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Artificial Neural Network Modelling of a Mobile Air Conditioning System Using Refrigerant R1234yf

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Abstract

This study investigates modelling of various performance parameters of a Mobile Air Conditioning (MAC) system using artificial neural networks (ANNs). For this aim, a laboratory MAC system was set up from the original components of an automobile air conditioning system. Then, the system was charged with alternative refrigerant R1234yf and tested in a wide range of operating conditions. Using experimental results, various performance parameters including the cooling capacity and coefficient of performance of the system were determined. Some of the input-output data pairs were used for training the proposed ANN model, while the remaining pairs were employed for testing the prediction performance of the developed model. Yielding correlation coefficients in the range of 0.9159–0.9962 and mean relative errors in the range of 2.24–7.46%, the ANN model provided quite accurate predictions. The results imply that ANN approach can be used for predicting the performance of MAC systems with R1234yf.

Key words: Air conditioning, automotive, R1234yf, ANN.

1. Introduction

Having a global warming potential (GWP) of 1430, the use refrigerant R134a in mobile air conditioning (MAC) systems was restricted by European Union's f-gas regulation which prohibits the use of Hydrofluorocarbon refrigerants with a GWP above 150 in the MAC systems of all new vehicles placed in the EU market starting from 2017 [1]. There are three major potential alternatives to R134a, namely CO_2, R152a and R1234yf. Because CO_2 yields extremely high refrigerant pressures causing low efficiency and leakage issues while R152a has serious flammability, R1234yf, a recently developed refrigerant from hydrofluoroolefin family, seems to be the best alternative. Because R1234yf has a GWP of just 4 and can work under operating conditions similar to R134a [2], it can replace R134a in MAC systems.

It is difficult to model MAC systems using classical mathematical modelling techniques requiring very detailed information about the components of the system, their geometrical characteristics as well as thermodynamic/transport properties of the refrigerant and air streams involved. Instead, MAC systems can be modelled using soft computing techniques such as artificial neural networks (ANNs) to determine their performance under various operating conditions. ANNs have the ability of extracting expertise from data without requiring any explicit mathematical representation. Therefore, they can easily model the physical phenomena in complex systems to predict their outputs under given input conditions.

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Many studies can be found in literature on the modelling of air conditioning and refrigeration systems using ANNs. Various applications of ANNs in energy systems such as refrigeration, heating, ventilating and air conditioning systems were reviewed by Kalogirou [3]. Hosoz and Ertunc [4] employed ANNs for predicting the performance of a MAC system with R134a. Their ANN model predicted various performance parameters of the system with correlation coefficients in the range of 0.968 − 0.999 and mean relative errors in the range of 1.52−2.51%. Ertunc and Hosoz [5] also used ANNs for predicting performance parameters of a refrigeration system with an evaporative condenser. Atik et al. [6] applied ANNs to a MAC system operating with different refrigerant charges at various compressor speeds. Mohanraj et al. [7] reviewed the studies about the use of ANNs in refrigeration, air conditioning and heat pump systems. Kamar et al. [8] predicted the cooling capacity, compressor power and coefficient of performance (COP) of a standard car air conditioning system using ANNs. Ledesma and Belman-Flores [9] obtained energetic maps of a vapour compression refrigeration system with R1234yf using ANNs to visualize and identify the zones with the best performance. Tian et al. [10] developed an ANN model for the performance of an electric vehicle air conditioning system with scroll compressor and electronic expansion valve.

In this study, the ANN approach has been used for modelling the performance of a MAC system employing alternative refrigerant R1234yf. Then, the predictions of the developed ANN model were compared with experimental ones using statistical performance indicators.

2. Materials and Method

2.1. Description of the experimental setup

The MAC system for the proposed ANN model was developed from the original components of an R134a MAC system of a compact car, as shown in Figure 1. The major components were a five-cylinder swash plate compressor, a parallel-flow micro-channel condenser, a laminated type evaporator, a receiver/filter/drier and a thermostatic expansion valve (TXV).

The condenser and evaporator were inserted into 1-meter-long separate air ducts with different flow areas. A condenser air stream with a flow rate of 0.182 m^3s^{-1} was obtained by an axial fan, while an evaporator air stream with a flow rate of 0.112 m^3s^{-1} was obtained by a centrifugal fan. The required air temperatures at the inlets of the condenser and evaporator were maintained by two electric heaters installed in these ducts and controlled by voltage regulators. The compressor was driven by a three phase 4 kW electric motor via a frequency inverter to operate the system at various speeds. All piping of the refrigeration circuit was made of copper tubing insulated by elastomeric-insulator. Using a service station, the MAC system was charged with 2.00 kg of R1234yf and tests were performed.

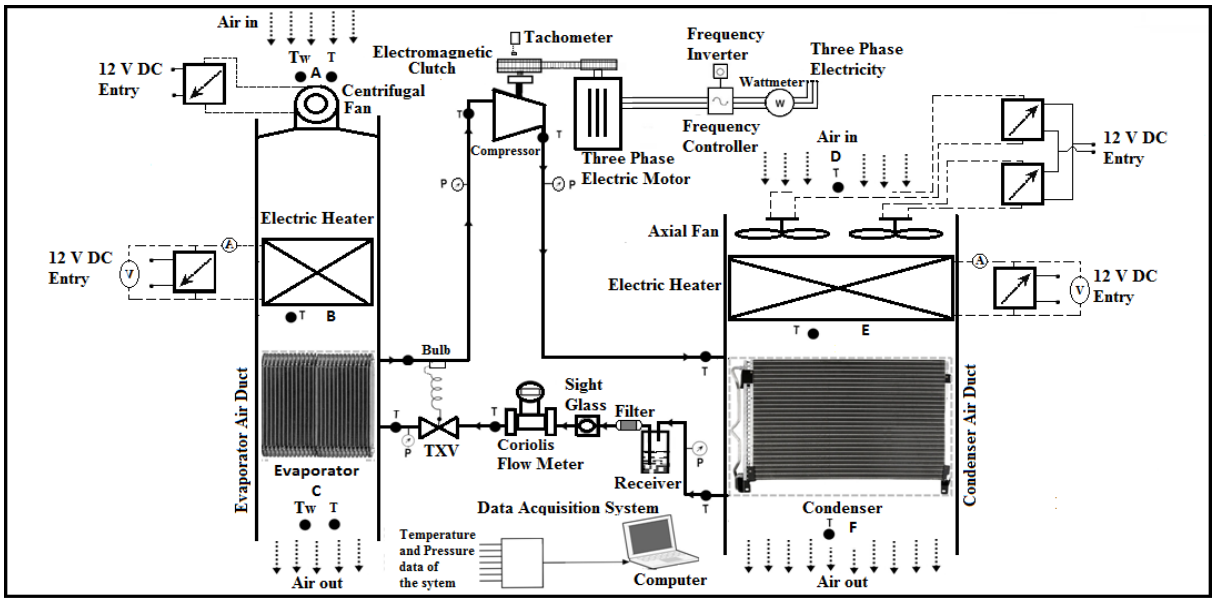

Figure 1. Schematic illustration of the experimental MAC system

The compressor speed was measured by a photoelectric tachometer. The refrigerant mass flow rate was measured by a Coriolis mass flow meter located in the liquid line. The condenser and evaporator pressures were monitored by both Bourdon type manometers and pressure transmitters. The refrigerant temperatures and air dry/wet bulb temperatures were measured at the inlet and outlet of each important component by type K thermocouples. The measured variables were usually acquired through a data acquisition system and recorded on a computer. The characteristics of the instrumentation are shown in Table 1.

Table 1. Characteristics of Instrumentation

Measured Variable	Instrument	Range	Accuracy
Temperature	Type K thermocouple	-50 to 500 °C	± 0.3 °C
Pressure	Pressure transmitter	0 to 25 bar	± 0.2 %
	Bourdon gauge	1 to 10, 0 to 30 bar	0.1, 0.5 bar
Air flow speed	Anemometer	0.1 to 15 m s^{-1}	± 3.0 %
Refrigerant mass flow rate	Coriolis flow meter	0 to 350 kg h^{-1}	± 0.1 %
Compressor speed	Photoelectric tachometer	10 to 100000 rpm	± 2 %

2.2. Experimental procedure

The experimental MAC system was tested at the compressor speeds of 1000, 1500, 2000 and 2500 rpm. At each speed, the air temperature entering the evaporator ($T_{evap,ai}$) was changed between 25 and 40 °C with intervals of 5 °C, while the air temperature entering the condenser ($T_{cond,ai}$) was changed between the selected $T_{evap,ai}$ and 40 °C with intervals of 5 °C. Furthermore, the relative humidity of the air stream entering the evaporator varied between 25% and 64%. Totally, 58 tests were applied to the MAC system by varying the input conditions. Each

test usually took 15 minutes, and only steady state test data were employed in the performance evaluations. The thermodynamic properties of refrigerants were obtained from REFPROP software as a function of the temperature and pressure measurements.

2.3. Thermodynamic analysis

Major performance parameters of the experimental MAC system are the cooling capacity, compressor power, condenser heat rejection rate and coefficient of performance (COP). These parameters can be evaluated by applying the first law of thermodynamics to each component of the refrigeration circuit. The cooling capacity, i.e. the evaporator load, can be determined from

$$\dot{Q}_{evap} = \dot{m}_r \left(h_{evap,out} - h_{evap,in} \right) \tag{1}$$

where $h_{evap,out}$ and $h_{evap,in}$ are the refrigerant enthalpies at the outlet and inlet of the evaporator, respectively, and $\dot{m}_r$ is the refrigerant mass flow rate.

Assuming that the compression process is adiabatic, the compressor power absorbed by the refrigerant can be evaluated from

$$\dot{W}_{comp} = \dot{m}_r \left(h_{comp,out} - h_{comp,in} \right) \tag{2}$$

where $h_{comp,out}$ and $h_{comp,in}$ are the refrigerant enthalpies at the outlet and inlet of the compressor, respectively.

The condenser heat rejection rate can be obtained from

$$\dot{Q}_{cond} = \dot{m}_r \left(h_{cond,in} - h_{cond,out} \right) \tag{3}$$

where $h_{cond,in}$ and $h_{cond,out}$ are the refrigerant enthalpies at the inlet and outlet of the condenser, respectively.

Finally, the COP for the system, an indicator of its energetic performance, can be evaluated from

$$COP = \frac{\dot{Q}_{evap}}{\dot{W}_{comp}} \tag{4}$$

2.4. ANN modelling of the MAC system

The input parameters for the proposed ANN model were the compressor speed, inlet temperatures of the evaporator and condenser air streams and relative humidity of the air at the evaporator inlet. The output parameters, on the other hand, were the cooling capacity, power absorbed by the refrigerant in the compressor, condenser heat rejection rate, coefficient of performance, conditioned air temperature, compressor discharge temperature, refrigerant mass

flow rate and pressure ratio across the compressor. The architecture of the ANN for the MAC system with the names of input and output parameters is schematically illustrated in Figure 2.

The data set consisted of the input and output parameters of 58 tests applied to the experimental MAC system. This data set was separated into two sets which were training and test data sets. The separation was performed randomly in such a way that 70% of data were assigned as training data set, and the remaining 30% as test data set. To compare the prediction performances of the considered models properly, the same training and test data sets were used in each model.

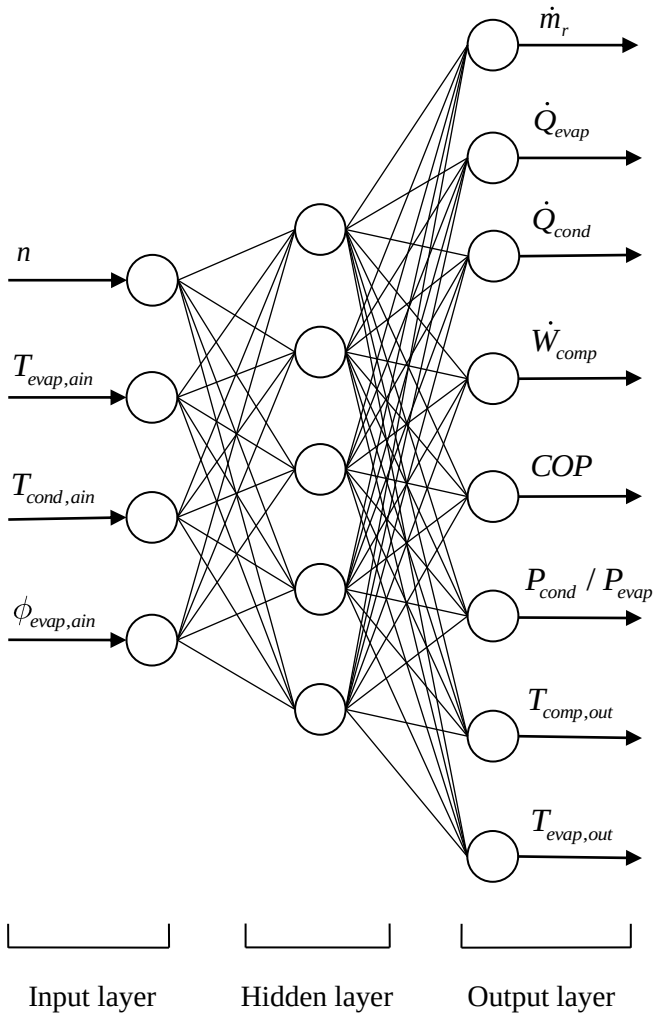

Figure 2. Structure of the ANN for modelling the experimental MAC system

The ANN model of the MAC system was developed using MATLAB Neural Network Toolbox [11]. The ANN model employed 4 input parameter vectors and their corresponding 8 output parameter vectors. Each vector consisted of 58 entries obtained from the experiments. An input matrix with dimension of 4×41 was trained for the associated outputs, and an input matrix with dimension of 4×17 corresponding to the remaining data was assigned to get the output parameters

in the test procedure. For training the ANN model, scaled conjugate gradient back propagation (SCG) algorithm was chosen to obtain the best ANN performance. While updating bias and weight values, the SCG algorithm used a training function derived from scaled conjugate gradient method. Other parameters compatible with the SCG algorithm was determined as indicated in Table 2.

Table 2. ANN Simulation Parameters

ANN Parameters	Values
Activation functions	Tansig, purelin
Learning rate	0.55
Max epochs	600
Target error	1e-7
Training algorithm	SCG

2.5. Statistical performance of the model predictions

Four different statistical performance indicators were used to determine the accuracy of the predictions of the models. These are the mean relative error (MRE), root mean square error (RMSE), correlation coefficient (r) and absolute fraction of variance (R^2). The definitions of these indicators can be found in [4] and [5]

3. Results

The ANN predictions for the performance parameters of the considered MAC system in comparison to the experimental ones are shown in Figures 3–10. Comparisons for all performance parameters were made by using data only from the test set, which were not used for training of the ANN model. All graphics have a straight line indicating prefect prediction and a ±5% error band. All considered statistical performance indicators were reported in the graphics.

The cooling capacity predictions of the ANN model as a function of the experimental cooling capacities are presented in Figure 3. The ANN predictions for the cooling capacity yield a correlation coefficient of 0.9414 and a mean relative error of 2.81%. It is seen that the ANN predictions for this parameter are quite accurate despite wide ranges of operating conditions.

The ANN predictions for the compressor power absorbed by the refrigerant in the compressor as a function of the experimental ones are indicated in Figure 4. The ANN predictions for the compressor power result in a correlation coefficient of 0.9780 and a MRE of 5.33%, which are quite accurate.

The condenser heat rejection rate predictions of the ANN model as a function of the experimental heat rejection rates are presented in Figure 5. The ANN predictions for the condenser heat rejection rate yield a correlation coefficient of 0.9781 and a MRE of 3.28%.

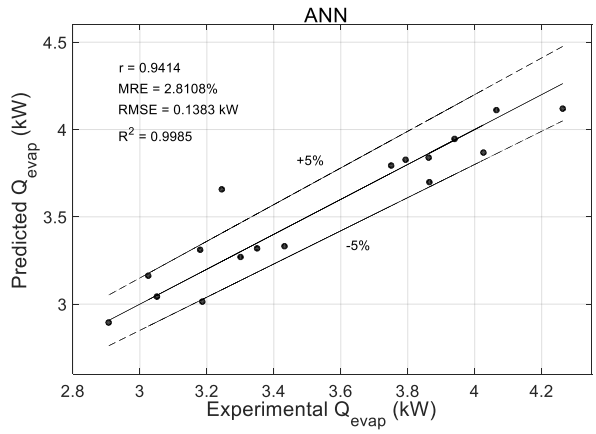

Figure 3. The ANN predictions for the cooling capacity with respect to experimental cooling capacity

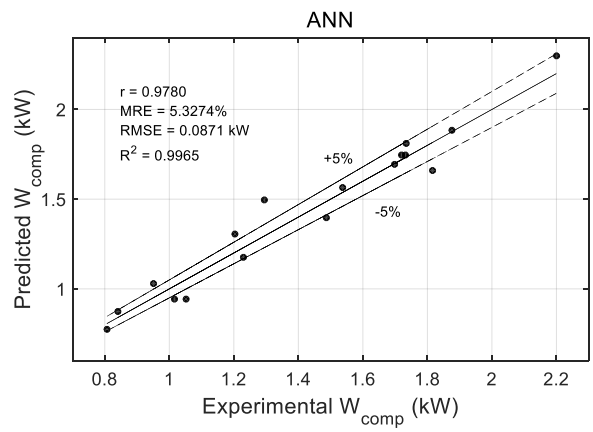

Figure 4. The ANN predictions for the compressor power with respect to experimental compressor power

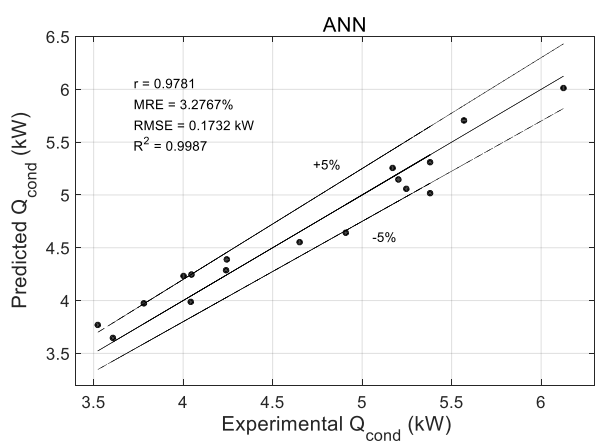

Figure 5. The ANN predictions for the condenser heat rejection rate with respect to experimental rate

The ANN predictions for the coefficient of performance of the MAC system as a function of the experimental COPs are reported in Figure 6. The ANN predictions for the COP yield a correlation coefficient of 0.9662 and a mean relative error of 4.37%. Because the COP depends on two performance parameters, namely the cooling capacity and compressor power, it has

several uncertainty sources. As a result, the ANN model was trained using COP data with high uncertainty, thereby yielding relatively poor statistical performance for the COP predictions.

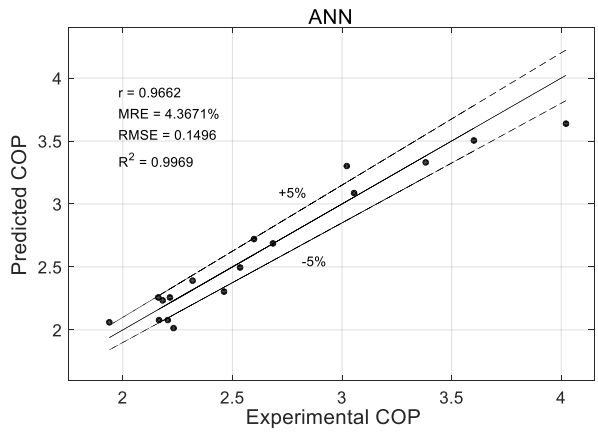

Figure 6. The ANN predictions for the coefficient of performance with respect to experimental COP

The predictions of the ANN model for the dry bulb temperature of the conditioned air stream are presented in Figure 7. For this performance parameter, the ANN predictions yield a correlation coefficient of 0.9159 and a MRE of 7.46%, which are the poorest results obtained so far.

The ANN predictions for the refrigerant temperature at the compressor outlet, i.e. compressor discharge temperature, are reported in Figure 8. When the compressor discharge temperature increases, so does the possibility of the thermal destruction of the compressor oil, thus causing a shorter compressor lifetime. Yielding a correlation coefficient of 0.9604 and a MRE of 2.69%, the ANN model predicts this temperature quite accurately.

The ANN predictions for the refrigerant mass flow rate circulating in the MAC system as a function of experimental ones are shown in Figure 9. The ANN predictions for this parameter yield a correlation coefficient of 0.9810 and a MRE of 2.24%. The superiority of the ANN predictions originates from the direct measurement of refrigerant mass flow rate.

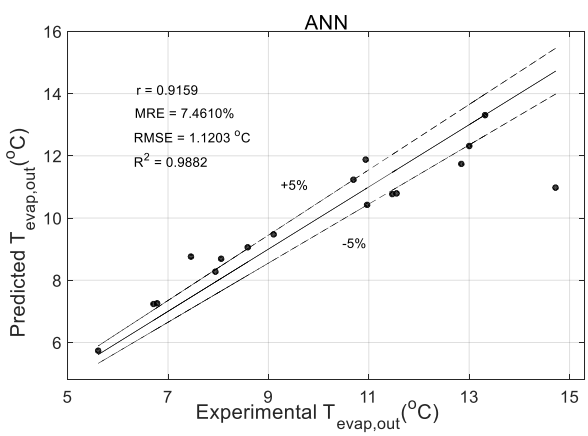

Figure 7. The ANN predictions for the conditioned air temperature with respect to the experimental ones

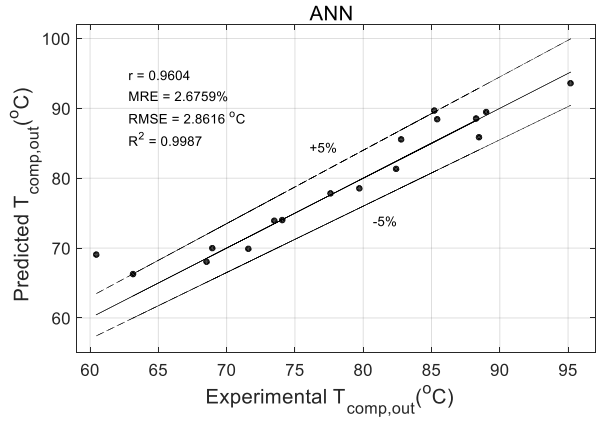

Figure 8. The ANN predictions for the compressor discharge temperature with respect to the experimental ones

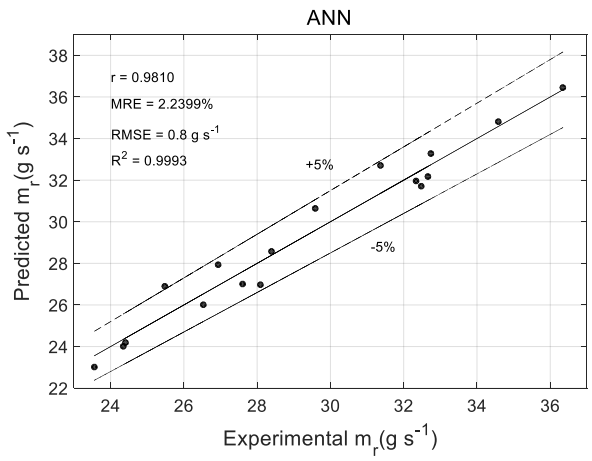

Figure 9. The ANN predictions for the refrigerant mass flow rate with respect to the experimental ones

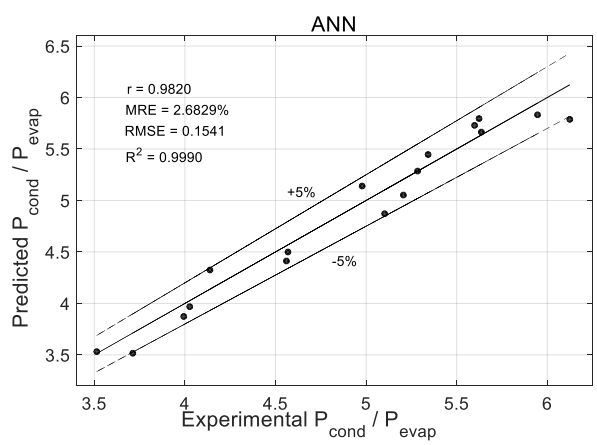

Figure 10. The ANN predictions for the compressor pressure ratio with respect to the experimental ratios

The ANN predictions for the pressure ratio across the compressor as a function of the experimental ones are indicated in Figure 10. Yielding a correlation coefficient of 0.9820 and a MRE of 2.68%, the ANN model provides very accurate predictions for the pressure ratio.

4. Discussion

The model predictions presented in Figs. 3−10 reveal that the ANN has an outstanding ability to learn from the input-output patterns and predict the behaviour of a MAC system. Therefore, the ANN approach can be used for predicting the performance parameters of a MAC system.

Conclusions

An experimental MAC system using R1234yf was set up and tested under various operating conditions. Then, an ANN model of the MAC system was developed to predict its performance based on test results. The prediction results were compared with the experimental ones, and their statistical performance was determined. With correlation coefficients in the range of 0.9159–0.9962 and MREs in the range of 2.24–7.46%, the ANN model yielded quite accurate predictions for the performance parameters of the MAC system. These results suggest that MAC systems can be modelled using ANN approach instead of detailed tests or complex mathematical modelling.

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