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MODELLING OF AN AUTOMOTIVE AIR CONDITIONING SYSTEM USING ANFIS

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Abstract: This study deals with modelling the performance of an R134a automobile air conditioning (AAC) system by means of adaptive neuro-fuzzy inference system (ANFIS) approach. In order to gather data for developing the ANFIS model, an experimental AAC system employing a variable capacity swash plate compressor and a thermostatic expansion valve was set up and equipped with various instruments for mechanical measurements. The system was operated at steady state conditions while varying the compressor speed, dry bulb temperatures and relative humidity of the air streams entering the evaporator and condenser as well as the mean velocities of these air streams. Then, utilizing some of the experimental data, an ANFIS model for the system was developed. The model was used for predicting various performance parameters of the system including the air dry bulb temperature at the evaporator outlet, cooling capacity, coefficient of performance and the rate of total exergy destruction in the refrigeration circuit of the system. It was determined that the predictions usually agreed well with the experimental results with correlation coefficients in the range of 0.966–0.988 and mean relative errors in the range of 0.23–5.28%. The results reveal that the ANFIS approach can be used successfully for predicting the performance of AAC systems.
Keywords: Air conditioning, Automotive, Refrigeration, Adaptive neuro-fuzzy inference system, ANFIS, R134a.

OTOMOTİV İKLİMLENDİRME SİSTEMİNİN ANFIS YAKLAŞIMI KULLANILARAK MODELLENMESİ

Özet: Bu çalışmada, R134a soğutucu akışkanı kullanan bir otomobil iklimlendirme sisteminin performansının ANFIS yaklaşımı ile modellenmesi yapılmıştır. Sistemin ANFIS modelinin geliştirilmesi için, eğik plakalı değişken kapasiteli kompresör ile termostatik genleşme valfi kullanan bir deneysel otomobil iklimlendirme sistemi kurulmuş ve çeşitli mekanik ölçüm cihazlarıyla donatılmıştır. Sistem, kompresör devri ile buharlaştırıcı ve yoğuşturucuya giren hava akımlarının kuru termometre sıcaklıkları, izafi nemleri ve ortalama hızları değiştirilerek, sürekli rejim şartları altında çalıştırılmıştır. Deneysel verilerin bir kısmının kullanılmasıyla, sistem için bir ANFIS modeli geliştirilmiştir. Bu model, buharlaştırıcı çıkışındaki hava akımı kuru termometre sıcaklığı, soğutma kapasitesi, soğutma tesir katsayısı ve sistemin soğutma devresinde birim zamanda yok edilen toplam ekserji gibi çeşitli performans parametrelerinin tahmin edilmesinde kullanılmıştır. Model tahminlerinin deneysel sonuçlar ile genellikle iyi bir uyum göstererek, 0.966–0.988 arasında değişen korelasyon katsayıları ve % 0.23–5.28 arasında değişen ortalama izafi hatalar verdiği belirlenmiştir. Ulaşılan sonuçlar, ANFIS yaklaşımının otomotiv iklimlendirme sistemlerinin performansının tahmininde başarılı olarak kullanılabileceğini göstermiştir.
Anahtar Kelimeler: İklimlendirme, Otomotiv, Soğutma, ANFIS, R134a.

NOMENCLATURE

AAC	Automotive air conditioning
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
CFC	Chlorofluorocarbon
COP	Coefficient of performance
$\dot{E}_d$	Rate of exergy destruction [W]
h	Specific enthalpy [kJ kg^{-1}]
h_f	Specific enthalpy of the condansate [kJ kg^{-1}]
h_g	Specific enthalpy of the water vapour [kJ kg^{-1}]
$\dot{m}$	Mass flow rate [g s^{-1}]
MRE	Mean relative error
n_{comp}	Compressor speed [rpm]
$\dot{Q}_{evap}$	Evaporator cooling capacity [W]
r	Correlation coefficient
R^2	Absolute fraction of variance
Rh	Relative humidity [%]
RMSE	Root mean square error

s	Specific entropy [kJ kg^{-1} K^{-1}]
T	Temperature [K]
T_0	Ambient temperature [K]
TXV	Thermostatic expansion valve
V_m	Mean air velocity [m s^{-1}]
$\dot{W}_{comp}$	Compressor power [W]

Greek Symbols

ϕ	Relative humidity [%]
ω	Specific humidity

Subscripts

a	Air
A...F	Points in the air lines as shown in Figure 1
ai	Air inlet
ao	Air outlet
comp	Compressor
cond	Condenser
dis	Compressor discharge
evap	Evaporator
r	Refrigerant
tot	Total
valve	Expansion valve

INTRODUCTION

Automotive air conditioning (AAC) systems have been advanced considerably to provide better thermal comfort and improved fuel economy along with minimum impact to the environment since General Motors and Packard Motor Car companies developed early AAC systems based on vapour compression refrigeration in 1930s (Bhatti, 1999a). Although AAC systems once used R12 as a standard refrigerant, beginning in 1992, car manufacturers started to use R134a as a result of Montreal Protocol, which called for a phase out of CFC compounds including R12. On the other hand, triggered by the regulations of the European Union that require all new vehicles receiving type approval in 2011 or later to use a refrigerant with a Global Warming Potential below 150, automotive industry is now performing research to use natural refrigerants such as CO_2 to substitute for R134a in AAC systems.

AAC systems are different from domestic air conditioning systems in a few ways. Because the compressor of an AAC system is driven by the engine, the compressor speed as well as the cooling capacity of the system changes as a function of the engine speeds. On the other hand, the passenger compartment of a vehicle can be exposed to varying climatic conditions, which changes the air conditioning load continually. Consequently, these challenges make AAC systems difficult to model using classical techniques and necessitate experimental studies.

The literature contains limited number of research studies on AAC technology due to its competitive nature. In response to the Montreal Protocol, some studies were evaluated the performance of AAC systems with refrigerants alternative to R12. Jung et al. (1999) presented experimental performance of supplementary/retrofit refrigerant mixtures for R12 used in existing AAC systems. Al-Rabghi and Niyaz (2002) found that the AAC system with R12 yields a higher coefficient of performance (*COP*) by 23% than the system with R134a. Joudi et al. (2003) simulated the performance of an ideal AAC system with R12 and several alternative refrigerants including some hydrocarbons. Bhattti (1999b) presented a method for augmentation of AAC systems with R134a to lower its global warming impact. Brown et al. (2002) evaluated various performance parameters of AAC systems with CO_2 and R134a, finding that both systems offer comparable performance. Liu et al. (2005) investigated experimental performance of an AAC system with CO_2. Ghodbane (1999) simulated the performance of AAC systems using several hydrocarbon refrigerants. Kaynakli and Horuz (2003) investigated experimental performance of an AAC system with R134a to find optimum operating conditions. Wongwises et al. (2006) determined experimental performance of an AAC system with several hydrocarbons. Hosoz and Direk (2006) investigated experimental performance of an R134a AAC and air-to-air heat pump system. Alkan and Hosoz (2010a) compared experimental performance parameters of an R134a AAC system for the cases of using fixed and variable capacity compressors. They also presented comparative experimental performance of an R134a AAC system for two different types of expansion devices, namely thermostatic expansion valve and orifice tube (Alkan and Hosoz, 2010b).

In addition to the experimental studies, the performances of AAC systems were simulated. Lee and Yoo (2000) developed a simulation model for an AAC system by combining the performance analysis models for the components. Jabardo et al. (2002) presented a steady-state simulation model for an AAC system using a variable capacity compressor, and indicated its validity on an experimental unit. Tian and Li (2005) simulated steady-state performance of an R134a AAC system employing a variable capacity compressor. Hosoz and Ertunc (2006) developed an artificial neural network model to predict the performance of an AAC system with R134a.

It is obvious that mathematical modelling of AAC systems require a large number of geometrical parameters defining the system, which may not be readily available, and the computer simulations employed in these models are usually complicated due to their dealing with the solution of complex differential equations. Furthermore, as mentioned before, changing compressor speed and air conditioning load make the modelling process more complex. Alternatively, the operation of AAC systems can be modelled using artificial intelligence techniques such as artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) with significantly less engineering effort. The main feature of these new techniques is the ability of self learning and self-predicting some desired outputs. These techniques can extract expertise from data without requiring any explicit mathematical representation, thus easily modelling the physical phenomena in complex systems to predict their behaviour under given conditions. Therefore, they can be applied to various engineering problems which are too complex to deal with using classical modelling techniques.

ANFIS, the less-known approach compared with ANN, is a soft computing technique that combines the benefits of feed forward calculation of output and back propagation of learning capability of ANNs and human-like reasoning style of fuzzy logic. Therefore, ANFIS based models are very powerful universal approximators with the ability of interpretable IF-THEN rules, and they are applied in many fields such as system identification, fuzzy control, data processing, etc.

The ANN modelling of air conditioning and refrigeration systems has been studied by many investigators. However, the application of ANFIS approach to the modelling of thermal systems is a more recent progress, although ANFIS was first introduced in early 90s (Jang, 1993). Hasiloglu et al. (2004) performed ANFIS modelling of the transient heat transfer in circular duct flow. Esen et al. (2007) predicted the performance of a ground-coupled heat pump system using ANFIS. They also compared the ANFIS predictions with the ANN ones for the ground-coupled heat pump system (Esen et al., 2008). Ertunc and Hosoz (2008) developed ANFIS and ANN models for predicting the performance of an evaporative condenser. They found that the accuracies of ANFIS predictions were slightly better than those of ANN ones. Soyguder and Alli (2009) predicted the fan speed for energy saving in an HVAC system using ANFIS. Das and Kishor (2009) developed an ANFIS model for predicting the heat transfer coefficient in pool boiling of distilled water. Ata and Kocyigit (2010) used ANFIS to predict the tip speed ratio in wind turbines. Hosoz et al. (2011) investigated the applicability of ANFIS to predict the performance of an R134a vapor-compression refrigeration system using a cooling tower for heat rejection. They found that the ANFIS approach can be used successfully for predicting the performance of refrigeration systems.

As can be seen from the literature survey outlined above, the performance of AAC systems has not been modelled yet using ANFIS approach. However, previous studies report that the predictions of ANFIS approach are usually slightly better than those of ANN, the other alternative artificial intelligence technique, for refrigeration and air conditioning systems (Ertunc and Hosoz, 2008; Esen and Inalli, 2010). Therefore, this study investigates the applicability and reliability of ANFIS modelling to predict various performance parameters of an AAC system. For this aim, an experimental R134a AAC system with a variable capacity compressor has been set up and tested under a broad range of operating conditions. Then, using experimental data, its performance parameters have been evaluated, and an ANFIS model for the prediction of the performance parameters of the AAC system has been developed. Finally, the model results have been compared with experimental ones for determining the performance of the ANFIS predictions.

DESCRIPTION OF THE EXPERIMENTAL AAC SYSTEM AND TESTING PROCEDURE

The ANFIS approach has been applied to the experimental AAC system shown in Figure 1. The experimental AAC system mainly consists of the original components from a compact size R134a automobile air conditioning system, namely a five-cylinder wobble-plate variable capacity compressor with a swept volume of 9.8–151 cc/rev, a parallel-flow micro-channel condenser, a liquid receiver/filter/drier, an internally-equilized thermostatic expansion valve and a laminated type evaporator. The experimental system also has some auxiliary equipment, which is used for providing the required test conditions and some instruments for mechanical measurements.

As seen in Figure 1, the evaporator and condenser were inserted into two separate air ducts. The evaporator and condenser air ducts have cross-section areas of 0.048 m^2 and 0.219 m^2, respectively, while they have the same length of 1 m. In order to provide the required air streams in these ducts, a centrifugal fan and an axial fan were placed at the entrances of the evaporator and condenser ducts, respectively. Because these fans are driven by DC motors, the air flow rates passing through the evaporator and condenser can be adjusted to the required values by varying the voltages across the fan motors via voltage regulators. These ducts also contain electric heaters located upstream of the evaporator and condenser. The evaporator and condenser electric heaters can be controlled between 0–1.8 kW and 0–5.6 kW, respectively, to provide the required air temperatures at the inlets of the related coils. Both air ducts were insulated with polyurethane foam of 3 cm thick.

The compressor was belt-driven by a three-phase 4 kW electric motor. In order to ensure that the compressor could be operated at any required speed, the electric motor was energized through a frequency inverter. Because the employed compressor was a variable capacity one and the experimental system was not equipped with a thermostat in order to test the system in steady-state operation without interruption, the compressor of the experimental AAC system operated continually until the end of the each test.

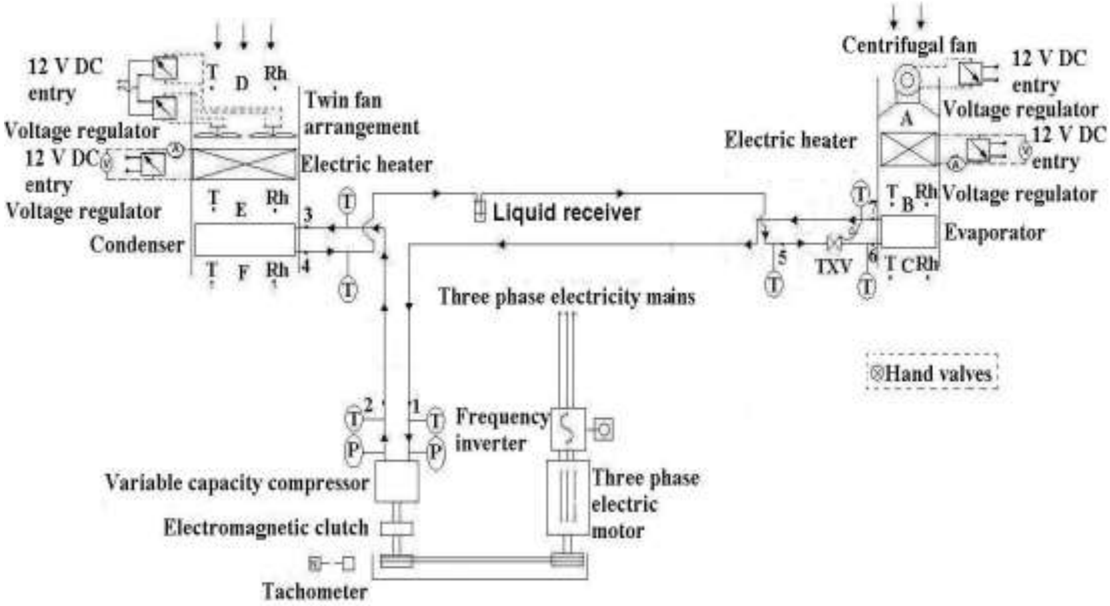

Figure 1. Schematic diagram of the experimental AAC system.

The refrigerant lines of the system were made from copper tubing with internal diameters equal to those of the original rubber hoses, and insulated by elastomeric material. The refrigeration circuit was charged with 800 g of R134a.

Figure 1 also indicates the locations and types of the measurements performed on the system. The refrigerant temperatures at the inlet and outlet of each component were measured by type K thermocouples soldered to the refrigeration lines. The dry bulb temperatures and relative humidities of the air streams at the inlet and outlet of the evaporator and condenser were also measured. The measurements at the evaporator outlet were performed at four locations, and the results were averaged. The suction and discharge pressures were measured by Bourdon tube gauges. It was assumed that the evaporating and condensing pressures were equal to the measured suction and discharge pressures, respectively. The compressor speed was measured by an optic tachometer. The air velocity at the outlet of the evaporator was measured at four uniformly-distributed locations by an anemometer, while the air velocity at the outlet of the condenser was measured at six uniformly-distributed locations. The air mass flow rates passing through the evaporator and condenser were determined by evaluating the average air velocities, air densities and duct flow areas in the continuity equation.

In the experiments, totally 70 different steady state test runs were performed to acquire data for the ANFIS modelling of the system. The inputs varied in the tests were the compressor speed, dry bulb temperature and relative humidity of the air stream entering the evaporator, dry bulb temperature of the air stream entering the condenser together with average air velocities at the outlets of the evaporator and condenser. The ranges of these inputs are shown in Table 1. It was assumed that the steady-state was achieved when the temperature deviations at the key points considered were lower than 0.5°C for 5 minutes. As soon as the stabilized conditions were occurred, data were collected to evaluate the performance of the system.

Table 1. Range of the inputs in the experiments.

Compressor speed (n_{comp} , rpm)	750−1500
Dry bulb temperature of the air stream entering the evaporator ($T_{evap,ai}$, °C)	23.3−40.0
Relative humidity of the air stream entering the evaporator ($\phi_{evap,ai}$)	16−55%
Dry bulb temperature of the air stream entering the condenser ($T_{cond,ai}$, °C)	23.3−40.0
Average air velocity at the evaporator outlet ($V_{m,evap}$, m s^{-1})	1.0−3.2
Average air velocity at the condenser outlet ($V_{m,cond}$, m s^{-1}))	0.4−4.2

THERMODYNAMIC ANALYSIS

Using the first law of thermodynamics, the cooling capacity of the experimental AAC system can be related to the heat taken from the air stream passing through the evaporator as given below.

$$\dot{Q}_{evap} = \dot{m}_a\left[(h_a + \omega h_g)_B - (h_a + \omega h_g)_C\right] - \dot{m}_a\left[(\omega_B - \omega_C)h_f\right] \quad (1)$$

As seen in Eq. (1), the cooling capacity is a function of the air mass flow rate, specific enthalpies of the moist air at the inlet and outlet of the evaporator, and enthalpy of the condensate leaving the evaporator.

Then, the refrigerant mass flow rate can be evaluated from

$$\dot{m}_r = \frac{\dot{Q}_{evap}}{h_7 - h_6} \quad (2)$$

With the assumption of adiabatic compressor, the power absorbed by the refrigerant in the compressor can be calculated from

$$\dot{W}_{comp} = \dot{m}_r (h_2 - h_1) \quad (3)$$

The energetic performance of the AAC system can be found by evaluating its coefficient of performance, which is the ratio of the cooling capacity to the compressor power, i.e.

$$COP = \dot{Q}_{evap} / \dot{W}_{comp} \quad (4)$$

The exergy destruction in the adiabatic compressor, which is due to gas friction, mechanical friction of the moving parts and internal heat transfer, can be determined from

$$\dot{E}_{d,comp} = \dot{m}_r T_0 (s_2 - s_1) \quad (5)$$

where T_0 is the environmental temperature representing the dead state.

The rate of exergy destruction in the condenser and liquid line, which is mainly due to the heat transfer originating from the temperature difference between the air and refrigerant streams, can be obtained from

$$\dot{E}_{d,cond} = \dot{m}_r T_0 \left[(s_5 - s_3) - \left(\frac{h_5 - h_3}{T_E} \right) \right] \quad (6)$$

With the assumption of adiabatic expansion, the exergy destruction in the expansion valve, which is due to the refrigerant friction accompanying the expansion across the valve, can be evaluated from

$$\dot{E}_{d,valve} = \dot{m}_r T_0 (s_6 - s_5) \quad (7)$$

The rate of exergy destruction in the evaporator, which mainly stems from the temperature difference between the refrigerant and air streams, can be determined from

$$\dot{E}_{d,evap} = \dot{m}_r T_0 \left[(s_7 - s_6) - \frac{(h_7 - h_6)}{T_B} \right] \quad (8)$$

Finally, the total rate of exergy destruction in the refrigeration circuit of the system can be found by summing up the individual destructions, i.e.

$$\dot{E}_{d,tot} = \dot{E}_{d,comp} + \dot{E}_{d,cond} + \dot{E}_{d,valve} + \dot{E}_{d,evap} \quad (9)$$

MODELLING OF THE EXPERIMENTAL AAC SYSTEM WITH ANFIS

In order to develop an ANFIS model for the experimental AAC system, the available data set, which consists of 70 input vectors and their corresponding output vectors from the experimental work, was divided into training and test sets. While 50 vectors of the data set were randomly assigned as the training set, the remaining 20 vectors were employed for testing the performance of the ANFIS predictions.

The output parameters of the experimental AAC system depends on six input parameters, namely the compressor speed (n_{comp}), dry bulb temperature ($T_{evap,ai}$) and relative humidity ($\phi_{evap,ai}$) of the air stream entering the evaporator, dry bulb temperature of the air stream entering the condenser ($T_{cond,ai}$) and the mean air velocities at the evaporator and condenser outlets ($V_{m,evap}$ and $V_{m,cond}$, respectively). The values of these input parameters used in 20 test vectors are reported in Table 2.

On the other hand, the considered output parameters of the experimental AAC system are the air dry bulb temperature at the evaporator outlet ($T_{evap,ao}$), cooling capacity ($\dot{Q}_{evap}$), compressor power ($\dot{W}_{comp}$), coefficient of performance (COP), total rate of exergy destruction in the refrigeration circuit of the system ($\dot{E}_{d,tot}$) and compressor discharge temperature (T_{dis}).

The ANFIS model was developed using MATLAB Fuzzy Logic Toolbox (2002). In this model, a subtractive fuzzy clustering was generated to establish a rule base relationship between the input and output parameters. Each input variable, which varies within a range, are clustered into several cluster values in Layer 1 of the ANFIS architecture given in Jang (1993) to build up fuzzy rules, and each fuzzy rule is associated with several parameters of membership functions in Layer 2 of the ANFIS architecture. As the number of rules is increased, the number of parameters of the membership functions increases as well. Therefore, the data was divided into groups called as clusters using the subtractive clustering method to generate fuzzy inference system. Since the subtractive fuzzy clustering can automatically determine the number of clusters, the Sugeno-type fuzzy inference system was implemented to obtain a concise representation of a system's behaviour with a minimum number of rules. The linear least square estimation was used to determine each rule’s consequent equation. The fuzzy c-means was used as a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. Therefore, a radius value was given in the MATLAB program to specify the cluster center’s range of influence to all data dimensions of both input

Table 2. Input variables of the ANFIS predictions.

Test vector no.	n_{comp} (rpm)	$T_{evap,ai}$ (°C)	$\phi_{evap,ai}$ (%)	$T_{cond,ai}$ (°C)	$V_{m,evap}$ (m s^{-1})	$V_{m,cond}$ (m s^{-1})
1	750	35.0	16	35.0	3.0	2.80
2	1000	35.0	16	40.0	3.0	2.80
3	750	40.0	16	40.0	3.0	2.80
4	1500	35.0	16	35.0	3.0	1.40
5	1000	35.0	16	35.0	3.0	2.80
6	1000	35.0	16	35.0	1.5	2.80
7	1000	23.3	26	23.3	3.0	0.84
8	1500	23.3	26	23.3	3.0	0.65
9	1000	27.7	55	27.7	3.0	0.78
10	1000	27.7	55	27.7	1.0	0.57
11	750	27.7	55	27.7	2.0	0.89
12	1000	27.7	55	27.7	2.0	1.04
13	750	27.7	55	27.7	3.0	0.73
14	750	27.7	55	27.7	2.0	0.66
15	750	27.7	55	27.7	1.0	0.64
16	1000	27.7	55	27.7	2.0	0.85
17	1500	27.7	55	27.7	2.0	0.84
18	1250	27.7	55	27.7	2.0	1.14
19	1500	27.7	55	27.7	2.0	1.25
20	1250	27.7	55	27.7	3.0	1.00

and output. In other words, that radius defines the neighbourhood of a cluster centre. If the cluster radius is specifying a large cluster radius will yield a few large clusters in the data resulting in fewer rules. In this study, by trial and error, the best cluster radius was determined as 1.5. The system parameters of the developed ANFIS model are given in Table 3. As seen in this table, the subtractive fuzzy clustering does significantly reduce the number of rules, which is 2.

Table 3. System parameters of the ANFIS model.

Number of nodes	37
Number of linear parameters	14
Number of nonlinear parameters	24
Total number of parameters	38
Number of training data pairs	46
Number of fuzzy rules	2

The neuro-fuzzy algorithm should be trained using a proper set of training data so that the outputs can be estimated based on the input-output data. Therefore, the data was trained to identify the parameters of Sugeno-type fuzzy inference system based on the hybrid algorithm combining the least square method and the backpropagation gradient descent method. After training, fuzzy inference calculations of the developed model were performed. Then, the input vectors from the test data set were presented to the trained network and the responses of the network, i.e. the predicted output parameters, were compared with the experimental ones for the performance measurement. The criterions used for measuring the network performance were the correlation coefficient (r), mean relative error (MRE), root mean square error (RMSE) and absolute fraction of specified a small number, then there will be many small clusters in the data that results in many rules. In contrast, variance (R^2). Detailed definitions of these criterions can be found in Hosoz and Ertunc (2006), and Ertunc and Hosoz (2008).

RESULTS AND DISCUSSION

The predictions of the developed ANFIS for the performance parameters of the AAC system as a function of the experimentally determined values are shown in Figures. 2–7. Note that the comparisons in all graphics were made using values only from the test data set, which was not introduced to the ANFIS during the training process. In order to assess the accuracy of ANFIS predictions, each graphic is provided with a straight line indicating perfect prediction and with an error band of either ±2% or ±10%.

As seen in Figure 2, the ANFIS predictions for the air dry bulb temperature at the evaporator outlet result in a mean relative error (MRE) of 0.23%, a root mean square error (RMSE) of 0.83 K, a correlation coefficient (r) of 0.968 and an absolute fraction of variance (R^2) of 0.9999 with the experimental data. These results demonstrate that the ANFIS predicts $T_{evap,ao}$ excellently, although the tests for acquiring data were not performed in a broad range of operating conditions.

As shown in Figure 3, the ANFIS predictions for the cooling capacity yields a MRE of 4.48%, an r value of 0.970 and an R^2 value of 0.9975, which are considerably poorer than the previous predictions. The evaluation of the cooling capacity requires the air mass flow rate, specific enthalpies of the moist air at the inlet and outlet of the evaporator, and enthalpy of the condensate leaving the evaporator, thus having several sources of uncertainty. Consequently, the resulting high uncertainty influences the training process, and causes a poorer performance for the $\dot{Q}_{evap}$ predictions.

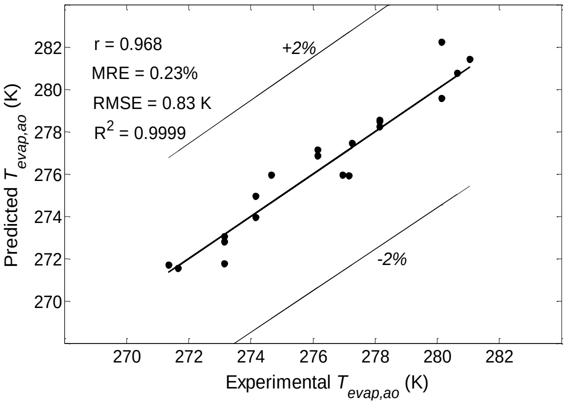

Figure 2. The ANFIS predictions for the air dry bulb temperature at the evaporator outlet vs. experimental values.

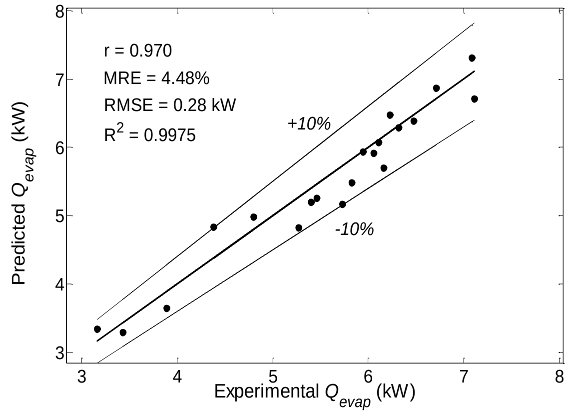

Figure 3. The ANFIS predictions for the cooling capacity vs. experimental values.

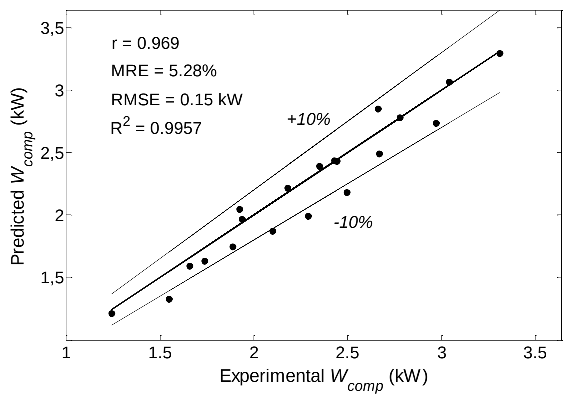

Figure 4. The ANFIS predictions for the compressor power vs. experimental values.

Because the evaluation of the compressor power requires the refrigerant mass flow rate and enthalpies of the refrigerant at the evaporator inlet and outlet, the accuracy of the ANFIS predictions for the compressor power is also not as good as those for $T_{evap,ao}$. In fact, the ANFIS yields even slightly poorer performance for $\dot{W}_{comp}$ predictions compared with that for $\dot{Q}_{evap}$ ones, as reported in Figure 4.

As shown in Figure 5, the ANFIS predictions for the coefficient of performance result in a MRE of 3.86%, an r value of 0.966 and an R^2 value of 0.9981. Because *COP* depends on two parameters, namely the cooling capacity load and compressor power, it has several uncertainty sources involved in the evaluation of these parameters. This leads to training of the proposed ANFIS using data with high uncertainty, which in turn causes a relatively poor statistical performance for the *COP* predictions.

Figure 6 shows that the ANFIS predictions for the total rate of exergy destruction in the refrigeration circuit of the system have a comparable accuracy with $\dot{Q}_{evap}$, $\dot{W}_{comp}$ and *COP* predictions. However, as seen Figure 7, the ANFIS outstandingly predicts the compressor discharge temperature with a MRE of 0.28%, an r value of 0.988 and an R^2 value of 0.9999. The excellent ANFIS predictions for T_{dis} are due to the high accuracy of the temperature measurements performed in the experiments. The discharge temperature is an indicator of the compressor durability. The possibility of the thermal destruction of the compressor oil increases with rising discharge temperature.

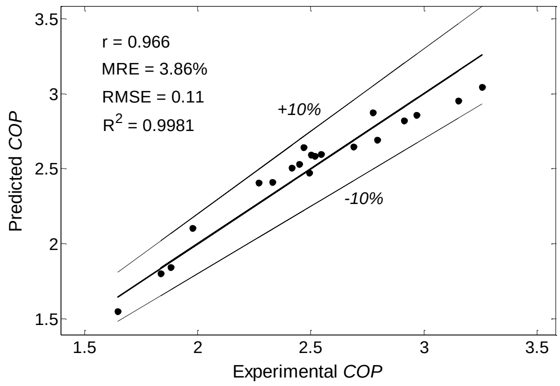

Figure 5. The ANFIS predictions for the coefficient of performance vs. experimental values.

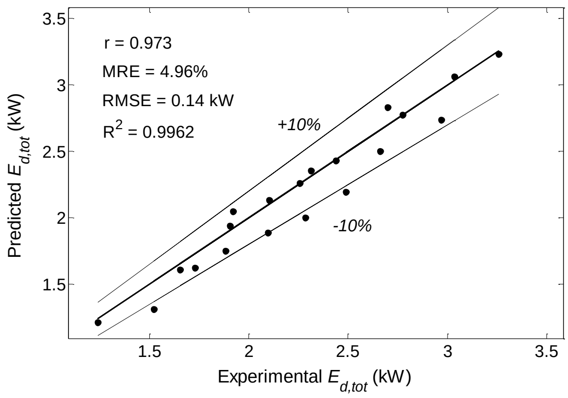

Figure 6. The ANFIS predictions for the total rate of exergy destruction in the refrigeration circuit of the refrigeration system vs. experimental values.

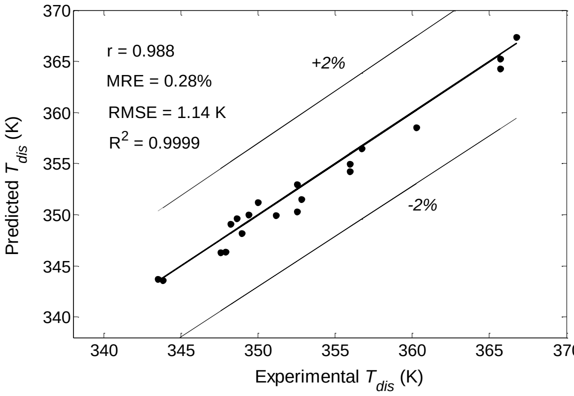

Figure 7. The ANFIS predictions for the compressor discharge temperature vs. experimental values.

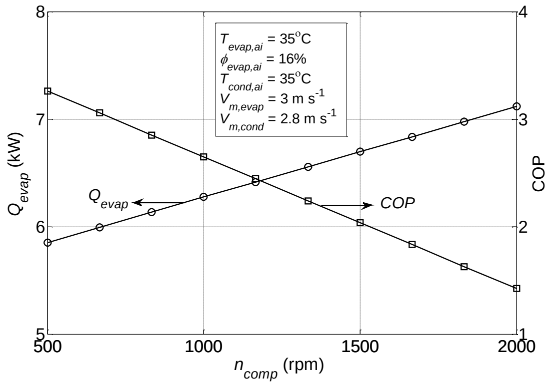

Figure 8. The ANFIS predictions for the cooling capacity and coefficient of performance as a function of compressor speed.

The comparisons of the ANFIS predictions for the six output parameters with the experimental results are alternatively presented in Table 4. It is seen that the ANFIS remarkably predicts all of the output parameters.

Considering the prediction performances reported in Figures 2–7 and Table 4, one can conclude that ANFIS has a great ability to learn from input-output patterns and predict the output variables of the system. The results demonstrate that the ANFIS can be successfully applied to predict the performance of an AAC system using R134a.

The developed ANFIS model can also be used for investigating the effects of the input parameters on the performance parameters of the system. For this aim, the ANFIS predictions for the cooling capacity and coefficient of performance as a function of the several input parameters are presented in Figures. 8–10 as sample results. Note that these figures report the predictions not only in the range of the inputs of the experimental study but also those beyond the range.

Figure 8 shows the changes in the predicted values of $\dot{Q}_{evap}$ and *COP* with respect to the compressor speed when other five input parameters are kept constant at the values shown in the figure. As expectedly, $\dot{Q}_{evap}$ gets higher with increasing compressor speed due to mainly the fact that the refrigerant mass flow rate gets higher on increasing the speed. However, the *COP* gets lower with increasing compressor speed. Although the cooling capacity increases on rising the speed, the compressor power increases faster than the cooling capacity does, thereby causing a drop in *COP*. Note that the accuracies of the predictions in Figure 4 can not be measured because the points in this graph were not obtained experimentally. However, the statistical prediction performance of the developed ANFIS model has already been presented in Figures 2–7.

Figure 9 indicates the changes in the predicted values of $\dot{Q}_{evap}$ and *COP* with respect to the mean air velocity at the evaporator outlet when other five input parameters are kept constant at the values shown in the figure. It is observed that $\dot{Q}_{evap}$ rises moderately while *COP* drops slightly with increasing $V_{m,evap}$. As the evaporator air flow rate is increased, the convection heat transfer coefficient between the air and evaporator external surface gets higher. Then, in response to the increasing tendency of the superheat at the evaporator outlet, the TXV opens up and tries to maintain the superheat at a constant value by increasing the refrigerant mass flow rate, thus causing an increase in $\dot{Q}_{evap}$. However, the compressor power rises faster than cooling capacity does on increasing $V_{m,evap}$ due to the increased refrigerant mass flow rate and elevated compression ratio. Consequently, *COP* gets slightly lower with increasing $V_{m,evap}$.

Figure 10 reports the changes in the predicted values of $\dot{Q}_{evap}$ and *COP* with respect to the mean air velocity at the condenser outlet when other five input parameters are kept constant at the values shown in the figure. It is observed that $\dot{Q}_{evap}$ and *COP* increases moderately with increasing $V_{m,cond}$. As the condenser air flow rate is increased, the condensing pressure drops, which eventually causes a decrease in the evaporating pressure. Because the evaporating temperature also drops with decreasing evaporating pressure, a higher rate of heat can be absorbed from the air across a higher temperature difference between the air and refrigerant streams, thus yielding a greater $\dot{Q}_{evap}$. On the other hand, an increase in the condenser air flow rate causes a decrease in the condensing pressure, thus yielding a lower compressor power and a higher *COP*.

The prediction results presented in Figures. 8–10 are in a good agreement with the results presented in Alkan and Hosoz (2010a), which reports the experimental results obtained from the same AAC system.

Table 4. Comparison of the ANFIS predictions with experimental results.

Test vector no.	Experimental Results						*ANFIS Predictions*					
	$T_{evap,ao}$ (K)	$\dot{Q}_{evap}$ (kW)	$\dot{W}_{comp}$ (kW)	COP	$\dot{E}_{d,tot}$ (kW)	T_{dis} (K)	$T_{evap,ao}$ (K)	$\dot{Q}_{evap}$ (kW)	$\dot{W}_{comp}$ (kW)	COP	$\dot{E}_{d,tot}$ (kW)	T_{dis} *(K)*
1	278.2	6.11	1.94	3.15	1.91	343.5	278.5	6.07	1.96	2.95	1.94	*343.7*
2	278.2	5.95	2.43	2.45	2.26	352.5	278.5	5.94	2.43	2.53	2.26	*352.9*
3	280.7	6.47	2.18	2.97	2.10	347.6	280.8	6.39	2.22	2.86	2.13	*346.3*
4	277.0	6.23	3.31	1.88	3.26	365.7	276.0	6.47	3.29	1.84	3.23	*364.3*
5	277.3	6.32	2.35	2.69	2.31	348.2	277.5	6.28	2.39	2.65	2.35	*349.1*
6	271.4	3.89	1.55	2.52	1.52	348.9	271.7	3.65	1.33	2.58	1.31	*348.2*
7	273.2	4.80	1.92	2.49	1.92	350.0	273.0	4.98	2.05	2.47	2.05	*351.2*
8	273.2	4.38	2.66	1.65	2.70	366.8	272.8	4.84	2.85	1.55	2.83	*367.4*
9	281.1	6.71	2.78	2.41	2.77	356.0	281.4	6.86	2.78	2.51	2.78	*355.0*
10	271.7	3.43	1.74	1.98	1.73	360.3	271.5	3.30	1.63	2.10	1.62	*358.5*
11	276.2	5.40	1.66	3.26	1.65	343.8	277.1	5.20	1.59	3.05	1.61	*343.6*
12	274.7	5.83	2.10	2.78	2.10	347.9	276.0	5.48	1.87	2.87	1.89	*346.4*
13	280.2	7.11	2.44	2.91	2.44	348.6	282.3	6.72	2.43	2.82	2.43	*349.6*
14	278.2	5.27	1.89	2.79	1.88	349.4	278.2	4.82	1.74	2.69	1.75	*350.0*
15	273.2	3.17	1.24	2.55	1.24	351.2	271.8	3.35	1.21	2.60	1.21	*349.9*
16	276.2	5.73	2.29	2.50	2.28	352.8	276.9	5.17	1.99	2.59	2.00	*351.5*
17	277.2	5.46	2.97	1.84	2.97	365.7	275.9	5.26	2.74	1.80	2.73	*365.2*
18	274.2	6.16	2.50	2.47	2.49	352.5	275.0	5.70	2.18	2.64	2.19	*350.3*
19	274.2	6.05	2.67	2.27	2.66	356.0	274.0	5.92	2.49	2.41	2.50	*354.2*
20	*280.2*	*7.08*	*3.04*	*2.33*	*3.03*	*356.7*	*279.6*	*7.31*	*3.07*	*2.41*	*3.06*	*356.5*

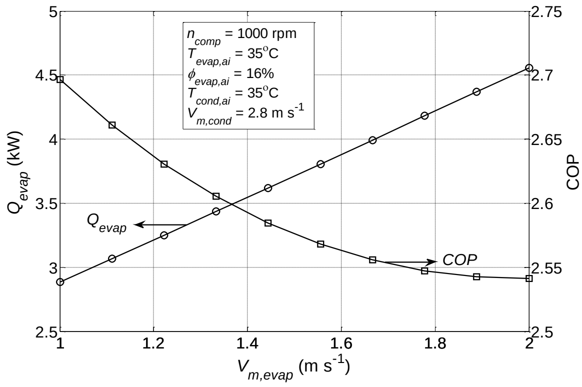

Figure 9. The ANFIS predictions for the cooling capacity and coefficient of performance as a function of the mean air velocity at the evaporator outlet.

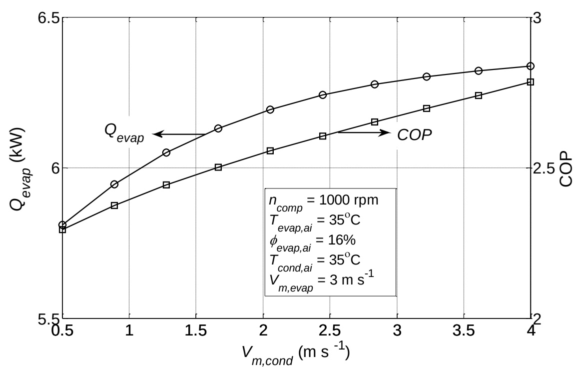

Figure 10. The ANFIS predictions for the cooling capacity and coefficient of performance as a function of the mean air velocity at the condenser outlet.

CONCLUSIONS

An ANFIS model for predicting the performance of an automotive air conditioning system with a variable capacity compressor has been developed. In order to gather experimental data and obtain input-output pairs required by the model, an experimental AAC system was set up and tested under varying operating conditions. The ANFIS model was trained using some of the experimental data, and used for predicting the output parameters in response to the input parameters not introduced to the model in the training process. The performance of the ANFIS predictions was measured using the correlation coefficient, mean relative error, root mean square error and absolute fraction of variance. The ANFIS model usually yielded a good statistical performance with the correlation coefficients in the range of 0.966–0.988, MREs in the range of 0.23–5.28% and absolute fractions of variance in the range of 0.9957–0.9999. Finally, using the developed model, the effects of the compressor speed and mean air velocities at the evaporator and condenser outlets on the cooling load and coefficient of performance were investigated.

The results reveal that AAC systems can be modelled accurately using the ANFIS approach, which is a powerful fuzzy logic neural network performing fuzzy modelling by learning information about the data set. Requiring only a limited number of tests instead of a comprehensive experimental study or dealing with a complex mathematical model, engineers can rely on the ANFIS technique for determining the performance of AAC systems.

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