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Neural network analysis of fin-tube refrigerating heat exchanger with limited experimental data

Arturo Pacheco-Vega, Mihir Sen*, K.T. Yang, Rodney L. McClain

Department of Aerospace and Mechanical Engineering, University of Notre Dame, Notre Dame, IN 46556-5637, USA

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Abstract

We consider the problem of accuracy in heat rate estimations from artificial neural network (ANN) models of heat exchangers used for refrigeration applications. Limited experimental measurements from a manufacturer are used to show the capability of the neural network technique in modeling the heat transfer phenomena in these systems. A well-trained network correlates the data with errors of the same order as the uncertainty of the measurements. It is also shown that the number and distribution of the training data are linked to the performance of the network when estimating the heat rates under different operating conditions, and that networks trained from few tests may give large errors. A methodology based on the cross-validation technique is presented to find regions where not enough data are available to construct a reliable neural network. The results from three tests show that the proposed methodology gives an upper bound of the estimated error in the heat rates. The procedure outlined here can also help the manufacturer to find where new measurements are needed. © 2001 Elsevier Science Ltd. All rights reserved.

1. Introduction

Heat exchangers are complex devices used in a wide variety of engineering applications, e.g. refrigeration and air-conditioning systems. The complexity of these systems is due to their geometrical configuration, the physical phenomena present in the transfer of heat and to the large number of variables involved in its operation. For a heat exchanger operating with humid air and refrigerant, some of the moisture in the air may condense or even freeze in the fins and tubes modifying the flow field, while inside the tubes, partial evaporation of the refrigerant may cause inhomogeneous distribution of the flow. These and the related physical processes increase the difficulty of solving the governing equations based on a first-principles approach. As a consequence, experimental information of the heat rates as functions of the variables of the system must be determined experimentally, usually by the manufacturer, and presented to the user, i.e. the design engineer. Such information is usually given by means of correlations. These, however, have very little physical bases and are usually sought to have the simplest form that will give the best accuracy. Some applications of correlations to condensers and evaporators are those by Yan and Lin [1], Srinivasan and Shah [2], and Kandlikar [3,4], among others. It is well known, however, that prediction errors in heat rates by means of correlations are much larger than the measurement errors, being mainly due to the data compression represented by them.

* Corresponding author. Tel.: +1-219-6315975; fax: +1-219-6318341.

E-mail address: mihir.sen.1@nd.edu (M. Sen).

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Nomenclature

c_p	specific heat (J/kg K)
D	tube diameter (m)
H	height of heat exchanger (m)
h_{fg}	enthalpy of transformation, liquid to vapor (J/kg)
h_{if}	enthalpy of transformation, solid to liquid (J/kg)
L	length of heat exchanger (m)
M	number of experimental data sets
$\dot{m}$	mass flow rate (kg/s)
N	number of independent inputs
N_{col}	number of columns
N_{row}	number of rows
N_{cir}	number of circuits
O_i	output variable for run i
$\dot{Q}$	heat transfer rate between fluids (W)
R	Euclidean distance to centroid
S_{cv}	absolute value of percentage error in cross-validation
S_{e}	root mean square of percentage error
T	fluid temperature (°C)
t	fin thickness (m)
W	width of heat exchanger (m)
w	humidity ratio (kg/kg)
x_a	tube spacing in the longitudinal direction (m)
x_b	tube spacing in the transverse direction (m)

Greek symbol

δ	fin spacing (m)

Subscripts and superscripts

a	air side
db	dry bulb
e	experimental value
in	inlet
l	latent
out	outlet
p	predicted value
s	sensible
t	total
r	refrigerant side
w	water

The problem of single-phase and condensing heat exchanger predictions has been previously addressed using artificial neural networks (ANNs) [5,6]. This is a technique that allows the modeling of physical phenomena in complex systems without requiring explicit mathematical representations. ANNs have been developed in recent years and used in many application areas, among them thermal engineering [7]. Some examples are: analysis of thermosyphon solar water heaters [8], heat transfer data analysis [9], HVAC computations [10] and predictions of critical heat flux [11].

Empirical information necessary for design and selection of heat exchangers is generated by means of experiments. Ideally, the experimental data should uniformly cover the entire region of parameter space where predictions are to be made. However, the set of geometrical and operational parameters is extremely large and, even if each quantity is allowed to assume a few different values, the resulting number of required measurements is prohibitive. A common alternative to reduce the number of experiments to a practical and economical level is the use of systematic methodologies such as those in the design of experiments [12]. The drawback of these methods, however, is that they fundamentally sacrifice information about the interaction of the variables of the system on behalf of reducing the number of tests and thus generate data which are limited and cannot always represent complex interactions in a high-dimensional independent-parameter space.

Limited data offer only partial information about the true phenomena in heat exchangers and therefore empirical models, either in the form of correlations or ANNs constructed from them, cannot accurately reproduce their behavior under different conditions. Several techniques have been proposed in the context of neural networks to determine the confidence intervals of estimations using the convex hull of the data [13], linearization theories [14], wavelets [15] or self-organizing maps [16], among others. These, however, are not adequate for undersized data. Recently, Niyogi and Girosi [17] discussed mathematically the problem of approximating functions from scattered data using linear superpositions of nonlinearly parameterized functions.

In the present study we are interested in expanding the applicability of the ANN method to the prediction of the performance of heat exchangers used for refrigeration applications using very limited amount of data. To this end, we will use typical experimental data provided by a heat exchanger manufacturer. Initially, the ANN approach will be applied to the data to show its capability in the representation of heat rates. Later, we will develop a methodology based on the cross-validation procedure to estimate the expected error of the ANN approach constructed from undersized data when determining heat exchanger behavior under different conditions. Finally, the proposed technique will be applied to the available experimental measurements to confirm the validity of the method.

2. Experimental data

Limited experimental data from a series of tests of several multi-row multi-column fin-plate type heat exchangers with staggered tubes, schematically shown in Fig. 1, were provided by the manufacturer Tyler Refrigeration Corp. The type of heat exchangers tested were all for refrigeration applications with atmospheric air flowing outside the tubes and between the fin passages, and refrigerant Freon 22 as the fluid inside the tubes. In the air-side, under certain conditions, not only condensation but also frost formation over the fins and tubes would occur. Inside the tubes, in the refrigerant-side, regions of liquid and vapor also coexist. The heat exchangers had nominal sizes in the range from 818-mm length by 100-mm height to 3328-mm length by 230-mm height, and were similar in shape. All the geometrical parameters are shown in Fig. 1. The experiments were conducted for a limited number of operating conditions with large variations of the geometrical parameters. Different geometries were considered by varying the lengths, L; fin spacings, δ; numbers of rows, N_{row}; number of columns, N_{col}; number of circuits, N_{cir}; and tube–center distances, x_a and x_b. However, the tube diameter, D, was kept unaltered. The measured variables were the inlet and the outlet air temperatures, $T^{\text{in}}_{\text{a,db}}$ and $T^{\text{out}}_{\text{a,db}}$, respectively, the inlet refrigerant temperature, T^{in}_{r}; the inlet humidity ratio of air, w^{in}_{a}; the mass flow rate of air, $\dot{m}_{\text{a}}$; and the rate of defrosted water, $\dot{m}_{\text{w}}$. The sensible and latent heat transfer rates, $\dot{Q}_{\text{s}}$ and $\dot{Q}_{\text{l}}$ were determined for each geometry under conditions of thermal equilibrium between the air-side and the refrigerant-side by means of

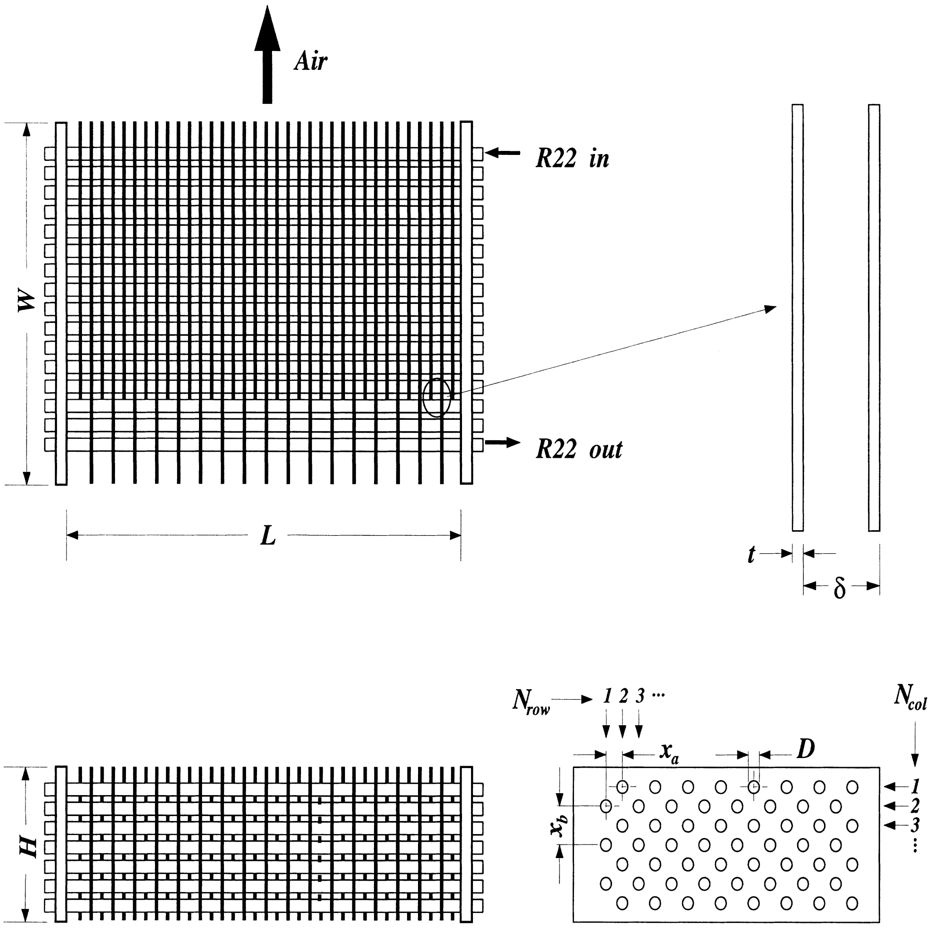

Fig. 1. Schematic of a compact heat exchanger with air and R22 as fluids.

$$\dot{Q}_{\mathrm{s}} = \dot{m}_{\mathrm{a}} c_{\mathrm{p,a}} (T^{\mathrm{in}}_{\mathrm{a,db}} - T^{\mathrm{out}}_{\mathrm{a,db}}) \tag{1}$$

$$\dot{Q}_{\mathrm{l}} = \dot{m}_{\mathrm{w}} (h_{if} + h_{fg}) \tag{2}$$

where, $c_{\mathrm{p,a}}$ is the specific heat of air, h_{if} is the latent heat of transformation of the water from solid to liquid and h_{fg} is the latent heat from liquid to vapor. The total heat rate is given by

$$\dot{Q}_{\mathrm{t}} = \dot{Q}_{\mathrm{s}} + \dot{Q}_{\mathrm{l}} \tag{3}$$

The total number of experiments carried out were only $M = 38$ by varying the $N = 11$ independent variables L, δ, N_{row}, N_{col}, N_{cir}, x_a, x_b, $\dot{m}_{\mathrm{a}}$, $T^{\mathrm{in}}_{\mathrm{a,db}}$, $w^{\mathrm{in}}_{\mathrm{a}}$, $T^{\mathrm{in}}_{\mathrm{r}}$.

3. Prediction of the heat rate

Among the various kinds of ANNs that exist, the feedforward configuration has become the most popular in engineering applications [18], and it is the type of network used in this study. A fully connected ANN consists of a large number of interconnected processing elements that are organized in layers. An input layer, one or several hidden layers and an output layer form the structure of a feedforward neural network, with all the nodes of each layer being connected to all the nodes of the following layer by means of synaptic connections. A typical feedforward architecture is schematically illustrated in Fig. 2. This configuration has one input layer, two hidden layers and one output layer. During the feedforward stage, a set of input data is supplied to the input nodes and the information is transferred forward through the network to the nodes in the output layer. The nodes perform nonlinear input–output transformations by means of a sigmoid activation function. Such nonlinear mapping capability and the fact that the neurons are massively connected enable the ANN to estimate any function without the need of an explicit mathematical model of the physical phenomenon. The training process is carried out by comparing the output of the network to the given data. The weights and biases are changed in order to minimize the error between the output values and the data [5] for which the scheme used in this study is the backpropagation algorithm [19]. Feedforward followed by backpropagation of all the data comprises a training cycle. The configuration of the ANN is set by selecting the number of hidden layers and the number of nodes in each hidden layer, since the number of nodes in the input and output layers are determined from physical variables. All variables are normalized in the (0.15, 0.85) range. The mathematical background, the procedures for training and testing the ANN, and an account of its history can be found in the text by Haykin [20].

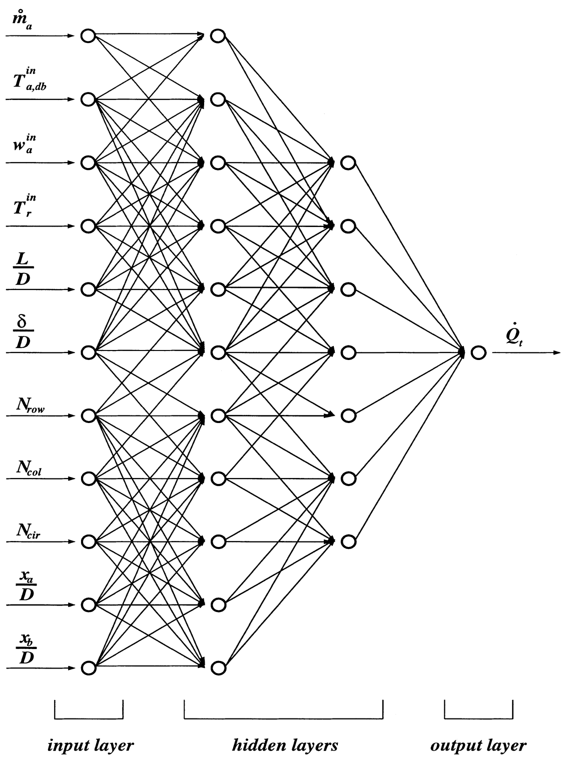

Fig. 2. Configuration of an 11-11-7-1 neural network for fin-tube heat exchanger.

A first step is to select the configuration of the ANN and the number of training cycles. This is a trial and error process [5] in which either may be changed if the performance of the network during training is not good enough. The performance is evaluated by calculating the rms values of the output errors

$$\mathrm{S_e} = \left[\frac{1}{M} \sum_{i=1}^{M} \left(\frac{O^{\mathrm{p}}_{\mathrm{i}} - O^{\mathrm{e}}_{\mathrm{i}}}{O^{\mathrm{e}}_{\mathrm{i}}} \right)^2 \right]^{1/2} \tag{4}$$

at each stage of the training. Here $i = 1, \ldots, M$, where $O^{\mathrm{p}}_{\mathrm{i}} = \{\dot{Q}_{\mathrm{t}}\}^{\mathrm{p}}_{\mathrm{i}}$ are the predictions, $O^{\mathrm{e}}_{\mathrm{i}} = \{\dot{Q}_{\mathrm{t}}\}^{\mathrm{e}}_{\mathrm{i}}$ are the experimental output values, and M is the total number of training data sets.

In order to show the capability of the ANN to model complex phenomena with very few data sets, we took the total of $M = 38$ experimental runs and trained the fully connected 11-11-7-1 ANN shown in Fig. 2. A reasonably low-level of error in the training process [6] is obtained when a number of cycles of 400 000 is chosen. The $N = 11$ input nodes correspond to the variables: $\dot{m}_{\mathrm{a}}$, $T^{\mathrm{in}}_{\mathrm{a,db}}$, $w^{\mathrm{in}}_{\mathrm{a}}$, $T^{\mathrm{in}}_{\mathrm{r}}$, L, δ, x_a and x_b, N_{row}, N_{col}, and N_{cir}, with the geometrical quantities scaled by tube diameter D; the output node corresponds to the total heat rate $\dot{Q}_t$. The resulting function

$$\dot{Q}_t = \dot{Q}_t\left(\dot{m}_a, T^{in}_{a,db}, w^{in}_a, T^{in}_r, \frac{L}{D}, \frac{\delta}{D}, N_{row}, N_{col}, N_{cir}, \frac{x_a}{D}, \frac{x_b}{D}\right)$$

is a manifold in a 12-dimensional space. The prediction of $\dot{Q}_t$ obtained from the trained ANN plotted against the available experimental data is shown in Fig. 3. The straight line indicates the equality between the predicted and experimental values of the heat transfer rates. It can be noticed that both the accuracy and the precision of the results are remarkable. The root-mean-square error of the percentage difference between the predictions and measurements is less than 1.5%, approaching the uncertainties in the experiments.

4. Error estimation

In order to use ANNs as a reliable tool for thermal analysis and design of heat exchangers, we have to take into account the factors that influence its predictions. As noted by several authors [14–17,21], the performance of neural networks is influenced by noise corruption, spatial distribution and size of the data used to construct the ANN model, and the characteristics of the ANN, i.e. the number of layers, number of hidden nodes, the architecture, etc. Noisy data associated with uncertainties in measurements are generated in the experiments. The noise can be maintained at a very small value if the experiments are carried out with care and using accurate instruments. The fact that the ANN is comprised of a finite number of hidden layers and nodes per layer to approximate an unknown function also introduces an error. The magnitude of this error depends on the representational capability of the ANN may increase due to overfitting. It as the size of the ANN becomes large. Another source of error stems from the fact that only finite data are available for training. As the number of training data sets increases, the error decreases. Niyogi and Girosi [17] demonstrated that it is not possible to reduce the upper bounds on errors due to ANN size and limited training data simultaneously. Thus if we want to rely on the ability of the ANN to generalize the relationship between the input and output quantities that govern the heat transfer phenomena in a heat exchanger we will have to be very careful in providing an adequate training set. On the other hand, as a consequence of being applied in regions beyond the range of available training data, ANNs are very likely to have a poor performance on their predictions. In fact, for a fixed neural network configuration, we may have two limits depending on the availability of the training data and the number of inputs to the ANN. The first arises when the number of measurements is very large. In such a case, if the network is used outside the convex hull of the training data [13], then the error in the predictions of the ANN will be large because there are no data in the region to support the predictions. Inside the domain given by the convex hull, the empty spaces, where measurements are absent, are small in size and

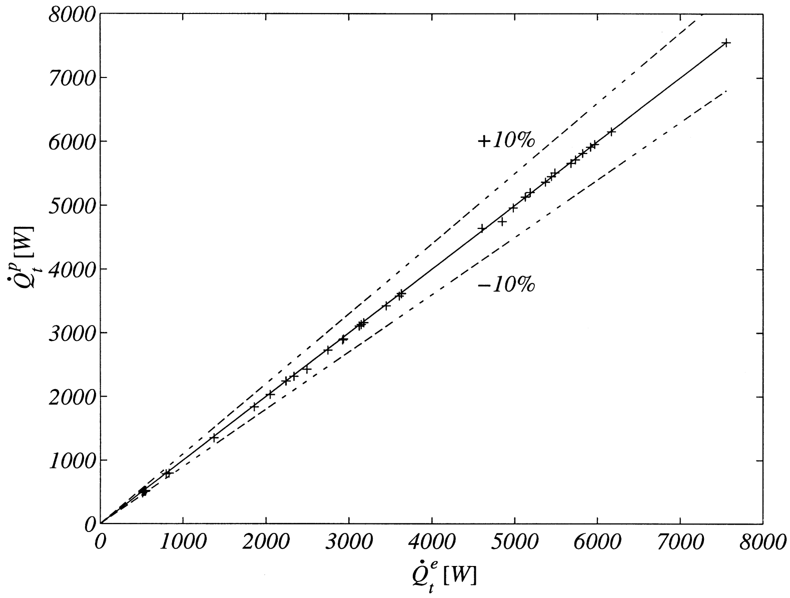

Fig. 3. Experimental vs. predicted $\dot{Q}_t$. Straight line is the prefect prediction.

there is little degradation of the ANN predictions. The second limit appears when there are very few training experiments. The voids inside the convex hull of the data are large enough so that they contribute to the inaccuracy of predictions made by the ANN in these regions.

Since the size, density and distribution of the training data are intrinsically linked to the reliability of the ANN predictions, it is crucial to determine the importance or influence of each data set. We use a variant of the statistical tool known as *cross-validation* [22] to establish a methodology to determine the validity of the ANN predictions by relying on the importance that each training data set has in the trained ANN. This method estimates the error of statistical prediction models [23] and has been widely applied to different types of neural networks in a number of ways. Prechelt [24] presents a guide to select the criteria for automatic early stopping in order to detect overfitting when training multilayer perceptrons using the cross-validation, while Leonard et al. [25] use the technique to find the optimal architecture in radial basis functions networks.

From the M available sets of experimental data, ($M - 1$) are used to train the ANN. After the training is finished, the data set left out is predicted and the result is compared to the experimental value. The percentage error, S_{cv}, is a measure of the importance of that particular set of data with respect to all the measurements. If, for instance, a large value of this error is obtained, the point excluded during the training process is important and its absence will produce an ANN with poor estimation and generalization capabilities. On the other hand, if the associated error S_{cv} is small, it means that the data set has enough support from its neighbors that its presence is not very important. This procedure is repeated M times, once for each training data set. We now create a neural network model of the error surface associated with S_{cv}, which can estimate the error associated for a new set of design variables.

In order to test the methodology proposed we take the $M = 38$ data sets provided by the manufacturer and follow the procedure outlined above. The error surface is shown in Fig. 4 as a bar-plot of S_{cv} as a function of the data set. The latter are ordered according to its Euclidean distance R in 11-dimensional space from the centroid of all M sets. It can be observed that the error values are in the range 0–60%.

5. Validation of error estimate procedure

In order to confirm the estimate of the procedure presented in the previous section, we take one experiment out of the manufacturer's data and look at the remaining measurements as if they were the total available. Thus, we have $M = 37$. The experiment taken out is put aside and considered to be a 'test experiment'. The error estimation technique is applied to the M data sets and the actual error of the test experiment compared with the estimation.

Three typical test experiments were selected in the small, medium and large error range, respectively. For

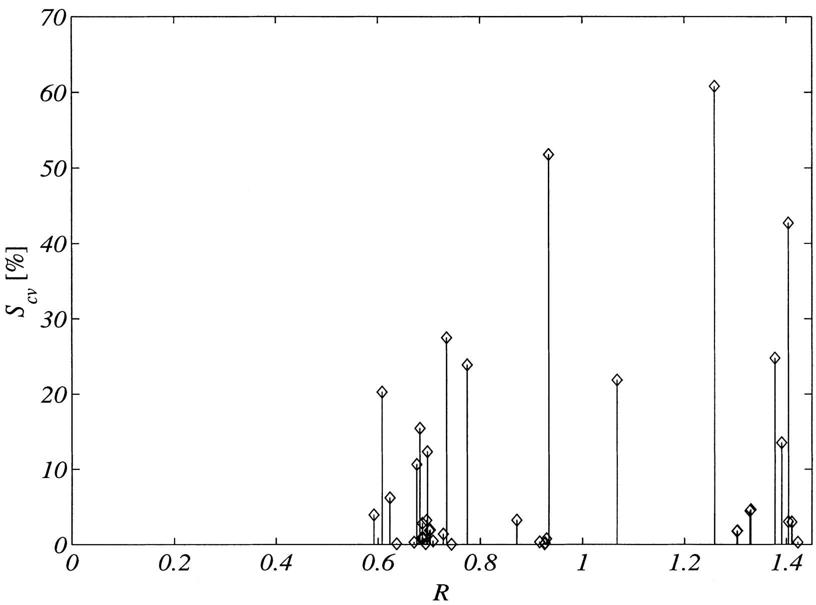

Fig. 4. Bar diagram of error estimation.

the first test, the estimated error was determined to be 0.761% while the actual error was calculated as 0.112%. The second test gave 23.3% and 6.19%, respectively, while the 48.78% and 14.21% were the values for the third one. All the networks considered had an 11-11-7-1 configuration and 400 000 training cycles were used to ensure a reasonable level of error. For all the three tests, the error estimates are larger than the actual errors, indicating that the method provides an upper bound estimate for the error in ANN predictions.

6. Conclusions

In the present study we have applied the ANN approach to accurately model the thermal characteristics of refrigerating heat exchangers. Because of the inherent attributes of the ANN technique, which traditional analysis including standard correlations does not have, ANNs can predict given experimental data with errors of the same order as the uncertainty of the measurements. Even when discrete variables such as those in heat exchanger geometry are involved, its ability to recognize patterns allows the neural network to capture all the complex physics without the need of assuming mathematical models of the process. These features, in principle, make the ANN approach suitable for use in the estimation of the heat rates under different conditions.

Correlations and neural networks, being empirical models of complex systems, are constructed based on the experimental information. Their effectiveness in estimating the heat rates under operating conditions different from those used in their development, depend on the number and distribution of these measurements. Models constructed from large, dense and well-distributed measurements will tend to have smaller errors, while those built from undersized data will perform poorly. Limited data arise from the fact that in industrial applications, such as heat exchanger manufacture, it is not economically possible to perform a large number of experiments.

We have presented a methodology for the estimation of errors from an ANN trained with a limited number of data sets. A low value of the estimated error is an indication that there are sufficient experimental data to support the ANN prediction; while a large error will indicate the absence of enough points to aid in the ANN predictions and more experiments would be needed in order to improve these. The procedure proposed here can help the manufacturer to plan new measurements by showing where these are needed.

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