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MASS FLOW PREDICTION IN A REFRIGERATION MACHINE USING ARTIFICIAL NEURAL NETWORKS

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Abstract. *In the works related to mathematical modeling of refrigeration systems, the correct estimation of mass flow rate is essential. This parameter can also be used to monitor the system and evaluate aspects related to performance and system maintenance. Measuring with flow meters can be expensive taking into account the cost of the equipment itself and the costs related to installation and maintenance. Alternatively, mathematical correlations can be used to estimate the mass flow rate. Considering this last approach, a model based on Artificial Neural Networks (ANNs) can be used to predict the value of the mass flow, at low cost, through easily observed and measured parameters, like pressures and temperatures. Additionally, well-known correlations to calculate parameters that directly influence the mass flow rate can be used as input data for the ANN, to improve its accuracy. Within this context, the present study aims to develop a Multilayer Perceptrons (MLP) model to predict the mass flow rate of a refrigeration systems. The test bench consists of a refrigeration machine, operating with R134a as the primary fluid and pure water as the secondary fluid in the evaporator and condenser. Experimental data was collected for several different permanent and transient regimes. Step disturbances were introduced in the mass flow rate to produce data during the transient response. Two training cases were considered, with only the steady-state data and with both, steady-state and transient response The mass flow rate estimated had maximum error of 4.71 % with all data in the training and 3.81 % with only the steady-state data in the training.*

Keywords: *Mass flow prediction, Refrigeration machines, Artificial neural networks.*

1. INTRODUCTION

The main purpose of refrigeration systems is to reduce the temperature of an enclosed place or substance, and keep that temperature. To this end, these systems usually have a thermostat control, which results in high energy consumption (Kizilkan, 2005). As described by Buzelin *et al.* (2004), the commercials and domestic refrigeration systems with on-off controllers have poor temperature control, limited operation conditions and reduced lifetime. In addition, refrigeration and air conditioning are responsible for a significant part of the world's energy consumption, because of their wide use in commercial activities (Buzelin *et al.*, 2004).

As discussed by Aprea *et al.* (2003), theoretically, the best solution to the problem would be a refrigeration machine capable to control the compressor speed. Therefore, with a variable speed, the compressor refrigeration capacity would be able to continuously match the cooling load.

To achieve a better performance and, therefore, better efficiency, many types of solutions can be used. In this context, the use of control systems becomes increasingly interesting, to reduce that consumption and allow it to obtain the desired temperature more quickly (Maia, 2005). To develop this control system, it is necessary to build a mathematical model of the refrigeration system, which often requires knowing the mass flow of refrigerant. The measurement with a flow meter has a high cost with installation and maintenance, in addition, it is also invasive and often sensitive to vibration and magnetic fields, which can hinder a correct measurement.

Belman-Flores and Ledesma (2015) also discuss the energy problem, including the greenhouse gas emission problem. Furthermore, they highlight the importance of modeling refrigeration systems, because, through the use of these models, it is possible to analyze and improve the energy performance of vapor compression systems.

Ding (2007) criticizes the conventional method of designing a refrigeration system, which consists of determining the required performance and estimating the work conditions, to calculate the structural parameters at last. Even though this process is straightforward to understand, the actual performance of the system usually deviate from the required, because of the design limitations. On the other hand, using computational methods and advanced modeling, the results can be far better.

Considering the necessity of modeling refrigeration systems and developing a better method of estimating the refrigerant mass flow in a refrigeration system, many approaches can be used. One of them is the Artificial neural networks (ANNs), which are widely used in cooling systems for forecasting various parameters. Kamar *et al.* (2013) used this model to discover the performance coefficient, the work in the compressor, and the cooling capacity in a machine refrigerator. Kizilkan (2005) and Saleh and Aly (2016) used an approach similar to predict, in addition to those previously mentioned, mass flow and the irreversibility of the cycle. Hosoz and Ertunc (2006) also used the ANN approach to model an automobile air conditioning system, using it to predict the mass flow rate.

For the past decades, the use of artificial intelligence systems in refrigeration gradually increased, as mentioned by Mohanraj *et al.* (2012). One of the main advantages of the ANN approach is its simplicity and capability to model complex, multivariable and non-linear problems. Usually, conventional approaches involve more complicated analytical equations and many theoretical assumptions. ANNs can overcome that by extracting the necessary information from the training data, being able to make consistent predictions (Mohanrai *et al.*, 2012).

With the use of ANNs in this study, it is possible to correlate mass flow values with other quantities more easily observed during the operation of the refrigerating machine. Thus, the mass flow could be assessed indirectly, from easily measured quantities, and at a low cost. On the contrary of Kizilkan (2005), which used six different parameters as inputs, this work will try to use as little as possible. So, the objective of the work is to predict the value of the mass flow in a refrigerating machine indirectly, from the correlation of few easily observed parameters, using an artificial neural network.

2. EXPERIMENTAL MEASUREMENTS

The data used in this work were extracted from the study Maia *et al.* (2013).

In this work, a refrigeration machine operating in a vapor compression refrigeration cycle was used. The primary fluid consisted of R134a and the secondary fluid was pure water. Figure 1 shows the schema of the experimental test bench used.

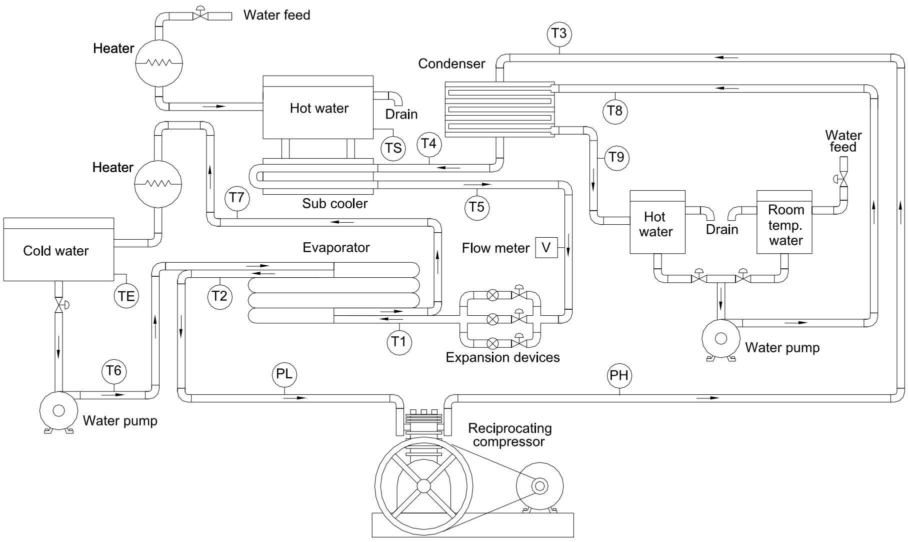

Figure 1. Schematic configuration of the experimental bench

The experimental data were collected for several different permanent and transient regimes, considering four evaporating temperatures (-5 °C, 0 °C, 5 °C and 10 °C) and two compressor speeds (650 rpm and 750 rpm). For each operation point, the refrigeration machine first achieved a steady-state. After that, a step disturbance was introduced in the mass flow rate to induce a transient regime, this was done by manually closing the manual expansion device, reducing the fluid flow at the inlet of the evaporator by about 5%. Then, data were collected until the refrigeration machine achieved a new steady-state. Therefore, data from eight transient and sixteen permanent regimes were collected. That includes values of condensation and evaporation temperatures, mass flow rate and the compressor rotation speed for each case.

After all the tests, the data passed through a pretreatment stage to eliminate outliers that were polluting the measurements. The technique chosen to mitigate the outliers was Atman's Z-score formula - It consists of calculating a score for each point collected, using the average and standard deviation values. The following equation shows the Z-score formula:

$$Z = \frac{X - \mu}{\sigma}, \tag{1}$$

where Z is the Z-score, X is the point value, μ is the data average and σ is the data standard deviation.

If the absolute value of the Z-score is higher than one, then the point is considered an outlier. In this case, the point is substituted by the sample average before it passes through the ANN.

3. EVALUATION OF MASS FLOW RATE

In a vapor compression refrigeration system, the mass flow rate of the refrigerant can be estimated by the equation (Maia, 2013):

$$\dot{m} = \mathrm{N} \,.\, \mathrm{V} \,.\, \rho \,.\, \eta, \tag{2}$$

where $\dot{m}$, is the mass flow at the compressor outlet, N, is the compressor rotation, V, is the compressor displacement, ρ, is the specific mass, and η is the volumetric efficiency. The volumetric efficiency can be calculated using the equation (Maia, 2013):

$$\eta = 1 + \mathrm{c} - \mathrm{c} \,.\, \left(\frac{P_c}{P_e}\right)^{\frac{1}{n}}, \tag{3}$$

where η, is the volumetric efficiency, c is the compressor dead space coefficient, which is given by the ratio between the volume when the piston is at its top position and bottom position. P_c and P_e are, respectively, the condensation pressure, evaporation pressure. As the compressor used in this work is considered adiabatic, n is the ratio between the fluid specific heat at constant pressure and the specific heat at constant volume.

Thus, the mass flow rate depends directly on the values of condensation pressure, evaporation pressure, and specific mass. The pressures are thermodynamically related to temperatures. So, were evaluated for the inputs to the model the values of temperatures and specific mass.

The specific mass can be estimated using well-known correlations, from the values of the superheat, condensation and evaporation temperatures. This means that, by only knowing the temperatures and the superheat, it is possible to acquire the necessary inputs to model a refrigeration machine using ANN's. The relation to estimating the specific mass given by the equation (Cleland, 1986):

$$\rho = \frac{1}{v_v \,.\left(1 + a_1.\Delta T + a_2.\Delta T^2 + a_3.\Delta T.T_e + a_4.T_e.\Delta T^2 + a_5.\Delta T.{T_e}^2 + a_6.(\Delta T.T_e)^2\right)} \tag{4}$$

where ρ, v_v, ΔT, and T_e are, respectively, the specific heat, the vapor specific volume, the superheat, and the evaporation temperature. The constants from a_1 to a_6 values are given by Table 1 (Cleland, 1986):

Table 1. Constants values for the specific mass equation.

Constant	Value
a_1	$5.029847 \,.\, 10^{-3}$
a_2	$-5.313493 \,.\, 10^{-6}$
a_3	$2.696488 \,.\, 10^{-5}$
a_4	$-1.603707 \,.\, 10^{-7}$
a_5	$4.673455 \,.\, 10^{-7}$
a_6	$-2.016173 \,.\, 10^{-9}$

Since the superheat, the evaporation temperature and condensation temperature, usually, are already measured to characterize the thermodynamic cycle, they were considered simple and valuable inputs for the model.

4. ARTIFICIAL NEURAL NETWORKS

The ANN approach was based on the anatomy of the human brain. This model has the ability to organize neurons in order to recognize patterns and solve complex and nonlinear problems (Haykin, 2009). There are many ANN's models in the literature, which are used for several different applications.

The type of ANN used in this work was the multilayer perceptron. It consists of a combination of the input layer, hidden layers and output layer. Each layer has a certain number of neurons, a weight matrix and an output vector. Each neuron has a bias (Azizi and Ahmadloo, 2016), which is a value independent of the input variables. This value must be added to the neuron's final result to eliminate the influence of external factors. From the input layer, the values enters in the model and go to a hidden layer, where the values are passed by multiplying by the respective weights. All neuron inputs are added together, and transmit information according to the activation function of the neurons.

The result passed by the neuron is given by the equation (Haykin, 2009):

$$y_j = f(\sum_{i=1}^{n} x_i w_{ij} + b_j), \quad (5)$$

where y_j, $f()$, x_i, w_{ij} and b_j are, respectively, the output of the j^{th} neuron, the activation function, the incoming signal, the signal weight and the neuron bias.

This process is done until you get the final result in the exit. The number of neurons in the hidden layer is defined to obtain the simplest possible model, which gives satisfactory results.

Figure 2 shows the model architecture of a multilayer perceptron (Haykin, 2009).

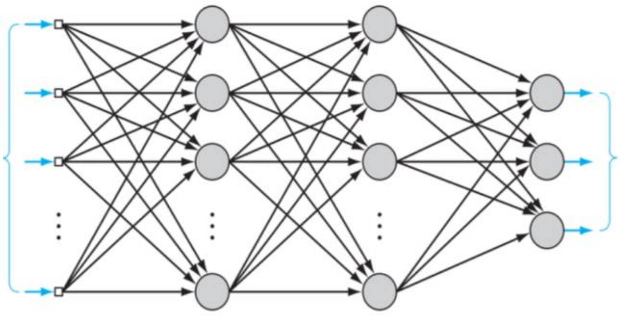

Figure 2. Schematic representation of a multilayer perceptron network model.

The model of the neural network was made using the python programming language and the Keras library.

To elaborate the net, it is necessary to establish the value of the hyperparameters that are the number of layers, the number of neurons, the learning rate, the dropout rate, and the activation function. The hyperparameters are chosen in order to achieve the most efficient model, meaning that it can successfully solve the real problem without being too complex.

Taking this into account, the hyperparameters were optimized using a hyperband algorithm, which is a variation of a random search. Comparing the random search to a grid search algorithm, which is commonly used in ANN problems as in Pisa et al. 2020 and Sá et al. 2019, Bergstra and Belgio 2012 showed that a random search is more efficient for a hyper-parameter optimization. The reason is that not all hyper-parameters are equally important to tune an ANN, so the grid search allocates too much time in unnecessary trials. The random search usually finds better models and requires less computational effort.

Improving the random search optimization, Li *et al*. 2018 introduced the Hyperband, which is a speeded-up random search using adaptive resource allocation and early-stopping. This was the hyperparameter optimization algorithm used in this work, to achieve satisfactory results faster.

The training of ANNs is based on experimental data or in numerical model results, it consists of adjusting the weights and biasses of each neuron in the network. The training process is done to minimize the final error obtained by ANN (Ertunc, 2005).

The process of placing the input values, multiplying them by the weights, go through the neurons and add them up to arrive at the final value it is called feedforward. When comparing the obtained value with the expected one, there is the network error. Using it to correct the weights is called backpropagation. By repeating this step several times to all of the training data, the training of the neural network is carried out.

When a value enters a neuron, it is passed by the activation function, which normally returns a value between -1 and 1, or between 0 and 1. Since this function does not have linear behavior, it is what brings non-linearity to the neural network model.

Since neurons only return values in this range, the input data must be normalized before it is used, so that they are all in the same order of greatness. This is necessary because if there are data with a different order of magnitude, one will stand out, which will result in the creation of a wrong model.

The data from this work were normalized using the equation:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \cdot (r_{max} - r_{min}) + r_{min}, \quad (6)$$

where x_n, x, x_{max}, x_{min}, r_{max} and r_{min} are, respectively, the normalized sample, the original data, the variable maximum and minimum values, and maximum and minimum values of the desired range."

To evaluate the network performance, the Mean Squared Error (MSE) of the results after each iteration was calculated. This is given by the equation:

$$\text{MSE} = \frac{\sum_i^n (d_i - p_i)^2}{n}, \quad (7)$$

where n, d_i and p_i are, respectively, the sample size, the desired value and the predicted value.

To develop the ANN, the experimental data was divided into three parts: training data, validation data and test data. The training data is used to build the ANN model so it is capable of making predictions. The validation data enters in the net fewer times, and it is used to check how the training is going and if is there any indications of overfitting. The test data is a completely new data set, used to check if the net can correctly make predictions. It is important to use unpublished data in the test to prevent good results just because the ANN has already memorized the data used. Therefore, it is possible to compare the estimated values for mass flow with actual values collected in the experiment. If the average error is less than the measurement uncertainty, it is proved that the ANN successfully predicts the mass flow rate.

The overfitting happens when the model created by the ANN is more complex than it needs to be, so the net just memorizes every input in the training data and loses the capability to generalize and make good predictions.

5. RESULTS AND DISCUSSION

The experimental data were collected for two different compressor rotations, 650 rpm and 750 rpm, and four different evaporating temperatures, 10 °C, 5 °C, 0 °C, and -5 °C, totalizing eight operation points. For each one, a step disturbance was introduced, collecting data during the transient response until the refrigeration system achieved the next steady-state.

Before the model construction began, the data pretreatment stage eliminated some of the outliers, cleaning the inputs for the ANN. Figure 3 shows the original input for the network and the input after the Z-score treatment, as an example, showing the data for the evaporating temperature of one operation point.

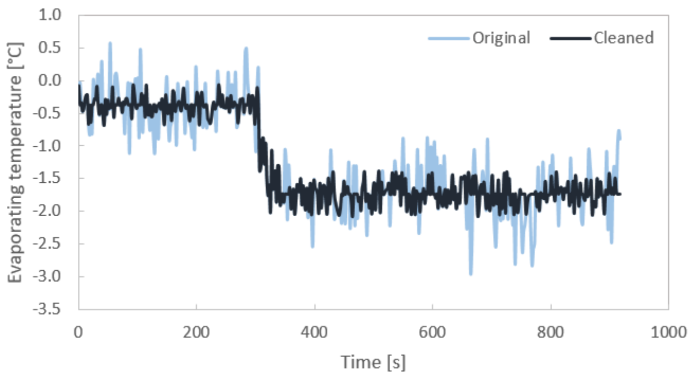

Figure 3 – Example of an input denoise after removing outliers

The hyper-parameters optimization was done using all the data and the best configuration found by the hyperband algorithm are shown in Table 2. That was the configuration used to build all of the models.

Table 2. Local best network setup found by the hyperband algorithm.

Hyperparameters	**Value**
Activation function	tanh
Optimizer	Adam
Number of hidden layers	3
1st layer number of neurons	32
2nd layer number of neurons	26
3rd layer number of neurons	10
Dropout ratio	0.01

To evaluate how well the ANN model can predict the mass flow rate, two different cases were considered. In the first one, the data from the steady-state and transient responses were used in the training. Then, in the second one, only the data from the steady-states were used in the training. In both cases one ANN was built for each compressor rotation. The neural networks were trained, validated, and tested using three operation points in that rotation, and later tried to predict the mass flow rate for a new operating point.

5.1 Steady-state and transient response in the training

For each compressor rotation, the data from the operation points with the evaporating temperatures of 10 °C, 5 °C and -5 °C were used in the training. These data were divided into training, test and validation, in the proportion of 70%, 15% and 15%, respectively. The main objective was to evaluate the training and to see if the ANN model can successfully predict mass flow for steady-state and transient response. So, two ANN's were built, Figure 4 and Figure 5 shows the MSE evolution during the training and validation for each one.

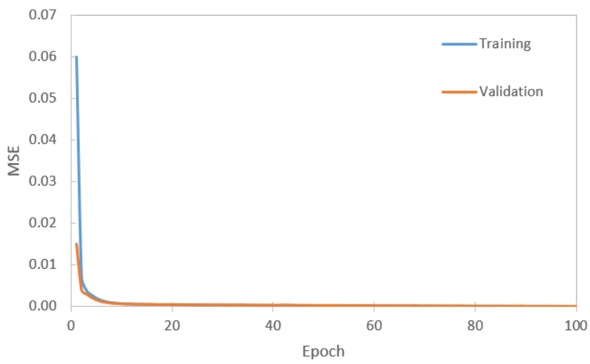

Figure 4 – MSE evolution during the ANN training and validation for 650 rpm

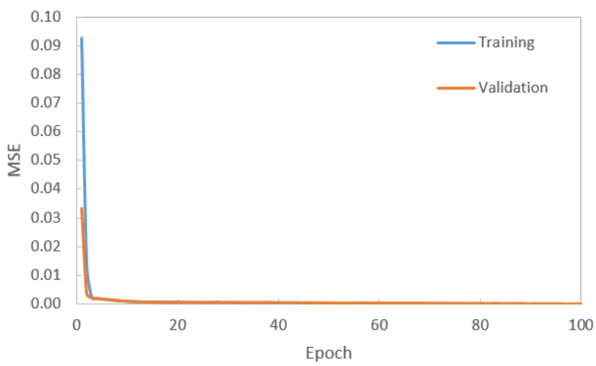

Figure 5 – MSE evolution during the ANN training and validation for 750 rpm

As the training began, the MSE was calculated in each epoch. It was possible to see that the MSE is almost the same after a certain number of epochs and there is not a significant improvement in the results. All of the training made in this work reached this state. In this case, the training and validation MSE are equal to 1.1×10^{-3} and 8.8×10^{-5}, for 650 rpm, and 1.2×10^{-3} and 9.5×10^{-5}, for 750 rpm, respectively. The training MSE is higher than the validation even though the ANN receives the training data many more times. This happens because, according to the Keras documentation, regularization mechanisms, such as Dropout and L1/L2 weight regularization, are turned off at testing and validation time. They are reflected in the training time loss but not in the others.

Figure 6 and Figure 7 show the relation between the predicted and expected values as validation for 650 rpm and 750 rpm, respectively.

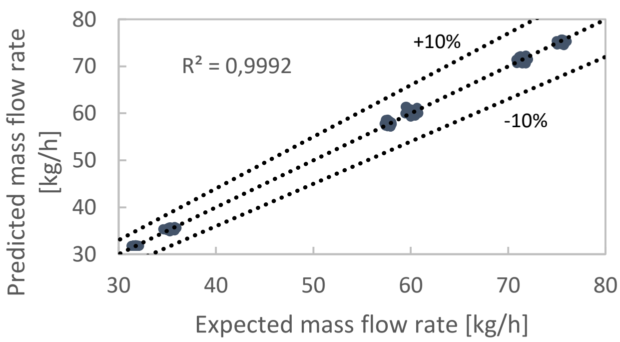

Figure 6 – Relation between predicted and expected values for the mass flow rate at 650 rpm

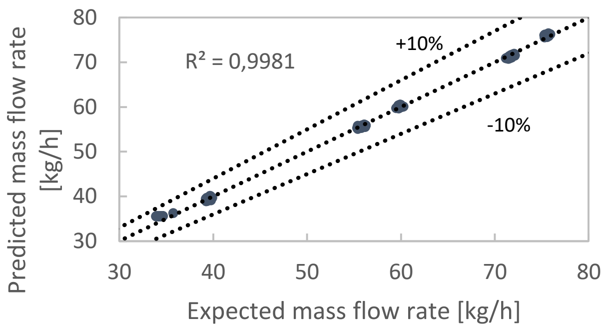

Figure 7 – Relation between predicted and expected values for the mass flow rate at 750 rpm

For the 650 rpm case, the average error achieved was 0.07 %, which is equivalent to 0.0014 kg/h. The maximum error achieved was 3.19 %, which represents 1.90 kg/h. For 750 rpm, the average error was 0.44 %, 0.11 kg/h, and the maximum error was 4.76%, 1.61 kg/h. Taking into account that Eq. (4), used to calculate the specific mass, is just an estimative, some error in the predictions was expected. Even though, considering that the average error is small for both compressor rotations, the predictions were satisfactory. This shows that an ANN can successfully model the refrigeration mass flow rate behavior.

Later, both networks were employed to predict the mass flow rate for the operation point of the evaporating temperature of 0 °C. Figure 8 shows the result for 650 rpm and Figure 9 for 750 rpm.

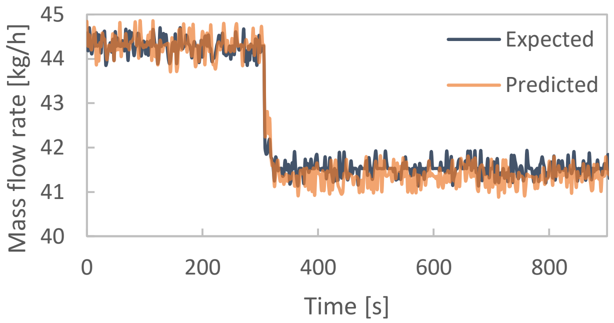

Figure 8 – Results for the prediction of a new operation point at 650 rpm

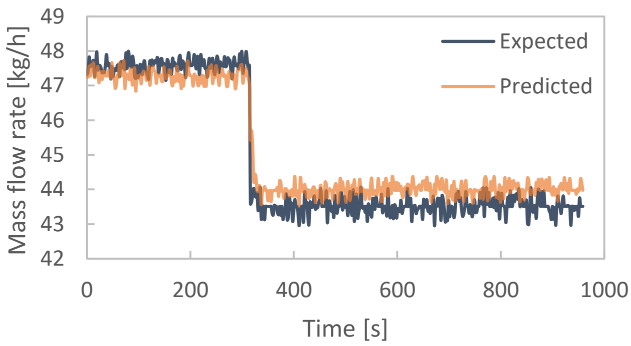

Figure 9 – Results for the prediction of a new operation point at 750 rpm

For 650 rpm, the average error for the mass flow prediction is 0.097 kg/h, equivalent to 0.23 %, and the maximum error is 0.93 kg/h, which represents 2.21 %. For 750 rpm, the average error for the mass flow prediction is 0.23 kg/h, equivalent to 0.56 %, and the maximum error is 2.06 kg/h, which represents 4.71 %. Analyzing both graphics, it is possible to see that, in both cases, the predicted mass flow rate was really close from the expected one. Even though the maximum error ir relatively high for 750 rpm, the overall average error is really small.

5.2 Steady-state response in the training

In this section, only the steady-state data was used for the training, even though the net predicted the mass flow rate for the transient response. Equally to the first case, for each compressor rotation, the training data contemplated only data from the operation points with the evaporating temperatures of 10 °C, 5 °C, and -5 °C. The data also were divided into training, test, and validation, in the proportion of 70%, 15%, and 15%, respectively. The main objective was to compare the ANN performance with only part of the training data. Figure 10 and Figure 11 show the MSE evolution during the training and validation for each compressor rotation.

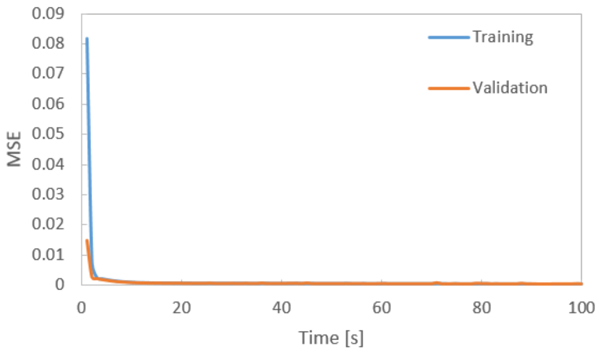

Figure 10 – MSE evolution during the ANN training and validation for 650 rpm

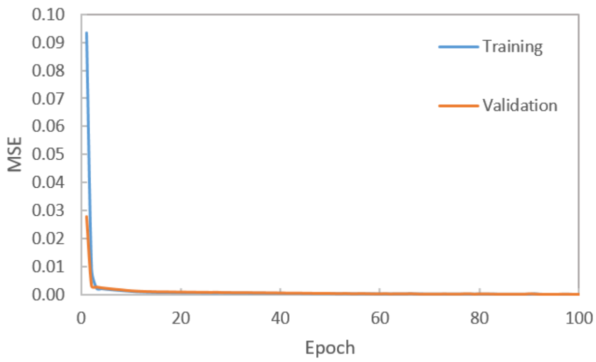

Figure 11 – MSE evolution during the ANN training and validation for 750 rpm

In this case, the training and validation MSE is equal to 3.3×10^{-4} and 2.5×10^{-4}, for 650 rpm, respectively. For 750 rpm, the MSE is 1.5×10^{-4} and 1.6×10^{-4}, for training and validation, respectively.

Figure 12 and Figure 13 shows the relation between the predicted and expected values as validation for 650 rpm and 750 rpm, respectively.

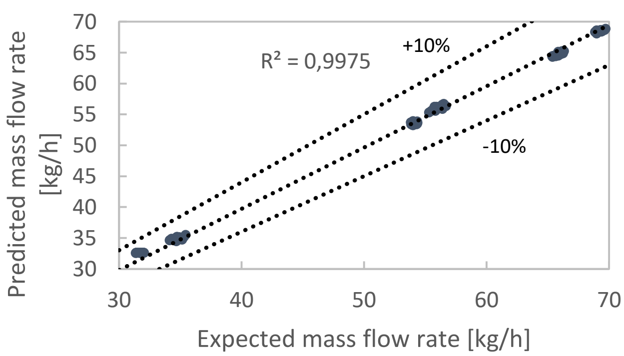

Figure 12 – Relation between predicted and expected values for the mass flow

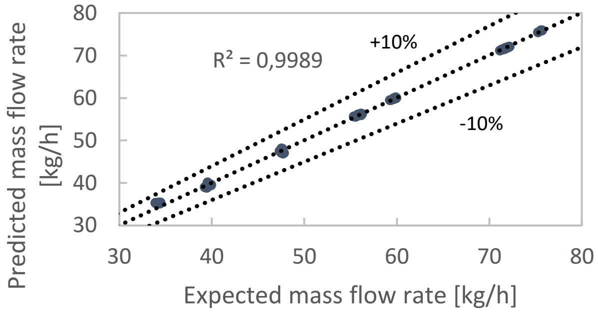

Figure 13 – Relation between predicted and expected values for the mass flow

For the 650 rpm case, the average error achieved was 0.012 %, which is equivalent to 0.20 kg/h. Although the maximum error achieved was 3.68 %, which represents 1.15 kg/h. For 750 rpm, the average error was 0.39 %, 0.14 kg/h, and the maximum error was 3.81 %, 1.29 kg/h. It is possible to see that the maximum error was not very different from the previous case, and for 750 rpm, it was even smaller. This was expected considering that a model to predict only steady-state data needs to be simpler, meaning that the chosen hyperparameter configuration suited more in this case.

Also, both networks tried to predict the mass flow rate for the operation point of the evaporating temperature of 0 °C. Figure 14 shows the result for 650 rpm and Figure 15 for 750 rpm.

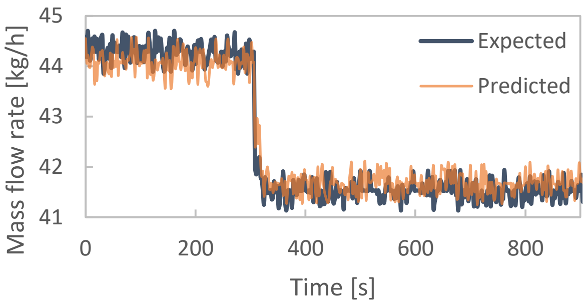

Figure 14 – Results for the prediction of a new operation point at 650 rpm

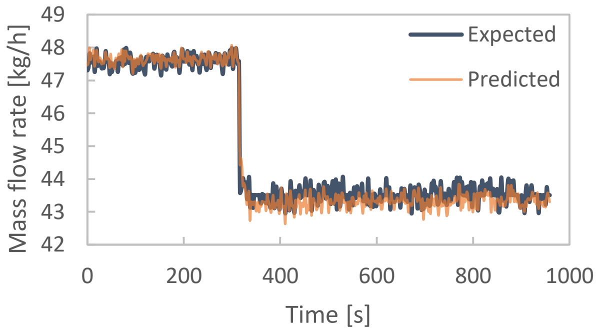

Figure 15 – Results for the prediction of a new operation point at 750 rpm

For 650 rpm, the average error for the mass flow prediction is 0.033 kg/h, equivalent to 0.092 %, and the maximum error is 1.08 kg/h, which represents 2.57 %. For 750 rpm, the average error for the mass flow prediction is 0.10 kg/h, equivalent to 0.24 %, and the maximum error is 0.99 kg/h, which represents 2.27 %. Again, the results were very similar, and 750 rpm was smaller. Taking into account that the transient response was successfully predicted with only steady-state data in the training set, it is possible to conclude that modeling two close steady-states allows the ANN to predict the transient response in between, without taking part in the training.

6. CONCLUSION

In this work, an ANN model was proposed to forecast the mass flow rate of refrigerant fluid in a refrigeration machine. The data were collected from eight different operation points, including transient response data. The specific mass, evaporation, and condensation temperatures were used as inputs for the model. The ANN used was a multilayer perceptron, with hyperbolic tangent as the activation function and Adam as the optimizer. Two different cases were considered in the training part. For each rotation, two forecasts were made, in all of them the average error was very low and under the experiment uncertainty, although the maximum error was higher in some cases. For the ANN's trained with steady-state and transient response data, the maximum error was 4.71 %. For the ANN's trained with only the steady-state data, the maximum error was 3.81 %. Considering that in every case the average error was really small, it is possible to conclude that the ANN model can fairly represent the refrigerant fluid mass flow rate. The error with only the steady-state data in the training being smaller shows that if the ANN has information about two close steady-state conditions, the transient response in between is not necessary for forecasting the mass flow rate.

7. ACKNOWLEDGEMENTS

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