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Daily peak electricity demand forecasting based on an adaptive hybrid two-stage methodology

Abderrezak Laouafi [a,*], Mourad Mordjaoui [a], Farida Laouafi [a], Taqiy Eddine Boukelia [b]

[a] Department of Electrical Engineering, University of 20 August 1955-Skikda, Skikda, Algeria
[b] Department of Mechanical Engineering, University of Constantine 1, Constantine, Algeria

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ABSTRACT

This paper describes daily peak load forecasting using an adaptive hybrid two-stage methodology. Because the time series of electricity consumption is mainly influenced by seasonal effects, the double seasonal Holt–Winters exponential smoothing method is firstly used for next-day peak electricity demand forecasting. In the second stage, the secondary forecasting model is applied taking into account the benefits of Fuzzy c-means clustering; K-nearest neighbors algorithm; Wavelet packet decomposition; and Adaptive Neuro-Fuzzy Inference System, for further improvement in forecasting accuracy. The whole architecture of the proposed model will be presented and the results will be compared with neural networks and stand-alone adaptive neuro-fuzzy inference system based approaches by using a gathered data from the Algerian power system. The results show that: (1) the proposed methodology is the best among all the considered schemes, (2) the FKW-ANFIS has satisfactory performance in both normal and special daily conditions.

Introduction

Electric load forecasting is a very important tool for ensuring economic and reliable operation in power systems. To achieve this end, electric utilities use load forecasting models, to ensure that the energy supplied meets the load of their customers plus the energy lost in the system. For this specialized function, a trained staff is needed to increase or decrease the produced power so as to adjust the supply–demand balance at any time in the best conditions of cost and safety. Accurate load forecasting models are needed for a variety of time horizons, these could be listed as: very short-term for load–frequency control and economic dispatch functions; short-term for the day-to day operation in power system, medium-term for generators maintenance scheduling, and long-term to build new lines and sub-stations or to upgrade the existing systems. Very short-term (VSTLF), short-term (STLF), medium-term (MTLF) and long-term load forecasts (LTLF) are ranged respectively from few minutes to an hour, an hour to one week, one week to one year, and one year to decades. Because of its great importance for performing many operations in power systems, including generator unit commitment; hydro-thermal coordination; load flow study; fuel allocation; and power interchange [1], short-term electricity demand forecasting has been extensively studied in the literature [2–10]. Instead, a lower number of works can be found in the literature about VSTLF [11–13], MTLF [14–17] and LTLF [17–19].

STLF forecasting covers the daily minimum and maximum electricity demand, total daily energy, and daily load curve as a series of 24 hourly forecasted loads. Particularly, daily peak load forecasting (DPLF) is very important task for decision making processes in the national electricity supply system of a country, as the consequences of over- or underestimation may increase the operating cost. Overestimation of future electric load may cause the startup of too many generating units and leads to a redundant reserve of electric power. In contrast, underestimation of load causes failure in providing enough electricity, which may lead into supply interruption and blackouts during periods of peak demand. If the entire national electricity supply system were to shut down, it would take days, possibly even weeks to restore [20].

In the last few decades, many techniques have been developed to improve the accuracy of peak load forecasting. Reported models in the literature of DPLF could be principally divided into two groups: classical techniques and artificial intelligence based approaches. Conventional techniques include time series models [20,21], multivariate regression [22], and robust regression models [23]. Artificial intelligence based approaches include neural networks [1,24,25], fuzzy systems [26], and neuro-fuzzy systems

* Corresponding author.
E-mail address: laouafi_abderrezak@yahoo.fr (A. Laouafi).

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[27]. Although they are accurate in normal days, univariate conventional techniques such as the seasonal autoregressive integrated moving average (SARIMA) model cannot give satisfactory results when subject to special daily conditions, because they ignore important weather effects and cannot be updated for facing the change in load demand during holidays. Even though multivariate classical methods such as multiple regression models express the peak load as a function of exogenous inputs, the linear modeling process faces difficulty to determine empirically the correct complex relationship that exists between the peak load and the other explanatory inputs. In recent years, the advent of new intelligent techniques such as neural networks and adaptive neuro-fuzzy inference system (ANFIS) enabled to model automatically complex nonlinear input–output relationships through learning process using a database of load and independent variables. Current trends in research in the field of load forecasting are focused on the use of hybrid and combined methods [28–31].

The main objective of this paper is to present a novel model for performing the DPLF. The proposed methodology can be viewed as a two-stage forecasting model. Since the time series of peak electricity demand is mainly influenced by seasonal effects (daily and weekly cycles), the double seasonal Holt–Winters–Taylor technique (HWT) is firstly used to perform a primary forecasted load. In the second part, the primary forecasted peak load is verified and improved by a secondary forecasting model; called FKW-ANFIS, which uses the benefits of Fuzzy c-means (FCM) clustering, k-Nearest neighbors (k-NN) algorithm, Wavelet packet decomposition (WPD), and Adaptive neuro-fuzzy inference system. Our idea for this structure is to take the output of HWT model as an entry to the secondary forecasting model. FCM and k-NN are used for classifying data into somewhat similar patterns, which lead to noise reduction and to an improvement on the quality of the amount of data should be taken by the Wavelet packet-Adaptive neuro-fuzzy inference system models; and therefore, to a higher accuracy. To illustrate the suitability of the proposed methodology, the approach is implemented to a peak load data from the Algerian power system.

The rest of the paper is organized as follows. Section "The Algerian peak electricity demand time series" presents the Algerian peak electricity demand time series. Section "Proposed daily peak load forecasting methodology" describes the proposed estimation method. Section "Results and discussion" provides and explains forecasting results. Finally, Section "Conclusion" concludes the paper.

The Algerian peak electricity demand time series

In this study, we consider the power peak load data that consist of thirty-five months of observations for electricity demand in Algeria from 01 January 2012 to 30 November 2014. These data were collected from OSE (Operateur du Systeme Electrique) website [32]. The top subplot of Fig. 1 shows that the used data consist of two time series. The first series records the morning peak electricity demand, while the second series consists of the evening peak load observations. The figure illustrates that the daily peak load usually occurs during the evening period. Therefore, we limited our interest in the present work to the evening peaks prediction. The second subplot of Fig. 1 presents box-plots for the evening electricity demand data. One can perceive an intraweek seasonal cycle, where weekdays show similar patterns of demand, but Fridays are somewhat different and the load on which is relatively low compared to in workdays.

By considering both two series cited above, the data will contain then daily seasonal cycle of duration two periods (morning and evening peak), and weekly cycle of duration fourteen periods (workdays and weekends). Hence, it seems natural to try to include both seasonal cycles in a HWT forecasting model. This is the approach taken by J.W. Taylor as part of their modeling of half-hourly England and Wales electricity consumption for a lead time up to a one day ahead [33]. This method compete well in normal days, but it may faces some difficulty when subject to special daily conditions such the case of the rapid change in load demand during holidays. The whole architecture of the proposed methodology for forecasting the peak load in both normal and special daily conditions will be presented in the next section.

To evaluate the performance of the proposed strategy, the electricity peak load data for four different months: January 2014; April 2014; July 2014; and November 2014, and for the public holidays of 2014 were used as an illustrative example.

Proposed daily peak load forecasting methodology

The structure of the proposed DPLF method consists of two principal stages. Through the use of morning and evening peak electricity demand records, HWT method is applied as a first part at the day J_{L-1} for ensuring a primary forecasted peak load for the day J_L. At its turn, the second part of our model consists of five basic parts. First, the temperature observations are used as inputs to the Fuzzy c-means clustering method for classifying the peak load data into two classes (load of a hot or cold period). Then, the morning peak loads; the evening peak electricity demand information; and the primary forecast of HWT, are used as inputs for k-NN to distinguish whether the day J_L is workday or weekend and so that to select closest samples that have the similar characteristic of the day J_L. The third part of the secondary forecasting method decomposes the clustered morning and evening peak load data; via wavelet packet method, into approximation parts associated with low frequencies and detailed parts associated with high frequencies. At the fourth part, the ANFIS is introduced to predict the future patterns of each wavelet packet space. Finally, the evening peak load forecasting values of all the spaces are added up to produce the final electricity demand forecasting result.

Holt–Winters–Taylor method

Holt–Winters–Taylor technique is an extension to the standard Holt–Winters exponential smoothing, which allows accommodating the intraday and intraweek seasonal cycles in the electricity demand series. This is the approach taken by J.W. Taylor as part of their modeling of half-hourly England and Wales electricity consumption for a lead time up to a one day ahead [33]. However, the present paper is the first in term of using HWT method for forecasting daily peak electricity demand. The formulation for HWT method is given in the following expressions:

$$S_t = \alpha(y_t/D_{t-s1}W_{t-s2}) + (1-\alpha)(S_{t-1} + T_{t-1}) \quad (1)$$

$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)(T_{t-1}) \quad (2)$$

$$D_t = \delta(y_t/S_tW_{t-s2}) + (1-\delta)D_{t-s1} \quad (3)$$

$$W_t = \omega(y_t/S_tD_{t-s1}) + (1-\omega)W_{t-s2} \quad (4)$$

$$\hat{y}_t(k) = (S_t + kT_t)D_{t-s1+k}W_{t-s2+k} + \phi^k(y_t - ((S_{t-1} + T_{t-1})D_{t-s1}W_{t-s2})) \quad (5)$$

S_t and T_t, are the smoothed level and trend; D_t and W_t are respectively the seasonal indices for the intraday $s1$ ($s1 = 2$) and intraweek $s2$ ($s2 = 14$) seasonal cycles; α, γ, δ and ω are the smoothing parameters; y_t is the actual value of the time series in period t; and $\hat{y}_t(k)$ is the k step-ahead forecast made from forecast origin t. The term involving the parameter ϕ in the forecast function expression Eq. (5) is a simple adjustment for first-order autocorrelation.