Analytical and Numerical Methods in Mechanical Design
Vol.1, Issue 2, Summer & Autumn 2022, 11-16

Prediction of Heating Energy Consumption in Houses via Deep Learning Neural Network

Newsha Valadbeygi [1], Ali Shahrjerdi [1,*]

[1] *Faculty of Mechanical Engineering, Islamic Azad University, Karaj Branch, Karaj, Iran*
Received: 11 September 2022- Accepted: 17 November 2022
*Corresponding author: *shahrjerdi.mail@gmail.com*

Abstract

This paper presents a novel model for prediction of energy consumption and heat transfer in houses on the basis of neural network by the use of experimental dataset of some cities of Iran for the learning process. To this end, a deep learning neural network (DNN) is designed by means of real set of data as input. In order to evaluate the proposed network, the predicted results are compared with the results obtained from the practical schemes. The comparison approved the effectiveness and feasibility of the suggested network in prediction of energy consumption and heat transfer with a low error for regression.

***Keywords*:** Heat transfer; Energy consumption; Deep learning; Neural network

1. Introduction

Analysis of heat transfer and energy consumption in buildings has always been an interesting field of study for researchers to obtain a procedure for prediction and enhancement of the efficiency. To this end, different schemes and algorithms have been proposed by the designers. Variety of designing methods along with high amount of data are some of the challenges that researchers are dealing with.

[1] proposed a DNN-based model for prediction of energy consumption in Korean houses. Key parameters that affect the system are chosen precisely and the network is optimized regarding the parameters. The system is evaluated by implementing the system the low-cost houses. [2] used experimental data set in the learning process to predict the Nuselt number and thermal efficiency. Porosity of the medium was predictable too. [3] developed a network based on computational fluid dynamics (CFD) for predicting the characteristics of heat transfer in the roof. The results were compared with practical results. [4] focused on application of Physics-Informed Neural Network (PINN) in inverse forced and mixed heat transfer problems. Furthermore, two-phase Stefan problem for moving surfaces is studied in [4].

A model for prediction of Nuselt number and energy consumption is developed in [5] for shell and tube heat exchangers via Perceptron Neural Network. To find a solution for nonlinear heat transfer and free convection in porous fins, [6] described the mathematical model in terms of Euler polynomial firstly, and proposed the optimized Euler neural network. Differential equations of the neural network were generated unsupervised and the neurons are learned by the use of generalized normal distribution algorithm. [7] investigated the effect of friction, Nuselt number and thermal efficiency by neural network to estimate the efficiency of a two-tube heat exchanger. The system is evaluated via linear regression. [8] used neural network for solar heaters. Statistical analysis of heat transfer is developed along with regression analysis to predict the heat transfer in terms of Nuselt number and the thermohydrolic efficiency. Three unique models for three different operating fluids were presented in [9] for predicting the radiation, convection and total coefficients for a floor heating system in real size. On the other hand, [10] used neural network for analyzing the Ferrofluid flow in the presence of bipolar magnet. The system was presented in terms of partial derivatives equations at first and transferred into ordinary differential equations. The system was investigated by the use of regression, histogram and correlation index. For prediction of friction and heat transfer coefficients in turbulent flow in tubes, [11] presented a novel model on the basis of neural network which is useful for all helical blades. Moreover, dataset of Nuselt number for tubes was extended.

In this paper at first, a dataset which is obtained from heat transfer in houses of Khorram abad, Tehran, Semnan and Shiraz is used for designing a deep learning neural network. The network is used for prediction of energy consumption in houses. Finally, in order to evaluate the effectiveness and feasibility of the proposed model the obtained results are compared with the practical results that are derived via Energy plus software. The comparison approves effectiveness of the proposed model.

2. Heat transfer, Thermal Efficiency and Insulation

Heat transfer and related problems are challenging fields for designers. These challenges include heat transfer rate, energy consumption, thermal efficiency and using these concepts for further actions such as insulation. There are disparate solutions for these complicated problems that suggest different algorithms and procedures. The first step in designing a heating system is to obtain an accurate estimation from the heat transfer rate. Then, the equipment with high thermal efficiency is needed. The higher efficiency for the equipment, the higher quality and performance. Thus the thermal efficiency is a key parameter for choosing and a reason for better performance that culminates in less energy and fuel consumption.

On the other hand, any change in temperature, density and humidity results in change in conductivity. Increase in humidity leads to increase in heat transfer. Therefore, thermal insulators should be dry during the insulation process. In order to decrease heat loss from the walls, the outer area of the building should be minimized. Although the volume of the building has to be taken into account. These are the limitations and constrains in the designing process. Weight and porosity of the materials are the other important factors in designing procedure. Consequently insulation process is affected by the mentioned factors. All the mentioned remarks are provided to obtaining a precise estimation about heat transfer and energy consumption.

3. Deep neural network structure for prediction of energy consumption

In order to achieve an accurate description about thermal properties of a building, neural network is an appropriate tool. Thus, by the use of newer sets of data, a neural network can be designed and by comparing the results with older results, the performance of the network can be investigated. Neural networks consist of layers and neurons. Each layer is made of the nodes for calculation. In each node, data are multiplied in a weight factor. The more layers and neurons the more complicated model.

Deep neural networks are made of more than three input and output layers. Deep learning is training the deep neural networks. In other words, deep learning is a function that transforms input into output and estimates the relation between input and output. In the training process, a network can find the correct value of a function even if the input and output would not have any logical relation. Deep learning has a wider range of capabilities than other structures and includes reinforcement learning algorithms. Thus, DNN structure is chosen for prediction of energy consumption in this research, due to well performance, high capability and low error in estimation. Figure 1 presents schematic structure of the DNN.

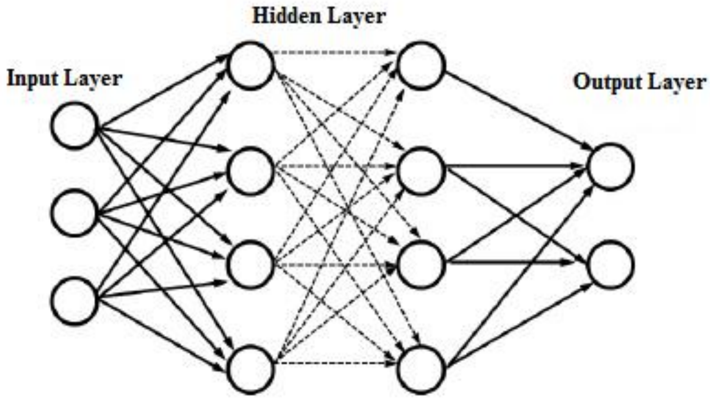

Fig. 1. Schematic structure of the DNN [1].

The obtained data from cities of Iran [1, 12, 13, 14, and 15] are classified into input and output. More details about the data set are presented in table 1. Properties of the DNN are presented in table 2. Number of layers and neurons are chosen based on the designing targets by try and error and evaluating the performance of the model in each step. Moreover, back propagation algorithm is used for tuning the synapse weights. Number of training epochs increased due to enhancing the accuracy of the network. Consequently, the training process last longer. It is worth to mention that the data division percent is 60:20:20 for training, validation and test respectively. The rate is obtained after evaluating the performance with different rates.

Table 1. Input and Target variables in the DNN structure

Feature	Input	Target
Details	Region (4 cities) Orientation of the building Structure of the building Year ACH Boiler type Efficiency of the boiler	
Area (m^2)	Heating space Wall Roof Floor Window Door	Energy Consumption (kWh/a)
$U(W/(m^2.K))$	Wall Roof Floor Window Door	

Table 2. Feature and structural parameters of the DNN

Parameter		Feature	Value
Model		Back propagation for better computation of the gradient of the loss function	Levenberg-Marquardt algorithm
Data division (%)		Training:Validation:Test	60:20:20
Structural Parameters	Hidden Layer	A tradeoff is needed between the prediction performance and learning time	1
	Neuron of Hidden Layer		12
	Learning rate	A tradeoff is needed between the prediction performance and learning	0.1

Learning Parameters		time	
	Momentum	Basic value is 0.1, the bigger value the faster learning	0.6
	Epochs	Number of learning	1000
	Goal	Target error	0.01

Levenberg – Marquardt algorithm is chosen for training due to better performance in comparison with other algorithms. Data division percent was firstly chosen to be 70:15:15 but the current percent showed better results according to the references and tuning the network. Number of layers and neurons chosen by try and error and after evaluating the results. Other parameters such as epochs, learning rate and momentum were selected on the basis of practical data. The structure of the DNN is shown on figure 2.

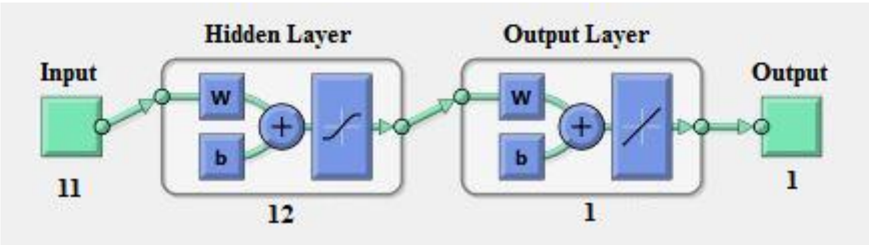

Fig. 2. structure of the DNN

After designing the network regarding to the values and considerations mentioned before, the network should be evaluated and analyzed. Table 3 presents the performance of the DNN model after implementation.

Table 3. DNN model performance

μ	Gradient	Evaluation	Training	Data division
1×10^{-7}	3.33×10^{5}	Mean Square Error	Levenberg-Marquardt	Random

Regression of the DNN model is plotted in figure 3.

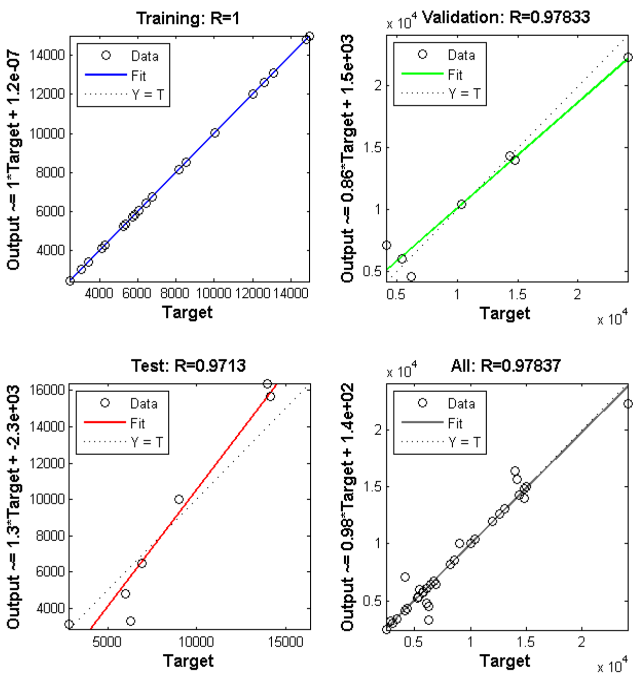

Fig. 3. DNN model Regression

4. Results and Discussion

In this section results, obtained from DNN model are compared with the practical results that are derived by the use of heat transfer concepts and formulas via Energy Plus software. Details on building and obtained energy consumption from software are listed on table 4.

Table 4. Building details and Heating consumption obtained from Energy Plus software

Parameter	Value
Annual Heating consumption per area (kWh/m^2*yr*)	270
Annual Heating consumption (kWh/*yr*)	11980
Efficiency of Boiler (%)	75
Area of the Roof (m^2)	45
$U_{Roof}\ (W\ /\ m^2.K)$	1
Area of the Floor (m^2)	45
$U_{Floor}\ (W\ /\ m^2.K)$	1
Area of the Wall (m^2)	55
$U_{Wall}\ (W\ /\ m^2.K)$	1
Window Area (m^2)	7
$U_{Window}\ (W\ /\ m^2.K)$	5.73
Heating Space (m^2)	45

The predicted heating energy consumption via the DNN model is presented in table 5.

Table 5. Heating energy consumption predicted by the DNN model

Parameter	Value
Predicted annual Heating consumption per area (kWh/m^2*yr*)	281
Predicted annual Heating consumption (kWh/m^2*yr*)	12157

5. Conclusions

In this paper a DNN model for prediction of heating energy consumption in houses was presented. To this end, all the details about structure of the network discussed. Thus, a neural network consisted of 12 layers and neurons based on Levenberg – Marquardt algorithm with data division percent of 60:20:20 for training, validation and testing respectively, was designed. The data driven to train the network was obtained from database of 4 cities of Iran. Performance of the network was evaluated in terms of regression. On the other hand, heating energy consumption of a house was obtained through heat transfer concepts via Energy Plus software. The results obtained from DNN model and Practical method were compared. According to the results of the comparison between results, the DNN model was able to predict the annual heating consumption per area with nearly 4% error. The predicted annual heating consumption had an error of 2% with practical value. Furthermore, the results in comparison with [1] that has a similar network structure, depicts the superiority of the presented model. According to the results, effectiveness and feasibility of the DNN model presented in this research in prediction of heating energy consumption is proved.

References

[1] Lee S, Cho S, Kim SH, Kim J, Chae S, Jeong H, Kim T. Deep neural network approach for prediction of heating energy consumption in old houses. Energies. 2020 Dec 28;14(1):122

[2] . Duan J, Li F. Transient heat transfer analysis of phase change material melting in metal foam by experimental study and artificial neural network. Journal of Energy Storage. 2021 Jan 1;33:102160.

[3] Karakoyun Y, Acikgoz O, Çebi A, Koca A, Çetin G, Dalkilic AS, Wongwises S. A comprehensive approach to analyze the discrepancies in heat transfer characteristics pertaining to radiant ceiling heating system. Applied Thermal Engineering. 2021 Mar 25;187:116517.

[4] Cai S, Wang Z, Wang S, Perdikaris P, Karniadakis GE. Physics-informed neural networks for heat transfer problems. Journal of Heat Transfer. 2021 Jun 1;143(6).

[5] Zolghadri A, Maddah H, Ahmadi MH, Sharifpur M. Predicting parameters of heat transfer in a shell and tube heat exchanger using aluminum oxide nanofluid with artificial neural network (ANN) and self-organizing map (SOM). Sustainability. 2021 Aug 6;13(16):8824.

[6] Khan NA, Khalaf OI, Romero CA, Sulaiman M, Bakar MA. Application of Euler neural networks with soft computing paradigm to solve nonlinear problems arising in heat transfer. Entropy. 2021 Aug 16;23(8):1053.

[7] Khan MZ, Aziz M, Wijayanta AT. Prediction of heat transfer enhancement of delta-wing tape inserts using artificial neural network. Case Studies in Thermal Engineering. 2021 Oct 1;27:101322.

[8]] Bhattacharyya S, Sarkar D, Roy R, Chakraborty S, Goel V, Almatrafi E. Application of new artificial neural network to predict heat transfer and thermal performance of a solar air-heater tube. Sustainability. 2021 Jul 5;13(13):7477.

[9] Çolak AB, Karakoyun Y, Acikgoz O, Yumurtaci Z, Dalkilic AS. A numerical study aimed at finding optimal artificial neural network model covering experimentally obtained heat transfer characteristics of hydronic underfloor radiant heating systems running various nanofluids. Heat Transfer Research. 2022;53(5).

[10] Shoaib M, Raja MA, Farhat I, Shah Z, Kumam P, Islam S. Soft computing paradigm for Ferrofluid by exponentially stretched surface in the presence of magnetic dipole and heat transfer. Alexandria Engineering Journal. 2022 Feb 1;61(2):1607-23.

[11] Skrypnik AN, Shchelchkov AV, Gortyshov YF, Popov IA. Artificial neural networks application on friction factor and heat transfer coefficients prediction in tubes with inner helical-finning. Applied Thermal Engineering. 2022 Apr 1;206:118049.