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Modeling short-run electricity demand with long-term growth rates and consumer price elasticity in commercial and industrial sectors

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A B S T R A C T

This paper specifies and estimates state-level models of short- and long-term electricity demand in the United States. The short-term model predicts hourly load based on weather and calendar inputs. The long-term model estimates interannual demand, and includes population, prices, and gross state product as predictors. These models are combined to incorporate the short- and long-term trends in electricity consumption when generating forecasts of diurnal patterns into the future. Finally, the authors investigate the effects of short-run price elasticities of demand. The short-term model is shown to be within 95% accuracy of actual levels in out-of-sample tests.

1. Introduction

The demand for electricity fluctuates on familiar cycles and with known influences in the short-term, and its long-term growth coincides with trends in macroeconomic indicators. Accurately forecasting the level of demand on disparate time scales is necessary for utilities to schedule generators, plan system maintenance, and devise long-term investments. Short-term forecasts are commonly made in half- or 1-h intervals 24–168 h in advance of the pertinent period. Seasonal patterns such as day of week and month of year, as well as temperature and humidity, are the most significant factors influencing demand within a year. Both types of factors work in conjunction with each other—although on a day-to-day basis the specific day of the week is of great importance, temperature also matters. Monthly seasonality primarily reflects meteorological conditions. These variables become less significant with longer time horizons; models of long-run electricity demand typically forecast aggregate monthly or annual levels. Changes in long-run demand are normally correlated with changes in economic indicators such as gross domestic product and prices of electricity and other fuels.

In the short-term, regression techniques are common for modeling the quantity of electricity demanded. Pardo et al. [1] use autoregressive least-squares regression to explore the effects of temperature and seasonality on daily load. For modeling the daily peak and monthly aggregate demand levels, Mirasgedis et al. [2] also use regressions which include seasonal and temperature variables. Both of these papers are primarily concerned with the role of weather in demand quantity fluctuations. The peak load, average load, temperature, and calendar particulars of the previous day are the basis for the bivariate model of next-day hourly peak in the work of Engle et al. [3]. Forecasts for diurnal load profiles can be made in a comparable manner; Ramanathan et al. [4] build 24 separate regression models, one for each hour of the day with unique regressors. A similar approach is used by Taylor and Buizza [5] to forecast load at various cardinal points of the day, including midday and midnight.

Similar methods are applied to long-term forecasts as well. For example, Mohamed and Bodger [6], Amarawickrama and Hunt [7] and Bianco et al. [8] use annual demand regression models that consider macroeconomic factors, such as gross domestic product and population. Efforts to combine monthly and annual aggregate forecasts from the same data set through cointegration of time series can be found in the work of Engle et al. [9]. The authors capture short-term effects in a monthly model, and then improve it by introducing a factor from a separate annual model influenced more by long-term trends. Artificial neural networks are another

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method common in the literature for both time scales. Ringwood et al. [10] investigate the influences on demand in multiple time frames by modeling daily, weekly, and yearly quantity demanded using neural networks. More recently, Taylor et al. [11] develop an intra-hour neural network and compare it to double exponential smoothing, regression with principal component analysis, and seasonal ARMA models for two data sets of diurnal load profiles on hourly and half-hourly intervals.

A natural extension of predicting the quantity of electricity demand is investigating how this quantity changes under different pricing policies. Price elasticities are a measure of how much the quantity demanded for a good changes given a change in price. These elasticities can be estimated for changes in the price of the good itself (own) or a change in the price of a different good (cross). With respect to electricity load, the different goods can be thought of as electricity in different hours of the day. An increase (decrease) in price in an hour may decrease (increase) demand in that hour, and change the quantity demanded in adjacent hours as well. Prices can be structured in several ways, for instance a constant time-invariant price or a time-of-use tariff, with different prices applied to consumption during different blocks of time. The hourly own- and cross-price elasticities of demand used in this work are determined by Taylor et al. [12]. These elasticities are estimated from eight years of data for industrial customers across all hours of the day.

Despite the existing body of literature on short- and long-term forecasting, little work which utilizes multiple time horizons is available. In the short-run, models frequently only predict peak or aggregate daily load. We investigate how similar modeling techniques to those found in the literature can be used to predict continuous demand with one function. Furthermore, by predicting the entire diurnal load profile with a single regression model, exploring the interactions in quantity demanded between different hours is possible. Thus, effects of different pricing strategies can be captured by utilizing customers' price elasticities. We explore cases where there is a simple peak and off-peak structure and where the price increases with the consumption level. In addition, as a population and economy grow, the amount of electricity demanded in aggregate can grow as well. We develop a second model of annual aggregate electricity demand regressed against macroeconomic variables. Using the long-term growth rates, as determined by this annual aggregate model, fine-grain predictions further into the future are possible. Although predictions of peak and aggregate load as found in the literature are necessary for planning, forecasting temporally disaggregated load allows further refinement.

The remainder of this paper is organized as follows. Section 2 details the development of the two models; first, the diurnal model form and the data used to develop it are considered and then a similar treatment for the annual regression is undertaken. How these models are combined to forecast loads in the future is also discussed. In Section 3, the estimated regression coefficients are reported along with results from out-of-sample validation of the proposed short-term model and forecasted results and the application of cross- and own-price elasticities. Section 4 concludes and summarizes the work.

2. Data and methodology

2.1. Diurnal model

Our initial regression model for diurnal load profiles is of a log-linear form incorporating calendar and weather variables. Electricity demand has daily, weekly, and monthly cycles which can be described by Fourier series over the respective period. A Fourier series is a linear combination of sine and cosine functions of

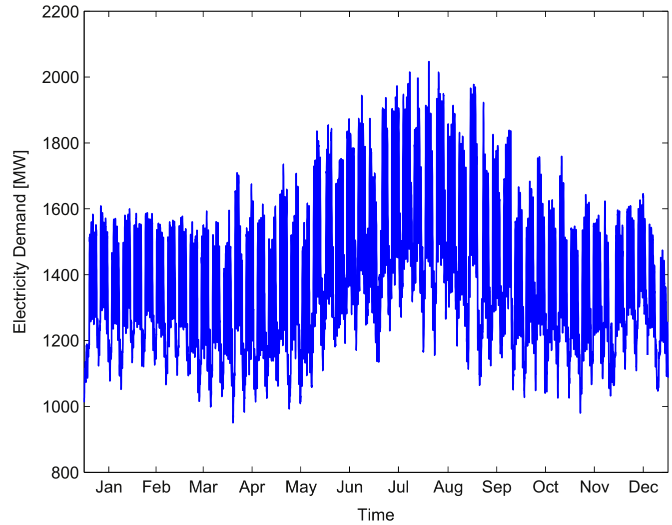

Fig. 1. Hourly electricity demand of 78,000 commercial and industrial customers in the state of Ohio in the year 2010. Data obtained from AEP.

differing frequencies used to approximate a given function arbitrarily well. This method is advantageous over the classic approach of dummy variables to represent the particular hour, day, and month of an observation. Fewer variables are necessary to represent each time frame; a model with two frequencies at each time scale is optimal with our data, for a total of 16 predictors instead of 40. The three cycles modeled with this method are hour of the day patterns, hour of the week patterns, and month of the year patterns. The longest of these cycles is evident in Fig. 1, which shows hourly load in the state of Ohio by a subset of American Electric Power's (AEP's) commercial and industrial customers in the year 2010. Demand peaks during the summer months, but otherwise is relatively steady on a seasonal basis. This may be in part because cooling technologies used in the summer tend to be electric, while heating technologies used in winter months are not. Fig. 2 displays the first two weeks of hourly demand levels from the same consumers as in Fig. 1. The weekly and daily cycles are apparent. Also evident is the difference in demand from weekdays to weekends, as the first 48 h are over a holiday weekend, and the next 120

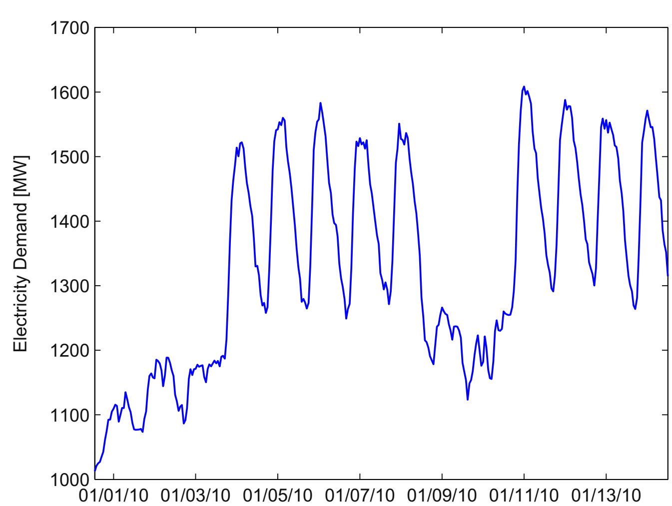

Fig. 2. Diurnal demand patterns for same subset of commercial and industrial customers shown in Fig. 1 in the first two weeks of the year. Data obtained from AEP.