

Short Term Load Forecasting by Adaptive Neural Network

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Abstract. The Generation and load balance is required in economic scheduling of the generating units and in electricity market trades. Energy forecasting became very important to mitigate some of the challenges that arise from the uncertainty in the resource. The paper presents a structure of artificial neural network with an adaptive learning algorithm used for a short-term forecasting of hourly electric power load. Historical data are sourced from Global Energy Forecasting Competition 2017 (GEFCom2017) including forecasting in the domains of electric load, weather, wind power, solar power, and electricity prices. An adaptive learning algorithm is derived from analysis of system stability to ensure convergence of training process. A simplified condition of learning factor is driven for use of computer simulation. An upper bound of learning factors is derived from the theory of convergence. At iteration of network training, a learning factor is defined to satisfy the convergence condition. The simulations with different initial state of network structure demonstrate that training error steadily decrease with an adaptive learning factor starting at different initial values whereas errors behave volatile with constant learning factors. 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.

1. Introduction

Electricity energy cannot be stored as it should be generated as soon as it is demanded. Since there is no “inventory” from generation to end users (customers), ideally, power systems need to be built to meet the maximum demand, the so called peak load, to ensure 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 the 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 prove 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 the training



process by updating the learning factor at iteration. The data are sourced from the Global Energy Forecasting Competition 2017 (GEFCOM2017) which also including forecasting in the domains of electric load, weather, wind power, solar power, and electricity prices. In the following section, the artificial neural network and an adaptive algorithm are described and simulation results are presented.

2. Statistical forecasting models

2.1. Non-learning approach models

The Non-learning models describe the connection between solar irradiance from numerical weather predictions and electric power production directly by statistical analysis of time series from historical data without considering the physics of the system. This connection can be used for forecasts in the future plant outcomes. Many regression models are already implemented as time-series forecasting models, some of which include autoregressive integrated moving averages, and multiple linear regression analysis model.

2.2. Artificial neural network (ANN) model

The Artificial intelligence (AI) methods are used to learn the relation between prior electric load along with predicted weather condition and the power output. AI methods use algorithms that are able to implicitly describe nonlinear and highly complex relationship between input data and output power. High quality time series data consisting of weather predication and power output of the past are very important. One of the most common statistical learning models is the artificial neural network.

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 Backpropagation algorithm is used for learning – that is, weight adjusting. In the Backpropagation concept, information flows in one direction between the neurons (nodes) and the errors backpropagate in the opposite direction, changing the strength (weights) of the synapses (links) between the nodes while attempting to minimize the errors by using appropriate optimization technique such as the gradient descent method. After sufficient training iterations with known input data, the weights between the nodes are adjusted until the give correct response. Then, the ANN will give predicted output to the (unknown) input data. More sophisticated algorithms are introduced for training ANNs with different optimization methods to improve the performance [7].

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 of value of learning factors 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 the connection weight accordingly.

The ANN model problem can be outlined as follows: a set of data is collected from the system including input data and corresponding output data observed or measured as the 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. 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 ; v_{jj} is called connection weight of local feedback at j th node with i th delay; $f: R \rightarrow (-1, 1)$ is a nonlinear sigmoid function

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

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

The Backpropagation algorithm has become a common algorithm used for training feed-forward multilayer perceptron. It is a generalized Least Mean Square algorithm that minimizes the mean square 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 Backpropagation algorithm was presented in [7] 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 p th pattern at the k th 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 k th node and $Y_k^L(p)$ is the output of network at the k th 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 j th 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:

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

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

3. Short term load forecasting

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 [8, 9]. 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.

3.1. Data source

The Global Energy Forecasting Competition 2017 (GEFCOM2017) provides historical data, including electric load, weather, and electricity prices, etc. The hourly data file is downloaded from the ISO New

England website which is publicly available to researchers. The object is to determine hourly electric load. Historical hourly load and temperature from year 2016 are used in this research.

Data from 2016 are used to train the ANN model. In Figure 1, hourly real time electric load of 60 days from January to February are in a scatter plot.

The scatter plot in Figure 2 demonstrated the relation of electric load that increases when the temperature is low.

The target is the hourly load. For every hour of electric load as output, the 13 inputs are defined as follows:

1 – 8: Electric load of every three hour from the previous 24 hours

9 – 16: Temperature of every three hour from the previous 24 hours

Data are used to setup a set of training data of 1400 patterns. Inputs and outputs are normalized to range from -1 to 1. After the ANN model is trained, the 10 hours forecast of electric load is calculated from the model and demoralized and then compared with the real time electric load.

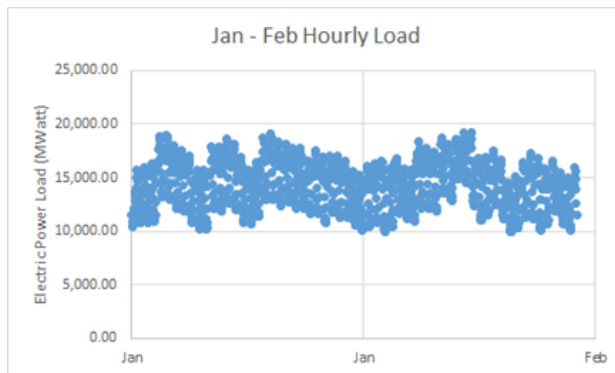


Figure 1 Scatter Plot of Load Data from Jan. and Feb.

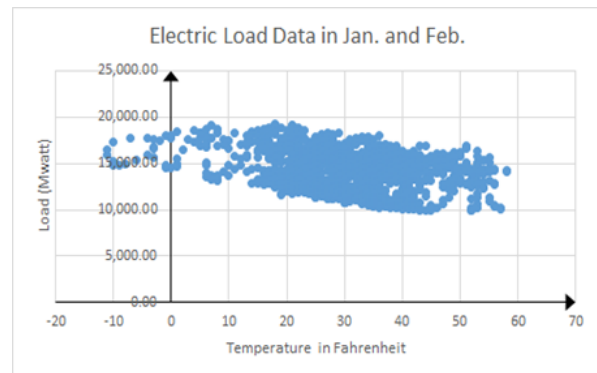


Figure 2 Scatter Plot of Load with Temperature Data in Jan. and Feb.

3.2. Adaptive learning factor

In neural network training using Backpropagation algorithm, the initial weights are randomly selected and the learning factor is preselected. The performance of the learning can sometimes be 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 bound 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).

3.3. Simulation results

A three layers neural network structure is selected with 16 inputs, 8 and 4 nodes in the hidden layer and one output. The connection weights are randomly generated between 0 and 1 as initial values. With learning factor, slope, and momentum term set as 0.8, 0.75 and 0.2 respectively, the training with the fixed learning factor stays at local minimum error 0.6964 shown in Figure 3 whereas with adaptive learning factor, the training reached to absolute error 0.031 shown in Figure 4. The Figure 5 and Table 1 demonstrate forecasting of electric load of 10 hours from the ANN model compared with the real time electric load.

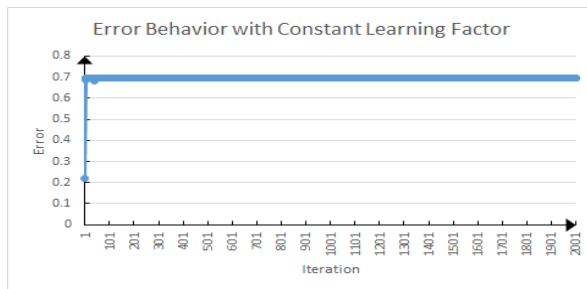


Figure 3 Error Behavior of ANN Training with Constant Learning Factor

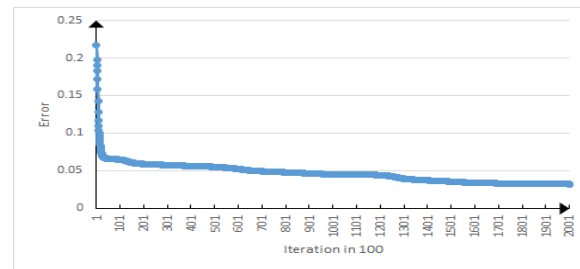


Figure 4 Error Behaviour of ANN Training with Adaptive Learning Factor

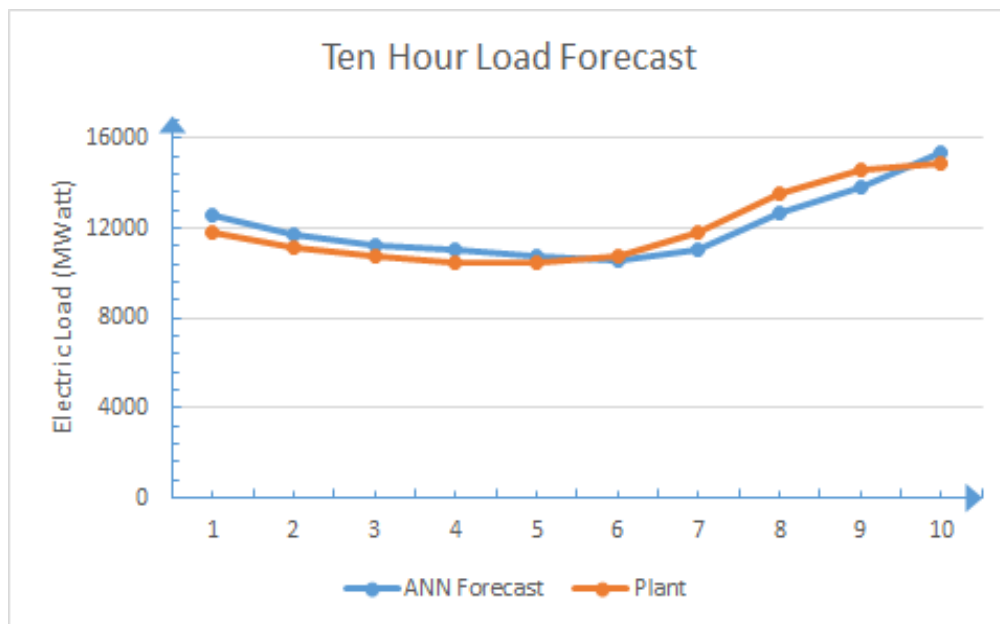


Figure 5 Ten Hour Load Forecasting

Table 1 10 Hours Forecasting of Electric Alload

hour	Electric Load (MWatt)	
	ANN Forecasting	Real Time Load
1	11696.8484	11120.818
2	11267.3753	10712.213
3	11054.60513	10485.787
4	10777.6042	10471.03
5	10537.2718	10778.012
6	11083.74692	11774.682
7	12692.034	13509.232

hour	Electric Load (MWatt)	
	<i>ANN Forecasting</i>	<i>Real Time Load</i>
8	13863.0863	14560.125
9	15355.1231	14851.957
10	15137.3306	14886.081

4. Conclusion

An Artificial Neural Network model is trained to give short term forecasting of electric load. The historical data of time-series electric load and weather temperature are used for training the model which successfully provide 10 hours forecasting. To ensure the convergence of training and avoid unstable phenomena, an adaptive learning factor is 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 simulations demonstrate 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 60 days of data, including electric load and weather temperature and 10 hours forecasting is presented.

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