ELECTRICITY LOAD FORECASTING USING AUTO-REGRESSIVE AND ARTIFICIAL NEURAL NETWORK MODEL

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Abstract: In this paper a short review of two forecasting models Autoregressive and Artificial neural network is presented. Both models were used to demonstrate its superior performance in load forecasting issues. In the third section the results of load forecasting experiment are given. For obtained forecasted results mean absolute percentage error for autoregressive model was 0.644 % and for artificial neural network model 2.31 %. In this paper error distribution for both models is also shown.

Keywords:Load, load forecast, load prediction, autoregressive model, artificial neural network

1. INTRODUCTION

A knowledge of electricity load and its changes in time is one of crucial information necessary for operation and planning decision for distribution and transmission operators companies. It is important to know the expected changes in electricity load or "load forecasting (LF)" to make appropriate arrangements like to specify the suitable time for maintenance, load switching or infrastructure development. In deregulated electricity market this information is also necessary for all market participants (energy suppliers, financial institutions, transmission and distribution operators) to help them make important decision on purchasing electricity, generation capacity and spinning reserve etc. Thus it is essential to develop accurate methods and techniques for electricity load forecasting. Accurate load forecasts can improve the overall economic of electricity power system and also increase the reliability of the network. Load forecasts can be divided into three categories [1]: short term load forecast (STLF) which is usually from one hour to one week, medium term load forecast which is usually from one week to one year and long term forecast which is usually from one year to longer forecasts. STLF can help to estimate optimal load flow or avoid overloading. Also in recent years with the deregulation of market and increasing number of renewable energy sources (RES) the importance of accurate LF methods is growing. However with the rollout of smart grid implementation plan and smart meters the importance of LF methods grew even further.

Several methods were developed for STLF [1] that are usually based on statistical or artificial intelligence approach like Similar day approach, Polynomial regression, Fuzzy logic, Support vector machine or Expert systems. In this paper STLFs were based on the other ones:

Time series – Time series are statistically considered as time sampled values (usually discrete or continuous). Those methods are based on assumption that the data have an internal structure, like an autocorrelation, trend or seasonal variation. Time series forecasting methods learn such structure. For single input and single output models, the forecasted value is obtained as a linear combination of any amount (order) of previously observed values – i.e. simple autoregressive (AR) model. Other time series models are (ARMA, ARIME, ARMAX, ARIMAX, FARMAX etc.)

Neural networks – Artificial neural network (ANN or NN) is a method that allows to overcome the need of functional notation. With the development of computer technology and its computation capacity this method can be used for many different applications. The idea and behaviour of ANN is derived from biological neural network. This fitting/prediction model can be used to forecast or to fit any linear or nonlinear dependency. For load forecasting use, multiple different inputs can be considered as weather, day of week, hour etc.

2. AR AND ANN FORECASTING METHODS DESCRIPTION

Notation of single input and single output autoregressive model AR(p) of order p used for prediction can be written as [2]

$$Y_t = \sum_{i=1}^{p} (a_i \cdot Y_{t-i}) + e_t \tag{1}$$

Where Y_t is a load value at time t (i.e. forecasted value), Y_{t-i} are load values at time $t-i$, p is an order of AR model and that also means from how many previous values is the next value calculated, a_i are the unknown coefficients and e_t is a white noise. The unknown coefficients of AR model can be determined by using ordinary well known least mean square (LMS) algorithm.

Another used model for STLF in this paper was ANN because of its ability to compute complex problems with multiple inputs and outputs without the need of finding exact functional notation [3]. ANN can be seen as a network of connected neurons (nodes). ANN consist of multiple layers with the first one input layer and the last one output layer. Between input and output layer, there can be any amount of hidden layers, simple network architecture is depicted in Figure 1 a).

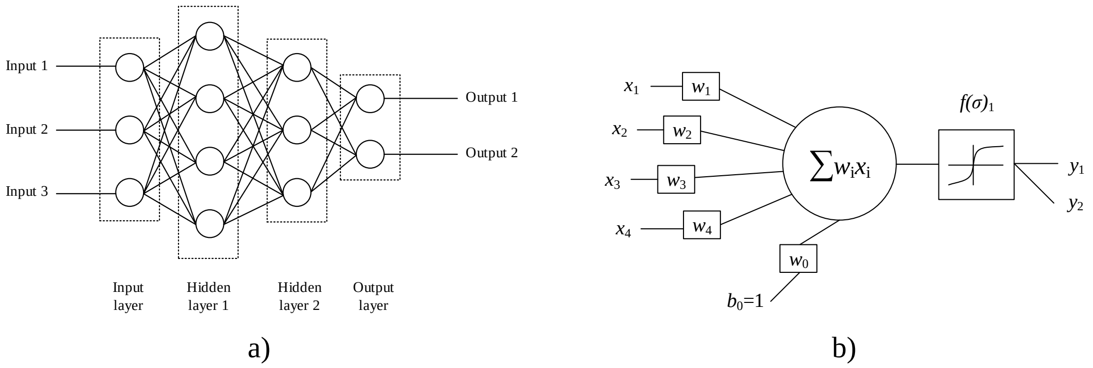

Figure 1: Multilayer NN architecture a) and detail of one node in hidden layer b)

For most of the problems ANN with only one hidden layer is capable to learn any nonlinear dependency between inputs and outputs. Each node of the network has its respective weight vector $\boldsymbol{w}_i$, summation function $\sum$ and activation or threshold function $f(\sigma)_1$. Before the inputs can be applied to the ANN they have to be pre-processed. In this process the input data are transformed between interval 0 to 1 just that the network will be able to easily learn the pattern and generate better results.

$$f(\sigma) = \frac{1}{1+e^{-\sigma}} \tag{2}$$

$$\frac{\partial f}{\partial \sigma} = f(\sigma)[1 - f(\sigma)] \tag{3}$$

Vector of weights is usually at the beginning of learning process initialized with random values from interval between 0 to 1. As a threshold function the most commonly used function is a sigmoid function (2) or hyperbolic sigmoid function. This function makes the network possible to learn nonlinearity between inputs and outputs and this function is also used because it is mathematically convenient (is differentiable (3)). According to the path of the information going through the network there are two basic network types. Feedforward network is the simplest ANN. All inputs to the layer are first multiplied by respective weights, summed together and applied to threshold function and makes output of the layer. Other type may be the ANN with feedback loop.

The main task of ANN is the learning process of respective weights. In this case supervised type of learning is briefly described. In supervised learning technique, the learning algorithm tries to minimize the mean square error between the inputs and already known outputs. For this purpose an error function is introduced (4) in accordance with [3]

$$E = \frac{1}{N}\sum_{i=1}^{N}(T_i - A_i)^2 \tag{4}$$

Where E is the sum of mean square errors for all inputs, T_i is the target output that should be achieved and A_i is the actual output that can differ from T_i and N is the number of samples. It can be derived that the error function depends on the weight vectors. According to the gradient descent algorithm the local/global minimum of such error function can be than calculated in iterative loop matter, when in each iteration step weight vector is updated with the negative proportion of gradient of the error function (5), where index k represents the k-th loop value and $k-1$ the previous loop value

$$\boldsymbol{w}_{\mathrm{i,k}} = \boldsymbol{w}_{i,k-1} - \nabla \boldsymbol{E}_k = \boldsymbol{w}_{i,k-1} - \frac{\partial E_i}{\partial w_i} \tag{5}$$

To determine the accuracy of forecasting models the Absolute Percentage Error (APE) and its mean value over all samples (Mean Absolute Percentage Error MAPE) (6) was used. Root mean square error or others methods would also work. *MAPE* is given as

$$MAPE = \frac{1}{N}\cdot\sum_{i=1}^{N} APE_i = \frac{1}{N}\sum_{i=1}^{N}\frac{100\cdot|T_i - A_i|}{T_i} \tag{6}$$

The learning process of ANN is finished when error function reaches desired minimum value.

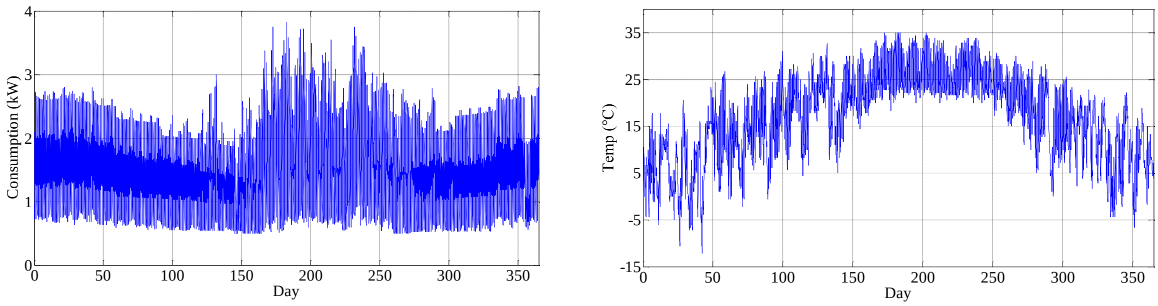

Figure 2: Annual consumption and temperature curve

3. EXPERIMENT DESCRIPTION AND RESULTS

In this section the results of week ahead load forecast by two previously described forecaster models are presented - Autoregressive and ANN. As the input data for the load forecast were used residential hourly load data simulated by EERE [5]. The simulation was performed for slightly more than one thousand locations in US and is based on statistical data for typical meteorological year (TMY3). The usage of energy, water, electricity etc. were considered according to the weather and Building America House Simulation Protocol [6]. The consumption curve with its temperature curve data are depicted for entire year in Figure 2.

To set the AR and ANN model forecasters the data was divided into three groups. The first group contained load data for the first 49 days of the year. This data starts with Sunday 1st of January and ends after 7 weeks on Saturday 18th of February. This data was considered for the learning purpose and consists of more than 11 hundred time samples. For the forecasting purpose another one week data was used starting from Sunday 19th of February and ending on 25th of February and represented 168 time samples to be forecasted. The real load data form 1st of January to 25th of February (i.e. learning data and one week data to forecast) are depicted in Figure 3. The rest of the data wasn't used. The coefficients a_i of autoregressive model AR (1) was estimated with the use of Matlab tool AR. The order of AR model was set to 25 according to empiric estimation and also with respect to autocorrelation function. This Matlab tool also allows to use different algorithms to calculate the least squares (Burg´s method, Yule-Walker method (YW), Forward-Backward method etc.). Except YW method other gave almost the same results but bit better than YW, thus Forward-Backward method was chosen.

Model of ANN was obtained by using Matlab and its NN tool nftool. This tool enables to create feedforward neural network with input, output and one hidden layer. The number of neurons in hidden layer can be arbitrarily changed by the user. To avoid overfitting and to improve the performance of training, the data were divided into three categories-training, validation and testing. These categories were set as default (70 %, 15 %, 15 %) and its influence can be examined in further research. To minimize the square error (error function) Levenberq-Marquardt algorithm was used, which is similar but more robust algorithm than simple gradient descent. According to empirical experiments and also trial and error method the number of neurons in hidden layer was set to 15. For higher number of neurons the performance didn't improve or was even worse. Probably because of overfitting problem. As the inputs for the ANN were chosen day of week, logical information if its weekend or not, hour, outside temperature and dew point temperature (DP). As paper [3] proposes DP value should theoretically has impact on the load curve.

In Figure 4 and 5 the Absolute Percentage Error for fitted and forecasted data is depicted. From these figures can be also seen the quality of regression (fitting) because of both models being used also on learning dataset.

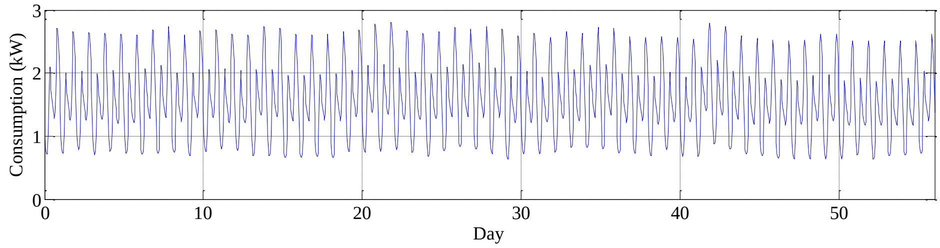

Figure 3: Real load data used for learning and forecasting

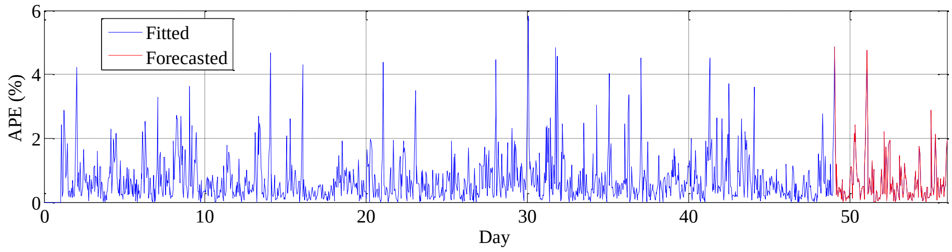

Figure 4: Distribution of Absolute Percentage Error (APE) among fitted and forecasted consumption for AR model

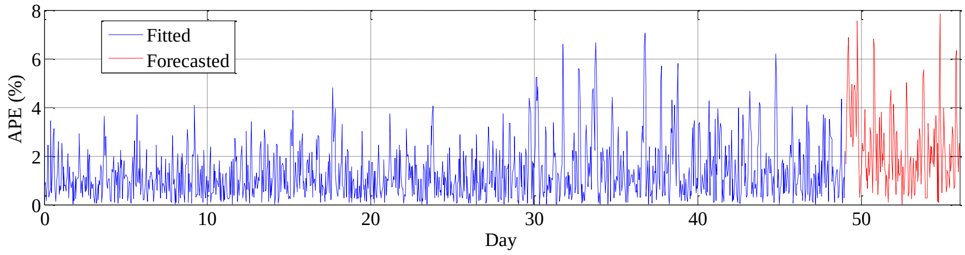

Figure 5: Distribution of Absolute Percentage Error (APE) among fitted and forecasted consumption for ANN model

For AR model the MAPE for forecasted values was 0.644 % whereas for ANN MAPE was 2.31 %. The maximum absolute percentage error for AR was 4.87 % and for ANN 7.84 %. The distribution of error among forecasted values for both methods is depicted in Figure 6. The MAPE was calculated only from data of 7 forecasted days, not including the fitted data (day 1-49 that are also ploted in Figures 4 and 5).

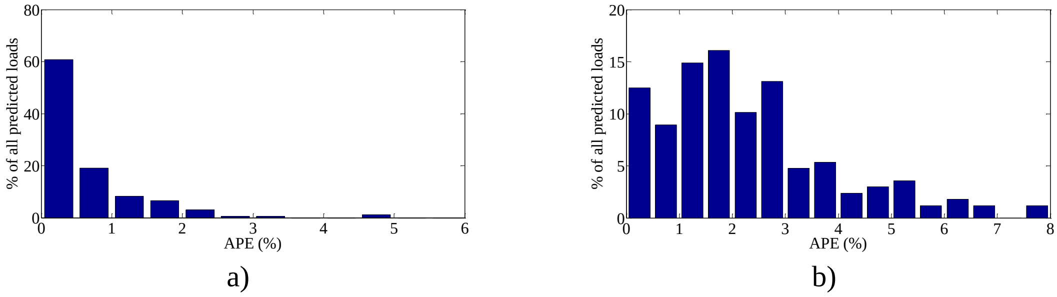

Figure 6: Distribution of error among forecasted data, AR a), ANN b)

4. CONCLUSION

In this paper the suitability of AR and ANN models for electricity consumption was introduced. From obtained values of week ahead hourly load forecast, it can been seen that AR model achieves superior accuracy to ANN model. From the experiment it was also found that the AR model is quite simple to learn. ANN model is quite different but allows to consider other factors that can influence the forecasted load. Different input setups were tested, and as [3] proposes including DP temperature slightly improved the results reducing the maximal APE by 1% but not influencing overall MAPE. However to achieve better accuracy ANN model had to be trained more times to find best fit. For future development it is supposed to try other Autoregressive models and also for ANN extend the inputs by information of past load (i.e. the same day last year, same day last week).

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