Innovative Predictive Modelling: Artificial Neural Networks for Chilled Ceiling Panel

Mina Alafzadeh[1,*], and Ali Nadizadeh[2]

[1] *Department of Mechanical engineering, faculty of engineering, Ardakan University, P.O.Box 184, Ardakan, Iran*
[2] *Department of Industrial engineering, faculty of engineering, Ardakan University, Ardakan, Iran*
**Corresponding author: m.alafzadeh@ardakan.ac.ir*

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In this research, a model using a machine learning algorithm based on artificial neural networks (ANN) has been developed to predict the cooling capacity of the chilled ceiling panel as the cooling, ventilation and air conditioning system. The structure of the ANN architecture and the accuracy of the model based on Neural Net Fitting are evaluated in terms of input layers, which include the number of input variables, the proportion of training data, and the number of neurons. For this purpose, Energy plus is used to generate simulation data for the chilled ceiling panel system. Computational results on the real data of a company state that the developed model can predict the cooling capacity of the chilled ceiling panel with an average value of 97.1% accuracy based on seven input variables, 80% training data and 8 neurons. In addition, the results of the ANN model compared to the MLR model show the superiority of the proposed ANN model, which can be used to better design of the chilled ceiling panel systems.

Keywords: *chilled ceiling panel, cooling capacity, prediction, Artificial Neural Network, accuracy.*

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1. Introduction

The growth of conventional energy consumption in the world forces decision-makers to optimize energy efficiency in all countries. According to report of the International Energy Agency, buildings and building construction sectors are collectively responsible for more than a third of global final energy consumption and nearly 40% of all direct and indirect CO_2 emissions [1]. For a country like Iran, according to the power balance of 2008, the building area of this United States consumed approximately 42% of total electricity [2]. It ought to be mentioned that there are numerous environmental problems consisting of ozone layer leakage and global warming can also arise because of multiplied energy consumption. Therefore, imparting long-term solutions that reduce power consumption in buildings will be helpful. One of the most essential answers is an appropriate design of the cooling device to growth efficiency and decrease electrical energy, due to the fact the highest percent of strength intake in ventilating and air-conditioning (HVAC) systems is in electricity among all building electric powered home equipment [3]. As a consequence, the usage of optimized techniques together with optimization algorithms which explored many perfect layout answers for cooling systems with high efficiency, electricity use may be optimized in the early levels of design. In current years, device learning techniques have emerge as popular in imparting the answer for specific problems in diverse fields. Recently, system studying algorithms have been used to reveal the optimized design parameters in heating and HVAC systems for reducing electricity intake [4]. As an example, Abdou et al. used an improved gadget-gaining knowledge of approach to optimize heating and cooling loads in Morocco [5]. The consequences showed that the whole annual load changed into reduced by means of about 68% in comparison to comparable instances. Blackburn et al. confirmed a brand new software of the system getting to know method to optimize a multi-cellular cooling tower with fan pace. They conserved more sources by means of the usage of this technique [6].

Ghasemkhani et al. used the tri-layered neural network and most relevance minimum redundancy algorithms to be expecting the heating and cooling masses in clever buildings. They showed that the important parameters decrease strength intake in buildings [7]. Lee et al. focused at the device mastering method to provide a brand new correlation for the condensation heat switch coefficient. The outcomes indicated that the gadget learning method turned into extra correct than different methods [8]. Yuan and Coskun designed a multi-output convolutional neural network regression as a deep learning method to version the quality cooling structures with finest parameters [9]. Kim et al. used a device mastering set of rules primarily based on artificial Neural Networks (ANN) to optimize power consumption in a brand new layout of a chiller in air conditioning structures. They confirmed that the proposed version should predict power consumption with 99.07% accuracy [10].

The purpose of this research is to design the most suitable shape of the chilled ceiling panel based totally on different factors. The

Table 1. Summary of literature review on the effect of input variables on different models of the chilled ceiling panel cooling capacity

Author	Model	Input variables							
		Thickness of plate (mm)	Inlet temperature (℃)	Inlet velocity (m/s)	Space of tubes (mm)	Pipe diameter (m)	Flow rate (kg/s)	Temperature difference (℃)	Thermal conductivity
Zhang et al. [11]	Metal ceiling radiant cooling panel with serpentine tube arrangement	+			+		+		+
Andrés-Chicote et al. [12]	Cooling capacity of the radiant cooled ceiling system							+	
Li et al. [15]	Radiant heating/cooling ceiling panel system							+	
Xie et al. [16]	Cooling capacity of the capillary ceiling radiant cooling panel		+	+	+	+	+		
Conroy et al. [17]	Integrated ceiling radiant cooling panels with dedicated outdoor air systems		+				+	+	
Jeong and Mumma [13]	Cooling capacity of the insulated metal ceiling radiant cooling panels	+	+	+	+	+		+	+
Jeong and Mumma [14]	Cooling capacity of the suspended metal ceiling radiant cooling panel	+	+	+	+	+		+	+
Okamoto et al. [18]	Heat flux from ceiling radiant panels		+					+	
Tye-Gingras and Gosselin [19]	Heat transfer modeling for the radiant panels with serpentine layout		+		+		+		
This paper	Cooling capacity of the chilled ceiling panel	+	+	+	+	+	+	+	+

cooling capacity of the chilled ceiling panel can alternate below the effect of different variables. Within the literature, researchers have investigated the effects of a number of those variables in their works. Table 1 indicates the reputation of the research accomplished in the subject of cooling potential of the chilled ceiling panel in line with the attention of different enter variables. The ultimate row of this desk additionally expresses the reputation of this article. As this desk shows, a number of studies have investigated the effect of best one variable on the cooling ability of the chilled ceiling panel [11, 12], and a number of them have investigated the most effect of seven variables [13, 14]. For the first time, this paper examines the effect of eight variables on the cooling capacity of the chilled ceiling panel. Moreover, the Artificial Neural Network is used as a predictive model to design the chilled ceiling panel.

It is important to note that cooling capacity prediction is in the category of time series or regression forecasting problem, and recently, data-driven methods have gained more attention among researchers due to their powerful ability to model complex relationships without expert knowledge. Artificial neural networks are considered to be the most appropriate methods that have the ability to develop deep learning quickly [20]. Therefore, in this research, Artificial Neural Network has been used as a predictive model for designing the chilled ceiling panel.

The contribution of this work can be summarized as follows. First, the effect of eight variables on the cooling capacity of the chilled ceiling panel has been investigated and the ranking of the impact of these variables on the cooling capacity has also been done. Second, Artificial Neural Network based on Neural Net Fitting has been used as machine learning for the prediction model and optimal design of the chilled ceiling panel. Moreover, using simulated data from Energy plus, the structure and parameters of the designed Artificial Neural Network have been examined. Third, the effectiveness of the developed prediction model has been tested in a case study and also compared with an MLR model.

The rest of the paper is organized as follows. Section 2 describes the predictive model for cooling potential of the chilled ceiling panel with ANN. In section 3, the accuracy of the prediction version is evaluated in line with the adjustments of the input values. Section 4 offers a few computational experiments to evaluate the accuracy of the chilled ceiling panel cooling potential prediction model and the performance of the advanced ANN model. Subsequently, the conclusions of the work are stated in section 5.

Table 2: Correlation coefficient between input variables and chilled ceiling panel cooling capacity

Variables	Thickness of plate (mm)	Inlet temperature (°C)	Inlet velocity (m/s)	Space of tubes (mm)	Pipe diameter (m)	Flow rate (kg/s)	Temperature difference (°C)	Thermal conductivity
Pearson correlation	0.828	-0.974	0.983	-0.997	-0.978	0.858	0.993	0.662
The rank of variables (based on the absolute value of the correlation coefficient)	7	4	3	1	5	6	2	8

2. Predictive model for cooling capacity of the chilled ceiling panel

2.1. The Geographical Location of Kaveh

In phrases of community structure, a standard ANN consists of three input, hidden and output layers. The wide variety and structure of neurons is decided in the enter layer [21]. The number of neurons in the enter layer strongly relies upon on the corresponding physical quantities and is very touchy to the expected effects. The essential point is that if there's little correlation among the variables used as input values inside the ANN version and the cooling ability of the chilled ceiling panel as the output layer, the accuracy of the final outcomes can be affected. Therefore, in this newsletter, the correlation between the cooling potential of the chilled ceiling panel and each of the enter variables has been analyzed the usage of the Pearson correlation coefficient. Like other correlation coefficients, the cost of Pearson's correlation coefficient is within the variety of [-1,1].

Table 2 provides the Pearson correlation coefficient for every variable used within the ANN of the chilled ceiling panel cooling ability. At the beginning, eight variables are concurrently taken into consideration: thickness of plate, inlet temperature, inlet pace, area of tubes, pipe diameter, float fee, temperature difference, and thermal conductivity. As cited in advance, this is the first time that we bear in mind all of the parameters affecting the chilled ceiling panel cooling capacity compared to different references within the literature.

It is mentioned that the correlation coefficients of the variables are obtained from SPSS 27.0. The correlation coefficients suggest that the space of tubes, temperature difference and inlet pace are the principle parameters, respectively. Moreover, the final row of table 2, which indicates the rank of the variables based totally at the absolute fee of the correlation coefficient, states that the cooling potential has the bottom correlation with the thermal conductivity. it's far crucial to say that the terrible correlation coefficient of the three variables means that the growth in cooling potential is followed by way of a decrease within the corresponding variable and vice versa.

2.2. Basics of ANN

An ANN model is similar to a network that is created by connecting a number of nodes together. The learning process is constantly updated based on the weights of the nodes between the input and target values and produces predictive results. An ANN model is made of three input, hidden and output layers, respectively. In the input layer, the input values for training are derived and the input signal is sent to the next node. By connecting to all the nodes of the input layer, the hidden layer receives the input signals and performs neural network operation calculations through the connection between the nodes of the hidden layer. Finally, the final result is calculated through the operation values of the hidden layer and displayed from the output layer [22]. In this study, to predict the cooling capacity of the chilled ceiling panel, the input values for the ANN input layer are carefully selected after preparing a list of influencing factors. A schematic diagram of how to connect the layers of the neural network of the ANN model used in this study is shown in Figure 1, which is implemented by coding in MATLAB R2022b. The Neural Net Fitting in MATLAB R2022b uses a two-layer feed-forward network. It can help the modeler in data selection, proportion of data into training sets, validation and testing, defining the network architecture and training the network. After training the network, its performance is evaluated using mean squared error (MSE) and regression analysis.

The training algorithm is the main driver in Artificial Neural Networks. Levenberg-Marquardt algorithm has been used in this research to train the Artificial Neural Network. It is noted that the Levenberg-Marquardt algorithm is specifically designed to work with loss functions that are in the form of a sum of squared errors [23].

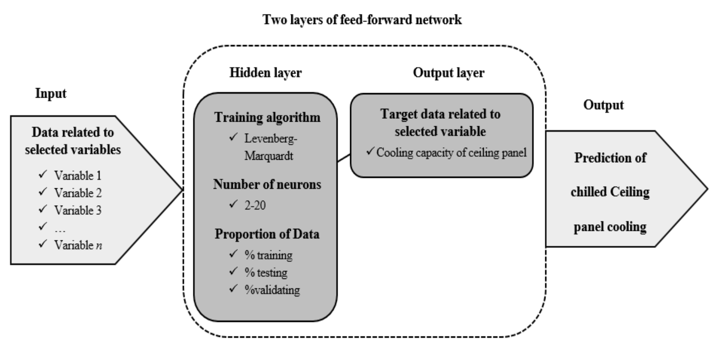


Fig. 1: Schematic diagram of the chilled ceiling panel cooling capacity prediction model using the Neural Net Fitting of the ANN model.

Table 3 states enter and output conditions for the prediction model of chilled ceiling panel cooling capacity. in line with the enter settings to find the most appropriate situations for the proposed Neural net becoming of the ANN model, the accuracy of the predicted effects for the fee of the cooling capacity is analyzed and tested. For this cause, 3 types of input settings are considered on this research: the wide variety of input variables, the quantity of neurons, and the amount (percentage) of education records. By means of applying those inputs to the neural net becoming of the ANN model, the accuracy of the predicted results can be computed. Seven enter variables had been used in place of 8 predominant variables, because the thermal conductivity had the lowest absolute value of the correlation coefficient among other variables. Seven input variables were used instead of eight main variables, because the thermal conductivity had the lowest absolute value of the correlation coefficient among other variables. The seven enter variables are delivered to the version consistent with the price of their correlation coefficient, and the accuracy of the effects is compared in keeping with the quantity of input variables proven with the seven 'modes' in section three.1. For schooling information, the share of total records generated is numerous from 50% to 90% to analyze what is the most appropriate fee for cooling potential prediction model. The quantity of neurons, that's any other of the maximum important ANN inputs, is considered based on the range of 2 to 20 neurons to take a look at the accuracy of the model.

Table 3. Input and output conditions for chilled ceiling panel cooling capacity prediction model.

Setting type	Input variables	Number of neurons	Proportion of the training data	Output value
Value(s)	1) Temperature difference (°C) 2) Inlet velocity (m/s) 3) Flow rate (kg/s) 4) Thickness of plate (mm) 5) Inlet temperature (°C) 6) Pipe diameter (m) 7) Space of tubes (mm)	2 – 20	50% – 90%	Cooling capacity of chilled ceiling panel

It should be mentioned that ASHRAE (American Society of Heating, Refrigeration, and air conditioning Engineers) tenet 14, size of strength and demand savings, is used to affirm the reliability of the take a look at outcomes whilst the tolerance limits are within the specified tolerances [20]. Next, in keeping with the results acquired from 10 runs in every 'mode', the accuracy of the prediction model is showed via the CvRMSE index. In line with the ASHRAE, the acceptable tolerance price for CvRMSE index is 30%.

The variance coefficient of the root mean rectangular error is described CvRMSE and is calculated as follows:

$$CvRMSE = 100 \times \frac{\sqrt{\frac{(x_i - \hat{x}_i)^2}{(n - p)}}}{\bar{x}} \qquad (1)$$

where n is the number of data, p is the number of parameters, x_i is the real data used for calibration, $\hat{x}_i$ is the predicted data, and $\bar{x}$ is considered as the arithmetic mean of the sample of n observations. It is noted that the lower values of CvRMSE indicate better calibration.

3. Computational results

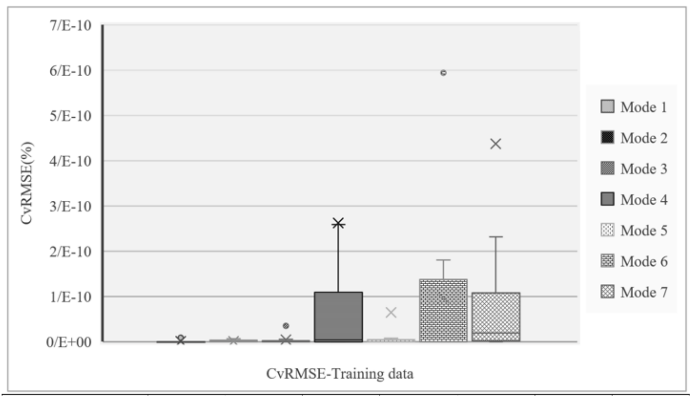
In this section, primarily based on the Neural net fitting of the ANN model, the accuracy of the chilled ceiling panel cooling ability prediction has been calculated based totally at the effects of the wide variety of input variables, the information percentage and the variety of neurons all through the schooling and testing periods. On this studies, no evaluation is carried out for the validation length due to the lack of part of the statistics as well as the duration of the exams. The subsequent sections gift and talk these effects.

3.1. Examining the effect of the number of input variables for the training and testing periods

In this section, the accuracy of the predicted results is checked according to the number of input variables to the ANN. As can be seen in Table 4, the input variables are added to the network one by one, from the temperature difference to the space of the tubes. It is necessary to explain that in order to carry out experiments, the proportion of training data is 50% of the total data set and the number of neurons is fixed at 20.

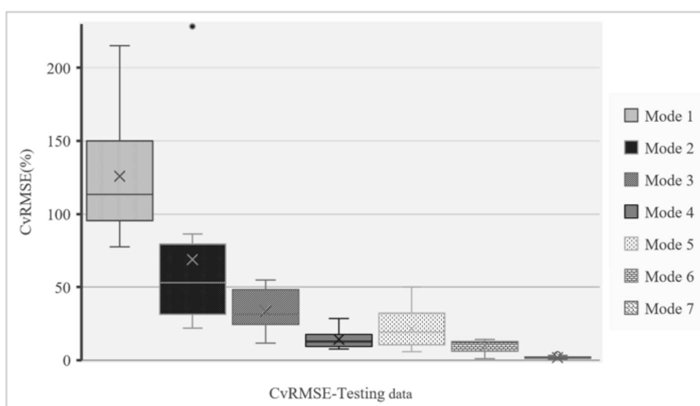
Figure 2 shows the CvRMSE of the predicted cooling capacity of the chilled ceiling panel for each 'mode' (number of input variable) during the training period. This figure indicates that in all 'modes', the predicted value does not exceed the ASHRAE Guideline standard of 30%. In addition, as shown in Figure 2, the index values for all 'modes' are very small, indicating that the cooling capacity of the chilled ceiling panel can be simulated with very good accuracy by considering all input variables.

Figure 3 shows the CvRMSE of the predicted cooling capacity of the chilled ceiling panel for each 'mode' (number of input variables) during the testing period. Contrary to Figure 2, where all CvRMSE values were small and within the acceptable range, in Figure 3, for the first three 'modes', CvRMSE exceeded the standard limit of 30% of the ASHRAE Guideline. These values show that by considering only 3 variables, it is not possible to accurately predict the cooling capacity of the chilled ceiling panel. On the other hand, Figure 3 indicates that by increasing the number of input variables (increasing the number of 'modes'), the prediction accuracy increases significantly. When the number of input variables is more than 3, the average CvRMSE index is less than 30% based on ASHRAE standard. 'Mode' 7 shows the best results with a minimum of 0.9%, a maximum of 4.0%, a mean of 1.9% and a standard deviation of 1.0. In fact, considering a greater number of input variables, even those that had a lower correlation coefficient, such as the thickness of plate, have improved the prediction accuracy during the testing period. As a general conclusion from the analysis of the input variables in Neural Net Fitting of the ANN model for training and testing periods, it can be said that by considering the seven input variables, the cooling capacity of the chilled ceiling panel can be accurately predicted.



	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7
Min	5/92E-14	2/48E-14	2/58E-14	1/02E-14	0	0	9/36E-14
Max	8/52E-12	6/83E-12	3/55E-11	2/25E-09	6/38E-10	5/94E-10	3/99E-09
Mean	1/02E-12	1/59E-12	4/32E-12	2/62E-10	6/51E-11	9/70E-11	4/37E-10
Standard deviation	2/64E-12	2/52E-12	1/11E-11	7/04E-10	2/01E-10	1/86E-10	1/25E-09

Fig. 2: Display the prediction accuracy based on the number of input variables during the training period



	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7
Min	77/6	21/9	11/5	7/6	6/0	1/0	0/9
Max	215/0	228/3	54/8	28/5	50/0	14/2	4/0
Mean	126/0	68/6	33/8	14/2	21/6	9/5	1/9
Standard deviation	41/1	60/7	13/6	6/3	13/7	4/3	1/0

Fig. 3. Display the prediction accuracy based on the number of input variables during the testing period

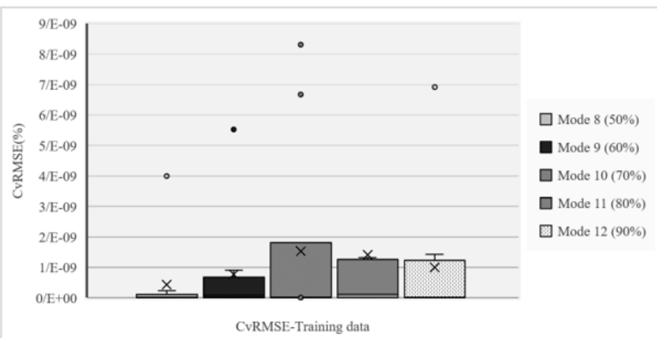
3.2. Effect of data proportion for training and testing periods

In this section, the accuracy of the anticipated cooling potential of the chilled ceiling panel is evaluated by means of changing the share of schooling statistics from 50% to 90% and trying out records from 50% to 10%. It is stated that the quantity of enter variables and the wide variety of neurons are constant at 7 and 20, respectively. Table 5 indicates the training and testing situations of the data size.

Figure 4 indicates the accuracy cooling capacity of the chilled ceiling panel in line with the percentage of the schooling information within the education period. The outcomes verify that the prediction accuracy is suitable for all ‘modes’. In different words, the share of the schooling statistics isn't always touchy to the prediction and every of the ‘modes’ is in the popular restriction of the ASHRAE guiding principle.

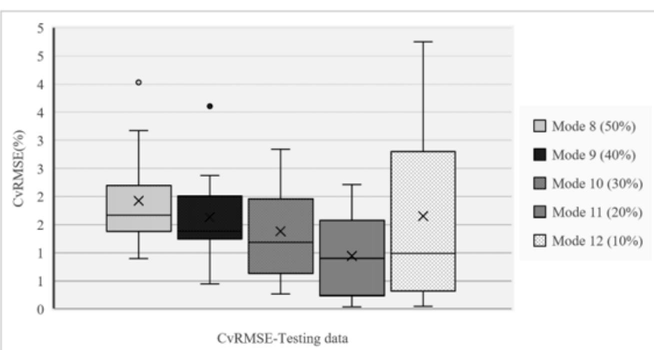
Figure 5 suggests the accuracy of the cooling ability of the chilled ceiling panel according to the percentage of the testing facts in terms of share used during the trying out period. This discern suggests that

the accuracy of the predictions is cheap, with a median of much less than 1.nine for all modes. As determine 5 indicates, although the prediction accuracy in all ‘modes’ is in the allowed range, the fine



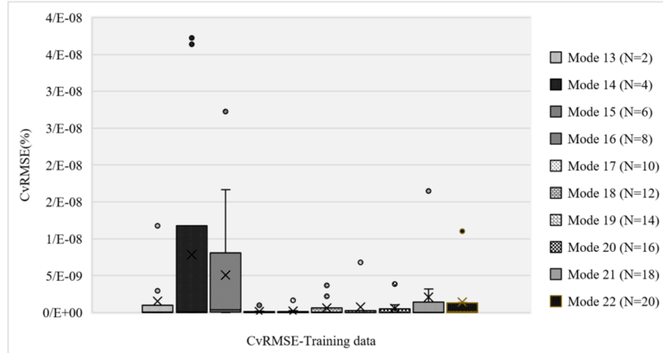
	Mode 8	Mode 9	Mode 10	Mode 11	Mode 12
Min	9/36E-14	6/71E-14	0/00E+00	6/55E-14	8/28E-14
Max	3/99E-09	5/53E-09	8/31E-09	1/10E-08	6/91E-09
Mean	4/37E-10	7/68E-10	1/53E-09	1/42E-09	1/00E-09
Standard deviation	1/25E-09	1/70E-09	3/17E-09	3/41E-09	2/14E-09

Fig. 4: Prediction accuracy results with respect to the changes in proportion of the training data for training period



	Mode 8	Mode 9	Mode 10	Mode 11	Mode 12
Min	0/9	0/4	0/3	0/0	0/0
Max	4/0	3/6	2/8	2/2	4/7
Mean	1/9	1/6	1/4	0/9	1/7
Standard deviation	1/0	0/8	0/8	0/8	1/7

Fig. 5: Prediction accuracy results with respect to the changes in proportion of the testing data for testing period



	Mode 13	Mode 14	Mode 15	Mode 16	Mode 17	Mode 18	Mode 19	Mode 20	Mode 21	Mode 22
Min	3/81E-14	0	1/42E-11	3/78E-14	1/76E-14	3/05E-14	3/90E-13	1/75E-14	1/44E-14	6/55E-14
Max	1/18E-08	3/72E-08	2/73E-08	9/72E-10	1/67E-09	3/63E-09	6/76E-09	3/83E-09	1/65E-08	1/10E-08
Mean	1/52E-09	7/81E-09	5/06E-09	1/32E-10	1/96E-10	6/01E-10	7/37E-10	5/20E-10	2/05E-09	1/42E-09
Standard deviation	3/71E-09	1/53E-08	9/38E-09	3/01E-10	5/22E-10	1/27E-09	2/12E-09	1/21E-09	5/17E-09	3/41E-09

Fig. 6: Prediction accuracy results with respect to the changes in the number of neurons in the training data

results are obtained with a median CvRMSE of 0.9% and a fashionable deviation of 0.8 when 80% of the education statistics and 20% of checking out data are used. Since the Neural net becoming of the ANN version gives a method for making predictions via facts learning, the quantity of information set used for mastering has a large impact at the accuracy of predictions. Therefore, the accuracy differs in keeping with the proportion of the overall statistics used inside the education and trying out durations, respectively. The results in this section show that a suitable method for accurately predicting the cooling capacity of the chilled ceiling panel is to fit the data up to 80% for the training period and 20% for the testing period.

3.3. Effect of the number of neurons for training and testing periods

In this segment, the sensitivity evaluation on the quantity of neurons inside the Neural net fitting of the ANN model has been performed for the schooling and testing periods, respectively. due to the fact increasing the quantity of neurons can delay the execution time of ANN algorithms, the variety of neurons ought to be carefully determined after deciding on the range of enter variables and proportioning of the training and checking out information. For this purpose, the sensitivity evaluation is done in the special stages of 2 to 20 neurons, taking into account seven input variables and the facts percentage of 80% and 20%, respectively, for the schooling and testing intervals acquired inside the preceding sections.

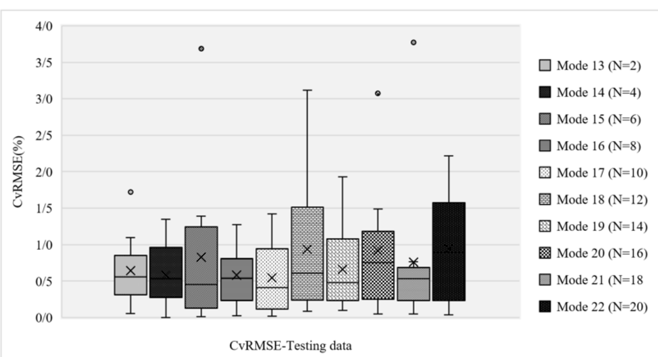
Figure 6 shows the accuracy based on the number of neurons used in the training period. This Figure confirmed that the prediction accuracy obtained from the cooling capacity of the chilled ceiling panel is suitable for all numbers of neurons and is within the standard range, and no significant difference is evident in all ‘modes’. Therefore, it can be said that during the training period, the prediction results of the ANN model are not sensitive to the neuron number. Figure 7 also shows the accuracy of predictions for different numbers of neurons for the testing period. In this Figure, it is clear that for the different numbers of neurons, all the accuracy of the predictions is within the acceptable range of less than 30%. But for ‘mode’ 16, which shows the number of neurons 8, with an average value of CvRMSE equal to 0.5 and a standard deviation of 0.4, it has the best accuracy among the rest of the ‘modes’. Therefore, according to the results of the sensitivity analysis of this section on the number of neurons for the training and testing periods, it can be concluded that choosing the number of 8 neurons can maximize the prediction accuracy of the Neural Net Fitting of the ANN model.

Table 4. Conditions for input variables.

No. of Variables	Input variables						
	Temperature difference (℃)	Inlet velocity (m/s)	Flow rate (kg/s)	Thickness of plate (mm)	Inlet temperature (℃)	Pipe diameter (m)	Space of tubes (mm)
Coefficient of Pearson Correlation	0/993	0/983	0/858	0/828	-0/974	-0/978	-0/997
Mode 1	+						
Mode 2	+	+					
Mode 3	+	+	+				
Mode 4	+	+	+	+			
Mode 5	+	+	+	+	+		
Mode 6	+	+	+	+	+	+	
Mode 7	+	+	+	+	+	+	+

Table 5. Conditions for data proportion

Modes	Data proportion	
	Training data (%)	Testing data (%)
Mode 8	50	50
Mode 9	60	40
Mode 10	70	30
Mode 11	80	20
Mode 12	90	10



	Mode 13	Mode 14	Mode 15	Mode 16	Mode 17	Mode 18	Mode 19	Mode 20	Mode 21	Mode 22
Min	0/1	0/0	0/0	0/0	0/0	0/1	0/1	0/0	0/0	0/0
Max	1/7	1/3	3/7	1/3	1/4	3/1	1/9	3/1	3/8	2/2
Mean	0/6	0/6	0/8	0/5	0/5	0/9	0/7	0/9	0/8	0/9
Standard deviation	0/5	0/4	1/1	0/4	0/5	0/9	0/6	0/9	1/1	0/8

Fig. 7: Prediction accuracy results with respect to the changes in the number of neurons in the testing data

4. Computational experiment on the proposed Neural Net Fitting of the ANN model

To evaluate the accuracy of the chilled ceiling panel cooling potential prediction model and the efficiency of the advanced Neural internet fitting of the ANN version, computational experiments had been finished inside the following sections.

4.1. Performance evaluation with a case study

In this section, the accuracy of chilled ceiling panel cooling capacity prediction is evaluated on a case observe in step with the excellent obtained situations for the proposed Neural net becoming of the ANN version. The condition that resulted inside the highest stage of accuracy includes 80% of the education statistics, and eight neurons. To carry out the computational experiments of this segment, the cooling capacity of the chilled ceiling panel is calculated based on those derived finest conditions and in comparison with actual information from an Iranian enterprise- TACwin Company in Tehran. It must be noted that during this situation examine, best the facts of three input variables had been available, which included temperature difference, glide price, and inlet temperature. Consequently, simplest the referred to 3 input variables were entered into the provided ANN model to perform computational experiments.

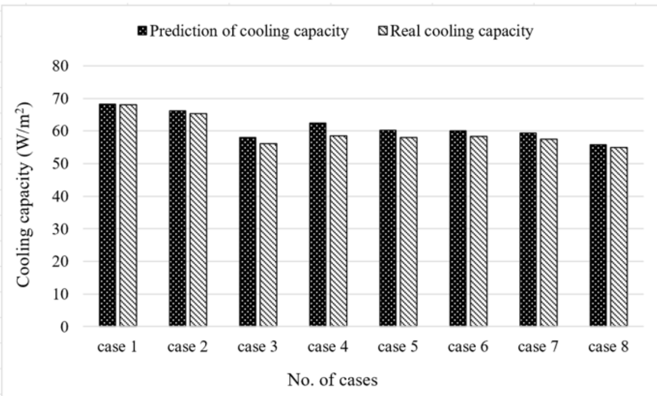
Figure 8 suggests the outcomes of predicting the cooling capability of the chilled ceiling panel in comparison to the real information of the referred to enterprise. This figure shows that the prediction error percentage varies from 0.4 to 6.6 for distinctive samples. It's far mentioned that the error percentage between the effects of Prediction value and actual fee of the cooling ability is computed as 100 × [(Prediction value of cooling capacity - Real value of cooling capacity)/ Real value of cooling capacity] for each 'case'. In conclusion, the figure eight suggests that the proposed Neural net becoming of the ANN model with the selected conditions and parameters can as it should be are expecting the cooling potential of the chilled ceiling panel in actual cases with a median errors of 2.9%.

As another evaluation, a few regression plots obtained from the proposed neural net becoming are supplied to expose the accuracy of the prediction model. The regression plot indicates the community predictions (output) with appreciate to responses (target) for the training and checking out records. Figure 9 suggests the regression plot (R) of training, trying out and all records. As an interpretation of the fee of R, it could be stated that the nearer the cost of R is to one, the nearer the match between the real data and the expected statistics, and the accuracy of the proposed model is higher. As figure 9 shows, the fee of this index is super for training, checking out, and all facts, it suggests that the version expressed with adjusted parameters described in section three has an excessive accuracy for cooling potential chilled ceiling panel prediction.

4.2. Comparing the performance of the proposed ANN model with the MLR model

Different computational experiments are presented to measure the accuracy of the proposed neural net fitting of the ANN version as compared to the MLR version. Multiple linear regression (MLR) is a statistical technique that uses numerous explanatory (impartial) variables to predict the price of a reaction (structured) variable. In reality, in MLR, the modeling of the linear courting among explanatory variables (independent) and response variables (established) is investigated and finished [24]. In this studies, SPSS 26.0 software is used to use the MLR model and decide the mathematical courting. Further, the cooling ability fee has been decided on because the depended variable and three variables noted within the case observe are selected as unbiased variables.

Table 6 indicates the computational consequences of MLR from SPSS 26.0. model precis table 6 offers the R, R^2, adjusted R^2, and the standard blunders of the estimate, that are used to decide how well a regression version fits the facts. The cost of R may be considered as one of the excellent measures of the prediction of the based variable. A price of 0.982, in this case study, indicates a splendid level of



	case 1	case 2	case 3	case 4	case 5	case 6	case 7	case 8
Prediction value of cooling capacity	68.3	66.2	58.0	62.4	60.2	60.1	59.4	55.9
Real value cooling capacity	68.0	65.4	56.1	58.5	58.0	58.3	57.5	55.0
Error(%)	0.4	1.3	3.4	6.6	3.7	3.0	3.2	1.6

Fig. 8: Prediction of the chilled ceiling panel cooling capacity for a case study

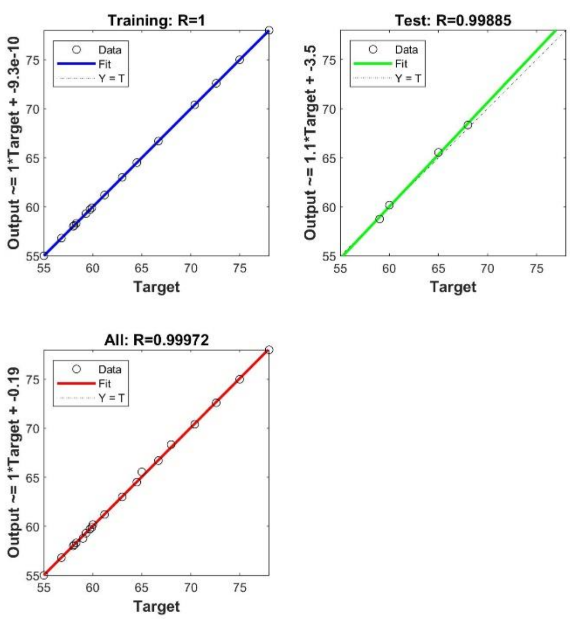


Fig. 9: Neural Net Fitting Regression for the training, testing and all data

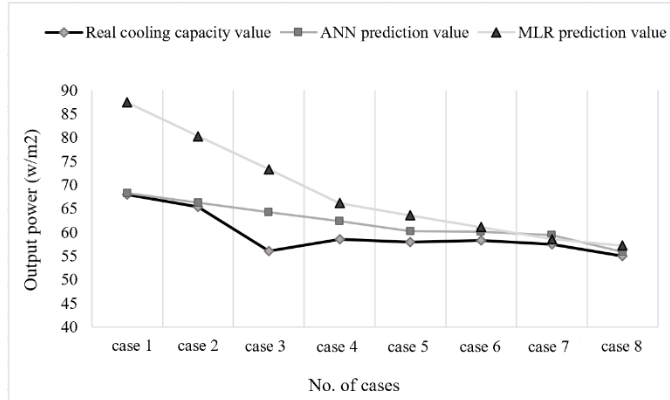


Fig. 10: A comparison between ANN model and MLR model

prediction. The F-ratio within the ANOVA exams whether the overall regression version is a great healthy for the information. The ANOVA of table 6 indicates that the unbiased variables statistically significantly predict the dependent variable, $F(3,16) = 147.730$, $p < .0005$ (i.e., the regression model is a great fit of the statistics). Subsequently, the Coefficients of desk 6 nation that the overall shape of the equation to predict cooling potential from independent variables is as follows:

Prediction (Cooling capacity) $= 29.343 + 1.139 \times$ *(Temperature difference)* $- 2240.736 \times$ *(Flow rate)* $+ 3.616 \times$ *(Inlet temperature)* (2)

Consistent with equation (2) that is received based totally on the MLR version, cooling ability can be expected primarily based on specific values of three input variables. Table 7 compares the prediction consequences of the two provided MLR and ANN models, concurrently. The primary column indicates the wide variety of case examine, the next 3 columns show the unique values of the enter variables used within the prediction, and the fifth column shows the real values of the cooling potential of the chilled ceiling panel. The closing four columns of table 7 also show the prediction values and the mistake percentage received for the ANN and MLR fashions, respectively. The amount of mistakes for each model is calculated as $100 \times$ [(Prediction model value - Real cooling capacity value)/ Real cooling capacity value] for every case. Consistent with the final row of table 7, which suggests the average mistakes, it's far clear that the ANN model has less errors and is greener than the MLR version with an average of 2.9% and has more accuracy in predicting the cooling ability. The effects of table 7 display that the presented ANN is able to predicting cooling ability of the chilled ceiling panel with an accuracy of 11.5% higher than the MLR model. For in addition comparisons, the real cooling capacity fee and the values of the two prediction models are supplied in figure 10. It may be visible that the anticipated cost for ANN version is toward the real cooling potential fee for maximum of the cases, although there are a few exceptions. Therefore, beneath the same conditions, the ANN version can predict the chilled ceiling panel cooling ability with better accuracy than MLR model. Overall, results correctly reveal that the proposed neural internet fitting of the ANN can be used as a suitable version to be expecting the cooling capacity of the chilled ceiling panel.

5. Conclusions

This research was conducted in order to find the optimal conditions of the chilled ceiling panel in the cooling, ventilation and air conditioning system by using Neural Net Fitting of the ANN model in MATLAB R2020a. The chilled ceiling panel cooling capacity prediction model was developed and evaluated in terms of parameters of input conditions, number of input variables, proportion of training and testing data, and number of neurons. The research findings were as follows. Due to the optimization of the input variables, especially in the testing period, the prediction accuracy in this research was guaranteed by increasing the number of input variables; even those with lower correlation coefficients, such as the thickness of plate, have improved the prediction accuracy. With seven input variables selected from eight initial variables, the CvRMSE reflected high accuracy for both the training and testing periods. According to the effect of the proportion of training data, the prediction accuracy was guaranteed by increasing the percentage of training data. The computational results showed that with an average CvRMSE of 0.9% and a standard deviation of 0.8, the proportion of 80% of training data and 20% of testing data was the best condition. According to optimizing the number of neurons, when the number of input variables and proportion of training data was fixed according to the previously verified conditions, no significant change in accuracy was found in terms of the number of neurons in training period. But for testing period, the number of neurons 8 with an average value of CvRMSE equal to 0.5 and a standard deviation of 0.4 had the best accuracy among the other numbers and this value was chosen as the appropriate number of neurons in the proposed Neural Net Fitting of the ANN model. Consequently, to evaluate the developed Neural Net Fitting of the ANN model, computational experiments were performed on a real case with the above conditions and parameters. In fact, by predicting the chilled ceiling panel cooling capacity based on seven input variables, 80% training data and 20% testing data, and 8 neurons, the predicted cooling capacity values could be compared to the real case ones. The comparison results indicated high prediction accuracy for the proposed ANN model with an average error of only 4.4%. In addition, comparing the performance of the presented ANN model against the MLR model, the results proved that the accuracy of the ANN model for predicting the chilled ceiling panel cooling capacity was 11.5% better than the MLR model. Due to the accuracy and superiority of the developed ANN, its results can be used to improve the performance of HVAC systems, especially in the design of the chilled ceiling panel.

Table 6. Displaying the computational results of MLR model in SPSS 26.0 on the case study

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
MLR	.982[a]	.965	.959	1.3143

a. Predictors: (Constant), Temperature difference, Flow rate , Inlet temperature

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
MLR	Regression	765.579	3	255.193	147.730	.000[b]
	Residual	27.639	16	1.727		
	Total	793.218	19			

a. Dependent Variable: Cooling capacity

b. Predictors: (Constant), Temperature difference, Flow rate , Inlet temperature

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	29.343	15.836		1.853	.002
	Temperature difference	1.139	.273	1.367	4.170	.001
	Flow rate	-2240.736	992.846	-2.082	-2.257	.000
	Inlet temperature	3.616	2.208	1.680	1.638	.001

a. Dependent Variable: Cooling capacity

Table 7. Comparison of accuracy between proposed ANN model and MLR model

No. of case	Input variable values			Real cooling capacity value	Proposed ANN model		MLR model	
	Temperature difference(°C)	Flow rate (kg/s)	Inlet temperature(°C)		Prediction value	Error(%)	Prediction value	Error(%)
case 1	30	0.02	19	68	68.3	0.4	87.4	28.5
case 2	25	0.019	18	65.4	66.3	1.3	80.3	22.8
case 3	20	0.018	17	56.1	58.0	3.4	73.3	30.6
case 4	15	0.017	16	58.5	62.4	6.6	66.2	13.1
case 5	10	0.014	15	58	60.2	3.7	63.6	9.7
case 6	9	0.013	14	58.3	60.0	3.0	61.1	4.8
case 7	8	0.012	13	57.5	59.4	3.2	58.6	1.9
case 8	6	0.01	12	55	55.9	1.6	57.2	3.9
Average						**2.9**		**14.4**

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