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Effective scheduling of residential energy storage systems under dynamic pricing

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ABSTRACT

We address the control of a residential energy storage system under dynamic pricing, for scenarios with and without local electricity generation, by combining a dynamic programming approach with real-time correction of predictions of load and generated power. We performed simulations using energy generation and consumption data for 64 residences in the Pecan Street Project, and a range of seasonal dynamic price tables. Our algorithm was more effective than other approaches in reducing electricity costs under most tariffs, especially when the amount of electricity generated locally is small.

1. Introduction

In the operation of residential or industrial electric grids, the amount of electricity entering the grid as a result of generation must balance the amount leaving the grid, which is the load. However, new technologies such as utility-scale wind power, rooftop solar photovoltaics (PV), and electric vehicles, make it more difficult to predict power generation and requirements. Technologies based on energy storage systems (ESSs) make it easier to balance power generated locally and supplied by the grid, by acting as a buffer against a varying generation and load. ESSs can help commercial and industrial understandings to improve the stability of their energy supplies and reduce costs.

Soon, ESSs are likely to become important not only to commercial and industrial end users but also to residential customers, particularly as dynamic pricing policies are introduced by utilities. Economists have long argued for the replacement of fixed retail prices for energy with prices that change during the day. Such dynamic pricing would reflect wholesale prices, and this is expected to reduce peaks in demand, and hence the volatility of the wholesale price, as well as the average level [1]. The recent introduction of smart-grid technologies such as smart meters makes the widespread introduction of dynamic pricing a feasible, and indeed imminent, scenario.

A form of dynamic pricing that is being widely adopted is time-of-use (TOU) pricing in which daily variations in the price of electricity are set for a specific period in advance. Typically, TOU tariffs do not change more than twice a year. A representative TOU tariff will have two or three price levels (e.g., ‘off-peak’, ‘mid-peak’, and ‘on-peak’), which apply at different times of day. Because consumers are informed of prices in advance, they can reduce their overall expenditure on energy by shifting their usage to a lower-cost period, by storing energy during low-price periods and using that stored energy when the price is high. Residential TOU has been adopted in many states in the US and, although only industrial TOU is currently available in Korea, it will most likely be extended to residential supplies.

Extensive research on scheduling the charging and discharging of an ESS (which is typically based on one or more batteries and an inverter) to maximize cost savings under TOU pricing has been undertaken [2–5], particularly on residential ESS [3,6,7], but also from the utility operator's point of view [8]. Researchers have addressed the ESS charge/discharge scheduling problem using various optimization methods, including dynamic programming [3,8–12], linear programming [13], nonlinear programming [2,7,14], mixed integer linear programming [15], stochastic optimization [16,17], particle swarm optimization [4], and genetic algorithm [18].

In this paper, we define the residential ESS control problem with dynamic pricing. We then address the problem of controlling an ESS with and without the availability of renewable energy sources

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such as wind and solar power, whereas previous studies only investigated one of these scenarios. We use a dynamic programming approach that considers prediction of generation and load over 24 h. Although dynamic programming was used in other studies [3,8–12], those studies did not consider prediction of generation and load; indeed, most previous research has assumed a predetermined daily pattern of generation and load. We maintain that this is clearly unsatisfactory, because domestic power generation and load is most unlikely to follow the same pattern every day, and predicted values provide much greater reality. However, generation and load predictions will have errors, and a real-time correction algorithm is required. In this paper, we will introduce a method of controlling a residential ESS which combines dynamic programming with predictions which are taken subject to real-time correction.

The remainder of this paper is structured as follows: In Sections 2.1 and 2.2, we describe the problem of ESS scheduling under dynamic pricing, without and with generation respectively. In Section 3.1, we describe how dynamic programming can be applied to solve these ESS scheduling problems efficiently, and in Section 3.2, we show how the backward tracing method can be customized to specific requirements. In Section 4, we describe the real-time correction of the errors incurred in predicting load and generation in ESS operation. In Section 5, we assess the performance of the proposed algorithms through simulations using data from the Pecan Street Project [19] in the US. In Section 5.1, we describe the test environment, and in Sections 5.2 and 5.3, we analyze the simulation results. Finally, we draw conclusions in Section 6.

2. ESS scheduling scenarios

2.1. Consumption alone

For a household that only consumes energy from the grid, and has no generation facilities, the problem minimizing its electricity bill by using an ESS can be formulated as follows:

$$\text{Minimize} \quad \sum_{i=1}^{T} p_i(x_i + l_i) \tag{1}$$

$$\text{subject to} \quad 0 \le \sum_{i=1}^{k} fx_i \le C, \quad k = 1, 2, \ldots, T \quad \text{and} \tag{2}$$

$$-P_d \le fx_i \le P_c, \quad i = 1, 2, \ldots, T, \tag{3}$$

where p_i is the price of electricity over the ith time interval, x_i is the amount by which the ESS is charged (positive) or discharged (negative) during the ith time interval, l_i is the amount of energy used during the ith time interval, C is the capacity of the battery, T is the number of time intervals, P_c is the maximum charge rate, P_d is the maximum discharge rate, and f is the battery efficiency. The problem can be addressed by linear programming techniques such as the simplex method and dynamic programming. The optimal solution depends only on the values of p_i.

2.2. ESS with auxiliary generation

Local generation equipment, such as a rooftop array of solar cells, or ESS, can allow electrical energy to be sold to the grid, as well as purchased. Therefore, in this scenario, specifying the ESS scheduling problem requires prices for buying and selling electricity. In this subsection, variations on this scenario, and the problems that they pose, are discussed.

If the consumer's electricity meter simply runs backwards when power is sent back to the grid, the sales price matches the purchase price. That is, $p_i = q_i$ for $i = 1,2,\ldots,T$, where p_i is the purchase price over the ith time interval and q_i is the sales price over the same period. In this case, the problem is defined as follows:

$$\text{Minimize} \quad \sum_{i=1}^{T} p_i(x_i + l_i - g_i) \tag{4}$$

$$\text{subject to} \quad 0 \le \sum_{i=1}^{k} fx_i \le C, \quad k = 1, 2, \ldots, T \quad \text{and} \tag{5}$$

$$-P_d \le fx_i \le P_c, \quad i = 1, 2, \ldots, T, \tag{6}$$

where g_i is the amount of energy generated over the ith time interval and other notations and expressions are the same as those in previous subsection.

This problem can be addressed by linear programming, like the scenario without local generation discussed in the previous subsection.

Alternatively, different prices can be set for electricity flowing to and from the grid, by installing a bi-directional meter. If the sales price is lower than the purchase price, residential customers can be expected to consume most of the energy that they generate themselves, and this has environmental benefits. Conversely, a sales price which is higher than the purchase price promotes stability of supply at on-peak times. The problem of minimizing the consumer's bill when the purchase and sales tariffs are different can be formulated as follows:

$$\text{Minimize} \quad \sum_{i=1}^{T} (I(x_i + l_i - g_i \ge 0) \times p_i \tag{7}$$

$$+ I(x_i + l_i - g_i < 0) \times q_i)(x_i + l_i - g_i) \tag{8}$$

$$\text{subject to} \quad 0 \le \sum_{i=1}^{k} fx_i \le C, \quad k = 1, 2, \ldots, T, \quad \text{and} \tag{9}$$

$$-P_d \le fx_i \le P_c, \quad i = 1, 2, \ldots, T, \tag{10}$$

where $I(\omega)$ is the indicator function, i.e., the value of $I(\omega)$ is 1 if ω is true, otherwise, it is 0.

This object function is not linear, and methods such as dynamic programming or nonlinear programming must be used to solve this problem.

We now consider the scenario in which energy cannot be sold to the grid by consumers. This policy is becoming increasingly common in Europe, with the aim of promoting consumption of locally generated energy in the residence where it was generated, and it is likely to be adopted elsewhere. In this case, when the battery is fully charged, surplus electricity simply flows into the grid without any monetary compensation. In this case, the lowest bill can be found as follows:

$$\text{Minimize} \quad \sum_{i=1}^{T} I(x_i + l_i - g_i > 0) \times p_i(x_i + l_i - g_i) \tag{11}$$

$$\text{subject to} \quad 0 \le \sum_{i=1}^{k} fx_i \le C, \quad k = 1, 2, \ldots, T, \quad \text{and} \tag{12}$$

$$-P_d \le fx_i \le P_c, \quad i = 1, 2, \ldots, T. \tag{13}$$