ARTIFICIAL NEURAL NETWORK MODEL FOR MICROCLIMATE PERFORMANCE OF SOLAR GREENHOUSE WITH THERMAL STORAGE

Salah BEZARI[1*], Asma ADDA[2,3], Salem MERABTI[4], Golgen Bahar ÖZTEKIN[5]

[*1] Unité de Recherche Appliquée en Energies Renouvelables, URAER, Centre de Développement des Energies Renouvelables, CDER, 47133 Ghardaïa, Algeria

[2] Institute of Sciences, University Center of Morsli Abdellah, 42000 Tipaza, Algeria

[3] Laboratory of Biomaterials and Transport Phenomena, University of Medea, 26000 Urban Pole, Medea, Algeria

[4] Acoustics and Civil Enineering Laboratory, University of Djilali Bounaama, 44225 Khemis Miliana, Algeria

[5] Ege University, Faculty of Agriculture, Department of Horticulture, 35100 Bornova-Izmir, Türkiye

[*] Corresponding author: s.bezari@cder.dz , salahbezari@gmail.com

Greenhouses are closed environments that allow growing plants out of season. Hence, indoor conditions of greenhouses are critically important and adjuste to support plant growth. Controlling the indoor environment is essential to maintain an ideal microclimate, which directly affects plant health and, consequently, their yields. By optimizing environmental conditions inside the greenhouse, it is possible to increase yields while reducing energy consumption, taking into account information from both indoor and outdoor environments, as internal parameters are influenced by the external environment. Therefore, the main objective of this study is to create a predictive model of key variables, including indoor air temperature and relative humidity, in a greenhouse equipped with an integrated thermal storage system located in southern Algeria (in Ghardaïa). The greenhouse's microclimatic data were gathered daily for two months during the winter period. A total of 2833 input samples were collected and analyzed based on the Levenberg-Marquardt training algorithm model. This model uses meteorological variables as inputs and evaluates them with Artificial Neural Network techniques. The back-propagation neural network training was divided into three sets for testing (15%), validation (15%) and training (70%). The results of applying neural network technology proved highly satisfactory in predicting indoor temperature and relative humidity, with correlation coefficients estimated at 0.984 and 0.975 respectively, enabling successful management of the indoor environment for optimal yield.

Key words*: artificial neural network, greenhouse, thermal storage, temperature, microclimate, sensitivity analysis*

1. Introduction

The global nature of the energy challenges in arid and semi-arid areas requires that particular emphasis be placed on the management and rational use of local renewable energy sources in various activities as industrial, agricultural and environmental. Exploiting solar energy is a priority in the agricultural sector, and is especially valuable when it comes to meeting the energy needs for heating or cooling greenhouses. Greenhouses are complex and multifunctional systems where plants are grown outside their natural season and can create a microclimate suitable for agricultural production. They can be considered confined environments in which multiple components exchange energy and matter. Their thermal behavior is influenced by several factors [1, 2]. Thermal storage improves the greenhouse microclimate, making it more sustainable and efficient [3], which in turn contributes to higher agricultural yields.

According to the latest statistics, there are approximately 3.64 million hectares of greenhouses in the world [4]. Greenhouse agriculture in Algeria plays a crucial role in the country's economy. The country has enormous solar potential and vast agricultural lands, ebanling a significant expansion of greenhouse cultivation from 7,859 hectares in 2010 to 21,025 hectares in 2022 [5]. Although renewable energy is widely used to power greenhouses, there is insufficient focus on properly monitoring and managing indoor environmental factors, such as temperature and humidity. Therefore, the intelligent control and management of greenhouses are paramount.

Many research studies have focused on controlling the indoor climate of the greenhouse with different modelling approaches such as physical-law greenhouse models [6, 7], simulation by computational fluid dynamics [8, 9], and artificial intelligence-based prediction methods [10, 11]. Artificial Neural Network (ANN) models are powerful predictive tools for the relationship between external climate data and those inside the greenhouse by analyzing diverse factors such as temperature [12], solar radiation [13], relative humidity [14], and CO2 concentration [15]. Lee et al. [16] develops AI-GECS, an automated system integrating weather and microclimate forecasts with AI to optimize greenhouse conditions. It was tested in an experimental greenhouse in Taiwan, demonstrating improved agricultural management by reducing costs and increasing efficiency. The results confirmed its potential for more sustainable and climate-resilient agriculture. Seginer et al. [17] have presented neural network models for controlling greenhouse climate. The ANN model is a useful method: as a model for optimal environmental control and as a screening tool for physical model development. Zeng et al. [18] have used ANNs for predicting two parameters in greenhouse microclimate, temperature and relative humidity. They have taken into consideration solar radiation, wind speed, carbon dioxide concentration, heating, ventilation, and carbon dioxide injection. Furthermore, Laribi et al. [19] used multimode modeling and neural networks to predict greenhouse microclimates based on external factors. This highlights the benefits of integrating ANN into smart greenhouse control systems. Interesting results were obtained by Petrakis et al [20]. The model created by using ANN for the greenhouse gave the lowest error value between the observed and predicted data. In a study by Taki et al. [21] ANN and SVM models were compared to estimate air, soil, and plant temperatures in a polyethylene greenhouse in Iran. The results showed that the ANN model outperformed the others, providing accurate predictions with low root mean square error (RMSE) and mean absolute error (MAE) values, ensuring a reliable estimation of energy loss.

From the literature review, it can be observed that the ANN method is rarely used in greenhouses equipped with heating or cooling systems. However, the exploration and use the artificial neural network approach to analyzing the internal environment of an integrated greenhouse with a solar thermal storage system have not been thoroughly and comprehensively investigated, despite its critical role in optimizing and localizing thermal storage in its various forms. Although ANN models are increasingly applied in greenhouse microclimate prediction, the most existing studies focus on conventional greenhouses without incorporating energy storage systems or real experimental data. In contrast, this study proposes a novel approach by applying ANN modeling to a greenhouse equipped with a rock-bed thermal storage system, based on a comprehensive dataset collected under real climatic conditions in a semi-arid region. This integrated modeling and data-driven analysis provide a more realistic and energy-efficient solution, addressing the combined effects of climatic variables and thermal storage behavior. Furthermore, the inclusion of sensitivity analysis enables the identification of dominant environmental drivers, offering valuable guidance for improved greenhouse design and intelligent climate control strategies.

Considering the above, the aim of this work is to use artificial neural networks to create a model that allows precise control, in particular prediction of climatic parameters, such as indoor temperature and relative humidity, inside a greenhouse equipped with thermal storage through a rock bed, constructed at the Applied Research Unit for Renewable Energies (URAER) in Ghardaia/Algeria. This model forms the basis for further research on microclimate control, providing valuable insights for future designers and builders of advanced greenhouses with thermal storage systems.

2. Materiel and methods

2.1. Experiment site and materials

In this study, an experimental tunnel greenhouse equipped with a thermal storage system was implemented in the (URAER), which is situated 20 km of Ghardaïa, Algeria. It is located at an altitude of 469 m above sea level, with a latitude of 32°38' N and a longitude of 3°81' E (Fig. 1). Solar energy and daily heat storage were harnessed within a rock-bed heat storage system using the sensible heat storage technique.

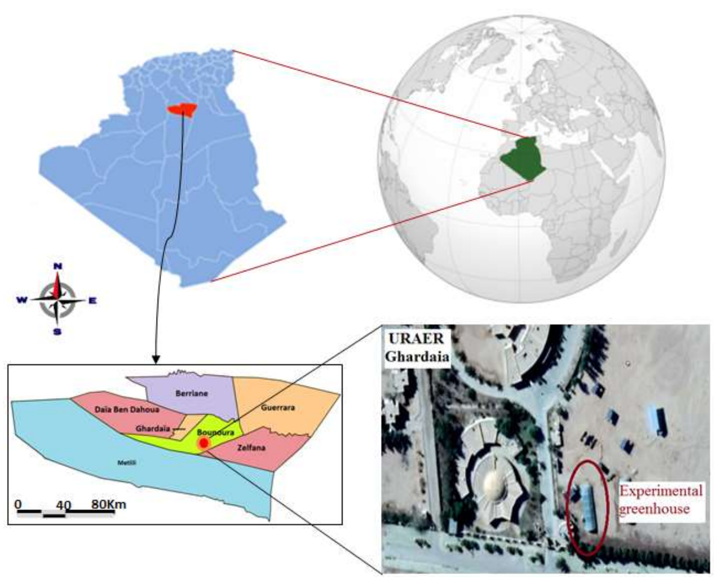


Figure 1. Location geographical of the experiment

The greenhouse had a semi-cylindrical shape and was oriented north-south, with a slight deviation of approximately 20 degrees to the west. It was covered with a 0.18 mm thick low-density polyethylene material containing ultraviolet and infrared stabilizers to protect the plants inside. The tunnel greenhouse measured 8 m in width, 25 m in length, and 3 m in height.

During the data collection process, microclimatic parameters such as temperature, relative humidity, and solar radiation were analyzed and recorded inside and outside the greenhouse. An Automatic Weather Station (WS2 550) from La Crosse Technology was installed to monitor air temperature, relative humidity, and atmospheric pressure in the greenhouse. Global solar radiation transmitted through the cover is monitored with the use of pyranometer situated just above the crops and it is connected to data acquisition unit of Agilente (34970A type). The sensor of the pyranometer is basically, thermocouples of white and black type having EPPLY model 8-48 (serial N° 27037). It measures the global radiations inside the greenhouse on horizontal surface with 1% precision and sensibility approximately of 9.94 10^{-6} $V/W.m^{-2}$. A radiometric station solys2 with a KYPP and ZONEN pyranometer measured the global solar radiation on a horizontal surface outside the greenhouse (Fig. 2). Metrological station automatically recorded outside temperature, relative humidity, wind direction, and wind speed. To provide a comprehensive understanding of the experimental setup and measurement equipment used in this study, the following description has been structured in accordance with the relevant literature [22].

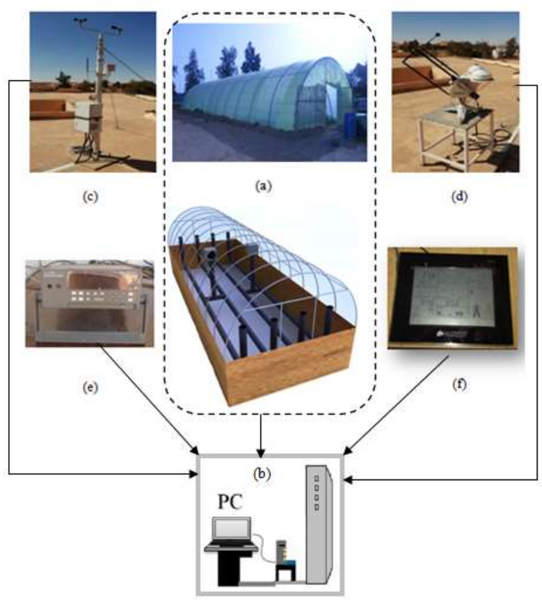


Figure 2. An overview of all the experiments: (a) greenhouse with storage system, (b) shelter/server, (c) meteorological station, (d) radiometric station, (e) agilente device and (f) comsol station wse-550

To accurately control and predict the inside temperature and relative humidity, an Artificial Neural Network (ANN) algorithm was utilized. In this study, a total of 2833 data samples were used, and six meteorological variables serving as input parameters: outside temperature (°C), relative humidity (%), wind speed ($m\ s^{-1}$), wind direction (degrees) and solar radiation ($w\ m^{-2}$) from the both side of the greenhouse. The inside temperature and relative humidity were considered as the target outputs.

Daily data analyses of meteorological parameters measured outside the greenhouse are presented in Figures 3(a), 3(b), 3(c) and 3(d). As shown in fig. 3(a), the minimum and maximum temperatures ranged from 1.5°C to 13°C and from 14°C to 26°C, respectively. Relative humidity exhibited daily minimum and maximum values of approximately 16% and 87%, as illustrated in Fig. 3(b). Regarding global solar radiation, measurement data indicate that irradiation values are high during the summer months and relatively low during the winter season, as depicted in Fig. 3(c). Additionally, wind speed, as shown in Fig 3(d), was randomly distributed throughout the year.

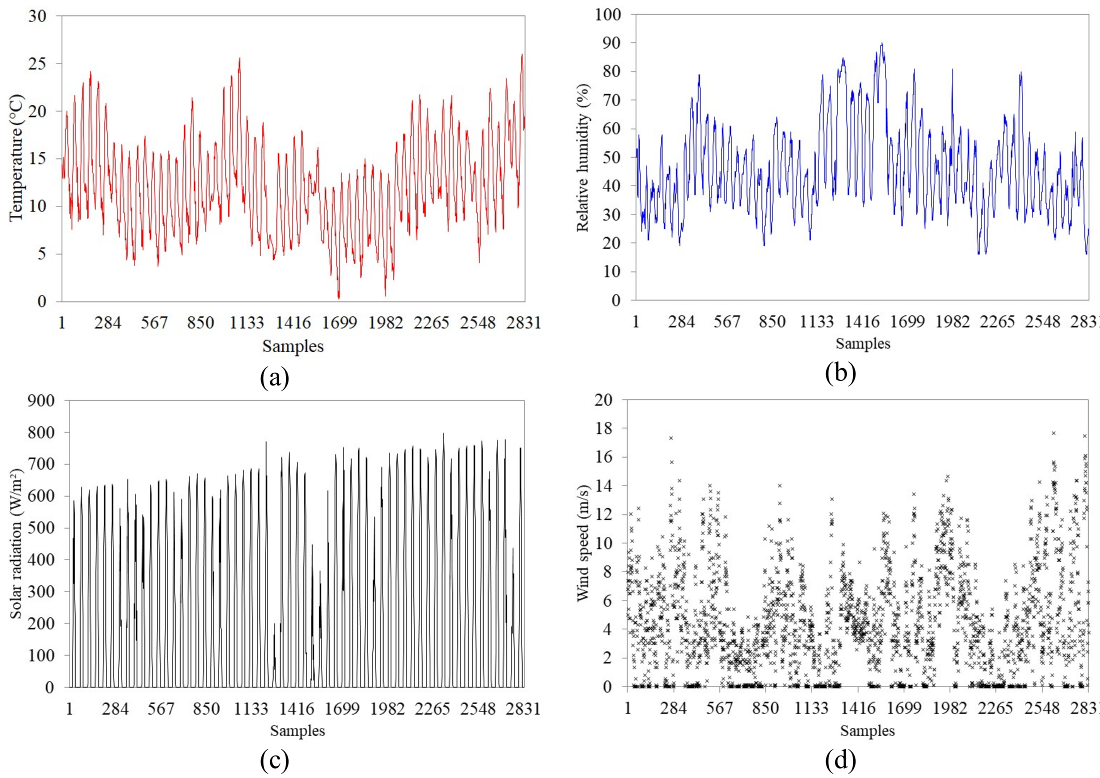


Figure 3. The inputs parameters meteorological of the ANN: (a) air temperature (b) relative humidity, (c) solar radiation (d) wind speed

As shown in Table 1, the inputs and outputs database underwent static analysis. The values of standard deviation (STD), mean, minimum (Min), and maximum (Max) have been displayed.

Table 1. Factors statistics of inputs and outputs

Factors	STD	Mean	Min	Max
Outside radiation	241.85	164.93	0	798.50
Outside temperature	4.718	12.05	0.3	26
Outside humidity	15.30	45.83	16	90
Wind speed	3.63	4.29	0	17.65
Wind direction	117.61	194.25	0	355
Inside radiation	176.55	120.40	0	582.90
Inside temperature	9.645	18.08	3.1	44.1

Inside relative humidity	15.84	41.67	11	82

2.2. Modelling with Neural Network

Recently, artificial neural networks (ANNs) have gained widespread recognition across various engineering fields for their effectiveness in modeling non-linear relationships between input and output data. In agriculture, particularly in greenhouse systems, ANNs are increasingly utilized. According to the literature, they often produce better analytical results than conventional statistical methods [23] and provide an appropriate control strategy for process optimization.

The feed-forward neural network (FFNN) was chosen for its high performance, primarily due to its strong ability in modeling complex nonlinear relationships, which is particularly relevant for greenhouse microclimate prediction. Given the complex interactions between outdoor climatic conditions (temperature, solar radiation, wind) and indoor variables (air temperature and humidity), FFNN provides an effective predictive framework for capturing these dependencies. This architecture was selected due to its fast convergence, multi-input multi-output capability, and proven effectiveness in prior agricultural studies [21, 24]. Additionally, the Levenberg-Marquardt algorithm was used to optimize training performance, ensuring reliable predictions with minimal error. The organization of artificial neurons occurs in a layered manner, and the relationship is represented by eq. (1):

$$x_{norm} = \frac{2(x_i - \min(x_i))}{\max(x_i) - \min(x_i)} - 1 \quad (1)$$

The proposed ANN architecture is given in Fig. 4. The model consist of seven neurons in the input layer, twenty-four neurons in the hidden layer and two neurons in the output layer. Inner, outer irradiation, outside relative humidity and temperature, wind speed/direction and time were selected for input data. The output are the inside air temperature and relative humidity of greenhouse.

In this study, 2833 datasets were collected for training and testing. 70% of the data was used for training, and 15% each for validation and testing, selected randomly. The ANN models were implemented in MATLAB to evaluate performance. The proposed ANNs were implemented in Matlab software to evaluate the developed models' performance.

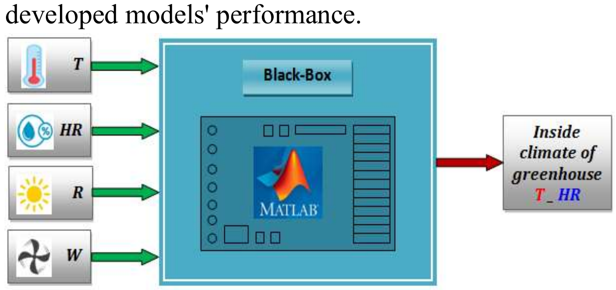


Figure 4. ANN architecture of the present work

Several statistical methods have been used in the literature to evaluate the robustness of ANN models [25], the correlation coefficient R is one of the most stringent criteria for comparing the final performance of different networks.The root mean square error (RMSE) is used as a criterion for minimizing errors during network optimization, while mean absolute error (MAE) is calculated for the predicted inside air temperature and relative humidity. Additionally, other statistical measures such as the mean absolute percentage error (MAPE) or the coefficient of determination R² can provide a more comprehensive assessment of performance. The equation used to express these statistical parameters are listed below:

$$R = \frac{\sum_i (y_{\exp} - \overline{y_{\exp}})(y_{cal} - \overline{y_{cal}})}{\sqrt{\sum_i (y_{\exp} - \overline{y_{\exp}})^2} (\sqrt{\sum_i (y_{cal} - \overline{y_{cal}})^2}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_{\exp} - y_{cal})^2} \tag{3}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \left| (y_{\exp} - y_{cal}) \right| \tag{4}$$

$$MAPE = 100 \frac{1}{N} \sum_{i=1}^{N} \left| \frac{(y_{\exp} - y_{cal})}{y_{\exp}} \right| \tag{5}$$

3. Results and discussion

3.1 The ANN model performance analysis

Due to its fast convergence and high network performance, the trainlm algorithm of Levenberg-Marquardt was used in this study. This choice is justified by the algorithm's ability to achieve the highest correlation coefficient while minimizing errors. The Levenberg–Marquardt back- propagation algorithm used to determine the optimal network structure, expressed through the transfer function which connects the inputs (x1,……,x7), weights and bias. The relationship between these variables is described by the following equation:

$$Z_j = f_h \left\lfloor \sum_{i=1}^{7} w_{ji} x_i + b_j^h \right\rfloor \tag{6}$$

Subsequently, the Logsig sigmoid transfer function (fh) was utilized in hidden layer eq. (7), while and the Tansig is the (tangent sigmoid) transfer function (fo) was applied in the output layer eq. (8). The target parameters, namely the inside air temperature (Tin) and relative humidity (Hin) are described by the output function, which is expressed by eq. (9).

$$f(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{8}$$

$$S = f_0 (\sum_{i=1}^{24} w_{ij} Z_j + b_2^0) \tag{9}$$

The mathematical equation of model is the combination of all eqs. (6), (7), (8) and eq. (9), The neural network can model and predict greenhouse parameters to optimize the internal environment.

In the current research, the neural network algorithm successfully predicted the indoor environment parameters of the greenhouse. After performing the procedure of neural training and testing the model for different numbers of hidden layer nodes the ANN multilayer feed-forward back propagation network provides the best topology (7-24-2) corresponds to (input layer - hidden layer - output layer), which gave the model the most reliability and robustness. Fig. 5 presents the topology extracted from MATLAB of the structure of the model used.

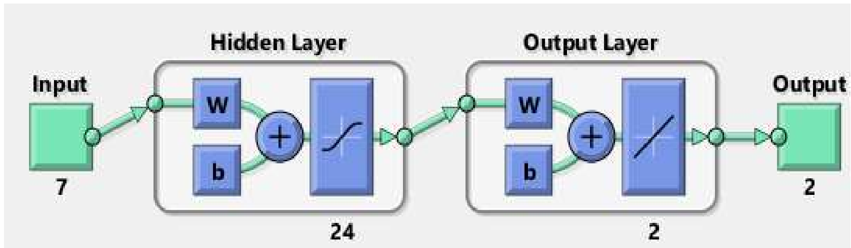


Figure 5. The optimal model of ANN architecture

The performance of the ANN model is indicated in Fig. 6 for all three phases of data at increasing epochs. It can be noted that the training MSE decreases drastically up to epoch 10 after observed stability for the three types of data up to epochs 94. The optimal neural model structure for the database is given a best MSE value of 7.8936 of sets at epoch 88. In addition, the error values for the test and validation subset exhibit similar characteristics, indicating the model's consistency and generalization capability.

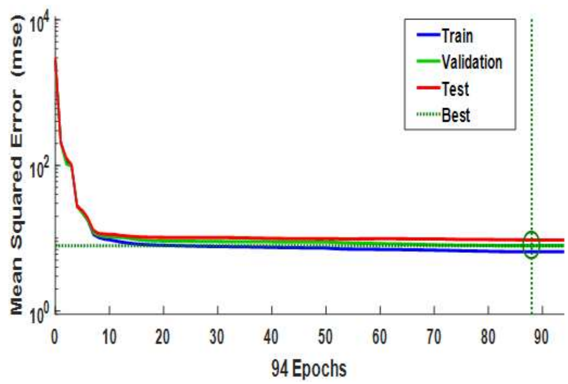
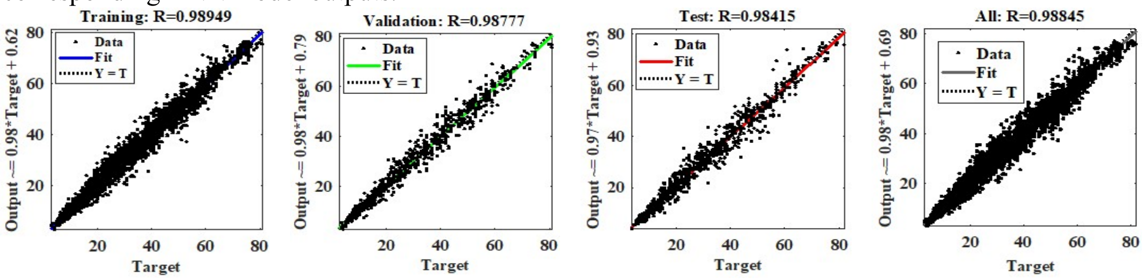


Figure 6. MSE convergence throughout different epochs

Figure 7 illustrates the regression results of the ANN training for the three phases: training, validation, and testing for both variables. Fig. (7a) displays the performance of the training phase, where the statement shows the ability of the model to predict the training data as it was used for training through the value of R, which reaches a maximum value of 0.98949. The network accurately predict the training data confirming that selecting the optimal number of input and output parameters enhances network performance. The validation process is performed once after each iteration to assess the network's performance on data. Fig. (7b) illustrates the validation dataset's arrangement where the trained network achieves an R-value of up to 0.98777. Fig. (7c) displays the generalization capability of the trained network, with a performance represented by an R-value of 0.98415 for the testing phase.

Fig. (7d) shows all data points from the training, validation, and prediction phases and their corresponding ANN model outputs.



(a) (b) (c) (d)

Figure 7. Regression plot of each phase: training, validation, testing and overall dataset

The evaluation of the model for predicting the microclimate of the solar greenhouse was performed based on the calculated errors. For the indoor temperature RMSE and MAE were found to be = 0.9680°C and 0.7258°C, respectively. Regarding relative humidity, the errors were of 3.46 % for RMSE and 2.67 % for MAE respectively. These results show that the model for predicting the two factors (inside temperature and relative humidity) of the greenhouse is satisfactory to a quite remarkable degree, at the same time we notice that there is not a big difference between the values of MAE and the RMSE indicating the absence of significant errors produced by the model for the two parameters studied according to the results indicated in Table 2.

To further evaluate the prediction performance, additional metrics such as (R^2) and (MAPE) were calculated. The high R^2 values (0.969 for temperature and 0.950 for relative humidity) indicate a strong goodness of fit, while the low MAPE values highlight the model's consistent accuracy across different data ranges.

Table 2. Statistical metrics: R, R^2, RMSE, MAE, MAPE , Linear equation: $y^{predict} = \alpha y^{exp} + \beta$

Parameters	α	β	R	R^2	RMSE	MAE	MAPE
Inside temperature	1.005	-0.086	0.984	0.969	1.67	1.257	7.83
Inside relative humidity	0.998	0.068	0.975	0.950	3.46	2.67	7.46

Fig. 8 and Fig. 9 present a comparison between the prevision results obtained by the developed ANN model and the experimental data for temperature and relative humidity inside the heated greenhouse, respectively. It is clearly observed that the predicted values closely follow the experimental trends throughout the evaluation period, indicating a strong agreement between the model outputs and real measurements. This is further confirmed by the high correlation coefficients (R = 0.984 for temperature and R = 0.975 for relative humidity) and low error values (RMSE and MAE) reported earlier. However, some minor deviations are noticeable, particularly during peak thermal storage activity periods. These discrepancies, more evident in temperature predictions, are attributed to the dynamic nature of heat release and absorption in the rock-bed thermal storage system, which introduces short-term fluctuations that are not fully captured by the current input parameters. The model's performance could be improved by incorporating additional inputs, such as storage system temperature or control timing parameters. Nevertheless, the overall strong fit of the model confirms its reliability and robustness in accurately simulating greenhouse microclimate conditions.

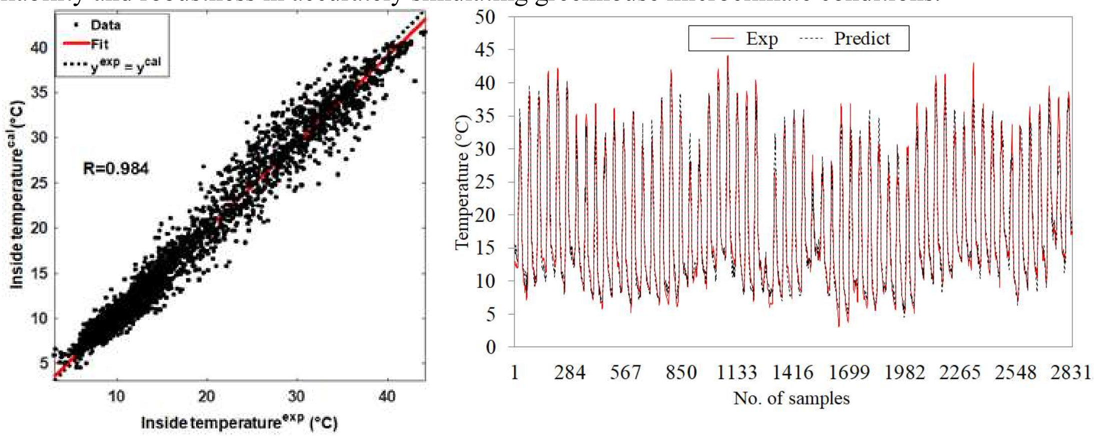


Figure 8. Comparison between experimental and estimated temperature of greenhouse

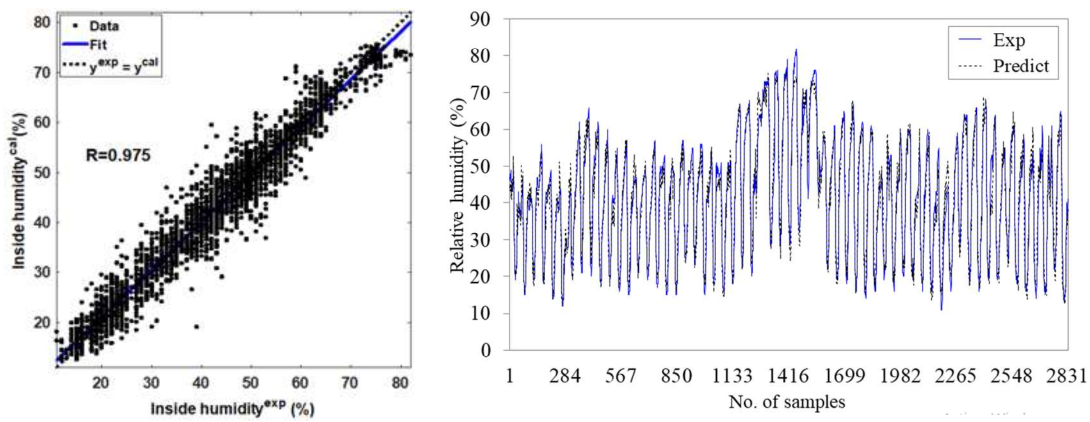


Figure 9. Comparison between experimental and estimated relative humidity of greenhouse

3.2 Sensitivity study

The study of the sensitivity of local climate parameters in the greenhouse is crucial, as it relies on formulas provided in the literature and the method originally proposed by Garson [26], which assesses the contribution of different input variables. The sensitivity analysis of the seven selected input parameters and their impact on the expected outputs was conducted by creating a weight matrix, which was subsequently applied following the approach outlined by Adda et al. [25].

According to the results of the weight method, we calculated the influence of each input factor on the target outputs in the network. By analyzing these two parameters, we were able to develop our neural network optimal to predict the prevailing indoor climate in the greenhouse, enabling effective climate control and ultimately leading to improved crop yields both quantitatively and qualitatively.

Fig. 10 present the percentages of relative importance (obtained by the weights method) of each input variable of the ANN on the relative humidity and air temperature inside the greenhouse. The phenomena of forced convection and heat transfer significantly impact the internal environment of the greenhouse. Furthermore, the sensitivity analysis revealed that outdoor air temperature, solar radiation, and indoor radiation are the most significant factors influencing the greenhouse's microclimate, with relative contributions of 18%, 15%, and 14%, respectively. These variables directly affect thermal energy accumulation and dissipation within the rock-bed thermal storage system, thus playing a crucial role in optimizing energy efficiency. The strong influence of outdoor temperature and solar radiation highlights the necessity of precise thermal management strategies to reduce energy losses and improve heating efficiency in greenhouses. Furthermore, maintaining a stable indoor temperature and humidity enhances plant growth conditions, leading to improved agricultural productivity. These findings underscore the importance of real-time monitoring and adaptive control strategies for optimize greenhouse performance in semi-arid regions.

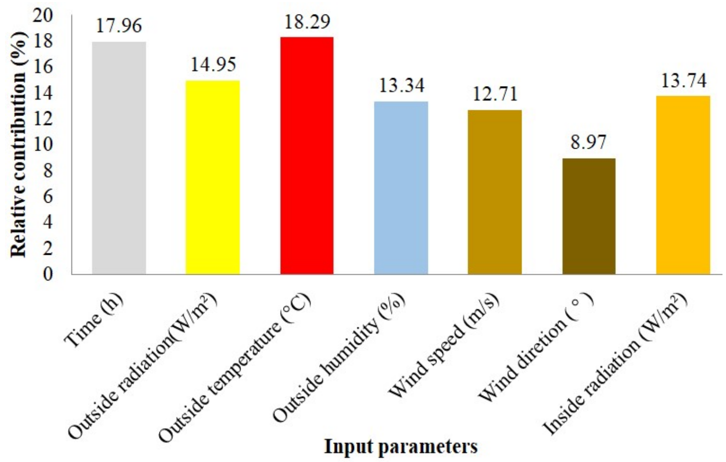


Figure 10. Influence of input parameters on the output target

Conclusion

The integration of artificial neural networks (ANN) in managing the internal environmental parameters of greenhouses offers promising prospects for modern agriculture. In this study, an ANN model was developed to enhance the microclimatic performance of a solar greenhouse equipped with a thermal storage system in southern Algeria, characterized by a semi-arid climate using outdoor meteorological data as inputs.

The neural network, based on the Levenberg-Marquardt algorithm, was structured into three distinct layers and was effective in capturing the complex climatic variations that influence the indoor conditions of the greenhouse. Validation and testing of the model revealed high correlation coefficients (R=0.984 for temperature and R=0.975 for humidity), confirming its robustness and reliability. A sensitivity study also highlighted that external ambient temperature is the most influential factor affecting indoor conditions, emphasizing the importance of precise control of this parameter.

Furthermore, the model's ability to predict key variables with high precision allowed for optimized energy management of the greenhouse**.** Enhancing thermal storage contributes to stabilizing indoor climate conditions**,** thereby improving the overall system efficiency. Future research will focus on enhancing the model by integrating it into real-time adaptive control systems, allowing automated adjustments to greenhouse parameters based on dynamic environmental conditions. Additionally, the model could be expanded and validated for different greenhouse configurations, structural materials, and climatic zones, enabling broader application across various agricultural contexts. Incorporating additional variables such as CO_2 levels, soil temperature, and plant growth feedback could also improve predictive accuracy and decision-making support in smart greenhouse systems.

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