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Study on dryout point by wavelet and GNN

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ABSTRACT

In this study, the local modulus maxima of cubic B-spline wavelet transform is introduced to determine the location of dryout point. Based on genetic algorithm and artificial neural network, a Genetic Neural Network (GNN) model predicting dryout-type critical heat flux (CHF) for flowing upward in vertical narrow annuli with bilateral heating has been developed. The GNN mode has some advantages of its global optimal searching, quick convergence speed and solving non-linear problem. The methods of establishing the model and training of GNN are discussed in the article. The mainly parametric trends of the CHF are analyzed by applying GNN. The results agree well with practical behavior as they are generally understood. They proved the validity of GNN. At last, the prediction of dryout point is investigated by GNN with distilled water flowing upward through narrow annular channel with 0.95 mm and 1.5 mm gaps, respectively. The GNN prediction results have a good agreement with experimental data. Simulation and analysis results show that the network model can effectively predict CHF.

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1. Introduction

Critical heat flux (CHF) is one of the most important quantities when considering the safety limits of nuclear reactors, steam generators, and other thermal units. Various mechanisms for the onset of the CHF conditions have been proposed. In general, they may roughly be classified into the departure from nucleate boiling (DNB) and the dryout of liquid film (DO) [1]. From the point of view of engineering, the dryout-type CHF caused by the latter mechanism is of particular importance since boiling annular flow is one of the most common flow patterns in vapor–liquid two-phase flow and it occurs in a wide range of vapor equilibrium quality of interest. Dryout is an important limiting phenomenon in the design of heat exchangers. The study of dryout heat transfer has received considerable attention because of its importance in determination of maximum wall temperature in nuclear reactors, steam generators, and other thermal units. The position of the dryout point can provide us with useful information on the design and operating range of microheat pipes.

A large number of experimental and theoretical studies [2–5] have been conducted over the past several decades to understand and quantify the processes leading to dryout in a heat exchanger tube. Hetsroni et al. [6] studied the dryout phenomenon that may occur in some flows. The information about physical mechanisms leading to the dryout is obtained by analyzing the hydrodynamic behavior of air–water flow in an 88 inclined tube of inner diameter 25 mm. The dryout phenomenon at low mass velocities and pressures is investigated by Kuzma-Kichta et al. [7]. Tian et al. [8] studied the dryout point in vertical narrow annuli. They developed an empirical correlation to calculate dryout quality based on Kutateladze correlation, which has a good agreement with experimental data. An experimental research on the dryout point of flow boiling in narrow annular channels is performed by Wu et al. [9]. They discussed the parametric trends of CHF. Moreover, a criterion of the appearance of DO point for bilateral heating is presented. The prediction of DNB and DO point is the most crucial in designing transfer units such as nuclear reactors and steam generators. Therefore, the study on DO point in bilaterally heated narrow annuli under low flow rate condition is discussed. A new method GNN for predicting the DO point is given. Simulation and analysis results show that the network model can effectively predict the dryout-type CHF.

In this study, we employ the local modulus maxima of cubic B-spline wavelet transform to determine the location of DO. Wavelet analysis is a kind of methods that have the characteristics of time–frequency analysis. Comparing with Fourier analysis, wavelet analysis overcomes the weakness of analyzing signals only in frequency domain [10]. Generally, the wavelet transform can be easily realized. Wavelet analysis is the best choice for analyzing complex non-linear signals [11]. At present, wavelet analysis has been applied in the research of two-phase flow widely and successfully, such as Paulo and Milioli [12] used wavelet de-noising techniques to determine the bubble sizes in two-phase flow, Kulkarnia et al. [13] employed wavelet to measure the fraction of gas in a bubble column flow, Shang et al. [14] used wavelet theory to determine the oscillation periods and investigate the oscillation of density wave type of TYPE I and Wu et al. [15] used wavelet

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Nomenclature

A	flow area (m^2)
A_i	the ith prediction signal
BP	back propagation
C	wetted perimeter (m)
CHF	critical heat flux (kW m^{-2})
d_o	inner diameter of outside tube (m)
d_i	outer diameter of inside tube (m)
D_e	hydraulic diameter (m)
DNB	departure from nucleate boiling
DO	dryout
$F(\cdot)$	the activation function
F_{fitness}	fitness function
F_i	the fitness of ith individual
g	acceleration due to gravity
G	mass flow velocity (kgm^{-2} s^{-1})
GA	genetic algorithm
GNN	genetic neural network
h_{fg}	latent heat of vaporization (kJ kg^{-1})
L	heated length (m)
P	pressure (MPa)
P_i	the selection probability of ith individual
q	critical heat flux (kW m^{-2})
q_{exp}	experimental critical heat flux (kW m^{-2})
q_I	critical heat flux for inner tube (kW m^{-2})
q_{IDO}	dryout for inner tube (kW m^{-2})
q_o	critical heat flux for outer tube (kW m^{-2})
q_{ODO}	dryout for outer tube (kW m^{-2})
q_{pre}	prediction critical heat flux (kW m^{-2})
T_i	the ith goal signal
w_k	synaptic weights of neuron
x_p	input signal
X_c	critical quality

Greek symbols

θ_k	the threshold of kth neuron
ρ_f	density of fluid
ρ_g	density of vapor

theory to denoise and analyze the signals of pressure in a oil–gas–water multiphase flow. Daubechies wavelets and B-spline wavelets have been dominantly used in wavelet analysis. Compared to Daubechics wavelets, the compactly supported cardinal B-spline wavelets have several distinctively desirable properties including small support of scaling functions and wavelets, total positivity of the scaling functions and easy construction and fast implementation [16,17].

GA is a global search technique that borrows natural genetics and evolutionary principle [18–20]. GA is capable of a global exploration of a solution space. GA is different from other search methods in that it can consider many points in the search space. They are also reported to have less chance of converging to local optima. It searches for an optimal value of a complex objective function by simulating the biological evolutionary process, based on selection, crossover and mutation in genetics. They have been demonstrated to be effective and robust in searching very large spaces in a wide range of applications [21–24]. GA begins with a set of solutions (chromosomes in GA) to the problem under investigation. The set of solutions are randomly selected. A fitness function is defined which measures the fitness of each individual. To make a chance of survival more, its survival probability is considered according to its fitness value. Base on the fitness value of each chromosome, the algorithm performs a series of operations (selection, crossover and mutation) to transform the population into a new set of chromosomes. This process continues until the initial population evolves to the generation that will best solve the optimization problem.

ANNs are powerful tools for the prediction of nonlinearities. One ANN which has received most attention is the BP neural network. Because of its good diagnostic capability, it has been applied in many domains. But it has a slow rate of convergence and the convergence is confronted with locally optimal phenomenon. This is very disadvantageous under limited experiment data of CHF. There are many modifications of the BP algorithm in the literature [25–29]. In order to overcome this drawback, a new GNN model is proposed in this study. GNN has the advantages of GA and ANN. It utilizes GA to optimize the weight and threshold of the BP neural network. The prediction results by GNN have a good agreement with experimental data.

The aim of this study is to propose a new method GNN to predict DO point for bilaterally heated narrow annular tubes within the widely applicable ranges. The GNN model has some advantages of its globe optimal searching, quick convergence speed and solving non-linear problem. In this work, firstly, we introduce the basic theory of GNN. Secondly, the location of DO point was determined by using detection on the basis of local modulus maxima of cubic B-spline wavelet transformation. The experimental data of DO point are used to train and test the network. Next, the DO point is predicted by using GNN. We give the comparisons between the experimental data and prediction results of GNN. At last, the effects such as pressure, mass flow rate and equilibrium quality of main parameters on DO are analyzed by using the GNN. The results agree well with practical behavior as it is generally understood.

The detection of wavelet and the training of GNN model are all needed experimental data. Therefore, the basic experimental apparatus is briefly introduced in the following section.

2. Experimental apparatus

The schematic diagram of the experimental apparatus is shown in Fig. 1. The experimental system consists of a pump, pressurizer, preheater, calibrated flow meter, condenser, test section, valves, and connected pipes. The working fluid is distilled water. It was driven by a pump through the pre-heaters, the flow meter, the test section, and then flowed through the condenser where the fluid is

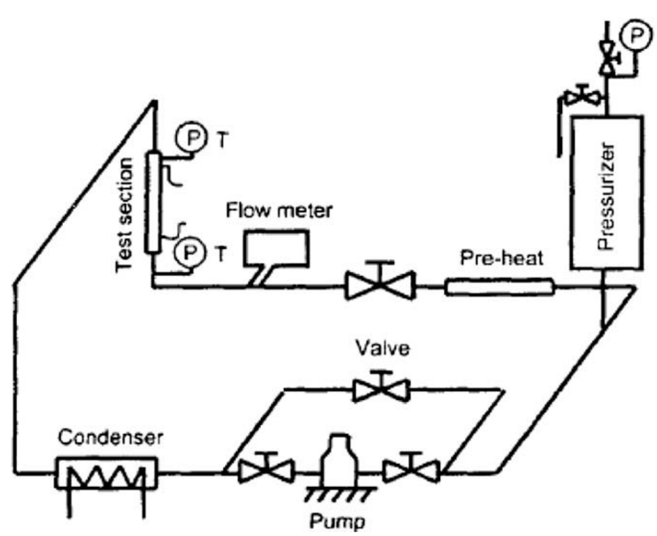

Fig. 1. Schematic of experimental apparatus.

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