Climate Optimization in Greenhouses Using the NARMA-L2 Model: An Advanced Integration of Environmental Variables

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Abstract

Agricultural systems, such as greenhouses, can be used to control environmental factors, such as temperature and humidity, to increase output by employing traditional automation techniques. The advancement of science has resulted in the utilization of mathematical models to understand the behavior of data by analyzing its variability. The objective of this project is to validate a method for controlling temperature and humidity in controlled experimental environments using artificial intelligence and Neutrosophy. The transfer functions obtained from temperature and humidity readings gathered via a SCADA system are utilized. Neutrosophic numbers are used to adjust the temperature and humidity values based on the experimental conditions of the greenhouse, indicating the optimal, important, and sensitive ranges. The control system being investigated employs NARMA-L2 neural networks that belong to the multilayer perception category. This facilitates efficient system administration and showcases outstanding performance in simulations conducted across several temperature and humidity scenarios. The observed errors consistently remain below 5% and any instances of exceeding this threshold are insignificant.

Keywords: NARMA-L2, neutrosophy; nonlinear models; temperature; humidity.

1. Introduction

The dynamism of agriculture today is developing through the movement of increased productivity into ensured demand for high-quality products at competitive prices in quantities that are sufficiently large. Together with them, transformation of the agricultural chain with a focus on digital agriculture is constant, as it was stated in [1]. These changes are started by using new technologies: automation, efficiency of resource use, and sustainability to boost production efficiency, as noted in [2].

A prime example of this development is that of greenhouse farming practice, as referred to in [3]. Among the factors associated with greenhouse farming practice, crop growth management is one of the most visible factors impacting both the quality and quantity of products. It is widely recognized that the control of indoor climate conditions represents a key parameter to achieve optimal levels of crop growth and productivity [4].

This, therefore, necessitates the monitoring and controlling of climate variables; these mainly include temperature, humidity, CO2 levels, and radiation if greenhouse operations are to be automated with ease, as highlighted in [5]. Temperature is regulated majorly by the convective air exchange between the indoor and outdoor environments of a greenhouse, whereby the outside environment is normally kept at a lower temperature from the findings of a study done by [5]. This natural ventilation process is usually brought about by a side perimeter of windows around the greenhouse, with or without roof windows, as shown in [6]. Air movement with this type of ventilation is driven by the pressure differences created from wind forces and temperature gradients between indoor and outdoor air masses when the windows are open [7].

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These new methodologies in modern control have been applied over the past couple of years to various applications, including those in agriculture, which consequently brought forward the advancement in climate crop models and greenhouse management. All these innovations are supposed to increase the efficiencies of agricultural practices by ensuring that the system is sustainable [8, 9, 10]. Climatic models can be built according to the physical principles under which the system operates or derived from the analysis of the input-output data [10]. Here the first one considers the principles of thermodynamics, the second considers the time-variable nature of the system's parameters and distorts them in efforts to correctly describe the dynamics of greenhouses using such complex energy- and mass-balance equations [11]. The latter uses the theory of system identification with the support of measurement data and computational tools or makes use of artificial intelligence techniques in model development, as has been seen in [12].

Generally, agricultural greenhouses are considered to execute complex processes. In fact, they feature a non-linear behaviour and several inputs and outputs (MIMO systems). As a result, analytical models, and control with the use of conventional regulators are usually performed with much labour, and, in many cases, it is difficult to predict states or recognize patterns of system behaviour based on the historical data [13].

In this example, an energy balance-based model of an agricultural greenhouse with optimal control is used for simulating the greenhouse climate and giving foreseen set-points of the set temperature and hygrometry values. Moreover, a new greenhouse model considering crop transpiration was proposed and compared in a one-day simulation between optimal control and predictive control [13]. In [14], the operation of the MPC to control the greenhouse temperature by means of the MPC algorithm is detailed. Constraints on the controlled variables and the linearization technique were used. The advanced method of control seemed to perform well for this kind of process. By these results it is possible to infer that applying advanced control techniques in greenhouse operations it is possible to ensure a climatic regime appropiate for the crop's development, under the more demanding terms of the producer.

Neutrosophic theory is an extension of the set theory and logic created by Florentin Smarandache way back in 1995. For the generalization of the fuzzy set theory and logic, it tackles one grade of something: truth, falsity, or, possibly, indeterminacy regarding a statement. This may prove particularly useful when information is incomplete, uncertain, or contradictory. Neutrosophic analysis of the uncertainty and variations related to greenhouse environment may be applied in this context, and robustness against uncertainties and variations associated with temperature and humidity control of an experimental greenhouse provided. The objective of this work is to implement a methodology to control temperature and humidity under experimental conditions by artificial intelligence and/or neutrosophy.

2. Neutrosophy

Neutrosophy is the newest branch of philosophy, propounded by Professor Florentin Smarandache, in the quest to probe into the origins, nature, and extent of neutralities in different situations. Studies employing neutrosophy cater to the natural presence of uncertainty inherent in a process of decision-making. This caters for those situations when experts are called upon to make an assessment based on linguistic and nonnumeric parameters, a natural mode of measurement among human beings. Moreover, neutrosophic logic and sets are an extension of Zadeh's fuzzy logic and Atanassov's intuitionistic logic; they find applications in different decision-making strategies, and in the field of machine learning [17]:

Let $N = \{(T, I, F) : T, I, F \subseteq [0,1]\}n$, be a neutrosophic evaluation of a mapping of a group of formulas propositional to N, and for each sentence p :

$$\boldsymbol{v(p) = (T, I, F)} \tag{1}$$

To facilitate the practical application in real-world problems [17], the use of Single-Value neutrosophic Sets (SVNS) was proposed, through which it is likely to use linguistic terms to obtain greater interpretability of the results[8]. Let X be a universe of discourse, an SVNS A over X has the following form [18]:

- $\boldsymbol{A = \{\langle x, u_a(x), r_a(x), v_a(x)\rangle : x \in X\}}$ (2)

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- Where $\boldsymbol{u_a(x)}: \boldsymbol{X} \to [\mathbf{0}, \mathbf{1}], \boldsymbol{r_a(x)}: \boldsymbol{X} \to [\mathbf{0}, \mathbf{1}]\ \boldsymbol{y}\ \boldsymbol{v_a(x)}: \boldsymbol{X} \to [\mathbf{0}, \mathbf{1}]$
- With

$$\mathbf{0} \leq \boldsymbol{u_a(x)}, \boldsymbol{r_a(x)}, \boldsymbol{v_a(x)} \leq \mathbf{3}, \forall\ \boldsymbol{x} \in \boldsymbol{X} \tag{3}$$

The intervals $u_a(x), r_a(x)$ y $v_a(x)$ denote the memberships related to true, indeterminate, and false from x in A, respectively[10]. For convenience reasons, a Single Value Neutrosophic Number (SVN) is expressed as A = (a, b, c), where a, b, c ∈ [0.1] and 0 ≤ a + b + c ≤ 3 [18]**.**

Let A = (a, b, c) be a single-valued neutrosophic number, a score function S related to a single-valued neutrosophic value, based on the truth-membership degree, indeterminacy-membership degree and falsity membership degree is defined [18]**:**

$$\boldsymbol{s(V_i) = 2 + T_i - F_i - I_j} \tag{4}$$

3. Neural Network Model and NARMA-L2 (Nonlinear Auto-Regressive Moving Average)

It is a linearization model, which allows obtaining a linear model over a working region from a model built on input-output data already observed [19] according to equation 1.

$$yt = f[y\ t-1, \dots, y\ t-n, u\ t-2, \dots, u\ t-m] + g[, y(t-1), \dots, y(t-n), u(t-2), \dots, u(t-m)]u(t-1) \tag{5}$$

This model has been implemented within the Matlab Neural Networks Toolbox with the inclusion of the NARMA-L2 model into the classical NARMA model. For both, the NARMA and NARMA-L2 models, a linearization of the plant was made by adapting it for the Companion form [19]. Essentially, this provides linearization, due to the cancellation of nonlinearities of the system. Thus, this model can be taken as generating several linearized modules, depending on the load region, in which linearization is achieved by means of a voltage reducer for use in systems where the only one input and one output can operate in such a manner using just the voltage signal as feedback [19].

Presently, ANN-based control techniques have become quite handy with the capabilities and learning capacity to improve the control of nonlinear systems. Such control techniques are being used quite frequently in controlling and identifying dynamic systems, where one of the most appropriate ways is through the use of the NARMA-L2 controller when it comes to time-dependent control in nonlinear systems [20]. The controller synthesis is done in two procedures as follow once the system which requires control is defined where the behaviour of the nonlinear discrete-time system analysis is done in the system determination and can be represented using equation 6.

$$y(k+d) = N\big(y(k)\big), y(k-1), \dots, y(k-n+1), u(k), u(k-1), \dots, u(k-m+1)) \tag{6}$$

Where:

u(k): System input (internal temperature and humidity).

y(k): System output (air and water flow rates).

m and n: Are the values of input and output delays, respectively.

d: Is the relative degree.

Multilayer neural networks can be used to define N nonlinear functions. If the system follows a reference, the nonlinear controller can be represented as equation 7. The training of neural networks allows determining the function G that minimizes the mean squared error, using the backpropagation algorithm, and in this case, the NARMA-L2 controller can be represented through equation 8.

$$u(k) = G(y(k), y(k-1), \dots, y(k-n+1)), y_r(k+d), u(k-1) \dots, u(k-m+1)) \tag{7}$$

$$\hat{y}(k+d) = f[y(k), y(k-1) \dots, y(k-n+1), u(k-1), \dots, u(k-m+1)] + g[y(k), y(k-1), \dots, y(k-n+1),\ u(k-1), \dots, u(k-m+1)].u(k) \tag{8}$$

The advantage of using this form of output from the reference system is that it allows the system tracking to be resolved for the control input with the compact form of the controller shown in equation 9.

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$$u(k) = \frac{y_r(k+d) - f[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-n+1)]}{g[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-n+1)]} \quad (9)$$

However, it is not practical to define the input that depends on the output, and therefore equation 10 is used in the system definition for the value d≥2.

$$y(k+d) = f[y(k), y(k-1) \ldots, y(k-n+1), u(k), u(k-1), \ldots, u(k-n+1)] + g[y(k), y(k-1), \ldots, y(k-n+1), u(k), \ u(k-1), \ldots, u(k-n+1)].u(k+1) \quad (10)$$

Finally, the obtained NARMA-L2 controller is shown in equation 11.

$$u(k+1) = \frac{y_r(k+d) - f[y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-n+1)]}{g[y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-n+1)]} \quad (11)$$

In Figure 1, the general form of the NARMA-L2 controller is illustrated, which results in a simpler structure where the hidden layer also has only one neuron. However, more neurons are needed in practice, and at the same time, the number of delayed inputs is also important to consider because the degree of the system model is unknown.

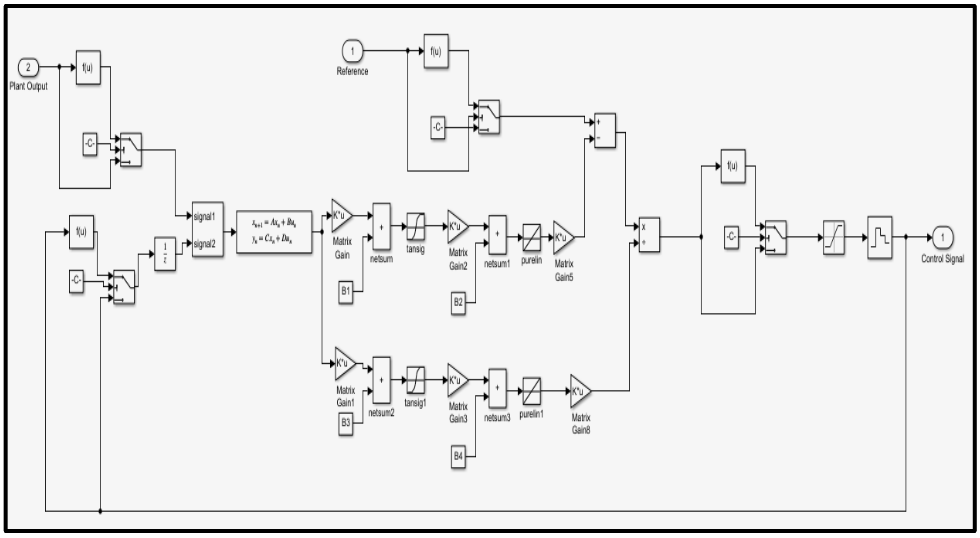

Figure 1: The simplest form of the NARMA-L2 controller. Source: Own elaboration.

Therefore, for the control of internal temperature and humidity variables, the process begins with reading the data which are normalized before entering the neural control for training. Subsequently, it is connected to the plant, which is represented by the transfer functions, and finally, the recorded data are normalized again to obtain the respective output of internal temperature and humidity as observed in Figure 2.

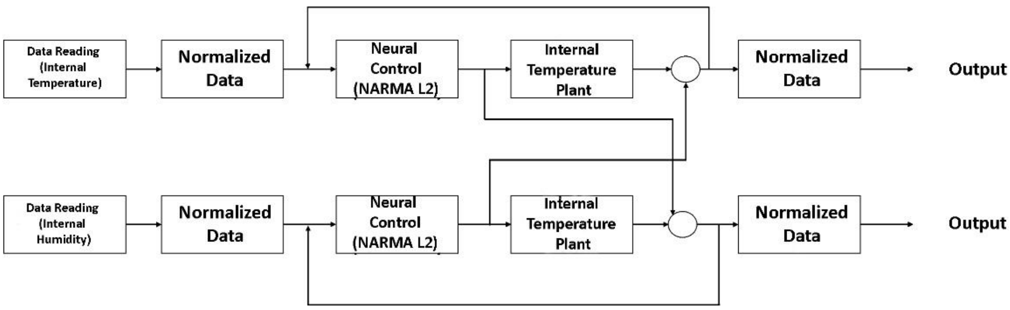

Figure 2: System Control Diagram. Source: Own elaboration.

The NARMA-L2 controller must be connected to the system as shown in Figure 3, after the training process has been completed.

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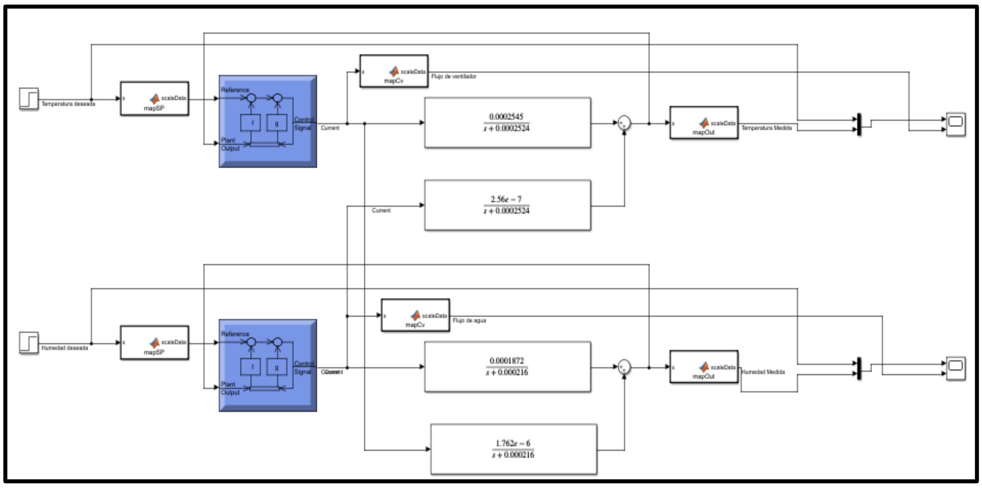

Figure 3: The block diagram of the NARMA-L2 controller. Source: Own elaboration.

4. Data processing

To develop temperature and humidity control in an experimental greenhouse, the optimal and tolerable ranges for both variables are defined in Table 1. These ranges allow for the assignment of neutrosophic numbers based on the degree of truth (T), falsehood (F), and indetermination (I) for different readings of temperature and humidity.

Table 1: Neutrosophic numbers for temperature and humidity values.

Temperature Range (°C)	**Temperature T**	**Temperature F**	**Temperature I**
Less than 18	0.0	1.0	0.0
18 - 20	0.3	0.3	0.4
20 - 25	1.0	0.0	0.0
25 - 27	0.3	0.3	0.4
More than 27	0.0	1.0	0.0
Humidity Range (%)	Humidity T	Humidity F	Humidity I
Less than 50	0.0	1.0	0.0
50 - 60	0.3	0.3	0.4
60 - 70	1.0	0.0	0.0
70 - 80	0.3	0.3	0.4
More than 80	0.0	1.0	0.0

Source: own elaboration.

Where:

T = high values within the optimal range and decrease outside this range.

F = optimal and tolerable ranges.

I = reflects the uncertainty near the boundaries of each range.

The ideal conditions for the greenhouse are:

- Temperature: 20-25°C (optimal), 18-20°C and 25-27°C (tolerable), less than 18°C or more than 27°C (non-optimal).

- Humidity: 60-70% (optimal), 50-60% and 70-80% (tolerable), less than 50% or more than 80% (non-optimal).

To model the greenhouse, the SCADA system database is used for a period of one year of operation in an experimental inacral-type greenhouse with a volume of 150 m³, which has an area of lateral windows of 20 m² and is equipped with an air extractor with a flow rate of 4500 m³/h. Data from a

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representative month were taken to evaluate the average behavior of the internal temperature and humidity on a typical workday in the greenhouse under the action of a control system for both variables.

In Figure 4, the maximum and minimum daily values under the control action can be seen, particularly during the critical midday period when the highest level of solar radiation occurs. To understand the water consumption values, the water expenditure records measured in a reservoir tank with an ultrasonic level meter with a precision range of ±0.3% are considered.

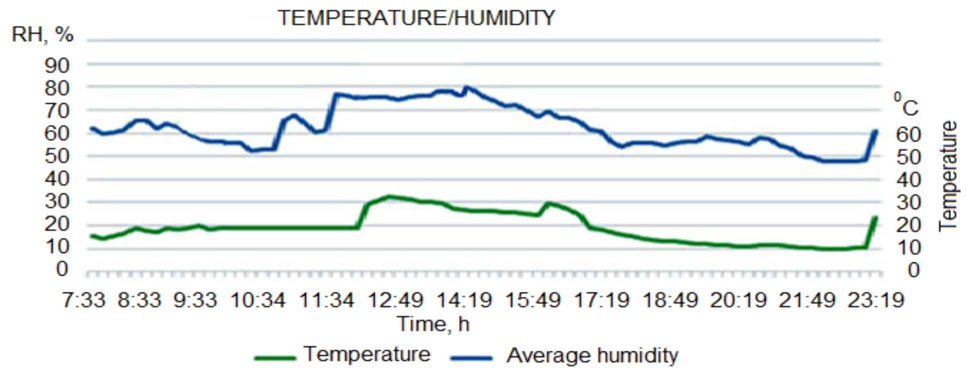

Figure 4: Temperature and humidity behavior during a day in the greenhouse. Source: Own elaboration.

5. Methodology for the Construction of the Temperature and Humidity Control Model Under Experimental Conditions Using a Neutrosophic and NARMA-L2 Model in Matlab Software with Automated Python Language

To create a model that combines a neutrosophic model and a neural network using NARMA-L2 for temperature and humidity control in a greenhouse under experimental conditions, the following simplified model has been designed in Python:

- Step 1: Define the Physical Model

First, we will define a basic physical model that describes how the temperature and humidity in the greenhouse change in response to actuators (such as heaters or humidifiers) and external conditions.

```python import numpy as np def physical_model (state, actuator, dt=0.1): state: [current_temperature, current_humidity]

actuator: [heating_level, humidification_level]

dt: time step in hours

Model parameters (these should be adjusted based on experimental data or literature)

k_temp = 0.1 # heat transfer coefficient

k_hum = 0.05 # moisture transfer coefficient

Temperature dynamics

new_temp = state[0] + dt * (-k_temp * (state[0] - 20) + actuator[0])

Humidity dynamics

new_hum = state[1] + dt * (-k_hum * (state[1] - 50) + actuator[1]) return np.array([new_temp, new_hum])``

- Step 2: Integrate the neutrosophic model with the neural network

A neural network is used to learn and adjust the physical model based on the observed data. For simplicity, here we employ a simple neural network with a hidden layer, using PyTorch.



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```

```python
import torch

import torch.nn as nn

class NeutrosophicNetwork (nn.Module):

def __init__(self):

super(NeutrosophicNetwork, self).__init__()

self.fc1 = nn.Linear(4, 10) # 4 inputs: state and actuator

self.fc2 = nn.Linear(10, 2) # 2 outputs: settings to temperature and humidity

def forward(self, x):

x = torch.relu(self.fc1(x))

x = self.fc2(x)

return x

Instantiating the model

model = NeutrosophicNetwork ()
```

- Step 3: Training the combined model

To train the model, historical data of states and actuators, as well as actual temperature and humidity responses, are used. Below is a simplified outline of the training cycle:

```python
criterion = nn.MSELoss() optimizer = torch.optim.Adam(model.parameters(), lr=0.01) for epoch in range(1000): for state, actuator, real in zip(input_data, actuator_data, real_data): optimizer.zero_grad()

Model input

input = torch.from_numpy(np.concatenate([state, actuator]))

Prediction of the neutrosophic model adjusted by the neural network: fit = model(input.float()) prediction = physical_model(state, actuator) + fit.detach().numpy()
```

6. Results and discussion

The methodology is designed for the two variables being studied: temperature and humidity. In Figures 5 and 6, a Neural Network with NARMA-L2 was trained with the data contained in the two signals under study: temperature and humidity. This is an instant of the Matlab software programmed using automated Python.

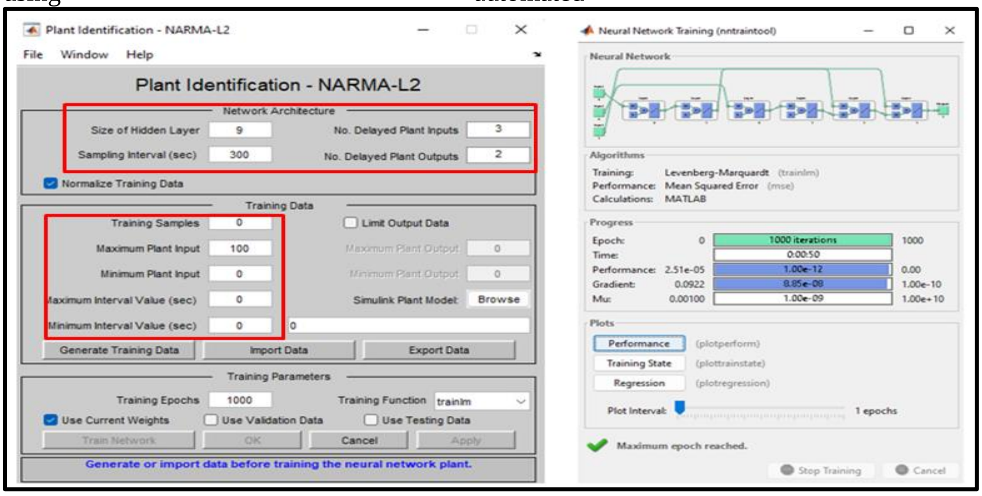

Figure 5: Neural Network Training for Temperature in NARMA-L2. Source: own elaboration.

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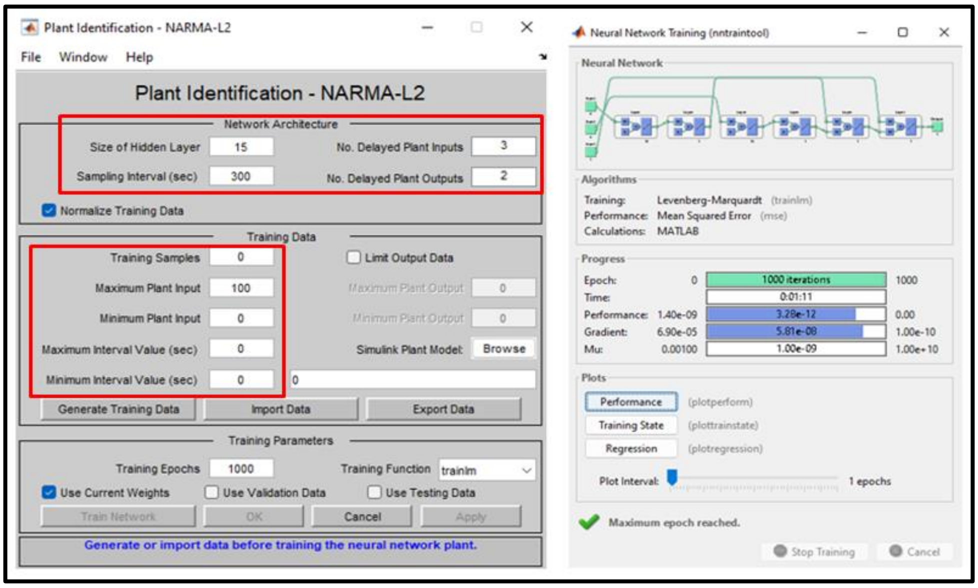

Figure 6: Neural Network Training for Humidity. Source: Own elaboration.

Figure 7: data obtained after finishing the training of the neural network; the input is airflow data and output is temperature data; "NN" indicates output of a neural network, while observing validation of neural network for that sample of input-output datas not entering in neural network is taken and "NN" shows its output, demonstrating the training of neural network is valid because error tends to zero.

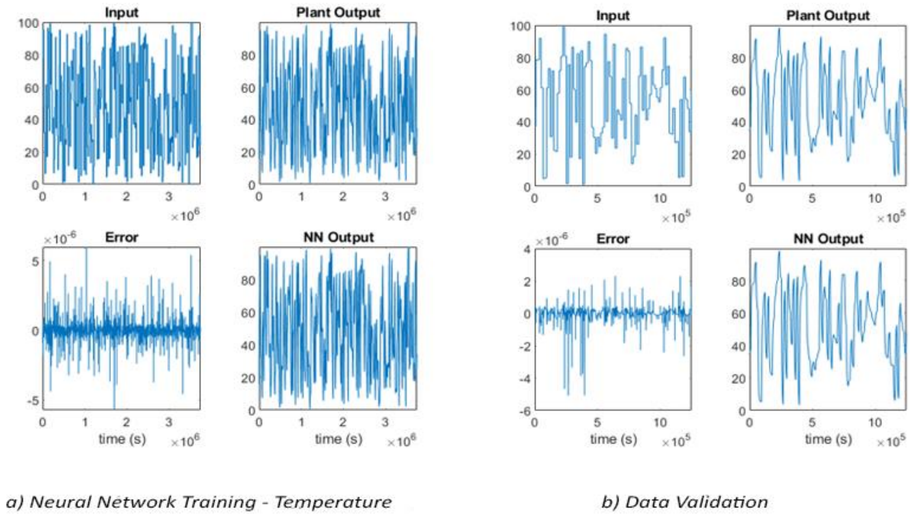

Figure 7: Temperature Training Data. Source: Own elaboration.

Paraphrase

content_copy

Figure 8: The training that was done on the neural network for the variable of humidity. The input is water flow, and the output is humidity values, where "NN" denotes the output from the neural network. It also shows the validation of the neural network, for which it takes a sample of the input and output data that does not enter the neural network and shows the series "NN" using the series. Just as in the variable temperature

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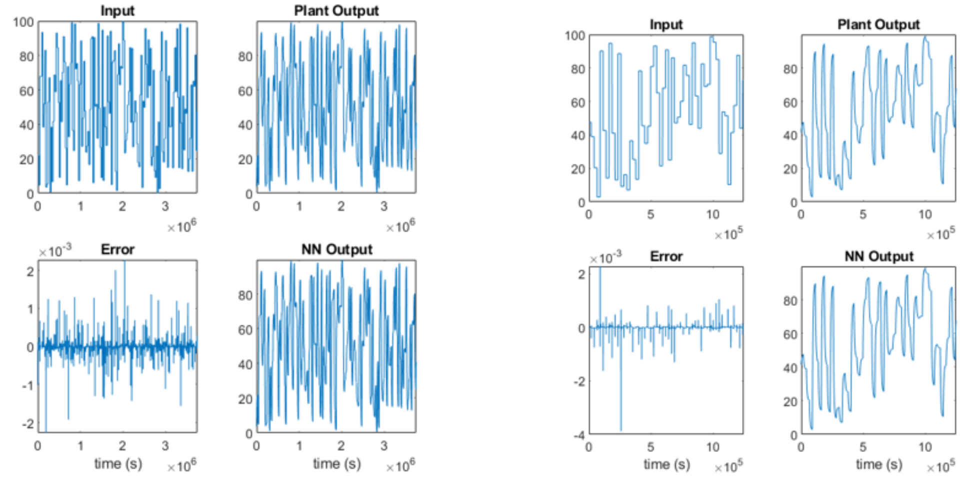
example, only the correct training of the neural network forces the error to go towards zero.



a) Neural Network Training - Humidity *b) Data Validation*

Figure 8: Humidity Training Data. Source: Own elaboration.

When connecting the control to the plant for temperature and humidity variables, optimal control is achieved with negligible overshoot in disturbances for temperature variations of 3°C with a settling time of 30 minutes for a 2% error. Meanwhile, in extreme variations of 30% in temperature as shown in Figure 9, for a desired value of 32°C, the time required to reach a steady state exceeds one hour due to the insufficient capacity of the air extractor to perform the necessary air volume renewals inside the greenhouse under this extreme condition in a shorter time.

Regarding internal humidity in the presence of disturbances of 10% in humidity variation, the system stabilizes in 11 minutes for the desired value of 56% relative humidity. In the extreme case for a step from 0% to 56% to evaluate the overshoot of the response, the system stabilizes in approximately 60 minutes for a 5% error as observed in Figure 10 with negligible overshoot.

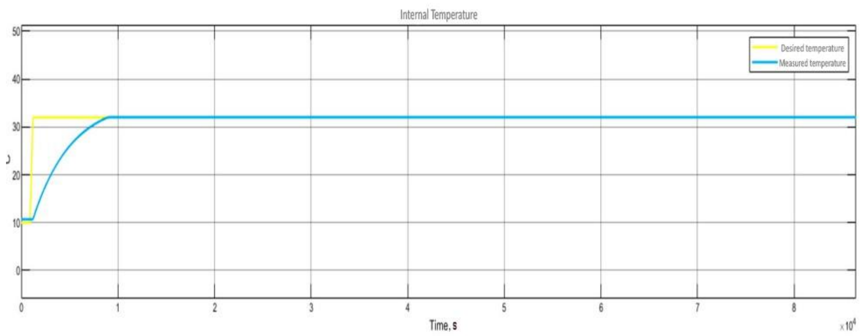


Figure 9: Temperature Control. Source: Own elaboration.

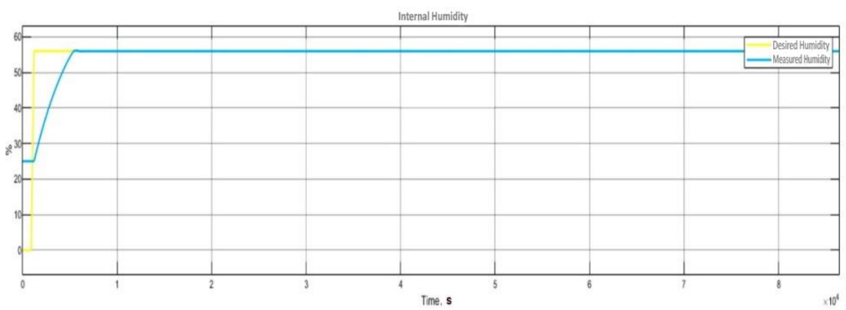


Figure 10: Humidity Control. Source: Own elaboration.

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7. Conclusions

Neural networks are currently finding successful applications in greenhouse management, showing the effectiveness of using these systems. The application uses a NARMA-L2 controller based on multilayer neural networks to control the research greenhouse. These models are used for indoor temperature and humidity variables that represent first-order transfer functions. These functions are obtained with the Ident tool of Matlab software, which facilitates the approximation of the system model, with a good setting of 72.43% for indoor temperature and 74.18% for indoor humidity.The control system shows good reliability because the simulation results closely match the real system data. This allows simulation of temperature and humidity fluctuations in different scenarios, which ensures optimal performance of the controller. The internal temperature stabilizes in approximately 30 minutes, while the internal humidity stabilizes in only 11 seconds, resulting in a stable error of 2% and 5%. Checking both variables shows negligible overflow during operation. of.

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