Available online at www.sciencedirect.com
SCIENCE DIRECT®
International Journal of Thermal Sciences 45 (2006) 643–663
International Journal of Thermal Sciences
www.elsevier.com/locate/ijts

Modeling flow boiling heat transfer of pure fluids through artificial neural networks

G. Scalabrin *, M. Condosta, P. Marchi

Dipartimento di Fisica Tecnica, Università di Padova, via Venezia 1, I-35131 Padova, Italy

Received 28 June 2005; received in revised form 5 August 2005; accepted 16 September 2005

Available online 22 December 2005

Abstract

The heat transfer modeling of flow boiling inside horizontal tubes at saturation conditions is studied. The conventional models in the literature tend to modify an elementary historical correlation trying to empirically follow the heat flux trends as evidenced by the experimental data. The problem basically constitutes a highly non-linear phenomenon for which it is advisable to use a very flexible function approximator to draw case-specific heat transfer coefficient correlations from the experimental data alone. Artificial neural networks (ANN) were here used for this purpose, proving able to precisely represent conventional heat transfer surfaces. The most synthetic correlation architecture, based on the directly-accessible physical quantities controlling the phenomenon as independent variables, was considered for the ANN function. Eight pure fluids and a constant composition ternary mixture were studied and for each of them an individual heat transfer equation was obtained in the same ranges of the respective data set. With respect to data these ANN equations reach individual absolute average deviations of few parts per cent with biases virtually null. The obtained accuracy is lower than the claimed experimental uncertainties, but the heuristic technique also evidenced for the data both a frequent incoherence among the sets and a rather questionable reliability posing serious limits to the drawing of precise fluid specific heat transfer surfaces. A great improvement of performance with respect to five conventional correlations was found for the present modeling.

Keywords: Artificial neural networks; Flow boiling; Heat transfer correlations; Inside horizontal tubes; Modeling; Pure fluids; Smooth tubes

1. Introduction

Considering the convective flow boiling of pure fluids inside horizontal tubes the problem of getting reliable heat transfer coefficient relations is a very challenging task, particularly looking at the number of different versions proposed in the literature up to now. The procedure for the development of a heat transfer correlation for this problem, as well as for a lot of other heat transfer cases, is usually empirical. Traditionally, the correlations have been developed assuming an initial tentative model, which undergoes successive modifications to correct discrepancies with respect to experimental results therefore using a "trial-and-error" type of approach. Depending on the initial structure of the tentative model and on the criteria of the subsequent modifications the resulting correlations proposed in the literature often present a formalism quite different one from the other.

One could wonder whether such forms, both so unlike and involving different sets of input variables, could accurately represent a same heat transfer phenomenon. This evident discrepancy is reasonably due to the different approaches in evaluating the essential elements composing the initial tentative model from which to start the functional form development. Also the basic problem of the recognition of the set of independent variables controlling the heat transfer mechanism is not trivial. The subsequent searching out of the analytical dependence of the output variable on the controlling variables is furthermore a higher level difficulty.

Because a conventional heat transfer correlation starts from an empirical tentative model in which successive modifications, arranged to allow the fitting of experimental data, are introduced, the question can be posed whether a completely empirical heat transfer correlation could be directly drawn uniquely from data through a heuristic procedure. This would allow both to find the correct set of the independent variables and to ob-

* Corresponding author. Tel.: +39 049 8276875; fax: +39 049 8276896.
E-mail address: gscala@unipd.it (G. Scalabrin).

1290-0729/$ – see front matter
doi:10.1016/j.ijthermalsci.2005.09.009

Nomenclature

AAD	average absolute deviation
$A_{\min}$, $A_{\max}$	compressed input range limits
Bias	bias
c_p	isobaric heat capacity ..... $\mathrm{kJ\,kg^{-1}\,K^{-1}}$
Bo	boiling number
d	diameter ..... m
F	corrective factor
$f(x)$	transfer function
f_{ob}	objective function
Fr	Froude number
H_i	output layer value
Δh^{vap}	vaporization enthalpy ..... $\mathrm{kJ\,kg^{-1}}$
I	number of neurons in input layer
J	number of neurons in hidden layer
K	number of neurons in output layer
$\dot{m}$	mass flow rate ..... $\mathrm{kg\,m^{-2}\,s^{-1}}$
M	number of experimental sets
N	points of an experimental set
NPT	number of points
Nu	Nusselt number
P	pressure ..... MPa
p_r	reduced pressure
Pr	Prandtl number
$\dot{q}$	heat flux ..... $\mathrm{W\,m^{-2}}$
Re	Reynolds number
S	corrective factor
S_i	output layer value
T	temperature ..... K
T_c	critical temperature ..... K
U_i	input layer value
V_i	physical input
$V_{\min,i}$, $V_{\max,i}$	independent input limits
W_k	physical output
w_{ij}, w_{jk}	weighting factors
$W_{\min,k}$, $W_{\max,k}$	output limits
x	generic independent variable
$\dot{x}$	vapor quality
X	Lockhart–Martinelli parameter

Greek symbols

α	heat transfer coefficient ..... $\mathrm{W\,m^{-2}\,K^{-1}}$
β	span coefficient
γ	steepness coefficient
Δ	error deviation
η	dynamic viscosity ..... Pa s
λ	thermal conductivity ..... $\mathrm{W\,m^{-1}\,K^{-1}}$
ρ	density ..... $\mathrm{kg\,m^{-3}}$
σ	surface tension ..... $\mathrm{N\,m^{-1}}$

Superscripts

calc	calculated
exp	experimental

Subscripts

c	convective boiling
i	target fluid
l	liquid
n	nucleate boiling
r	reduced
v	vapor

tain an effective functional form without the formulation of any preliminary tentative model.

This is the general purpose of the present work which has in fact a heuristic nature and aims to obtain analytical formulations directly from experimental data, provided that these are presented in an organized form.

The problem posed here is then how to heuristically develop individual analytical expressions for the heat transfer coefficients in the case of flow boiling inside horizontal tubes.

2. Conventional heat transfer correlations

The literature concerning the modeling of flow boiling heat transfer inside horizontal tubes presents a large number of references even though they can be divided into few groups sharing a same framework of initial tentative model. Among these groups that originating from the method of Chen [1] is by far the largest. According to this method the heat transfer coefficient α for a fluid of interest is represented as the sum of two contributions, the nucleate boiling and the convective boiling:

$$\alpha = \alpha_n S + \alpha_c F \tag{1}$$

where α_n is the heat transfer coefficient for nucleate boiling derived from pool boiling correlations, and α_c is the convective heat transfer coefficient derived from single phase forced convection correlations. In Eq. (1) S and F are fluid dependent corrective factors which modify the α_n and α_c coefficients taking into account the differences between the flow conditions at which the correlations were obtained and the present conditions of the flow boiling. In particular S accounts for the nucleate boiling suppression in the case of flow boiling with respect to the basic pool boiling condition, while F accounts for the enhancement exerted by the vapor bubbles on the single phase forced liquid flow.

In the present study a couple of known models sharing the framework of the Chen method is assumed for comparison with respect to the new model proposed in the following. The works of Jung et al. [2,3] and of Jung and Radermacher [4,5] have considered the flow boiling of refrigerants, both as pure fluids and binary mixtures; in the present case comparison is made with the pure fluid model as from Jung et al. [3].

Liu and Winterton [6] proposed a pure fluid model which is assumed for comparison in this work as well.

The model of Steiner [7] could be considered as a substantial evolution of the Chen method. It still assumes the coexistence of the nucleate and convective flow regimes; if the heat flux is lower than the onset of nucleate boiling value, predicted from a specific relation, the overall heat transfer coefficient is calculated only from a relation specialized for the convective boiling. In the case the heat flux is higher than the nucleate boiling threshold the total heat transfer coefficient is calculated from an asymptotic combination rule:

$$\alpha = \left(\alpha_c^n + \alpha_n^n\right)^{1/n} \tag{2}$$

where the value $n = 3$ is usually suggested. The model introduces a rigorous diversification of the dynamic and thermal flow conditions according to which specific heat transfer formulations have to be assumed. After a first subdivision into horizontal and vertical flow conditions a further diversification between stratified-wavy and non-stratified-wavy flow regimes is required. As a consequence of such flow regime subdivision a flow pattern map is needed to identify the corresponding flow regime for each flow boiling condition. In other words the model introduces a diversification of the flow boiling heat transfer coefficient according to the flow pattern and this has to be accounted at each section along the tube. A preliminary fluodynamic study of the two-phase flow is then required for such heat transfer model. The model of Steiner [7] has been as well assumed for comparison in the present study.

In the last years a flow regime-based heat transfer model for boiling inside horizontal tubes has been proposed by Thome and coworkers [8–11]. In this modeling architecture a new flow pattern model, moving from the Steiner [7] flow pattern map, has been developed. A new flow boiling heat transfer model is then proposed presenting one of the first examples of a dependence of the local heat transfer coefficient on the flow pattern condition at the same section. The latest version of this model from Thome [11] is here assumed for comparison.

Most of the former conventional models are either not suitable to be applied for the ternary mixture R407C here considered or they have not the proper embedded elements allowing their application for a generality of cases. As a consequence for R407C the models of Choi et al. [12] and of Thome and coworkers [11,13] have been applied for comparison.

For the formal details of all the conventional models here considered reference is made to the original papers.

Considering both the cited conventional models and in general the literature models for flow boiling one can see that in any case the models have been developed using some kind of empirical approach. In fact a preliminary tentative model is assumed and it undergoes successive modifications to correct discrepancies using a "trial-and-error" approach. The analytical terms of these modifications are substantially empirical and were historically developed through a long series of changes. For the enhancements of the correlations new series of experimental data are always required to study in more detail the unreliable behaviors of the models leading them to be substantially tuned on the data, but through a sort of conflictual relationship with them. These models aim to predict the heat transfer data but are in the meantime always conditioned by them.

Furthermore, it cannot be assured that an empirical preliminary tentative model is in general suitable to "converge", through a series of "trial-and-error" successive modifications, to a reliable formulation able to accurately describe a heat transfer phenomenon. Due either to the preliminary model architecture or to the successive modification strategy or to both of them, the method on the whole could not be able to "converge" at all, also independently from the efforts spent for the study.

One could wonder whether a possibility exists to exit from this circle assigning to the experimental data the leading role, because they are the first and the last of any modeling technique. This consequently means to move to a totally heuristic modeling leaving out any 'theoretical foundation', similarly to what has been very effectively done in recent times in the thermodynamic [14] and transport properties [15,16] domains.

3. Neural networks

A new correlation technique is proposed here for the heat transfer coefficient, based on artificial neural networks (ANN). The ANN have already been applied to directly correlate experimental data of heat transfer coefficients as a function of the working conditions [17,18], in particular for the case of supercritical carbon dioxide heating [19] and cooling [20] inside tubes.

Considering different ANN architectures, the multilayer feedforward neural network (MLFN) with only one hidden layer proves to be a very effective universal approximator of continuous functions in a compact domain [21–23]. In this architecture there are several neuron layers (*multilayer*) and the information goes in only one direction, from input to output (*feedforward*).

Reference is here made to Fig. 1. The $I-1$ inputs U_i enter the $I-1$ neurons of the input layer. The inputs U_i represent the independent variables of the problem, which for the present case will be defined further on. The last neuron, at the number I, receives the *Bias* 1. The J neurons of the hidden layer receive the weighted sum of signals from the input layer. A non-linear transfer function is applied to this sum. The neuron number $J+1$ receives only the *Bias* 2 value. The output H_j of the j hidden layer is:

$$H_j = f\left(\sum_{i=1}^{I} w_{ij} U_i\right), \quad 1 \leqslant j \leqslant J \tag{3}$$

$$H_{J+1} = Bias\ 2 \tag{4}$$

where f is a non-linear transfer function and w_{ij} are *weighting factors*. Finally, the K neurons of the output layer receive the weighted sum of signals from the hidden layer and, once again, apply a non-linear transfer function to the sum. In our case $K = 1$ and the output S_1 represents the dependent variable of the problem, which is here the flow boiling heat transfer coefficient α. S_1 is the output of the output layer, i.e., the final output of the MLFN

$$S_1 = f\left(\sum_{j=1}^{J+1} w_{j1} H_j\right) \tag{5}$$

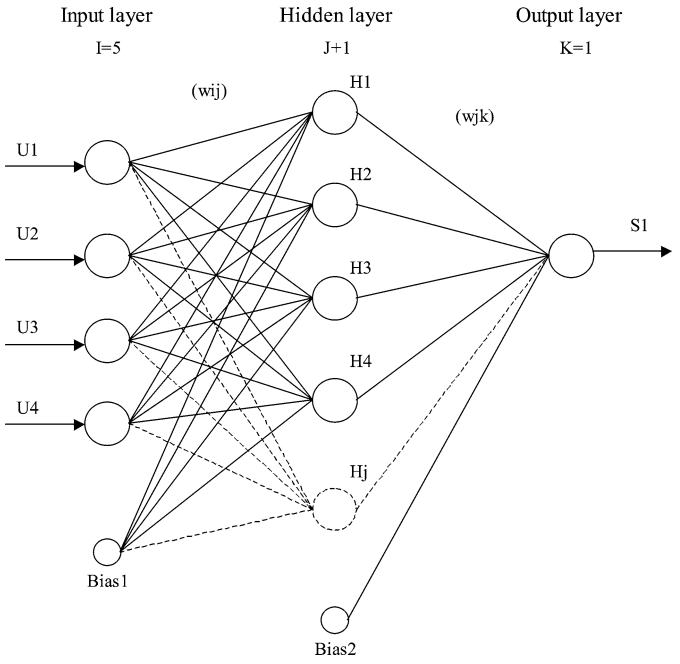

Fig. 1. Schematic representation of the multilayer feedforward neural network (MLFN) for the present study.

Once J and f have been chosen, the values of the elements of the weighting factors matrixes $\bar{w}_{ij}[I \times J]$ and $\bar{w}_{jk}[(J+1) \times K]$ can be fitted on the experimental heat transfer coefficient data sets of the target fluid. This regression procedure is called *training* step. *Bias* 1 and *Bias* 2 are two constants able to make the convergence easier and faster during the fitting.

The transfer function used in the present work has a sigmoid form:

$$f(x) = \gamma \frac{1}{1 + e^{-2\beta x}} \tag{6}$$

As a consequence of the choice of the transfer function, Eq. (6) it is, $0 < S_1 < \gamma$. In addition, the training step is faster if all the inputs are of similar magnitude and for this aim filtering functions, compressing and expanding the variables, are introduced.

For the present case the filtering equations read

$$u_i = \frac{A_{\max} - A_{\min}}{V_{\max,i} - V_{\min,i}}, \quad 1 \leqslant i \leqslant I-1 \tag{7}$$

$$s_1 = \frac{A_{\max} - A_{\min}}{W_{\max,1} - W_{\min,1}}, \tag{8}$$

$$W_1 = s_1(S_1 - W_{\min,1}) + A_{\min}, \tag{9}$$

$$U_i = u_i(V_i - V_{\min,i}) + A_{\min}, \quad 1 \leqslant i \leqslant I-1 \tag{10}$$

$$U_I = \mathit{Bias}\ 1 \tag{11}$$

where, in general, $A_{\min}$ and $A_{\max}$ are the allowable range limits of the compressed input variables, $V_{\min,i}$ and $V_{\max,i}$ are the limits of the independent input variables V_i for the training set, and $W_{\min,1}$ and $W_{\max,1}$ are the limit values of the output function W_1. Due to the characteristics of the present problem, the MLFN parameters are set here to the following values:

$$\mathit{Bias}\ 1 = 1.0, \qquad A_{\min} = 0.05, \qquad \gamma = 1.0$$
$$\mathit{Bias}\ 2 = 1.0, \qquad A_{\max} = 0.95, \qquad \beta = 0.005$$

In this way the input variables and the output function have both been compressed in the range 0.05 to 0.95. The parameter I varies from 4 to 6, depending on the choice of the input variables as discussed in the following.

To complete the MLFN definition, the following parameters have to be determined for each target fluid through the training step: J, $V_{\min,i}$, $V_{\max,i}$, $W_{\min,k}$, $W_{\max,k}$, w_{ij}, w_{jk}. Since the MLFN architecture is always the same, its connotative contents are in general the number of hidden layers, the number of nodes, and the matrixes of weighting factors $\bar{w}_{ij}$ and $\bar{w}_{jk}$. It has been established that a single hidden layer suffices for effectively representing a continuous function. The number J of neurons in the hidden layer has to be found by subsequent trials and this number has to minimize the residual error after the training procedure. The optimal value of J has to be determined as an ideal compromise between computational speed and accuracy of the resulting MLFN function. In addition, for each number of hidden layer nodes, the two matrixes of coefficients $\bar{w}_{ij}$ and $\bar{w}_{jk}$ have to be found. The determination of the optimum number of hidden nodes and the fitting of the two matrixes $\bar{w}_{ij}$ and $\bar{w}_{jk}$ are part of the training procedure.

The weighting factors are found by minimizing an objective function by means of an optimization procedure. Given an experimental data set of the output, in correspondence of a set of independent variables, the weighting factors matrixes $\bar{w}_{ij}$ and $\bar{w}_{jk}$ are found by minimizing the objective function:

$$f_{\mathrm{ob}} = \frac{1}{NPT} \sum_{i=1}^{NPT} \left(\frac{\alpha_i^{\mathrm{calc}} - \alpha_i^{\mathrm{exp}}}{\alpha_i^{\mathrm{exp}}} \right)^2 \tag{12}$$

where NPT is the number of experimental points, α_i^{exp} an experimental value of heat transfer coefficient, and α_i^{calc} the corresponding calculated value.

Since the method is totally heuristic, it is essential to have the available experimental data evenly-distributed. In fact, the primitive data base can be seen as a sparse set of points, whereas a MLFN, as a universal function approximator, needs to be applied to a compact data domain according to the Kolmogorov theorem [23]. The validity ranges have to be based on this criterion as well.

For more details about the characteristics of the MLFN applications reference is also made to previous viscosity modeling of refrigerants [15,16,24,25].

4. Neural networks modeling in terms of physical variables

From the foregoing discussion and considering some of the conventional models for flow boiling heat transfer one can note that the independent variables assumed for the correlations are from case to case physical variables (as temperature T, pressure P, mass flow rate $\dot{m}$, heat flux $\dot{q}$, vapor quality $\dot{x}$, tube inner diameter d), dimensionless groups (as Nusselt number Nu,

Reynolds number Re, Prandtl number Pr, Froude number Fr, boiling number Bo, Lockhart–Martinelli parameter X), thermodynamic functions (as liquid density ρ_l, vapor density ρ_v, liquid isobaric heat capacity $c_{p,l}$, vaporization enthalpy Δh^{vap}) and transport properties functions (as liquid viscosity η_l, vapor viscosity η_v, liquid thermal conductivity λ_l, vapor thermal conductivity λ_v, and surface tension σ). The choice of the set of the independent variable is not consolidated but it is different for each correlation and often no particular care is taken to avoid the involvement of the same quantity more than once in the correlation. For instance a quantity can be simultaneously used as an external variable and as a component of one or more dimensionless groups. The functional combination of the selected variables has the character of a particular recipe of the authors of the correlation which has been arranged through several tuning tentatives of the correlation itself over experimental sets. The type and number of fluids for which the arrangement was developed is often omitted in the correlation presentation and the user would consequently have to preliminarily verify the reliability of such correlation through a validation with respect to some set of experimental data for his own case, if available. The conventional correlations are not assured to perform satisfactorily with both different fluids and working conditions and their prediction accuracy is in general rather poor, as it will be shown in the following.

On the other hand, during saturated liquid boiling a condition of thermodynamic equilibrium could be assumed, even if not rigorously complied due to the presence of inevitable gradients.

Coming back to the independent variables customarily assumed for the conventional correlations, in a condition of supposed vapor–liquid equilibrium the aforementioned thermodynamic and transport properties of a pure fluid are all individually dependent on only a single variable, to be chosen between temperature and pressure, since the two are bound together by the vapor pressure relation which allows to eliminate one of the two. In general the dependence of a thermodynamic and transport property at vapor–liquid saturation varies more smoothly with respect to temperature than to pressure and this leads to assume the first one as the independent variable to represent the thermophysical properties of a pure fluid at the present condition. In particular the reduced temperature $T_r = T/T_c$, where T_c stands for the critical temperature, is at last chosen as a synthetic variable allowing to compare data sets of different fluids at similar conditions.

Furthermore, considering the involved dimensionless groups it is evident that all of them are functions depending either on functions or on quantities representing operative conditions. The functions are once more the fluid-dependent thermophysical properties at saturation previously mentioned, whereas the operative conditions quantities are all fluid-independent variables as mass flow rate $\dot{m}$, heat flux $\dot{q}$, vapor quality $\dot{x}$, and tube inner diameter d.

For the present problem the whole family of independent variables usually assumed for a single fluid can then be limited to the reduced temperature T_r, on which all the thermodynamic and transport properties of the target fluid at saturation are dependent, and to the four operative quantities $\dot{m}$, $\dot{q}$, $\dot{x}$, and d. Through these five independent variables an individual flow boiling heat transfer correlation for a target fluid could then be obtained.

The choice of the reduced temperature T_r can be justified considering that the thermodynamic and transport property functions here involved can be accurately represented in a three parameter corresponding states framework [24,26–31], which is based on the hypothesis of the linear scaling of the property surface by a suitable scaling factor which is both fluid and property specific. This linear scaling works as an enhancement of the basic two parameters corresponding states principle to which the model regresses in the case the scaling factor is eliminated from the model. The simplification inevitably causes some accuracy loss in the prediction of the property surface of a generic system, but on the other hand it offers the advantage that for a fluid at saturation conditions the thermophysical properties independent variables become only the reduced temperature.

Anyway, the present technique is not aiming at a generalization of the heat transfer relations using the equation heuristically obtained for a fluid to predict that of another one. In the proposed method each relation has an individual validity, limited to only the target fluid, and in this context the problem of the scaling of the thermophysical properties surfaces, predictively moving from a fluid to the other, is vanishing. This concept is confirmed in the following where it is shown that the 'crossing' of the heat transfer relation from a fluid to the other does not give satisfactory results.

It is worth noting that in this model architecture the assumed variables coincide with the directly accessible physical variables, avoiding the need for any thermodynamic and transport property model for the target fluid, which is always a latent cause of a sensible decrease of the final accuracy of a conventional heat transfer relation.

Having identified the set of the essential independent variables controlling the heat transfer coefficient surface the remainder problem is the definition of its functional form, which has to be individually developed. Instead of going through the usual method of setting up a heat transfer correlation empirically assuming an initial tentative model, which undergoes successive modifications to correct discrepancies using a 'trial-and-error' type of approach, in the present work a completely different and innovative method is proposed for this purpose, applying a heuristic technique aiming to draw analytical formulations directly from experimental data, providing they are presented in an organized form. In any case, the data are at the same time needed to set up any correlation with the conventional method.

Neural networks have been used in this case because they are a very versatile and powerful function-approximator tool. Having proved through preliminary tests their ability to represent a conventional heat transfer surface for the present case, a neural network was trained on a limited amount of data more or less homogeneously covering the working conditions range. Once the network has been trained successfully, the neural network function is able to accurately represent the behavior of the whole data set. Anyway, extrapolation to further data sets

not too far from the present validity range often proves to be satisfactory.

An architecture is then considered in which the independent variables for the present flow boiling heat transfer case are the reduced temperature T_r, the mass flow rate $\dot{m}$, the heat flux $\dot{q}$, and the vapor quality $\dot{x}$, and in case the tube diameter d, whereas the dependent variable is the heat transfer coefficient α_i of the target fluid i. Through this procedure the functional form of the heat transfer coefficient can then be expressed as a fluid specific continuous function:

$$\alpha_i = \alpha_i(T_r, \dot{m}, \dot{q}, \dot{x}, d) \tag{13}$$

or, alternatively:

$$\alpha_i = \alpha_i(T_r, \dot{m}, \dot{q}, \dot{x}) \tag{14}$$

in the case data are not present at different diameters.

Going back to the preceding analysis of the MLFN general formalism at Section 3, Eqs. (6)–(10), we can now indicate the input variables as $V_1 = T_r$, $V_2 = \dot{m}$, $V_3 = \dot{q}$, $V_4 = \dot{x}$, $V_5 = d$, and the output variable as $W_1 = \alpha_1$.

This procedure has been individually applied to eight pure fluids and a ternary mixture at constant composition for which data are available in the literature.

Only for the case of R11 experimental data taken at different tube diameters are made available in literature and only for this fluid a heat transfer model with the diameter as a further variable has then been studied.

The validity range of the correlation is the same of the data set used for the ANN training and the ranges are mentioned in the study of each fluid.

After the training, the heat transfer coefficient can be calculated as a fluid specific continuous function $\alpha_i = \alpha_i(T_r, \dot{m}, \dot{q}, \dot{x})$ or, alternatively, $\alpha_i = \alpha_i(T_r, \dot{m}, \dot{q}, \dot{x}, d)$ if data are present at different diameters.

In the present work the error deviations (Δ), the average absolute deviation (*AAD*) and the bias (*Bias*) are evaluated as:

$$(\Delta\%)_n = \frac{\alpha_n^{\text{calc}} - \alpha_n^{\text{exp}}}{\alpha_n^{\text{exp}}} \times 100$$

$$AAD\% = \frac{1}{NPT} \sum_{n=1}^{NPT} |\Delta\%|_n$$

$$Bias\% = \frac{1}{NPT} \sum_{n=1}^{NPT} (\Delta\%)_n \tag{15}$$

In each *ANN* application the choice of the number of hidden neurons J is an important element. The parameter J is in principle unknown and has to be determined by trial-and-error. A detailed study about this choice is for instance presented by Scalabrin et al. [20] for the case of convective cooling of carbon dioxide inside tubes. In that case it is evidenced how decreasing J beyond a critical value both the training residual AAD and the validation AAD dramatically increase, greatly reducing the ANN performance.

In the present work it was verified that for each studied case J was always greater than the critical value and, moreover, that an overfitting usually was not present since the AAD of the validation set, where available, was always quite close to the training residual AAD.

5. Models training and validation

The application of the method to the real context of experimental data in the literature makes it evident that the error noise becomes a very important drawback reducing the final accuracy of any regressed surface of heat transfer.

Moreover, for a precise result the data have to satisfy some basic requirements as shown earlier: they have to form a domain as compact as possible in the independent variables and scattered data sets should be avoided within the validity ranges of the equation. The data points should be also regularly distributed on an ideal grid of the independent variables. These conditions are largely lacking for the data currently available in the literature, also because heuristic methods have never been systematically considered in the past for heat transfer studies, apart from occasional cases, and therefore the experimenters do not take into account these requirements. Besides, as for many research sectors of heat transfer, for the flow boiling it is customary neither to usually publish the data nor to make them available to those concerned. This situation greatly prevents any systematic study about the complex behavior of flow boiling and much more the use for it of heuristic methods, also because in this case the analysis of the data base and its necessary screening become extremely important. On the other hand it has to be stressed that a very effective heuristic method is an excellent screening tool through which the experimenter can check his own data.

The proposed heuristic modeling method for the flow boiling heat transfer has been applied in the following to a number of pure fluids for which the experimental data were made available. For all of them the saturation temperature, the only thermodynamic quantity to input in this technique, has been calculated through the Refprop software [32]. The same software has been also used for the calculation of the pure fluid thermodynamic and transport properties entering the conventional models assumed for comparison.

For each of the studied fluids the weighting factors w_{ij} and w_{jk} and all the parameters needed to implement the obtained MLFN equations are given in Table 13, together with few values generated from the equations useful for the code validation.

5.1. Case of fluid R11

The available heat transfer data for R11 from Chawla [33] are regularly enough distributed with respect to the assumed independent variables and this is valid also for the tube inside diameter. This is the only fluid, among those studied here, whose data present a dependence on the inside diameter. In this case the internal diameter d is then included as an independent variable and for the present case it is then $I = 6$ (including the input bias) with:

$$V_1 = T_r, \qquad V_2 = \dot{m}, \qquad V_3 = \dot{q}, \qquad V_4 = \dot{x}, \qquad V_5 = d$$

Table 1
Training results of the MLFN for fluid R11

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	d range [mm]	*AAD* %	*Bias* %
Chawla [33]	684	0.58–0.62	12–173	350–23 200	0.1–0.90	6–25	6.94	−0.80

Table 2
Training and validation results of the MLFN for fluid R12

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	*AAD* %	*Bias* %
Training							
Schmidt [34]	695	0.65–0.76	0.5–578	11–80 200	0.01–0.84	20.13	−7.40
Validation							
Hihara and Saito [36]	8	0.75	250	20 000	0.08–0.80	5.90	−2.94
Malyschev et al. [35]	61	0.76	50–244	2000–25 000	0.01–0.82	43.33	21.77
Wattelet et al. [37]	112[a]	0.72	50–300	2000–30 000	0.11–0.84	8.96	−0.54
Wattelet et al. [37]	120	0.72	50–300	2000–30 000	0.11–0.94	9.04	−0.48

[a] Points inside the range of the training data set.

Table 3
Training and validation results of the MLFN for fluid R22

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	*AAD* %	*Bias* %
Training							
Shin et al. [38] Choi et al. [12]	689	0.71–0.78	240–1064	4250–30 000	0.01–0.90	6.00	−0.63
Lallemand et al. [39]	456	0.78	150–300	10 000–30 000	0.08–0.98	4.27	−0.61
Overall	1145	0.71–0.78	150–1064	4250–30 000	0.01–0.98	5.31	−0.62
Validation							
Wang et al. [40]	38[a]	0.76–0.77	200–300	6000–14 000	0.13–0.83	13.30	4.06
Wang et al. [40]	42	0.76–0.77	100–300	6000–14 000	0.13–0.83	13.42	4.89
Hihara and Saito [36]	8	0.78	250	22000	0.08–0.80	49.42	49.42

[a] Points inside the range of the training data set.

The training results obtained for the MLFN equation are reported in Table 1. The data are represented very satisfactorily with a bias value virtually null, proving that no systematic shifting is present, and with a quite good representation accuracy, given by the AAD value.

5.2. Case of fluid R12

For this fluid the data of Schmidt [34] have been used for training whereas the data of Malyschev et al. [35], Hihara and Saito [36], and Wattelet et al. [37] have been used for validation. The results obtained for both training and validation are reported in Table 2 and they show that both the Wattelet et al. [37] and the Hihara and Saito [36] data are predicted very well, even much better than the residual error deviation of training, whereas for the Malyschev et al. [35] data the result is significatively worse. Considering the agreement of the ANN function with the large number of data of the first three sets, the set of Malyschev et al. [35] seems to have a quality not consistent with the others. The Schmidt [34] data are represented with a rather lower accuracy probably due to a high noise of experimental error leading to a high AAD value and to a probable uneven distribution of the points inside the variables range. The case of this fluid can also be considered as an example of evident reciprocal discrepancy of the data sets.

5.3. Case of fluid R22

For the fluid R22 the MLFN has been trained on a data base composed of the data from Shin et al. [38], from Choi et al. [12], and from Lallemand et al. [39]. The first two sets have been considered together, since they are from the same research group. It was also preliminarily verified that the training of a single ANN for each of these data sets gave two ANN with very similar performances. A wider data base of 1145 points was then composed, also considering that the independent variables of the two sets have similar ranges. The overall result is excellent and a separate validation of the global ANN on each of the two sets confirmed their homogeneity, as shown in Table 3.

The validation has been separately performed on the data set of Wang et al. [40], which disposes of a limited number of points, and on few data from Hihara and Saito [36]: for the first source a good enough result was obtained, both inside and outside the range of the training data set, whereas for the only eight points of Hihara and Saito [36] the results are rather negative. It

Table 4
Training and validation results of the MLFN for fluid R134a

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	*AAD* %	*Bias* %
Training							
Shin et al. [38] Choi et al. [12]	501	0.70–0.78	239–854	4200–30 000	0.00–0.89	4.89	−0.50
Validation							
Wattelet et al. [37]	129[a]	0.74	300	5000–30 000	0.06–0.89	25.95	−24.71
Wattelet et al. [37]	166	0.74	50–300	2000–30 000	0.06–0.99	30.93	−16.85
Yun et al. [41]	54	0.74	240	10 000–20 000	0.11–0.86	23.61	−23.61
Zhang et al. [42]	8	0.78	250	10 000	0.19–0.82	8.07	−7.88

[a] Points inside the range of the training data set.

Table 5
Training results of the MLFN for fluid R32

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	*AAD* %	*Bias* %
Shin et al. [38] Choi et al. [12]	400	0.75–0.82	240–852	10 000–30 000	0.08–0.62	5.49	−0.52

Table 6
Training results of the MLFN for fluid R290

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	*AAD* %	*Bias* %
Shin et al. [38]	143	0.77–0.78	265–583	10 000–30 000	0.05–0.89	2.57	−0.14

Table 7
Training results of the MLFN for fluid R600a

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	*AAD* %	*Bias* %
Shin et al. [38]	137	0.70–0.75	265–583	10 000–30 000	0.01–0.87	2.95	−0.17

is suspected that these data are not at all in agreement with the remainder data for this fluid.

5.4. Case of fluid R134a

The training for R134a was done using the data from Shin et al. [38] and Choi et al. [12] with excellent results as shown in Table 4. The MLFN has been validated on the data of Wattelet et al. [37] and of Yun et al. [41], with modest results for both of them, and on the few data of Zhang et al. [42] with good results, even if with a systematic shifting.

5.5. Case of fluid R32

For this fluid the data of Shin et al. [38] and Choi et al. [12] have been used for training with an excellent result, Table 5, both for the average absolute deviation and for the total absence of shifting. Unluckily no further data were available to validate this equation.

5.6. Case of fluid R290

The case of propane (R290) is similar to that of the former fluid: here there is a single experimental source, that of Shin et al. [38], but the result has an even better quality than before, Table 6. Also in this case no further data source was found to validate the equation. For this case the temperature is omitted from the independent variables of the heat transfer equation because the data were taken in a very narrow temperature range and with an uneven distribution inside the range.

5.7. Case of fluid R600a

The case of isobutane (R600a) is quite similar to the former one for propane and the resulting equation has a quality practically of the same level. The results are reported in Table 7. For the same reason of the former fluid the functional dependence from temperature was not taken into account for R600a.

5.8. Case of fluid Argon

In the work performed for Argon the data from Müller et al. [43] and from Müller-Steinhagen et al. [44] have been used together for training to get a sufficiently large set, Table 8. For lack of further data sets the validation has been separately done on each of the former two sets and the error deviations for each of the sets have then to be intended as residual errors. The results are very good for the training and, evidently, for the validation as well.

Table 8
Training results of the MLFN for fluid Argon

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	*AAD* %	*Bias* %
Müller et al. [43]	129	0.61–0.85	117–460	220–97 900	0.10–0.91	8.38	−0.21
Müller-Steinhagen [44]	317	0.61–0.70	104–478	649–76 400	0.00–0.87	10.20	−2.10
Overall	446	0.61–0.85	104–478	220–97900	0.00–0.91	9.67	−1.55

Table 9
Training and validation results of the MLFN for pseudo-pure mixture R407C

Reference	*NPT*	T_r range	$\dot{m}$ range [kg m^{-2} s^{-1}]	$\dot{q}$ range [W m^{-2}]	$\dot{x}$ range	*AAD* %	*Bias* %
Training							
Choi et al. [12]	652	0.72–0.81	240–854	12 80–28 000	0.02–0.89	3.94	−0.29
Validation							
Zhang et al. [42]	10[a]	0.81	250–370	10 000	0.13–0.71	8.70	−8.68
Zhang et al. [42]	12	0.81	180–370	10 000	0.13–0.71	7.82	−7.29
Wang et al. [40]	5[a]	0.77–0.78	300	10000	0.20–0.63	18.18	11.66
Wang et al. [40]	38	0.77–0.79	100–300	6000–14 000	0.11–0.80	38.97	33.09

[a] Points inside the range of the training data set.

5.9. Case of mixture R407C

The ternary mixture R407C, composed of R32/R125/R134a at the fixed mass composition 23/25/52%, respectively, is here considered as a pseudo-pure fluid for which the same former procedure is applied to check if a constant composition mixture might be considered equivalent, for the flow boiling, to a pure fluid. For the presents fluid the heat transfer data of Choi et al. [12] have been used for training, while the data of Wang et al. [40] and of Zhang et al. [42] have been used for validation, Table 9. The training results are excellent, also considering the consistent number of the available points, and equal the best former cases for pure fluids demonstrating that in the present context a constant composition mixture can be studied as a pure fluid. The validation results are good for the Zhang et al. [42] data, even if a systematic shifting was found, while are unsatisfactory for the Wang et al. [40] data. In this case too it is suspected that both the validation data sets are not in agreement with the training data set.

5.10. Comparison with conventional correlations

The performances of MLFN correlations previously discussed for the eight fluids and the mixture at constant composition were also compared with those of the five conventional heat transfer correlations presented at the former Section 2. by examining the corresponding prediction accuracies with respect to the available data sets. The comparison results are given in Table 10 for the pure fluids and in Table 11 for the constant composition mixture R407C, where the data sets used for the MLFN training and the corresponding relative results are reported in italics.

The unsatisfactory performances of the conventional correlations are evident for both the prediction accuracies, represented by the AAD values, and the systematic shifting of the heat transfer surfaces with respect to the data, represented by the bias values. The comparison with respect to the conventional correlations shows also a clear inconsistency among them. All the models show a strong variability of performance with the data sets. The comparison of the performances of both the present MLFN model and the conventional ones also show a certain inconsistency among the experimental sets. For the pure fluids the model of Liu and Winterton [6], followed by the model of Thome et al. [10], looks to have a better performance, but both for these and for the others a systematic shifting and a poor prediction accuracy are always shown. For the mixture R407C, Table 11, both the models of Choi et al. [12] and of Thome et al. [10,13] have been applied for comparison and their performances are quite similar to those of the other cases.

On the contrary the performance of the MLFN formulations is in general much more reliable, even if the experimental uncertainty of some of the sets is questionable as well as the consistency of the data sets for some of the fluids. For instance in the case of R22 the sources of Shin et al. [38], Choi et al. [12], and Lallemand et al. [39] are very coherent each other, but this is not in general the case for the other fluids.

For the fluids and the mixture a total of 5236 data have been considered and 4803 of these were used for training with an overall AAD of 7.72% and a Bias of −1.62%; excluding the cases of R12 and Ar with lower performances, for the remainder ones the residual error for training achieved an overall AAD of 4.45% and a Bias of −0.44%. The accuracy of these results is absolutely superior to the current experimental uncertainty in heat transfer measurements of flow boiling.

The present approach makes evident that this analysis method is very effective and that the real limit in the obtained prediction accuracy is due to the data themselves, i.e., both to their uncertainty level and to their distribution inside the validity range of the correlation.

The proposed method makes furthermore possible a systematic screening of the available data based on statistical methods,

Table 10
Comparison among the individual MLFN equations and the four conventional models for the pure fluids studied

Fluid	Data		MLFN, present		Conventional models							
	First author	*NPT*			Jung et al. [3]		Liu and Winterton [6]		Steiner [7]		Thome [11]	
			AAD %	*Bias* %	*AAD* %	*Bias* %	*AAD* %	*Bias* %	*AAD* %	*Bias* %	*AAD* %	*Bias* %
R11	*Chawla* [33]	*684*	*6.94*	*−0.80*	79.64	73.22	22.72	−8.61	40.77	−35.87	36.43	−34.73
R12	*Schmidt* [34]	*695*	*20.13*	*−7.40*	91.35	73.12	56.88	35.44	74.08	46.32	50.03	20.57
	Wattelet [37]	112[a]	8.96	−0.54	16.16	9.37	14.47	−10.12	20.26	15.53	26.12	3.06
	Wattelet [37]	120	9.04	−0.48	16.65	10.32	14.96	−10.91	19.93	13.47	27.93	4.51
	Hihara [36]	8	5.90	−2.94	42.83	42.83	29.67	29.67	110.44	110.44	53.07	53.07
	Malyschev [35]	61	43.33	21.77	93.90	88.56	40.76	−11.39	74.62	71.74	27.36	15.88
R22	*Shin* [38] *Choi* [12]	*689*	*6.00*	*−0.63*	33.71	31.16	33.19	30.55	83.64	83.60	55.95	54.28
	Lallemand [39]	*456*	*4.27*	*−0.61*	26.08	−15.46	23.10	−16.14	22.28	17.91	15.37	0.60
	Wang [40]	38[a]	13.30	4.06	20.76	−14.42	20.40	−20.40	12.50	11.45	17.77	−3.19
	Wang [40]	42	13.42	4.89	21.29	−15.56	19.85	−19.81	12.74	11.79	19.05	−5.86
	Hihara [36]	8	49.42	49.42	20.46	19.84	22.27	21.19	107.23	107.23	46.08	46.08
R134a	*Shin* [38] *Choi* [12]	*501*	*4.89*	*−0.50*	50.38	48.77	46.58	44.23	68.70	68.45	66.35	63.95
	Wattelet [37]	129[a]	25.95	−24.71	18.26	3.33	8.00	−2.96	9.09	5.08	19.23	13.11
	Wattelet [37]	166	30.93	−16.85	19.33	6.62	11.46	−7.54	12.35	−1.34	26.63	4.64
	Yun [41]	54	23.61	−23.61	8.84	−8.07	12.52	−2.51	23.75	13.64	8.23	4.34
	Zhang [42]	8	8.07	−7.88	15.41	6.27	2.99	−1.65	44.20	44.20	26.49	25.21
R32	*Shin* [38] *Choi* [12]	*400*	*5.49*	*−0.52*	23.30	15.26	20.23	10.95	–[b]	–[b]	38.66	36.14
R290	*Shin* [38]	*143*	*2.57*	*−0.14*	22.58	22.48	36.28	36.23	70.03	69.77	55.34	55.02
R600a	*Shin* [38]	*137*	*2.95*	*−0.17*	40.90	40.90	58.29	58.29	75.87	75.87	69.05	68.40
Argon	*Müller-Steinhagen* [44]	*317*	*10.20*	*−2.10*	78.56	62.10	25.42	7.96	27.01	13.38	31.44	7.14
	Müller [43]	*129*	*8.38*	*−0.21*	–[c]	–[c]	105.74	105.44	91.76	89.64	78.18	75.50
ANN-Training		*4151*	*8.32*	*−1.83*	55.04	43.35	37.29	21.26	59.29	38.36	46.10	25.04
Validation	(in range)	418	22.20	−6.53	28.20	15.43	16.82	−6.52	28.34	24.01	22.01	9.83
Overall	(in range)	4569	9.59	−2.26	52.51	40.72	35.41	18.72	56.18	36.92	43.90	23.65

Italics: training sets for MLFN.
[a] Points inside the range of the training data set.
[b] Model not suitable.
[c] Very bad performance.

Table 11
Comparison among the individual MLFN equations and the conventional models for R407C

Fluid	Data		MLFN, present		Conventional models			
	First author	*NPT*			Choi et al. [12]		Thome [11]	
			AAD %	*Bias* %	*AAD* %	*Bias* %	*AAD* %	*Bias* %
R407C	*Choi* [12]	*652*	*3.94*	*−0.29*	50.52	49.99	110.02	108.20
	Zhang [42]	10[a]	8.70	−8.68	33.90	33.90	31.60	25.36
	Zhang [42]	12	7.82	−7.29	38.38	38.38	32.45	27.26
	Wang [40]	5[a]	18.18	11.66	64.06	64.06	79.98	79.98
	Wang [40]	38	38.97	33.09	96.22	96.22	84.35	71.46
Overall	(in range)	667	4.12	−0.33	50.37	49.85	108.62	106.75

Italics: training sets for MLFN.
[a] Points inside the range of the training data set.

before drawing from them a heat transfer individual correlation.

On the other hand, the limit of the proposed procedure in evaluating possible systematic errors of the data is implied by the number of independent experimental sources and by the distribution of the points with respect to the independent variables. If a sufficiently large number of independent sources would be available with the points more or less regularly distributed on

the same ranges, the systematic errors of this or that source would be evidenced by this method. If one of the sources would present a trend, i.e., the data would be affected by a systematic error, this would shift the Bias of the source, since all the error deviations would show to be either positive or negative. This could not be verified if the points of such source would be spread in a region not converted by other sources.

The availability from the literature of the experimental data in numerical form, their more or less regular distribution on a regular grid of the independent variables and the objective evaluation of their experimental uncertainty through a statistical screening are all fundamental elements for any heuristic study. But, for a satisfactory application of this approach to heat transfer in flow boiling all these conditions are at the moment not substantially fulfilled.

6. Models sensitivity to the physical variables

A sensitivity analysis for each of the models has been developed considering in particular the variation of the heat transfer coefficient α_i with the three more important independent variables, the vapor quality $\dot{x}$, the mass flow rate $\dot{m}$, and the heat flux $\dot{q}$, keeping constant the reduced temperature T_r and the tube diameter d. For this validation the fluid R22 has been considered and the experimental data are from the Lallemand et al. [39]. Being the total number of data rather large it is possible to find enough points to validate the models following the different variables to consider.

Further on in this section another sensitivity analysis is presented for the dependence of the heat transfer coefficient from the tube diameter for the case of R11, the only fluid for which the data were available in a discrete form for the diameter.

6.1. MLFN heat transfer models

For the fluid R22 the MLFN training result was very good, Table 3. In fact the AAD is 5.31% and the Bias is −0.62%; this is also shown by the two diagrams of Figs. 2 and 3 where the model plots follow very carefully the points trends.

Since for the fluid R11 the MLFN heat transfer equation has been determined as a function also of the tube internal diameter it is possible to compare the diameter dependence of the present equation with respect to the four conventional models. Assigning the example values $T_r = 0.58$, $\dot{m} = 130\ \mathrm{kg\,m^{-2}\,s^{-1}}$, $\dot{q} = 16\,000\ \mathrm{W\,m^{-2}}$, and $\dot{x} = 0.1$ the heat transfer models become functions of only the diameter $\alpha = \alpha(d)$ and these can be plotted as shown in Fig. 4. The MLFN heat transfer equation obtained an excellent result for the large number of experimental points of the training set so that it is sure that it accurately represents the data and that the corresponding curve on the diagram is reliable. Nevertheless, it was not possible to find experimental points near the chosen condition. The four models considered for comparison are in evident disagreement with the present MLFN equation, with the Thome [11] model presenting the greater deviation.

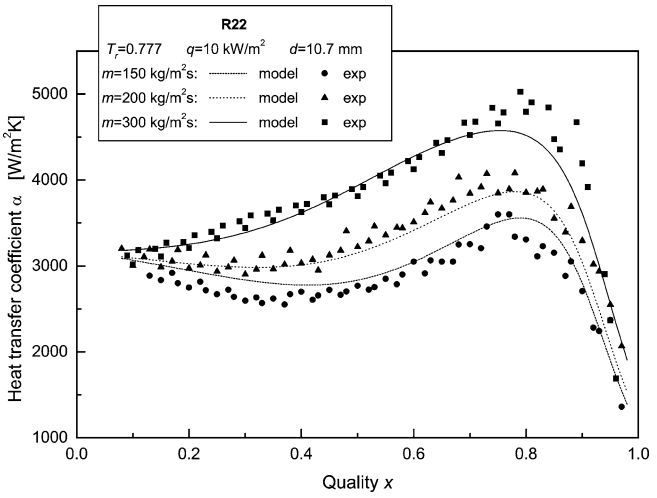

Fig. 2. Fluid R22: heat transfer coefficient α vs. vapor quality $\dot{x}$, parametric in mass flow $\dot{m}$ for assigned values of T_r, $\dot{q}$. Comparison between the MLFN equation prediction (lines) and experimental data from Lallemand et al. [39].

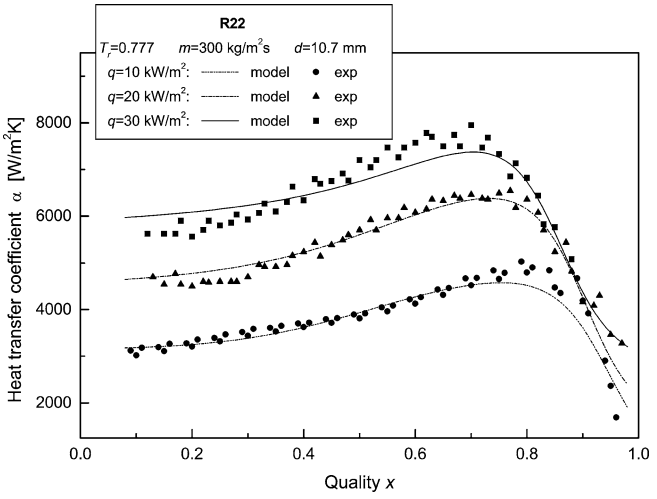

Fig. 3. Fluid R22: heat transfer coefficient α vs. vapor quality $\dot{x}$, parametric in heat flux $\dot{q}$ for assigned values of T_r, $\dot{m}$. Comparison between the MLFN equation prediction (lines) and experimental data from Lallemand et al. [39].

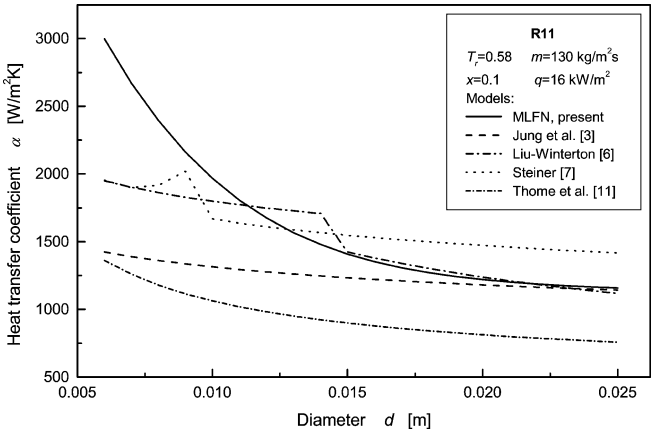

Fig. 4. Fluid R11: heat transfer coefficient α vs. diameter d, for assigned values of T_r, $\dot{m}$, $\dot{q}$ and $\dot{x}$. Comparison between the MLFN equation and the conventional models of Jung et al. [3], Liu and Winterton [6], Steiner [7], and Thome [11].

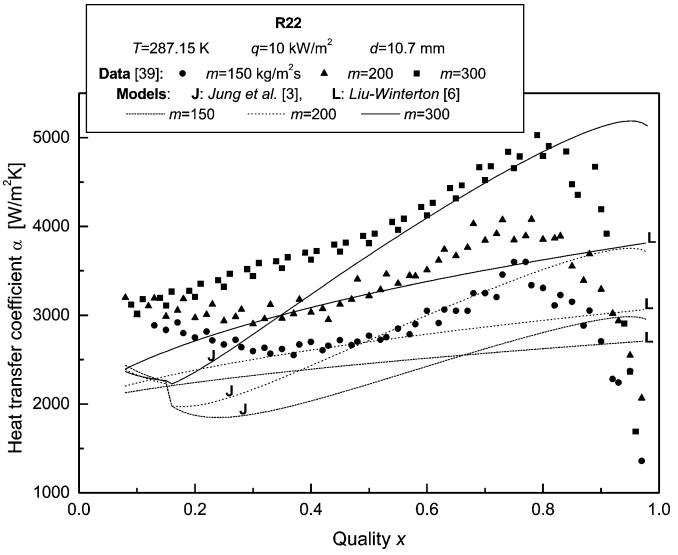

Fig. 5. Fluid R22: heat transfer coefficient α vs. vapor quality $\dot{x}$, parametric in mass flow $\dot{m}$ for assigned values of T_r, $\dot{q}$, d. Experimental data from Lallemand et al. [39] and model predictions by Jung et al. [3] and Liu and Winterton [6].

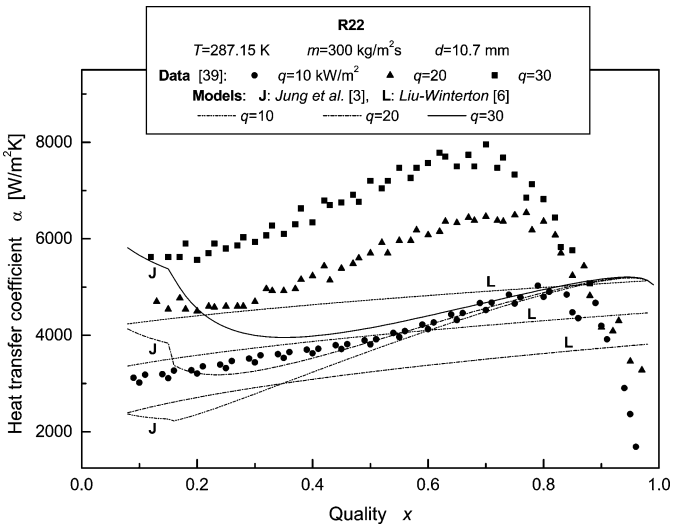

Fig. 6. Fluid R22: heat transfer coefficient α vs. vapor quality $\dot{x}$, parametric in heat flux $\dot{q}$ for assigned values of T_r, $\dot{m}$, d. Experimental data from Lallemand et al. [39] and model predictions by Jung et al. [3] and Liu and Winterton [6].

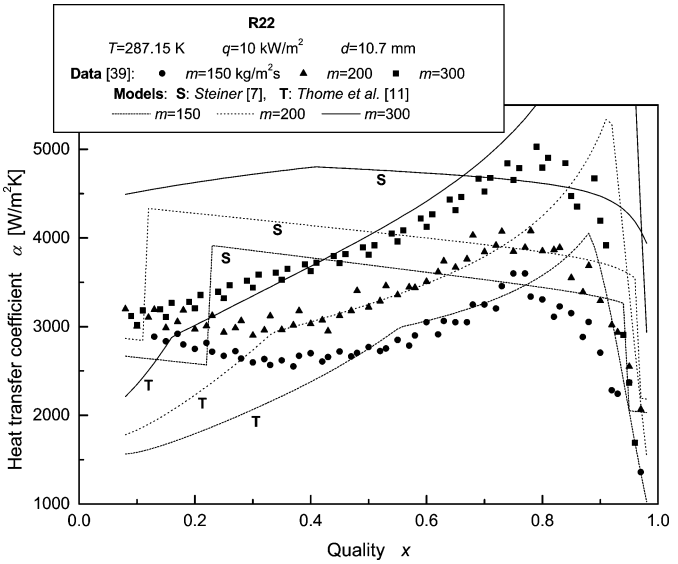

Fig. 7. Fluid R22: heat transfer coefficient α vs. vapor quality $\dot{x}$, parametric in mass flow $\dot{m}$ for assigned values of T_r, $\dot{q}$, d. Experimental data from Lallemand et al. [39] and model predictions by Steiner [7] and Thome [11].

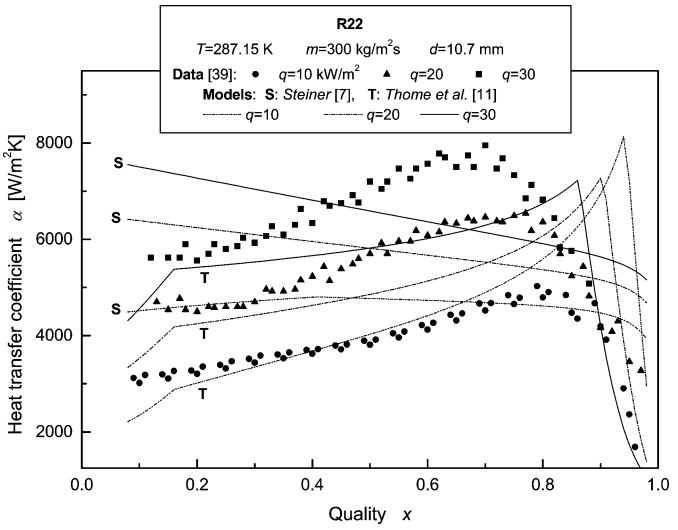

Fig. 8. Fluid R22: heat transfer coefficient α vs. vapor quality $\dot{x}$, parametric in heat flux $\dot{q}$ for assigned values of T_r, $\dot{m}$, d. Experimental data from Lallemand et al. [39] and model predictions by Steiner [7] and Thome [11].

6.2. Conventional heat transfer models

The model of Jung et al. [3] has for R22 a very poor performance, Table 10, with an AAD of 33.71% and a Bias of 31.16% for the Shin et al. [38] and the Choi et al. [12] data together, and an AAD of 26.08% and a Bias of −15.46% for the Lallemand et al. [39] data. The plots of this model parametric in the mass flow rate $\dot{m}$, Fig. 5, show to slightly follow the trend but with too high errors particularly evident al lower quality values. The heat flux $\dot{q}$ dependence, Fig. 6, is absolutely wrongly represented, even without a basic trend prediction.

The model of Liu and Winterton [6] gives for R22 wrong results, even if for both the mass flow rate $\dot{m}$ and the heat flux $\dot{q}$ dependences, Figs. 5 and 6, the general trends are more or less predicted. Among the four conventional models this and the former one have the better performance for R22; in fact Table 10 reports an AAD ranging from 33.19 to 23.10% and a Bias from 30.55 to −16.14% for the two data sets of Shin et al. [38] and the Choi et al. [12], and for the Lallemand et al. [39] data, respectively. The errors are particularly evident at higher values of vapor quality.

The performance of the Steiner [7] model for R22 is the worst among the four conventional models, Table 10, and even if a tentative dependence from the mass flow rate $\dot{m}$ could be roughly outlined the dependence from the heat flux $\dot{q}$ has completely failed reporting high systematic errors, Figs. 7 and 8.

Also the recent model of Thome [11] has for R22 a questionable performance. Both the dependences from the mass flow

Table 12
Crossing the individual MLFN equations application for three fluids

Training					Validation				
Fluid	First author	*NPT*	*AAD* %	*Bias* %	Fluid	Ref.	*NPT*[a]	*AAD* %	*Bias* %
R22	Shin et al. [38] Choi et al. [12] Lallemand et al. [39]	1145	5.31	−0.62	R134a	Shin et al. [38] Choi et al. [12]	485	9.69	2.95
					Argon	Müller et al. [43] Müller-Steinhagen [44]	0[b]	–	–
R134a	Shin et al. [38] Choi et al. [12]	501	4.89	−0.50	R22	Shin et al. [38] Choi et al. [12] Lallemand et al. [39]	863	11.92	−8.49
					Ar	Müller et al. [43] Müller-Steinhagen [44]	23	44.87	−44.87
Argon	Müller et al. [43] Müller-Steinhagen [44]	446	9.67	−1.55	R22	Shin et al. [38] Choi et al. [12] Lallemand et al. [39]	809	28.22	11.24
					R134a	Shin et al. [38] Choi et al. [12]	315	47.69	43.03

[a] Points inside the validity range of the MLFN equation for the fluid of training.
[b] No points inside the validity range of the MLFN equation for the fluid of training.

rate $\dot{m}$ and the heat flux $\dot{q}$ are roughly predicted, Figs. 7 and 8, but the resulting errors are too high for the Shin et al. [38] and the Choi et al. [12] data, even if a more equilibrated result with a very low bias is obtained for the set from Lallemand et al. [39]. The functional dependence from the variable $\dot{x}$ seems to be too much nervous in the region of higher vapor quality leading the model to easily exceed the points to represent. The description of the heat transfer at high vapor quality, in the zone where the coefficient α reaches its maximum value and then decreases due to intermittent dry patches in the upper part of the tube, is also represented with an exaggeratedly abrupt trend when compared with the experimental points. Furthermore, the functional dependence of the heat transfer coefficient α from the heat flux $\dot{q}$, as shown in Fig. 8, is partially misunderstood because higher heat transfer coefficients are obtained at lower heat fluxes, introducing an evident discrepancy with the data.

7. Crossing of the fluid specific MLFN models

The representation of the heat transfer coefficient surfaces for flow boiling inside smooth tube by the proposed method has been shown to be very effective. It has been also demonstrated that the method may be highly suitable to heuristically draw a heat transfer surface only from experimental data of the heat transfer coefficient.

Nevertheless, the correlations that can be drawn from the experimental data are assumed to be fluid specific so that the correlation for a fluid cannot be applied to another one without large errors. The individuality of the heat transfer correlations has been verified applying them to not pertinent fluids and for this study the three fluids R22, R134a, and Argon were chosen. The MLFN equations were systematically crossed from a fluid to the other with the results reported in Table 12. In the training section of the table the training results of the fluid pertinent MLFN equation are summarized. Considering the validation section the results were obtained by applying the MLFN equation for the fluid of training to the data sets of the other two fluids. For each of the two fluids assumed for validation only points inside the validity ranges of the fluid pertinent MLFN equation were used, reducing the NPT of their original data sets.

It results with evidence that the MLFN correlations are fluid specific and it is not allowed to cross their application from fluid to fluid. Only for the two fluoroalkanes R22 and R134a the crossing does not produce totally negative predictions, even if they result shifted.

At saturation condition the reduced temperature T_r is the only independent variable to control both the thermodynamic and the transport properties of each interest fluid. At the mean time the thermodynamic and the transport properties condition each fluid specific heat transfer coefficient. The MLFN equation has only the reduced temperature T_r as thermophysical variable and it does not directly consider the individual thermodynamic and transport properties as influencing variables. Nonetheless, these properties are controlling the individual heat transfer: they are therefore implicitly present in the MLFN equation representing the resulting dependent variable, i.e., the heat transfer coefficient itself. The functional dependences on T_r of the thermodynamic and transport quantities controlling the transport phenomena of flow boiling are fluid specific and in the case a fluid specific MLFN equation is applied for another fluid the thermodynamic and transport properties functional dependences of this new fluid are different, but they have not been identified as a function of the boundary variable T_r like in the case of the original fluid. This is the main reason why the crossing of the MLFN equations fails.

8. Conclusions

The present work shows that in the case of flow boiling of pure fluids inside a horizontal tube the proposed method is

Table 13

R11

I	6	γ	1	$A_{\max}$	0.95
J	9	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv T_r^{\min}$	0.4	$V_{\min,3} \equiv \dot{q}^{\min}$	0	$V_{\min,5} \equiv d^{\min}$	0
$V_{\max,1} \equiv T_r^{\max}$	0.8	$V_{\max,3} \equiv \dot{q}^{\max}$	40000	$V_{\max,5} \equiv d^{\max}$	0.04
$V_{\min,2} \equiv \dot{m}^{\min}$	0	$V_{\min,4} \equiv \dot{x}^{\min}$	0	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,2} \equiv \dot{m}^{\max}$	400	$V_{\max,4} \equiv \dot{x}^{\max}$	1	$W_{\max,1} \equiv \alpha^{\max}$	10000

i	j	w_{ij}
1	1	27.9817536
2	1	701.532165
3	1	−164.349560
4	1	−251.984744
5	1	726.407559
6	1	−252.609525
1	2	346.379805
2	2	−413.221696
3	2	188.018349
4	2	233.623743
5	2	146.664715
6	2	532.608519
1	3	208.289153
2	3	222.415534
3	3	88.0321569
4	3	−171.317599
5	3	251.343919
6	3	77.7388276
1	4	−600.364220
2	4	1215.52694
3	4	197.345129
4	4	701.643208
5	4	873.769908
6	4	−466.776327
1	5	1048.23397
2	5	−2093.71198
3	5	778.246956
4	5	−384.747004
5	5	387.587777
6	5	−205.769312
1	6	1165.64654
2	6	−2189.42985
3	6	1339.40874
4	6	2247.97104
5	6	336.961870
6	6	−694.694410
1	7	1745.59208
2	7	−600.214553
3	7	505.322130
4	7	−266.310831
5	7	711.720979
6	7	−539.260724
1	8	1101.30947
2	8	110.144891
3	8	−76.6450111
4	8	−423.897032
5	8	1531.74018
6	8	−282.046524
1	9	−483.684957
2	9	1019.27117
3	9	264.047924
4	9	573.190710
5	9	746.507525
6	9	−421.914403

j	k	w_{jk}
1	1	−237.184273
2	1	224.215558
3	1	2143.66841
4	1	−449.126898
5	1	−112.431791
6	1	58.3946785
7	1	−1253.54827
8	1	−958.284481
9	1	525.009332
10	1	−111.115766

Data generated for code validation

T_r	$\dot{m}$	$\dot{q}$	$\dot{x}$	d	α
0.58	100	10000	0.3	0.006	3878.96
0.60	50	20000	0.8	0.025	874.46
0.62	150	5000	0.5	0.025	2192.92
0.62	50	2000	0.2	0.014	465.65

R12

I	5	γ	1	$A_{\max}$	0.95
J	7	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv T_r^{\min}$	0.5	$V_{\min,3} \equiv \dot{q}^{\min}$	0	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,1} \equiv T_r^{\max}$	1.0	$V_{\max,3} \equiv \dot{q}^{\max}$	120000	$W_{\max,1} \equiv \alpha^{\max}$	10000
$V_{\min,2} \equiv \dot{m}^{\min}$	0	$V_{\min,4} \equiv \dot{x}^{\min}$	0		
$V_{\max,2} \equiv \dot{m}^{\max}$	1000	$V_{\max,4} \equiv \dot{x}^{\max}$	1		

(*continued on the next page*)

Table 13 (*continued*)

R12

i	j	w_{ij}	i	j	w_{ij}
1	1	−1707.52	3	5	−464.473
2	1	−900.338	4	5	−186.643
3	1	−1403.94	5	5	−77.9072
4	1	177.305	1	6	−2309.01
5	1	475.683	2	6	137.278
1	2	−1923.72	3	6	−2783.00
2	2	425.990	4	6	183.198
3	2	−2.08989	5	6	634.243
4	2	−1522.07	1	7	1485.95
5	2	444.433	2	7	272.492
1	3	435.672	3	7	−10963.8
2	3	−1722.71	4	7	127.148
3	3	45.9731	5	7	−640.156
4	3	−50.3348	j	k	w_{jk}
5	3	312.114	1	1	−1100.61
1	4	−36.5380	2	1	−594.034
2	4	1066.02	3	1	−152.237
3	4	−479.279	4	1	−147.895
4	4	884.297	5	1	−769.155
5	4	−86.0165	6	1	1141.77
1	5	−80.3989	7	1	−2012.36
2	5	−0.166564	8	1	171.271

Data generated for code validation

T_r	$\dot{m}$	$\dot{q}$	$\dot{x}$	α
0.66	400	1000	0.5	7960.62
0.69	300	60000	0.2	4067.08
0.72	200	20000	0.7	2204.19
0.75	100	5000	0.4	936.40

R22

I	5	γ	1	$A_{\max}$	0.95
J	7	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv T_r^{\min}$	0.5	$V_{\min,3} \equiv \dot{q}^{\min}$	0	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,1} \equiv T_r^{\max}$	1.0	$V_{\max,3} \equiv \dot{q}^{\max}$	40000	$W_{\max,1} \equiv \alpha^{\max}$	10000
$V_{\min,2} \equiv \dot{m}^{\min}$	0	$V_{\min,4} \equiv \dot{x}^{\min}$	0		
$V_{\max,2} \equiv \dot{m}^{\max}$	1500	$V_{\max,4} \equiv \dot{x}^{\max}$	1		

i	j	w_{ij}	i	j	w_{ij}
1	1	−5047.40	3	5	−711.000
2	1	230.834	4	5	22.7179
3	1	−1483.69	5	5	−172.747
4	1	−2201.01	1	6	−4934.50
5	1	4934.61	2	6	937.541
1	2	286.779	3	6	2448.20
2	2	−479.257	4	6	−2058.09
3	2	864.215	5	6	1083.90
4	2	−649.962	1	7	−8477.47
5	2	198.306	2	7	5921.67
1	3	−74.4716	3	7	525.733
2	3	−82.5864	4	7	93.8153
3	3	−1093.86	5	7	3084.29
4	3	597.836	j	k	w_{jk}
5	3	−137.685	1	1	212.095
1	4	8232.97	2	1	−393.581
2	4	−5659.02	3	1	−331.315
3	4	−672.056	4	1	−1026.46
4	4	−99.2162	5	1	−3509.13
5	4	−2996.07	6	1	−1186.20
1	5	−300.617	7	1	−1042.29
2	5	171.244	8	1	1207.30

(*continued on the next page*)

Table 13 (*continued*)

R22					
Data generated for code validation					
T_r	$\dot{m}$	$\dot{q}$	$\dot{x}$	α	
0.71	900	5000	0.5	2846.50	
0.72	700	30000	0.2	4003.46	
0.74	500	20000	0.7	6214.82	
0.76	300	10000	0.4	2983.22	

R32					
I	5	γ	1	$A_{\max}$	0.95
J	7	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv T_r^{\min}$	0.5	$V_{\min,3} \equiv \dot{q}^{\min}$	0	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,1} \equiv T_r^{\max}$	1.0	$V_{\max,3} \equiv \dot{q}^{\max}$	40000	$W_{\max,1} \equiv \alpha^{\max}$	12000
$V_{\min,2} \equiv \dot{m}^{\min}$	0	$V_{\min,4} \equiv \dot{x}^{\min}$	0		
$V_{\max,2} \equiv \dot{m}^{\max}$	1200	$V_{\max,4} \equiv \dot{x}^{\max}$	1		

i	j	w_{ij}	i	j	w_{ij}
1	1	−1608.05	3	5	−670.202
2	1	−3342.33	4	5	7002.91
3	1	219.875	5	5	1502.46
4	1	−735.670	1	6	8000.37
5	1	3472.54	2	6	−573.206
1	2	4700.93	3	6	113.791
2	2	1285.14	4	6	398.877
3	2	−1095.15	5	6	−5237.47
4	2	111.268	1	7	−862.074
5	2	−1819.36	2	7	−1007.21
1	3	972.211	3	7	−475.849
2	3	3628.34	4	7	846.819
3	3	−534.050	5	7	592.064
4	3	3002.88	j	k	w_{jk}
5	3	−1387.43	1	1	−1046.88
1	4	−21.5397	2	1	1813.25
2	4	−39.0634	3	1	−1285.50
3	4	51.8805	4	1	1305.40
4	4	178.952	5	1	−77.0599
5	4	−107.819	6	1	−3402.83
1	5	−4156.34	7	1	−233.085
2	5	951.218	8	1	179.713

Data generated for code validation				
T_r	$\dot{m}$	$\dot{q}$	$\dot{x}$	α
0.75	850	15000	0.3	7772.47
0.77	650	30000	0.2	7226.19
0.79	450	10000	0.6	6646.28
0.81	250	20000	0.4	2305.15

R134a					
I	5	γ	1	$A_{\max}$	0.95
J	7	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv T_r^{\min}$	0.5	$V_{\min,3} \equiv \dot{q}^{\min}$	0	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,1} \equiv T_r^{\max}$	1.0	$V_{\max,3} \equiv \dot{q}^{\max}$	120000	$W_{\max,1} \equiv \alpha^{\max}$	10000
$V_{\min,2} \equiv \dot{m}^{\min}$	0	$V_{\min,4} \equiv \dot{x}^{\min}$	0		
$V_{\max,2} \equiv \dot{m}^{\max}$	1500	$V_{\max,4} \equiv \dot{x}^{\max}$	1		

(*continued on the next page*)

Table 13 (*continued*)

R134a

i	j	w_{ij}	i	j	w_{ij}
1	1	−8297.56	3	5	−1222.70
2	1	−555.081	4	5	433.322
3	1	−1410.28	5	5	332.442
4	1	4037.79	1	6	−1722.75
5	1	140.785	2	6	912.601
1	2	−3196.79	3	6	−652.214
2	2	542.972	4	6	358.492
3	2	−3.20690	5	6	483.856
4	2	3633.94	1	7	750.285
5	2	1449.70	2	7	5584.17
1	3	−668.777	3	7	2111.58
2	3	292.180	4	7	4922.50
3	3	−598.767	5	7	−7326.02
4	3	−112.089	j	k	w_{jk}
5	3	241.972	1	1	−4599.39
1	4	−707.684	2	1	−949.132
2	4	672.680	3	1	−578.727
3	4	0.153170	4	1	−466.557
4	4	700.622	5	1	−278.863
5	4	−2467.25	6	1	270.117
1	5	−1001.91	7	1	−2922.30
2	5	−51.6420	8	1	958.104

Data generated for code validation

T_r	$\dot{m}$	$\dot{q}$	$\dot{x}$	α
0.72	800	15000	0.4	4588.49
0.73	650	30000	0.2	5210.09
0.75	450	5000	0.9	3198.94
0.77	250	20000	0.6	4174.74

R290

I	4	γ	1	$A_{\max}$	0.95
J	5	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv \dot{m}^{\min}$	0	$V_{\max,2} \equiv \dot{q}^{\max}$	40000	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,1} \equiv \dot{m}^{\max}$	1200	$V_{\min,3} \equiv \dot{x}^{\min}$	0	$W_{\max,1} \equiv \alpha^{\max}$	12000
$V_{\min,2} = \dot{q}^{\max}$	0	$V_{\max,3} \equiv \dot{x}^{\max}$	1		

i	j	w_{ij}	i	j	w_{ij}
1	1	−331.416481	3	4	83.8805399
2	1	89.596744	4	4	−2.53465011
3	1	728.473882	1	5	12.9380996
4	1	147.063148	2	5	−61.9220156
1	2	33.3711280	3	5	−1612.25128
2	2	−221.061503	4	5	−29.2364898
3	2	96.3941756	j	k	w_{jk}
4	2	18.0667975	1	1	707.524702
1	3	−608.523100	2	1	−230.326840
2	3	397.507216	3	1	−298.740430
3	3	−567.323708	4	1	−787.173516
4	3	245.046690	5	1	1014.16478
1	4	−53.7911510	6	1	−127.420726
2	4	−98.4427001			

Data generated for code validation

$\dot{m}$	$\dot{q}$	$\dot{x}$	α
300	30000	0.4	5325.09
400	25000	0.2	4520.71
500	20000	0.8	8228.99
550	10000	0.6	7190.42

(*continued on the next page*)

Table 13 (*continued*)

R600a

I	4	γ	1	$A_{\max}$	0.95
J	5	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv \dot{m}^{\min}$	0	$V_{\max,2} \equiv \dot{q}^{\max}$	40000	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,1} \equiv \dot{m}^{\max}$	1200	$V_{\min,3} \equiv \dot{x}^{\min}$	0	$W_{\max,1} \equiv \alpha^{\max}$	12000
$V_{\min,2} = \dot{q}^{\max}$	0	$V_{\max,3} \equiv \dot{x}^{\max}$	1		

i	j	w_{ij}	i	j	w_{ij}
1	1	−503.155994	3	4	8.01314787
2	1	57.0472112	4	4	−774.764215
3	1	−1002.65469	1	5	−928.074252
4	1	132.633589	2	5	612.461079
1	2	−678.315766	3	5	−3861.62610
2	2	−89.1308264	4	5	657.218441
3	2	−693.032867	j	k	w_{jk}
4	2	269.343058	1	1	634.137466
1	3	−1422.91323	2	1	−478.918244
2	3	−249.867508	3	1	−945.654645
3	3	−178.482201	4	1	−1333.83388
4	3	896.616246	5	1	−79.6592453
1	4	1225.05012	6	1	915.844927
2	4	159.720121			

Data generated for code validation

$\dot{m}$	$\dot{q}$	$\dot{x}$	α
300	30000	0.4	5058.33
400	25000	0.2	4336.78
500	20000	0.8	10487.92
550	10000	0.6	8165.35

Argon

I	5	γ	1	$A_{\max}$	0.95
J	7	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv T_r^{\min}$	0.5	$V_{\min,3} \equiv \dot{q}^{\min}$	0	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,1} \equiv T_r^{\max}$	1.0	$V_{\max,3} \equiv \dot{q}^{\max}$	120000	$W_{\max,1} \equiv \alpha^{\max}$	15000
$V_{\min,2} \equiv \dot{m}^{\min}$	0	$V_{\min,4} \equiv \dot{x}^{\min}$	0		
$V_{\max,2} \equiv \dot{m}^{\max}$	800	$V_{\max,4} \equiv \dot{x}^{\max}$	1		

i	j	w_{ij}	i	j	w_{ij}
1	1	−559.958834	3	5	1273.46952
2	1	−3617.84571	4	5	212.470780
3	1	−1801.26205	5	5	−751.498691
4	1	1113.47595	1	6	−407.552071
5	1	779.166185	2	6	−607.571984
1	2	2503.97393	3	6	871.135421
2	2	22.3420532	4	6	22833.5457
3	2	−5232.40003	5	6	−304.653506
4	2	1.63655805	1	7	212.401900
5	2	−1808.60635	2	7	−134.010080
1	3	6648.32565	3	7	−412.704481
2	3	−3908.13711	4	7	968.802470
3	3	−6056.54138	5	7	−82.8624285
4	3	3733.50380	j	k	w_{jk}
5	3	−4739.35797	1	1	−107.217713
1	4	−206.034807	2	1	−3805.14885
2	4	−113.051268	3	1	32.7219097
3	4	−116.556618	4	1	−1150.73531
4	4	−513.482384	5	1	−1469.91082
5	4	−8.30505692	6	1	4610.05501
1	5	3322.44488	7	1	−156.124724
2	5	691.966932	8	1	−3052.53816

(*continued on the next page*)

Table 13 (*continued*)

Argon				
Data generated for code validation				
T_r	$\dot{m}$	$\dot{q}$	$\dot{x}$	α
0.65	450	20000	0.6	4450.53
0.70	350	70000	0.1	7328.30
0.75	250	1000	0.8	2538.96
0.85	150	50000	0.4	4618.30

R407c					
I	5	γ	1	$A_{\max}$	0.95
J	7	β	0.005	*Bias* 1	1
K	1	$A_{\min}$	0.05	*Bias* 2	1
$V_{\min,1} \equiv T_r^{\min}$	0.5	$V_{\min,3} \equiv \dot{q}^{\min}$	0	$W_{\min,1} \equiv \alpha^{\min}$	0
$V_{\max,1} \equiv T_r^{\max}$	1.0	$V_{\max,3} \equiv \dot{q}^{\max}$	40000	$W_{\max,1} \equiv \alpha^{\max}$	12000
$V_{\min,2} \equiv \dot{m}^{\min}$	0	$V_{\min,4} \equiv \dot{x}^{\min}$	0		
$V_{\max,2} \equiv \dot{m}^{\max}$	1200	$V_{\max,4} \equiv \dot{x}^{\max}$	1		

i	j	w_{ij}	i	j	w_{ij}
1	1	−66.1421	3	5	−86.9470
2	1	−500.163	4	5	510.734
3	1	−842.114	5	5	83.3458
4	1	−45.3918	1	6	1112.58
5	1	661.615	2	6	−391.073
1	2	−199.890	3	6	286.508
2	2	480.456	4	6	−801.173
3	2	−1864.28	5	6	−319.679
4	2	−111.567	1	7	38.3943
5	2	349.591	2	7	−1131.06
1	3	−330.843	3	7	135.986
2	3	170.262	4	7	−175.338
3	3	511.965	5	7	327.724
4	3	−164.072	j	k	w_{jk}
5	3	−2.93739	1	1	−258.019
1	4	−875.627	2	1	−151.704
2	4	71.6287	3	1	−290.015
3	4	−420.720	4	1	−208.033
4	4	882.096	5	1	−537.364
5	4	286.975	6	1	−534.339
1	5	−599.893	7	1	−195.539
2	5	513.309	8	1	1031.76

Data generated for code validation				
T_r	$\dot{m}$	$\dot{q}$	$\dot{x}$	α
0.72	850	10000	0.4	2776.11
0.75	650	25000	0.2	5192.30
0.78	450	2000	0.9	2304.77
0.81	250	20000	0.6	2612.18

highly suitable for heuristically deriving the heat transfer coefficient surface of a target fluid from experimental data alone.

The application of the method to the real context of literature experimental data makes it evident that the error noise becomes an important drawback that reduces the final accuracy of the regressed surface. As shown earlier, the data have to satisfy some basic requirements: they have to form a domain as compact as possible in the independent variables; scattered data sets should be avoided within the validity ranges of the equation; the data points should be evenly distributed on an ideal grid of the independent variables. These conditions are largely lacking for the data currently available in the literature and this greatly prevents the study of flow boiling and much more the use of heuristic methods for which the data distribution and their screening are extremely important elements.

Eight pure fluids and a constant composition ternary mixture have been studied and for each of them an individual MLFN heat transfer equation has been drawn from data. For seven of the nine cases the training results are in general of few parts per cent with biases virtually null.

In particular, a total of 5236 experimental points formed the data base for the present study and the MLFN equations were

trained on a total of 4803 points with an overall AAD of 7.72% and a an overall bias of −1.62%. But, excluding the two fluids R12 and Ar presenting lower performances, for the 3791 points of the remainder six pure fluids and the mixture the training reached an overall AAD of 4.45% and a bias of −0.44% which is an excellent result because these figures are evidently lower than the current experimental uncertainties for heat transfer measurements in flow boiling.

Both the validation of the obtained relations and their comparison with five conventional heat transfer equations show the promising validity of the method and indicate that an MLFN equation in the physical variables is very effective. It should be borne in mind that the introduction of the individual equations of state and transport property equations of a target fluid into a conventional heat transfer correlation turns it into a fluid specific one in the operative physical variables, analogous to the MLFN heat transfer equations here developed.

In the case of the availability of regularly distributed data for several fluids, with overlapping ranges, the heat transfer equations could be studied in more detail and the problem would be worth examining experimentally from this new heuristic point of view. In addition to the data distribution, the experimental quality of the data and their availability become then the key elements in the present case.

Moreover, the assumed variables of this model architecture coincide with the experimentally accessible physical variables, avoiding the need for any thermodynamic and transport property model for the target fluid.

It is also worth noting that the method can be used to check the consistency of new data sets before using them for processing.

When the outlined requirements are strictly met the method proves capable to always "converge" to a reliable formulation, drawing a high-accuracy heat transfer correlation at the limit of the experimental uncertainty for the present difficult problem.

References

[1] J.C. Chen, Correlation for boiling heat transfer to saturated fluids in convective flow, Ind. Engrg. Chem. Process Des. Dev. 5 (1966) 322–329.

[2] D.S. Jung, M. McLinden, R. Radermacher, D. Didion, Horizontal flow boiling heat transfer experiments with a mixture of R22/R114, Int. J. Heat Mass Transfer 32 (1989) 131–145.

[3] D.S. Jung, M. McLinden, R. Radermacher, D. Didion, A study of flow boiling heat transfer with refrigerant mixtures, Int. J. Heat Mass Transfer 32 (1989) 1751–1764.

[4] D.S. Jung, R. Radermacher, Prediction of evaporation heat transfer coefficient and pressure drop of refrigerant mixtures in horizontal tubes, Int. J. Refrig. 16 (1993) 201–209.

[5] D.S. Jung, R. Radermacher, Prediction of evaporation heat transfer coefficient and pressure drop of refrigerant mixtures, Int. J. Refrig. 16 (1993) 330–338.

[6] Z. Liu, R.H.S. Winterton, A general correlation for saturated and subcooled flow boiling in tubes and annuli, based on a nucleate pool boiling equation, Int. J. Heat Mass Transfer 34 (1991) 2759–2766.

[7] D. Steiner, Heat transfer to boiling saturated liquids, in: VDI Heat Atlas, Section Hbb, VDI-Verlag, Düsseldorf, 1993.

[8] N. Kattan, J.R. Thome, D. Favrat, Flow boiling in horizontal tubes, Part 3: Development of a new heat transfer model based on flow patterns, J. Heat Transfer 120 (1998) 156–165.

[9] O. Zürcher, D. Favrat, J.R. Thome, Development of a diabatic two-phase flow pattern map for horizontal flow boiling, Int. J. Heat Mass Transfer 45 (2002) 291–301.

[10] J.R. Thome, J. El Hajal, Two-phase flow pattern map for evaporation in horizontal tubes: latest version, Heat Transfer Engrg. 24 (6) (2003) 3–10.

[11] J.R. Thome, On recent advances in modeling of two-phase flow and heat transfer, Heat Transfer Engrg. 24 (6) (2003) 46–59.

[12] T.Y. Choi, Y.J. Kim, M.S. Kim, S.T. Ro, Evaporation heat transfer of R-32, R-134a, R-32/134a, and R-32/125/134a inside a horizontal smooth tube, Int. J. Heat Mass Transfer 43 (2000) 3651–3660.

[13] O. Zürcher, J.R. Thome, D. Favrat, In-tube flow boiling of R-407C and R-407C/oil mixtures. Part II: Plain tube results and predictions, HVAC&R Research 4 (1998) 373–399.

[14] R. Span, Multiparameter Equations of State, Springer, Berlin, 2000.

[15] G. Cristofoli, L. Piazza, G. Scalabrin, A viscosity equation of state for R134a through a multi-layer feedforward neural network technique, Fluid Phase Equilibria 199 (2002) 223–236.

[16] G. Scalabrin, G. Cristofoli, The viscosity surfaces of propane in the form of multilayer feed forward neural networks, Int. J. Thermophys. 24 (2003) 1241–1263.

[17] J. Thibault, B.P.A. Grandjean, A neural network methodology for heat transfer data analysis, Int. J. Heat Mass Transfer 34 (1991) 2063–2070.

[18] K. Jambunathan, S.L. Hartle, S. Ashforth-Frost, V.N. Fontama, Evaluating convective heat transfer coefficients using neural networks, Int. J. Heat Mass Transfer 39 (1996) 2329–2332.

[19] G. Scalabrin, L. Piazza, Analysis of forced convection heat transfer to supercritical carbon dioxide inside tubes using neural networks, Int. J. Heat Mass Transfer 46 (2003) 1139–1154.

[20] G. Scalabrin, L. Piazza, M. Condosta, Convective cooling of supercritical carbon dioxide inside tubes: heat transfer analysis through neural networks, Int. J. Heat Mass Transfer 46 (2003) 4413–4425.

[21] G. Cybenko, Approximation by superposition of a sigmoidal function, Math. Control Signals and Systems 2 (1989) 303–314.

[22] K. Hornik, M. Stinchcombe, H. White, Multilayer feedforward networks are universal approximators, Neural Networks 2 (1989) 359–366.

[23] V. Kůrková, Kolmogorov's theorem and multilayer neural networks, Neural Networks 5 (1992) 501–506.

[24] G. Scalabrin, G. Cristofoli, D. Richon, Viscosity equations of pure fluids in an innovative extended corresponding states framework. I. Modeling techniques, Fluid Phase Equilibria 199 (2002) 265–280.

[25] G. Scalabrin, G. Cristofoli, D. Richon, Viscosity equations of pure fluids in an innovative extended corresponding states framework. II. Application to four fluids, Fluid Phase Equilibria 199 (2002) 281–294.

[26] G. Scalabrin, G. Cristofoli, M. Grigiante, A corresponding states predictive viscosity model based on a new scaling parameter: Application to hydrocarbons, halocarbons and mixtures, Int. J. Energy Research 26 (1) (2002) 1–26.

[27] G. Scalabrin, L. Piazza, G. Cristofoli, A corresponding states thermodynamic model for pure and mixed refrigerants in terms of the Helmholtz energy, Fluid Phase Equilibria 199 (2002) 79–99.

[28] G. Scalabrin, L. Piazza, M. Grigiante, M. Baruzzo, Thermal conductivity modeling of pure refrigerants in a three-parameter corresponding states format, Int. J. Thermophys. 26 (2005) 373–398.

[29] G. Scalabrin, L. Piazza, M. Grigiante, M. Baruzzo, Thermal conductivity modeling of refrigerant mixtures in a three-parameter corresponding states format, Int. J. Thermophys. 26 (2005) 399–412.

[30] G. Scalabrin, M. Grigiante, G. Cristofoli, L. Piazza, A predictive density model in a corresponding states format. Application to pure and mixed refrigerants, Int. J. Refrig. 26 (2003) 35–50.

[31] G. Scalabrin, M. Grigiante, G. Cristofoli, Modeling enthalpy and entropy of pure and mixed refrigerants with an innovative corresponding states method, Int. J. Refrig. 26 (2003) 936–950.

[32] M.O. McLinden, S.A. Klein, E.W. Lemmon, A.P. Perkin, NIST Standard Reference Database 23—REFPROP, Version 6.01, National Institute of Standards and Technology, 1998.

[33] J.M. Chawla, Wärmeübergang und Druckabfall in waagerechten Rohren bei der Strömung von verdampfenden Kältemitteln, VDI-Forschungsheft, vol. 523, VDI-Verlag, Düsseldorf, 1967.

[34] H. Schmidt, Beitrag zum Verständnis des Wärmeübergangs im horizontalen Verdampferrohr, Fortschr.-Ber. VDI, Reihe 19, vol. 6, VDI-Verlag, Düsseldorf, 1986.
[35] A.A. Malyschev, G.N. Danilova, W.M. Azarskov, Kolodilnaja Technika 8 (1982) 30–34.
[36] E. Hihara, T. Saito, Forced convective boiling experiments of binary mixtures, JSME Int. J. 32 (1989) 98–106.
[37] J.P. Wattelet, J.C. Chato, A.L. Souza, B.R. Christoffersen, Evaporative characteristics of R-12, R-134a, and a mixture at low mass fluxes, ASHRAE Trans. 100 (1994) 603–615.
[38] J.Y. Shin, M.S. Kim, S.T. Ro, Experimental study on forced convective boiling heat transfer of pure refrigerants and refrigerant mixtures in a horizontal tube, Int. J. Refrig. 20 (1997) 267–275.
[39] M. Lallemand, C. Branescu, P. Haberschill, Local heat transfer coefficients during boiling of R22 and R407C in horizontal smooth and microfin tubes, Int. J. Refrig. 24 (2001) 57–72.
[40] C.C. Wang, C.S. Kuo, Y.J. Chang, D.C. Lu, Two-phase flow heat transfer and friction characteristics of R-22 and R-407C, ASHRAE Trans. 102 (1996) 830–838.
[41] R. Yun, J.H. Hwang, Y.C. Kim, in: Proceedings of the Joint Meeting of IIR, Comm. B1, Paderborn, Germany, 2001/5.
[42] L. Zhang, E. Hihara, T. Saito, J.T. Oh, Boiling heat transfer of a ternary refrigerant mixture inside a horizontal smooth tube, Int. J. Heat Mass Transfer 40 (1997) 2009–2017.
[43] H.M. Müller, W. Bonn, D. Steiner, in: J. Taborek, G.F. Hewitt, N. Afgan (Eds.), Heat Exchangers: Theory and Practice, Hemisphere, Washington, DC, 1983.
[44] H. Müller-Steinhagen, D. Steiner, Wärmeübergang beim Strömungssieden von Argon in einem horizontalen Rohr, Chem. Engrg. Process. 20 (1986) 201–212.