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Enhancing predictive accuracy of inside temperature and humidity in an agricultural greenhouse using data-driven modeling with artificial neural networks

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ABSTRACT

This work presents an original and innovative approach by combining greenhouse cooling with artificial intelligence models to ensure food security. The study is divided into two parts: Experimental and theoretical. In the first part, a cooling system was implemented in a tunnel-type agricultural greenhouse and compared to a control system. The cooling system consists of multiple fans powered by two solar panels. Data was collected using an acquisition system (Arduino) over approximately one month. This data, along with external data, was utilized to predict the internal temperature of the greenhouse using back-propagation neural network models. The results obtained demonstrate the reliability of the model based on all tests, as evidenced by the coefficient of determination (R^2) and the mean square error (MSE) for the prediction.

Keywords: Climate, temperature, agricultural greenhouse; cooling system, and neural network

1. INTRODUCTION

Fresh water is scarce in arid climates. They also have low humidity, high potential evapotranspiration, and high temperatures. So, we've needed protected agriculture to grow crops. The rising population brings concerns about food security. It also brings recognition of dwindling freshwater resources. The adoption of protected agriculture is rising in arid regions, which make up about 30% of the world's landmass. They support roughly 20% of the global population (Al-Sulaiman, 2002). In these areas, dry climates get little rain each year. They also face high rates of potential evapotranspiration. Arid steppe climates get less rain than the potential evapotranspiration. Arid desert climates get very little or no rain (Aziz et al., 2018). Under such circumstances, mitigating thermal stress and managing evapotranspiration are critical considerations.

In dry areas, raising humidity in greenhouses can cut crop water loss. This is especially true in deserts with high heat and very low humidity (Doğramacı and Aydın, 2020). Nonetheless, in many regions across the Middle East and North Africa, temperatures can soar to 46°C. Access to fresh water is also restricted. So, providing the right growing conditions there is very hard. Research shows that people often use active cooling systems like misting and fan and pad ventilation to reduce heat in arid climates (Aziz et al., 2018). These systems, plus evaporative cooling and shading, can cut the greenhouse air temperature by up to 8°C. But, misting systems might not cool as much as fan and pad systems. But they do provide more even conditions in the greenhouse (Helmy et al., 2013). But, it's crucial to regulate active ventilation to pre-vent excessive crop transpiration.

Although these cooling systems prove effective, they also consume a great deal of water. Evaporative cooling in greenhouses can use up to 67% of the total water demand (Kassem et al., 2005). To tackle this challenge, passive ventilation is often used first to cool. When passive ventilation is not enough, people use evaporative cooling. Passive greenhouse technology emphasizes taller greenhouses. They do this to reduce peak air temperatures (Koca et al., 1991; Lalmi et al., 2021). Still, as greenhouses get bigger, active vents and cooling systems work less well. Adding retractable roofs and adjustable openings is essential. They let passive and active cooling and ventilation systems Liao et al., (1998) integrate well. In arid climates, energy and water conservation are crucial. To use less water and energy, there's growing interest in combining passive and active ventilation. Recent studies show that misting and shading cool plants.

They improve the plant environment in semi-arid regions (Mahmood and Aljubury, 2022; Malli et al., 2011). Researchers have studied alternative evaporative cooling techniques for greenhouses in arid climates. These techniques need less forced ventilation than traditional fan and pad systems (Nada et al., 2019). But, it's still necessary to develop cheap cooling methods. These methods should use materials available in arid climates. Recent research has focused on protected agriculture in semi-arid regions. It shows that misting and shading are key. They use passive evaporative cooling. It's the best way to improve the plant environment. Other studies have looked at ways to cool greenhouses in arid climates. They do it without forced ventilation. They demand less ventilation than fan and pad systems. But none have focused on low-cost cooling techniques using local materials (Sellam et al., 2022).

This study aims to conduct an experiment. It will investigate the heat dynamics of two tunnel greenhouses. One has a cooling system, and the other does not. The greenhouse lacking a cooling system will act as a control, facilitating comparison to check the impact of the cooling system. The setup is at the Unit of Applied Research in Renewable Energies (URAER) in Ghardaïa. Ghardaïa lies at a latitude of 32.37° north and a longitude of 3.77° west. This location is good for studying greenhouse thermal performance. The study has four sections. The first section provides a detailed description of the experimental site. It includes its geography and other key details. This section helps establish a clear understanding of the experimental conditions. In the second section, researchers set up the experiment, took measurements, and analyzed the results.

This phase involved monitoring and recording temperatures inside the greenhouses. This allowed for a full evaluation of their thermal behavior. The third section of the study involved the use of a feed-forward backpropagation neural network. We've used this neural network to predict the inside temperature of the greenhouse, based on the collected data. This analysis can help predict how well the cooling system works. It can show how the system affects the greenhouse's temperature. The study aims to improve our understanding of tunnel greenhouses. It will do this by conducting experiments and using advanced data analysis. The green-houses will either have or not have cooling systems. This research can help make greenhouse designs more efficient and sustainable. This will benefit the agricultural industry.

The final section presents the results obtained and their interpretations, with its conclusion. We used the feed-forward back-propagation neural network to predict greenhouse temperatures. This analysis can offer insights into cooling system effectiveness. The study aims to improve understanding of greenhouse thermal behavior. This research can help develop better greenhouse designs. The final section discusses the results and conclusions.

2. MATERIALS AND METHODS

Our experiment took place at the Unit of Applied Research on Renewable Energies in Ghardaïa, Algeria, from 15-03-2023 to 15-06-2023. We studied temperature and humidity gradients in a greenhouse. We used a Fan-Pad cooling system under Ghardaia's conditions.

Experimental Site description

Before describing the region of our research work, it should be noted that about 77% of the Algerian surface area is arid and semi-arid regions. The characteristics of the region of Ghardaïa, (Figure 1), are:

Figure 1 Ghardaïa position in Algeria maps

Location 595 km south of the Mediterranean Sea.
Latitude and 32°36 N.
Longitude 3°80E.
Altitude of 469 m above sea level.
Rate of sunny days per year: 77%
Annual average daily global solar irradiation is about 7 kWh/m^2.

It experiences a desert climate characterized by hot and dry summers, and mild winters. The monthly temperature in Ghardaia can vary throughout the year. During the summer months, from June to August, Ghardaia experiences high temperatures. Average temperatures during this period can range from 35°C to 42°C (95°F to 107.6°F), with occasional spikes reaching even higher. Intense heat and minimal rainfall characterize these months (Shaik et al., 2020). In contrast, the winter months, from December to February, are mild in Ghardaia. Average temperatures during this period range from 14°C to 20°C (57.2°F to 68°F). The temperatures are cooler than in the summer. But, Ghardaia still has pleasant weather in the winter, (Figure 2).

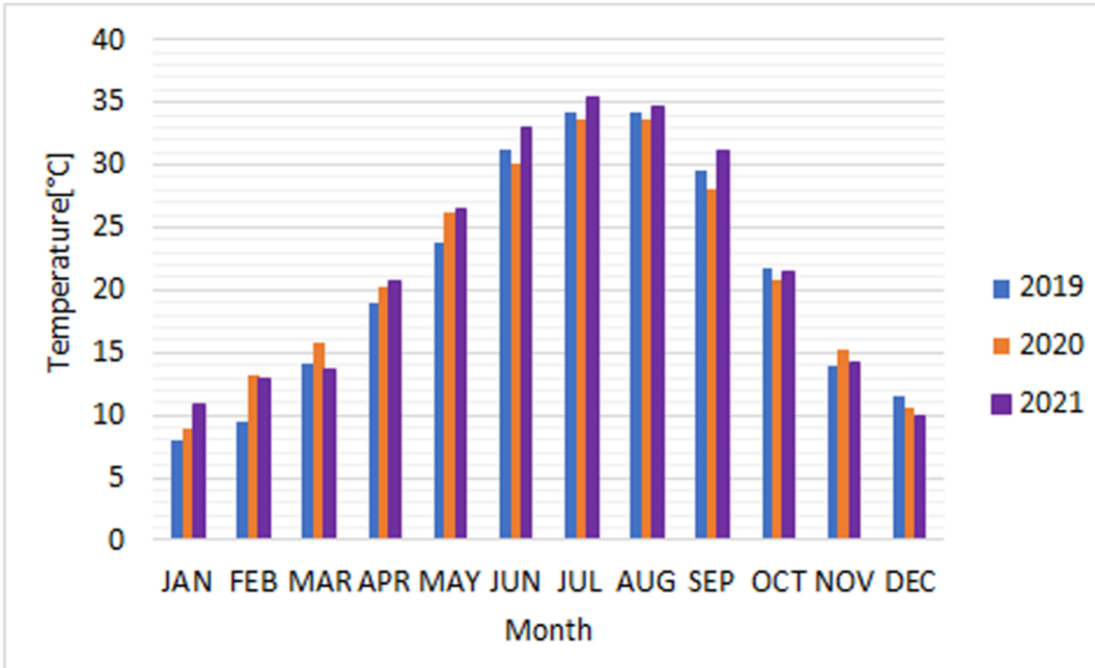

Figure 2 Annual monthly temperature evolution in 2019, 2020 and 2021

As for solar radiation, Ghardaia receives abundant sunshine throughout the year due to its desert location. The city has clear skies and high solar radiation. This happens in summer. Levels reach about 8 kW-hr/m²/day (Figure 3). This parameter represents the amount of solar energy received at the Earth's surface. It includes energy from all directions, from direct sunlight and scattered light from the atmosphere (Singh et al., 2013). This makes Ghardaia great for solar energy. It also draws visitors seeking warm, sunny weather. This is according to NASA data (Smith et al., 2020).

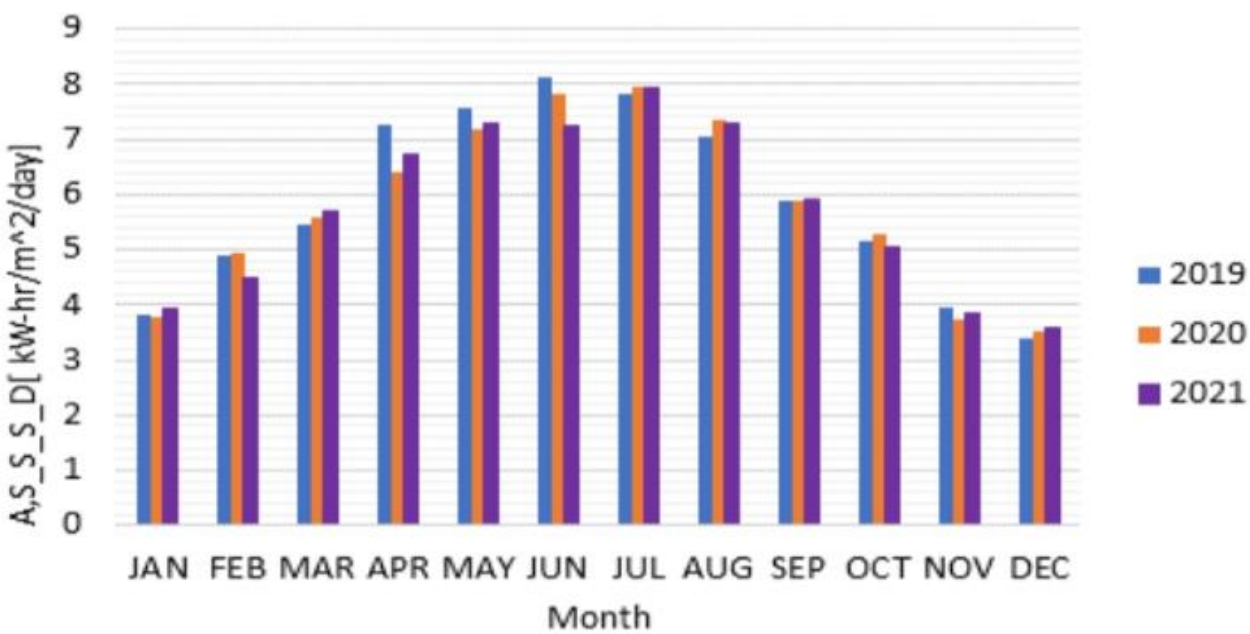

Figure 3 Monthly all-sky surface shortwave downward irradiance in 2019, 2020, and 2021

Design of the greenhouse

To conduct this study, we used two plastic tunnel greens. They were identical in size (200cm long, 100cm wide, 80cm tall) and design. Researchers designed one greenhouse as the test. They used the other as the control. Using plastic packaging, we've built the greenhouses. They also used plastic tubes. This makes them easy to modify and adapt. The choice of materials made the needed changes easier. The study required modifications and adjustments.

Cooling system design

We determined the cooling system's parameters using psychrometric calculations. We based these on data from inside and outside the greenhouse. This study aimed to test the Fan-Pad system's effectiveness at keeping good plant growth conditions. It also aimed to map these conditions in the greenhouse. The study's results will help improve the design and operation of greenhouse cooling systems in similar climates. They will enhance the productivity and quality of crops grown in these places. In the experiment, they installed shading screens in the greenhouse. The screens control how much sunlight enters. Additionally, we've closed the side and top windows of the greenhouse. This prevented any outside air from entering or leaving. We created a lab to isolate the Fan-Pad cooling system's effects. It focuses on the temperature and humidity gradients in the greenhouse.

Components of the fan-pad cooling system

A direct evaporative cooler cools air: It does this by evaporating water. This makes it a simple and effective device. It operates based on the principle that when water evaporates, it absorbs heat from the surrounding air, resulting in a cooling effect. Researchers have applied the fan-pad evaporative cooling system in the experimental greenhouse. Figure 4 shows a general view of the fan-pad cooling system. It contains the following elements:

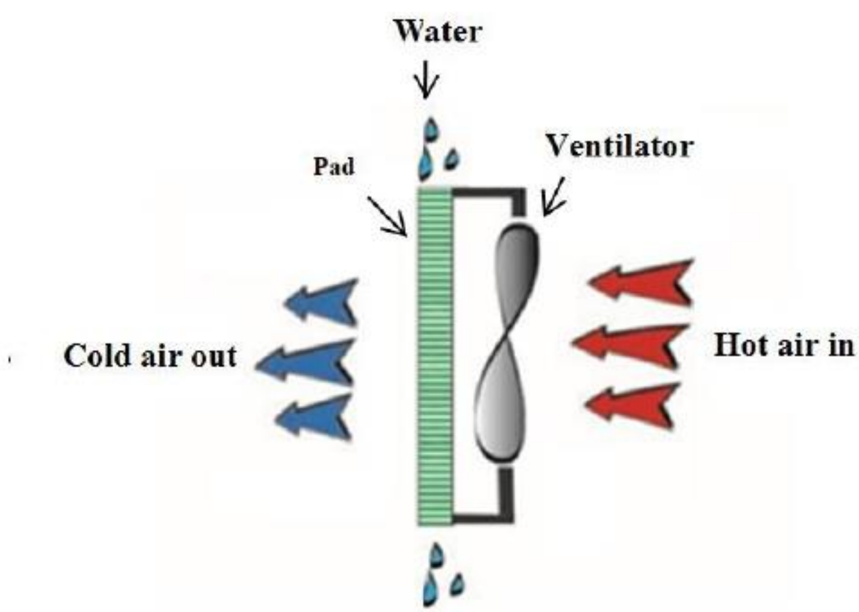

Figure 4 Fan-pad cooling system design (Nada et al., 2019)

The cover is made of burlap: It encloses the system's internal parts, as shown in Figure 5(a) for protection. This burlap cover serves the purpose of safeguarding the palm leaf from external elements and potential damage. Additionally, it helps keep the system intact. It does this by stopping dust, debris, and other dirt from getting in. Burlap is durable and breathable. It is ideal for this cover. It ensures the functionality of the water system.

Filter Media: A highly wettable porous material made from palm leaf, has a thickness, and they are kept moist by water continuously dr ipping onto its upper edges.

An evaporative cooling pad, also known as a wet pad, is key to evaporative cooling systems. The pad is 80 cm by 4 cm by 40 cm, as seen in Figure 5(a). It's placed on the air inlet at the east end, 10 cm above the ground.

Blower Fan: The described system includes two large blower fans, each operating at a voltage of 12V and consuming 50Kw of power, Figure 5(b). The housing contains and uses these fans to draw in warm air from the outside. Afterward, the fans push the cooled and humidified air into the greenhouse.

The water distribution system incorporates two perforated tubes positioned above the filter media, as shown in Figure 5(c). These tubes are essential for dispersing water across the entire surface of the pad. This careful distribution mechanism ensures that the filter media stays saturated well. This level helps efficient cooling. The system ensures even water distribution. This maximizes the cooling process's effectiveness, enhancing its capabilities.

The water collection tube sits at the bottom of the evaporative cooling pad. Its main job is to collect and channel extra water, as well as it's impurities or sediments. These impurities and sediments pass through the pad during evaporation. This tube collects water and prevents it from pooling or causing damage to the pad or surrounding areas. A pump directs the water collected in the pipe to the tank for recycling back into the system for further use.

Figure 5 Components of Fan-Pad cooling system: a) Evaporative cooling pad, b) Fan, Palm leaf, c) Palm leaf, d) Arranging palm leaf inside an evaporative cooling pad

Operating of Fan-Pad cooling system

A fan-pad system works by evaporation. First, close all openings and doors while the fans are running. Then, water flows along two pipes and into the pad. The two fans draw outside air through the filter media. The air passes through the wet pad. Water evaporates from the pad into the air, absorbing heat from the warm air and cooling it. The cooled air is then blown into the greenhouse, providing a refreshing and cooler environment inside, (Figure 6).

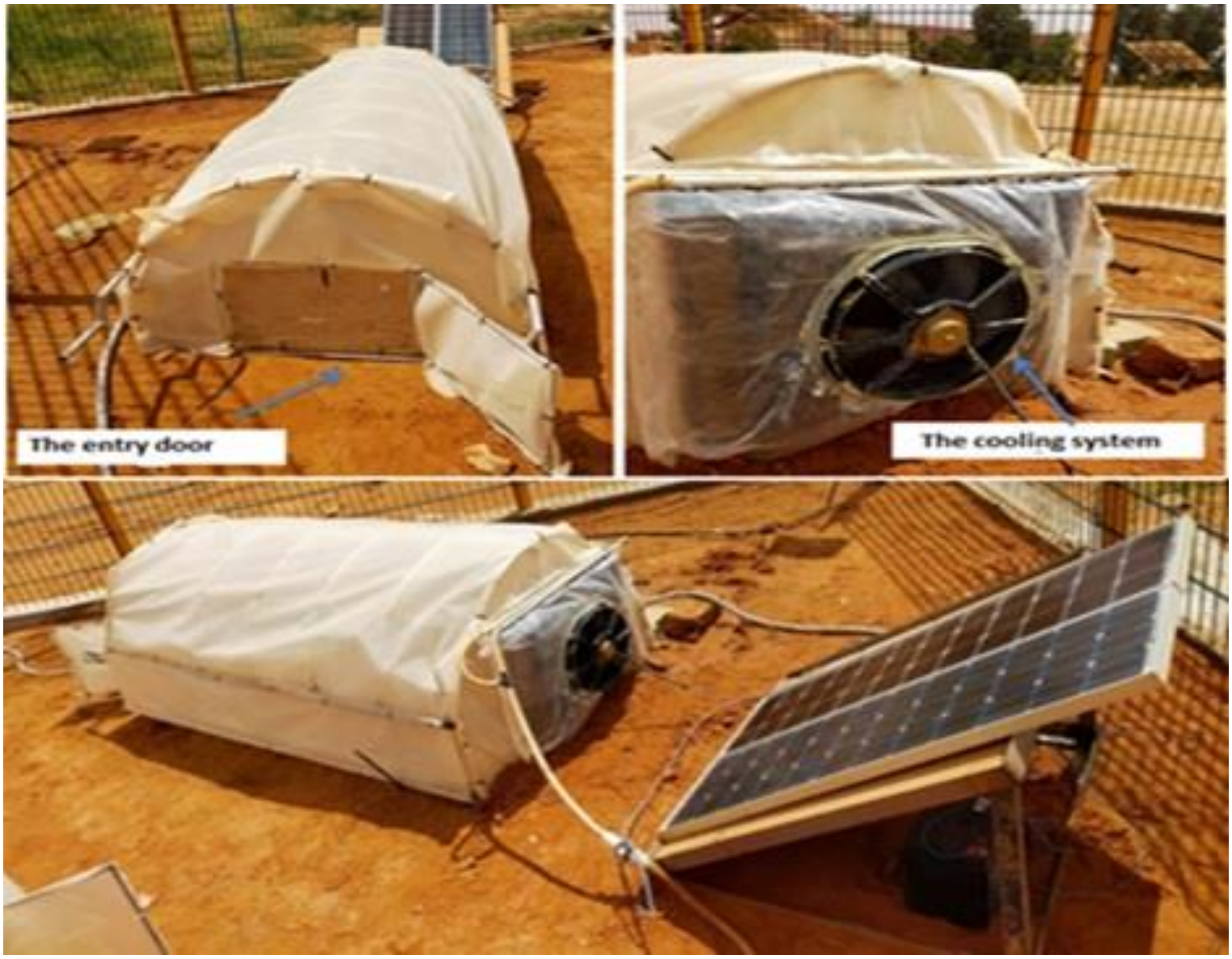

Figure 6 Cooling system in the experimental greenhouse

In our study, we've utilized a total of seven DHT22 sensors to measure temperature and humidity. We placed three sensors in the experimental greenhouse. We put another three in the control greenhouse, which lacks a cooling system. We positioned one sensor outside. For data acquisition, we've employed an Arduino board of the Mega 2560 type along with a relay block. The wiring system involved connecting the Arduino board, memory card, and clock. Two solar panels powered the system, which consisted of a regulator (24V) and fans. You can find the specifications of these components in (Table 1). Figure 7 presents all system concepts.

Table 1 Characterization of the two Solar Monocrystalline Panels 100W 12V

Maximum power (Pmax):	100 Wp.
Tolerance between	0 if + 3% the 25°C.
Optimal voltage (Vmp):	18.4V.
Optimal current (Imp):	5.40 A.
Vacuum voltage (Voc):	22,25V.
Short circuit current (Isc):	5.8A.
3 diodes bypass	36 cells in a series of 125 x 125 mm.

Size:	1000 x 670 x 35 mm.
Weight	9 kg

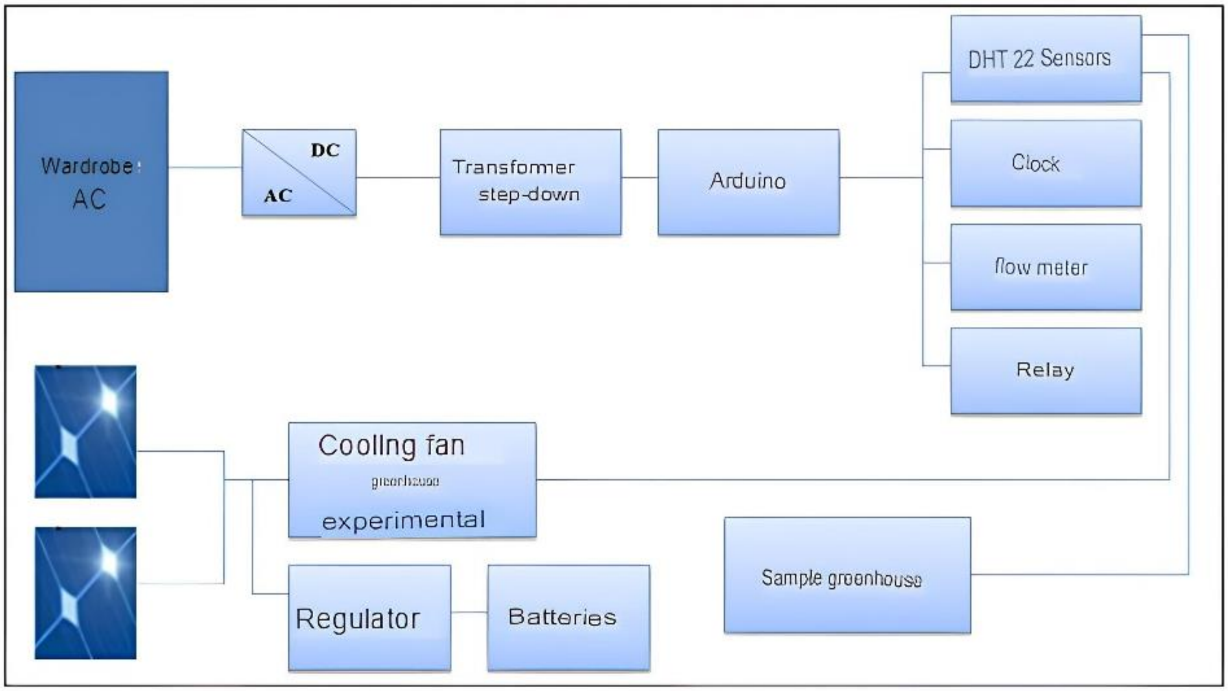

Figure 7 Schematic representation figure

Experimental results

The researchers conducted the trials during the period specified in section one. They did them at the same location as the previous trials to cool the greenhouse. We've installed a cheap evaporative system. It has pads and a chopper. It also has a water recovery and reuse system. This system saves and uses water well. The system only wasted 100 ml per minute during water evaporation. Standard engineering data recommends keeping the greenhouse temperature below 30-32°C.

Figure 8 shows a comparison. It is between the outdoor temperatures and the greenhouse temperatures. The greenhouse lacks a cooling system. The period is from June 4th to June 15th. The results show a big temperature increase in the greenhouse. Peak temperatures ranged from 18°C to 50°C, and they were from 13:00 to 14:00. This temperature rise is likely due to the influence of global warming inside the greenhouse. Similarly, when comparing temperatures inside the greenhouse to the outside, there is a big difference. The inside can be over 10°C hotter during the day. This is clear during the hot, dry weather from days 8 to 10. Temperatures range from 25°C to 50°C. The difference was up to 4°C in the day. This variation is due to the effectiveness of the large evaporative system in the greenhouse. Its economic cost did not exceed 10,000.00 DZ.

To ensure efficient water usage, we've implemented a water recovery system to replenish moisture in the pad. We measured the amount of lost water and evaporated it in the greenhouse. We used a controlled water flow. The water tank set the downward flow at 6 L/min and maintained the upward flow at 5.9 L/min. This configuration allowed for an evaporation rate of 100 mL/min. The observed evaporation rate shows a cost-effective performance. This performance is rational compared to the system. Figure 9 illustrates the temporal variation of humidity in both greenhouses. Throughout the day, we've observed a big inverse link. It's between temperature and humidity. As the temperature increases, the humidity decreases, and vice versa. These findings support past studies. They also confirm the well-known link. It is between high temperature and low humidity.

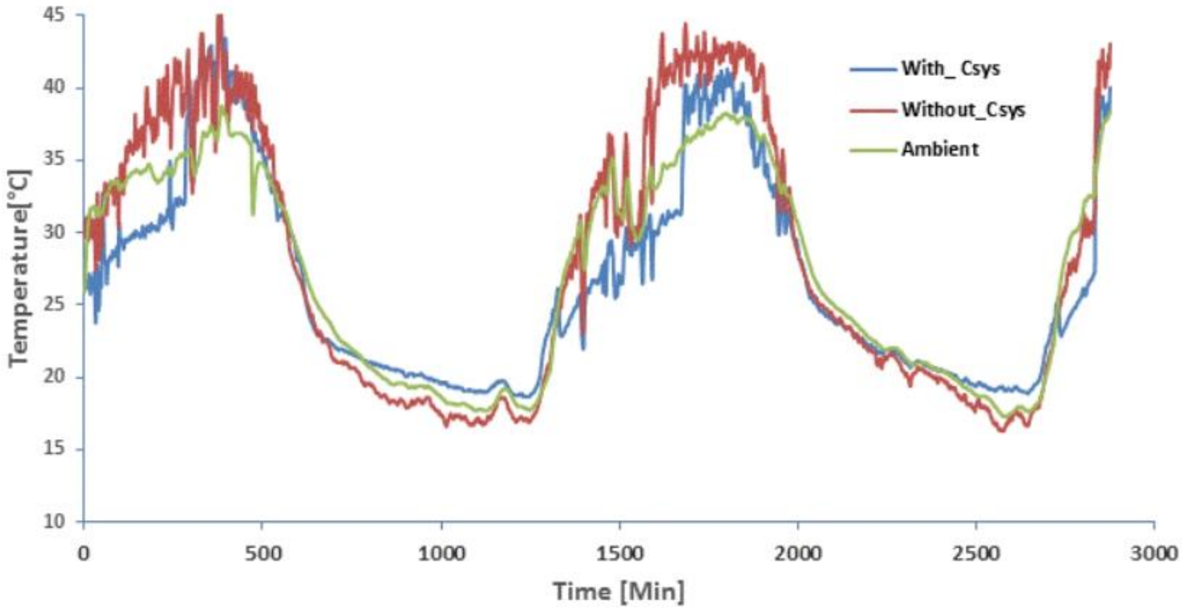

Figure 8 The evolution of inside greenhouse temperature (with and without a cooling system), versus outside greenhouse temperature

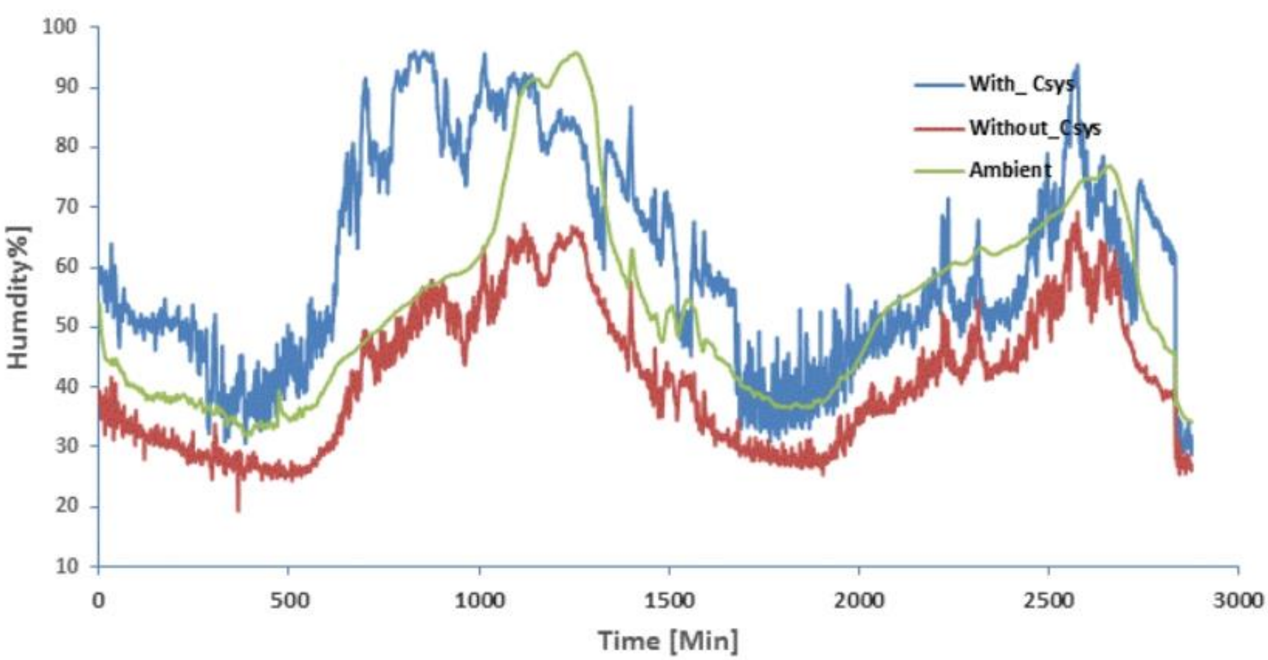

Figure 9 Inside with and without cooling system and outside humidity evolution

Theoretical part

ANNs are a type of machine learning algorithm. Designers have created them to simulate the human brain. In our case, we utilized the Feed Forward Back Propagation Network (FFBPN) model, which operates based on two iterations. The first iteration involves step-by-step input weight calculation. The second iteration involves a backward pass calculation for weight updates and error. We divided the training data as follows: 70% was for model training, 30% was for testing and validation. Next, we trained the model based on equation (1) until we met the criteria.

$$x_k = \sum_{1}^{n} (w_{ki} x_i) + b \qquad (1)$$

Where x_i is the new variable, xi is the initial variable, and $(w_k)$is the weight link value of the neuron/variable. The activation function between the input layer and the hidden layer was as indicated by equation (2):

$f(x) = 1/(1 + e^{-x})$ (2)

The pure function was used as Equation (3) between the hidden layer and the output layer:

$f(x) = x$ (3)

We tested the FFBPN model using MATLAB software. During training, the model trained on input measurement data. It used the Levenberg-Marquardt (LM) backpropagation algorithm. After completing the training, we've used 15% of the data to confirm the model. Once the model reached the desired accuracy, it proceeded to the testing phase and tested the remaining 15% of the data sets. We check the fit between the FFBPN-predicted value and the real value using R2. R2 ranges from 0 to 1. A higher R2 value indicates a better fit. The following expression gives R^2 and MSE.

$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{inp} - y_{otp})^2}{\sum_{i=1}^{n}(y_{inp} - \bar{y}_{inp})^2}$ (4)

$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{inp} - y_{outp})$ (5)

We found the results to be accurate with an R2 value close to 1.0.

The network comprises three layers: The input layer, the hidden layer, and the output layer. The input layer receives signals from an external source, and the hidden layer's role is to process the signals for use by the output layer. The researchers created the FFBPN model, depicted in Figure 10, using eight parameters obtained from the data. The included parameters are: outside temperature, humidity, wind speed, and pressure. The control greenhouse also includes the temperature and humidity inside. It doesn't have a cooling system. They also included the time and solar radiation. We've used the greenhouse's inside temperature, with the cooling system, as the output variable.

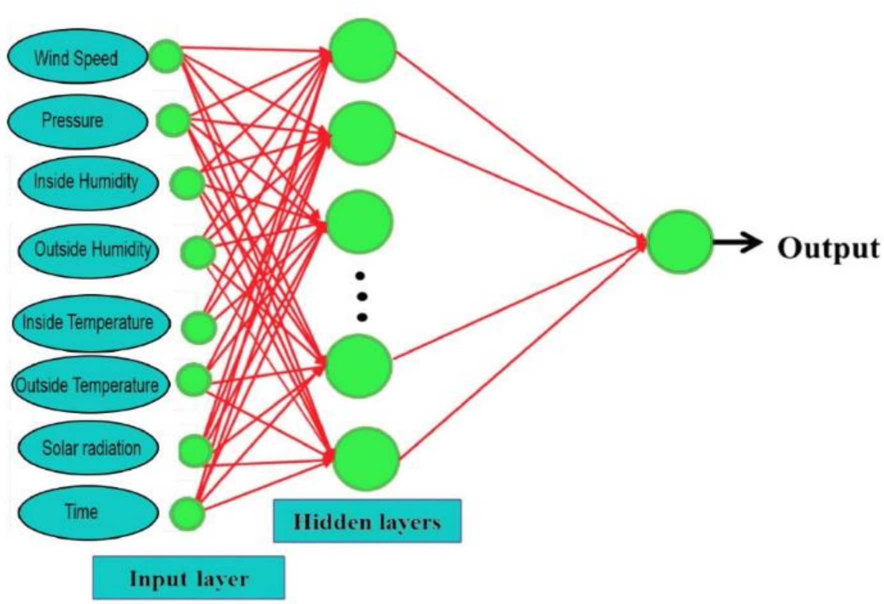

Figure 10 Neural architecture

The multi-layer perceptron (MLP) is a neural architecture used in machine learning. It falls under the category of artificial neural networks (ANNs). MLPs consist of many layers of connected neurons (nodes). They include an input layer, one or more hidden layers, and an output layer. These networks can approximate any quantifiable function.

3. DISCUSSION OF RESULTS

Figure 11 shows a strong correlation between measured and predicted values. The agreement is strong. The low mean squared error (MSE) values show this. They measure the average squared difference between actual data and model predictions. The small MSE values confirm that the multi-layer perceptron works well. It's so by aligning its predictions with the real data.

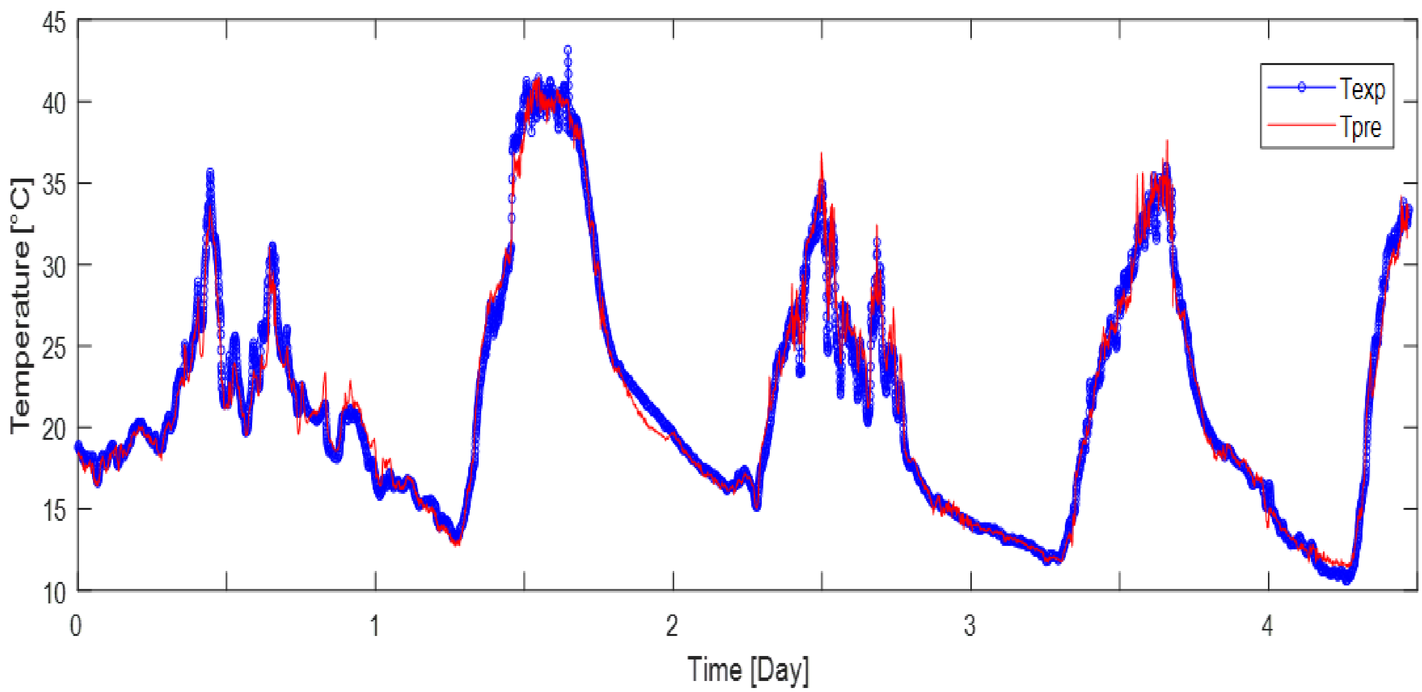

Figure 11 Evolution experiment (Texp), predict (Tpre) temperature and error

In Figure 12, we provide an overview of the R^2 plots of the model during the training, testing, and validation phases. The model achieved an impressive R^2 value of 0.99275 during training, indicating high predictive accuracy. We trained the neural network using historical data. This made a reliable model with the best predictive performance. When compared to existing literature, our multi-layer perceptron model stands out. Similar studies in predictive modeling usually report R^2 values ranging from 0.85 to 0.95. For example, achieved an R^2 value of 0.94 using a support vector machine on a similar dataset. Reported an R^2 of 0.91 with a convolutional neural network. Our study surpasses these figures with an R^2 value of 0.99275, demonstrating superior model performance.

Furthermore, the observed low MSE aligns with recent neural network research. For instance, in a study by Taki et al., (2016), a multi-layer perceptron obtained a mean squared error of 0.02 on a similar task. This result is similar to the ones presented here. This consistency further validates the robustness and accuracy of our current model. Figure 13 depicts the relationship between the mean squared error (MSE) and the number of training epochs. An epoch corresponds to a complete pass through the entire training dataset. The graph tracks the MSE. The MSE quantifies the squared difference between actual and predicted values.

It shows how the MSE changes as the model trains over many epochs. The optimal validation performance occurred at epoch 25, where the validation graph reached its lowest MSE value of 0.2625. This shows that after 25 epochs, the model made very accurate predictions on the validation dataset. This led to minimal average error. A lower MSE value is better. It means the model's predictions align with actual values. Epoch 25 represents the point in the training process. It was where the model was best tuned and most effective at generalizing from the training data to unseen validation data.

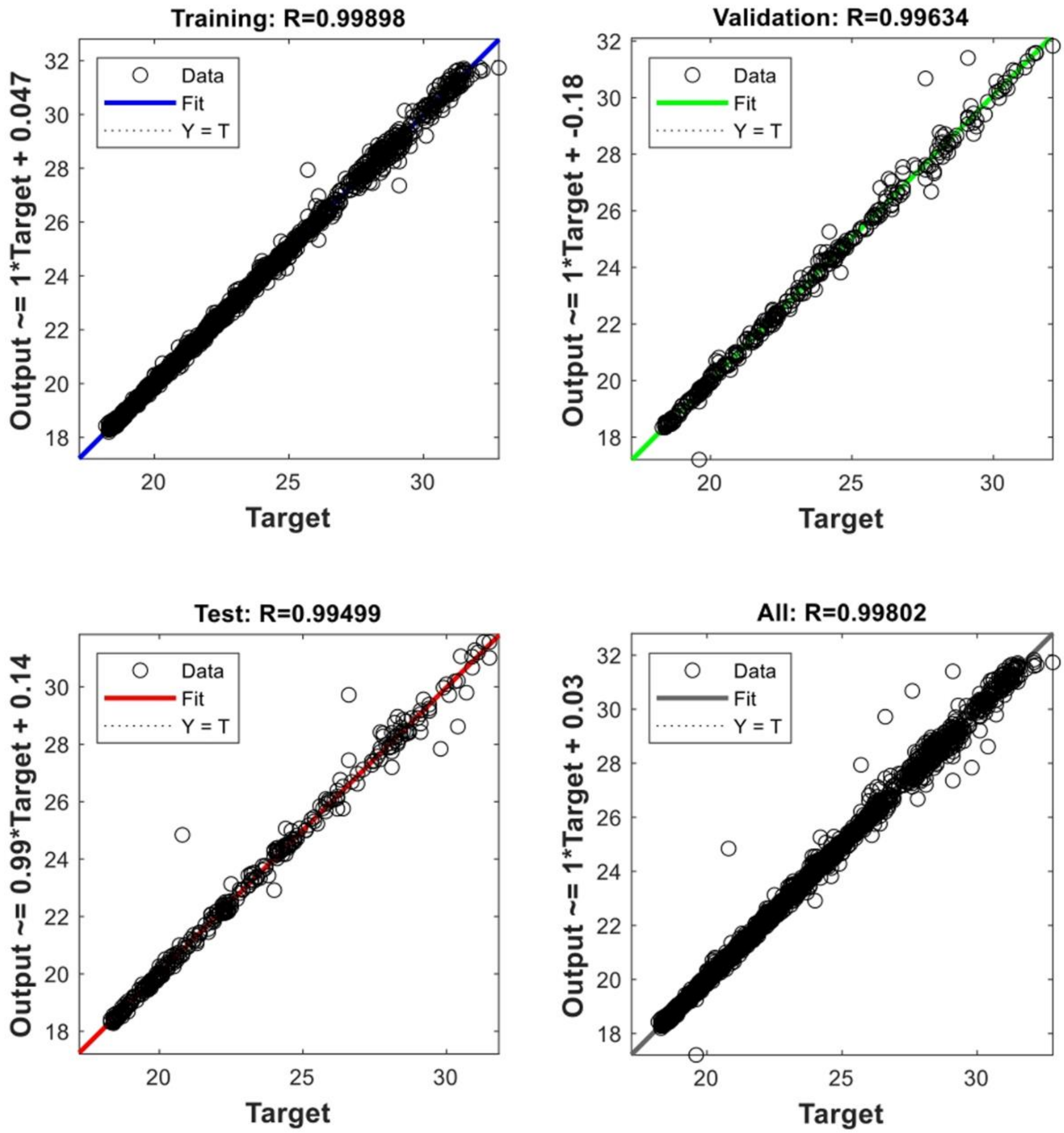

Figure 12 Evolution training, test, validation, and global error

The accuracy of the developed model was sensitive to the number of hidden neurons in the neural network. Table 2 shows R^2 values for different numbers of hidden neurons. It also shows the MSE and R^2 values at various training and validation stages. The best network architecture tested was [8 × 10 × 1]. This means 8 input neurons, 10 hidden neurons, and 1 output neuron. The R^2 value and the number of neurons had a consistent relationship. It shows that the model's predictive accuracy improved with this neuron configuration. MSE was the loss function in this study.

It evaluated the neural network's performance. It did this by measuring the average squared difference between observed and predicted values. When we compare our results with existing literature, the performance of this neural network model stands out.

Typically, studies report R^2 values ranging from 0.85 to 0.95 for various predictive models. For instance, Vala et al., (2016) achieved an R^2 of 0.95 using deep learning for a similar task. And Watson et al., (2019) reported an R^2 of 0.93 with a different neural network. In contrast, our study got R^2 values of 0.99898, 0.99634, and 0.99499. These values surpass those and show better model performance.

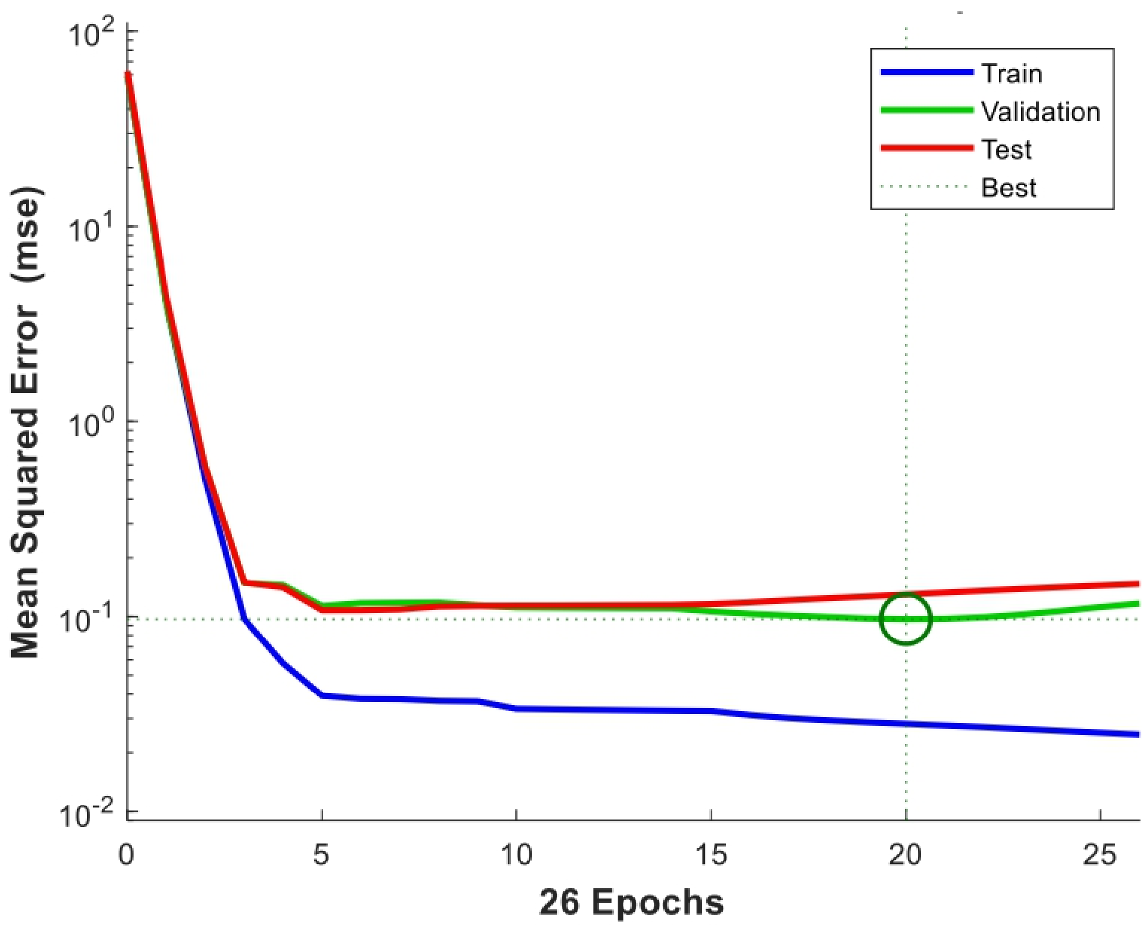

Figure 13 Best Validation Performance Chart

Table 2 Statistical parameters

No. of Neurons	Training		Validation		Testing		Overall R^2
	MSE	R^2	MSE	R^2	MSE	R^2	
10	0.2654	0.99293	0.2625	0.99279	0.2321	0.99179	0.99275

Neural network literature shows the impact of hidden neurons on model accuracy. Optimizing their number enhances performance, as our findings confirm. The best architecture is [8 × 10 × 1]. It follows a trend seen in another research. Tuning the network's architecture boosts predictive accuracy. In summary, our neural network model has exceptional predictive accuracy. It's high R^2 values and low MSE show this. These results compare well with current studies. They highlight the model's effectiveness in predicting outcomes across different setups.

4. CONCLUSION

This study aims to predict and control the temperature inside an agricultural greenhouse. The study's experiment compares an agricultural greenhouse with a cooling system to a control one. We observed the system's success in the experimental greenhouse. It did better than the control greenhouse. This was clear in the average internal temperature. The control greenhouse reached 40 degrees

Celsius. The experimental one kept a lower temperature during the data collection period. The solar-powered cooling system, with pillows and fans, reduced internal temperatures. Also, the steam cooling system's activation increased humidity. This made a good atmosphere for crop growth in the area. The greenhouse design includes foldable side openings. It also has anti-insect screens on hatches and doors. They protect against insects that could harm products or transmit diseases to plants. Shading techniques are also used to cut solar radiation. This leads to a significant temperature decrease.

Windbreaks installed around the greenhouse reduce wind speed and prevent sand encroachment. A strong wind of 65 km/h damaged and moved the control greenhouse, demonstrating this. The experimental greenhouse stayed undamaged. This system provides a good atmosphere for plant growth. It works in hot, dry climates and solves common agriculture problems. We've used artificial intelligence tools. Specifically, we used a neural network. They let us predict the greenhouse's internal temperature using data collected over a month. We assessed the efficiency of the model using statistical calculations such as MSE and R2. In conclusion, many external factors influence the greenhouse's microclimate. These include wind speed, temperature, solar irradiation, and the greenhouse's location and cover. The location can be Mediterranean or Saharan. As a future perspective, we recommend testing this system on a farm in our region.

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We thank the participants who all contributed to the study.

Authors Contribution

Djemoui Lalmi: Research concept and design.
Kamel Bouaraour: Writing the article.
Abdelouahab Benseddik: Data analysis and interpretation
Ahmed Badji: Data analysis and interpretation.
Hocine Bensaha: Critical revision of the article.
Abdeslem Kifouche: Data analysis and interpretation.
Khadidja Khodja: Collection and assembly of data.

Ethical approval

Not applicable.

Informed consent

Not applicable.

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Conflict of Interest

The author declares that there are no conflicts of interests.

Data and materials availability

All data associated with this study are present in the paper.

REFERENCES

1. Al-Sulaiman FA. Evaluation of the performance of local fibers in evaporative cooling. Energy Convers Manag 2002; 43(16):2 267-2273.
2. Aziz RA, Zamrud NF, Rosli N. Comparison on the cooling efficiency of cooling pad materials for an evaporative cooling system. J Mod Manuf Syst Technol 2018; 1(1):61-68. doi: 10.15 282/jmmst.v1i1.199

3. Doğramacı PA, Aydın D. Comparative experimental investigation of novel organic materials for direct evaporative cooling applications in hot-dry climate. J Build Eng 2020; 30 (11):101240. doi: 10.1016/j.jobe.2020.101240
4. Helmy MA, Eltawil MA, Abo-shisha RR, El-Zan NM. Enhancing the evaporative cooling performance of the fan-pad system using alternative pad materials and water film over the greenhouse roof. Agric Eng Int: CIGR J 2013; 15(2):17 3-87.
5. Kassem AM, Bahnassy AM, Sharobeem YF. The Effect of Pad Cooling Materials on Environmental Control for Greenhouses. Egypt J Agric Res 2005; 83(1):361-371. doi: 10.21608/ejar.2005. 242807
6. Koca RW, Hughes WC, Christianson LL. Evaporative cooling pads: test procedure and evaluation. Appl Eng Agric 1991; 7 (4):485-90. doi: 10.13031/2013.26250
7. Lalmi D, Benseddik A, Bensaha H, Bouzaher M, Arrif T, Guermoui M, Rabehi A. Evaluation and estimation of the inside greenhouse temperature, numerical study with thermal and optical aspects. Int J Ambient Energy 2021; 42(11):1269-80.
8. Liao CM, Singh S, Wang TS. Characterizing the performance of alternative evaporative cooling pad media in thermal environmental control applications. J Environ Sci Health Part A 1998; 33(7):1391-417. doi: 10.1080/10934529809376795
9. Mahmood DMN, Aljubury IMA. Experimental investigation of a hybrid photovoltaic evaporative cooling (PV/EC) system performance under arid conditions. Results Eng 2022; 15(1):1 00618. doi: 10.1016/j.rineng.2022.100618
10. Malli A, Seyf HR, Layeghi M, Sharifian S, Behravesh H. Investigating the performance of cellulosic evaporative cooling pads. Energy Convers Manag 2011; 52(7):2598-603. doi: 1016/j.enconman.2010.12.015
11. Nada SA, Fouda A, Mahmoud MA, Elattar HF. Experimental investigation of energy and exergy performance of a direct evaporative cooler using a new pad type. Energy Build 2019; 203(15):109449. doi: 10.1016/j.enbuild.2019.109449
12. Sellam SH, Moummi A, Mehdid CE, Rouag A, Benmachiche AH, Melhegueg MA, Benchabane A. Experimental performance evaluation of date palm fibers for a direct evaporative cooler operating in a hot and arid climate. Case Stud Therm Eng 2022; 35:102119. doi: 10.1016/j.csite.2022.1021 19
13. Shaik NB, Pedapati SR, Taqvi SAA, Othman AR, Dzubir FAA. A feed-forward back propagation neural network approach to predict the life condition of a crude oil pipeline. Process 2020; 8(6):661. doi: 10.3390/pr8060661
14. Singh S, Singh DS, Kumar S. Modified mean square error algorithm with reduced cost of training and simulation time for character recognition in backpropagation neural network. Proceedings of the International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2013; 137-145.
15. Smith CJ, Kramer RJ, Myhre G, Alterskjær K, Collins W, Sima A, Boucher O, Dufresne JL, Nabat P, Michou M, Yukimoto S, Cole J, Paynter D, Shiogama H, O'Connor FM, Robertson E, Wiltshire A, Andrews T, Hannay C, Miller R, Nazarenko L, Kirkevåg A, Olivié D, Fiedler S, Lewinschal A, Mackallah C, Dix M, Pincus R, Forster PM. Effective radiative forcing and adjustments in CMIP6 models. Atmos Chem Phys 2020; 20 (16):9591-9618. doi: 10.5194/acp-20-9591-2020
16. Taki M, Ajabshirchi Y, Ranjbar SF, Matloobi M. Application of Neural Networks and multiple regression models in greenhouse climate estimation. Agric Eng Int: CIGR J 2016; 18 (3):29-43.
17. Vala K, Kumpavat MT, Nema A. Comparative performance evaluation of evaporative cooling local pad materials with commercial pads. Int J Eng Trends Technol 2016; 39(4):198-203. doi: 10.14445/22315381/IJETT-V39P234
18. Watson JA, Gómez C, Bucklin RA, Leary J, McConnell DB. Fan and Pad Greenhouse Evaporative Cooling Systems: CIR1135/AE069, rev. 9/2019. EDIS 2019; 6. doi: 10.32473/edis-ae069-2019