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Fin-and-tube condenser performance modeling with neural network and response surface methodology

Ze-Yu Li, Liang-Liang Shao, Chun-Lu Zhang *

School of Mechanical Engineering, Tongji University, Shanghai 201804, China

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ABSTRACT

This paper presents a new approach of combining response surface methodology and neural network for performance evaluation of fin-and-tube air-cooled condensers which are widely used in refrigeration, air-conditioning and heat pump systems. Box–Behnken design (BBD) and Central Composite design (CCD) are applied to collect a small dataset for neural network training, respectively. It turns out that 41 sets of data are collected for heating capacity and refrigerant pressure drop, and 9 sets of data are collected for air pressure drop. Additional 2000+ sets of data are served as the test data. Compared with the test data, for the heating capacity, the average deviation (A.D.), standard deviation (S.D.) and coefficient of determination (R^2) of trained neural network are −0.43%, 0.98% and 0.9996, respectively; for the refrigerant pressure drop, those are −2.09%, 4.98% and 0.996, respectively; and for the air pressure drop, those are 0.11%, 1.96% and 0.992, respectively. Classical quadratic polynomial response surface models were also included for reference. By comparison, the developed neural networks gave much better results. Moreover, the proposed method can remarkably downsize the neural network training dataset and mitigate the over-fitting risk.

Modélisation de la performance d'un condenseur à tube aileté par réseau neuronal et méthodologie de surface de réponse

Mots clés : Condenseur ; Modèle ; Réseau neuronal ; Méthodologie de surface de réponse

1. Introduction

Fin-and-tube refrigerant-to-air heat exchangers are widely used in air conditioning, refrigeration and heat pump systems as condensers and evaporators. Owing to the involvement of intricate heat transfer processes and plenty of geometric combinations, generalized physics-based tube-by-tube models were recommended to design and evaluate fin-and-tube heat exchangers (Domanski and Yashar, 2007; Jiang et al., 2006; Liu

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* *Corresponding author.* School of Mechanical Engineering, Tongji University, Shanghai 201804, China. Tel.: +86 136 71825 133.
E-mail address: chunlu.zhang@gmail.com (C.-L. Zhang).

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Nomenclature

b	bias of neuron
g	transfer function
m	mass flow rate (kg s^{-1})
N	total number of data samples
N_d	number of training data
N_o	number of hidden neurons
N_{wb}	total number of weights and biases
Δp_a	pressure drop on air side (mmH_2O)
Δp_r	pressure drop on refrigerant side (kPa)
Q	capacity (kW)
T	temperature (°C)
u	connection weights between input and hidden layers
V	volume flow rate (m^3 s^{-1})
w	connection weights between hidden and output layers
x	input of neural network; variable

Greek symbols

β	regression coefficient

Subscripts

a	air
db	dry-bulb
in	inlet
out	outlet/output layer
r	refrigerant
s	saturated
wb	wet-bulb

et al., 2004). However, this type of models usually suffers from time-consuming simulations and fairly low robustness, particularly in modeling of complex system with multiple heat exchangers.

In order for fast and robust simulations of heat exchanger performance, many simple semi-empirical and empirical models have been developed, especially for complex systems with multiple heat exchangers. Among them neural network (NN) models were widely employed because of its excellent accuracy and generalization in nonlinear mapping. Yang (2008) and Mohanraj et al. (2012) reviewed NN applications in thermal engineering and in air-conditioning, refrigeration and heat pump systems, respectively. As for the heat exchanger analysis, there have emerged abundant researches for the past decades (Diaz et al., 1999; Islamoglu, 2003; Pacheco-Vega et al., 2001b; Peng and Ling, 2008; Wang et al., 2006; Xie et al., 2007; Yang et al., 2014; Zhao and Zhang, 2010). In all related researches, good agreement using neural network was always claimed. However, researchers in this area may realize that there still exist several severe difficulties in application.

Firstly, a large number of data are usually required for NN training to achieve high accuracy as well as mitigate over-fitting risk. Unfortunately, it is impractical to get sufficient data from experiments due to high cost and time-consuming process. As one alternative in Zhao and Zhang (2010), the authors used limited condenser performance data validating a detailed model to generate a bunch of data for NN training and testing. But it is inapplicable when no detailed model is available. Moreover, more than five hundred sets of data are needed as the training data to balance the accuracy and possible over-fitting risk after a grueling trial-and-error process. As another alternative, Pacheco-Vega et al. (2001b) develop a NN model with limited experimental data and use cross-validation method to find regions where data are insufficient. It is uncertain how many data points are missing or whether the addition of data in one region will affect the accuracy in other region.

Secondly, very complicated NN configurations are chosen for small number of experimental data, which greatly increases over-fitting risk of neural network. In a case study done by Sha (2007), it showed that less than 40 experimental data are collected for NN training while the total unknown parameters in the network amount to 1966. The model is not mathematically sound or justified if the unknown parameters are much more than the available data points. As a matter of fact, such misuse of neural network is not uncommon.

Lastly, most researchers only considered the heat transfer rate of heat exchanger and missed other important performance parameters such as pressure drops (Islamoglu, 2003; Pacheco-Vega et al., 2001a, 2001b).

In this work, we propose a new approach to model the fin-and-tube condenser performance using RSM (Response Surface Methodology) and neural networks. As one of the systematic DOE (Design of Experiment) methodologies, RSM is usually adopted to design experiments and establish a quadratic polynomial model for function approximation. The hybrid method of RSM and NN can be found in other fields. Betiku et al. (2014) took the experimental data designed by RSM and divided them into training and testing sets of NN, which shrinked the response surface envelope and lead to higher risk of over-fitting. Unlike them, we use all RSM designed experiments in NN training and additional data for NN testing. Regarding the condenser performance, in addition to the heating capacity, both refrigerant side and air side pressure drops are taken into account so that the NN model can fit well in system modeling. With limited but well-distributed data selected by RSM, the training dataset as well as the over-fitting risk of neural network can be remarkably reduced. The proposed model is also found to be more accurate than the classical quadratic polynomial response surface model.

2. Condenser performance virtual lab

The real experiment is time-consuming and costly. Since we are trying to validate a new idea, instead of conducting a real experiment, we use a well-validated tube-by-tube first-principle condenser model in this study. The model is developed by Liu et al. (2004), the same as the one used by Zhao and Zhang (2010). Figure 1 shows the geometry of the fin-and-tube condenser investigated in this work. The working fluid is R410A.

Different from the condenser models for design purpose, in this study, the neural network was developed for performance evaluation of a designed condenser. This kind of simple and robust model is more suitable for complex system