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Neural networks for pattern-based short-term load forecasting: A comparative study

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ABSTRACT

In this work several univariate approaches for short-term load forecasting based on neural networks are proposed and compared. They include: multilayer perceptron, radial basis function neural network, generalized regression neural network, fuzzy counterpropagation neural networks, and self-organizing maps. A common feature of these methods is learning from patterns of the seasonal cycles of load time series. Patterns used as input and output variables simplify the forecasting problem by filtering out a trend and seasonal variations of periods longer than a daily one. Nonstationarity in mean and variance is also eliminated. In the simulation studies using real power system data the neural network forecasting methods were tested and compared with other popular forecasting methods such as ARIMA and exponential smoothing. The best results were achieved for generalized regression neural network and one-neuron perceptron learned locally.

1. Introduction

Short-term load forecasting (STLF) is essential for power system control and scheduling. Load forecasts of short horizon (from minutes to days) are necessary for energy companies to make decisions related to planning of electricity production and transmission, such as unit commitment, generation dispatch, hydro scheduling, hydro-thermal coordination, spinning reserve allocation, interchange and low flow evaluation. Electricity markets also require the precise load forecasts because the load is the basic driver of electricity prices. The forecast accuracy translates to financial performance of energy companies (suppliers, system operators) and other market participants and financial institutions operating in energy markets.

Neural networks are widely used in STLF due to their flexibility which can reflect process variability in uncertain dynamic environment and complex relationships between variables. The main drivers of the power system load are: weather conditions (temperature, wind speed, cloud cover, humidity, precipitation), time, demography, economy, electricity prices, and other factors such as geographical conditions, consumer types and their habits. The relationships between explanatory variables and power system load are often unclear and unstable in time. In this work we focus on univariate forecasting methods, in which only historical load time series is used as input to predict the future values of power system load.

The load time series contains a trend, multiple seasonal variations and a stochastic irregular component. From Fig. 1, where the hourly electrical load of the Polish power system is shown (these data can be downloaded from the website http://gdudek.el.pcz.pl/varia/stlf-data), it can be observed annual, weekly and daily cycles. A daily profile, on which we focus in STLF, depends on the day of the week and season of the year. Moreover, it may change over the years. The noise level in a load time series depends on the system size and the customer structure. A trend, amplitude of the annual cycle, weekly and daily profiles and noise intensity may change considerably from dataset to dataset.

Due to the importance of STLF and the problem complexity many various STLF methods has been developed. They can be roughly classified as conventional and unconventional ones. Conventional STLF approaches use regression methods, smoothing techniques and statistical analysis. The most commonly employed conventional models are: the Holt-Winters exponential smoothing (ES) and the autoregressive integrated moving average (ARIMA) models [1]. In ES the time series is decomposed into a trend component and seasonal components which can be combined additively or multiplicatively. ES can be used for nonlinear modeling of heteroscedastic time series, but the exogenous variables cannot be introduced into the model. The most important disadvantages of ES are overparameterization and a large number of

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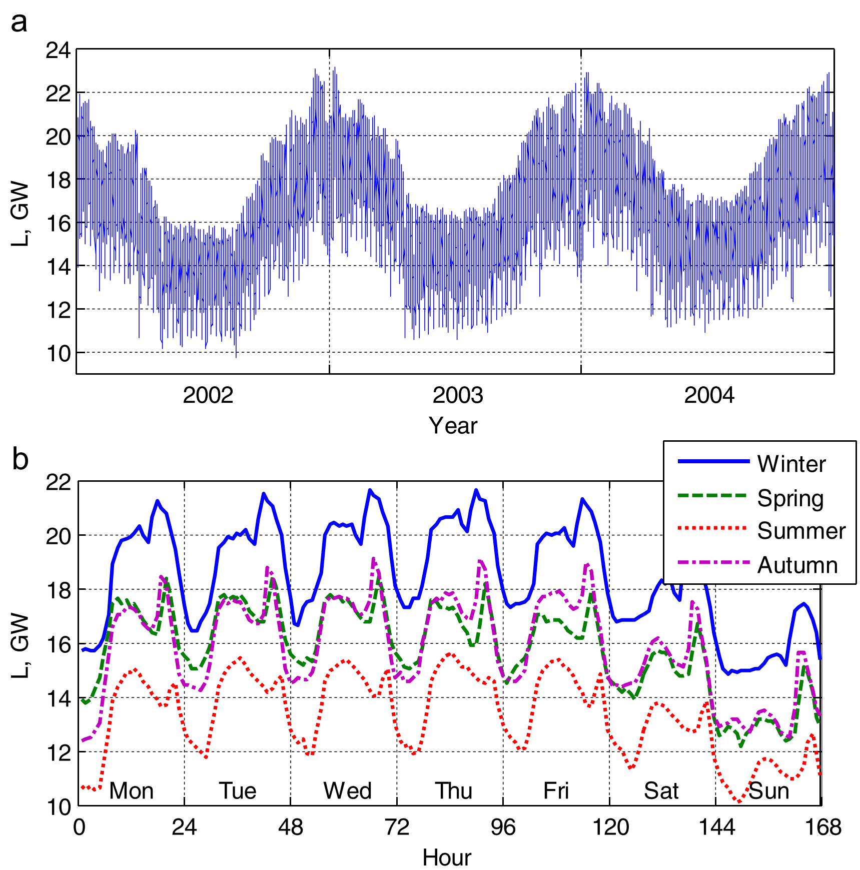

Fig. 1. The hourly electricity demand in Poland in three-year (a) and one-week (b) intervals.

starting values to estimate. Recently developed exponentially weighted methods in application to STLF are presented in [2].

ARIMA processes are well suited to express the stochastic nature of the load time series. Modeling of multiple seasonal cycles as well as introducing exogenous variables is not a problem in ARIMA. The disadvantage of ARIMA models is that they are able to represent only linear relationships between variables. The difficulty in using ARIMA is the problem of order selection which is considered to be subjective. To simplify the forecasting problem the time series is often decomposed into a trend, seasonal components and an irregular component. These components, showing less complexity than the original series, are modeled independently (see [3]). Another decomposition way based on wavelet transform is described in [4].

Unconventional STLF approaches employ new computational methods such as artificial intelligence and machine learning ones. These approaches are reviewed in [5,6]. They include: neural networks (NNs), fuzzy inference systems, neuro-fuzzy systems, support vector machines and ensembles of models. Among them the most popular are NNs. They have many attractive features, such as: universal approximation property, learning capabilities, massive parallelism, robustness in the presence of noise, and fault tolerance. But there are also some drawbacks of using NNs: disruptive and unstable training, difficulty in matching the network structure to the problem complexity, weak extrapolation ability and many parameters to estimate (hundreds of weights). These issues with NNs as well as problems with load time series complexity are addressed in STLF literature in various ways. For example in [7] the Bayesian approach is used to control the multilayer perceptron (MLP) complexity and to select input variables. As inputs are used: lagged load values (unprocessed), weather variables, and dummies to represent the days of the week and calendar variables. In [8] the load time series is decomposed using wavelet transform into lower resolution components (approximation and details). Each component is predicted by MLP using gradient-based algorithm. After learning the MLP weights are adjusted using evolutionary algorithm to get result nearer to the optimal one. Similar decomposition of the load time series using the wavelet transform for extraction relevant information from the load curve was used in [9]. A particle swarm optimization algorithm was employed to adjust the MLP weights. In [10] a generic framework combining similar day selection, wavelet decomposition, and MLP is presented. The MLP is trained on the similar days which are first decomposed using Daubechies wavelets. The similar day is a day which has the same weekday index, day-of-a-year index and similar weather to that of tomorrow (forecasted).

Another popular NN architecture used for STLF is radial basis function NN (RBFNN). It approximates the relationship between explanatory variables and load by a linear combination of radial basis functions (usually Gaussian), which nonlinearly transform the input data. Comparing to MLP the learning algorithm for RBFNN is simpler (there is no need for laborious error backpropagation). In [11] a hybrid system for STLF is described, where RBFNN forecasts the daily load curve based on historical loads. The RBFNN weights are optimized using genetic algorithm. Then the Mamdani-type fuzzy inference system corrects the forecast depending on the errors and maximal daily temperature. RBFNN is employed in [12] to forecast loads based on historical loads and historical and forecasted temperatures. Then the neuro-fuzzy system corrects the forecast depending on changes in electricity prices. In the approach described in [13] the load time series is decomposed into five components using wavelet transform.