Nucl. Sci. and Tech., Vol.13, No. 2 (2023), pp. 01-06

Nuclear Science and Technology

Journal homepage: http://jnst.vn/index.php/nst

ANN-based model integrated in thermal-hydraulics codes: A case study of two-phase wall friction model

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Abstract: Accurate prediction of two-phase parameters is essential for the development, operation and safety of nuclear power plants. In this paper, the ANN-based model has been developed, implemented with PDE (Partial Differential Equation) solver in case study of two-phase frictional pressure drop prediction.

Keywords: *Two-phase pressure drop; ANN-based model; PDE-Solver.*

I. INTRODUCTION

The main drawback of empirical correlations in thermal-hydraulics system codes is that the prediction capability heavily relies on the quality of the data and vastness of the experimental data employed in the study. Previous authors indicated that most of the empirical correlations give poor prediction when they are used beyond the range of data that they were developed [1-2]. Fortunately, the ANN is a powerful machine learning tool for modeling and solving some complicated physical problems that cannot be described with simple mathematical models, and thus can be able to cope with the uncertainty issues and replace the traditional methods of modeling and simulations. Many investigators proposed ANN-based model and demonstrated the predictive capability of the model [3-8]. However, these studies have only stopped at building predictive models on the basis of experimental data, not yet integrated into the thermal-hydraulics analysis code. Therefore, in a long-term research program to improve the accuracy and reliability of the safety analysis methods of nuclear reactors at Hanoi University of Science and Technology (HUST), we have developed a method of integrating data-driven and machine learning models with a 1-D system-level computing program on the basis of the following two basic modules: (1) experimental data analysis and predictive model development based on experimental data; (2) code development module based on conservation equations using the finite volume element method.

In this paper, we present some results in the construction of two basic modules, thereby testing and evaluating a case study of building an ANN-based wall friction model using module (1) and integrating into the calculation program in module (2). It should be noted that the two-phase wall friction model, which describes frictional pressure drop for a two-phase flow, is one of the key elements in the constitutive equations of a system code.

https://doi.org/10.53747/nst.v13i2.443
Received 20 September 2023, accepted 07 November 2023

II. FRAMEWORK FOR DATA-DRIVEN MODEL DEVELOPMENT

A framework to construct an ANN-based model with wide-range collected data from literature has been developed at HUST. With the specific problem of two-phase flow, the input and output parameters must be determined in advance, and then the database will be collected from existing experimental database to optimize the ANN structure and develop ANN-based model. A comprehensive workflow for ANN framework is proposed which consists of several main steps as illustrated in Figure 1 [9].

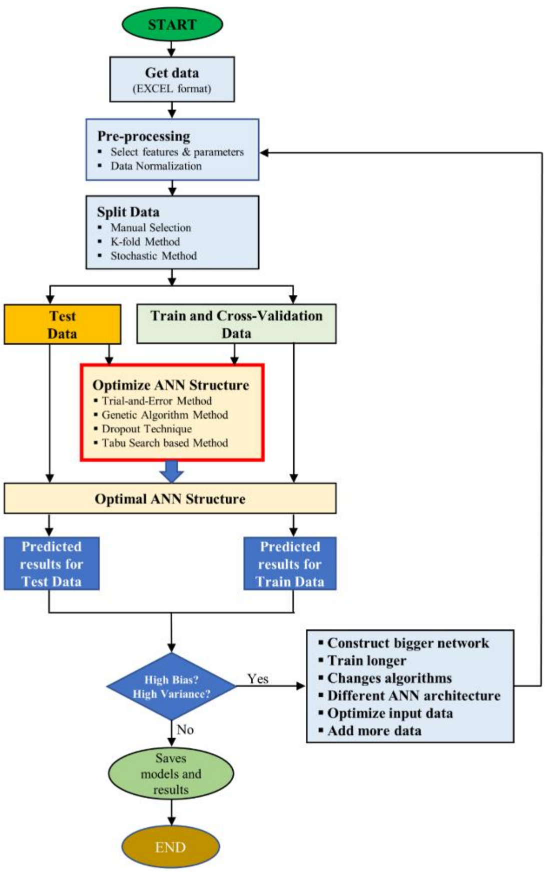

Fig. 1. The ANN Method Workflow [6]

III. CODE STRUCTURE DEVELOPMENT

Following code architecture and methodology of mature system and CFD codes such as RELAP5 [10], MARS [11], and EAGLE [12], a basic pilot EAGLE 1-D code for one-dimensional, transient, two-fluid model has been developed to solve averaged conservation equations and constitutive relations for α_k (phase fraction), U_k (phase velocities), and h_k (phase enthalpies) with Finite Volume Method (FVM) and the semi-implicit SMAC numerical scheme in a "non-staggered" grid as shown in Figure 2.

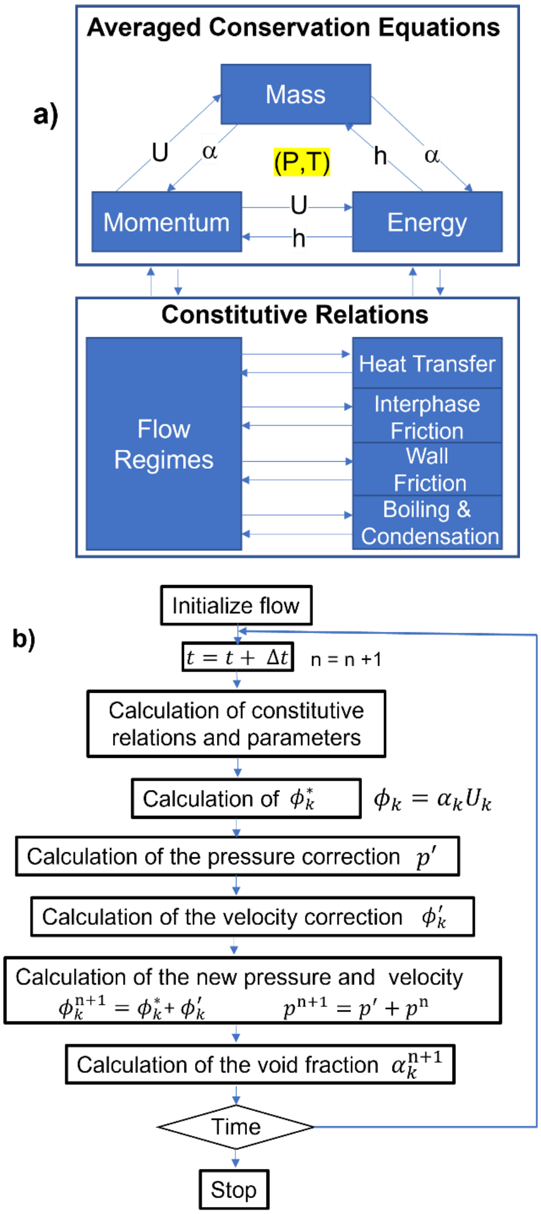

Fig. 2. Pilot code structure (a) & algorithm (b)

Firstly, the explicit Euler method is the simplest method in which all the fluxes and sources are evaluated using known values at an earlier time step n. The discretized momentum equations were then solved using the pressure p^n and phase velocities ϕ_k^n to find p^* and ϕ_k^* where the values with superscript * do not satisfy the mass conservation equations. Finally, the velocities and pressure were corrected at time step n+1 based on the mass conservation equations and the calculation process is advanced to the new time step.

IV. A CASE STUDY OF WALL FRICTION MODEL

Wall friction models predict the amount of friction between the wall and each phase of the fluid, and that are needed to solve the momentum conservation equations 1 and 2 as shown below:

$$\alpha_g\rho_g\frac{\partial U_g}{\partial t}+\frac{1}{2}\alpha_g\rho_g\frac{\partial U_g^2}{\partial x}=-\alpha_g\frac{\partial p}{\partial x}+\alpha_g\rho_g B_x-\alpha_g\rho_g FWG(U_g)+\Gamma_g(U_{gi}-U_g)-\alpha_g\rho_g FIG(U_g-U_f)-C\alpha_g\alpha_f\rho_m\left[\frac{\partial(U_g-U_f)}{\partial t}+U_f\frac{\partial U_g}{\partial x}-U_g\frac{\partial U_f}{\partial x}\right] \quad (1)$$

$$\alpha_f\rho_f\frac{\partial U_f}{\partial t}+\frac{1}{2}\alpha_f\rho_f\frac{\partial U_f^2}{\partial x}=-\alpha_f\frac{\partial p}{\partial x}+\alpha_f\rho_f B_x-\alpha_f\rho_f FWF(U_f)-\Gamma_g(U_{fi}-U_f)-\alpha_f\rho_f FIF(U_g-U_f)-C\alpha_g\alpha_f\rho_m\left[\frac{\partial(U_f-U_g)}{\partial t}+U_g\frac{\partial U_f}{\partial x}-U_f\frac{\partial U_g}{\partial x}\right] \quad (2)$$

Where Γ_k is the rate of a phase change for the k phase, ρ_m is a mixture density defined as $\rho_m=\alpha_f\rho_f+\alpha_g\rho_g$, FWG and FWF are part of the wall frictional drag, FIG and FIF are part of the interface frictional drag.

In RELAP5, the two-phase wall friction model is based on a two-phase multiplier approach calculated from the Heat Transfer and Fluid Flow Service (HTFS)-modified Baroczy correlation [10] and the wall friction of each phase are calculated based on two-phase wall friction as follows:

$$\alpha_g\rho_g FWG(U_g)=\alpha_g\left(\frac{dp}{dx}\right)\Big|_{2\phi}\left(\frac{1}{\alpha_g+\alpha_f Z^2}\right) \quad (3)$$

$$\alpha_f\rho_f FWG(U_f)=\alpha_f\left(\frac{dp}{dx}\right)\Big|_{2\phi}\left(\frac{Z^2}{\alpha_g+\alpha_f Z^2}\right) \quad (4)$$

Where Z is the ratio of the phasic shear stresses and phasic wetted perimeters

With ANN approach, experimental databases are used in the training process in which the weights (*W*) and biases (*B*) are modified to attain better approximation of the desired output (Figure 3).

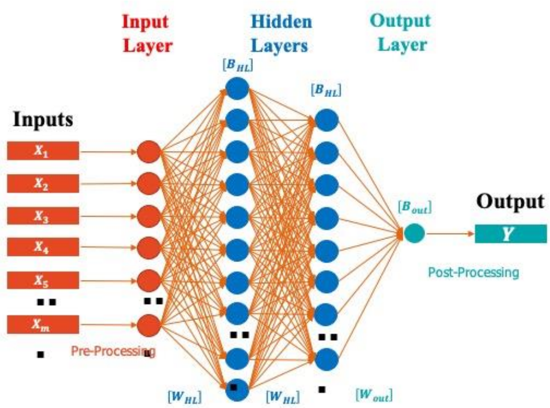

Fig. 3. ANN-based model

The two-phase flow phenomena are primarily governed by the flow boundary conditions as well as the geometry of the flow domain, therefore these key parameters must be selected as inputs for ANN structure design and optimization. Nine key parameters of flow boundary conditions including hydraulic diameter (D), mass flux (G), flow quality (x), phase velocities (U_g, U_f), phase viscosities (μ_g, μ_f) and phase densities (ρ_g, ρ_f) are chosen as input variables of ANN. Consequently, the following relation for independent input variables and dependent output has been developed as below equation:

$$\left.\left(\frac{dp}{dx}\right)\right|_{2\phi} = f\left(U_g, U_f, D, G, x, \rho_g, \rho_f, \mu_g, \mu_f\right) \quad (5)$$

In this case-study work, 604 experimental data points of frictional pressure drop in air–water two-phase flows in horizontal pipes are used for training and testing the ANN model (Table I). The data is collected and randomly divided into two parts based on practical experience: 75% is used for training and 25% is used for testing. Each of these models has its weights and biases initialized using Nguyen-Widrow method [13] and its subsequently trained with the Levenberg-Marquardt algorithm [14]. To avoid "overfitting", the training process will be stopped early after a certain number of epochs, this method is called early stop training. The overfitting occurs when the model produces high accurate results on the training set but does not work well on the testing set; in other words, the model is not generalizable [15]. After the process of selecting, comparing, and balancing training performance and time, the employed ANN configuration to predict the frictional pressure drop gradient in this study is four hidden layers with the number of neurons in each layer as folows (9-80-50-1). The coefficients R-Test and R-All are 0.9991 and 0.9983, consecutively, showing that the ability to predict the frictional pressure drop gradient of the ANN is quite accurate. And then the weights (W) and biases (B) of ANN network are extracted and implemented in the EAGLE 1-D code for the frictional pressure drop gradient terms. For each control volume in EAGLE 1-D code, nine input parameters as well as the pressure gradient are calculated based on volume-averaged approach.

Table I. Experimental database for ANN-based model development

Authors	j_f (m/s)	j_g (m/s)	D(mm)
Lu et al. (2018) [16]	2.0-6.0	0.07-2.78	38.1
Lu et al. (2018) [16]	2.0-4.0	0.08-2.85	50.8
Lu et al. (2018) [16]	4.0-6.0	0.10-0.32	101.6
Badie et al. (2000) [17]	0.0-0.047	14.51-25.34	78
Shannak (2008) [18]	0.06-0.70	0.0-32.39	52.5
Ottens (2001) [19]	0.0045-0.0151	4.48-15.94	52
Sun (2023) [20]	0.096-1.70	0.1-8.0	20
Hamad et al. (2017) [21]	0.29-1.32	0-0.51	25.4
Hamad et al. (2017) [21]	0.58-2.34	0-0.9	19.05
Hamad et al. (2017) [21]	1.17-5.27	0-2.02	12.7
Triplett (1999) [22]	0.043-6.02	0.058-70.16	1.097
Triplett (1999) [22]	0.023-3.02	0.042-66.00	1.447

Figure 4 shows the nodalization scheme for for RELAP5 (staggered grid) and EAGLE 1-D (non-staggered grid) simulations of Lu et al. (2018) Experiments. After carrying out grid sensitivity study, the appropriate number of control volume is 100. In this experiment, a differential pressure transducer with an accuracy of ± 0.1% is connected to the two instrumentation ports in the test section through two flexible plastic tubes to directly measure the pressure difference. Therefore, the pressure difference between two control volumes which cover two instrumentation ports are used for comparison. Results in Table II have demonstrated the capability of data-driven model integrated in the system code to improve the accuracy of the prediction results.

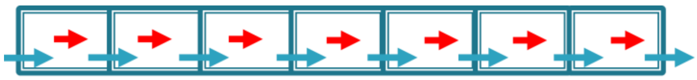

Fig. 4. Nodalization schemes

Table II. Experimental database for ANN-based model development

j_f (m/s)	j_g (m/s)	D(mm)	dP/dz (Pa/m)		
			EXP	RELAP5	1-D EAGLE with ANN-based Model
6	0.0776	38	6952	6725	6852
6	0.1308	38	7058	6832	6885
6	0.2607	38	7287	7068	7201
6	0.5000	38	7638	7383	7583
6	0.8692	38	8237	8064	8122
5	0.0945	38	5013	4903	5073
5	0.1499	38	5058	5007	5106
5	0.2942	38	5240	5104	5198
5	0.5154	38	5500	5322	5402
5	0.8824	38	6006	5803	5956
4	0.1011	38	3382	3122	3306
4	0.1719	38	3442	3247	3322
4	0.3056	38	3563	3403	3506
4	0.4600	38	3870	3699	3769
4	0.9235	38	4313	4132	4207

V. CONCLUSIONS

A method of integrating data-driven and machine learning models with a 1-D system-level computing program has demonstrated good prediction capability of pressure drop.

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