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Abstract: An artificial neural network (ANN) model was developed to determine the efficiency parameters of a horizontal falling film absorber at operating conditions of interest for absorption cooling systems. The aqueous nitrate solution LiNO3+KNO3+NaNO3 was used as a working fluid. The authors created the ANN from the database they had compiled with the results of experiments that they had performed in a set-up designed and built for this purpose. The ANN structure consisted of 6 input variables: inlet solution and cooling water temperatures, cooling water and solution mass flow rates, absorber pressure and inlet solution concentration; 4 output variables which facilitated the assessment of the performance of the absorber : heat and mass transfer coefficients, absorption mass flux and the degree of subcooling of the solution leaving the absorber. The hidden layer contained 9 neurons which were determined by training and test procedures. The results showed that the deviation between the experimental data and the estimated values was well adjusted. This indicated that the ANN model was an effective tool for predicting the efficiency parameters of the absorber. The solution flow rate was also observed to be the most significant operating variable which affected the performance of the absorber.

Modelling the performance parameters of a horizontal falling film absorber with aqueous (lithium, potassium, sodium) nitrate solution using artificial neural networks

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Abstract

An artificial neural network (ANN) model was developed to determine the efficiency parameters of a horizontal falling film absorber at operating conditions of interest for absorption cooling systems. The aqueous nitrate solution $LiNO_3$+KNO_3+$NaNO_3$ with salt mass percentages of 53%, 28% and 19%, respectively, was used as a working fluid. The authors created the ANN from the database they had compiled with the results of experiments that they had performed in a set-up designed and built for this purpose. The ANN structure consisted of 6 input variables: inlet solution and cooling water temperatures, cooling water and solution mass flow rates, absorber pressure and inlet solution concentration; 4 output variables which facilitated the assessment of the performance of the absorber : heat and mass transfer coefficients, absorption mass flux and the degree of subcooling of the solution leaving the absorber. The hidden layer contained 9 neurons which were determined by training and test procedures. The results showed that the deviation between the experimental data

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and the estimated values was well adjusted. This indicated that the ANN model was an effective tool for predicting the efficiency parameters of the absorber. The solution flow rate was also observed to be the most significant operating variable which affected the performance of the absorber.

Keywords: triple-effect absorption cooling cycle, horizontal falling film absorber, aqueous nitrate solution, alkitrate, artificial neural network.

Highlights

- An ANN model was developed for predicting the efficiency parameters of a falling film absorber working with an aqueous nitrate solution.
- The ANN model was created from a database compiled from experiments carried out at the operating conditions of a triple-effect absorption cooling cycle.
- The results indicate that the ANN model effectively predicts the efficiency parameters of falling film absorbers.
- The solution flow rate is the operating variable that most affects the performance of the absorber.

Nomenclature

a_{exp}	Experimental value (target)
a_{sim}	Value obtained from the simulation with the neural network
b	Intercept in the slope-intercept statistical test
b_1	Bias vector of the ANN input layer
b_2	Bias vector of the ANN output layer
COP	Coefficient of performance
h_s	Falling film heat transfer coefficient ($W.m^{-2}.ºC^{-1}$)
i	Counter of the number of data
I	Total number of input variables to the ANN
IR	Relative influence of an input variable on the output variable of the ANN (%)
IW	Matrix weight of the ANN hidden layer
J	Total number of neurons in the hidden layer
k_m	Overall mass transfer coefficient ($m.s^{-1}$)
LW	Matrix weight of the ANN hidden layer
m	Slope in the slope-intercept statistical test
m_{abs}	Absorption mass flux ($kg.s^{-1}.m^{-2}$)
m_c	Cooling water flow rate ($kg.s^{-1}$)
N	Number of data
P_{abs}	Absorber operating pressure (kPa)
P_i	Normalized input variable

59 r^2 Linear regression coefficient

60 rmse root mean square error

61 $T_{c,in}$ Cooling water temperature at the absorber entrance (ºC)

62 $T_{s,in}$ Solution temperature at the absorber entrance (ºC)

63 $x_{s,in}$ Solution concentration in salts at the absorber entrance (mass fraction)

64

65 **Greek letters**

66 $\Delta T_{sub,out}$ Degree of sub-cooling of the solution leaving the absorber (ºC)

67 Γ Solution mass flow rate per unit of wetted tube ($kg.m^{-1}.s^{-1}$)

68

69 **Subscripts**

70 I Number of neurons in the inlet layer

71 Inf Lower limit

72 J Number of neurons in the hidden layer

73 K Number of neurons in the output layer

74 min Minimum value

75 max Maximum value

76 sup Upper limit

77

78

1. Introduction

Recent research works reported on absorption cooling systems focus on improving the coefficient of performance (COP) by using advanced cycle configurations and compact equipment. Triple-effect absorption cooling cycles represent a substantial improvement in performance when compared with double-effect absorption cycles. Nevertheless, triple-effect cycles face more difficulties with working fluids and construction materials because they need to support temperatures of over 180ºC. Álvarez et al. [1] developed a simulation model for the triple-effect absorption cooling cycle called "Alkitrate topping cycle" shown in Figure 1. The triple-effect cycle consists of a parallel double-effect cycle with H_2O/LiBr as a working fluid and a single-effect cycle with an aqueous nitrate solution as a working fluid. These are coupled through the heat exchanged between external streams. The aqueous nitrate solution composed of $LiNO_3$, KNO_3, $NaNO_3$ with mass percentages of 53%, 28% and 19%, respectively, was used. Davidson and Erickson [2] proposed the use of this mixture as a working fluid in absorption chillers driven by high temperature heat sources. Later, Erikson and Howe [3] called this working fluid "Alkitrate".

The absorber is usually the largest component in absorption cooling systems. An improvement in the absorption process leads to a reduction in area of the heat exchangers, and therefore a significant reduction in the costs of absorption chillers. For this reason, many researchers have focused their theoretical and experimental studies on the simultaneous processes of heat and mass transfer which take place in the absorber. In those absorption cooling systems which use water as a refrigerant and a non-volatile substance as an absorbent, the falling film absorber is generally the most frequently used design. This is because it achieves high values of heat and mass transfer coefficients in the falling film region of the solution and the pressure drop values are acceptable for the pressure conditions of this equipment. Therefore, many experimental investigations focus on falling film absorbers with horizontal tubes and most use H_2O/LiBr as a working fluid.

The most complex aspect of the study of absorbers is the heat and mass transfer processes which ocurr simultaneously and are interdependent. One of the main difficulties encountered in developing a mathematical model for the absorption process is the definition of the boundary conditions at the liquid-vapour interphase. The thermal effects associated with mass transfer during the absorption process also affect the pressure, the concentration and in turn the mass transfer. Some authors proposed the use of experimental correlations to describe heat and mass transfer processes. These correlations require the calculation of dimensionless numbers, the type of equation that defines the relation between these parameters and finally an analysis of the regression between the variables [4]. It is obvious that the proposal of a precise correlation for heat and mass transfer would require an appropiate selection of the driving force for the temperature and concentration profiles [4].

In this work, the authors developed a model to predict the efficiency parameters of a falling film absorber with horizontal tubes, which uses the aqueous solution of $LiNO_3$+KNO_3+$NaNO_3$ as a working fluid. This predictive model describes the absorber from a global perspective in order to avoid any uncertainties in local variations of temperature and concentration at the interface that need to be taken into consideration when using an analytical or semi-empirical model. Artificial Neural Networks (ANN) are promising alternative modelling tools which belong to the group of models with the black-box approach, where the estimated parameters do not need either physical interpretation nor mathematical description of the phenomena involved in the process. The ability of ANN to recognize and reproduce cause-effect relationships for multiple inputs and/or outputs by training means that they are an efficient model to represent complex systems [5].

The model developed in the present work incorporates the experimental database obtained from the doctoral thesis of Álvarez [6] which was carried out to characterize the process of water-vapour absorption in a falling film of an aqueous nitrate solution at operating conditions of absorption cooling cycles driven by high temperature heat sources. To predict the parameters of heat and mass transfer processes, the ANN model uses, mass flow rates, temperatures, solution concentration and

absorber pressure as input variables. In addition, this study provides the correlations for the parameters that define complex heat and mass transfer processes by using the minimum number of inlet parameters. This makes it easier to predict the behaviour of the absorber. The correlations were validated using the experimental database developed in the doctoral thesis of Álvarez [6].

2. Application of the artificial neural network (ANN) method in absorption cooling systems

The following is a brief description of the most significant studies available in literature regarding the use of the artificial neural network method in absorption cooling systems and the prediction of thermophysical properties of the working fluids used in these systems.

Kalogirou [7] presented a diversity of neural network applications which were mainly for renewable energy systems. In this study, the author used ANNs to model and to predict the performance of solar water heating systems, photovoltaic systems, solar radiation and wind speed. ANNs were also studied to estimate heating loads for buildings, to predict the airflow in a room with natural ventilation and the energy consumption in a passive solar energy building. The errors reported in these models were found to be within acceptable limits, clearly suggesting that ANNs can indeed be used to model renewable energy systems.

Chow et al. [8] introduced the use of a new concept in the control system of absorption chillers which involved integrating artificial neural networks with genetic algorithms. Fuel and energy costs incurred in the operation of direct fired absorption cooling systems were reduced gobally using this concept. Yang et al. [9] presented an ANN application system to control energy consumption in buildings. The study developed an optimised ANN model to determine the best time of day at which to operate the heating system in a building.

Sözen and Akcayol [10] used the ANN approach to analyse the performance of an absorption cooling cycle with an ejector activated by solar energy. As input variables, the model uses only the

operation temperatures of the four main components to predict chiller performance. The results showed that the artificial neural networks are an efficient method to predict the performance parameters of the system.

Another study reported by Manohar et al. [11] applied the ANN method to model a double-effect absorption chiller. The neural network was trained using experimental data and went on to predict the cooling capacity of the double-effect absorption chiller. The error margin was of ±1.2% compared with the experimental data.

Kalogirou [12] described artificial intelligence systems (neural networks, diffuse logic, genetic algorithms and hybrid systems) applied in different renewable-energy engineering disciplines.

Hernández et al. [13] proposed the use of an ANN predictive model to determine the performance of a water purification process integrated into an absorption heat transformer. The model predicts on-line, the coefficient of performance (COP) and takes into account the inlet and output temperatures of each one of the four components i.e. absorber, generator, evaporator and condenser. It also considered two pressure parameters of the absorption heat transformer and the concentration of the water/LiBr solution. This model could be used in the control of the water purification process integrated into the absorption heat transformer. Later, Hernández et al. [14] developed a model of inverted artificial neural network (ANNi) to calculate the optimal operating conditions to achieve the highest COP value of the same water purification process integrated into the absorption heat transformer with a heat recoverysystem.

Labus [15] used the ANN approach, using experimental data obtained on a test bench, to obtain stationary models for low-capacity absorption refrigeration machines. The study proposed a method to control commercial absorption chillers by means of adjusting various parameters on the water side (external circuits). For this purpose, a model using experimental data was developed and a sensitivity analysis was carried out to determine which parameters most influenced the thermal loads and to optimize them further using the methodology of inverse neural network (ANNi).

177 An important field for the application of artificial neural networks is the prediction of thermodynamic
178 and transport properties of working fluids for absorption cooling systems. There have been very few
179 studies carried out using ANN methods to predict physical-chemical properties. Some of the studies
180 that have used the method to predict the properties of working fluids are the following:

181 Sharma et al. [16] applied artificial neural networks (ANNs) to estimate the liquid-vapour equilibrium,
182 using a back-propagation algorithm. Methane-ethane and ammonia-water systems were studied.
183 Their results demonstrated the interesting possibilities of using neural networks to analyse
184 thermodynamic mixtures.

185 Homer et al. [17] developed a method, using artificial neural networks, to predict the viscosity,
186 density, heat of vaporization, boiling point and Pitzer's acentric factor for pure organic liquid
187 hydrocarbons applying a wide range of temperatures. Using ANNs to predict viscosity they obtained
188 an absolute average deviation between the estimated values and the experimental values
189 approximately two times lower than those obtained with other predictive methods.

190 Nashawi and Elgibaly [18] developed a neural network model to predict viscosity in organic
191 compounds. They used a set of 110 experimental data at an interval for viscosity between 0.197 and
192 19.9 mPa.s.

193 Chouai et al. [19] applied artificial neural networks to predict pressure-volume-temperature data and
194 other thermodynamic properties like enthalpy, entropy, compressibility factor and heat capacity of
195 R134a, R32 y R143a refrigerants.

196 Sözen et al. [20, 21] used artificial neural networks to predict the properties of the two alternative
197 refrigerant/absorbent couples (methanol/LiBr and methanol/LiCl) used in absorption cooling systems.
198 The model used the back-propagation learning algorithm with three input variables, namely
199 temperature, pressure and composition, and specific volume was considered as an output variable.

200 In order to train the neural network they used experimental data and after training they obtained an
201 average error margin of approximately 1%.

202 Sözen et al. [22] used the artificial neural networks to determine the thermodynamic properties
203 (specific volume, enthalpy and entropy) of an alternative refrigerant (R508b) for both the saturated
204 liquid-vapour region and the superheated vapour region. They used the back-propagation learning
205 algorithm and the sigmoidal transfer function. The authors showed that the ANN method reduced
206 error in predicting property values and also eliminated the need for complex analytic equations that
207 require long computational time and effort.

208 Sençan et al. [23] used the ANN approach to predict the enthalpy of the working fluids H_2O/LiBr and
209 H_2O/LiCl used in absorption cooling systems. The study also included comparing the performance of
210 the absorption cooling systems employing these working fluids.

211

212

3. Structure of the artificial neural network

Artificial neural networks are inspired by the biological process of the human brain where the neurons are interconnected to process a large quantity of information. The neural network is an adaptive system which can be trained to perform a particular function and uses the input and output information flowing through the network. An artificial neural network is made up of processing units called neurons and each network has a set of neurons grouped together in layers that inter-relate with others by means of interconnections called weights. These weights can be adjusted to model complex relationships between inputs and outputs. The first layer forming the neural network is the inlet layer, which receives information from outside (input data). The last layer is called the output layer and propagates the information from the network back to the outside. Between these layers there are one or more layers called 'hidden' layers because they are located inside the network and only exchange information with the layers adjacent to them, i.e. inlet and outlet. Each unit (neuron) in the hidden layer carries out a weighted addition of its inputs and then applies its transfer function to pass on the information from the input layer to the hidden layer. The number of neurons present in the hidden layer is determined by the required precision of the data predicted at the outlet. There is no explicit rule to determine the structure of artificial neural networks, i.e. to know the number of neurons present in the hidden layer or the number of hidden layers, so a training and test method is usually applied to find out the best structure. The response from the neurons in the hidden layer acts as input to the neurons in the output layer, producing the weighted sum and applying another transfer function.

The activation or transfer functions at the outlet of each neuron are the response of the network to the input that it receives. The most usual transfer function used for the hidden layer is the hyperbolic tangent sigmoid transfer function (tansig):

$$f(x) = \frac{2}{1+\exp(-2x)} - 1 \qquad (1)$$

For the output layer however, the linear transfer function (purelin) is generally used:

$$f(x) = x \qquad (2)$$

The main characteristic of artificial neural networks is the capacity to learn from their environment, which means that there is a continuous improvement in their performance. With artificial neural network methodology, the data is divided into three groups: training, validation and testing. The number of neurons present in the input and output layers is, respectively, the number of variables required to make the prediction and the number of variables to be predicted [24]. The back-propagation uses an algorithm with a descending gradient which makes a comparison between the inlet to the network and the target output and iterates it until the difference reaches the value of tolerance set. The error margin is calculated as the difference between the target output value and the network output for N data, the root mean square error (rmse) is applied and is defined as:

$$\text{rmse} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(a_{sim(i)} - a_{exp(i)}\right)^2} \qquad (3)$$

where a_{sim} is the value obtained from the ANN simulation, a_{exp} is the experimental value at the outlet, N is the number of data used and i is the data counter.

4. Database for the ANN model

The success of obtaining a reliable and robust artificial neural network depends mainly, on the choice of the process variables involved, the data available and the domain used for training [25]. An experimental database was obtained by the authors [6] for the absorption process of water vapours in a falling film on horizontal tubes of an aqueous nitrate solution of lithium, potassium and sodium (working fluid called Alkitrate). The experimental tests were carried out to characterize the absorption process with this working fluid at operating conditions of interest for triple-effect absorption cooling

cycles driven by high temperature heat sources. The following is a brief description of the experimental device used and the experimental database developed.

4.1 Description of the experimental device used to study the absorption process

The experimental set-up used to characterize the absorption process of water vapour in a falling film on horizontal tubes of an aqueous nitrate solution was described in detail by Álvarez [6]. This experimental device was designed to operate under continuous steady-state mode and to register the experimental data at different operating conditions. It was composed of three main circuits: the solution fluid circuit, the cooling water circuit and the vapour circuit. The absorber is the heart of the experimental set-up and is made up of a cylindrical chamber which contains a bundle of 6 copper tubes horizontally aligned and connected in series; a solution distributor at the inlet and a solution collecting tray at the absorber exit. The nitrate solution of lithium, potassium and sodium flows over the surface of the tubes forming a falling film in counter-flow with the water vapour coming from the generator. At the absorber exit there is only a solution stream with a lower concentration in absorbent than at the entrance, because water vapour has been absorbed. The falling film formed over the surface of the absorber tubes is cooled by the cooling water flowing at a cross-flow direction with the solution inside the tubes that make up the absorber. Figure 2 shows an internal view of the absorber.

4.2. Operating conditions and structure of the experimental database

The nominal operating conditions of the application studied here establish a mass fraction in salts of 0.82 of the aqueous nitrate solution at the absorber entrance, an operating pressure of 30 kPa and an inlet cooling water temperature varying between 70 and 90ºC. A study of sensitivity was carried out for the following operating variables: absorber pressure (P_{abs}), temperature and flow rate of the cooling water entering the absorber ($T_{c,in}$ and m_c, respectively), solution flow rate per unit of absorber

length (Γ), temperature and concentration of the solution at the absorber inlet ($T_{s,in}$ and $x_{s,in}$, respectively).

The operating parameters of the absorber, namely P_{abs}, $T_{c,in}$, m_c, Γ, $T_{s,in}$ and $x_{s,in}$ were established as input variables to the neural network. A series of experiments were performed at a solution mass fraction of 0.82 with a total of 49 experimental data points. These experiments covered the range of operating conditions in a triple-effect absorption cooling cycle driven by high temperature heat sources. In this first set of data, 37 data points were obtained at an absorber pressure of 30.0 kPa and 12 data points at 35.0 kPa. Afterwards a second set of 8 experimental data points was obtained at a lower mass fraction in absorbent of 0.75. In both cases, some parameters were maintained constant while others were changed. Hence, 57 experimental data points were used to feed the neural network. The experimental database was divided into three groups: training (80%), validation (10%) and trials (10%), all of which were selected randomly from the total set of data.

In the artificial neural network approach, it is generally a requirement to normalize the data in the input layer to guarantee that the influence of each input variable in the model is not determined by the magnitude of its original values or by its range in variation. The normalization technique used consists in applying a linear transformation of the inputs to variables in the range [0, 1]. As the transfer function used in the hidden layer is the hyperbolic tangent sigmoid function (tansig), all inputs have been normalized within the range [0.1, 0.9] so all input data I_i was increased to a new value P_i employing the following equation [25]:

$$P_i = 0.8.\left(\frac{I_i - I_{min}}{I_{max} - I_{min}}\right) + 0.1 \qquad (4)$$

The following values were taken from the experimental database and used for the model: maximum (I_{max}) and minimum (I_{min}) inlet values of 35.1 kPa and 29.95 kPa for the absorber pressure (P_{abs}), 0.822 and 0.748 for the absorbent mass fraction in the solution at the absorber inlet ($x_{s,in}$), 108.4 ºC and 89.6 ºC for the solution temperature at the absorber inlet ($T_{s,in}$), 86.1 ºC and 70.9 ºC for the inlet

cooling water temperature ($T_{c,in}$), 0.063 kg.s^{-1} and 0.040 kg.s^{-1} for the cooling water flow rate at the absorber inlet (m_c), and 0.0213 kg.m^{-1}.s^{-1} and 0.0095 kg.m^{-1}.s^{-1} for the solution flow rate by unit of the absorber length.(Γ).

5. Results and discussion

This section presents the artificial neural network model used to determine the performance parameters of a horizontal falling film absorber that uses aqueous nitrate solution as a working fluid. The validation of the artificial neural network model with the experimental database elaborated by the authors is also reported together with the analysis of sensitivity performed to assess the variable most influential in the absorber performance.

5.1. Artificial neural network model

The calculations were carried out using Matlab software (Natick, MA, USA) and its specific application for artificial neural networks. As reported above, the following 6 input variables were selected: absorber pressure (P_{abs}), solution temperature at the absorber inlet ($T_{s,in}$), inlet cooling water temperature ($T_{c,in}$), solution concentration at the absorber inlet ($x_{s,in}$), inlet cooling water flow rate (m_c) and solution flow rate by unit of absorber length (Γ). For the output variables, the following four parameters that characterize the absorption process were defined: the heat transfer coefficient of the falling film (h_s), the mass flow rate of water vapour absorbed per unit area of the absorber (m_{abs}), the mass transfer coefficient (k_m) and the degree of sub-cooling of the solution leaving the absorber ($\Delta T_{sub,out}$). The input variables were normalized within the range [0.1, 0.9] by the equation (4). The artificial neural network model was developed in two stages. The first one involved learning and validating the network and the second, evaluating the model with the data which had not been used in the training stage (Figure 3). Training of the neural network was based on the back-propagation technique using the Levenberg-Marquardt optimization algorithm that adjusts the

330 weights and biases to minimize the error (rmse) between simulated values and experimental values
331 (target).

332 During the learning stage, training and test methods were used to evaluate different network
333 structures. The performance of each structure analysed was then evaluated with the parameters, the
334 root mean square error (rmse) and the linear regression coefficient (r^2). It was observed that the
335 ANN structure containing nine neurons in the hidden layer was the one that obtained the best results
336 (minimum rmse and maximum r^2) for predicting performance parameters of the absorber. Therefore,
337 the following 6-9-4 neural network structure was chosen as shown in Figure 4. An input layer
338 composed of 6 neurons, a hidden layer of 9 neurons and an output layer of 4 neurons. The algorithm
339 uses a hyperbolic tangent sigmoid transfer function (tansig) in the hidden layer and a linear transfer
340 function (purelin) in the output layer.

341 Finally, the ANN model for the performance parameters of the horizontal falling film absorber using
342 an aqueous nitrate solution as a working fluid was defined by the equation (5):

343
$$a_k = \sum_{j=1}^{J} \left[LW_{k,j} \frac{2}{\left(1+\exp\left(-2\left(\sum_{i=1}^{I} IW_{j,i}P_i + b_{1_j}\right)\right)\right)} - 1 \right] + b_{2k} \qquad (5)$$

344 where I is the number of inputs (I=6), J is the number of neurons in the hidden layer (J=9), P_i is the
345 input "i" normalized, IW and LW are the weight matrix in the hidden and output layers respectively, b_1
346 and b_2 are the bias vectors in the hidden and output layers respectively, a is the output variable and
347 k is the number of the output variable, where k=1 refers to the output $a_1=h_s$, k=2 to m_{abs}, k=3 to k_m
348 and k=4 to $\Delta T_{sub,out}$.

349 Table 1 shows the best adjustment in weights ($IW_{j,i}$ and $LW_{k,j}$) and biases (b_{1j} and b_{2k}) of the neural
350 network structure with 9 neurons in the hidden layer (Figure 4) obtained during the learning stage of
351 the model developed for the performance parameters of the horizontal falling film absorber. As a

sample of the calculation process, the following equations were developed for the output 1 (k=1) which corresponds to the falling film heat transfer coefficient h_s depending on the input variables, the weights and the biases.

$$h_s = 2\left[\frac{LW_{1,1}}{1+\exp(n_1)}+\frac{LW_{1,2}}{1+\exp(n_2)}+\frac{LW_{1,3}}{1+\exp(n_3)}+\frac{LW_{1,4}}{1+\exp(n_4)}+\frac{LW_{1,5}}{1+\exp(n_5)}+\frac{LW_{1,6}}{1+\exp(n_6)}+\frac{LW_{1,7}}{1+\exp(n_7)}+\frac{LW_{1,8}}{1+\exp(n_8)}+\ldots\right.$$

$$\left.+\frac{LW_{1,9}}{1+\exp(n_9)}\right]-\left(LW_{1,1}+LW_{1,2}+LW_{1,3}+LW_{1,4}+LW_{1,5}+LW_{1,6}+LW_{1,7}+LW_{1,8}+LW_{1,9}\right)+b2_1 \quad (6)$$

where,

$$n_1 = -2\left[IW_{1,1}P_1+IW_{1,2}P_2+IW_{1,3}P_3+IW_{1,4}P_4+IW_{1,5}P_5+IW_{1,6}P_6+b1_1\right] \quad (7)$$

$$n_2 = -2\left[IW_{2,1}P_1+IW_{2,2}P_2+IW_{2,3}P_3+IW_{2,4}P_4+IW_{2,5}P_5+IW_{2,6}P_6+b1_2\right] \quad (8)$$

$$n_3 = -2\left[IW_{3,1}P_1+IW_{3,2}P_2+IW_{3,3}P_3+IW_{3,4}P_4+IW_{3,5}P_5+IW_{3,6}P_6+b1_3\right] \quad (9)$$

$$n_4 = -2\left[IW_{4,1}P_1+IW_{4,2}P_2+IW_{4,3}P_3+IW_{4,4}P_4+IW_{4,5}P_5+IW_{4,6}P_6+b1_4\right] \quad (10)$$

$$n_5 = -2\left[IW_{5,1}P_1+IW_{5,2}P_2+IW_{5,3}P_3+IW_{5,4}P_4+IW_{5,5}P_5+IW_{5,6}P_6+b1_5\right] \quad (11)$$

$$n_6 = -2\left[IW_{6,1}P_1+IW_{6,2}P_2+IW_{6,3}P_3+IW_{6,4}P_4+IW_{6,5}P_5+IW_{6,6}P_6+b1_6\right] \quad (12)$$

$$n_7 = -2\left[IW_{7,1}P_1+IW_{7,2}P_2+IW_{7,3}P_3+IW_{7,4}P_4+IW_{7,5}P_5+IW_{7,6}P_6+b1_7\right] \quad (13)$$

$$n_8 = -2\left[IW_{8,1}P_1+IW_{8,2}P_2+IW_{8,3}P_3+IW_{8,4}P_4+IW_{8,5}P_5+IW_{8,6}P_6+b1_8\right] \quad (14)$$

$$n_9 = -2\left[IW_{9,1}P_1+IW_{9,2}P_2+IW_{9,3}P_3+IW_{9,4}P_4+IW_{9,5}P_5+IW_{9,6}P_6+b1_9\right] \quad (15)$$

The experimental and calculated data using the ANN model were compared to evaluate how the model performed in the prediction of the output variables. Table 2 shows the values obtained for rmse, r^2 and Figure 5 shows the comparison between the experimental and simulated values of each output variable (h_s, m_{abs}, k_m and $\Delta T_{sub,out}$). The results obtained show that the experimental and

simulated data are well in line and this indicates that the model is effective for predicting the performance parameters of the absorber.

The slope-intercept statistical test was carried out to evaluate the performance of the neural network proposed. In accordance with the results obtained by Verma et al. [26] and to satisfy this statistical test, the range established between the values of the upper slope (m_{sup}) and lower slop (m_{inf}) must contain the value 1, and the range established between the values of the upper intercept (b_{sup}) and the lower intercept (b_{inf}) must contain the value 0. Table 3 shows the limits i.e. maximum and minimum values of the slopes and the intercepts. Both conditions have been satisfied and the model proposed passed the test with a confidence level of 99%.

5.2. Validation of the artificial neural network model proposed

Figure 6 shows the ability of the artificial neural network model to predict the performance parameters for a horizontal falling film absorber. It compares the results of the 4 performance parameters selected for the absorber obtained from experimental data (h_s, m_{abs}, k_m y $\Delta T_{sub,out}$) and the values calculated from the neural network model, depending on the solution flow rate. The model effectively predicts the behaviour of the absorber depending on the input variables. Figure 6 also shows how the concentration of the solution entering the absorber affects the performance parameters of the absorber. The model corresponds well with the experimental data with respect to the disturbances occurring at the inlet. This shows how capable artificial neural networks are in simulating the behaviour of complex processes.

5.3. Sensitivity analysis

This section contains the results of a sensitivity study carried out to evaluate the relative importance of each input variable in the absorption process. The approach employed by El-Hamzaoui et al. [27], was used for the analysis of sensitivity presented in the present work and applies the following equation (Garson [28]):

396
$$IR_{i(k)} = \frac{\sum_{j=1}^{J}\left(\frac{|IW_{j,i}|}{\sum_{i=1}^{I}|IW_{j,i}|}|LW_{k,j}|\right)}{\sum_{i=1}^{I}\left[\sum_{j=1}^{J}\left(\frac{|IW_{j,i}|}{\sum_{i=1}^{I}|IW_{j,i}|}|LW_{k,j}|\right)\right]} \quad (16)$$

397 where IR is the relative importance of the input variable I on the output variable k; I is the number of
398 input variables (I=6), J is the number of neurons in the hidden layer (J=9), and IW and LW are the
399 weights of the hidden and output layers, respectively. This way, the relative importance of each inlet
400 variable can be determined. Figure 7 shows the relative importance of each input variable on each of
401 the output variables calculated by the equation (16). In general, all the input variables have a
402 significant effect on the performance parameters of the absorber. However, the most relevant
403 variable is the flow rate of the solution entering the absorber (Γ). The relative influence of the solution
404 flow rate is always above 20% for all the performance parameters of the absorber, except for the
405 falling film heat transfer coefficient h_s, which has a relative influence of 13.5%. It is therefore
406 concluded that the absorber can operate more efficiently if the solution flow rate of the horizontal
407 falling film is controlled. On the other hand, the lesser relative effect of the solution flow rate on the
408 falling film heat transfer coefficient coincides with the trend observed during the experimental study
409 reported by Álvarez [6]. Within the range of solution flow rates considered in this study, the falling
410 film heat transfer coefficient shows an asymptotic trend, so the effect of the solution flow rate on the
411 falling film heat transfer coefficient is not as pronounced as on other performance parameters. This is
412 another example of the ability of the ANN model to predict performance parameters of horizontal
413 falling film absorbers of absorption cooling systems.

414

415

6. Conclusions

Artificial neural network methodology was applied in this work to predict the performance parameters of horizontal falling film absorbers using an aqueous (lithium, potassium and sodium) nitrate solution as a working fluid. The model used 6 input variables: absorber pressure (P_{abs}), solution temperature at the absorber inlet ($T_{s,in}$), inlet cooling water temperature ($T_{c,in}$), solution concentration at the absorber inlet ($x_{s,in}$), inlet cooling water flow rate (m_c) and solution flow rate by unit of absorber length.(Γ). As output variables, the following four parameters that characterize the absorption process were used: the heat transfer coefficient of the falling film (h_s), the mass flow rate of water vapour absorbed per unit area of the absorber (m_{abs}), the mass transfer coefficient (k_m) and the degree of sub-cooling of the solution leaving the absorber ($\Delta T_{sub,out}$)

The structure of the neural network was determined by a training and test procedure and is made up of 6 inputs, 9 neurons in the hidden layer and 4 outputs. The model developed used an experimental database built up by the authors in a previous work with experiments to characterize the absorption process of water vapour in a falling film of an aqueous nitrate solution. This study provides an artificial neural network model to predict the performance parameters defining the complex heat and mass transfer processes by using the minimum number of input variables.

The artificial neural network performance was measured statistically by root mean square error (rmse) and linear regression coefficient (r^2) calculations, which were carried out using the experimental values and the predictions from the model. The rmse values were: 1.183, 0.020, 0.013 and 0.025 for h_s, m_{abs}, k_m and $\Delta T_{sub,out}$, respectively and the r^2 values were: 0.9989, 0.9683, 0.9867 and 0.9543 for h_s, m_{abs}, k_m and $\Delta T_{sub,out}$, respectively. The low rmse values and the high r^2 values demonstrated the efficiency of the model to predict the output variables. The model proved to be very reliable when the slope-intercept statistical test was applied.

439 The relative importance (IR%) of each input variable to influence the performance parameters of the
440 absorber was also evaluated in this study. In accordance with the sensitivity study carried out it was
441 seen that: (i) all the input variables considered had a significant effect on the absorber performance
442 parameters, (ii) The most relevant variable was the mass flow rate of the solution entering the
443 absorber (Γ). All the performance parameters of the absorber had a relative influence of over 20%,
444 except for the falling film heat transfer coefficient h_s, which had an influence of 13.5%. This suggests
445 that, for the absorber to operate more efficiently, the flow of the horizontal falling film must be
446 specifically controlled.

447

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452

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521

522 **Figures Caption**

523 Figure 1. Configuration of the triple-effect absorption cooling cycle with a high temperature Alkitrate
524 stage [1]

525 Figure 2. Internal view of the absorber employed to build the experimental database used in the ANN
526 model

527 Figure 3. Architecture of the neural network employed to model the performance parameters of the
528 absorber and the procedure used to train the network

529 Figure 4. Structure of the neural network employed to predict the performance parameters of the
530 horizontal falling film absorber that uses an aqueous nitrate solution as a working fluid.

531 Figure 5. Comparison between experimental data and the values obtained using the ANN model (a)
532 Falling film heat transfer coefficient, h_s; (b) Absorption mass flux, m_{abs}; (c) Mass transfer coefficient,
533 k_m; (d) Degree of sub-cooling of the solution leaving the absorber, $\Delta T_{sub,out}$.

534 Figure 6. Validation of the ANN model to predict the absorber performance parameters: ♦ 75%
535 (experimental data), ◊ 82% (experimental data), __ prediction by the neural network of: (a) Falling
536 film heat transfer coefficient (h_s); (b) Absorption mass flux (m_{abs}); (c) Mass transfer coefficient (k_m);
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540 transfer coefficient (k_m); (d) Degree of sub-cooling of the solution leaving the absorber ($\Delta T_{sub, out}$).

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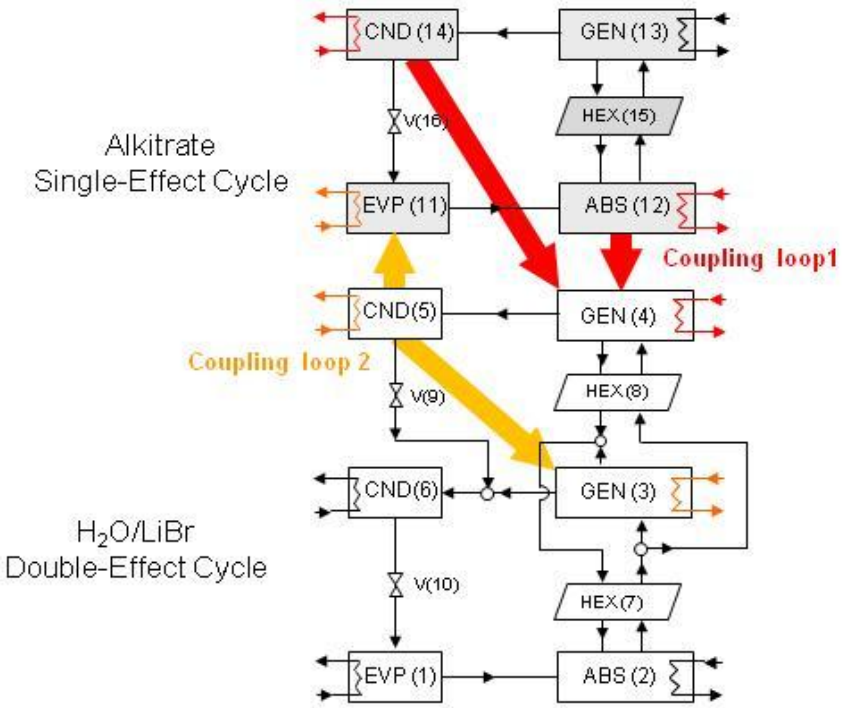

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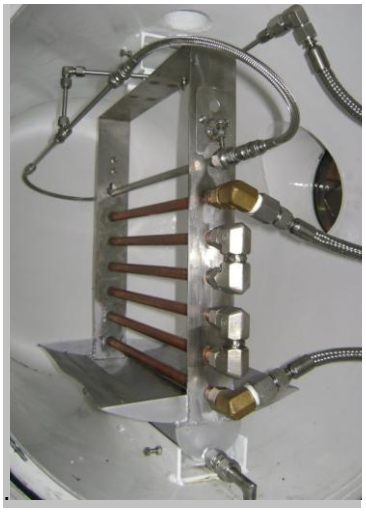

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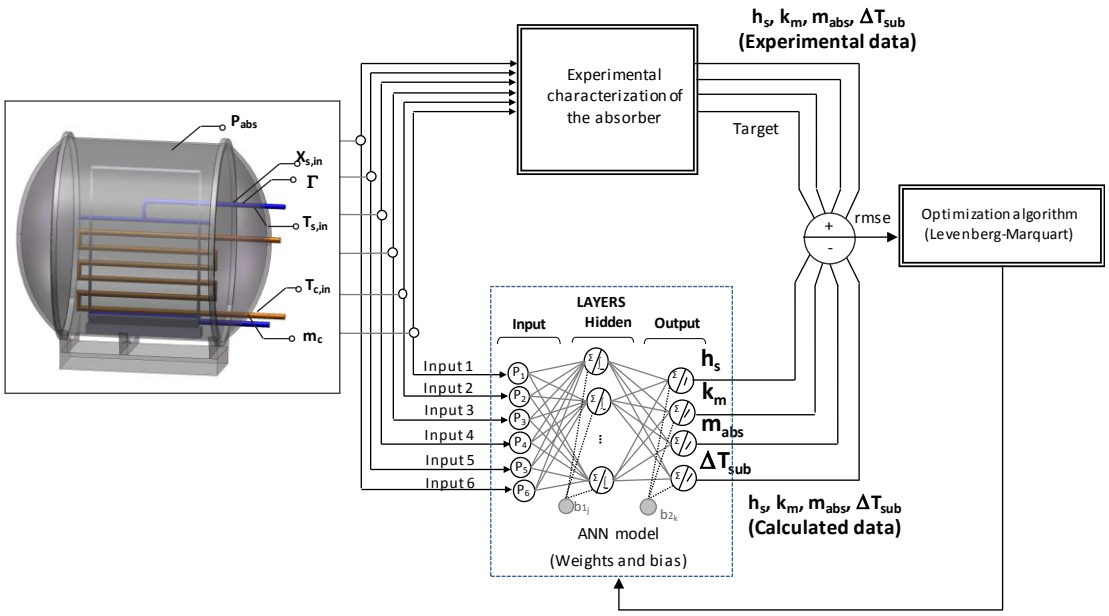

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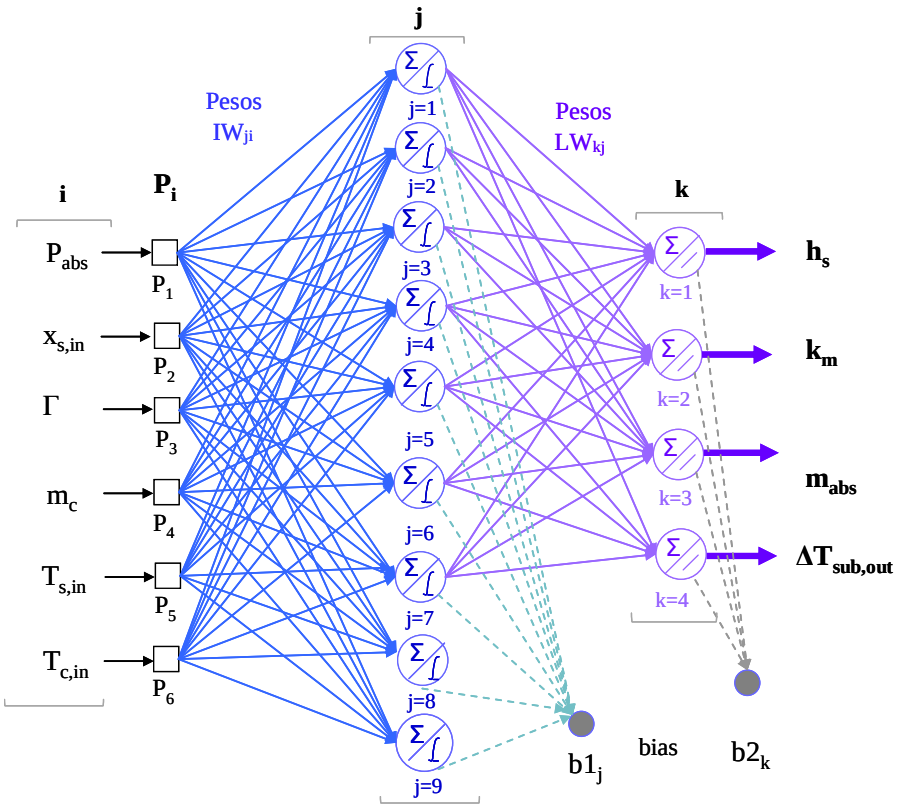

Figure 4. Structure of the neural network employed to predict the performance parameters of the horizontal falling film absorber that uses an aqueous nitrate solution as a working fluid.

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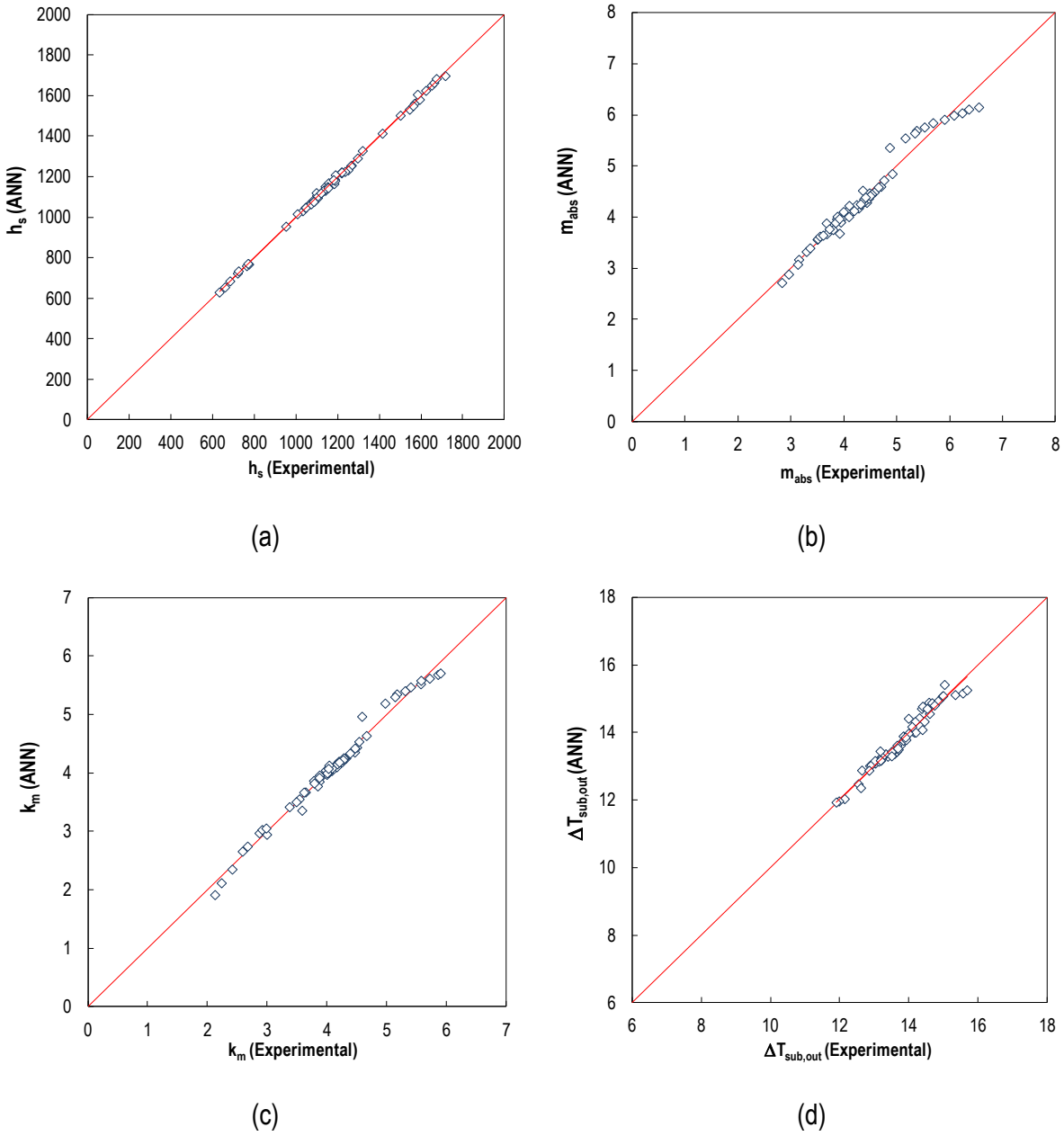

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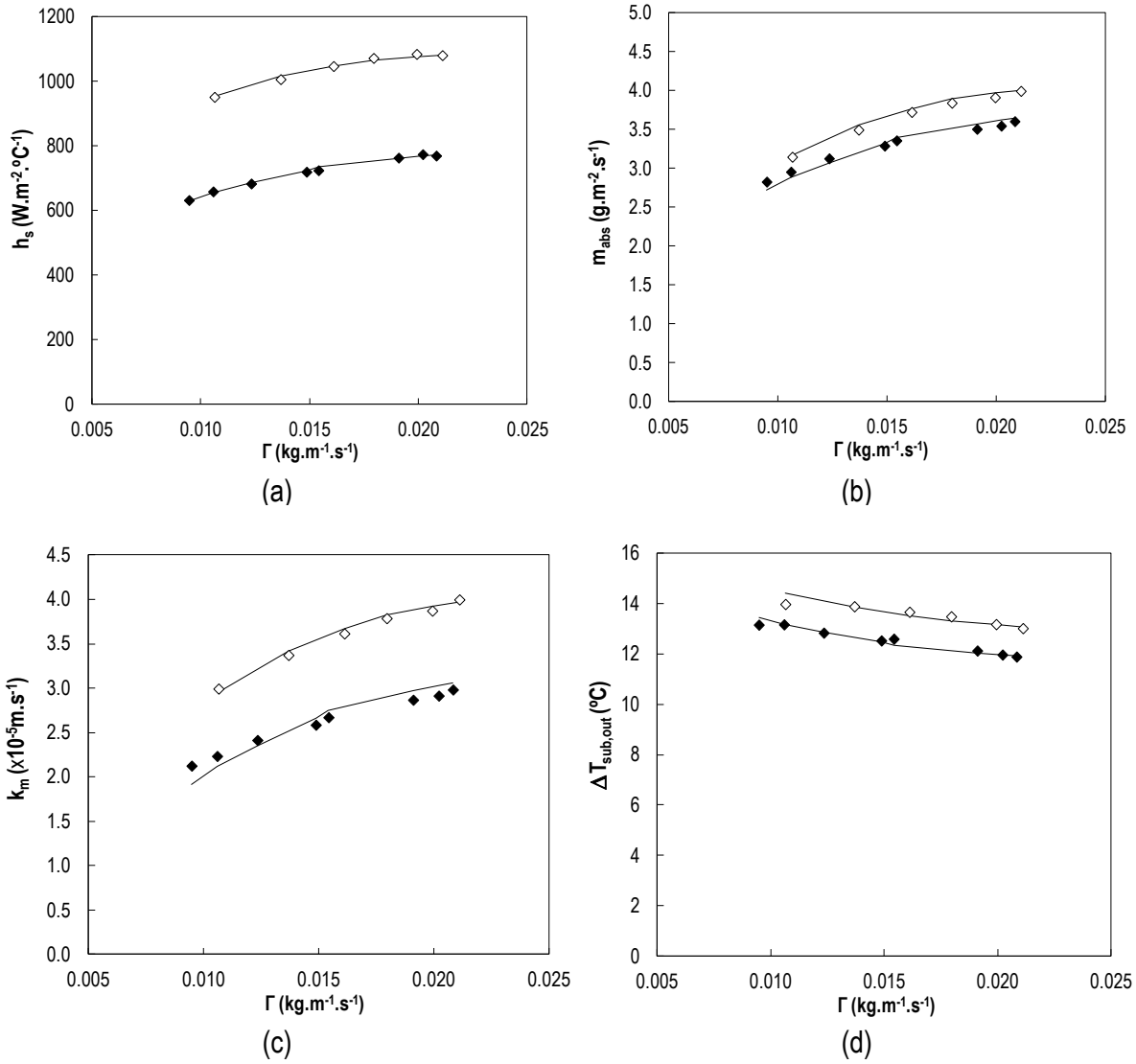

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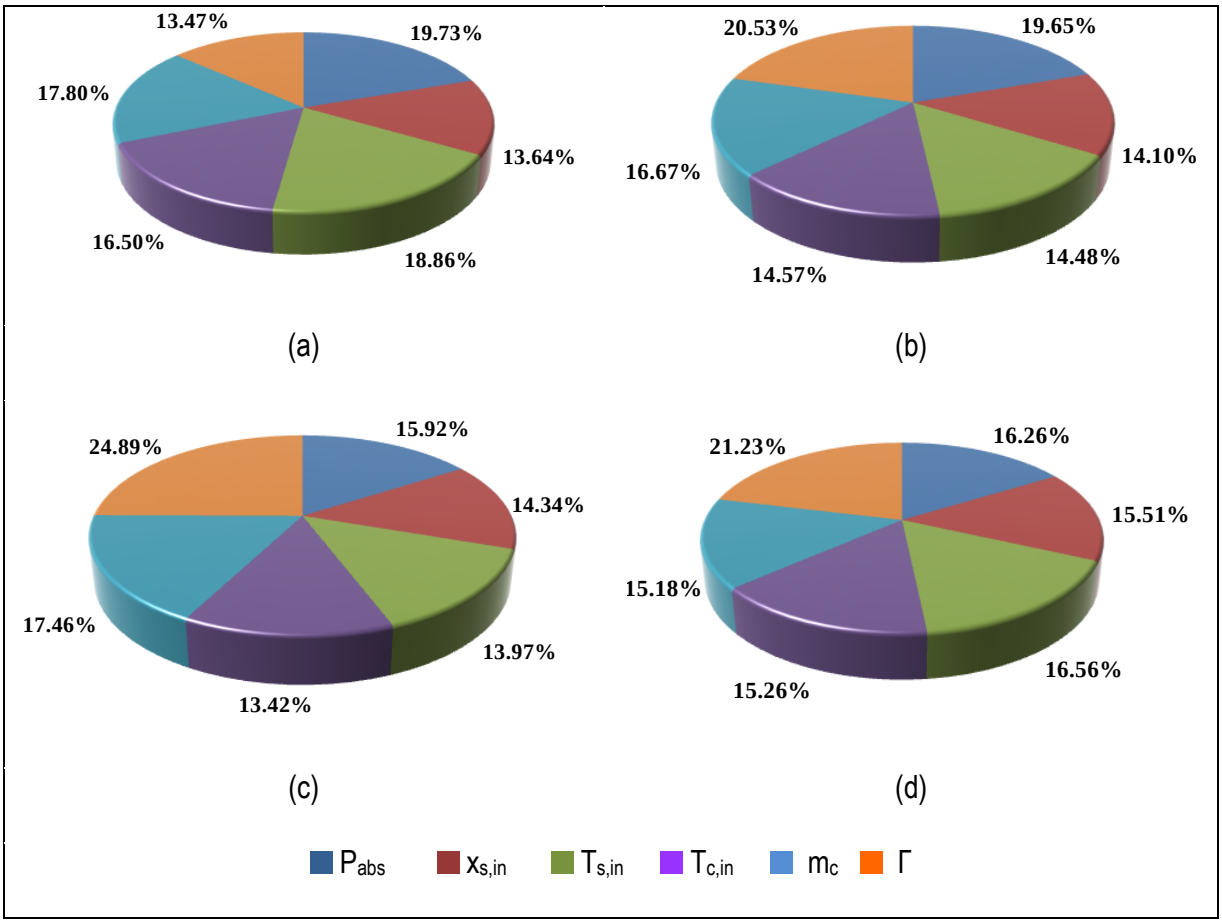

Figure 7. Relative importance (%) of the inlet variables on each one of the performance parameters of the absorber: (a) Falling film heat transfer coefficient (h_s); (b) Absorption mass flux (m_{abs}); (c) Mass transfer coefficient (k_m); (d) Degree of sub-cooling of the solution leaving the absorber ($\Delta T_{sub,\,out}$).

580 **Tables Caption**

581 Table 1. Weights and biases of the ANN model to predict the performance parameters of the
582 horizontal falling film absorber.

583 Table 2. rmse and r^2 parameters for the ANN model used for the horizontal falling film absorber.

584 Table 3. Slope and intercept statistical test.

585

586

Table 1. Weights and biases for the ANN model to predict the performance parameters of the horizontal falling film absorber.

Hidden layer									
Weight Matrix ($IW_{j,i}$)									Bias (b_{1j})
-15.3474	43.1751	37.4287	15.0731	-25.3140	39.152				-70.0893
41.6522	0.0969	13.2400	-15.5765	14.1442	-0.8481				7.1959
-1.3711	-0.674	0.5508	1.3897	-0.3482	-0.0102				-0.2131
0.4072	1.7606	-1.8388	-0.3248	0.1481	-1.5220				-0.1545
-5.1331	-1.9946	1.7932	-0.6573	-13.8820	-1.9034				-40.7141
-1.9445	2.5227	1.5022	1.1478	-6.2838	-14.3789				-13.4683
3.1148	5.2899	6.0414	8.8363	5.5466	8.4793				8.2982
0.3912	14.2885	7.0517	8.3928	8.4764	13.6098				12.4825
32.4550	3.4598	-82.0933	-5.5388	-77.5926	20.119				41.1858
Output layer									
Weight Matrix ($LW_{k,j}$)									Bias (b_{2k})
64.9502	182.8450	-521.7766	-204.2631	104.7731	-111.9695	199.2661	156.8972	-295.553	214.1182
0.8390	2.9389	-1.8251	-1.3573	-0.5997	-2.6249	-0.8077	-2.0161	-0.0665	-0.6629
0.7732	3.1975	-1.4863	-1.6778	0.6430	-4.8402	-1.9724	-3.3902	-0.2799	0.0420
0.5458	2.8476	-1.7919	2.2732	0.0820	-2.4784	2.6958	3.1648	-0.7091	3.4573

593 Table 2. rmse and r^2 parameters for the ANN model used for the horizontal falling film absorber.

	h_s	m_{abs}	k_m	$\Delta T_{sub,out}$
rmse	1.183	0.020	0.013	0.025
r^2	0.9989	0.9683	0.9867	0.9543

594

595

596 Table 3. Slope and intercept statistical test.

	h_s	m_{abs}	k_m	$\Delta T_{sub,out}$
m_{sup}	1.0107	1.0642	1.0523	1.0829
m_{inf}	0.9819	0.9081	0.9505	0.8936
b_{sup}	21.3065	0.4123	0.2108	1.4691
b_{inf}	-13.4416	-0.2784	-0.2147	-1.1450

597