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Development of energy storage system scheduling algorithm for simultaneous self-consumption and demand response program participation in South Korea

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A B S T R A C T

This paper presents an Energy Storage System (ESS) scheduling algorithm for the simultaneous self-consumption and Demand Response (DR) program participation in South Korea. To do this, two ESS scheduling algorithms are developed to participate in the DR program in South Korea. The first algorithm is designed to maximize the customer's profit using energy arbitrage, after which the remaining ESS capacity is used to participate in the DR program. The second algorithm is designed to maintain its self-consumption at a minimum so that the ESS can participate in the DR program as much as possible. In addition, both algorithms have the same objectives of minimizing the peak demand in order to reduce the contract power as well as to minimize the charge/discharge cycles in order to lengthen the life of ESS. The developed algorithms are validated using the actual industrial load profiles with ESS. Furthermore, the economic analysis is performed when ESS that applies two different algorithms participates in the DR program. The simulation results indicate that the proposed algorithm prioritizing the self-consumption shows a relatively higher profit than that obtained by prioritizing the DR participation owing to uncompetitive compensation of the current South Korea DR program.

1. Introduction

The fundamental changes in both the supply and demand of a nation's electric grid introduce both challenges and opportunities to advance the capabilities and system design of the existing electric grid. This has resulted in a collaborative effort to enable the modernization of the electric grid [1]. Grid modernization involves achieving an improved efficiency by reducing electrical losses and promoting energy conservation, a reduced electrical demand during peak demand periods, improved reliability, better utilization of existing assets, and realizing a more effective integration of distributed generation [2,3]. Modern grids are required to be more flexible, robust, and reliable.

In grid modernization, Demand Response (DR) is considered as a promising way of improving the system flexibility by accommodating variable generation sources. Electric utilities in many countries are considering and operating DR to reduce the power delivery cost by avoiding new investments in terms of the addition of new generation and power delivery facilities [2]. DR can be classified into two types: price-based DR and incentive-based DR [4]. Price-based DR refers to changes in the electricity usage from the normal consumption pattern by employing bid participation in the electricity market [4]. The goal of price-based DR is to induce customers to shift their consumption from peak-time to off-peak time in response to the changes in the electricity price over time [5,6]. Incentive-based DR is conducted using a contract between DR operators and DR participants. The DR operators request that the DR participants reduce their demand when grid reliability problems occur or when the price is too high [4,6]. Then, the DR participants receive either incentives or penalties from the operators depending on their reduction levels [7].

Energy Storage System (ESS) that is installed at industrial facilities can be utilized when responding to dispatch signals of the DR program [8]. However, their use requires a sophisticated control algorithm not only to maximize the customer's profit in order to reduce the Return On Investment (ROI) of the ESS, but also to minimize the ESS operation in order to lengthen the life of the ESS.

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Thus, there is a need for an intelligent ESS scheduling algorithm that dynamically responds to the changes in the electricity price of the DR program over time [9–11].

Several ESS scheduling algorithms have been studied by many researchers. Model Predictive Control (MPC) was applied to the energy management system for the control of multiple ESSs, which are coordinated based on a rule-based manner to regulate the peak demand [12]. This reduced the daily electricity charge and reduces the peak demand by updating the schedule using predictive control and monitoring to check the state of charge of ESS as well as the uncertainty of the forecasted load. Furthermore, an optimal ESS charge and discharge scheduling algorithm was developed to increase the energy efficiency of the daily ESS cycle, and to simultaneously minimize the demand charge [13]. This method emphasized the balancing of reliable load forecasting, the charge-rate limit, energy pricing, and peak load. In addition, the optimal scheduling of ESS was proposed to reduce the electricity bill by load-shifting and peak-shaving using Genetic Algorithm (GA) [14]. However, this approach only uses a daily single charge-discharge cycle to reduce the ESS operation cost. The Real Coded Genetic Algorithm (RCGA) is also used to schedule the charging and discharging operation of ESS to reduce the sum of the energy charge and the demand charge by performing operations corresponding to Time-of-Use (TOU) pricing in smart-grid [15].

However, the previously introduced ESS scheduling algorithms focus only on maximizing the profit for self-consumption. The ESS scheduling algorithm is recently required to consider newly developed energy trading markets such as the DR program. Therefore, this study focused on the development of two different scheduling algorithms for ESS to simultaneously achieve both self-consumption and DR program participation. The ESS scheduling algorithm that simultaneously operates both self-consumption and DR program participation improves the system flexibility as a part of grid modernization from a national perspective, and maximizes the profit of the ESS customers. These algorithms are designed to achieve different participation capacity of ESS into the DR program by varying the ESS self-consumption capacity. The proposed algorithms are validated by performing simulations based on the current DR program in South Korea using the actual industry load profile with ESS.

This paper is organized as follows. Section 2 proposes two ESS scheduling algorithms that simultaneously achieve both self-consumption and DR program participation. In addition, the DR program in South Korea is summarized and the operational strategy of ESS required to participate in this program is proposed. Section 3 presents the simulation results of two proposed algorithms for self-consumption based on the actual industrial load profiles with ESS. Section 4 compares the total profits when two different algorithms that apply ESS participate in the DR program. Finally, the conclusion and future work are presented in Section 5.

2. ESS scheduling algorithm to simultaneous achieve self-consumption and DR program participation

This section describes the ESS scheduling algorithm that enables the maximization of profits by realizing self-consumption as well as DR program participation. First, a 24-h Load Forecasting Model (LFM) is developed for ESS scheduling. Using this model, two different ESS scheduling algorithms are proposed. Both algorithms involve three steps to find the optimal schedule of ESS. The first two steps are common for both algorithms, but the 3rd step is different. The first algorithm is designed to maximize the profit by self-consumption, and the remaining ESS capacity is then used to participate in the DR program. The second algorithm is designed to minimize the ESS operation for self-consumption, but to maximize the profit from DR program participation. Then, the DR program in South Korea is summarized and the operational strategy of ESS required to participate in this program is proposed.

2.1. ESS scheduling algorithm for self-consumption

2.1.1. Step 1: input data calculation

To develop the optimal ESS scheduling algorithm, the accurate prediction and modeling of the uncertainty load pattern is an important input [16]. Therefore, the 1st common step predicts the load using the 24-h LFM, which combines two load forecasting models: a very-short-term forecasting model that uses the previous intra-hour information, and a short-term forecasting model that uses information from the previous day. Each model runs within its Forecasting Time (FT) period separated by Optimal Forecasting Time (OFT), which is the conversion point from the very-short-term to the short-term forecasting model. In addition, the 24-h LFM uses two meteorological factors including temperature and humidity. The 24-h LFM is described as follows:

$$L_{t(d)}(p,q) = \begin{cases} \sum_{i=1}^{p} a_i L_{t(d)-i} + bT_{t(d)} + cH_{t(d)} + \varepsilon_{t(d)} & (15min \le FT \le OFT) \\ \sum_{j=1}^{q} e_j L_{t(d-j)} + fT_{t(d)} + gH_{t(d)} + \varepsilon_{t(d)} & (OFT < FT \le 24\ hour) \end{cases} \tag{1}$$

where p and q are the number of previous loads used in the very-short-term and short-term forecasting models, respectively. $L_{t(d)}$ is the load at time t on day d, $L_{t(d)-i}$ is the load at time $t-i$ on day d, and $L_{t(d-j)}$ is the load at time t on day $d-j$. To improve the accuracy, the day d is separated into weekdays and holidays. $T_{t(d)}$ and $H_{t(d)}$ are respectively the temperature and humidity forecast at time t. $\varepsilon_{t(d)}$ is a white noise having an average of 0 and variance σ^2. The Ordinary Least Square (OLS) method is used to estimate the coefficient of the model as follows:

$$Coeff = \left(X^T X\right)^{-1} \times X^T y \tag{2}$$

where $Coeff$ is the vector of the coefficients (a_i, b, c and e_j, f, g), X is the matrix of the input data ($L_{t(d)-i}, T_{t(d)}, H_{t(d)}$ and $L_{t(d-j)}, T_{t(d)}$, $H_{t(d)}$), and y is the vector of the result ($L_{t(d)}$). These coefficients are recalculated and updated every month. In addition, the OFT is determined when the minimum Mean Absolute Percentage Error (MAPE) is observed as follows:

$$\mathrm{MAPE} = \frac{1}{N}\sum_{k=1}^{N}\frac{|A_k - F_k|}{|A_k|} \times 100 \tag{3}$$

where A_k is the actual value, F_k is the forecast value, and N is the number of forecast values.

In addition to the load forecasting information, in this step, ESS information and the electricity tariff structure for the selected customer are the inputs to the algorithm. ESS information includes the rated capacity of ESS, the rated power of the Power Conversion System (PCS), the upper and lower operating limit of ESS, the State of Charge (SOC), and the State of Health (SOH).

2.1.2. Step 2: search ESS schedule to satisfy the constraints

The 2nd common step searches the possible ESS schedule to satisfy the constraints. First, the capacity of the ESS at time t (Cap_t)