Implementation of Learning-Based Dynamic Demand Response on a Campus Micro-Grid

Sanmukh R. Kuppannagari, Rajgopal Kannan, Charalampos Chelmis and Viktor K. Prasanna
Ming Hsieh Department of Electrical Engineering
University of Southern California, Los Angeles, California
{kuppanna,rajgopalk,chelmis,prasanna}@usc.edu

Abstract
Demand Response (DR) allows utilities to curtail electricity consumption during peak demand periods. Real time automated DR can offer utilities a scalable solution for fine grained control of curtailment over small intervals for the duration of the entire DR event. In this work, we demonstrate a system for a real time automated Dynamic DR (D2R). Our system has already been integrated with the electrical infrastructure of the University of Southern California, which offers a unique environment to study the impact of automated DR in a complex social and cultural environment including 170 buildings in a “city-within-a-city” scenario. Our large scale information processing system coupled with accurate forecasting models for sparse data and fast polynomial time optimization algorithms for curtailment maximization provide the ability to adapt and respond to changing curtailment requirements in near real-time. Our D2R algorithms automatically and dynamically select customers for load curtailment to guarantee the achievement of a curtailment target over a given DR interval.

1 Introduction
The reliable operation of a power grid requires the constant matching between fluctuating load and supply. Demand Response (DR) is a technique whereby customers are asked to curtail their demands, typically during peak demand periods - when the grid exhibits very high demands potentially surpassing the generation capacity. Given the availability of bi-directional smart meters, we have developed a system for performing DR optimization in real time which we call Dynamic Demand Response (D2R).

We have implemented D2R on our campus micro-grid to demonstrate its large scale feasibility and identify and resolve the challenges associated with practical deployment. Our D2R technique uses learning of occupant energy strategy preferences (at fine grained scales ranging from buildings to floor levels within buildings) to make accurate electricity consumption predictions and individual curtailment recommendations using only a small subset of consumption data.

2 D2R Implementation
Buildings on our campus are instrumented with smart metering and control that can be used to implement a large number of advanced energy curtailment strategies such as resetting temperature set points, reducing air flow, duty cycling. A simplified control and data flow diagram of our D2R implementation is shown in Figure 1. The micro-grid utility initiates a DR event using OpenADR messages and provides a curtailment target \( \gamma \) to be achieved over a given DR interval \( T \), typically 4 hours. The Policy Engine (PE) module provides campus wide curtailment strategy policy recommendations based on the analysis of historical consumption data and curtailment maximization customer (building) selection algorithms. Smart meter data is aggregated over 15 minute intervals into a consumption database. State-of-the-art data-driven models are then used by the PE module to predict energy consumption values over each 15 minute period comprising the entire DR interval \( T \) for each building across campus. This information is then provided to the optimization module in the form of a discrete time varying curtailment matrix. The outputs of the PE are sets of buildings-strategy pairs at 15 minute intervals that will achieve the required curtailment target \( \gamma \) over \( T \).

Figure 1: Control and Data Flow For D2R Implementation

Our Policy Engine (PE) is composed of an influence model based demand prediction engine that feeds into a building-strategy selection optimization module as shown in Figure 2.

---

*This work has been funded by the U. S. Department of Energy under Award Number DE-OE0000192, the Los Angeles Department of Water and Power (LADWP) and the U. S. National Science Foundation under grant number ACI 1339756.*
Historical data from the energy consumption database before the DR day is used in conjunction with time series forecasting techniques such as ARIMA and Lasso-Granger (for learning temporal dependencies among multiple timeseries) to learn occupant energy strategy preferences and load profiles. A significant challenge is to ensure accurate prediction in the absence of high quality consumption data. To ensure quality data we have developed several techniques: interpolation methods for estimating intermittent missing data and sophisticated influence based learning models for estimating systematically unavailable data over larger periods. We have shown that only a small subset (≃7%) of the meters are required in real-time to make predictions for buildings across the campus micro-grid [Aman et al., 2015].

4 Innovations, Benefits and Importance
Traditionally, DR programs communicate the schedule to customers much ahead of time and are very inefficient due to inaccuracies over long prediction horizons. We have addressed these inefficiencies using our innovative real-time D^2R techniques which can be dynamically adjusted to manage supply/demand imbalances over short timescales (15 minutes). Using D^2R, we have achieved curtailment values as high as 1.2 MW in a single DR event in our campus micro-grid.

A key innovation of our D^2R technique is the development of influence based machine learning techniques to predict consumption even with partial or missing data. Another key innovation is the development of fast polynomial time optimization algorithms for customer selection which provide near optimal results.

By addressing the various challenges, we have implemented a DR program with very low curtailment errors (due to prediction inaccuracies and errors due to the approximation algorithms for SDR) which are ≤ 10% as opposed to 30% in other techniques [Kwac and Rajagopal, 2014]. Hence, our state-of-the-art implementation can be used as a model to implement city scale efficient automated DR programs as is being currently undertaken in our city.

5 Details of the Demo
We will demonstrate a delayed implementation of a live DR event that occurred earlier. The consumption values until 12 noon of the DR day will be used by our prediction engine. A simulated curtailment request with a timestamp of 12 noon will be sent to the PE which is implemented as a webserver. We will show the consumption predictions and strategies recommended by the PE over 15 minute intervals. Finally, we will evaluate the success of our DR algorithm by measuring the curtailment error.

References

Figure 2: Policy Engine