

Original Research

Performance assessment of packed bed systems for humidity control in greenhouse applications: An experimental based AI modelling approach

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Abstract

Optimal humidity control is essential for enhancing crop yields and ensuring favourable growth conditions in greenhouse agriculture. Packed bed devices are effective tools for regulating humidity levels; however, accurately assessing their performance, especially for temperate oceanic climates, is yet explicitly unexplored. The current paper presents a packed bed system using water as the working fluid to increase humidity during winter for greenhouse cultivation. An experimental setup is developed, and a detailed parametric study is conducted. Also, an artificial intelligence (AI) based multi-layer perceptron neural network (MLPNN) is designed to evaluate the performance of packed bed systems under varying environmental conditions with different inlet air flow rates (176 m³/hr, 286 m³/hr, 383 m³/hr, and 428 m³/hr). The results show that the system achieves a significant 50% increase in humidity ratio, transitioning from an inlet humidity ratio of 6 g/kg_{da} to an outlet ratio of 9 g/kg_{da} when operating with water at an average temperature of 15.7°C and a flow rate of 12.8 kg/min. The MLPNN is trained with 112 non-repeated datasets and observed that a topology of 2-10-10-1 includes 2 input neurons, 2 hidden layers with 10 neurons each, and 1 output neuron, has high prediction accuracy in estimating $\Delta\omega_a$ values for the packed bed system. The predictions closely align with experimental data, showing a maximum discrepancy within $\pm 2.5\%$. This research advances the use of packed bed systems by providing a comprehensive framework for assessing and improving humidity control in greenhouse environments.

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Keywords: humidity control; packed bed systems; greenhouse cultivation; multi-layer perceptron neural network

1. Introduction

Traditionally, greenhouse operators have relied on various methods to control humidity, including ventilation, misting systems, and evaporative cooling. However, these approaches often lack precision and efficiency, leading to suboptimal growing conditions and resource wastage [1–4]. In recent years, packed bed systems have emerged as promising solutions for humidity management. These systems employ porous/packing materials that allow the working fluid to interact effectively and control humidity levels within the greenhouse environment.

Despite their potential benefits, the performance assessment of packed bed systems in greenhouse applications remains complex and challenging. Because of the dynamic interplay of environmental factors, such as temperature fluctuations, air flow patterns, and plant transpiration rates, comprehensive methodologies are needed to evaluate system performance and optimise operation. In this context, during the winter, the humidity level needs to be enhanced to maintain the required humidity level for optimum growth of the plants in the greenhouse.

Further, AI-based algorithms are paying attention to simulating and predicting complex systems' behaviour under varying conditions [5–8]. By training models on experimental datasets and simulation results, AI-based approaches enable accurate system performance predictions and facilitate the identification of optimal operating strategies. In the context of packed bed systems for humidity control in greenhouses, AI-based modelling can hold significant promise for enhancing the system's applicability, minimising resource consumption, and maximising crop yields.

The current study aims to investigate the packed bed system using water as the working fluid to increase humidity levels for greenhouse cultivation. Additionally, an AI-based model is developed and validated for assessing the performance of packed bed systems in greenhouse applications. To achieve this, an experimental setup is designed and constructed to provide insights into the performance of packed bed systems for a temperate oceanic climatic condition. The novelty of the current study lies in investigating the packed system in temperate oceanic climatic conditions with water as a working fluid and applying MLPNN model to predict humidity levels, which is crucial for optimising plant growth for greenhouse cultivation. The current model, focused on

inputs and output parameters, demonstrates higher accuracy in real-time humidity prediction. This research sets the stage for integrating additional parameters, such as mixing and venting, for a comprehensive climate control system. While known for its input-output fitting capability, MLPNN's application in the greenhouse can enhance automated control loops by dynamically adjusting humidifier settings to maintain optimal conditions. This targeted use of MLPNN in greenhouse climate control marks a significant advancement in precision crop cultivation practices. The specific objectives of this research are:

- To design and characterise a packed bed system for humidity management in a greenhouse environment.
- To study the packed bed system with different working conditions.
- To develop and validate AI-based models for predicting the performance of the packed bed system under various operating conditions.

By addressing these objectives, this research will contribute to advancing sustainable and intelligent humidity management solutions for greenhouse applications, with potential benefits for crop production and environmental sustainability.

2. Materials and Methods

2.1 Experimental setup and procedures

An experimental setup is designed and implemented to obtain real-time greenhouse conditions specifically for the UK environmental conditions. The current packed bed system is designed for lettuce cultivation in the greenhouse. Figure 1 details the various components and their interconnections, which work together to increase humidity levels in the greenhouse. The experimental procedures involve the installation of packing material with variations in air temperature, humidity, and flow rates. Ambient air is drawn into the system through the air inlets. The air then passes through the packed bed chamber, where the packing materials are installed. Here, the air interacts with the water, increasing the air's moisture level. The relatively humid air is then directed to the air outlet for introduction into the greenhouse environment. After releasing water vapour into the air, the water goes to the tank and is again pumped to the packed bed chamber. Data collection instruments like sensors and loggers are utilised to monitor environmental parameters and system performance.

The system is compact, with overall dimensions of 1.6 m × 0.9 m × 0.9 m, and utilises a counter-flow pattern for efficient air and water interaction. The core of the system is the packed bed, which is constructed using PVC corrugated sheets with dimensions of 0.4 m × 0.15 m × 0.4 m. The packing material of the packed bed chamber has a specific surface area

of $256 \text{ m}^2/\text{m}^3$ that facilitates effective interaction between working fluids. The system features two liquid pumps, specifically Iwaki Magnet Pumps MX-70VM-13, with a capacity range of 90–100 L/min, which circulates the water between the packed bed and the water tank. Additionally, two blowers ensure a nominal air volume of $300 \text{ m}^3/\text{h}$. The dehumidifier and regenerator are connected via 0.02 m diameter pipes, and the outlet/inlet ducts have a diameter of 0.1 m. The air velocity is measured using a Testo 405I hot wire thermo-anemometer, which has an accuracy of $\pm 0.1 \text{ m/s}$ and a range of 0 to 20 m/s. It was calibrated against a standard air velocity at the wind tunnel lab to verify its accuracy. Water temperature is monitored with a K-type thermocouple, accurate to $\pm 0.5 \text{ }^\circ\text{C}$, capable of measuring within a broad range of -200 to $1100 \text{ }^\circ\text{C}$. The thermocouple was calibrated using an ice bath for low temperatures and a temperature-controlled water bath for high temperatures, ensuring accuracy across the desired range. Air humidity is assessed with Venatronics LLC THS14-A11-30-N, which offers an accuracy of $\pm 0.6 \text{ }^\circ\text{C}$ and $\pm 2.5\%$ within a humidity range of 0 to 100% RH and an operating temperature range of $-30 \text{ }^\circ\text{C}$ to $75 \text{ }^\circ\text{C}$. Dry and wet bulb temperature readings are used to calibrate humidity sensors. Subsequently, the relative humidity values were obtained from a psychrometric chart to verify its accuracy. The water flow rate is measured by an RS 257-133 radial flow turbine flow meter, which has a similar accuracy of $\pm 2\% \text{ L/h}$ and a flow range of 1.5 L/min to 30 L/min. The corresponding calibration was performed by comparing the flow meter readings with those obtained using the catch bucket method, where the volume of water collected over a specific time period was measured.

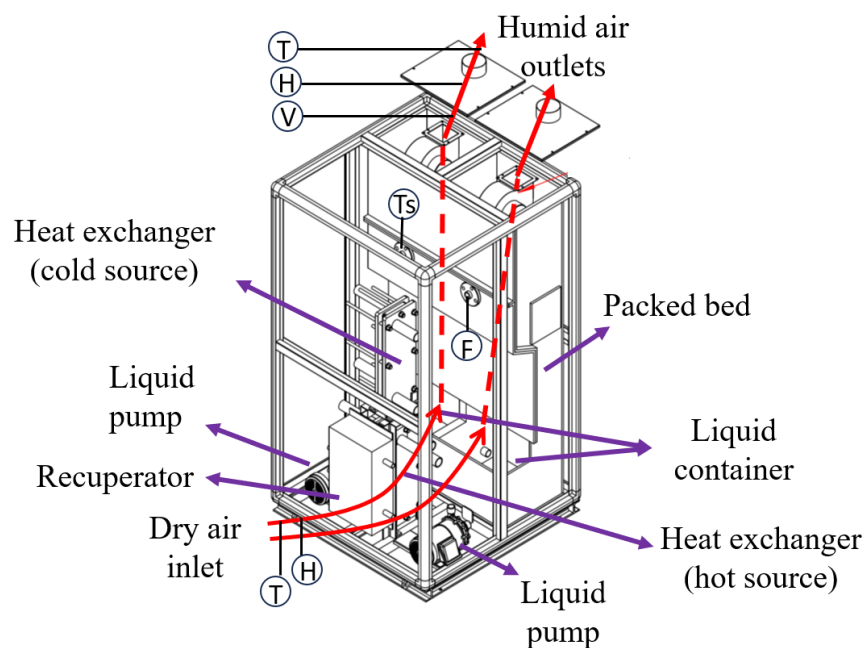


Figure 1 Schematic of experimental setup.

2.2 Methodology of intelligent models

The intelligent modelling approach involves machine learning algorithms to predict the behaviour of packed bed systems. Training datasets are generated using experimental data collected from the packed bed setups, including input parameters such as humidity, air flow rates, and corresponding output parameters representing system performance ($\Delta\omega_a$). Artificial neural network (ANN) is considered in the present study. An ANN is a standard method of artificial intelligence constructed in a manner analogous to the human brain's information-processing system. They serve as computational tools for modelling complex non-linear relationships between independent and dependent variables, with extensive applications in various energy systems as documented in existing literature [9–12]. Among the various types of ANNs, the Multi-Layer Perceptron (MLP) neural network is particularly notable for regression tasks. MLPNNs are structured with an input layer, one or more hidden layers, and an output layer, each comprising numerous units known as neurons. This architecture enables MLPNNs to perform deep learning, accurately predicting both simple and complex functional behaviours. An MLPNN is characterised by having at least three layers: the input layer, which receives the initial data; the hidden layers, which process the data through transfer functions to identify patterns; and the output layer, which delivers the final prediction. The connections between neurons across these layers are established through weights, which adjust over time to strengthen or weaken the influence of each input. Generally, the number of neurons in the input and output layers is determined by the number of input and output variables. In the hidden layers, neurons work to pattern the behaviour of the input data, ultimately influencing the predictions made by the output layer neurons [13].

Equation (1) outlines the process of adjusting the weight value for the connection between the p^{th} neuron in layer M and the q^{th} neuron in layer $(M+1)$.

$$\Delta W_{pq} = \beta \delta_q o_p \quad (1)$$

Here, β signifies the learning rate, δ_q denotes the residual error between the q^{th} neuron in layer $(M+1)$ and the p^{th} neuron in layer M , as detailed in Equations (2)–(3), and o_p represents the output value of index p in the M^{th} layer.

$$\delta_q = o_q(d_q - o_q)(1 - o_q) \quad (2)$$

where d = target value of output layer for that neuron.

$$\delta_q = T_q(1 - T_q) \sum_k \delta_k w_{kq} \quad (3)$$

where T = target value of hidden layer for that neuron.

Equation (2) serves to compute the residual error of the output layer's neuron, while Equation (3) is dedicated to the hidden layer's neuron, which significantly relies on the alteration in the weight of the k^{th} neuron in the $(M+2)$ layer adjacent to layer $(M+1)$. The adjustment of β holds paramount importance within the network dynamics: small β values entail a lower convergence rate, whereas excessively large β values tend to induce oscillations. As suggested in the literature [9], the β value can be stabilised by introducing a momentum factor into the weight equation – Equation (1). Consequently, Equation (1) transforms into Equation (4).

$$\Delta w_{qp}(n+1) = \beta \delta_q o_p + \xi \Delta w_{qp}(n) \quad (4)$$

where, n = iteration number; ξ represents a momentum factor (positive) that governs the impact of previous variations in weight values on the current direction of movement within weight space. In the present study, ξ is used with a value of 0.3. With ' n ' inputs considered in the network, the net input function 'A' can be constructed by multiplying the input values by their corresponding weights. Subsequently, the output "Y" is derived by applying a transfer function to the resulting net function, as described in Equation (5).

$$Y = F(A) = F \left[\sum_{i=1}^n X_i w_i + b \right] \quad (5)$$

In the aforementioned context, X , b , and w denote the input, bias, and weight, respectively. This procedure is elucidated through a schematic representation, as depicted in Figure 2.

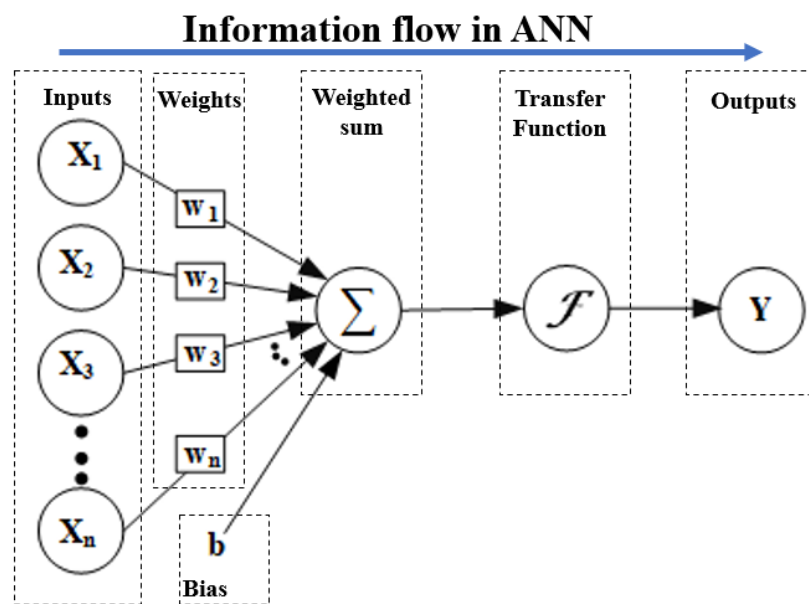


Figure 2 Schematic representation of an ANN illustrating overall model architecture and information flow.

Additionally, the output of the MLPNN model can be directly influenced by the choice of transfer (activation) function, which may exhibit either linear or non-linear characteristics. MATLAB offers three fundamental activation functions: purelin, logsig, and tansig, each tailored to different requirements. These functions are visually represented in Figure 3, accompanied by their respective function equations.

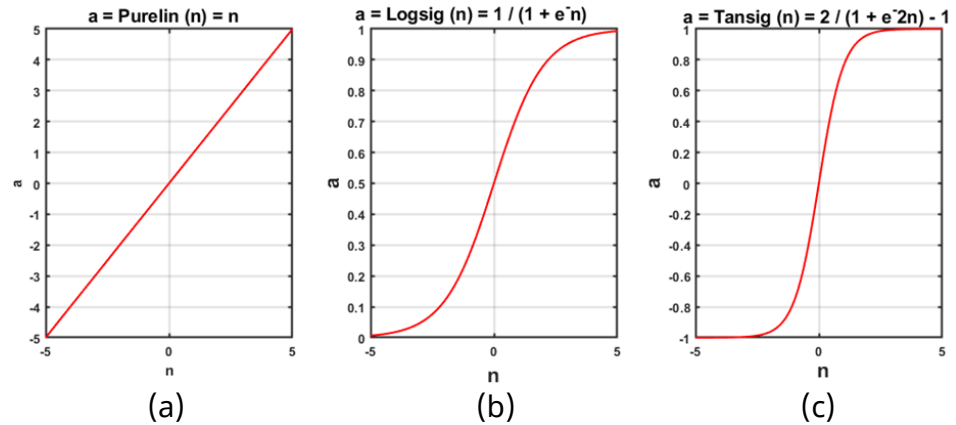


Figure 3 Comparative analysis of activation functions in ANN. (a) Purelin; (b) Logsig; (c) Tansig.

2.3 Performance parameters

Performance parameters are identified to assess the effectiveness of the packed bed systems in controlling humidity levels in the greenhouse. The critical parameter is the humidity change during the operation. This parameter is quantified based on experimental measurements and simulation results obtained from the AI-based models. Humidity change ($\Delta\omega_a$) represents the amount of water vapour added downstream of the air, and that can be expressed as Equation (6).

$$\Delta\omega_a = (\omega_{a,o} - \omega_{a,i}) \quad (6)$$

In this context, $\omega_{a,i}$ represents the specific humidity of the incoming air, while $\omega_{a,o}$ denotes the specific humidity of the outgoing air.

3. Results and Discussion

3.1 Parametric study

Figure 4 represents the real-time experimental datasets obtained from the packed bed system that tracks the system's performance. The constant air flow rate value in Figure 4 suggests that the system is designed to handle a particular air volume per hour.

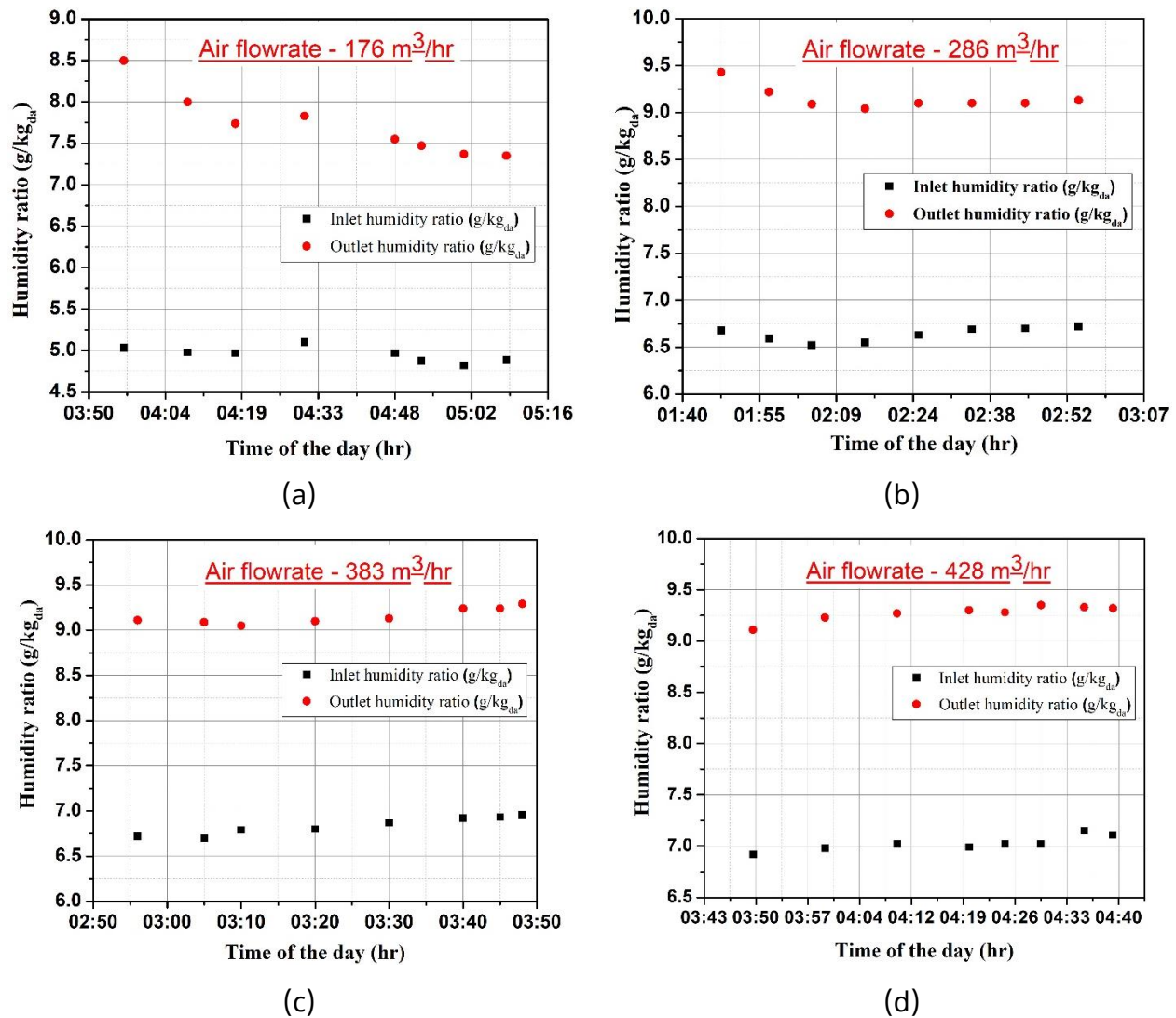


Figure 4 Effect of air flow rate on outlet humidity ratios. Inlet and outlet humidity ratios over time for air flow rates of (a) 176 m³/hr, (b) 286 m³/hr, (c) 383 m³/hr, and (d) 428 m³/hr.

Figure 4 also presents a comprehensive parametric analysis to evaluate system performance under various operating conditions. This would involve the time-average water temperature and the water flow rate. The water, with a mean temperature of 15.7 °C, circulates through the system at a flow rate of 12.8 kg/min, which is maintained in the present study. Figure 4 contains four sub-figures that illustrate the relationship between air flow rate and humidity ratio throughout different times of the day to analyse the performance of a packed bed system designed to increase the humidity level of air using water as the working fluid. Figure 4(a) corresponds to an air flow rate of 176 m³/hr. It is observed that the inlet humidity ratio remains relatively constant over the time period, while the outlet humidity ratio exhibits more variability. This suggests that the packed bed system is effectively adding moisture to the air, as the outlet humidity is consistently higher than the inlet. Figure 4(b), at an air flowrate of 286 m³/hr, shows a similar pattern, with the

outlet humidity ratio again being higher than the inlet, indicating successful humidification. Figure 4(c), with an air flow rate of 383 m³/hr, and Figure 4(d), at 428 m³/hr, both continue to display the trend of a higher outlet humidity ratio compared to the inlet. More specifically, for instance, when the inlet humidity ratio is 6 g/kg_{da} and the outlet is 9 g/kg_{da}, this would represent a 50% increase in humidity ratio due to the system's operation. In summary, Figure 4 demonstrates the effectiveness of the packed bed system in humidifying air, with the outlet humidity ratio consistently higher than the inlet across various air flow rates.

Figure 5 represents quantitative data of $\Delta\omega_a$ estimated over a specific time interval. The y-axis represents the change in a parameter denoted as $\Delta\omega_a$ (g/kg_{da}), and the x-axis represents the duration in minutes. Figure 5 includes four different flow rate conditions, as indicated by the legend: 176 m³/hr (purple line), 286 m³/hr (blue line), 383 m³/hr (red line), and 428 m³/hr (black line). The general trend of Figure 5 indicates that the parameter $\Delta\omega_a$ (g/kg_{da}) tends to decrease with time, especially at lower flow rates (176 m³/hr and 286 m³/hr). The higher flow rates (383 m³/hr and 428 m³/hr) show more stability in the parameter value over time.

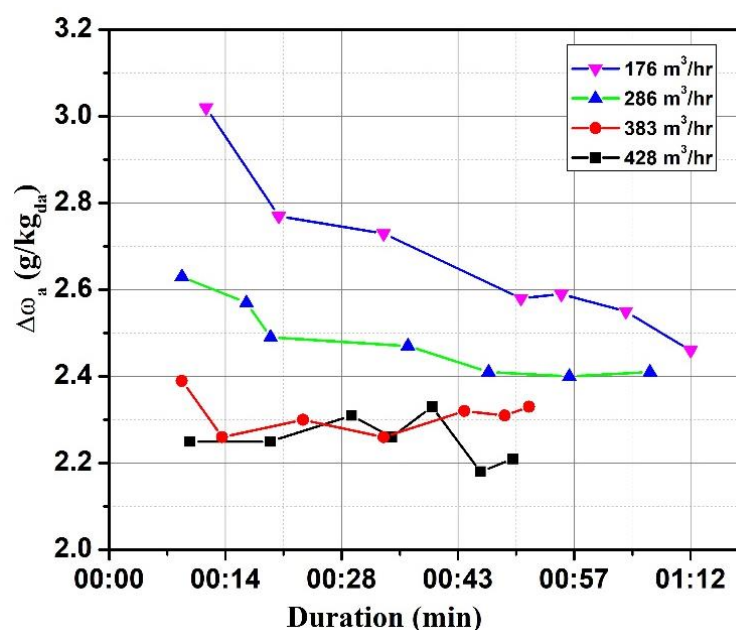


Figure 5 Effect of air flow rate on humidity change, inlet and outlet humidity ratio basis.

3.2 AI modelling and its results

The MLPNN model was trained using comprehensive datasets that included multiple parameters: inlet air flow rate, humidity ratio, air temperature, liquid flow rate, and liquid temperature. These parameters were crucial for capturing the complex interactions affecting the system's performance. However, in the context of the present study, the variations

in air temperature (16 ± 0.7 °C), liquid flow rate (12 ± 0.8 kg/s), and liquid temperature (15 ± 0.9 °C), were relatively stable. Due to these constrained variations, their influence on the model's predictions was less pronounced compared to the inlet air flow rate and humidity ratio. Therefore, the network inputs utilise two key variables, namely $\dot{m}_a$ and ω_a . To establish an accurate and resilient model, $\Delta\omega_a$ is trained through the different configurations of MLPNN. The optimum structure of the MLPNN model is depicted in Figure 6. This study employed 112 non-repeated datasets (comprising 56 input and 56 target data points) to map the input-output correlation. A feed-forward neural network, enhanced with a backpropagation learning algorithm, was employed for model training. From the total datasets, 70% were randomly selected for training purposes, while the remaining 30% were allocated for testing and validation. Various activation functions were utilised to ensure the MLPNN algorithm achieves commendable predictive accuracy. Details on the optimal hyper-parameters for the ANN model can be found in Appendix A. In the present MLPNN modelling, the primary stopping criterion used was epoch number 10,000, which monitored validation error during training and halted the process when improvements stagnated or declined, thus mitigating overfitting risks. Further, regularisation techniques were employed, specifically L1 and L2 regularisation, to penalise large weights and prevent the model from becoming overly complex. In addition, cross-validation played a crucial role; the dataset was divided into training, validation, and testing subsets. This approach allowed for hyperparameter tuning and performance evaluation, ensuring robust generalisation beyond the training datasets. The architecture, including the number of layers and neurons, was optimised based on empirical validation and domain expertise, balancing model complexity with generalisation to predict humidity variations in greenhouse conditions accurately.

The TrainLM training function was identified as the most appropriate for this present research study. The architecture of the neural networks utilised a tangent sigmoid activation function for both the output and hidden layers. To minimise the risk of overfitting during the training phase, a portion of the data samples, amounting to 15%, was allocated for validation purposes, while another 15% was set aside for testing the efficacy of the trained networks. The initial trials, which employed networks with a single hidden layer, did not yield satisfactory results due to a pronounced discrepancy between the experimental data and the predictions, attributed to the complexity of the problem at hand and regardless of other parameter settings. This observation led to the exploration of networks with multiple hidden layers for further testing and evaluation, aiming to enhance the accuracy of the predictions. Adjustments were made to the number of neurons within these layers, ranging from 8 to 12. The findings revealed that the optimal network configurations for predicting $\Delta\omega_a$ were those with two hidden layers,

specifically the 2-10-10-1 topology, which comprises two input neurons in the first layer, ten hidden neurons in each of the two hidden layers, and one output neuron, as depicted in Figure 6.

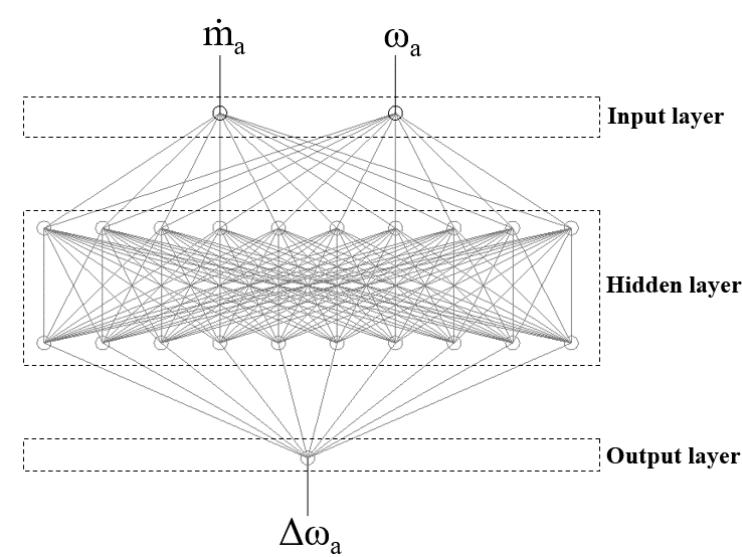


Figure 6 Structure of proposed ANN model, featuring two hidden layers, each containing ten neurons (2-10-10-1 configuration).

Figure 7 illustrates the predicted $\Delta\omega_a$ values as obtained by the MLPNN model, alongside a comparison with the corresponding experimental data. The predictive patterns of the packed bed system's output parameters generated by the AI model closely agree with the experimental outcomes across all tested conditions. The most significant observed discrepancy between the ANN predictions and the experimental $\Delta\omega_a$ values was within a margin of $\pm 2.5\%$.

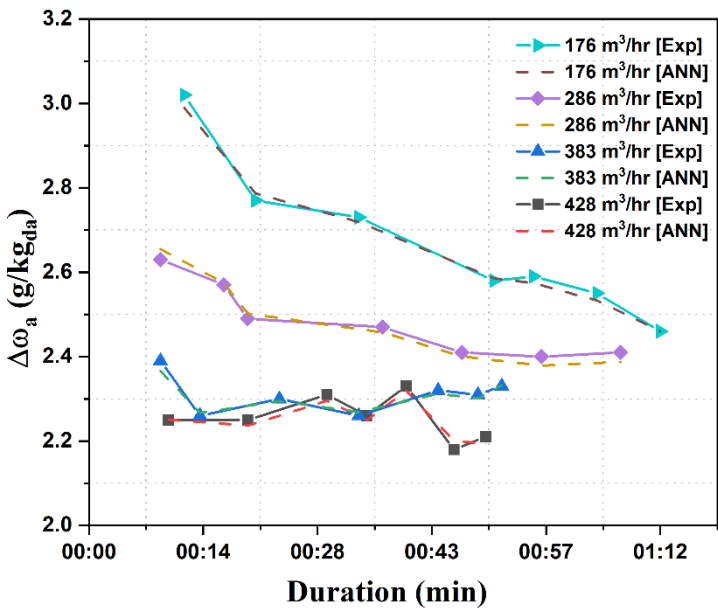


Figure 7 Comparison between experimental and AI models outcomes for $\Delta\omega_a$.

4. Conclusions

In conclusion, a packed-bed system is studied with water as the working fluid to increase the humidity level during the winter for greenhouse cultivation. Accordingly, an experimental setup is developed, and a detailed parametric study is conducted. Further, an AI-based MLPNN model is developed to evaluate the performance of packed bed systems for greenhouse applications under varying environmental conditions. Based on the findings of the present study, the following significant conclusions can be articulated:

- The packed bed system with water as a working fluid can consistently raise the outlet humidity ratio over the inlet, indicating effective humidification.
- Under the specified operating conditions, with a designed packed bed system, the outlet humidity ratio increases from 6 g/kg_{da} to 9 g/kg_{da}, representing a 50% rise in humidity. This demonstrates the system's effective capability to enhance air humidity levels using water as the working fluid, highlighting its efficiency and practical application in humidity control processes.
- The multi-layer perceptron neural network, designed to estimate $\Delta\omega_a$ precisely, demonstrated high accuracy and resilience by effectively mapping the input-output correlation.
- The optimal architecture for the MLPNN model consists of a 2-10-10-1 topology with two hidden layers, utilising the TrainLM training function and tangent sigmoid activation functions.
- The MLPNN's predictions of the $\Delta\omega_a$ values closely align with the experimental data across all tested conditions, demonstrating the model's accuracy in forecasting the packed bed system's output parameters.
- The maximum discrepancy observed between the MLPNN model's predictions and the experimental $\Delta\omega_a$ values was within a margin of $\pm 2.5\%$.

In future work, a study will be conducted on the mixing, venting, consumption, and production of humidity in the greenhouse. This research will enhance the understanding of these processes and further improve greenhouse environments' overall climate control system.

Availability of Data and Material

Dataset available on request from the authors.

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Competing Interests

Anthony Paul Roskilly is the Editor-in-Chief of the journal *Green Energy and Sustainability*. The author was not involved in the journal's review of or decisions related to this manuscript. The authors have declared that no other competing interests exist.

Author Contributions

Mrinal Bhowmik: Writing – Original Draft, Conceptualization, Methodology, Investigation, Software, Visualization, Validation, Data Curation; Alessandro Giampieri: Writing – Review & Editing, Conceptualization, Methodology, Investigation, Visualization, Data Curation; Anthony Paul Roskilly: Supervision, Funding Acquisition, Formal analysis; Zhiwei Ma: Writing - Review & Editing, Resources, Project Administration, Conceptualization, Methodology, Investigation, Visualization.

Appendix A: Details of ANN model

For the ANN in this study, the Levenberg-Marquardt algorithm, also known as TrainLM, was selected due to its superior convergence properties, particularly in regression tasks. Prior to the commencement of training, bias and weight values are assigned randomly. These values are then iteratively updated by the TrainLM function, which employs the gradient descent method to optimise the network. The training of the MLPNN model adheres to specific stopping criteria, namely a minimum gradient of 10^{-7} and a maximum of 10,000 epochs [12–16]. The ideal hyper-parameters for the MLPNN model are identified in Table A1. The tangent sigmoid function was the chosen transfer function for the output layer. Analysis of Table A1 indicates that the configuration utilising a hyperbolic tangent sigmoid transfer function for both hidden layers, with each layer containing ten neurons, results in the lowest mean squared error (MSE) when compared to other tested algorithms.

Table A1. Performance Results for Different Numbers of Neurons in Two Hidden Layers.

Model	Neurons Number	Activation function	Overall regression co-efficient (R)	Average MSE
		(layer1-layer 2)	MRR	
M1	8	purelin-purelin	0.94843	0.015191
M2	8	logsig-logsig	0.96777	0.086996
M3	8	tansig-tansig	0.97812	0.005298
M4	10	purelin-purelin	0.91429	0.025876
M5	10	logsig-logsig	0.95998	0.089812
M6	10	tansig-tansig	0.97159	0.001100
M7	12	purelin-purelin	0.95308	0.006389
M8	12	logsig-logsig	0.94268	0.052457
M9	12	tansig-tansig	0.95540	0.099106

Note: Bold indicates the optimal value.

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