viable battery swapping station. In this model, the BSS would determine an optimized charging schedule for the batteries to minimize the cost to the BSS. The cost includes the number of batteries taken from stock to serve all the swapping orders from incoming EVs, potential charging damage with the use of high-rate chargers, and electricity cost for different time period of the day. A mathematical model is designed to formulate the charging process following the constant-current/ constant-voltage charging strategy. Three optimization algorithms (GA, DE, and PSO) have been studied and compared. A new integrated algorithm (IA) has been developed and extensive evaluation results have shown that the proposed algorithm is applicable for obtaining an optimization solution.

Appendix

Genetic algorithm (GA):

Algorithm 1 Genetic Algorithm

parameters
NumO: number of incoming orders
NumP: number of parents in the GA process
NumGen: number of generations in the GA process
Input: a set of order data with arrival time and remaining capacity
Output: charging schemes corresponding to each incoming orders as vector ***X***

generate an initial parent population $\boldsymbol{P} \leftarrow \{\boldsymbol{X}^1, \boldsymbol{X}^2, \ldots, \boldsymbol{X}^{NumP}\}$
for each generation g less than *NumGen* **do**
  $\boldsymbol{C} \leftarrow 0$
  $\boldsymbol{T} \leftarrow 0$
  for each parent p less than *NumP* **do**
    randomly choose two parents from $\boldsymbol{P}$ as $\boldsymbol{P_1}$ and $\boldsymbol{P_2}$
    randomly choose a breakpoint from $\boldsymbol{P_1}$ as b
    combine $\boldsymbol{P_1}(1{:}b)$ and $\boldsymbol{P_2}((b+1){:}NumO)$ as a child $\boldsymbol{C_1}$
    combine $\boldsymbol{P_2}(1{:}b)$ and $\boldsymbol{P_1}((b+1){:}NumO)$ as a child $\boldsymbol{C_2}$
    Add $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$ to $\boldsymbol{C}$
  for each parent p less than *NumP* **do**
    randomly choose a number i from 0 to *NumO*
    assign the charger of order i randomly as $\boldsymbol{C_3}$
    Add $\boldsymbol{C_3}$ to $\boldsymbol{C}$
  combine $\boldsymbol{P}$ and $\boldsymbol{C}$ as $\boldsymbol{T}$
  calculate the scores of each solution from $\boldsymbol{T}$
  rank the scores
  choose the *NumP* solutions with the highest score as new $\boldsymbol{P}$
$\boldsymbol{X} \leftarrow \boldsymbol{P}(1)$
return $\boldsymbol{X}$

Particle swarm optimization (PSO):

Algorithm 2 Partial Swarm Optimization

parameters
NumO: number of incoming orders
NumP: number of particles in the PSO process
NumGen: number of generations in the PSO process
V_{max}: the maximum value of velocity
c_1, c_2: two values set for adjustment parameter
r_1, r_2: two random decimal value between 0 and 1
Input: a set of order data with arrival time and remaining capacity
Output: charging schemes corresponding to each incoming orders as vector ***X***

generate an initial population of particles $\boldsymbol{P} \leftarrow \{\boldsymbol{X}^1, \boldsymbol{X}^2, \ldots, \boldsymbol{X}^{NumP}\}$
generate an initial velocity of each particle $\boldsymbol{V} \leftarrow \{\boldsymbol{V}^1, \boldsymbol{V}^2, \ldots, \boldsymbol{V}^{NumP}\}$
calculate the scores of all particles from $\boldsymbol{P}$
set the particle with highest score as $\boldsymbol{X_p}$ and $\boldsymbol{X_g}$
for each generation g less than *NumGen* **do**
  calculate the scores of each solution from $\boldsymbol{P}$
  choose the solution with highest score as $\boldsymbol{X_{Best}}$
  for each particle p less than *NumP* **do**
    if PSO is original **then**
      $V_i^p = V_i^p + c_1 r_1 (X_{p,i} - X_i^p) + c_2 r_2 (X_g - X_i^p)$
    if PSO is PSO-In **then**
      $w = (0.8 - 0.4) \times \frac{NumGen - g}{NumGen} + 0.4$
      $V_i^p = w V_i^p + c_1 r_1 (X_{p,i} - X_i^p) + c_2 r_2 (X_g - X_i^p)$
    if PSO is PSO-Co **then**
      $\varphi = c_1 + c_2$
      $\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}$
      $V_i^p = \chi V_i^p + c_1 r_1 (X_{p,i} - X_i^p) + c_2 r_2 (X_g - X_i^p)$
    if $V_i^p > V_{max}$ **then**
      $V_i^p = V_{max}$
    if $V_i^p < -V_{max}$ **then**
      $V_i^p = -V_{max}$
    $X_i^p = X_i^p + V_i^p$
    if the objective score of X_i^p is larger than that of $\boldsymbol{X_p}$ **then**
      $X_p = X_i^p$
    if the objective score of X_i^p is larger than $\boldsymbol{X_{Best}}$ **then**
      $X_g = X_i^p$
      $\boldsymbol{X_{Best}} \leftarrow$ objective value of $\boldsymbol{X_g}$
return $\boldsymbol{X_{Best}}$

Differential evolution (DE):

Algorithm 3 Differential Evolution

parameters
NumO: number of incoming orders
NumP: number of parents in the DE process
NumGen: number of generations in the DE process
λ: a decimal value between 0 and 1
α, β: two decimal values between 0 and 1
Input: a set of order data with arrival time and remaining capacity
Output: charging schemes corresponding to each incoming orders as vector $\boldsymbol{X}$
generate an initial parent population $\boldsymbol{P} \leftarrow \{X^1, X^2, \ldots, X^{NumP}\}$
for each generation g less than *NumGen* **do**
  calculate the scores of each solution from $\boldsymbol{P}$
  choose the solution with highest score as $\boldsymbol{X_{Best}}$
  for each parent p less than *NumP* **do**
    $C \leftarrow 0$
    randomly choose two other parents from $\boldsymbol{P}$ as $\boldsymbol{P_1}$ and $\boldsymbol{P_2}$
    for each order i less than *NumO* do
      obtain a random decimal between 0 and 1 as $\boldsymbol{r}$
      if $r < \lambda$ **then**
        $X_i^p = X_i^p + \alpha \times (X_{Best} - X_i^p) + \beta \times (P_1(i) - P_2(i))$
        if $X_i^p < 1$ **then**
          $X_i^p = 1$
        if $X_i^p > 4$ **then**
          $X_i^p = 4$
        add the integer part of X_i^p to the vector $\boldsymbol{C}$
      else
        add X_i^p to the vector $\boldsymbol{C}$
    if the objective score of $\boldsymbol{C}$ is larger than X^p **then**
    change the p-th parent in $\boldsymbol{P}$ to $\boldsymbol{C}$
  calculate the scores of each solution from $\boldsymbol{P}$
  choose the solution with the highest score as $\boldsymbol{X}$
return $\boldsymbol{X}$

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