

A New Approach for Long-Term Electricity Load Forecasting

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Abstract

Long-term electricity load and price forecasts have become critical inputs to energy service provider (ESP) decision makings in restructured environments. This paper presents a three-stage hierarchical approach for long-term electricity load forecasting. These stages are called yearly trend model (YTM), weekly trend model (WTM), and daily trend model (DTM). The first stage fits an appropriate function to data and extracts its yearly trend. The weekly and daily trends are then extracted using the Box-Jenkins method in WTM and DTM, respectively. For doing so, candidate trends are identified using auto correlation function (ACF) and partial auto correlation function (PACF) plots. Then, Akaike information criterion (AIC) and Schwarz information criterion (SIC) are used to select the best-fitted trends. The different behavior of weekends and night times is captured using dummy variables. The obtained yearly, weekly, and daily trends are finally used for electricity load forecasting.

1. Introduction

In restructured power systems, ESPs are responsible to serve the electricity demand of their customers. They participate in wholesale electricity markets, buy electricity, and resell it to the customers [1]. ESPs as private entities decide about involvement in different electricity markets with the goal of procurement cost minimization. However, volatile pool prices and uncertain customers' loads impose some levels of risk to ESPs. To hedge the risks, they can sign fixed-quantity fixed-price forward contracts at higher average prices [2]. Forward contracts are usually signed in monthly, seasonal, and yearly basis. In such a situation, attaining the minimum cost and risk takes a fair decision framework to optimally design ESP procurement strategy. This in turn requires appropriate statistical techniques for modeling and forecasting future loads and prices. Besides, forecasted loads and prices are input parameters for planning studies [3]. This paper aims to develop a new load forecasting technique. Several researches can be found in the literatures dedicated to electricity load forecasting. [4]-[7] adopted artificial neural networks for short-term and near short-term load forecasting. In [8]-[9], wavelet models were used to improve the load forecasting accuracy. Knowledge-based expert systems were utilized in [10] for short-term load forecasting of Taiwan power system. [11] developed a short-term load forecasting approach based on a hybrid network with a self-

organizing map and a support vector machine. Statistical methods were employed in [12]-[15] to forecast future electricity loads from their past values and the present and past values of exogenous factors such as weather conditions. All of the reported papers focused on near future load forecasting; while, ESPs require to estimate hourly loads during several months ahead. Recall that forward contracts are signed in monthly, seasonal, and even yearly basis. This paper presents a three-stage hierarchical approach to forecast the year-ahead electricity load. These stages are called YTM, WTM, and DTM. YTM extracts yearly seasonality through fitting an appropriate function to data. The function can be determined by looking at data plot and engineering judgment. In this paper, without loss of generality, a sinusoidal function plus a polynomial function is adopted as the fitting function. The extracted yearly trend is omitted from the data to prepare it for the next stage. The weekly behavior is then extracted through the Box-Jenkins method in WTM where a set of dummy variables is incorporated to model different behavior of weekends. The obtained weekly trend is also subtracted from data to prepare it for the last stage. Lastly, DTM extracts the daily trend using the Box-Jenkins approach and a set of dummy variables. Once the YTM, WTM, and DTM models are obtained, they are used individually to forecast yearly, weekly, and daily components of the future electricity load. Thereafter, the complete forecast of electricity load is achieved by adding the forecasted components.

2. The Box-Jenkins Method

In 1970s, George Box and Gwilym Jenkins introduced a combination of auto regressive and moving average models for forecasting the future of a time series. The method fits an auto regressive moving average (ARMA) model to the past behavior of a time series in order to make a forecast. Conceptually, an ARMA model is a linear regression of the current value of a time series against its past values and the current and past values of an error term. A general ARMA model can be written as:

$$\varphi(B)S_t = \theta(B)\varepsilon_t . \quad (1)$$

$$\varphi(B) = 1 - \varphi_1 B^1 - \varphi_2 B^2 - \dots - \varphi_p B^p . \quad (2)$$

$$\theta(B) = 1 - \theta_1 B^1 - \theta_2 B^2 - \dots - \theta_q B^q . \quad (3)$$

Where, S_t denotes the value of time series S at time t , ε_t is the error term at time t , and B is the backshift operator, i.e.,

$B^h S_t \equiv S_{t-h} \cdot \varphi_1, \dots, \varphi_p$ and $\theta_1, \dots, \theta_q$ are the coefficients of auto regressive and moving average polynomials respectively. Also, p and q are order of the polynomials. The Box-Jenkins method estimates the above parameters in the following steps:

2.1. Model Identification

In this step, order of auto regressive and moving average polynomials is determined so that the model adequately describes the data. Obviously, with increasing p and q in (2) and (3) and thus complexity, fitness of the model would be improved. However, a complicated model with enormous number of parameters is not desirable. Therefore, a systematic method is required for model identification to compromise between accuracy and complexity. The most common approach to identify order of a model is to iteratively fit several candidate models and select the best one through goodness-of-fit statistics. The observation of ACF and PACF plots is also usually helpful.

Several statistics can be found in the literatures used for selecting the best model. Amongst, AIC and SIC are the most widely used ones. The philosophy behind the statistics is that the best model is the simplest one that describes the data with fewest parameters. AIC and SIC statistics are computed as:

$$AIC = \ln\left(\frac{RSS}{n}\right) + \frac{2K}{n}. \quad (4)$$

$$SIC = \ln\left(\frac{RSS}{n}\right) + \frac{[K \ln(n)]}{n}. \quad (5)$$

Where, RSS is the sum of residual squares, n is sample size, and K is number of parameters. The best model is the one with the smallest AIC and SIC. Interested readers are referred to [16] for detailed explanations on AIC and SIC statistics.

2.2. Model Estimation

Once the model structure is identified, the parameters of the model should be estimated. Adopting regression approaches, this step uses past data for calculating the coefficients in (2)-(3). The least square method is usually used for regression. The objective of this technique is to maximize likelihood. This can be done by several statistical software packages.

2.3. Model Validation

The third and the final step is the verification of the obtained model. Model validation can be done by analyzing the model residuals. A model adequately describes time series behavior if the residuals are completely random. A simple way to investigate randomness of the residuals is to investigate ACF and PACF plots. The coefficients of the ACF and PACF are close to zero for all lags if the residuals are white noise. Several software packages are already available for calculating these coefficients. As an alternative way, the Jarque-Bera is a goodness-of-fit test wherein the third and fourth moments of the residuals are compared to those of the Gaussian distribution.

3. The Proposed Methodology

This section provides a new methodology to forecast hourly electricity load throughout one year ahead. This method extracts

behavior of the electricity load in three separate stages. Let $Y(t)$, $W(t)$, and $D(t)$ be the yearly, weekly, and daily trends of the electricity load, respectively. The proposed method, in the first stage, extracts $Y(t)$ from original data. The first stage is called YTM. $Y(t)$ is then subtracted from the initial time series to prepare the next stage input data. In the second stage, weekly behavior of load, i.e., $W(t)$, is identified and omitted from the time series. This stage is called WTM. Lastly, in the third stage, $D(t)$ is extracted from the residuals of the second stage. The third stage is named DTM. Once YTM, WTM, and DTM models are achieved, they are employed individually to predict yearly, weekly, and daily components of the future load. Then, the complete forecast can be obtained by adding the time series forecasted by YTM, WTM, and DTM as follows:

$$L(t) = Y(t) + W(t) + D(t). \quad (6)$$

Where $L(t)$ denotes the load value at time t . The overall procedure of the approach is discussed and detailed explanations on how to determine $Y(t)$, $W(t)$, $D(t)$, and the respective models are thoroughly described in the following sub-sections.

3.1. Yearly Trend Model (YTM)

Electricity load exhibits seasonal fluctuations which are fundamentally because of seasonal changes in weather conditions. The Finland average daily load during 2010 is shown in Fig. 1. As can be seen, the demand is much more in cold months, since cold weather initiates extensive use of electricity for heating. This increased consumption is diminished in hot months and is observed again in cold months of the next year. In this paper, a sinusoidal function is adopted to model this periodic behavior of electricity load. Beside the mentioned cyclic behavior, average consumption is not constant in long term in most of countries (e.g., electricity demand is usually growing in developing countries). Here, a linear polynomial is used to model the long term changes in electricity consumption. According to the above discussions, yearly trend of electrical load is formulated as follows:

$$Y(t) = a \sin\left(\frac{2\pi t}{T}\right) + b \cos\left(\frac{2\pi t}{T}\right) + ct + d. \quad (7)$$

Where a , b , c , and d are coefficients of the model which should be estimated by fitting (7) to time series of electricity load. Also, T is the yearly period of data. Since electricity load is in hourly basis in this paper, T is equal to 8760 here. Once the model is determined, yearly behavior of electricity load in the future can be forecasted through extrapolation.

3.2. Weekly Trend Model (WTM)

Electricity use is not uniform throughout a week. As shown in Fig. 2, demand is usually much lower during weekends due to lower industrial activities. This paper adopts the Box-Jenkins method for modeling of intra-week seasonality. Since electricity use in weekends deviates from the typical behavior, dummy variables are employed to improve the accuracy of the model. Dummy variables are incorporated here for Saturdays and Sundays. Therefore, (1) is modified as follows:

$$\varphi(B)S_t = \theta(B)\varepsilon_t + d^{sat} + d^{sun}. \quad (8)$$

Where, d^{sat} and d^{sun} are Saturdays and Sundays dummy variables. Note that d^{sat} and d^{sun} are zero for all weekdays except Saturdays and Sundays respectively. Interested readers are referred to [16] for more information on dummy variables.

As mentioned heretofore, the model structure can be determined by looking at ACF and PACF plots or by iteratively testing different possible models. In this paper, several candidate structures are firstly determined considering ACF and PACF plots. The candidate models are then fitted and the final model is selected considering AIC and SIC statistics. The randomness of the residuals is also investigated through the ACF and PACF plots of the residuals and their histogram. Once the WTM model is achieved, weekly behavior of load in the future can be predicted using the past data and the obtained model.

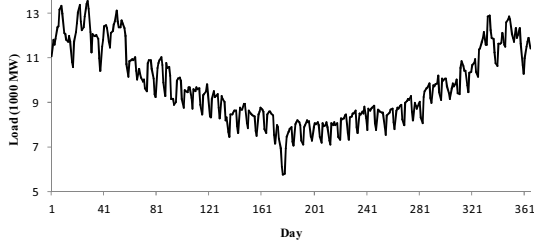


Fig. 1. Finland average daily load during 2010

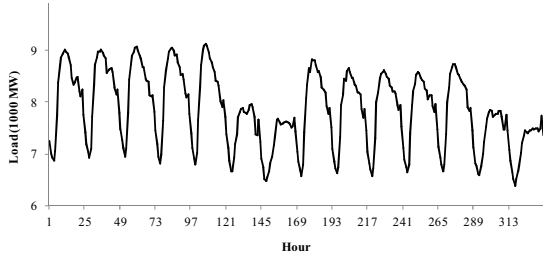


Fig. 2. Finland hourly load since July 4 until July 17, 2011

3.3. Daily Trend Model (DTM)

Electricity load fluctuates during a day. A three-day period of Finland electricity load is plotted in Fig. 3. This figure clearly illustrates the substantial intra-day variability. As can be seen, demand is much lower in night times when major businesses are closed. The modeling of intra-day seasonality is analogous to that of the weekly trend. Therefore, (1) is modified as follows:

$$\varphi(B)S_t = \theta(B)\varepsilon_t + \sum_{i=1}^{24} d^i. \quad (9)$$

Where, d^i denotes the dummy variable at hour i . Similar to WTM, several candidate models are firstly determined by looking at ACF and PACF plots and the best one is selected using the AIC and SIC statistics. Also, ACF and PACF plots of the residuals along with their histogram are employed to investigate the goodness of the fitted model. Once the DTM model is obtained, the daily behavior of load in the future can be forecasted using the past data and the achieved model.

Finally, the obtained yearly, weekly, and daily components are added up to attain a complete forecast of the future demand.

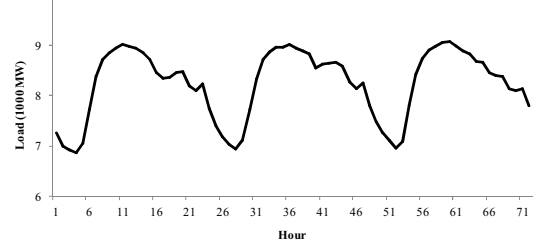


Fig. 3. Finland hourly load since July 4 until July 6, 2011

4. Numerical Analysis

In this section, the proposed method is applied to the hourly electricity load of Finland since early 2010 until late 2011.

As mentioned in Section 3, the yearly seasonality is extracted using sinusoidal and linear polynomial functions. The Curve Fitting GUI of MATLAB is employed to fit (7) to the hourly data. The coefficients of the fitted curve are shown in Table 1. The hourly electricity load and the obtained yearly seasonality are depicted in Fig. 4.

Table 1. Coefficients of the yearly seasonality model (7)

Coefficient	Value	95% confidence band
a	1864	(1843 , 1884)
b	512.5	(490.7 , 534.4)
c	-0.05369	(-0.05674 , -0.05064)
d	10010	(9975 , 10040)

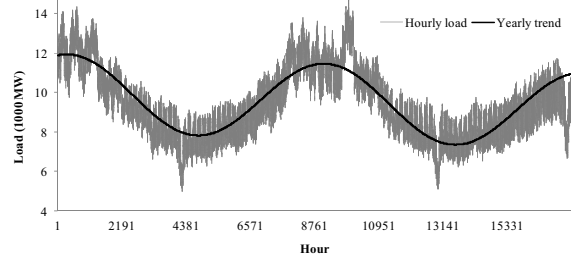


Fig. 4. The hourly load and the extracted yearly seasonality

The extracted yearly seasonality of load is removed from the data. Now, the obtained time series is investigated to identify an appropriate model for extracting weekly seasonality. As discussed in Section 3, daily time series should be used in this stage. Therefore, the hourly time series of electricity load is converted to a daily time series. This is done by averaging the data over each day. Then, ACF and PACF plots of the daily time series are studied. In this paper, EViews software package is used for ACF and PACF plots. Thereafter, several candidate models are identified by looking at the plots. Parameters of the candidate models are estimated through least square regression method. Ultimately, AIC and SIC statistics are calculated for candidate models and the most appropriate model is selected. Note that the most appropriate model is the simplest one that adequately describes the data. Table 2 provides the parameters of the selected model.

Table 2. Parameters of the weekly seasonality model (8)

par. value	par. value	par. value	par. value	par. value
φ_1 0.438	φ_4 -0.529	θ_1 0.631	θ_5 0.640	d^{sat} -649.25
φ_2 0.408	φ_7 0.353	θ_4 0.557	θ_6 0.499	d^{sun} -865.16

Par.: Parameter

It should be noted that the selected model has an intercept with the value of 194.43 MW. Also, it is worthwhile to note that the coefficients of the selected model are estimated through least square regression method in EViews software. The extracted weekly seasonality obtained by fitting the selected model to the daily time series is depicted in Fig. 7.

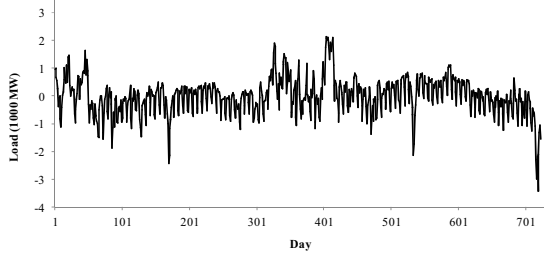


Fig. 7. The extracted weekly seasonality

The ACF and PACF values for 30 first lags are provided in Table 3. Since ACF and PACF values for all of the lags are negligible, randomness of the residuals is verified and hence, the selected model adequately describes the behavior of data. The histogram of the residuals is shown in Fig. 8. As can be seen, the histogram is nearly Gaussian. Therefore, the hypothesis of randomness of the residuals is also validated by the histogram.

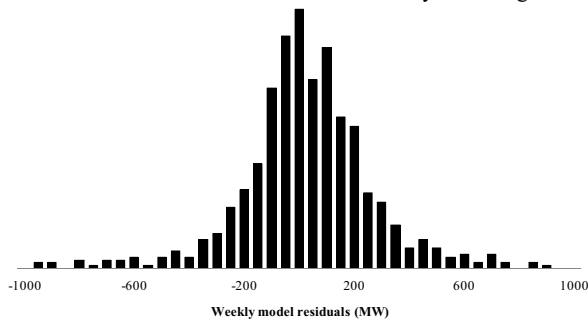


Fig. 8. Histogram of the weekly model residuals

Table 3. ACF and PACF values for 30 first lags of the weekly model residuals

lag	ACF	PACF	lag	ACF	PACF	lag	ACF	PACF
1	0.013	0.013	11	0.021	0.027	21	0.028	0.029
2	0.011	0.011	12	-0.034	-0.037	22	0.064	0.067
3	-0.003	-0.003	13	-0.017	-0.021	23	0.008	0.019
4	-0.028	-0.028	14	-0.025	-0.030	24	0.000	0.005
5	-0.013	-0.013	15	0.024	0.029	25	0.012	0.012
6	0.007	0.009	16	-0.040	-0.045	26	0.036	0.037
7	0.046	0.049	17	-0.040	-0.048	27	-0.093	-0.102
8	-0.016	-0.019	18	0.025	0.022	28	0.052	0.059
9	-0.017	-0.020	19	0.025	0.035	29	0.012	0.006
10	-0.017	-0.017	20	0.032	0.037	30	-0.029	-0.038

The weekly seasonality model is obtained in previous sub-section. The trend described by the obtained weekly seasonality model is subtracted from the hourly time series. Now, we have an hourly time series in which yearly and weekly trends are removed. The aim of this sub-section is to extract daily seasonality of load from the obtained time series. To do so, the Box-Jenkins method equipped with a set of dummy variables is applied to data. Also, in order to remove the remained weekly seasonality, the series at hand is differenced by lag of 168. Again, ACF and PACF plots are used as the basis of model identification. After constituting a set of candidate models by looking at ACF and PACF plots, the most appropriate model is selected through AIC and SIC statistics. These steps are performed for at hand time series in EViews software. Parameters of the selected model are provided in Table 4. The extracted daily trend obtained by fitting the selected model to the hourly time series is depicted in Fig. 9.

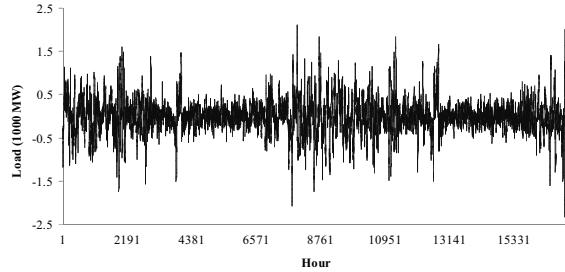


Fig. 9. The extracted daily seasonality

Table 4. Parameters of the daily seasonality model (9)

par. value	par. value	par. value	par. value
φ_1 1.053	θ_{120} 0.241	d^7 132.9	d^{16} 305.8
φ_2 -0.104	θ_{144} 0.230	d^8 320.7	d^{17} 384.6
φ_{18} -0.031	θ_{168} -0.618	d^9 405.0	d^{18} 430.00
θ_{23} 0.013	d^1 -744.5	d^{10} 421.1	d^{19} 513.75
θ_{24} 0.275	d^2 -975.2	d^{11} 429.7	d^{20} 450.81
θ_{43} 0.015	d^3 -1080.5	d^{12} 407.5	d^{21} 141.96
θ_{48} 0.248	d^4 -1094.1	d^{13} 330.9	d^{22} 194.17
θ_{72} 0.225	d^5 -903.3	d^{14} 258.1	d^{23} 76.15
θ_{96} 0.217	d^6 -295.5	d^{15} 265.2	d^{24} -376.92

Table 5 provides the ACF and PACF values for 30 first lags. Since ACF and PACF values for all of the lags are negligible, randomness of the residuals is verified and hence, the obtained model successfully describes the behavior of data. Fig. 10 shows the histogram of the residuals. As can be seen, distribution of the residuals is approximately Gaussian. Therefore, the hypothesis of randomness of the residuals is also verified by the histogram.

The yearly, weekly, and daily seasonalities of the Finland electricity load were extracted in the above. Here, the models are separately used to forecast yearly, weekly, and daily components of Finland electricity load since January 2012 until December 2012. The complete forecast of electricity load is calculated by adding the yearly, weekly, and daily components. Fig. 11 depicts the complete forecast of Finland electricity load in 2012.

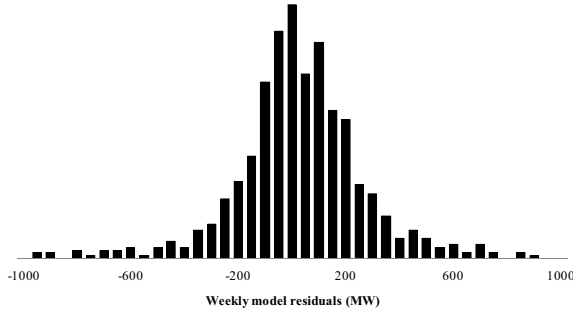


Fig. 10. Histogram of the daily model residuals

Table 5. ACF and PACF values for 30 first lags of the daily model residuals

lag	ACF	PACF	lag	ACF	PACF	lag	ACF	PACF
1	0.056	0.056	11	-0.001	-0.001	21	0.001	-0.002
2	0.014	0.011	12	-0.007	-0.007	22	0.003	0.001
3	0.012	0.011	13	-0.005	-0.004	23	0.010	0.007
4	0.004	0.002	14	-0.003	-0.002	24	0.035	0.035
5	0.021	0.020	15	0.004	0.004	25	0.010	-0.032
6	0.013	0.010	16	0.002	0.002	26	0.001	-0.007
7	0.005	0.004	17	0.011	0.011	27	0.005	-0.003
8	0.003	0.002	18	0.043	0.042	28	0.010	0.011
9	0.002	0.002	19	0.067	0.063	29	0.027	0.024
10	-0.005	-0.006	20	0.008	0.000	30	0.019	0.014

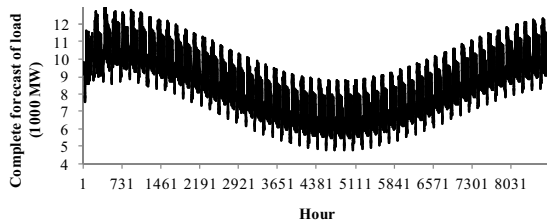


Fig. 11. The complete forecast of Finland load in 2012

5. Conclusions

In this paper, a three-stage hierarchical technique for electricity load forecasting has been proposed. In the first stage, yearly seasonality of load is extracted through fitting a predefined function to data. The function can be determined by looking at data plot and engineering judgment. After removing yearly trend, the proposed technique uses Box-Jenkins method for modeling the weekly seasonality of load. For the sake of accuracy, two dummy variables have also been incorporated into the model. Dummy variables were used to model significant reduction in electricity consumption in weekends. Once the weekly trend is removed, daily seasonality of the electricity load is extracted using the Box-Jenkins method in the third stage. Also, a set of dummy variables are employed for modeling different behavior in night times. In the proposed method, the complete forecast can be achieved by adding the yearly behavior, weekly behavior, and daily behavior of electricity load. A two-stage approach has been employed here to identify the structure of Box-Jenkins model. At first, a set of candidates for the structure of weekly and daily models has been identified by looking at ACF and PACF plots. Thereafter, the most

appropriate models have been selected through AIC and SIC statistics. Finally, the proposed technique has been applied to forecast the electricity load in Finland. The obtained results indicate appropriate performance of the technique.

6. References

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