Prediction model of a shell and tube heat exchanger based on the technique of artificial neural networks

Modelo de predicción de un intercambiador de coraza y tubos basado en la técnica de redes neuronales artificiales

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Abstract

The purpose of this paper is to report the proposal of a temperature prediction model methodology for a shell and tube heat exchanger using Artificial Neural Networks (RNAs). For the generation of the model, a set of historical data of five years was used, where 1633 readings from the equipment were obtained. The recorded data were the heat transfer coefficients and the fuel flow to predict the fluid temperature. The proposed methodology uses three stages. The first was the scaling of the data set between 0 and 1, this was done to facilitate the training of the RNA model: The second was to apply data mining techniques to create data clusters to model the behavior of the heat exchanger. The last stage was the evaluation of the prediction models. 5 proposals for Neural Network models were evaluated, these used 10 neurons in the hidden layer, the main difference between them was the number of clusters used in the training data that increased one by one. The average training errors obtained by the four types of data pools were 0.00220, 0.00190, 0.00133, 0.00098, and 0.00080. According to the results obtained, it was possible to conclude that the model that uses a greater number of clusters has a lower prediction error.

Exchanger, Neural network, Flow

Resumen

El presente trabajo tiene como finalidad reportar la propuesta de una metodología de modelo de predicción de temperatura de un intercambiador de coraza y tubos empleando Redes Neuronales Artificiales (RNAs). Para la generación del modelo se empleó un conjunto de datos históricos de cinco años donde se obtuvieron 1633 lecturas provenientes del equipo. Los datos registrados fueron los coeficientes de transferencia de calor y el flujo de combustibles para predecir la temperatura del fluido. La metodología propuesta utiliza tres etapas. La primera fue el escalamiento del conjunto de datos entre 0 y 1 esto se realizó para facilitar el entrenamiento del modelo de RNA: La segunda fue aplicar técnicas de minería de datos para crear agrupamientos de datos para modelar el comportamiento del intercambiador de calor. La última etapa fue la evaluación de los modelos de predicción. Se evaluaron 5 propuestas de modelos de Redes Neuronales estos emplearon 10 neuronas en la capa oculta, la principal diferencia de ellos fue la cantidad de clúster utilizados en los datos de entrenamiento que se fueron incrementando de uno en uno. Los errores promedios de entrenamiento obtenidos por los cuatro tipos de agrupamientos de datos fueron 0.00220, 0.00190, 0.00133, 0.00098 y 0.00080. De acuerdo a los resultados obtenidos se pudo concluir que el modelo que emplea mayor cantidad clúster tiene un error menor de predicción.

Intercambiador, Red neuronal, Flujo

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Introduction

Artificial Intelligence (AI) is a branch of computational science that has been used in modeling the behavior of industrial equipment and processes (Casteleiro-Roca, Barragan, Segura, Calvo-Rollea, & Andújar, 2019). This presents the advantage of facilitating the processing and treatment of the data that form the knowledge base of the system to be modeled (Wetenriajeng Sidehabi, Suyuti, Sari Areni, & Nurtanio, 2018). Furthermore, this has been used in different application models such as: heat exchangers, controllers and vision systems (Villaseñor-Aguilar, Ramírez-Agundis, Padilla-Medina, & Orozco-Mendoza, 2011) (Villaseñor-Aguilar, et al.

AI is divided into different branches such as fuzzy logic, genetic algorithms and expert systems (Ponce Cruz). Neural Networks allow mapping and modeling the behavior of the knowledge base associated with systems or processes without using their mathematical model. Its operation is focused on mapping input and output data, this is achieved by using a nonlinear processor called perceptron (Villaseñor-Aguilar, Ramírez-Agundis, Padilla-Medina, & Orozco-Mendoza, 2011). This modifies its synaptic weights to provide the desired response as shown in Figure 1 (Villaseñor Aguilar , Montecillo-Puente, Obed-Noé, & López Enriquez, 2017). The synaptic weights are calculated by means of an ANN training algorithm (Vazquez-Cruz, Luna-Rubio, Contreras-Medina, Torres-Pacheco, & Guevara-Gonzalez, 2012) that learns the desired behavior from the knowledge base to predict variables such as: temperature, Nussult number and Reynolds number (Wang, Xie, Zeng, & Luo, 2006).

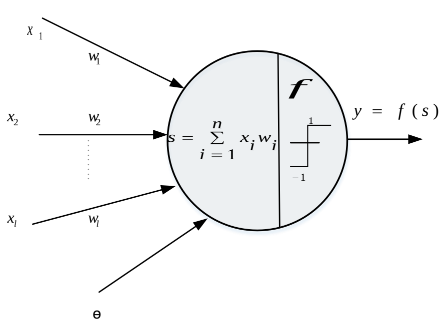

Figure 1 Perceptron model: Xi input signals, Wi weights, S weighting of the perceptron, f activation function

(Wang, Xie, Zeng, & Luo, 2006) applied an ANN to the heat transfer analysis of a shell and tube heat exchanger. The output variables of their model were the outlet temperature difference on each side and the total heat transfer rates. (Duran, Rodriguez, & Airton Consalter, 2009) proposed a cost estimation model for shell and tube heat exchangers. (Anand, 2016) presented a comparison of four ANN configurations to calculate the outlet temperature. (Hemmat Esfe, 2017) designed an ANN to determine the heat transfer characteristics and pressure drops of nanofluids in a heat exchanger. (Zeeshan, Azmi Hazarika, Nath, & Bhanja, 2017) estimated the heat transfer performance of the exchanger, jointly reported an ANN that predicts the transfer coefficient, Nussult number and Reynolds number.

This work proposes a methodology that models the behavior of a shell and tube exchanger using a fluid and thermal properties. The objective of the research is to generate a proposal of heat exchanger prediction models based on the ANN technique. The proposed models can be used as a support tool for data reconstruction and support the solution of industrial problems.

Description of the method

This section presents the methodology used for the development of the work. Figure 2 shows a flow diagram of the different stages used in the ANN-based model. The set of operating blocks of the model was developed in Matlab®. The first stage involved the selection of data that were complete in order to form the knowledge base, which were then normalized from 0 to 1. The next stage was responsible for varying the number of groups to be used for training the ANN. Subsequently, the ANN models were created using the Matlab® toolbox. The architecture used uses the fuel flow and the transfer coefficient as input, and the temperature as output. The next stage consisted of training the ANN models using 75% of the data and the rest was used for validation. During the training stage, the number of neurons contained in the hidden layer and the number of data sets were varied. The last stage consisted of selecting the ANN model with the lowest error.

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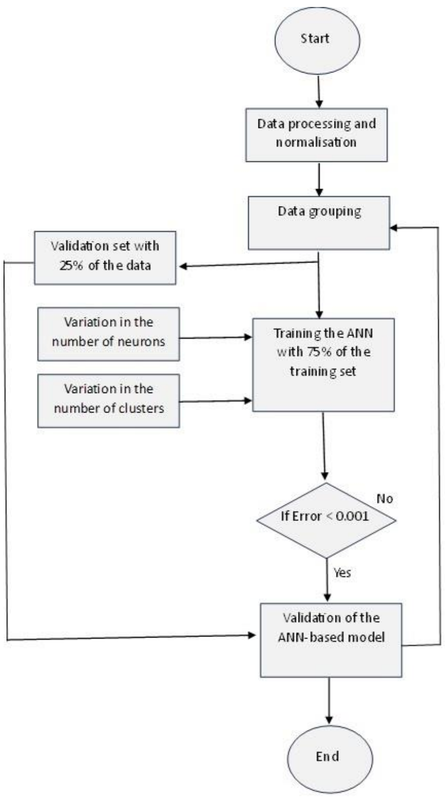

Figure 2 Block diagram of the system developed in Matlab ®: a) User interface, b) Processing and treatment, c) Clustering module, d) ANN prediction system

Data Collection

The database provided was processed to select the modeling information. Two criteria were used. The first was to select the data where their information records were complete. The second was that the thermal change was fulfilled.

Data processing and treatments

The second block consists of forming the training set with completed records and scaled to a range of (0 to 1). The scaling is required as it facilitates the learning of the network. The recorded data are divided into two parts, the input data and the output data to the network. The input data corresponds to the fluid flow, coefficient and the output data consists of the output temperatures. Equation (1) was used to *perform the normalization.*

$$X_{normalzado} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Clustering

The third block, performed in the clustering of data using the K-means algorithm. For the development of the clustering, the Matlab® Statistics and Machine Learning toolbox was used. The K-means algorithm consists of establishing K centroids, then using each element of the database and positioning it in the nearest centroid. The next step is to recalculate the centroids of each cluster and redistribute the elements to their nearest cancroid. This process is repetitive until there are no variations in the centroids.

ANN prediction system

This section presents the methodology used for the development of the ANN. In addition, the training response of the neural network is analyzed by varying some of the characteristics, mainly the number of neurons in the hidden layer and the number of data sets. This is done in order to choose the best possible network configuration.

In the first phase of the development of the prediction system I used the whole training set. Using as inputs the fluid exchanger fluid and transfer coefficient as output fluid outlet temperature 1. Figure 3 shows the ANN architecture used for training without clustering in the inputs.

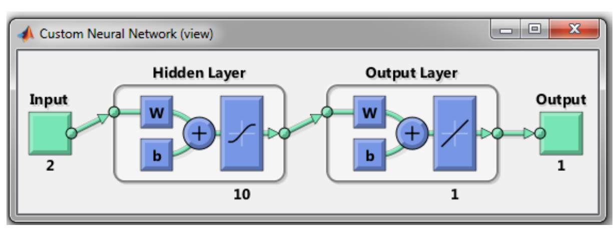

Figure 3 ANN schematic of the proposed model without input clustering.

Table 1 shows the results obtained from the training of five proposed architectures for the temperature prediction model. The ANN of 10 neurons in both layers is the one that presented the lowest minimum error of 0.00187. The training of the ANNs was performed using the Matlab Neural Network Toolbox.®.

RNA	Inputs	Layer 1	Layer 2	Outputs	Error MSE
Model 1	2	10	-	1	0.00220
Model 2	2	25	-	1	0.00205
Model 3	2	10	10-	1	0.00187
Model 4	2	25	25-	1	0.00197

Table 1 Proposed models without input grouping

In Figure 4, the histogram of the ANN errors between the ANN output and the actual data is shown. The error interval is shown on the horizontal axis. The vertical axis shows the number of trials falling into a specific error interval. The amount of data used in the input and output training was 1706, with dimensionality 2 and 1, respectively.

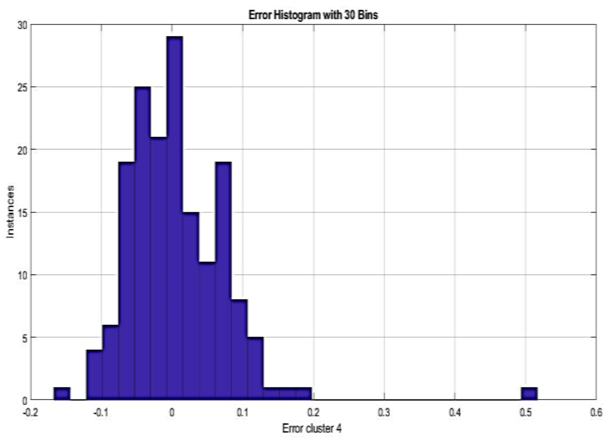

Figure 4 Training error of the temperature prediction ANN. This histogram shows the errors of the output data together, 1x 17066 data

During the process of developing the prediction model, it was proposed to create several ANN models by clustering the data. Table 2 shows the errors of each ANN model using data clustering. All models used 2 inputs, 1 output and 10 neurons in both hidden layers. Subsequently, the average error of each cluster was determined to select which model presents the best response for training.

RNA	Error Cluster 1	Error Cluster 2	Error Cluster 3	Error Cluster 4	Error Cluster 4
Model 1	0.00180	0.00200	-	-	-
Model 2	0.00199	0.00202	0.00183	-	-
Model 3	0.00208	0.00187	0.00220	0.00167	-
Model 4	0.00190	0.00210	0.00218	0.00190	0.00239

Table 2 Proposed models with input grouping.

Table 3 shows that model 5 had the lowest average error of all the models.

RNA	Cluster	Error average
Model 1	2	0.00190
Model 2	3	0.00133
Model 3	4	0.00098
Model 4	5	0.00080

Table 3 Average error of the proposed models with input clustering
Source: Own elaboration

Results

The system predictions are shown in Figure 3 using the training set. Each figure describes the behavior of the data using the five clusters. The input variables are transfer coefficients corresponding to the x-axis, the y-axis the fluid flow and as a predicted variable the fluid outlet temperature is the z-axis.

However, pronounced variations can also be observed at some points; these could be reduced by training the ANN continuously using more recent data or by creating new clusters of information. After inputting the data to the prediction model, a mean square error of approximately 0.0005 was obtained. The error histograms for these data are shown in Figures 5-8

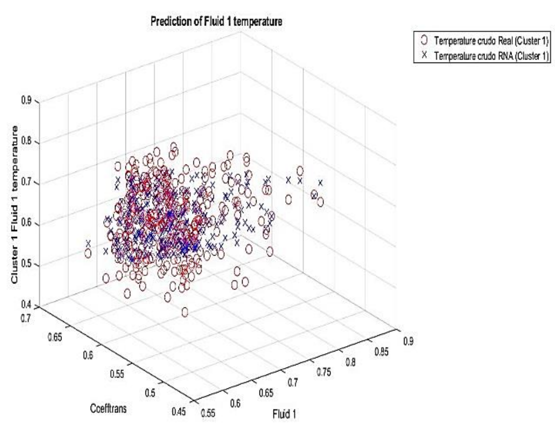

Figure 5 Comparative plots of actual temperature vs. RNA temperature of cluster 1 (cluster 1)

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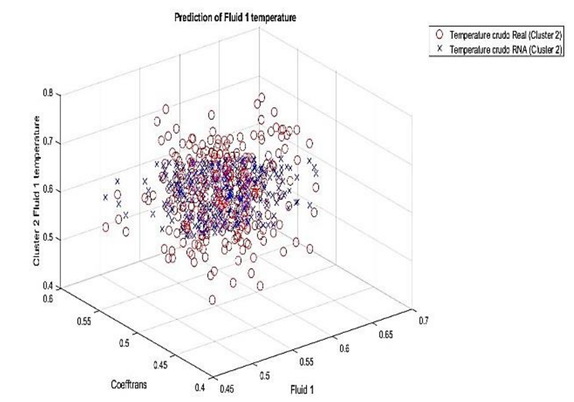

Figure 6 Comparative plots of actual temperature vs. RNA temperature of cluster 2)

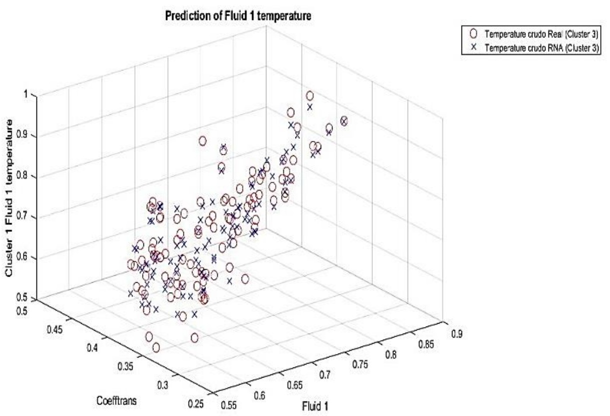

Figure 7 Comparative plots of actual temperature vs. RNA temperature of cluster 3)

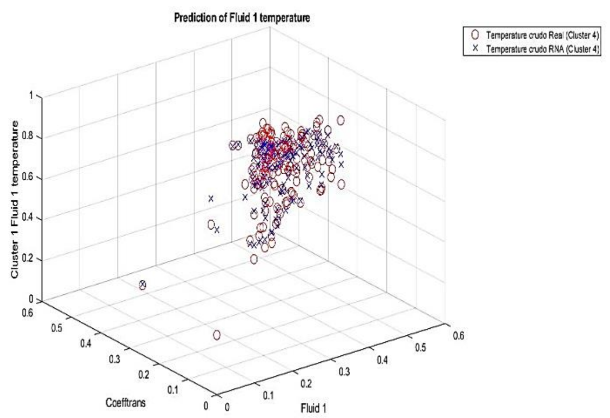

Figure 8 Comparative plots of actual temperature versus RNA temperature of cluster 4

Conclusions

It can be concluded that the application of the use of Artificial Neural Networks facilitates the modeling of complex systems such as heat exchangers.

In conjunction, it identified that the use of the K-means technique and the artificial neural network models present a good prediction of the temperature output and a small prediction error. An essential part of having a good shell and tube heat exchanger model is to have a good pooling of the training and log data.

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