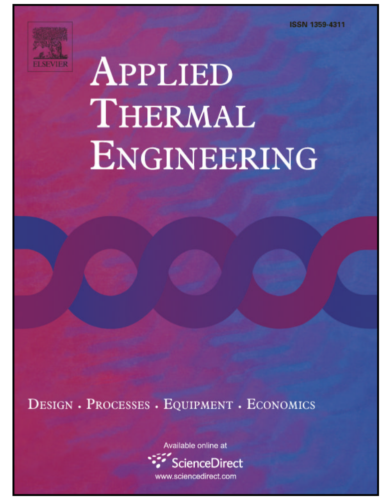

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Using ANNs to approach to the energy performance for a small refrigeration system working with R134a and two alternative lower GWP mixtures

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Abstract

In this paper, an artificial neural network application to model a small refrigeration system is presented. The main objective of this study is an energy comparison of three refrigerants: R134a, R450A and R513A. The application of the artificial neural network was designed to model individually three typical energy parameters: the cooling capacity, the power consumption and the coefficient of performance, as a function of the evaporating temperature and the condensing temperature. Each model was validated using a technique called cross-validation, producing minimum relative errors of 0.15 for the cooling capacity and the coefficient of performance, while 0.05 for the power consumption. Based on the appropriate validation results, computer simulations were performed to build 3D color surfaces. After inspecting these 3D color surfaces, it was concluded that R450A presented a slightly lower cooling capacity than R134a, actually a 10 % reduction in the cooling capacity was estimated. Similar results were observed for the power consumption, that is,

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R450A had about 10 % less power consumption than the other two refrigerants. On the other hand, it was observed that R134a and R513A presented very similar energy behaviors. With respect the COP, it was concluded that all three refrigerants showed a very similar behavior. After the analysis performed with the artificial neural networks and the use of 3D surface color, it was concluded that R450A and R513A are appropriate refrigerants to replace R134a in the short term in applications at medium evaporating temperature.

Keywords: vapor compression system, artificial neural network, R450A, R513A, cross-validation, energy performance

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1. Introduction

Vapor compression systems are the most extensively used technology for cold generation. This type of refrigeration has been affected by two subjects that are currently under investigation: the reduction of energy consumption and the decrease of greenhouse gas emission. In this regard, different strategies to reduce energy consumption [1, 2], or achieve more efficient configurations [3] are important investigation topics in this field. Additionally, the research and use of environmentally friendly refrigerants [4, 5, 6], are also very important topics for research in this area.

In order to reduce energy consumption, different models of vapor compression systems have been developed to characterize the behavior of this type of facilities. Some of them are based on equations derived from physical laws and empirical correlations, and in some cases, these two methods can be combined [7, 8]. These models frequently require geometric data that are difficult to obtain, and in some cases, operating parameters that are not available. Additionally, this type of models are very difficult to export to other systems with different geometric characteristics. Because it is difficult to accurately characterize a refrigeration system, empirical models have been proposed. In this way, the application of artificial intelligence in the field of refrigeration systems has notably increased in the last few years. Thus, the use of artificial neural networks, ANNs, shows interesting applications in the refrigeration field [9, 10], this is mainly due to the fact that ANNs have very good approximation capabilities and offer additional advantages such as: short development and fast processing time.

For example, Rashidi et al. [11] applied an ANN modeling technique to an ejector refrigeration cycle for predicting the unknow data. The authors concluded that the advantages of using ANN compared to other methods were speed and simplicity. Hosoz and Ertunc [12] developed an ANN model for a cascade vapor compression refrigeration system using R134a in both higher and lower cycles. This model was used for predicting the energy parameters of the overall cascade system. Their results suggest that the ANN model could alternatively and reliably be used for modeling. Esen et al. [13] used an ANN model to predict the performance of an experimental ground-coupled heat pump system with minimum input data. They concluded that the ANN approach could be used for the forecasting of the coefficient of performance, COP. Tong et al. [14] analyzed the performance of the refrigeration system through the application of an ANN with three input data. This model could provide guidance about how to create a saving energy control method of a refrigeration system working at part-load conditions. Önder [15] developed an approach based on an ANN with a small data set to determine the performance of a refrigeration system in terms of its thermodynamic aspects and its energy consumption. Their prediction results were very close to the actual values. Li et al. [16] applied an ANN modeling technique to a direct expansion air conditioning system using 169 sets of experimental data. This model could help to design a strategy to simultaneously control indoor air temperature and humidity. Belman-Flores et al. [17] developed a new method to model a refrigeration system, this method accurately estimated the number of neurons in the hidden layer, and the model predicted the energy performance with good results. Further to this study, they proposed a new tool that uses ANN to build energy maps for a vapor compression system working with R1234yf. From these maps, it is possible to identify the best performance zones [18]; in a later study, they built 3D plots for visualization of the energy performance and its variability when the input operating parameters change [19]. Cao et al. [20] developed an ANN model for an electronic expansion valve using the refrigerant pressures at the inlet and at the outlet, the inlet subcooling and the refrigerant mass flow rate as output. Their results showed that the ANN model was much more accurate than the literature correlations.

On the other hand, R134a has been the most important and dominant refrigerant in diverse refrigeration systems as well as in air conditioning systems. This refrigerant has a high global warming potential, GWP, of 1300, contributing significantly to the greenhouse effect [21]. In this regard, there are different options to replace hydrofluorocarbons, HFCs, in the refrigeration systems; the alternatives are natural refrigerants and synthetic refrigerants.

Focusing on synthetic fluids such as hydrofluoroolefins, HFOs, their mixtures with HFCs have emerged as low GWP alternatives to replace conventional refrigerants in refrigeration systems currently working with R134a. For example, R450A is a mixture of R1234ze and R134a; while R513A is a mixture of R1234yf and R134a. Both, R450A and R513A, are main options for medium temperature refrigeration and air conditioning systems. However, in literature there is little information about these two fluids. For example, Schultz and Kujak [22] evaluated experimentally R450A in a water-cooled chiller and compared it with R134a. Their results showed a decrease of 15% and 2% for the cooling capacity and for the COP, respectively, when compared to R134a. Mota-Babiloni et al. [23] presented an experimental study of R450A as R134a drop-in replacement. Their experimental tests were carried out in a vapor compression system with a variable-speed compressor. They concluded that R450A could be used directly in R134a systems obtaining a good energy performance. Later, they demonstrated that the incorporation of an internal heat exchanger improved the energy performance of the overall system working with R450A [24]. Mendoza-Miranda et al. [25] evaluated the evaporator performance through a shell-and-microfin tube evaporator model for various refrigerants, including R450A, which behavior was very similar to R134a. With regard to R513A, Mota-Babiloni et al. [26] experimentally assessed the main operation and the performance differences between retrofit replacement of R513A and R134a in a test bench equipped with a hermetic rotary compressor, a plate condenser and a plate evaporator. They concluded that the use of R513A could be recommended for refrigeration systems that use R134a.

Based on the above and because there are no studies about the modeling of refrigeration systems that operate with lower GWP mixtures, this paper presents the development of a model for a small refrigeration system that can be used to analyze the energy performance of alternative refrigerants to R134a. The model is based on the use of artificial neural networks to compare the behavior of three refrigerants: R450A, R513A and R134a. The proposed ANN was trained and their performance was analyzed using a special type of validation called cross-validation. The main contribution is the use of a technique of artificial intelligence known as artificial neural network in combination with a special type of validation to analyze the replacement of R134a with two lower GWP refrigerants; note that there are not any similar studies for these type of refrigerants. The primary advantage of the application of an ANN is that it can create a model from measurement data and predict the behavior under other operating conditions. Finally, computer simulations were made to predict the main energy parameters of the facility such as cooling capacity, power consumption and COP.

2. Characteristics of R450A, R513A and R134a

The main characteristics of the refrigerants under study in this work are shown in Table 1. It can be seen that the properties are very similar between refrigerants. However, it is possible to highlight the difference between GWP values, for instance it can be observed that R450A and R513A have a 42% and 44% reduction respectively, when compared to R134a. Another important fact is that R450A and R513A are non-flammable mixtures.

The normal boiling points of the refrigerants are in a similar range, and therefore, they can be used as an alternative for R134a in food conservation applications as well as in air conditioning applications. The glide of both refrigerants is low enough to consider R513A azeotropic mixture and R450A near-azeotropic mixture as replacements of R134a. The latent heat of vaporization of both alternatives is slightly lower than the one of R134a, so that the variation on cooling capacity will depend on the operating conditions and the mass flow rate. The slightly lower liquid density indicates that the system could require less refrigerant charge, but the great variation of vapor density could affect: the geometric volume of the compressor, the heat transfer in the heat exchangers of the circuit and the pressure drop in components and pipelines. Another parameter that could affect the heat exchanger design could be the liquid thermal conductivity, when it is compared to the vapor thermal conductivity, the liquid specific heat, and the vapor specific heat, it can be observed that the liquid thermal conductivity is the parameter with the greatest difference between R134a and its alternatives. By comparing R134a with the other two refrigerants, it can be observed that the major difference is exhibited in the viscosity of both the liquid and the vapor of R513A.

Therefore, these main characteristics make R450A and R513A good options as alternatives of R134a in applications at medium evaporating temperature.

	R450A	R513A	R134a
Composition (mass %)	R134a/R1234ze	R134a/R1234yf	
	42/58	44/56	100
ASHRAE safety class	A1	A1	A1
ODP	0	0	0
GWP [21]	547	573	1300
Critical temperature^{a} (°C)	105.6	97.7	101.1
Critical pressure^{a} (kPa)	3913.5	3855.3	4059.3
Glide^{a,b} (K)	0.61	0.10	0
Normal boiling point ^{a,b} (°C)	-23.65	-29.87	-26.36
Latent heat of vaporization ^{a,c} (kJ/kg)	204.42	194.94	217.16
Liquid density ^{a,c} (kJ/kg)	1259.64	1221.90	1294.78
Vapor density ^{a,c} (kJ/kg)	13.18	17.23	14.43
Liquid specific heat ^{a,c} (kJ/kg K)	1.33	1.31	1.34
Vapor specific heat ^{a,c} (kJ/kg K)	0.89	0.92	0.90
Liquid thermal conductivity ^{a,c} (mW/m K)	86.24	79.20	92.01
Vapor thermal conductivity ^{a,c} (mW/m K)	11.71	11.73	11.51
Liquid viscosity^{a,c} (μ Pa s)	260.27	224.69	266.53
Vapor viscosity ^{a,c} (μ Pa s)	10.73	10.57	10.73

^{a} Values obtained using REFPROP V9.4 Program [27]

^{b} at 100 kPa

^{c} at 0 °C

Table 1: Characteristics of the studied refrigerants.

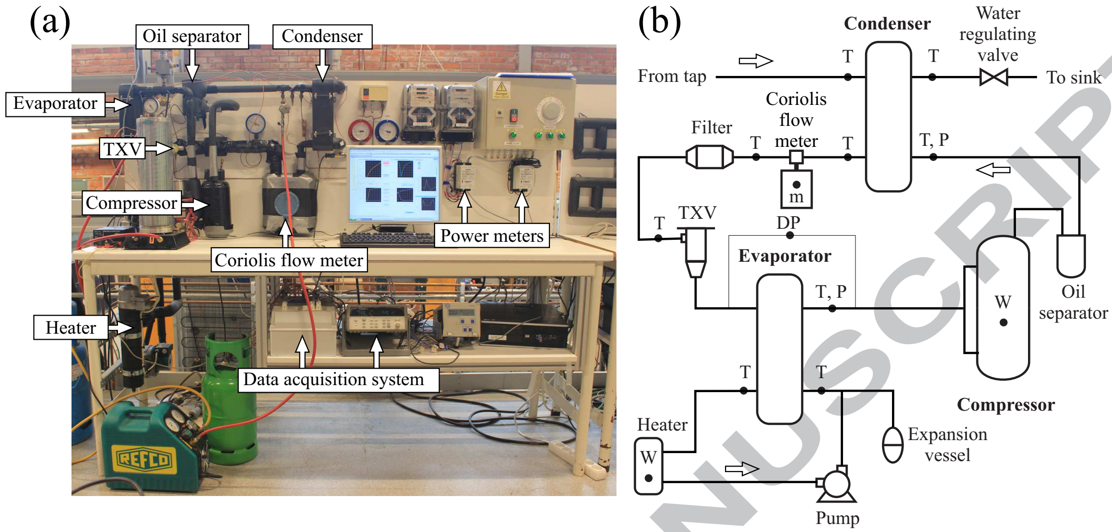

Figure 1: a) Experimental setup, and b) schematic diagram.

3. Experimental test bench

3.1. Experimental setup

The experimental data needed for the development of the ANN model have been obtained from a fully instrumented small capacity refrigeration unit (see Figure 1a). This vapor compression system has been designed to simulate the R134a typical operation in: mobile air conditioning, domestic and commercial refrigerators, heat pump water heaters and other small refrigeration systems (working at medium evaporating temperature). Figure 1b shows the schematic of the experimental setup, the main components and measurement points are indicated. It is composed of the main circuit, which simulates the operation of a vapor compression system, and two secondary circuits: the secondary fluid (ethylene glycol) close loop connected to the evaporator and the water open loop connected to the condenser.

The installation is composed of four main components, common to every vapor compression system: a full hermetic rotary compressor for R134a with an internal motor protector, two plate heat exchangers (an evaporator and a condenser) with a channel volume of 62 cm^3, and a R134a thermal expansion valve (TXV) with external pressure equalization (see Table 2). Additional accessories to ensure right operation of the system such as, a filter dryer, a sight glass and an oil separator, are also located in the installation. It should

Compressor	Value
Motor rating	550 W
Displacement	15.4 cm^3 per revolution
Rotating speed	2840/2860 rpm at 220/240 V
Oil type / charge	POE NEO32 / 300 cm^3
Condenser/Evaporator	
Plate heat exchanger	
Channel volume	62 cm^3
Max volume flow	9 m^3/h
Expansion valve	
Thermostatic expansion valve, TEN 2	
Designed for	R134a

Table 2: Characteristics of the main components.

be noted that the components and the pipes of the system are completely isolated using closed cell elastomeric nitrile rubber foam (with a thermal conductivity of 0.033 W/m·K at 0°C) to minimize losses to ambient, and thus, allow measuring more accurate results. The secondary circuits allow setting a wide range of evaporating and condensing conditions of the vapor compression circuit. The heat load circuit is a close loop composed of a pump that drives an 43 wt-% ethylene glycol based secondary fluid heated by a set of adjustable resistances capable of delivering 2.6 kW power that are immersed in a small isolated deposit. The heat removal circuit is a running water open loop which flow is controlled by a water regulating valve.

The measuring instrumentation of the system is described in the following:

- The temperatures at the inlet and the outlet of each main component (main and secondary circuits) were measured by thermocouples T type with an uncertainty of ±0.11 K.
- The condensation and evaporation pressures were measured by two calibrated pressure sensor transducers with ±0.08% of uncertainty (full scale best straight line). The maximum measurement for the low pressure transducer was 1000 kPa, while for the high pressure transducer was 2000 kPa.

Operating conditions	R134a	R450A	R513A
Evaporating temperature (°C)	[-15.5, 13]	[-15.5, 13]	[-15.5, 13]
Condensing temperature (°C)	[24, 45]	[24, 45]	[24, 45]
Refrigerant amount (kg)	0.450	0.500	0.510

Table 3: Tests operating conditions.

- The evaporation pressure drop was measured by a differential pressure sensor with an uncertainty of ±0.25% (reading).
- The refrigerant mass flow rate was measured by a Coriolis type flow meter with an uncertainty of ±0.5% (reading).
- The electric consumption of the motor-compressor set and the heaters was registered by a configurable multi transducer with an uncertainty of ±0.2% (reading).

Finally, all measurements were collected every 10 seconds by a data acquisition system and gathered to a personal computer, in which the data were displayed and registered.

3.2. Test conditions

All recorded tests were carried out at steady-state conditions taking a time period of 30 min. To define a steady-state test, the high and low pressures should be within an interval of ±2.5 kPa and the measured temperatures should be within ±0.5 K. Then, the data used as a steady-state test were obtained averaging over a time period of 10 min. The average output properties were calculated using the REFPROP.

The performed tests were intended to simulate a wide range of medium evaporating temperature conditions. These conditions are typical for a small capacity refrigeration system operating under very different condensing temperatures (summer/winter conditions or cold/warm country). These tests included twelve evaporating temperatures (in steps of 2.5°C) and five condensing temperatures (in steps of 5°C) for each of the three analyzed refrigerants, see Table 3. In order to have more points, some additional measurements were made at other intermediate conditions. A total of approximately $N = 100$ points were measured and used for the ANN model

4. Artificial neural networks

An artificial neural network, ANN, is a computational method inspired in biologic processes that is typically used to solve problems that are too difficult for computers or humans. An ANN can be considered a black box because it has a set of inputs and a set of outputs. In addition, ANNs have the benefit that they can adapt to an ample range of situations where a mathematic equation or model is missing. ANNs are organized in layers: the input layer, the output layer and some hidden layers. An ANN can have zero, one or more hidden layers depending on the application, in this paper, the modeling of the vapor compressor system required only one hidden layer because this configuration provided the best results.

In practical terms, ANNs can be implemented in hardware and software [28]. Thus, in this research, ANNs were implemented in software by the use of the Neural Lab simulator. In this simulator, it is possible to setup the number of neurons in each layer. A neuron is the basic component of an ANN, and is a processing unit that receives signals from other neurons to produce a single output signal as it is shown in Figure 2. Each neuron is composed of an adder and an activation function; the activation function must be real, continuous, limited, have a positive derivative and typically must have a sigmoid shape. In this work, the network has two inputs the temperature at the condenser (T_{cond}) and the temperature at the evaporator (T_{evap}). The network has only one output, represented by z in Figure 2. The number of neurons in the hidden layer was adjusted to avoid overfitting, see [29]; thus 10 neurons in the hidden layer were used. Three different ANNs were designed and tested; one for each output parameter. One for the cooling capacity, another for the power consumption, and a last network for the COP. These three networks were trained using a hybrid method based on Simulated Annealing and the Conjugate Gradient method [29]. There are other training methods that can be used to train an ANN, however, the hybrid method used provided the best performance. The network in Figure 2 has two sets of weights: one set connecting the input layer and the neurons in the hidden layer (h_{11}, h_{12}, ...) and the other set of weights connecting the neurons in the hidden layer with the neurons in the output of the network (w_{11}, w_{12}, ...). The value of these weights is estimated during a process called training which will be discussed next.

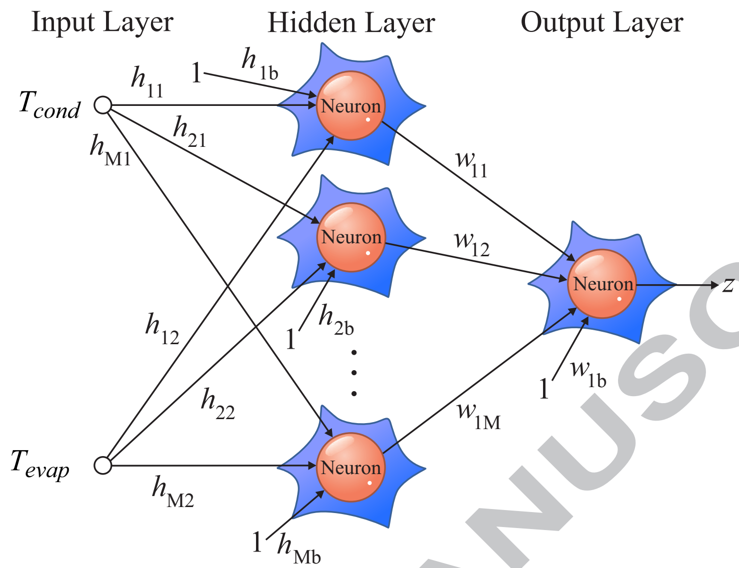

Figure 2: Artificial neural network

4.1. Cross-validation

Before an ANN can be used for any practical purpose, an ANN must be trained. During training, the network weights are adjusted using a data set called the training set. The training set has two components: the input and the target. The training set target includes the set of desired values at the output of the ANN when each of the inputs specified in the training set is applied to the network. In order to assess how well an ANN will behave in real applications, the network must be validated. Typically, the validation process is performed using a data set called the validation set. Thus, the proper use of ANNs requires two data sets: the training set and the validation set. When using conventional validation, the original data set is split into two sets: 70% is used for training and the remaining 30% is used for validation. However, in the data sets of this work, there is not enough data available to used conventional validation without comprising the significance of the results. Consequently, a general technique called cross-validation which combines measures to derive an accurate estimate of the performance of the model was used. There are several types of cross-validation: exhaustive cross-validation, leave-p-out cross validation, leave-one-out cross validation and some more. In this paper, leave-one-out cross validation (which is typically

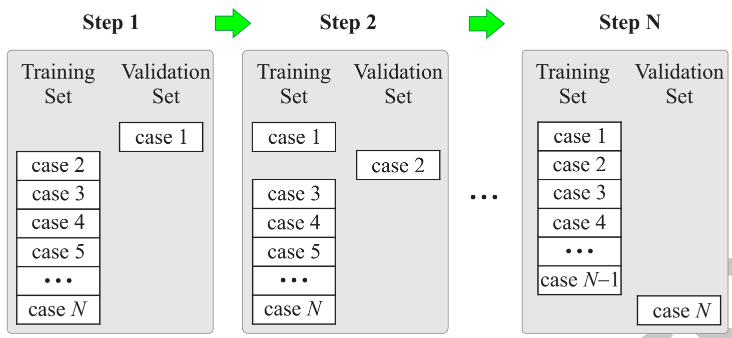

Figure 3: The steps of cross-validation

abbreviated as LOOCV) was used.

Figure 3 illustrates how to perform LOOCV, in this case, the data set includes N data samples. The algorithm begins by using for training the original data set without case one; this is indicated by Step 1 in Figure 3. After the ANN has been trained, the validation error is computed using only case one. During Step 2, case two is excluded during the training of the ANN, and validation is performed using case two. The process is repeated N times, and consequently, by the end of LOOCV there are N validation errors. Finally, the mean value of these errors is used to evaluate the performance of the network.

5. Results and discussion

After the three networks were trained, the performance of the ANNs was evaluated. As previously indicated, this evaluation was based on one special type of cross-validation, called leave-one-out cross-validation, LOOCV. The three energy parameters selected for validation by the estimation of the relative error are: the cooling capacity, the power consumption and the COP. Then, the performance results obtained from the simulation for the three refrigerants are discussed and compared.

5.1. Cooling capacity

Figure 4 shows the relative error for the cooling capacity for all refrigerants. The horizontal axis (the x-axis) represents the validation sample, that is a non-dimensional sequential number representing each measurement. The vertical axis (the y-axis) represents the relative error, and therefore, it does

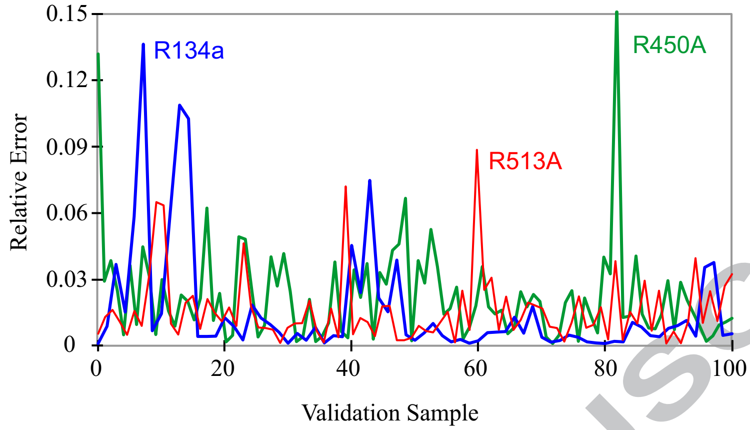

Figure 4: Validation for the cooling capacity.

not have any units. The computer simulations in Figure 4 were performed using uniformily distributed values in the ranges included in Table 3.

Each refrigerant is displayed with a color: R134a is shown in blue, R513A in red and R450A in green. The validation is shown for the 100 data used in the development of the ANN. In the figure, it can be seen that there is a maximum relative error of 0.15 for a particular test of the R450A refrigerant, however, it can also be observed that there are several errors practically null. The maximum peak error values displayed in this figure might be produced by the operation of the system under extreme conditions in which the measurement devices do not present full accuracy. Other possible cause of these peaks might be that some validation cases may not be fully represented for the cases that were used for training.

In addition, it can be noted that for most of the data and for the three refrigerants under study, there is a relative error below 0.05. Consequently, this indicates acceptable validation results for the cooling capacity, CC, which confirms an adequate prediction for this parameter by the ANN.

Based on the previous validation results, Figure 5 illustrates the computer simulation for the behavior of the cooling capacity which is presented for the refrigerants: R134a (Figure 5a), R450A (Figure 5b) and R513A (Figure 5c). This behavior is based on the operating variation of the condensing temperature (T_{cond}) and the evaporating temperature (T_{evap}) as it is indicated in Table 3; these parameters were used in the ANN model of Figure 2. The graphs in these figures show 3D color surfaces, which represent magnitude variation of the cooling capacity in Watts. For instance, a value of 480 W is represented in dark blue, when the cooling capacity increases the color changes until a maximum value of 2780 W, which is shown in black.

By inspecting the 3D surfaces in Figure 5, it can be appreciated that the behavior of the cooling capacity is very similar for the three refrigerants. According with the color surfaces and using as reference the results obtained for R134a refrigerant, it can be observed that R450A exhibits a slightly lower cooling capacity than the R134a; in fact a 10 % reduction in the cooling capacity is obtained from the computer simulations. This can be noted because the R134a refrigerant displays a greater zone that includes the colors: red, magenta and black. On the other hand, R513A exhibits a slightly higher cooling capacity when compared with R134a, this can be observed by a big zone that includes the colors magenta and black; these results can be justified attending to the related mass flow rate and refrigerating effect (evaporator enthalpy difference) of the refrigerants under the same operating conditions. As has been proved experimentally [23, 26], R450A presents lower mass flow rate than R134a while R513A presents higher value. Then, the difference of the deviation of refrigerating effect is lower, and attenuates the difference in cooling capacity.

In addition, it can be noticed that the evaporating temperature affects more the cooling capacity than the condensing temperature because of the influence of the first parameter in the suction conditions and pressure ratio. In fact, the condensing temperature produces variations in the cooling capacity of approximately 10 % for the R134a, 5 % for the R513A and 1 % for the R450A. With the simulation of this first energy parameter, it can be concluded that the refrigerants R450A and R513A present a similar cooling capacity to the R134a refrigerant, this under the same operating conditions. Thus, the cooling capacity of the system is not going to be affected, if R134a is substituted by these lower GWP refrigerants.

5.2. Power consumption

Regarding the validation of the power consumption, it is represented in Figure 6. The computer simulations in Figure 6 were performed using the same operating conditions as those used for the cooling capacity. It can be observed that for the three refrigerants a maximum error value of the order of 0.05 has been obtained, and for most of the data relative errors below 0.02 are presented. This confirms the correct performance of the ANN to predict the power consumption of the test facility. Another important point to note

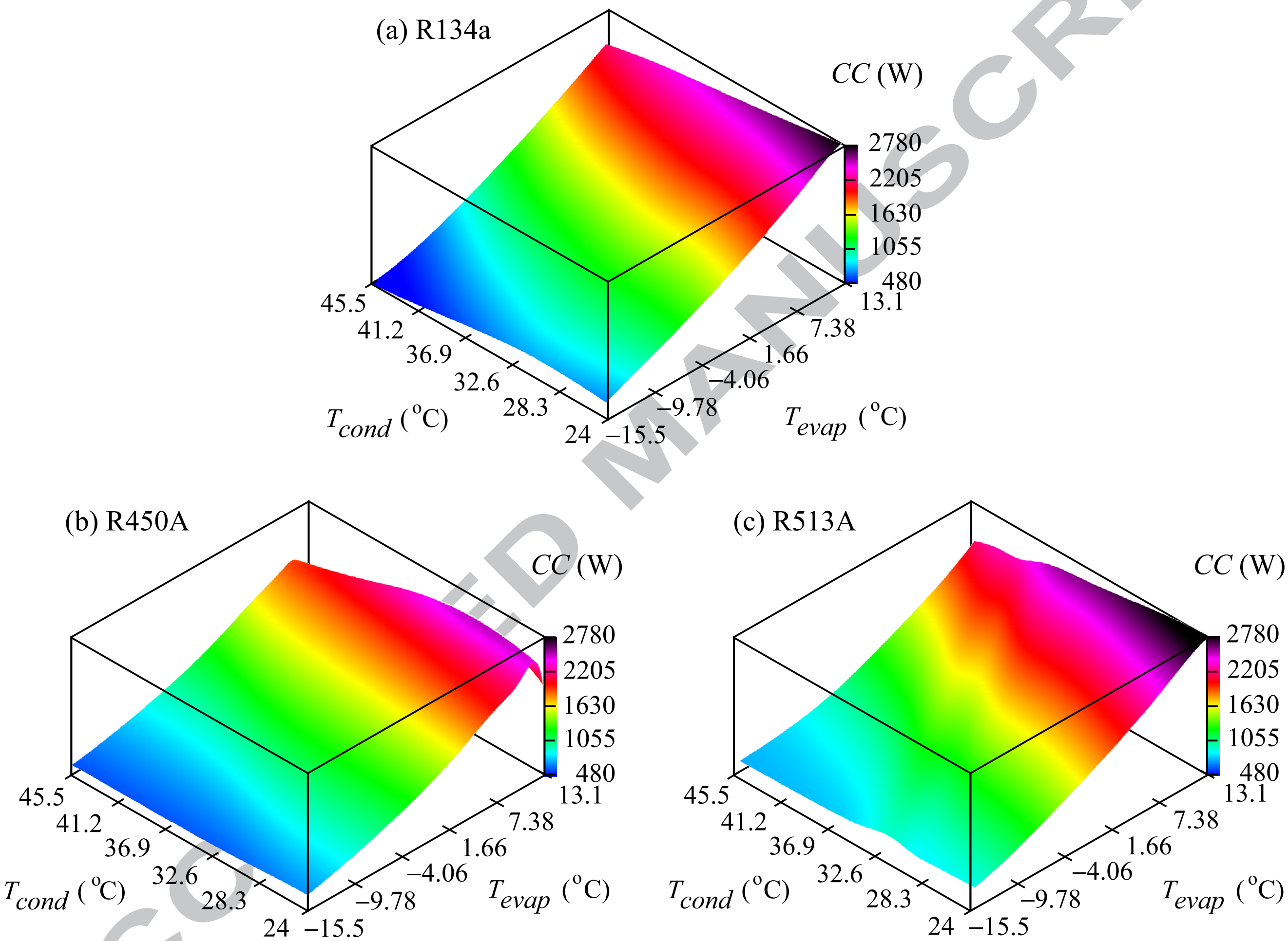

Figure 5: Computer simulation results for the cooling capacity.

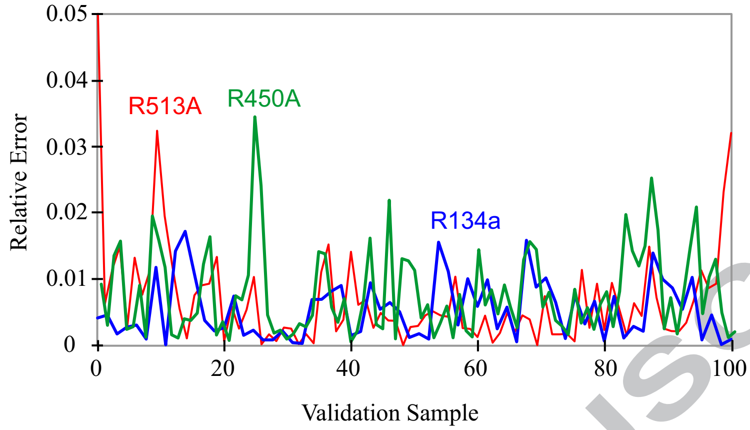

Figure 6: Validation for the power consumption.

is the order of magnitude for this parameter in comparison to the cooling capacity (see Figure 4), that is, the maximum relative error value for the cooling capacity was 0.15; three times greater than the maximum error for the power consumption. This is because the power consumption is directly obtained by a measuring device, however, the cooling capacity is estimated using other measurements such as: temperature, pressure (both parameters were used in the equations of state to calculate the enthalpy values) and mass flow rate.

Figure 7 illustrates the computer simulations for the motor-compressor power consumption for the installation working with the three refrigerants. The minimum power consumption, 350 W, is displayed in dark blue; a gradual color change indicates a power increase until a maximum value of 640 W which is displayed in black. By inspecting the computer simulations results for the three refrigerants, it can be noted that the surface color for R450A includes less red area than R134a and R513A, and more blue area than the other refrigerants. Consequently, the R450A refrigerant represents a lower power consumption than the other two. The ANN model produced a maximum power consumption of 568 W for R134a, 513 W for R450A and 586 W for 513A. Thus, it can be concluded that the behavior of the R513A refrigerant is very similar to the behavior of R134a.

These computer simulations indicate that the condensing temperature influences more the power consumption than the evaporating temperature; an increase in the condensing temperature produces an increase in the compression ratio and hence in the specific compression work. Contrary to the cooling capacity results, where the condensing temperature does not significantly affect the cooling capacity. This is due to the shape of the isentropic curves, where the variation of the condensing temperature affects more the specific compression work than the evaporating temperature [30]. Then, both parameters also affect the compression ratio that varies the compressor global efficiency, and hence, the power consumption.

5.3. COP

The validation of the COP for the three refrigerants under study is shown in Figure 8. Similar to the other two parameters, very small relative errors are observed for most tests. Specifically, very few measurements exhibit maximum errors of 0.15, in fact, most of the validation samples exhibit an error that is less than 0.03. The low relative errors guarantees an adequate prediction of the coefficient of performance of the refrigeration plant through the use of the ANN model.

The simulation for the COP is shown in Figure 9 where it is possible to notice that the color variation is very similar for the three refrigerants. Therefore, it can be concluded that the installation operating with R450A and the installation working with R513A offers a very similar COP to the installation working with R134a. Additionally, it can be observed that an increase in the evaporating temperature produces an increase in the cooling capacity (see Figure 5) resulting a slightly decrease in power consumption (see Figure 7), thus, increasing the overall COP of the system. From the figure, it can also be seen that for a low evaporating temperature and a high condensing temperature, the COP is a little smaller for R134a than for R450A and R513A, in fact the COP is 6 % smaller for R134a; as the blue color is more intense in Figure 9a than in Figure 9b and c.

Based on the behavior of the energy parameters analyzed in this work, the lower GWP values and the safety classification, it can be concluded that the refrigerants R450A and R513A are appropriate fluids to replace R134a in applications at medium evaporating temperature.

6. Conclusions

The phase-out of HFCs requires new refrigerants and accessible techniques to determine their energetic behavior in new and existing vapor compression systems. This paper proposed a new approach to analyze the behavior of

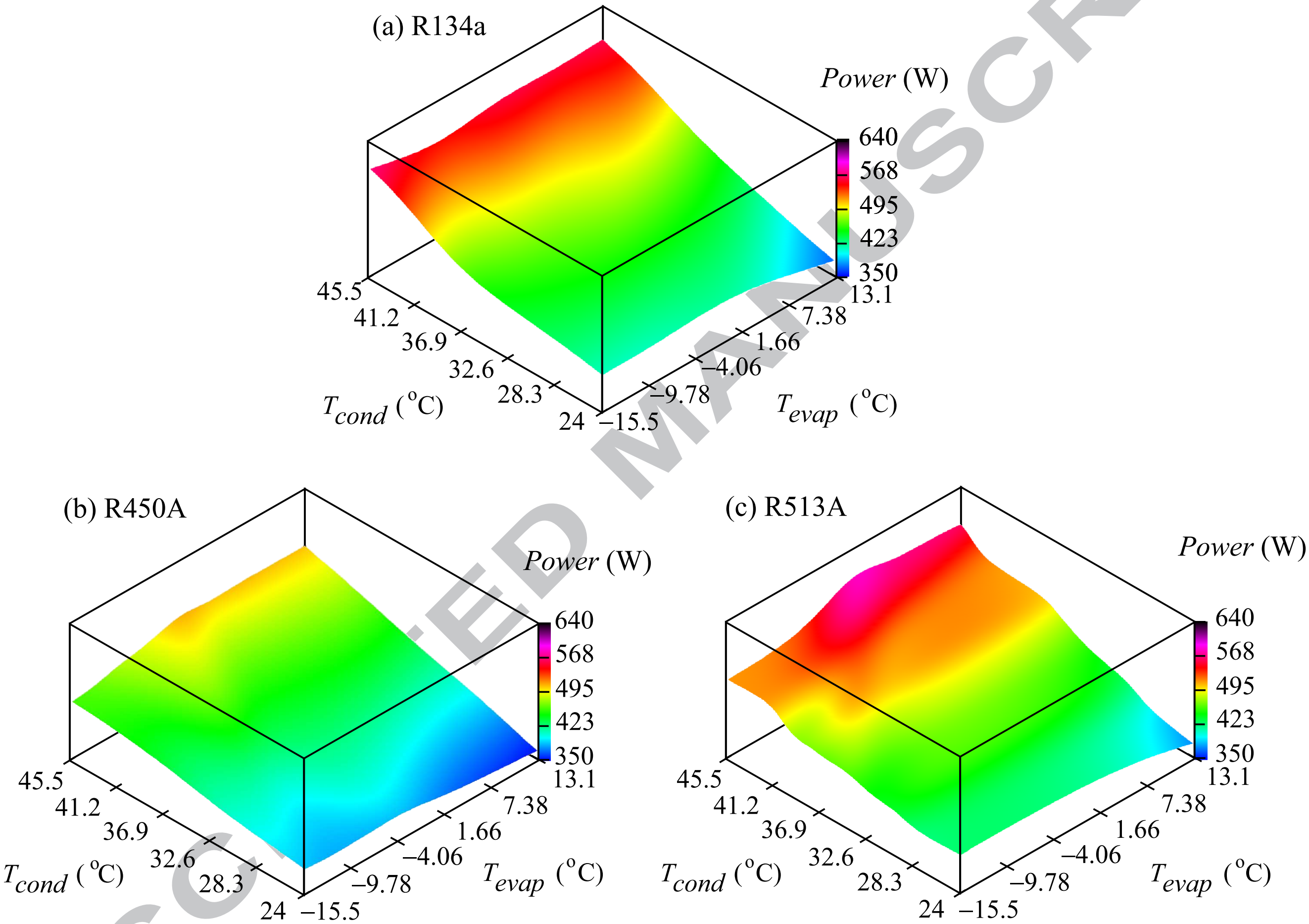

Figure 7: Computer simulation results for the power consumption.

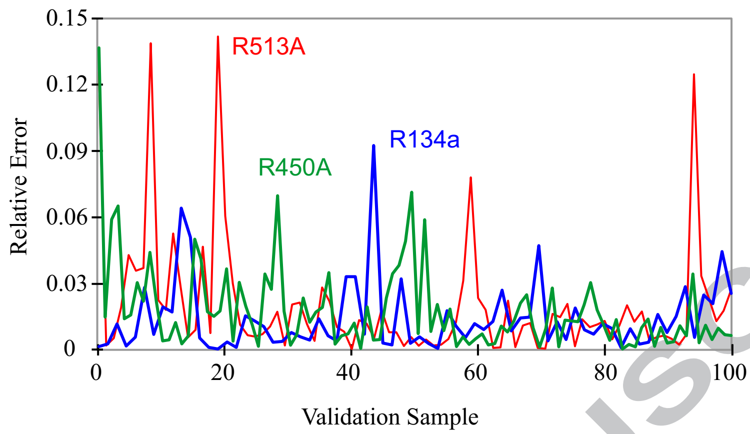

Figure 8: Validation of the COP.

R134a and two lower GWP mixtures, R450A and R513A using artificial neural networks. The neural network models were used to simulate: the cooling capacity, the power consumption and the COP. The artificial neural networks were training using a data set obtained from a vapor compression system with a full hermetic rotary compressor. This data set was built using a fully instrumented installation. The input parameters used in this study were: the condensing temperature and the evaporating temperature. Three separated data sets were built, one for R134a, another for R450A, and a last one for R513A.

In order to assess the performance of the network, a technique called cross-validation was used; this validation technique is the most recommended method for the size of the data set used in this work. Using the results of cross-validation, graphs to display the relative error for each parameter were built.

After computer simulations were completed, the networks were used to create 3D color surfaces. These 3D surfaces show the behavior for each energy parameter when the condensing temperature and the evaporating temperature are changed. Based on the computer simulations, it was observed that the R450A refrigerant exhibits around 10 % lower cooling capacity than R134a and R513A for most operating conditions. With respect the power consumption, it was concluded that R134a and R513A had very similar power consumption, while R450A exhibited approximately a 10 % less power consumption than the other two refrigerants. For the COP simulations, it was

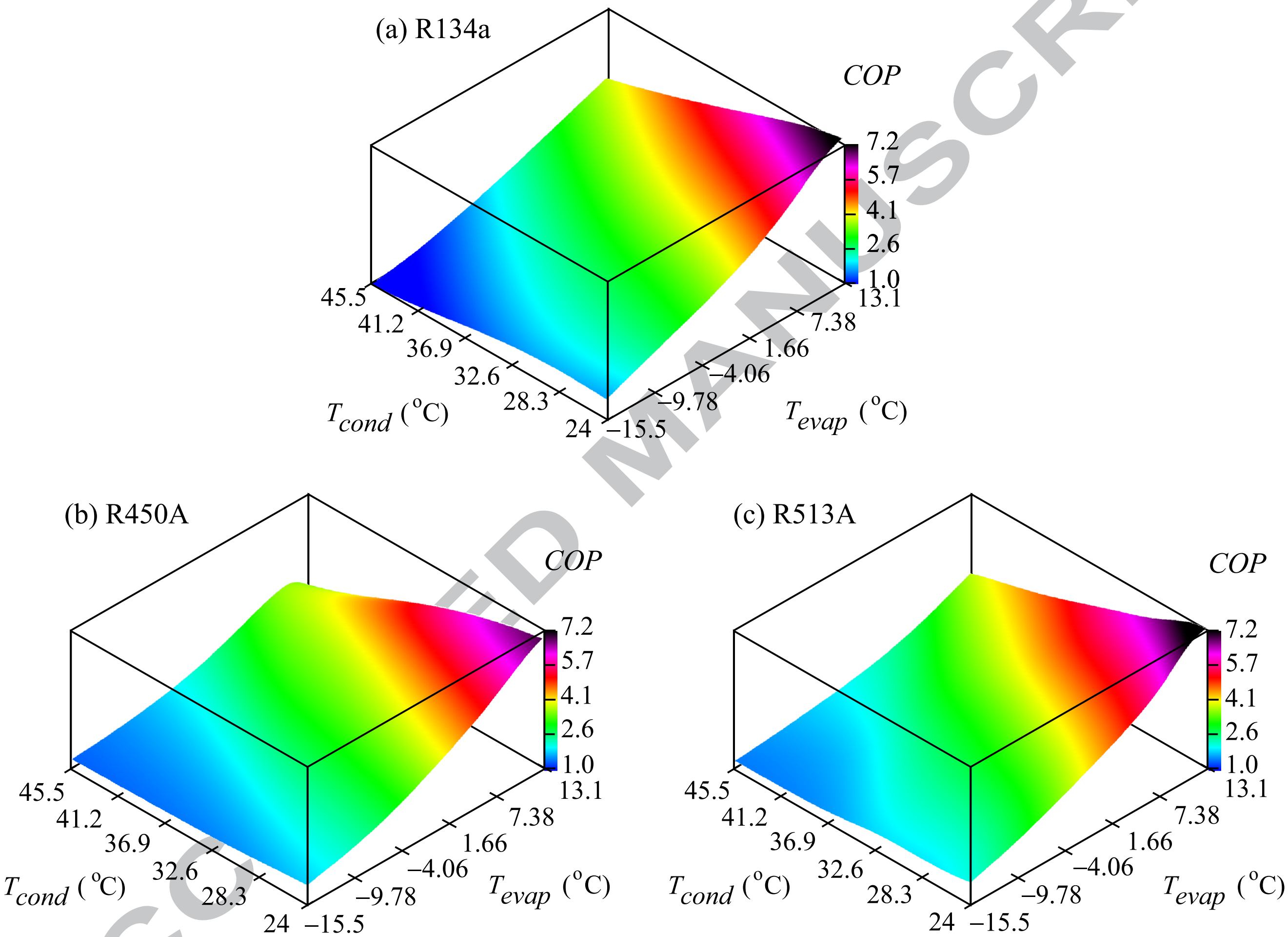

Figure 9: Computer simulation results for COP.

observed that all three refrigerants displayed very similar behaviors. By visually comparing the 3D surfaces generated for each energy parameter, it was concluded that R450A and R513A are adequate refrigerants to replace the R134a in currently refrigeration systems that present similar characteristics to the presented in this work.

Finally, it can be concluded that artificial neural networks can be used to model the behavior of a vapor compressor system, and thus, predict the energy performance of the system when the evaporating temperature as well as the condensing temperature are changed.

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Highlights

- A new approach to analyze the energy behavior of R134a, R450A and R513A is discussed.
- An artificial neural network application to model a small refrigeration system is developed.
- The performance of the model was verified using cross-validation.
- Computer simulations were performed to build 3D color surfaces for each energy parameter.
- Based on the results, R450A and R513A are adequate refrigerants to replace R134a.