Global Journal of Engineering Science and Research Management

FORECASTING ENERGY DEMAND FOR A HOUSE USING ARTIFICIAL NEURAL NETWORK

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KEYWORDS: Levenberg-Marquardt Algorithm, Artificial Neural Network, Training, Forecasting, Dataset, Pre-processing.

ABSTRACT
Electricity demand prediction is an essential aspect for the planning and development process of the power system industry. Further, the nature of electricity demand is highly dynamic, the accurate electricity demand forecasting becomes a complex issue. This work made an attempt for the application of Artificial Neural Network structure with Levenberg-Marquardt as the learning algorithm for predicting the electricity demand. In particular, this paper had concentrated on the hourly forecasting of electricity demand for a particular month. From the experimental results, it can be observed that the chosen Artificial Neural Network model is well suited for solving the problem and it provide significant accuracy with an acceptable error rate.

INTRODUCTION
Forecasting techniques could play an important role in the decision making process to select the optimal control strategies to DRES in the power system The DRES control can be fast or slow, i.e. planning. For fast control, it is essential to measure and monitor the current situation in the power system. On the other hand it is important to know that short term decisions can affect also the mid or long term operation. That is why it is important to predict the future values of controlled devices in the power system.

Forecasting methods are characterized as physical or statistical. The physical approach uses solar and photovoltaic (PV) models to generate PV power forecasts. The statistical approach relies primarily on historic data using it to train models. The statistical analysis methods used in solar power generation forecasting are persistence predictions, similar day models, stochastic time series models, machine learning techniques etc.

To generate forecasts covering all systems from forecasts of a subset of the well characterized systems up scaling methods are used. The situation is challenging for new plants for which a long history of measurements is not yet available. In that case, models able to provide accurate production forecasts based on a small amount of historical production data are required.

TYPES OF FORECASTING
Long term forecasting
Long term forecast spans a horizon of one or more years. It is required for strategic planning and is targeting return on investment estimates. Long term forecasting requires a large amount of historical data. Historical power production data as well as the historical data from a weather station can be used in long term forecasting models. Because of the high level of uncertainty long term forecasting is inaccurate.

In this paper the solar irradiance time series was classified by seasons. The time series of each season were decomposed in a trend term and a random term. The term has mainly influenced by the geographical factors such as latitude, altitude, etc. While the random term more reflect the weather conditions. The trend term was fitted by the least square method.

Wind-Forecasting
The problem of the wind energy it comparing to conventional dispatch able units or even other renewable (PVs, Hydrous) is the extreme volatility of the wind. The nature of the wind time series has been studied extensively in various time scales,

1) **The scale of milliseconds to seconds**, for which wind speed forecasting or simulation finds applications in wind turbine control or design.

 ISSN 2349-4506
Impact Factor: 2.265
Global Journal of Engineering Science and Research Management

2) **The scale of minutes, quarters and hours**, which relates to the optimal integration of wind power in the electrical grid. That includes issues like Real-time Grid Operations, Ancillary Services Requirements, Dynamic Security Assessment, Economic Dispatch and Scheduling of Conventional Power Plants and Electricity Market Clearing.

CLASSIFICATION OF WIND FORECASTING

As mentioned above there are various time scales for forecasting. Not everybody agrees with the following classification, but in general the classification is as follows,

1) Very Short Term Forecasting (often called Immediate Short Term or simply Short Term Forecasting) that ranges from minutes up to 3 or 4 hours ahead. This is often displayed in 15-minute values.
2) Short Term Forecasting (often called Long Term) that covers Day-Ahead Forecasting and probably few days ahead (3 or 4 days and rarely up to one week ahead). These forecasts are of course displayed in hourly values.

PROBLEM FORMULATION

Neural Networks for Forecasting

The problem with the time series models is that they assume a linear relationship between the current and future values of load and a linear relationship between the weather variables and the load. It is overcome this by the neural network which is offer the potential for general purpose nonlinear time series forecast. A good nonlinear model should be general enough to capture some of the nonlinear phenomena in the data. The neural network forecasters can be thought of as mappings from a set of previous load, current load and future variables such as temperature, humidity, etc.

The Data Set

The original data set is contain the measure hourly load and temperature values. A few missing load and temperature data indicate 0's in the dataset which has filled-in by interpolating between neighboring values. Monthly energy demand data is calculate by an integrating hourly loads for every month. It is used to the data for the fifteen years (2000-2015) evaluation. Here, all monthly demand data were first normalized for all years an annual energy demand equal to that of the last training year. Let the annual energy demand for the year i will be Ei and the normalization factor fi for that year is defined as following,

fi=E2016/Ei; i = 2001, 2002, …, 2015 (15)

Design the Neural Networks for Forecasting

The designing neural networks for forecasting is an iterative procedure that is begin with collecting the data and pre-processing them to make training more efficient. Then it is training the data which has to be divided into training, validation and testing. After that, the appropriate network type and architecture for forecasting. After decided the network and architecture it is select a training algorithm which is calculate the forecasting problem. After training the network it is need to analyze the network to performance is satisfactory. If find any problem, have to re-start our process from the beginning, as shown in Fig.1.

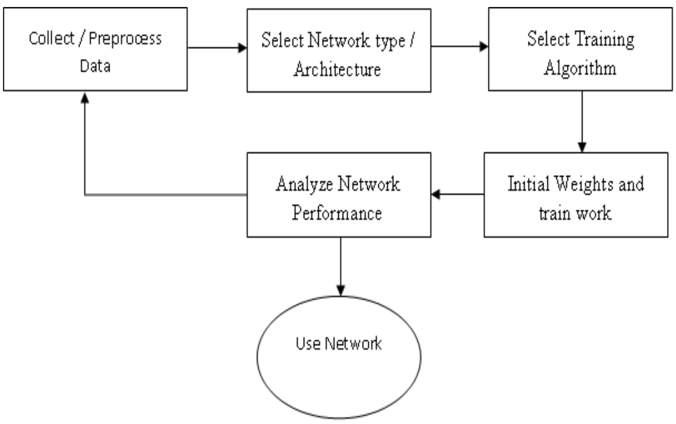

Fig. 1 Neural Network Training Process

Data Collection and pre-processing

The first stage in designing the neural network for forecasting is collecting data. The required amount of data depends on the complexity of the underlying function that are trying to approximate. The choice of data set is closely related to the choice of the number of neurons in the neural network. To make the forecasting problem more manageable, data are pre-processed before being used to train the neural network. The several types are there for data pre-processing, such as normalization, nonlinear transformations, feature extraction, coding of discrete inputs/targets, handling the missing data, etc. Normalization is the main step in data pre-processing. It will help the neural network to extract relevant information in the training process.

RELATED REVIEW WORKS

1) **R. E. Abdel-Aal** ***"Univariate Modeling and Forecasting of Monthly Energy Demand Time Series Using Abductive and Neural Networks"*****, Computer Engineering Department,2011.**

   The Neural networks are widely using for short-term, and to a lesser degree medium and long term, demand forecasting. The latter two applications and multivariate modeling is adopt in the majority of cases. The demand time series is related with the socio-economic, weather and demographic time series. This approach has some disadvantages which are it include the fact that is difficult to determine influential exogenous factors, and accurate data for them may not available. This paper is forecasting the demand for the seventh year which is based on time series for univariate modeling of the monthly demand. It is using both neural network and abductive network for modeling, and comparing their performance. A technique is described for remove the upward growth trend prior to modeling the time series of demand to avoid the problems which are associate with extrapolating the data range used in training.

   Automatic selection of the most related inputs are using the abductive learning algorithm. It provides the better insight into modeled process and it is allow the constructing simple neural network models with the reduced data dimensionality and improve the performance of forecasting.

2) **SuciDwijayanti,** ***"Short Term Load Forecasting Using A Neural Network Based Time Series Approach"*****, Electrical Engineering, May-2013.**

   The Short Term Load Forecasting (STLF) is an important one that is used to maintain the optimal performance in day-to-day operation of electric utility systems. The model Autoregressive Integrated Moving Average (ARIMA) is a linear prediction method has used for STLF. This method has a weakness. It is assume a linear relationship between the current and the future values. The linear relationship between weather variables and load consumption. The Neural networks has the ability of nonlinear relationships and the model complex. So it can be used as a robust method for the nonlinear prediction, and it can train with the historical hourly load data. The purpose of the work is to describe the neural networks transform linear ARIMA models which are to create the short term load prediction.

   This model has introduces a new neural network architecture that is use to the model Periodic Nonlinear ARIMA (PNARIMA). In this work, first, we make the linear predictions of the daily load using by ARIMA models, and it test the PNARIMA. The results show that the PNARIMA predictor is better than the ARIMA predictor in all testing. This method is demonstrating the nonlinear characteristics of the load that can't capture by the ARIMA models. Demonstrate that a single model can provide accurate predictions throughout the year. Also it demonstrates the load characteristics can't to change substantially between the wet and dry seasons of the tropical climate.

3) **Mohamed Chaouch** ***"Clustering-based improvement of nonparametricfunctional time series forecasting. Application to intraday household-level load curves"*****, Department of Mathematics and Statistics,February 2013.**

   Energy suppliers are facing ever increasing competition, so the factors are like quality and the continuity of an offered services must be properly take in the account. Furthermore, in last few years, so many countries are interested in Renewable Energy's(RE). The RE resources are mainly using for economic and environmental reasons such as reducing carbon emission. It also using in reinforce electric network especially during the high periods. The injection of the energy resources in Low-Voltage(LV) network can lead to a high voltage.

 ISSN 2349-4506
Impact Factor: 2.265
Global Journal of Engineering Science and Research Management

The forecasting household-level electricity demand which represents a key factor for assure the balance of supply/demand in the LV network. A novel methodology able to improve short term functional time series forecasting. Irish smart meter application data set show the performance of the proposed method is forecasting the intra-day household level load data.

PROPOSED METHOD

Levenberg-Marquardt Algorithm

Levenberg- Marquardt algorithm is working as a training algorithm with the capability of pruning methodologies. Pruning is a process of examining a solution network that determines the units are not necessary to the solution and removing those units. The artificial neural network is achieve the reduced complexity and computational effort to run.

Since training can be considered as an optimization problem, it is used many different optimization algorithms. The Levenberg-Marquardt algorithm and some variations of the conjugate gradient algorithm is produce the best result. And the training process can be summarized as follows,

Initialize the weight and evaluate the performance.

1) Update the weights,
   $W_{k+1} = w_k - (J^T_k J_k + \mu I)^{-1} J_k e_k$,
   Where J is the Jacobian matrix.
2) The performance calculation by the using of the updated weight.
3) If the performance increases after updating the weight, it use the previous weight and it expand the coefficient μ by a factor of 10. Go to step 2 and try an update again.
4) If the performance is decrease update the weight, accept the updated weight as current and it contract the coefficient μ by 10.
5) Move to the step 2 with the new weights until the performance is smaller than the required value.

A. Algorithm Specification

The steps of these algorithms, based on this described below,

1) Initialize α and β and the weights. It is suggested to set $\alpha = 0$ and $\beta = 1$ and to use the Nguyen-Widrow method for weight initialization. Compute ED and EW using the initialization parameters with $\gamma = n$.
2) Take one step of the Levenberg-Marquardt algorithm to minimize the objective function $F(x) = \beta ED + \alpha EW$.
3) Compute the effective number of parameter $\gamma = N - 2\alpha tr(H)^{-1}$ making Gauss-Newton approximation for Hessian available in the Levenberg-Marquardt training algorithm,
   $H = \nabla^2 F(w) \approx 2\beta J^T J + 2\alpha I_N$.
   Where J is the Jacobian matrix of the training set errors.
4) Compute new estimates for the objective function parameter.
5) Iterate step 2 through 4 until convergence.

Where EW is the sum of squares of the network weights, and α and β are the parameters of objective function. If $\alpha << \beta$ the training algorithm will drive the errors smaller. If $\alpha >> \beta$, training emphasizes weight reduction at the cost of network errors, thus producing a smoother network response.

RESULT AND DISCUSSION

For this study, data were obtained from electricity demands at all times. Moreover, the economic growth has become very rapid. It has to be more diligent in delivering electricity to industrial and residential consumers.

Household is defined as residential, individual or social organizations who use the electricity personally and for daily activities. The business consumer is a commercial organization or small industry, such as hotels, banks, law firms, etc. Industrial consumers are large-scale industries, e.g., manufacturing. The general consumer is a non-profit entity, such as schools, hospitals or religious organizations. The last category is the multipurpose consumer. Government buildings, street lights, or Base Transceiver Stations (BTS) can be classified as multipurpose consumers. As of 2000-2015, the total number of customers, based on data. The daily activities for the years 2000-2015is shown in Fig. 2.

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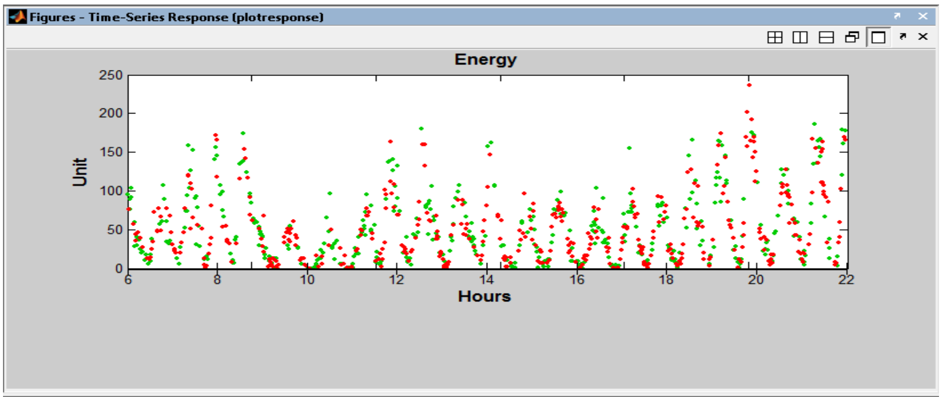

Fig. 2 Energy Prediction

In this Fig. 2 the energy is calculated the hourly based in the daily activities for the years 2000-2015. The Levenberg Marquardt algorithm with Artificial Neural Network is predict the energy consumption for the future years from the present data.

Analyzing Network Performance
In time series forecasting also need to test the performance of the network after training is complete which is shown in Table.1. There are two important concepts that are used when analyzing a trained forecasting network,

1) The forecasting error should not be correlated in time and,
2) The forecasting error should not be correlated with the input sequence.

In summary, a neural network can be said to be properly trained if,

1) It is well fitted to the training data.
2) Its performances on the training sample and on the test samples are comparable.
3) Its performances across different test samples are coherent.

TABLE I
CLASSIFICATION AND COMPOSITION OF CONSUMERS

YEAR	HOUSEHOLD	GENERAL	MULTIPURPOSE	TOTAL
2000	109112	1571	1478	112161
2001	123692	1802	1380	126874
2002	138095	2025	1281	141401
2003	151025	2222	1157	154404
2004	164776	2411	1524	168711
2005	178888	2892	1064	182844

CONCLUSION
The electricity consumption plays an important role in determining the economic growth of the country. This research work makes use of the ANN model for predicting the hourly electricity demand. The models are trained, tested and evaluated using electrical energy consumption data during the period from January 2000 to 2015. The performance of the proposed system was evaluated by computing the accuracy measures between the actual and predicted output values. The results showed that the ANN model used led to good performance and reasonable prediction accuracy. Due to the many other external influencing factors, the accuracy of electricity demand prediction becomes complex. So, in future, the ANN model would also be extended to incorporate the additional input variables such as seasonal factors and environmental factors.

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