HYBRID ARTIFICIAL NEURAL NETWORK SYSTEM FOR SHORT-TERM LOAD FORECASTING

by

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This paper presents a novel hybrid method for short-term load forecasting. The system comprises of two artificial neural networks (ANN), assembled in a hierarchical order. The first ANN is a multilayer perceptron (MLP) which functions as integrated load predictor (ILP) for the forecasting day. The output of the ILP is then fed to another, more complex MLP, which acts as an hourly load predictor (HLP) for a forecasting day. By using a separate ANN that predicts the integral of the load (ILP), additional information is presented to the actual forecasting ANN (HLP), while keeping its input space relatively small. This property enables online training and adaptation, as new data become available, because of the short training time. Different sizes of training sets have been tested, and the optimum of 30 day sliding time-window has been determined. The system has been verified on recorded data from Serbian electrical utility company. The results demonstrate better efficiency of the proposed method in comparison to non-hybrid methods because it produces better forecasts and yields smaller mean average percentage error.

Key words: *short-term load forecasting, multilayer perceptron, prediction model, hybrid neural network structure*

Introduction

In today's electric utility industry restructuring, opening of the wholesale power market has laid down key groundwork for deregulation and competition. Under competitive pressure brought on by deregulation, an intelligent and professional approach to energy management becomes of utmost importance. Forecasting electricity demand (or load) on an hourly basis, from one to several days ahead is referred to as short-term load forecasting (STLF) [1]. The usual horizon of STLF is typically the next day. The STLF plays an important role in operating decisions, such as dispatch scheduling of generating capacity, reliability analysis, security assessment, maintenance plan for generators and economical optimization [1]. The errors in forecasting have significant implications on profits, market shares and shareholder values. The STLF is becoming increasingly difficult due to the variability and nonstationarity of time series resulting from dynamic bidding strategies, time-varying electricity price, and price-dependent

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loads [2]. Therefore, advanced and more sophisticated methods for STLF need to be developed for the modern power system.

This paper introduces a new hierarchical hybrid artificial neural network (ANN) model to tackle the problem of STLF. This model consists of two ANNs, the scheme of which is represented in fig. 1. The first ANN in the input layer of the entire model acts as the predictor of integrated load value, creating the context for current inputs of the second ANN in the output layer. The second ANN acts as typical hour load predictor for the next day horizon. Each input of the second ANN is not taken as an isolated value, but instead, in a short context relating to the predicted integrated value (the value produced by the input layer). The hierarchical topology gives this model the power to process efficiently the context of input time series, and therefore the possibility to produce better forecasts. Hierarchical hybrid ANN model is compared to an ordinary multilayer perceptron (MLP), which has been extensively applied for the STLF problem [3].

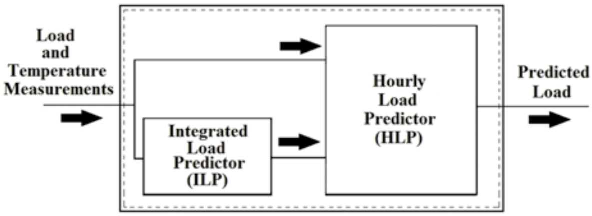

Figure 1. The scheme of hierarchical hybrid ANN model

The ANN has been applied for STLF for over two decades with varying degrees of success. Hippert, et al. offered a high-level methodology for developing ANN models for STLF in their review paper [3]. However, most research papers and reports present only the final design of the model rather than introducing the steps or summarizing the procedure to reach to the model, which makes the reproduction of the former research work quite challenging. On the other hand, since those forecasting models have been developed for specific utilities, their exact reproduction, even if possible, is not always meaningful for comparison purposes.

In the recent years, a number of different strategies [3] have been developed to deal with the problem of forecasting electricity load. Early methods included exponential smoothing [4], regression [5], Box-Jenkins models [6], Kalman filters [7], state-space model [8], and then time-series techniques [1, 8]. Artificial intelligence (AI)-based methods such as pattern recognition [9], neural networks (NN) [3, 8], and fuzzy NN [10, 11] have been also proposed for the STLF. In [12], it is explained that forecast methodologies have registered evolution during last three decades which is influenced both by increasing complexity of factors that affects consumption and by a trend to apply an increasing number of different methodologies that have been proposed and tested. However, increasing importance and complexity of the STLF (especially at electricity markets) necessitates more accurate load forecast methods. For this purpose, hybrid STLF methods have been proposed recently. In [13], the combination of fuzzy linear regression and the general exponential smoothing is proposed. The STLF method based on adaptive two-stage hybrid network with self-organized map (SOM) and support vector machine (SVM) has been presented in [2]. In [14], authors have proposed the combination of wavelet transform and neuro-evolutionary algorithm. ANN have also been used to forecast integrated load value [15], as well as single load values as peak, valley and mean daily loads. Load forecasting in a smart grid by means of bi-level prediction strategy that combines feature selection method and forecast engine is investigated in [16]. In [17], authors have developed neural network based on adaptive resonance theory, which has shown better results than traditional MLP in the STLF field.

In [15], a simple learning type neural network has been developed for load forecasting. The neural network consists of three layers. The input layer consists of five units that have the following values:

– IL(d-1) - previous day integrated load,
– MaxT(d-1) - previous day max. temperature,
– MinT(d-1) - previous day min. temperature,
– MaxT(d) - forecasting day max. temperature, and
– MinT(d) - forecasting day min. temperature.

The output layer consists of only one neuron which gives forecasted integrated load for the forecasting day, IL(d). A variable called "Integrated Load" is defined as the sum total of 24 hour load readings recorded for one day. In the essence, integrated load variable combines peaks and troughs of the load curve. Prior works [18-20] indicate that the integrated load is affected by maximum and minimum daily temperatures and by the type of the day. In [19], a hybrid model is proposed for load forecasting and consists of a SOM and the MLP. In this architecture, at one step, the MLP is used for mean daily load forecasting. For oscillation forecasting, the hybrid structure composed of the MLP and SOM is used. The MLP used for predicting mean daily load is a 3 layer MLP. The automatic tuning of regularization coefficients by utilization of Bayesian approach is proposed in [21]. The problem of input space and complexity is addressed in [22] where authors have proposed original automatic procedures for selecting input variables of NN based electricity load forecasters. More recently, load prediction of 1-24 hour ahead with the minimum set of input variables is demonstrated in [23] where authors have applied echo state network (ESN) as state-of-the-art recurrent neural network (RNN).

Neural networks and short-term load forecasting

Artificial neural networks are software or hardware models inspired by the structure and behavior of biological neurons and the nervous system but after this point of inspiration all resemblances to biological systems cease [24]. The basic unit of ANN operation is an artificial neuron. The neuron receives (numerical) information through a number of input nodes, processes it internally, and puts out a response. The processing is usually done in two stages: first, the input values are linearly combined, and then the result is used as the argument of a nonlinear *activation function*. The activation function must be a nondecreasing and differentiable function; the most common choice is either the identity function or bounded sigmoid (s-shaped) function. The neurons are organized in a way that defines network *architecture*. The one we are going to deal with the most in this paper is the MLP type in which neurons are organized in layers. Typically, all neurons in the same layer pose the same activation function (AF). The neurons in each layer may share same inputs but they are not connected to each other. If the architecture is *feed-forward*, outputs of one layer are used as inputs to the following layer. The layers between input nodes and *output layer* (OL) are called *hidden layers* (HL). The strength of connections between two neurons, called the weight, is true network parameters and is subject to learning. The non-linear AF in the hidden layer of the ANN enable it to be a universal approximator. The differentiability of the HL neurons' AF makes possible the solution of non-linear training. The important ability of the ANN is its possibility to perform learning task. The most elementary learning algorithm is the error back-propagation algorithm (EBP). The basic idea behind the EBP is that the error signal terms for HL neurons are calculated by back-propagating the error signal terms of the OL neurons.

The objective of this section is to give brief introduction of ANN in forecasting load consumption (demand) or any other (financial, weather, biomedical) time series. In the STLF, there are many different parameters that influence the behavior of load consumption time series, such as environmental, social and historical data. It is still the matter of great debate which parameters are most correlated to the prediction of behavior of the process in question. Furthermore, it is not always useful to apply the results obtained for any specific application, to a larger class of problems, because any different field of the STLF displays a set of different properties (related to the consumer type, the size of the geographical area, the climate zone, *etc.*). The structure that is most commonly used for the STLF is the MLP. In the next section, detailed description of the MLP used herein will be given together with test results and their schemes.

The hybrid structure

The hybrid structure of the neural network proposed in this paper is motivated by the idea that a simple MLP can be used in predicting integrated load value of the next day [15]. Such an ANN is called the integrated load predictor (ILP). The ILP can be trained online because of its short training period and it can eliminate signal noise because inputs are integrated load and integrated temperature. The integrated load variable is defined as the sum total of 24 hour load readings recorded for one day. The integrated temperature variable is defined as the sum total of the 24 hour temperature forecasts. The output of ILP is the integrated load (the total energy) for the forecasting day. This output is then fed to another more complex MLP, which is used to obtain the forecasts for each of the 24 hours for the forecasting day, and is called the hour load predictor (HLP). The inputs to the HLP represent hour load for the previous day – $L_{\mathrm{d}-1}(t)$, hour temperature for the forecasting day – $T_{\mathrm{d}}(t)$, the predicted integrated load for the forecasting day, and the type of the forecasting day – day type (d). The scheme of the hierarchical hybrid model is shown in fig. 2.

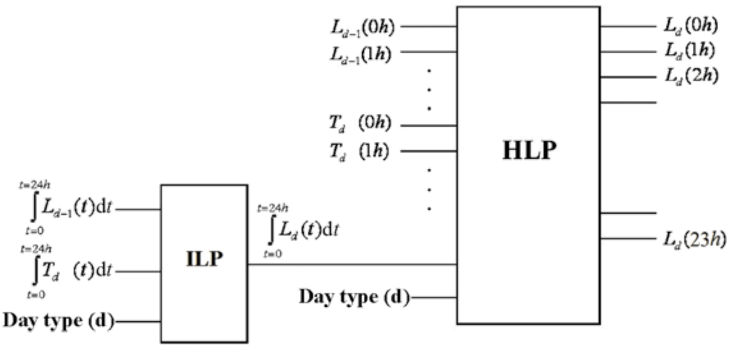

Figure 2. The structure of hierarchical hybrid model used for obtaining forecasts for each of 24 hours of the forecasting day

Prediction of the integrated load for the forecasting day

In our research, it has been determined by experimentation that the configuration of the network for predicting integrated load providing best results is a simple 3 layer MLP which has three units in the input layer representing:

– $\int\limits_{t=0}^{t=24\,\mathrm{h}} L_{\mathrm{d}-1}(t)\,\mathrm{d}t$ – previous day integrated load

– $\int\limits_{t=0}^{t=24\,\mathrm{h}} T_{\mathrm{d}}(t)\,\mathrm{d}t$ – forecasting day integrated temperature

– day type (d) – type of forecasting day

The hidden layer consists of five neurons while the output layer represents one neuron that gives forecasted integrated load for forecasting day:

$$\int_{t=0}^{t=24\,\mathrm{h}} L_{\mathrm{d}}(t)\,\mathrm{d}t$$

This structure of the MLP has given best results as compared to other proposed structures. The scheme of this MLP is shown in fig. 1.

Integrated load predictor (ILP) training

Due to low variability of integrated power load data, and in order to maximize network generalization ability, five neurons in hidden layer are chosen. This configuration has provided best results (least mean square error) in comparison to other tested structures. Moreover, this network is very resistant to anomalous spikes because of integration effect and it has always produced meaningful output in all our tests.

The MLP training set is produced both by input and target vectors. Input vectors are obtained by integrating daily power load measurements of the day before the forecasting day, and by integrating predicted hour temperature measurements of the forecasting day. Also, one additional member of the input vector is the forecasting day type. The simple way of coding data type has been adopted, where the workdays are coded as 1, while the weekdays are coded as 0. The holydays are not taken into consideration. The output vectors are obtained by integrating daily power load measurements for the forecasting day. The input and output vectors are normalized with respect to their minimum and maximum values.

The network is trained using modified back-propagation algorithm with momentum and adaptive learning rate [18]. The weights are updated by the following formula:

$$\Delta w_{ji}(n) = \eta\delta_j(n)\,y_j(n) + \alpha\Delta w_{ji}(n-1)$$

where n points out the epoch, η is the learning rate, and α – the momentum (between 0 and 1). During training, learning rate value is dynamically changed according to the global error of the epoch. It is either increased or decreased in comparison to the global error of the previous epoch. It is necessary that the system avoids training abrupt interruption caused by local minimum typical error surface. The number of epochs is not pre-specified because training procedure is performed in Matlab using Neural Network toolbox which continues to update ANN parameters as long as the error on the test subject keeps diminishing without over-fitting the network. The data set used for ANN training is 30 days before the forecasting day. This is determined by experimentation.

Predicting the integrated load

The forecasting procedure is as follows.

First, the neural network is trained. The data set which consists of prior 30 days (before the forecasting day) is used. The training procedure can be repeated periodically but best results are obtained if the network parameters are updated daily as shown in [25]. For the daily forecast, the input data of today's day are collected (integrated load and forecasted (expected) integrated temperature for the next day) and presented to the network. The network calculates the expected integrated load for the forecasting day (next day). After actual integrated load value and temperature readings are collected for one forecasting day, the training data set is updated with this most recent information. The procedure is repeated daily.

Prediction of the next 24 hour load consumption

Designing a three-layer feed forward ANN model for the STLF involves several major steps:

– *Determine the number of outputs:* The ANN model may have only one output which can correspond to the load of one hour or several outputs which can represent 24-hour load profile if there are 24 outputs [26]. Our hour load predictor (HLP) is one of several-output MLPs, of which the output is hour load for the forecasting day.
– *Determine the number of inputs:* The inputs may include weather variables, calendar variables, and preceding hour's load. In this paper, we have used several previous hour load data of the current day, as well as several predicted temperature data for the forecasting day. Also, a very important input is the integrated load of the forecasting day. This input is provided as the forecast of the ILP in the exploitation phase.
– *Determine the number of hidden neurons:* There is no common rule for determining the number of hidden neurons. In this chapter, we have used a trial-and error approach. The scheme of the HLP inside the hierarchical structure is shown in fig. 2.

HLP training

The input vectors are obtained by selecting hour power load data and hour temperature data of the day before the forecasting day which are normalized to the maximum value of all available data, respectively. Also, an additional member of the input vector which presents the integrated load of the forecasting day is computed by adding up all hour data of the forecasting day. This procedure is only possible in the training phase because this integrated load of the forecasting day will not be available in the exploitation phase. The output vector of the MLP for predicting the integrated load is used instead. Day type of the forecasting day is also included in the input vector as previously explained in the case of MLP for predicting integrated load. The output vectors are obtained by selecting hour power load data for the forecasting day for every hour.

The training procedure is the same as explained in the case of integrated load prediction except for different data sets used for MLP training.

Predicting the next 24 hour load

The exploitation phase is the same as explained in the case of integrated load prediction, except for different data sets used as MLP inputs.

Results

The model proposed in this paper is implemented in Matlab using Neural Network toolbox. For both ILP and HLP, the feed forward structure of the ANN is used. Activation functions of the hidden layer neurons are sigmoid type while those of output layer neurons are linear. For the purpose of comparison, an ordinary MLP that predicts hour load is also implemented. The structure of this network is basically the same as that of the HLP (*i. e.*, its inputs are hour load of the previous day and forecasted hour temperature of the forecasting day) except for the lack of predicted integrated load input. By comparing these two structures, we can clearly see the advantage of the proposed model. The developed system is tested with two sets of historical data containing electricity load for months January and July 2006 on an hourly basis. They consist of real-life measurements at the specific consumer of the power grid supplied by the Serbian electrical utility company. The model is evaluated based on its prediction errors. The error measure which is most commonly employed in the STLF and which is used in the evaluation of results presented here is the mean absolute percentage error (MAPE) defined as:

$$MAPE = \left(\frac{|x_i - y_i|}{x_i} \right) \cdot 100$$

where x_i is the actual value and y_i – the predicted value at time instance i. Figure 3 shows the scheme of forecasting results for integrated load prediction for the first 14 days of February 2006 while the fig. 4 shows the scheme of forecasting results for hour load prediction for the first week of February 2006.

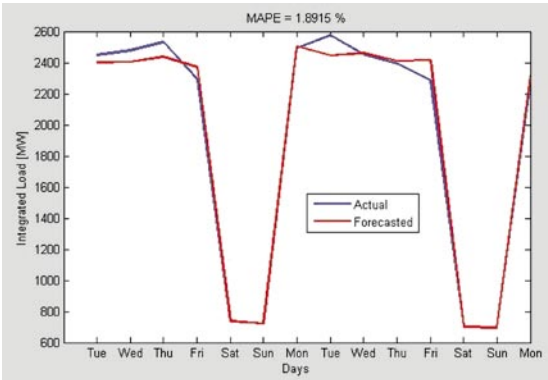

Figure 3. Forecasting results for integrated load prediction for the first 14 days of February 2006. The average MAPE is 1.89%

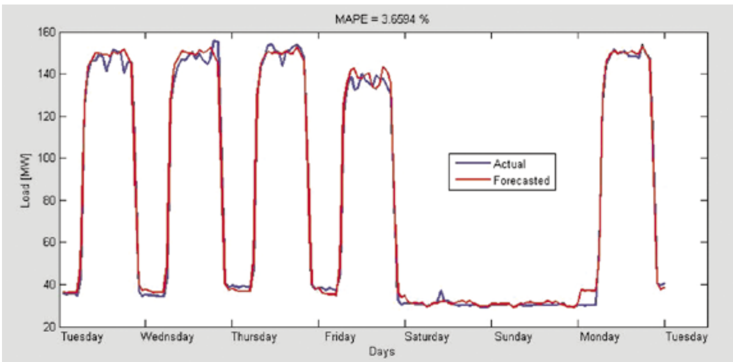

Figure 4. Forecasting results for hour load prediction for the first week of February 2006. Proposed model MAPE is 3.66%. Ordinary MLP average MAPE is 4.86%

Figure 5 shows the scheme of forecasting results for integrated load prediction for first 14 days of July 2006.

Figure 6 shows the scheme of forecasting results for hour load prediction for the first week of July 2006.

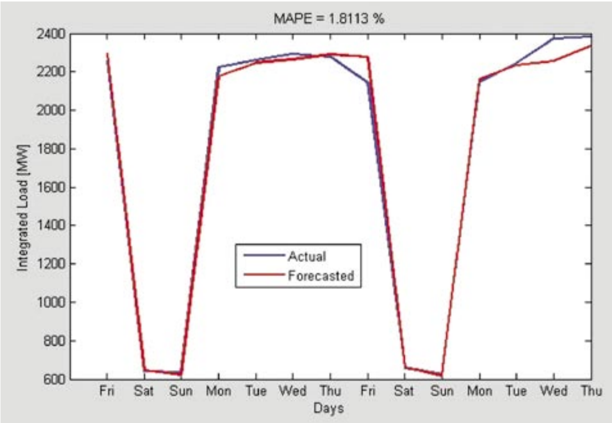

Figure 5. Forecasting results for integrated load prediction for the first 14 days of July 2006. Average MAPE is 1.8%

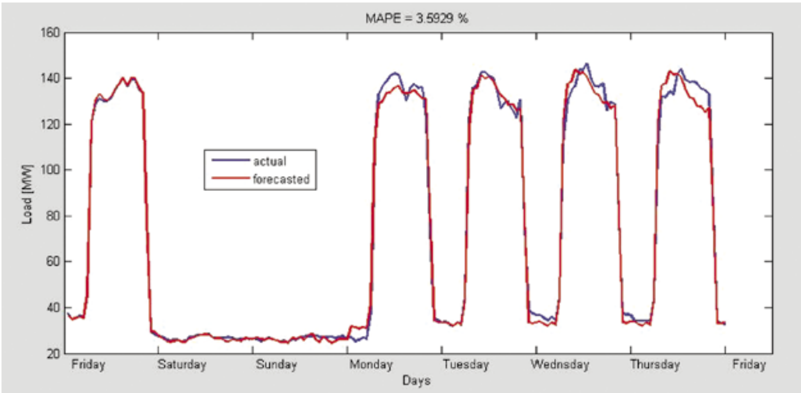

Figure 6. Forecasting results for hour load prediction for the first week of July 2006. Proposed model MAPE is 3.59%. Ordinary MLP average MAPE is 5.24%

Conclusions

The paper presents a novel hierarchical hybrid ANN model for the problem of short-term load forecasting. The model has a topology made up of two MLP connected in a sequence. The first one acts as a predictor of integrated load and the second one uses this information in correlation with its inputs to produce better forecasts. The experiments show that the performance of the hierarchical model on short-term hour load prediction is better than that of an ordinary MLP. The proposed model outperformed the ordinary MLP in all our test cases by producing smaller MLP over tested data set. The improvement introduced by the proposed model, calculated in the MAPE is in the range from 1.2% to 1.65% depending on the test case considered. Although producing better results, potential drawbacks of the hierarchical structure are longer training time as compared to non-hierarchical structure, as well as the need for data pre-processing (*i. e.*, calculating load and temperature integrals). However, bearing in mind that the structure of both MLPs entering the hierarchical structure is fairly simple, these drawbacks do not prevent the proposed model to be used as an online predicting tool. It is also worth mentioning that there is a strong need for benchmark testing in the STLF field. It will be necessary to define the standardized set of procedures for determining actual effect and contribution of proposed STLF methodology in order to have comprehensive overview of the field. For example, given method may outperform traditional methods for one type of application (*e. g.*, residential consumers) while it may fail to do so for a different one (*e. g.*, industrial consumers). Finally, it is worth mentioning that the results achieved by the hierarchical model presented herein still have the space for improvements. For instance, the usage of different training techniques for the ANN or the pre-processing techniques applied to load measurements will certainly lead to improvements. On the other hand, standardizing algorithms for benchmark testing and method comparison will yield more robust model, as well as the possibility for improving other already presented models.

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