Multi-layer Perceptron Neural Network to Assess the Thermal Behaviour of a Moroccan Agriculture Greenhouse

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Abstract: The aim of this research is to demonstrate how machine learning algorithms can estimate the temperature and relative humidity of a Moroccan greenhouse's inside air. The prediction model was created using a Multi-Layer Perceptron neural network (MLPNN) trained using the Levenberg-Marquardt backpropagation technique. The weather data and indoor air temperature and relative humidity of a greenhouse located in Agadir, Morocco were used. The results reveal that the MLPNN's Root Mean Square Error (RMSE) values are very low, and the Karl Pearson's coefficient of correlation (R) values are very close to 1, indicating that the MLPNN has a high predicting accuracy. In addition the result of the comparison between the results obtained by the MLPNN model and the data from the experiment shows that the predicted and measured indoor thermal behaviour are similar, which mean that the MLPNN have a high ability to predict the greenhouse thermal behaviour.

1 INTRODUCTION

With the growing global demand for food, farming in a controlled environment is an effective way to produce plants year-round. The greenhouse system is one of the main types of controlled agricultural environments (Iddio et al., 2020). The greenhouse is a translucent building that produces a microclimate ideal for plants and shields them from the outside environment by reflecting incident solar energy (Choab et al., 2020). This helps to increase the production and quality of these plants (Choab et al., 2019).

The greenhouse is not entirely insulated from the outside environment. Therefore, the thermal behavior of indoor greenhouse air is strongly affected by the outdoor climate. As a result, it's difficult to control and predict the temperature and humidity inside the greenhouse (Moon et al., 2018). Accurate prediction of the greenhouse indoor air temperature and humidity has been studied in various studies (Yu et al., 2016).

Artificial neural network (ANN) is used for greenhouse thermal modeling since as it is suitable for nonlinear system models (Castañeda-Miranda and Castaño-Meneses, 2020; Dariouchy et al., 2009; Giuseppina Nicolosi et al., 2017; Wang et al., 2009). Taki et al. (2016) compared the ANN technique to a mathematical model to see which method was best for forecasting the temperature of the inside air, the temperature of the roof, and the energy loss in a semi-solar greenhouse. This comparison revealed that the ANN technique is a viable way for solving the non-linear relationship between greenhouse internal environment factors and forecasting interior air temperature, cover temperature, and greenhouse energy loss with high precision. The ANN was used by Francik and Kurpaska (2020) to develop a model that predicted temperature change within a heated foil tunnel. Trejo-Perea et al. (2009) used an MLPNN to predict greenhouse energy usage. The temperature and relative humidity outputs are used as inputs in the model's cascade architecture. When compared to the regression model, Duncan's

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Multiple Range Test demonstrates that ANN has a high confidence level of 95%. Yue et al. (2018) used an upgraded Levenberg-Marquardt Radial Basis Function Neural Network (LM-RBF) to construct a model to predict the inside air temperature and humidity of a greenhouse, and this model achieves the goal with a maximum relative error of less than 0.5 percent.

From the previous literature review, it appears that machine learning techniques show great potential in predicting thermal behavior in greenhouse applications. Also, the majority of applications employed ANN as a prediction technique. The aim of this research is to forecast the internal air temperature and relative humidity of a realistic greenhouse used for tomato cultivation in Agadir, Morocco's semi-arid region.

2 MATERIALS AND METHODS

2.1 Greenhouse Description

The experiments were carried out in a Canarian greenhouse in the Khmiss Ait Amira Souss Massa region by APEF&V (Association of producers and exporters of fruits and vegetables) (Figure 1). The surface of the greenhouse's ground is 8200 m² (88.23 m length, 95 m width, a height of 5 m at gutter level and 6 m at span level). Tomatoes are the crop grown in greenhouses.

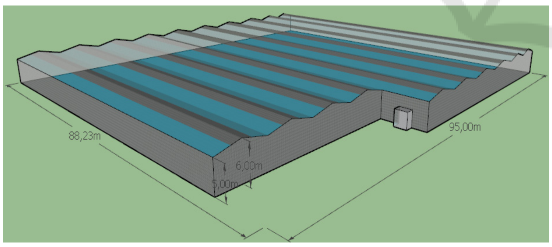


Figure 1: Schematic view of the Canarian-type greenhouse

Inside air temperature, outside solar radiation, wind speed, ambient temperature, and relative humidity are all needed in the greenhouse's air temperature and relative humidity forecast model. These data were collected using a weather station located inside (middle) and outside of the greenhouse. A number of 4000 values were obtained as the main dataset. To measure the air temperature and relative humidity inside and outside the greenhouse, ADCON TR1 was used. The ADCON Silicium-Pyranometer SP-Lite was used to measure the outside solar irradiance. The wind velocity measurement was provided by ADCON Wind Sensor Set Pro 10/2. Table 1 shows the details of the sensors used for the measurement.

Table 1: sensors details

Sensor	Parameter measured	Accuracy
pt1000 (ADCON TR1)	air temperature	±0.1% at 20 °C
HC101 (ADCON TR1)	air relative humidity	± 1% from 0 to 90% and ± 2% from 90 to 100% at 20 °C
ADCON Silicium-Pyranometer SP-Lite	solar irradiance	sensitivity (nominal) between 60 and 100 µV/W/m²
ADCON Wind Sensor Set Pro 10/2	wind velocity	± 0.3 m/s

2.2 Artificial Neural Network

The artificial neural network (ANN) appeared as a modeling and prediction technology due to its flexible mathematical structure able to describe complex non-linear relationships between inputs and outputs (Castañeda-Miranda and Castaño, 2017). The multilayer perceptron neural network (MLPNN) is one of the ANN variants used (Ali-Ou-Salah et al., 2021). In this research, MLPNN was developed to accurately forecast the indoor air temperature and relative humidity in a greenhouse. The MLPNN is able to obtain an efficient approximation of nonlinear functions by using three interconnected layers. The first one is the input layer, the second one consists of one or more hidden layers, while the third one is the output layer (Ali-Ou-Salah et al., 2021; Bahani et al., 2020) (Figure 2). Each layer is made up of neurons, which are processing units. In addition, each hidden and output layer neuron has an activation function that determines its output. Weights and biases are synaptic connections that carry information from one layer to the next (Ali-Ou-Salah et al., 2021). A backpropagation (BP) training algorithm is used to modify weights and biases in order to learn the network. The Levenberg Marquardt (LM) algorithm was employed as a training algorithm in this work.

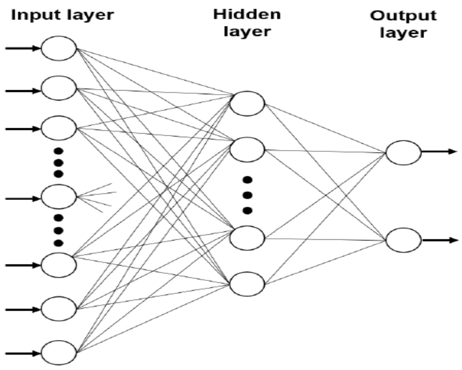


Figure 2: Structure of a multilayer perceptron feedforward neural network.

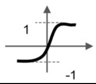
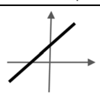
The output of the artificial neuron is described by Equation (1):

$$y_j = f\left(\sum_{i=1}^{n} \omega_{ji} x_i + b_j\right) \qquad (1)$$

where y_j is the neuron output of the j-th hidden layer, ω_{ji} is the synaptic weight between the j-th layer and the i-th layer, x_i is the input of the j-th layer, b_j is the bias weight of neuron j and $f(x)$ is the activation function.

In the current study, the linear and hyperbolic tangent functions were employed (Table 2). The output layer typically uses linear functions, but the hidden and output layers can apply non-linear activation functions. The most used non-linear activation functions is hyperbolic tangent, because it is compatible with the back-propagation algorithm (Escamilla-García et al., 2020).

Table 2: The used Activation functions in this study.

Name	Graphic	Function
Hyperbolic tangent		$f(\xi) = \frac{2}{1+e^{-2\cdot\xi}} - 1$, interval [-1,1]
Linear		$f(\xi) = a \cdot \xi + b$

The predictors are the available external weather data that are recorded in the experimental setup of the greenhouse. These data cover the ambient air temperature, solar radiation, relative humidity and wind speed. These variables are physically influencing the thermal behavior of the indoor environment of the greenhouse as highlighted by many physical models as shown in (Choab et al., 2019). These variables can be considered as significant for predicting the internal air temperature of the greenhouse.

2.2.1 The Architecture of MLPNN Model

In order to find the optimal architecture of the ANN model, the grid search technique is applied using 5 folds cross validation method.

The grid search method involves investigating a large number of hidden neurons in order to discover the best design. 5 folds cross validation is used to evaluate the constructed model, which consists of randomly dividing the data set into five folds of data, each of which is utilized as a testing set and the rest as a training set. The average of all testing errors is the 5 folds cross validation error. The grid search technique's outcomes are shown in Figure 3.

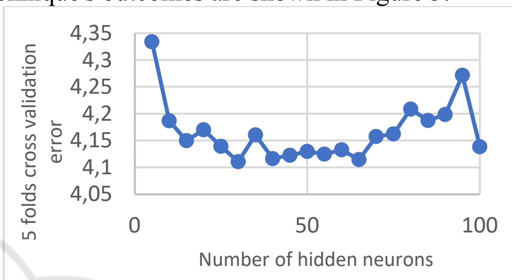


Figure 3: The grid search technique for finding the optimal number of hidden neurons.

The results shows that 30 neurons give the lowest 5 folds cross validation error. As a conclusion, the optimal architecture of the ANN model is shown in the Figure 4.

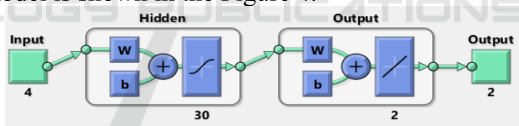


Figure 4: the ANN architecture used for the current study

2.2.2 Model Evaluation Criteria

Two metrics indicators were applied to evaluate the performance of the developed models (Alghamdi et al., 2020):

- Karl Pearson's Coefficient of Correlation (R)

$$R(A,B) = \frac{\sum(A_i - \bar{A})(B_i - \bar{B})}{\sqrt{\sum(A_i - \bar{A})^2 (B_i - \bar{B})^2}} \qquad (2)$$

$\bar{A}$ and $\bar{B}$ are the mean of A and B variables, respectively.

- Root Mean Square error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \widehat{Y}_i\right)^2} \qquad (3)$$

Y_i and $\widehat{Y_i}$ are the actual and predicted values values, respectively, whereas $\overline{Y}$ is the mean of Y_i and N represents the number of observations.

3 RESULTS AND DISCUSSION

The internal air temperature and relative humidity of the greenhouse were predicted using an MLPNN model trained using a Levenberg-Marquardt backpropagation approach.

3.1 Prediction Performances

The results of the predicting stage were summarized in figures 5 and in Table 3. In the regression plot between the forecasted and measured values, it could be noticed that the majority of data points are falling on the regression line, which means that the MLPNN model gives very accurate forecasting for the greenhouse thermal behavior. The RMSE values for the MLPNN, as shown in Table 3, are very low, and the R values are very close to 1, which mean that MLPNN have a high accuracy of forecasting.

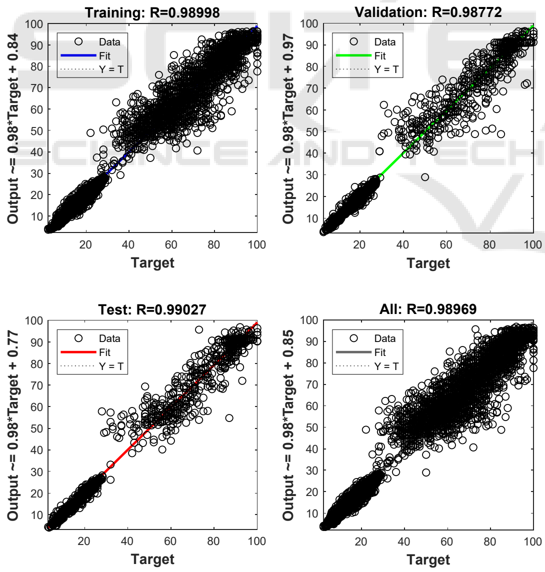


Figure 5: The Regression plot between the forecasted and measured values

Table 3: Performance metrics of the MLPNN model

	Training	Validation	Testing
RMSE	4.686367	5.152746	4.637304
R	0.989980	0.987724	0.990269

3.2 Greenhouse Thermal Behavior

In this section, we randomly selected days from an unused dataset (29 Avril to 3 Mai 2019), in order to make a comparison between the results obtained by the MLPNN model and the data from the experiment. Based on the current model, the inside air temperature and relative humidity profiles of the greenhouse were obtained (Figure 6 and 7). It can be seen that the predicted and measured indoor thermal behavior are similar, which mean that the MLPNN have a hight ability to predict the greenhouse thermal behaviour.

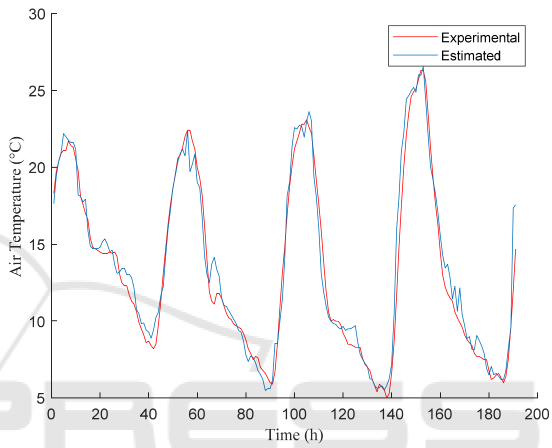


Figure 6: Experimental and estimated indoor air temperature of the greenhouse

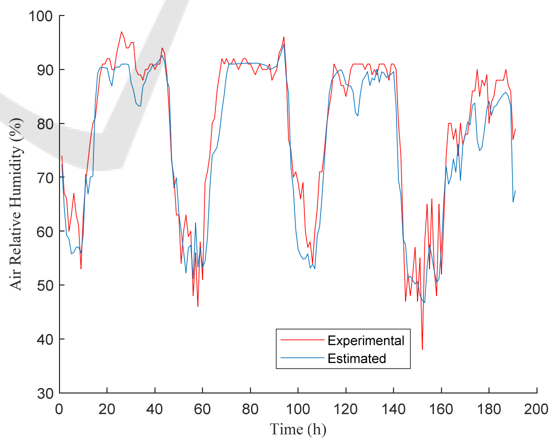


Figure 7: Experimental and estimated indoor air relative humidity of the greenhouse

4 CONCLUSION

The present work examined the potential of adopting machine learning-based techniques for the prediction of air temperature and relative humidity inside a Moroccan greenhouse for Tomato cultivation. The main predictors were the available recorded external weather data that can be easily obtained by low-cost measurements, such as the ambient temperature, solar radiation, relative humidity and wind speed. The results shows that the RMSE values for the MLPNN, are very low, and the R values are very close to 1, which mean that MLPNN have a high accuracy of forecasting. In addition the result of the comparison between the results obtained by the MLPNN model and the data from the experiment shows that the predicted and measured indoor thermal behavior are similar, which mean that the MLPNN have a high ability to predict the greenhouse thermal behaviour.

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