Optimal Scheduling of Energy Storage System for Self-Sustainable Base Station Operation Considering Battery Wear-out Cost

Yohwan Choi and Hongseok Kim
Department of Electronic Engineering
Sogang University
Seoul, Korea
Email: hongseok@sogang.ac.kr

***Abstract*—Self-sustainable base station (BS) where renewable resources and energy storage system (ESS) are interoperably utilized as power sources is a promising approach to save energy and operational cost in communication networks. However, high battery price and low utilization of ESS just for uninterruptible power supply (UPS) necessitates active utilization of ESS. This paper proposes a multi-functional framework of ESS using dynamic programming for realizing a sustainable BS. We develop an optimal charging and discharging scheduling algorithm considering detailed battery wear-out model to minimize operational cost as well as to prolong battery lifetime. Our approach significantly reduces total cost compared to the conventional method that does not consider battery wear-out. Extensive experiments for several scenarios exhibit that total cost is reduced by up to 70.6% while battery wear-out is also reduced by 53.6%. The virtue of the proposed framework is its wide applicability beyond sustainable BS and thus can be also used for other types of load in principle.**

Keywords*—*energy storage system, battery wear-out cost, dynamic programming, peak shift, demand response, photovoltaic, sustainable base station

I. INTRODUCTION

Recently, as a concern that the existing base stations (BSs) without multiple power sources cannot handle the power crisis grows, a great attention about sustainable BS combining energy storage system (ESS) with renewable energy has been paid than ever from mobile operator [1]. In this regard, the viability of energy harvesting with ESS and solar panel at BS [2], and different types of power solutions for off-grid BS [3] are studied. These works were triggered by the fact that a conventional BS using the grid as a major power source indeed cannot cope with emergency power failure caused by malfunctions or natural disasters. Energy saving is another key factor for sustainable BS. In the communication networks, around 350 TWh was consumed as the amount of worldwide electricity in 2012, which corresponds to an average annual growth rate of 10% since 2007 [4]. In particular, BSs are responsible for over 70% of the required electricity bill to maintain the cellular networks [5]. For this reason, we see that there is a sufficient room for saving the energy expense in proportion to lots of energy consumption if BS works in concert with both ESS and renewable energy actively.

One of the essential factors to be considered while using the ESS is a battery degradation since high price of battery consisting of ESS makes it difficult to be utilize widely. Therefore, it is surely necessary to apply the battery characteristics related with lifetime in optimization process. We summarize our contribution as follows. First, we provide a framework for multi-functional ESS operation to exploit demand response (DR), peak shift and time of use (TOU) all together to minimize total operational cost. In doing this we further investigate detailed battery wear-out cost and propose an optimal ESS charging and discharging strategy using dynamic programming (DP). Second, we verify the results of battery lifetime extension through practical BS operational scenarios. We analyze the trade-off between operational cost and battery cost with respect to the weighting factor β, which reflects how much an operator cares about battery wear-out in optimization process. Third, our approach outperforms the conventional method without battery wear-out model. Our extensive experiments show that total cost and battery cost can be reduced by up to 70.6% and 53.6%, respectively. In order to provide practically meaningful cost analysis, we comprehensively consider practical sustainable BS environment such as photovoltaic (PV) generator, converter, BS load, and demand side management (DSM) conditions, i.e., DR, peak shift and TOU.

II. SYSTEM MODEL

A. Sustainable BS model in smart grid environment

We consider a system model for smart grid environment where BS load, grid, PV generator with converter and ESS have interoperable connections with each other as illustrated in Figure 1. Let N be the number of BSs, and each BS is equipped with PV generation facility. We assume that electricity generated by PV resource is firstly used with priority for supporting BS load. The rest of required power is provided by output power of ESS at time t denoted by $P_B(t)$ and the power from grid denoted by $P_G(t)$. The basic power balance equation then can be represented by $P_B(t) + P_G(t) = \sum_{i=1}^{N}(P_{L_i}(t) - P_{PV_i}(t))$ where i is the BS site index and $P_{PV_i}(t)$ is the output power of PV_i. $P_G(t)$ should be less than or equal to maximum grid constraint denoted by $P_G^{\max}$. Our main objective is to draw an optimal ESS charging and discharging trajectory with

This work was supported in part by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT and Future Planning under Grant NRF-2014R1A1A1006551.

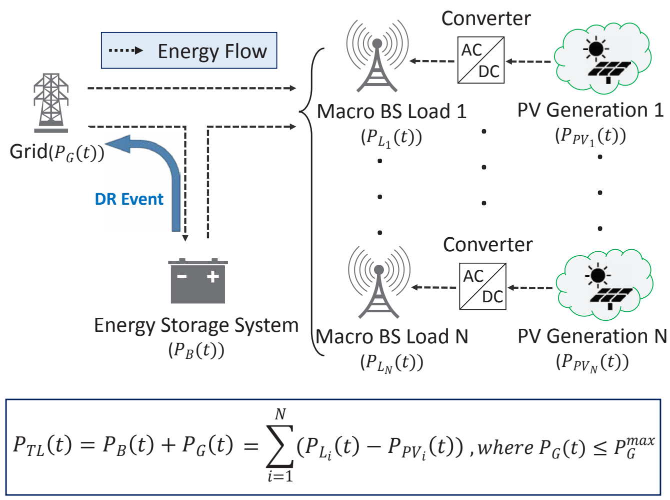

Fig. 1. ESS system model for sustainable base stations.

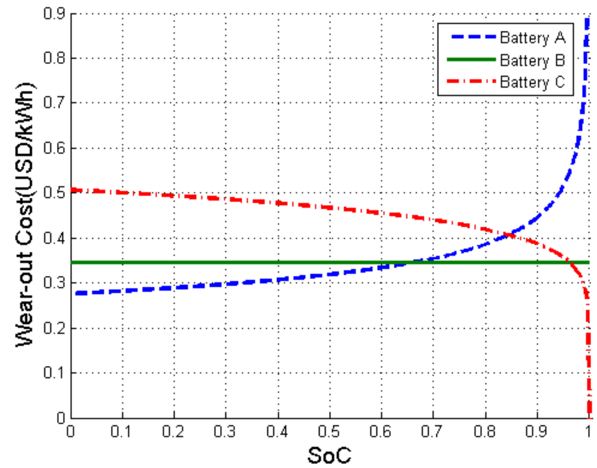

Fig. 2. Battery wear-out models.

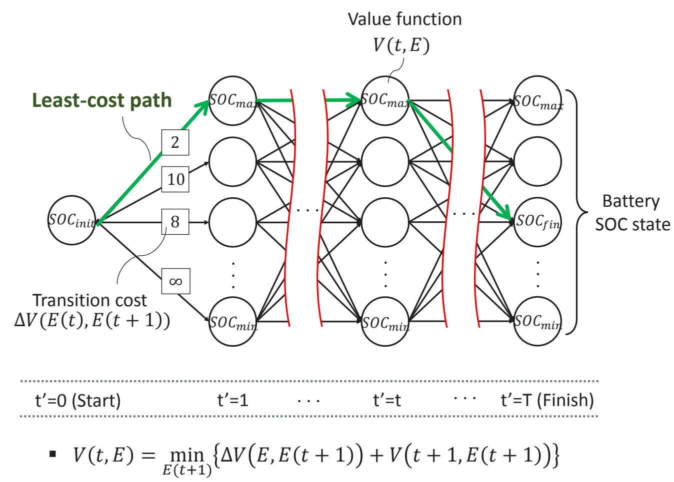

Fig. 3. Simple graph representing the dynamic programming.

minimum operational cost considering battery degradation and multi-functional benefits such as DR, peak shift and TOU, while satisfying power balance equation.

B. Battery Wear-out Model

To capture battery degradation cost, which is critical in minimizing BS operational cost, we leverage the cycle life data; the battery lifetime is measured by the number of charging and discharging cycles, i.e., cycle life. Cycle life is mainly determined by how deeply the battery is used, i.e., by the depth of discharge (DoD). In this work, we consider three types of cycle data obtained from different kinds of batteries, denoted by Battery A, B and C. In [6], wear-out density function $W(s)$ is defined as a cost density where s denotes state of charge (SOC); it is interesting that battery degradation from using the battery by depth D can be obtainable by integrating $W(s)$. Thus the wear-out density function $W(s)$ is derived as (1) [6],

$$W(s) = \frac{Battery\ price(USD/kWh)}{2 \times Battery\ capacity(kWh) \times \mu^2} \times \frac{b(1-s)^{b-1}}{a}, \quad (1)$$

where both a and b are battery specific coefficients which can be obtained by curve fitting of battery cycle life test data and μ denotes the battery efficiency. Three kinds of $W(s)$ are shown in Figure 2 as follows.

III. Multi-Functional ESS Optimization

A. Multi-Functional Framework Using DP

The optimization of ESS scheduling is to obtain the charging and discharging path achieving the minimum value function $V(t, E)$ in (2), where $t \in \mathcal{T}$ is the *discrete* time index, $\mathcal{T} = \{1, \cdots, T\}$ and E is the stored energy state in the battery. We split $V(t, E)$ into two parts, the *operational cost* denoted by $U(t, E)$ from a certain discrete time t to end time T, and the *battery wear-out cost* arising from charging and discharging, denoted by $W(t, E)$. Then $U(t, E)$ and $W(t, E)$ are combined by a weighting parameter β that controls the trade-off between operational cost and battery wear-out cost.

$$V(t, E) = U(t, E) + \beta W(t, E). \quad (2)$$

$U(t, E)$ and $W(t, E)$ are defined as follows

$$\begin{aligned} U(t, E) &= \sum_{t'=t}^{T}(P_G(t')C(t')\mathbf{1}\{P_G(t') \ge 0\} \\ &- P_B(t')D(t')\mathbf{1}\{DR\ is\ activated\}), \quad (3) \end{aligned}$$

$$W(t, E) = \sum_{t'=t}^{T} C_B(E(t'), E(t'+1)), \quad (4)$$

where $C(t')$ is TOU electricity price; $\mathbf{1}\{\}$ is an indicator function returning 1 if the condition is true, and 0 otherwise; $P_B(t')$ is the output power of battery; $D(t')$ is the DR incentive price; $C_B(E(t'), E(t'+1))$ in (4) is the battery wear-out cost when the stored energy in the battery changes from $E(t')$ to $E(t'+1)$. Second term in (3) is for maximizing economic profit from DR incentive by discharging the ESS. Then the state transition cost from the state $(t, E(t))$ to $(t+1, E(t+1))$ is given as $\Delta V(E(t), E(t+1))$. By using this state transition cost and satisfying the power, energy and maximum peak constraints, we calculate the value function $V(t, E)$ for every t and E by solving the Bellman equation. The process starts at $t = T$ where the value function has zero value and goes backward until reaching the initial time. This results in determining the least cost path for every possible energy state at every time step as can be seen in Figure 3.

IV. Analytical Experiment Results

In Figure 4 and Figure 5, we investigate the effect of the multi-functional DP with battery wear-out model. SOC reaches only up to 0.73 because, beyond that point, the profit from TOU would be less than the cost from the battery wear-out. This result does not have frequent charging and discharging processes after the DR event. This is to reduce the battery cost caused by changes of battery SOC. As a result, although the electricity cost increases by 16.4%, the total cost decreases by 70.6% compared to the conventional method without considering battery wear-out. This is mainly due to the reduced battery cost. In Figure 6, as changing β from 0 to 1, we plot the operational cost and the battery cost; the battery cost generally decreases when β grows while the operating cost increases. This is because if we focus more on battery degradation by increasing β, the transition cost calculated by the wear-out function increases. Thus, the scheduler tries to suppress the battery cost, which results in the increase of the operating cost. Consequently, there is a trade-off relationship between the operating cost and the battery cost.

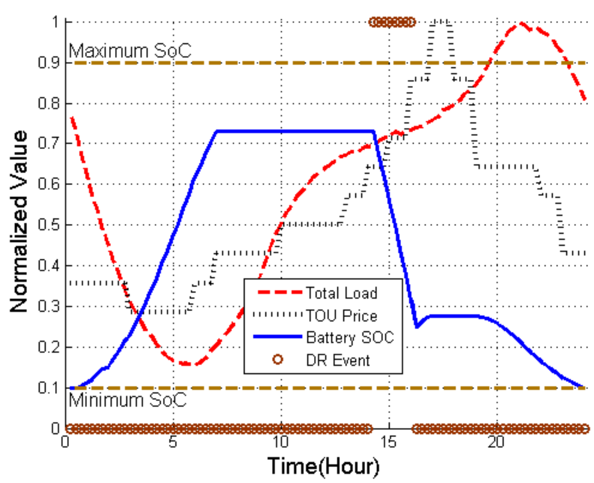

Fig. 4. SOC strategy based on multi-functional ESS with battery wear-out.

V. Conclusion

In this paper, we have proposed a novel framework for multi-functional ESS scheduling to minimize total operational cost of sustainable BS using DP optimization. In designing this strategy, we have considered practical sustainable BS environment as well as detailed battery wear-out model based on realistic data. Multi-function of ESS includes DR, peak shift and TOU to get the most profit and guarantee the maximum peak constraint as well. Our scenario-based simulations have demonstrated that the proposed approach significantly reduces the total cost and battery usage by up to 70.6% and 53.6%, respectively, compared to the conventional method without considering battery wear-out.

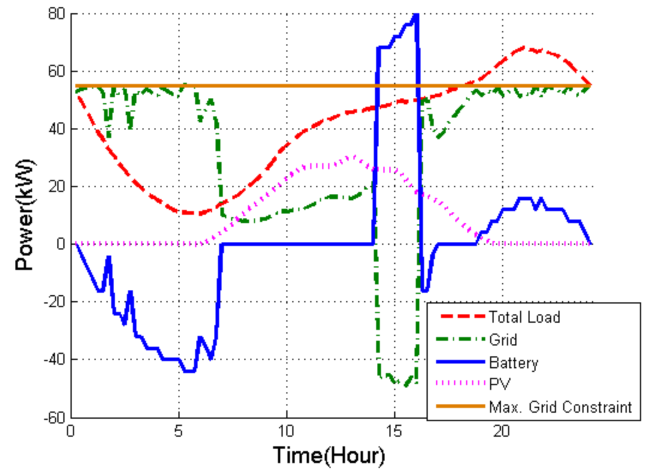

Fig. 5. Power strategy based on multi-functional ESS with battery wear-out.

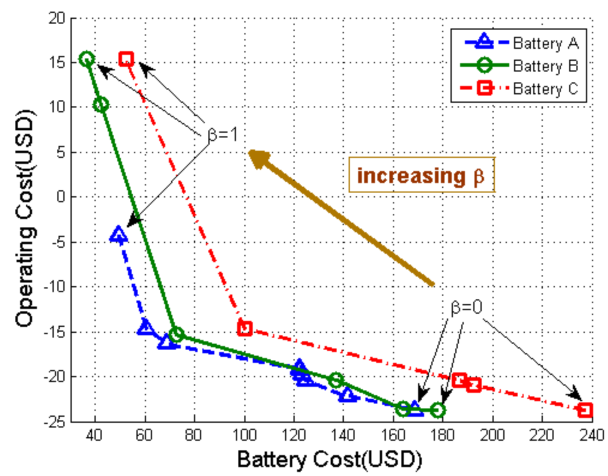

Fig. 6. Trade-off between operating and battery cost.

References

[1] W. Issaadi, A. Khireddine, and S. Issaadi, "Management of a base station of a mobile network using a photovoltaic system," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 1570–1590, 2016.

[2] D. Zordan, M. Miozzo, P. Dini, and M. Rossi, "When telecommunications networks meet energy grids: cellular networks with energy harvesting and trading capabilities," *Communications Magazine, IEEE*, vol. 53, no. 6, pp. 117–123, 2015.

[3] A. M. Aris and B. Shabani, "Sustainable power supply solutions for off-grid base stations," *Energies*, vol. 8, no. 10, pp. 10 904–10 941, 2015.

[4] Y. Ye, F. Jimenez Arribas, J. Elmirghani, F. Idzikowski, J. Lopez Vizcaino, P. Monti, F. Musumeci, A. Pattavina, and W. Van Heddeghem, "Energy-efficient resilient optical networks: Challenges and trade-offs," *Communications Magazine, IEEE*, vol. 53, no. 2, pp. 144–150, 2015.

[5] C.-X. Wang, F. Haider, X. Gao, X.-H. You, Y. Yang, D. Yuan, H. Aggoune, H. Haas, S. Fletcher, and E. Hepsaydir, "Cellular architecture and key technologies for 5g wireless communication networks," *Communications Magazine, IEEE*, vol. 52, no. 2, pp. 122–130, 2014.

[6] S. Han, S. Han, and H. Aki, "A practical battery wear model for electric vehicle charging applications," *Applied Energy*, vol. 113, pp. 1100–1108, 2014.