Joint Optimal Scheduling for Electric Vehicle Battery Swapping-charging Systems Based on Wind Farms

Mingfei Ban, Member, IEEE, Jilai Yu, and Yiyun Yao, Member, IEEE

Abstract—Insufficiencies in charging facilities limit the broad application of electric vehicles (EVs). In addition, EV can hardly represent a green option if its electricity primarily depends on fossil energy. Considering these two problems, this paper studies a battery swapping-charging system based on wind farms (hereinafter referred to as W-BSCS). In a W-BSCS, the wind farms not only supply electricity to the power grid but also cooperate with a centralized charge station (CCS), which can centrally charge EV batteries and then distribute them to multiple battery swapping stations (BSSs). The operational framework of the W-BSCS is analyzed, and some preprocessing technologies are developed to reduce complexity in modeling. Then, a joint optimal scheduling model involving a wind power generation plan, battery swapping demand, battery charging and discharging, and a vehicle routing problem (VRP) is established. Then a heuristic method based on the exhaustive search and the Genetic Algorithm is employed to solve the formulated NP-hard problem. Numerical results verify the effectiveness of the joint optimal scheduling model, and they also show that the W-BSCS has great potential to promote EVs and wind power.

Index Terms—Battery swapping station, electric vehicle, vehicle routing problem, wind power.

NOMENCLATURE

A. Sets and Indices

\( k/K \) Index/set of battery transporter (BTs).
\( m(n)/B \) Index/set of battery swapping stations (BSSs).
\( t/T \) Index/set for scheduling periods.
\( r_{k,t}/P_k \) Index/set for battery supplement stations (W-CCS\(^R\)).

B. Parameters

\( C_{\text{total}} \) Total cost [$.]
\( C_{\text{plan}} \) Penalty for failing to complete generation plan [$.]
\( C_{\text{BSS}} \) Cost for buying electricity from power grid [$.]
\( C_{\text{delivery}} \) Penalty for wind curtailment of the W-CCS [$.]
\( C_{\text{grid}} \) Penalty for failing to fulfill demand of BSSs [$.]
\( C_{\text{wind}} \) Cost for BT\(_k\) travel cost between vertices \( m \) and \( n \) [$.]
\( \gamma_{\text{t plan}} \) Price for buying electricity from power grid [$/MWh].
\( \gamma^*_m \) Price for BT\(_k\) travel cost between vertices \( m \) and \( n \) [$.]
\( r_{\text{grid}}^* \) Penalty for wind curtailment of the W-CCS [$/MWh].
\( r_{\text{grid}}^* \) Penalty for failing to fulfill demand of BSSs [$/MWh].
\( \rho_{\text{grid}}^* \) Upper limit of the time window of CCS [[$/MWh].
\( \Delta \tau_{\text{m,n}}^\tau \) Upper limit for total carrying capacity of BT\(_k\) [MW].
\( m \) A sufficiently large positive constant.
\( t \) Driving distance between \( m \) and \( n \) [km].
\( \eta_{\text{ch}} \) Discharging efficiency of batteries in W-CCS [%].
\( \eta_{\text{ds}} \) Charging efficiency of batteries in W-CCS [%].
\( \Delta \tau_{\text{grid}}^\tau \) Upper limit of the time window of CCS [[$/MWh].
\( \Delta \tau_{\text{grid}}^\tau \) Upper limit for driving distance of BT\(_k\) [km].
\( \Delta \tau_{\text{grid}}^\tau \) Travel time of BT\(_k\) between vertices \( m \) and \( n \) [$/MWh].
\( \Delta \) Lower limit of the time window of CCS [[$/MWh].
\( \Delta \) Lower limit of the time window of CCS [[$/MWh].
\( \Delta \) Lower limit of the time window of CCS [[$/MWh].

Penalty for failing to fulfill demand of BSSs [$.]
Routing cost for the battery delivery vehicles [$.]
Cost for buying electricity from power grid [$.]
Penalty for wind curtailment of the W-CCS [$.]
Price for failing to complete generation plan [$/MWh].
Price for failing to fulfill demand of BSSs [$/MWh].
Price for BT\(_k\) travel cost between vertices \( m \) and \( n \) [$.]
Price for wind curtailment of the W-CCS [$/MWh].
Upper limits for the visit times of BTs to a BSS.
A sufficiently large positive constant.
Charging efficiency of batteries in W-CCS [%].
Discharging efficiency of batteries in W-CCS [%].
Limit ratio for the abandonable demand of BSS\(_m\) [%].
Fully-charged battery demand of BSS\(_m\) [MWh].
Wind power generation of W-CCS at time \( t \) [MW].
Planned generation of W-CCS during time \( t \) [MW].
Limit for uncompleted generation plan at time \( t \) [%].
Limit for total uncompleted generation plan [%].
Limits for fluctuations in FCB level in W-CCS [%].
Limits for the stored FCB level in W-CCS [MWh].
I. INTRODUCTION

TRANSPORTATION electrification will help to address various social and environmental problems associated with mass motorization and rapid urbanization, e.g., it benefits oil conservation, climate change mitigation, air quality improvement, and transit mode upgrading. Electric vehicles (EVs) play an essential role in realizing transportation electrification. During the last decade, EVs were rapidly developing, with the strong support of ambitious governments. By the end of 2017, the global stock of EVs surpassed 3 million [1], and their applications in power systems [2, 3], including energy storage [4], load shifting [5], frequency regulation [6, 7], operation reserves [8, 9], renewable energy integrating [10], vehicle to grid [12, 13], transmission congestion relief [13], [14], resilience enhancing [15], and demand response [16], [17], etc., are widely studied. Yet environmental and charging concerns are still haunting the promotion of EVs.

On the one hand, with the rapid increase in charging demand of EVs, environmental concerns are gaining in importance in regions where power generation is primarily supplied by coal-fired power plants [17]. For example, China is the largest EV market in the world, while coal-fired power plants generated more than 70% of China’s supplied electricity in 2018. In this setting, electricity supply EVs would produce large quantities of greenhouse gas and air pollutants. Even worse, some controlled EV charging solutions may reduce the generation cost, but they may also increase emissions primarily due to increased use of cheap coal-fired power plants [18], [19]. Therefore, EVs can represent clean electric mobility only if the potentially significant environmental concerns at the supply side can be effectively addressed via promoting renewable generation [20]. In this setting, charging EVs directly with renewables is undoubtedly the most effective approach.

On the other hand, rapidly growing charging demands of EVs require mass charging facilities [21]–[23]. However, it would be difficult to perform the widespread deployment of charging stations and charging piles in some highly populated regions, which have insufficient parking spaces and weak distribution grids [11], [12]. Network congestion, power losses, and large voltage drops limit deploying EV chargers in some old residential areas. Battery swapping technology can easily address these concerns [24], [25], and it is a promising alternative for promoting electric mobility [26], [27]. Thus, some populated countries with congested urban areas, such as India, Japan, and China, are early adopters that are pushing hard for battery swapping technology [28], [29], e.g., the State Grid Corporation of China is vigorously promoting the battery swapping station (BSS) option with pilot installations in multiple cities [30]–[33]. And very recently, a novel battery swapping-charging system (BSCS) was proposed. In this novel framework, modular EV batteries are centrally charged in a centralized charging station (CCS) and then dispatched to multiple BSSs via battery transporters (BTs) [34]–[36]. The CCS can be built nearby a substation and thus it will have little impact on local distribution grids [37]. Compared to the traditional charging stations [38] and BSSs [39], [40], the BSCS offers a more controllable and viable option for...
transporting large quantities of electricity through the coupled transportation and power networks [41].

Based on the points mentioned above, a novel BSCS framework based on wind farms (hereinafter referred to as W-BSCS) is attracting attention. In a W-BSCS, the CCS can not only charge EV batteries with wind power but also support wind farms to supply high-quality electricity to the power grid. Reference [42] analyzes the benefits of the integration of wind farms and electric vehicle supporting facilities, and it points out that the integrated system will boom due to the development in dispersed wind power. In practice, dispersed wind power is expected to reach 20GW by 2020 in China, and most of the dispersed wind power projects will be built around urban areas. This will make the W-BSCS one of the most promising applications for promoting both wind power and EVs.

This paper focuses on the W-BSCS and establishes a joint optimal scheduling model, which optimally manages the W-BSCS to minimize the operational cost while satisfying the generation plan of the wind farm and the FCB demands of individual BSSs. It contributes to the literature by developing a joint optimization framework of battery charging/discharging scheduling of the CCS, and battery swapping scheduling between individual units, and the vehicle routing problem (VRP) of the BTs. Since the proposed scheduling model is an NP-hard problem, a heuristic solution method is designed. The major contributions of this paper are summarized as follows:

1) A W-BSCS consisting of a CCS, wind farms, BTs and BSSs is introduced. And several processing technologies for simplifying the optimal scheduling of the W-BSCS is designed. Then, it formulates a comprehensive joint optimization model that simultaneously schedules battery charging/discharging, battery swapping, and VRP for the W-BSCS.

2) A heuristic method based on the exhaustive search and Genetic Algorithm is designed to solve the proposed NP-hard problem. Numerical results demonstrate the proposed model, and they indicate that the W-BSCS will benefit in promoting EVs and wind power. Also, it briefly discusses the potential expansion of the model for dealing with wind power uncertainty.

The rest of this paper is organized as follows. Section II introduces the framework of a W-BSCS system, and it also shows some processing technologies and assumptions for simplifying modeling. Section III formulates the joint optimal scheduling model, and Section IV provides a solution method. Section V performs numerical case studies with discussions, and the conclusion is provided in Section VI.

II. FRAMEWORK OF A W-BSCS SYSTEM

This section presents the framework of a W-BSCS, and then it develops several preprocessing assumptions and technologies for simplifying sequent joint optimal modeling.

A. Frame of a W-BSCS System

A W-BSCS framework is shown in Fig. 1. A CCS and wind farm form a W-CCS, where EV batteries can balance wind power fluctuations. The CCS primarily uses wind power
to charge EV batteries, and it can also purchase electricity from the power grid when the wind power is insufficient. The massive FCBs of the W-CCS will be distributed to multiple BSSs to serve local EVs, by heavy trucks (referred to as battery transporter, BTs). The proposed W-BSCS represents a novel framework for performing energy & storage sharing and trading [43], [44], and it will help to address the environmental concerns on promoting EVs. Interested readers are referred to our previous study [37] for more details about the BSS and BSCS applications.

In the W-BSCS, the master controller is responsible for system-level management, and it establishes communication with individual BSSs, BTs and the W-CCS. In daily operations, the master controller collects various data (e.g., battery demand, wind power forecast, etc.) from individual units, and then it deals with them by solving a mathematical programming problem to find a day-ahead optimal scheduling solution. In other words, the master controller comprehensively controls the wind power generation plan and battery charging/discharging scheduling of the W-CCS, battery delivery scheduling of the BTs, and battery swapping scheduling among individual units.

The day-ahead scheduling of the W-BSCS primarily consists of two coupled parts. The first one is the battery charging and discharging, and it controls the CCS batteries to coordinate with the wind farm to complete the released generation plan. The second one is the VRP of the BTs, and it manages the delivery routes and battery swapping scheduling among the W-CCS and the BSSs (see Fig. 2). Note that the system-level scheduling will not cover detailed station-level management of the BSSs and demand patterns of EVs, and it assumes that the BSSs will address such issues before submitting their FCB demands.
B. Preprocessing Assumptions and Technologies

To simplifying joint modeling of a W-BSCS, the employed preprocessing assumptions and technologies are as follows:

1) The battery swapping is only applied between two types of batteries, namely fully-charged batteries (FCBs) and empty ones, to improve energy exchange efficiency. And it assumes that individual units will prepare enough idle fully-charged and/or empty batteries for performing the following swapping operation, which is based on the assumption that the W-CCS and the BSSs can perform monotonic charging/discharging strategies for their local batteries connected in parallel [43].

2) The amount of energy exchange via battery swapping are presumed to be continuous variables. This is not the case in practical applications. However, if they are modeled as integer variables, they will badly aggravate the computation complexity. Similarly, the FCB level is presumed to be a continuous variable, and the stored energy of the W-CCS solve.

3) In order to facilitate the joint modeling of VRP of BTs and scheduling of W-CCS, the planning interval is discretized. Thereby, the time window of each BSS can be approximately represented by several consecutive time periods (see Fig. 3). For example, the 1st time window of B1 can be approximated as [4Δt, 7Δt]. Although this preprocessing will sacrifice some modeling accuracy, it can effectively reduce the complexity of the proposed problem.

4) If a BSS has multiple battery requirements and corresponding multiple time windows, copies can be set for it. For example, if a BSS, e.g., B1, has three time windows, then three copies of it can be set, i.e., B11, B12, and B13, which have the same sites as B1, but their time windows are the same as the 1st, 2nd and 3rd time windows of B1, respectively. Therefore, three BSSs with single time windows can replace B1, and the original VRP with multiple time windows is converted into VRP with a single time window that is easier to model and solve.

5) Copies are also set for the W-CCS, which are defined as supplementary stations (W-CCS(B)). Each W-CCS(B) has the same site of the W-CCS but only one-period time window that allows a BT to obtain a FCB supplement. W-CCS(B) allows a BT to leave it to continue their subsequent delivery tasks. It is distinguished from the W-CCS, which is the start and end of each BT’s route. In this way, the original problem is simplified to an easier single depot VRP.

C. Joint Scheduling Description for a W-BSCS System

The joint optimal scheduling for a W-BSCS system can be described as: a fleet of BTs visit a set of customers (i.e., all BSSs and their copies) during their specific time windows, and each BT starts and ends its daily tour from the same one depot (i.e., W-CCS), which optimally charge and discharge the local batteries. The objective is to pick a cost-minimizing scheduling scheme to meet the generation plan of the wind farm and the FCB demand of the BSSs. This paper restricts its attention to the W-BSCS with one W-CCS, and the studied problem is a strict one-depot VRP. Moreover, the modeling of multiple W-CCSs is also an important subject, but it is beyond the scope of this paper, and we intend to consider it in a future study.

For notational convenience, the variables and parameters are described as: \( \mathcal{B} = \{1, \ldots, m(n)\} \) denotes the set of BSSs and their copies, \( \mathcal{K} = \{1, \ldots, k\} \) denotes the set of BTs, \( \mathcal{R}_k = \{r_k, 1, \ldots, r_k, t\} \) denotes the set of W-CCS(B), and vertices 0 and \( |\mathcal{B}| + 1 \) denote the W-CCS (i.e., the depot), in which every route starts at 0 and ends at \( |\mathcal{B}| + 1 \). To indicate that a vehicle routing set contains the respective instance of the depot, the set is subscripted with 0 or \( |\mathcal{B}| + 1 \), and thereby, \( \mathcal{Y}_0 = \mathcal{B} \cup \{0\} \) and \( \mathcal{Y}_{|\mathcal{B}|+1} = \mathcal{B} \cup \{|\mathcal{B}| + 1\} \). Then we can define the problem on a complete directed graph \((\mathcal{V}_0, \mathcal{B} + 1, \mathcal{A})\) with the set of arcs \( \mathcal{A} = \{(m, n)|m, n \in \mathcal{V}_0 \cup \mathcal{B} + 1, m \neq n\} \), in which each arc is associated with a specific travel cost and time. The binary state variable \( f_{k,m,n} \) is equal to 1 if BT \( k \) travels from vertex \( m \) to \( n \), and 0 otherwise. The W-CCS can control at most \( |\mathcal{K}| \) BTs to serve the BSSs, and each BSS at vertices \( m \in \mathcal{B} \) has a FCB demand and corresponding time window \( \tau_m, \tau_m^* \).

III. JOINT SCHEDULING MODEL FOR A W-BSCS SYSTEM

This section presents the MILP formulation of the proposed optimization model of the joint scheduling for the W-BSCS.

A. Objective

\[
\min \quad C_{\text{total}} = C_{\text{plan}} + C_{\text{BSS}} + C_{\text{delivery}} + C_{\text{grid}} + C_{\text{wind}} \tag{1}
\]

where,

\[
C_{\text{plan}} = \sum_{t \in T} \gamma_{t}^m \delta_{t}^m \Delta t \tag{2}
\]

\[
C_{\text{BSS}} = \sum_{m \in \mathcal{B}} \xi_{m,n} \Delta t \tag{3}
\]

\[
C_{\text{delivery}} = \sum_{k \in \mathcal{K}, m \in \mathcal{V}_0 \cup \{1, \ldots, |\mathcal{B}| + 1\}, m \neq n} \sum_{n \in \mathcal{V}_0 \cup \{1, \ldots, |\mathcal{B}| + 1\}} \psi_{k,m,n}^m \Delta t \tag{4}
\]

\[
C_{\text{grid}} = \sum_{t \in T} \psi_{t} \Delta t \tag{5}
\]

\[
C_{\text{wind}} = \sum_{t \in T} \psi_{t} \Delta t \tag{6}
\]

The objective minimizes the sum of the penalty for failure in completing the power generation plan, the penalty for failure...
in meeting the battery swapping demand, the delivery cost of the BTs, the cost for buy power from the power grid, and the virtual penalty for wind curtailment. Note that the battery transportation cost is not modeled in detail but covered by the delivery cost of BTs.

B. Constraints for Delivery Routes

The constraints for delivery routes are similar to traditional VRP problems, (7) and (8) state that each BSS is visited at least once and at most \( N_{\text{max}} \) times by BTs, (9) states the flow conservation (a BT that enters a BSS site must leave), (10) denotes that each BT must return to CS, (11) states that each BT can be assigned at most one trip, and (12) limits the maximum delivery distance for each BT. In addition, the unreasonable delivery routes can be relaxed by assigned extreme values.

\[
\begin{align*}
\sum_{k \in K} \sum_{n \in B} l_{k,m,n} &= 1 \quad \forall m \in V_0, m \neq n \quad (7) \\
\sum_{k \in K} \sum_{n \in B} l_{k,m,n} &\leq N_{\text{max}} \quad \forall m \in V_0, m \neq n \quad (8) \\
\sum_{k \in K} \left( \sum_{m \in V_0, m \neq n} l_{m,n} - \sum_{m \in V_0, m \neq n} I_{k,m,n} \right) &= 0 \quad \forall n \in V \quad (9) \\
\sum_{n \in B} I_{k,m,n} - \sum_{m \in B} I_{k,m,n} &= 0 \quad \forall k, m \neq n \quad (10) \\
\sum_{k \in K} l_{k,m,n} &\leq 1 \quad \forall k \quad (11) \\
\sum_{n \in V_{\mid B | + 1}} d_{m,n} &\leq D_{\text{max}} \quad \forall k, m \in V_0, m \neq n \quad (12)
\end{align*}
\]

C. Constraints for Time Windows

Constraints (13) and (14) guarantee BT\(_k\) visits each BSS location within the specified time window, (15) tracks the time that BT\(_k\) arrives at each BSS, and (16) ensures that BT\(_k\) returns to the CS during its operational periods. The proposed approach assumes that the battery swapping operation can be completed within one period, that is, if a BT arrives at a BSS, it will complete the battery swapping operation and then leave within the same time period.

\[
\begin{align*}
-M(1 - l_{k,m,n}) + \tau_n &\leq \tau_k \quad \forall k, m \in V_0, \forall n \in V \quad (13) \\
\tau_k &\leq M(1 - l_{k,m,n}) + \tau_n \quad \forall k, m \in V_0, \forall n \in V \quad (14) \\
\tau_k + \Delta \tau_k + l_{k,m,n} &\leq \tau_k + M(1 - l_{k,m,n}) \quad \forall k, m \in V_0, \forall n \in V_{\mid B | + 1} \quad (15) \\
\sum_{n \in B} I_{k,m,n} &\leq \tau_k + \tau_{\text{max}} \sum_{n \in B} I_{k,m,n} \quad \forall k \quad (16)
\end{align*}
\]

D. Constraints for Battery Swapping Between BT and W-CCS

A BT unloads FCBs and loads empty ones at the BSSs: (17) and (18) tracks the remaining amount of the FCBs when BT\(_k\) travels between BSSs \( m \) and \( n \), while (19) limiting the amount of the FCBs that BT\(_k\) can supply to a BSS; (20) limits the total carrying capacity of BT\(_k\); (21) states the FCB demand of a BSS can be met by swapping batteries with all BTs and parts of its demand can be abandoned, and (22) limits the total amount of abandoned FCB demand of BSS\(_m\).

\[
\begin{align*}
0 &\leq e_{k,m} - e_{k,m} + M(1 - l_{k,m,n}) - \Delta e_{k} \quad \forall k, m \in V_0, \forall n \in V_{\mid B | + 1} \quad (17) \\
&\leq e_{k,m} + M(1 - l_{k,m,n}) - \Delta e_{k} \quad \forall k, m \in V_0, \forall n \in V_{\mid B | + 1} \quad (18) \\
0 &\leq -\Delta e_{k} \sum_{m \in V_0} I_{k,m,n} \quad \forall k, m \in V_0, \forall n \in V_{\mid B | + 1} \quad (19) \\
0 &\leq e_{k,m} - Q_{\text{max}} \quad \forall k, m \in V_0, \forall n \in V_{\mid B | + 1} \quad (20) \\
0 &\leq e_{k,m} - e_{k,m} + e_{k,m} - e_{k,m} \quad \forall m \in B \quad (21) \\
0 &\leq e_{k,m} - e_{k,m} \quad \forall m \in B, \forall r_{k,t} \in R_k \quad (22)
\end{align*}
\]

E. Constraints for Battery Swapping Between BT and W-CCS

As for the W-CCS, equations (23)–(25) link the relationships between the period that BT\(_k\) departs from (returns to) the W-CCS and its delivery task. For example, if BT\(_k\) starts (ends) its delivery at period \( t \), then \( I_{k,t} \) will be 1, and then the period \( t_{k} \) and \( t_{|B | + 1} \) that BT\(_k\) departs from (or returns to) the W-CCS is \( t \); (26) and (27) define the amount of FCBs that BT\(_k\) can load when it departs from the W-CCS, while (28) and (29) define the final amount of FCBs when BT\(_k\) returns to the W-CCS. Note that if BTs only take empty batteries from the BSSs and then gives them all to the W-CCS, then (28) and (29) can be omitted.

\[
\begin{align*}
\sum_{t \in T} I_{k,t} &= e_{k}^0 \quad \forall k \quad (23) \\
\sum_{t \in T} I_{k,t} &= e_{k}^0 \quad \forall k \quad (24) \\
\sum_{t \in T} I_{k,t} &= e_{k}^0 \quad \forall k \quad (25) \\
0 &\leq e_{k}^{\text{start}} \leq e_{k}^{\text{end}} \quad \forall k \quad (26) \\
0 &\leq e_{k}^{\text{start}} \leq e_{k}^{\text{end}} \quad \forall k \quad (27) \\
0 &\leq e_{k}^{\text{end}} \leq e_{k}^{\text{end}} \quad \forall k \quad (28) \\
0 &\leq e_{k}^{\text{end}} \leq e_{k}^{\text{end}} \quad \forall k \quad (29)
\end{align*}
\]

As for W-CCS\(^{R}\)’s, the constraint (30) states that the BT\(_k\) can obtain FCB replenishment from a W-CCS\(^{R}\), and (31) restricts the lower and upper limits for the FCB replenishment, and (32) limits the total carrying capacity of BT\(_k\). Note that the battery swapping operation between BT\(_k\) and a W-CCS\(^{R}\) is the same as that between BT\(_k\) and a BSS, while the difference is that BT\(_k\) can load FCBs at a W-CCS while (28) and (29) define the final amount of FCBs when BT\(_k\) returns to the W-CCS. As the FCB demand of a BSS can be met by swapping batteries with all BTs and parts of its demand can be abandoned.
Remark: $I_{k,t}^{\text{start}}$, $I_{k,t}^{\text{end}}$, $e_{k,t}^{\text{start}}$, $e_{k,t}^{\text{end}}$, $I_{k,t}^{\tau_{k,t}}$, and $e_k^{\tau_{k,t}}$ are complicating variables linking independent W-CCS scheduling and VRP subproblems.

F. Constraints for CCS Operation

The equation (33) states the power balance in the CCS, and it shows that when the battery storage can hardly balance the wind power and the generation plan, wind curtailments or generation violations will occur. Note that the electricity bought from the power grid has no participation in the (33). Equations (34)–(36) limit the charging and discharging operations; (37) limits the wind curtailment and (38) limits the power that the W-CCS can buy from the grid, (39) and (40) limits the failed plan during period $t$ and the total amount of the failed plan.

$$E_t = E_0 + \sum_{v \in (1,\ldots,t)} \left[ \left( \eta_{\text{grid}}^v p_{\text{grid}}^v + \eta_{\text{ch}}^v p_{\text{ch}}^v - \frac{p_{\text{dis}}^v}{\eta_{\text{dis}}} \right) \Delta t - \Delta E_v \right] \quad \forall t$$

$$\Delta E_t = \sum_{k \in K} (e_{k,t}^{\text{start}} - e_{k,t}^{\text{end}}) + \sum_{k \in K} \Delta I_{k,t}^{\tau_{k,t}} \quad \forall t$$

$$E_t \leq E_{\text{lim}} \quad \forall t$$

B. Genetic Algorithm

The Genetic Algorithm is a typical method used in solving VRPs. Its main steps include encoding, decoding, and calculating fitness [44]. It continuously forms new populations, via selection, crossover, mutation operations, in each iteration process, and finally, it will obtain an approximate optimal solution.

Here, we would like to introduce the coding and decoding processes of the employed Genetic Algorithm. Unlike the traditional VRPs, the proposed model involves issues, such as the number of FCBs that a BT takes from the W-CCS and the BSS set. This will dramatically increase the difficulty of the coding operation, and the traditional coding methods can hardly meet the new requirements. Therefore, the segmented chromosome hybrid coding method is used, and the chromosome is divided into two parts: the delivery route based on integer coding and the FCB amount based on floating-point coding. A simple illustration of the employed coding method is given in Fig. 4.

The other parts of the employed Genetic Algorithm are the same as its typical applications, and thus this paper has no specific introduction for them, while the interested readers are referred to reference [44] for more details. Besides, in order to reduce the size of the formulation, we also employ some preprocessing techniques to eliminate infeasible routes in the scheduling for the W-BSCS and apply a dominance rule to find non-dominated routes [46].

C. Relationship Between Exhaustive Search and Genetic Algorithm

Figure 5 illustrates the brief solution processes of the proposed problem, which primarily depends on cooperation between the exhaustive search and the Genetic Algorithm. On
On the other hand, the Genetic Algorithm finds other decision variables (e.g., $I_{k}^{m,n}$) and corresponding delivery routes of BTs, see Step 1 (B). During each iteration process of the Genetic Algorithm, the effective delivery routes, which are obtained by decoding the current population, will match all the ready-made depart periods (Step 2), and then all the feasible combinations are compared to find the optimal one, whose objective value will be used as the fitness of the current population in the Genetic Algorithm (Step 3). The stopping criteria of the Genetic Algorithm depends on the total number of generations (i.e., $G_{\text{max}}$, Step 4), while the exhaustive search stops as long as all the possible solution candidates are found in Step 1. Finally, it will obtain the approximate optimal solutions of the problem by decoding the last-generation population, see Step 5.

V. CASE STUDIES

This section presents numerical examples that demonstrate the effectiveness of the proposed approach, show the benefits of the W-BSCS (Section A), and gives some discussion about wind power uncertainty (Section B).

A system consisting of a W-CCS and 14 BSSs (see Fig. 6) is employed, and the delivery routes for the BTs are modified from the sets of a benchmark problem for VRP. The W-CCS controls 7 BTs to serve the BSSs. Each BC has a 3360 kWh maximum battery carrying capacity and can take about 50 standard batteries with a capacity of a 67.2 kWh package. And the maximum driving distance of each BT is 252 km, while the driving price is assumed as $1.25/km. The total number of simulation periods is 96, and the length of each period ($\Delta t$) is 15 minutes. The W-CCS is based on a 66 MW wind farm, while the wind power generation plan ($p_{\text{plan}}$) and forecasted wind power ($p_{\text{wind}}$) of the W-CCS are shown in Fig. 7. The specific data for $p_{\text{plan}}$, $p_{\text{wind}}$, $d_{m,n}$, $\Delta t_{k}^{m,n}$, $p_{\text{BSS}}$ and time windows are given in motor.ece.iit.edu/data/WBSCS. The studied W-BSCS can meet daily electricity requirements of 7600 private electric cars [14], and thus has the potential to serve city-level EV clusters using renewable energy.

The penalty price ($\gamma_{t}^{\text{plan}^*}$) for failing to complete the original power generation plan ($p_{\text{plan}^*}$) is 1.5 times the price of the wind power generation plan ($p_{\text{plan}}$). The benchmark price of the wind power generation plan is set as $100/MWh, while the prices during peak periods (40–60, 72–84) and valley periods (0–28, 92–96) are 1.5 and 0.5 times the benchmark price. The
penalty price ($\gamma_{\text{BSS}}^t$) for failing to complete the FCB demand is twice the revenue ($\$95/MWh$) of providing battery swapping services to BSSs, i.e., $\$190/MWh$. In order to simplify the analysis, this study has no consideration of the arbitrage of using EV battery storage to participate in the time-of-use price mechanism, while the price that the W-CCS purchases electricity from the power grid ($\gamma_{\text{grid}}^t$) is set as $\$240/MWh, and the wind curtailment price ($\gamma_{\text{wind}}^t$) is $\$11.5/MWh$.

The maximum battery capacity of the W-CCS is 50 MWh, and the corresponding maximum stored FCB level is 48.75 MWh. The maximum charging and discharging powers are 15 MW and 10 MW, and the charging/discharging loss is 2.5%, while the other key parameters are listed in Table I. In addition, the parameters of the Genetic Algorithm are listed in Table II, which are selected based on multiple simulation experiments with different values.

<table>
<thead>
<tr>
<th>Item</th>
<th>Value</th>
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<tbody>
<tr>
<td>$N_{\text{max}}$</td>
<td>3</td>
</tr>
<tr>
<td>$\Delta p_{\text{max}}$</td>
<td>1.25 MWh</td>
</tr>
<tr>
<td>$p_{\text{grid}}$</td>
<td>5 MW</td>
</tr>
<tr>
<td>$p_{\text{BSS}}$</td>
<td>5%</td>
</tr>
<tr>
<td>$E$</td>
<td>48.75 MWh</td>
</tr>
<tr>
<td>$\rho_{\text{total}}$</td>
<td>5%</td>
</tr>
<tr>
<td>$\rho_{\text{Elite}}$</td>
<td>25 MWh</td>
</tr>
<tr>
<td>$\eta_{\text{dis}}$</td>
<td>97.5%</td>
</tr>
<tr>
<td>$\eta_{\text{ch}}$</td>
<td>97.5%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Item</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
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</tr>
<tr>
<td>$G_{\text{max}}$</td>
<td>Maximum number of generations</td>
<td>300</td>
</tr>
<tr>
<td>$N_e$</td>
<td>Population size of elite chromosomes</td>
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</tr>
<tr>
<td>$P_e$</td>
<td>Probability of crossover</td>
<td>0.9</td>
</tr>
<tr>
<td>$P_m$</td>
<td>Probability of mutation</td>
<td>0.1</td>
</tr>
</tbody>
</table>

A. Results with Forecasted Wind Power

Considering the randomness in the mutation and crossover operations of the Genetic Algorithm, the proposed problem is repeatedly solved six times, and the solution time of the individual tests varies from 15 to 22 minutes. The iteration processes of all the tests are compared in Fig. 8, which shows that the Genetic Algorithm begins to converge after 200-250 iterations, and when the iteration exceeds 275 times, the resulted objective value no longer significantly changes. Fig. 8 shows that the objective value of each test tends to converge to a certain value, and the difference between the results of individual tests is within a gap no larger than 5%.

And thus, it demonstrates the effectiveness of the employed Genetic Algorithm.

Table III compares the detailed results of the individual tests in Fig. 8, respectively. Since the W-CCS can effectively balance the difference between the power generation plan and the wind power, all the dispatch schemes in Table III have completed most of the power generation plan and thus avoid high penalty costs. In addition, the FCB demands of all the BSSs are also basically met. Test 4 performs better than all the other tests, since it completes all the expected generation plans and has the lowest wind curtailment, and it is used in the following analysis.

<table>
<thead>
<tr>
<th>Test No.</th>
<th>$C_{\text{fan}}$ ($$)$</th>
<th>$C_{\text{BSS}}$ ($$)$</th>
<th>$C_{\text{delivery}}$ ($$)$</th>
<th>$C_{\text{wind}}$ ($$)$</th>
<th>$C_{\text{total}}$ ($$)$</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>28.6</td>
<td>1493.4</td>
<td>56.1</td>
<td>1578.1</td>
</tr>
<tr>
<td>2</td>
<td>86.5</td>
<td>56.4</td>
<td>1412.2</td>
<td>68.5</td>
<td>1623.6</td>
</tr>
<tr>
<td>3</td>
<td>104.5</td>
<td>0</td>
<td>1502.8</td>
<td>77.7</td>
<td>1685.0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>15.2</td>
<td>1473.8</td>
<td>55.6</td>
<td>1544.6</td>
</tr>
<tr>
<td>5</td>
<td>180.0</td>
<td>38.2</td>
<td>1334.9</td>
<td>65.1</td>
<td>1618.2</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>34.3</td>
<td>1498.3</td>
<td>56.7</td>
<td>1598.3</td>
</tr>
</tbody>
</table>

In the case study, if the wind farm has no cooperation with a CCS, the wind curtailment will be 100.4 MWh, which accounts for 12.2% of the total wind power generation. In comparison, wind curtailment can be significantly reduced to 5.1 MWh after equipping a CCS. The FCB demand of BSSs (72.0 MWh) can be fully satisfied by wind power. Using recycled wind power, the proposed W-CCS can serve about 7600 EVs using wind power. In this way, it will help to enhance the cleanliness of electricity consumed by EV clusters. At the same time, the W-CCS will improve its income. For example, if the CCS charges the BSSs at a price of $95/MWh, then it can get at most $6840 for providing battery swapping service to the BSSs. In contrast, if the wind farm has no cooperation with a CCS, then it will hardly complete the 27.2 MWh generation plan, and therefore, it has to pay $3067.3, which accounts for 3.9% of its total generation income. This will badly influence the economic performance of the wind farm.

Figure 9 shows the charging/discharging power, the stored FCB level, and the exported FCBS of the W-CCS. During high wind power periods, such as periods 0–12, the W-CCS will continuously charge the batteries. Otherwise, during the periods that the wind power is insufficient, the W-CCS will discharge the batteries to support the wind farm to complete the generation plan. In addition, since the W-CCS can output
its FCBs to the BSSs and then receive empty EV batteries in return, it can always keep enough storage capacity to absorb the high wind power during low load periods. In this way, the W-CCS and the BSSs at different sites can perform effective energy and storage sharing, and thereby, the proposed W-BSCS can achieve multiple benefits.

The delivery routes of BTs are shown in Table IV, in which W represents the W-CCS and B represents a BSS. Table IV demonstrates how the W-CCS uses the transportation system to enhance its operational flexibility. For example, during the 2nd period, BT1 and BT2 begin their delivery task. Therefore, after serving the BSSs, i.e., B4, B14, B13 . . ., they can return to the W-CCS very early, in addition to taking away FCBs, they will timely take back empty EV batteries to the W-CCS, who will correspondingly supply more storage capacity for aborting additional wind power.

B. Results with Volatile Wind Power

To take wind power uncertainty into account, the wind power is assumed to follow a normal distribution $N(\mu, \sigma)$ with expected value $\mu$ equal to the forecasted wind power at each period and standard deviation (volatility) $\sigma$, which is a percentage of $\mu$, i.e., 2% in this case. Then the LHS and scenario reduction techniques generate 10 scenarios according to $N(\mu, \sigma)$ [46]. In each scenario, a wind power generation profile is considered using the solutions of all the tests, and then the average costs are given in Table V. To keep consistent with the above deterministic analysis, the following study has no consideration that the W-CCS purchases electricity from the power grid.

An interesting finding is that the scheduling scheme in Test 4 may no longer necessarily perform better than other schemes in the stochastic scenarios (see Table V). This outcome indicates that modifying the scheduling schemes to consider wind power uncertainty is essential for achieving more practical benefits of the proposed W-CCS. In a future study, the proposed model will be expanded into stochastic models for addressing issues, such as uncertainties and fluctuations in wind power.

The proposed approach can be expanded to consider wind power uncertainty by referring to typical two-stage stochastic optimization methods. Generally, in a two-stage stochastic optimization model, decisions are divided into two categories: here-and-now versus wait-and-see decisions [47]. Using similar ideas, a posterior approach is employed to solve our problem. For the sake of conciseness, the problem is shown as:

$$\min_{x \in \Omega, y \in \Omega_2, \zeta \in \Omega_3} \left\{ c^T x + E_{\zeta} [Q(x, y, \zeta)] \right\} A x + B y + H \zeta \leq d \right\}$$

(45)

where $x$, $y$ and $\zeta$ represent the VRP related integer variables (i.e., routing selections of BTs), the other variables (i.e., charge and discharge states, charge and discharge power, changes in FCB levels, etc.), and uncertain vector (i.e., wind power), while $\Omega_1$, $\Omega_2$ and $\Omega_3$ represent the corresponding sets of feasible decisions, respectively; $(c, A, B, H, d)$ represent parameters for modeling the problem; and the second term in the objective is the expected cost considering uncertainty. The employed approach is as follows:

<table>
<thead>
<tr>
<th>Test No.</th>
<th>$C_{\text{min}}$ ($)</th>
<th>$C_{\text{BSS}}$ ($)</th>
<th>$C_{\text{delivery}}$ ($)</th>
<th>$C_{\text{wind}}$ ($)</th>
<th>$C_{\text{total}}$ ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>112.1</td>
<td>59.2</td>
<td>1493.4</td>
<td>96.2</td>
<td>1760.9</td>
</tr>
<tr>
<td>2</td>
<td>122.5</td>
<td>76.6</td>
<td>1412.2</td>
<td>88.5</td>
<td>1699.8</td>
</tr>
<tr>
<td>3</td>
<td>109.3</td>
<td>65.2</td>
<td>1502.8</td>
<td>97.7</td>
<td>1775.0</td>
</tr>
<tr>
<td>4</td>
<td>127.8</td>
<td>65.2</td>
<td>1473.8</td>
<td>95.5</td>
<td>1762.3</td>
</tr>
<tr>
<td>5</td>
<td>186.2</td>
<td>56.4</td>
<td>1334.9</td>
<td>105.0</td>
<td>1682.5</td>
</tr>
<tr>
<td>6</td>
<td>102.3</td>
<td>65.2</td>
<td>1498.3</td>
<td>95.5</td>
<td>1761.3</td>
</tr>
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</table>

TABLE IV

<table>
<thead>
<tr>
<th>BT</th>
<th>Routing of BTs</th>
</tr>
</thead>
<tbody>
<tr>
<td>BT1</td>
<td>W-B4-B14-B13-B6-W-B12-B7-B5-B6-B4-W-B13-B10-B9-B12-W</td>
</tr>
<tr>
<td>BT2</td>
<td>W-B4-B1-B2-B3-B6-W-B13-B10-B9-B12-B7-W-B12-B9-B8-B7-B6-W</td>
</tr>
<tr>
<td>BT3</td>
<td>W-B14-B5-B7-B8-B12-W-B14-B1-B2-B3-B4-W-B4-B3-B5-B7-B12-W</td>
</tr>
<tr>
<td>BT5</td>
<td>W-B12-B9-B10-B13-B4-W-B6-B5-B7-B8-B12-W-B7-B8-B9-B11-B10-W</td>
</tr>
<tr>
<td>BT7</td>
<td>W-B14-B13-B7-B5-B6-W-B4-B1-B2-B3-B6-W-B7-B8-B9-B10-B13-W</td>
</tr>
</tbody>
</table>

TABLE V

<table>
<thead>
<tr>
<th>Test No.</th>
<th>$C_{\text{min}}$ ($)</th>
<th>$C_{\text{BSS}}$ ($)</th>
<th>$C_{\text{delivery}}$ ($)</th>
<th>$C_{\text{wind}}$ ($)</th>
<th>$C_{\text{total}}$ ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>112.1</td>
<td>59.2</td>
<td>1493.4</td>
<td>96.2</td>
<td>1760.9</td>
</tr>
<tr>
<td>2</td>
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<td>1412.2</td>
<td>88.5</td>
<td>1699.8</td>
</tr>
<tr>
<td>3</td>
<td>109.3</td>
<td>65.2</td>
<td>1502.8</td>
<td>97.7</td>
<td>1775.0</td>
</tr>
<tr>
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<td>102.3</td>
<td>65.2</td>
<td>1498.3</td>
<td>95.5</td>
<td>1761.3</td>
</tr>
</tbody>
</table>
1) Obtaining Integer Variables
With the forecasted wind power ($\zeta^0$), the heuristic method in Section IV will find a group of solutions by solving the following deterministic problem

$$\min_{\mathbf{x} \in \Omega_1, \mathbf{y} \in \Omega_2} \{ c^T \mathbf{x} + Q(\mathbf{x}, \mathbf{y}, \zeta) \mid A \mathbf{x} + B \mathbf{y} + H \zeta \leq d, \zeta = \zeta^0 \}$$  \hspace{1cm} (46)

and then the obtained solution of the VRP related integer variables $\mathbf{x}$, which is denoted as $\mathbf{x}^*$, are saved. Accordingly, after solving the problem multiple times, it will form a possible solution set ($\Omega^*_2$) of $\mathbf{x}^*$.

2) Checking Feasibility
Since most integer variables ($\mathbf{x}$) have been set to fixed values ($\mathbf{x}^*$), the size of the remaining part of the problem is greatly reduced, and then it can be directly solved by general MILP solvers. For computational purposes, discrete simulated scenarios are employed to represent the uncertainty of $\zeta$ that follows a known probability distribution, e.g., $N(\mu, \sigma)$, and in this setting, for each realization scenario (i.e., $s$) of the uncertain $\zeta$, a new formulation is as

$$\min_{\mathbf{x} \in \Omega_1^*_1, \mathbf{y} \in \Omega_2^*_1, \zeta \in \Omega_3} \{ Q(\mathbf{x}, \mathbf{y}, \zeta^s) \mid A \mathbf{x}^* + B \mathbf{y} + H \zeta \leq d, \mathbf{x} = \mathbf{x}^* \}$$  \hspace{1cm} (47)

where $\zeta^s$ presents wind power in scenario $s$. If it (47) has no solutions, then $\mathbf{x}^*$ is not a feasible solution in scenario $s$, and consequently, it will be removed from $\Omega^*_1$. Furthermore, other options, such as checking the available probability of the solution and then determine whether it is a chance-constrained feasible one, can also be employed according to practical requirements.

3) Comparing Solutions
Using the same realization set of $\zeta$, individual feasible solution $\mathbf{x}^*$ in the remaining $\Omega^*_1$ will be compared. And a scenario-based stochastic model with non-anticipative constraints is as

$$\min_{\mathbf{x} \in \Omega_1^*_1, \mathbf{y} \in \Omega_2^*_1, \zeta \in \Omega_3} \left\{ \sum_{s \in S} \text{Prob}^s Q(\mathbf{x}, \mathbf{y}, \zeta^s) \mid A \mathbf{x}^* + B \mathbf{y} + H \zeta^s \leq d, \mathbf{x} = \mathbf{x}^* \right\}$$  \hspace{1cm} (48)

where $\text{Prob}^s$ is the probability of scenarios $s$. After testing individual group of $\mathbf{x}^*$ with all the scenarios, the solution which has the best performance can be selected as the final one.

Note that the proposed posterior approach has its inherent flaws, in the sense of optimization, since it can hardly ensure the optimality of the selected solution. Still, it can make our model more practical when considering wind power uncertainty. Using the above approach and forecasted wind power, 30 groups of possible solutions are obtained, and they are tested by wind power scenario sets with different standard deviation (volatility) values, which are generated according to $N(\mu, \sigma)$. Fig. 10 illustrates the feasibility checking results under different standard deviation values equal to 1, 2, …, and 10 percent, respectively (see 100% case). In addition, Fig. 10 also shows the counterpart results in which a case a possible solution is defined as a feasible one as long as it can meet the requirements of 90% of the scenarios (see 90% case). The results illustrate that the proposed approach helps to eliminate unusable solutions while meeting different levels of robust requirements, and thus, it will improve the reliability of the proposed approach.

To further verify the benefits of the proposed approach, the best one of the above 30 solutions is selected, using the scenario set with $\sigma$ equals to 5%. Then it is compared with the 6 solutions in Section A, and Fig. 11 shows the comparing results. The new solution performs better than the others, e.g., its cost results distribute in a more concentrated interval and it also has the lowest median value. The results demonstrate that the proposed approach, even though it has not incorporated wind power uncertainty into the entire optimization process, still has certain potentials to deal with such issues in practical applications.

VI. CONCLUSION AND FUTURE WORK
This paper introduces a novel integrated system, consisting of wind farms, a CCS, and BSSs, to promote both EVs and wind power, and it establishes a joint optimal scheduling model for the proposed W-BSCS. The model comprehensively considers the generation plan of wind power, the charging/discharging scheduling of EV batteries in the W-CCS, the FCB demands and time windows of BSSs, and the VRP of BTs. And it is solved using a heuristic method based on the exhaustive search and the Genetic Algorithm. Case studies demonstrate the effectiveness of the proposed model and show that the W-BSCS can effectively improve the economics of
the integrated system, reduce wind curtailment, and address environmental concerns of deploying large scale EVs.

This study contributes to the integrated development of the power system and the transportation system. In a future study, we will focus on developing some exact solution methods for the proposed problem, and two-stage or multi-stage stochastic programming will be employed to enhance the effectiveness of the proposed model in practical applications.

REFERENCES


Mingfei Ban received the B.S., M.S. and Ph.D. degrees in Electrical Engineering at Harbin Institute of Technology (HIT), Harbin, China, in 2011, 2013, and 2019 respectively. He was a visiting Ph.D. student at Illinois Institute of Technology. He is currently an Associate Professor with the College of Mechanical and Electrical Engineering, Northeast Forestry University, China. His research interests include sustainable energy, electrical vehicles, and microgrids.

Jilai Yu received the B.S. and M.S. degrees in Harbin Institute of Technology (HIT), Harbin, China, in 1988 and 1990, respectively, and the Ph.D. degree in North China Institute of Electric Power, Baoding, China, in 1992. As a postdoctoral researcher, he joined the Department of Electrical Engineering of HIT in 1992. He was an Associate Professor in the Department of Electrical Engineering of HIT in 1994. He has been a professor in the Department of Electrical Engineering of HIT since 1998. His current research interests include power system analysis and control, optimal dispatch of power system, green power and smart grid.

Yiyun Yao received the B.S. degree from Chongqing University, China, in 2012, M.S. degree and Ph.D. degree from the Illinois Institute of Technology (IIT), Chicago, in 2015 and 2019, all in Electrical Engineering. He is currently working at National Renewable Energy Laboratory. His research interests include operation, security and economics of electric power systems.