Multivariate inverse artificial neural network to analyze and improve the mass transfer of ammonia in a Plate Heat Exchanger-Type Absorber with NH$_3$/H$_2$O for solar cooling applications

Oscar May Tzuc$^1$, Jorge J. Chan-González$^1$, Iván E. Castañeda-Robles$^2$, Francisco Lezama-Zárraga$^1$, Moises Moheno-Barrueta$^3$, Mario Jiménez Torres$^4$ and Roberto Best$^5$

Abstract
This work presents a numerical approach to compute optimal operating conditions that maximize the absorption flux into a heat exchanger designed for absorption refrigeration systems. Experimental data were obtained from a test circuit that operates in bubble absorption mode with an inner vapor distributor into a Plate Heat Exchanger-type (PHE-type) and interacts with ammonia vapor, NH$_3$-H$_2$O refrigerant, and cooling water. An artificial neural network (ANN) was trained to correlate the thermal properties of the solution and absorption flux in function of easily measurable parameters (concentrations, mass flows, and pressures of saturated and diluted

$^1$Facultad de Ingeniería, Universidad Autónoma de Campeche, Campeche, México
$^2$Universidad Autónoma del Estado de Hidalgo, Mineral de la Reforma, México
$^3$Universidad Juárez Autónoma de Tabasco, Villahermosa, México
$^4$Facultad de Ingeniería, Universidad Autónoma de Yucatán, Mérida, México
$^5$Instituto de Energías Renovables, Universidad Nacional Autónoma de México, Temixco, México

Corresponding authors:
Oscar May Tzuc, Facultad de Ingeniería, Universidad Autónoma de Campeche, Campus V, Av Humberto Lanz, Col. Ex Hacienda Kalá, C.P. 24085, San Francisco de Campeche, Campeche, México.
Email: oscajmay@uacam.mx

Jorge J. Chan-González, Facultad de Ingeniería, Universidad Autónoma de Campeche, Campus V, Av Humberto Lanz, Col. Ex Hacienda Kalá, C.P. 24085, San Francisco de Campeche, Campeche, México.
Email: jorjchan@uacam.mx

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solutions, flow and temperature of the ammonium vapor, environment temperature, and solution temperature). According to results, ANN is adequate to correlate the operational parameters and the transport phenomena inside the heat exchanger with a precision > 99%. ANN also quantitatively identified the ammonium vapor flow (43.1%), dilute solution flow (18.1%), and dilute solution concentration (13.1%) as the variables most importantly in influencing absorption flux optimization. Subsequently, a multivariable inverse artificial neural network was applied to improve the mass transfer into the PHE-type. It was identified that simultaneous optimization of the ammonia and dilute concentration flow rates improves the absorption flow performance by up to 96.3% under a worst-case scenario (ammonia flow rate < 1.4 kg/min) and even 7.04% when even when operating near the amino vapor flow limit (ammonia flow rate > 2.0 kg/min). Finally, it was confirmed that incorporating the diluted solution concentration into the optimization contributes to improving the performance of the absorption process 1%. Results obtained are relevant in the search to produce more competitive absorption cooling systems, demonstrating the feasibility of improving the performance of heat exchangers without structural modifications. The proposed methodology represents an interesting option to be implemented to improve performance in solar cooling systems.

Keywords
Artificial intelligence, metaheuristic optimization, absorption refrigeration, solar cooling application, heat exchanger

Introduction
Currently, refrigeration systems based on mechanical vapor compression driven by electricity represent a fifth of the world’s energy consumption. Unfortunately, their use produces a vast volume of greenhouse gases by requiring a large amount of energy to power the compressor and contributes to ozone depletion and global warming by using elements such as hydrochlorofluorocarbons (HCFCs) (Castillo-Téllez et al., 2020; Nikbakhti et al., 2020). One of the main alternatives to mitigate these effects is the substitution by absorption refrigeration systems. Since these employ thermal compressors, they present certain advantages such as reduced electricity consumption, low maintenance costs, as well as using environment-friendly refrigerants (Cézar et al., 2020). In addition, they allow the integration of solar energy as the input source, being a fundamental piece for the development of solar cooling systems (Alayi et al., 2019).

The correct selection of the absorber configuration and the heat exchanger is crucial for making competitive absorption solar cooling systems against those based on vapor compression (Alayi et al., 2021; Dhindsa, 2021). In this context, several studies have shown that the plate heat exchangers (PHEs) used as the absorber element in bubble absorption mode improve the heat transfer, the contact of the refrigerant with the solution, and allow modular designs (Castro et al., 2009; Chan et al., 2018; Lee et al., 2002; Lima et al., 2021; Tae Kang et al., 2002). However, during the absorption of the ammonium vapor produced inside the PHEs, complex heat and mass transfer phenomena occur where multiple parameters interact, making it challenging to find the appropriate operating conditions.

Modeling for diverse PHE bubble mode designs has been reported to provide a detailed compression of the thermal phenomena in the absorber element. Among the configurations analyzed are corrugate absorber (Wang et al., 2019), L-type absorber (Cerezo et al., 2011), vertical tubular absorber (Jiang et al., 2019), and plate absorber (Altamirano et al., 2020), to mention a few. The results indicate that the estimation of specific characteristics of the fluids used and the thermodynamic properties of the PHEs requires the calculation of the speed and diameter of the
steam bubbles as well as the knowledge of the heat and mass transfer coefficients of the mixtures (in its different states). Although this does not represent a problem for the analysis of the absorption process, it is not easy to implement during the online operation of these systems.

In recent years, artificial neural networks (ANN) have been used as a numerical alternative for analyzing thermodynamic systems due to their ability to correlate transport phenomena with operational parameters. In the case of thermal systems based on renewable energies, this computational tool has been successfully implemented for the modeling and optimization of conventional geothermal processes and with the organic Rankine cycle, with relatively high precision (Haghhighi et al., 2021). They have also been used to improve the thermal performance of various components such as heat exchangers (Alayi et al., 2021a), absorber tubes (Alayi et al., 2021b), and energy storage systems (Alhuyi Nazari et al., 2021a) in solar thermal installations for process heat and desalination (Alhuyi Nazari et al., 2021b). On the other hand, ANN has also proven to be a helpful alternative for modeling the physical properties of thermofluids to improve the energy conversion processes in various thermal systems; being relevant for those cases where they are used for thermal solar systems (Rashidi et al., 2021). Finally, for the case of heat exchangers, ANN has been presented as an option to easily study the properties of fluids without resorting to complex analytical functions (Aasi and Mishra, 2021; Baghban et al., 2019; Bahiraei et al., 2021).

Nevertheless, despite its proven benefits, this approach has been sparsely addressed in the case of absorption refrigeration systems. Şencan (2006) studied the feasibility of using ANN as an alternative for the thermodynamic analysis of ammonia-water absorption refrigeration systems. The work modeled the coefficient of performance (COP) and the circulation rate (f) as a function of the temperatures of the generator, absorber, evaporator, and condenser, as well as the dilute and saturated concentration solution. The results showed a precision in the estimation superior to 98.5% for both parameters, demonstrating the ANN as a quick and simple alternative to the complex conventional equations. Álvarez et al. (2016) developed a multi-output ANN model to compute the heat and mass transfer coefficients, absorption mass flux and the degree of subcooling of the solution leaving the absorber for different aqueous solutions that operate in a horizontal falling film absorber. By using pressure, solution concentration and temperatures as input parameters the model achieved $R^2>95\%$. Amaris et al. (2020) compared ANN and a semi-empirical model applied to a bubble plat absorber that operates with NH$_3$/LiNO$_3$ to estimate the absorption flux, the convective coefficient of the solution, and the mass transfer coefficient from operational variables. The results showed that the ANN is a more effective method for predicting and controlling the absorption process performance parameters. On the other hand, in the case of Verma et al. (2017), the ANN were used to estimate the thermodynamic properties of the fluids that interact with the heat exchanger from the mass flows, and the inlet and outlet temperatures of both the hot and cold fluid.

Based on the aforementioned, all the studies reported to date focus on improving the information available on the performance of the absorption systems without identifying works committed to the detection of the optimal operating conditions on the absorption element. This can be approached from the computational perspective through a modification in the structure of the ANN known as inverse ANN (ANNi). ANNi is composed of two stages; in the first one, the ANN is applied directly to obtain an objective function with an accuracy greater than 90%, which guarantees optimization reliability. In the second stage, optimization algorithms, mainly heuristics, are applied to perform the inverse process and obtain the operational parameters that guarantee the desired value. This approach has been successfully used to improve the performance of thermal processes such as heat pumps (Conde-Gutiérrez et al., 2018; Solís-Pérez et al., 2019) and industrial solar heat systems (Ajbar et al., 2021; May Tzuc et al., 2017; Moheno-Barrueta et al., 2021); Nevertheless, according to the review, there are no reports of its use to improve the performance of absorption refrigeration systems.
The present work addresses the implementation of direct and inverse ANN to model and optimize the mass transfer of ammonia in a Plate Heat Exchanger-Type Absorber with NH₃-H₂O. The study has two main objectives:

- It seeks to synthesize in an expert model the thermal behavior of the solution used based on easily measurable variables in the absorption system.
- It demonstrates the feasibility of improving the absorption flux, based exclusively on modifications in operating parameters by ANNi, which would contribute to finding the best-operating conditions when hybridizing these cooling systems with solar technology.

The study’s novelty lies in being the first work that proposes an approach to improve energy performance in absorption refrigeration systems by optimizing the operating variables in the absorber element (heat exchanger), prioritizing operational variables over design conditions. The above, through the use of artificial intelligence, which contributes both to the online implementation (operation of absorption refrigeration systems) and the extrapolation of the methodology to improve performance in refrigeration systems with other types of heat exchangers.

The content of the work is divided as follows: Section ‘Description of the experimental system’ describes the experimental absorption system, the heat exchanger used, the instrumentation used, the variables measured, the tests carried out. Sections ‘Artificial neuronal network modeling’ and ‘Direct artificial neural network implementation’ describe ANN as the modeling technique, its direct application, and the analysis of the modeled thermodynamic properties. Finally, Section ‘Multivariate optimization of absorption flux by ANNi’ shows the hybridization of the ANN with a multivariate optimization algorithm to obtain the operating conditions that improve the performance of the absorption flux.

**Description of the experimental system**

A test loop was designed to study the effect of bubble mode absorption with an inner vapor distributor in a Plate Heat Exchanger-type absorber (PHE-type absorber) with NH₃-H₂O. A stainless steel PHE model T2-BFG from Alfa Laval was implemented as the absorber to conduct the experimental tests. The PHE consisted of three channels, ammonia vapor and NH₃-H₂O flowed in the central channel, and cooling water flowed into the side channels. The experimental system also has two stainless-steel vessels to store concentrated and diluted solutions and the rugate ammonia mixture concentration. In addition, the facility was instrumented with high precision sensors to record the temperature, pressure and mass flow of the cold water and the diluted and saturated concentrations that interact with the heat exchanger. Measurements were conducted by using an Agilent brand model 34970A Data Acquisition System. Table 1 summarizes the main characteristics of the PHE-type absorber and measurement instruments.

Figure 1 illustrates the experimental system comprised of three principal circuits: (i) the ammonia vapor (yellow pipes), (ii) ammonia-lithium nitrate solution (orange pipes), (iii) and the cooling water. The solution and ammonia vapor circuits were made of stainless steel, while cooling pipes were of PVC. During the experimental test, liquid ammonia (contained in the ammonia vapor circuit) was stored in a vessel and pumped through a micrometric expansion valve. The valve abruptly reduces fluid pressure forces it to change to vapor. Vapor ammonia is subsequently injected into the bottom side of the PHE-type absorber. Then, the absorption process is carried out in the solution circuit. The diluted solution (poor in ammonia solution) is stored in a stainless-steel container. It is pumped to the bottom side of the absorber, where solution
and ammonia vapor are mixed. The concentrate solution (strong solution) abandons the PHE-type absorber and is stored in the other stainless-steel container. The heat generated by the absorption process is dissipated by the cooling water, which is pumped from a cistern (approximately 15,000 liters capacity) to the side plates of the PHE-type absorber, restraining the absorption heat. The cooling water mass flow was regulated with a needle valve.

The thermal properties of Reynolds number ($Re_{sol}$), Nusselt number ($Nu_{sol}$), coefficient of convection ($h_{sol}$), and absorption flux ($F_{ABS}$) of the solution that interact with the studied heat exchanger were calculated during the experimental tests. The interest in $Re_{sol}$, $Nu_{sol}$, and $h_{sol}$ lies in identifying the complex thermodynamic behavior of the solution when interacting with the heat exchanger. At the same time, $F_{ABS}$ is a relevant parameter to optimize the absorption process for solar cooling by indicating the capacity of ammonium vapor absorbed by the heat exchanger. For this purpose, the tests were carried out by modifying the operational parameters: concentration of the saturated solution ($x_{CS}$), the concentration of the dilute solution ($x_{DS}$), mass flow of saturated concentration $m_{CS}$, the mass flow of diluted concentration $m_{DS}$, and mass flow mass rate of cooling water $m_{CW}$. In the same way, the effects of the temperature of the solution ($T_{sol}$), the flow and temperature of the ammonia vapor ($m_{NH_3}$ and $T_{NH_3}$), and the pressures of the concentrations ($p_{DS}$ and $p_{CS}$) were also considered. Finally, fluctuations in ambient temperature were included due to its relevance in the absorption process as well as its impact when implementing it in solar cooling systems. Table 2 contains the ranges of interest experimental data measurement during the system evaluation.

### Artificial neuronal network modeling

ANN was selected because it is one of the multivariate regression techniques with excellent adaptability in complex thermal processes and can produce mathematical models with multiple outputs.

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**Table 1.** Main characteristics of the experimental system designed to study the bubble absorption by using a Plate Heat Exchanger-type absorber.

| Parameter                              | Values       |
|----------------------------------------|--------------|
| Spacing between channels ($\Lambda$)    | 6.0 mm       |
| Inter-plate channel height ($B$)        | 2.18 mm      |
| Effective width length ($L_w$)          | 77.0 mm      |
| Pattern length ($L_p$)                  | 275.0 mm     |
| Effective height length ($H$)           | 280.0 mm     |
| Inside width between gaskets edges ($L_{w}$) | 82.0 mm  |
| Port diameter ($D_p$)                   | 25.0 mm      |
| Number of passes ($N_p$)                | 1            |
| Chevron angle ($\beta$)                | 30°          |

| Variable | Sensor                  | Operating range | Accuracy |
|----------|-------------------------|-----------------|----------|
| Temperature | Resistance Temperature Detector | −180 to 520°C | ± 0.20°C |
| Pressure   | Piezoelectric           | 0 to 10 bar     | ± 0.15%  |
| Mass flow  | Turbine                 | 0 to 30 kg/min  | ± 0.20%  |
|            | Coriolis                | 0 to 5 kg/min   | ± 0.10%  |
In this paper, ANN is applied as a dual-purpose tool. On the one hand, it is used to correlate the ammonia vapor absorption process produced into the PHE-type absorber with the thermal properties of the solution ($\text{Resol}$, $\text{Nusol}$, and $\text{hsol}$); providing a numerical expression to compute its thermodynamic properties during the complex heat transfer process. On the other hand, ANN creates the objective function to conduct the inverse optimization process and improve the absorption flux into the heat exchanger.

In summary, an ANN is composed of a set of mathematical subfunctions called neurons, distributed in layers. The basic architecture of an ANN consists of an input layer, at least one hidden layer, and an output layer. The neurons in the input and output layers are defined by the experimental variables, while the hidden layer comprises sigmoid neurons that require an iterative process to determine their quantity. The connection between layers occurs through weights ($w$) and bias ($b$) matrix,
used by the network to learn from the process it models. The neurons of the hidden and output layer(s) operate according to equation (1) (May Tzuc et al., 2021), considering as input the weighted sum of the signals from the previous neurons (\(u\)) and evaluating them in an activation function (\(\varphi\)); the result acts as an incoming signal to the subsequent layers.

\[
\alpha_j = \varphi(\eta_j) = \varphi\left(\sum_{i=1}^{a} w_{ij} u_i + b_j\right)
\]

For the present study the activation functions used at the hidden and output layers were the tangential-sigmoidal (equation (2), Tansig) and the linear function (equation (3), Purelin), respectively (Simons, 2009):

\[
\varphi = \text{Tansig}(\eta_k) = \frac{2}{1 + e^{-2\eta_k}} - 1, \quad -1 < \varphi < 1
\]

\[
\varphi = \text{Purelin}(\eta_s) = \eta_s
\]

where \(\eta\) represents the weighted sum that enters the artificial neuron and the suffixes \(s\) and \(k\) refer to the neurons contained in the hidden (S) and input (K) layer, respectively.

To validate the performance of the ANN models, a statistical process is conducted comparing the predicted data versus experimental samples. The statistical parameter were the Mean Absolute Percentage Error (MAPE); Root Mean Square Error (RMSE); and the Coefficient of Determination (\(R^2\)), whose mathematical expressions are detailed by Cruz May et al. (2022) and summarized in Table 3. An optimal model is defined as one that presents \(R^2\) closest to one, and RMSE and MAPE with the closest approach to zero.

Table 2. Main parameters monitored during the operation of the ammonia vapor-based experimental system.

| Experimental parameters | Minimum | Maximum | Units |
|-------------------------|---------|---------|-------|
| **Inputs:**             |         |         |       |
| Cooling water temperature (\(T_{CW}\)) | 16.32   | 39.09   | °C    |
| Ambient temperature (\(T_a\)) | 19.48   | 27.66   | °C    |
| Solution temperature (\(T_{sol}\)) | 27.97   | 44.48   | °C    |
| Ammonia vapor temperature (\(T_{NH_3}\)) | 1.81    | 29.15   | °C    |
| Cooling water flow rate (\(\dot{m}_{CW}\)) | 10.80   | 23.16   | [kg/min] |
| Diluted solution flow rate (\(\dot{m}_{DS}\)) | 1.47    | 2.03    | [kg/min] |
| Concentrated solution flow rate (\(\dot{m}_{CS}\)) | 1.59    | 2.17    | [kg/min] |
| Ammonia vapor flow rate (\(\dot{m}_{NH_3}\)) | 1.46 \times 10^{-3} | 2.96 \times 10^{-3} | [kg/s] |
| Diluted solution (\(x_{DS}\)) | 0.0412  | 0.1204  | [kgNH_3/kg_{sol}] |
| Concentrated solution (\(x_{CS}\)) | 0.0136  | 0.1010  | [kgNH_3/kg_{sol}] |
| Diluted solution pressure (\(p_{DS}\)) | 3.96    | 8.96    | [bar] |
| Concentrated solution pressure (\(p_{CS}\)) | 0.92    | 8.90    | [bar] |
| **Outputs:**            |         |         |       |
| Reynolds number of the solution (\(Re_{sol}\)) | 368.94  | 502.838 | [dimensionless] |
| Nusselt number of the solution (\(Nu_{sol}\)) | 21.64   | 50.019  | [dimensionless] |
| Heat transfer coefficient of the solution (\(h_{sol}\)) | 2.752   | 6.112   | [kW/m^2 °C] |
| Absorption flux (\(F_{ABS}\)) | 2.902 \times 10^{-2} | 5.880 \times 10^{-2} | [kg/m^2s] |

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importance of the input variables on the solution’s thermodynamic properties and the absorption flux. For this purpose, Garson’s equation takes advantage of the ANN’s weights and biases matrix, estimating the impact of each variable from the following mathematical expression (Olden and Jackson, 2002):

\[
I_j = \frac{\sum_i S |iw_{js}|}{\sum_i (\sum_k S |iw_{ks}|) \cdot |lw_{sq}|} \times 100(\%)
\]

where \(I_j\) is the relevance of the \(j\)-th input variable on the values estimated by the ANN; \(K\) and \(S\) are the number of neurons contained in the input and hidden layers, respectively; and \(iw\) refers to the connection weight between the input and hidden layer, while \(lw\) are the weights between the output and hidden layer. Finally, the subscripts “\(k\)”, “\(s\)”, and “\(q\)” represent the input, hidden, and output neurons, respectively.

### Direct artificial neural network implementation

The modeling process to simultaneously estimate \(R_{e_{solv}}, N_{u_{solv}}, h_{solv}\) and \(F_{ABS}\) was conducted considering an ANN architecture with a single hidden layer. Experimental tests were compiled in a spreadsheet, building a working database composed of 506 samples. The modeling process contemplates as input variables the 12 operational parameters contained in Table 2, given in the following order: \(T_{CW}, m_{CW}, m_{CS}, m_{DS}, m_{NH_3}, T_{solv}, x_{CS}, x_{DS}, T_{av}, T_{NH_3}, P_{DS}\), and \(P_{CS}\).

The numerical process to obtaining the ANN model was carried out based on the computational framework presented in Figure 2. According to this, modeling begins by normalizing and fragmenting the working database. Normalization was carried out in the range between 0.1 and 0.9 to avoid overcompensation due to variables with great values and comply with the operating ranges of hidden neurons (equation (2)). The normalized database was randomly divided into three subsets: training (70%), validation (15%), and testing (15%). During learning, the ANN uses a backpropagation algorithm based on Levenberg-Marquardt (Mathworks, 2017) to adjust the weights and biases matrix value and reduce the error between experimental (\(y_{exp(i)}\)) and simulated data (\(y_{sim(i)}\)). The study contemplates an iterative process based on a gradual increase in the number of neurons in the hidden layer to find the ANN architectures that present the best simultaneous fit for the four output variables. The best models are statistically analyzed using the equations in Table 3 to quantify the one with the best performance and obtain the optimization’s objective function. Subsequently, a sensitivity analysis is applied to the best model to select the operating variables that have the most significant impact on the
thermodynamic solution properties ($Re_{sol}$, $Nu_{sol}$, and $h_{sol}$) and select the relevant parameters for the optimization phase.

Table 4 presents the evaluation of the different network architectures by varying the number of hidden neurons from 2 to 12, with intervals of 2 neurons. As can be seen from the implementation of 10 neurons in the hidden layer, there are no significant improvements in the estimation of the thermodynamic properties of the NH$_3$-H$_2$O mixture, nor in the $F_{ABS}$. In general terms, the 12-10-4 network architecture presented high levels of coefficient of determination ($R^2 > 99.98\%$) and error rates close to zero (RMSE $<0.003$ and MAPE $<0.2\%$) for data subsets (training, testing, and validation) of the four modeled outputs. Moreover, the number of neurons in the hidden layer is consistent with the complexity of the transport phenomenon inside the heat exchanger. Therefore, this architecture emerges as the least complex that generates reliable estimates.

Figure 2. Schematic diagram for the modeling and optimization of the mass transfer of a plate heat exchanger-type absorber with NH$_3$-H$_2$O using ANNM.
Furthermore, it is essential to note that its statistical indicators for $F_{\text{ABS}}$ acclimate the model obtained as a good option for its implementation in ANNi (optimization process) given its high value of $R^2$ and low RMSE and MAPE.

Figure 3 illustrates the linear regression coefficients for the outputs modeled by the ANN. According to the results, each output presents a high index of linear adjustment (with slope $\approx 1$ and intercept $\approx 0$), concerning their experimental counterparts. In addition, the results between the training, testing, and validation data sets show the good generalizability of the model by presenting estimation errors of less than 0.16%. This means that the developed model estimates with high accuracy the properties of $Re_{\text{sol}}$, $Nt_{\text{sol}}$, and $h_{\text{sol}}$ during the absorption process with the working pair NH$_3$-H$_2$O. The contribution in modeling these properties lies in the few reports based on experimental data and their calculation from measurable properties during the system’s operation. On the other hand, the results of the absorption flux guarantee reliable estimates in the search for increase the mass transfer at solar cooling operating conditions.

### Table 4. Statistical results of diverse ANN architectures developed to estimate thermal properties of NO$_3$-H$_2$O mixture in interaction with PHE-type exchanger.

| ANN architecture | RMSE Training | Validation | Testing | MAPE Training | Validation | Testing | $R^2$ Training | Validation | Testing |
|------------------|---------------|------------|---------|---------------|------------|---------|----------------|------------|---------|
| **Estimation of Reynolds number of the solution** | | | | | | | | | |
| 12-2-4           | 0.0117        | 0.0185     | 0.1269  | 1.2085        | 1.3091     | 1.2550  | 0.9750         | 0.9690     | 0.9744  |
| 12-4-4           | 0.0015        | 0.0178     | 0.0090  | 0.7145        | 1.0492     | 0.6559  | 0.9891         | 0.9767     | 0.9945  |
| 12-6-4           | 0.0051        | 0.0038     | 0.0048  | 0.2785        | 0.2851     | 0.3050  | 0.9980         | 0.9989     | 0.9979  |
| 12-8-4           | 0.0031        | 0.0008     | 0.0081  | 0.0804        | 0.0640     | 0.1933  | 0.9993         | 0.9995     | 0.9940  |
| **12-10-4**      | **0.0044**    | **0.0013** | **0.0012** | **0.1469**   | **0.0966** | **0.0958** | **0.9985**   | **0.9998** | **0.9996** |
| 12-12-4          | 0.0040        | 0.0016     | 0.0024  | 0.1530        | 0.1315     | 0.1363  | 0.9987         | 0.9988     | 0.9996  |
| **Estimation of Nusselt number of the solution** | | | | | | | | | |
| 12-2-4           | 0.0117        | 0.0163     | 0.0110  | 0.7942        | 1.0615     | 0.8138  | 0.9818         | 0.9722     | 0.9859  |
| 12-4-4           | 0.0059        | 0.0058     | 0.0057  | 0.4475        | 0.4789     | 0.4541  | 0.9954         | 0.9966     | 0.9957  |
| 12-6-4           | 0.0024        | 0.0018     | 0.0059  | 0.1242        | 0.1193     | 0.2523  | 0.9993         | 0.9996     | 0.9937  |
| **12-10-4**      | **0.0031**    | **0.0020** | **0.0024** | **0.1808**   | **0.1601** | **0.1879** | **0.9989**   | **0.9996** | **0.9988** |
| 12-12-4          | 0.0027        | 0.0020     | 0.0017  | 0.1477        | 0.1525     | 0.1156  | 0.9990         | 0.9993     | 0.9997  |
| **Estimation of convective coefficient of the solution** | | | | | | | | | |
| 12-2-4           | 0.0089        | 0.0130     | 0.0073  | 0.6391        | 0.7521     | 0.5679  | 0.9898         | 0.9831     | 0.9939  |
| 12-4-4           | 0.0080        | 0.0109     | 0.0107  | 0.6139        | 0.7210     | 0.6987  | 0.9918         | 0.9882     | 0.9857  |
| 12-6-4           | 0.0020        | 0.0014     | 0.0051  | 0.0925        | 0.0955     | 0.1531  | 0.9995         | 0.9998     | 0.9958  |
| **12-10-4**      | **0.0028**    | **0.0016** | **0.0018** | **0.1473**   | **0.1254** | **0.1244** | **0.9995**   | **0.9997** | **0.9994** |
| 12-12-4          | 0.0026        | 0.0016     | 0.0019  | 0.1252        | 0.1227     | 0.1441  | 0.9991         | 0.9996     | 0.9997  |
| **Estimation of absorption flux into the Plate Heat Exchanger type absorber with NO$_3$-H$_2$O** | | | | | | | | | |
| 12-2-4           | 0.0161        | 0.0189     | 0.0139  | 1.1430        | 1.2437     | 0.9861  | 0.9682         | 0.9560     | 0.9703  |
| 12-4-4           | 0.0012        | 0.0016     | 0.0010  | 0.0840        | 0.0989     | 0.0780  | 0.9999         | 0.9998     | 0.9999  |
| 12-6-4           | 0.0015        | 0.0017     | 0.0020  | 0.1098        | 0.1114     | 0.1330  | 0.9998         | 0.9998     | 0.9997  |
| 12-8-4           | 0.0003        | 0.0003     | 0.003   | 0.0233        | 0.0217     | 0.0231  | 0.9999         | 0.9998     | 0.9977  |
| **12-10-4**      | **0.0002**    | **0.0002** | **0.002** | **0.0184**   | **0.0199** | **0.0166** | **0.9999**   | **0.9998** | **0.9998** |
| 12-12-4          | 0.0006        | 0.0009     | 0.0013  | 0.0422        | 0.0540     | 0.0758  | 0.9999         | 0.9999     | 0.9999  |
The aforementioned concludes that the ANN model is representative of the thermal phenomena considered and adequately synthesizes the absorption system based on NH$_3$-H$_2$O. Therefore, according to the transfer functions described in Section ‘Artificial neuronal network modeling’, the mathematical expression of the developed ANN is given by:

$$y_{q,\text{ANN}} = \sum_{s=1}^{S} \left[ \frac{2 \times lw_{q,s}}{1 + \exp(-2(\sum_{k=1}^{K} (iw_{k,s} \cdot \ln(k)) + b_{1(i)})) + 1} \right] + b_{2(q)}$$  \hspace{1cm} (5)

where $y_q$ refers to the vector made up of the four ANN model output values ($y_1 = Re_{sol}$, $y_2 = Nu_{sol}$, $y_3 = h_{sol}$ and $y_4 = F_{ABS}$); $s$ is the number of neurons in the hidden layer ($S = 10$); $k$ is the number of neurons in the input layer ($K = 12$). $\ln(k)$ refers to the value of the operational variable in turn; $iw_{k,s}$ are weights between input and hidden layer; $lw_{q,s}$ the weights between output and hidden layer; while $b_1$ and $b_2$ are biases for the neurons at the hidden and output layer, respectively. Table 5 shows values of weights and biases obtained during the ANN learning process.

Figure 4 shows in percentage form the relevance of the operational variables on the thermodynamic properties modeled in the absorption process with NH$_3$-H$_2$O. In the case of $F_{ABS}$, the ammonia vapor flow was identified as the most significant element with 43.1% of the influence. This coincides with what has been reported in various studies (Kang et al., 2002; Lee et al., 2002; Tae Kang et al.,
Table 5. Matrix of optimal weights and bias of the best ANN model for its application as an objective function.

| Hidden Neurons | $T_{CW}$ ($k_1$) | $m_{CW}$ ($k_2$) | $m_{DS}$ ($k_3$) | $m_{CS}$ ($k_4$) | $m_{NH_3}$ ($k_5$) | $T_{soil}$ ($k_6$) | $x_{CS}$ ($k_7$) | $x_{DS}$ ($k_8$) | $T_a$ ($k_9$) | $T_{NH_3}$ ($k_{10}$) | $p_{DS}$ ($k_{11}$) | $p_{CS}$ ($k_{12}$) | $b_1$ | $b_2$ |
|----------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------|------|
| 1              | 0.209            | 0.239            | 0.115            | 0.301            | 0.139            | 0.277            | 0.300            | 0.365            | 0.376            | 0.156            | 0.504            | 0.191            | 0.086 | 0.540 |
| 2              | 0.676            | 0.107            | 0.195            | 0.867            | 0.121            | 0.281            | 0.506            | 0.612            | 0.073            | 0.116            | 0.281            | 0.159            | 0.667 | 0.454 |
| 3              | 0.327            | 0.146            | 0.065            | 0.314            | 0.034            | 0.009            | 0.887            | 0.008            | 0.309            | 0.080            | 0.600            | 0.104            | 0.059 | 0.373 |
| 4              | 1.092            | 0.403            | 0.023            | 0.053            | 0.140            | 0.034            | 0.966            | 0.356            | 0.478            | 0.304            | 0.467            | 0.173            | 0.236 | 0.077 |
| 5              | 0.062            | 0.370            | 0.031            | 1.181            | 0.152            | 0.043            | 0.317            | 0.606            | 0.044            | 0.059            | 0.428            | 0.031            | 0.256 | 0.452 |
| 6              | 0.119            | 0.096            | 0.001            | 0.464            | 0.174            | 0.107            | 0.151            | 0.365            | 0.022            | 0.066            | 0.115            | 0.012            | 1.507 | 1.231 |
| 7              | 0.023            | 0.015            | 0.001            | 0.096            | 0.298            | 0.014            | 0.014            | 0.063            | 0.007            | 0.010            | 0.010            | 0.001            | 0.069 | 0.659 |
| 8              | 1.553            | 0.273            | 0.061            | 0.518            | 0.508            | 0.145            | 0.379            | 0.884            | 0.551            | 0.033            | 0.033            | 0.123            | 0.196 | 0.133 |
| 9              | 0.112            | 0.047            | 0.004            | 0.073            | 0.160            | 0.250            | 0.715            | 0.197            | 0.218            | 0.046            | 0.046            | 0.001            | 0.727 | 0.624 |
| 10             | 0.237            | 0.042            | 0.056            | 0.102            | 0.049            | 0.630            | 0.361            | 0.666            | 0.008            | 0.528            | 0.528            | 0.022            | 0.243 | 0.363 |
Similarly, the diluted solution’s flow and concentration were identified as the second (18.4%) and third (13.1%) variables that most influence the absorption flux. This is understandable if we consider that the diluted concentration’s flow absorbs the ammonia so that the less dilute ammonia in the solution, there is a more significant potential for absorption of ammonia gas.

Regarding Resol, Nusol, and hsol present in the solution, the sensitivity analysis detected that they are more than 60% affected by 4 of the 12 input variables. For these three thermodynamic properties, the \( \dot{m}_{CS} \) was identified as the most representative element (Resol = 17.6%, Nusol = 17.1%, and hsol = 18.7%), followed by \( x_{CS} \) (Resol = 14.3%, Nusol = 14.6%, and hsol = 15.0%), \( x_{DS} \) (Resol = 14.9%, Nusol = 14.2%, and hsol = 14.9%), and \( m_{NH_3} \) (Resol = 14.1%, Nusol = 12.1%, and hsol = 12.7%). From these results it stands out that the influence percentages of both the concentrated and diluted solution are almost identical. The explanation for this directly affects the Reynolds number of the solution, which is strongly influenced by its viscosity (Cerezo et al., 2009; Lee et al., 2003; Tae Kang et al., 2000). Diluted ammonia affects the viscosity of the solution in such a way that decreasing ammonia increases the viscosity. On the contrary, by increasing the ammonia concentration from 35% to 40%, the viscosity decreases significantly, providing a transition from a transition regime to a turbulent regime. It is also observed that derived from the change in viscosity in the solution, other thermodynamic properties, such as thermal conductivity (\( \kappa_{sol} \)), and specific heat (\( C_{p,sol} \)), are modified, causing by definition the variation of \( Pr_{sol} \) (Chan et al., 2018). It should be remembered that the Nusol number and the convective heat transfer coefficient of the solution (hsol), are strongly influenced by \( Re_{sol}, K_{sol}, C_{p,sol} \), and \( Pr_{sol} \).

The results also quantify the importance of other operating parameters, among which stand out the pressure of the diluted solution, the temperature of the solution, and the conditions of the water supply for cooling. This is understandable considering several factors. Within them, the pressure at which the absorption occurs must be as low as possible. Similarly, it is crucial that the temperature of the diluted solution is as low as possible when it reaches the absorber, and finally, that the cooling water has a good flow and that the temperature is as low as possible. This causes the mass flow of the water to remove the heat generated by the exothermic reaction that occurred during the mixing
process between the ammonia and the absorbent. Generally, these temperature and pressure conditions are subject to the evaporator’s conditions in an absorption refrigeration system.

As can be seen, the results of this analysis contribute to identifying those parameters on which attention must be focused when operating these refrigeration systems based on PHE-type absorbers. Specifically, in the case of optimization, it allows determining those operating parameters with the more significant relevance for improving the $F_{ABS}$. On the other hand, the sensitivity analysis shows that the model has a good fit concerning the experimental data and adequately interprets the phenomenology that occurs during the absorption process in the heat exchanger; complying with the established by Razabi et al. (Razavi et al., 2021).

**Multivariate optimization of absorption flux by ANNi**

The inverse multivariate ANN (ANNim) was adopted to find the operating conditions that improve the absorption flux for solar cooling applications. The advantage of implementing the ANNim is its capacity to optimize based on experimental data, unlike other methods that employ mathematical models with assumptions (Moheno-Barrueta et al., 2021). This approach is based on inverting the ANN model, considering the simulated value as the input and a subset of input variables ($X_1$, $X_2$, and $X_3$) as the unknowns. The purpose is to create a multivariate objective function requiring the desired absorption flux ($F_{ABS,des}$). The optimal values of the operational parameters that allow reaching it are determined; this is achieved by coupling the objective function with metaheuristic algorithms (Figure 5).

To perform the optimization, the multivariate objective function was constructed (based on the approach proposed by Solís-Pérez et al. (2019)) using the weighting and bias coefficients calculated for $F_{ABS}$, contained in Table 4:

$$
\text{Multivariate objective function} = \min\left(f(X_1, X_2, X_3) = -F_{ABS,des} + \frac{1}{2} \left[ 1 + e^{-0.7069 X_1 + 0.6327 X_2 + 0.7383 X_3 - 1} \right] \right)
$$

**Figure 5.** Schematic diagram for multivariate optimization of absorption flux through ANNim.
\[
\min (f(X_1, X_2, X_3)) = -F_{ABS, \text{des}} + \left[ -0.112 \left( \frac{2}{1 + e^{-(0.278X_1+0.602X_2+0.73X_3+P_1)}} - 1 \right) \right] \\
- \left[ 0.063 \left( \frac{2}{1 + e^{-(0.242X_1+1.224X_2+1.734X_3+P_2)}} - 1 \right) \right] \\
+ \left[ 0.019 \left( \frac{2}{1 + e^{-(0.068X_1+0.016X_2+0.628X_3+P_3)}} - 1 \right) \right] \\
- \left[ 0.003 \left( \frac{2}{1 + e^{-(0.280X_1+0.712X_2+0.106X_3+P_4)}} - 1 \right) \right] \\
+ \left[ 0.028 \left( \frac{2}{1 + e^{-(0.304X_1+1.212X_2+2.362X_3+P_5)}} - 1 \right) \right] \\
+ \left[ 0.611 \left( \frac{2}{1 + e^{-(0.348X_1+0.73X_2+0.928X_3+P_6)}} - 1 \right) \right] \\
- \left[ 3.075 \left( \frac{2}{1 + e^{-(0.596X_1+0.126X_2+0.192X_3+P_7)}} - 1 \right) \right] \\
- \left[ 0.004 \left( \frac{2}{1 + e^{-(1.016X_1+1.768X_2+1.036X_3+P_8)}} - 1 \right) \right] \\
+ \left[ 0.055 \left( \frac{2}{1 + e^{-(0.32X_1+0.394X_2+0.146X_3+P_9)}} - 1 \right) \right] \\
- \left[ 0.039 \left( \frac{2}{1 + e^{-(0.098X_1+1.332X_2+0.204X_3+P_{10})}} - 1 \right) \right] + 0.05 \tag{6}
\]

where \(X\) represents each operational parameter to be optimized, selected based on the sensitivity analysis’ relevance results for \(F_{ABS}(X_1 = \dot{m}_{NH_3}, X_2 = \dot{m}_{DS}, X_3 = x_{DS})\); whose inequality restrictions are given by:

\[
1.44 \leq X_1 \text{(Ammonia vapor flow rate)} \leq 2.98 \tag{7}
\]
\[
1.5 \leq X_2 \text{(Diluted solution flow rate)} \leq 2.2 \tag{8}
\]
\[
0.13 \leq X_3 \text{(Diluted solution)} \leq 1.05 \tag{9}
\]

On the other hand, the values of \(P_1\) to \(P_{10}\) correspond to the sum of the non-optimizable inputs multiplied with their respective \(iw\), which are considered as constants for the multivariate objective function:

\[
P_1 = 2(0.209T_{CW} + 0.239\dot{m}_{CW} + 0.115\dot{m}_{CS} + 0.277T_{sol} \\
+ 0.3x_{cs} + 0.365T_a + 0.156T_{NH_3} + 0.504p_{DS} + 0.191p_{CS} + 2.253) \tag{10}
\]
\[
P_2 = 2(0.676T_{CW} + 0.107\dot{m}_{CW} + 0.195\dot{m}_{CS} + 0.281T_{sol} \\
+ 0.506x_{cs} + 0.073T_a + 0.116T_{NH_3} + 0.281p_{DS} + 0.159p_{CS} + 1.448) \tag{11}
\]
\[
P_3 = 2(0.327T_{CW} + 0.146\dot{m}_{CW} + 0.065\dot{m}_{CS} + 0.009T_{sol} \\
+ 0.887x_{cs} + 0.309T_a + 0.080T_{NH_3} + 0.6p_{DS} + 0.104p_{CS} + 0.958) \tag{12}
\]
\[ P_4 = 2(1.092 T_{CW} + 0.403 \dot{m}_{CW} + 0.023 \dot{m}_{CS} + 0.034 T_{sol} + 0.966 x_{cs} + 0.478 T_a + 0.304 T_{NHs} + 0.467 p_{DS} + 0.173 p_{CS} - 0.805) \]  \tag{13}

\[ P_5 = 2(0.062 T_{CW} + 0.37 \dot{m}_{CW} + 0.031 \dot{m}_{CS} + 0.043 T_{sol} + 0.317 x_{cs} + 0.044 T_a + 0.059 T_{NHs} + 0.428 p_{DS} + 0.031 p_{CS} + 0.09) \]  \tag{14}

\[ P_6 = 2(0.119 T_{CW} + 0.096 \dot{m}_{CW} + 0.001 \dot{m}_{CS} + 0.107 T_{sol} + 0.151 x_{cs} + 0.022 T_a + 0.066 T_{NHs} + 0.115 p_{DS} + 0.012 p_{CS} + 0.42) \]  \tag{15}

\[ P_7 = 2(0.023 T_{CW} + 0.015 \dot{m}_{CW} + 0.001 \dot{m}_{CS} + 0.014 T_{sol} + 0.014 x_{cs} + 0.007 T_a + 0.010 T_{NHs} + 0.010 p_{DS} + 0.001 p_{CS} + 0.029) \]  \tag{16}

\[ P_8 = 2(1.553 T_{CW} + 0.273 \dot{m}_{CW} + 0.061 \dot{m}_{CS} + 0.145 T_{sol} + 0.379 x_{cs} + 0.551 T_a + 0.033 T_{NHs} + 0.033 p_{DS} + 0.123 p_{CS} + 0.378) \]  \tag{17}

\[ P_9 = 2(0.112 T_{CW} + 0.047 \dot{m}_{CW} + 0.004 \dot{m}_{CS} + 0.25 T_{sol} + 0.715 x_{cs} + 0.218 T_a + 0.046 T_{NHs} + 0.046 p_{DS} + 0.001 p_{CS} + 0.421) \]  \tag{18}

\[ P_{10} = 2(0.237 T_{CW} + 0.042 \dot{m}_{CW} + 0.056 \dot{m}_{CS} + 0.63 T_{sol} + 0.361 x_{cs} + 0.008 T_a + 0.528 T_{NHs} + 0.528 p_{DS} + 0.022 p_{CS} + 1.334) \]  \tag{19}

For the current study, the meta-heuristic algorithm selected was the Water Cycle Algorithm (WCA). It is a nature-inspired technique, proposed in 2012 by Eskandar et al. (Eskandar et al., 2012), based on the geographic forming streams and rivers from the hydrological cycle. The algorithm considers that water disperses along various paths flowing downhill during the creation of the rivers, the optimal path being the one that manages to flow out into the sea (Bahreininejad, 2019; Eskandar et al., 2012; Sadollah et al., 2015b). Starting from the idea that the process begins when rain or precipitation occurs, an initial population called raindrop is randomly generated. After this, the best individual (raindrop) in terms of presenting the best fitness is selected as sea (Bahreininejad, 2019; Sadollah et al., 2015a). Subsequently, a certain number of best raindrops (cost function values closest to the best existing ones) are selected as rivers and streams (Sadollah et al., 2015b). On the other hand, to avoid a rapid and immature convergence of the algorithm, an evaporation condition is added, which closes the hydrological cycle and gives the guideline for forming new paths of rivers and streams that allow exploring and possibly finding better optimization solutions (Iterative process). The iterative process of the cycle comes to an end when all or most of the raindrop converge on a single point of arrival at the ocean. Table 6 presents the pseudocode for the WCA coupled with ANNim (ANNim-WCA) as well as the parameters proposed to perform the optimization. Without counting the input variables \( N_{var} = 12 \), the other values were chosen by a trial and error approach; they are presented as the best performing (Yadav and Verma, 2020).

Three experimental tests with different operating conditions were assessed to validate the ANNim-WCA coupling and ensure its optimization capacity. The computes for optimization were carried out through a MATLAB script by using the WCA external-toolbox (Sohani, 2021). Table 7 shows the input variables corresponding to the selected experimental tests, which were not part of the training and validation, and the error obtained when searching for the operating parameters of interest \( (X_1, X_2 \text{ and } X_3) \). As can be seen, in the three cases, the maximum error for optimized input variables does not exceed 3.3%, while the estimates for the \( F_{ABS,des} \) are on an accuracy
Once the WCA-ANNim approach was validated, it was used to find the values of $X_1 = \dot{m}_{\text{NH}_3}$, $X_2 = \dot{m}_{\text{DS}}$, and $X_3 = x_{DS}$ which allow obtaining the maximum experimental absorption fluxes. For this purpose, three scenarios were assessed. In the first scenario, each of these variables was optimized one at a time, improving the $F_{\text{ABS}}$ keeping 11 input variables fixed except for $\dot{m}_{\text{NH}_3}$, and subsequently doing the same for $x_{DS}$ and $\dot{m}_{\text{DS}}$. Table 8 shows the WCA-ANNim model results for the three experimental data tests optimizing only one variable at a time. In the first test, it is observed that increasing the ammonia vapor flow from 1.933 to 2.964 kg/min produces a significant improvement in the absorption flux of (81.7%). The preceding coincides with what has been stated in the bibliography and demonstrates that it is not necessary to reach the...
Table 7. Validation of the ANNiM effectiveness to identify the optimal parameters that guarantee the desired output.

| Input variables | $T_{CW}$ ($k_1$) | $m_{CW}$ ($k_2$) | $m_{DS}$ ($k_3$) | $m_{CS}$ ($k_4$) | $m_{NH_3}$ ($k_5$) | $T_{sol}$ ($k_6$) | $x_{CS}$ ($k_7$) | $x_{DS}$ ($k_8$) | $T_a$ ($k_9$) | $T_{NH_3}$ ($k_{10}$) | $p_{DS}$ ($k_{11}$) | $p_{CS}$ ($k_{12}$) | $F_{ABS}$ ($q_4$) |
|-----------------|------------------|------------------|------------------|------------------|-------------------|------------------|------------------|------------------|----------------|---------------------|------------------|------------------|------------------|
| Test 1          | 24.27            | 18.86            | 1.66             | 1.54             | 1.93              | 41.80            | 2.00             | 5.40             | 21.82          | 21.37               | 7.53             | 6.01             | 3.0836           |
| Test 2          | 32.24            | 18.27            | 1.95             | 1.87             | 2.77              | 35.54            | 6.62             | 10.10            | 24.08          | 4.86                | 8.87             | 6.74             | 5.4870           |
| Test 3          | 30.44            | 11.14            | 1.198            | 1.85             | 2.02              | 39.70            | 8.14             | 10.68            | 22.16          | 13.05               | 6.57             | 3.19             | 3.7270           |

Experimental test

|              | Test 1 |                   | Test 2 |                   | Test 3 |                   |
|--------------|--------|-------------------|--------|-------------------|--------|-------------------|
|               | $m_{NH_3}$ | $m_{DS}$ | $x_{DS}$ | $F_{ABS}$ | $m_{NH_3}$ | $m_{DS}$ | $x_{DS}$ | $F_{ABS}$ | $m_{NH_3}$ | $m_{DS}$ | $x_{DS}$ | $F_{ABS}$ |
| Simulated    | 1.920  | 1.700             | 0.055  | 3.0835           | 2.80   | 2.03              | 0.103  | 5.4869           | 1.880  | 1.981             | 0.090  | 3.7269           |
| Experimental | 1.933  | 1.664             | 0.054  | 3.0836           | 2.77   | 1.95              | 0.101  | 5.4870           | 1.879  | 2.018             | 0.093  | 3.7270           |
| Error (%)    | 0.673  | 2.163             | 0.926  | 0.0032           | 1.266  | 3.889             | 2.352  | 0.0018           | 0.053  | 1.846             | 3.226  | 0.0027           |
maximum experimental value of $X_1$ to obtain the best thermal performance of the system. On the other hand, an improvement of 25.7% was obtained by increasing the flow of the concentrated solution from 1.664 to 1.8115 kg/min. By optimizing the diluted solution, decreasing from 0.0540 to 0.0412 kgNH$_3$/kg$_{sol}$, the absorption flux improves by (25%). In test 2, applying the optimization, a decrease in system efficiency was observed. Increasing the ammonia vapor flow to 2.964 kg/min shows a decrease in system efficiency of (−0.49%). The efficiency of the absorption flow decreased (−5.5%) as $\dot{m}_{DS}$ decreased from 1.954 to 1.8291 kg/min. Finally, decreasing the value of the diluted solution from 0.1010 to 0.0840 kgNH$_3$/kg$_{sol}$ results in a negative impact of (−5.79%) on efficiency. In test 3, the most significant increase in efficiency (45.5%) occurs in the first scenario when the ammonia vapor flow rate increases from 1.879 to 2.964 kg/min. From the observed behaviors, it can be concluded that the process finds an optimal ammonia flow for all scenarios, it is also seen that optimization one at a time is not effective when the values of the absorption flow and operation ammonia flow close to the limit of experimental tests.

The second scenario shown in Table 9 considers a process optimizing two variables simultaneously. The variables chosen for this scenario were the ammonia vapor flow rate and the flow rate of the diluted solution because they are the two with the greatest impact. As can be seen, from the optimization of more than one variable, it was possible to increase the efficiency of the absorption flow in all tests. In test 1, the increase in efficiency (96.3%) is obtained by increasing the ammonia vapor flow from 1.933 to 2.964 kg/min and at the same time decreasing the flow of the diluted solution from 1.664 to 1.59 kg/min. In test 2, by increasing the ammonia vapor flow rate from 2.77 to 2.964 kg/min and decreasing the diluted solution flow rate from 1.954 to 1.819 kg/min, the efficiency...
of the absorption flow improved (7.04%). This result is striking since despite operating near the experimental ammonia flow limit, it was identified that the absorption process in the heat exchanger is still better. It can be inferred that reducing the absorption flow rate gives the ammonia vapor more residence time and a greater opportunity to be absorbed. In the third case, the increase in the absorption flow efficiency (58.07%) was obtained by increasing the ammonia vapor flow from 1.879 to 2.964 kg/min while decreasing the concentrated solution flow from 2.018 to 1.7957 kg/min.

Finally, the last scenario considers the optimization of the three variables simultaneously (Table 10). In the first case, the efficiency in the absorption flow was improved (97.25%) by increasing the ammonia vapor flow from 1.933 to 2.964 kg/min, decreasing the flow of the concentrated solution from 1.664 to 1.59 kg/min as well as the diluted solution from 0.054 to 0.0412 kgNH3 / kg_sod simultaneously. In test 2, it was observed that by increasing the ammonia vapor flow rate from 2.77 to 2.964 kg/min and decreasing both the concentrated solution and the dilute solution (from 1.954 to 1.8092 kg/min and 0.1010 to 0.0412, respectively) \( F_{ABS} \) increase in 8.07%. For the third test, an improvement in the efficiency of the absorption flow (59.8%) was obtained by increasing the ammonia vapor flow from 1.879 to 2.964 kg/min, decreasing the concentrated solution flow from 2.018 to 1.7802 kg/min, as well as the diluted solution 0.093 to 0.0412 kgNH3 / kg_sod. In all cases, incorporating the \( x_{DS} \) into the optimization contributes to improving the performance of the absorption process with little more than 1%, as can be seen in Table 8.

In general, the results of the three scenarios show the possibility of improving the absorption processes in the PHE-Type absorber. In all cases, a fixed value of the ammonia flux was identified. In addition, it was found that multivariate optimization improvement is necessary when the ammonia flow operates near the experimental limit, the most common cases being the reduction of the \( \dot{m}_{DS} \) and \( x_{DS} \) to obtain the best results (inversely proportional). Finally, the \( x_{DS} \) proved to be important when seeking to improve the operation of the absorption process.

### Table 9. Application of the ANN model to improve (absorption flux) by optimizing two variables at a time in the three experimental tests.

| Variable | Experimental data | Optimization \( \dot{m}_{NH_3} \), \( \dot{m}_{DS} \) |
|----------|------------------|--------------------------------|
| \( \dot{m}_{NH_3} \) | Test 1 | 1.933 | 2.964 |
| \( \dot{m}_{DS} \) | | 1.664 | 1.590 |
| \( F_{ABS} \) | | 3.086 | 6.06 |
| \( \Delta \) (%) | | 96.3% |
| Computation time (s) | | 5.5704 |
| \( \dot{m}_{NH_3} \) | Test 2 | 2.770 | 2.964 |
| \( \dot{m}_{DS} \) | | 1.954 | 1.819 |
| \( F_{ABS} \) | | 5.487 | 5.873 |
| \( \Delta \) (%) | | 7.04% |
| Computation time (s) | | 5.2733 |
| \( \dot{m}_{NH_3} \) | Test 3 | 1.879 | 2.964 |
| \( \dot{m}_{DS} \) | | 2.018 | 1.795 |
| \( F_{ABS} \) | | 3.7270 | 5.8915 |
| \( \Delta \) (%) | | (58.07%) |
| Computation time (s) | | 4.9812 |
The optimization results and the proposed computational approach show a relevant application in the search for operating conditions of Plate Heat Exchanger-Type Absorber, such as the one presented here with direct applications in the online operation of absorption processes. In addition, it provides promising results for incorporating solar systems through future advanced control strategies.

Conclusions

This work presented the direct and inverse application of ANN to model heat transfer phenomena into Plate Heat Exchanger-Type Absorber (PHET-type) with NH$_3$-H$_2$O and the subsequent optimization of its absorption flux. A multi-output ANN was trained to predict the solution’s Reynolds number, Nusselt number, solution convective coefficient, as well as PHE absorption flux. The development model proved to be feasible to estimate the thermal behavior inside the heat exchanger based on operational parameters. The results of the ANN show that the simultaneous calculation of the 4 outputs can be carried out through simple mathematical operations with lower error (> 0.1%) and high correlation (> 99%). Thus, the contribution in modeling these properties lies in the few reports based on experimental data and their calculation from measurable properties during the system’s operation. On the other hand, the results of the absorption flux guarantee reliable estimates in the search for increase the mass transfer at solar cooling operating conditions. On the other hand, the sensitivity analysis results showed that the ANN is also an adequate tool to synthesize and assimilate the nature of the mass transfer processes in the PHET-type, when comparing the results of the level of importance with respect to the literature.

### Table 10. Application of the ANN model to improve absorption flux by optimizing three variables at a time in the three experimental tests.

| Variable | Experimental data | Optimization |
|----------|------------------|--------------|
| $\dot{m}_{NH_3}$ | 1.933 | 2.9640 |
| $\dot{m}_{DS}$ | 1.664 | 1.5900 |
| $x_{DS}$ | 0.054 | 0.0412 |
| $F_{ABS}$ | 3.0836 | 6.0826 |
| $\Delta$ (%) | 97.25% | 97.25% |
| Computation time (s) | | 6.9099 |
| $\dot{m}_{NH_3}$ | 2.77 | 2.9640 |
| $\dot{m}_{DS}$ | 1.9540 | 1.8092 |
| $x_{DS}$ | 0.1010 | 0.0412 |
| $F_{ABS}$ | 5.4870 | 5.93 |
| $\Delta$ (%) | 8.07% | 8.07% |
| Computation time (s) | | 5.0761 |
| $\dot{m}_{NH_3}$ | 1.879 | 2.9640 |
| $\dot{m}_{DS}$ | 2.018 | 1.7802 |
| $x_{DS}$ | 0.093 | 0.0412 |
| $F_{ABS}$ | 3.7270 | 5.9573 |
| $\Delta$ (%) | (59.8%) | (59.8%) |
| Computation time (s) | | 4.3971 |
Regarding optimization, the hybridization between ANN and the metaheuristic algorithm improved the absorption flux. The scenario evaluation varying the number of operational parameters to optimize showed that simple univariate optimization approaches are not suitable for the evaluated plate heat exchanger, even worsening performance in some cases. On the other hand, when the ammonia vapor flow rate and the flow rate of the diluted solution are simultaneously optimized, the absorption flow improves even when operating near the amino vapor flow limit. Finally, the last scenario made it clear that the correct choice of dilute fluid concentration improves the absorption in the exchanger by 1%.

The results obtained are relevant in the search to make absorption cooling systems more competitive, demonstrating the feasibility of improving the performance of the devices from an efficient operation of the system and without structural or components. It is important to emphasize that the models presented are not intended to replace conventional semi-empirical approaches. However, the main contribution of these models is the ability to link the absorption flow with operational variables, which makes them an excellent option for programming on development boards as smart sensors. In addition, the reduced compute times obtained during optimization prove to be a promising option for improving performance in solar cooling systems.

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ORCID iDs
Oscar May Tzuc https://orcid.org/0000-0001-7681-8210
Francisco Lezama-Zárraga https://orcid.org/0000-0003-3397-7881

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**Appendix**

**Notation**

\[ B \] inter-plate channel height [mm]

\[ b \] bias of the artificial neural network
$C_i$ cost of each raindrop
$C_p$ specific heat [kJ/kg °C]
$D_p$ port diameter [mm]
$d_{max}$ evaporation condition
$f$ circulation rate
$F_{ABS}$ absorption flux [kg/m²s]
$h$ convective heat transfer coefficient [W/m² K]
$K$ input layer of the ANN
$k$ input neurons of the ANN model
$I_j$ relevance of the input variable
$iw$ weights between the input and hidden layer
$L_h$ effective width length [mm]
$L_p$ pattern length [mm]
$L_v$ effective height length [mm]
$L_w$ inside width between gaskets edges [mm]
$lw$ weights between the output and hidden layer
$\dot{m}_{NH_3}$ ammonia mass flow rate [kg/s]
$\dot{m}_{CS}$ concentrate solution mass flow rate [kgNH3/kgsol]
$\dot{m}_{CW}$ cooling water flow rate [kg/min]
$\dot{m}_{DS}$ diluted solution mass flow rate [kgNH3/kgsol]
$N_p$ number of passes
$N_{pop}$ number of population
$N_{var}$ number of design variables
$N_{sr}$ number of rivers and sea
$NS_n$ number of streams
$N_{raindrops}$ number of raindrops
$N_{var}$ number of variables
$P_n (n = 1, \ldots, 10)$ sum of the non-optimizable inputs
$Pr$ prandtl number [dimensionless]
$p_{DS}$ diluted solution pressure [bar]
$p_{CS}$ concentrated solution pressure [bar]
$q$ output neurons of the ANN model
$rand$ random number
$Re$ Reynolds number [dimensionless]
$S$ hidden layer of the ANN model
$s$ hidden neurons of the ANN model
$T_a$ ambient temperature [°C]
$T_{CW}$ cooling water temperature [°C]
$T_{NH_3}$ ammonia vapor temperature [°C]
$T_{sol}$ solution temperature [°C]
$u$ input of the weighted sum of previous neurons
$x_{DS}$ diluted solution [kgNH3/kgsol]
$x_{CS}$ concentrated solution [kgNH3/kgsol]
$w_{i,j}$ weights of the ANN
$X$ operational parameter to be optimized
$X_{\text{stream}}$ flow of the stream
$X_{\text{River}}$ flow of the sea
$y_{\text{sim}}$ simulated outputs of the ANN
$y_{\text{exp}}$ experimental samples
$\bar{y}_{\text{exp}}$ average of the experimental samples
$y_q$ vector made up of the four ANN output values

**Greek letters**

Λ spacing between channels [mm]
α work of the hidden and output neuron of neural network
β Chevron angle [°]
κ$_{\text{sol}}$ solution thermal conductivity [W/mK]
η$_j$ weighted sum that enters at the artificial neuron
φ activation function of the artificial neuron

**Abbreviations**

ANN artificial neural networks
COP coefficient of performance
HCFCs hydrochlorofluorocarbons
LINO$_3$ lithium nitrate
MAPE mean absolute percentage error
PHE plate heat exchangers
RMSE root mean square error
$R^2$ coefficient of determination