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Greenhouse Energy Consumption Prediction using Neural Networks Models

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ABSTRACT

This work analyzes an energy consumption predictor for greenhouses using a multi-layer perceptron (MLP) artificial neural network (ANN) trained by means of the Levenbergh-Marquardt back propagation algorithm. The predictor uses cascade architecture, where the outputs of a temperature and relative humidity model are used as inputs for the predictor, in addition to time and energy consumption. The performance of the predictor was evaluated using real data obtained from a greenhouse located at the Queretaro State University, Mexico. This study shows the advantages of the ANN with a focus through analysis of variance (ANOVA). Energy consumption values estimated with an ANN were compared with regression-estimated and actual values using ANOVA and mean comparison procedures. Results show that the selected ANN model gave a better estimation of energy consumption with a 95% significant level. The study resents an algorithm based in ANOVA procedures and ANN models to predict energy consumption in greenhouses.

Key Words: Greenhouse; Energy consumption prediction; Artificial neural network; ANOVA

INTRODUCTION

Currently, agricultural operations have to adapt to a more competitive environment and consequently, use new intelligent technologies (Mahmoud, 2004). Hydroponics and greenhouse production is a way of obtaining profitable crops (Boodley, 1996; Nelson, 2002). A sustainable crop production system requires keeping a high-quality harvest, while keeping energy and raw material consumption low. The agricultural sector is an important energy consumer. The agricultural sector is a great consumer of energy in Mexico, representing an increasing 5% of total electrical energy generated. Energy consumption increased from 7,480,035 MWh to 7,803,778 MWh from 2006 to 2007 (Sistema de Información Energética en México, 2005). The increase in energy demand under greenhouse agricultural production has made its use, administration and estimation to be essential issues (Lusine *et al.*, 2007). Farmers have an option for reducing energy use by investing in intelligent systems (Alfons *et al.*, 2001; Korner & Straten, 2008). Currently, the use of energy consumption prediction systems points out to the use of artificial neural networks (ANN). Park and Sandberg (1991) reported the use of a simple neural network using temperature information capable of predicting hourly, peak and total energy consumption, better than the conventional techniques based on regression. Bacha and Meyer (1992) discussed why neural networks are appropriate for load prediction and propose a cascading sub-network system. Srinivasan *et al.* (1994) used a four-layer multilayer perceptron to predict hourly load in a power system. These previous studies point out the importance of internal temperature as an input variable. Therefore, a strategy to improve energy consumption prediction is starting from a given temperature model that provides information on the expected future temperature.

A lot of information on greenhouse temperature modeling for optimal crop development can be found in literature. Some of these strategies and techniques also applied in other areas include: linear autoregressive models (ARX) (Aal-Faraj & Al-haidary, 2006; Ríos *et al.*, 2007), physical model (Castañeda *et al.*, 2006; Lafont & Balmat, 2002) and neural networks (Ferreira *et al.*, 2002). Generally, these temperature models are used for planning strategies for optimal control; however, they do not consider the costs associated to water, energy and raw material usage. To obtain the best crop yield, climate variables have to be kept within an appropriate range, while minimizing production costs.

The goal of this study was to develop an energy consumption predictor for greenhouses from a neural network multilayer perceptron. The predictor uses a cascading architecture, where the outputs of a temperature and relative humidity model are used as inputs for the predictor, in addition to time and energy consumption. Validation model was performed by comparing the results

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with a nonlinear regression model and actual data, using analysis of variance (ANOVA) procedures and Duncan's multiple range test (DMRT).

MATERIALS AND METHODS

Theoretical considerations. In recent years, ANN's have emerged as a technology for load modeling and forecasting, because of their ability to learn complex, non-linear functions. They allow the estimation of possibly nonlinear models without the need of specifying a precise functional form. ANN can be viewed as parallel and distributed processing systems that consist of a huge number of simple and massively connected processors called neurons. Each individual neuron consists of a set of synaptic inputs, through which the input signals are received; then, the incoming activations are multiplied by the synaptic weights and summed up. The outgoing activation is determined by applying a threshold function to the summation. The threshold function can be a linear, or a non-linear function that decides the output of the neuron. The structure of the neuron is shown in Fig. 1 wherein X_1, X_2, X_n present the input of the neuron. W_1, W_2, W_n are their weights, θ is the threshold value and Y represents the output. The input to output relationship is characterized by:

$$Y(X) = f(\sum_{i=1}^{n} w_i x_i + \theta) = f(W^T X + \theta) \quad (1).$$

Where W is the vector of synaptic weights, X is the input vector and θ is a constant called offset or bias, f is the activation function. The superscript T denotes the transpose operator and Y(X) is the output of the neuron. In this work, the activation function used is a sigmoid that has the form of:

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

The training of an ANN is mainly undertaken using the back propagation (BP) based learning algorithm, which is a supervised algorithm. This method requires a set of training patterns and their corresponding desired outputs and autonomously adjusts the connection weights among neurons. Correction of the weights is made according to imposed learning rules and thereby, obtains unique knowledge from the data.

Although it is successfully used in many real-world applications, the standard back propagation algorithm (SBP) suffers from a number of shortcomings. One of these is the rate at which the algorithm converges. Several iterations are required to train a small network, even for a simple problem. Reducing the number of iterations and speeding learning time of NN are subjects of recent research; some improvements of the SBP algorithm are the gradient descent (Zhou & Si, 1998) and the Levenberg-Marquardt algorithms (Hagan & Menhaj, 1994; Parisi *et al.*, 1996).

The model of neural network is determined by three factors as the topological structure of the network, the neuron characteristic and the training algorithm. The ANN implemented in this study is a multilayer perceptron (MLP) with an input layer of 4 nodes, an hidden layer with a variable number of hidden nodes and an output layer with only one node. Several networks with variable number of hidden nodes were implemented and tested; variables in the input layer are temperature, humidity, time and power consumption; a representative schematic of the ANN used is depicted in Fig. 2.

In greenhouses, the power consumption is highly dependent on the temperature and humidity conditions because in fully automated and semi-automated greenhouses, it determines the operation sequences of the various actuators (heaters, fans, humidifiers, etc.) required to maintain the proper crop environment. A model for forecasting interior air temperature and relative humidity (Castañeda *et al.*, 2006) of the greenhouse was cascaded to the ANN predictor. The inputs variables to this model were wind speed (V_w), outside temperature (T_o), relative humidity (H_{Ro}) and solar radiation (R_a). Information about these variables was gathered and recorded using the system TUNA™ SCII v5.0. This model provided the presumable value of the environment inside regarding temperature and relative humidity, which are inputs to the ANN-MLP model.

The third input variable of the ANN is time: the hour of the day and the day of the week. The hour is coded as reported in the literature (Dodier & Henze, 1996) by means of its sine and cosine values. Time is required because there are some tasks that must be accomplished according to a schedule, in this way power consumption could vary among the hour of the day and day of the week. The last input variable is the power consumption in KW h^{-1}, since the predictor is designed to predict the consumption at time k+1, the used value for this input is the value of the consumption at the time k, supplied by an energy consumption instrument called SMEI, (Trejo *et al.*, 2008). This information is of great importance since it reflects how the energy consumption of the installation behaves. General view of the cascaded predictor is presented in Fig. 3.

In order not to saturate the conditions of the neurons, a data normalization is required. If neurons get saturated, then the changes in the input value will produce a very small change or no change at all in the output value. For this, data must be normalized before being presented to the artificial neural network. Data normalization compresses the range of the training data between 0 and 1. The normalization was carried out by means of the following expression:

$$X_n = \frac{(x - x_{\min}) * range}{x_{\max} - x_{\min}} + startingva\ lue \quad (3).$$

Where X_n is the value of the normalized data and X_{min} y X_{max} are the mínimum and máximum of the entire data set, respectively.

Greenhouse description. The procedure for designing the energy consumption forecasting model using an algorithm implemented in a neuronal network was performed in a Venlo-type 1000 m^2 greenhouse covered with a plastic sheet. The greenhouse floor is covered with a plastic white cover. The greenhouse structure is 37.1 m long, four 6.75 m wide sections, 4.5 m height to the ridge, and 3 m to the gutter. Orientation is N-S. The greenhouse is equipped with lateral ventilation on the four walls and the ceiling windows are about 62 m^2 in each section. The greenhouse is equipped with the TUNA^{TM} SCCII v5.0 climate and irrigation control system developed by the Biotronics Lab., University of Queretaro, Mexico. The greenhouse has also an energy monitoring system (SMEI) that allows to check out electrical energy and water consumption in real time via Internet (Trejo *et al.*, 2008).

Algorithm's description. A neural network algorithm for the energy consumption model in greenhouses was proposed. Firstly, the mean absolute percent error (MAPE) was used to select the best network architecture ANN-MLP. Then, the best network was compared with actual and regression data using the MAPE. Finally, analysis of variance (ANOVA) and Duncan's multiple range test (DMRT) procedures were used to compare, verify and validate the models. The description of the algorithm was as follow:

(a) The input and output model variable(s) were determined, (b) a group of data, namely *B,* of the input and output variables for past times describing the input/output relationship is collected, (c) B is divided into two subsets: training (B_1) and testing (B_2). This procedure requires independent validation data to be used in order to test the neuronal network capability for generalizing non-predicted data. Representative testing (validating) data are taken from the training data. It is necessary to find a balance between the size of the training and validation data. The validation data are chosen near the actual period. (d) Once the B_1 and B_2 subsets of data are correctly defined, a conventional regression model of the training data was performed. Then, the consumption of energy for the testing periods was predicted, (e) finally, the ANN method to estimate the inputs/outputs relationship is used. In order to find an appropriate number of hidden nodes, the above steps are repeated using different architectures and training parameters for the network with one to *q* nodes in its hidden layer.

If the *q* value is optional, then it can be modified. If after applying the above steps the minimum relative error is not obtained, the following procedures have to be followed: choose the architecture and the training parameters, train the model using the learning data (B_1), evaluate the model using the testing data (B_2), select the best network architecture (ANN) of the testing data with the desired error and apply ANOVA procedures to the formal testing data for the verification and validation of the ANN results.

Accuracy measurements. Multiple determination coefficient (R^2) is a measurement of the correlation between the observed and predicted values (Neter *et al.*, 1996). Some measurements of variance are the standard error prediction (SEP) (Ventura *et al.*, 1995), the mean square error (MSE) (Neter *et al.*, 1996) and the mean absolute percent error (MAPE) (Griño, 1992). These methods are used determined the model's capability of explaining total data variance. The MAPE was calculated for each model by the following equation:

$$MAPE = \frac{1}{N}\sum_{J=1}^{N}\frac{Ue_j - Ua_j}{Ua_j} \quad (4).$$

Where Ue_j is the estimated electrical power consumption, Ua_j is the actual energy consumption value and N is the total number of generalized samples. The MSE, R^2 and SEP are determined by Neter *et al.* (1996) and Ventura *et al.* (1995).

In the following section the application of the ANN algorithm in a greenhouse will be applied. On the other hand, its advantages and superiority will be shown by using ANOVA y Duncan's Multiple Range Test (DMRT) procedures.

RESULTS AND DISCUSSION

The recorded data of the greenhouse electric energy consumption were taken from February 9, 2008 starting at 16:51 h and ended on February 15, 2008 at 15:51 h. Data were divided into two groups: the first 137.5 h were selected for network training (B_1) and the last 5.5 h for testing the ANN (B_2). Different MLP networks were generated and tested. The Levenberg-Marquardt back propagation algorithm was used to adjust the learning procedure, while the data taken from 10:21 to 13:51 h on February 15, 2008 were used for testing the network.

Once the network was trained, it could be used to forecast data associated with the validation set to obtain the corresponding prediction errors, so the performance of the forecasting process could be studied. The Mean Absolute Percentage Error (MAPE) has been widely used as a performance measure to examine the quality of the models of prediction as it repeatedly appears in the consulted literature (Srinivasan *et al*., 1994; Dodier & Henze, 1996). In order to determine the best ANN model, MAPE values were computed for each one of them; the obtained results are summarized in (Table I).

Table I shows the best models and their reliability and performance estimators. The MLP model with the best results was the (4-3-1) model, in comparison with the other three, obtaining a 0.0586 MAPE, a 0.1875 MSE, a 0.9353 R^2 and finally a 0.08828 SEP. The results are shown in the ANN model graph (4-3-1) versus actual data (Fig. 4).

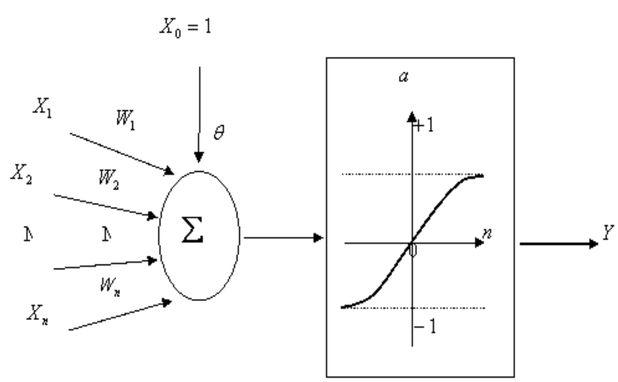
Table I. Coefficient of determination and error estimators for different MLP models

Model MLP	R^2	MAPE	SEP	MSE
4-5-1	0.9107	0.0662	0.108241	0.2528
4-4-1	0.9009	0.0692	0.114008	0.2804
4-3-1	0.9353	0.0586	0.08828	0.1875
4-2-1	0.9030	0.0697	0.112805	0.2745

Table II. Comparison of measured and estimated values using Neural network and Regression models

Hour	Meassured	Neural Network	Regression
137.5	4.1768	4.2456	3.5180
138.0	4.3275	4.5623	4.1169
138.5	4.2967	4.3624	4.1884
139.0	4.1924	4.2453	4.1728
139.5	3.9340	4.1230	4.1213
140.0	3.7397	3.9923	3.9669
140.5	3.6858	3.8742	3.8240
141.0	3.9989	4.1210	3.7771
141.5	4.1242	4.3215	4.0058
142.0	3.9714	4.2105	4.0784
142.5	4.1687	4.3548	3.9831
143.0	4.3379	4.5521	4.0990
MAPE error		**0.0626**	**0.0921**

Fig. 1. Neural model



The results of the MLP network were compared with the non-linear regression model (Table II). It can be observed that the MLP output has a smaller error than the non-linear regression model. The error comparison of MAPE, MSE, R^2 and SEP for the MLP and regression is shown at Fig. 5.

A forecasting neural network model that uses weather data was proposed in (Islam *et al*., 1995). The model was capable to predict electrical energy monthly demand, where a MAPE of 2.03% was accomplished; however, the prediction errors are more sensitive to temperature. The aforementioned work uses data sets obtained in different countries under different social and economical behaviors. For this reason, it is not easy to carry out a quantitative comparison, because the data sets used in other works are different from the one considered here. The results presented in this work allow energy consumption prediction with a good level of reliability.

Fig. 2. A typical feed forward neural network (MLP)

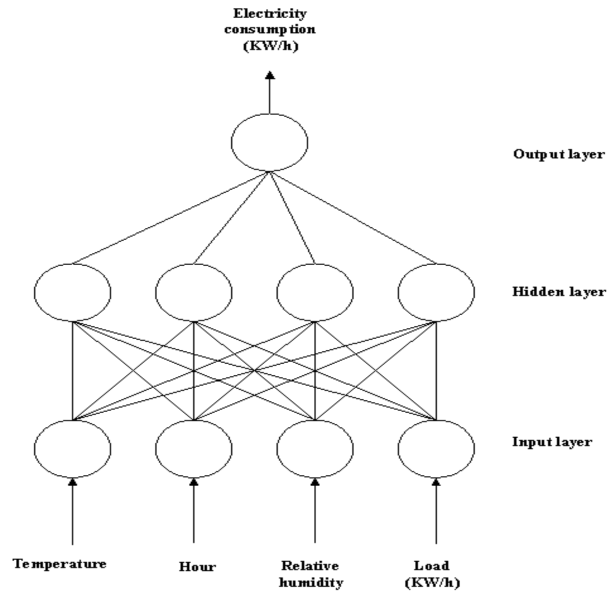
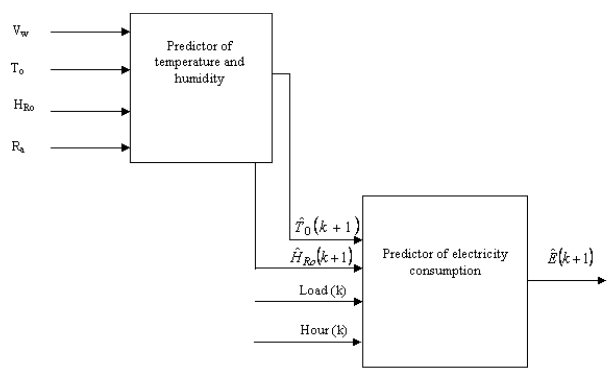


Fig. 3. Proposed cascading predicting model structure



Analysis of variance: validation and verification. The selected ANN's results were estimated and the regression method and the real data were compared by using ANOVA procedures. The experiment was designed in such way that variability was derived from external systematically-controlled sources. Time is the common external source of variability in the experiment and can be systematically controlled by blocking (Montgomery, 1999). Therefore, one-way ANOVA was used. The results are shown in Table III. The hypothesis test was defined as follow:

$$\begin{aligned} &H_0 : \mu_1 = \mu_2 = \mu_3, \\ &H_1 : \mu_i \neq \mu_j \quad i, j = 1, 2, 3, \quad i \neq j, \end{aligned} \tag{5}$$

Where μ_1, μ_2 and μ_3 are average values obtained from the regression model, actual data and the ANN model. From Table III, it can be concluded that the null-hypothesis is rejected with a significant level α = 0.05, since $f_{0.05,2,33} = 4.9$, $fcv = 0.12$ and $4.9 > 0.12$.

Table III. ANOVA table for comparison of regression, actual data and neural network

Summary								
Groups		**Count**			**Sum (kw/h)**			**Average (kw/h)**
Meassured		12			48.954			4.0795
Neural Network		12			47.851			4.2471
Regression		12			50.965			3.9876
Source of variation	**Sum square**		**Degree of freedom**	**Mean square**		**Fcv**	**F(α=0.05)**	**P**
Between groups(treatment)	0.4153		2.0	0.2076		0.12	4.9	0.0137
Within groups	1.3991		33	0.0424				
Total	**1.8144**		**35**					

Duncan's multiple range test (DMRT). Before the DMRT is performed, the standard deviation for each treatment has to be calculated as:

$$B_{\bar{y}i} = \sqrt{\frac{MS\,(error\,)}{a}} \qquad (6).$$

Where a is the number of replicates or observations for the three treatments (actual, ANN & regresión). Then, the state values for Rp are calculated as $Rp = r\alpha\left(p, f\right)B_{\bar{y}i}$ (10). $r\alpha\left(p, f\right)$ is obtained from the DMRT table. After means treatment classification, each treatment can be compared as follow:

$$B_{\bar{y}i} = 0.05944$$

$$r_{0.05}(2{,}33) = 2.877$$

$$R_2 = r_{0.05}(2{,}33)B_{\bar{y}i} = 2.877 \;\; x \;\; 0.05944 = 0.1710.$$

Comparing treatments 2 and 3 $= 4.2471 - 3.9876 = 0.2595$

$$0.2595 > 0.1710 \quad \rightarrow \mu_2 \neq \mu_3.$$

Comparing treatments 1 and 2 $= 4.2471 - 4.0795 = 0.1676$

$$0.1676 < 0.1710 \;\; \rightarrow \mu_1 = \mu_2.$$

From the above results, it can be observed that only one third of the mean (actual data) and the second treatment (the selected ANN) equals to $\alpha = 0.05$. This indicates that the average of energy consumption estimated values for the selected ANN and the real data were approximately similar with a 95% confidence level. Therefore, results from the ANN are significantly better than the obtained by conventional regression.

CONCLUSION

The method for the prediction of energy consumption from a multilayer perceptron neural network was proven. The predictor uses a cascading architecture. Using ANOVA procedures, this study proved the advantages of the ANN in comparison with real data and the conventional regression model data. This is one of the first studies presenting an algorithm based on ANOVA and ANN models to predict the energy demand in greenhouses. The (4-3-1) MLP built model produced better results, with an error estimation of 0.0586 in the testing data. The ANOVA statistical method was used to compare the neuronal network and the regression model results versus real data. It was found that with an $\alpha = 0.05$, there was significant difference among treatments. Therefore, the DMRT was used to find the closest model to the real data, considering a significance level of 95%. The Energy Consumption Prediction model presented in this work will be the base for the design of new

Fig. 4. Measured and predicted values of energy consumption in a Venlo-type green house

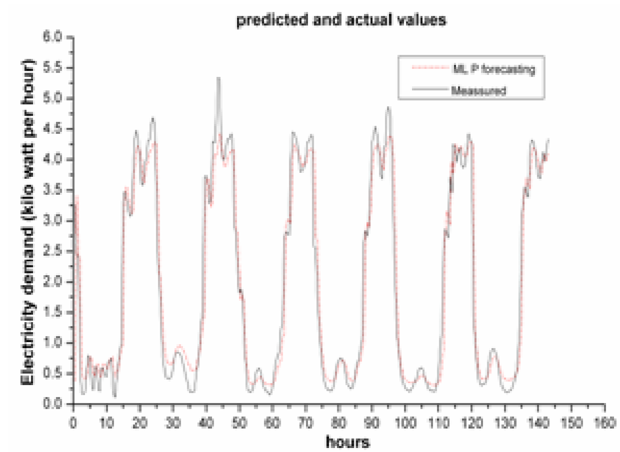
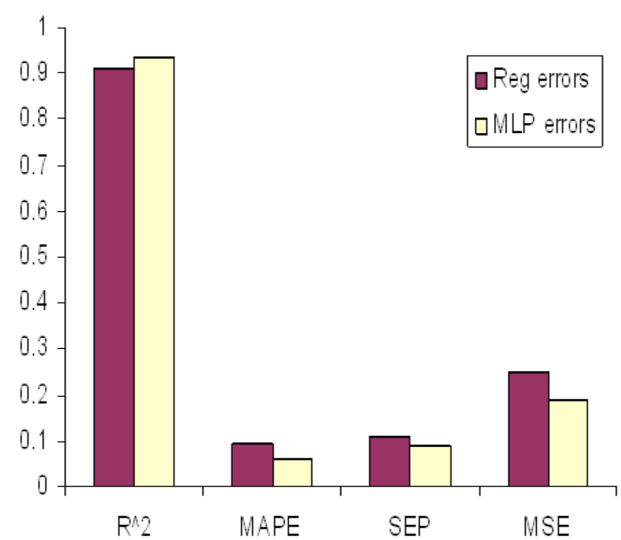


Fig. 5. Comparing regression and MLP errors



intelligent climate controllers. To obtain the best crop yield, climate variables have to be kept within an appropriate range, while minimizing production cost.

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