Energy Management of Green Small Cells Powered by the Smart Grid

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Abstract. In this paper, we investigate energy management strategies for a small cell base station powered by local renewable energy, local storage, and the smart grid to simultaneously minimize electricity expenditures of the mobile network operators and enhance the life span of the storage device. Simulation results in different cases show that important cost reductions can be achieved by properly using the battery.

Keywords: Green communication · Small cell · Battery · Smart grid · Renewable energy · Energy controller

1 Introduction

The increasing growth of data traffic has led to a massive deployment of Small cell Base Stations (SBSs) to offer improved capacity and coverage [1]. As a consequence, the energy demand of cellular networks is growing, essentially because of the power consumption done at the level of base stations [2]. Based on this, managing the energy usage is primordial for Mobile Network Operators (MNOs) to ensure the economic and environmental sustainability of the future heterogeneous cellular networks.

Several concepts have been proposed to improve the energy consumption in mobile networks addressing network planning, protocols, and equipment [3]. Additionally, a lot of interest has been shown towards Renewable Energy (RE) usage in cellular networks as it provides the ability to lower the carbon emissions (by reducing dependence on fossil fuels) and realize long term cost savings thanks to reduced operating expenditure (OPEX) [4]. Moreover, local harvested energy enables off-grid base station deployment, where the connection to the electricity grid is expensive or impossible [5].

The difficulty associated with integrating RE sources is due to their inherent intermittence. In fact, their power fluctuates over the day and does not always correspond to the imminent energy demand. Energy storage is then introduced

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to ensure the reliability of RE and maintain the balance between energy supply and demand. In addition, the Smart Grid (SG) brings new opportunities to enable a better utilization of RE sources by allowing a two-way flow connection of decentralized production to the power grid.

In this paper, we are interested in the energy cost minimization of a SBS powered by the SG, the RE, and a local battery. Existing works in the literature have adopted two different approaches to address this issue. The first consists on formulating a cost minimization problem assuming that all the characteristics of the model are known or perfectly predictable. In this category, Leithon et al. [6] have studied an offline energy management for green base stations connected to the SG and equipped with a battery. He showed the impact of different energy pricing profiles and battery setups on the energy cost by solving the optimization problem using the Karmarkar algorithm. The second category uses online (or adaptive) methods to take into account the uncertainty of power price, production, and consumption. In particular, Niyato et al. [7] have investigated an online stochastic approach based on multi-period recourse to minimize the energy cost of a SG-powered green micro BS. This study has been extended in [8] by allowing a two way energy flow between the BS and the power grid. Additionally, by using the Kalman filter to forecast the power consumption and the RE generation profiles, the benefit of estimation-based models has been discussed in [9].

It is important to realize that the battery is an expensive investment of the system, and enhancing its life span is vital for an efficient return on investment. However, to the best of our knowledge, none of the proposed strategies have taken into consideration the battery life maximization. This motivated us to investigate the design of an energy controller and model its stochastic environment to jointly optimize the energy cost while operating the system in the most effective way to improve the battery life span.

The rest of the paper is organized as follows. System architecture is provided in Sect. 2. In Sect. 3, we propose a formulation of the cost minimization problem while extending the battery life span. Results are presented in Sect. 4. Finally, conclusions and perspectives are discussed in Sect. 5.

2 System Architecture

In the proposed architecture (illustrated in Fig. 1), the SBS, deployed to offer high data rate services to local mobile users, is powered by two sources of energy: the SG and RE. RE usage provides several benefits compared with a classic grid-powered SBS such as long-term cost savings and reduced carbon emissions. Moreover, a battery is used as a local storage device to offer flexibility in the energy utilization. The system is interconnected to the SG in a two-way energy flow, i.e., energy can be sold or bought from it. Finally, an energy supervision system (ESS) is in charge of scheduling the energy flow between each component of the system to reduce the cost of energy transactions with the SG and improve the battery life span. In the following, we present the chosen model for each component of the system.

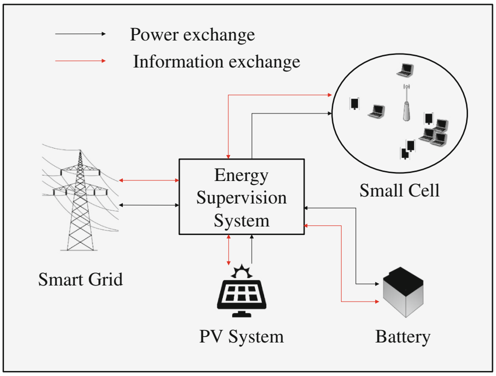

Fig. 1. System architecture of small cell power supervision.

2.1 Small Cell Base Station Power Consumption Model

We assume that the SBS load ρ follows a non-homogeneous Poisson process, which intensity depends on time. Additionally, the SBS can be either in the active state ($\rho > 0$) or sleep state ($\rho = 0$). The following equation gives the overall SBS power consumption P_{BS} [W] as a function of the traffic load [10]:

$$P_{BS}(t) = \begin{cases} P_0 + \Delta_p \cdot \rho(t) \cdot P_{max}, & \text{if } 0 < \rho(t) \leq 1 \\ P_{sleep}, & \text{if } \rho(t) = 0 \end{cases} \tag{1}$$

where P_0 is the power consumption at the minimum non-zero output power, Δ_p is the slope of the input-output power consumption, P_{max} is the maximum output power, and P_{sleep} is the power consumed in sleep mode.

2.2 Energy Storage Model

We use a Lithium-ion battery as the power storage device in our architecture. It can be charged by the locally produced energy or from the SG, and discharged to cater the SBS or sell energy to the SG. The battery is described by two parameters: its power and its State Of Charge (SOC), which describes the present battery capacity as a percentage of the nominal capacity C_N [Ah] (a SOC of 100 % means fully-charged and 0 % means fully-discharged). In the following, we present the selected models for the battery SOC and power.

State of Charge Model. The SOC variation is generally calculated using current integration. The rate at which the battery is charged or discharged, noted C_{rate} [s^{-1}], corresponds to the charge or discharge current intensity $i(t)$ [A] relative to the battery nominal capacity:

$$C_{rate}(t) = \frac{i(t)}{3600 \cdot C_N} \tag{2}$$

Periodically, for a given C_{rate}, we use the Ampere-Hour integral model to estimate the SOC variation [11]:

$$z(t+\delta t) = z(t) + \eta \int_t^{t+\delta t} C_{\text{rate}}(u)\mathrm{d}u \tag{3}$$

where δt represents the time between two SOC estimations and η is the battery Coulombic efficiency, equals to η_{dis} when discharging and η_{chg} when charging.

Battery Power Model. The battery is a pack that consists of individual modules, which are composed of cells organized in series and parallel. For simplicity of description, we assume that the battery pack comprises n_{s} cell modules connected in series, where each cell module comprises an individual cell. The following equation gives a simplified relation between charge or discharge current $i(t)$ and the voltage of cell k V_k [V] [12]:

$$V_k(t) = OCV(z(t)) + R_k \cdot i(t) \tag{4}$$

where OCV [V] (Open Circuit Voltage) is the cell voltage when the cell is disconnected from any circuit, z is the battery SOC, and R_k [Ω] is the internal resistance of the cell k, which depends on several parameters (SOC, current intensity, temperature, and State Of Health (SOH)) [13]. The OCV relationship with a given SOC can be measured experimentally by allowing the battery to reach equilibrium after being disconnected from any load for a long period of time [14]. Reiterating this method for different SOCs, the obtained OCV-SOC look-up table can then be used to elaborate an analytical OCV model. In this paper, we consider an n-order polynomial approximation model such that [15]:

$$OCV(z(t)) = \sum_{j=0}^{n} a_j \cdot z^j(t) \tag{5}$$

where $(a_j)_{j=1..n}$ are the polynomial coefficients calculated from the experimental OCV-SOC dependency function.

As a sign convention, we assume that the charge (resp. discharge) current and power have a positive (resp. negative) sign. Consequently, the power P_{batt} $[W]$ of the battery can be calculated using the sum of all cell powers :

$$P_{\text{batt}}(t) = \sum_{k=1}^{n_s} i(t) \cdot V_k(t) \tag{6}$$

From (Eq. 2) to (Eq. 6), and by supposing for simplicity that C_{rate} is constant during the period δt, we can rewrite the battery power formula as a function of two consecutive SOC values:

$$\begin{aligned} P_{\text{batt}}(z(t), z(t+\delta t)) = \sum_{k=1}^{n_s}\sum_{j=0}^{n} & A_{j,k} z^j(t) z(t+\delta t) \\ & - B_{j,k} z^{j+1}(t) + \alpha^2 \cdot R_k \cdot z^2(t+\delta t) \end{aligned} \tag{7}$$

Such that,

$$A_{j,k} = \alpha \cdot (a_j - 2\alpha \cdot R_k \cdot \delta_{1,j}),$$
$$B_{j,k} = \alpha \cdot (a_j - \alpha \cdot R_k \cdot \delta_{1,j}),$$
$$\alpha = \frac{3600 \cdot C_N}{\eta \cdot \delta t}$$

and $\delta_{1,j}$ is the Kronecker symbol, equals to 1 when $j = 1$ or 0 otherwise.

Battery Ageing. In general, batteries must operate within a safe operating area restricted by temperature, current, and voltage windows [11]. Not respecting these restrictions leads to a rapid attenuation of the battery performance (capacity loss and decrease of charge and discharge efficiencies) and even results in safety problem. The voltage restrictions can be translated into recommendations for the operating range of the battery SOC. In this paper, we restrict the battery usage on the specific range of the SOC $\Delta_{\text{soc}} = [20\,\%, 90\,\%]$ (see Fig. 2). Additionally, by using (Eq. 3), the current restriction can be reformulated as a limitation of the SOC variation in each decision period:

$$\forall t,\ \Delta SOC_{\min} \le z(t+1) - z(t) \le \Delta SOC_{\max} \tag{8}$$

2.3 Harvested Energy Model

A solar panel is used in the proposed architecture to collect solar energy and transform it into electricity via photo-voltaic (PV) effect. We assume that the solar radiation I_g [W/m^2] varies on a hourly basis and depends on several factors such as geographical location, time of the day, and local weather.

Let I_t be the random variable corresponding to the solar radiation at hour t. The vector $(I_1, ..., I_{24})$ of daily radiation is supposed to follow a multivariate Gaussian distribution (or Gaussian Process) $GP(\boldsymbol{\mu}_{\text{irrad}}, \boldsymbol{\Sigma}_{\text{irrad}})$, where $\boldsymbol{\mu}_{\text{irrad}}$ is

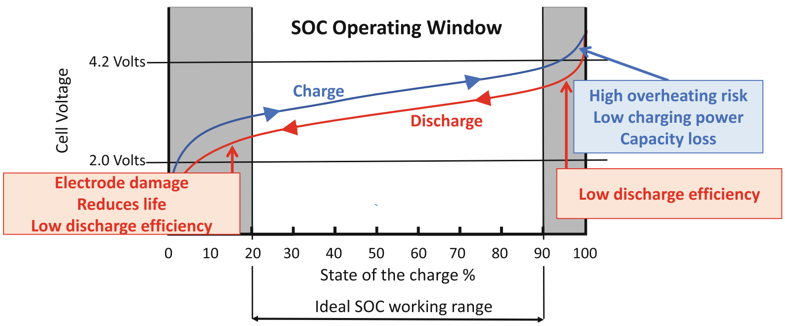

Fig. 2. Recommendations for the operating range of SOC of lithium ion battery [16].

a vector of size 1×24 composed of the hourly average radiations of the day, and $\boldsymbol{\Sigma}_{\text{irrad}}$ is the covariance matrix 24×24. These parameters are inferred from historical measures of solar radiations during one year [17]. Given the utilization of real historical data, the obtained stochastic process can capture all the phenomena that influence the solar radiation. Then, the hourly photo-voltaic output power P_{PV} [W] is given by the following relation [18]:

$$P_{\text{PV}}(t) = \eta_{\text{PV}} \cdot S \cdot I_{\text{g}}(t) \tag{9}$$

where η_{PV} is the energy conversion efficiency of the solar panels and S [m^2] is the total panels surface.

2.4 Price Signal Model

Maintaining a permanent balance between the power consumption and production is a major requirement for power grid operators to guarantee the security of energy supply. Dynamic pricing, which consists in varying the energy price with time, is a promising mechanism to adapt consumption profiles to the energy availability. In this study, we consider a stochastic dynamic energy price: the buying price $p_{\text{buy}}(t)$ [\$/kWh], i.e., the price at which energy is bought from the SG, is modeled by the Gaussian process $GP(\boldsymbol{\mu}_{\text{price}}, \boldsymbol{\Sigma}_{\text{price}})$, where $\boldsymbol{\mu}_{\text{price}}$ is a vector of size 1×24 composed of the hourly average buying prices of the day, and $\boldsymbol{\Sigma}_{\text{price}}$ is the covariance matrix. These parameters are inferred from historical data of electricity pricing for residential customers during one year [19]. Moreover, the price at which energy is sold back to the SG is set proportional to the buying electricity price such that $p_{\text{sell}} = \kappa \cdot p_{\text{buy}}$ [6].

3 Energy System Supervisor

We aim at minimizing the energy expenditures of a SBS powered by the SG, the RE, and a local battery under the constraint of the battery operating range Δ_{soc}, ΔSOC_{min}, and ΔSOC_{max} defined in Sect. 2.2. This optimization consists in managing the energy exchange between the SBS and the power grid over a horizon divided into T decision periods. We consider the length of a period to be Δ_t, in which the SBS load, the PV power, and the energy price are fixed. The ESS, in charge of the energy management, is composed of two layers:

1. The High Level Controller (HLC) minimizes the energy cost by imposing an objective value of SOC to the battery at each decision period.
2. The Low Level Controller (LLC) manages the energy flow between each subsystem in real time to realize the HLC objective while respecting the energy supply-demand balance.

Therefore, the ESS can schedule the amount of energy to exchange with the SG by selecting a succession of SOCs (the SOC variation means that the battery is being charged or discharged, see Sect. 2.2). In fact, for a given SOC value, if the energy locally produced is not sufficient to power the SBS and the battery, the LLC can evaluate the missing energy and notify the HLC to buy it from the SG. Similarly, if the energy produced or offered by the battery is excessive compared to the consumption, the surplus is sold. In this paper, we focus on the objective and constraints of the optimization problem at the HLC level to find the optimal SOC strategy $\mathbf{z}^* = (z^*(1), ..., z^*(T+1))$, which are defined as follows:

$$\mathbf{z}^* = \underset{(z(1),...,z(T+1))\in\mathbb{R}^{T+1}}{\text{argmin}} \sum_{t=1}^{T} p(t) \cdot E(t, z(t), z(t+1)) \tag{10}$$

Subject to

$$\frac{E(t, z(t), z(t+1))}{\Delta t} = P_{\text{BS}}(t) + P_{\text{Batt}}(z(t), z(t+1)) - P_{\text{PV}}(t) \tag{11}$$

$$z(t) \in \Delta_{\text{soc}},\ t = 1, ..., T+1 \tag{12}$$

$$\Delta SOC_{\min} \leq z(t+1) - z(t) \leq \Delta SOC_{\max},\ \text{t = 1,...,T} \tag{13}$$

where $(z(1), ..., z(T+1))$ is the multivariable decision vector that represents the battery SOCs over the optimization horizon, E is the amount of energy exchanged with the SG, and p is the buying energy price when $E > 0$ or the selling price when $E < 0$. (Eq. 10) is the objective function to minimize, which corresponds to the long term cost due to power transaction with the electrical grid. At all times, the balance between the power supply and demand is illustrated by the constraint (Eq. 11). In addition, during all the decision periods, the constraints (Eqs. 12 and 13) on the SOC have to be respected to improve the battery life span.

4 Results and Discussions

We consider a finite horizon of 24 h, i.e., T = 24 and Δ_t = 1 h. The profiles illustrated in Fig. 3 describe the average hourly SBS load, solar radiation, and energy buying price used in our simulations to model the intensity of the SBS load, the average vector of the solar radiation, and the average vector of the energy price, respectively. Concerning the SBS, the traffic load grows progressively and reaches the maximum around 21:00-22:00. In addition, we assume that the traffic between 2:00 and 9:00 is handled by the under-layer macro base station, such that the SBS load in this period is zero. For the solar radiation, the profile is characterized by a peak around midday and positive values during daytime. Finally, the energy price is marked by an increasing trend from low prices late at night to high values attained during the afternoon.

The battery OCV (Eq. 5) is modeled by a 2nd order polynomial such that $OCV(z(t)) = 2.9 + 0.13 \cdot z(t) - 0.008 \cdot z^2(t)$. Other simulation settings for each component of the system are summarized in Table 1. Without loss of generality, we consider that the battery parameters (nominal capacity, cell resistance, and

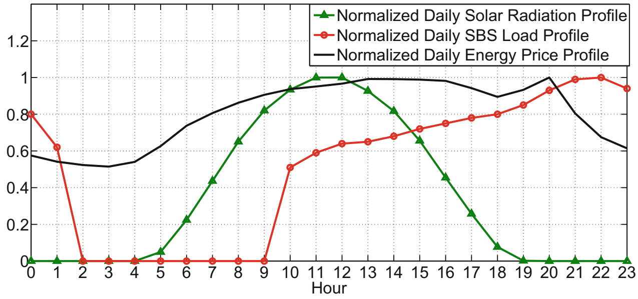

Fig. 3. Normalized average solar radiation [17], SBS load (based on [21]), and energy price profiles [19].

Table 1. Simulation Parameters.

	Parameter	Value	Parameter	Value
SBS	P_0	13.6 W	Δ_{p}	4
	P_{max}	0.13 W	P_{sleep}	8.6 W
Battery	n_{s}	5	C_{N}	12 Ah
	$\forall k\ R_k$	50 mΩ	η_{chg}	96 %
	η_{dis}	100 %	z_0	30 %
	$\Delta SOC_{\mathrm{min}}$	−70 %	$\Delta SOC_{\mathrm{max}}$	70 %
Solar panel	η_{PV}	14 %	S	0.25 m^2
Energy price	κ	90 %		

charge/discharge efficiency) are independent of the SOH, current intensity, and temperature.

Energy management of the SBS is a challenging issue due to the uncertainty in the environment. To address this issue, we first solve the non-linear constrained problem of Sect. 3 in the ideal case, i.e. the variations of the SBS load, solar radiation and energy price over all the optimization period are perfectly predicted by the ESS. The objective is to obtain the maximum performance of the ESS in term of the energy cost that can serve as an upper-bound in the realistic case, where the stochastic variables cannot be totally forecast. To converge to the optimal solution, we perform multiple runs of the interior-point algorithm implemented in Matlab [20]. Then we compare the performance of the above described *ideal* strategy with three other strategies averaged over five years:

1. The *reference strategy* systematically buys energy from the SG, in which the battery and the solar panel are not used.
2. The *naive strategy* seeks to reduce the immediate energy cost. At each decision period, either the PV production is sufficient to cover the SBS consumption, in which case the energy surplus is sold or the SBS consumes more than the energy produced, in which case the missing energy is purchased from the SG. Consequently the battery is never used.

3. The *optimized strategy* utilizes the solution of the optimization problem of Sect. 3, obtained in the case where the SBS load, the solar radiation, and the energy price variations correspond exactly to their respective average profiles (Fig. 3). Consequently, this strategy exploits the a priori knowledge of the environment to implement the same policy every day, for five years, without further adaptation to the actual variation of the stochastic environment variables.

Figure 4 represents the average SBS energy consumption, RE production, energy transactions with the SG, and energy stored in the battery with the ideal strategy. Notice that the energy transaction can be positive or negative, which means that the energy is purchased or sold to the SG, respectively. In general, the ESS buys electricity at night, when the PV system can not produce any energy, to power the SBS or/and store it into the battery. Additionally, we can observe that the amount of energy purchased from the SG depends closely on the energy price. Once the PV production becomes available or when the price is high, the ESS prioritizes the use of the energy produced by the PV panels and the energy already stored in the battery to feed the SBS, and sells a quantity of the surplus to the SG. Notice that all the decisions made by the ESS are consistent with

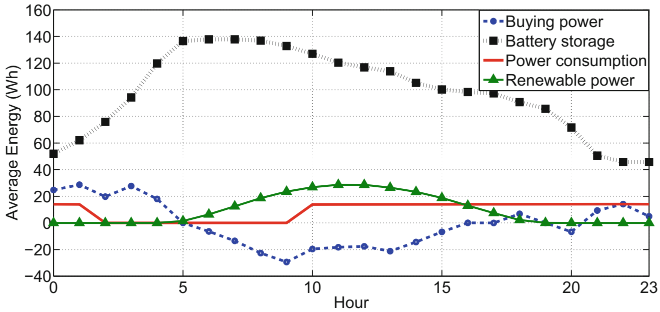

Fig. 4. Energy transaction, consumption, production, and storage with the ideal strategy, averaged over 5 years.

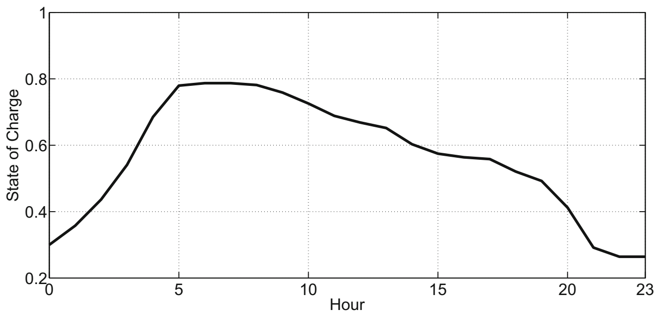

Fig. 5. Battery SOC with the ideal strategy, averaged over 5 years.

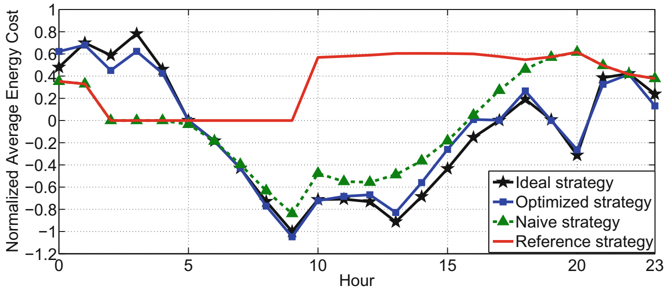

Fig. 6. Normalized daily energy cost for different strategies, averaged over 5 years.

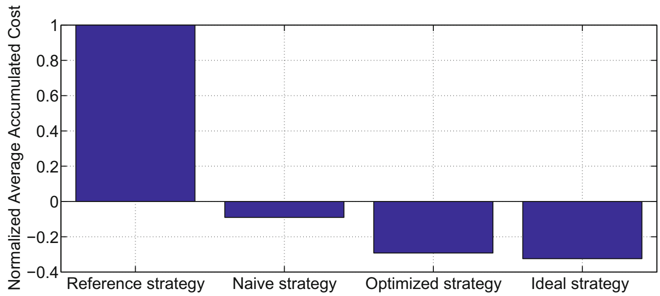

Fig. 7. Normalized strategies accumulated daily cost.

the recommended operating SOC range Δ_{soc} and SOC variations $\Delta SOC_{\mathrm{min}}$ and $\Delta SOC_{\mathrm{max}}$ as shown in Fig. 5.

Next we analyze the behavior of the *ideal* strategy in the light of the three strategies presented earlier. Figure 6 illustrates how the decisions in each case impact the hourly energy cost: although powering the SBS is a priority for all strategies, the energy surplus (when existing) is not similarly handled. On the one hand, the absence of local storage leads the *naive strategy* to always sell back the energy as soon as there is production excess; on the other hand, the *ideal* and *optimized* schemes buy electricity when the price is low and store energy for later consumption or transaction with the SG.

In Fig. 7, we compare the average cost over a day for each strategy normalized with respect to the *reference strategy* cost. The largest cost saving of 132 % compared to the *reference* is naturally achieved in the *ideal* case. The information about the energy consumption, production, and price trends carried in the average profiles allow the *optimized strategy*, even though not being totally adapted to its environment, to perform only 10 % less compared to the *ideal strategy* cost. Finally, the naive strategy achieves only one third of the *ideal strategy* cost savings. To finalize, we can observe that the supervised usage of the battery plays an important role for two reasons: 1. it allows more flexibility in energy purchase such that the system does not buy electricity only to match the energy consumption, but also to feed the SBS later when buying energy becomes expensive and 2. it creates opportunities to increase the RE value by offering it to sell when the prices are high.

5 Conclusion

In this paper, we have investigated the impact of using local renewable production and local storage to reduce small cell energy expenditures. We have proposed a controller that can jointly optimize the energy cost and maximize the battery lifespan. Simulation results have shown that the solution achieves very large cost reduction compared to basic strategies while respecting the battery constraints. As a future work, we aim at modeling the battery SOH and evaluating the quantitative impact of the proposed solutions on the battery life span improvement. We will also consider an online approach to minimize the SBS energy cost in stochastic environment.

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