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Dynamic Short Term Load Forecasting using Functional Principal Component Regression

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Abstract

Short term load forecasting plays an important role for the energy industry as accurate predictions are vital in utilizing available resources to optimize the electricity production. Literature reveals that commonly used approaches for such predictions are done using multiple regression, stochastic time series, exponential smoothing, state-space models, neural network models and fuzzy logic, to name a few. In the recent past however, functional data analysis has been an emerging trend to analyse time related data. The electricity demand for a particular day varies with time and as such the daily load curve can be modelled using functional data analysis. Instead of using hourly electricity demand of each day, the dimensionality of the dataset could be reduced using functional principal component analysis. The principal component scores of the selected components were used for prediction. Seasonality and speciality of the day were incorporated using dummy variables and ARIMA models with regressors have been used to predict the principal component scores. Significant variables for the model were identified prior to ARIMA modelling and residual analysis was performed to validate the fitted models. From the predicted principal component scores, the next day's load curve is evaluated. A moving window has been used to make the predictions real time and for the prediction process to be more efficient. This proposed functional analysis based methodology when compared with a commonly used error back-propagated neural network approach have shown improved predictions of the forecasted electricity demands.

Keywords: functional principal analysis, short term load forecasting, time series

1. INTRODUCTION

Electricity demand forecasting or load forecasting is a vital aspect in the energy industry. The prediction can be short term, medium term or long term and each prediction is used at different stages helping the electricity generation companies in their operation and management of the supply to their consumers. Short Term Load Forecasting (STLF) is predicting electricity demand a few hours ahead to one week ahead. The challenge related to STLF is increasing the prediction accuracy. A vast range of literature can be found regarding STLF using multiple regression, stochastic time series, exponential smoothing, state-space models, neural network models and fuzzy logic based approaches indicating the prominence given to STLF. Daily load curve, a plot of electricity demand against time, can be considered as a function with respect to time for which techniques related to functional data analysis can be utilized to do the prediction. In the recent past, functional data analysis has been an emerging trend to analyse time related data due to the promising results obtained through those techniques. The main objective of this study was to forecast the next day's hourly electricity demand using functional data analysis techniques considering the fixed functional patterns of the dataset.

2. LITERATURE REVIEW

A large number of published research regarding short term load forecasting can be found using various approaches. Among them some of the most commonly used technique are multiple regression (Moghram & Rahrnan , 1989), stochastic time series, exponential smoothing (Moghram & Rahrnan , 1989), Bayesian modeling (Cottet & Smith, 2003), neural network models and fuzzy logic (Seetha & Saravanan, 2007, Hsu & Ho, 1992). In the recent past, the use of functional data analysis techniques have shown a rapid increment in various statistical analysis for clustering (Jacques & Preda, 2014), prediction (Antoch, Prchal, De Rosa, & Sarda, 2010, Jornaz, 2016 and Shang, 2013) and system investigation (Gubian, Torreira, & Boves, 2014). Moreover, it can be identified that functional data analysis approaches have been used in various fields such as energy, medical, physics and also environmental sciences. In most of such applications accurate results could be observed using functional data analysis techniques.

When broadly discussing the techniques used in the energy industry for electricity demand prediction, functional data analysis approaches have been used to predict short term (Jornaz, 2016 and Antoch, et al., 2010) and very short term load forecasting (Shang, 2013).In most of the studies the first step is reducing the dimensionality through functional principal component analysis and then the prediction techniques have been used accordingly. The above mentioned studies have compared their research findings with other statistical and artificial intelligence approaches where they have proven that their suggested method using functional data analysis method yield superior results.

3. THEORY AND METHODOLOGY

For this study, the univariate time series of hourly electricity demands was considered as separate load curves representing the electricity demands of each day. In this research, an observation was a load curve for a particular day. The dataset also included the specialty of the day as normal working day, public bank mercantile holiday and New Year's effect. The methodology consists of reducing the dimensionality of the curves using functional principal component analysis and the functional principal component scores of the selected components were used to do the prediction. As the system should be dynamic, new data should be added to the system and the prediction should be performed with the updated data. In order to make the predictions more accurate, a moving window was incorporated to identify the required most recent data that should be used to do the prediction and to exclude past data accordingly. The length of the moving window was also to be chosen and the model validated for the updated data.

3.1. Functional Principal Component Analysis

At a population level, a stochastic process denoted by *f* can be decomposed into the mean function and the sum of the multiplications of orthogonal functional principal components and uncorrelated principal component scores. It can be expressed as, (Hyndman & Shang, Functional time series forecasting, 2009)

$$f = \mu + \sum_{k=1}^{\infty} \beta_k \phi_k \tag{1}$$

where μ is the unobservable population mean function, β_k is the k^{th} principal component scores, and ϕ_k is the k^{th} population functional principal component. (Shang, Modeling and forecasting for Functional Time Series)

3.2. Forecasting using ARIMA model with regressors

These models combine regression models and ARIMA models to give regression with ARIMA errors. Such models can be used when the errors from a regression are subjected to autocorrelation. (Hyndman & Athanasopoulos, 2012). An ARIMA forecasting equation for a stationary time series is a linear equation in which the predictors consist of lags of the dependent variable and/or lags of the forecast errors. These models aim to describe the autocorrelations in the data. (Hyndman & Athanasopoulos, Forecasting: principles and practice, 2012)

4. DESCRIPTIVE ANALYSIS

For this study, the total hourly electricity demand of Sri Lanka for the period 2008-2012 was obtained from the Ceylon Electricity Board of Sri Lanka (CEB). For model building, data during 2008 - 2011 period was used and data obtained for year 2012 were used for model validation and testing.

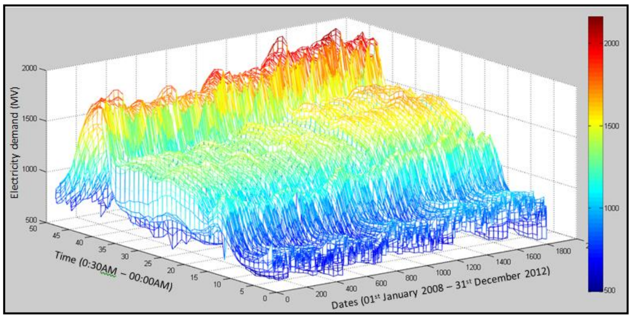


Figure 1: Fluctuations of electricity load curves over the years

When the hourly electricity demands were plotted with respect to each day as in Figure 1, similar shaped daily load curves can be clearly seen. Over the years, the shape seem to be consistent but a gradual increment of the electricity demand can be observed. The electricity consumption within a day varies with respect to time, the day of the week, specialty (whether it a holiday or not), special events and also the weather. These specialties were carefully chosen based on the findings of Deshani, Attygalle, Hansen, & Karunaratne (2014) and Deshani, Hansen, & Attygalle (2014). Figure 2 displays how the load curve varies with respect to day of the week and a holiday. The peak electricity demand is the maximum electricity demand in a particular day usually recorded around 7.00 p.m. In predictions, this peak demand plays a major role as the CEB has to bare a substantial cost due to the use of alternate methods of generating electricity as oppose to using hydroelectricity. (Sri Lanka Electricity Board, 2015)

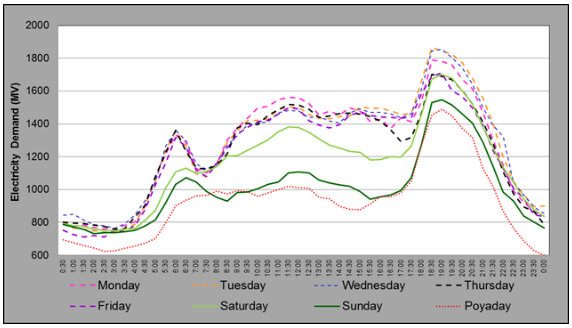


Figure 2: Patterns of daily load curves with respect to specialty of the day

The load curve can be taken as functions with respect to time where they show a fix seasonal pattern among the days as well as years. After a thorough descriptive analysis, different day types that influence the slight changes of the curve shapes were identified.

5. ADVANCED ANALYSIS

This section describes the advanced analysis of this study and it mainly consists of two stages. Dimensionality reduction of the curves using functional principal component analysis and forecasting using ARIMA models with regressors.

5.1. Functional Principal Component Analysis

Firstly, the dimensionality of the daily load curves was reduced using functional principal component analysis. Two principal components could explain nearly 93% of the total variations of the data and their principal component scores were used to do the prediction.

Figure 3 depicts the first two weighted functional principal components and associated scores. The two line plots in the second row of Figure 3 clearly indicate the strong seasonal nature of the first two principal component scores namely Beta 1 and Beta 2.

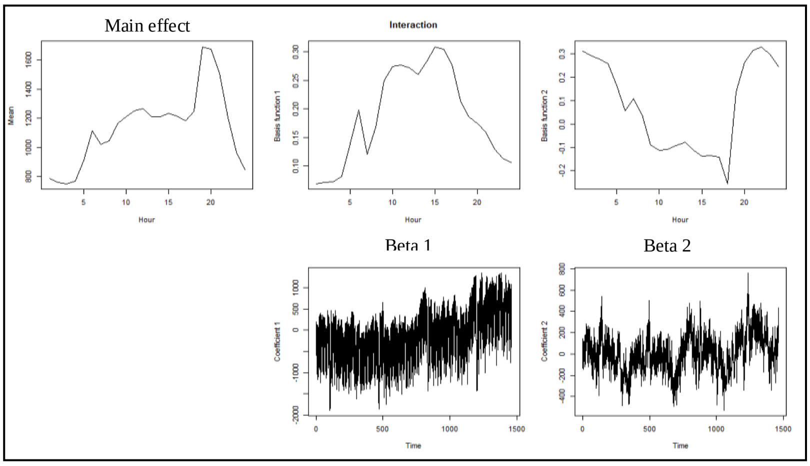


Figure 3: The first two weighted functional principal components and associated scores

5.2. ARIMA Models with Regressors

As there were fixed seasonal patterns, the seasonality could not be just removed by differencing each series. Therefore ARIMA models with regresses were used for the prediction of both Beta1 and Beta2. As regressors, six dummy variables (S1, S2, …, S6) were added to capture the weekly seasonality of the series. Another four dummy variables (Sp1, Sp2, Sp3, Sp4) were added to incorporate the specialty of the day as 4 categories. Where the five categories represented Category 1: No specialty, Category 2: Poyaday and Public Bank Mercantile holiday, Category 3: Public and Bank holiday, Category 4: Day prior new year and New year day, Category 5: One day after new year and Two days after new year. These categories were previously identified by Deshani et al. (2014) .

Separate regression models were fitted to the two series to check for the significance of the added dummy variables with the index term and the squared index terms. All the regression terms for Beta1 were significant at 5% significance level and for Beta2 all the terms except two variables Sp2 and Sp4 were significant at 5% significance level. Therefore those Sp2 and Sp4 variables were not added as regressors when fitting an ARIMA model for Beta2.

Table 1: Model summary of the fitted regressions for Beta 1 and Beta 2

	Beta 1			**Beta 2**		
Coefficients	**Estimate**	**t value**	**Pr (>|t|)**	**Estimate**	**t value**	**Pr (>|t|)**
Intercept	-1.056e+03	-36.672	<2e-16	1.514e+02	10.262	< 2e-16 ***
Index	-6.407e-01	-9.119	<2e-16 ***	-2.498e- 01	-6.939	5.94e-12 ***

IndexSq	9.013e-04	19.370	<2e-16 ***	2.407e-04	10.094	<2e-16 ***
S1	1.137e+03	40.954	<2e-16 ***	-2.689e+02	-18.905	< 2e-16 ***
S2	1.228e+03	44.290	<2e-16 ***	-1.827e+02	-12.861	< 2e-16 ***
S3	1.234e+03	44.465	<2e-16 ***	-1.762e+02	-12.391	< 2e-16 ***
S4	1.225e+03	44.166	<2e-16 ***	-1.694e+02	-11.922	< 2e-16 ***
S5	1.179e+03	42.458	<2e-16 ***	-1.639e+02	-11.519	< 2e-16 ***
S6	6.656e+02	24.004	<2e-16 ***	-7.167e+01	-5.044	5.13e-07 ***
Sp1	-1.046e+03	-30.887	<2e-16 ***	1.527e+02	8.869	< 2e-16 ***
Sp2	-2.143e+02	-3.269	0.0011 **	-4.249e+01	-1.265	0.2060
Sp3	-1.573e+03	-15.666	<2e-16 ***	1.023e+02	1.988	0.0471 *
Sp4	-1.542e+03	-15.357	<2e-16 ***	-5.891e+01	-1.145	0.2524
R-Squared	0.8274			0.3463		
F Statistics	578.6 on 12 and 1448 DF			63.91 on 12 and 1448 DF		
p-value	< 2.2e-16			< 2.2e-16		

The residuals of the fitted regression models were used to make the initial guesses for AR and MA terms of the models observing the ACF and PACF plots. Thereafter, the best ARIMA model for each series was selected considering AIC, BIC, and AICc values for several ARIMA models with the regressors mentioned above. Best ARIMA model for Beta1 and Beta 2 was selected based on the lowest AICc, AIC and BIC values and the Ljung Box test. ACF and PACF plots also suggested that the models were adequate for the dataset. The best model for Beta1 was ARIMA(3,1,1) and ARIMA(1,1,3) for Beta2.

5.3. Predicting Next Day's Load Curve

From the predicted functional principal component scores, the electricity hourly demand is predicted using the function $f = \mu + \sum_{k=1}^{2} \beta_k \phi_k$ according to in Equation 1.

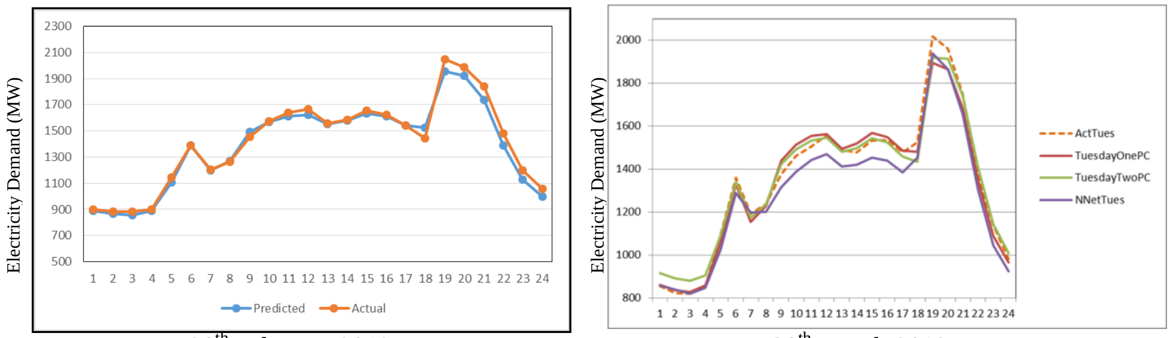
5.4. Dynamic Prediction

In order to predict in a dynamic manner, two main aspects were considered. First, it is identified whether the best ARIMA model is consistent with different time periods and then the best size of the moving window is selected. The four years that used to build the model, therefore, were further examined separately as 1 year, 2 year, 3 year and 4 year periods. For each period the best ARIMA models for Beta1 and Beta2 were consistent over the considered period. Therefore for the dynamic model, ARIMA(3,1,1) model was used to predict the first principal component scores and ARIMA(1,1,3) was used to predict the second principal component scores.

Thereafter the most appropriate size of the moving window was is selected. The accuracy and the execution time was considered for selecting the most suitable size of the moving window. A moving window of 1 year time period was used to carry out dynamic forecasting because of the accuracy and less execution time compared to longer window sizes. As such, after each day, a new load curve will be added to the database and the moving window will be shifted by one day to do the next prediction.

6. RESULTS

The test data consisted of daily load curves of year 2012 and the R software was used to do the analysis. **Error! Reference source not found.** shows predictions made for randomly selected two days using the suggested approach. Right side figure includes the predicted daily load curves using one PC and a neural network. The results using the proposed approach seem promising. Moreover, the results were compared with an error back propagated neural network where the features have been selected based on mutual information criteria. The proposed method predicted more accurately than the neural network approach. While comparing the predictions among the different methods, it can be clearly seen that two component predictions yield higher accuracies and can predict the peak time quite accurately than other techniques. Temperature also needed to be added to the model as future work as literature reveals that temperature has a considerable influence on the load forecasting. (Cottet & Smith, 2003, Taylor & Buizza, 2003)



20th February 2012 30th March 2012

Figure 4: Some predicted daily load curves with actual curves

7. CONCLUSION

Using functional time series regression approach, high accuracies could be obtained for this dataset except for a few situations. The days having less accuracies could be due to extremes weather conditions and by incorporating weather information the unexpected fluctuations of the daily load curves may be captured. In most situations the suggested methodology yielded higher accuracies than iterative error back propagated neural network. Using two component functional principal component the peak time was well captured than other techniques mentioned in this paper.

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