Aggregation of 5G Base Station Backup Batteries for Flexibility Enhancement of Power System

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***Abstract*—As the penetration rate of wind and solar power in the power system rapidly increases, the power system requires more flexible resources to ensure the balance of power supply and demand. Advancements in information and communication technologies have led to the widespread deployment of 5G base stations, whose backup batteries remain idle most of the time and thus represent untapped potential for providing flexibility for the power system. In this regard, this paper applies the maximum inner approximation method to aggregate the scheduling feasible regions of massive 5G base station backup batteries (BSBBs) to provide flexibility for the power system. Case studies demonstrate that the proposed method can significantly improve the renewable energy consumption capacity and operational economy of the power system.**

Keywords—Base station backup batteries; Maximum inner approximation; Flexibility; Renewable energy

I. Introduction

With the relentless evolution of mobile communication technology towards higher data rates, reduced latency, and broader bandwidths, communication base stations can accommodate a significantly larger number of user accesses and are set to assume a greater volume of communication services than in previous eras. To guarantee the continuous power supply of base stations during mains power disruptions, a specific capacity of energy-storage batteries is customarily installed as backup power-supply apparatuses during the deployment of communication base stations. These batteries function as the energy source for base stations when the mains power is unavailable.

However, as China's power distribution network becomes more reliable, under normal mains power supply, 5G BSBBs remain idle, resulting in inefficient use of storage resources. Consequently, exploring strategies to integrate BSBBs into the unit commitment (UC) model emerges as a pivotal area of research. Existing literature has researched the evaluation methods of the schedulable capacity of 5G BSBBs.

As the proportion of new energy in the power system continues to increase and new energy becomes more important, efficient integration methods are urgently needed. Reference [1] proposed a control strategy for 5G base station energy storage considering communication load, which is conducive to evaluating the schedulable capacity under such special circumstances. Reference [2] developed a two-stage distributed collaborative dispatching method for massive flexible resources, which can be applied to coordinate 5G BSBBs with new energy sources. Reference [3] explored the collaborative optimization of the distribution network and 5G base stations considering communication load migration and energy storage dynamic backup flexibility, which helps understand how 5G BSBBs can support new energy integration in the distribution network.

The congestion problem in the distribution network has always been a challenge in the operation of the power system. Reference [4] put forward a method to eliminate distribution network congestion based on the spatial-temporal migration of multiple base stations, which shows the potential of 5G BSBBs in solving congestion problems.

Due to the limitation of computing power, the scheme of modeling numerous 5G BSBBs together with large-scale generating units is not feasible.

To address the above issues, the concept of aggregators has been widely adopted. Aggregators combine the feasible regions of numerous distributed resources into one entity and handle the decomposition and dissemination of scheduling commands. However, due to the diverse physical models and parameters of distributed resources, the shapes of their scheduling feasible regions in the decision-variable space differ. Computing the precise aggregated feasible region of massive distributed

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resources (i.e., calculating the Minkowski sum of distributed resources' feasible regions) is computationally challenging [5]. Thus, to strike a balance between the computational load and the accuracy of obtaining the aggregated feasible region, researchers have carried out numerous studies on approximation techniques. In aggregating distributed resources, the inner approximation method has emerged as the mainstream approach[6].

Inner-approximation methods guarantee that the approximated aggregated feasible region is a subset of the original. Thus, the derived aggregator scheduling strategies can be disaggregated to each resource. Existing inner approximation methods often seek the maximum inner approximation (MIA) feasible regions for distributed resources. Common approaches include box-based [7-8], ellipsoid-based [9-10], and polytope-based [11-16] MIA methods. The polyhedron-based MIA method has more advantages in representing complex-shaped feasible regions, covering the actual operation capabilities of resources more comprehensively. Moreover, its linear form enhances the efficiency of solving scheduling models [6]. This enables the aggregated feasible regions obtained by the MIA method to provide more reasonable scheduling schemes when participating in power system scheduling, further optimizing the operation of the power system, reducing costs, and improving reliability.

This paper applies the polytope-based maximum inner approximation (MIA) method to approximate the dispatch feasible region of 5G BSBBs, aggregating them to provide power and energy balancing services for the power system. Case studies verify that the proposed method can significantly improve the renewable energy consumption capacity and operational economy of the power system.

II. Aggregation of 5G Base Station Backup Batteries' Flexibility

A. Modeling of 5G Base Station Backup Batteries' Flexibility

Owing to the tidal-like patterns exhibited by the communication services and electrical loads of 5G base stations, the state of charge (SOC) of their backup batteries does not need to be constantly sustained at its peak level [17]. This characteristic endows the backup batteries with the potential to engage in power system auxiliary services.

For a single battery, its constraint conditions are as follows:

(1) Charging and discharging power constraint

$$-\overline{P_k^{BSBB,dis}} \le P_{k,t}^{BSBB} \le \overline{P_k^{BSBB,ch}} \tag{1}$$

Where k is the index of the BSBBs, t is the index of the period, $-\overline{P_k^{BSBB,dis}}$, $\overline{P_k^{BSBB,ch}}$ are the maximum discharging power and charging power of the BSBBs.

(2) SOC constraints

$$E_{k,t}^{BSBB} = E_{k,t-1}^{BSBB} + P_{k,t}^{BSBB}\Delta t \quad \forall t \ge 1 \tag{2}$$

$$E_{k,T}^{BSBB} = E_{k,0}^{BSBB} \tag{3}$$

$$\underline{E_{k,t}^{BSBB}} \le E_{k,t}^{BSBB} \le \overline{E_k^{BSBB}} \tag{4}$$

Where $E_{k,t}^{BSBB}$ is the battery capacity of the BSBB at time t; $E_{k,0}^{BSBB}$, $E_{k,T}^{BSBB}$ are the initial and final states of the battery respectively; $\underline{E_{k,t}^{BSBB}}$ is the minimum SOC at time t, $\overline{E_k^{BSBB}}$ is the maximum SOC.

Notably, the minimum SOC values of base-station backup batteries for each period are set based on the predicted power-consumption curves of individual base stations in their constraints, effectively ensuring the power-supply reliability of 5G base stations [18].

Nevertheless, incorporating numerous decision variables and constraints related to these batteries into the scheduling optimization problem leads to insufficient computing resources. To address this, existing studies have employed a battery aggregation model.

B. MIA-Based Aggregation of 5G Base Station Backup Batteries' Flexibility

According to the single battery model, the decision variable x_b^B of the BSBB can be represented as a polyhedron in a high-dimensional space formed by the intersection of a set of half-spaces:

$$P_b^B = \left\{ x_b^B \in R \mid A_b^B x_b^B \le B_b^B \right\} \tag{5}$$

The following will introduce the steps of aggregating the feasible regions of BSBBs using the MIA (Maximum Inner Approximation) method. First, by taking the average value of the feasible region parameters of all base station backup batteries under the same aggregator k, a basic polyhedron $P_k^{Bagg,0}$ of the aggregator k is constructed:

$$P_k^{Bagg,0} = \left\{ x^{Bagg,0} \in R \mid A_k^{Bagg,0} x^{Bagg,0} \le B_k^{Bagg,0} \right\} \tag{6}$$

$$A_k^{Bagg,0} = \sum_{b\in\Theta_k} A_b^B / |\Theta_{kk}|, \sum_{b\in\Theta_k} B_b^B / |\Theta_{kk}| \tag{7}$$

where, Θ_k is the set of all base station backup batteries within the jurisdiction of aggregator k.

Subsequently, the maximum inner-approximation feasible region (MIA-FR) of each base-station backup battery b under aggregator k is obtained by scaling and translating the basic polyhedron $P_k^{Bagg,0}$. The corresponding scaling coefficient ϕ_b^{MIA*} and translation coefficient $\varphi_b^{MIA^*}$ can be determined by solving the linear programming MIA problem, which is derived from Farkas' lemma [15]:

$$\begin{aligned} &\min_{s_b>0,\mathbf{G}_b\ge 0,\mathbf{r}_b} s_b \\ &\text{s.t.} \begin{cases} \mathbf{G}_b \mathbf{B}_k^{\text{Bagg},0} \le s_b \mathbf{B}_b^B + \mathbf{A}_b^B \mathbf{r}_b \\ \mathbf{G}_b \mathbf{A}_k^{\text{Bagg},0} = \mathbf{A}_b^B \end{cases} \end{aligned} \tag{8}$$

where $\phi_b^{MIA*} = 1/s_b^*$ and $\phi_b^{MIA*} = 1/s_b^*$ are the scaling and translation coefficients obtained from solving the MIA problem, respectively; $\phi_b^{MIA*} = 1/s_b^*$ is the matrix of auxiliary decision variables.

By calculating the Minkowski sum of all base station backup batteries $P_b^{B,MIA}$ under aggregator k, the aggregated feasible region of aggregator k under the MIA method can be obtained:

$$P_k^{Bagg,MIA} = \biguplus_{b\in\Theta_k} P_b^{B,MIA} = \sum_{b\in\Theta_k} \phi_b^{MIA*} P_b^{B,MIA} + \sum_{b\in\Theta_k} \varphi_b^{MIA*}$$
$$= \left\{ x_k^{Bagg} \in R \mid A_k^{Bagg,0}(x_k^{Bagg} - \sum_{b\in\Theta_k} \varphi_b^{MIA*}) \le \sum_{b\in\Theta_k} \phi_b^{MIA*} B_k^{Bagg,0} \right\}$$

III. Modeling of Unit Commitment With Flexibility Support from 5G Base Station Backup Batteries

A. UC Model

Add the above battery model to the Unit Commitment (UC) problem, and the proposed UC model is as follows:

The objective function is to determine an optimal set of unit start-stop schedules, output schedules of thermal units, and changes in the SOC of BSBBs, so as to minimize the total operating cost of the system. Its mathematical expression is as follows:

$$\min : \sum_{t=1}^{N_T} \left(\begin{array}{l} \sum_{i=1}^{N_G} \left(F_{Ci}\left(P_{i,t}\right) \cdot I_{i,t} + C_{i,t}^U + C_{i,t}^D \right) + \\ \sum_{w=1}^{N_W} C_{wd} \cdot P_{wd,t} + \sum_{k=1}^{N_K} C_{Bagg} \cdot P_k^{Bagg,MIA} \end{array} \right) \tag{9}$$

Among them, F_{C_i} represents the output cost function of the thermal unit i, and its unit is $\$/\mathrm{MW\cdot h}$. $P_{i,t}$ represents the active power output of thermal unit i at time t. $I_{i,t}$ represents a 0-1 variable indicating the start-stop status of the thermal i unit at time t. $C_{i,t}^U$ and $C_{i,t}^D$ represent the start-up cost and shut-down cost of the thermal unit i at time t respectively. C_{wd} represents the wind curtailment penalty cost of the wind turbine generator w, and $P_{wd,t}$ represents the wind curtailment power of the wind turbine generator w at time t. C_{Bagg} represents the battery charging and discharging cost, and $P_k^{Bagg,MIA}$ represents the charging and discharging power of aggregator k. N_G, N_W, N_K and N_T represent the total number of thermal units, the number of wind turbine generators, the number of aggregators and the total number of scheduling periods respectively.

Corresponding UC constraints are as follows:

(1) Power Balance Constraint

$$\sum_{i=1}^{N_G} P_{i,t} + \sum_{w=1}^{N_W} P_{w,t} = \sum_{d=1}^{N_D} \left(D_{d,t} - L_{d,t} \right) \tag{10}$$

$P_{w,t}$ represents the actual active power output of the wind turbine generator w at time t; $D_{d,t}$ represents the actual load of the load bus d; N_W and N_D represent the total number of wind turbine generator s and the total number of load nodes respectively.

(2) Thermal Unit Output Constraint

$$I_{t,t} P_t^{\min} \le P_{t,t} \le I_{t,t} P_t^{\max} \tag{11}$$

$P_i^{\min}$ and $P_i^{\max}$ represent the minimum active power output and the maximum active power output of the thermal unit i respectively.

(3) Wind-Turbine Output Constraint

$$0 \le P_{w,t} \le P_{w,t}^{\mathrm{f}} \tag{12}$$

$P_{w,t}^f$ is the predicted active power output of the wind turbine generator w at time t.

(4) Wind-Curtailment Constraint

$$0 \le P_{wd,t} \le P_{w,t} \tag{13}$$

$P_{wd,t}$ is the wind-curtailment power of the wind-turbine generator w at time t.

(5) Thermal Unit Ramp-Rate Constraint

$$\begin{cases} P_{i,t} - P_{i,t-1} \le \left(1 - I_{i,t}\left(1 - I_{i,t-1}\right)\right) R_i^U + I_{i,t}\left(1 - I_{i,t-1}\right) P_i^{\min} \\ P_{i,t-1} - P_{t,t} \le \left(1 - I_{t,t-1}\left(1 - I_{t,t}\right)\right) R_t^D + I_{t,t-1}\left(1 - I_{t,t}\right) P_t^{\min} \end{cases}$$

R_i^U and R_i^D represent the upper and lower limits of the increase and decrease of the output of the thermal unit i during the ramp-up process respectively.

(6) Thermal Unit Minimum Start-Stop Time Constraint

$$\sum_{k=t+1}^{t+t_i^{\mathrm{on}}} I_{i,k}^{\mathrm{g}} \ge t_i^{\mathrm{on}} S_{i,t}^{\mathrm{u}}, \sum_{k=t+1}^{t+t_i^{\mathrm{off}}} \left(1 - I_{i,k}^{\mathrm{g}}\right) \ge t_i^{\mathrm{off}} S_{i,t}^{\mathrm{d}} \tag{14}$$

t_i^{on} and t_i^{off} are the minimum start-up time and minimum shut-down time respectively, $S_{i,t}^{\mathrm{u}}$ and $S_{i,t}^{\mathrm{d}}$ is the start-stop state of the unit during the start-up/shut-down process.

(7) Power Balance Equation

$$\begin{aligned} F_{l,t} = &\sum_{i=1}^{N_c} \left(\Gamma_{l,i} P_{i,t} \right) + \sum_{w=1}^{N_w} \Gamma_{l,w} \left(P_{w,t} - P_{wd,t} \right) \\ &- \sum_{k=1}^{N_k} \left(\Gamma_{l,Bagg} P_k^{Bagg,MIA} \right) \end{aligned} \tag{15}$$

$\Gamma_{l,i}$, $\Gamma_{l,w}$ and $\Gamma_{l,Bagg}$ are the transfer factors of line l with the thermal unit i , the wind turbine generator w , and the battery aggregator k respectively.

B. *Aggregated Feasible Region*

This section takes an aggregator with 2 base-station backup batteries as an example to show the aggregated feasible region of the MIA method in two scheduling periods (T = 2). The parameters of the base-station backup batteries are shown in TABLE I. For simplicity, the charging and discharging efficiency of the battery is set to 1.

TABLE I. Parameters of base-station backup battery equipment

Equipment Parameters	Battery 1	Battery 2
Power Capacity (kW)	5	8
Energy Capacity (kWh)	16	25
Initial Energy Storage (kWh)	7	12
Minimum Energy Storage Value within 1 h (kWh)	10	14
Minimum Energy Storage Value within 2 h (kWh)	13	22

For the above system, two operating scenarios are set: S1: The output of new energy in the power system is abundant in two scheduling periods, and the dispatching center expects the base-station backup batteries to absorb as much new energy as possible.

In scenario S1, using the proposed MIA method, to achieve the maximum absorption of new energy by base-station backup batteries, the objective function of the MIA problem is set as:

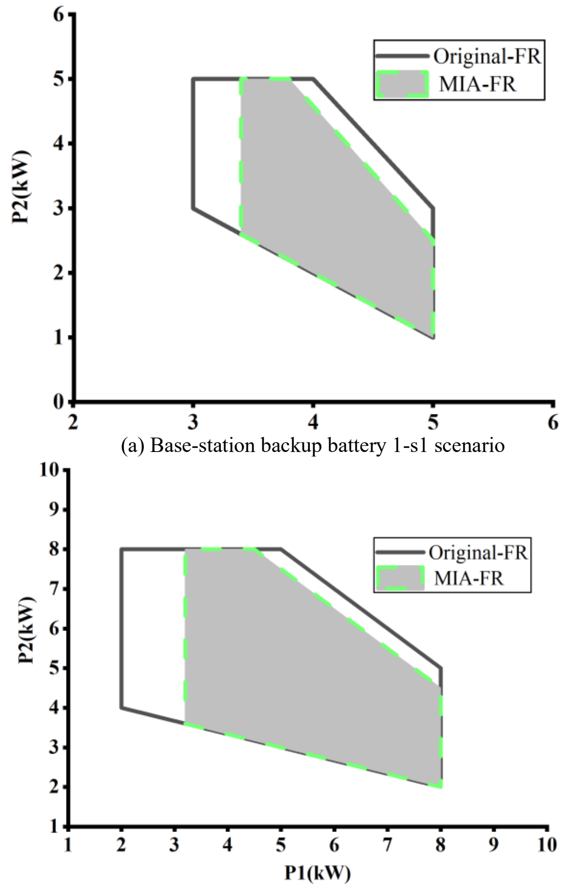
$$\max_{S_b>0,G_b\geq 0,r_b}\left(P_{b,1}^{B}+P_{b,2}^{B}\right) \tag{16}$$

$P_{b,1}^{B}$ and $P_{b,2}^{B}$ are the power decision variables of the base-station backup battery corresponding to period 1 and period 2 respectively. The inner approximation results of the original feasible regions of two base-station backup batteries are shown in Fig. 1.

First, analyze the inner-approximation effect of the MIA method. For scenario S1, to maximize the absorption of new energy in two scheduling periods, the two base stations should operate at the feasible solutions on the upper-right hypotenuse of their original feasible regions (theoretically optimal solutions).

Although the MIA method may not cover the optimal solutions of the original feasible regions, it significantly reduces the complexity. This reduction in complexity leads to a remarkable improvement in the calculation speed, enabling more efficient processing in power system scheduling scenarios involving base-station backup batteries.

In summary, the MIA-FR can cover as many feasible solutions for base-station backup batteries as possible and reduce the model complexity.



(a) Base-station backup battery 1-s1 scenario

(b) Base-station backup battery 2-s1 scenario

Fig. 1. BSBB original and MIA feasible region

IV. CASE STUDY

This chapter proves that base station backup batteries can improve the economic efficiency of power systems and increase the consumption rate of new energy sources. The case is run using the GUROBI solver on the MATLAB platform in a Windows 10 system with an AMD Ryzen 7 CPU and 16 GB of RAM.

A. *Parameter Settings*

The network configuration of the modified IEEE 14-bus system is depicted in Fig. 2. The day-ahead forecasted load and wind power output curves are shown in Fig. 3. A new wind farm with a capacity of 90 MW is added at both bus 1 and bus 2. The wind curtailment penalty is set at \$70 per MWh. It is assumed that the system is connected to 350 5G BSBBs, which can be incorporated into the power system dispatch operation. The capacity of a single 5G BSBB ranges from 5 to 10 kW. Additionally, the charging and discharging energy cost of the base-station backup batteries is set at \$30 per MWh.

Three comparative cases are established:

Case 1: The participation of base-station backup batteries in the UC model is not considered.

Case 2: Feasible region aggregation is not considered, and the UC model for numerous BSBBs is made directly.

Case 3: The MIA method is employed for the aggregation of BSBBs in the UC model.

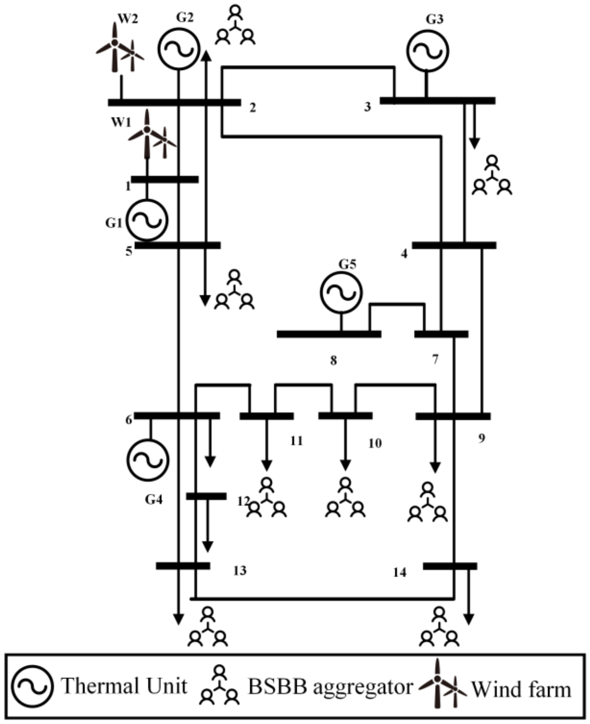


Fig. 2. Topology of the modified IEEE14-bus system

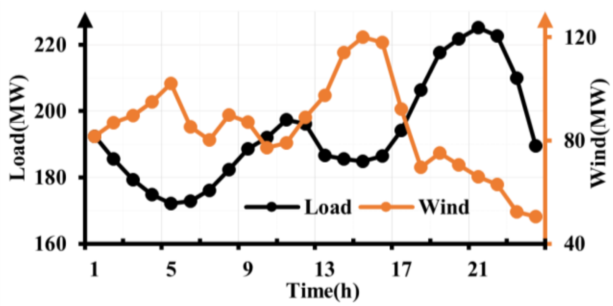


Fig. 3. Load and wind power output curves

TABLE II. Comparison of operating costs for cases 1 – 3

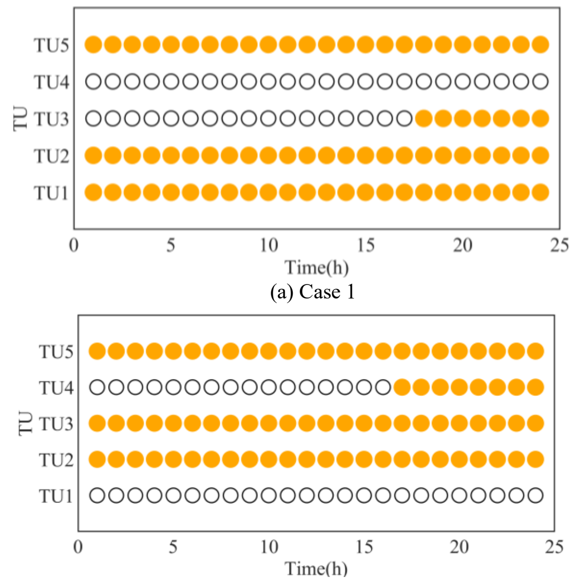
Comparison Items		Case 1	Case 2	Case 3
Thermal Unit Costs ($)	Start-Stop	1250	1375	1375
	Fuel	7663	7594	7597
BSBBs Costs ($)		\	504	543
Wind Curtailment ($)		9207	385	406
Total Cost ($)		19041	11227	11656

B. *Verification of the economic efficiency of Base-Station Backup Batteries Dispatch*

The operating costs of Cases 1-3 are presented in TABLE II, and the corresponding start-up state is shown in Fig. 4. In Fig. 4, solid circles represent the booted state, and hollow circles indicate the powered-off state.

A comparison of the costs of Case 1 and Case 2 reveals that when base-station backup batteries are involved in the dispatch operation, the system cost of Case 2 is 41.4% lower than that of Case 1. This indicates a significant improvement in economic efficiency, validating the effectiveness of incorporating base-station backup batteries into the UC model.

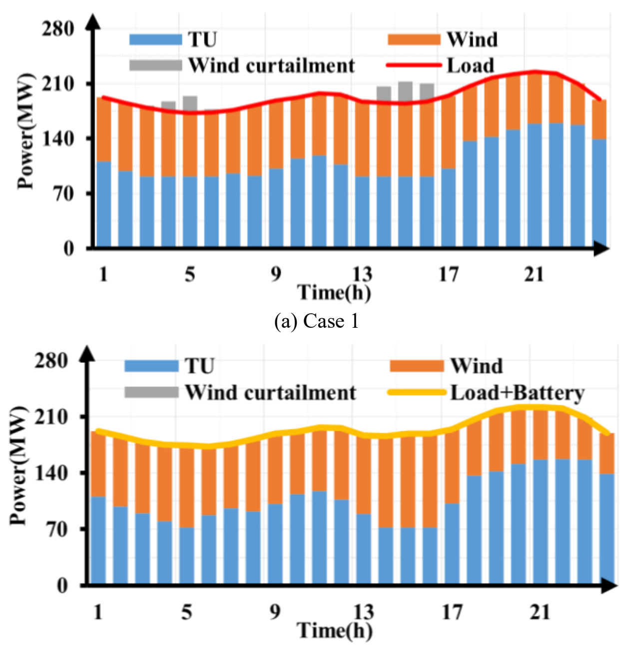
Fig. 5 shows the power outputs under Case 1 and Case 2 respectively. In Case 1, the TU1 was forced to start up to maintain the minimum power output limit of the system, resulting in a large amount of wind power curtailment.



(a) Case 1

(b) Case 2-3

Fig. 4. Comparison of switch state for Case 1-3



(a) Case 1

(b) Case 2

Fig. 5. Comparison of power output for Case 1–2

In contrast, in Case 2 the TU3 and TU4 with a smaller capacity were selected to start up, and the insufficient power output was supplied by the backup batteries of the base stations. The minimum power output of TU1 is 40MW, and the minimum power outputs of TU3 and TU4 are 25MW. As a result, the minimum power output limit of the system was reduced, leaving room for the integration of wind power. Additionally, the charging behavior of the backup batteries of the base stations during the 4-5h and 14-16h also promoted the integration of wind power into the power system. The above results verify the effectiveness of incorporating the backup batteries of base stations into the power and energy balance service of the power system for improving the integration of wind power and economic efficiency.

C. Verification of the Superiority of the Aggregation Method

A comparison of Case 2 and Case 3 is conducted to verify the effect of the MIA method in enhancing the superiority of the UC model with numerous BSBBs. The wind curtailment and the state of charge (SOC) of the base-station backup batteries under the two cases are shown in Fig. 6.

According to Fig. 5, wind curtailment occurs within 4-5 h and 14-16 h in Cases 2-3. Therefore, the base-station backup batteries should be charged during this period to absorb as much wind power as possible. Based on the solution results, the wind curtailment amounts in Case 2 and Case 3 are 365 and 406 respectively. This indicates that the MIA method (Case 3) has only a 5% deviation from the theoretical optimal situation (Case 2). Meanwhile, its solution complexity is significantly reduced, demonstrating its application value in large-scale energy storage scenarios.

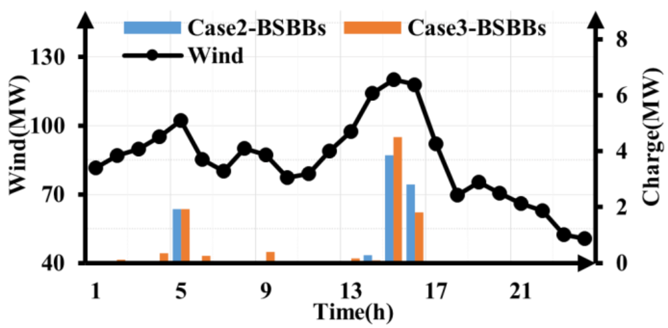


Fig. 6. Wind Curtailment and SOC Curves of Base-Station Backup Batteries under Case 2-3

V. Conclusion

This study has demonstrated the potential of integrating 5G base station backup batteries (BSBBs) into the power system to enhance flexibility and improve renewable energy consumption, and operational economy. By applying the polytope-based maximum inner approximation (MIA) method, we aggregated the scheduling feasible regions of massive BSBBs to provide valuable flexibility resources for the power system.

The case analysis verified the effectiveness of the proposed method, showing significant improvements in both renewable energy consumption capacity and the economic performance of the power system. These findings highlight the practical benefits of leveraging idle BSBBs as flexible resources and underscore the importance of innovative aggregation techniques for enhancing power system flexibility and efficiency.

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