

Irradiance and Demand Forecasting Using Neural Networks

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ABSTRACT: Forecasting is always been an essential part of an efficient power system's planning and operation. Several electric power companies are forecasting load power based on conventional methods. However, since the relationship between power and factors influencing load power is nonlinear, it is very difficult to identify its nonlinearity by using conventional methods. Load forecasting and Irradiance forecasting is being done here. Since conventional methods find difficulty in forecasting purposes, Artificial intelligence(AI) is a method that deals with stochastic data. Artificial neural network is one of the AI method used here.

KEYWORDS: Load forecasting, Irradiance forecasting, Artificial neural network.

I. INTRODUCTION

Forecasting, the process of making predictions of the future based on past and present data and analysis of trends. A common example might be estimation of some variable of interest at some specified future date. Prediction is a similar, but a general term. Both might refer to formal statistical methods employing time series, cross sectional or longitudinal data or alternatively to less formal judgment methods. The usage can differ between areas of application: for example, the terms forecast and forecasting are reserved for estimates of values at specific future time, while the term prediction is used for more actual estimates, such as the number of times will occur over a long period.

Many techniques have been developed for load forecasting. They can be divided into three broad categories: parametric, nonparametric, and artificial intelligence(AI) based methods. The parametric methods formulate mathematical or statistical models of load by examining qualitative relationships between the load and load affecting factors. Some examples of the models used are polynomial functions, ARMA models, Fourier series, and multiple linear regression [1]-[3]. Nonparametric methods allow a load forecast to be calculated directly from historical data. For example, using nonparametric regression, a load forecast can be calculated as an average of observed past loads with the size of the local neighbourhood and the specific weight on the loads defined by a multivariate product kernel[4], [5]. Artificial intelligence(AI) based methods use artificial neural networks (ANN) as load models. The main advantage of using neural networks lies in their abilities to group the mentioned dependencies directly from the historical data without the necessity of selecting an appropriate model. There are different types of neural networks that have been applied for load forecasting. A multilayer feed forward network is most commonly used [6]-[9]. Artificial Neural Network (ANN), one of the Artificial intelligence method is actually implemented here for the forecasting. It is developed to basic biological neural systems. An ANN is an information processing paradigm that is beghested by the way biological nervous systems, such as the brain, process information. It consists of a large number of interconnected processing elements (neurons) working to solve specific problems. Some reported techniques include first or second order polynomial extrapolation, autoregressive (AR) and autoregressive moving average (ARMA) models, and artificial neural networks [10]-[12]. Artificial neural networks is defined by Kohonen as "massively parallel networks of simple and preferable elements and their hierarchical organizations which are intended to interact with the objects of the real world in the that way as biological nervous system do [13]." Neural networks attempt to achieve good performance via dense mesh of computing connections. They also go by many names such as connectionist models, parallel distributed processing models. We will use the term neural networks or simply networks in the following discussion. Neural networks have the many benefits. The basic components of a neural network are nodes (neurons) and weight. The adjustable weights actually correspond to biological synapses. A positive weight represents an excitatory connection. A negative weight

gives an inhibitory connection. The weighted inputs to a neuron are accumulated and then passed to an activation function that determines the neuron's response

Back propagation Algorithm At present, the artificial neural network model has many formats and new models were successively developed which efficiently estimate solar irradiance. The Backpropagation (BP) is the most commonly used neural network because basic nature makes it adaptable to many application. The back propagation algorithm is the part of the artificial neural network which is the multi-layer perceptron, also known as the Widrow-Hoff learning rule. The network will adjust the weight value, and after that input the data form for the network training once each one is finished. The output value of network is compared with the target value then the error value is calculated. The error - value is returned to the network and used to adjust the next weighted value. The process of training a back propagation neural network is shown as in Fig 1.

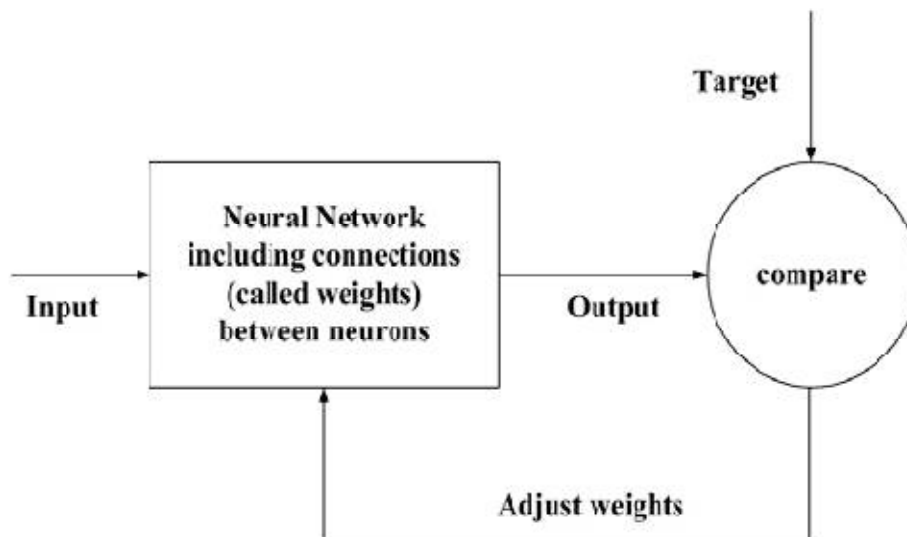


Fig 1. The training process of BP network.

A single-input neuron is shown in Figure 2. The scalar input p is multiplied by the scalar weight w to form wp , one of the terms that is sent to the summer. The other input, 1 , is multiplied by a bias b and then passed to the summer. The summer output n , often referred to as the net input, goes into a transfer function f , which produces the scalar neuron output a .

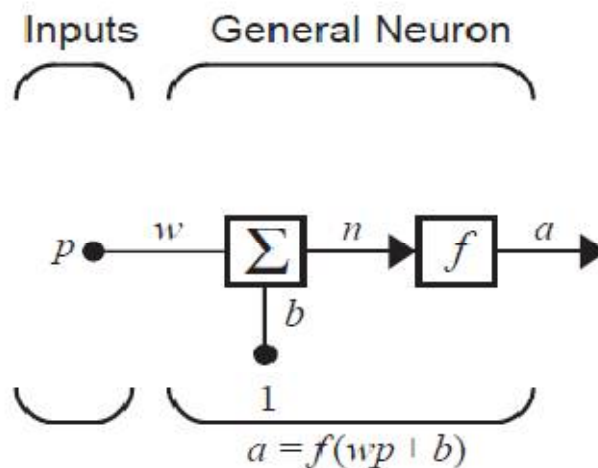


Fig 2. Single-Input Neuron

The neuron output is calculated as $a = f(wp + b)$. The actual output depends on the particular transfer function that is chosen. w and b are both adjustable scalar parameters of the neuron. Typically the transfer function is chosen by the designer and then the parameters will be adjusted by some learning rule so that the neuron input/output relationship meets some specific goal. The log-sigmoid transfer function is commonly used in multilayer networks that are trained using the back propagation algorithm, in part because this function is differentiable

II. FORECASTING

A. Load Forecasting

Accurate load models for load forecasting are essential to the operation and planning of a company. Load forecasting helps electric utilities to make important decisions on purchasing and generating electric power, load switching and foundation development. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electricity generation, transmission, distribution, and markets.

Load forecasts is divided into three categories: short-term forecast which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and forecasts which are longer than a year. The forecasts for different time horizons are very important for operations within a utility company. The natures of these forecasts are different as well. For example, for a particular region, it is easy to predict the next day load with an accuracy of approximately 1-4%. However, it is impossible to predict the coming year peak load with the similar accuracy since accurate weather forecasts are not available. For the coming year peak forecast, it is easy to provide the probability distributions of the load based on historical weather remarks. It is also possible, according to the industry practice, to predict weather normalized load, which will take place for average annual peak weather conditions and worse than average peak weather condition for a given area. Weather normalized load is the calculated load for the so-called normal weather conditions which are the average of the weather indicatives for the peak historical load over a certain period of time. The duration of this period varies from one utility to other. Most methods use statistical techniques or artificial intelligence algorithms such as regression method, neural networks, fuzzy logic, and expert systems. Two of the methods, end-use and econometric approach are used for medium- and long-term forecasting. Variety of methods, which include the so-called similar day approach, various regression models, neural networks, statistical algorithms, fuzzy logic, and expert systems, have been promoted for short-term forecasting.

For training purpose, first of all a neural network should be formed. The details to be included in the Network formation are Input data, Target data, Training function, Adaption learning function, Performance function, Hidden layers, Neurons and Transfer function.

Back propagation method is used for the training of neurons for the forecasting purpose. Data regarding the Demand for the year 2013 was taken for training the neurons and then predicting future data. Data includes the Months in the year and corresponding Demand values. i.e. Input data and Target data. Training Function adopted here is TRAINOSS(One Step Secant). The peculiarity of this function is, it needs only smaller storage and computation requirements. Adaption learning function adopted here is LEARNNGDM (gradient descent with momentum weight and bias learning function). The Performance function used is Mean Square Error (MSE). It measures the network's performance according to the mean of squared errors. Another important step is selection of number of neurons. Depending upon this number, the performance will vary. If there are more number of neurons, the network get over trained, and if there are less number, the network will be undertrained. So selection of number of neurons is important. This can only be set by Trial and error method and optimal numbers of neurons are obtained as 10. The Transfer function used is TANSIG (Tan sigmoid). It is selected over LOGSIG (log sigmoidal) and PURELIN (pure linear) because TANSIG gives better performance than the other two in this case.

B. Irradiance forecasting for the photovoltaic systems

Solar irradiance is the power per unit area produced by the Sun in the form of electromagnetic radiation. Irradiance may be measured in space or at the Earth's surface after atmospheric absorption and scattering. Total solar irradiance (TSI), is a measure of the solar radiative power per unit area normal to the rays, incident on the Earth's upper atmosphere. The solar constant is a conventional measure of mean TSI at a distance of one Astronomical Unit (AU). Irradiance is a function of distance from the Sun, the solar cycle, and cross-cycle changes. Irradiance on Earth is most intense at points directly facing (normal to) the Sun. Solar irradiance is the sun's energy spread to the surface of world. A part of the

solar energy is absorbed energy by the earth's atmosphere the absorption percentage depends on meteorological conditions. The remaining part will be used to generate electricity in photovoltaic system. However, many factors will affect solar irradiances; particularly the weather in each location varies with time of the year. As global climate change becomes more widely recognized, a key mitigation strategy lies in identifying opportunities to increase deployments of renewable energy generation technologies that directly offset greenhouse gas emissions. There are many ways to reduce greenhouse gas emissions, such as improving load efficiency, increasing generator efficiency, distributed electricity generation technologies with improved demand-side control and management techniques. One of the exciting approach to greenhouse gas reduction is to use renewable energy from the wind and sun to produce electricity. The Virtual Power Station (VPS) concept[14 - 16]has been proposed recently. It aims to combine a large number of geographically disperse, and technically diverse, renewable energy generators that will allow them to present to the electricity market as a single reliable dispatchable entity. Unfortunately, the sun does not always shine, and the wind does not always blow to provide a constant source of renewable energy. Renewable generation outputs are very dependent on local environmental conditions. This means that it can be difficult to rely on, particularly for applications. such as ameliorating the need for network augmentation. This periodicity of renewable resources has limited their acceptance as assets to the wider electricity network. Because of this natural variability, one of the challenges of integrating renewable energy into the national grid is the short-term forecasting of renewable sources. Our research is developing algorithms to improve solar generation forecasting. Improved forecasting allows the energy storage requirements of the VPS to be minimized, thus reducing system cost while achieving the reliability needed to allow deferral of network augmentation costs. Overall, such an approach can improve the economic case for the widespread deployment of photovoltaic systems. Since the output of PV is a function of the irradiance[17], most developed algorithms focus on the irradiance forecasting. As long as irradiance information available, output of PV will be easily generated.

The training methods adopted for Demand forecasting are used here too for the forecasting of Irradiance data because of its good performance. The Irradiance data of different months in the year 2011 are taken for training purpose. The Irradiance from 7AM to 5PM of each day is taken, since solar energy is available only during that time periods.

III. RESULTS

A. Forecasting results of Demand forecasting

Forecasting of load demand was done and an error curve, Actual demand vs forecasted demand was plotted. The data for an year was taken actually and error curve for each month for the year 2013 was plotted and results of January and March are given below.

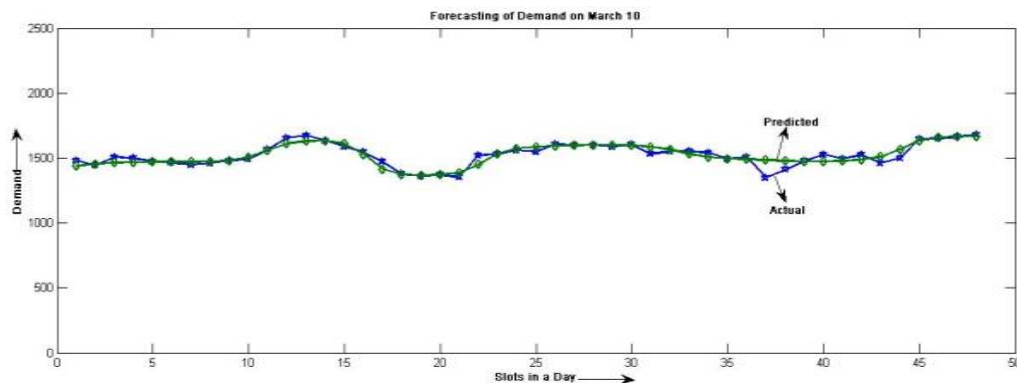


Fig 3. Error curve of Demand forecasting for the month March

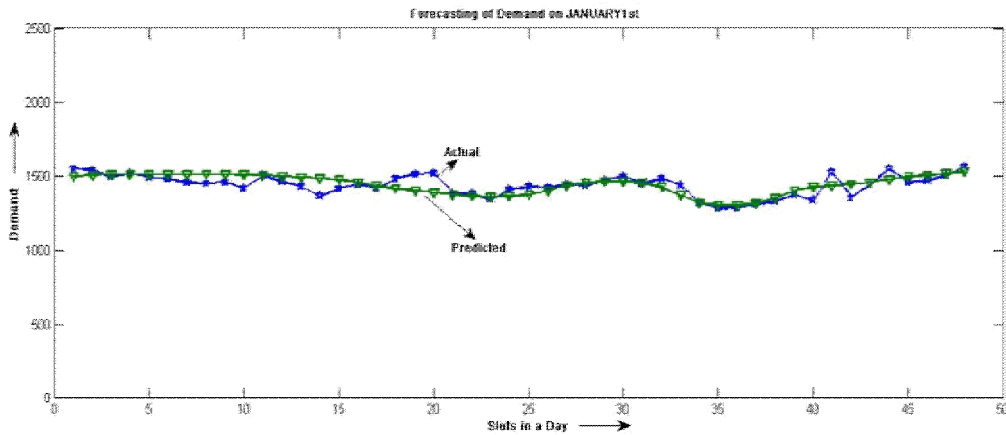


Fig 4. Error curve of Demand forecasting for the month January

B. Forecasting Results of Irradiance forecasting

The model has been implemented by using MATLAB program. The simulation data for testing the BP model are data in 2011. The simulation data are tested. The solar irradiance on January and March, which has the condition of weather, thus causes fluctuation and reduction of solar irradiance during afternoon period. Comparison between actual value and the forecast value by using the Mean Absolute Percentage Error (MAPE). The simulation result has shown that MAPE is only 4.5%. Although, during 11:00 to 16:00 has the width range but it still has the little error value. The simulation result is tracking to actual value. The simulation result compared actual value is shown in Figure 4. Forecasting of Irradiance was done and an error curve, Actual Irradiance vs forecasted irradiance was plotted. The data for an year of Trissur area in Kerala state was taken NREL site and error curve for each month for the year 2011 was plotted and results of January and March are given below.

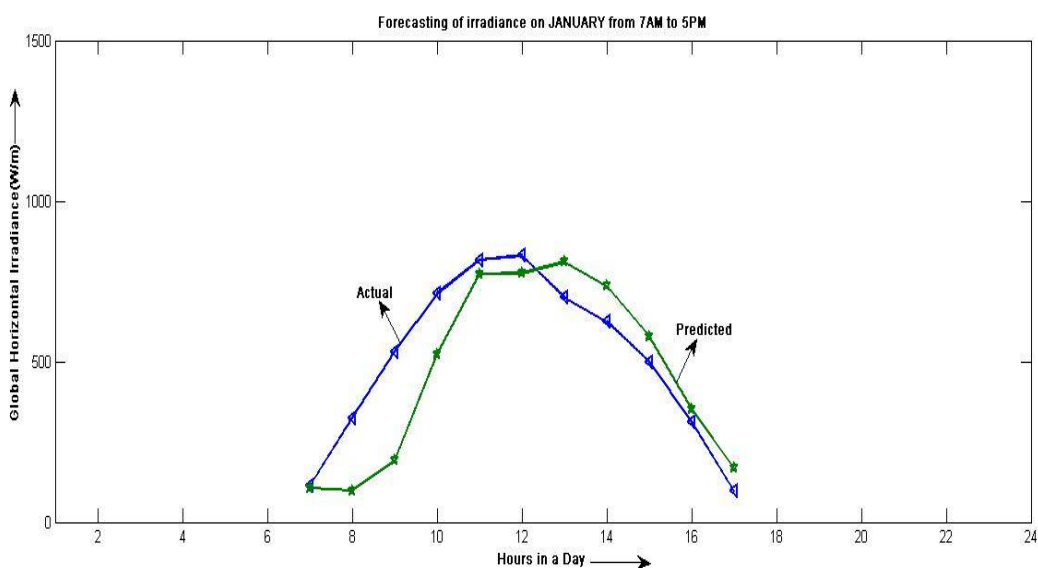


Fig 5. Error curve for the month January

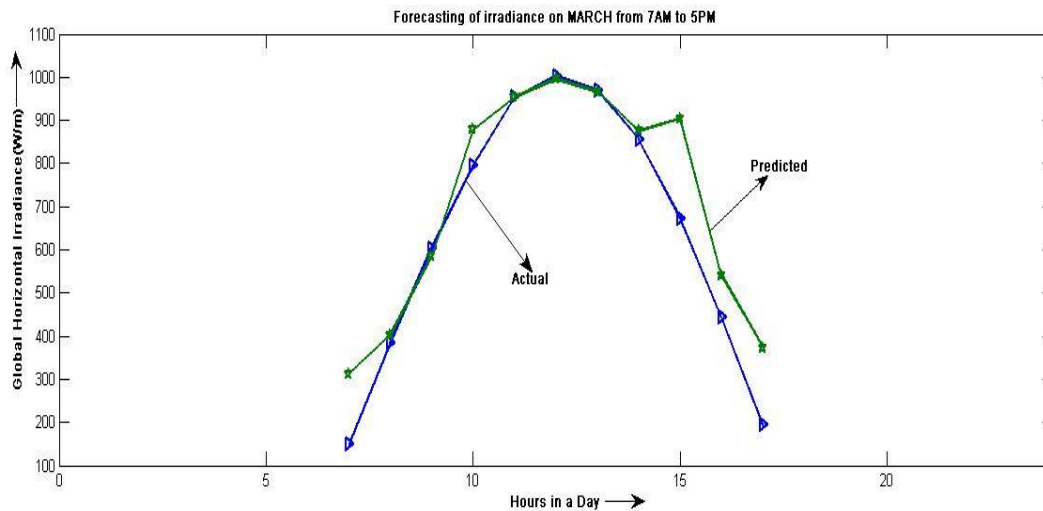


Fig 6. Error curve for the month March

IV. CONCLUSION

Forecasting of Load demand and Irradiance were carried out using Neural networks and error curve was plotted, i.e. predicted and actual values are found to be almost same. This paper presents the forecasting of solar irradiance and load demand by the BP algorithm. In the training process, solar irradiance data, demand data and meteorological data are used in the model. In the testing BP model, data that not use in the training are used as testing the forecast results. The simulation results have shown that accuracy of forecast of BP model. Although, it has changing condition weather and changing load demand, the forecasts model is still accuracy. This solar irradiance forecasting system can be used to calculate the PV power output, which can assist power supply authorities to determine the power output capacity.

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