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Optimal Operation Scheduling of a Microgrid Incorporating Battery Swapping Stations

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***Abstract*—This paper proposes optimal operation scheduling of a Microgrid (MG) and Battery Swapping stations (BSSs) as two independent stakeholders with inherently conflicting objectives. In this regard, a bi-level scheduling framework for optimal decision making of MG and BSSs is presented. Moreover, battery degradation cost is explicitly modeled based on the depth of discharge and the cycle life's intrinsic behavior of batteries. In order to tackle both historical data-based and human-related uncertainties under incomplete information including load demand of MG, photovoltaic (PV) generation, wholesale market prices, and swapping requests, a hybrid probabilistic-possibilistic approach considering correlation among uncertainties has been developed. To solve the proposed MG-BSS optimization problem, Alternative Direction Method of Multipliers (ADMM) with restart algorithm in a fully decentralized fashion is implemented. The effectiveness of the proposed model is demonstrated on a real-test MG system under different scenarios. Moreover, to compare the computational complexity of the proposed algorithm with the standard ADMM and investigate the scalability of the algorithm, extensive simulations are carried out on different standard test systems.**

***Index Terms*— Alternating direction method of multipliers, battery swapping station, microgrid, operation scheduling, uncertainty.**

NOMENCLATURE

Indices and sets

t / i / bss	Indices for time/ bus/ BSS.
m, p	Indices for MT/ PV.
bat, seg	Indices for battery/ segment.
k	Index of ADMM iteration.
s	Set of scenarios.

Parameters

ρ_t^{WM}	Wholesale market price at time *t*.
ρ_t^{TOU}	TOU price at time *t*.
ρ_t^{swap}	Swapping price at time *t*.
$\alpha_m^{MT}, \beta_m^{MT}$	Cost coefficients related to MT *m*.
$\alpha_i^{PV}, \beta_i^{PV}$	Cost coefficients related to PV *p*.
$P_{i,t}^{L}$	Amount of total load for bus *i* at time *t*.
$C_{bat}^{f} / C_{bat}^{d}$	Capacity of full/depleted battery *bat*.
N_t^{EV}	Number of EVs in the BSS for the swapping services at time *t*.
N_{bss}^{bat}	Total number of batteries in BSS *bss*.
$\alpha_{seg}, \beta_{seg}$	Piecewise approximation coefficients.
$\eta_{bat}^{ch} / \eta_{bat}^{dch}$	Charge/discharge coefficient of battery *bat*
$N_{BSS,t}^{bat,f} / N_{BSS,t}^{bat,d}$	Number of full/depleted batteries in BSS *bss* at time *t*.
$C_{bat}^{initial}$	Initial capacity of battery *bat* at time $t=0$.
A, B, c	Known parameters for the compact form of the problem.
N_s	Number of generated scenarios for wholesale market price/ PV output power/ demanded load/EVs in the BSS.
π_s	Probability of scenarios for wholesale market price/ PV output power/ demanded load/ EVs in the BSS.
$\varepsilon_{prim} / \varepsilon_{dual}$	Convergence tolerance for the primal/ dual feasibility.

Variables

$C_t^{MT} / C_t^{PV} / C_t^{L}$	Costs related to MT/PV/load.
C_t^{MG-BSS}	Cost of exchanged power between MG and BSS at time *t*.
C_t^{MG-DSO}	Cost of exchanged power between MG and DSO at time *t*.
C_t^{swap}	Swapping costs at time *t*.
$C_t^{\deg}$	Batteries degradation cost at time *t*.
C_t^{MG-BSS}	Cost of exchanged power between MG and BSS at time *t*.
C_t^{MG-DSO}	Cost of exchanged power between MG and DSO at time *t*.
P_t^{DSO-MG}	Exchanged power between DSO and MG.
P_t^{bss-MG}	Exchanged power between BSS *bss* and MG.
$P_{m,t}^{MT} / P_{p,t}^{PV}$	Hourly Output power of MT *m*/ PV *p*.
P_t^{bss2MG}	The amount of transmitted power from BSS *bss* to MG at time *t*.
P_t^{MG2bss}	The amount of transmitted power from MG to BSS *bss* at time *t*.
Z_{ij}	Spearman rank correlation coefficient.
R_i, R_j	Related rank of the samples for the variables.
$D_{t,seg}$	DoD of battery at the begining of a cycle in segment *seg*.
$r_{prim}(k) / r_{dual}(k)$	Residual convergence for the primal/ dual feasibility at iteration *k*.
$P_{bss,t}^{ch} / P_{bss,t}^{dch}$	Charge/discharge rate of BSS *bss* at time *t*.
$C_{bss,t}^{BSS}$	Available capacity of BSS *bss* at time *t*.
$N_{bss,t}^{bat,ch} / N_{bss,t}^{bat,dch}$	Number of batteries in the charging/discharging mode at time *t*.

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$C_{b,t}^{bat}$	Available capacity of battery *bat* at time *t*.
N_{bat}^{cyc}	The total number of charge/discharge cycles of each battery over a day.
$J_{t,seg}$	Binary variable to determine the active segments.
n_d	Number of cycles at the DoD of *d*.
x, z	Decision variables related to the MGO and BSS optimization problems.

I. INTRODUCTION

Electric vehicles (EVs), as an emerging mode of transportation, are now being widely proliferated, not only to emit less greenhouse gas emissions, but also to reduce reliance on fossil fuels. However, potential EV customers are still confronted some unpromising challenges in the practical application of EVs such as long battery charging time duration, limited travel distance per charge, short battery life cycle, expensive EV battery replacement cost, and stochastic charging patterns. Commercialization of Battery Swapping Stations (BSSs) in modern power systems addresses these challenges by swapping depleted batteries of EVs with stocked fully-charged batteries in a short period of time (e.g., it takes only 2.5 minutes for a real Chinese State Grid BSS in Hangzhou [1], whereas the fast-charging stations would take around 80 minutes to recharge the EV batteries of Tesla Model-S [2]). This feature is more crucial for taxicab and bus drivers, where they run for about 400-600 kilometers per day in typical cities [3]. On the other hand, available EVs such as BYD and Tesla with a full-charge battery are able just to run for about 250-350 kilometers [1], which necessitates the use of swapping facilities to shorten refueling time by BSSs. Therefore, the well-known range anxiety would be reduced from EV owner's viewpoint. Moreover, BSS operators can control the charging and discharging pattern of stocked batteries to lessen the stress on the network, specifically at peak-time periods [4]. Furthermore, superior to a single charging entity, BSS acts as an aggregator with more predictable demand [5]. By introducing the BSS concept, the ownership of the EV and the battery is decoupled, which results in lowering the upfront cost of purchasing an EV. There have been some studies carried out on various aspects of BSSs such as planning, operation, and control strategies. Reference [6] puts forward a simultaneous optimal planning and operation scheduling of BSSs by taking into account optimal charging location and charging priority. An optimal charging operation policy is presented in [7] to minimize the associated costs of the BSS, while guaranteeing a certain quality-of-service. The intended constrained Markov decision process problem is solved by standard dynamic programming. To seek the maximum BSS's battery stock level and minimum average charging damage, a centralized optimization model for EV charging scheme at a BSS is formulated in [8], which is solved by different population-based evolutionary algorithms. In [9], a stochastic decision-making model based on the Monte-Carlo simulation for a BSS serving electric buses is proposed, which gives rich insights into evaluation of uncertain patterns.

Based on the envisioned Microgrid (MG) concept [10], BSSs can be implemented in MG's authority. Up till now, there are only a few studies, which have considered the operation scheduling of BSSs incorporating an MG. In [11], a centralized energy management system for optimal charging of EVs has been proposed to minimize the operational cost of BSS and to maximize the benefit of Microgrid Operator (MGO) in both grid-connected and islanded modes. A Photovoltaic (PV)-based BSS in a DC MG is modeled in [12] by considering the self-consumption of PVs and service availability. Likewise, in [13], the dispatching strategy of MG incorporating with a BSS has been established in different energy supplying modes to minimize the operating costs. However, all the aforementioned studies [11]-[13] devote the decision authority to the MGOs without considering the interest demand of independent stakeholders. To the best of our knowledge, none of the reviewed literature has yet provided an optimal operation scheduling for decision-making of MGO and BSSs as independent entities. Taking into account the mutual interaction between these two entities, in this paper a bi-level model for optimal operation scheduling of Distribution System Operator (DSO) and independent BSSs is presented, in which an Alternative Direction Method of Multipliers (ADMM)-based algorithm is employed to solve the proposed optimization problem. ADMM method, as a fully decentralized computing framework, ensures the decision independency and information privacy of entities, which fulfils the operating philosophy of integrated subsystems [14]. In [15], the existing distributed optimization algorithms are categorized into two main groups. The first group of algorithms is based on the Karush-Kuhn-Tucker (KKT) optimality conditions [16]. The second group of the decentralized algorithms is based on the augmented Lagrangian decomposition, including Analytical Target Cascading (ATC) [17], Dual Decomposition [18], ADMM [19] and Auxiliary Problem Principle (APP) [20]. Due to the existence of binary and integer variables in our model, the KKT condition-based algorithms are not applicable as a solution method in this paper. In other words, for the non-linear lower-level problems, the decision-making process is thoroughly different, which renders KKT optimality conditions invalid. In this regard, ADMM method is proved to demonstrate an appropriate performance from the convergence speed and information privacy aspects, compared to the other decomposition-based algorithms [21]. Besides, by employing an easy-to-use decomposition algorithm in ADMM method and eliminating unnecessary computational operations, ADMM method can be an effective tool from algorithmic aspect. Thus, in this paper ADMM method is implemented to solve the proposed bi-level MG-BSSs optimization problem in a fully decentralized fashion for the first time. In the proposed algorithm, the restart rule is utilized to improve the stability of convergence rate. In this model, for the upper-level, the total cost from MGO's point of view including the cost of exchanging power between MGO and DSO, cost of exchanging power between BSSs and MGO, and costs related to the MTs, PVs, and loads is minimized. In the lower-level optimization problem, the total cost of each BSS, including the cost related to the exchanged power between BSS and MG (i.e., charging/discharging cost of stock batteries), the swapping incomes gained from EV owners, cost related to PV panels installed in the rooftop of BSS, and the batteries degradation cost is minimized. Moreover, battery degradation cost is modeled based on the Depth of Discharge (DoD) and the cycle life's intrinsic behavior of batteries. In order to tackle both historical data-based and human-related uncertainties under incomplete information including load demand, PV generation, wholesale market prices, and swapping requests, a hybrid probabilistic-possibilistic approach considering correlation among uncertainties is developed.

Briefly, the major contributions of this paper are highlighted as follows:

- Proposing a new MG operation scheduling model incorporating BSSs as independent stakeholders including both historical data-based and human-related uncertainties,
- Developing an ADMM-based algorithm with restart rule to solve the proposed MG-BSS optimization model in a fully decentralized fashion,
- Modelling the battery degradation cost explicitly based on the DoD and the cycle life's intrinsic behavior of batteries considering BSSs' facilities.

The rest of the paper is organized as follows: In section II, the general description of the proposed MG-BSS model is explained. The stochastic formulation of the optimization problem is proposed in section III. The decentralized algorithm is proposed to solve the bi-level optimization problem in section IV. In section V, the case study and simulation results are investigated. Finally, section VI summarizes the contribution of the paper.

II. General Description of the Proposed MG-BSS Model

A general framework of the proposed MG-BSS system is illustrated in Fig. 1. As can be seen, the MG includes Micro Turbines (MTs) and PVs, which can exchange power with DSO. Moreover, MGO can exchange power with BSS as two independent stakeholders with different objectives according to the predefined Time-of-Use (TOU) price. Meanwhile, the BSS equipped with rooftop PVs can sell power to MG during the peak periods, and purchase power (i.e., charging the batteries) from MG during off-peak periods. The BSS, as a mediator between MG and EVs, swaps depleted batteries of EVs with stocked fully-charged batteries in a short period of time.

The following assumptions are made for the proposed MG-BSS model:

- **A1: EV arrivals.** EV arrivals have been modeled by trapezoidal fuzzy membership functions and are dealt with α-cut method. This assumption allows us to neglect the effect of travelling speed/traffic flow on the model.
- **A2: Batteries owning.** It is assumed that BSSs own the batteries and lease them to the customers. Due to this assumption, BSSs are responsible for the degradation and maintenance costs. Regarding this arrangement, customers are neither concerned with the battery charging method nor with the battery lifetime.
- **A3: Power limit on the BSS.** It is assumed that the maximum power consumption of the BSS is limited to the total installed capacity of chargers at the place.
- **A4: Homogenous batteries and charging system.** For the sake of simplicity, it is assumed that all the batteries and charging systems are the same.
- **A5: Remained capacity of depleted batteries.** After swapping batteries in the BSS, the remaining state of charge of depleted battery is measured. Thus, the remained capacity of depleted batteries are known.

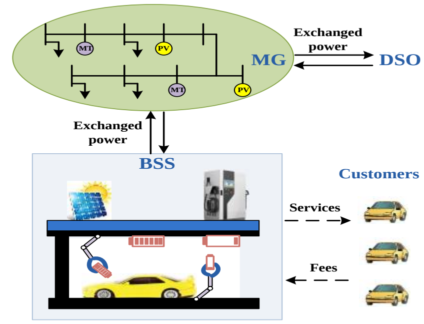

Fig. 1. BSS interactions with MG and customers.

- **A6: Exchanging power with MGO.** Each BSS can sell/purchase power to/from MGO according to the TOU price.

III. Problem Formulation

In this section, the centralized bi-level deterministic model including MGO and BSSs is presented. Then, the intrinsic uncertainties related to load demand, PV generation, market prices, and swapping requests are addressed.

A. Upper-level: MGO decision making

At this level, the objective function is formulated to minimize the MGO total cost as follows:

$$OF_{MGO} = Min\left(\sum_{t=1}^{24}\left(C_t^{MG-DSO} + C_t^{MG-BSS} + C_t^{MT} + C_t^{PV} + C_t^{L}\right)\right) \tag{1}$$

As stated in (1), the objective function includes five cost terms (2)-(6).

$$C_t^{MG-DSO} = \rho_t^{WM} P_t^{DSO-MG} \tag{2}$$

$$C_t^{MG-BSS} = \rho_t^{TOU} \sum_{bss=1}^{N_{BSS}} (P_t^{bss-MG}) \tag{3}$$

$$C_t^{MT} = \sum_{m\in MG} (\alpha_m^{MT} P_{m,t}^{MT} + \beta_m^{MT}) \tag{4}$$

$$C_t^{PV} = \sum_{p\in MG} (\alpha_p^{PV} P_{p,t}^{PV} + \beta_p^{PV}) \tag{5}$$

$$C_t^{L} = -\rho_t^{TOU} \sum_{i\in MG} (P_{i,t}^{L}) \tag{6}$$

The first term in (1) calculates the cost of exchanging power between MGO and DSO which is represented by (2). The second term indicates the cost of exchanging power between BSSs and MGO calculated by (3). The remaining terms are the costs related to the MTs, PVs, and loads, which can be calculated by (4), (5), and (6), respectively. Moreover, the negative sign in (6) indicates that MGO could make profit by selling power to loads.

1) Constraints:

To guarantee the stable operation of the MG, a set of technical constraints should be met as follows:

- *Power balance of MG:*

$$\sum_{m=1}^{N_{MT}} P_{m,t}^{MT} + \sum_{p=1}^{N_{PV}} P_{p,t}^{PV} + P_t^{DSO-MG} + \sum_{bss=1}^{N_{BSS}} (P_t^{bss-MG}) = \sum_{i=1}^{N_L} P_{i,t}^{L} \tag{7}$$

- *Operation limit of MTs:*

$$P_{\min}^{MT} \le P_{m,t}^{MT} \le P_{\max}^{MT} \tag{8}$$

- *Exchanged power limit between MG and DSO:*

$$P_{\min}^{DSO-MG} \le P_t^{DSO-MG} \le P_{\max}^{DSO-MG} \tag{9}$$

- *Exchanged power limit between MG and BSSs:*

$$P_t^{bss-MG} = P_t^{bss2MG} - P_t^{MG2bss} \quad (10)$$

$$P_{\min}^{bss-MG} \le P_t^{bss-MG} \le P_{\max}^{bss-MG} \quad (11)$$

B. Lower-level: BSS decision making

The objective function of the lower-level problem is modeled to minimize the cost of each BSS, which includes four cost terms as follows:

$$OF_{BSS_i} = Min\left(\sum_{t=1}^{24}\left(C_t^{BSS\text{-}MG} + C_t^{swap} + C_t^{PV} + C_t^{\deg}\right)\right) \quad (12)$$

where the first term is the cost related to the exchanged power between BSS and MG (i.e., charging/discharging cost of stock batteries) based on the TOU price (stated in **A6**), which is calculated by (13).

$$C_t^{BSS-MG} = -\rho_t^{TOU}\sum_{bss=1}^{N_{BSS}}(P_t^{bss-MG}) \quad (13)$$

The second term in (12) is associated with the swapping incomes gained from EV owners, which can be calculated by (14).

$$C_t^{swap} = -(\rho_t^{swap} \times (C_{bat}^{f} - C_{bat}^{d}) \times N_t^{EV}) \quad (14)$$

As it is assumed in **A5**, after swapping batteries in the BSS, the remaining state of charge of depleted battery is measured, and the EV owner only has to pay for the difference electricity charge.

The third term, represented by (12), is the cost related to PV panels installed in the rooftop of BSSs, which can be calculated by the same equation formulated in (5).

The last term in (12), considers batteries degradation cost due to the frequent charging cycles as follows:

$$C_t^{\deg} = N_{bss}^{bat}\sum_{seg=1}^{N_{seg}}(\alpha_{seg}D_{t,seg} + \beta_{seg}J_{t,seg}) \quad (15)$$

where, parameters α_{seg}, β_{seg} are the piecewise approximation coefficients for the batteries degradation cost. Due to cycling patterns in batteries, some chemical reactions are occurred, and thus degradation over their life span happens. Analysis of this chemical phenomenon is beyond the scope of this paper. Here, battery degradation cost is modeled based on the DoD and the cycle life's intrinsic behavior of batteries. For a given DoD at the beginning of charging cycle, the degradation cost is as follows [22]:

$$C_{cyc}^{\deg}(d) = \frac{C_{ini}}{n_{100}}d^{k_p} \quad (16)$$

$$n_d = n_{100}d^{-k_p} \quad (17)$$

where, k_p is a constant ranging from 0.8 to 2.1 [23]-[24], and can be extracted by life cycle-DoD curve fitting provided by manufacturer. n_{100} is the total number of cycles before failure at 100% DoD. As can be seen, (16) is nonlinear, thus it is linearized in (15) through the piecewise approximations in some required segments [3]. Fig. 2 illustrates an example for a 3 kW lithium-ion battery, which is linearized into 6 segments. First, (17) evaluates the resulted seven equally points. Next, parameters α_{seg}, β_{seg} in (15) are calculated by implementing curve fitting within each segment.

1) Constraints:

To guarantee the stable operation of the BSSs, following constraints should be considered in the optimization model.

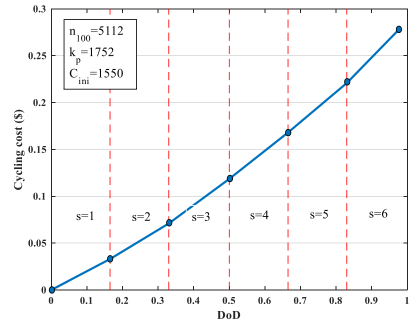

Fig. 2. Example for piecewise linearization in (15).

- *BSS charge/discharge rate limit:*

Due to technical specifications, BSS charge/discharge rates must be kept below certain values:

$$0 \le P_{bss,t}^{ch} \le P_{\max}^{ch} \quad (18)$$

$$0 \le P_{bss,t}^{dch} \le P_{\max}^{dch} \quad (19)$$

- *BSS capacity limit:*

To ensure the BSS capacity during each period within the allowable range, it must obey the following constraint:

$$C_{\min}^{BSS} \le C_{bss,t}^{BSS} \le C_{\max}^{BSS} \quad (20)$$

- *Total number of batteries balance limit:*

$$N_{bss,t}^{bat,f} + N_{bss,t}^{bat,d} + N_{bss,t}^{bat,ch} + N_{bss,t}^{bat,dch} = N_{bss}^{bat} \quad ,\forall t \quad (21)$$

Equation (21) states that the total number of fully charged, empty, charging, and discharging batteries during period t should be equal to the predefined number of stock batteries in BSS.

- *Batteries constraints:*

Each battery of the BSS should meet the following constraints:

$$P_{\min}^{ch,bat} \le P_{bat,t}^{ch} \le P_{\max}^{ch,bat} \quad (22)$$

$$P_{\min}^{dch,bat} \le P_{bat,t}^{dch} \le P_{\max}^{dch,bat} \quad (23)$$

$$C_{b,t}^{bat} = C_{b,t-1}^{bat} + \eta_{bat}^{ch}P_{bat,t}^{ch} - \frac{P_{bat,t}^{dch}}{\eta_{bat}^{dch}} \quad , \ \forall t \ge 1 \quad (24)$$

$$C_{b,t}^{bat} = C_{bat}^{initial} \quad , \ t = 0 \quad (25)$$

$$C_{\min}^{bat} \le C_{b,t}^{bat} \le C_{\max}^{bat} \quad (26)$$

- *Charge/discharge cycle constraints:*

As previously mentioned, the frequent charge/discharge cycles could shorten the actual lifetime of batteries. To this end, the total number of charge/discharge cycles of each battery over a day should be limited as follows:

$$N_{bat}^{cyc} \le N_{\max}^{bat,cyc} \quad (27)$$

C. Uncertainty modelling

In the above-described deterministic model, it is assumed that the intrinsic uncertain parameters, i.e., load demand of MG, PV generation, wholesale market prices, and swapping requests (number of EVs in the BSS queue), are accurately forecasted. However, in practical applications, it is relatively unrealistic to achieve a set of data without forecasting errors. In order to tackle both kinds of uncertainties (i.e., the historical data-based uncertainties and human-related uncertainties under incomplete information), a hybrid probabilistic-possibilistic approach has been developed. Load demand of MG, PV generation, and wholesale market prices are modeled probabilistically, since their related Probability Density Function (PDF) and historical data are available. On the other hand, swapping requests are modeled possibilistically due to anthropogenic factors in EV arrivals and lack of historical data. In this regard, PV generation has been modeled by Beta distribution [25], while Load demand of MG and wholesale market prices have been modeled by normal PDF's. The uncertainty of swapping requests has been modeled by trapezoidal fuzzy membership functions [25] as follows:

$$A^{\alpha} = (\alpha_{\min}, \alpha_L, \alpha_U, \alpha_{\max}) \tag{28}$$

where, $\alpha_{\min}, \alpha_L$ are the interval of the distribution and $\alpha_U, \alpha_{\max}$ denote its most likely amounts.

Scenario-based analysis and α-cut method are used for dealing with these uncertainties. To reduce the large number of generated scenarios into a trackable set while maintaining solution accuracy, the Kantorovich distance method [26] based on the concept of the probability distance [27] is applied. After implementing α-cut method and determining membership function of output variable related to swapping requests, Centroid method [25], as a defuzzification strategy, is used to find a crisp output value.

Spearman rank correlation coefficient matrix [28] has been implemented into the model to consider the correlation among the uncertain variables (i.e., load demand, PV generation, and wholesale market prices) according to the available historical data. This matrix can be represented by:

$$Z = \begin{bmatrix} 1 & Z_{12} & \dots & Z_{1n} \\ Z_{21} & 1 & \dots & Z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ Z_{n1} & Z_{n2} & \dots & 1 \end{bmatrix} \tag{29}$$

$$Z_{ij} = \frac{\mathrm{cov}(\mathrm{R}_i, \mathrm{R}_j)}{\sigma(\mathrm{R}_i)\sigma(\mathrm{R}_j)} \tag{30}$$

where, $\mathrm{cov}(\mathrm{R}_i, \mathrm{R}_j)$ denotes the covariance of rank R_i and R_j ; $\sigma(\mathrm{R}_i)$ is the standard deviation of rank R_i .

- *Correlation constraints:*

$$Z_s(P^L, P^{PV}, \rho^{WM}) = Z_{OF} \tag{31}$$

where, $Z_s(P^L, P^{PV}, \rho^{WM})$ is the Spearman rank correlation coefficient matrix of load demand, PV generation, and wholesale market prices in the optimization process; Z_{OF} can be calculated by (30).

D. ADMM method

Considering the coupling variables between MGO and BSSs, the compact form of the proposed bi-level optimization problem can be written as follows:

$$\begin{aligned} &\underset{x \in \Omega_x, z \in \Omega_z}{Min} \quad f(x) + g(z) \\ &s.t. \quad Ax + Bz = c \end{aligned} \tag{32}$$

In (32), x which involves $\{P_t^{DSO-MG}, P_t^{bss-MG}, P_t^{MT}, P_t^{PV}\}$ and z which includes $\{P_t^{bss-MG}, D_{t,seg}, J_{t,seg}, P_t^{PV}, P_{bss,t}^{ch}, P_{bss,t}^{dch}\}$ are the decision sets of the MGO and BSS, respectively. Ω_x and Ω_z are the feasible regions with the constraint sets (7)-(9) and (18)-(27), respectively. Moreover, the linear equality constraint in (32) relates to (10).

The augmented Lagrangian function of (32) is expressed by (33), where ξ represents the Lagrangian multiplier vector for the constraints in (32), and $\rho > 0$ is a penalty factor controlling the violation of primal feasibility (i.e., determining the step size of the dual updates). When $\rho = 0$, the augmented Lagrangian function is reduced to the standard one.

$$\begin{aligned} L_{\rho}(x, z, \xi) = f(x) + g(z) + \xi^T (Ax + Bz - c) \\ + \frac{\rho}{2}\|Ax + Bz - c\|_2^2 \end{aligned} \tag{33}$$

Under the framework of ADMM, variables x and z are solved in a distributed manner, i.e., at each iteration ($k = 1, 2, ..., K$), ADMM first updates x with fixed amounts for z based on (34), then updates z with fixed amounts for x based on (35), and finally updates the dual variable ξ based on (36).

$$x(k+1) = \underset{x \in \Omega_x}{\arg\min}\, L_{\rho}(x, z(k), \xi(k)) \tag{34}$$

$$z(k+1) = \underset{z \in \Omega_z}{\arg\min}\, L_{\rho}(x(k+1), z, \xi(k)) \tag{35}$$

$$\xi(k+1) = \xi(k) + \rho(Ax(k+1) + Bz(k+1) - c) \tag{36}$$

The convergence criteria of ADMM method is considered as the residuals for the primal and dual feasibility as follows:

$$r_{prim}(k) := \|Ax(k) + Bz(k) - c\|_2 \le \varepsilon_{prim} \tag{37}$$

$$r_{dual}(k) := \left\|\rho A^T B(z(k+1) - z(k))\right\|_2 \le \varepsilon_{dual} \tag{38}$$

The restart algorithm relies on combining the primal and dual residuals as follows:

$$r_{com}(k) := \|Ax(k) + Bz(k) - c\|_2 + \|\rho B(z(k+1) - z(k))\|_2 \tag{39}$$

where, the first term in (39), considers the primal residual (37), and the second term is closely represented the dual residual (38). This simple restart rule can improve the convergence accuracy of the algorithm [29]. By satisfying these criteria, it can be claimed that the optimization problem is solved to optimality (please see **Theorem 1**).

Theorem 1[30]: Considering the convex objective functions $f(\cdot)$ and $g(\cdot)$ in (34) the ADMM iterates meet the following:

- *Residual convergence:* If $k \to \infty$, then $r_{prim}(k) \to 0$, $r_{dual}(k) \to 0$, and $r_{com}(k) \to 0$, i.e., the solution approaches feasibility.
- *Objective convergence:* If $k \to \infty$, then $f(x(k)) + g(x(k)) \to m^*$, i.e., the objective function reaches to an optimal point.
- *Dual variable convergence:* If $k \to \infty$, then $\xi(k) \to \xi^*$, where ξ^* is an optimal point.

Proof: For the proof of **Theorem 1**, please refer to [30], which is out of the scope of this paper.

E. Algorithm design and implementation

As is it stated in previous sub-section, the augmented Lagrangian function of the optimization problem (1)-(27) is formed as (40). As can be seen in (40), the operating problems of MGO and BSSs can be optimized iteratively in a decentralized fashion by preserving the ownership of each entity.

The detailed solution algorithm based on the ADMM method with restart algorithm is summarized in the following steps

$$L_{\rho}(x,z,\xi)=\sum_{s_{PV}=1}^{Ns_{PV}}\pi_s^{PV}\sum_{s_L=1}^{Ns_L}\pi_s^{L}\sum_{s_{WM}}^{Ns_{WM}}\pi_s^{WM}\sum_{s_{EV}}^{Ns_{EV}}\pi_s^{EV}\left(\sum_{t=1}^{24}\left(\begin{array}{l}\rho_t^{WM}P_{t,s}^{DSO-MG}+\rho_t^{TOU}\sum_{bss=1}^{N_{BSS}}(P_{t,s}^{bss-MG})+\sum_{m\in MG}(\alpha_m^{MT}P_{m,t,s}^{MT}+\beta_m^{MT})+\sum_{p\in MG}(\alpha_p^{PV}P_{p,t,s}^{PV}+\beta_p^{PV})\\ -\rho_t^{TOU}\sum_{i\in MG}(P_{i,t,s}^{L})-(\rho_t^{swap}\times C^{bat}\times N_t^{EV})+\sum_{p\in BSS}(\alpha_p^{PV}P_{p,t,s}^{PV}+\beta_p^{PV})+N_{bss}^{bat}\sum_{seg=1}^{N_{seg}}(\alpha_{seg}D_{t,seg,s}+\beta_{seg}J_{t,seg,s})\end{array}\right)\right)$$
$$+\sum_{t=1}^{24}\sum_{bss=1}^{N_{BSS}}\xi_t(P_t^{bss-MG}-(P_t^{bss2MG}-P_t^{MG2bss}))+\frac{\rho}{2}(\sum_{t=1}^{24}\sum_{bss=1}^{N_{BSS}}(P_t^{bss-MG}-(P_t^{bss2MG}-P_t^{MG2bss}))^2 \tag{40}$$

$$x(k+1)=\arg\min_{x\in\Omega_x}\sum_{S_{PV}=1}^{Ns_{PV}}\pi_s^{PV}\sum_{S_L=1}^{Ns_L}\pi_s^{L}\sum_{S_{WM}}^{Ns_{WM}}\pi_s^{WM}\sum_{S_{EV}}^{Ns_{EV}}\pi_s^{EV}\left(\sum_{t=1}^{24}\left(\rho_t^{WM}P_{t,s}^{DSO-MG}+\rho_t^{TOU}\sum_{bss=1}^{N_{BSS}}(P_{t,s}^{bss-MG})-\rho_t^{TOU}\sum_{i\in MG}(P_{i,t,s}^{L})\sum_{m\in MG}(\alpha_m^{MT}P_{m,t,s}^{MT}+\beta_m^{MT})+\sum_{p\in MG}(\alpha_p^{PV}P_{p,t,s}^{PV}+\beta_p^{PV})\right)\right)$$
$$+\sum_{t=1}^{24}\sum_{bss=1}^{N_{BSS}}\xi_t(k)P_t^{bss-MG}+\frac{\rho}{2}(\sum_{t=1}^{24}\sum_{bss=1}^{N_{BSS}}(P_t^{bss-MG}-(P_t^{bss2MG}(k)-P_t^{MG2bss}(k)))^2 \tag{41}$$

$$z(k+1)=\arg\min_{z\in\Omega_z}\sum_{S_{PV}=1}^{Ns_{PV}}\pi_s^{PV}\sum_{S_L=1}^{Ns_L}\pi_s^{L}\sum_{S_{WM}}^{Ns_{WM}}\pi_s^{WM}\sum_{S_{EV}}^{Ns_{EV}}\pi_s^{EV}\left(\sum_{t=1}^{24}\left((\rho_t^{swap}\times C^{bat}\times N_t^{EV})+\sum_{p\in BSS}(\alpha_p^{PV}P_{p,t,s}^{PV}+\beta_p^{PV})+N_{bss}^{bat}\sum_{seg=1}^{N_{seg}}(\alpha_{seg}D_{t,seg,s}+\beta_{seg}J_{t,seg,s})\right)\right)$$
$$+\sum_{t=1}^{24}\sum_{bss=1}^{N_{BSS}}\xi_t(k)(P_t^{bss2MG}-P_t^{MG2bss})+\frac{\rho}{2}(\sum_{t=1}^{24}\sum_{bss=1}^{N_{BSS}}(P_t^{bss-MG}(k+1)-(P_t^{bss2MG}-P_t^{MG2bss}))^2 \tag{42}$$

Step 1) *Initialization:* Initialize the primal variables $P_t^{BSS_{bss}-MG}(0)$ and dual variable $\xi_t(0)$ for each entity. Set the iteration index $k=1$ and the convergence tolerance $\varepsilon_{prim}=10^{-3}$, $\varepsilon_{dual}=10^{-3}$.

Step 2) *MGO updating:* MGO minimizes the associated operation cost by solving the Mixed Integer Quadratic Programming (MIQP) problem stated in (41).

Step 3) *BSSs updating:* At each iteration, MGO sends the amount of exchanged power $P_t^{bss-MG}(k+1)$ to the related BSS. Each BSS solves the MIQP (42) to optimize the operation scheduling.

Step 4) *Convergence checking:* The restart parameter $\nu\in(0,1)$ is implemented to improve the convergence accuracy rate of the algorithm, by checking if the last ADMM step has decreased the combined residual by a factor of ν. Then MGO checks the convergence criteria (37)-(38) by computing the primal and dual residues. If it is met, stops the iteration procedure and returns the optimal results; else, goes to the next step.

Step 5) *Dual variables updating:* Dual variables are updated as follows:

$$\xi_t(k+1)=\xi_t(k)+\rho(P_t^{bss-MG}(k+1)-(P_t^{bss2MG}(k+1)-P_t^{MG2bss}(k+1))) \tag{43}$$

In order to summarize the proposed solution methodology, the pseudo code for the algorithm is illustrated in **Algorithm 1**.

IV. NUMERICAL RESULTS AND DISCUSSION

In this section, after introducing the case study and defined scenarios, simulation results of the proposed MG-BSS optimization model are discussed. All the simulations are implemented in GAMS 24.5 and solved by the CPLEX solver.

A. Case study

In order to investigate the effectiveness of the proposed model, a grid-connected MG including two MTs, two PVs, and a BSS is considered as the case study [31] over a day scheduling horizon with one hour per slot. The technical and topological data related to this real case study can be obtained from [31]. The predicted amounts for the hourly load profile, the wholesale market prices, and PV output powers can be extracted from [31]. Moreover, the data related to the swapping requests can be found in [32]. The other required technical parameters are proposed in Table I. Furthermore, similar lithium-ion battery packs are chosen with a nominal capacity of 85 kWh, which are currently used on Tesla Model-S [2].

Algorithm 1. Decentralized Solution Algorithm of MGO-BSS Problem

Initialize input data {solar irradiation , load, market price, and swapping requests}
Set $k=1$ and $\varepsilon_{prim}=\varepsilon_{dual}=10^{-3}$
Forming Spearman rank correlation coefficient matrix
  Generate scenarios {S}
  Applying scenario reduction method {S_{red}}
  Implementing α-cut method
  Implementing Centroid method as the defuzzification strategy
    for $s=1:S_{red}$ **do**
      repeat
        Update primal variables by (41) and (42).
        Update iteration index $k=k+1$
        Update dual variable $\xi(k)$ by (43)
        if $r_{com}(k)\geq \nu r_{com}(k-1)$ **then**
          $r_{com}(k)\leftarrow \nu^{-1}r_{com}(k-1)$
        end if
      until stopping criteria (37)-(38) are satisfied.
    end for $\rightarrow$ show the results

B. Simulation results

1) Optimal operation scheduling

Hourly operation scheduling of the MTs, PVs, and exchanged power between the BSSs, MGO, and DSO is presented in Fig. 3. Due to the increased market prices in peak load periods (i.e., 19:00-22:00), BSSs sell power to the MG, while in off-peak load periods (i.e., 3:00-7:00 and 13:00-17:00) BSSs purchase power from MG to achieve higher profit. Similarly, MGO purchases more power from DSO in off-peak load periods comparing to that in peak load periods. Moreover, MTs operate at their maximum available output power in peak load periods. It is also worth mentioning that the correlations among different uncertain variables (i.e, load demand, PV generation and market price) according to the available historical data were determined as follows using (29)-(30):

$$Z = \begin{bmatrix} 1 & 0.082 & 0.136 \\ 0.082 & 1 & -0.039 \\ 0.136 & -0.039 & 1 \end{bmatrix} \tag{44}$$

Numerical values indicate that the pairs of (load demand, PV generation) and (load demand, wholesale market price) are positively correlated, while the pair (PV generation, wholesale market price) is negatively correlated. However, the very week positive/negative correlations denote a negligible dependence of uncertain variables to each other.

2) *Economic analysis*

In order to investigate the cost-benefit analysis of joint optimization between BSSs and MGO, three different scenarios are considered. MGO independent optimization, BSS independent optimization, and joint optimization are respectively considered as scenario 1, 2, and 3. Table II, states that the total amount of exchanged power between BSSs and MGO, exchanged power between DSO and MGO, BSSs and MGO costs over a day are significantly different under the defined scenarios. More specifically, the MGO cost is the lowest in the scenario 1, but it leads to the highest operation cost for BSSs. On the other hand, the BSSs cost reaches the lowest amount in the scenario 2, but the MGO cost is the highest. Results of scenario 3 indicate that a balance between BSSs cost and MGO cost can be achieved according to the joint optimization of MG-BSS.

TABLE I
TECHNICAL PARAMETERS

Parameter	Value	Parameter	Value
α_m^{MT} $(\$/MWh)$	65	ρ_t^{swap} $(\$/MWh)$	105
β_m^{MT} $(\$)$	13	N_{bss}^{bat}	20
α_i^{PV} $(\$/MWh)$	1.3	$P_{\max}^{ch,bat}, P_{\max}^{dch,bat}$ (kW)	80, 80
β_i^{PV} $(\$)$	5	$\eta_{bat}^{ch}, \eta_{bat}^{dch}$ $(p.u.)$	0.92, 0.92
$C_{\min}^{bat}, C_{\max}^{bat}$ (kWh)	13, 81	$C_{bat}^{initial}$ (kWh)	25
$N_{\max}^{bat,cyc}$	2	$\rho, \varepsilon_{prim}, \varepsilon_{dual}$	1.5, 0.001, 0.001

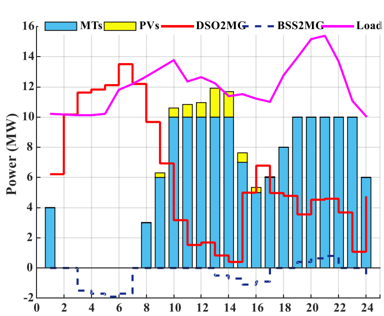

Fig. 3. Hourly operation scheduling of MG and BSSs.

TABLE II
ECONOMIC COST ANALYSIS

Parameter	Scenario 1	Scenario 2	Scenario 3
Exchanged power between BSSs and MGO (MW)	8.3	9.1	12.6
Exchanged power between DSO and MGO (MW)	159.7	153.7	145.1
BSSs cost ($)	4690	4274	4383
MGO cost ($)	6384	6995	6704

3) *Algorithm convergence and running time*

In this section, stopping criteria (37)-(38) and total costs are considered to compare the convergence performance of standard ADMM and ADMM with restart algorithm. As can be seen in Fig. 4, standard ADMM algorithm has converged to the global optimal solution within 43 iterations, where ADMM with restart algorithm has converged in 32 iterations, which illustrates better convergence performance. Moreover, Table III shows the amounts of cost, number of iterations, and calculation time for standard ADMM and ADMM with restart algorithm in both deterministic and stochastic optimization models. The results for cost, iterations, and calculation time for ADMM with restart algorithm are significantly less than those of standard ADMM. Due to the excess generated scenarios in stochastic model, the iterations, calculation time, and thus the total cost are larger than the deterministic optimization model. Additionally, to test the applicability and scalability of the proposed ADMM with restart algorithm, larger distribution systems with 13 buses, 34 buses, 123 buses, and 1300 buses [33] are utilized in Table IV as case studies. It could be observed that ADMM with restart algorithm converges faster.

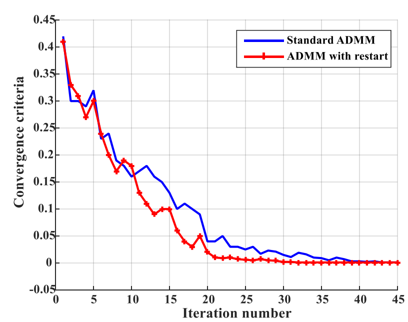

Fig. 4. Convergence performance of the ADMM with restart algorithm.

TABLE III
CONVERGENCE EVALUATION OF THE ALGORITHM

Model	Algorithm	Cost ($)	Iterations	Calculation time (s)
Deterministic	ADMM with restart	10410	28	27
Stochastic	ADMM with restart	10876	32	41
Deterministic	Standard ADMM	10797	37	36
Stochastic	Standard ADMM	11264	43	52

TABLE IV
THE NUMBER OF REQUIRED ITERATIONS FOR THE ALGORITHM

Test system	Number of required iterations	
	Standard ADMM	ADMM with restart
IEEE 13-bus	48	35
IEEE 34-bus	51	37
IEEE 123-bus	68	49
IEEE 1300-bus	191	126

V. Conclusion

In this paper, a bi-level optimal operation scheduling of MG and BSSs as two independent stakeholders with conflicting objectives was investigated. In this regard, for the upper-level optimization problem, the total cost of MGO including the cost of exchanging power between MGO and BSSs, cost of exchanging power between DSO and MGO, and costs related to the MTs, PVs, and loads was minimized. Lower-level optimization problem minimized BSSs' total cost including the cost related to the exchanged power between MG and BSSs, the swapping incomes, cost related to PV panels installed in the rooftop of BSS, and batteries degradation cost. In order to deal with the uncertainties, which some of them are modelled possibilistically and some of them can be described probabilistically, the possibilistic-scenario based approach considering correlation among uncertainties has been developed. Moreover, battery degradation cost was considered based on the DoD and the cycle life's intrinsic behavior of batteries. To solve the proposed MG-BSS operation scheduling problem, ADMM with restart algorithm in a fully decentralized fashion was put forward. To verify the effectiveness of the proposed model, a real-test MG system under different scenarios was considered. Moreover, to investigate the CPU time and scalability of the algorithm, extensive simulations of the standard ADMM and ADMM with restart algorithm were done on different standard test systems and results were compared accordingly. The simulation results revealed that BSSs sell power to the MG in peak load periods, while in off-peak load periods BSSs purchase power from MG to achieve higher profit. Similarly, MGO purchases less power from DSO in peak load periods comparing to that in off-peak load periods. Furthermore, it was shown that a trade-off between MGO cost and BSSs cost was achieved according to the proposed joint optimization of MG-BSS. It was illustrated that ADMM with restart algorithm has converged to the global optimum solution in less iterations, and thus less CPU time, compared to a standard ADMM. The results related to the cost, calculation time, and number of iterations for ADMM with restart algorithm were significantly less than those of standard ADMM, which indicates a superior performance and better convergence behavior.

As future works, the effect of traffic flow and operation of EVs on charging stations and the power grid will be studied and accordingly EVs' spatial moving and charging stations' working states will be analyzed through simulations. Also, to take market practices into account, participation of BSS aggregators as key players in the reserve market will be examined. Computationally efficient algorithms will also be implemented to facilitate solving larger-scale models representing more complex test systems.

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