International Journal of Heat and Mass Transfer 62 (2013) 481–494

Contents lists available at SciVerse ScienceDirect

International Journal of Heat and Mass Transfer

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

Combination of support vector regression and artificial neural networks for prediction of critical heat flux

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ARTICLE INFO

Article history:
Received 26 December 2012
Received in revised form 8 March 2013
Accepted 9 March 2013
Available online 9 April 2013

Keywords:
Support vector regression
Critical heat flux
Annealing robust back propagation
Back-propagation network

ABSTRACT

This paper presents a hybrid model that couples ν-support vector regression (ν-SVR) with radial basis function networks (RBFNs) for prediction of critical heat flux (CHF). The hybrid model is achieved in two steps. The first step is to determine the initial architecture and initial weights of the hybrid model by an ν-SVR. The second step is to adjust the initial weights using an annealing robust back propagation (ARBP) learning algorithm. Then the hybrid model is used to predict CHF, which is divided into two parts: prediction of CHF for water flow in vertical round tubes and prediction of dryout type CHF for deionized water upflowing through a narrow annular channel with 0.95 mm gap. The dataset used in this paper is taken from literature. In the first part, prediction of CHF and analysis of parametric trends of CHF are both carried out based on three conditions, fixed inlet conditions, local conditions and fixed outlet conditions. The predicted results agree better with the corresponding dataset than that of ε-SVR. In the second part, the predicted results are in better agreement with the experimental data than that of back-propagation network (BPN) employed in the literature. Therefore, the hybrid model presented in this paper is a potential tool for predicting CHF and has advantages over other methods.

1. Introduction

Critical heat flux (CHF) has been thought as one of the most important parameters in the design and operation of high heat flux systems, such as pressurized water reactors, steam generators and other boiling heat transfer units. Nuclear reactors are deigned to receive maximum efficiency under full working power and its efficiency will be improved when the core exit temperature increases. In this case, the nuclear reactors shall be designed with appropriate thermal margin to assure that specified acceptable fuel design limits are not exceeded during any condition of normal operation. Thus, the thermal margin has a vital importance in the design and safety assessment of nuclear reactors. However, in the thermo hydraulic design of nuclear reactor, CHF limits the heat flux from the fuel rods and the power capabilities of nuclear reactors. The CHF condition is characterized by a sharp reduction of the local heat transfer coefficient that results from the replacement of liquid by vapor adjacent to the heat transfer surface [1,2]. For a nuclear reactor core, exceeding CHF can lead to a sudden large increase in cladding temperature due to the relatively poor heat transfer characteristics of vapor, which for most coolants, can lead to a catastrophic failure of nuclear fuel.

The ability to predict CHF is therefore a vital issue for the performance and the safety of nuclear reactors. CHF prediction in nuclear reactors could be useful to know the real causes of the failure, like the burnout of tubes or leaks that appear as consequences of an accelerated process of corrosion caused by the high temperature reached in the material. A considerable amount of significant experimental and theoretical research concerning CHF has been performed over the last five decades with the development of water cooled nuclear reactors. As a result of these efforts, several prediction methodologies have been developed to predict CHF. They can be categorized as three principal approaches: look-up tables, empirical correlations and phenomenological models.

Although many analytical and experimental studies on CHF have been presented in the literature, it would be incorrect to say that a commonly shared apprehension of this problem has been established [3] because CHF is a complex phenomenon and is influenced by many parameters. Even these three principle approaches have their own limitations, which are described below. Firstly, Tong and Tang [4] evaluated look-up tables and empirical correlations and summarized the limitations of these two methods as follows. On the one hand, the Groeneveld CHF look-up table [5,6] does not provide much more convenience when it is applied to reactor design, since in this case proper adjustments for detailed geometrical effects of a prototype rod bundle would be needed. Such adjustments are usually expressed in empirical formulae that are as complicated as the existing CHF design correlations. On the

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http://dx.doi.org/10.1016/j.ijheatmasstransfer.2013.03.025

Nomenclature

b	bias of the final regression function
D	tube diameter (m)
G	mass flow rate (kg/m^2 s)
ID	inner diameter (mm)
OD	outer diameter (mm)
Q_{CHF}	critical heat flux (kW/m^2)
q_o	heat flux of outside tube (kW/m^2)
$\mathbf{w}$	support vector weight
X	exit quality
C	regularization parameter
dH	hydraulic diameter (m)
H_{fg}	latent heat of vaporization (kJ/kg)
L/dH	length to hydraulic to diameter ratio
P	pressure (MPa)
q_i	heat flux of inside tube (kW/m^2)
$\mathbf{u}$	weight of the network
X_e	equilibrium quality
X_c	critical quality

Greek symbols

ν	tunable parameter
ξ_i	slack variable
β	deterministic annealing schedule
η	learning constant
Δh_i	inlet subcooling (kJ/kg)
ε	insensitivity zone
α	lagrangian multiplier
λ	weight of the network
φ	influence function

other hand, a CHF correlation is accurate only in the particular flow regimes within the ranges of the operating parameters in which it was developed, thus the application of CHF correlations should be limited to within these ranges of parameters. Secondly, the limitations of phenomenological models are also summarized as follows. Phenomenological models were initiated in the 1970s [7] and fined tuned in the 1990s [8]. Although the phenomenological approach is the most reliable as it is a mechanistic model, it does require a lot of empirical input in the form of rates of entrainment and redeposition, etc. [9]. Therefore, there has not yet developed a universal correlation for CHF prediction up to now.

Alternatively, advanced information processing approaches and numerical optimization techniques have been applied to predict CHF. In the past two decades, artificial neural networks (ANNs), as one of artificial intelligence (AI) techniques, have been used to predict CHF. There have been many studies on this topic. Most of them were summarized in Table 4 of [10] and the others were reported in the references [11,12]. Besides, genetic algorithm (GA), as one of the optimization techniques, has also been used to predict CHF [13]. Generally, these above studies can be divided into two categories: one is that ANNs alone were used to predict CHF and the other is that ANNs were combined with other techniques to predict CHF. In the first category, one commonly used type of ANNs was back-propagation network (BPN), since BPN has the characteristics of simple structure and easy implementation. Besides, two other types of ANNs, radial basis function networks (RBFNs) and high order neural network (HONN), were also used in this category. In the second category, ANNs were combined with wavelet transform [11], fuzzy theory [12] and GA [14] for CHF prediction and approximation. Additionally, as can be seen from Table 4 of [10], some other researchers proposed adaptive network-based fuzzy inference systems (ANFIS) and genetic neural network (GNN) to predict CHF. Both ANFIS and GNN methods were also a combination of ANNs and fuzzy theory, GA. Compared with using ANNs alone, those methods combined with the advantages of ANNs and other techniques. In the GNN method, GA was used to optimize the weight and threshold of BPN. In the proposed nonparametric model of [14], GA was used to find useful input features in BPN. Thus, an accurate degree of CHF prediction and approximation was obtained by these methods. Compared with conventional modeling approaches, ANNs do not require a deep knowledge of CHF phenomena or their best-fit correlations. However, ANNs have some limitations due to the algorithm itself, such as depending on researchers experience or knowledge to select structure parameters, difficulty in coming up with a reasonable interpretation of the overall structure of the network [15], and easily getting stuck in a local minimum.

Recently, support vector regression (SVR) is considered to be a promising technique that can overcome the drawbacks of ANNs. SVR is the application of support vector machine (SVM) to the general regression problem. SVM, originally developed by Vapnik and his colleagues [16], is a machine learning method based on statistical learning theory (SLT). SVR implements the structural risk minimization principle (SRM) principle, which has been shown to be superior to the traditional empirical risk minimization (ERM) principle employed by conventional ANNs. It is the difference that equips SVR with many attractive features and good generalization performance, which is the goal in statistical learning. In the last few years, SVR has been used as an alternative method to ANNs in many nuclear engineering applications [17–23]. In [17,18], SVR alone was applied to two different prediction problems. In [19,20], SVR was combined with GA, in which GA was used to optimize the parameters of SVR. In [21–23], SVR was used to predict departure from nucleate boiling ratio (DNBR), which is an important design parameter for water-cooled reactors. As we all know, departure from nucleate boiling (DNB) is one type of CHF. Although these studies have been carried out in various areas of nuclear engineering, few studies have been conducted on the use of SVR for prediction of CHF with the exception of studies by Cai [24,25]. In [24,25], SVM was applied to predict CHF in concentric-tube open thermosiphon. The parameters of SVM were optimized using a stepwise searching method [24] and chaotic particle swarm optimization (CPSO) [25]. However, the effect of various input parameters on CHF, which was important to develop reliable prediction models, was not investigated in [24,25].

In this paper, a hybrid model that combines ν-SVR and RBFNs is presented to predict CHF. The proposed hybrid model is based on the following two considerations. First, there are two common types of SVR based on different loss functions, ε-SVR and its modified version, ν-SVR. All SVR used in [17–25] were ε-SVR. However, a shortcoming of ε-SVR is that it is difficult to choose an appropriate value of ε- in practice. To avoid this difficulty, Schölkopf et al. [26] proposed ν-SVR, which introduces a new parameter ν in the primal problem to trade-off the tube size against model complexity and empirical risk. We thus choose ν-SVR in our hybrid model. Second, because the kernels of the ν-SVR are similar to the basis functions of the RBFNs with scatter partitioning [27], we use RBFNs as another component of our hybrid model. However, since RBFNs are a kind of ANNs, they also have the disadvantages of ANNs. One disadvantage is that it is difficult to determine the number of neurons