Transactions of the Korean Nuclear Society Autumn Meeting
Changwon, Korea, October 24-25, 2024

Pressure Loss Prediction in Circular Pipe using Artificial Neural Network

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***Keywords :** pressure loss, artificial neural network, circular pipe, regression, small modular reactor

1. Introduction

Small modular reactor (SMR) capable of collaborating with a renewable source such as solar, wind, or water energy attracts attention as alternative roles instead of power plants using fossil fuel during the climate crisis [1, 2].

KAERI developed a system-integrated modular advanced reactor (SMART) that received standard design approval (SDA) as a world-first licensed SMR in 2012 [3]. In addition, SMART100 which improves safety by adopting a fully passive design for engineered safety features (ESF) to respond to the Fukushima accident is now under a final process for standard design approval (SDA). Recently, team Korea led by Korea Hydro & Nuclear Power (KHNP) has also been developing innovative SMR (i-SMR) to become a global leader in the future global market.

KAERI also participated in the i-SMR consortium; one of its roles was to design reactor internals mechanically and hydraulically. The pressure drops in the entire reactor internals were estimated by evaluating the hydraulic events such as sudden contraction of the channel, friction loss in the pipe, etc [4]. These routines should be iterated until the hydraulic evaluation satisfies the mechanical design conditions.

Meanwhile, several approaches have been conducted to predict the flow characteristics using artificial neural networks (ANN) with an assumption as the data-driven problem. Several concepts developing ANN [5], such as convolution neural networks, physics-informed neural networks [6], etc., also have shown superior performances in specific engineering fields.

This study has suggested using ANN for the design routines about reactor internals with an expectation for better efficiency and response. A simple hydraulic event for circular pipe is initially considered herein to estimate the pressure drop using ANN.

2. Methods and Results

This section describes generating the data, details for ANN learning, and results for predicting the pressure drop in the circular pipe.

2.1 Empirical correlation

The friction coefficient (λ) for the circular pipe having a smooth wall can be categorized as a function of the Reynolds number (Re) as follows [4],

1. laminar regime (Re $\leq$ 2000)

$$\lambda = \frac{\Delta P}{(\rho u^2/2)(l/D_h)} = \frac{64}{\mathrm{Re}}$$

2. Transition regime (2000 $\leq$ Re $\leq$ 4000)

$$\lambda = f(\mathrm{Re})$$

3. Turbulent regime 1 (4000 $\leq$ Re $\leq$ 10^5)

$$\lambda = \frac{0.3164}{\mathrm{Re}^{0.25}}$$

4. Turbulent regime 2 (Re $\geq$ 10^5)

$$\lambda = \frac{1}{(1.8\log(\mathrm{Re}) - 1.64)^2}$$

The friction coefficient is a dimensionless number which is a ratio of the pressure drop and dynamic pressure. The calculation for pressure drop is trivial if the friction coefficient is known.

2.2 ANN modeling

Pytorch (ver. 2.3.1) [7] and pandas (ver. 2.2.2) [8] modules provided by Python are used for supervised learning of ANN, as shown in Fig. 1. The input is Reynolds number. The output is the friction coefficient. The hidden layers fully connect input and output. ReLU is used for the activation function.

The data was obtained from laminar, transition, and turbulent regimes in Section 2.1. Log scaling is applied for

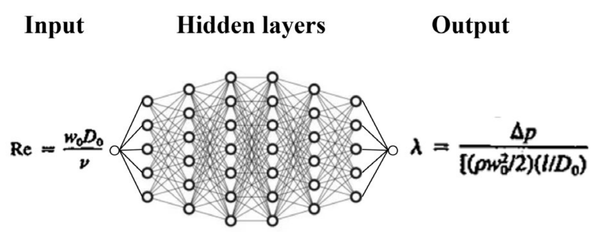

Fig. 1. ANN of supervised learning for prediction pressure loss in circular pipe.

Re from 500 to 10^8. The datasets are divided into training (80%), validation (10%), and testing (10%). Batch size is 5. Epoch is 3000. If the average validation loss is less than 10^{-6}, the train is stopped. The loss function selects the mean square error (MSE). Adam method is used for an optimizer.

2.3 Results

Fig. 2 shows the friction loss coefficient depending on logarithm Re using ANN that has five hidden layers (nodes: 20 – 30 – 20 – 30 – 20 – 65) fully connected with single input and output layers. The number of datasets is 274 (laminar: 75; transition: 101; turbulent 98).

The laminar region ranges from 0 to 3.3. The transition region ranges from 3.3 to 3.6. The turbulent region ranges from 3.6 to 8. The model prediction for friction coefficient in all flow regions shows good agreement with labels (ground-truth). For instance, ANN estimation also well catches the sudden fluctuation of friction coefficient in the transition region due to the initiation of flow mixing before turbulence. In addition, ANN can successfully release the curvature in both semi-linear (laminar regime) and non-linear (transition and turbulent regimes) regions.

Although the test dataset is separated for individual performance tests, the averaged test loss (= 2.07×10^{-7}) has the same order as the averaged validation loss (= 1.70×10^{-7}) because validation and test datum are produced from the identical regression equations.

It takes only 30 seconds to train the model and estimate the pressure loss using the trained model (including automatically drawing a graph such as Fig. 2) in case of using CPU of Intel Core i7-1260p. ANN (if well-modeled and -trained) has the potential to save time for routines such as manually calculating pressure drops in various events.

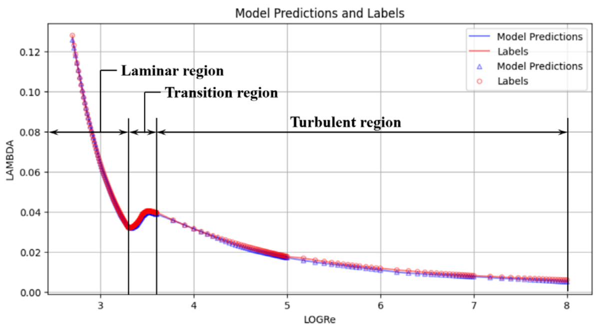

Fig. 2. Friction loss coefficient depending on logarithm Re (blue line and symbols: prediction; red line and symbols: labels).

3. Conclusions

ANN is preliminarily tested to predict the pressure drop in the circular pipe. ANN can successfully reproduce the friction coefficient curve depending on logarithm Reynolds numbers, including semi-linear and non-linear plots and sudden variations in transition regions. If various events are well-modeled and -trained under supervised learning, ANN is expected to save time for routines.

ACKNOWLEDGEMENT

This work was supported by the National Research Foundation of Korea (NRF) (Ministry of Science and ICT–Grant No. 2020M2D7A1079178).

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