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Forecasting residential air conditioning loads

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HIGHLIGHTS

- Accurate forecasts are necessary for using direct load control in energy markets.
- We use a doubly censored Tobit model to forecast hourly air-conditioner usage.
- We get much more accurate forecasts than the typical methods used for forecasting.
- This helps to enable a variety of demand response applications.

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ABSTRACT

A doubly censored Tobit model is used to forecast hourly air-conditioner usage for individual households. The model worked well over a wide range of temperatures, 9–38 °C, making it possible to accurately forecast the electricity load for a variety of demand response applications including operational reserves for renewable energy integration. Individual models are simulated and summed to obtain aggregate forecasts and confidence intervals. The model allows for correlation between the individual shocks that occur in a region. This approach gives substantially more accurate results than the moving average method typically used for forecasting and measuring direct load control. Applying the model to data from three U.S. utilities produced mean square error values from 0.027 to 0.041 with average load values per customer ranging from 0.49 to 0.62 kW.

1. Introduction

Demand response is the reduction of electric loads in response to market signals or system conditions. Electric grid operators and electrical utilities implement demand response to maintain grid reliability or provide electrical service at lower cost. One type of demand response is direct load control (DLC) where electrical appliances are remotely powered off. Grid operators must balance generation and load for reliability. From this perspective, load reduction (decrease in demand) is similar to generation increase (increase in supply). Unlike generation where the supply is deterministic (barring events that lead to a forced outage), the DLC resource is uncertain and must be forecasted. While generators are paid according to the quantity of energy supplied, DLC participants are paid based on the amount of load reduction.[1] Load reductions cannot be directly measured; they are calculated by subtracting actual load during a DLC event from a customer's estimated load conditional on the DLC event not occurring. In this paper we propose a new method for forecasting and measuring DLC of residential ACs using a Tobit model with upper and lower censoring.

1.1. Direct load control

Effective DLC is widely used to reduce peak load, which delays the need to build power plants or transmission lines. In recent years it is also used as reserve capacity for contingencies in the grid. PJM, a northeastern regional transmission organization (RTO) in the US, provides 20% of its contingency reserves with DLC resources [1]. Supplying operating reserves with DLC lowers overall costs and allows increased active power output from low cost generators no longer needed to supply reserves [2]. DLC can also be used to adjust load as a means of balancing variability of wind and solar resources [3–6]. The Department of Energy stated that increased reliance on electricity generation from wind and solar power is one factor that will drive demand response programs [7]. A German study analyzed the potential of DLC from different industries to provide operating reserves for wind power. It concluded that full use of the potential

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[1] Load aggregators and large customers usually receive the market prices. However, residential customers usually receive a flat rate for participation from a load aggregator.

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industrial DLC resources would result in operating cost savings of nearly 0.5 billion Euros [8].

Direct load control programs are tailored for different types of customers. Commercial and industrial customers agree to interrupt or curtail specific loads when called upon by the utility in exchange for reduced electric rates. Residential customers often agree to allow utilities limited control of thermal loads such as air conditioners and water heaters. Studies have shown significant economic benefits from incorporating interruptible load into dispatch decisions [9].

For residential customers, utilities and RTOs generally control air conditioner loads by cycling the power to the compressor. Power to the compressor unit is turned off for brief periods in order to temporarily reduce demand. Alternatively, thermal energy storage systems can be used to reduce AC use during peak hours by cooling a storage medium in the evenings and using the cold material to cool the air in a building [10].

Increased use of DLC will require more accurate load forecasting techniques that are easy to implement, like the method we develop in this work. Model accuracy is needed over a range of temperatures since DLC can be called for peak load reductions at high temperatures as well as contingency reserves at lower temperatures.

ACs are well suited for DLC since they can be powered off for short periods of time without much customer discomfort. A California utility surveyed customers during a pilot study and found the majority did not notice DLC events lasting 15 min or less [11]. ACs also comprise a large portion of residential loads (roughly 20% of residential electricity consumption) [12].

Advanced electric meters (i.e. smart meters) allow finer control over electric loads and provide more load data which will enable greater use of DLC in electric grids [13–15]. Two-way communication between the utilities and customers may also allow customers to offer load curtailments for specified prices [16]. As of 2011, 13.4% of all electricity customers had advanced meters [17], but the Department of Energy is providing funds to quickly increase this level [18]. There is a need for models to efficiently take advantage of this new data. This Tobit model captures the realistic situation that AC loads are bounded below by zero and above by the maximum energy consumption for a particular AC.

Recent changes in wholesale electric markets will also increase the use of DLC. In 2011, the Federal Energy Regulatory Commission (FERC) issued order number 745 which directs wholesale energy market operators to compensate demand side resources (eg. DLC) the full energy market price as long as dispatching the DR resource is cost-effective [19]. Each market operator sets a threshold price based on historical data which is used as the minimum price at which DR resources are compensated.

1.2. Load forecasting

Accurate load forecasts are essential for efficient DLC. DR resources are paid the energy market locational marginal price for the reduced load based upon the customer baseline (CBL). This is an estimate for a counterfactual event, i.e. the expected load conditional on the DLC event not happening. Inaccuracies in the CBL lead to incorrect and unfair payments. Underpayments for DR resources discourage participation while overpayments lead to excessive charges on load serving entities who pay for the reductions. System planners need to accurately know how much load reduction to expect during a DLC event. Reducing uncertainty in the load forecasts will become more important as DLC resources provide more ancillary services to help balance the smart electricity grid.

Default CBLs differ across RTOs and independent system operators (ISOs) [20,21]. Most are simple moving averages. In the PJM RTO, the default CBL is the average hourly load profile from the 4 highest load days of the previous 5 similar day types (weekdays, Saturdays, Sundays/holidays) [22]. The California ISO, the New York ISO and the New England's ISO calculate CBLs by averaging loads from the previous 10 similar days [23–25]. The Electric Reliability Council of Texas publishes 3 different default CBL calculations: a linear regression of energy consumption on covariates representing weather conditions, daylight hours, season and day of the week; a moving average of 8 of the previous 10 similar days; or a model that averages days with load profiles similar to the event day [26]. All ISO/RTOs accept alternative methods for CBL determination as long as it is approved. This paper presents such an alternative.

Broadly speaking, air conditioner load forecast models can be classified into two distinct categories: engineering models and statistical models. Both model types attempt to forecast AC load as a function of several variables, primarily: temperature and time of day. The most common are engineering models of a house that consist of a system of differential equations that capture the evolution of indoor temperature and the on/off cycles of the air conditioner compressor given weather variables such as temperature, solar radiation, etc. These models requires measuring the thermal characteristics and thermostat settings of each house for use as parameters [27–30]. Another approach is to use maximum likelihood to estimate these parameters from historical data [31–33]. The latter method still requires knowledge of the thermostat setpoints. Unfortunately, these models are sensitive to changes in the physical properties of the residence such as home improvements.

There is comparatively less work on statistical models applied to AC load forecasts, especially residential. Statistical models do not directly model the dynamics of energy flows. Instead they capture trends in historical AC load data to predict future loads.

Parametric models of AC duty cycles have been used to estimate load reductions by comparing controlled and non-controlled AC data [34]. Autoregressive models have been used in AC forecasts for non-residential buildings [35], but not the highly variable residential data. Machine learning type models have been proposed to forecast building energy consumption using support vector regression [36] and artificial neural networks [37,38]. These types of models capture the non-linearities in energy demand, but are data intensive for each household. A recent proposal to forecast load reduction from AC DLC relies on fitting a model to load measurements at a feeder circuit level [39]. This method cannot forecast load for individual households and requires a large fraction of ACs on each feeder participate in DLC so that it can distinguish the signal from the noise. This is a concern for forecasts at lower temperatures.

This paper considers a doubly censored Tobit model to forecast hourly individual AC loads. The model uses ambient temperature and time of day as covariates. The individual forecasts are aggregated via simulation to create day-ahead hourly aggregate load forecast and forecast intervals. A Tobit model accounts for the non-linearities inherent in AC energy consumption while not requiring extreme amounts of data. Other non-parametric methods such as neural networks require vast amounts of data for each customer. The model developed in this paper may be adopted by RTOs such as PJM under their current rules and is therefore immediately applicable, while more complicated methods may take years to adopt.

The remainder of this paper is organized as follows: Section 2 describes the dataset. Section 3 describes the Tobit model and the theoretical framework of the model. The results are in Section 4, and Section 5 covers the policy implications.

2. Data

Under a confidentiality agreement, a dataset was obtained from Pepco Holdings, Inc. The dataset contains AC energy consumption