Optimal Scheduling of Energy Storage System for Self-Sustainable Base Station Operation

Yohwan Choi and Hongseok Kim *

Abstract – In this paper we aim to develop an optimal charging/discharging scheduling of energy storage system (ESS) for energy self-sustainable base station operation. Specifically, we minimize the operational cost under time of use (TOU) electricity pricing of smart grid considering the battery characteristics and the implementation of demand response. We obtain an optimal ESS scheduling for energy self-sustainable base station operation and also analyze the results from economic perspective.

Keywords: Base Station, Energy Storage System, Renewable Energy, Dynamic Programming, Optimization, Battery Charging/Discharging Scheduling, Demand Response

1. Introduction

A conventional base station (BS) using the grid as a major power source cannot cope with emergency power failure caused by malfunctions or natural disasters [1]. As an example, India suffered the largest electrical blackout in 2012, affecting an area of encompassing about 670 million people, or roughly 10 percent of the world's population. The infrastructure including communication facilities was not available from a low of 24 hours to a high of 50 hours. As a perception that the existing BS without multiple power source cannot handle the crisis grows, an attention about energy self-sustainable BS combining energy storage system (ESS) with renewable energy is also increasing recently. The definition of ESS is used by the California Public Utilities Commission (CPUC) stated as 'Commercially available technology that is capable of absorbing energy, storing it for a period of time, and thereafter dispatching the energy [2]. The main contribution of this research is to build an optimal ESS scheduling strategy specialized in global system for mobile communications (GSM) BSs based on a real database of load profile and renewable generation as well as consider demand response (DR) event signal, time of use (TOU) and battery depreciation cost in terms of battery chemical characteristics. TOU rate is one of the pricing strategies used to drive down demand at peak load hours by imposing high electricity price in order to influence customer's consumption and improve power system efficiency.

From this perspective, we present the remainder of the paper is organized as follows. We introduce the system model in Section 2. The optimal energy cost minimization problem is discussed in Section 3. In Section 4, we present the simulation results about our proposed optimal algorithm. Conclusions and future works are presented in Section 5.

* Dept. of Electronic Engineering, Sogang University, Korea (hongseok@sogang.ac.kr)

2. System Modeling

In this section, we provide analytical descriptions for the representation of ESS operating environment and review the dynamic programming applied to solving the optimization problems briefly. Based on these definitions, we will formulate a design optimization problem in Section 3.

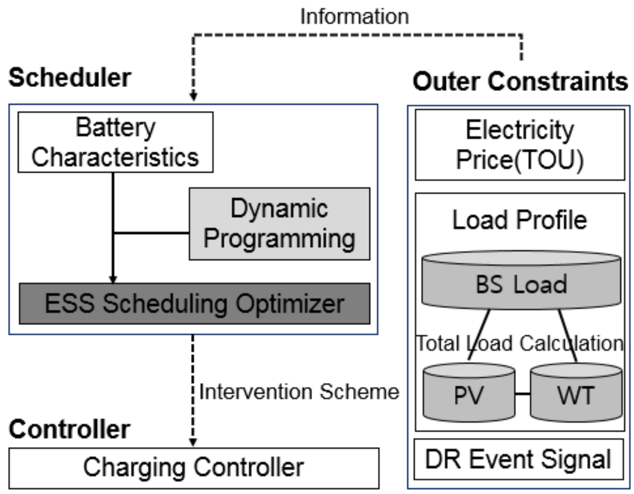

Fig. 1. Structure of overall ESS scheduling system

2.1 Problem Formulation

The overall ESS scheduling system needs to have a systematic structure. For instance, a three part structure including external constraints, scheduler, and controller can be used as illustrated in Fig. 1. Fig. 2 illustrates a scenario for the proposed smart grid environment where BS load, grid, renewable generator and ESS have interoperable connections with each other.

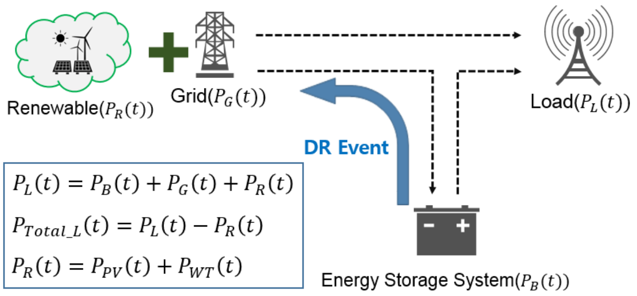

Fig. 2. System Model

We assumed that electricity generated by photovoltaic (PV) and wind turbine (WT) is totally used for supporting the BS load. Basic notations used in this work are defined in Table 1.

Table 1. Notations used in this paper

$P_B(t)$	Output power of ESS (kW)
$P_G(t)$	Power from grid (kW)
$P_L(t)$	Original BS load profile (kW)
$P_R(t)$	Renewable generation (kW)
	$P_{PV}(t) + P_{WT}(t)$
$P_{PV}(t)$	Photovoltaic (kW)
$P_{WT}(t)$	Wind turbine (kW)
$P_{Total\_L}(t)$	Total BS load profile (kW)
	$P_L(t) - P_{PV}(t) - P_{WT}(t)$

2.2 Dynamic Programming

Dynamic programming was introduced by Richard Bellman in the 1950s as a general optimization approach widely used. It can provide globally optimal solution under the non-linear systems which have various types of constraints. More detailed fundamental principles may be found in [3]. By using backward recursion, the process starts at the end time step until reaching the first time step, then optimal ESS scheduling solution achieving the least cost path is numerically computed [4].

3. ESS Management Optimization

$V(k,E)$ in (1) is defined as the sum of electricity price considering battery chemical characteristics from time step k to end step T and $W(k,E)$ in (2) means a battery depreciation cost arising from charging/discharging. Therefore, possible value function can be formulated as the superposition of $V(k,E)$ and $W(k,E)$ in (3) [4].

$$V(k,E) = \sum_{t=k}^{T} P_G(t)C(t)1_{\{P_{G(t)} \geq 0\}}, \tag{1}$$

$$W(k,E) = \sum_{t=k}^{T} C_B(E(t), E(t+1)), \tag{2}$$

$$U(k,E) = V(k,E) + \eta W(k,E), \tag{3}$$

where η marks weighting factor; $C(t)$ is an electricity price; $C_B(t)$ is a battery price; $1_{\{\}}$ is an indicator function returning 1 if the condition is true, and 0 for opposite case. Since it is assumed that the state of charge (SOC), an index that shows the available battery capacity expressed as a percentage, is zero at start and end operation point, we transform (3) into the objective function (4) with the constraints as (5)-(7) by applying $k = 0$ and $E = 0$. (4) is equivalent to minimizing $U(0,0)$, that is, to find minimum cost over the whole period, starting with an empty ESS $E = 0$. $E(t)$ marks energy in a battery and P marks output power from a battery.

$$\text{Min}\ U(0,0), \tag{4}$$

$$\text{s.t}\ \ P_L(t) = P_B(t) + P_G(t) + P_R(t), \tag{5}$$

$$0 \leq E(\mathrm{t}) \leq E_{max}, \tag{6}$$

$$\frac{d}{dt}E = f(P,E), \tag{7}$$

4. Simulation Results

To extract the BS load profile, 60 instant power consumption data for one day are sampled randomly from the real GSM BS for each season over one year and averaged. The results is taken once every 15 minutes over a duration of one day (24 hours). Following this, a time step in our simulation refers to a 15 minutes time interval, and we have 96 time steps during 24 hours. We conduct the simulations on the real database of the GSM base station as well as PV and WT farms in Belgium (Belgium, Elia, Aug. 2014). Also, TOU used in this work is based on Industrial(B) high-voltage(A) option(Ⅱ) electricity tariff in summer season of the Korea Electric Power Corporation (KEPCO). Based on the power consumption data per day, we assume that a large number of GSM BSs share ESS and electricity generated from PV and WT, and they are connected with the same bus.

By observing Fig.3, the ESS stores energy bought from the main grid when the electricity price is low (12 am to 9am), and consumes the stored energy to support required BS load when the electricity price in main grid is high (10 am to 12 pm and 1 pm to 5 pm). Especially, DR incentive has been applied during the period when DR event signal is activated (1 pm to 4 pm). Customers can get an economic profit by the amount of power reduction that they achieve during this period (0.47 US dollar/kWh). Hence, the ESS is able to store the cheap energy and discharge it when the energy in main grid is expensive, thus reduces the total operating cost. Gains with dynamic programming optimization are around 17.6% higher than with the conventional management in terms of electricity price per day. Total operation profit including DR incentive and capacity payment is about 431 US dollar per day. Indeed, the performance of ESS helps the BS operator maximize the profits.

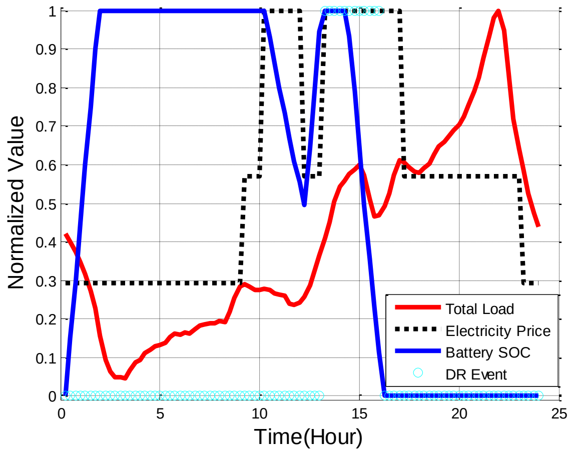

Fig. 3. ESS schedule with DP optimization

5. Conclusion and Future Work

In this paper, we proposed an optimal ESS scheduling policy for minimizing ESS operating cost in supplying real GSM BS facilities. Specifically, we considered the environment where ESS and renewable generators are installed. Our novel contribution includes the consideration of battery depreciation cost, various inner characteristics of battery, e.g., cycle life, DoD and SOC. Furthermore, we investigated the latest energy policy of government by considering the model that BSs directly participate in DR market with surplus electricity to get an economic profit. The energy efficiency issue, such as the bounds on the operation temperature of battery or charging/discharging efficiency according to SOC, will be studied in future work.

Acknowledgements

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

References

[1] GSMA, “GREEN POWER FOR MOBILE BI ANNUAL REPORT”, 2014

[2] Elizaveta Malashenko, Rebecca Lee, et al. "Energy Storage Framework Staff Proposal", *California Public Utilities Commission*, p.4, April, 2013

[3] D. P. Bertsekas, Dynamic Programming and Optimal Control, Belmont, MA, USA: Athena Scientific, 1995, vol. I

[4] Levron, Yoash, Josep M. Guerrero, and Yuval Beck. "Optimal power flow in microgrids with energy storage." *Power Systems, IEEE Transactions on* 28.3 (2013): 3226-3234.P.

Yohwan Choi
He received the B.S. degree in Electronic Engineering from Sogang University in 2013. He is working toward the MS-Ph.D. Integrated degree in Electronic Engineering at the same university. His current research interests are smart grid, ESS scheduling, Battery Management System (BMS), and Electrical Vehicle (EV).

Hongseok Kim
He is an Associate Professor in the Department of Electronic Engineering at Sogang University, Korea. He received his B.S. and M.S. degrees in electrical engineering from Seoul National University in 1998 and 2000, respectively, and the Ph.D. degree in electrical and computer engineering at the University of Texas at Austin in 2009. His research interests include energy big data analysis, optimization and control in smart grid with ESS and renewable, demand response, etc.