Quality-of-service Closed-loop Supply Chain Based Battery Swapping and Charging System Operation: A Hierarchy Game Approach

Tianyang Zhao, *Student Member, IEEE,* Jianhua Zhang, *Member, IEEE, and* Peng Wang, *Senior Member, IEEE*

Abstract—To realize the optimal operation of a battery swapping and charging system (BSCS), a game theory based closed loop supply chain (CLSC) management system is proposed. A CLSC is adopted to represent the battery-swapping-charging process between a battery charging station (BCS) and multiple battery swapping stations (BSSs). The arrival, departure and swapping service of the electric vehicles (EVs) at a BSS is modeled as distinct queues based on the network calculus theory. The depleted batteries (DBs) and well-charging batteries (WBs) based interaction among the BCS and BSSs is modeled as a Stackelberg game, where the BCS is the leader and the BSSs are the followers. The BCS sets optimized prices to maximize its utility and the BSSs optimally demand WBs, supply DBs and provide battery swapping services to maximize their own utilities while guaranteeing the quality of service (QoS) needed for battery swapping. The existence of Stackelberg equilibriums (SEs) of the proposed game is proved. A differential evaluation based hybrid algorithm is proposed to compute a SE. Simulation results have demonstrated the effectiveness of the proposed method, guaranteeing the QoS and balancing the benefits among the BCS and BSSs while maximizing social welfare.

Index Terms—Battery swapping, closed loop supply chain, network calculus, game theory

NOMENCLATURE

A. Indices, sets and parameters

i	Index of time epochs.
n	Index of battery swapping stations (players).
m	Index of players.
t_i	Arrival time epochs.
d_i	Deadline time epochs.
n_i	Number of EVs during i-th time slot.
Γ	SG.
$\mathcal{G}$	Game.
$\mathcal{C}$	BCS.
$\mathcal{S}_n$	Strategy set of player n.
$\mathcal{N}$	Set of battery swapping stations.
T	Number of time slots.
N_S	Number of BSSs.
N	Number of players in the SG, N=N_S+1.
$B_n(t)$	Maximal queue length in BSS n during time slot t.
$\lambda_{\mathrm{DA}}(t)$	Day-ahead energy prices during time slot t.
C_{A}	Price for backup batteries within BCS.
C_{p}	Cost of charging and discharging for batteries.
$\eta_{\mathrm{C}}/\eta_{\mathrm{DC}}$	Charging/discharging efficiency of batteries.
ΔE	Amount of energy needed by per DB.
$p_{\mathrm{C,max}}$	Maximal charging rate of per DB.
$p_{\mathrm{DC,max}}$	Maximal discharging rate of per DB.
$P_{\mathrm{PV}}(t)$	Day-ahead forecasting output of photovoltaic generation. during time slot t.
$P_{\mathrm{D}}(t)$	Day-ahead forecasting of demand during time slot t.
$p_{\mathrm{D,min}}$	Minimal prices of DBs.
$p_{\mathrm{D,max}}$	Maximal prices of DBs.
$p_{\mathrm{W,min}}$	Minimal prices of WBs.
$p_{\mathrm{W,max}}$	Maximal prices of WBs.

B. Functions

$A(t)$	Cumulative arrived EVs during [0, t].
$D(t)$	Cumulative departed EVs during [0, t].
$D_{\min}(t)$	Cumulative minimum number of EVs by time t.
$\mathcal{U}_n(\ )$	Utility function of player n.
$\beta_n(t)$	Service curve of BSS n.
$\Phi(\boldsymbol{x})$	Potential function.

C. Variables

$N_{\mathrm{W},n}(t)$	Demand for WBs of BSS n during time slot t.

Manuscript received July 31, 2016; revised January 4, 2017; accepted April 1, 2017. This work was supported by the Fundamental Research Funds for the Central Universities (No. 2014XS09) and Chinese Scholarship Council of the Ministry of Education.

T. Y. Zhao, W.X. Liu and J. H. Zhang (corresponding author, e-mail: jianhuazhang001@163.com) are with the State Key Laboratory of Alternate Power System with Renewable Energy Resources, North China Electric Power University, Beijing 102206, China.

P. Wang is with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798.

DOI: 10.17775/CSEEJPES.2016.00820

$N_{D,n}(t)$	Supply for DBs of BSS n during time slot t.
$N_{S,n}(t)$	Swapped batteries in BSS n during time slot t.
$p_W(t)$	Prices of WBs during time slot t.
$p_D(t)$	Prices of DBs during time slot t.
$C_{D,0}(t)$	Base prices of DBs during time slot t, $C_{D,0}(t)\geq 0$.
$C_{D,1}(t)$	Coefficients with respect to total DBs during time slot t.
$C_{W,0}(t)$	Base prices of WBs during time slot t, $C_{W,0}(t)\geq 0$.
$C_{W,1}(t)$	Coefficients with respect to total WBs during time slot t.
$\boldsymbol{x}_n$	Strategy of player n.
$\boldsymbol{x}_{-n}$	Strategy profile of players other than player n.
$\boldsymbol{x}$	Strategy profile of all players, $\boldsymbol{x}=\Pi\, \boldsymbol{x}_n$.
$Q_{W,n}(t)$	Cumulative WBs of BSS n received from BCS by time t.
$Q_{D,n}(t)$	Cumulative DBs of BSS n sent to BCS by time t.
$N_{W,n}(t)$	Number of DBs arrived at BSS n during $(t, t+\Delta t]$.
$N_{D,i}(t)$	Number of DBs delivered from BSS n during $(t, t+\Delta t]$.
$P_{DA}(t)$	Day-ahead power exchange between the distributions. network and wholesale market.
$N_A(t)$	Demand of backup batteries during time slot t.
$P_C(t)$	Charging rate of BCS during time slot t.
$P_{DC}(t)$	Discharging rate of BCS during time slot t.

D. Abbreviations

EV	Electric vehicle.
BSCS	Battery swapping and charging system.
BSS	Battery swapping station.
BCS	Battery charging station.
DB	Depleted battery.
WB	Well-charged battery.
CLSC	Closed loop supply chain.
FSC	Forward supply chain.
RSC	Reverse supply chain.
QoS	Quality of service.
SG	Stackelberg game.
SE	Stackelberg equilibrium.
NE	Nash equilibrium.
DE	Differential evaluation.
CG	Congestion game.
DSO	Distribution system operator.
BLPP	Bi-level optimization problem.
MILP	Mixed-integer linear programming.

II. Introduction

WITH rapid development of battery technologies [1], EVs are being widely adopted around the world, for their effectiveness in reducing emission, energy utilization and so on [1-2]. Plug-in charging and battery- swapping charging are two popular ways to fulfill the energy demand of EVs [2], [3]. Compared with plug-in charging, battery swapping charging has some attractive features, e.g., shorter serving time, and lower replacement cost [2]–[5]. These features can meritoriously stimulate the successful rollout of EVs, especially for electric buses and electric taxis [3]–[9].

To realize the benefits of battery swapping charging, a well-designed and efficiently operated battery swapping and charging system (BSCS) is the cornerstone. There are three subsystems in BSCSs, i.e., battery swapping stations (BSSs), battery charging stations (BCSs) and logistics systems between the BSSs and BCSs [2]–[12]. Some outstanding works have been carried out in the planning [3-5, 10] and operation [2], [6]–[9], [11], [12] of BSCS. Based on the life-cycle cost method, an optimal design framework of BSSs and BCSs in distribution systems is presented in [3]. Optimally charging facility design and inventory management are given in [4] and [5], respectively. With limited information on battery swapping demand, a robust BSS design method is proposed in [10], where BSSs are selected for gas stations.

The day-ahead operation of BCSs is the hot research area in BSCS operations. A robust optimization model for maximizing the day-ahead revenue of BCSs is proposed in [2], including the uncertainty of battery swapping demand and day-ahead wholesale market prices. In [6], an optimization free real-time decision making technique for a BSS is proposed to ensure the service availability. To manage the scalable charging in the BCS, a distributed optimal scheduling method is provided in [8]. A real-time operational strategy is proposed for an individual BCS to maximize its revenue under a market environment [9]. Furthermore, BSCS can provide ancillary services to power systems, e.g., operation reserves [9] and black start capacity [11]. Unlike the fixed charging method mentioned above, where EVs should come to the BSSs [1]–[11], an interesting mobile charging method is proposed in [12], including mobile battery swapping and mobile charging.

According to the aforementioned works, BCSs establish the interaction between the BSCS [2], [3], [7], [9], [11] and power systems, while BSSs link BSCSs with EV users [5], [6], [8], [10]. However, these works only take the benefits of power systems [11], BSCS [2]–[4], [6]–[10] or EV users [5], [12] into consideration, while omitting the benefits of the others. To balance the benefits of all three entities, a detailed operational model of the BSCS is necessary. A BSCS has its own operational characteristics. Depleted batteries (DBs) should be swapped at BSSs and shipped to BCSs. After being charged, batteries should be delivered to BSSs as spares. The battery-swapping-charging operation within the BSCS is a closed logistic loop for batteries [13]. The logistic loop for batteries can be treated as a closed-loop supply chain (CLSC) [14].

CLSC is a novel logistical concept, which was proposed in 2003 [14]. It has both forward supply chain (FSC) and reverse supply chain (RSC) features. CLSC management makes products achieve value maximization in the whole lifecycle through systematic design, control, and operations. Energy can be saved and environmental pollution can be reduced in the process of value maximization of the products [15], [16]. In the BSCS, providing well-charged batteries (WBs) from the BCSs to BSSs is a FSC, while collecting DBs from BSSs to BCSs and charging these batteries is a RSC. To guarantee QoS of battery swapping services, BSSs should store spare WBs at BSSs [13] and the BSCS can have more flexibility with more batteries being available. However, the capital cost of batteries is still high [1], [2], maintaining too great a battery inventory is unaffordable [1], [5]. An efficient BSCS operation should be proposed to capture the conflict between economic efficiency (e.g., operational cost) and QoS.

Drawing on the existing results, this work provides a CLSC framework to analyze the operation of BSCSs, where BCSs, BSSs and EV users are manufacturer, retailers and customers, respectively. Unlike the existing centralized operational methods [9], [12], [13], a game theory based management method is proposed to balance the benefits among BCSs and BSSs, while guaranteeing the QoS of the battery swapping service. There are two general classifications in game theory, i.e., cooperative game and non-cooperative game models [17]. Cooperative game models show how players cooperate as coalitions in unstructured interactions to create and capture value, by make binding agreements before playing the game [17]. The non-cooperative game model focuses on the strategy, utility and procedure, which enables each player to make decisions individually. In this paper, a non-cooperative game is adopted to model the competition among the BCSs and BSSs of the CLSC, where the BCS and BSSs are owned by different entities.

As far as we know, it is the first time anyone has applied CLSC to model the closed battery loop in the BSCS. The contribution of this paper can be summarized as follows:

1) The battery-swapping-charging process in a BSCS is modeled as a CLSC, including optimization of the charging process in the BCS and battery swapping services among BSSs. The queues of a BSS are modeled based on network calculus theory [18].

2) The interaction among the BCSs and BSSs is modeled as a Stackbelberg game (SG), in which the BCS acts as the leader by setting prices for DBs and WBs; the BSSs act as the followers by optimizing their demand for the WBs, supply for DBs and battery swapping services.

3) The competition among the BSSs is modeled as an exact potential game, which includes at least one pure Nash equilibrium (NE).

4) An evolutionary algorithm framework, i.e., differential evaluation (DE) is employed to compute the Stackelberg equilibrium (SE) of the proposed SG.

The rest of this paper is organized as follows. Section II presents the CLSC based BSCS, which serves as the system model in the SG. The SG between the BCS and BSSs are presented in Section III. The mathematical features of the proposed SG are shown in Section IV. A DE based SE computing algorithm is shown in Section V. The simulation and conclusion are given in Section VI and Section VII, respectively.

III. Closed Loop Supply Based EV Battery Swapping Networks

A. Battery Swap and Charging System

In this section, a genetic BSCS is introduced. As shown in [7], a BSCS has at least one BCS, multiple BSSs and a logistics system. BSSs are battery swapping service providers, who are responsible for providing battery swapping services to EV users within a certain area. BCS is a battery charging service provider, who is responsible for charging DBs collected from BSSs. The logistic system is the battery transportation between the BCS and BSSs, who is responsible for transferring WBs from the BCS to BSSs and collecting DBs from the BSSs to the BCS. A classical BSCS consists of three layers: 1) terminal device layer, 2) station management layer and 3) management center layer [7]. Focusing on the operation of a BSCS, this paper studies the station and management center layer operation. Here, the station refers to BSSs and a BCS management center refers to the interaction between the BCS and BSSs.

A CLSC is an integrated logistics system, composed of manufacturer, retailers, consumers and logistic systems [14], [15]. In a BSCS, EV users are consumers, BSSs are retailers, BCS is the manufacturer and the logistics are the batteries between the BCS and BSSs, which can be observed in Fig. 1. With the features of the battery swapping model of the EVs considered, the following assumptions are made for illustrating the proposed strategy in this paper.

1) Batteries within the BSCS are owned by the BCS, and there is only one BCS in this BSCS.

2) Batteries are of the same type, DBs have the same state of charge, and the batteries are of the same SOC after charging.

3) BSSs are owned by different entities.

4) BCS are owned and operated by a distribution system operator.

5) The deliver time between the BCS and BSSs is not taken into consideration.

6) The total operational period is divided into discrete time slots. Let t denote the time epoch, $t \in \{1,2,\ldots,T\}$.

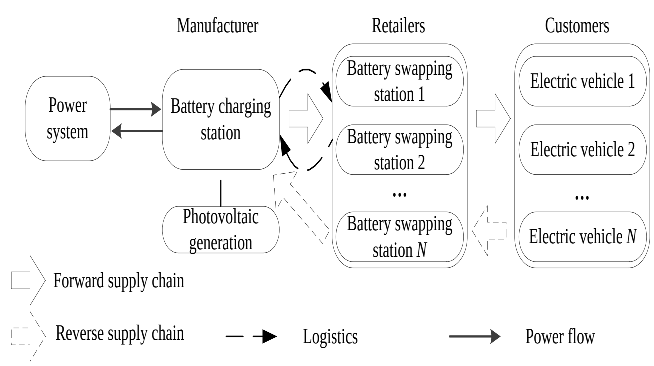


Fig. 1. CLSC based battery swapping and charging system. Providing WBs from the BCS to EV users via BSSs is the FSC. Collecting DBs from the EV users to the BCS via BSSs and charging the DBs at the BCS is the RSC. The logistics system is responsible for transferring WBs from the BCS to the BSSs and collecting DBs from the BSSs to the BCS. Bith theFSC and RSC, along with the logistics system formulate the CLSC. The relationship among the logistic system, the manufacturer and retailers leads to distinct types of CLSCs, as shown in Section III.C.

B. Battery Swap Station

There are three queues in a BSS, as shown in Fig. 2, one queue of EVs, one queue of WBs and one queue of DBs. All these three queues capture the coupling nature of the battery-swapping-collecting process, which can be a general performance analysis framework for an individual BSS. These queuing models are presented based on the network calculus theory.

1) EV Flow Model

To describe the flow of EVs for a given BSS, a cumulative curves methodology is employed in this work [18], [19]. This method model shows that the EVs can arrive in packets (packetized model) or in a continuum (fluid model). Let $A(t)$, $D(t)$ and $D_{\min}(t)$ denote the arrival curve, departure curve, and the minimum departure curve, respectively. These functions are assumed to be right-continuous functions and are defined as follows.

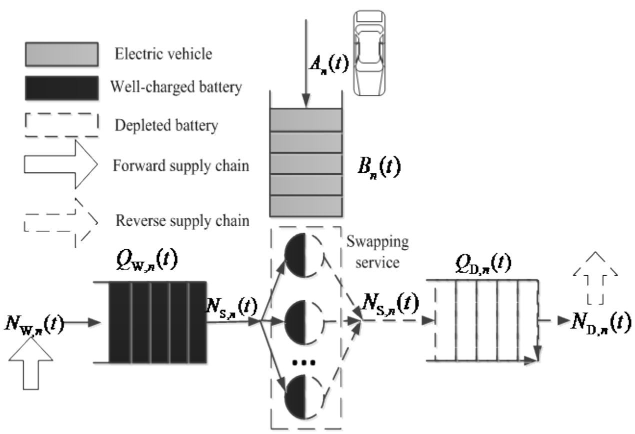


Fig. 2. Queue models in BSS *n*.

Definition 1 (Arrival Curve): An arrival curve $A(t)$, $t\geq0$, $t\in\mathbb{R}$, is the total number of EVs which have arrived in the time interval $[0, t]$.

Definition 2 (Departure Curve): A departure curve $D(t)$, $t\geq0$, $t\in\mathbb{R}$, is the total number of EVs which have departed (served) in the time interval $[0, t]$.

To model the arrival curve of EVs for a given BSS, a discrete-time model is adopted, as shown in Fig. 3. $D(t)\leq A(t),\forall t\geq0$ is treated as the *causality constraint*. To model the QoS requirements, a minimal departure curve concept is introduced as follows.

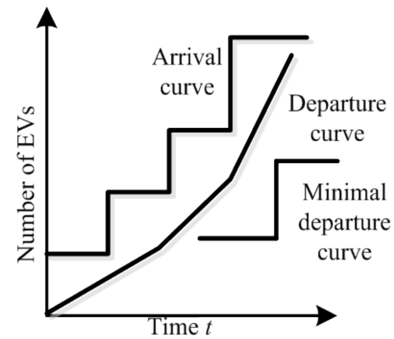


Fig. 3. Network calculus based queuing model for EVs.

Definition 3 (Minimal Departure Curve): For a given arrival curve $A(t)$, a minimum departure curve $D_{\min}(t)$ is a function such that $D_{\min}(t)\leq A(t)$, $\forall t\geq0$, and is defined as the cumulative minimum number of EVs which would satisfy the QoS requirements if they departed by time t.

Consider a fleet of EVs arrives at BSS n according to an arrival curve $A(t)$. Let $\{t_i\}$ denote the arrival epochs, $\{d_i\}$ the deadlines, and $\{n_i\}$ the sizes of the EVs, respectively. $D_{\min}(t)$ is a piecewise constant function which jumps at times $\{t_i+d_i\}$, the sizes of the jumps being $\{d_i\}$, as shown in Fig.3 [18]. The function $D_{\min}(t)$ can be viewed as the constraint function such that $D(t)\geq D_{\min}(t)$, $\forall t\geq0$, which the departure curve must $D(t)$ satisfy to satisfy the QoS requirements. It should be noted that the service policy in the BSSs is earliest-deadline-first, unlike the first-come-first in most network calculus models [19].

2) Battery Flow Model

The battery flow is the description of 1) WBs from the BCS to BSSs and BSSs to EV users and 2) DBs from EV users to BSSs and BSSs to the BCS, which corresponds to the FSC and RSC as shown in Fig. 1 and Fig. 2.

To guarantee QoS, each BSS should store sufficient WBs to fulfill the battery swapping demand of EV users. Each BSS should submit its bid for WBs, $N_{W,n}(t)$, $\forall t\geq0$ to the BCS for the following day, according to prices of WBs set by the BCS. To charge DBs and manage the battery inventory, the BCS should collect DBs from BSSs. BSSs submit their offer for DBs, $N_{D,n}(t)$, $\forall t\geq0$ to BSSs, responding to prices of DBs set by the BCS.

C. Closed Loop Supply Chain for BSCS

When managing the BSCS, three types of CLSCs can be applied, i.e., model C, model R, and model M, based on roles played by each player in the CLSC [15]. In model C, the manufacturer and retailer belong to one integrated firm, who is in charge of production, sales, and logistics. In Model R, the manufacturer produces the products, and the retailer is responsible for sales and logistics. In Model M, the manufacturer produces the products and manages the logistics, and the retailer is responsible for new product sales. Model C is a theoretical model and acts as a benchmark to evaluate the distributed models, namely, model R and model M. In this paper, BSSs and the BCS are assumed to be owned and operated by different entities. Model M type CLSC is preferred in this paper, where the logistics is managed by the BCS.

IV. Closed Loop Supply Chain Game

A. Game Formulation

As shown in Section II, in the day-ahead operation of the BSCS, BSSs submit their bids of WBs and offers of DBs to the BCS, responding to the prices set by the BCS. The BCS makes optimal scheduling to charge DBs, provide WBs to the BSS and collect DBs from BSSs according to the best bids and offers of the BSSs. Thus, the day-ahead operation of a BSCS is a leading-following decision making process, where the BCS is the leader and BSSs are the followers. This leading-following interaction among the BCS and BSSs is modeled as a SG in this section.

SG, which is a type of non-cooperative game, deals with the multi-level decision making process of a number of independent decision makers or players (the followers) in response to the decision taken by a leading player (the leader) [21]. To model the competition among the BCS and BSSs, a SG is defined in normal form, $\Gamma = \{(\mathcal{N}\cup\mathcal{C}), \{\mathcal{S}_n\}_{n\in\mathcal{N}\cup\mathcal{C}}, \{\mathcal{U}_n\}_{n\in\mathcal{N}\cup\mathcal{C}}\}$. $\mathcal{S}$ is N-tuple of pure strategy sets; $\mathcal{U}$ is N-tuple of payoff functions. The SG has the following components.

1) BSSs which act as the followers in the game and respond to the price set by the BCS..

2) The strategy space $\mathcal{S}_n$, $n \in \mathcal{N}$ which corresponds to the battery swapping service, demand for WBs and supply for DBs, satisfying the constraints (6)–(13). The utility function of each BSS$\in \mathcal{N}$ (1) captures the benefit of the BSS by providing battery swap services.

3) The strategy space $\mathcal{S}_{\mathcal{C}}$, corresponds to the scheduling plan of the BCS and prices of providing and collecting batteries from BSSs, and satisfying the constraints (15)–(22). The utility function (14) captures the benefit of the BCS operator.

B. Decision Model for An Individual Bss

For a BSS, it balances its benefits by providing battery swapping services and collecting DBs for the BCS and administering the cost of ordering well charged batteries from the BSSs. Its utility function can be depicted as follows.

$$\max_{N_{\mathrm{D},n}(t),N_{\mathrm{W},n}(t),N_{\mathrm{S},n}(t),\forall t\geq 0} \mathcal{U}_n = \sum_t \{p_{\mathrm{D}}(t)N_{\mathrm{D},n}(t) - p_{\mathrm{W}}(t)N_{\mathrm{W},n}(t)\}, \forall n \in \mathcal{N} \quad (1)$$

To avoid simultaneously demand of WBs or supply of DBs, $p_{\mathrm{F}}(t)$ and $p_{\mathrm{D}}(t)$ are set according to the following functions.

$$p_{\mathrm{D}}(t) = C_{\mathrm{D},0}(t) - C_{\mathrm{D},1}(t)\sum_{n\in\mathcal{N}} N_{\mathrm{D},n}(t) \quad (2)$$

$$p_{\mathrm{W}}(t) = C_{\mathrm{W},0}(t) + C_{\mathrm{W},1}(t)\sum_{n\in\mathcal{N}} N_{\mathrm{W},n}(t) \quad (3)$$

What is more, the price for supplying DBs should always be bigger than 0. $C_{\mathrm{D},0}(t)$ and $C_{\mathrm{D},1}(t)$ should meet the following constrains.

$$C_{\mathrm{D},0}(t) \geq C_{\mathrm{D},1}(t)\max(\sum_{n\in\mathcal{N}} N_{\mathrm{D},n}(t)), \forall t \geq 0 \quad (4)$$

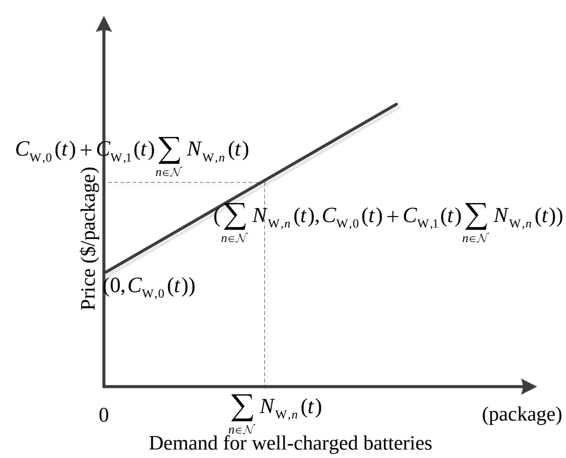
Remark 1: With the price rules (2), (3), the utility function (1) has the following characteristics.

1) The utility function (1) of a BSS is non-decreasing with respect to per package of DBs to the BCS, when condition (4) holds. And the utility functions of the BSS are non-increasing with respect to per package of WBs from the BCS, as each BSS should pay for any increase demand of WBs unless it reaches its maximum demand level.

2) The marginal benefit of a BSS is a non-increasing function, as the level of benefit of the BSSs gradually becomes saturated as more WBs are consumed and DBs are supplied, i.e.,

$$\frac{\partial \mathcal{U}_n}{\partial N_{\mathrm{D},n}(t)} \leq 0, \frac{\partial \mathcal{U}_n}{\partial N_{\mathrm{W},n}(t)} \leq 0, \forall t \geq 0, n \in \mathcal{N} \quad (5)$$

3) With (2), (3), the utility of a BSS depends not only on its strategy but also other BSSs' strategies. When demand of WBs rises at BSS n, the market price for WBs would rise. On behalf of their own utilities, the other BSSs should decrease their demand of WBs in the FSC. The supply of DBs can be explained through a similar way. Thus, BSSs and the BCS are price makers for DBs and WBs, i.e., the prices of WBs and DBs are decided by BSSs and the BCS.



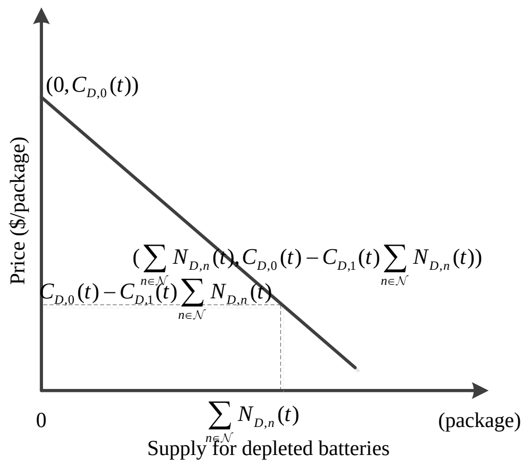


Fig.4 Demand and supply prices of the BCS. (a) Demand curve of well-charged batteries at time *t*. (b) Supply curve of at time *t*.

For a given BSS, its strategy $\boldsymbol{x}_n$, $n \in \mathcal{N}$ should be subjected to the following constrains guarantee QoS.

1) *Deadline Constraint*: For BSS *n*, the deadline constrains can be represented as follows.

$$A_n(t) \ge D_n(t) \ge D_{\min,n}(t), \forall t \ge 0, n \in \mathcal{N} \tag{6}$$

2) *Queue Length*: For a given arrival curve $A_n(t)$ and departure $D_n(t)$, the number of EVs within the queue is $A_n(t)$–$D_n(t)$. Let $B_n(t)$ denote the maximum queue length for BSS *n* at time *t*, the queue length can be depicted as follows.

$$\max[A_n(t) - B_n(t), 0] \le D_n(t), \forall t \ge 0, n \in \mathcal{N} \tag{7}$$

Furthermore, $B_n(t)$ can be time-varying or time-constant.

3) *Service-Curve Constraint:* The notion of service curves is an integral part of network calculus theory [13]. Given a service curve $\beta_n(t)$ and an arrival curve $A_n(t)$, the quantity $A_n(t)\otimes\beta_n(t)$ represents the minimum cumulative EVs that must be served by time *t*, where $\otimes$ is convolution in the min-plus algebra. Therefore, under network calculus theory, for any given service curve $\beta_n(t)$, the minimum departure curve can be obtained as follows.

$$D_{\min,n}(t) = A_n(t) \otimes \beta_n(t), \forall t \ge 0, n \in \mathcal{N} \tag{8}$$

4) *Inventory Constraint:* There are two kinds of batteries in a BSS, i.e., DBs and WBs. To provide guaranteed quality of the battery swapping service, a BSS should store sufficient WBs. Furthermore, the quantity of DBs within a BSS is limited by the number of EVs being served. Constrains for inventory can be represented as follows.

$$Q_{\mathrm{W},n}(t) = \sum_{h=1}^{t} N_{\mathrm{W},n}(h), \forall t \ge 0, n \in \mathcal{N} \tag{9}$$

$$Q_{\mathrm{D},n}(t) = \sum_{h=1}^{t} N_{\mathrm{D},n}(h), \forall t \ge 0, n \in \mathcal{N} \tag{10}$$

$$D_n(t) = \sum_{h=1}^{t} N_{\mathrm{S},n}(h), \forall t \ge 0, n \in \mathcal{N} \tag{11}$$

$$Q_{\mathrm{W},n}(t) \ge D_n(t), \forall t \ge 0, n \in \mathcal{N} \tag{12}$$

$$Q_{\mathrm{D},n}(t) \le D_n(t), \forall t \ge 0, n \in \mathcal{N} \tag{13}$$

$$Q_{\mathrm{D},n}(T) = D_n(T), \forall n \in \mathcal{N} \tag{14}$$

Cumulative number of DBs, WBs and EVs departure are shown in (9)–(11). Constrains for DBs and WBs are shown in (12), (13), respectively. To efficiently utilize batteries, all DBs should be sent to the BCS by the end of operations, as shown in (14).

C. Decision Model for BCS

Since the BCS is managed by DSO, a day-ahead DSO optimal scheduling is proposed as the decision model of the BCS. For given day-ahead wholesale market prices, DSO makes optimal day-head bidding to minimize its cost or maximize its revenue. Thus, the utility function for $\mathcal{U}_{\mathcal{C}}$ can be depicted as follows:

$$\begin{aligned} \max_{\substack{P_{\mathrm{DA}}(t), P_{\mathrm{C}}(t),\\ P_{\mathrm{DC}}(t), N_{\mathrm{A}}(t),\\ \forall t\ge 0, n\in\mathcal{N}}} \mathcal{U}_{\mathcal{C}} = & -\sum_{t=1}^{T} \lambda_{\mathrm{DA}}(t) P_{\mathrm{DA}}(t) - C_{\mathrm{p}} \sum_{t=1}^{T} [P_{\mathrm{C}}(t) + P_{\mathrm{DC}}(t)] \\ & - C_{\mathrm{A}} \sum_{t=1}^{T} N_{\mathrm{A}}(t) - \sum_{n\in\mathcal{N}} \mathcal{U}_n \end{aligned} \tag{15}$$

The strategy of the BCS, $\mathrm{x}_{\mathcal{C}}$, should meet the following constraints.

$$0 \le P_{\mathrm{DC}}(t) \le p_{\mathrm{DC,max}} [\sum_{h=1}^{t} \sum_{i} N_{\mathrm{D},n}(h)\Delta\mathrm{E} + \sum_{h=1}^{t} N_{\mathrm{A}}(h)\Delta\mathrm{E}], \forall t \ge 0 \tag{16}$$

$$0 \le P_{\mathrm{C}}(t) \le p_{\mathrm{C,max}} [\sum_{h=1}^{t} \sum_{i} N_{\mathrm{D},n}(h)\Delta\mathrm{E} + \sum_{h=1}^{t} N_{\mathrm{A}}(h)\Delta\mathrm{E}], \forall t \ge 0 \tag{17}$$

$$\sum_{h=1}^{t} [P_{\mathrm{C}}(t)\eta_{\mathrm{c}} - \frac{P_{\mathrm{DC}}(t)}{\eta_{\mathrm{dc}}}]\Delta t \ge \sum_{h=1}^{t} \sum_{i} N_{\mathrm{D},i}(h)\Delta\mathrm{E}, \forall t \ge 0 \tag{18}$$

$$\sum_{h=1}^{t} [P_{\mathrm{C}}(t)\eta_{\mathrm{c}} - \frac{P_{\mathrm{DC}}(t)}{\eta_{\mathrm{dc}}}]\Delta t \le \sum_{h=1}^{t} \sum_{i} N_{\mathrm{D},i}(h)\Delta\mathrm{E} + \sum_{h=1}^{t} N_{\mathrm{A}}(h)\Delta\mathrm{E}, \forall t \ge 0 \tag{19}$$

$$0 \le N_{\mathrm{A}}(t), \forall t \ge 0 \tag{20}$$

$$P_{\mathrm{DA}}(t) + P_{\mathrm{C}}(t) - P_{\mathrm{DC}}(t) + P_{\mathrm{PV}}(t) = P_{\mathrm{D}}(t), \forall t \ge 0 \tag{21}$$

$$p_{\mathrm{D,min}} \le C_{D,0}(t) - C_{D,1}(t) \sum_{n\in\mathcal{N}} N_{D,n}(t) \le p_{\mathrm{D,max}}, \forall t \ge 0 \tag{22}$$

$$p_{\mathrm{W,min}} \le C_{\mathrm{W},0}(t) + C_{\mathrm{W},1}(t) \sum_{n\in\mathcal{N}} N_{\mathrm{W},n}(t) \le p_{\mathrm{W,max}}, \forall t \ge 0 \tag{23}$$

The charging and discharging rate limitations within the BCS are shown in (16), (17), respectively. To meet the demand for WBs, the minimum energy should be absorbed in the BCS as shown in (18). Considering that backup batteries are DBs, the maximum energy the BCS can consume is shown in (19). The quantity limitation of backup batteries is shown in (20). Equation (21) depicts the power balance constrain within the distribution network. The price ranges of DBs and WBs are shown in (22), (23), respectively.

Definition 4 (Stackelberg equilibrium): Consider the SG $\Gamma=\{\mathcal{P}, \mathcal{S}, \mathcal{U}\}$ defined in Section III.A. A strategy profile $\boldsymbol{x}^* \in\mathcal{S}$ constitutes the NE of game Γ, if and only if it satisfies the following set of inequalities:

$$\mathcal{U}_i(\boldsymbol{x}_n^*, \boldsymbol{x}_{-n}^*) \geq \mathcal{U}_i(\boldsymbol{x}_n, \boldsymbol{x}_{-n}^*), \forall \boldsymbol{x}_n \in \mathcal{S}_n, n \in \mathcal{P} \quad (24)$$

V. Existence of Stackelberg Equilibrium

A. Existence of NE for game among BSSs

In noncooperative games, the existence of equilibriums (in pure strategies) is not always guaranteed [18]. Therefore, for the proposed closed loop supply chain game Γ, it is necessary to investigate the existence of SEs. As show in Section IV.A and Fig. 5, the best reaction of an individual BSS depends on not only the prices set by the BCS, i.e., $C_{\mathrm{D},0}(t)$,$C_{\mathrm{D},1}(t)$, $C_{\mathrm{W},0}(t)$ and $C_{\mathrm{W},1}(t)$, but also the strategy of other BSSs. In addition, game Γ is a hierarchical game, where the BCS is the leader and the BSSs are the followers. To verify the existence of a SE corresponding to game Γ, the competition among the BSSs is scrutinized first to reveal the relationship between the best reactions of the BSSs and the strategy of the BCS.

Definition 5 (Potential game)**:** A function Φ: $\mathcal{S} \rightarrow$ R is called an exact potential function for the game $\mathcal{G}$ if for each $n \in \mathcal{N}$ and all $x_{-n}\in\mathcal{S}_{-n}$,

$$\Phi(\boldsymbol{x}_n, \boldsymbol{x}_{-n}^*) - \Phi(\boldsymbol{y}_n, \boldsymbol{x}_{-n}^*) = \mathcal{U}(\boldsymbol{x}_n, \boldsymbol{x}_{-n}^*) - \mathcal{U}(\boldsymbol{y}_n, \boldsymbol{x}_{-n}^*), \forall n \in \mathcal{N} \quad (25)$$

Game $\mathcal{G}$ is called an exact potential game if it admits a potential function.

Proposition 1**:** The competition among BSSs, i.e., game $\mathcal{G}=\{\mathcal{N}, \{\mathcal{S}_n\}_{n\in \mathcal{N}}, \{\mathcal{U}_n\}_{n\in \mathcal{N}}\}$ is an exact potential game.

Proof of proposition 1 is referred to in Appendix A.

Lemma 1: Every potential game includes at least one pure Nash equilibrium (NE) [21].

Theorem 1: For fixed parameters, $C_{\mathrm{D},0}(t)$,$C_{\mathrm{D},1}(t)$, $C_{\mathrm{W},0}(t)$ and $C_{\mathrm{W},1}(t)$, at least one pure NE exists for game $\mathcal{G}$.

Proof of theorem 1 is referred to in Appendix B.

Proposition 2: The NE of game $\mathcal{G}$ is the solution of following optimizaiton problem,

$$\max_{\boldsymbol{x}\in\prod \mathcal{S}_n, n\in\mathcal{N}} \Phi(\boldsymbol{x}) \quad (26)$$

Proof of proposition 2 is referred to in Appendix C.

B. Existence of the SE for the Game Among the BCS and BSSs

As shown in Section IV-A, the competition among BSSs, i.e., game $\mathcal{G}$ is an exact potential game, which admits at least one pure NE, when $C_{\mathrm{D},0}(t)$,$C_{\mathrm{D},1}(t)$, $C_{\mathrm{W},0}(t)$ and $C_{\mathrm{W},1}(t)$ are given. It indicates that when $C_{\mathrm{D},0}(t)$,$C_{\mathrm{D},1}(t)$, $C_{\mathrm{W},0}(t)$ and $C_{\mathrm{W},1}(t)$ exist, the best reactions of BSSs responding to the strategy of the BCS exist. Thus, the existence of a SE for game Γ depends on the existence of $C_{\mathrm{D},0}(t)$,$C_{\mathrm{D},1}(t)$, $C_{\mathrm{W},0}(t)$ and $C_{\mathrm{W},1}(t)$.

Proposition 3: The decision space of the BCS would not be empty, i.e., there exists at least one feasible operational plan for the BCS.

Proof of proposition 3 is referred to in Appendix D.

Theorem 2: There exists at least one SE for game Γ.

Proof of theorem 2 is referred to in Appendix E.

A SE of game Γ is the solution of the following optimization problem[22], in which the BCS sets its optimal strategy in response to the equilibrium demand of WBs and supply of DBs, i.e.,

$$\begin{aligned} &\max_{\boldsymbol{x}_C} \mathcal{U}_C \\ &s.t. \begin{cases} (16)-(23) \\ \max\limits_{\boldsymbol{x}_i\in\prod \mathcal{S}_i, i\in\mathcal{N}} \Phi(\boldsymbol{x}) \end{cases} \end{aligned} \quad (27)$$

VI. Solving Method

As shown in Section IV, a SE of game Γ is the optimal solution of (27) and (27) is a bi-level optimization problem (BLPP). Popular ways to solve these kinds of BLPPs are mathematical programming with equilibrium constraints (MPEC)[22] and evolutionary algorithms [23]. The MPEC requires assumptions of smoothness, linearity or convexity of the lower level optimization problem, based on the optimal conditions for lower level optimization problems [22]. However, the lower level optimization problem (26) is non-continuous, due to the variables in (1)–(14) being discrete. Consequently, an evolutionary algorithm, i.e., DE, is adopted to solve (27). Furthermore, with attracting features, e.g., fast convergence speed and robust searching ability [5], DE has been applied to compute the NE of two player games [24]. However, classical DE does not provide the constraint handling techniques, which is also a hot topic in evolutionary algorithms [25]. Luckily, when $C_{\mathrm{D},0}(t)$, $C_{\mathrm{W},0}(t)$, $C_{\mathrm{D},1}(t)$ and $C_{\mathrm{W},1}(t)$, $\forall t\geq 0$ are optimized by DE, the upper level problem and lower level problem in (27) can be solved separately and efficiently by using mathematical algorithms, e.g., branch and bound, spatial branch and bound.

In (27), the lower problem is an integer convex quadratic programming (ICQP) problem. ICQP can be solved efficiently by classical optimization techniques, e.g., spatial branch and bound [26]. In this paper, this ICQP is solved by a commercial software package, i.e., CPLEX 12.6 [26].

For the upper level problem of (27), when the prices, i.e., $C_{\mathrm{D},0}(t)$, $C_{\mathrm{W},0}(t)$, $C_{\mathrm{D},1}(t)$ and $C_{\mathrm{W},1}(t)$, $\forall t\geq 0$ are predefined, the decision model is a mix-integer linear programming (MILP) problem. MILPs can be solved efficiently by employing mathematical algorithms. This MILP is solved by the commercial software package, Gurobi 6.0, in this paper.

Based on the foregoing statement, when the prices, i.e., $C_{\mathrm{D},0}(t)$, $C_{\mathrm{W},0}(t)$, $C_{\mathrm{D},1}(t)$ and $C_{\mathrm{W},1}(t)$, $\forall t\geq 0$ are given, the upper and lower problems can be solved separately by using mathematical methods. Thus, an enhanced DE is adopted in this paper to optimize the price profiles, i.e., adjusting prices considering the BCS and BSSs' decisions simultaneously. The details about DE are referred to in [27]. The pseudo code of the self-adapting DE algorithm, together with the mathematical algorithms for becoming a SE, is presented in algorithm 1.

Algorithm 1. Self-adapting DE algorithm
Step 1 Randomly generate Np number of initial trial solutions P, F and C_R parameters.
Step 2 For i = 1 to Np Produce an offspring Q_i using the standard DE [27]. For offspring i = 1 to Np **do** 2.1 Solve (26) by using CPLEX 12.6 2.2 Obtain the solution in 2.1, solve (27) by using Gurobi 6.0, and obtain the fitness of offspring Q_i by (15). 2.3 Assess the violation of constrains by using the constrain handling method in [25].
Step 3 Select between P and Q using the selection operation in [27].
Step 4 while *stop criterion*[1] *is not met*, **go to step 2.**

Noted: 1.The stop criterion in DE is an open question and depends on the problems in [27]. The stop criterion in this paper is referred to the maximal iteration should not exceed a predefined iteration, e.g., 1000 iterations.

VII. Case Study

A. *Case Description*

To verify the effectiveness of the proposed method, a simulation test system is adopted in this paper. In this test system, there are one BCS with three BSSs. Among the BSSs, two of them are for electric taxis and the other one is for electric buses. There are 1,000 of electric taxis and 200 electric buses in the test system, where each electric bus has four battery packages. The battery swapping demand for each of the EVs is taken from [28]. It is further assumed that the EVs should be swapped within 1h, 2h with proposition 0.5 and 0.5, respectively. The arrival and minimal departure curve for each BSS is shown in Fig.5.

The day-ahead price profile is taken from CAISO on July-1 2016 [29]. The load profile and outputs of the PV are taken from [30]. The upper boundaries for $C_{D,0}(t)$, $C_{D,1}(t)$, $C_{W,0}(t)$ and $C_{W,1}(t)$ are set to 23.2927 \$/package, 0.1288 \$/package^2, 5.7906 \$/package and 0.01 \$/ package^2, respectively. The lower boundaries for $C_{D,0}(t)$, $C_{D,1}(t)$, $C_{W,0}(t)$ and $C_{W,1}(t)$ are set to 10.0534 \$/package, 0 \$/package^2, 0 \$/package and 0 \$/ package^2,respectively. 23.2927 \$ is calculated according to the fuel price [31], electric vehicle efficiency and fueled vehicle efficiency [32], the equivalent price for each WB. 10.0534\$ is calculated according to the net present value of batteries and electric price obtained from [31], where the discount rate is set to 10%, which can guarantee the benefit of the BCS. C_A = 200\$/kWh, which is the same prices of Tesla batteries nowadays [33]. $p_{C,\max}$ =120 kW, $p_{DC,\max}$ =120kW, ΔE=50kWh, η_c=0.9, η_{dc}=0.85, C_p = 0.0884\$/kWh, $p_{D,\min}$=0 \$/package, and $p_{D,\max}$=5.7906 \$/package, $p_{W,\min}$=10.0534 \$/package and $p_{W,\max}$ =23.2927 \$/package.

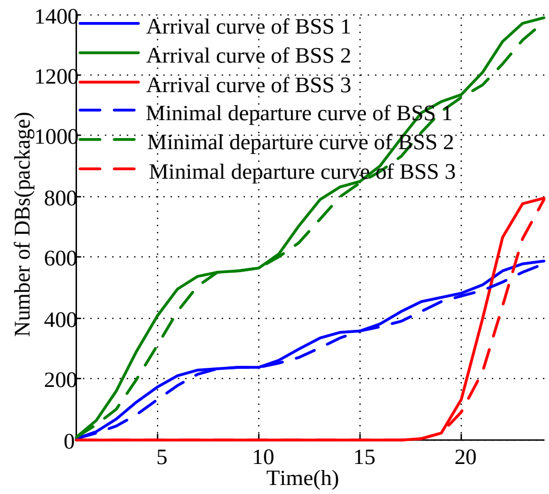


Fig.5 Arrival curves and minimal departure curves of BSSs.

In CLSCs, the model C type CLSC is always treated as a benchmark for other type CLSCs [15]. The decision model for model C type CLSC is depicted as follows.

$$\max_{\substack{P_{DA}(t),P_C(t),\\ P_{DC}(t),N_A(t),\\ N_{D,n}(t),N_{F,n}(t),\\ N_{S,n}(t),\forall t\geq 0,n\in\mathcal{N}}} \mathcal{U} = -\sum_{t=1}^{T}\lambda_{DA}(t)P_{DA}(t) - C_p\sum_{t=1}^{T}[P_C(t)+P_{DC}(t)] - C_A\sum_{t=1}^{T}N_A(t) \tag{28}$$

$$s.t.(6)-(14),(16)-(21)$$

The objective function in (28) is referred to as the social welfare of game Γ.In this paper, model (28) is a benchmark of the proposed method. Furthermore, three step by step scenarios are established to verify the proposed model M based CLSC BSCS operation method. These three scenarios are shown as follows.

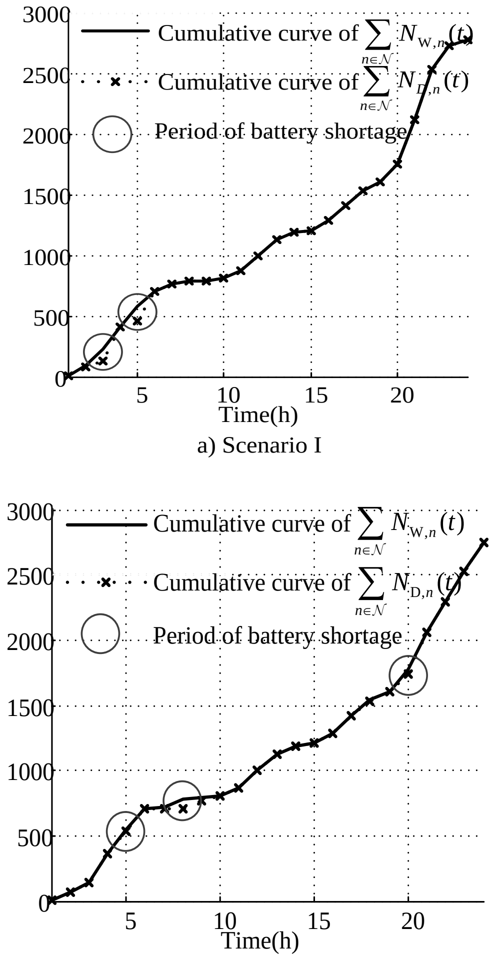
- Scenario I: The departure curve of each BSS *i* equals its arrival curve, which means each BSS would provide battery swapping service as EVs' arrival curve. Model C type CLSC management is applied.
- Scenario II: Model C type CLSC management is applied.
- Scenario III: Model M type CLSC management is adopted, where the BSCS is managed by the proposed Stackelberg game in Section IV.

It is noted that, the comparison between scenario I and scenario II is to show the benefits for BSCS considering the flexibility of the battery swapping demand, and the comparison between scenario II and scenario III is to show whether the competitions among the BSSs and BCS will result in efficiency lose and whether the proposed method can balance the benefits among players or not.

The maximal iteration of DE is set to 1,000, and N_p=300. The simulation is implemented on a PC with 8G RAM and Intel i7-4770MQ@2.4GHz.

B. *Results of Scenario I and Scenario II*

When BSSs provide battery swapping services as EVs' arrival curve and the BCS optimizes the charging process, the results are shown in Fig.6. As shown in Fig. 6 (a), to meet BSSs' demand for WBs during 1:00 to 5:00, which can be observed from Fig.5, the BCS needs to charge more backup batteries in Scenario I. On the other hand, the battery shortage periods is shifted to 5:00, 8:00 and 20:00, as shown in Fig. 6 (b). This shift reduces the number of backup batteries from 142 to 101, which is about 28.87% smaller than scenario I, as shown in Table I. The reduction of backup batteries results in the decrease of total cost by 92.22%.



a) Scenario I

b) Scenario II

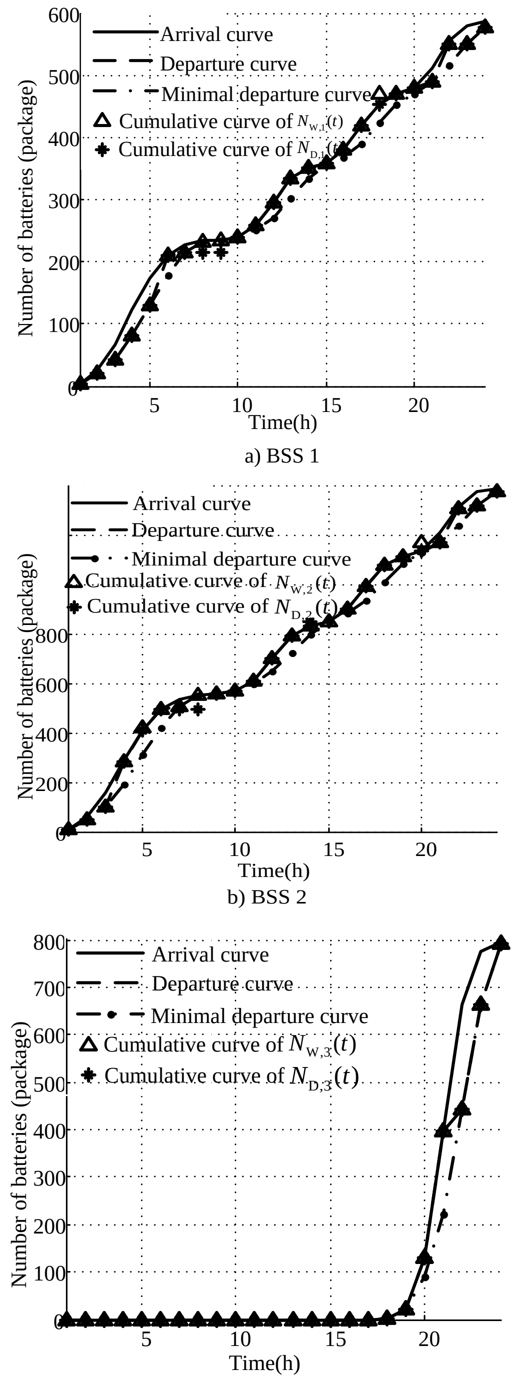
Fig.6 Curves of DBs and WBs under scenario I and scenario II

Table I

SIMULATION RESULTS UNDER SCENARIO I AND II

	Energy Cost ($)	Number of Backup Batteries (package)	Total Cost ($)[1]
Scenario I	15361.54	142	13174651.99
Scenario II	15269.62	101	1025236.00
Scenario III	15269.62	101	1025236.00

Note: Total cost is the total cost related to the BCS and BSSs, i.e. , negative value of the objective function in (28).



a) BSS 1

b) BSS 2

c) BSS 3

Fig. 7. Arrival, departure and minimal departure curves under scenario II.

The battery swapping service curve of each BSS is shown under scenario II in Fig.7. As shown in Fig.7, 1) the battery swap service curve is below both the arrival curve and WBs curve, 2) the battery swap service curve is beyond the minimal departure curve , and 3) the WBs curve is beyond the DBs curve. It can be concluded that, when model C type CLSC is adopted, the QoS of battery swapping can be guaranteed.

Base on the simulation results shown in Fig. 6, Fig. 7 and Table I, it can be concluded that through the optimal operation of the BSSs, the BSCS can realize optimal inventory management while guaranteeing QoS of the battery swapping service.

C. Results of the Proposed Method

In this section, model M type CLSC is implimented. When algorithm 1 is adopted to compute the SE, the convergence curve of the BCS' utility (15) is shown in Fig.8. As shown in Fig.8, after 1,000 iterations, the BCS' utility converges to 970 702.41\$. Considering the result in Table I, the utility for each BSS is –12 894.46\$, –30 837.24\$ and –16107.60\$, respectively, and the total utility of BSSs is –54533.59 \$. It should be noted that the operational plan under Scenario II and Scenario III are the same, i.e., the swapping service, supply of DBs, demand of WBs in each BSS and operational plan in the BCS are the same under Scenario II and Scenario III.

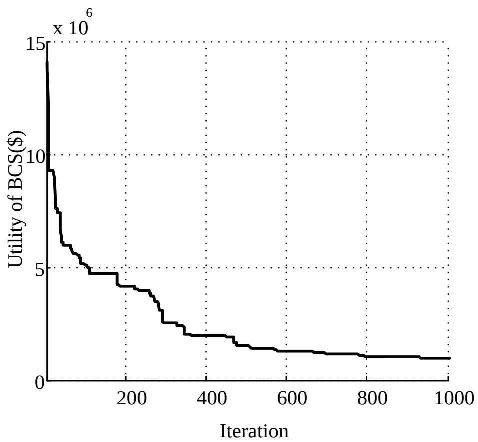


Fig. 8. Convergence curve of the BCS' utility under Scenario III.

As shown in Fig. 9 and Fig. 10, $p_W(t) \in [11.7906, 23.2927]$\$/package, $p_D(t) \in [0, 5.7906]$\$/package. These prices are within a feasible boundary, which means the EVs are more attractive than fuel vehicles while guaranteeing the benefit of the BCS and BSSs.

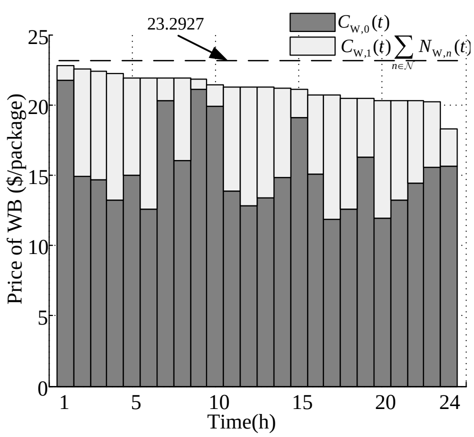


Fig. 9. Prices for WBs under Scenario III.

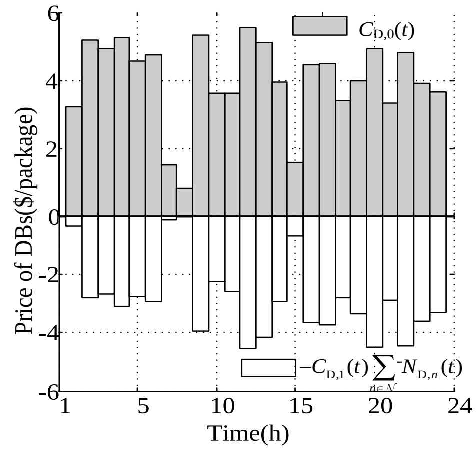


Fig. 10. Prices for DBs under Scenario III.

The simulation results above have demonstrated the merits of the proposed method: balance the benefits among the BCS and BSSs while guaranteeing the efficiency and QoS, since the total costs under Scenario II and Scenario III are the same, which is shown in Table I.

VIII. Conclusion

In this paper, a closed-loop supply chain management system is proposed for a BSCS. In the BSCS, there is one BCS and multiple BSSs, where the BCS is managed by a DSO and the BSSs are owned and operated by other players. The network calculus is employed to model the arrival, departure and swapping services of EVs at a BSS. An M type CLSC is proposed to model the battery-swapping-charging characteristics between the BCS and BSSs. Furthermore, a SG based method is proposed to balance the benefits among the BCS and BSSs. In the SG, the BCS acts as the leader to maximize its utility by setting optimal prices and a operational day-ahead operational plan. BSSs act as followers to maximize their own benefits by optimally demanding WBs, supplying DBs and providing battery swapping services while guaranteeing the QoS. The existence of SEs for the proposed game is proved. A DE based hybrid algorithm is proposed to compute the SE for the SG.

Based on real-world data and a step by step simulation, results have demonstrated the effectiveness of the proposed method, 1) improving the operational efficiency, 2) guaranteeing QoS and 3) balancing the benefits among the BCS and BSSs while maximizing the social welfare.

As the SOC of the DBs might not be the same, further work should propose some classification methods [34]. The BCS can provide not only demand response but also ancillary services to power systems. Last but not least, network calculus has the potential to model the demand flexibility in the smart grid.

In this paper, the batteries are assumed to be owned by the BCS and the logistic system is managed by the BCS. When the batteries are owned by the BSSs and the BSSs compete for the charging capacity in the BCS, a generalized Stackelberg game is a powerful tool to manage the competition among this BSCS. This will be our future work in managing the BSCS.

APPENDIX

A. Proof of Proposition 1

Proof: Considering the following potential function $\Phi(\boldsymbol{x})$ for game $\mathcal{G}$.

$$\begin{aligned}\Phi(\boldsymbol{x}_n,\boldsymbol{x}_{-n}) = &\sum_{n\in\mathcal{N}}\sum_{t}\{C_{D,0}(t)N_{D,n}(t)-C_{D,1}(t)N_{D,n}^2(t)\}\\ &-\sum_{t}\sum_{m\in\mathcal{N},\ n\in\mathcal{N},\ m\neq n}C_{D,1}(t)N_{D,m}(t)N_{D,n}(t)\\ &+\sum_{n\in\mathcal{N}}\sum_{t}\{C_{\mathrm{W},0}(t)N_{\mathrm{W},n}(t)-C_{\mathrm{W},1}(t)N_{D,n}^2(t)\}\\ &-\sum_{t}\sum_{m\in\mathcal{N},\ n\in\mathcal{N},\ m\neq n}C_{\mathrm{W},1}(t)N_{\mathrm{W},m}(t)N_{D,n}(t)\end{aligned} \quad (A1)$$

$\Phi(\boldsymbol{x})$ meets condition (25). This completes the proof.

B. Proof of Theorem 1

Proof: According to proposition 1, game $\mathcal{G}$ is an exact potential game, when $C_{\mathrm{D},0}(t)$,$C_{\mathrm{D},1}(t)$, $C_{\mathrm{W},0}(t)$ and $C_{\mathrm{W},1}(t)$ are given. Furthermore, an exact potential game admits at least one pure NE. Thus, game $\mathcal{G}$ has at least one pure NE.

C. Proof of Proposition 2

Proof: Consider the optimal solution $\boldsymbol{x}^*=\Pi_{N\ n=1}\ x_n^* \in\mathcal{S}$ of (26). For any $n\in\mathcal{N}$, if there exist any better strategies for y_n, with respect to $\Pi_{N_s m=1,n\neq m}\ x_m^*$, i.e.,

$$\Phi(\boldsymbol{y}_n,\boldsymbol{x}_{-n}^*)-\Phi(\boldsymbol{x}_n^*,\boldsymbol{x}_{-n}^*)=\mathcal{U}(\boldsymbol{y}_n,\boldsymbol{x}_{-n}^*)-\mathcal{U}(\boldsymbol{x}_n,\boldsymbol{x}_{-n}^*)>0,\exists i\in\mathcal{N} \quad (C1)$$

Consequently, $\boldsymbol{x}^*$ is not the optimal solution of (26), which is contradictory to the premise. This completes the proof.

D. Proof of Proposition 3

Proof: Consider following $\boldsymbol{x}_{\mathcal{C}}$, where $C_{\mathrm{D},0}(t)$=0, $C_{\mathrm{D},1}(t)$=0, $C_{\mathrm{W},0}(t)$=0, $C_{\mathrm{W},1}(t)$=0, $N_{\mathrm{A}}(t)$=$N_{\mathrm{D}}(t)$, $P_{\mathcal{C}}(t)\eta_{\mathrm{c}}$=$N_{\mathrm{D}}(t)\Delta E$ and $P_{\mathrm{DC}}(t)$=0,$\forall t\geq 0$. $\boldsymbol{x}_{\mathcal{C}}$ is a feasible solution to the BCS's decision making problem (14)–(22), which completes the proof.

E. Proof of Theorem 2

Proof: as shown in proposition 2, the strategy space of the BCS is non-empty. Based on Theorem 1, the NE of game $\mathcal{G}$ depends on the prices set by the BCS. Thus, the optimal solution of the BCS's decision making problem is the SE of game Γ. This completes the proof.

REFERENCES

[1]. J. B. Greenblatt, S. Samveg. "Autonomous taxis can greatly reduce greenhouse-gas emissions of US light-duty vehicles." *Nature Climate Change* . vol. 5, pp: 860–863, May 2015.

[2]. M. R. Sarker, P. Hrvoje, A. O. Miguel. "Optimal operation and services scheduling for an electric vehicle battery swapping station." *IEEE Transactions on Power Systems*, vol. 30, no.2, pp: 901-910, Feb. 2015.

[3]. Y. Zheng, Z.Y. Dong, Y. Xu, et al. "Electric vehicle battery charging/swap stations in distribution systems: comparison study and optimal planning." *IEEE Transactions on Power Systems*, vol.29, no.1, pp: 221-229, Jan. 2014.

[4]. N. Liu, Z. Chen, J. Liu, et al. "Multi-objective optimization for component capacity of the photovoltaic-based battery switch stations: towards benefits of economy and environment," *Energy*, vol. 64, pp: 779-792, Jan. 2014.

[5]. N Liu, X Lin, Q Chen, et al. "Optimal configuration for batteries and chargers in battery switch station considering extra waiting time of electric vehicles." *Journal of Energy Engineering*, 04016035, Jul. 2016.

[6]. N. Liu, Q. Chen, X. Lu, et al. "A charging strategy for PV-based battery switch stations considering service availability and self-consumption of PV Energy." *IEEE Transactions on Industrial Electronics*, vol.62, no.8, pp: 4878-4889, Aug. 2015.

[7]. X.H. Xu, L.Z. Yao, P.L. Zeng, et al. "Architecture and performance analysis of a smart battery charging and swapping operation service network for electric vehicles in China." *Journal of Modern Power Systems and Clean Energy*, vol.3, no.2 pp: 259-268, May 2015.

[8]. P. You, Z. Yang, Y. Zhang, et al, "Optimal charging schedule for a battery switching station serving electric buses, " *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 3473–3483, Sep. 2016.

[9]. S. Yang, J. Yao, T. Kang, et al. "Dynamic operation model of the battery swapping station for EV (electric vehicle) in electricity market." *Energy*, vol.65, pp: 544-549, Feb. 2014.

[10]. H.Y. Mak, R. Ying, Z. M. Shen. "Infrastructure planning for electric vehicles with battery swapping." Management Science, vol. 59, no.7, pp: 1557-1575, Apr. 2013.

[11]. L. Sun, X. Wang, W. Liu, et al. "Optimization model for power system restoration with support from electric vehicles employing battery swapping." IET Generation, Transmission & Distribution, vol.10, no.3, pp: 771 – 779, Feb. 2016.

[12]. S. Huang, L. He, Y. Gu, et al. "Design of a mobile charging service for electric vehicles in an urban environment." *IEEE Transactions on Intelligent Transportation Systems*, vol.16, no.2, pp: 787-798, April 2015.

[13]. B. Sun, X. Tan, DHK Tsang. "Optimal charging operation of battery swapping stations with qos guarantee.", *2014 IEEE International Conference on Smart Grid Communications*. Venice, 2014. pp: 13 – 18, IEEE, Nov. 2014.

[14]. B. Lebreton. *Strategic closed-loop supply chain management*. Vol. 586. Springer Science & Business Media, 2006.

[15]. Z. Miao, K. Fu, Z. Xia, et al. "Models for Closed-Loop Supply Chain with Trade-ins." *Omega* (2016).(Article in press)

[16]. K. Govindan, H. Soleimani, D. Kannan. "Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future." *European Journal of Operational Research* , vol.240, no.3,pp: 603-626, Feb. 2015.

[17]. O. Chatain. "Cooperative and non-cooperative game theory." *The Palgrave Encyclopedia of Strategic Management* , 2014.

[18]. Y. Jiang, Y. Liu. *Stochastic network calculus*. vol. 1. Heidelberg: Springer, 2008.

[19]. M.A. Zafer, E. Modiano. "A calculus approach to energy-efficient data transmission with quality-of-service constraints." *IEEE/ACM Transactions on Networking (TON),* vol.17, no.3,pp: 898-911, June, 2009.

[20]. A. V. Balakrishnan, M. Thoma. "*Stackelberg Differential Games in Economic Models*." Berlin: Springer2Verlag,1984.

[21]. D. Bauso, *Game Theory with Engineering Applications*. vol. 30. SIAM, 2016.

[22]. J. F. Bard, *Practical bilevel optimization: algorithms and applications*. vol. 30. Springer Science & Business Media, 2013.

[23]. K. Deb, A. Sinha. "An efficient and accurate solution methodology for bilevel multi-objective programming problems using a hybrid evolutionary-local-search algorithm." *Evolutionary computation*, vol. 18, no.3, pp: 403-449, Aug. 2010.

[24]. U. Boryczka, P. Juszczuk. "Differential evolution as a new method of computing Nash equilibria." *Transactions on Computational Collective Intelligence IX*. Springer Berlin Heidelberg, pp: 192-216. 2013.

[25]. R. Storn. "System design by constraint adaptation and differential evolution." *IEEE* Transactions *on Evolutionary Computation*, vol.3, no.1,pp: 22-34, Apr. 1999.

[26]. C. Bliek1ú, P. Bonami, A. Lodi. "Solving mixed-integer quadratic programming problems with IBM-CPLEX: a progress report." *Proceedings of the Twenty-Sixth RAMP Symposium*, Tokyo, pp: 171-180. Oct. 2014.

[27]. U.K. Chakraborty. *Advances in differential evolution*. vol. 143. Springer, 2008.

[28]. X. Wang, L. Sun, F. Wen, et al. "Modeling charging demands of various types of electric vehicles in *an* actual distribution system." *2015 IEEE PES Asia-Pacific Power and Energy Engineering Conference*, Brisbane, QLD, pp: 1 - 5. IEEE, Nov. 2015.

[29]. California ISO - Price Maps, [Online]. Available: www.caiso.com/pages/pricemaps.aspx

[30]. The Open PV Project, [Online]. Available: https://openpv.nrel.gov/
[31]. MIT Electric Vehicle Team: Information, [Online]. Available: http://web.mit.edu/evt/info.html
[32]. Gasoline and Diesel Fuel Update , [Online]. Available: http://www.eia.gov/petroleum/gasdiesel/
[33]. A Breakthrough Super Battery Technology, [Online]. Available: http://www.biosolar.com/
[34]. T. Zhao, L.L. Zhang, W. Liu, et al. "Centralized spatial and temporal decomposition charging strategy for electric vehicles: A bi-level optimization approach." *2014 IEEE Conference and Expo Transportation Electrification Asia-Pacific*. Beijing, pp:1 – 6, IEEE, Oct. 2014.

Tianyang Zhao (S'13) received B.Sc. and M.Sc. degrees in automation of electric power systems from North China Electric Power University, Beijing China in 2011 and 2013. Currently, he is pursuing his Ph.D. degree in automation of electric power systems in North China Electric Power University, Beijing, China. His research interests include power system operation optimization and game theory.

Jianhua Zhang (M'98) received B.Sc. and M.Sc. degrees in electrical engineering from North China Electric Power University, Baoding, China in 1982 and 1984, respectively. Currently, he is working as a Professor in the Department of Electrical and Electronic Engineering, North China Electric Power University. He has been the IET Fellow from the year of 2005, and also a member in the PES Committee of China National"973 Project".

Peng Wang (M'00, SM'11) received a B.Sc. degree in electronic engineering from Xian Jiaotong University, Xian, China, in 1978, a M.Sc. degree from Taiyuan University of Technology, Taiyuan, China, in 1987, and M.Sc. and Ph.D. degrees in electrical engineering from the University of Saskatchewan, Saskatoon, SK, Canada, in 1995 and 1998, respectively. Currently, he is an Associate Professor of the School of Electrical and Electronic Engineering at Nanyang Technological University, Singapore.