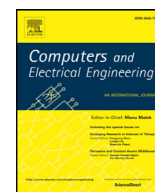




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journal homepage: www.elsevier.com/locate/compelecengSmart grid load forecasting using online support vector regression[☆]Petra Vrablcová^{a,*}, Anna Bou Ezzeddine^a, Viera Rozinajová^a, Slavomír Šárik^a, Arun Kumar Sangaiah^b^a Faculty of Informatics and Information Technologies, Slovak University of Technology in Bratislava, Ilkovičova 2, 842 16 Bratislava, Slovakia^b School of Computing Science and Engineering, VIT University, Vellore 632014, Tamil Nadu, India

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ABSTRACT

Smart grid, an integral part of a smart city, provides new opportunities for efficient energy management, possibly leading to big cost savings and a great contribution to the environment. Grid innovations and liberalization of the electricity market have significantly changed the character of data analysis in power engineering. Online processing of large amounts of data continuously generated by the smart grid can deliver timely and precise power load forecasts – an important input for interactions on the market where the energy can be contracted even minutes ahead of its consumption to minimize the grid imbalances. We demonstrate the suitability of online support vector regression (SVR) method to short term power load forecasting and thoroughly explore its pros and cons. We present a comparison of ten state-of-the-art forecasting methods in terms of accuracy on public Irish CER dataset. Online SVR achieved accuracy of complex tree-based ensemble methods and advanced online methods.

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1. Introduction

Smart grid has brought new ways of energy management [1]. The smart grid research branched into several directions – from the core technologies, sensors, network, communication, through grid security, to storing, processing and mining of the smart grid data. In order to get real value from the smart grid, a thorough analysis and processing of a huge amount of generated data has to be performed. The ultimate goal of smart energy approach is to control energy supply and balance effectively. From this point of view, precise prediction models are becoming very important for all stakeholders of the energy market. When considering the fact that 40% of electrical energy is used in the buildings [2], then it is clear that even a small improvement in prediction accuracy means big cost savings and also a great contribution to the environment.

Smart meters produce streaming data; therefore, the processing methods require mining techniques which are different from the classical ones. When considering the main characteristics (3V) of big data, the smart meter data fulfill these characteristics – particularly when the smart meters will be fully deployed (in Europe the plan is to deploy them till 2020). Even a small improvement of the prediction and optimization methods in energy domain means big savings not only from economic, but also from environmental point of view. In order to take informed decisions concerning the smart grid operation,

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the only way is to process these data online. Therefore, we have decided to investigate online support vector regression (SVR) method. The ultimate limitations of stream processing are memory and time. Since the stream contains an infinite number of records, it is not possible to store them all in memory or read them more than once. Hence, the stream processing method should work incrementally and allow online processing. The learning algorithms should be able to process new data without intensive usage of the already considered data and also to forget and unlearn old or obsolete information. In order to create flexible models, the techniques should be adaptive – i.e., they should adjust to the features of the current data flow.

In this paper, we present our research in the area of power load forecasting methods. The relevance and usefulness of power load forecasts have been increasing, considering the recent trends of liberated energy market allowing to trade electricity even one hour ahead. To minimize the energy imbalance (i.e., the online gap between contracted supply and actual demand) and the costs associated with it, the market interactions based on accurate power load forecasts need to be performed promptly. Power load forecasting methods that are able to process online stream of data from smart meters became a subject undergoing intense study. We have studied several forecasting methods that are based on statistical, as well as on artificial intelligence, approaches and have compared them with each other. We focused on SVR, because it was established that it is a method with very good accuracy [3]. We employed its less known online variant, which needs to store less amount of data than the standard SVR, as it is able to forget certain data. The method is particularly suitable for short-term predictions (i.e., for the next hour or for the next day).

The presented ideas are designed for power engineering domain and they have been verified there. However, many of the proposed methods are applicable also in other areas of smart cities. Vast amounts of data are generated by city systems (e.g., using IoT technologies): transportation data, data about water and gas consumption, social and economic datasets, satellite data, city governance data, social media data, etc. As the character of the generated data is in many cases similar to the smart meter data, the prediction models and optimization methods could be easily adopted.

The paper is structured as follows: Section 2 introduces the state of the art in power load prediction and SVR applications. The online SVR is described in Section 3. The experiments and their evaluation can be found in Section 4. We discuss our results in Section 5, and the conclusion is in the last section.

2. Related work

Approaches for short-term power load forecasting can be, in general, divided into statistical techniques, such as *regression analysis* and *time series analysis*; and *artificial intelligence* (AI). The review by Singh et al. [4] reports major advantages of AI (or soft computing) techniques, and growing use of hybrid methods, which combine two or more of these techniques.

In our research, we focus on SVR, because its characteristic property is the ability to model nonlinear time series, such as power load series, in a high dimensional feature space via the kernel trick, in which the training data may exhibit linearity [5]. It was reported to be a very accurate forecasting method [3]. We studied also the performance of other load forecasting techniques to create a self-contained comparison. In the literature, we encountered only a small number of similar reports comparing multiple power load forecasting techniques. Taylor and McSharry [6] published an empirical comparison of univariate methods for one-day ahead forecasting. Among ARIMA, exponential smoothing and PCA-based methods, the double seasonal Holt-Winters exponential smoothing method (DSHW) was the best. In the more recent comparison [7], the best results were obtained by an ensemble of DSHW and kernel ridge regression (also called sigma SVR).

In the next subsection, we briefly describe the techniques that we chose based on their generally good results in forecasting. We aimed for a variety of methods that represent all of the main groups of load forecasting techniques.

2.1. Overview of load forecasting methods

2.1.1. Time series analysis

Double Seasonal Holt-Winters Exponential Smoothing (DSHW) (an extension of Holt-Winters exponential smoothing method) [8] predicts future values of a time series as a weighted average of past values. The weights decay exponentially as the observations get older. The forecast by DSHW is a combination of 4 time series' components; each is smoothed by its smoothing parameter: level (α), trend (β), and two seasonal components (daily – δ and weekly – ω). We used its multiplicative variant. To improve the forecast accuracy, a simple adjustment for first-order autocorrelation is included (ϕ). The forecast by DSHW for k th horizon from time t can be expressed as (1).

$$\text{forecast}_{t+k} = (\text{level}_t + k \cdot \text{trend}_t) \cdot \text{dailyseas}_{t-ds+k} \cdot \text{weeklyseas}_{t-ws+k} + \phi^k \cdot \text{error}_t \quad (1)$$

ds and ws are lengths of daily and weekly cycles, e.g. 48 and 336 for half-hourly load measurements, error_t is the difference between the actual and forecasted value at time t .

Seasonal decomposition of time series by Loess (STL) [9] decomposes a seasonal time series into three parts: trend, seasonality and remainder. The seasonal component is found by Loess (local regression) smoothing of the original time series. The rest is smoothed to find the trend. The remaining component represents the residuals from the seasonal plus trend fit. These resulting 3 time series were separately forecasted by Holt-Winters exponential smoothing (STL + EXP) and ARIMA (STL + ARIMA). The components' forecasts were summed to obtain the final forecast.

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