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DEVELOPING ANN MODEL TO EVALUATE COP OF VCR SYSTEM FOR SUCTION PRESSURE & TEMPERATURE, DELIVERY PRESSURE & TEMPERATURE AS INPUT PARAMETER

Rakesh Kumar Agrawal[1], G. K. Agrawal[2]

1 Research scholar, Mech. Engg. Department, Dr C.V.R.U. Kota Bilaspur (C.G.)
2 Professor, Mech. Engg. Department G.E.C. Bilaspur (C.G.)

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Email: info@jusres.com

ABSTRACT

Artificial neural network (ANN) network3 is developed to evaluate coefficient of performance of simple vapor compression system for various values of suction pressure, suction temperature, delivery pressure & delivery temperature as input parameter. 51 set of experimental set of parameters is used to train ANN, network3 and 12 set of experimental parameters is used to test ANN, network3. Value of experimental COP and that predicted by ANN network3 resemble close to each other with **R^2 = 0.9996346, RMSE = 0.111, COV=1.928 %.** In developed ANN model network3, network type feed forward back propagation, Training function TRAINLM, Adaptation learning function LEARNGDM, performance function MES, no of layer 01, No of neuron 08 and Transfer function LOGSIG, with other training parameter has been used to successfully train ANN network3. It is concluded that ANN with developed network3 can be successfully applied for evaluation of coefficient of performance of simple vapor compression refrigeration (**VCR**) system & hence ANN may be very useful tool for performance analysis of refrigeration system.

KEYWORDS: ANN Model, VCR System, Temperature and Pressure.

Nomenclature & Abbreviation

ANN	Artificial neural network.
VCR	Vapor Compression Refrigeration.
COP	Coefficient of Performance.
p	Pressure (kJ/kg).
T	Temperature (0C).
h	Enthalpy (kJ/kg).
R^2	Absolute Fraction of Variation.
RMSE	Root Mean Square Error.
COV	Coefficient of Variance.
RACHP	Refrigeration, Air Conditioning & Heat Pump.
GRNN	Generalized Regression Neural Network.
RBFNN	Radial Biased Function Neural Network.

1. INTRODUCTION

The proposed research study is about to find refrigerating effect, power consumption & COP of a simple vapor compression refrigeration system under real steady state conditions/transient state for different combinations of capillary tube size in the system, and to find the impact of different lengths of capillary tube over the performance of system under same boundary conditions.

More is the temperature difference between external fluid and refrigerant across evaporator and condenser, better would be heat transfer across evaporator and condenser. A vapor compression refrigeration system can be theoretically optimized and balanced under steady state conditions, but it is more practical to use ANN for transient condition for performance analysis of VCR system.

Practically a refrigeration system has to work under transient conditions. The conditions over condenser may be considered steady state but over the evaporator, condition remains transient. In evaporator, a fixed mass or space has to be cooled from some initial room temperature to final refrigeration temperature. As a result of continuous decrease of temperature of external fluid over evaporator, environment surrounding evaporator does not remain steady and whole system works under transient conditions. With the decrease in difference of temperature of refrigerant and external fluid across evaporator with respect to time, the heat transfer across the evaporator tubes should also get reduced deteriorating the performance of system. In this way, a condition may come when the difference of temperature of refrigerant and external fluid over evaporator is too less to sustain a reasonable amount of heat transfer and evaporation rate in evaporator. The length and diameter of capillary tube in general decides the evaporator and condenser pressure. Larger the length of capillary tube lower is the evaporator pressure and vice versa. Similarly, larger the diameter of capillary higher is the evaporator pressure and vice versa. The length and diameter of capillary tube may be theoretically optimized if the heat transfer situations over evaporator and condenser and so the evaporation and condensation pressures are steady state.

Generally, to investigate the dynamic behavior of refrigeration systems, usually the heat exchangers are treated by transient models while the expansion valve as well as the compressor is considered in steady state. But need was felt to observe experimental values of refrigeration effect, power consumption, and COP and also to find the role of capillary tube length, while working of system under real transient conditions. So weather steady or transient condition ANN can be successfully applied to vapor compression refrigeration system for optimization of its performance. In this research work Experimentation is conducted for different combination of capillary length & diameter, which in turn vary suction pressure. Refrigeration effect, power consumption, and COP is experimentally evaluated for different value of suction pressure, suction temperature, delivery pressure & delivery temperature. Then Artificial neural networks (ANN) network3 is developed and successfully trained to evaluate coefficient of performance of simple vapor compression system for various values of suction pressure, suction temperature, delivery pressure & delivery temperature as input parameters.

2. REVIEW OF LITERATURE

A summary of ANN applications by [1] for vapor compression systems are listed in Table 1.

Table 1 -Applications of ANN for vapor compression systems

Authors [references]	**Network architectures**	**Year**	**Equipment**
Swider et al. [2]	GRNN	2001	Chillers
Navarro-Esbrı et al. [3]	RBFNN	2007	Chillers
Chang [4]	MLFFN	2007	Chillers

The performance of two vapor compression chillers (chiller-A and chiller-B) was forecasted by using ANN [2]. They used GRNN (Generalized Regression Neural Network) model for predicting the performance factors such as COP, compressor power input, chill water inlet and cooling outlet temperatures with reference to cooling capacity, chill water outlet and cooling water inlet temperatures. Their results showed that 94% of ANN predicted values for chiller-A and 87% for the chiller-B were within ±5% of the experimental values. The maximum COV of ANN predicted results for the chiller-A and chiller-B were reported as 1.7% and 3.9%, respectively.

A RBFNN (Radial Biased Function Neural Network) model was developed for predicting the performance factors (such as cooling capacity, power consumption and chiller water outlet temperature) of a variable speed compression based refrigeration systems with reference to speed, chill water temperature inlet, condensing water temperature inlet and refrigerant evaporator temperature [3]. It was reported that the network forecasted cooling capacity, chill water outlet temperature and power consumption were closer to experimental values within ±2%, ±0.2 K and ±5% deviations, respectively with RMS errors of 0.084, 0.054 and 0.048 respectively.

Chang [4] testified the suitability of ANN model to determine the optimal sequencing of six chillers used in a semiconductor industry. In his work, MLFFN with four neurons in input layer (representing supply temperature of chill water, return temperature of chill water, supply temperature of cooling water and return temperature of cooling water), one neuron in the output layer (power consumption) was developed. Two hidden layers comprising of 20 and 40 neurons were used. It was stated that significant energy savings can be made by changing the chiller start-up sequences using ANN model.

3. ARTIFICIAL NEURAL NETWORK AN OVERVIEW

ANN has a powerful ability in recognizing accurately the inherent relationship between any set of inputs and outputs without requiring a physical model, and the predicted results using ANN do account for all the physics relating the outputs to the inputs [5].

The fundamental processing element of a neural network is a neuron. A biological neuron actually obtains inputs from other sources and combines them in some way. Then performs normally a nonlinear operation on the result and then outputs the final result [6]. Neural networks operate much as a black box model, requiring no detailed information about the system. On the other hand, they learn the relationship between the input and the output. The network usually consists of an input layer, some hidden layers and an output layer [7]. In Fig. 1 and 2, an artificial neuron and a schematic diagram of a multi-layer network are shown.

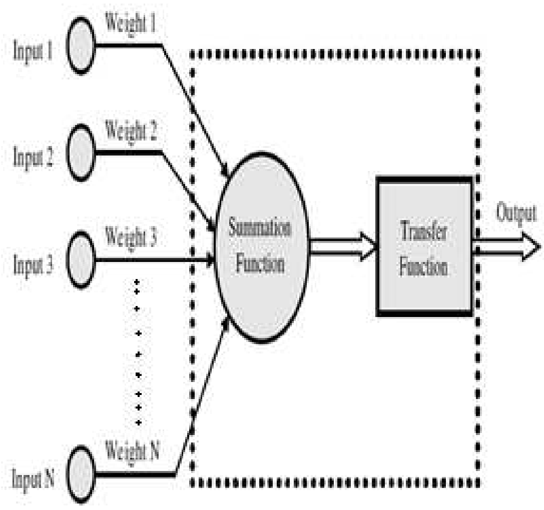

Fig 1 Artificial Neuron [6]

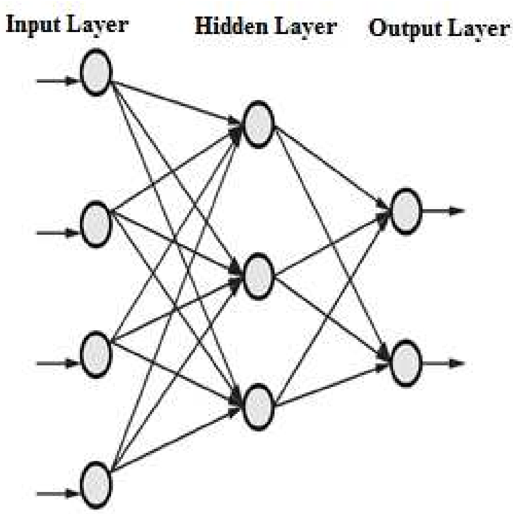

Fig 2 Multi-layer feed forward [6]

Most commonly used network architectures in the field of RACHP (Refrigeration, Air Conditioning & Heat Pump) are

01. Multi-layer feed forward,
02. Radial biased function network,
03. Generalized regression neural networks and
04. Adaptive neuro fuzzy system

4. METHODOLOGY

1. Experimental setup of Refrigeration System Fig 3.

Fig.3 Experimental setup

By experimental setup as shown in fig 3, we can collect following experimental data

- p_1, Suction pressure is measured using analog pressure gauge.
- p_2, Delivery pressure measured using analog pressure gauge.
- To change suction pressure different combination of length and diameter of capillary is used apart from auto expansion valve.
- Mass flow rate of refrigerant is measured by Rotameter.
- Can use refrigeration system with/without internal heat exchanger.
- Current is measured by ammeter (Amp).
- Voltage is measured by voltmeter in (Volt).
- T_1, Temperature of refrigerant inlet to compressor.
- T_2, Temperature of refrigerant outlet to compressor.
- T_3, Temperature of refrigerant at outlet to condenser.
- T_4, Temperature of refrigerant at outlet to expansion valve.
- T_5, Temperature inlet to heat exchanger (suction line).
- T_6, Temperature of refrigerant outlet to heat exchanger (suction line).
- T_7, Temperature of refrigerant Inlet to heat exchanger (delivery line).

- T_8, Temperature of refrigerant outlet to heat exchanger (delivery line)/ Temperature of refrigerant entering the expansion valve/capillary.
- T_9, Temperature of brine entering to evaporator.
- T_{10}, Temperature of brine coming out of evaporator.
- T_{11}, Temperature of brine.

With suitable modification other necessary data can be collected. From experimental Data enthalpy value at different states are calculated using peace software [7] and then ANN is applied for further analysis and optimization of system.

5. TRAINING OF ANN

Experimentation is performed for various suction pressure p_1 for refrigerant R134a and value of other parameter like p_2 (Delivery pressure), T_1 (Temperature of refrigerant inlet to compressor), T_2 (Temperature of refrigerant outlet to compressor), T_8 (Temperature of refrigerant entering the expansion valve/capillary tube) and other parameters are recorded till the steady state is reached with respect to time. Enthalpy values are calculated at different pressure and temperature using peace software [7], and with the help of other parameter compressor work per kg of refrigerant heat absorbed per kg of refrigerant in the evaporator and COP of VRC system is calculated. Out_of huge experimental data few steady state data are selected for different p_1. Out of which 51set of input and target data is used to train ANN network3. The 12 set of sample data, which are excluded while training the ANN network3, are used to test trained network3.

The performance of the ANN is measured by absolute fraction of variation (R^2), Root mean square error (RMS) and coefficient of variance (COV), which can be calculated by using following equations (1), (2), (3) suggested by [1].

The fraction of absolute variance is given by

$$R^2 = 1 - \frac{\sum_{m=1}^{n}\left(y_{pre,m} - t_{mea,m}\right)^2}{\sum_{m=1}^{n}\left(t_{mea,m}\right)^2} \qquad (1)$$

The root mean square value is calculated by

$$RMS = \sqrt{\frac{\sum_{m=1}^{n}\left(y_{pre,m} - t_{mea,m}\right)^2}{n}} \qquad (2)$$

Coefficient of variance is calculated by the following equation

$$COV = \frac{RMS}{\sum_{m=1}^{n}\left(t_{mea,avg}\right)} \times 100 \qquad (3)$$

Here, n is the number of data patterns in the independent data set, $Y_{pre,\ m}$ indicates the values predicted by ANN, $t_{mea,m}$ is the measured value of one data point m and $t_{mea,avg}$ is the mean value of all measured data points [1]. Here in research work R^2**,** RMSE, COV is calculated for data used to test the network.

Training of artificial neural network network3 is done by MATLAB software using neural network tool box. Input parameters to the network are p_1, T_1, p_2 and T_2. Output parameter is COP of VCR system. 51 set of data is used to train network. And 12 set of experimental data are used to test the network.

For this in MATLAB software in workspace three new worksheet is opened, renamed it as input, target and sample. Input data of 51 set is saved in input sheet. Similarly, experimental output of 51 data set is saved as target sheet. 12 set of experimental data are used to test the network. Input parameter of these 12-data value are saved in worksheet named as sample. As the training is over complete workspace is as shown in fig 4. Predicted output of ANN is saved as **network3_outputsample**.

In command window under command prompt we run nntool. As a result, neural network /data manager (nntool) window appeared and then by selecting import tab import to network /data manager window opened and we import input data sheet from MATLAB as input data, target data sheet as target data, sample data sheet as input data and then closed the window as shown in fig 5.

New network is generated by selecting new tab in network /data manager (nntool) window. By doing so "create network/data" window is opened, here new network appeared and renamed it as network3. Output parameter for this network is COP of VCR system.

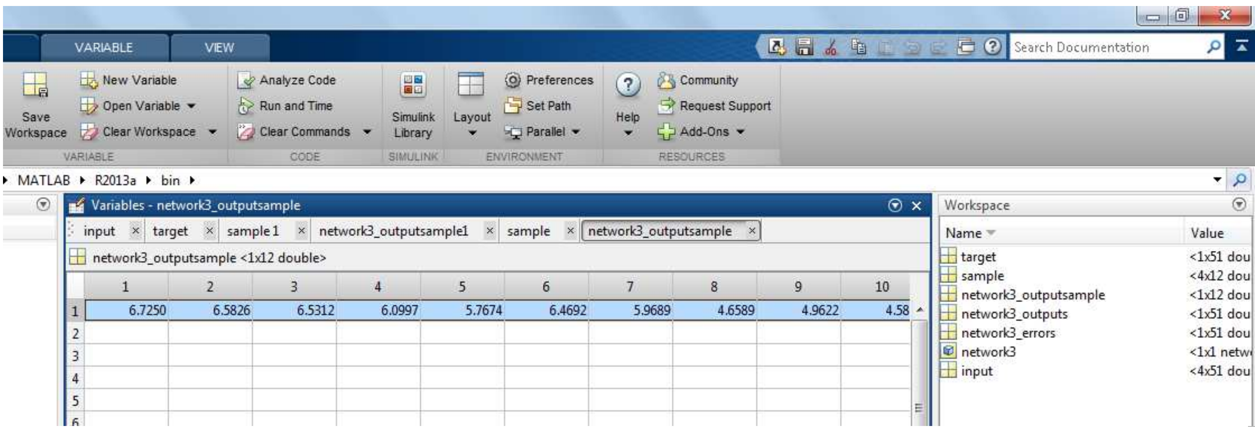

Fig 4 Workspace of MATLAB as training is over.

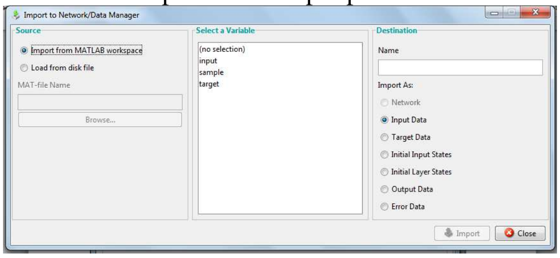

Fig 5 Import to network /data manager window in MATLAB

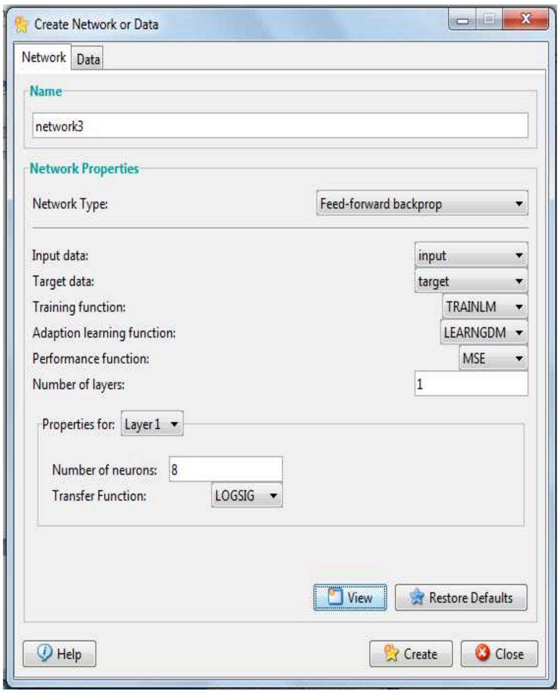

Fig 6 Create network/data in MATLAB

After so many trial finally selected Network property is as shown in fig 6, as network type feed forward back propagation, Adaptation learning function as LEARNGDM, target data as target,

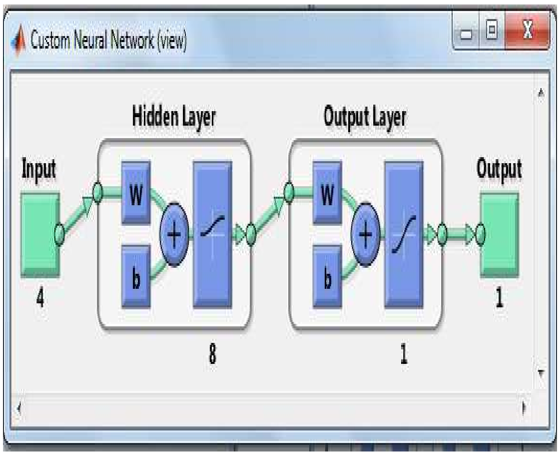

Fig 7 Custom neural network (view) ANN.

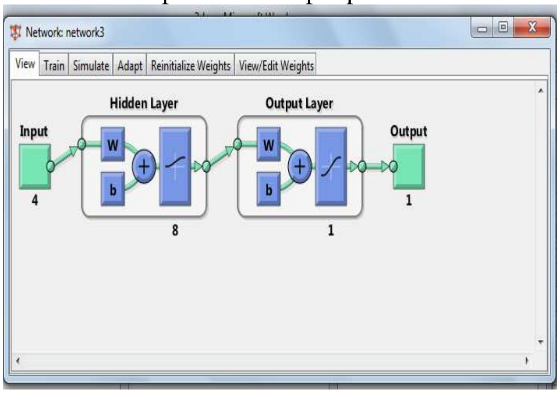

Fig 8 Creating network3 in MATLAB

Training function as TRAINLM, input data as input, Performance function as MES, number of layer 1, no of neuron as 8, transfer function LOGSIG. By pressing view tab, in "create network/data" window, network to be created can be viewed in "custom neural network (view)" window as in fig 7.

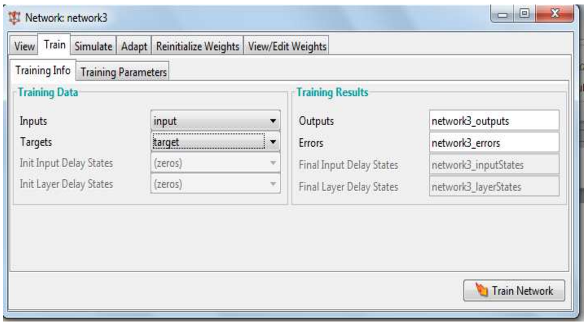

Fig 9 Training information of network3

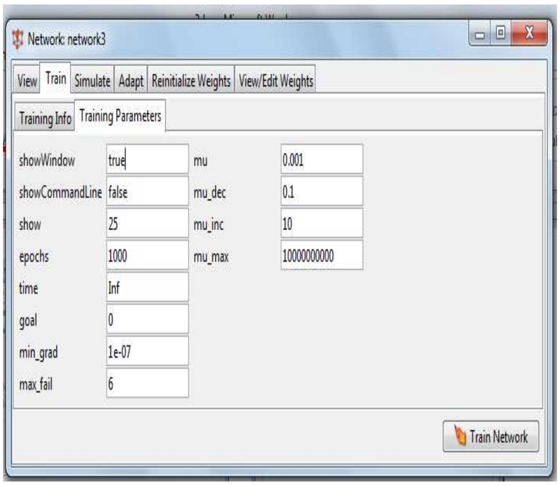

Fig 10 Training parameter of network3

Custom neural network (view) window is opened and it shows trend of input and output data as trend is matched, we created the artificial neural network called network3 and added it to "neural network/data manager". Created network3 is selected in "neural network/data manager" window and is opened as shown in fig 8. For training of network, Train tab is selected and then under training information, in training data, input is selected as input and target as target to train network3. Training result under in same window shows predicted outputs of data used for training as **network3_output** and error as **network3_error** of the 51 sets of data used for training as shown in fig 9.

Then selected the training parameter tab under same train tab and after so many trial finally selected training parameter as shown in fig 10, which gives training of ANN network3 in fig 11 and corresponding regression analysis as shown fig 12

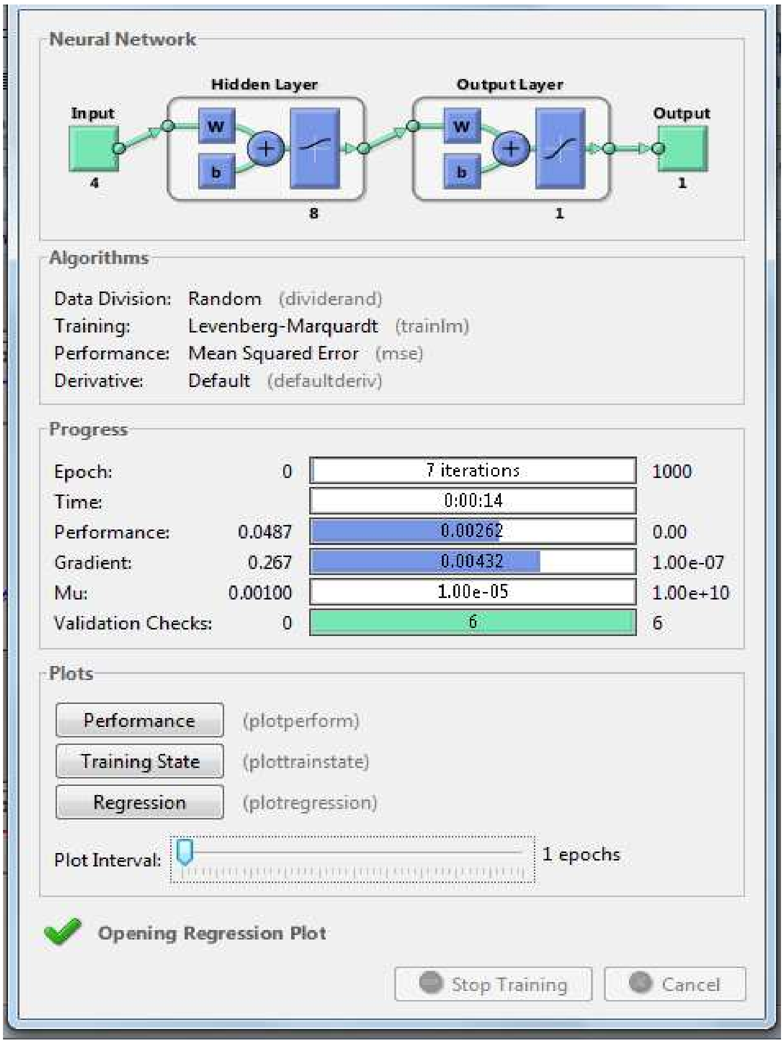

Fig 11 Training of Network3

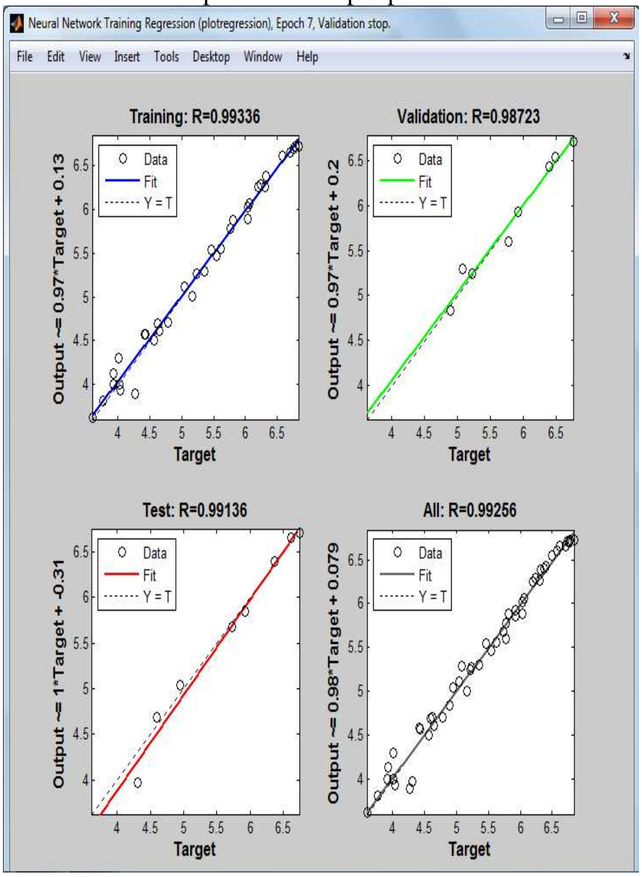

Fig 12 Regression analysis of network3

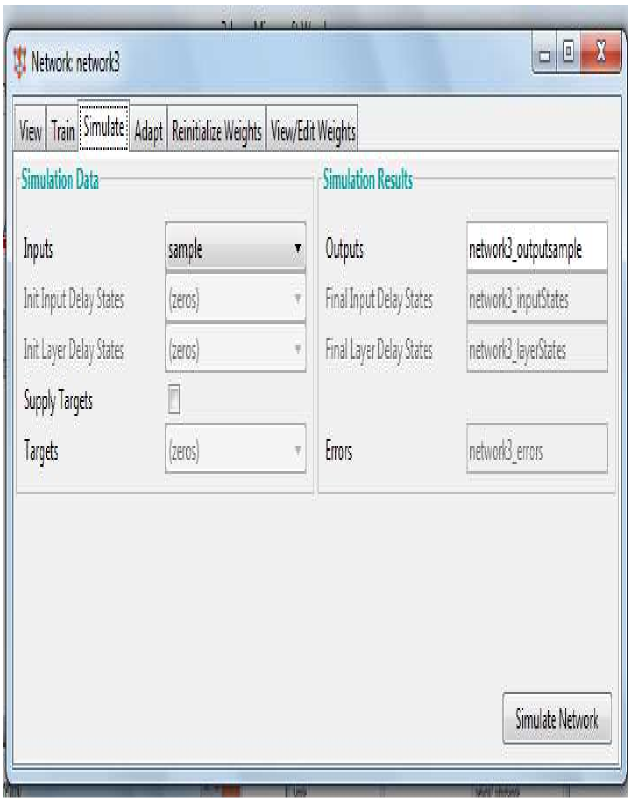

Fig 13 Simulation of network3 on ANN

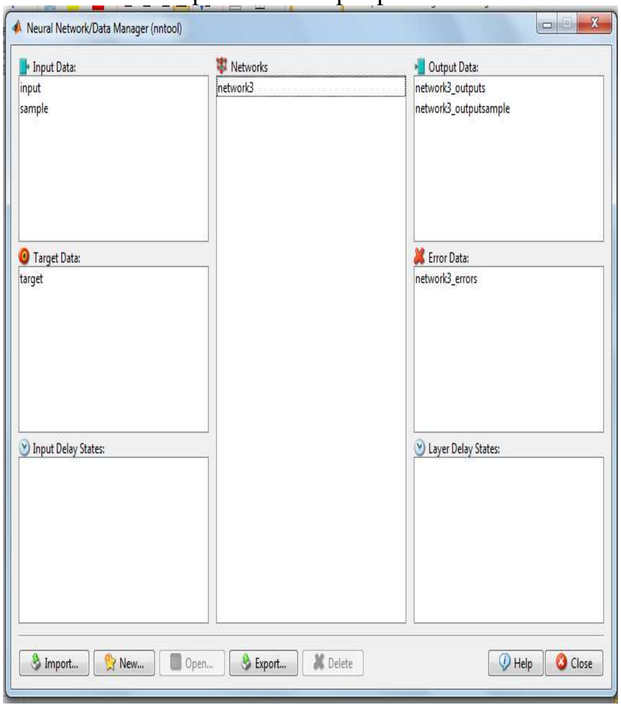

Fig 14 network3_outputsample on ANN

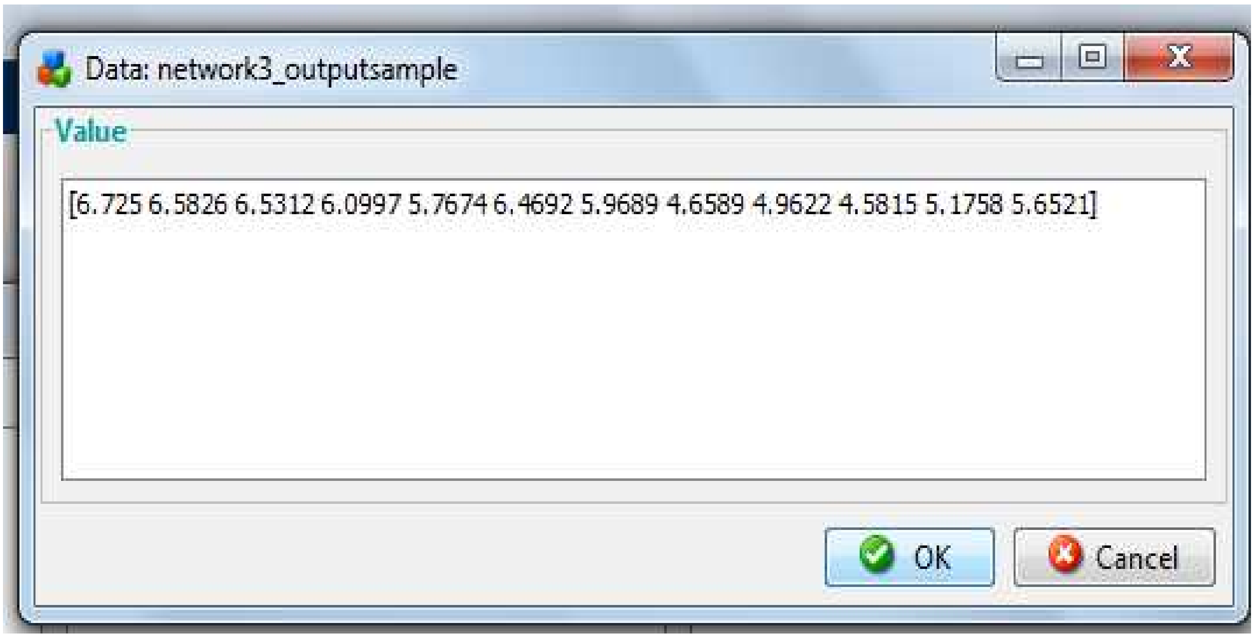

Fig 15 Predicted output of sample used to test network3 as network3_outputsample

Then to simulate trained ANN network3 we selected simulate TAB as shown in fig 13, with under simulation data selected input as sample and output as **network3_outputsample**. Then result i.e. output /predicted data of 12 set of sample input data used to test network is stored in "neural network /data manager" as shown in fig 14. Predicted output value of network3 as "**network3_outputsample"** for given 12 set of input data used as sample to test networ3 is shown by fig 15. Predicted output, network3_outputsample value which is exported to work sheet and compared with experimental output of 12 sample data used to test ANN network3, which resembles to each other as shown in table 2.

Table 2 Response Data by ANN

S.NO	DATA TO TEST TRAINED NETWORK						Measured output –predicted output	R^2	RMSE	COV
	INPUT				OUT-PUT	ANN OUT PUT				
	p_1 kPa (kilo Pascal)	T_1 (°C) -Inlet to Compressor	p_2 kPa (kilo Pascal)	T_2 (°C) outlet to compressor	COP of VCR system	COP of VCR system				
1	149.62	23	1170.05	71	6.86	6.72	0.14	0.9996346	0.111	1.928 %
2	156.51	23	1170.05	72	6.52	6.58	-0.06			
3	163.41	25	1204.52	74	6.48	6.53	-0.05			
4	170.30	23	1204.52	74	6.12	6.10	0.02			
5	170.30	26	1239.00	78	5.76	5.77	-0.01			
6	170.30	27	1239.00	76	6.43	6.47	-0.04			
7	177.20	27	1273.47	78	6.01	5.97	0.04			
8	184.09	16	1301.05	81	4.52	4.66	-0.14			
9	190.99	15	1301.05	79	4.72	4.96	-0.24			
10	197.88	17	1280.36	80	4.69	4.58	0.11			
11	211.67	28	1328.63	82	5.32	5.18	0.14			
12	253.04	26	1425.16	78	5.56	5.65	-0.09			

6. RESULT:

Result is shown in Table2, as experimental output and Output parameter predicted from ANN network3 resembles close to each other with **R^2= 0.9996346, RMSE = 0.111**, **COV= 1.928 %** & we can reach to conclusion that ANN named network3 with network architect feed forward back propagation, Adaptation learning function as LEARNGDM, Training function as TRAINLM, Performance function as MES, number of layer 1, no of neuron as 8 , transfer function LOGSIG, can be effectively applied in the field of performance analysis of simple vapor compression refrigeration system. Actual performance of network is evaluated using 12 set of test data, since these were not used for training and table 2 shows that R^2 is **0.9996346** which is very close to 1 for test data and RMS error is very small **0.111.**

It is clear that ANN (network3) gives very accurate representation of statistical data over the full range of operating condition and indicates that trained network3 predicted COP of VCR system for given inputs very accurately. Evaluation of these result suggest that COP of VCR system are predicted within acceptable error.

7. CONCLUSIONS

The ANN model developed in this research work, network3 is ready to analyze performance analysis of vapor compression refrigeration system to find out effect of inputs to the output as COP of VCR system. Input parameter are suction pressure(p_1), suction temperature/inlet temperature to compressor(T_1), Delivery pressure(p_2) and outlet temperature to compressor(T_2) which gives the effect on the output parameter COP of VCR system.

Effort has been made to train ANN's named here as network3 with network type feed- forward back propagation with p_1, p_2 T_1 T_2 as input parameter and COP of VCR system as output parameter. ANN is commendably trained as experimental output and Output parameter predicted from network3 is very close to each other for 12 set of test data with **R^2= 0.9996346, RMSE = 0.111, COV= 1.928 %.**

These ways we can conclude that ANN network3 is trained with Network type - feed forward back propagation, Training function- TRAINLM, Adaptation learning function – LEARNGDM, Performance function as MES, number of neuron as 8, number of layer 1 and transfer function LOGSIG. Developed ANN, model network3, can be successfully applied in the field of performance analysis of simple vapor compression refrigeration system and for given set of input parameters, COP of VCR system, as output parameter can be predicted very accurately.

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