A Seasonal Design Evaluation of an Earth-Air Heat Exchanger for Cooling and Heating in Saharan Algerian Regions Using ANN Model

Abdessalam Kifouche[1], Abdelmadjid Kaddour[*2], Abderrezak Guessoum[3], Medjahed Driss Meddah[4], Medjadji Nassira[4]

[1]Department of Automatics and Electromechanics, Faculty of Science and Technology, University of Ghardaia, 47000 Ghardaia, Algeria.

[2]Unité de Recherche Appliquée en Énergies Renouvelables, URAER, Centre de Développement des Énergies Renouvelables, CDER, 47133, Ghardaïa, Algeria.

[3]LATSI, University of Blida1, Algeria.

[4]Centre universitaire de Naama, Laboratoire Intelligence Artificielle pour Structures Mécaniques, Civiles et Sol 45000, Algeria.

*Corresponding author: *kaddour.majid@gmail.com*

Received October 10, 2023; Revised December 01, 2023; Accepted January 05, 2024; Published January 19, 2024

Abstract

Earth-Air Heat Exchanger (EAHE) systems leverage the consistent temperature of the ground to optimize the pre-conditioning of air for a building's ventilation. This technology involves a network of buried pipes or tubes through which outdoor air circulates before entering the building. The main objective of the paper is to study the modeling of the variation of the outlet temperature of the EAHE air-ground exchanger using neural networks. This modeling was carried out based on multilayer neural networks.

Keywords: Geothermal, ANN model, Earth-air heat exchanger, Regression.

Tob Regul Sci.™ 2024;10(1): **1358 - 1371**

DOI: doi.org/10.18001/TRS.10.1.87

Introduction

Global primary energy demand is increasing day by day, and approximately one-third of the total energy demand is essential for space heating and cooling. Therefore, most of the countries have directed towards passive and low-grade energy systems to meet their heating and cooling needs. Earth-air heat exchangers (EAHE) can be given as a good example for these energy systems. The EAHE systems are used to improve thermal conditions of buildings with less energy by utilizing the heat of the earth. Many researchers have carried out various studies regarding EAHE systems [1,2].

The conventional air conditioners (ACs) used for achieving thermal comfort conditions in offices, buildings, residential, and industries are responsible for global warming and ozone layer depletion because of the use of chlorofluorocarbons (CFCs) as refrigerants in these machines. To minimize depletion of the ozone layer and global warming and to reduce high-grade energy consumption [3].

Hasan et al. 2019, studied numerically the effect of some design parameters such as pipe diameter, inlet condition, pipe length, and outlet condition on the overall performance of the EAHE system under the climatic

conditions of Nasiriyah city in the south of Iraq [4].

Bughio et al. 2022, showed that a pipe diameter above 0.1 m is unsuitable because of the reduction in convective heat transfer due to the increase in the pipe's surface area and the decrease in pressure in the pipe. [5].

Sofyan et al. 2023, examined the performance of EAHE with several variations in design parameters, such as pipe length, pipe diameter, number of pipe bends, and the type of soil. [6].

Serageldin et al. 2016, used the thermal performance of an Earth-Air Heat Exchanger (EAHE) for heating and cooling under Egyptian weather conditions. [7]

Albarghooth et al.2023, revealed that at an air velocity of 7m/s, the length required to obtain 26 °C at the outlet of EAHE is 62.1 m which is 55% higher than the case of 29 °C (39.9m). [8]

Hasan et al. 2018, studied numerically the effect of some design and environmental parameters (moist content of soil, pipe material and thickness of pipe wall) on the overall performance of EAHE system. [9]

Molina-Rodea et al. 2023, achieved the experimental evaluation of vertical heat exchangers, and they concluded that the system is suitable for cooling purposes in areas with space restrictions. [10]

Misra et al. 2015, investigated with modeling, analyzing the effect of materials and assessing the performance of EAHE system suitable for small residential houses without open space in urban as well as rural areas with earth-pipe-air heat exchangers in open loop mode. [11]

Kaddour et al. 2022, presented a numerical study on the performance of a surface-to-air heat exchanger in desert arid regions of Algeria. [12]

Shingala et al 2022, found that in both seasons like in summer and winter; heat exchanger gives efficient result of cooling and heating result respectively. [13]

Agrawal et al. 2018, carried out a CFD-based parametric analysis in order to optimize the parameters affecting the temperature drop and heat transfer rate achieved from earth air tunnel heat exchanger (EATHE) system. [14]

Bughio et al. 2022, investigated the potential reduction in indoor temperatures via energy-efficient ventilation through EAHEs in an existing architectural campus building (ACB) with an energy-efficient renovated building envelope in the hot and humid climate of Karachi, Pakistan [15].

Kumar et al. 2003, studied whether a transient asymmetric EAT system is capable of predicting humidity and ground temperature variations accurately. The proposed model was coupled with a building model to predict the thermal performance of the building and comfort conditions [16].

Namgial et al. 2019, presented the one-dimensional simple analytical method in order to analyze the influence of the design parameters on thermo-hydraulic performance of the heat exchanger [17].

Hasan et al. 2021,showed that the heat released by heat exchanger decrease with increase the outside temperature and increase with increasing the lengths of pipe. Also, they saw a reduction with increasing in the diameter, and the coil design gives higher value of heat released by heat exchanger. [18]

Peretti et al. 2013, achieved the literature research in order to analyze the design, characteristics of earth-to-air heat exchangers and whether they could be coupled with HVAC system coupling. [19]

Al-Salihiet al. 2017, improved an ANN model in order to estimate daily soil temperature for diverse depths by employing different meteorological parameters as input in three Iraqi cities [20].

Ewim et al. 2021, detailed a short review of various heat transfer applications and the applicability of artificial neural networks in modeling of these systems [21].

Inalli et al. 2022, examined the cooling of an office building without a heat pump, using only ground heat exchangers (GHE) and implementing artificial neural network (ANN) to train it on experimental data.[22]

Mohanraj et al. 2015, reviewed the applications of ANN for thermal analysis of heat exchangers. [23]

Tan et al. 2009, reported the use of artificial neural network models to simulate the thermal performance of a compact, fin-tube heat exchanger with air and water/ethylene glycol anti-freeze mixtures as the working fluids. [24]

Zhang et al. 2010, described the development of an Artificial Neural Network based Heat Convection (ANN-HC) algorithm to predict local average Nusselt Numbers along the duct surfaces. [25]

Kumar et al. 2006, used the concept of artificial neural network and goal-oriented design to propose a computer design tool that can help the designer to evaluate any aspect of earth-to-air heat exchanger and behavior of the final configuration. [26]. Ricardo et al. 2014, revealed the convenience of using artificial neural networks as accurate predictive tools for determining convective heat transfer rates of evaporative processes. [27]

Bhattacharyya et al. 2021, describes a statistical analysis of heat transfer by developing an artificial neural network-based machine learning model [28].

This research aims to investigate the temperature of air outlet in an EAHE that contribute to the pursuit of air conditioning (building conditioning) using ANN with their ability of modeling nonlinear systems instead of using deterministic model which presents many limits in their investigation. The proposed architecture is the feed forward with back-propagation training. A Feed-Forward Back Propagation Network (FFBP) is a type of neural network architecture frequently employed for training purposes. In this network, information flows in a unidirectional manner from the input layer through hidden layers to the output layer. The Back Propagation algorithm, a supervised learning approach, is integral to the training process. It iteratively adjusts the network's weights and biases based on the disparity between the predicted output and the actual output, ultimately minimizing the error. The learning rule, governing the weight and bias adjustments, aims to achieve the most accurate mapping of relationships between inputs and outputs. The primary objective of training an FFBPN is to fine-tune the network's parameters, particularly weights and thresholds, to minimize errors in predicting output based on given inputs.

1. Geographical description of the studied region

The system under study is applied in Ouargla city, which is located in the Southeast regionof the Algerian desert with a latitude of 31°55′ 53′North and a longitude of 5°24′ 24″East, [12,29] as shown in Figure 1. Its total area is 211 980 km² and it has a dry desert climate. The temperature ranges between 24.5 to 53°C in summer and between -2 to 24°C in winter.

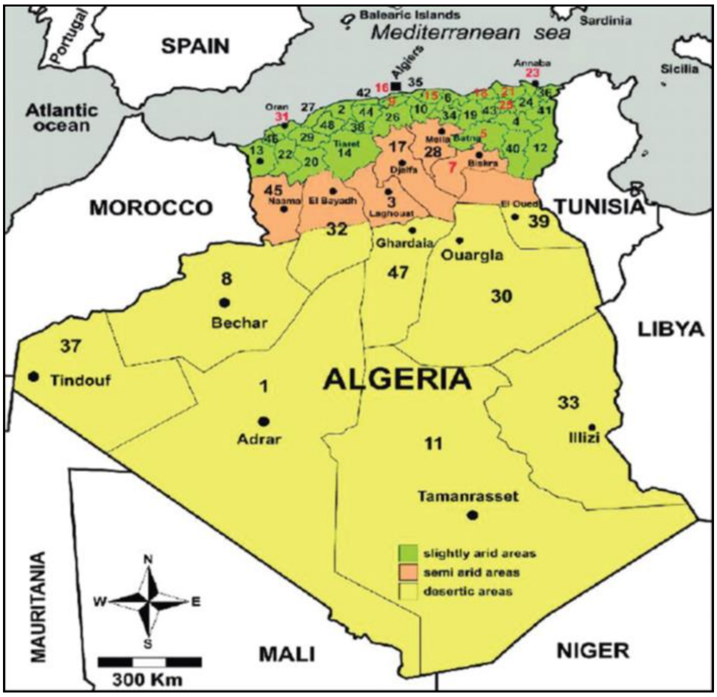


Fig 1. Case study location (Ouargla, Algeria) [12]

The Earth-Air Heat Exchanger takes advantage of the earth's stable temperature to either cool or warm the incoming air, depending on the prevailing season. This process helps reduce the reliance on traditional heating or cooling mechanisms, contributing to energy efficiency and environmental sustainability.

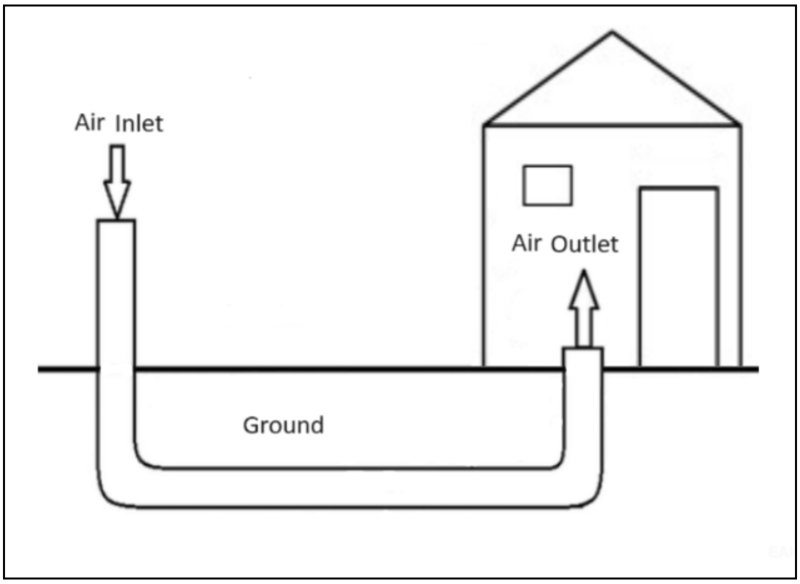


Fig 2. Diagram of EAHE system.

2. Proposed ANN architecture approach

Artificial Neural networks (ANNs) are computational models inspired by the structure and functioning of the human brain. They are composed of interconnected nodes, commonly referred to as neurons, organized into layers. The network typically consists of three main types of layers. (i) The input layer which receives the initial data, with each neuron representing a distinct feature or input variable. Input values are fed into the network to initiate the process. (ii) The hidden layer between the input and the output layers, there can be one or more hidden layers. Neurons in these layers process the input through weighted connections and activation functions. Each connection between neurons has an associated weight, which is adjusted during the training phase to optimize the network's performance and finally, (iii) the output layerwhich produces the final result or prediction. The number of neurons in this layer depends on the nature of the problem the network is designed to solve. For instance, a classification task may have as many output neurons as there are classes. The question to be asked is how is any neuron work? The idea is to calculate the weighted sum of its inputs (z) and pass it through an activation function.

$$z = \sum_{i=1}^{n}(w_i x_i) + b \qquad (1)$$

Where x_i are the inputs variables and w_i their corresponding link weights. Each stat of a neuron is biased by adding the bias b. The activation function can be linear (exp. purelin) or nonlinear (exp. logsig).

The first way includes the forward step computation of input weights and the second way is backward step computation for updating weights and calculating errors. 70% of collected data was used for the training of the ANN, whereas the rest of 30% is divided into two equal parts respectively for the testing and validation.

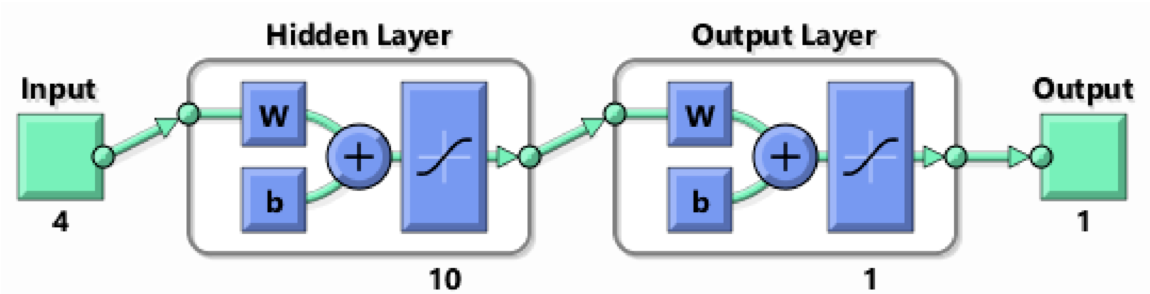


Fig 3. Feed Forward Back-Propagation neural network architecture

3. Evaluation of EAHE system by using ANN model

The table 1 exhibits the results of training and tests of Feed-forward back propagation neural networks with one hidden layer of different number of hidden neurons. Results contain the R-squared parameter of training, validation, test and overall dataset; the R-squared is described as an evaluation metric to assess how well a model fits the data. It evaluates the correctness of the model's predictions. The R-squared is statistical measure that represents the proportion of the variance in the dependent variable that is predictable from the independent variable in a regression model. An R-squared (R^2) value close to 1 indicates a good fit, while a value close to 0 suggests a poor fit of the model. The R-squared is given by equation:

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \qquad (2)$$

Wherey_i represents the actual values of air outlet temperature, $\hat{y}_i$ represents its predicted values and $\bar{y}$ is the mean of the actual values.

The best overall R-squared is given for 15 neurons in the hidden layer and the best validation MSE is given at 10 neurons in the hidden layer. It can be seen from the table that both of trained architectures achieve accuracies up to 0.99 which indicate the high levels of precision in their predictions.

Table 1: MSE and R2 of train, validation, and test.

Number of neurons in the hidden layer	R-squared				MSE
	Train	Validation	Test	overall	
5	0.99387	0.99201	0.99268	0.99342	0.05017
10	0.99377	0.99394	0.99518	0.99400	0.03924
15	0.99432	0.9934	0.99287	0.99398	0.04112
20	0.9946	0.99513	0.99134	0.99419	0.03139

25	0.99435	0.99109	0.99592	0.99408	0.06040
30	0.99439	0.99294	0.99295	0.99397	0.04739
35	0.99418	0.99466	0.99364	0.99418	0.03803
40	0.99378	0.99505	0.99334	0.99390	0.03409
45	0.99416	0.99362	0.99331	0.99392	0.04483
50	0.99436	0.99313	0.99411	0.99414	0.04737

In Figure 4, is illustrated the relationship between Mean Squared Error (MSE) and the number of epochs during a training process. The optimal validation performance was observed at epoch 337, where the MSE reached its lowest value of 0.03139. This signifies that the model demonstrated its best predictive accuracy after 337 epochs, as reflected by the minimized MSE.

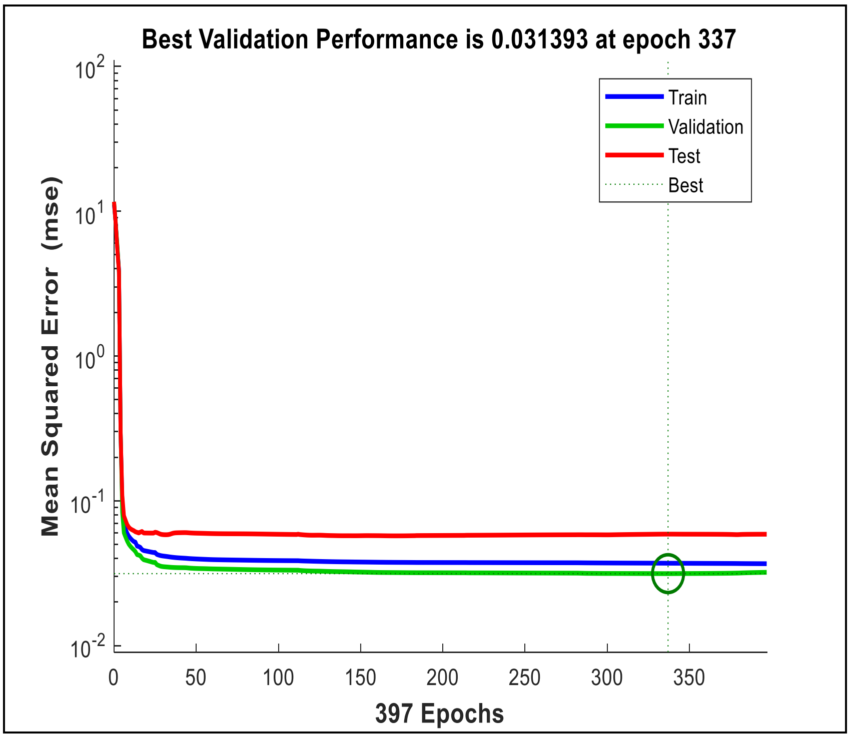


Fig 4. Training performance for 20 neurons in the hidden layer

The Mean Squared Error (MSE) exhibited noticeable fluctuations while adjusting the number of hidden neurons. This adjustment is spanned from a minimum of 5 to a maximum of 50, with increments of 5. The MSE values were computed using equation:

$$MSE = \frac{1}{n}\sum_i (y_i - \hat{y}_i)^2 \qquad (3)$$

Where n is the number of data points, y_i represents the actual values of air outlet temperature and $\hat{y}_i$ represents its predicted values.

As depicted the variation of the MSE along the number of hidden neurons in figure 5, it can be seen that the best architecture of 20 neurons in the hidden layer. The other architectures show a good performance in the prediction of the air outlet temperature.

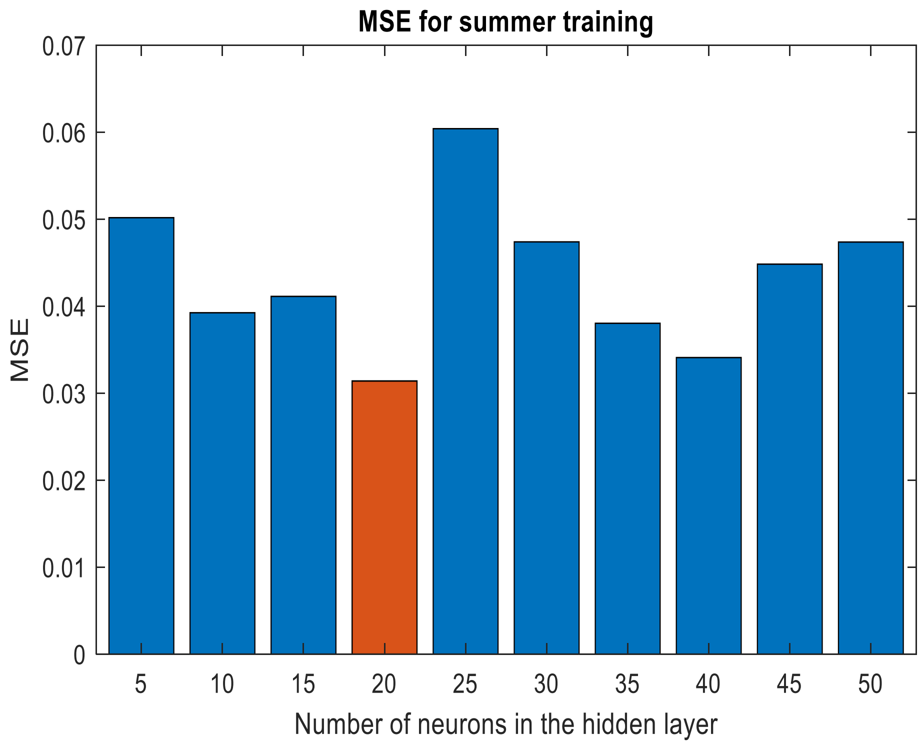


Fig 5. MSE values based on the number of neurons in the hidden layer

In Figure 6is presented a comprehensive summary of R-squared plots across various stages of the training process, about training, testing, validation and overall. In the training dataset, an outstanding overall R-squared value of 0.9946was achieved. The neural network underwent thorough training and validation utilizing historical data to construct a robust model, resulting in highly accurate predictions. The results obtained are deemed satisfactory, given the close proximity of the overall R-squared value (0.99419) to 1.0, signifying a high degree of predictive accuracy for the output. Noteworthy is the consistency observed across stages, with R-squared values in close proximity to 1.0 for each stage - 0.9946 for training, 0.99513 for validation, and 0.99134 for testing, as visually depicted in Figure 6. This uniformity underscores the reliability and effectiveness of the model in capturing intricate patterns within the dataset.

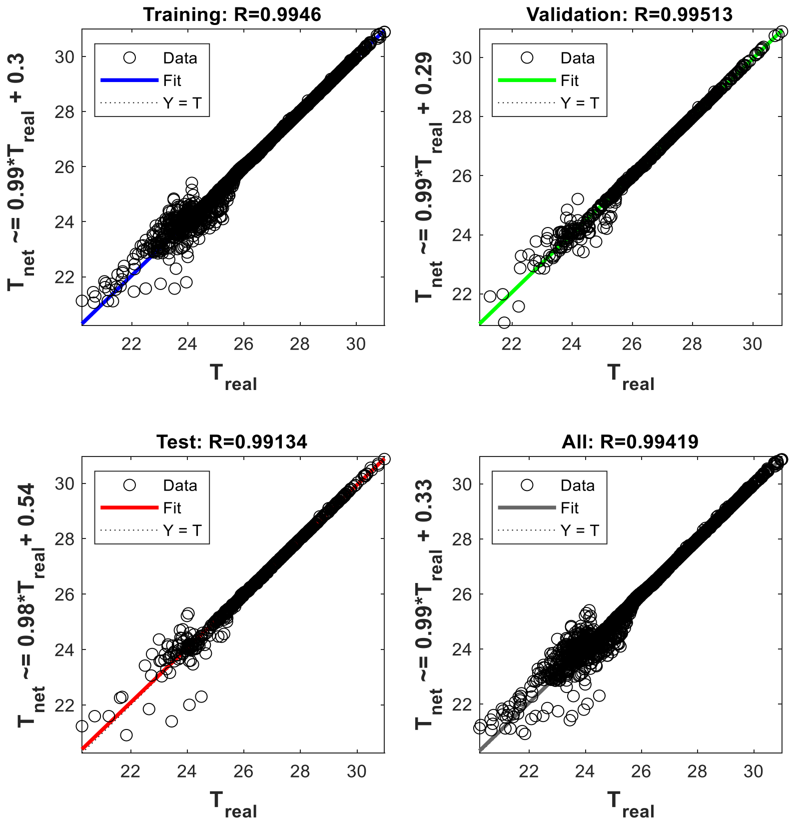
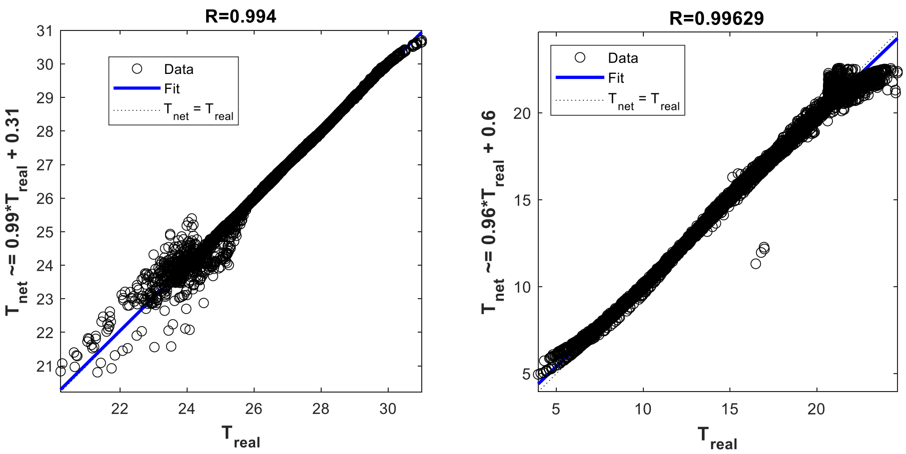


Fig 5. Regression results of training stages with 20 neurons in the hidden layer.

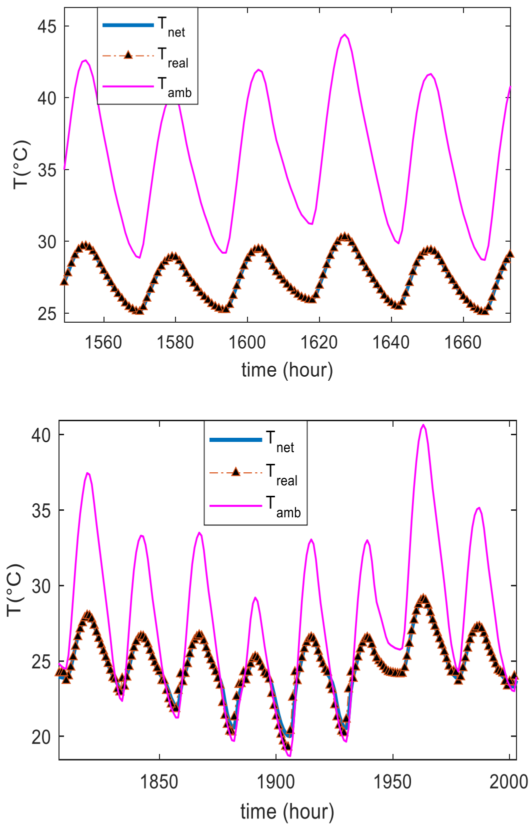
In another side, other architecture is used to the prediction of the air outlet temperature in winter season. Results were near to them given for summer as presented previously. The best architecture is that with 15 hidden neurons. The overall regression is illustrated in figure 6 with an R-squared go up to 0.9963 which improve the ability of the FFBP architecture to well predict the air outlet temperature in winter and summer but with two different architectures.



(a)summer (b)winter

Fig 6. Regression of overall data results using a FFB (a) of20 neurons for summer and (b) of 15 neurons for winter in the hidden layer.

Figure 7 shows the variation of the ambient temperature T_{amb}, the real air outlet temperature T_{real} and its predicted temperature T_{net} using ANN along time in hours. The EAHE can make a maximum temperature reduction near to 15°C (reduction from 45 to 30°C) in normal summer days as seen in figure 7.a. in the other side for little cold days in summer where it can be seen the maximum temperature reduction can't reach more than 5°C (reduction from 30 to 25°C) as seen in figure 7.b. The ANN architectures predict well the air outlet temperature with near to zero error for normal summer days but when the temperature comes close to low values the error become important which is an important point of view to limit the application of the trained architecture on high temperatures and for normal summer days.



(a) (b)

Fig 7. Ambient temperature and real temperature with its predicted in summer for (a) normal period and (b) little cold period.

In the second part, we used FFBP architecture with one hidden layer for the prediction of the air outlet temperature applied on winter data. It results a good prediction as seen in figure 8. It can be seen that the EAHE have a maximum increase of 2°C in winter because the soil temperature is near to the ambient temperature.

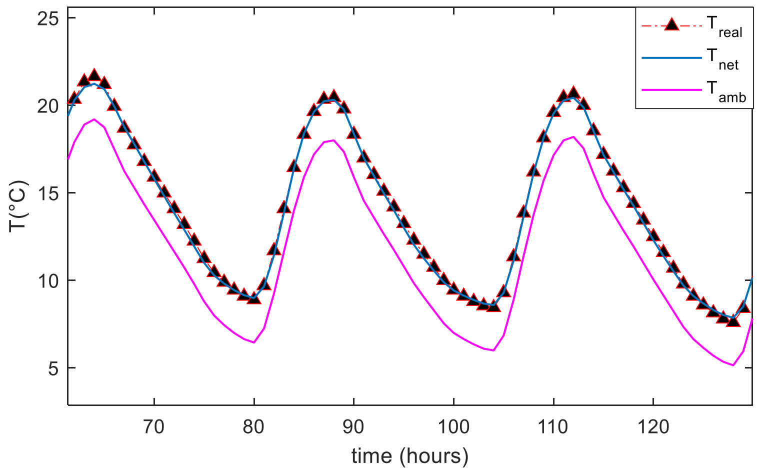


Fig 8. Winter ambient temperature and air outlet temperature with its predicted.

Conclusion

The article presents an intelligent design tool of an earth-to-air heat exchanger in terms of passive environmental performance. A neural network model based on a feed forward back propagation algorithm for the estimation of hourly values of air temperature at the buried pipe's exit was developed. The adopted architectures based on one hidden layer with different number of hidden neurons from 5 to 50 with a step of 5 between the input and the output layers trained and tested on summer and winter. The data driven model uses as inputs, ground temperatures, air temperature, at burial depth, air mass flow rate and tunnel length. Two metrics were used to validate, test and compare the outcome of the different architectures; (i) the R-squared for training, test and validation; and (ii) the mean squared error (MSE) after their validations. Architectures improve an ability of the tracking of the pipe's outlet with near to 1 (0.99419) R-squared and an MSE equal to 0.03139 which translates the high quality of estimation. Results proved highly satisfactory and provided enough confidence for the process to be extended to a larger solution space for which there is uneconomical way of calculating the solution.

Acknowledgments

The authors would like to thank the LATSI Laboratory at Blida 1 University for their great support.

References

[1] Tasdelen, F., &Dagtekin, I. (2022). A numerical study on heating performance of horizontaland vertical earth-air heat exchangers with equal pipe lengths. Thermal Science, 26(4 Part A), 2929-2939.

[2] Agrawal, K. K., Misra, R., Yadav, T., Agrawal, G. D., &Jamuwa, D. K. (2018). Experimental study to investigate the effect of water impregnation on thermal performance of earth air tunnel heat exchanger for summer cooling in hot and arid climate. Renewable energy, 120, 255-265.

[3] Bisoniya, T. S., Kumar, A., &Baredar, P. (2015). Heating potential evaluation of earth–air heat exchanger system for winter season. Journal of building physics, 39(3), 242-260.

[4] Hasan, M. I., Noori, S. W., &Shkarah, A. J. (2019). Parametric study on the performance of the earth-to-air heat exchanger for cooling and heating applications. Heat Transfer—Asian Research, 48(5), 1805-1829.

[5] Bughio, M., Bahale, S., Mahar, W. A., &Schuetze, T. (2022). Parametric Performance Analysis of the Cooling Potential of Earth-to-Air Heat Exchangers in Hot and Humid Climates. Energies, 15(19), 7054.

[6] Sofyan, S. E., Khairil, K., Maulana, Z., Tamlicha, A., Jalaluddin, J., &Syaukani, M. (2023). Development of CFD simulation model of earth air heat exchanger for space cooling of a 36 M2 house in tropical climate Banda Aceh, Indonesia. JurnalPolimesin, 21(2), 170-178.

[7] Serageldin, A. A., Abdelrahman, A. K., &Ookawara, S. (2016). Earth-Air Heat Exchanger thermal performance in Egyptian conditions: Experimental results, mathematical model, and Computational Fluid Dynamics simulation. Energy Conversion and management, 122, 25-38.

[8] Albarghooth, A., Ramiar, A., &Ramyar, R. (2023). Earth-to-air Heat Exchanger for Cooling Applications in a Hot and Dry Climate: Numerical and Experimental Study. International Journal of Engineering, 36(1), 78-89.

[9] Hasan, M. I., &Noori, S. W. (2018). Evaluating the influence of some design and environmental parameters on the performance of earth to air heat exchanger. Journal of Engineering and Sustainable Development, 22(2), 10-29.

[10] Molina-Rodea, R., Wong-Loya, J. A., Pocasangre-Chávez, H., & Reyna-Guillén, J. (2023). Experimental evaluation of a “U” type earth-to-air heat exchanger planned for narrow installation space in warm climatic conditions. Energy and Built Environment.

[11] Misra, A. K., Gupta, M., Lather, M., &Garg, H. (2015). Design and performance evaluation of low cost Earth to air heat exchanger model suitable for small buildings in arid and semi arid regions. KSCE Journal of Civil Engineering, 19, 853-856.

[12] Kaddour, A., Attia, M. E. H., ARICI, M., Benbelgacem, K., &Driss, Z. (2022). A numerical evaluation on the utilization of earth to air heat exchangers in arid regions Algeria. Journal of Thermal Engineering, 8(4), 505-514.

[13] Shingala, N. R., & Patel, C. M. (2022, August). Mathematical Analysis of Earth Air Heat Exchanger (EAHE) for Storage system. In ICSET: International Conference on Sustainable Engineering and Technology (Vol. 1, No. 1, pp. 76-91).

[14] Agrawal, K. K., Bhardwaj, M., Misra, R., Das Agrawal, G., & Bansal, V. (2018). Optimization of operating parameters of earth air tunnel heat exchanger for space cooling: Taguchi method approach. Geothermal Energy, 6(1), 1-17.

[15] Bughio, M., Bahale, S., Mahar, W. A., &Schuetze, T. (2022). Parametric Performance Analysis of the Cooling Potential of Earth-to-Air Heat Exchangers in Hot and Humid Climates. Energies, 15(19), 7054.

[16] Kumar, R., Ramesh, S., &Kaushik, S. C. (2003). Performance evaluation and energy conservation potential of earth–air–tunnel system coupled with non-air-conditioned building. Building and environment, 38(6), 807-813.

[17] Namgial, D., Singh, K. G., Hans, V. S., Aggarwal, R., & Singh, A. (2019). Performance of Thermo Hydraulic Designed Single Pass Earth Air Heat Exchanger. International Journal of Agriculture, Environment and Biotechnology, 12(1), 55-62.

[18] Hasan, M. I., & Muter, D. M. (2021). Study the effects configuration and design parameters on the performance of earth to air heat exchanger used in poultry houses. Journal of Mechanical Engineering Research and Developments, 44(7), 159-79.

[19] Peretti, C., Zarrella, A., De Carli, M., &Zecchin, R. (2013). The design and environmental evaluation of earth-to-air heat exchangers (EAHE). A literature review. Renewable and Sustainable Energy Reviews, 28, 107-116.

[20] Al-Salihi, A. M., & AL-Ramahy, Z. A. (2017). A neural network model for estimation soil temperature bases on limited meteorological parameters in selected provinces in Iraq. Journal of Applied and Advanced Research, 2(5), 292-300.

[21] Ewim, D. R. E., Okwu, M. O., Onyiriuka, E. J., Abiodun, A. S., Abolarin, S. M., &Kaood, A. (2021). A quick review of the applications of artificial neural networks (ANN) in the modelling of thermal systems.

[22] Inalli, M., Tutumlu, H., &Duman, E. (2022). An estimation of the performance of a passive cooling system incorporating a ground heat exchanger using a multilayer artificial neural network.

[23] Mohanraj, M., Jayaraj, S., &Muraleedharan, C. (2015). Applications of artificial neural networks for thermal analysis of heat exchangers–a review. International Journal of Thermal Sciences, 90, 150-172.

[24] Tan, C. K., Ward, J., Wilcox, S. J., & Payne, R. (2009). Artificial neural network modelling of the thermal performance of a compact heat exchanger. Applied Thermal Engineering, 29(17-18), 3609-3617.

[25] Zhang, J., &Haghighat, F. (2010). Development of Artificial Neural Network based heat convection algorithm for thermal simulation of large rectangular cross-sectional area Earth-to-Air Heat Exchangers. Energy and Buildings, 42(4), 435-440.

[26] Kumar, R., Kaushik, S. C., &Garg, S. N. (2006). Heating and cooling potential of an earth-to-air heat exchanger using artificial neural network. Renewable Energy, 31(8), 1139-1155.

[27] Ricardo, R. M., Manuel, H. L. J., Martín, D. G. H., & Arturo, P. V. (2014). Use of artificial neural networks for prediction of convective heat transfer in evaporative units. Ingeniería, investigación y tecnología, 15(1), 93-101.

[28] Bhattacharyya, S., Sarkar, D., Roy, R., Chakraborty, S., Goel, V., &Almatrafi, E. (2021). Application of new artificial neural network to predict heat transfer and thermal performance of a solar air-heater tube. Sustainability, 13(13), 7477.

[29] Nettari, M., Kaddour, A., Benbelgacem, K., Ikumapayi, O.M., Bezari, S., Al-Dujaili, A.Q., Hebbal, B., Abdulkareem, A.I., Humaidi, A.J., Lorenzini, G., Menni, Y. (2023). Numerical assessment of EAHE systems for refreshment in desert Algerian regions. International Journal of Design & Nature and Ecodynamics, Vol. 18, No. 3, pp. 501-508. https://doi.org/10.18280/ijdne.180301.