College of Engineering- Center for Environmental Research & Technology

Battery Energy Storage System Dynamic Control Based on Real-Time Load Forecasting

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Introduction (Background)

Battery energy storage systems (BESS) can perform load shifting as an energy management strategy by discharging during peak periods and charging during off-peak periods. For electricity rate payers, load shifting brings direct economic benefit due to the significant energy costs between on-peak and off-peak period (both \$/kW and \$/kWh). This work is part of a demonstration project in peak-demand reduction, an economic benefit analysis, and a micro-grid demonstration of an optimization-based control strategy at City Hall in Rancho Cucamonga. This work consists of two research efforts: load prediction and battery control algorithm. The accuracy of the predicted load profile is an essential component of the control strategy. Load forecast methods can be broadly divided into two categories: Day-ahead forecast and short-time forecast. According to best practices, days are normally classified on the basis of day types and weather characteristics. Days classified into the same group are called similar days. Real-time load prediction applies linear regression analysis according to both historical load data on similar days and acquired load data on the actual day being controlled. Dynamic programming (DP) can handle discontinuous and nonlinear constraints. It can be applied to solve the load shifting control problem, while also taking into consideration the battery state of charge (SOC). The battery charge-discharge strategy is determined by the DP technique, based on the predicted load profile, which is continuously updated as new load data is obtained.

Load Forecast Block Diagram

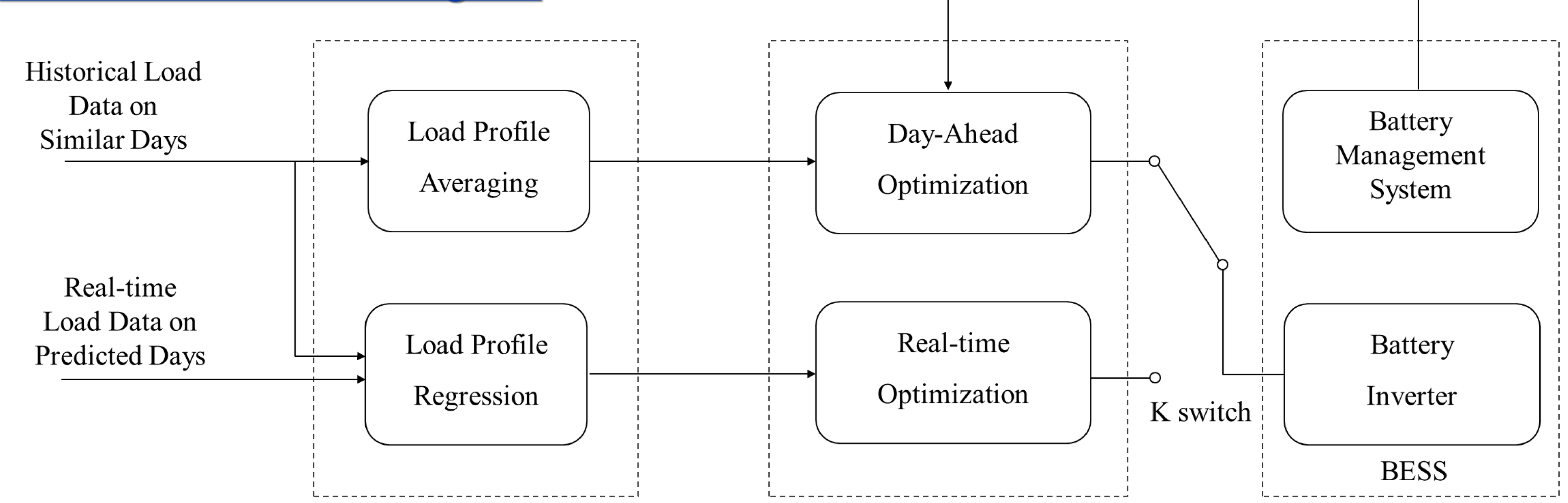

Figure 1. Block diagram of BESS control system for load shifting application.

Day-ahead optimization uses average historical load profiles from similar days, while real-time optimization uses predicted load profiles calculated by a linear regression method. Before the zero hour of the predicted day, K switch connects to point 1; during real-time control the K switch connects to point 2. The battery management system (BMS) acquires SOC information and delivers it to load shifting optimization block. Using the predicted load profile, actual SOC, and the battery model specs and parameters, the charge-discharge strategy is optimized by DP. The charge (or discharge) power control signal is then sent to the battery inverter, effectively managing the flow of power.

Short-time load forecasting makes use of the load data from the current day to update the predicted load profile and to improve the load shifting effect. The control algorithm solves the optimal strategy according to the updated SOC value.

Optimization Algorithm

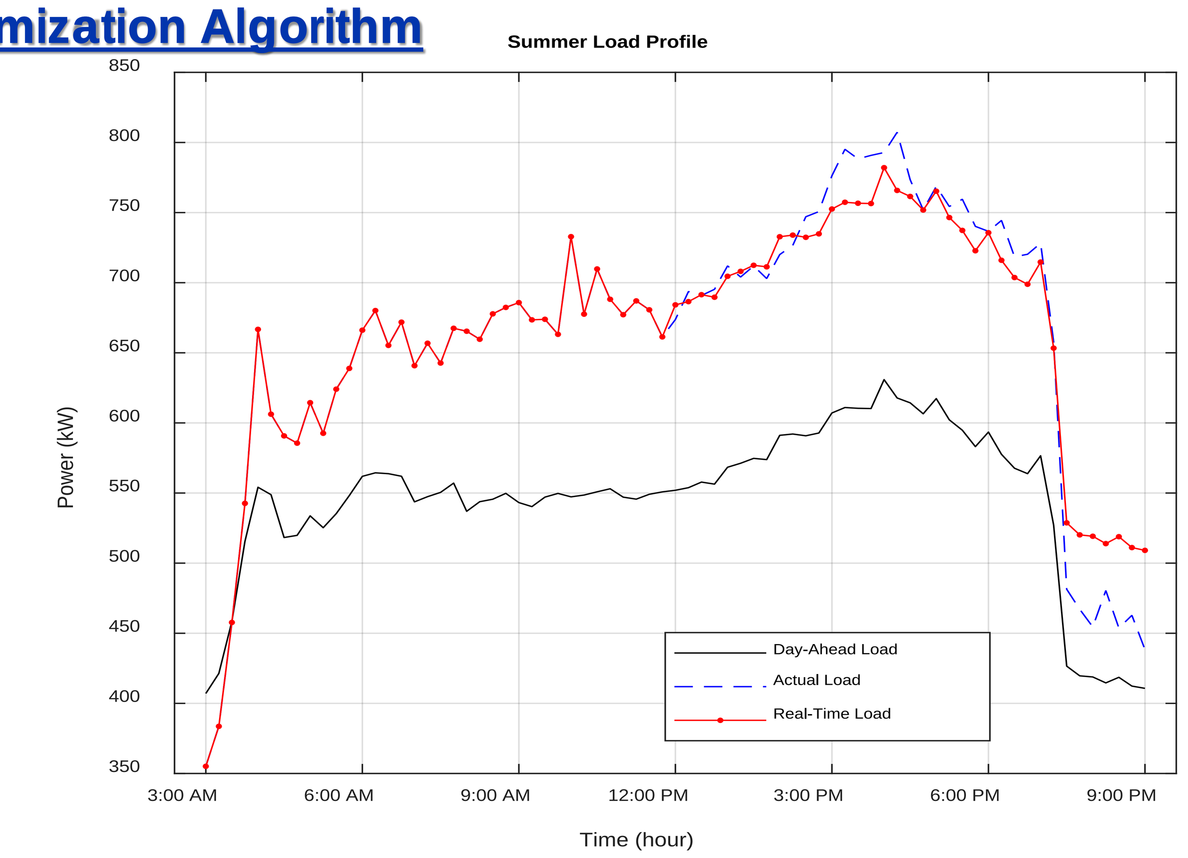

Figure 2. *rj* predicted Load Profile (*jth* = 12 PM).

At any given moment, previous m load data are acquired from the real load profile r, while the left N - m data in *r* are unknown. Supposing that the real load profile is the linear combination of n historical load profiles on similar days: h1, h2,…hn. The *jth* point on the predicted load profile *r* is expressed as:

$r_{r_j} = \sum_{i=1}^{n} a_i h_{ij}$ $(j > m)$ (1)

The objective of the weighted least square fitting is to minimize the error.

$\text{error} = \sum_{i=1}^{n} (a_i h_{ij} - r_j)^2$ (2)

Optimization Algorithm

In this work, the main goal is to use dynamic control to maximize the benefits captured from the battery energy storage system. This can be achieved by maintaining a relatively flat load demand profile by reducing the fluctuation in demand. The developed algorithm aims to utilize load demand and solar production forecasts as inputs to determine the optimal solution for the charge/discharge of the battery. In the optimization model, solving for the BESS charge-discharge strategy is driven by minimizing the variance of the load profile.

Constraints:

Energy capacity constraints: Battery remaining energy capacity at every stage is within the allowable range.

$Slow \le s(i) \le Shigh \;\; for\; i = 0,1,2,\cdots N$ (3)

In real-time control, the battery remaining capacity at a given moment S (m) is the initial value, and the battery remaining capacity at stage N is the final value. The reduced capacity equals the output capacity of BESS in Δt (if losses are neglected).

$s(m) = Sinitial$ (4)

$s(i) = s(i-1) + b(i) \times \Delta t,\; i = m, m+1, \cdots, N$ (5)

$s(N) = Sfinal$ (6)

Power constraints: Because of the limits of battery and the power conversion system (PCS), the output power should not exceed the upper and lower boundaries.

$-P\max \le b(i) \le P\max,\; i = 1,2,\cdots N$ (7)

Depth of Discharge (*DOD*) constraints: The *DOD* of *jth* discharge behavior should be larger than or equal (≥)to the limit $DOD(j)$ $(j = 1,2,\cdots k)$. $0 \le DOD(j) < 1$. $DOD(j) = 0$ (8)

meaning that the battery may release its whole electric energy during *jth* discharge behavior.

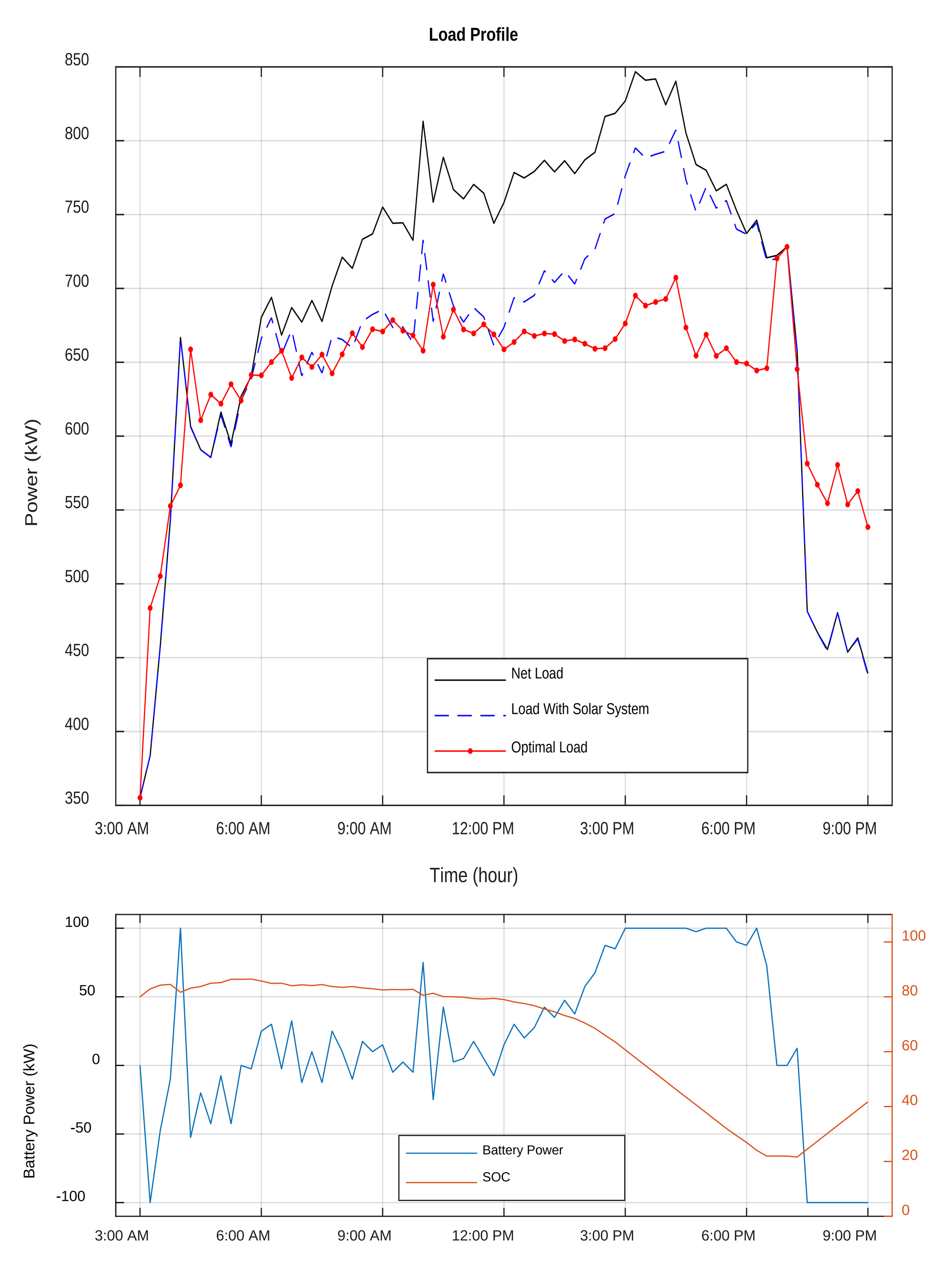

Figure 3. Summer Load Profile and corresponding Battery Power and SOC.

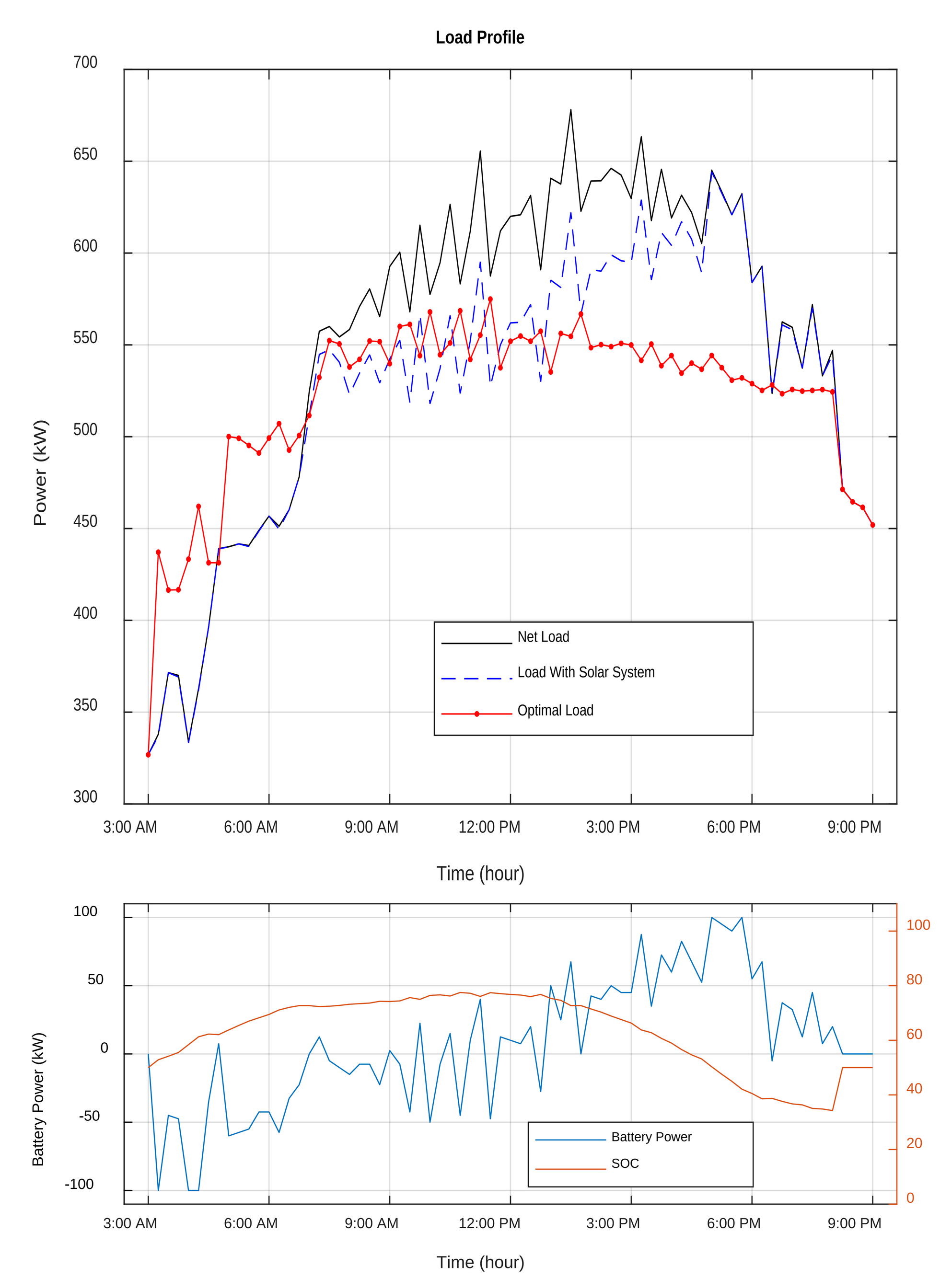

Figure 4. Winter Load Profile and corresponding Battery Power and SOC.

Summary

This research work shows a control strategy for implementing a load shifting application based on real-time demand load forecasting and a dynamic programing control algorithm; that takes into account the charge-discharge rate, the BESS SOC, and DOD. The solar generation data is obtained using SAM[2]. The simulation results are based on the actual demand load data obtained form Rancho Cucamonga City Hall (RCCH). The day-ahead predicted load profile is an average of historical data. The real-time predicted load profile is forecasted based on the acquired load data before time index *jth* on the prediction day. Battery SOC is corrected online which is favorable for responding to other BESS functions. The control strategy satisfies all the constraints, which are beneficial towards prolonging the battery lifetime. As Figure 3 and 4 show, this control strategy can charge and discharge the BESS at the appropriate times and rate to manage power fluctuations, effectively leveling the demand load profile.

References

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Acknowledgments

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