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Using Artificial Neural Network for the Analysis of Refrigerating Performance in a Refrigeration System

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Abstract
In this study, an artificial neural network (ANN) application which predicts of factor refrigerating capacity in a mechanical compression refrigeration system was developed. Mechanical compression refrigeration cycle, the most common cooling cycle. Element that provides heat by the evaporation of the refrigerant evaporator at low pressure environment. The Network, which has three layers as input, output, and hidden layer, has four input and one output cells. Six cells were used in hidden layers. Which back propagation algorithm was used for training. Desired error value was achieved in ANN and, ANN was tested with both data used for training ANN and data not used. Resultant low relative error value of the test indicates the usability of ANNs in this area. Capacity of change in a refrigeration system can be studied by different proceeding. Changing condenser temperature also changes the capacity of the refrigeration system. In this study, a series of experiments were performed in order to determine the effects of changing cooling water flow rate (changing condenser temperature) in a mechanical heat pump experimental setup on the refrigerating capacity of the system. Performance values obtained were used for training Artificial neural network (ANN) whose structure was designed for this operation.

1. Introduction

Mechanical compression refrigeration cycle, the most common cooling cycle. Element that provides heat by the evaporation of the refrigerant evaporator at low pressure environment.

High pressure steam from the evaporator to condenser compressor element is pressed. Taking the temperature of the hot gas from the compressor angry he intensification of the element condenser (condenser). Collected into a liquid refrigerant from the liquid element is stored. (receiver) Liquid various methods by restricting the passage of liquid refrigerant from the evaporator tank low pressure build up so the elements that make vaporize the refrigerant expansion valve.

Performance values of a refrigerating cycle, besides a number of other factors, depend theoretically on the temperatures of the cold and warm heat sources between which the system works. Refrigerating capacity of heat pump changes depending on various parameters including temperatures of evaporator and condenser, ambient temperature, temperature of the medium to be cooled or heated, etc. Most of these parameters are not constant and can be changed on preference.

Major elements of Cooling Cycle Plan as follows: 1. Condenser 2. Expansion Valve (throtle valve) 3. Evaporator 4. Compressor. A refrigeration cycle, the refrigerant absorbs heat from a fluid and then the changes defined by smear held in a cooling cycles.

By the low pressure compressor high pressure refrigerant condenser is sent by removing the condense rand expansion valve, condensation is created and from there through the low pressure evaporator is converted into a liquid cooling is carried out by means of in practice, the low temperature heat source, a high temperature environment, living space or storage volume by pumping cooled. Heat is normally followed by a movement in the opposite direction of it (high temperature, low temperature, right) [1].

In practice, the importance of the insulation is very large. Therefore, insulating materials with A low coefficient of thermal conductivity is used. Polyurethane is often at the beginning of today's systems those used. Insulation chilled are a to protect low temperature and low temperature and power is used to reduce the energy needed to reach. The principle of refrigeration cycle mathematically by Sadi Carnot heat engine is defined by a1824.

A reversible refrigerant heat a working machine. The most common form cooling systems, phase change heat pump cycle is based on the uses however, absorbed heat pumps are used in most of the applications [2].

In this study, an experimental heat pump setup on which capacity adjustment can be performed by changing condenser temperature was constructed and experiments of monitoring capacity changes were performed on this experimental setup as shown in Fig. 1. Technical details of the set are given in Table 1. Condenser temperature in the experiments was adjusted by changing the water flow rate in the water cooled condenser. Then the data obtained from the test results was used for modeling the system performance by artificial neural network (ANN).

Recent developments in information technology and increased computer powers led to the development of new programming techniques; ANN as an artificial intelligence application is one of those improvements. ANNs, resembling neural cells of a human brain are used successfully in many science branches on modeling and control applications. ANNs have also being used in heating, cooling and acclimatization areas [3].

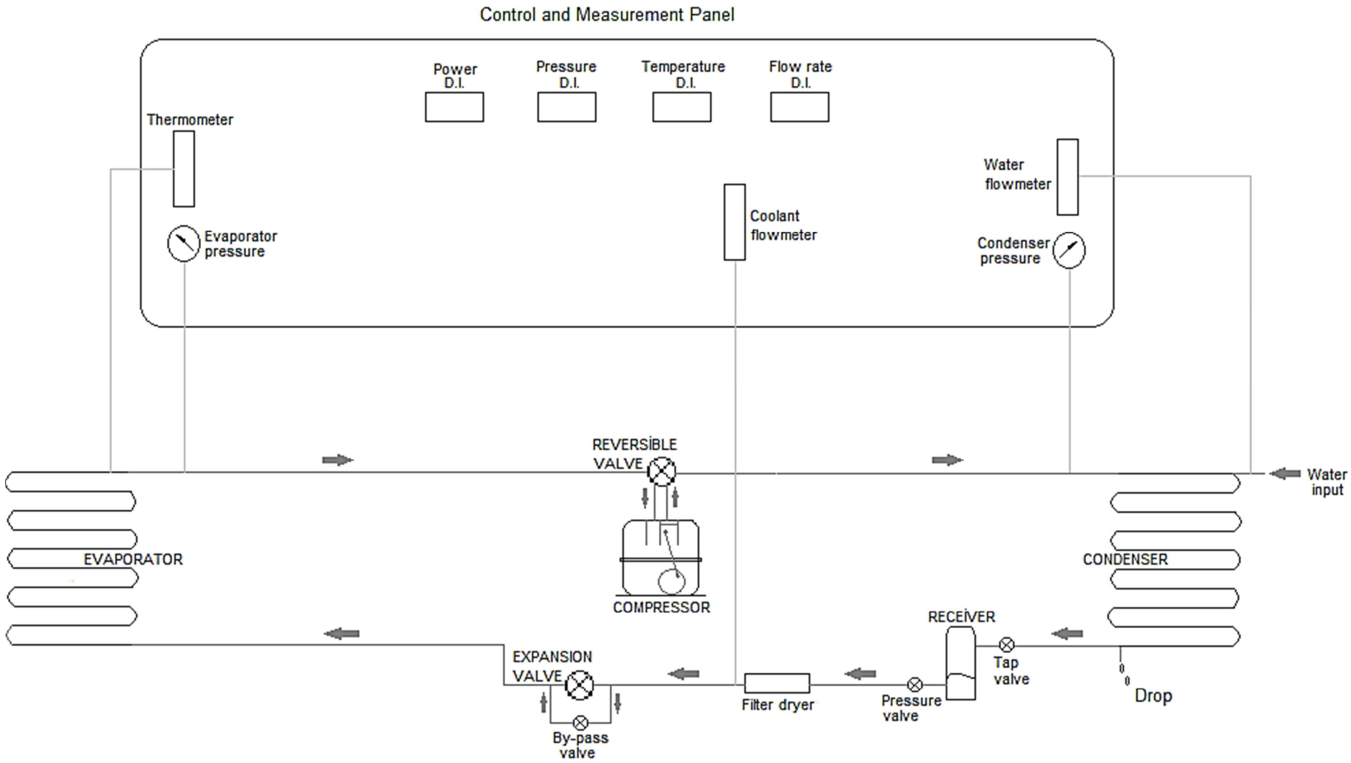

Fig. 1. The view of experimental scheme.

The performance of an experimental cooling cycle was modeled by ANN in this study. Technical specifications of the cooling system are given in Table 1. Ten experiments were conducted on the system by changing the flow rate of the condenser cooling water.

Table 1. Technical specifications of the refrigeration system.

Refrigerant	**Flordikloretan (R141-b) C2CL2FH3**
Compressor	Air pressed. Sweeping volume; 8.95 cm^3/rev. Rotation speed: 2750 rpm, frequency: 50 Hz,-50 Hz at 3500 rpm. Protected against over heating load
Condenser	Pipes are with horizontal parallel flow to one direction and watercooled

Refrigerant	Flordikloretan (R141-b) C2CL2FH3
Tank	1.49 of capacity. Fluid is pumped to the system from the tank by opening a tap
Expansion valve	fixed orifice(capillary tube) is a designed restriction Control of refrigerant is mainted by a hot gas by pass value. It controls the flow rate of R 141 b going through evaporator.
Evaporator	Double line copper pipe, aluminum shutters, steel sheet metal trunk, drainage channel, supported by axial air ventilator
Temperature Measurements	600 ^{O}C to 1280 ^{O}C, it has linear characteristics with sensible 41 V/ ^{O}C
Pressure Measurements	Bourdon tube pressure with a measurement ratio from 0 to 20 K pa
Power Measurements	Measure input power by using watt-hour method
Flow-rate Measurements	flow meter type flow rate measurement device (0 g /s – 50 g/s ratio)

Experimental results, achieved and used for modeling ANN are given in Table 2. Input power, condenser heating power, heating C_H, cooling C_C and error values of these (RE, MRE) found by ANN as well as the experimental values can be seen in Table 2.

Table 2. *Experimental measurements used in the training and the results obtained by the ANN.*

Experiments no	Condenser Water flow rate (g/s)	ANN			
		Condenser Cooling Power (watt)	Condenser Heating Power (watt)	C_H	C_C
1	6	360.42	655.97	3.18	2.62
2	12	350.09	911.48	3.26	2.74
3	18	314.33	1009.90	3.76	3.10
4	24	269.78	1057.44	4.11	3.44
5	30	258.00	1099.07	4.15	3.54
6	36	250.13	1174.43	4.42	3.67
		----------	----------		
12	72	238.14	1217.41	4.60	3.90
13	78	235.23	1236.91	4.70	4.03
14	84	229.28	1243.27	4.77	4.17
15	90	226.25	1250.49	4.86	4.35
16	96	221.15	1254.00	4.95	4.45

Table 2. *Continue.*

Experiments no	Condenser Water flow rate (g/s)	Experiments			
		Condenser Cooling Power (watt)	Condenser Heating Power (watt)	C_H	C_C
1	6	359.46	654.90	3.19	2.61
2	12	351.67	912.50	3.27	2.72
3	18	317.00	1011.23	3.74	3.11
4	24	271.89	1058.41	4.09	3.48
5	30	256.90	1097.89	4.17	3.55
6	36	249.32	1172.57	4.40	3.69
		----------	----------		
12	72	239.11	1215.05	4.62	3.92
13	78	236.54	1237.80	4.69	4.01
14	84	231.14	1242.53	4.75	4.20
15	90	227.42	1249.71	4.88	4.32
16	96	223.78	1253.60	4.97	4.43

2. Artificial Neural Networks

Artificial neural networks (ANN) have an algorithm that can learn and decide by its own throughout the process and are inspired by human brain neuron structure. They have data processing units called cells. These networks have their own weights and involve connections between the cells. ANNs are computational models, which simulate the function of biological network, composed of neurons. The system has three layers of neurons; input layer, a hidden layer and an output layer. The neurons or units of the net-work are connected by the weights. Input layer consist of all the input factors, information from the input layer is then processed through one hidden layer, following output vector is computed in the final (output) layer. Fig. 2 gives a schematic description of an ANN structure, as well as the network configuration used in this study [4].

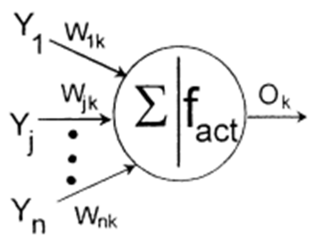

Fig. 2. *Structure of an artificial neural network cell.*

Back propagation (BP), which is one of the most famous training algorithms for multilayer perceptions, is a gradient descent technique a minimize the error for particular training pattern. Although BP training algorithm has some drawbacks, this method was used because it is simple and reliable. The important aspects of the neural network will be described briefly. Each input unit of the input layer receives input signal X_i and broad casts this signal to all units in the hidden layer. Each hidden unit Y_j sums its weighted input signal and applies its activation function to compute output signal [5].

Usually structure of an artificial neural network cell have three layers as input layer, hidden layer, and output layer. Number of the layers can change and can be rebounded between the layers. This completely depends on the usage purpose of the network and the design of the designer. Number of the nodes in the input layer equals to the number of data to be given to ANN. Number of nodes at the output layer equals to the number of knowledge that will be taken from ANN. Node number of the hidden layer is found experimentally. Learning capability of ANN improves as the number of nodes and the connections increases; however it takes more time to train ANN [6].

$$Y_j = f_{act}\left(\sum_{i=1} W_{ij} X_i\right) \tag{1}$$

Where W_{ij} is the weight from the input unit X_i to the hidden unit Y_j. The output signal of the hidden unit Y_j is sent to all units in the output layer. Each output unit O_k sums its weighted input signal and applies its activation function to compute its output signal,

$$O_k = f_{act}\left(\sum_{i=1} W_{jk} Y_j\right) \tag{2}$$

Where W_{jk} is the weight from the hidden unit Y_j to the output unit O_k. The activation function used in this study is a logistic sigmoid function defined as:

$$f_{act}(x) = \frac{1}{1+e^{-x}} \tag{3}$$

The BP training algorithm is an iterative gradient descent algorithm designed to minimize the sum of square error (E) which is averaged all patterns is calculated as follows,

$$E = \frac{1}{2}\sum_{i=1}^{p}\left(d_p - O_p\right)^2 \tag{4}$$

Where d_P is the desired or actual output, O_P the predicted output for the P_{th} pattern. During training, an ANN is presented with the data of thousands of times, which is referred to as cycles. After each cycle, the error between the ANN output (predicted) and desired values are propagated back ward to adjust the weight in a manner mathematically guaranteed to converge [7]. Adjustments of the weights ΔW_{ji} can be calculated as:

$$\Delta W_{ji} = -\alpha \frac{\partial E}{\partial W_{ji}} \tag{5}$$

Where α is learning rate. Detailed description of the mathematical formulation of the BP algorithm has been covered in literature extensively. Training is the act of continuously adjusting the connection weights until they reach unique values that allow the network to produce outputs that are close enough to the actual desired outputs [8].

The accuracy of the developed model, therefore, depends on these weights. Once optimum weights are reached, the weights and biased values encode the network's state of knowledge. Nodes process these input data and feeds forward to the next layer. A node has many inputs while it has only one output. Input data are processed as follows; each data are added up after it was multiplied by its weight and then it is subjected to activation function. Thus the data, which will be transferred to the next layer, is obtained. The algorithm used in training ANN and the type of activation function used at the output of the node are the mathematical differences [9].

In an ANN, number of the input cells is equal to number of data at input and output cell number equals to the number of data taken from the output. Some equations were given for the hidden cell number but it is generally found by trial and error method. The equation below was proposed for the hidden cell number [10].

$$\text{Number of hidden cells} = \tfrac{1}{2}\,(\text{inputs} + \text{outputs}) + \sqrt{\textit{number of training data}} \tag{6}$$

Following the completion of training ANN, relative error (RE) for each data and mean relative error (MRE) for all data are calculated according to the formula below for testing network:

$$RE = \left(\frac{100(d_k - o_k)}{d_k}\right) \tag{7}$$

BP training algorithm is a ramp descent algorithm. BP algorithm is used to improve the performance of the network by reducing the total error through changing the weights along the ramp. Training is stopped when the mean square error (MRE) values stop decreasing and when there is an increase in these values, which is an indication of over-training [11]. perpendicular, "0.1"; and parallel, "0.9". In order to facilitate the comparisons between predicted values for different network parameters (learning rate, momentum coefficient and neuron number in hidden layer) and desired values, there is a need for error evaluation. Mean relative error (MRE) was calculated following expression,

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{100(d_i - o_i)}{d_i}\right) \tag{8}$$

Where d_i is desired value, o_i the predicted output value and n, the number of data. Relative error values were calculated for the data used and not used in training according to Eqs. (7) and (8) .After the ANN structure was developed, it was normalized within the 0-1 value set using Eqs. (9) in order to improve the training characteristics of the data set.[12]

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

The training data set was used to determine ANN neuron and bias weight values. Training was repeated by changing the number of neurons in the hidden layer and the iteration number in order to obtain the lowest error value. After the most suitable network structure was determined, the trained algorithm was applied to the test data set. The ANN parameters that were used are given in Table 3.

Table 3. *Parameters that were used in ANN.*

Parameters	Properties
The number of neurons in the input layer	4
The number of neurons in the hidden layer	6
The number of neurons in the output layer	1
Learning rate (α)	0.8
Momentum rate (β)	0.9
Learning algorithm	Gradient reduction algorithm (train lm)
Transfer function	Logarithmic sigmoid (tan sig)

The network is subjected to two processes, namely training and test, to develop an ANN model. In the case of training, the network is educated for an output prediction depending on the input data. In the case of test, on the other hand, the network is tested for stopping or for saving training data and is used for predicting an output. The process of network training is stopped when the error that is being tested has reached the desired tolerance value [13].

Back Propagation (BP) algorithm is the most popular algorithm which also has the largest area of use. BP consists of two phases, i.e. feed forward and back propagation procedures. During feed forward, information that is subjected to processing from the input layer to the output layer is generated. In the case of back propagation, on the other hand, the difference between the network output value obtained from the feed forward procedure and the desired value is compared with the desired difference tolerance and the error in the output layer is calculated. The obtained error is back propagated to update the links in the input layer neurons [14].

3. Results and Discussion

ANN used in modeling this cooling system was made by a program written in MATLAB code. There are three layers in this ANN as input layer, hidden layer and output layer. There is one neural cell in input layer. Condenser water flow rate is the data given to the cell at input layer. Four cells at the output layer give input power, condenser heating power, coefficients of performance (C_H,C_C). Hidden Layer cell number of the ANN shown in Fig. 3 was found 6 from Eq. (6). 6 out of 16 experiments conducted were used in training, and the other six experiments were used to test ANN. Square error condition of $e \leq 0.005$ was tried to be realized in training and it was achieved for the ANNs with six hidden cells.

Back propagation algorithm was used for training ANNs. All weights were corrected and repeated after the calculation of each data set. ANN with six hidden cells reached to desired error value after repeating 128,398 times. No more ANNs having hidden layer cells other than this number was tested since the desired error value was reached by this ANN.

Apses of the graphic shows the condenser cooling water flow rate and ordinate shows the values measured and estimated by the ANN. Test results of ANN were also given in figures. Input power, condenser heating power, heating C_H and cooling C_C results predicted by ANN and the calculated results were compared in Figs. 4–7. Coefficients of multiple determination (R^2) between the experimental values and the values predicted by ANN were also given in the graphs. Relative error of ANN in these values is 3.97% and multiple determination coefficient isR^2= 0.981.

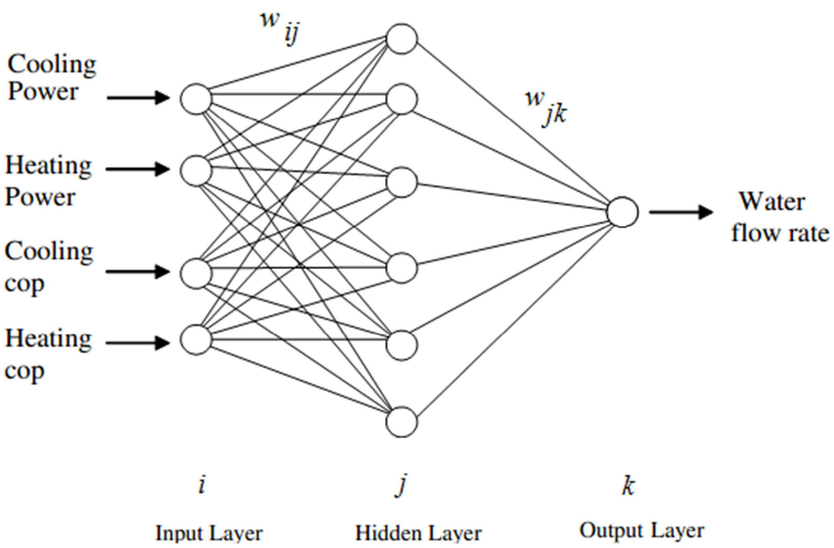

Fig. 3. *The structure of three layered neural network in present study.*

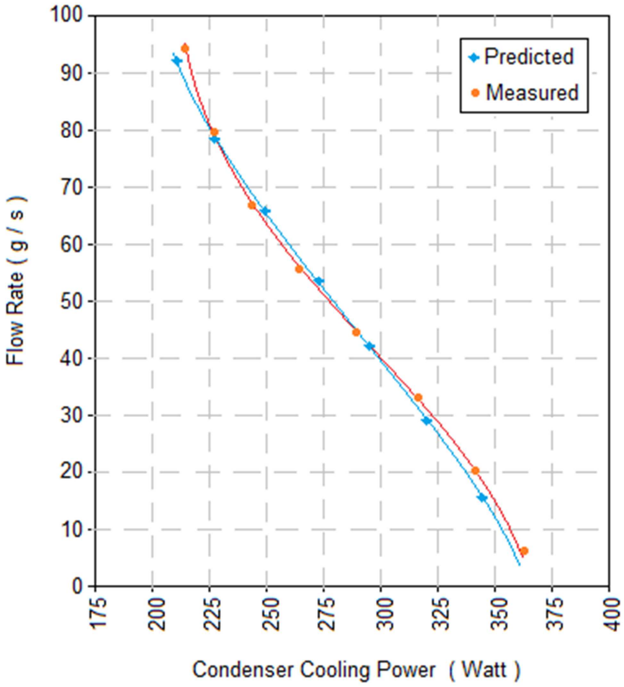

Fig. 4. Comparison of the input power calculated from the experimental data, and the one obtained from ANN.

Fig. 5 shows the changes in cooling water flow rate and the electric power spent in compressor. Artificial neural network learned the data not used in training with a relative error of 1.41 % and a multiple determination coefficient of R^2= 0.996.

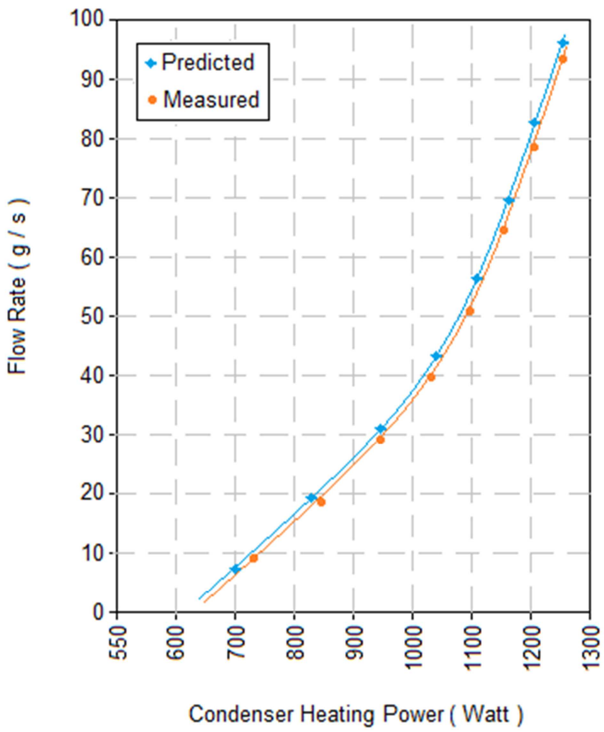

Fig. 5. Comparison of the output power calculated from the experimental data, and the one obtained from ANN.

The change in cooling water flow rate and the exhausted heat value in the condenser are shown in Fig. 6.

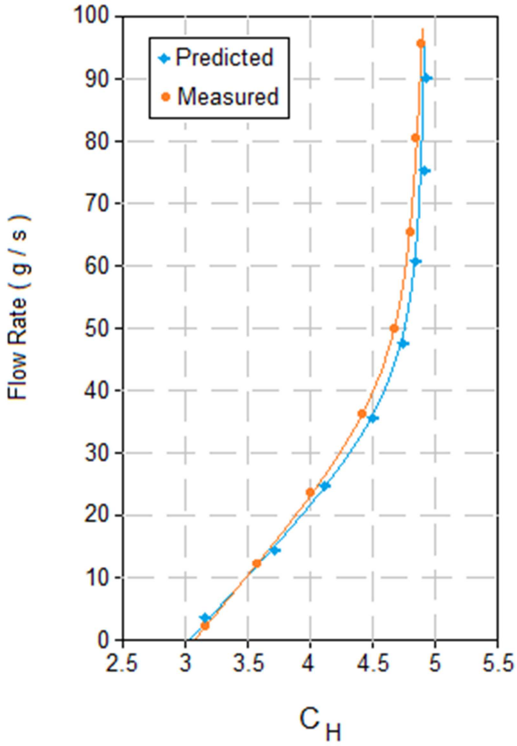

Fig. 6. Comparison of the heating C_H calculated from the experimental data, and the one obtained from ANN.

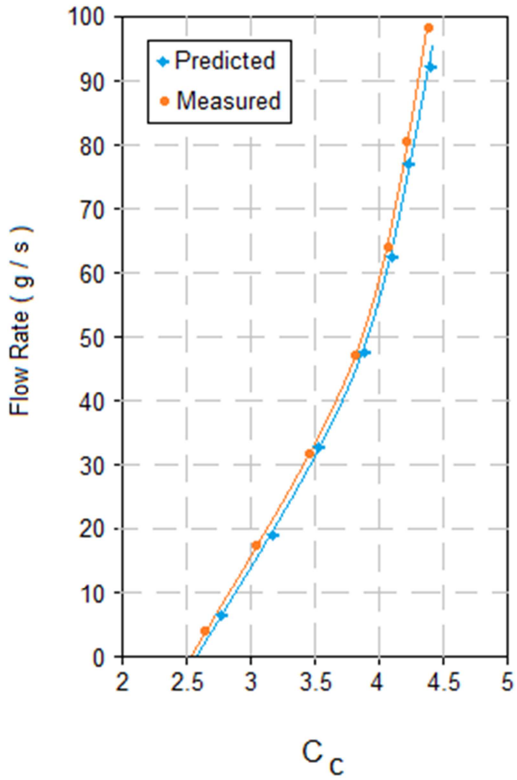

Fig. 7. Comparison of the cooling C_C calculated from the experimental data, and the one obtained from ANN.

Heating C_H and cooling C_C values versus cooling water flow rate are shown in Figs. 6 and 7 respectively. ANN learned heating C_H with a relative error value of 2.01% and a multiple determination coefficient of R^2=0.993 and cooling C_C with a relative error value of1.92% and a multiple determination coefficient of R^2=0.994.

Fig. 8 shows a plot of the estimated weights of the parts at various process settings versus the actual weights. A linear relation with a high correlation factor (98%) indicates the ability of the network to estimate the flow rate of the cooling water with high accuracy. The actual weights of the parts varied at10% of the ANN predicted weight at various experimental settings. Besides, to assess the accuracy of ANN prediction, the regression curves are shown in Figs. 8.ANN's prediction values of flow rate were assessed with regression an analysis between predicted and experimental data.

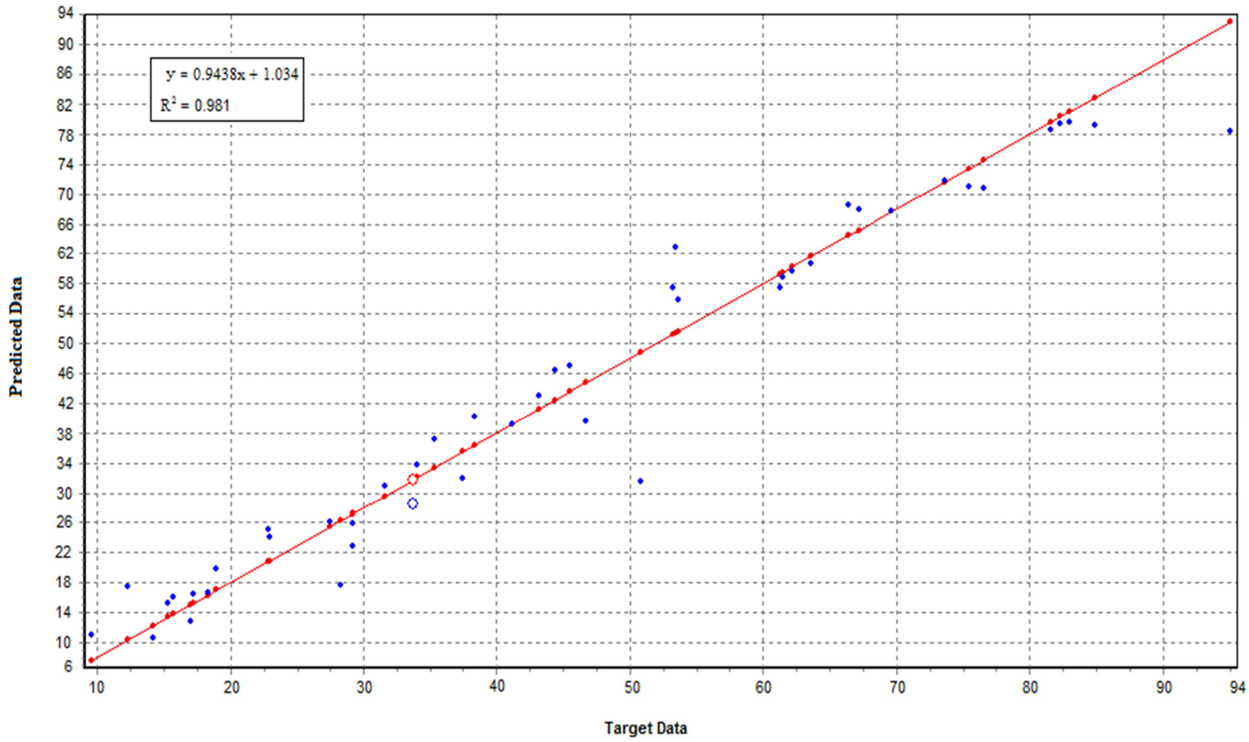

***Fig. 8.** The predicted outputs vs. the measured values of flow rate.*

4. Conclusion

The performance prediction of refrigeration system was made according to the experimental values by using ANNs, a type of artificial intelligence. Results of 6 experiments out of 16, which were conducted at laboratory conditions were used to train ANN and the other 6 were used to test ANN. Average relative errors of the test of artificial neural net-work were found as; 1.41% for input power, 3.97% for heating power, 2.01% for heating C_H, and 1.92% for cooling C_C.

Multiple determination coefficient found by ANN were as; 0.996 for input power, 0.981 for heating power, 0.993 for heating C_H, and 0.994 for cooling C_C. These values showed that ANN can be used in performance prediction of heating and cooling devices with appropriate network architecture and training set and it gave a good prediction of results.

Nomenclature

ANN	artificial neural network
BP	back propagation
C_H	heating coefficient of performance
C_C	cooling coefficient of performance
d_k	result expected from layer 2
d_o	error occurred at layer 2
d_y	error occurred at layer 1
e	square error occurred in one cycle
$f(net_i)$	activation function
MRE	mean relative error
n	data number
net_i	calculation result of layer 1
net_k	calculation result of layer 2
O_k	result of layer 2
RE	relative error for each data
R^2	coefficient of correlation
x_i	input data
w_{ij}	weights in layer 1
w_{jk}	weights of layer 2
y_i	results obtained from layer 1
α	learning constant
β	momentum constant
ε	approximately constant
Δw_{ij}	correction made in weights at the previous calculation
Δw_{jk}	correction made in weights at the previous calculation

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