

Article

Energy Management of PV-Enabled Battery Charging Swapping Stations for Electric Vehicles in Active Distribution Systems Under Uncertainty

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Abstract

In this paper, we propose a data-driven distributionally robust optimization (DRO) framework that ensures the economical and robust operation of solar photovoltaic (PV)-integrated battery charging swapping stations (BCSSs) for electric vehicles (EVs) under uncertainties in active distribution systems with stand-alone PV systems. In the proposed framework, multiple inventory batteries in each BCSS are used through their charging and discharging real and/or reactive power scheduling to perform Volt/VAR control (VVC) along with stand-alone PV systems, and to reduce the BCSS operational cost via battery-to-battery (B2B)-based real power exchange and demand response (DR) while satisfying the desired EV battery swapping load. To handle the uncertainties in both PV generation outputs and DR-induced maximum demand reduction capability, the proposed framework is formulated as a data-driven DRO problem based on the Wasserstein metric using historical samples of the probability distributions of the uncertainties. Using a duality theory, the original Wasserstein-based DRO problem is reformulated into a tractable optimization problem that calculates the distributionally robust bounds of uncertainties using their support information. The effectiveness of the proposed framework was assessed on an IEEE 33-node power distribution system in terms of real power loss reduction via VVC and BCSS operational cost savings via B2B/DR capability.

Keywords: battery charging swapping station; electric vehicle; distributionally robust optimization; uncertainty; battery to battery; demand response; Volt/VAR control; active distribution system



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1. Introduction

Conventional fossil fuel vehicles are being replaced by carbon emission-free electric vehicles (EVs) via transportation electrification [1] to achieve carbon neutrality by 2050 and maintain reliable distribution system operations through the efficient charging and discharging of EVs [2]. To accelerate the deployment of massive EVs for low-carbon stable distribution grid operations, EVs require adequate charging facilities where they charge or discharge to mitigate their detrimental impacts on the distribution grid while meeting their charging demands.

In general, there are two types of EV charging facilities: (i) plug-in charging stations (PCSs) and (ii) battery charging swapping stations (BCSSs) [3]. Currently, most EVs charge

their batteries via charging poles at PCSs. However, they may suffer from long battery charging times, undesired battery maintenance and degradation due to aging, and have a huge impact on the grid during peak periods with complex EV charging scheduling. In contrast, BCSSs provide EVs with time-efficient battery charging through quickly swapping depleted EV batteries with fully charged inventory batteries. In addition, the purchase cost of battery swapping-oriented EVs can be significantly reduced by separating the battery from the EV body [4]. Furthermore, when there is no battery swapping, the inventory batteries at BCSSs can be used via their inverters for grid operation-related applications such as Volt/VAR Control (VVC) [5] and demand response (DR)-based power peak shaving [6] by charging and discharging their real and/or reactive powers from and to the grid. While modern battery technologies and ultrafast charging infrastructure have developed rapidly in recent years, battery swapping is not necessarily a global charging solution. Nevertheless, battery swapping technology can be regarded as an alternative solution with viable applications in specific system operational scenarios. For example, battery swapping can be more beneficial for commercial EVs and electric buses in fleet-based transportation systems, which require rapid turnaround times and centralized energy management. In addition, BCSSs can function as controllable energy resources in active distribution systems, which provide grid-level services such as VVC and DR. To achieve the aforementioned advantages of BCSSs, it is necessary to develop an optimal framework for distribution system operators (DSOs) to economically manage the battery swapping schedules of EVs while ensuring stable distribution grid operations using the inventory batteries of the BCSS.

In general, based on the locations of inventory battery charging and EV battery swapping, BCSSs are categorized as centralized or distributed [7]. In centralized BCSSs, battery charging stations (BCSs) are located centrally to store and charge inventory batteries, whereas battery swapping stations (BSSs) are placed in geographically different locations to perform only EV battery swapping. Trucks are dispatched to deliver depleted EV and fully charged inventory batteries between BCSs and BSSs through a transportation network [8]. However, the centralized BCSS scheme has several limitations such as the high transportation costs of trucks, the unsatisfactory EV battery swapping services of trucks in uncertain traffic congestion, and unstable grid operation owing to the simultaneous charging of a large number of batteries in central BCSs [9]. In contrast, in distributed BCSSs, BCS and BSS are installed at the same site. Compared with the centralized BCSS scheme, the distributed BCSS scheme has the following advantages: (i) economical BCSS operations without battery delivery via trucks in uncertain transportation networks, and (ii) the stable distribution of grid operation owing to the distributed charging of inventory batteries in geographically distant BCSSs. Considering the advantages of the distributed BCSS scheme, through this study we contribute to the development of an optimal operational framework for distributed BCSSs deployed in distribution systems.

Numerous studies have reported various optimal planning and operational methods for centralized and distributed BCSSs. For the centralized BCSS scheme, a two-stage optimization problem was formulated in [10] in which the first stage determines the optimal locations of stationary energy storage systems (ESSs), whereas the second stage coordinates stationary ESSs with portable ESSs to transport batteries for efficient battery charging/discharging/swapping and economical portable ESS routing. In [11], a joint optimization model was developed to minimize the total battery charging cost of BCSs and the total battery transportation cost between BCSs and BSSs while BCSs participate in the DR program for coupled power and transportation system operation. In [12], a deep reinforcement learning algorithm using a soft actor-critic method was presented to reduce the operational costs of swappable battery charging/replenishment and EV waiting while

addressing uncertainties in EV arrivals, electricity prices, and renewable generation. For a distributed BCSS scheme, the optimal location and sizing of BCSSs for electric buses were determined in [13], where the charging and discharging schedules of batteries in BCSSs were optimally calculated to maximize the profits of BCSSs in microgrid systems. A traditional distributed BCSS model was transformed into an advanced BCSS model equipped with solar photovoltaic (PV) systems, namely PV-enabled BCSSs, for economical and eco-friendly BCSS operations and reliable distribution grid operations. Previous studies related to optimal PV-enabled BCSS operation include various optimization methods using chance-constrained optimization to address the uncertainties in EV battery swapping demand and PV generation output [14], grey wolf optimization to minimize the electrical energy costs of BCSSs and peak power demand based on the notion of peak-to-average ratio [15], and particle swarm optimization to maximize the profits of BCSSs based on the prediction of speed-variable battery charging, PV generation output, and EV traffic flow to BCSSs [16]. In addition, distributed BCSSs have increased their profits via battery-to-battery (B2B) function that transfers energy among batteries. In [17], a day-ahead scheduling method for B2B-integrated BCSSs was presented to maximize the profits of BCSSs. In this study, inventory robust optimization (RO) and multi-band RO methods were employed to handle uncertainties in battery demand and electricity price, respectively. Recently, the B2B-integrated BCSS model has evolved into a more advanced model [18] equipped with additional vehicle-to-vehicle and vehicle-to-battery functions to coordinate the charging/discharging of both inventory batteries and EVs. In [19], in contrast to existing studies that assumed an identical inventory battery utilization for EV battery swapping, a long-term (lifecycle) and short-term (daily) scheduling problem for BCSSs was formulated to maximize their profit considering heterogeneous inventory batteries with different state-of-health levels. A dual-based Benders decomposition algorithm was developed in [20] in which the privacies of BCS and BSS operators were preserved while ensuring efficient BCSS scheduling, saving computation time via its parallel implementation. A detailed survey of the literature on optimal operational scheduling of BCSSs was presented in [21].

However, previous studies on the development of scheduling algorithms for distributed BCSSs in a distribution grid have posed several challenges. First, no previous studies have modeled an advanced PV-enabled BCSS that considers the functions of inverter-based VVC, B2B, and DR simultaneously. Evidently, the optimal scheduling of the aforementioned advanced PV-enabled BCSSs in active distribution grids may induce more cost-effective BCSS operations via B2B and DR while ensuring stable distribution grid operation via VVC. Second, in previous studies, the uncertainties in both PV generation output and the DR-induced maximum demand reduction capability of BCSS have not been considered simultaneously. They employed RO and stochastic optimization (SO) methods to handle the uncertainty of only the PV generation output in the distributed BCSS model. However, the former and latter methods have the following limitations, respectively: (i) they require knowledge of the true distribution of uncertain parameters, and (ii) they generate solutions that are too conservative. Recently, data-driven distributionally robust optimization (DRO) using Wasserstein metric has been developed to resolve the aforementioned disadvantages of the RO and SO methods. The DRO method offers several merits, including tractable reformulation, finite sample guarantee, and asymptotic consistency [22]. Table 1 shows the representative literature related to the present study and emphasizes the research gaps between existing and proposed studies in the distributed BCSS model. As shown in Table 1, the novelty of the proposed study is to develop an optimal operation framework of PV-enabled BCSSs with advanced functions of VVC, B2B, and DR while handling the uncertainties in both PV generation output and demand reduction using a state-of-the-art uncertainty-aware DRO method in the active distribution system. Com-

pared with SO, which relies on accurate probability distributions and sufficient scenario generation, DRO provides improved robustness under limited data availability and distributional ambiguity. Compared with RO, which guarantees a worst-case solution, DRO mitigates excessive conservativeness while maintaining robustness against uncertainty. In recent years, DRO has attracted increasing attention in energy system applications, including microgrid scheduling [23], EV management [24], DR with renewable integration [25], and active distribution network operation [26], due to its ability to achieve a balanced trade-off between robustness and economic performance under distributional uncertainty. These characteristics may make DRO particularly suitable for PV-enabled BCSS operation in active distribution systems with uncertain renewable generation output and DR behavior.

Table 1. Summary of representative literature related to the proposed study.

Category	[18]	[27,28]	[29]	[30]	[31]	[32]	[33,34]	Proposed Study
Distributed BCSS	✓	✓	✓	✓	✓	✓	✓	✓
PV-enabled BCSS	✓	✓	✗	✗	✗	✓	✓	✓
DR	✓	✗	✗	✓	✓	✓	✗	✓
VVC	✗	✗	✓	✓	✗	✗	✗	✓
B2B	✓	✓	✗	✗	✗	✗	✗	✓
PV generation output uncertainty	✗	✗	✗	✗	✗	✗	✓	✓
Demand reduction uncertainty	✗	✗	✗	✗	✗	✗	✗	✓
DRO method	✗	✗	✗	✗	✗	✗	✗	✓

Overall, the main contributions of this study can be summarized as follows.

- We present a PV-enabled BCSS model in which inventory batteries stored in the BCSS are employed to ensure an economical BCSS operation (via B2B and DR functionalities) and maintain a stable active distribution grid operation (via inverter-based VVC associated with BCSS and stand-alone PV system) while satisfying the desired battery swapping demands of EVs.
- We propose a Wasserstein-based DRO framework that enables the DSO to optimally schedule the operations of PV-enabled BCSSs in the active distribution system while addressing the uncertainties in both PV generation output and DR-induced maximum demand reduction capability. A key part of the proposed DRO framework is to formulate a distributionally robust bound (DRB) problem that determines the bounds of the aforementioned uncertain parameters in the distributionally robust chance constraints (DRCCs).
- We reformulate the original DRB problem as a duality theory-based tractable optimization problem by transforming the DRCCs into deterministic constraints, which can be efficiently solved by off-the-shelf optimization solvers.

The remainder of this paper is organized as follows. Section 2 introduces the aforementioned PV-enabled BCSS model and its functionality in active distribution systems with stand-alone PV systems. Section 3 formulates an uncertainty-free deterministic optimization (DO) problem for the stable and economical operation of the distribution system and BCSSs. In Section 4, the DO problem is transformed into a Wasserstein-based DRO problem that determines the DRBs of uncertain PV generation output and DR-induced maximum demand reduction. Section 5 reports the simulation results for the proposed DRO-based BCSS scheduling framework, and the conclusions are noted in Section 7.

2. System Model

Let us consider an active distribution system installed with (i) stand-alone PV systems and (ii) PV-enabled BCSSs. Stand-alone PV systems contribute to VVC by providing real and reactive power support via smart inverters. The PV-enabled BCSSs are assumed to have sufficient fully charged inventory batteries, which can be swapped with the depleted batteries of EVs visiting the BCSSs at reserved times. We consider a situation where the BCSSs provide EVs with a reservation-based battery swapping service. To reserve the battery swapping service, EV users are assumed to send reservation data (e.g., arrival time at BCSS and remaining/desired battery SOC level before and after battery swapping) via the electronic devices to the BCSSs. As shown in Figure 1, each PV-enabled BCSS performs the following four tasks using inventory batteries: (i) smart inverter-based VVC via the real/reactive power charging/discharging of batteries and reactive power absorption/injection of the PV system from/to the grid; (ii) smart inverter-based DR via real power charging reduction in batteries; (iii) power exchange via B2B mode using bidirectional chargers; and (iv) battery swapping between a BCSS and EVs. We specifically consider a situation in which a DSO aims to ensure the economical operation of the aforementioned advanced BCSSs via the charging and discharging of inventory batteries based on the B2B and DR functions, and supports the desired battery swapping service of EVs while maintaining stable distribution grid operation via VVC. In this paper, P [kW], Q [kVAR], and SOC [kWΔt] represent the real power, reactive power, and the state-of-charge of a battery in the active distribution system with stand-alone PV systems and PV-enabled BCSSs.

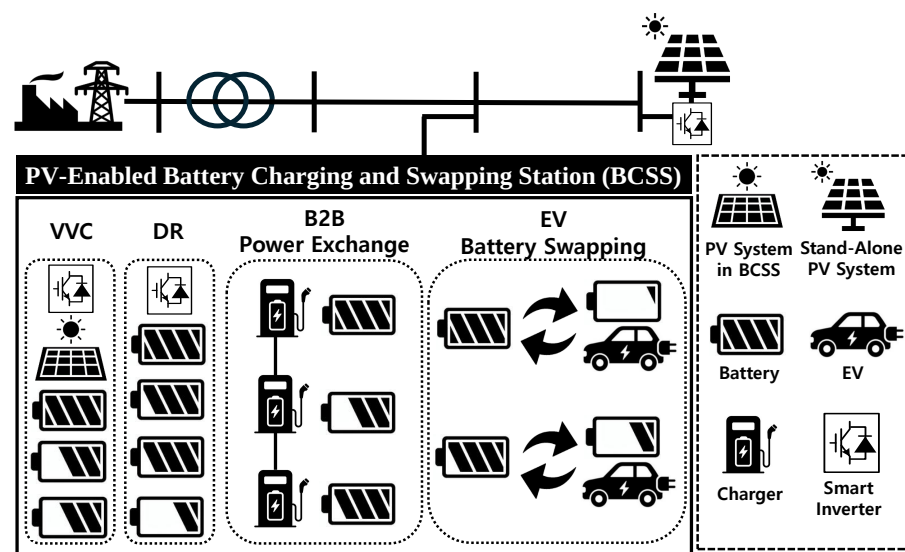


Figure 1. Functionality of proposed PV-enabled BCSS in active distribution network with stand-alone PV systems.

3. DO Problem Formulation for BCSS-Integrated Active Distribution System Operation

Let us denote the set of nodes in the active distribution network as $\mathcal{I}$. The set $\mathcal{I}$ includes the subsets of stand-alone PV systems ($\mathcal{I}^{PV*}$) and PV-enabled BCSSs ($\mathcal{I}^{BCSS}$). Note that $\mathcal{B}_i$ denotes the set of batteries in a BCSS at node $i \in \mathcal{I}^{BCSS}$, and $\mathcal{E}_i$ is the set of EVs visiting that BCSS at node $i \in \mathcal{I}^{BCSS}$ for battery swapping.

3.1. Objective Function

For nodes $i, j \in \mathcal{I}$, line $ij \in \mathcal{L}$ (the set of power distribution lines), and each battery $b \in \mathcal{B}_i$ of the BCSS at node $i \in \mathcal{I}^{BCSS}$ with scheduling period $t \in \mathcal{T} = \{1, \dots, T\}$, the pro-

posed BCSS scheduling problem aims to minimize a weighted multi-objective function that consists of the following five terms:

$$\min \sum_{t \in \mathcal{T}} (\omega_1 J_{1,t} + \omega_2 J_{2,t} + \omega_3 J_{3,t} + \omega_4 J_{4,t} - \omega_5 J_{5,t}) \quad (1)$$

where

$$J_{1,t} = \sum_{ij \in \mathcal{L}} r_{ij} I_{ij,t} \quad (2)$$

$$J_{2,t} = \pi_t^B \sum_{i \in \mathcal{I}^{BCSS}} P_{i,t}^{ch,G} - \pi_t^S \sum_{i \in \mathcal{I}^{BCSS}} P_{i,t}^{BCSS\ 2G} \quad (3)$$

$$J_{3,t} = \sum_{i \in \mathcal{I}^{BCSS}} \sum_{b \in \mathcal{B}_i} \alpha^d \left(\frac{P_{i,b,t}^{ch}}{\eta_{i,b}^{ch}} + \eta_{i,b}^{dch} P_{i,b,t}^{dch} \right) \quad (4)$$

$$J_{4,t} = \sum_{i \in \mathcal{I}^{BCSS}} \sum_{e \in \mathcal{E}_i} \left(SOC_{i,b,t} - SOC_{i,e,t}^d \right) b_{i,e,b,t}^{swap} \quad (5)$$

$$J_{5,t} = \pi_t^R \sum_{i \in \mathcal{I}^{BCSS}} \Delta P_{i,t}^{DR}. \quad (6)$$

In (2), $J_{1,t}$ [kW] is the total real power loss, which comprises the resistance (r_{ij}) and squared current flow ($I_{ij,t}$) for all lines at time t . The total electricity arbitrage cost of the BCSSs at time t , denoted as $J_{2,t}$ [\$], is described by (3). This cost includes the total cost ($\pi_t^B P_{i,t}^{ch,G}$) and revenue ($\pi_t^S P_{i,t}^{BCSS\ 2G}$), which are expressed in terms of BCSS i charging/discharging real power ($P_{i,t}^{ch,G}$, $P_{i,t}^{BCSS\ 2G}$) from/to the grid and the electricity buying/selling price (π_t^B , π_t^S) at time t . In (4), $J_{3,t}$ [\$] indicates the total degradation cost of batteries in the BCSSs at time t , which is expressed in terms of charging/discharging real power ($P_{i,b,t}^{ch}$, $P_{i,b,t}^{dch}$) and efficiency ($\eta_{i,b}^{ch}$, $\eta_{i,b}^{dch}$), along with depreciation parameter α^d [\$/kW] of battery b in the BCSS i . It is noted that the adopted battery degradation cost model represents a linearized operational-level approximation commonly used in short-term scheduling studies. Detailed electrochemical aging dynamics are beyond the scope of this study and may be considered in future work. In (5), $J_{4,t}$ [kWΔt] denotes the total state of charge (SOC) deviation of swapped batteries ($SOC_{i,b,t}$) from the desired SOC of each EV e ($SOC_{i,e,t}^d$) visiting BCSS i when the battery swapping service is initiated at time t (i.e., $b_{i,e,b,t}^{swap} = 1$). In (6), $J_{5,t}$ [\$] is the total reward obtained from the real power demand reduction ($\Delta P_{i,t}^{DR}$) in the BCSSs via the DR program based on a reward price π_t^R at time t .

3.2. Active Distribution System Model

For nodes $k, i, j \in \mathcal{I}$ and lines $ki, ij \in \mathcal{L}$, the convex power flow model [35] of an active distribution system is expressed as follows:

$$P_{i,t}^{con} = \sum_{ki \in \mathcal{L}} P_{ki,t} - \sum_{ij \in \mathcal{L}} (P_{ij,t} + r_{ij} I_{ij,t}) \quad (7)$$

$$Q_{i,t}^{con} = \sum_{ki \in \mathcal{L}} Q_{ki,t} - \sum_{ij \in \mathcal{L}} (Q_{ij,t} + x_{ij} I_{ij,t}) \quad (8)$$

$$v_{i,t} - v_{j,t} = 2(r_{ij} P_{ij,t} + x_{ij} Q_{ij,t}) - (r_{ij}^2 + x_{ij}^2) I_{ij,t} \quad (9)$$

$$P_{i,t}^{con} = \hat{P}_{i,t}^{load} + P_{i,t}^{ch,G} - P_{i,t}^{BCSS\ 2G} - \hat{P}_{i,t}^{PV*} \quad (10)$$

$$Q_{i,t}^{con} = \hat{Q}_{i,t}^{load} - Q_{i,t}^{BCSS} - Q_{i,t}^{PV*} \quad (11)$$

$$I_{ij,t} v_{i,t} \geq P_{ij,t}^2 + Q_{ij,t}^2 \quad (12)$$

$$v^{\min} \leq v_{i,t} \leq v^{\max}. \quad (13)$$

Constraints (7) and (8) represent the balance of the real and reactive powers at node i , respectively, where $P(Q)_{i,t}^{\text{con}}$ [kW(kVAr)] is the net real (reactive) power consumption at node i and time t ; $P(Q)_{ij,t}$ is the real (reactive) power flow spanning from node i to node j at time t ; and $r(x)_{ij}$ [Ω] is the resistance (reactance) of line ij . Constraint (9) describes the voltage drop between nodes i and j at time t , where $v_{i,t}$ [p.u.²] is the squared voltage magnitude of node i at time t , and $I_{ij,t}$ [A²] is the squared current flowing from node i to node j at time t . The net real ($P_{i,t}^{\text{con}}$) and reactive ($Q_{i,t}^{\text{con}}$) power consumptions described by (7) and (8) are defined in (10) and (11), respectively. They are expressed in terms of predicted real and reactive power load demand ($\hat{P}_{i,t}^{\text{load}}$ [kW], $\hat{Q}_{i,t}^{\text{load}}$ [kVAr]), real and reactive charging/discharging power of BCSS ($P_{i,t}^{\text{ch,G}}$ [kW], $P_{i,t}^{\text{BCSS 2G}}$ [kW], $Q_{i,t}^{\text{BCSS}}$ [kVAr]), and real and reactive power generation output of the stand-alone PV system ($\hat{P}_{i,t}^{\text{PV*}}$ [kW], $Q_{i,t}^{\text{PV*}}$ [kVAr]) at node i and time t . Constraint (12) describes the relaxed convex form of Ohm's law. The squared voltage magnitude $v_{i,t}$ at node i and time t is limited to $v^{\min} = 0.95^2$ and $v^{\max} = 1.05^2$ in (13).

3.3. Reactive Power Constraints of Stand-Alone PV System

The reactive power output ($Q_{i,t}^{\text{PV*}}$) at time t for a stand-alone PV system at node $i \in \mathcal{I}^{\text{PV*}}$ can be restricted as follows:

$$-Q_{i,t}^{\text{PV*,max}} \leq Q_{i,t}^{\text{PV*}} \leq Q_{i,t}^{\text{PV*,max}} \quad (14)$$

$$Q_{i,t}^{\text{PV*,max}} = \sqrt{\left(S_i^{\text{PV*,cap}}\right)^2 - \left(\hat{P}_{i,t}^{\text{PV*}}\right)^2}, \quad (15)$$

where $Q_{i,t}^{\text{PV*,max}}$ is the maximum allowable reactive power generation or consumption, and $S_i^{\text{PV*,cap}}$ [kVA] is the maximum capacity of the smart inverter of the stand-alone PV system at node i .

3.4. PV-Enabled BCSS Operational Constraints

For node $i \in \mathcal{I}^{\text{BCSS}}$, the operation of the PV-enabled BCSS is managed while satisfying the following five constraints: (i) the binary status of swapping and the charging/discharging of the battery b in the BCSS; (ii) the SOC dynamics of the battery b swapped with the battery of EV e ; (iii) the charging and discharging of aggregated batteries in the grid-connected BCSS; (iv) DR-induced demand reduction; and (v) the reactive power capability of the PV system and batteries for VVC.

3.4.1. Status of Battery Swapping and Charging/Discharging

Constraint (16) guarantees that each EV e visiting BCSS i must replace its battery with only a single battery b among the multiple inventory batteries in the BCSS at time t . Under this constraint, the binary decision variable $b_{i,e,b,t}^{\text{swap}}$ determines the status of battery swapping for EV e associated with battery b at time t . Constraint (17) ensures that inventory battery charging, discharging, and EV battery swapping are mutually exclusive, where the binary decision variables ($b_{i,b,t}^{\text{ch}}$ and $b_{i,b,t}^{\text{dch}}$) determine the status of charging and discharging of inventory battery b from/to the grid at time t , respectively. Constraint (18) limits the total number of the charging and discharging operations of battery b in BCSS i during the entire scheduling period according to threshold N^{B} [36].

$$\sum_{b \in \mathcal{B}_i} b_{i,e,b,t}^{\text{swap}} = 1 \quad (16)$$

$$b_{i,b,t}^{\text{ch}} + b_{i,b,t}^{\text{dch}} + \sum_{e \in \mathcal{E}_i} b_{i,e,b,t}^{\text{swap}} \leq 1 \quad (17)$$

$$\sum_{t \in \mathcal{T}} (b_{i,b,t}^{\text{ch}} + b_{i,b,t}^{\text{dch}}) \leq N^B. \quad (18)$$

3.4.2. SOC Dynamics of Battery for EV and BCSS

Constraint (19) expresses the dynamics of the SOC [kWΔt] for inventory battery b of BCSS i at time t [18]. If no battery swapping for any EV e at BCSS i occurs (i.e., $\sum_{e \in \mathcal{E}_i} b_{i,e,b,t-1}^{\text{swap}} = 0$), each inventory battery b interacts with the grid and its SOC at time t is updated in terms of the SOC at time $t - 1$, the charging/discharging real power ($P_{i,b,t}^{\text{ch}}, P_{i,b,t}^{\text{dch}}$), the charging/discharging efficiency ($\eta_{i,b}^{\text{ch}}, \eta_{i,b}^{\text{dch}}$), and the scheduling time unit (Δt). Otherwise, the SOC of battery b at time t is updated to the SOC of the battery ($\widetilde{\text{SOC}}_{i,e,t-1}$) for the EV arriving at the BCSS for battery swapping at time $t - 1$. Constraint (20) ensures that battery b with a sufficient SOC level ($\text{SOC}_{i,b,t}$) remains in BCSS i to satisfy the desired SOC of EV e ($\text{SOC}_{i,e,t}^{\text{d}}$) at time t during the battery swapping. The SOC of battery b at BCSS i and time t is limited by (21) to its minimum and maximum bounds ($\text{SOC}_{i,b}^{\text{min}}$ and $\text{SOC}_{i,b}^{\text{max}}$). Constraint (22) restricts the charging (discharging) real power of battery b ($P_{i,b,t}^{\text{ch(dch)}}$) at BCSS i and time t to its minimum and maximum limits ($P_{i,b}^{\text{ch(dch),min}}$ and $P_{i,b}^{\text{ch(dch),max}}$), where the binary decision variable $b_{i,b,t}^{\text{ch(dch)}}$ determines the charging (discharging) status of the battery.

$$\begin{aligned} \text{SOC}_{i,b,t} = & \left(1 - \sum_{e \in \mathcal{E}_i} b_{i,e,b,t-1}^{\text{swap}} \right) \left[\text{SOC}_{i,b,t-1} \right. \\ & \left. + \left(\eta_{i,b}^{\text{ch}} P_{i,b,t}^{\text{ch}} - \frac{P_{i,b,t}^{\text{dch}}}{\eta_{i,b}^{\text{dch}}} \right) \Delta t + \sum_{e \in \mathcal{E}_i} b_{i,e,b,t-1}^{\text{swap}} \widetilde{\text{SOC}}_{i,e,t-1} \right] \end{aligned} \quad (19)$$

$$\text{SOC}_{i,b,t} \geq \text{SOC}_{i,e,t}^{\text{d}} b_{i,e,b,t}^{\text{swap}} \quad (20)$$

$$\text{SOC}_{i,b}^{\text{min}} \leq \text{SOC}_{i,b,t} \leq \text{SOC}_{i,b}^{\text{max}} \quad (21)$$

$$b_{i,b,t}^{\text{ch(dch)}} P_{i,b}^{\text{ch(dch),min}} \leq P_{i,b,t}^{\text{ch(dch)}} \leq b_{i,b,t}^{\text{ch(dch)}} P_{i,b}^{\text{ch(dch),max}}. \quad (22)$$

3.4.3. Charging and Discharging of Grid-Connected BCSS

Constraint (23) denotes the aggregated charging real power ($\sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{ch}}$) of all batteries in BCSS i at time t , which is the sum of the charging power supported from the grid ($P_{i,t}^{\text{ch,G}}$), PV system ($P_{i,t}^{\text{ch,PV}}$) in the BCSS, and the aggregated exchanged power ($\sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{B2B}}$) via the B2B process. Constraint (24) encodes the real power ($P_{i,t}^{\text{BCSS 2G}}$) injected from BCSS i to the grid, which consists of the aggregated discharging real power of batteries ($P_{i,t}^{\text{dch,G}}$) and PV real power injection ($P_{i,t}^{\text{PV,G}}$) into the grid. Constraint (25) implies that the PV real power support (i.e., the sum of $P_{i,t}^{\text{PV,G}}$ and $P_{i,t}^{\text{ch,PV}}$) to the grid and batteries in BCSS i must be less than or equal to the predicted PV real power generation output ($\hat{P}_{i,t}^{\text{PV}}$). Constraint (26) implies that the aggregated discharging power of all batteries in BCSS i is greater than or equal to the sum of the discharging real power of the BCSS ($P_{i,t}^{\text{dch,G}}$) into the grid and the B2B-induced aggregated exchanged power ($\sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{B2B}}$). It is assumed that B2B power exchange occurs internally within the same BCSS through bidirectional charging interfaces. Therefore, distribution-level transmission losses are not involved. In addition, the dominant energy conversion losses are captured through the charging and discharging efficiency parameters of the batteries.

$$\sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{ch}} = P_{i,t}^{\text{ch,G}} + P_{i,t}^{\text{ch,PV}} + \sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{B2B}} \quad (23)$$

$$P_{i,t}^{\text{BCSS 2G}} = P_{i,t}^{\text{dch,G}} + P_{i,t}^{\text{PV,G}} \quad (24)$$

$$P_{i,t}^{\text{PV,G}} + P_{i,t}^{\text{ch,PV}} \leq \hat{P}_{i,t}^{\text{PV}} \quad (25)$$

$$P_{i,t}^{\text{dch,G}} + \sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{B2B}} \leq \sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{dch}}. \quad (26)$$

3.4.4. Demand Reduction via the DR Program

In this study, the BCSSs are assumed to participate in the DR program in which the reward is obtained through charging real power reduction in their inventory batteries. In this DR program, the charging real power of BCSS i from the grid has an upper bound at time t , as described by (27), which is written in terms of the fixed DR contract-based real power consumption ($P_{i,t}^{\text{DR}}$) of the BCSS delivered from DSO and the non-negative reduction in the real power consumption ($\Delta P_{i,t}^{\text{DR}}$) via DR. The allowable capability of $\Delta P_{i,t}^{\text{DR}}$ is constrained by its corresponding uncertain maximum demand reduction limit ($\Delta \hat{P}_{i,t}^{\text{DR,max}}$) at BCSS i and time t , according to (28).

$$P_{i,t}^{\text{ch,G}} \leq P_{i,t}^{\text{DR}} - \Delta P_{i,t}^{\text{DR}} \quad (27)$$

$$\Delta P_{i,t}^{\text{DR}} \leq \Delta \hat{P}_{i,t}^{\text{DR,max}}. \quad (28)$$

3.4.5. Reactive Power Capability of BCSS

Constraint (29) describes the net real power consumption of BCSS i at time t (i.e., the difference between the total charging power of batteries ($\sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{ch}}$) and the total discharging power of batteries ($\sum_{b \in \mathcal{B}_i} P_{i,b,t}^{\text{dch}}$) with the predicted PV real power output ($\hat{P}_{i,t}^{\text{PV}}$). The reactive power capability of the BCSS is given by (30), and its maximum reactive power ($Q_{i,t}^{\text{BCSS}}$) is expressed in terms of the maximum apparent power ($S_i^{\text{BCSS,cap}}$) and net real power consumption ($P_{i,t}^{\text{BCSS}}$) of the BCSS, according to (31).

$$P_{i,t}^{\text{BCSS}} = \sum_{b \in \mathcal{B}_i} (P_{i,b,t}^{\text{ch}} - P_{i,b,t}^{\text{dch}}) - \hat{P}_{i,t}^{\text{PV}} \quad (29)$$

$$-Q_{i,t}^{\text{BCSS,max}} \leq Q_{i,t}^{\text{BCSS}} \leq Q_{i,t}^{\text{BCSS,max}} \quad (30)$$

$$Q_{i,t}^{\text{BCSS,max}} = \sqrt{(S_i^{\text{BCSS,cap}})^2 - (P_{i,t}^{\text{BCSS}})^2}. \quad (31)$$

4. DRO-Based Solution Approach

In this section, a DO-based BCSS scheduling problem in the active distribution system (Section 3) is transformed into a DRO-based one that handles (i) uncertainties in the real power outputs from stand-alone PV ($\hat{P}_{i,t}^{\text{PV*}}$) and PV ($\hat{P}_{i,t}^{\text{PV}}$) systems in the BCSS and (ii) uncertainty in the DR-induced maximum demand reduction ($\Delta \hat{P}_{i,t}^{\text{DR,max}}$). The key part of the DRO problem is to calculate the DRBs of the aforementioned uncertain parameters in the DRCCs (Section 4.2) using an uncertainty-related ambiguity set based on a Wasserstein ball (Section 4.1).

4.1. Backgrounds of DRO

The following Wasserstein metric is employed in the data-driven DRO problem to capture the random characteristics of the real power outputs of stand-alone and BCSS-related PV systems, along with random DR-induced maximum demand reduction.

Definition 1 (Wasserstein Metric). *The Wasserstein metric $d_W(\mathbb{P}_1, \mathbb{P}_2)$ of two probability distributions ($\mathbb{P}_1, \mathbb{P}_2 \in \mathcal{M}(\Xi)$) is written as follows:*

$$d_W(\mathbb{P}_1, \mathbb{P}_2) := \inf \left\{ \int_{\Xi^2} \|\xi_1 - \xi_2\| \Pi(d\xi_1, d\xi_2) \right\} \quad (32)$$

where Π represents a joint distribution of two random vectors (ξ_1 and ξ_2) with marginal distributions ($\mathbb{P}_1, \mathbb{P}_2$), $\mathcal{M}(\Xi)$ indicates the probability space with all the probability distributions $\mathbb{P}$ supported on the uncertainty set Ξ , and $\|\cdot\|$ denotes an arbitrary norm in $\mathbb{R}^n$.

Based on the notion of the Wasserstein metric, an ambiguity set $\mathcal{P}_N(\epsilon)$ for the uncertain parameters is constructed, and it can be written as a Wasserstein ball of radius ϵ centered at the empirical distribution $\hat{\mathbb{P}}_N$ as follows:

$$\mathcal{P}_N(\epsilon) = \left\{ \mathbb{P} \in \mathcal{M}(\Xi) : d_W(\hat{\mathbb{P}}_N, \mathbb{P}) \leq \epsilon \right\}. \quad (33)$$

In (33), the empirical distribution $\hat{\mathbb{P}}_N$ is calculated using N historical samples $\hat{\xi}_i$ of the random vector as

$$\hat{\mathbb{P}}_N := \frac{1}{N} \sum_{i=1}^N \delta_{\hat{\xi}_i} \quad (34)$$

where $\delta_{\hat{\xi}_i}$ denotes the unit point mass at $\hat{\xi}_i$.

4.2. DRB Problem Formulation

To address the random real power outputs from the stand-alone PV ($\tilde{P}_{i,t}^{\text{PV}^*}$) and BCSS-related PV ($\tilde{P}_{i,t}^{\text{PV}}$) systems along with the random DR-induced maximum demand reduction ($\Delta \tilde{P}_{i,t}^{\text{DR,max}}$) in the DO problem, three deterministic constraints, namely (10), (25), and (28), are rewritten as the following DRCCs using their corresponding Wasserstein ball-based ambiguity sets:

$$\inf_{\mathbb{P} \in \mathcal{P}_{N^{\text{PV}^*}}(\epsilon^{\text{PV}^*})} \mathbb{P} \left[\hat{P}_{i,t}^{\text{load}} + P_{i,t}^{\text{ch,G}} - P_{i,t}^{\text{con}} - P_{i,t}^{\text{BCSS 2G}} \leq \tilde{P}_{i,t}^{\text{PV}^*} \right] \geq 1 - \alpha \quad (35)$$

$$\inf_{\mathbb{P} \in \mathcal{P}_{N^{\text{PV}}}(\epsilon^{\text{PV}})} \mathbb{P} \left[P_{i,t}^{\text{PV,G}} + P_{i,t}^{\text{ch,PV}} \leq \tilde{P}_{i,t}^{\text{PV}} \right] \geq 1 - \alpha \quad (36)$$

$$\inf_{\mathbb{P} \in \mathcal{P}_{N^{\text{DR}}}(\epsilon^{\text{DR}})} \mathbb{P} \left[\Delta P_{i,t}^{\text{DR}} \leq \Delta \tilde{P}_{i,t}^{\text{DR,max}} \right] \geq 1 - \alpha. \quad (37)$$

In (35)–(37), $\mathcal{P}_{N^{\text{PV}^*}}(\epsilon^{\text{PV}^*})$, $\mathcal{P}_{N^{\text{PV}}}(\epsilon^{\text{PV}})$, and $\mathcal{P}_{N^{\text{DR}}}(\epsilon^{\text{DR}})$ represent the ambiguity sets, which contain the distributions associated with the real power outputs of the stand-alone and BCSS-related PV systems and the DR-induced maximum demand reduction limit, respectively. These distributions reside within the Wasserstein balls of radii ϵ^{PV^*} , ϵ^{PV} , and ϵ^{DR} , whose centers correspond to the empirical distributions obtained using historical samples N^{PV^*} , N^{PV} , and N^{DR} , respectively, as expressed in (34). These DRCCs guarantee that the stand-alone and BCSS-related PV real power provisions for load demand, grid, BCSS batteries, and the DR-induced maximum demand reduction must be less than or equal to the stand-alone and BCSS-related PV real power outputs and DR-induced maximum demand reduction, respectively, with a minimum probability of $1 - \alpha$ under the worst-case probability distribution $\mathbb{P}$ within their Wasserstein balls. The empirical distribution constructed from historical realizations of the DR-induced maximum demand reduction inherently captures variability in user behavior, including the DR participation rate and response magnitude. Such behavioral uncertainty is therefore embedded within the Wasserstein-based ambiguity set.

Let us denote $\underline{p}_{i,t}^{\text{PV}^*}$, $\underline{p}_{i,t}^{\text{PV}}$, and $\Delta \underline{p}_{i,t}^{\text{DR,max}}$ as the lower-bound variables of $\tilde{p}_{i,t}^{\text{PV}^*}$, $\tilde{p}_{i,t}^{\text{PV}}$, and $\Delta \tilde{p}_{i,t}^{\text{DR,max}}$. Using these variables, DRCCs (35)–(37) can be rewritten as follows:

$$\inf_{\mathbb{P} \in \mathcal{P}_{N^{\text{PV}^*}}(\epsilon^{\text{PV}^*})} \mathbb{P} \left[\underline{p}_{i,t}^{\text{PV}^*} \leq \tilde{p}_{i,t}^{\text{PV}^*} \right] \geq 1 - \alpha \quad (38)$$

$$\inf_{\mathbb{P} \in \mathcal{P}_{N^{\text{PV}}}(\epsilon^{\text{PV}})} \mathbb{P} \left[\underline{p}_{i,t}^{\text{PV}} \leq \tilde{p}_{i,t}^{\text{PV}} \right] \geq 1 - \alpha \quad (39)$$

$$\inf_{\mathbb{P} \in \mathcal{P}_{N^{\text{DR}}}(\epsilon^{\text{DR}})} \mathbb{P} \left[\Delta \underline{p}_{i,t}^{\text{DR,max}} \leq \Delta \tilde{p}_{i,t}^{\text{DR,max}} \right] \geq 1 - \alpha \quad (40)$$

where

$$\tilde{p}_{i,t}^{\text{load}} + p_{i,t}^{\text{ch,G}} - p_{i,t}^{\text{con}} - p_{i,t}^{\text{BCSS 2G}} \leq \underline{p}_{i,t}^{\text{PV}^*} \quad (41)$$

$$p_{i,t}^{\text{PV,G}} + p_{i,t}^{\text{ch,PV}} \leq \underline{p}_{i,t}^{\text{PV}} \quad (42)$$

$$\Delta p_{i,t}^{\text{DR}} \leq \Delta \underline{p}_{i,t}^{\text{DR,max}}. \quad (43)$$

Then, the following DRO problem is formulated to calculate the tight lower bounds for $\tilde{p}_{i,t}^{\text{PV}^*}$, $\tilde{p}_{i,t}^{\text{PV}}$, and $\Delta \tilde{p}_{i,t}^{\text{DR,max}}$:

$$\max_{\underline{x}_t} \sum_{t \in \mathcal{T}} \underline{x}_t \quad \text{s.t. (38) or (39) or (40)} \quad (44)$$

where $\underline{x}_t$ denotes the lower-bound variable of $\tilde{p}_{i,t}^{\text{PV}^*}$, $\tilde{p}_{i,t}^{\text{PV}}$, and $\Delta \tilde{p}_{i,t}^{\text{DR,max}}$ (i.e., $\underline{x}_t \in \{\underline{p}_{i,t}^{\text{PV}^*}, \underline{p}_{i,t}^{\text{PV}}, \Delta \underline{p}_{i,t}^{\text{DR,max}}\}$ for the stand-alone PV $i \in \mathcal{I}^{\text{PV}^*}$ and PV systems in the BCSS $i \in \mathcal{I}^{\text{BCSS}}$). We define $\tilde{x}_t \in \{\tilde{p}_{i,t}^{\text{PV}^*}, \tilde{p}_{i,t}^{\text{PV}}, \Delta \tilde{p}_{i,t}^{\text{DR,max}}\}$ as a random variable with support $\Xi_t = [x_t^{\text{lb}}, x_t^{\text{ub}}]$. In this support, x_t^{lb} and x_t^{ub} denote the lower and upper bounds of $\tilde{x}_t$, respectively. Finally, using the result based on a duality theory in Theorem [37], the DRO problem (44) can be transformed into the following DRB problem with tractable constraints:

$$\check{\underline{x}}_t = \arg \max_{\underline{x}_t} \sum_{t \in \mathcal{T}} \underline{x}_t \quad (45)$$

$$\text{s.t. } \alpha N v_t - \sum_{n=1}^N \zeta_{t,n} \geq \epsilon_t N, \quad (46)$$

$$(-\underline{x}_t + \hat{x}_{t,n}) \gamma_{t,n} - (x_t^{\text{ub}} - \hat{x}_{t,n}) r_{t,n}^{\text{max}} \quad (47)$$

$$+ (x_t^{\text{lb}} - \hat{x}_{t,n}) r_{t,n}^{\text{min}} \geq v_t - \zeta_{t,n}, \quad (48)$$

$$\|-\gamma_{t,n} - r_{t,n}^{\text{max}} + r_{t,n}^{\text{min}}\|_1 \leq 1, \quad (49)$$

$$\gamma_{t,n}, r_{t,n}^{\text{min}}, r_{t,n}^{\text{max}}, \zeta_{t,n} \geq 0. \quad (50)$$

In this DRB problem, $\hat{x}_{t,n} \in \{\tilde{p}_{i,t,n}^{\text{PV}^*}, \tilde{p}_{i,t,n}^{\text{PV}}, \Delta \tilde{p}_{i,t,n}^{\text{DR,max}}\}$ is the n -th sample of the real power output of the stand-alone/BCSS-related PV system and the DR-induced maximum demand reduction limit at time t . $N \in \{N^{\text{PV}^*}, N^{\text{PV}}, N^{\text{DR}}\}$ represents their corresponding sample sizes. $\epsilon_t \in \{\epsilon_t^{\text{PV}^*}, \epsilon_t^{\text{PV}}, \epsilon_t^{\text{DR}}\}$ indicates the radius of the Wasserstein ball related to the real power output of the stand-alone/BCSS-related PV system and the DR-induced maximum demand reduction limit at time t . $\gamma_{t,n}, r_{t,n}^{\text{min}}, r_{t,n}^{\text{max}}, \zeta_{t,n}$, and v_t are auxiliary variables with non-negative values.

By employing the solution $\check{x}_t (\check{P}_{i,t}^{PV*}, \check{P}_{i,t}^{PV}, \Delta \check{P}_{i,t}^{DR,max})$ calculated from the DRB problem, the intractable DRCCs (35)–(37) are respectively transformed into the deterministic and tractable constraints as follows:

$$\hat{P}_{i,t}^{load} + P_{i,t}^{ch,G} - P_{i,t}^{con} - P_{i,t}^{BCSS,2G} \leq \check{P}_{i,t}^{PV*} \quad (51)$$

$$P_{i,t}^{PV,G} + P_{i,t}^{ch,PV} \leq \check{P}_{i,t}^{PV} \quad (52)$$

$$\Delta P_{i,t}^{DR} \leq \Delta \check{P}_{i,t}^{DR,max}. \quad (53)$$

In summary, the intractable DRCCs can be transformed into the tractable constraints in the following steps.

- Step (1): Construct the ambiguity sets using the Wasserstein metric, which contain the probability distributions associated with the uncertain real power outputs of the stand-alone and BCSS-related PV systems and the uncertain DR-induced maximum demand reduction.
- Step (2): Formulate Wasserstein-based DRCCs (35)–(37) associated with the aforementioned uncertainties.
- Step (3): Formulate the DRO problem (44) using the modified DRCCs (38)–(40) based on the lower-bound variables of uncertainties.
- Step (4): Based on a duality theory, reformulate the original DRO problem into the DRB problem (45)–(50) to calculate the robust bounds of the uncertainties.
- Step (5): Using the solution calculated from the DRB problem, transform the intractable DRCCs (35)–(37) into the tractable deterministic constraints (51)–(53). Finally, these deterministic constraints are employed in the optimization problem to handle the uncertainties in the real power outputs of the stand-alone and BCSS-related PV systems and the uncertain DR-induced maximum demand reduction.

Finally, Figure 2 summarizes the main tasks of the proposed approach described in Sections 2–4. Based on the PV-enabled BCSS model with the functions of VVC, DR, B2B, and EV battery swapping (Section 2), the uncertainty-free DO problem (Section 3) is extended to the uncertainty-aware Wasserstein-based DRO problem (Section 4).

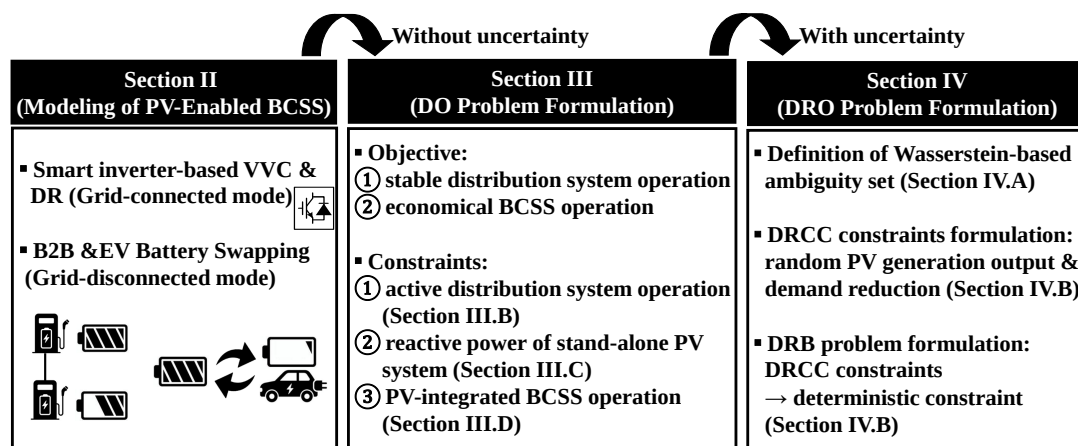


Figure 2. Conceptual diagram illustrating the proposed framework for three sections.

5. Simulation Results

5.1. Simulation Setup

The performance of the proposed DRO-based BCSS scheduling framework was evaluated using a modified IEEE 33-node power distribution system with three stand-alone PV systems and three PV-enabled BCSSs, as shown in Figure 3. Note that the IEEE 33-node dis-

tribution system is a widely adopted benchmark network, which is used for the validation and comparison of various distribution system optimization and control methods. This system does not represent the actual grid configuration of any specific country; it serves as a standardized reference model to facilitate proper methodological evaluation and the reproducibility of the research results. Three BCSSs (BCSS 1~3) and three stand-alone PV systems were connected to nodes 6, 15, and 30, and nodes 10, 19, and 27, respectively. It is assumed that within 15 min, each EV completes the battery swapping process and departs from the BCSS. Additionally, each BCSS is assumed to serve as a single EV at a time for battery swapping. Each BCSS has 20 inventory batteries and their corresponding chargers, each with a battery capacity of 80 kWh. Figure 4 shows the profiles of the remaining ($\widehat{SOC}_{i,e,t}$) and desired ($SOC_{i,e,t}^d$) battery SOC levels before and after EV battery swapping, respectively, for the three BCSSs during the entire scheduling period. In this figure, 69 EVs, 71 EVs, and 68 EVs arrive at BCSS 1, BCSS 2, and BCSS 3, respectively, for battery swapping. The value of $SOC_{i,e,t}^d$ was randomly generated by categorizing it into three levels of battery capacity, namely 50%, 70%, and 90%, while ensuring that the values of $SOC_{i,e,t}^d$ were greater than that of the randomly generated $\widehat{SOC}_{i,e,t}$. To further evaluate the variability of the SOC requirements, Table 2 summarizes the statistics of the initial SOC, desired SOC, and ΔSOC for each BCSS. Here, ΔSOC represents the difference between the desired SOC and initial SOC. Note from this table that, for BCSS 2 and BCSS 3, the average ΔSOC further increases to 43.74 kW Δt and 44.92 kW Δt , respectively. This indicates their higher overall charging demand than BCSS 1. In addition, the standard deviation of ΔSOC ranges from 13.10 kW Δt to 14.28 kW Δt across the three BCSSs. This demonstrates significant variability in EV users' charging requirements. The minimum and maximum values of ΔSOC vary from 8.68 kW Δt to 65.14 kW Δt . This reflects a wide spread of operational charging load at the BCSSs. For battery b at BCSS i , the maximum charging/discharging power ($P_{i,b}^{ch/dch,max}$) was set to 50 kW, and the minimum charging/discharging power ($P_{i,b}^{ch/dch,min}$) was set to 0 kW. The minimum ($SOC_{i,b}^{min}$) and maximum ($SOC_{i,b}^{max}$) SOC levels were 10% and 90% of the battery capacity, respectively. The charging ($\eta_{i,b}^{ch}$) and discharging ($\eta_{i,b}^{dch}$) efficiencies were both set to 95%. The depreciation parameter (α^d) of each battery was set to 0.01. The squared voltage magnitude ($v_{i,t}$) at node i and time t was bounded as $[0.95^2 \text{ and } 1.05^2]$, corresponding to $v_{i,t}^{min}$ and $v_{i,t}^{max}$, respectively. The maximum apparent powers of the stand-alone PV system ($S_i^{PV*,cap}$) and BCSS ($S_i^{BCSS,cap}$) were set to 3 MVA and 1.5 MVA, respectively. The total number of charging and discharging operations of the battery during one day was limited to $N^B = 30$.

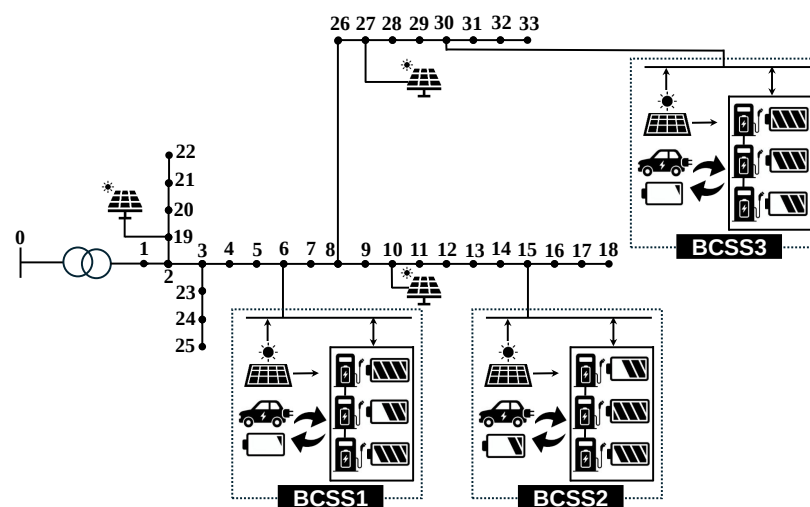


Figure 3. IEEE 33-node power distribution system with three stand-alone PV systems and three PV-enabled BCSSs.

Table 2. Statistical summary of initial SOC, desired SOC, and Δ SOC of EV batteries at each BCSS.

BCSS	Parameter	Mean (kW Δt)	Std (kW Δt)	Min (kW Δt)	Max (kW Δt)
1	Initial SOC	18.18	6.67	6.62	30.24
	Desired SOC	57.96	13.41	38.46	71.19
	Δ SOC	39.76	14.28	8.68	62.75
2	Initial SOC	17.59	7.64	6.81	30.35
	Desired SOC	61.34	11.75	38.89	71.60
	Δ SOC	43.74	13.10	11.08	64.53
3	Initial SOC	17.41	6.31	6.32	30.26
	Desired SOC	62.34	11.45	38.91	71.59
	Δ SOC	44.92	13.33	12.12	65.14

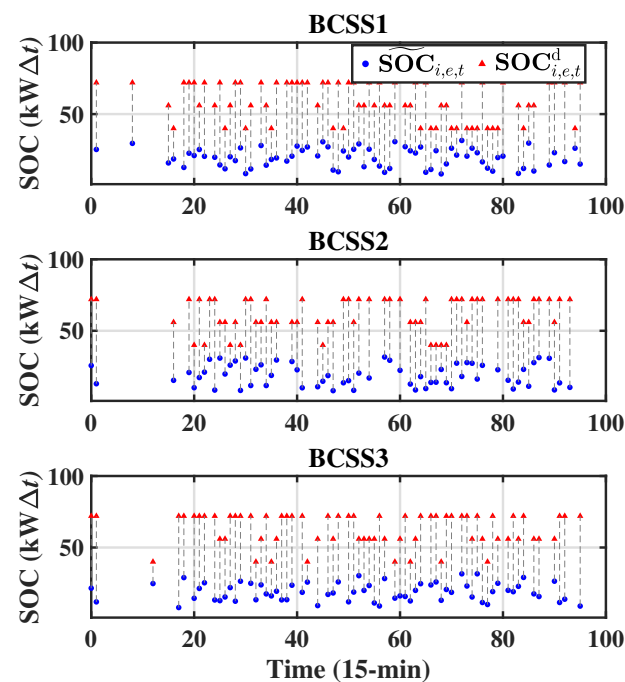
**Figure 4.** Profiles of the initial/desired SOC ($\widetilde{SOC}_{i,e,t}$, $SOC_{i,e,t}^d$) of EV batteries in three BCSSs.

Figure 5 depicts the profiles of electricity buying and selling prices (π_t^B , π_t^S) and the DR-induced reward price (π_t^R) under a time-of-use pricing tariff [38]. The profiles of PV generation outputs and DR requests were achieved from open datasets [39,40], respectively. In this study, the electricity buying/selling price and DR-based reward price are deterministic input parameters. They are not considered uncertain or scenario-dependent variables in the proposed DRO framework. Figure 6a,b shows the profiles of the predicted scenarios and the DRBs of the PV generation outputs and the DR-induced maximum demand reduction limits, respectively, along with their supports. Three scenarios with different coefficients of PV generation outputs and maximum demand reduction limits are shown in Figure 6c,d, respectively. The parameter values for the DRB problem were defined as $N^{PV*} = N^{PV} = N^{DR} = 30$, $\epsilon^{PV*} = \epsilon^{PV} = \epsilon^{DR} = 0.01$, and $\alpha = 0.95$. The profile of the fixed DR contract-based real power consumption ($P_{i,t}^{DR}$) of the BCSS was generated using a baseline real power of 500 kW. In this profile, compared to the baseline real power, the value of $P_{i,t}^{DR}$ was reduced by 30% and 15% in the scheduling periods of [44, 47] (peak period) and [52, 67] (mid-peak period), respectively. The weights in the objective function (1) were set to $\omega_1 = \omega_2 = \omega_3 = \omega_5 = 0.25$ and $\omega_4 = 1$.

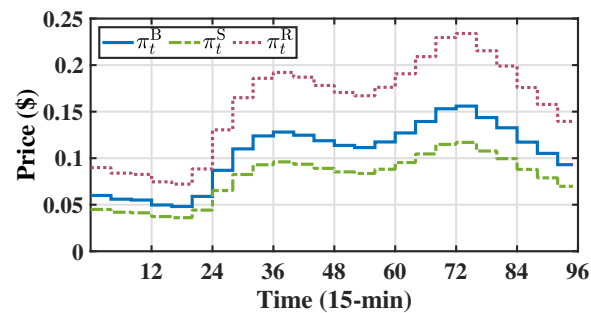


Figure 5. Profiles of electricity buying/selling price (π_t^B / π_t^S) and DR-based reward price (π_t^R).

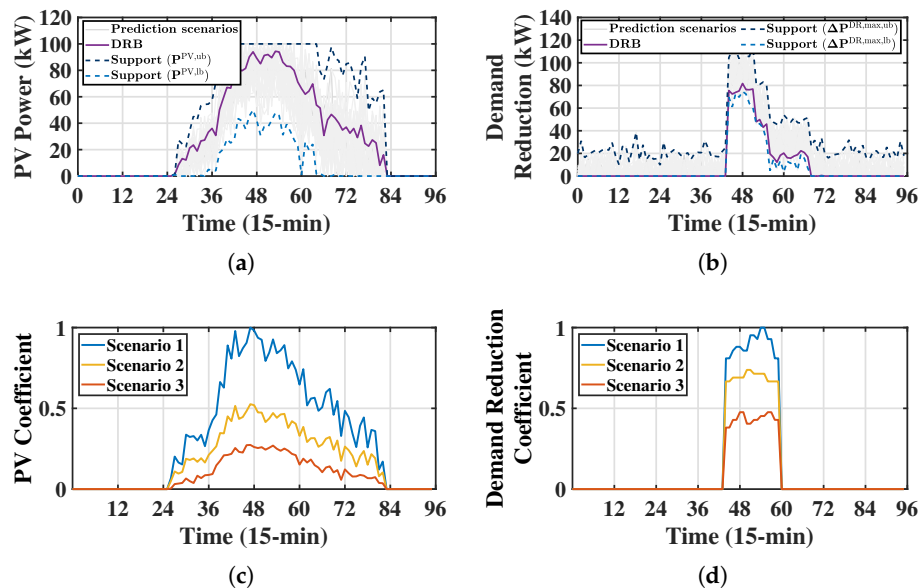


Figure 6. Profiles of DRO problem: (a) predicted scenarios and DRB of the random PV generation output with minimum and maximum supports; (b) predicted scenarios and DRB of the random DR-induced maximum demand reduction limit with minimum and maximum supports; (c) three scenarios with different PV generation coefficients; and (d) three scenarios with different maximum demand reduction limit coefficients.

The proposed framework was implemented using real-time model predictive control with a single-step prediction, rolling horizon ($T = 1$), and 15 min scheduling resolution ($\Delta t = 15$ min). The single-step rolling horizon was selected to enable real-time MPC while maintaining computational tractability in the DRO problem. The 15 min scheduling resolution is consistent with commonly adopted dispatch intervals in distribution system operation and DR programs. Although individual EV battery swapping events occur within a few minutes, BCSS energy management is coordinated at an aggregated station level. The proposed method was executed on an AMD Ryzen 9 5900X CPU at 3.7 GHz and 64 GB of RAM using Python 3.11 and Gurobi 10.0.3 solver.

5.2. BCSS Operation via EV Battery Swapping and Inventory Battery Charging/Discharging

Figure 7 shows the SOC schedules of randomly selected swapped batteries 11, 16, and 6 in BCSSs 6, 15, and 30 during one day, respectively. In this figure, the solid line represents the SOC trajectory of the selected battery, whereas the dotted lines indicate the SOC trajectories of the other batteries in the same BCSS. In addition, the 'x' marker denotes the time step when the inventory battery in the BCSS was swapped with the battery of the corresponding EV. Note from the upper and lower subfigures in Figure 7 that batteries 11 and 6 are swapped with the batteries of EVs four and six times, respectively. In

these subfigures, the swapped EV batteries 11 and 6 in BCSSs 6 and 30 increase their SOC levels via recharging three and five times, respectively, to prepare for battery swapping of the next EVs. Finally, these batteries decrease their SOC levels in the latter part of the scheduling period to perform B2B and/or BCSS 2G services. In contrast to batteries 11 and 6 in BCSSs 6 and 30, battery 16 in BCSS 15 gradually decreases its SOC level via only discharging to support the B2B and/or BCSS 2G service while it is swapped with the battery of the EV once, as shown in the middle subfigure in Figure 7. In summary, the results presented in Figure 7 demonstrate that the proposed BCSS scheduling framework can provide seamless EV battery swapping and maintain economical BCSS operation via B2B and BCSS 2G processes because of the efficient charging and discharging of inventory batteries in the BCSSs.

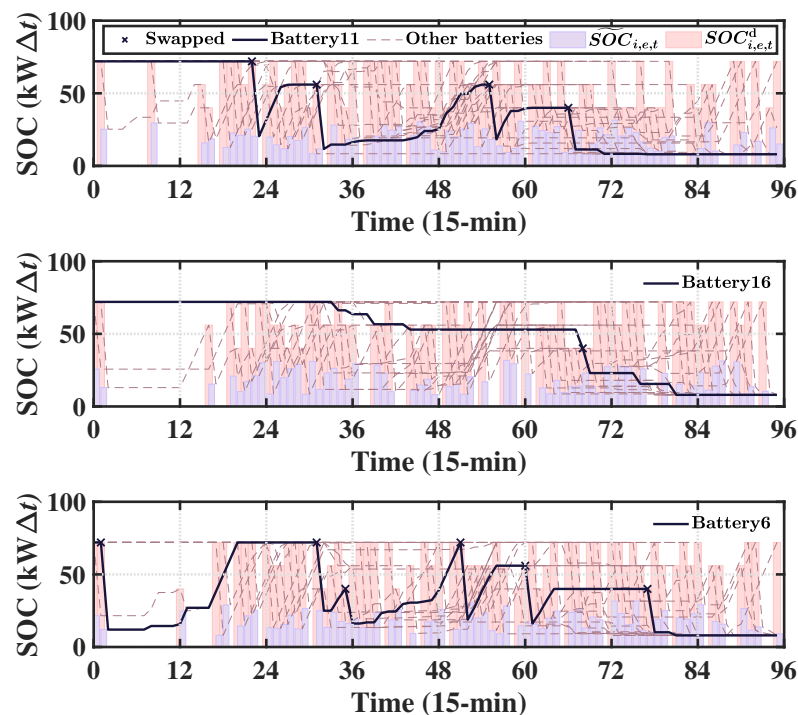


Figure 7. SOC schedules of swapped batteries 11, 16, and 6 in BCSSs 6, 15, and 30, respectively.

Figure 8a–c and Figure 8d–f show the charging and discharging real power schedules of BCSS 1, respectively, under three different PV generation scenarios as shown in Figure 6c. For Scenario 1, with high PV generation, as shown in Figure 8a,d, the BCSS charges and discharges more PV real power ($P_{i,t}^{ch,PV}$ and $P_{i,t}^{PV,G}$) to the grid in the PV generation period of [26, 82] compared to the charging real power from the grid ($P_{i,t}^{ch,G}$) along with B2B ($\sum_{b \in B_i} P_{i,b,t}^{B2B}$) and the discharging real power to grid ($P_{i,t}^{dch,G}$), respectively. This result confirms that the proposed framework yields cost-effective scheduling for BCSSs. However, for Scenario 2, with medium PV generation, Figure 8b,e show that the scheduling of the BCSS relies on more $P_{i,t}^{ch,G}$, $\sum_{b \in B_i} P_{i,b,t}^{B2B}$, and less $P_{i,t}^{PV,G}$ compared to the results presented in Figure 8a,d, respectively. This phenomenon becomes more prominent for Scenario 3, with low PV generation, as shown in Figure 8c,f. We conclude from the results presented in Figure 8a–f that a higher PV generation ensures a more economical BCSS operation by charging expensive grid power less and discharging more cost-free PV real power to the grid. From an aggregated energy perspective, the scenario-dependent operational shift becomes more prominent as follows. In Figure 8a–c, the total PV-based charging

energy amounts to 7,072 kWh, 7,045 kWh, and 5,517 kWh under Scenarios 1–3, respectively, while showing a gradual decline as PV availability decreases. In contrast, the total grid-based charging energy increases significantly from 164 kWh in Scenario 1 to 1,047 kWh in Scenario 3. Meanwhile, in Figure 8d–f, the total PV-to-grid discharging energy decreases dramatically from 12,073 kWh in Scenario 1 to only 41 kWh in Scenario 3. These aggregated results quantitatively demonstrate that a higher PV availability substantially decreases the grid dependency of BCSS and enhances the economic efficiency of BCSS operation.

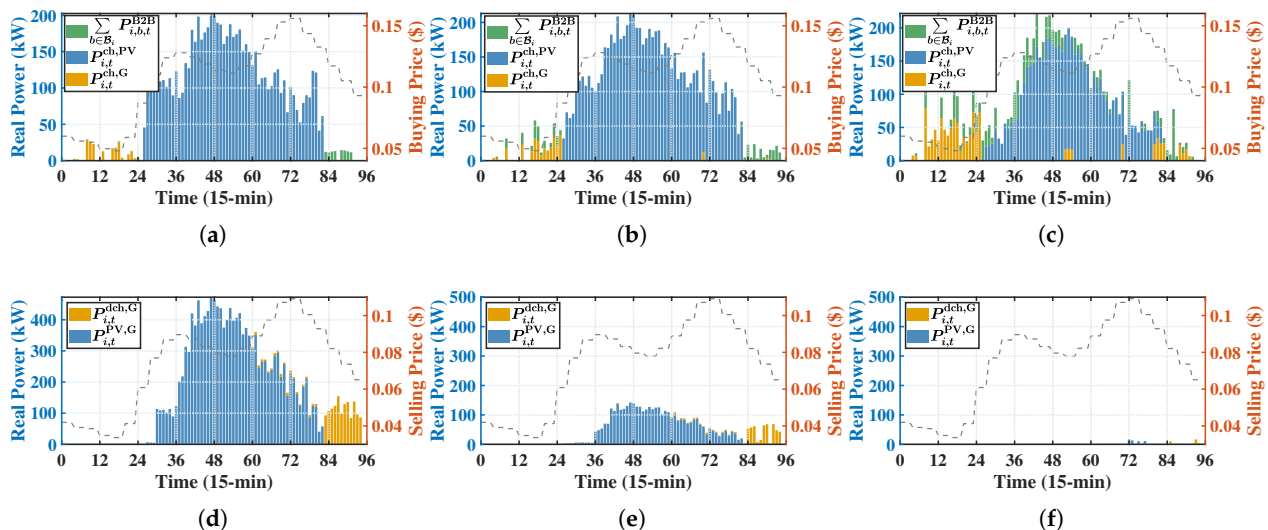


Figure 8. Charging and discharging real power schedules of BCSS 1 under three different amounts of PV generation outputs: (a) charging with a high PV generation; (b) charging with a medium PV generation; (c) charging with a low PV generation; (d) discharging with a high PV generation; (e) discharging with a medium PV generation; and (f) discharging with a low PV generation.

5.3. Benefits of B2B/PV Capability

Figure 9a compares the normalized cost of the proposed DRO-based BCSS model with and without B2B and BCSS-related PV systems under three PV generation scenarios, as shown in Figure 6c. Here, the normalized cost indicates the electricity arbitrage cost (J_2) of the proposed DRO models with B2B and/or PV systems, which is normalized to that of the DRO model without B2B and PV systems. Note from Figure 9a that, compared to the DRO model without B2B and PV systems, the DRO model decreases the cost with B2B and leads to a further significant reduction in the cost with the PV system in addition to B2B for all scenarios. As shown in Figure 9a, compared to the DRO model without B2B and PV systems, the inclusion of B2B reduces the operational cost by 13.9–16.1%. Furthermore, incorporating the PV system in addition to B2B results in a further cost reduction of 25.8–86.8% for all scenarios. Another observation is that the DRO model features the lowest cost in Scenario 1 with the highest PV generation among the three scenarios. This is expected because the BCSS charges its inventory batteries using a more cost-free PV real power. Figure 9b assesses the impact of the maximum demand reduction limit on the performance of the proposed DRO model under three maximum demand reduction scenarios, shown in Figure 6d, in terms of the normalized DR reward. Here, the normalized DR reward is the DR-induced reward (J_5) of the proposed DRO models with B2B and/or PV systems, which is normalized to that of the DRO model without B2B and PV systems. As shown in Figure 9b, the integration of B2B significantly enhances the DR reward, thereby leading to an increase of 37.5–54.2% compared to the DRO model without B2B and PV systems. When PV is additionally incorporated, the reward improvement becomes more substantial, reaching 64.7–77.8% for all scenarios. As expected, the DRO

model yields the largest DR reward in Scenario 1 with a high maximum demand reduction limit. This is because an increase in the maximum demand reduction limit allows the DR behavior of BCSS to be more flexible and profitable.

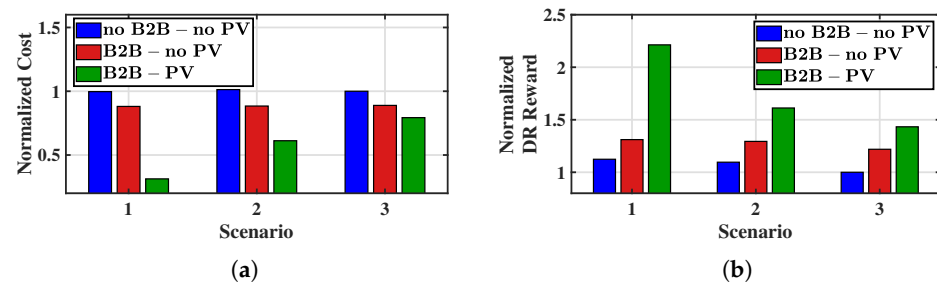


Figure 9. Performance comparison of the DRO method with and without B2B/PV capabilities under (a) three PV generation scenarios and (b) three DR-induced maximum demand reduction scenarios.

5.4. Reactive Power Capability of BCSS and Stand-Alone PV System

Figure 10 compares the reactive power schedules of three BCSSs and three stand-alone PV systems using their smart inverters for one day. In this figure, the negative and positive reactive powers represent the absorption and injection of reactive power from and to the grid, respectively. Note from Figure 10 that BCSS 2 and BCSS 3 at nodes 15 and 30 inject a large amount of reactive power into the grid whereas BCSS 1 at node 6 absorbs a relatively small amount of reactive power from the grid during the entire scheduling period. This is because BCSS 2 and BCSS 3 are located farther from the substation than BCSS 1 and the nodal voltage magnitudes at BCSS 2 and BCSS 3 may decrease below their minimum limits. To mitigate these under-voltage violations, BCSS 2 and BCSS 3 inject the reactive power into the grid to increase the voltage magnitude. Regarding the stand-alone PV systems, PV systems at nodes 19 and 27 always inject a large amount of reactive power into the grid, whereas the PV system at node 10 absorbs or injects a small amount of reactive power from and into the grid. This difference in the amount of reactive power dispatch is derived from the fact that the PV system at node 10 is surrounded by smart inverter-based BCSS 1 and BCSS 2, which restrict the reactive power capability of the PV system at node 10.

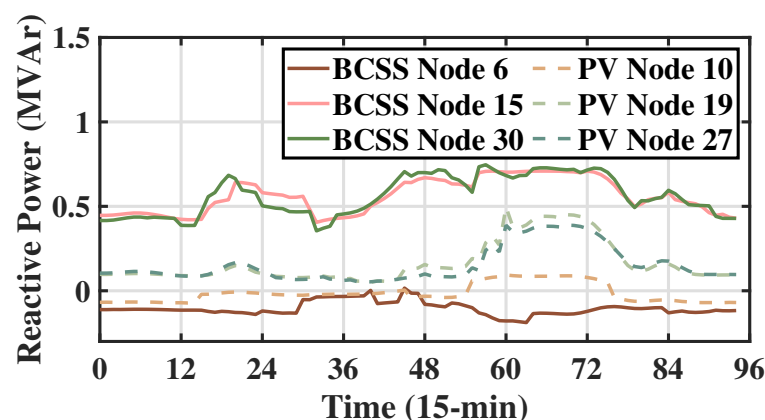


Figure 10. Reactive power schedules of three BCSSs and three stand-alone PV systems.

5.5. Performance Comparison with Different Radii of the Wasserstein Ball

Table 3 compares the values of the objective functions ($J_1 \sim J_5$) for the DO and proposed DRO methods in terms of Wasserstein ball radius (ϵ). Several observations can be made based on this table. First, as expected, the costs ($J_1 \sim J_3$) and reward (J_5) using the uncertainty-integrated DRO method are larger and smaller, respectively, than those

using the baseline approach of the uncertainty-free DO method. Second, a larger ϵ in the DRO method increases and decreases the costs and reward, respectively, thereby further increasing the deviation from the DO method. This is because the ambiguity set with a large radius ϵ in the DRO method includes a large number of probability distributions of uncertainty, and therefore yields more conservative solutions. Third, the values of the SOC mismatch function J_4 for both the DO and DRO methods are zero. This is because the weight ω_4 of J_4 was set to a larger value ($\omega_4 = 1$) than the other weights of the objective functions ($\omega_1 = \omega_2 = \omega_3 = \omega_5 = 0.25$) to completely satisfy the desired SOC of the EVs during battery swapping.

Table 3. Performance comparison between DO and DRO methods in terms of multi-objective function ($J_1 \sim J_5$) and Wasserstein ball radius (ϵ) in the IEEE 33-node power distribution system.

Multi-Objective Function	DO Method	DRO Method			
		$\epsilon = 0.001$	$\epsilon = 0.01$	$\epsilon = 0.1$	$\epsilon = 1$
J_1 (Total Real Power Loss (kW))	110.99	115.91	116.90	117.11	117.71
J_2 (Total Electricity Arbitrage Cost (\$))	1,466.59	1,526.64	1,531.16	1,549.58	1,620.23
J_3 (Total Battery Degradation Cost (\$))	7.79	7.86	7.89	7.90	7.95
J_4 (Total SOC Mismatch for Battery Swapping (kWΔt))	0	0	0	0	0
J_5 (Total DR-induced Reward (\$))	1,353.72	1,260.81	1,211.64	1,209.33	1,203.92

5.6. Performance Comparison with SO and RO Methods

In this subsection, the performance of the proposed DRO method is compared with that of the SO and RO methods. The SO model employs the sample average approximation method with a zero radius for the Wasserstein ball (i.e., $\epsilon^{PV*} = \epsilon^{PV} = \epsilon^{DR} = 0$ [22]). The RO model is formulated based on the results reported in [41]. Figure 11 compares the total electricity arbitrage cost (J_2) of the BCSSs for the three methods with varying numbers of stand-alone/BCSS-related PV generation output and maximum demand reduction samples (N^{PV*} , N^{PV} , and N^{DR}). Notably, the RO method has the highest electricity arbitrage cost. This is because the RO method employs only the upper and lower limits of the uncertain parameters to obtain the optimal solution, thereby leading to a more conservative solution. By contrast, the total electricity arbitrage costs of the SO and DRO methods are significantly lower than those of the RO method and decrease as the number of historical samples increases. This is because the larger the number of historical samples is, the more accurately the probability distribution of the uncertainty can be approximated, which reduces the total electricity arbitrage cost. Another observation is that the total electricity arbitrage cost of the DRO method is lower than that of the SO method within the sample range [10, 150]. This observation demonstrates the sample efficiency of the proposed data-driven DRO method over the SO method. Figure 12 compares the normalized total electricity arbitrage costs for the SO, RO, and DRO methods using 300 samples under six scenarios with different PV generation outputs (Scenarios 1~3 from Figure 6c) and demand reductions (Scenarios 4~6 from Figure 6d). In this figure, the normalized cost indicates normalization using the total electricity arbitrage cost of the SO method. Note from Figure 12 that, in general, the three methods are listed in decreasing order of normalized cost: RO > DRO > SO. Compared to the SO method, the RO method yields a substantial cost increase of 65.2–88.1%, whereas the proposed DRO method limits the cost increase to only 2.4–17.9% for all scenarios. This confirms that compared to the RO method, the DRO method successfully calculates a less conservative solution, which becomes closer to the solution of the SO method.

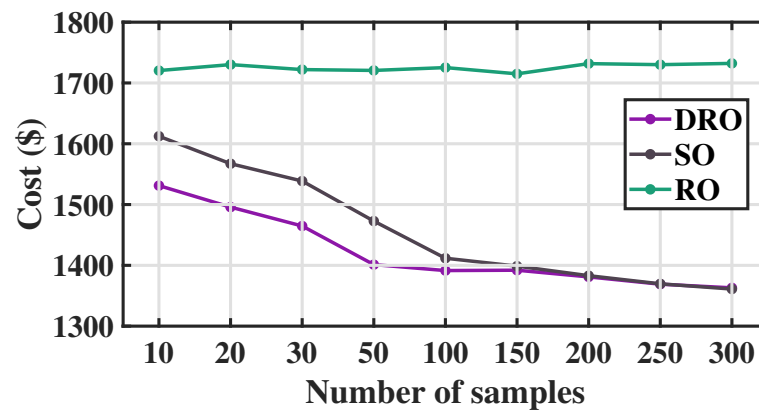


Figure 11. Comparison of the total electricity arbitrage costs (J_2) of the SO, RO, and proposed DRO methods in terms of the number of historical samples in the IEEE 33-node power distribution system.

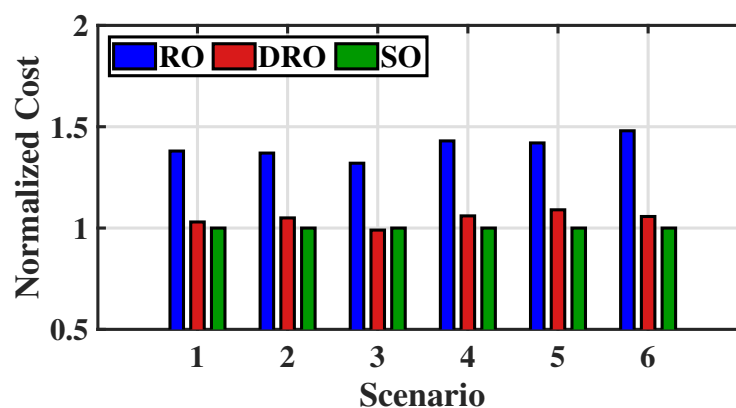


Figure 12. Comparison of the normalized total electricity arbitrage costs of the SO, RO, and proposed DRO methods under six scenarios in the IEEE 33-node power distribution system.

5.7. Sensitivity Analysis of the Objective Functions with Respect to Varying Weight

Figure 13 compares the results between the normalized total SOC mismatch (J_4) and cost ($J_1 + J_2 + J_3 - J_5$) with respect to varying weight ω_4 ($\omega_4 = 0.1, 0.25, 0.5, 1, 1.5$, and 2) given the fixed $\omega_1 = \omega_2 = \omega_3 = \omega_5 = 0.25$. Note from this figure that there exists a trade-off relationship between the normalized total SOC mismatch and cost according to the changes in ω_4 . The intersection of two curves does not indicate a structural change in system operation. It reflects the inherent trade-off between competing objective functions as the value of the weight varies. That is, a higher (or lower) ω_4 leads to a lower (or higher) SOC mismatch; however, it yields a higher (or lower) cost. In particular, the normalized total SOC mismatch rapidly decreases with increasing ω_4 and finally converges to zero after the value of ω_4 becomes larger than one. This study aims to place a higher priority on the complete satisfaction of the desired SOC of EVs for battery swapping than on the minimization of the distribution system and BCSS operational cost. Therefore, the value of the weight ω_4 is selected as $\omega_4 = 1$, which is larger than the value of the other weights. It is noted that DSOs may adaptively adjust the weights to situations in which they aim to perform their own purposes according to the aforementioned trade-off relationship between the objective functions in terms of the weights. For example, DSOs can adaptively increase the weights ω_1 and ω_2 to more reduce the total real power loss and BCSS electricity arbitrage cost, respectively.

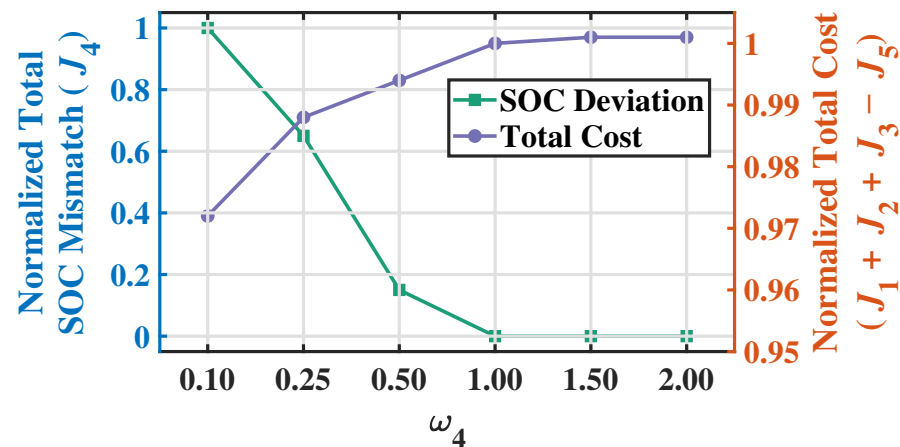


Figure 13. Sensitivity analysis of the normalized total SOC mismatch and cost with respect to varying weight ω_4 .

5.8. Computational Complexity

For the IEEE 33-node power distribution system (33 nodes and 37 lines) with three stand-alone PV systems and three PV-enabled BCSSs, the proposed DRO-based BCSS scheduling framework includes 40,572 constraints containing 442,952 decision variables (46,568 continuous variables and 396,384 binary variables). In this system, the total computation time of the proposed framework during one-day scheduling is 12,317 s and the average computation time per a scheduling time unit is 125 s. For the IEEE 69-node power distribution system (69 nodes and 73 lines) with four stand-alone PV systems and five PV-enabled BCSSs, the proposed DRO-based BCSS scheduling framework includes 93,316 constraints containing 1,063,085 decision variables (111,763 continuous variables and 951,322 binary variables). In this system, the total computation time of the proposed framework during one-day scheduling is 19,831 s and the average computation time per a scheduling time unit is 206 s. Considering a scheduling time unit of 15 min ($\Delta t = 15$ min), the proposed framework is practical for real-time BCSS operational scheduling.

5.9. Scalability

The scalability of the proposed DRO-based BCSS scheduling framework was validated using a modified IEEE 69-node power distribution system with four stand-alone PV systems and five PV-enabled BCSSs as shown in Figure 14. Five BCSSs (BCSS 1~5) and four stand-alone PV systems were connected to nodes 15, 25, 40, 51, and 60, and nodes 10, 20, 32, and 43, respectively. Figure 15 shows the profiles of the remaining ($\widehat{SOC}_{i,e,t}$) and desired ($SOC_{i,e,t}^d$) battery SOC levels before and after EV battery swapping, respectively, for the five BCSSs during the entire scheduling period. In this figure, 71 EVs, 63 EVs, 66 EVs, 69 EVs, and 71 EVs arrive at BCSS 1, BCSS 2, BCSS 3, BCSS 4, and BCSS 5, respectively, for battery swapping. For simplicity, the values of all parameters for the IEEE 69-node power distribution system are the same as those for the IEEE 33-node power distribution system. All observations from Table 3 (the IEEE 33-node power distribution system) can also be obtained from Table 4 (the IEEE 69-node power distribution system): (i) the suboptimality of the DRO method over the DO method, (ii) the increasing conservatism of the DRO method with a larger ϵ , and (iii) zero SOC mismatch for both the DO and DRO methods.

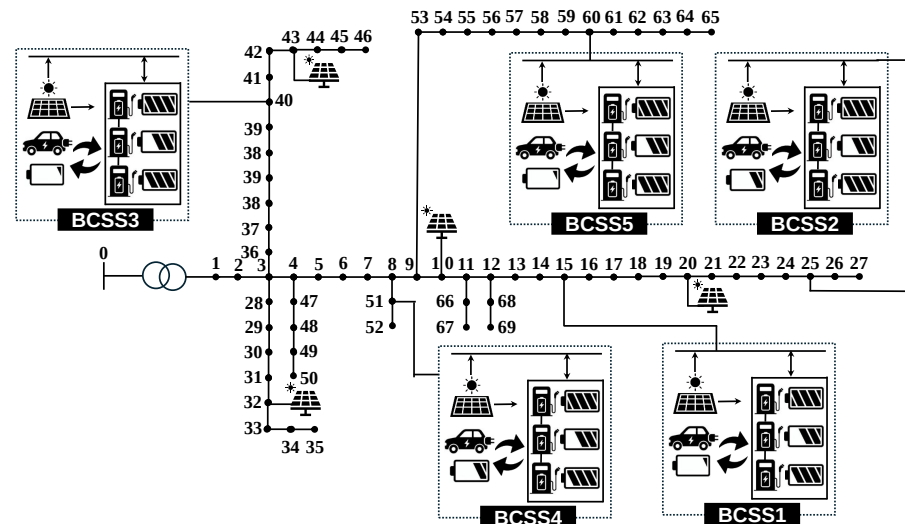


Figure 14. IEEE 69-node power distribution system with four stand-alone PV systems and five PV-enabled BCSSs.

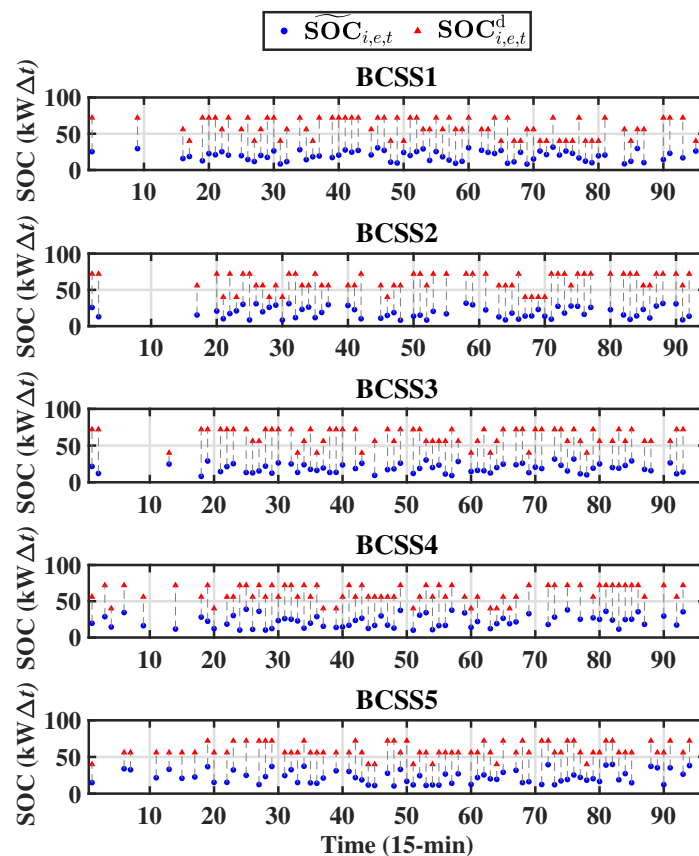


Figure 15. Profiles of the initial/desired SOC ($\widetilde{SOC}_{i,e,t}$, $SOC_{i,e,t}^d$) of EV batteries in five BCSSs.

Figure 16 compares the total electricity arbitrage cost (J_2) of the BCSSs for the SO, RO, and proposed DRO methods with varying numbers of stand-alone/BCSS-related PV generation output and maximum demand reduction samples (N^{PV*} , N^{PV} , and N^{DR}) in the IEEE 69-node power distribution system. Like the result in Figure 11, Figure 16 demonstrates the improved sample efficiency of the DRO method over the SO and RO methods.

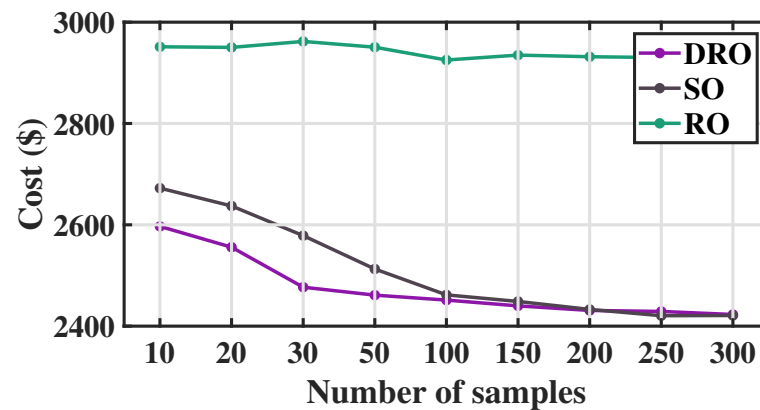


Figure 16. Comparison of the total electricity arbitrage costs (J_2) of the SO, RO, and proposed DRO methods in terms of the number of historical samples in the IEEE 69-node power distribution system.

Figure 17 compares the normalized total electricity arbitrage costs for the three methods using 300 samples under six scenarios with different PV generation outputs and demand reductions in the IEEE 69-node power distribution system. As expected, it is verified from this figure that the DRO method calculates a less conservative solution than the RO method while yielding a solution almost equivalent to the SO method.

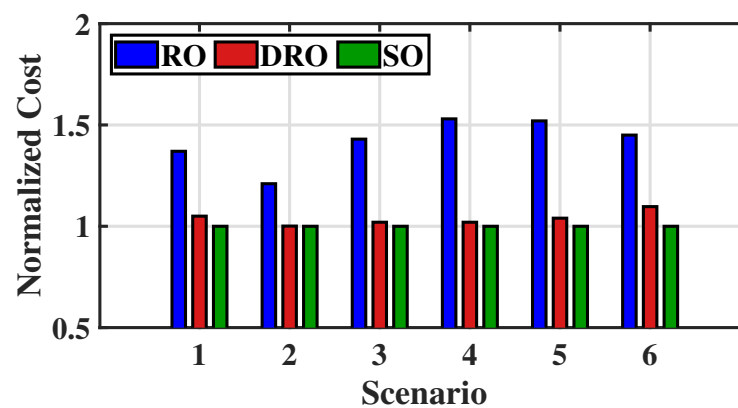


Figure 17. Comparison of the normalized total electricity arbitrage costs of the SO, RO, and proposed DRO methods under six scenarios in the IEEE 69-node power distribution system.

Table 4. Performance comparison of the DO and DRO methods in terms of multi-objective function ($J_1 \sim J_5$) and Wasserstein ball radius (ϵ) in the IEEE 69-node power distribution system.

Multi-Objective Function	DO Method	DRO Method			
		$\epsilon = 0.001$	$\epsilon = 0.01$	$\epsilon = 0.1$	$\epsilon = 1$
J_1 (Total Real Power Loss (kW))	183.33	185.14	187.63	187.91	188.17
J_2 (Total Electricity Arbitrage Cost (\$))	2,476.28	2,516.44	2,516.87	2,541.21	2,590.23
J_3 (Total Battery Degradation Cost (\$))	12.98	13.06	13.09	13.70	13.85
J_4 (Total SOC Mismatch for Battery Swapping (kWΔt))	0	0	0	0	0
J_5 (Total DR-induced Reward (\$))	2,256.21	2,244.61	2,231.47	2,217.23	2,209.91

The main observations from the simulation study can be summarized as follows:

- The proposed DRO-based BCSS scheduling framework successfully supported the EV battery swapping while ensuring the economical operation of the BCSSs through the charging and discharging of inventory batteries (see the results in Figure 7).
- In the proposed framework, a higher PV generation led to a more economical BCSS operation by fully utilizing the cost-free PV real power output (see the results in Figure 8).

- The proposed framework could increase and decrease the DR-induced reward and electricity arbitrage cost of BCSSs, respectively, via B2B and/or PV real power support (the results are shown in Figure 9).
- The uncertainty-integrated DRO method yielded a more conservative solution than that of the uncertainty-free DO method (baseline approach). This solution's conservatism became more pronounced with an increasing Wasserstein ball radius ϵ (i.e., a larger ambiguity set) (the results are shown in Table 3).
- Compared with the SO and RO methods, the DRO method improved sample efficiency and provided a less conservative solution, respectively (results are shown in Figures 11 and 12).

6. Practical Implications

The proposed DRO-based BCSS scheduling framework has the following practical implications for both BCSS operators and DSOs. First, the proposed DRO framework enhances the operational reliability of PV-enabled BCSSs by explicitly addressing the uncertainties in PV generation output and DR-induced maximum demand reduction. Second, the integration of VVC, B2B power exchange, and the DR process in a unified optimization framework can coordinate the operations of BCSSs and active distribution systems. This achieves accelerated renewable energy integration and provides voltage regulation when a large number of heterogeneous distributed energy resources are connected to active distribution systems. Lastly, the MPC model with a single-step prediction horizon and a 15 min scheduling resolution is well-matched with realistic distribution system operation intervals. This model guarantees that the proposed framework is practical for real-time BCSS operational scheduling while minimizing the computational burden for large-scale mixed-integer DRO problems.

7. Conclusions

In this study, we proposed a DRO framework to ensure the economical operation of multiple PV-enabled BCSSs while maintaining a stable and robust distribution of grid operation in the face of uncertainties in PV generation output and BCSS demand reduction capability. The proposed framework enabled a DSO to perform the following two tasks: (i) a smart inverter-based VVC minimized the real power loss by controlling the reactive powers of stand-alone PV systems and inventory batteries in BCSSs (from the distribution grid operation perspective) (ii) B2B and DR provided cost-effective and profitable BCSS scheduling while satisfying the desired EV battery swapping load completely (from the BCSS operation perspective). To address the uncertainties in random PV generation outputs and BCSS demand reduction capability, the proposed framework was formulated as a data-driven DRO problem based on the Wasserstein metric. Subsequently, the Wasserstein-based DRO problem was reformulated as a tractable optimization problem by calculating the DRBs of such uncertainties. The proposed framework was simulated using an IEEE 33-node power distribution system comprising three stand-alone PV systems and three PV-enabled BCSSs. The simulation results demonstrated that under uncertain environments, the proposed data-driven DRO method successfully maintained a stable and economical distribution grid, maintained BCSS operations in terms of real power loss reduction via smart inverter-based VVC, achieved savings in the BCSS operational cost associated with electricity arbitrage and battery degradation via B2B and DR functions, and achieved sample efficiency over the SO method.

The future research directions extending from the proposed framework are as follows. (i) To analyze the impact of EV user-side uncertainties (e.g., random EV arrival/departure times and initial/desired SOC of EV battery for battery swapping) and load profile un-

certainty on BCSS scheduling and distribution grid operation. (ii) To present an adaptive or data-driven method for the optimal selection of the size of the Wasserstein ball radius while considering heterogeneous battery degradation, (iii) To develop a distributed DRO framework between the DSO and BCSS operators using the alternating direction multiplier method in larger power distribution grids to reduce the computational complexity and preserve the privacy of EV data during battery swapping.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric vehicle
PCS	Plug-in charging station
BCSS	Battery charging swapping station
VVC	Volt/VAR control
DR	Demand response
DSO	Distribution system operator
BCS	Battery charging station
BSS	Battery swapping station
ESS	Energy storage system
PV	Photovoltaic
B2B	Battery-to-battery
RO	Robust optimization
SO	Stochastic optimization
DRO	Distributionally robust optimization
DRB	Distributionally robust bound
DRCC	Distributionally robust chance constraint
DO	Deterministic optimization
SOC	State of charge

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