Analytics for Demand Response Optimization in a Microgrid

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***Abstract*— In a Smart Grid, both the utility and the consumer can benefit from analytics based on electricity consumption data. In this abstract, we report our on-going research work on performing analytics for the USC campus micro-grid using electricity consumption and curtailment data available for campus buildings. Our goal is to provide the facility managers an insight into the changing electricity demand patterns on campus and enable them to efficiently plan consumption and curtailment activities; and to develop a policy engine for automating Demand Response (DR). The research challenge for us is to design, develop and field analytics solutions for various tasks in DR Optimization. We leverage characteristic information about the campus including academic schedules and building details to derive novel indirect indicators of electricity consumption. We use a combination of learning techniques such as Granger causality, regression trees and time series that together provide a better forecasting accuracy than individual approaches. Eventually, we expect to generalize and extrapolate the successful models that work for the campus to a city scale.**

I. Introduction

THE widespread use of Advanced Metering Infrastructure (AMIs) in the Smart Grid environment has made possible near real-time tracking of electricity consumption in individual households and commercial units. We need analytics for understanding this large-scale consumption data and to extract meaningful and actionable information. Previously, utilities have used static consumption models that are no longer valid with the rapidly changing infrastructure. Availability of large-scale streaming data in real-time allows the use of machine-learnt models that can adapt to changing scenarios in the Smart Grid. Both the utility and the consumer can benefit from data-driven analytics. The utility can reliably forecast electricity demand and plan generation and supply accordingly. Also, the consumers can better interpret their historical consumption and adopt energy-efficient practices.

In our dissertation, we plan to explore and develop advanced data analytic techniques that support the evolving needs of smart grids to perform reliable demand forecasting and predict the efficacy of curtailment strategies. The key research problems we tackle are: 1) derive reliable electricity consumption forecasting models that work for different spatial and temporal granularities; 2) derive prediction models for achievable curtailment for different electricity usage curtailment strategies; and 3) design a DR policy engine that could be used to automatically curtail electricity usage during peak-load periods in response to a signal from the utility. In this paper, we present initial results of this dissertation from experiments performed for the University of Southern California (USC) campus microgrid, which is a test-bed for the DOE-sponsored Los Angeles Smart Grid Demonstration Project [5]. Eventually, we expect to generalize and extrapolate the successful campus models to make them applicable to a city scale [2].

Our work is novel as it addresses an important problem that has not been studied in detail in literature. Several approaches have been applied for electricity demand forecasting models, including regression models, artificial neural network models and time-series models. The utilities have used simpler baseline forecasting methods, such as averaging the electric use profiles of the last few days [3]. Other works have focused on extensive instrumentation within buildings and monitoring of activities using sensors for estimating electricity consumption [7]. Our work is entirely data-driven and leverages data mining methods. Existing work addresses forecasting exclusively at specific coarse or fine temporal granularities, while we consider both fine and coarse-grained granularities and highlight the relevance of each for DR optimization. We also address a more diverse range of building types on campus in contrast to existing work that generally focuses exclusively on either residential buildings or commercial & industrial buildings [4].

II. Data Driven Analytics

We adopt a data-driven approach to the problem of DR optimization [6]. We describe below the diverse sources of information that we leverage in our research.

1) Electricity Consumption Data: We use electricity consumption data collected at 15-min intervals by means of smart meters by the USC's Facilities Management Services (FMS) for various buildings on the campus. This kind of time series data is generally available for individual buildings or households in microgrids and for city-level. The granularity at city-level may be coarser, for e.g., at 1-hour intervals.

2) Electricity Curtailment Data: The data is being collected from the curtailment experiments that are currently on for the USC campus microgrid. In these experiments, a particular curtailment strategy, such as HVAC duty cycling or global temperature reset is applied and corresponding reduced consumption is recorded. Similar controlled experiments may be performed in other microgrids and in certain areas of a city to collect data.

3) Customer Behavior Data: The customer behavior experiments and surveys regarding voluntary customer participation in DR on campus will be performed this summer. This kind of data is critical to model customer behavior for long-term success of DR programs.

4) Weather Data: We use temperature and humidity data collected from the Weather Underground website[1]. The data is publicly available, city-wise, at hourly intervals, which can be interpolated to finer 15-min granularity.

5) Building Data: We use publicly available data about the physical characteristics of the buildings, such as square footage, year of construction, etc. from the FMS website[2]. For city-scale, the corresponding information would be customer segments and type of equipment/appliances in use.

6) Schedule Data: Information about the working and non-working days, and semester durations is collected from the University's publicly available Academic Calendar[3]. For city-scale, customer demographics (e.g., single/multi-family units, number of working members, etc.) can provide indirect indicators of schedules.

III. Consumption Modeling

We demonstrate effective use of indirect indicators, such as academic schedule and building details, in campus-scale and building-scale regression tree models for predicting electricity consumption [1]. We also investigate causal relationships between the factors affecting energy consumption using the Granger causality method. In particular, we investigate causal relationships between the buildings on the campus and discover strong causal interactions. We propose a hybrid approach of combining time series and regression tree methods for of electricity consumption forecasting in buildings. We showed that the new method performs better or at least as good as these methods applied individually. The method of feature selection driven by causality analysis results leads to more succinct models that can be developed more efficiently.

IV. Curtailment Modeling *(Work-in-progress)*

The goal is to model the response of different curtailment strategies. This includes determining the extent of curtailment and the duration for which curtailment could be sustained before the conditions violate the guidelines for maintenance of indoor environments, as defined by ASHRAE[4]. Curtailment is governed to a large extent by customer preferences and involvement. We are using Markov chains based modeling technique for customer behavior modeling. We are investigating how to model changing preferences of the customer and results of financial and other incentives for participation in DR. The extent and duration of curtailment can be modeled as a supervised learning problem, and addressed using regression methods.

[1] http://www.wunderground.com/history/

[2] http://fmsmaps.usc.edu/mapguide6/upcmaps/Web/cfm/bl_list_no.cfm

[3] http://academics.usc.edu/calendar/

[4] http://www.ashrae.org/standards-research–technology/

V. DR Policy Engine *(Work-in-progress)*

The goal of the DR policy engine is to provide decision support for DR. The campus-level consumption forecasting model will be used by the the policy engine to determine when there is going to be a peak load at a certain time in future and load curtailment is necessary. The engine would then make use of building-level load forecasting model to determine the buildings and subsets of customers have a potential for load curtailment. At a city-scale, the primary decision to be made is the selection of customer groups for targeted load curtailment. The DR policy engine needs to adapt to changing profiles of customer participation. Thus we need dynamic models that compare the predicted and actual consumption of a customer, and use the statistics to infer customer's compliance to DR signals. Thus, we are exploring a dynamic priority-based policy engine that would apply a strategy based on a priority system that is dynamically changing according to changing scenarios.

VI. Conclusion

In this abstract, we present our ongoing research work for demand response optimization in a microgrid. We propose causality-driven hybrid model for electricity consumption and identify its cost-benefit trade-offs with respect to other existing modeling methods. We explore the methods for modeling curtailment based on the data collected from curtailment experiments on campus. We also discuss some initial thoughts regarding the DR policy engine. The models we develop for microgrid will eventually be extrapolated to city-scale.

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