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Short term electricity demand forecasting using partially linear additive quantile regression with an application to the unit commitment problem

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HIGHLIGHTS

- Use of a time varying trend variable improves forecast accuracy.
- Combining short term forecasting with the unit commitment problem.
- Modelling approach results in scheduling and dispatching of electricity at a minimal cost.
- Inclusion of temperature variables from two thermal regions improves forecast accuracy.

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ABSTRACT

Short term probabilistic load forecasting is essential for any power generating utility. This paper discusses an application of partially linear additive quantile regression models for predicting short term electricity demand during the peak demand hours (i.e. from 18:00 to 20:00) using South African data for January 2009 to June 2012. Additionally the bounded variable mixed integer linear programming technique is used on the forecasts obtained in order to find an optimal number of units to commit (switch on or off. Variable selection is done using the least absolute shrinkage and selection operator. Results from the unit commitment problem show that it is very costly to use gas fired generating units. These were not selected as part of the optimal solution. It is shown that the optimal solutions based on median forecasts ($Q_{0.5}$ quantile forecasts) are the same as those from the 99th quantile forecasts except for generating unit g_{8c}, which is a coal fired unit. This shows that for any increase in demand above the median quantile forecasts it will be economical to increase the generation of electricity from generating unit g_{8c}. The main contribution of this study is in the use of nonlinear trend variables and the combining of forecasting with the unit commitment problem. The study should be useful to system operators in power utility companies in the unit commitment scheduling and dispatching of electricity at a minimal cost particularly during the peak period when the grid is constrained due to increased demand for electricity.

1. Introduction

1.1. Context

Load forecasting is deemed important as it provides prediction of electricity needed for future consumption [1] and is essential for every electricity utility in order to maintain the demand and supply balance [2]. Load forecasts are also required for many other purposes such as system security, rate design, revenue projection as well as for scheduling activities [3–5]. Moreover, load forecasts are usually assessed periodically, ranging from hours, days, and weeks, months, up to a year, or even longer. However, the focus in this paper is on the short term load forecasts (STLF) which range from few hours up to a week [6]. Accurate and efficient forecasts are necessary for any power supplying company as they help in preventing problems such as under loading (i.e. load shedding, blackouts, etc.) or overloading (i.e. producing more capacity than needed), which are very costly to suppliers [2]. Accurate forecasts also help with the unit commitment decisions by reducing production costs [7].

1.2. An overview of the literature on load forecasting

Short term load forecasting (STLF) has been receiving a lot of attention [1]. Almost every year different models for STLF are developed, applied, reviewed and published. Short term forecasts are used to estimate the load demand up to a week ahead of a schedule [8]. Many

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utilities rely on them because they are useful when it comes to daily operation and scheduling of power systems [9]. For instance, obtained forecasts are used to schedule generation as well as transmission of units to consumers. A brief review on weather station and variable selection methods together with other methods used in short term forecasting as well as on the unit commitment problem (UC) follows.

South Africa (SA) is among developing countries around the world faced with electricity crisis. On the African continent, SA is considered as the most industrialized country with the highest electricity consumption [10]. The electricity demand pattern is complex in nature, due to the presence of several factors such as the economic, environmental, weather conditions and calendar effects [11,1]. However, many researchers use temperature in their forecasting models as it is one of the major drivers of electricity demand. A South African study that uses temperature is that of Chikobvu and Sigauke [12], their main aim being to assess its impact on the daily peak electricity demand. The results show that electricity demand is sensitive to cold weather in the country. Another study that examines meteorological effects is that of Taylor and MacSharry [13], in which the seasonality patterns and their effects were studied from European countries.

Other than meteorological effects, time factors also have a huge impact on electricity demand. Time factors include day-of-week, yearly seasonality, time of the day, etc. and generally are known as calendar effects and their impact in short term load forecasting are discussed in detail by [11]. For instance, load curves were used to explain electricity consumption patterns for different hours during the day and based on the load curves these two authors concluded that calendar effects mostly determine the daily life style of the consumers, i.e. highest peak load in the evening [11]. Moreover, the peak load demand is the most studied as highlighted by Hinman and Hickey [3].

Weather effects are generally known to have a major impact on load demand thus making selection of weather stations an important aspect to consider in load demand forecasting. The fact that station selection depends on the geographical location, climate as well as the industrial structure of a country or region of study was highlighted by Janicki [14]. One of the few papers that focused more on the weather stations selection is that of Hong et al. [15]. In this paper the authors propose a new weather station selection framework which they applied to two of the electricity utilities in the United States (US). Their focus was more on developing an algorithm that will help in determining the number of weather stations to consider as well as selecting the stations to use for a particular electricity utility.

Another important aspect in model building is to be able to identify the best set of input variables. For instance, over the past years many different variable selection methods have been used to select important variables to include when forecasting generally. There are many different available methods that can be used to select important variables in a study. These include the dimension reduction, shrinkage as well as the subset selection methods [16]. The most commonly used methods are subset selection which include techniques such as the stepwise criterion and many more.

A study that applied one of the variable selection methods mentioned above is that of Fan and Hyndman [1]. The authors in this paper used a stepwise variable selection technique was used to select a combination set of variables that were then used in models that were used to predict 48 half-hourly load demand in Australia. The authors used the stepwise backward selection method which involves including all the variables at first and removing one at a time while keeping the rest in the model. Then they continued by checking the performance of the model with removed variable using mean absolute percentage error (MAPE). Thus if the model resulted with a lower MAPE value, it was then selected as the best model for that period.

Although stepwise variable selection methods have been and are still widely used, they have limitations. Some of these limitations include their inability to deal with multicollinearity and less computational efficiency. These limitations are mostly ignored in many studies. For instance, according to Olusegun et al. [17] the stepwise selection criterion selects variables based on the correlation between a response and a set of explanatory variables only. Somehow the correlation within the explanatory variables is not considered which can lead to having one or more variables with the same characteristics in the model, due to their multicollinearity. Shrinkage methods are better equipped to handle multicollinearity.

Several methods have been proposed in the literature on variable selection in regression based models. In this study we use least absolute shrinkage and selection operator (Lasso) via hierarchical interactions. For modelling time series data with multiple seasonalities Bien et al. [18] developed a Lasso for hierarchical pairwise interactions in regression based models. In another study a method which satisfies the strong hierarchy for learning linear interaction models is presented in [19]. Results show that the developed method is comparable with past methods. The method caters for both continuous and categorical variables.

In a study short term load forecasting model based on the semi-parametric additive technique were developed [1]. The model was used to investigate the relationship between the load demand and the standard explanatory variables: calendar effects, temperature effects, as well as lagged load observations were included in the model to forecast the half-hourly load demand up to a week ahead. Another study also proposed the use of a more general semi-parametric technique known as generalized additive model (GAM) [2]. The GAM model was first developed by Hastie and Tibshirani [20] and discussed in detail in Wood [21]. These authors used the model to forecast the French hourly load data for over 5 years. The focus was to model effects that drove the French load consumption and also to compare the proposed model with the operational one. The effects included weather conditions, economic growth, weekly and yearly seasonality. The empirical results showed that the proposed model performs better and was able to capture the effects that the French's operational model could not capture [2]. Using functional approximation, Feng and Ryan [22] developed a day-ahead hourly electricity forecasting model. The developed model uses weather forecasts and also captures temporal patterns. The model provides accurate forecasts as well as prediction error bands which are narrow.

On the other hand, quantile regression (QR) models are used a lot in forecasting by different energy sectors, e.g. wind power forecasting, price forecasting, etc. A recent study [23], introduced an optimal forecast quantile regression (OFQR) model which was used to forecast the annual peak electricity demand in 32 zones in United States (US). The main aim was to compare the relative performance of the OFQR model with the ordinary least square (OLS) regression model, which is a standard method used by almost every utility. The OFQR model provided more accurate forecasts compared to OLS.

In another study, a QR model was also used to forecast electricity demand [24]. The data used in their study was collected from 3639 households in Ireland at both aggregated and disaggregated levels. The proposed QR model was compared with three other benchmark methods. Other authors also developed additive quantile regression models for forecasting both probabilistic load and electricity prices as part of the global energy forecasting competition of 2014 (GEFCom2014) [25]. A summary of the methods used in GEFCom2014 are given in [4]. The proposed new methodology of [25] ranked first in both tracks of the competition. The work done by [25] is extended by Fasiolo et al. [26] who developed fast calibrated additive quantile regression models. To implement the developed models, Fasiolo et al. [26] developed a new r statistical package "*qgam*". The same covariates used in [25] were also used in [26]. In both papers variable selection techniques are not discussed. In another study [27] used kernel support vector quantile regression and copula theory for short-term load probability density forecasting. Two criteria for evaluating the accuracy of the prediction intervals are proposed, the prediction interval normalized average width (PINAW) and the prediction interval coverage probability (PICP). Results from this study show that the Gaussian