INTERNATIONAL JOURNAL OF REFRIGERATION 38 (2014) 281–289

Available online at www.sciencedirect.com

SciVerse ScienceDirect

journal homepage: www.elsevier.com/locate/ijrefrig

Performance predictions using Artificial Neural Network for isobutane flow in non-adiabatic capillary tubes

M. Heimel[a,*], W. Lang[b], R. Almbauer[a]

[a] Department of Internal Combustion Engines and Thermodynamics, Graz University of Technology, Inffeldgasse 19, 8010 Graz, Austria

[b] SES-Tec OG (Scientific & Engineering Simulation – Technology), Plüddemanngasse 39, 8010 Graz, Austria

ARTICLE INFO

Article history:
Received 29 April 2013
Received in revised form
11 August 2013
Accepted 12 August 2013
Available online 20 August 2013

Keywords:
Capillary tube
Artificial Neural Network
Heat exchanger
Isobutane
Non-adiabatic

ABSTRACT

This work presents an Artificial Neural Network (ANN) model of non-adiabatic capillary tubes for isobutane (R600a) as refrigerant. The basis therefore is data obtained by a 1d homogeneous model which has been validated by own measurements and measurements from literature. With this method it is possible to account for choked, non-choked, and also for two-phase inlet conditions, whereas most of the correlations reported in literature are not capable of predicting mass flow rates for non-choked and two-phase inlet conditions. The presented models are valid for a broad range of input parameters in respect to domestic applications – the mass flow rates range from 0 to 5 kg h^{-1}, inlet pressure is from saturation pressure at ambient conditions up to 10 bar, the inlet quality is from 0.5 (capillary) and 0.7 (suction line) to 0 and subcooling (capillary) and superheating (suction line) from 0 K to 30 K.

Prévisions de la performance de l'écoulement d'isobutane dans un tube capillaire non-adiabatique utilisant un réseau neuronal artificiel

Mots clés : Tube capillaire ; Réseau neuronal artificiel ; Echangeur de chaleur ; Isobutane ; Non-adiabatique

1. Introduction

Modelling of refrigeration units such as household refrigerators, chillers or freezers becomes increasingly popular for development purposes over the course of years since the advantage of greater flexibility, better control of boundary conditions and less experimental effort seems to be inviting. This applies not only for cycle simulations but also for modelling strategies of the single components like heat exchanger, compressor and expansion device. This work

* *Corresponding author*. Tel.: +43 316 873 30235; fax: +43 316 873 1030230.
E-mail addresses: Heimel@ivt.tugraz.at, martin.heimel@tugraz.at (M. Heimel).

http://dx.doi.org/10.1016/j.ijrefrig.2013.08.018

Nomenclature

$\mathbf{a}$	neural network variable
$\mathbf{b}$	neural network bias
d	total number of cells
D	inner diameter [m]
h	enthalpy [J kg^{-1}]
i	cell index
$\mathbf{IW}$	weight matrix
L	capillary length [m]
$\mathbf{LW}$	weight matrix
$\dot{m}$	mass flow rate [kg s^{-1}]
$\mathbf{n}$	neural network input
p	pressure [Pa]
$\mathbf{t}$	neural network output
T	temperature [°C]
z	cell length
Superscripts	
–	normalized value
Subscripts	
in	inlet
out	outlet
pre	before heat exchanger
HTX	heat exchanger
CAP	capillary
Greek letters	
α	grid parameter
β	grid parameter
Δ	increment

focuses on the last mentioned, in particular a capillary tube. This device is commonly used due to its simplicity and low price. It also allows equalisation of system pressure during off-cycles of refrigeration systems and thus lowering the compressor starting torque (Peixoto and Bullard, 1994). The numerical treatment, though, may be more complex than at first glance, various effects like flash boiling, choking, friction, heat transfer or delay in evaporation contribute to a highly nonlinear behaviour as far as the connection between pressure, temperature, mass flow rate and vapour quality is concerned. But not only the numerical side, even the experimental approach is hindered since in most cases only the inlet and the outlet conditions can be measured appropriately in terms of pressure, temperature and mass flow. Phenomena inside the small diameter tube, which usually ranges between 1 and 5 m in length and 0.5 up to 2 mm in inner diameter (Bansal and Rupasinghe, 1996; Fang, 1999) can hardly be visualized nor can a vapour quality satisfactorily be measured.

In the course of numerical mapping of capillary tubes different approaches depending on its later assignment have been realized. Reviews about capillary tubes can be found in Ding (2007), Fang (1999), and Khan et al. (2009). Nearly all of the models which focus on one-dimensional grids, apply empirical correlations for friction or viscosity and are solved for the mass flow rate and if non-adiabatic behaviour is assumed, also for the outlet temperature of the cold side. 0d models are presented by Hermes et al. (2010) and Zhang and Ding (2004) which explicitly calculate the mass flow rate. The accuracy lies around ±15% for more than 90% of the data points. 1d models on the other hand side solve a set of equations for every cell along the flow direction and a mass flow rate is usually found iteratively. The homogeneous flow model is widely used, e.g. Bansal and Wang (2004), Vins and Vacek (2009) or Zhou and Zhang (2006). Concerning its accuracy it is difficult to state numeric values since many different descriptions of the quality of a model exist, and also the setup and the simulation parameters differ (adiabatic, non-adiabatic, helical geometry, choked, non-choked, ...). Nevertheless a rough estimate can be given by ±5% average deviation (Zhou and Zhang, 2006), 5% relative mean error (Seixlack and Barbazelli, 2009) or an agreement between experimental data and calculated data within ±7% (Bansal and Wang, 2004). Other numeric schemes like slip models, two fluid models and drift flux models are the most sophisticated ones, taking the relative motion of vapour and liquid phase into account.

Drawbacks of such models are firstly the time it takes one to implement the equations and adjust the program and finally validate the results and secondly the long computational time compared to explicit equations without iteration loops. Popular methods of circumventing that issue are dimensionless correlations (Choi et al., 2004a, 2004b; Vins and Vacek, 2009) or Neural Networks (Islamoglu et al., 2005; Vins and Vacek, 2009; Zhang, 2005; Zhang and Zhao, 2007). Both of these methods require a set of training data to fit its constants and weights accordingly. This training set usually is taken from measurements. However, the fact that extrapolation beyond the corner points of these measurements usually leads to highly erroneous results, restricts the range of validity to the range of before-mentioned experiments. To avoid such restrictions, the training data can also be provided by simulation which may not be as accurate as properly designed measurements but bears definitely the advantage of extending the range of input parameters to any desirable values. This method is used in the following to feed a Multilayer Neural Network with data which has been evaluated by a 1d homogeneous capillary tube model. Reasons therefore are those mentioned earlier, the 1d code is too slow for cycle simulations in refrigeration systems and usual correlations are only valid for choked conditions for a rather small range of parameters, both thermodynamically and geometric. In the following it is described how the 1d model is setup, how training data for ANN is acquired and how the network performs when off- design boundary conditions occur.

2. Capillary tube model and validation

The homogeneous flow assumption is used to describe the two phase flow, where the equations of continuity, momentum and energy are solved for the capillary tube and the equation of continuity and energy are taken into account for the suction line in the common heat exchanger. The solution method for this counter-flow heat exchanger is cell-wise iteration starting from an initial guess of a mass flow rate.