Alternative Approach For Thermal Analysis Of Transcritical Co_2 One-Stage Vapor Compression Cycles

Bayram KILIÇ

Mehmet Akif Ersoy University, Bucak Emin Gülmez Vocational School, Burdur
E-mail address: bayramkilic@mehmetakif.edu.tr

Received date: February 2016
Accepted date: March 2016

Abstract

In this paper, an application artificial neural network (ANN) is presented to estimation the coefficient of performance (COP) in the transcritical CO2 one-stage vapor compression cycles. The thermodynamic properties of the transcritical CO2 one-stage vapor compression cycles were obtained from CoolPack program. The obtained data were used for training and testing artificial neural network. The results of the ANN are compared with the actual data. The coefficient of multiple determination (R2) value was obtained as 0.99907 for the coefficient of performance (COP), which is very satisfactory. A new formulation was derived for the determination of the coefficient of performance (COP) in the transcritical CO2 one-stage vapor compression cycles.

Keywords: the coefficient of performance, transcritical, CO_2, vapor compression cycles, ANN

1. Introduction

Shin et al. have examined the performance characteristics of a two-stage CO_2 system with two different evaporating temperatures. The performance characteristics of a two-stage CO_2 system are outdoor air temperature, outdoor air velocity, and 2nd-stage electric expansion valve (EEV) opening. The results have been shown that the system performance was very sensitive to the variation of two-stage electric expansion valve (EEV) opening [1]. Ahammed et al. have carried out CO_2 based transcritical vapour compression refrigeration system by interfacing with the system simulation model. In the study, the efficiencies of nozzles and diffuser have been assumed to be 85% each for both design and parametric analyses. The results have been shown that coefficient of performance (COP) improvement of 21% compared to an equivalent conventional CO_2 system [2]. Pérez-García et al. have carried out a comparative study and energetic simulation of most common configurations for transcritical single stage cycle using CO_2 as refrigerant. In the study, a cycle components modelization has been suggested and results have been used to find the optimum configuration for a single stage vapor compression transcritical system [3]. Chesi et al. have carried out experimental analysis of R744 parallel compression cycle. The experimental results showed that the theoretically values in terms of refrigerating capacity and coefficient of performance are threatened by some cases which may occur in a real system [4]. Ge et al. have investigated the performance of the CO_2 gas coolers/condensers with different structure designs, controls and system integration at different operating conditions. The effects of the CO_2 gas cooler/condenser sizes and controls on the system performance have been compared and analysed [5]. Salazar and Méndez have been devoloped Proportionale Integral-Derivative (PID) control for a single-stage transcritical CO_2 refrigeration cycle. Results of the study show that it is easier to control the evaporator, the stable operation of the system can be severely modified by the thermal performance of the gas cooler [6].

From the literature review aforesaid above, it is seen that basic computational intelligence techniques are used in the transcritical CO_2 one-stage vapor compression cycles. However, an ANN method has not been carried out for the coefficient of performance (COP) in the transcritical CO_2 one-stage vapor compression cycles yet. This paper is focused on the applicability of ANN methods for estimation the coefficient of performance (COP).

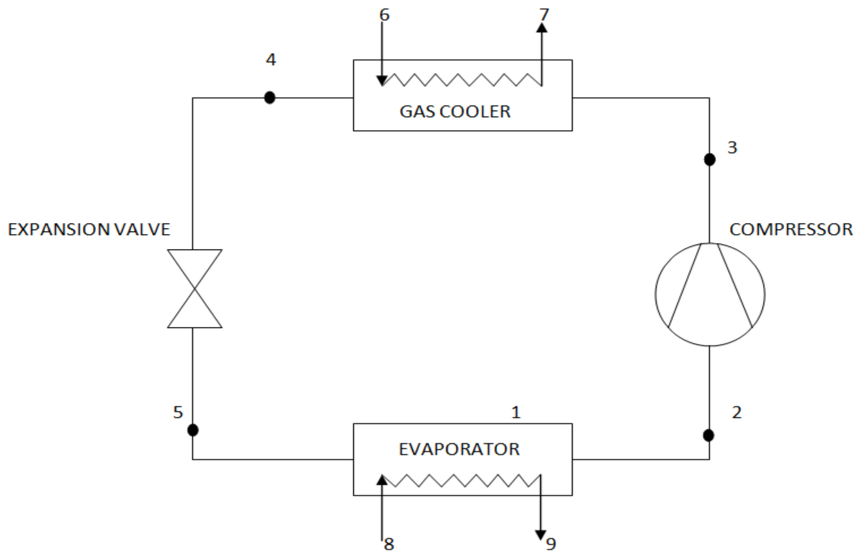

Figure 1: Schematic diagram of transcritical CO_2 one-stage vapor compression cycle

2. Artificial neural networks (ANN)

Neural network technology inspired by biological nervous systems is being used to solve a wide variety of complex scientific, engineering and business problems. A neural network consists of a large number of simple processing elements called neurons or nodes. Each neuron is connected to other neurons by means of direct communication links with associated weights. The weights represent information being used by the network to solve a problem [7]. Artificial neural network process is described in the Figure 2.

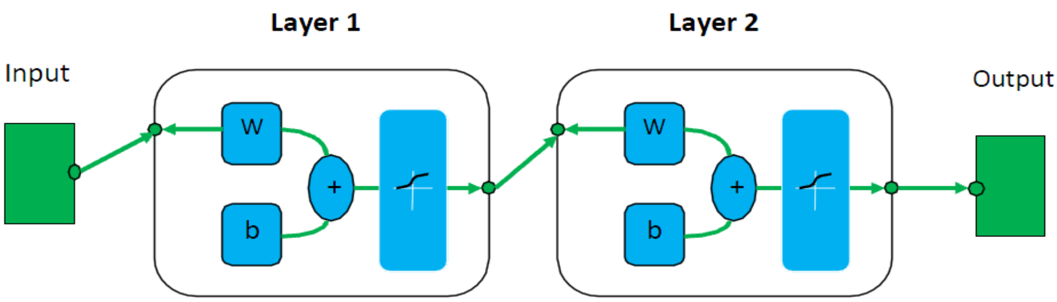

Figure 2: Artificial neural network process

The computer program was performed under MATLAB environment using the neural network toolbox. In order to train the network, obtained actual values from CoolPack program were used. Inputs for network are the cooling capacity (Q_{CC}), evaporator temperature (T_E), gas cooler temperature (T_{GC}), superheat temperature (T_{SH}) and gas cooler pressure (P_{GC}); outputs are the coefficient of performance (COP) as given Table 1. The data set for the coefficient of performance in the transcritical CO_2 one-stage vapor compression cycles available included 100 data patterns. From these, 80 data patterns were used for training the network and the remaining 20 patterns were randomly selected and used as the test data set. To forecast the coefficient of performance values depending on the cooling capacity, evaporator temperature, gas cooler temperature, superheat temperature and gas cooler pressure, the back-propagation learning algorithm has been used in a feed-forward, single hidden layer neural network. The algorithms used in the study are Levenberg–Marquardt (LM) and scaled conjugate gradient (SCG) algorithms. Inputs and outputs are normalized in the (0,1) range. Epoch numbers for the the coefficient of performance was selected as 1000. Statistical values such as the Root-Mean-Squared Error (RMSE), the coefficient of multiple determinations (R^2) and the coefficient of variation (cov) are given in Table 2 for the coefficient of performance. Logistic sigmoid (logsig) transfer function has been used for both the hidden layer and the output layer. The transfer function used is given by:

$$E_k = \sum_{n=1}^{3} \mathrm{l_n w_{nk}} + \mathrm{b_n} \tag{1}$$

$$F(k) = \frac{1}{1+e^{-k}} \tag{2}$$

where k is the weighted sum of the input.

During learning the error is estimated by RMSE defined as:

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n}\left(y_{p,m} - t_{m,m}\right)^2}{n}} \tag{3}$$

In addition, the coefficient of multiple determinations (R2) and coefficient of variation (cov) in percent are defined as follows:

$$R^2 = 1 - \frac{\sum_{m=1}^{n}\left(t_{m,m} - y_{p,m}\right)^2}{\sum_{m=1}^{n}\left(t_{m,m} - \bar{t}_{m,m}\right)^2} \tag{4}$$

$$\mathrm{cov} = \frac{RMS}{\left|\bar{t}_{m,m}\right|}100 \tag{5}$$

where n is the number of data patterns, $y_{p,m}$ indicates the predicted, $t_{m,m}$ is the measured value of one data point m, $\bar{t}_{m,m}$ and is the mean value of all measure data points [8].

Table 1. Input and output parameters

Input parameters	Output parameters
Cooling capacity (Q_{CC})	The coefficient of perfonmance (COP)
Evaporator temperature (T_E)	
Gas cooler temperature (T_{GC})	
Superheat temperature (T_{SH})	
Gas cooler pressure (P_{GC})	

3. Results and discussion

In this study, the coefficient of performance (COP) has been estimated in the transcritical CO_2 one-stage vapor compression cycles using artificial neural network (ANN). The necessary thermodynamic characteristics for estimation were obtained CoolPack program and obtained results were compared with actual results.

Input- output parameter used in artificial neural network (ANN) was given in Table 1. MATLAB artificial neural network (ANN) Toolbox is used for prediction for the coefficient of performance (COP) in the study. Input values are the cooling capacity, evaporator temperature, gas cooler temperature, superheat temperature and gas cooler pressure. The cooling capacity is in the range of 1 kW to 20 kW, the evaporator temperature is in the range of 0 °C to -25 °C, the gas cooler temperature is in the range from 30 °C to 55 °C, the superheat temperature is in the range of 5 °C to 10 °C and the gas cooler pressure is in the range of 8 MPa to 30 MPa. Output value is the coefficient of performance (COP) of the cycle.

From the data presented in Table 2 for the coefficient of performance, the LM algorithm with four neurons in the hidden layer (LM-4) appeared to be the most optimal topology. The performance of ANN model developed in this paper was evaluated using various standard statistical performance evaluation criteria. Table 2 presents statistical performance evaluation criteria values such as R^2, RMSE, and cov for ANN technique for the coefficient of performance estimation of the transcritical CO_2 one-stage vapor compression cycles.

Table 2. Statistical values for the coefficient of performance

Algoritma-Nöronlar	RMS	cov	R^2
Lm–3	0.04567	0.01978	0.99828
Lm–4	**0.03364**	**0.01457**	**0.99907**
Lm–5	0.03573	0.01548	0.99895
Lm–6	0.12677	0.05492	0.98680
Lm–7	0.04202	0.01820	0.99855
Lm–8	0.08885	0.03849	0.99351
Lm–9	0.03502	0.01517	0.99899
Lm–10	0.05212	0.02258	0.99776
Lm–11	0.23090	0.10003	0.95622
Lm–12	0.04191	0.01815	0.99855
SCG–3	0.06772	0.02934	0.99623
SCG–4	0.05652	0.02448	0.99737
SCG–5	0.06090	0.02638	0.99695
SCG–6	0.23090	0.10003	0.95622
SCG–7	0.03504	0.01518	0.99899

SCG–8	0.05343	0.02314	0.99765
SCG–9	0.23062	0.09991	0.95633
SCG–10	0.04023	0.01743	0.99867
SCG–11	0.11205	0.04854	0.98969
SCG–12	0.08343	0.03614	0.99428

The coefficients of Eq.1 for the coefficient of performance values of the transcritical CO_2 one-stage vapor compression cycles are given in Table 3. In weights n represents input number and k represent hidden neuron number.

Table 3. Weight coefficients and bias values used for determination of the coefficient of performance

Neuron position (W_{ni})	I_1 **(T_E)**	I_2 **(T_{GC})**	I_3 **(Q_{CC})**	I_4 **(T_{SH})**	I_5 **(P_{GC})**	b_n
1	7.7493	0.95778	0.78658	0.83336	-0.2575	-6.1425
2	-7.6861	9.4341	-2.2126	-5.185	9.5443	3.9242
3	-1.0179	1.0275	0.81053	-0.6986	1.9699	2.9246
4	-1.7196	0.73417	-1.608	1.5517	0.59622	0.71464

Table 4 shows a comparison is presented between the actual values and obtained results from ANN with the equations derived from this paper for the coefficient of performance (COP). As can be seen in Table 4, the maximum relative error is 3.03 %. The error in this study is acceptable.

Table 4. Comparison between the actual values and obtained results from ANN for the coefficient of performance (COP)

Q_{CC} (kW)	**T_E (^{0}C)**	**T_{GC} (^{0}C)**	**T_{SH}(^{0}C)**	**P_{GC}(MPa)**	**Actual COP**	**Obtained COP from ANN**	**Relative Error (%)**
10	-5	30	5	10	3.07	3.07	0
10	-11	30	5	10	2.63	2.64	0.38
10	-17	30	5	10	2.28	2.29	0.43
10	-23	30	5	10	1.98	2.04	3.03
10	-10	34	5	10	2.48	2.48	0
10	-10	40	5	10	2.05	2.06	0.48
16	-10	30	9	10	2.70	2.72	0.74
10	-10	30	5	16	2.02	2.05	1.48
10	-19	30	5	10	2.17	2.18	0.46
10	-20	30	5	10	2.12	2.12	0

As a result, coefficient of performance (COP) values depending on the cooling capacity, evaporator temperature, gas cooler temperature, superheat temperature and gas cooler pressure can be calculate from:

$$E_5 = F_1\,(7.2564) + F_2\,(-13.4151) + F_3\,(-6.0707) + F_4\,(-2.5064) + 2.9584 \tag{5}$$

$$(COP) = \frac{1}{1+e^{-E_5}} x7 \tag{6}$$

The relative error of every estimated output was described by:

$$Er = \frac{\left|A^p - A^q\right|}{A^p} x100 \qquad (7)$$

where A^p is the estimated results, A^q is the actual values.

4. Conclusions

In this paper, alternative approach is presented for thermal analysis of transcritical CO_2 one-stage vapor compression cycles. The ANN is applied to predict the coefficient of performance (COP) for the transcritical CO_2 one-stage vapor compression cycles. The comparison between actual values and predicted values of ANN model shows that there is a good results the predicted the coefficient of performance (COP) results with acceptable error values. ANN model is a suitable tool for use in the prediction of the coefficient of performance (COP). It is suggested that ANN model can be applied to estimation the coefficient of performance (COP) in the transcritical CO_2 one-stage vapor compression cycles, especially for engineers in engineering applications.

References

[1] Shin, E., Park, C., Cho, H., Theoretical analysis of performance of a two-stage compression CO_2 cycle with two different evaporating temperatures. *International journal of refrigeration*, 47, 164-175, 2014.
[2] Ahammed, E., Bhattacharyya, S., Ramgopal, M., Thermodynamic design and simulation of a CO_2 based transcritical vapour compression refrigeration system with an ejector. *International journal of refrigeration,* 45, 177-188, 2014.
[3] Pérez-García, V., Belman-Flores, J.M., Navarro-Esbrí, J., Rubio-Maya, C., Comparative study of transcritical vapor compression configurations using CO_2 as refrigeration mode base on simulation. *Applied Thermal Engineering,* 51, 1038-1046, 2013.
[4] Chesi, A., Esposito, F., Ferrara, G., Ferrari, L., Experimental analysis of R744 parallel compression cycle. *Applied Energy,* 135, 274–285, 2014.
[5] Ge, Y.T., Tassou, S.A., Santosa, I.D., Tsamos, K., Design Optimisation of CO_2 Gas cooler/Condenser in a Refrigeration System. *Energy Procedia*, 61, 2311 – 2314, 2014.
[6] Salazar, M., Méndez, F., PID control for a single-stage transcritical CO_2 refrigeration cycle. *Applied Thermal Engineering,* 67, 429-438, 2014.
[7] Selbas, R., Sencan, A., Kılıc, B., Alternative approach in thermal analysis of plate heat exchanger. *Heat Mass Transfer*, 45, 323–329, 2009.
[8] Dincer, K., Tasdemir, S., Baskaya, S., Ucgul, İ., Uysal, B.Z., Fuzzy Modeling of Performance of Counterflow Ranque-Hilsch Vortex Tubes with Different Geometric Constructions. *Numerical Heat Transfer Part B: Fundamentals*, 49, 51- 54, 2008.