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Short Term Electrical Load Forecasting by Artificial Neural Network

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ABSTRACT
This paper presents an application of artificial neural networks for short-term times series electrical load forecasting. An adaptive learning algorithm is derived from system stability to ensure the convergence of training process. Historical data of hourly power load as well as hourly wind power generation are sourced from European Open Power System Platform. The simulation demonstrates that errors steadily decrease in training with the adaptive learning factor starting at different initial value and errors behave volatile with constant learning factors with different values.
Keywords – Adaptive learning, neural network, short term load forecast, stability analysis

I. INTRODUCTION

The fundamental characteristic that makes the electric power industry unique is the product, electricity has limited storage capability. Electricity energy cannot be stored as it should be generated as soon as it is demanded. Since there is no “inventory” or “buffer” from generation to end users (customers), ideally, power systems have to be built to meet the maximum demand, the so called peak load, to insure that sufficient power can be delivered to the customers whenever they need it. Therefore, Electric Power Load Forecasting (EPLF) is a vital process in the planning of electricity industry and the operation of electric power systems. Accurate forecasts lead to substantial savings in operating and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development. However, forecasting, by nature, is a stochastic problem rather than deterministic. Since the forecasters are dealing with randomness, the output of a forecasting process is supposed to be in a probabilistic form, such as a forecast within error range under such value. Many researches have been focusing on load forecasting [1]. In work [2], a short term load forecasting was presented using multi parameter regression. In work [3], a scholastic method is investigated mainly based on decomposition and fragmentation of time series. A review of short term load forecasting using artificial neural network (ANN) is given in [4]. It concluded that the artificial intelligence based forecasting algorithms are proved to be potential techniques for this challenging job of nonlinear time series prediction. This research uses an adaptive learning algorithm which was proven to guarantee the convergence of training process by updating the learning factor at iteration. The simulation is based on the historical data between 2010 – 2015 including hourly electrical load and hourly wind power generation. The data are sourced from Open Power System Platform for European countries. In following section, the artificial neural network and an adaptive algorithm are described and simulation results are presented.

II. AN ARTIFICIAL NEURAL NETWORK MODEL

The ANN is a set of processing elements (neurons or perceptrons) with a specific topology of weighted interconnections between these elements and a learning law for updating the weights of interconnection between two neurons. In work [5], the Lyapunov function [6,7] approach was used to provide stability analysis of Backpropagation training algorithm of such network. However, the training process can be very sensitive to initial condition such as number of neurons, number of layers, and value of weights, and learning factors which are often chosen by trial and error. The Backpropgation algorithm is used for learning – that is, weight adjusting.

The Least Square error function is defined and verified satisfying the Lyapunov condition so that it guarantees the stability of the system. In the work [5], the analysis carries out a method that defines a range for value of learning factor at iteration which ensure the condition for stability are satisfied. In simulation, instead of selecting a learning factor by trial and error, author defines an adaptive learning factor which satisfies the convergence condition and adjust connection weight accordingly.

The ANN model problem can be outlined as follow: a set of data is collected from the system including input data and corresponding output data observed, or measured as target output of the ANN model. The set is often called "training set". An ANN model with parameters, called weights, is designed to simulate the system. When the output from neural network is calculated, an error representing the difference between target output and calculated output from the system is generated. The learning process of neural network is to modify the network, the weights, to minimize the error.

Consider a system with N inputs $X = \{X_1, \dots, X_N\}$ and M output units Y $= \{Y_1, \dots, Y_M\}$. A recurrent network combines number of neurons, called nodes, feed forward to next layer of nodes. Suppose N_l is number of nodes in lth layer, each output from the l-1th layer will be used as input for next layer. A system of a single layer with M outputs can be expressed in form of

$$Y_{jp} = f(Z) = f\left(\sum_{i=1}^{N} w_{ij} X_{ip} + \sum_{i=1}^{D} v_{ij} Y_{j(p-i)}\right) \quad (1)$$

where w_{ij} is called connection weight from input X_i to output Y_j;vij is called connection weight of local feedback at jth node with ith delay; $f()$ is a nonlinear sigmoid function

$$f(Z) = \frac{1 - e^{-\theta Z}}{1 + e^{-\theta Z}} \quad (2)$$

with constant coefficient θ, called slope; p = 1, …, T, T is number of patterns, D is number of delay used in local feedback.

The back-propagation algorithm has become a common algorithm used for training feed-forward multilayer perceptron. It is a generalized the Least Mean Square algorithm that minimizes the mean squared error between the target output and the network output with respect to the weights. The algorithm looks for the minimum of the error function in weight space using the method of gradient descent. The combination of weights which minimizes the error function is considered to be a solution of the learning problem. A proof of the Back-propagation algorithm was presented in [11] based on a graphical approach in which the algorithm reduces to a graph labeling problem.

The total error E of the network over all training set is defined as

$$E = \frac{1}{T} \sum_{k=1}^{N_L} \sum_{p=1}^{T} e_k^2(p) \quad (3)$$

where $e_k^2(p)$ is the error associated with *pth* pattern at the *kth* node of output layer,

$$e_k^2(p) = (\, d_k(p) - Y_k^L(p))^2 \quad (4)$$

where $d_k(p)$ is the target at kth node and $Y_k^L(p)$ is the output of network at the kth node. The learning rule was chosen following gradient descent method to update the network connection weights iteratively,

$$\Delta W_j = -\mu \frac{\partial E}{\partial w_j}; j = 1, \dots, M \quad (5)$$

$$\Delta v_j = -\mu \frac{\partial E}{\partial v_j}; j = 1, \dots, D \quad (6)$$

where $W_j = (w_{1j}, \dots, w_{Nj})$ and $v_j = (v_{j1}, \dots, v_{Dj})$ are weight vectors in jth node; μ is a constant called learning factor.

From work [5], an extended and simplified condition was derived such that the system defined in (1) – (2) converges if the learning factor in (5) – (6) satisfies the following conditions:

$$2 - \theta\, |v^o| > 0\,, \quad (7)$$

$$\mu < \frac{\left(2 - \theta |v_j^o|\right)^2}{4\theta\,(2 + \theta(|w^o| - |v_j^o|)} \quad (8)$$

III. SHORT TERM ELECTRICAL LOAD FORECASTING

To The changing energy landscape requires rigorous analysis to support robust investment and policy decisions. Power systems are complex, hence researchers and analysts often rely on large numerical computer models for a variety of purposes, ranging from price projections to policy advice and system planning. Such models include unit commitment, dispatch, and generation expansion models. These models require a large amount of input data, such as information about existing power stations, interconnector capacity, and yearly electricity consumption, and ancillary service requirements, but also (hourly) time series of load, wind and solar power generation, and heat demand. Fortunately, most of these data are publicly available, from sources such as transmission system operators, regulators, or industry associations. The Open Power System Data platforms provides free and open data of the European power system with restricted use for non-commercial applications. The Open Power System Data is implemented by four institutions, DIW Berlin, Europa-Universität Flensburg, Technical University of Berlin, and Neon Neue Energieökonomik and funded by the German Federal Ministry for Economic Affairs and Energy. This simulation used a data package which contains time-series data relevant for power system modeling. The data includes hourly electrical load of 36 European countries, wind and solar power generation from German transmission system operators. This simulation uses German electrical load and wind power generation data available from 2010- 2015 for ANN training and mainly demonstrates that the enhanced learning algorithm may avoid many trial and error for selection of learning factors.

In neural network training using Back propagation algorithm, the initial weights are randomly selected and the learning factor is preselected. The performance of the learning can sometime very volatile due to the selection of the learning factor. To find the optimal fit, the trial and error is common practice that runs the simulation with different values of learning factors. In this research, an upper boundary of learning factors (8) is derived from the theory of convergence. At iteration of network training, the norm of weights is calculated and a learning factor is defined to satisfy the convergence condition (8).

A three layer neural network structure was selected with 13 inputs, 8 and 5 nodes in the hidden layer, and one outputs. For every hour of electrical load as output, the 13 inputs are defined as follows:
1 – 10: previous 10 hours electrical load
11: previous hour's wind power generation
12: current hour wind power generation
13: next hours wind power generation

Data from 2010 to 2015 are used to train the ANN model. 100 days data are used to setup 2400 patterns of the training set. Input and output data are normalized to range from 0 to 1. After the ANN model is trained, the 48 hours forecast of electrical load are calculated from the model and denormalized and then used to compare with the actual electrical load. The following figures demonstrates error behaviors of ANN training with 100 days data and 48 hours forecasting.

With the constant learning factor, after number of trials with various values of learning factor and slope, momentum term set as 0.1, and random generated initial weights, the training reached to absolute error 0.0198 after 100000 iterations with learning factor 0.02, slope 0.6. The error behavior is sown in Fig. 1.

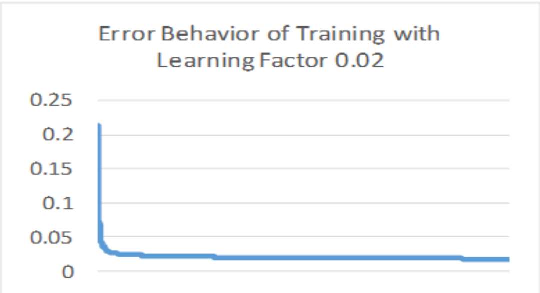

Figure 1. Error behavior of training with learning factor 0.02 and slope 0.6

Fig. 2 and Fig. 3 demonstrate error behavior of training with other randomly selected learning factor and slope. It is observed that the error stays around certain value and are not decreasing after some iteration. Fig. 2 is error behavior of training with learning factor 0.05 and slope 0.7, whereas figure 3 is error behavior of training with learning factor 0.4 and slope 0.6.

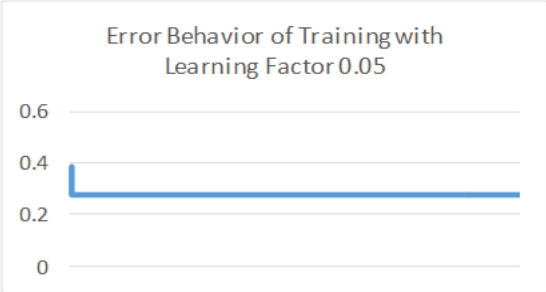

Figure 2. Error behavior of ANN training with learning factor 0.05 and slope 0.7

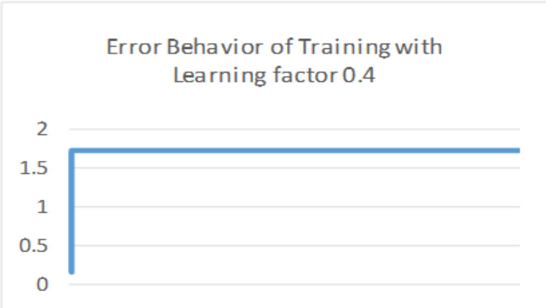

Figure 3. Error behavior of ANN training with learning factor 0.4 and slope 0.6

In comparison, the training process with adaptive learning factor are experimented with the same values of slope and initial learning factor. The learning factor at each iteration is calculated satisfying the convergence condition given in (7).

From Fig. 4 – Fig. 6, it is observed that error at iteration steadily decreases regardless of initial values of learning factor.

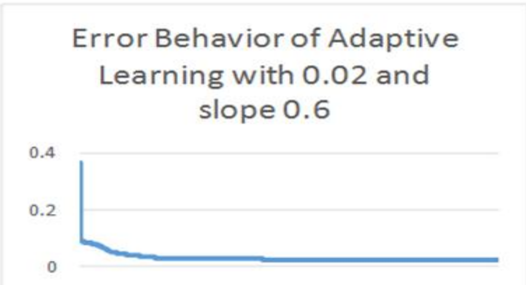

Figure 4. Adaptive training with initial learning factor 0.02 and slope 0.6

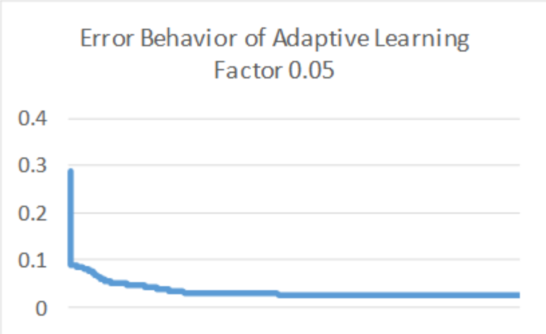

Figure 5. Error behavior of adaptive training with initial learning factor 0.05 and slope 0.7

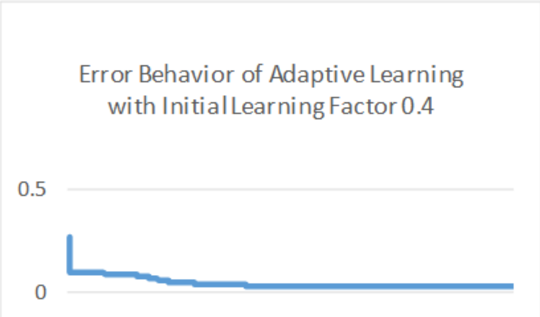

Figure 6. Error behavior of adaptive training with initial factor 0.4 and slope 0.6

The following Fig. 7 shows the 48 hours load forecasting using the model trained with adaptive learning comparing with the actual electrical load.

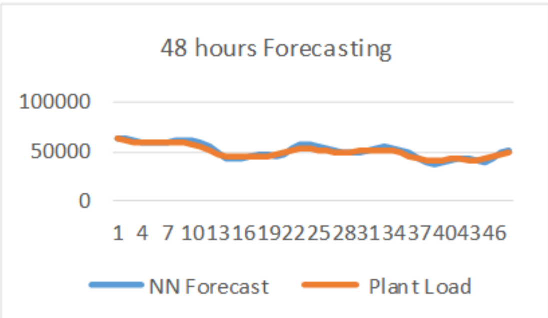

Figure 7. Forty eight hours load forecasting

IV. CONCLUSION

This research applied artificial neural network in short term forecasting of electrical load. The historical data of time-series electrical load and wind power generation are used for training the model which successfully provide 48 hours forecasting. The data of 36 European countries are sourced from Open Power System platform. To ensure the convergence of training and avoid unstable phenomena, an adaptive learning factor are calculated at iteration of training following the analysis of convergence theory satisfying the convergence condition. The analysis results in a condition which provides an upper boundary of the learning factor. Instead of selecting a constant learning factor by trial and error, an adaptive learning factor is calculated at iteration satisfying the convergence condition. Furthermore, a more simplified condition was used to provide a feasible implementation of the adaptive learning factor. The simulation result is based on the data of German power plant. The error behaviors were demonstrated for training with an adaptive learning factor as well as with a selected constant learning factor. The comparison demonstrated that a learning factor arbitrarily chosen out of the predefined stability domain leads to an unstable identification of the considered system; however, an adaptive learning factor satisfying the conditions chosen for this study ensures the stability of the identification system. The ANN network is trained with 100 days of data including electrical load and wind power generation and 48 hours forecasting is presented. Further work may focus on analysis of evaluation of performance of the model and the data selection for training.

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