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PREDICTING THE ENERGY PERFORMANCE OF A RECIPROCATING COMPRESSOR USING ARTIFICIAL NEURAL NETWORKS AND PROBABILISTIC NEURAL NETWORKS

PREDICCIÓN DEL DESEMPEÑO ENERGÉTICO DE UN COMPRESOR RECIPROCANTE USANDO REDES NEURONALES ARTIFICIALES Y REDES NEURONALES PROBABILÍSTICAS

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Abstract
This work presents an analysis to predict the energy performance of a reciprocating compressor working with refrigerant R134a using artificial intelligence. The compressor is located in a vapor compression system; tests were experimentally obtained and were used to develop two models: one using an artificial neural network and another one using a probabilistic neural network. Because the relationship between the compressor input variables and the respective output variables is complex, these techniques of the area of artificial intelligence are excellent methods to model this type of compressor. The compressor input variables were: compressor rotation speed, suction pressure, suction temperature and discharge pressure. The compressor output variables were: mass flow rate, discharge temperature and energy consumption. Computer simulations were performed to train and validate the proposed methods. In order to measure the performance of these methods, the mean squared error was computed for each experimental test and for each model. The simulations results were used to establish the validity of the models. Finally, the main contribution of this paper is to extend the use of artificial intelligence to predict and simulate the behavior of a reciprocating compressor.
Keywords: artificial intelligence, simulation, reciprocating compressor, energy performance, R134a.

Resumen
Este trabajo presenta un análisis para predecir el desempeño energético de un compresor reciprocante que trabaja con refrigerante R134a usando inteligencia artificial. El compresor se encuentra en un sistema de compresión de vapor; las pruebas se obtuvieron experimentalmente y se utilizaron para desarrollar un modelo de red neuronal artificial y otro con una red neuronal probabilística. Debido a que la relación entre las variables de entrada del compresor y las variables de salida es compleja, estas técnicas del área de la inteligencia artificial son excelentes métodos para modelar este tipo de compresores. Las variables de entrada fueron: velocidad de rotación, presión de succión, temperatura de succión y presión de descarga. Las variables de salida fueron: flujo másico, temperatura de descarga y el consumo energético. Se realizaron simulaciones computacionales para entrenar y validar los métodos propuestos. Con el fin de medir el rendimiento de estos métodos, la media del error cuadrático se calculó para cada prueba experimental y para cada modelo. Los resultados de las simulaciones se utilizaron para establecer la validez de los modelos. Por último, la principal contribución de este trabajo es extender el uso de la inteligencia artificial para predecir y simular el comportamiento de un compresor reciprocante.
Palabras clave: inteligencia artificial, simulación, compresor reciprocante, desempeño energético, R134a.

1 Introduction

The field of refrigeration is an area of great research because of the high impact on industrial processes, medicine, edifice comfort, domestic applications, etc. Inevitably, these applications are associated with a high energy consumption. For instance, the domestic refrigerator is among the home appliances that has the highest energy consumption; it has been estimated that there is one refrigeration

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system for each six people on Earth (Coulomb, 2006). The majority of these refrigerators are based on vapor compression technology which, for instance, United States homes are responsible for around 18% of the total energy consumption (U.S. Energy Information Administration, 2015). This percentage noticeably increases due to: malfunctioning events in the systems, deficient designs or wrong operating conditions. The study and analysis of refrigeration systems based on vapor compression are of great interest (Belman-Flores *et al*., 2015).

Since the compressor is responsible for most of the energy consumption, the modelling of this component is an open area for research. Thus, different methods for modeling reciprocating compressors are presented in the literature, from those that solve the Navier-Stokes equations (Rigola *et al*., 2005; Damle *et al*., 2011), to those models that are aided by empirical correlations (Liberia *et al*., 2000; Ma *et al*., 2000; Gonzalves *et al*., 2008; Barroso-Maldonado *et al*., 2015). Additionally, it is possible to find some experimental studies for compressors coupled in transcritical systems (Yuan *et al*., 2012), comparative analysis between alternate refrigerants (Navarro *et al*., 2013), studies about design parameters to reduce its energy consumption, studies for the diagnosis of faults, and finally, research for thermodynamic predictive monitoring (Yasar *et al*., 2007; Elhaj *et al*., 2008; Yu *et al*., 2013; Salazar-Pereyra *et al*., 2016), among others.

In the same context and because of the importance of cool generation, several methodologies have been proposed to optimize the compressor. Consequently, the field of the artificial intelligence has been used in the last decade for modeling, not only in the field of refrigeration, but also in other fields related with mechanical engineering (Soteris, 2001; Zhang and Friedrich, 2003; Hany, 2006; Mohanraj *et al*., 2012). The field of artificial intelligence includes: expert systems, artificial neural networks (ANNs), probabilistic neural networks (PNNs), simulated annealing (SA), genetic algorithms (GA), fuzzy logic, among others. In the case of ANNs and PNNs, it is important to mention some advantages of these models, such as their simplicity and ability of modeling a multivariable problem; they can extract non-linear relationships by means of training data. Therefore, models based on neural networks can predict outputs quite quickly and with high accuracy, even if the training data set is limited. Such models have already been explored in several scientific disciplines; for example, Rico *et al*. (2014) developed an artificial neural network that controls the system that affects the moisture content in the poultry litter to ensure that it can be used as fuel. Another example is geothermal issues, in the investigation of Diaz Gonzalez *et al*. (2013) a statistical analysis based on ANNs to determine the contribution of some chemical elements in the final estimation of downhole temperatures of geothermal wells.

In the field of thermal science, it is easy to find many applications of ANNs. For instance, ANNs have been proposed in: the analysis of a heat exchanger (Monharaj *et al*., 2015), solar thermal energy (Yaïci and Entchev, 2014). Also they have been used in refrigeration, specifically in air conditioning and heat pump systems (Mohanraj *et al*., 2013), automotive air conditioning systems (Haslinda *et al*., 2013), as well as the determination of thermophysical properties of alternative refrigerants (Secan *et al*., 2011). Likewise, Belman-Flores *et al*. (2013) modeled a variable speed vapor compression system and in the work of Ledesma and Belman-Flores (2014) are energy maps built using the refrigerant R1234yf. Despite the large number of applications of artificial intelligence in refrigeration, compressors analysis under this technique is not promoted at all. Therefore, there are few publications related to artificial intelligence applied to reciprocating compressors. For instance, Heinrich and Schwarse (2016) proposed a numerical model for the simulation of a centrifugal compressor and performed a genetic algorithm optimization to improve the compressor performance. Yang *et al*. (2009) developed a loss-efficiency compressor model using an ANN to simulate the compressor performance for both single and variable speed compressors. Ghorbanian and Gholamrezaei (2009) designed a neural network to predict the compressor performance map at the design stage. Sanaye *et al*. (2011) proposed two ANNs and a non-linear regression model to analyze experimental data obtained from a rotatory compressor. Tian *et al*. (2015) applied an ANN, a method based on partial least squares, and a regression to predict the energy performance of a scroll compressor.

On the other hand, regarding PNNs applications, they are not limited to a specific area. Since a PNN is by nature a classifier, in the literature the applications are oriented to data classification. These applications can be organized into categories namely: accounting, finance, marketing, health, biology, medicine, among others (Paliwal *et al*., 2009). In the field of mechanical engineering PNNs have been explored slightly. Thus, some applications in this field are used to detect faults in gas turbines (Romesis and Mathioudakis, 2003) and predict the power output of wind turbines (Tabatabaei, 2016). Some investigations for the diagnostic ability using a PNN in turbofan engines have been studied (Bin *et al*., 2000; Romessis *et al*., 2000).

In this paper, an analysis of a reciprocating compressor using ANNs and PNNs is presented. This analysis consists of the modeling or prediction of the energy performance of a variable speed reciprocating compressor which is mounted on a vapor compression system. First, measurement tests were captured from the experimental facility. Second, an ANN and a PNN were trained using these measurement tests to estimate the mass flow rate of the refrigerant, the discharge temperature and the energy consumption. The input compressor variables were: rotation speed, suction pressure, suction temperature and discharge pressure. Both networks were validated, and then, they were compared to each other. Computer simulations were performed to adjust the number of neurons in the hidden layer of the ANN. The main contribution of this paper is the proposal of two techniques from the area of artificial intelligence to model a reciprocating compressor. These models are based on experimental parameter measurements, therefore, they automatically adjust to the physical model.

2 Description of experimental facility

The principal refrigeration system includes a vapor compression circuit and two secondary circuits, see Fig. 1. The main circuit has: an open type variable speed compressor, a shell-and-tube evaporator, a shell-and-tube condenser, and a thermostatic expansion valve. The test facility is fully instrumented to measure variables such as pressure, temperature, mass flow rate, rotation speed, and energy consumption. The volumetric flow and the inlet temperature of the secondary fluids and the rotational speed are the controllable parameters in the experimental tests. The working fluid is R134a.

The compressor mounted on this circuit is an open type Bitzer V model. These compressors have a shell which is independent of the electrical engine so that the connection to the motor is made through a mechanical transmission by pulleys. In Table 1, some technical parameters of this component are presented.

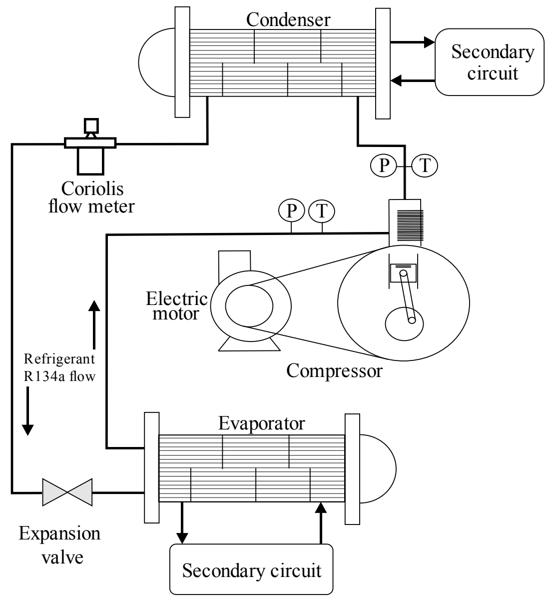

Fig. 1. Schematic diagram of the test bench.

Table 1. Geometric features of the compressor.

Number of cylinders	2
Piston diameter [m]	0.085
Stroke [m]	0.06
Rotation speed range [rpm]	400-600
Diameter-length of the internal suction line [m]	0.029-0.06
Diameter-length of the internal discharge line [m]	0.029-0.06
Displaced volume [m^3/h] @ 560 [rpm]	23.1

Various types of sensors are strategically located depending on the parameter to be measured obtaining records for the variables of interest such as: temperature, pressure, mass flow rate, rotation speed, and power consumption. Table 2 presents a summary of the type of sensors used and the uncertainty associated with each measurement. The signals generated by these sensors are directed to a SCXI 1000 data acquisition system from National Instrument.

3 Basics of ANNs and PNNs

Artificial neural networks are sophisticated modeling techniques capable of modeling extremely complex processes, they are used for: pattern recognition, optimization, simulation, prediction, etc.

Table 2. Measured parameters and their uncertainties.

Parameter	Instrument	Uncertainty
Temperature	Thermocouple K-type	±0.3 K
Pressure	Pressure transducers	±0.1%
Power	Digital wattmeter	±0.5%
Mass flow rate	Coriolis flow-meter	±0.22%
Rotation speed	Inductive sensor	±1%

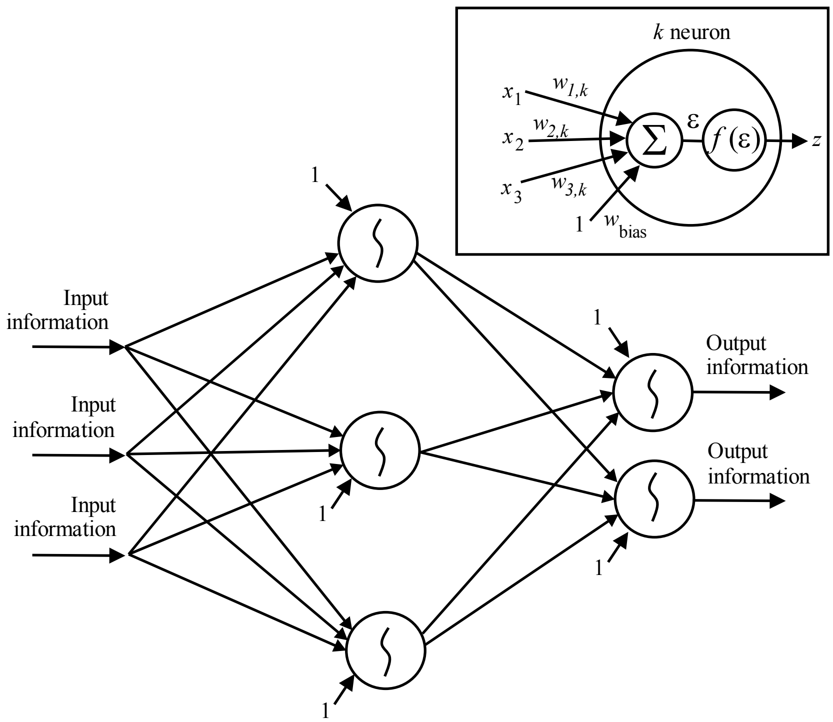

Fig. 2. Common architecture of an ANN with a hidden layer.

In particular, neural networks are nonlinear systems and they are inspired in biologic organisms. In literature, it is possible to find a vast amount of theoretical information about neural networks, particularly on ANNs and PNNs (Russel and Norving, 2009; Jones, 2008). In the following two subsections, the foundations, architecture and operation of both networks are reviewed.

3.1 Artificial neural network

The ANN is a feedforward network with one input layer, one output layer and several hidden layers (commonly just one hidden layer). Each layer is composed of neurons, in this work λ represents the number of neurons in the hidden layer. For instance, in Fig. 2 the network has three neurons in the hidden layer (λ = 3). These neurons are connected to each neuron to other neurons using a weight (w). One special type of weight is called the bias weight (w_{bias}); this can be visualized schematically in Fig. 2.

The network shown in Fig. 2 is designated as a black box model because it can be viewed in terms of its inputs and outputs without any knowledge of its internal workings. The ANN is composed of processing units called neurons as shown in the box in this figure. Each neuron unifies this information by means of linear accumulation, and then used an activation function to produce its output. This function basically executes a nonlinear irreversible transformation (see Eq. 1) between the neuron input (ε) and the neuron output (z).

$$z = \tanh(1.5\varepsilon) \tag{1}$$

This activation function has been widely investigated. Several studies include the 1.5 factor which appears in the argument of the hyperbolic tangent; for a more detailed theoretical information, see the work of Russel and Norving (2009) and Jones (2008).

The secret of learning in these models is the neuronal interconnections, thus neurons are linked using connecting lines. Each line has an assigned weight (w) which acts as a constant weighting factor (simulating the biology synapses), see Eq. 2.

$$\varepsilon = \sum_{m=1}^{M} x_m w_{m,k} + w_{bias} \tag{2}$$

where M is number of neurons in the previous layer. The process responsible for weights adjustment is typically called training. In order to train an ANN, it is necessary a data set that has a set of input values (**x**), and a set of desired values (**y**) usually known as the target. After the training process has completed, an input value (x) is presented to the network and the ANN produces an output value (y'). The learning is successful if y' is close to y for each case. The mean squared error, *mse*, is typically used to assess the performance of model, in this case of the ANN. The *mse* is computed between the actual network output y', and the target value y as follows:

$$mse = \frac{1}{N}\sum_{i=1}^{N}(y_{\mathrm{i}} - \mathrm{y'}_{\mathrm{i}})^2 \tag{3}$$

where N is the number of test samples. There are other errors that can be used, such as the mean relative error or the root mean squared error, however, the *mse* is one of the most used errors for performance evaluation of an artificial neural network.

3.2 *Probabilistic neural network*

The mathematical foundations on which PNNs are built has been known for several decades, even though they were proposed long before than ANNs (Meisel, 1972; Yenugu *et al*., 2010). However, because of the large computational requirements of their algorithm, they were considered as unpractical and inapplicable systems. It is known that PNNs were explored and applied widely after 1990 when Specht (1990) showed how this algorithm could be divided into components and how each component could operate in a parallel way. PNNs are, by their own nature, Bayes-Parzen classifiers (Masters, 1995). Thus, they use class members of one, two or more classes for their training. Therefore, their main application is to examine a set of inputs in order to decide to which class each of this inputs belongs to.

A PNN has four layers: the input layer, the pattern layer, the summation layer and the decision layer. The input layer normalizes the range of the values so that they can be used in the next layer. The number of columns in the training set input is equal to the number of inputs of the PNN (U), likewise, the number of columns in the training set target is equal to the number of outputs of the PNN. The pattern layer has one neuron for each case in the training set. In this layer, a neuron computes the Euclidean distance from the center of the neuron to the training case, and then applies a kernel function. The shape of the kernel function is determined by the parameter σ. The summation layer contains one neuron for each class, and finally the decision layer contains one neuron that simply retains the maximum of the summation neurons as is shown in Fig. 3.

In this layer, it is decided to which category the input vector **x** belongs using the Bayes' theorem. The output for each neuron located at the summation layer is defined as follows:

$$g_c(\mathbf{x}) = \frac{1}{\sigma_{c1}\sigma_{c2}\cdots\sigma_{cU}}\sum_{i=1}^{N}\delta_c(i)\exp\left[-\sum_{j=1}^{U}\left(\frac{x_j - x_{ij}}{\sigma_{cj}}\right)^2\right] \tag{4}$$

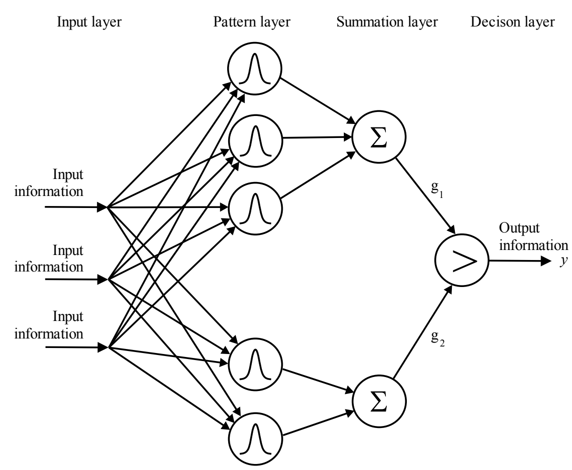

Fig. 3. Common architecture of a PNN.

where σ_{cj} is the smoothing parameter related to each cth class and to each jth input feature, it represents the standard deviation around the mean of U random variables included in vector **x**. And,

$$\delta_c(i) = \begin{cases} 1, & \text{if } i = c \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

A continuous error criterion was introduced to be able to use the PNN for mapping purposes, deep details and mathematical foundations can be found in Schioler and Hartmann (1992).

4 Proposed model and results

A data acquisition system was used to collect 4000 measurement samples at stationary state, see Section 2. Then, the acquired data were organized in digital files and split to create the training set and the validation set. An ANN learns by cases called training cases. Typically, a dataset is split to create the training set and the validation set; however, the training set must include all different test cases of the experimental plant. For instance, if 80% of the cases are used for training, then the 20% remaining cases must be used for validation. Other alternatives to split the data set may be: 70% for training / 30% for validation, 60% for training / 40% for validation, etc. However, when the percentage used for training is small, it is possible that some test cases are not included in the training set (Schioler and Hartmann, 1992). After performing computer simulations, it was concluded that the percentage rate that provided the best results was 85% (3,400 samples) of the total data for training and the remaining 15% (600 samples) for validation.
One of the main purposes of the compressor is to provide a pumping effect to push the working fluid along the vapor compression system. A compressor is characterized by the estimation of the mass flow rate. Throughout the internal processes that increase the pressure, the fluid experiences changes in temperature, and therefore, the discharge temperature becomes considerably higher than the suction temperature. Since the discharge pressure is a known parameter, determining the discharge temperature helps to define the thermodynamic state at the discharge line. Finally, according to the first law of thermodynamics, in order to pass from a state of low thermal energy to a state of high thermal energy, it is necessary to consume some amount of energy. In fact, in some optimization cases, this energy consumption is the objective function to be minimized. The knowledge of these energy parameters helps evaluate the performance of the compressor as

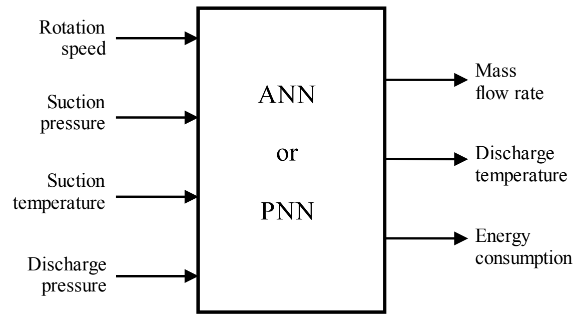

Fig. 4. Proposed models for mapping the energy performance compressor.

well as the performance of the whole refrigeration system. Each of these parameters is modeled using an ANN or a PNN as shown in Fig. 4. In this scheme, it can be seen that the network has four inputs and three outputs (one for each energy parameter).

There are two types of training methods: supervised training and unsupervised training. In supervised training, a network learns by extracting information from the input training set and the target training set; this type of learning is used in ANNs and PNNs. In this work, the training for both models was performed in two steps in order to improve the quality of the training. For the ANN, simulated annealing was used first, then the conjugate gradient method was used. For the PNN, the network was first trained using the conjugate gradient method, and then, the network was trained using the variable metric method. The parameters for each training method were adjusted to obtain the best results; the optimal values are shown in Table 3.

4.1 Mass flow rate

The analysis begins with the training of the ANN. In order to adjust the number of neurons in the hidden layer, the mean squared error (*mse*, defined in previous sections) for training and for validation was estimated for different number of neurons in the hidden layer. Thus, computer simulations began creating an ANN with zero neurons in the hidden layer; the number of neurons in this layer was increased one by one and the *mse* for training and the *mse* for validation were computed as it shown in Fig. 5. It can be seen from this figure that at the beginning of the simulation, both the *mse* for training and the *mse* for validation are close to 4.5×10^{-6}. As the number of neurons in the hidden layer λ increases, the *mse* for training and the *mse* for validation decrease. However, there is a point where further improvement is not obtained.

Table 3. Methods and parameters used for training.

ANN training	
Simulated annealing	Conjugate gradient
Initial temperature=30 Final temperature=0.1 Number of temperatures=100 Number of iterations per temperature=100 Cooling schedule=linear	Iterations=1000 mse goal=1E-5
PNN training	
Conjugate gradient	Variable metric
Iterations=1000 mse goal=1E-5	Iterations=1000 mse goal=1E-5

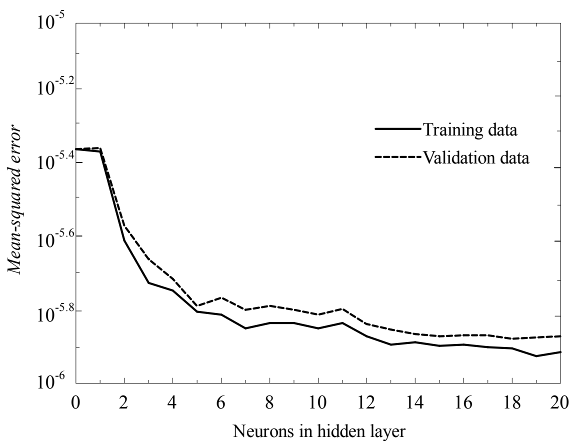

Fig. 5. ANN performance for the mass flow rate when the number of neurons in the hidden layer changes. The mean squared error is used to verify the network's quality since it is represented by: $mse = \frac{1}{N}\sum_{i=1}^{N}(y_i - y'_i)^2$. Where N is the total training cases, y is the expected value, y' is the calculated value and i is a particular case.

Therefore, it is anticipated that in order to model the mass flow rate, an ANN with seven neurons in the hidden layer is enough to obtain quite good results. For this specific number of hidden neurons, the *mse* for training was 1.4×10^{-6} and the *mse* for validation was 1.6×10^{-6}.

For the PNN model, first it is necessary to train the network by finding the optimum values of σ_{cj} in Eq. 4. There are several methods to perform this optimization; however most of them are based on the estimation of the error derivative with respect to each parameter σ_{cj}. Note that for this type of network, it is not required to adjust any parameter; that is, once it has been trained, the obtained performance is the best that

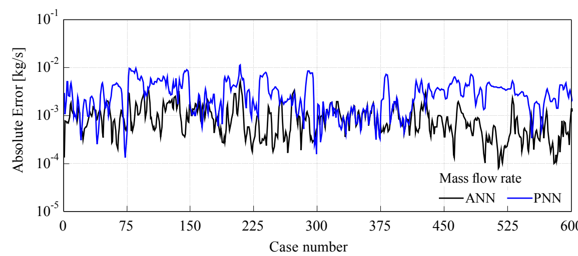

Fig. 6. Estimation of the mass flow rate using an ANN and a PNN.

can be attained by this method. After the computer simulations were completed, the *mse* for training was 1.48×10^{-5} and the *mse* for validation was 1.49×10^{-5}.

In Fig. 6, it is presented the mass flow rate validation for both the ANN and the PNN. From this figure, it can be seen that the ANN error lies in the range from 8×10^{-5} to 5×10^{-3} kg/s, while the PNN error lies in the range from 1.4×10^{-4} to 1.2×10^{-2} kg/s.

Based on the validation errors that were estimated from the computer simulations, it can be concluded that both models provide a relatively small error. However, the ANN model provides a slightly better approximation for the actual behavior of the compressor. In practical terms, both models are capable of adequately simulating the mass flow rate of the refrigerant.

4.2 Discharge temperature

The ANN model for the discharge temperature is similar to the ANN model used for the mass flow rate. In order to adjust the number of neurons in the hidden layer the same procedure described in Section 4.1 was used. At the beginning of the simulation with zero neurons in the hidden layer, the *mse* for training

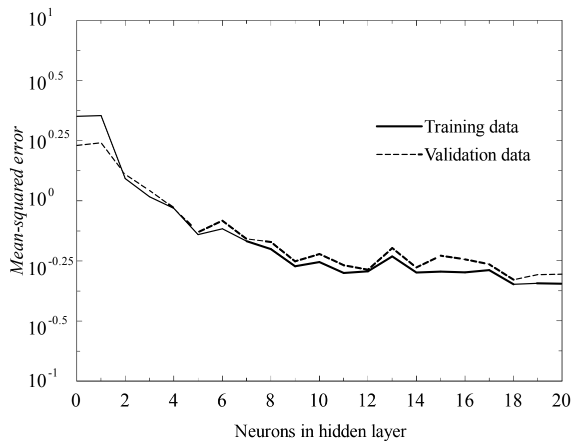

Fig. 7. ANN performance for the discharge temperature when the number of neurons in the hidden layer changes. The mean squared error is used to verify the network's quality since it is represented by: $mse = \frac{1}{N}\sum_{i=1}^{N}(y_i - y'_i)^2$. Where N is the total training cases, y is the expected value, y' is the calculated value and i is a particular case.

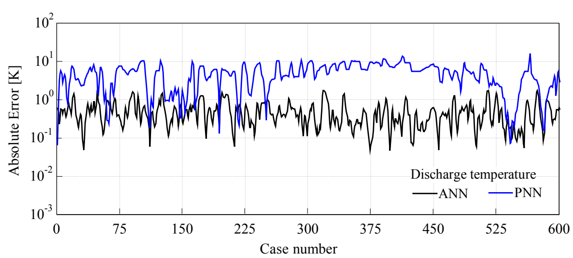

Fig. 8. Estimation of the discharge temperature using an ANN and a PNN.

was 3.02 and the *mse* for validation was 2.14, see Fig. 7. At the end of the simulation with twenty neurons in the hidden layer both the *mse* for training and the *mse* for validation were close to 0.38. It can be seen that with $\lambda > 9$, there is not a noticeable improvement obtained. Therefore, it is optimal to use an ANN with nine neurons in the hidden layer for predicting the discharge temperature. For this specific number of hidden neurons, both the *mse* for training and the *mse* for validation were close to 0.45. For the PNN model, the *mse* for training was 3.9 and the *mse* for validation was 4.2.

Fig. 8 shows the validation results for the ANN and the PNN. It can be observed from this figure that both models provide a minimum error of approximately 5.5×10^{-2} K. For the ANN, the maximum error is 1.6 K which is acceptable for most applications. On the other hand, the maximum error for the PNN is 8 K which

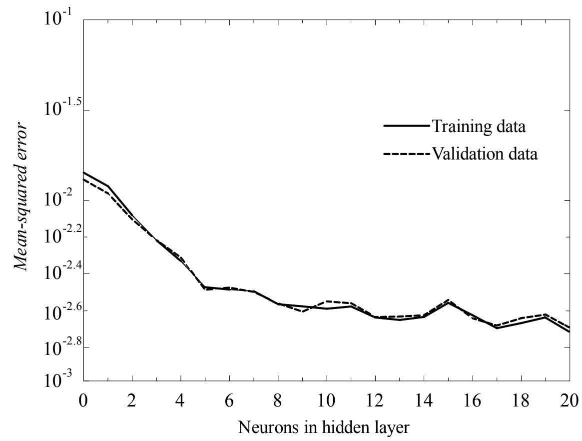

Fig. 9. ANN performance for the energy consumption when the number of neurons in the hidden layer changes. The mean squared error is used to verify the network's quality since it is represented by: $mse = \frac{1}{N}\sum_{i=1}^{N}(y_i - y'_i)^2$. Where N is the total training cases, y is the expected value, y' is the calculated value and i is a particular case.

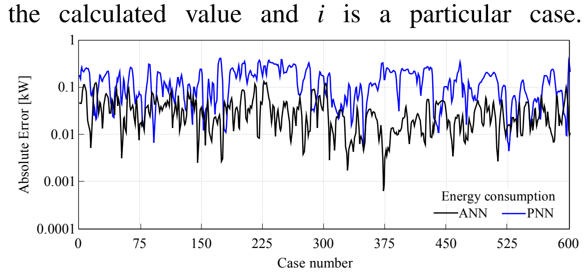

Fig. 10. Estimation of the energy consumption using an ANN and a PNN.

is higher than the error produced by the ANN model. Consequently, it can be concluded that the ANN model is a better option to predict the discharge temperature than the PNN model for this specific compressor.

4.3 Energy consumption

The last parameter to model is the energy consumption of the compressor. At the beginning of the simulation with zero neurons in the hidden layer, both the *mse* for training and the *mse* for validation were 0.013, see Fig. 9. It can see that with $\lambda > 5$, there is not an important improvement obtained. Therefore, it is optimal to use an ANN with five neurons in the hidden layer for predicting the energy consumption. For this specific number of hidden neurons, both the *mse* for training and the *mse* for validation were close to 3.2×10^{-3}. For the PNN model, the *mse* for training was 4.3×10^{-2} and the *mse* for validation was 4.1×10^{-2}.

Fig. 10 shows the validation results for the energy consumption. For this figure, it can be seen that the ANN model has a minimum error of 6.3×10^{-4} kW and a maximum error of 1.2×10^{-1} kW. While the PNN model has a minimum error of 4.5×10^{-3} kW and a maximum error of 4×10^{-1} kW. Finally, it can be appreciated that the ANN model provides a little better approximation than the PNN for the prediction of the energy consumption.

The results of the computer simulations show that these methods can be used to model a reciprocating compressor. For the prediction of mass flow rate, a comparison between the ANN and the PNN model, it can be concluded that both models provide a similar performance. For the discharge temperature, the results of the computer simulations indicated that the ANN model provided a better prediction than the PNN model. Finally, an inspection of the simulation results for the energy consumption showed that, from a practical point of view, both models offered a similar performance for the prediction of this parameter.

To end the discussions it is meaningful to mention that neural networks can handle data sets obtained from an experimental operation of a reciprocating compressor, even though this phenomena is considered as a complex thermal device. According to the results, ANNs is a good mapping tool for thermal prediction of a compression process. However, the main problem presented by this kind of model is that it is do not know how numerically it operates and there is not any theoretical explanation each weigh or neuron. Other disadvantage is its high training-time. On the other hand, PNNs has clear mathematical foundations and the training-time is lower than ANN. Its main disadvantages is that it is relatively slow to make the mapping and it requires a large amount of memory.

Conclusions

This paper proposes the use of an ANN and a PNN to model a reciprocating compressor. A data acquisition system was installed in a compressor located in a test bench to collect test samples. The input variables of the model to simulate the compressor were: compressor rotation speed, suction pressure, suction temperature and discharge pressure. While the compressor output variables were: mass flow rate, discharge temperature and energy consumption. These experimental measurement samples were processed to create a training set and a validation set. Finally, these data sets were used to train and validate an ANN and a PNN. Computer simulations were used to estimate the *mse* for training and for validation in order to assess the performance of each model for each parameter. A list of the principal conclusions of this work is shown below:

- Both models required a set of input variables that were easy to obtain from the experimental installation. The input variables and output parameters are the most representative to describe the energy behavior of the compressor.

- One of the main advantages of using neural networks is that they can create non-linear models that can adapt to experimental information. The ANN model and the PNN model are techniques that can be used to perform nonlinear statistical modeling and provide an alternative to model a compressor.

- Finally, the results from the computer simulations indicated that these models can be effectively used to predict the energy performance of the compressor, and provide the basis to simulate and control the energy consumption in vapor compression systems.

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