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Medium-term electric load forecasting using singular value decomposition

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ABSTRACT

Medium-term load forecasting is an important stage in electric power system planning and operation. It is used in maintenance scheduling, and to plan for outages and major works in the power system. A new technique is proposed which uses hourly loads of successive years to predict hourly loads and peak load for the next selected time span. The proposed method implements a new combination of some existing and well established techniques. This is done by first filtering out the load trend, then applying the *SVD* (singular value decomposition) technique to de-noise the resulting signal. Hourly load is thus divided to three main components: a) a load trend-following component, b) a random component, and c) a de-noised component. Results of applying the technique to the Jordanian power system showed that good forecasting accuracies are attained. In addition, the proposed method outperforms the traditional exponential curve fitting method. The peak load error was found to be less than 5% using the proposed methodology. It was also found that a lag period of 4 years suits the load forecasting purposes of the Jordanian power system. The proposed method is generic and can be implemented to the hourly loads of any power system.

1. Introduction

The term forecast stands for predictions of future events and conditions. The process of making such predictions is called forecasting [1]. The main purpose of forecasting is to meet future requirements, reduce unexpected cost and provide a potential input to decision making [2].

Since the electric load varies continuously in time, it is considered to be a time series. This enables applying different time series techniques and methodologies to predicting future loads based on the available historical data of the loads.

Time series techniques are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation. Time series forecasting methods detect and explore such structure. The goal here is to determine a model that explains the observed data and allows extrapolation into the future to provide a forecast. In other words, the aim is to find a filtering function that explores the structure of the load behavior and enables such extrapolation. In general, time series model of electric load comprises three added components, the trend component (T), the seasonal component (S), and the irregular or random component R [5]. In this paper, the time series approach is adopted, however, we propose finding the T and R components in addition to what we refer to as the de-noised component (D) instead of (S).

In operating a power system the mission of the utility/company, from the forecasting point of view, is to match demand for electric energy with available supply. This leads to the fact that a major objective of any power company is to accurately predict future loads. From this point on, forecasting can be broadly performed in the following time frames: a) long-term forecasting (1–20 years), b) medium term (1–12 months), c) short-term (1–4 weeks ahead), and d) very short term (1–7days ahead).

Medium-term load forecasting depends mainly on growth factors, i.e. factors that influence demand such as main events, addition of new loads, seasonal variations, demand patterns of large facilities, and maintenance requirements of large consumers. Moreover, this type of forecast uses hourly loads for prediction of the peak load of days or for the weeks ahead. With this information it can be decided to whether take certain facilities/plants for maintenance or not during a given period of time, plan major tests and commissioning events, and determine outage times of plants and major pieces of equipment. The analysis methods used for this type of forecast are similar to the short-term forecast except that there is less need for accuracy [3]. In other words, it can be said that the sensitivity of medium term forecasting on power system operations is less than that of the short-term forecasting.

In this research, electrical hourly loads are processed in three steps: a polynomial fit is performed to assess the non-linear trend of the hourly loads of each year. This is followed by applying the

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SVD method to the difference between the hourly loads and their trend. *SVD* serves to extract both the cyclic and the random components. The latter is fitted to a Normal distribution [$N(0,\sigma)$], i.e. of zero mean and a standard deviation, σ. The implementation of the SVD technique to hourly loads to predict medium term hourly loads of upcoming year represents a contribution of this research.

This paper is organized as follows: in section 2, a literature review is presented to illustrate the methods used in medium-term load forecasting. In section 3, the analysis methodology is presented starting with the discussion of polynomial regression and is followed by the description of the *SVD* (singular value decomposition) technique. The analysis procedure is also outlined. In section 4 the proposed forecasting technique is explained in addition to the definition of the estimated errors indicators. In section 5, results of implementing this technique to the Jordanian power system are presented and analyzed. A comparison of the results obtained using the proposed method with those obtained using the exponential regression method is also demonstrated. Section 6 presents the outcomes and conclusions of this study.

2. Literature review

Most forecasting models use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. The end-use and econometric approach is broadly used for medium- and long-term forecasting. Varieties of methods, which implement the similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, *ANN* (artificial neural networks), and expert systems, have been developed for short-term forecasting [4–7].

Moreover, forecasting methods are also classified into two basic types: *qualitative* and *quantitative* methods. In qualitative, such as: subjective curve fitting, Delphi method, and technological comparisons, future load is predicted subjectively. This is done based on using the opinions of experts. Such methods are implemented when historical data are not available or scarce. On the other hand, quantitative methods are based on mathematical formulation and include: regression analysis, decomposition methods, exponential smoothing, and the Box-Jenkins methodology [8,9]. The research carried out in this paper belongs to the second category, i.e. quantitative methods.

The authors agree to a large extent, with the conclusions of Dragomir et al. [10] stating that over the past decades, few models have dealt with the medium-term load forecasting, which represents a source of primary information for the safe and reliable operation of the power system. In Ref. [11] medium load forecasting was implemented using ANN resulting in mean absolute error of 5.42% depending on the time horizon of prediction.

The problem of producing long-range forecasts using a state-space model based on a short sampling interval [12] showed that the forecasting model based on weekly data can be improved by the incorporation of longer-time-scale information. A time span of 3 years was used which served in increasing the prediction accuracy by 10–20% with associated average error of about 4.5%.

It was stated in Ref. [13] that the daily and weekly loads correlated behavior was utilized in a first order linear regression model of the previous year, i.e. a 1 year time span to predict a one year-ahead loads. Results showed that the average error obtained was less than 3.8%.

Magnano and Boland [14] developed a model to generate synthetic sequences of half-hourly electricity demands using Fourier series and ARMA process. The ARMA model was used to filter out the data. The resulting sequences represent possible realizations of electricity load that could have occurred. They were developed to be used as input data in market simulation software, and to build probability distributions of the outputs to calculate probabilistic forecasts.

ARMA (autoregressive moving average) is used assuming a stationary process, while ARIMA (the acronym of autoregressive integrated moving average, also known as Box-Jenkins model), ARMAX, and ARIMAX(autoregressive integrated moving average with exogenous variables), and FARMAX (fuzzy autoregressive moving average with exogenous input variables) are used assuming ~~a~~ non-stationary processes. The mathematical formulation of these models is well formulated and is available in the literature. ARMA and the previously mentioned versions are used extensively in short-term load forecasting [8,9,15,16].

In their research [17], a long-term consumption forecasting model was developed to represent the historical data from 1970 to 2007. A comparison with national forecasts was performed and results showed that deviation from official projections ranges between $\pm1\%$ and $\pm11\%$.

The forecast performed within the Sri Lanka electricity authorities relied on six econometric techniques for a period ending at 2025. Results showed that there is a variation of around 452 MW in the base forecast peak demand [18].

It should be remarked that there is an appreciable number of publications that implement the SVD technique in conjunction with ANN to perform short-term load forecasting. The majority of these researches utilize the SVD analysis results in the training process, and thereafter in the forecasting stage. However, the SVD was not used as a major tool, up to authors' knowledge, in the medium-term load forecasting, in the sense of using it as proposed in this article as: a) a filtering technique, and b) applying it to hourly loads of the year(s).

3. Proposed analysis model

In this research we adopted the time series analysis line. The hourly loads are processed in three steps: a polynomial fit is performed to assess the non-linear trend of the hourly loads of each year. This is followed by applying the *SVD* method to the difference between the hourly loads and their trend. *SVD* serves to extract the cyclic and the random components. The latter is fitted to a Normal distribution [$N(0,\sigma)$], i.e. of zero mean and a standard deviation σ. Fig. 1 illustrates the analysis stage of the proposed technique. The figure shows that the analysis starts by implementing polynomial regression to the available hourly loads, this is followed by performing the SVD decomposition, and finally the statistical analysis of the random component R is done. The details of this stage are discussed in the following.

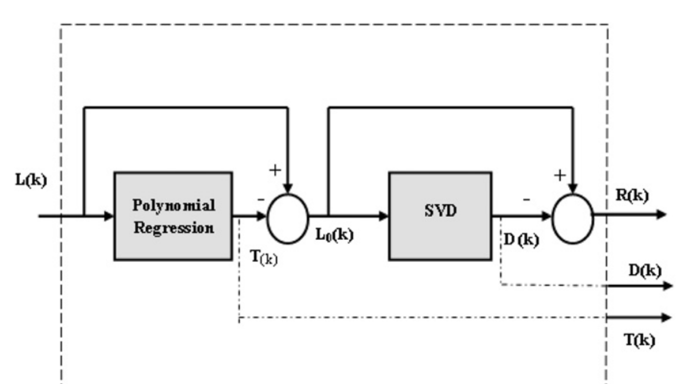

Fig. 1. Analysis stage.