Applied Soft Computing 11 (2011) 614–620

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

A meta-heuristic framework for forecasting household electricity consumption

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ARTICLE INFO

Article history:
Received 15 May 2008
Received in revised form 11 April 2009
Accepted 13 December 2009
Available online 21 December 2009

Keywords:
Artificial Neural Network
Multi Layer Perceptron
Forecasting
Regression
DOE
ANOVA
Household
Electricity consumption

ABSTRACT

It may be difficult to model household electricity consumption with conventional methods such as regression due to seasonal and monthly changes. This paper illustrates a flexible integrated meta-heuristic framework based on Artificial Neural Network (ANN) Multi Layer Perceptron (MLP), conventional regression and design of experiment (DOE) for forecasting household electricity consumption. Previous studies base their verification by the difference in error estimation, whereas this study uses various error estimation methods and design of experiment (DOE). Moreover, DOE is based on analysis of variance (ANOVA) and Duncan Multiple Range Test (DMRT). Furthermore, actual data is compared with ANN MLP and conventional regression model through ANOVA. If the null hypothesis is accepted, DMRT is used to select either ANN MLP or conventional regression. However, if the null hypothesis is accepted then the proposed framework selects either the MLP or regression model based on the average of Minimum Absolute Percentage Error (MAPE), Mean Square Error (MSE) and Mean Absolute Error (MAE). The significance of this study is the integration of ANN MLP, conventional regression and DOE for flexible modeling and improved processing, development and testing of household electricity consumption. Some of the previous studies assume that ANN MLP provide better estimation and others estimate electricity consumptions based on the conventional regression approach. However, this study presents a flexible integrated framework to locate the best model based on the actual data. Moreover, it would provide more reliable and precise forecasting for policy makers. To show the applicability and superiority of the integrated approach, annual household electricity consumption in Iran from 1974 to 2003 was collected for processing, training and testing purpose.

1. Introduction

Forecasting electricity consumption is a relatively difficult task. Electricity consumption represents two essential attributes, on the one hand it shows the strong annual changes and on the other hand it clearly shows the increasing trend. Furthermore, the time series is affected by other variations that make the problem hard to model. Artificial Neural Networks (ANNs) are the strong rival of regression and time series in forecasting. ANNs are suitable for modeling this kind of problem with unknown factors. The target is to find the essential structure of data to forecast future consumption with less error.

ANNs have been used in non-linear systems modeling and simulation. One of the most useful and interesting factors of ANNs is forecasting time series. This application of ANNs is suited where static condition or other conditions where using classic techniques are not suitable and applying time series is complicated [1]. It can be also applied to energy forecasting problems. Some of these applications are short- and medium-term load forecasting [2–12], adaptive price forecasting [13,14], forecasting transport energy demand [15]. ANN has also been used for long-term demand forecasting [16–19]. Azadeh et al. [20,21] use the integration of time series ANOVA and ANN to forecast electricity consumption with preprocessed data. Moreover, in some cases ANN can give us a better output if it is trained with the preprocessed data. ANN has also been used for condition monitoring [22]. Compton and Wu [23] projected the electricity consumption in China by Bayesian vector autoregression. However, rapidly developing countries like China, Iran and India face with complex requirements for their demands which require the use of intelligent tools such as ANN. Furthermore, there is no clear cut between conventional approach and intelligent tools such as ANN. However, this study presents a framework to integrate conventional regression approach with ANN through design of experiment and relative errors obtained from the two approaches versus actual data. The proposed framework always

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doi:10.1016/j.asoc.2009.12.021

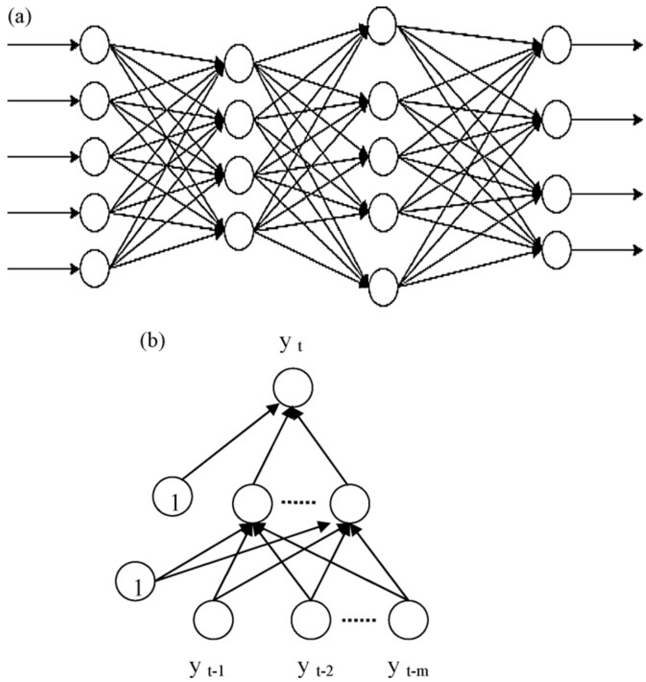

Fig. 1. The meta-heuristic framework for household electricity consumption forecasting. (a) General structure of the MLP networks and (b) a three-layer MLP network.

guarantees best solution whereas previous studies assume either the conventional regression or ANN leads to the best forecasting estimations.

In following section the integrated framework is introduced. Then, ANN approach is introduced. Next, design of experiment approach in the framework is discussed. To show the applicability and superiority of the integrated framework, annual household electricity consumption in Iran from 1974 to 2003 is applied to the proposed framework.

2. The integrated framework

The economic indicators used in this paper are price, value added, number of customers and electricity consumption in the last periods. To estimate and forecast annual electricity household consumption by the proposed integrated framework, five standard input variables are used: (1) electricity price, (2) TV price index, (3) refrigerator price index, (4) urban household size and (5) urban household income. The reader may easily add other inputs in addition to the standard ones for running the proposed framework. The proposed flexible framework may be used to estimate household electricity demand in the future by either ANN MLP or conventional regression. Furthermore, if the null hypothesis in ANOVA *F*-test is rejected, the Duncan Multiple Range Experiment (DMRE) method is used to identify which model is closer to actual data at α level of significance. It also uses minimum absolute percentage error (MAPE), mean square error (MSE) and Minimum Absolute Error (MAE) when the null hypothesis in ANOVA is accepted to select from MLP or regression model. The significance of the proposed algorithm is twofold. First, it is flexible and identifies the best model based on the results of ANOVA and MAPE, MSE and MAE whereas previous studies consider the best fitted ANN MLP model based on MAPE or relative error results. Second, the proposed algorithm may identify conventional regression as the best model for future electricity consumption forecasting because of its dynamic structure, whereas previous studies assume that ANN models always provide the best solutions and estimation. Fig. 1 depicts the proposed algorithm of this study. The reader should note all steps of the integrated algorithm are based on standard and scientific methodologies which are ANN MLP, conventional regression, ANOVA, DMRE, MAE, MSE and MAPE. The best model is distinguished by modeling, running and testing various regression and ANN MLP models and selecting the model with lowest error. Some of the previous studies assume that ANN MLP provide better estimation and others estimate electricity consumptions based on the conventional regression approach. However, this study presents a flexible integrated framework to locate the best model based on the actual data. Error estimated by Minimum Absolute Percentage Error (MAPE) is calculated from the following equation:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|EC_{i(estimated)} - EC_{i(actual)}\right|}{EC_{i(actual)}} \tag{1}$$

where n is the number of periods (months, years, etc.), $EC_{i(estimated)}$ is the estimated household electricity consumption and $EC_{i(actual)}$ is the actual value of household electricity consumption.

2.1. Artificial Neural Network

In general, ANNs are simply mathematical techniques designed to accomplish a variety of tasks. The research in the field has a history of many decades, but after a diminishing interest in the 1970s, a massive growth started in the early 1980s. Today, Neural Networks can be configured in various arrangements to perform a range of tasks including pattern recognition, data mining, classification, forecasting and process modeling [24–26]. ANNs are composed of attributes that lead to perfect solutions in applications where we need to learn a linear or non-linear mapping. Some of these attributes are: learning ability, generalization, parallel processing and error endurance. These attributes would cause the ANNs solve complex problem methods precisely and flexibly.

ANNs consists of an interconnection of a number of neurons. There are many varieties of connections under study, however here we will discuss only one type of network which is called the Multi Layer Perceptron (MLP). In this network the data flows forward to the output continuously without any feedback. Fig. 1a and b shows the general structure of MLP and a typical three-layer feed forward model used for forecasting purposes. The input nodes are the previous lagged observations while the output provides the forecast for the future value [27,28]. Hidden nodes with appropriate non-linear transfer functions are used to process the information received by the input nodes. The model can be written as:

$$y_t = \alpha_0 + \sum_{j=1}^{n}\alpha_j f\left(\sum_{i=1}^{m}\beta_{ij}y_{t-i} + \beta_{0j}\right) + \varepsilon_t \tag{2}$$

where m is the number of input nodes, n is the number of hidden nodes, f is a sigmoid transfer function such as the logistic: $f(x) = 1/(1 + \exp(-x))$. $\{\alpha_j, j = 0, 1, \ldots, n\}$ is a vector of weights from the hidden to output nodes and $\{\beta_{ij}, i = 1, 2, \ldots, m; j = 0, 1, \ldots, n\}$are weights from the input to hidden nodes. α_0 and β_{oj} are weights of arcs leading from the bias terms which have values always equal to 1. Note that Eq. (1) indicates a linear transfer function is employed in the output node as desired for forecasting problems. The MLP's most popular learning rule is the error back propagation algorithm. Back propagation learning is a kind of supervised learning introduced by Werbos [24] and later developed by Rumelhart and McClelland [29]. At the beginning of the learning stage all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input–desired output pattern pairs. Each input–output pair is obtained by the offline processing of historical data. These pairs are used to adjust the weights in the network to minimize the Sum Squared Error (SSE) which measures