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A computational intelligence scheme for the prediction of the daily peak load

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ABSTRACT

Forecasting of future electricity demand is very important for decision making in power system operation and planning. In recent years, due to privatization and deregulation of the power industry, accurate electricity forecasting has become an important research area for efficient electricity production. This paper presents a time series approach for mid-term load forecasting (MTLF) in order to predict the daily peak load for the next month. The proposed method employs a computational intelligence scheme based on the self-organizing map (SOM) and support vector machine (SVM). According to the similarity degree of the time series load data, SOM is used as a clustering tool to cluster the training data into two subsets, using the Kohonen rule. As a novel machine learning technique, the support vector regression (SVR) is used to fit the testing data based on the clustered subsets, for predicting the daily peak load. Our proposed SOM-SVR load forecasting model is evaluated in MATLAB on the electricity load dataset provided by the Eastern Slovakian Electricity Corporation, which was used in the 2001 European Network on Intelligent Technologies (EUNITE) load forecasting competition. Power load data obtained from (i) Tenaga Nasional Berhad (TNB) for peninsular Malaysia and (ii) PJM for the eastern interconnection grid of the United States of America is used to benchmark the performance of our proposed model. Experimental results obtained indicate that our proposed SOM-SVR technique gives significantly good prediction accuracy for MTLF compared to previously researched findings using the EUNITE, Malaysian and PJM electricity load datasets.

1. Introduction

Load forecasting is a key instrument in power system operation and planning. Many operational decisions in power systems such as unit commitment, economic dispatch, automatic generation control, security assessment, maintenance scheduling, and energy commercialization depend on the future behavior of loads. In particular, with the rise of deregulation and free competition of the electric power industry all around the world, load forecasting has become more important than ever before [1].

Along with the power system privatized and deregulated, the issue of accurately forecasting electricity load has received more attention in recent years. The error of electricity load forecasting increases operational costs [2–4]. Overestimation of future load results in excess supply, which is not welcome to the international energy network. In contrast, underestimation of load leads to failure in providing enough reserve and implies high costs. Thus, adequate electricity production requires each member of the global co-operation being able to forecast its demands accurately [5].

During the last four decades, a wide variety of techniques have been used for the problem of load forecasting [6–8]. Such a long experience in dealing with the load forecasting problem has revealed time series modelling approaches based on statistical methods and artificial neural networks (ANNs). Statistical models include moving average and exponential smoothing methods such as multi-linear regression models, stochastic process, data mining approaches, autoregressive moving average (ARMA) models, Box–Jenkins' methods, and Kalman filtering-based methods [9–15]. Since, load time series are usually nonlinear functions of exogenous variables; therefore, to incorporate non-linearity, ANNs have received much attention in solving problems of load forecasting [16–19]. ANN-based methods have reported fairly good performances in forecasting. However, two major risks in using ANN models are the possibilities of less or excessive training data approximation, i.e., under-fitting and over-fitting, which increase the out-of-sample forecasting errors. Hence, due to the empirical nature of ANNs their application is cumbersome and time consuming.

Recently, new machine learning techniques such as the support vector machines (SVMs) have been used for load prediction and electricity price forecasting, and have achieved good performances

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[20,21]. SVM, namely, support vector regression (SVR) is a powerful machine learning technique used for regression, which is based on recent advances in statistical learning theory [22]. Established on the structural risk minimization (SRM) principle (estimate a function by minimizing an upper bound of the generalization error), SVMs have shown to be very resistant to the under-fitting and over-fitting problems caused by ANNs [20].

In recent times, a Multi-layer Perceptron SVM (MLP-SVM) was introduced in literature [23]. Compared to standard SVM, MLP-SVM or Hidden Space Support Vector Machine (HSSVM) [24] can adopt to more kinds of kernel functions that are not satisfied by Mercer's conditions, because the positive definite property of the kernel function is not a necessary condition [24]. From the viewpoint of Mercer's condition, MLP-SVM's are less attractive because they are not sufficiently understood for which values of the hidden layer parameters the condition is satisfied [23]. Moreover, the drawbacks of the MLP-SVM in comparison to a standard SVM approach are their higher computational complexity, the problem of tuning a large number of parameters in the hidden layer and the problem of selecting the optimum number of hidden units [23]. Due to these reasons MLP-SVM's and their higher computation complexity, the choice of using standard SVM, namely SVR is considerably more suitable for the problem of MTLF.

In this paper, we present our approach on the problem of MTLF in order to predict the daily peak load for the next month. Our study develops a computational intelligence scheme of the Self Organizing Map (SOM) and Support Vector Regression (SVR) using the electricity load data from the 2001 European Network on Intelligent Technologies (EUNITE) competition [25]. In order to evaluate the performance of our forecasting technique, power load data obtained from (i) Tenaga Nasional Berhad (TNB) for peninsular Malaysia and (ii) PJM for the eastern interconnection grid of the United States of America is used to benchmark the performance of the proposed SOM-SVR model.

In our proposed model the SOM is applied to cluster the training data into separate subsets using the Kohonen rule. According to the similarity of time series samples the SOM clustered data is further used to fit the SVR model. Comparisons of recently proposed MTLF results as reported by authors on the EUNITE dataset have been conducted. The theoretical parts are addressed in Sections 2–5. Section 6 presents the development and implementation of the SOM-SVR load forecasting model. Section 7 shows experimental results and Section 8 presents concluding remarks.

2. Recent approaches to load forecasting

In the last few decades, there have been widespread references with regards to efforts improving the accuracy of forecasting methods. One of these methods is a weather-insensitive approach which uses historical load data. It is famously known as the Box–Jenkins' Autoregressive Integrated Moving Average (ARIMA) method discussed in [14,26–28]. Christianse [29] and Park et al. [30] proposed exponential smoothing models by Fourier series transformation to forecast electricity load. Douglas et al. [31] considered verifying the impacts of a forecasting model in terms of temperature. To avoid variable selection problems, Azadeh et al. [32] employed a fuzzy system to provide an ideal rule-base to determine the type of ARMA models that can be used. Wang et al. [33] proposed a hybrid Autoregressive and Moving Average with Exogenous variables (ARMAX) model with Particle Swarm Optimization (PSO) to efficiently solve the problem of trapping into local minimum caused by exogenous variables.

To achieve better accuracy of load forecasting, state space and Kalman filtering methods have been developed to reduce the difference between the actual load and the predicted load [34–36]. Moghram and Rahman [37] proposed a model based on historical data to construct the periodic load. Recently, Al-Hamadi and Soliman [38] employed a fuzzy rule-based logic by utilizing a moving window of current values of weather data, and historical load data to estimate the optimal fuzzy parameters for the hourly load of the day. Amjady [39] proposed a hybrid model of the Forecast-aided State Estimator (FASE) and the Multi-layer Perceptron Neural Network (MLPNN), to forecast the short-term bus load of power systems.

Regression models construct a causal-effect relationship between electricity load and independent variables. The most popular model is the *linear regression*, proposed by Asbury [40], considering the weather variable into his model. Papalexopoulos and Hesterberg [10] added holiday and temperature factors into their proposed model. Soliman et al. [41] proposed a multivariate linear regression model for load forecasting, including temperature, wind and humidity factors. Mirasgedis et al. [42] incorporated weather meteorological variables such as relative humidity, heating and cooling to forecast the electricity demand in Greece. In contrast, Mohamed and Bodger [43] employed economic and geographic variables such as GDP, electricity price and population to forecast the electricity consumption in New Zealand. Recently, Tsekouras et al. [44] introduced a non-linear multivariable regression approach to forecast the annual load by considering correlation analysis to select appropriate input variables.

In the recent decade, many researchers have tried to apply machine learning techniques to improve the accuracy of load forecasting. Rahman and Bhatnagar [45] constructed a Knowledge-based Expert System (KBES) approach to electricity load forecasting by simulating the experiences of the system operators [46]. Recently, applications of the Fuzzy Inference System (FIS) and fuzzy set theory have received attention in load forecasting. Ying and Pan [47] introduced an Adaptive Neuro-fuzzy Inference System (ANFIS) by looking for the mapping relation between the input and output data to. In addition, Pai [48] and Pandian et al. [49] employed fuzzy approaches to obtain superior performance in terms of load forecasting accuracy.

ANNs have been applied to improve the accuracy of load forecasting. Park et al. [50] proposed a Back-propagation Neural Network (BPNN) for daily load forecasting. Novak [51] applied the Radial Basis Function Neural Network (RBFNN) to forecast electricity load. Darbellay and Slama [52] applied ANNs to predict the regional electricity load in Czechoslovakia. Abdel-Aal [53] proposed an abductive network to conduct a one-hour ahead load forecast for five years. Hsu and Chen [54] employed an ANN model to forecast the regional electricity load in Taiwan. Recently, load forecasting applications of ANNs hybrid with statistical methods and other intelligence techniques have received a lot of attention. These include ANN models combined with: Bayesian inference [55,56], Self-organizing Map (SOM) [57,58], Wavelet transform [59,60], PSO [61] and Dynamic mechanism [62].

Other machine learning techniques such as Support Vector Machines (SVMs), are a promising technique for classification problems. SVMs implement the Structural Risk Minimization (SRM) principle [63], which minimizes the training error and maximizes the confidence interval, resulting in a good generalization performance [64]. With the introduction of Vapniks' ξ-insensitive loss function [65], SVMs have been extended to solving nonlinear regression estimation problems, and can be considered as successful tools for forecasting problems.

SVMs have been recently applied by researchers to solve load forecasting problems. Cao [66] used the SVM experts for time series forecasting. Cao and Gu [67] proposed a Dynamic SVM (DSVM) model to deal with non-stationary time series problems. Tay and Cao [68] used SVMs for forecasting the financial time series. Hong and Pai [69] applied SVMs to predict engine reliability. For electric-