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# DR-Advisor: A Data Driven Demand Response Recommender System

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# DR-Advisor: A Data Driven Demand Response Recommender System

## **Abstract**

A data-driven method for demand response baselining and strategy evaluation is presented. Using meter and weather data along with set-point schedule information, we use an ensemble of regression trees to learn non-parametric data-driven models for predicting the power consumption of the building. This model can be used for evaluating demand response strategies in real-time, without having to learn complex models of the building. The methods have been integrated in an open-source tool called DR-Advisor, which acts as a recommender system for the building's facilities manager by advising on which control actions should be during a demand response event. We provide a case study using data from a large commercial virtual test-bed building to evaluate the performance of the DR-Advisor tool. Keywords: demand response, regression trees, machine learning

## **Keywords**

Data-driven, CPS, demand response, buildings, modeling, control

## **Disciplines**

Computer Engineering | Electrical and Computer Engineering

## **Comments**

# DR-ADVISOR: A DATA-DRIVEN DEMAND RESPONSE RECOMMENDER SYSTEM

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## ABSTRACT

A data-driven method for demand response baselining and strategy evaluation is presented. Using meter and weather data along with set-point schedule information, we use an ensemble of regression trees to learn non-parametric data-driven models for predicting the power consumption of the building. This model can be used for evaluating demand response strategies in real-time, without having to learn complex models of the building. The methods have been integrated in an open-source tool called DR-Advisor, which acts as a recommender system for the building's facilities manager by advising on which control actions should be during a demand response event. We provide a case study using data from a large commercial vistrual test-bed building to evaluate the performance of the DR-Advisor tool. *Keywords: demand response, regression trees, machine learning*

## INTRODUCTION

In 2013, a report by the National Climate Assessment provided evidence that the most recent decade was the nations warmest on record [1] and experts predict that temperatures are only going to rise. Every year an overstressed electric grid faces increasing challenges to operate homes and buildings. Heat waves in summer and polar vortexes in winter are growing longer in duration which could result in energy shortages and blackouts.

To improve reliability of the electricity grid, across the United States, electric utilities and independent system operators (ISOs) are devoting increasing attention and resources to demand response (DR) [2]. While energy efficiency is a prominent component of growing efforts to supply affordable, reliable and clean electric power; most utilities and system operators are increasingly turning to demand response as a cost effective and environmentally responsible way to serve peak load. Potential peak reduction from demand response markets in U.S. increased by 2,451 MW or 9.3 percent to a total of 28,503 MW from 2012 to 2013 [3]. The estimated revenue for economic and load management DR markets with PJM alone is about \$700 million [4].

Buildings, particularly large commercial buildings, are large consumers of electricity and a significant contributor to peak load conditions in the grid. Their electricity demands are often sensitive to weather conditions, which can results in peaks in their power consumption on an extremely hot or an extremely cold day. Such customers are also increasingly looking to DR programs to help manage energy costs.

Demand response programs are designed to elicit changes in customers electric usage patterns. Some types of demand response, implemented through approved utility tariffs or through contractual arrangements, vary the price of electricity over time to motivate customers to change their consumption patterns; this approach is termed price-based demand response.

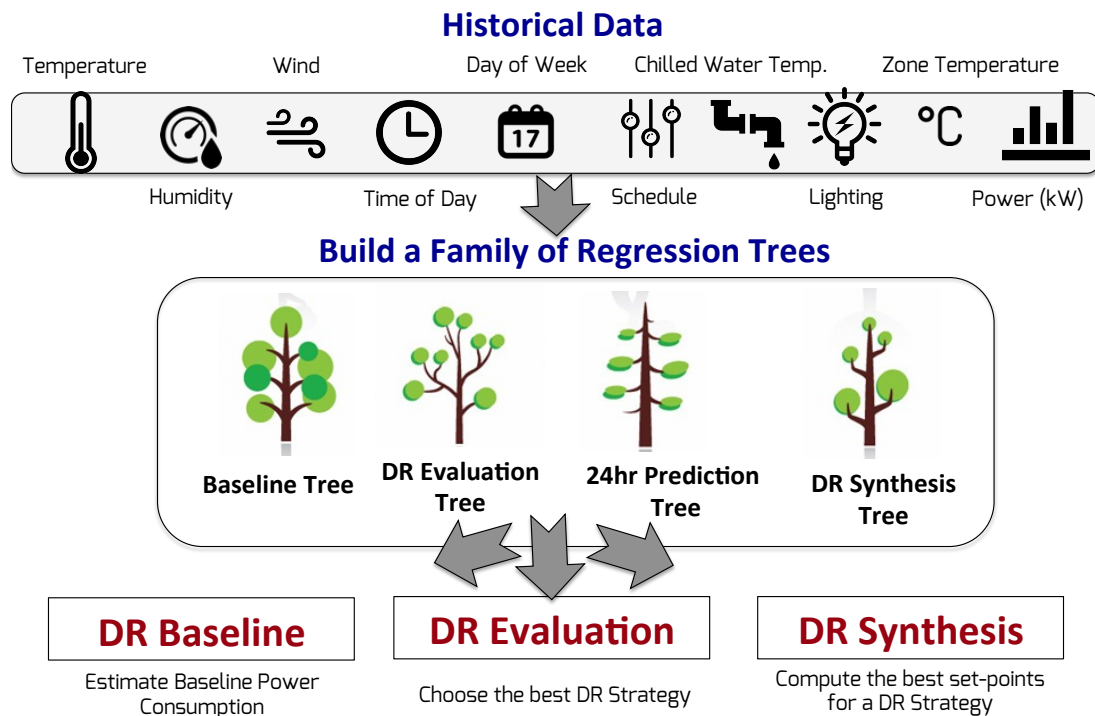


Figure 1: DR-Advisor Architecture

DR-Advisor is a data-driven tool for demand response baselining, strategy evaluation and synthesis. Using meter and weather data along with set-point and schedule information, it uses a family of regression trees to learn non-parametric data-driven models for predicting the power consumption of the building (Figure 1). These models can be used for real-time demand response strategy evaluation, without having to learn complex models of the building. DR-Advisor acts as a recommender system for the building's facilities manager by advising on which control actions should be taken during a DR event.

1. We demonstrate the benefit of using regression trees based methods for estimating demand response baseline power consumption and for evaluating pre-determined demand response strategies in real time. The use of such methods for demand response problems is novel.
2. We evaluate and compare the performance of several tree based methods on a Department of Energy's (DoE) Large Commercial Reference Building using actual meteorological data.
3. The biggest contribution of this work is the fusion of a family of regression trees into DR-Advisor, a simple and highly interpretable open source tool. It eliminates the cost of time and effort required to build and tune high fidelity models of buildings for DR.

### Problem Definition

The two most popular approaches to respond to a demand response event include rule based and model based DR strategies. In a rule based demand response strategy, different levels of curtailment are achieved by following a pre-programmed strategy. Such a DR strategy can include fixed setbacks for thermostat set-points, pre-determined dimming of lights and temporarily switching off large equipment e.g., elevators. Model based design

for DR involves explicitly mathematically modeling the building and its equipment in order to predict the overall power consumption. However, creating and learning such high fidelity models is both cost and time prohibitive. This is because the user expertise, time, and associated costs required to develop a software model of a single building is quite large.

In this paper, we focus on two challenging problems of demand response

1. **DR baseline prediction:** A baseline is an estimate of the electricity that would have been consumed by a customer in the absence of a demand response event. The measurement and verification of demand response is the most critical component of any DR program since any curtailment can only be measured relative to the estimate of the demand response baseline.
2. **Real-time DR strategy evaluation:** This is the problem of choosing good DR strategies from a pre-determined set of strategies, in real-time. During a DR event notification, there are several options available to a buildings facilities manager in the form of a control actions. These may include setbacks in the zone temperature set-point, increasing supply air temperature and chilled water temperature set-point, dimming or turning off lights, decreasing duct pressure set-points and switching off no-essential electrical load. However, there could be several such fixed rules or strategies. With our tree based models, we can predict the response of the building due to any strategy, and hence, choose the best action during the DR event.

In key to solving both the problems is the ability to predict the power consumption of the building in real-time.

## **DR-ADVISOR: DATA-DRIVEN DEMAND RESPONSE**

Regression trees are decision trees which predict responses to data. Regression trees belong to the class of recursive partitioning algorithms. At each node of the tree, we check the value of one the inputs (or features)  $X_i$  and depending of the (binary) answer we continue to the left or to the right subbranch. When we reach a leaf we will obtain the prediction of the response  $Y$ . The seminal algorithm for learning regression trees from data is the CART algorithm as described in [5]. Contrary to linear or polynomial regression which are global models (the predictive formula is supposed to hold in the entire data space), trees try to partition the data space into small enough parts where we can apply a simple different model on each part. They are conceptually simple yet powerful. Regression trees offer several advantages in addition to being simple, which make them suitable for solving the challenges of demand response and building modeling. We list some of these advantages here:

1. Trees require very low computation power, both running time and storage requirements.
2. Trees can easily handle the case where the data has lots of features which interact in complicated and nonlinear ways. the predictor variables themselves can be of any combination of continuous, discrete and categorical variables.
3. Sometimes, data has missing predictor values in some or all of the predictor variables. This is especially true for buildings, where sensor data streams fail frequently due to faulty sensors or faulty communication links. By design, regression trees can handle missing data better than most algorithms through the use of surrogate variables.
4. Tree based models are generally not affected by outliers but regression based models are.

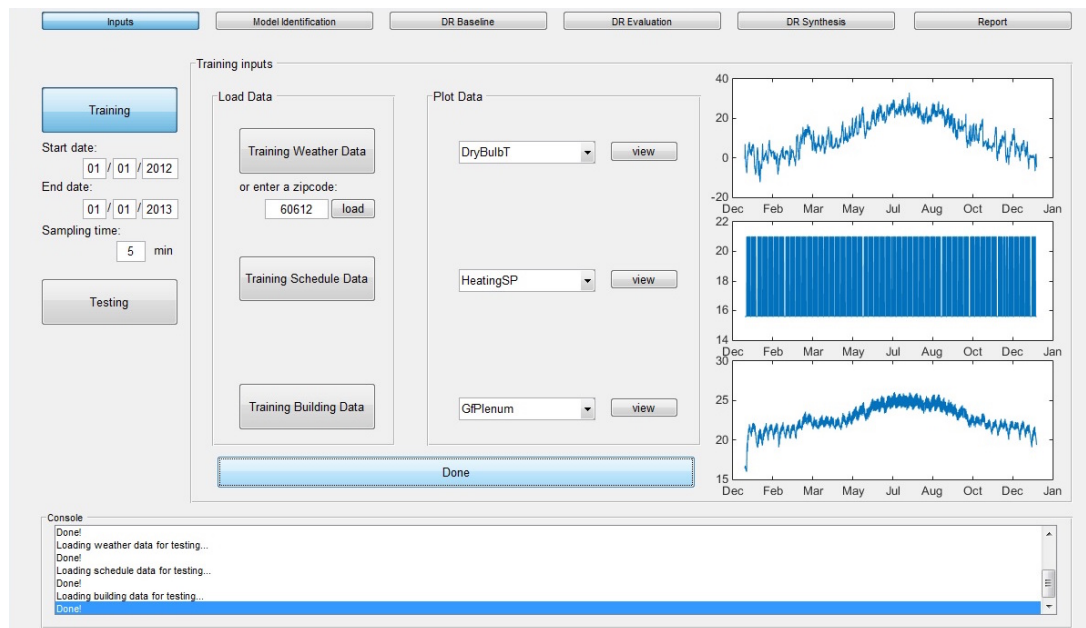


Figure 2: DR-Advisor graphical user interface

5. Trees are highly interpretable algorithms. Complex building models go through a long calculation routine and involve too many factors. It is not easy for a human engineer to judge if the operation/decision is correct or not or how it was generated in the first place. Trees only involve simple *if this then that* rules which are very easy to understand.

## Ensemble Methods

The problem with trees is their high variance and that they can over fit the data. It is the price to be paid for estimating a simple, tree-based structure from the data. While pruning and cross validation can help reduce over fitting, in DR-Advisor, we use ensemble methods for growing more stable trees. The goal of ensemble methods is to combine the predictions of several base estimators built with a given learning algorithm in order to improve generalizability and robustness over a single estimator. Two families of ensemble methods are usually distinguished: (a) In averaging methods, the driving principle is to build several estimators independently and then to average their predictions. On average, the combined estimator is usually better than any of the single base estimator because its variance is reduced. (b) By contrast, in boosting methods, base estimators are built sequentially and one tries to reduce the bias of the combined estimator. The motivation is to combine several weak models to produce a powerful ensemble. The DR-advisor tool used a combination of cross validated trees, random forest and boosted regression trees as the underlying ensemble methods. For a more comprehensive review we refer the reader to [6].

## CASE STUDY

The building under consideration is the DOE Commercial Reference Building simulated in EnergyPlus [7] This virtual test-bed is a large 12 story office building consisting of 73 zones with a total area of 500,000 sq ft. There are upto 2,397 people in the building during peak occupancy. The building has 2 electric water-cooled chillers, variable air volume (VAV) supply air terminals with reheat and plenum zones and a single gas based boiler. During peak load conditions the building can consume up to 1.6 MW of power. EnergyPlus

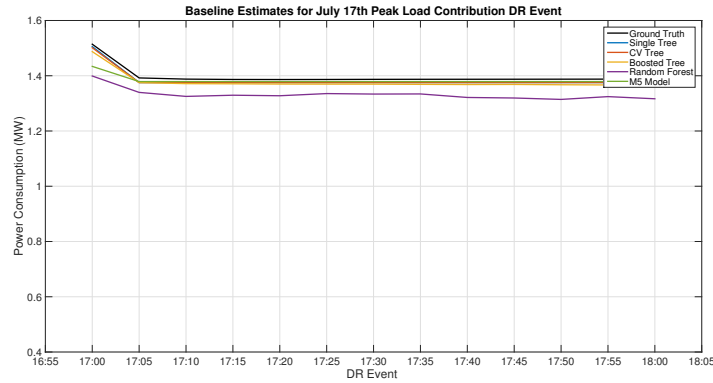


Figure 3: Comparison between the actual power consumption and the baseline prediction for July 17th, 2013; a peak load contribution day. The DR event is from 1700-1800 hrs.

provides typical meteorological year data files for many sites which are generated as averages of different weather characteristics across the past 15-30 years. However, for the purposes of the simulation we use **Actual Meteorological Year (AMY)** data from Chicago for the years 2012 and 2013.

The data that we use can be divided into three different categories as described below:

1. Weather data, which includes measurements of the dry bulb temperature, wet bulb temperature, relative humidity and wind conditions.
2. Schedule data, which includes fixed temperature set-points schedules of chilled water supply, supply air temperature and zone air temperature on the HVAC side and lighting schedules.
3. Building data, which includes the measurements of zone temperature, lighting, supply air and water temperatures, power consumption etc.

In addition to these data sets we also train on engineered features like the time of day and the day of week.

## DR Baseline

On July 17, 2013 a demand response event occurred across the PJM ISO from 1700 hrs to 1600 hrs. We estimate the baseline power consumption of the office building for the DR event for July 17, 2013. The result of this comparison is shown in Figure 3. In addition to evaluating a single regression tree, we implement and evaluate the performance of cross validated trees and the random forest and the boosted regression tree ensemble methods as well. The lowest root mean square error obtained in this case is only 12 kW on an average consumption of 0.62 MW, which corresponds to a normalised root mean square (NRMSE) of only 2.01%. Using the ensemble methods, the DR-Advisor is able to accurately predict the baseline consumption of the building using just weather and schedule data, which require little to no sensor installations at the building site.

## DR Strategy Evaluation

As stated earlier, the challenge is DR strategy evaluation is to predict the power consumption profile of the building in real-time due to a fixed policy. The following demand response strategy is evaluated. Upon receiving the notification of the DR event at 1600 hrs, the zone air temperature set-point for all the zones is increased from a nominal value of 24°C by 2° to 26°C. The chilled water supply temperature set-point is increased from 6.7°C by 1.5° to 7.2°C. At the beginning of the event at 1700 hrs, the zone air temperature set-point is further increased by 2° and the chilled water supply temperature set-point

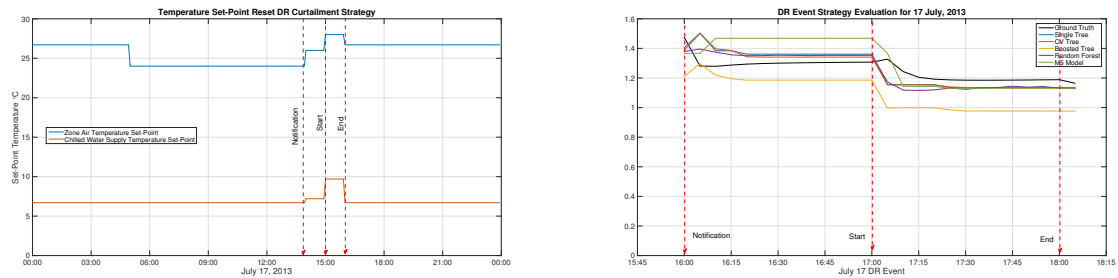


Figure 4: Left: Rule based demand response temperature set-point reset strategy executed for July 17, 2013. Right: Comparison between the actual power consumption and the predicted power for July 17th, 2013; There is a DR event from 1700-1800 hrs.

is increased by another  $1.5^\circ$ . This fixed, rule-based strategy is shown in Figure 4(left). The predicted response of the building compared to the actual response due to the fixed strategy is shown in Figure 4(right). We obtain an error of 6.23% for predicting the power consumption of the building in real time during a demand response event.

## DISCUSSION

We presented DR-Advisor, a data-driven tool which acts as a recommender system for demand response baselining and strategy evaluation. We evaluate the performance of DR-Advisor on a large scale DOE reference commercial building, using actual meteorological year data. We show how the tree based methods can achieve a good prediction accuracy of 3 – 6% on average for all the cases. The biggest advantage of DR-Advisor is that it completely bypasses the need to build high fidelity models of buildings e.g., with EnergyPlus or with RC networks. Another major advantage of DR-Advisor is that the models it builds are highly interpretable and simple, an attribute which is often completely neglected in the design of such algorithms. These advantages combined with the fact that the tree based methods can achieve high prediction accuracies, make DR-Advisor a very alluring tool for evaluating and planning DR curtailment responses. DR-Advisor (Figure 2) is being developed into a free and open source tool. Since DR-Advisor is a data-driven approach, it can be easily scaled to multiple buildings and can be used for campus-wide demand response which is a part of our on-going work.

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