Pressure Loss Prediction during Sudden Expansion using Artificial Neural Network

Jong Hui Lee [a*%], Gyeongseop Lee [b%], Seong Bae Pak [c], Jin Ho Oh [d], Cheong Bong Chang [a], Youngmin Bae [a], Seungyeob Ryu [a]
[a]*Korea Atomic Energy Research Institute, 111 Daedeok-daero 989beon-gil, Yuseong-gu, Daejeon, 34057*
[b]*Department of GSEP, Seoul National Univiersity, 1 Gwanak-ro, Gwanak-gu, Seoul, 08826*
[c]*Tae Sung S&E, 27 Seongsui-ro 7-gil, Seongdong-gu, Seoul, 04780*
[d]*Department of Mechanical Engineering, Kyungpook National University, 80 Daehak-ro, Buk-gu Daegu, 41566*

[*]*Corresponding author: jonghuilee@kaeri.re.kr*
[%]Jong Hui Lee and Gyeongseop Lee have equally contributed to this article

***Keywords* :** pressure loss, artificial neural network, sudden expansion, regression, small modular reactor

1. Introduction

Small modular reactors (SMRs), which can operate alongside renewable energy sources such as hydro, wind, or solar energy, are gaining attention as an alternative to fossil fuel-based power plants in the context of the climate crisis [1, 2]. Additionally, SMRs are expected to serve as independent distributed energy resources for artificial intelligence data centers.

In 2012, KAERI developed the system-integrated modular advanced reactor (SMART), which made it the world’s first SMR to receive standard design approval (SDA) [3]. SMART100, designed with fully passive engineered safety features (ESFs) to enhance safety in response to the Fukushima accident, also received SDA in 2024. More recently, team Korea, led by Korea Hydro & Nuclear power (KHNP), has been developing the innovative SMR (i-SMR) with the goal of securing a leading position in the global market. KAERI has also joined the i-SMR consortium, contributing to the hydraulic and mechanical design of the reactor internals. As part of this effort, the pressure drops across reactor internals were assessed by analyzing key hydraulic phenomena, including friction losses in pipes, sudden contractions in flow channels, and other related factors [4]. This evaluation process is continuously refined to ensure that the hydraulic performance meets mechanical design requirements.

Iterative design routines, aided by artificial neural networks (ANNs), which have demonstrated superior performance in a wide range of engineering applications, including predicting flow characteristics when properly trained [5, 6], may enhance efficiency and responsiveness. This study focuses on predicting pressure losses during sudden expansion, extending beyond predicting friction losses in a circular pipe [7].

2. Methods and Results

This section outlines the data generation process, provides details on ANN learning, and presents the results for predicting the pressure drop during sudden expansion.

2.1 Empirical correlation

The friction coefficient (λ) for the sudden expansion can be expressed as a function of the Reynolds number (Re) and the area ratio n (=A_0/A_1) as follows [4],

1. $500 \le \mathrm{Re} \le 3.3\times10^3$

$$\lambda = -8.5 - 26.2(1-n)^2 - 5.4(1-n)^4 + \log(\mathrm{Re})\times(6.0+18.5(1-n)^2+4.0(1-n)^4) + \log(\mathrm{Re})^2\times(-1.0-3.1(1-n)^2-0.7(1-n)^4)$$

Beyond a certain Reynolds number (3.3×10^3), the friction coefficient primarily depends on the area ratio, as shown below [4],

2. $\mathrm{Re} \ge 3.3\times10^3$

$$\lambda = (1-n)^2$$

Here, A_0 is the cross-section area before expansion, while A_1 is the area after expansion. The Reynolds number describes the ratio between inertia and viscous forces.

The friction coefficient is a dimensionless quantity defined as the ratio of pressure drop to dynamic pressure. Once the friction coefficient is known, calculating the pressure drop becomes straightforward.

2.2 ANN modeling

Pytorch (ver. 2.3.1) [8] and pandas (ver. 2.2.2) [9], both Python modules, are used for supervised learning of the ANN, as illustrated in Fig. 1. The input consist of

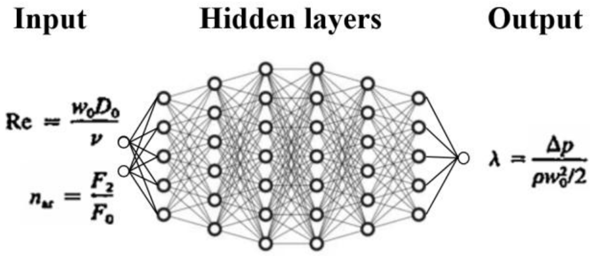

Fig. 1 ANN of supervised learning for predicting pressure loss during sudden expansion.

the Reynolds number and area ratio, while the output is the friction coefficient. The hidden layers are fully connected to both the input and output layers, and ReLU is employed as the activation function.

The data was obtained from the flow regime described in section 2.1. Log scaling is applied for Re from 500 to 10^8. The number of dataset is set to 2,466. The dataset is split into training (80%), validation (10%), and testing (10%) sets. The batch size is set to 50, and training runs for up to 3,000 Epochs. Training stops early if the average validation loss falls below 5×10^{-5}. The mean squared error (MSE) is used as the loss function, and the Adam optimizer is applied with learning rate of 0.001.

2.3 Results

Fig. 2 illustrates the friction loss coefficient as a function of the logarithm of the Reynolds number, predicted using an ANN with five hidden layers (nodes: 20 – 30 – 20 – 30 – 20 – 65) fully connected to an input layer (2 nodes) and an output layer (1 node).

During sudden expansion at n = 0.1 or for any constant area ratio, the friction loss coefficient exhibits a concave shape with a local peak below a Reynolds number of 3.3×10^3 and remains constant beyond this point. Furthermore, as the area ratio decreases, the concave slope becomes steeper, and the peak value increases. The model prediction for the friction coefficient during sudden expansion shows good agreement with the labels (ground truth). Interestingly, the ANN model successfully captures the overall trend, even when two input values are used beyond the Reynolds number of 3.3×10^3 (where the friction coefficient depends only on the area ratio, as shown in Section 2.1).

Although the test dataset is independently separated for performance evaluation, the averaged test loss (= 7.95×10^{-6}) is of the same order as the averaged validation loss (= 8.59×10^{-6}), since both validation and test data are generated from the same regression equations.

Training the model and estimating pressure loss using the trained model–including automatically generating graphs, shown in Fig. 2–takes approximately 70 seconds

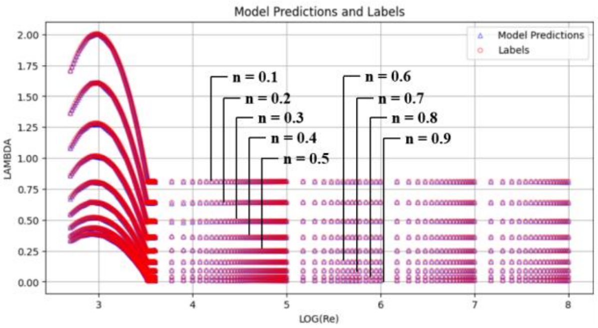

Fig. 2 friction loss coefficient depending on Reynolds number and area ratio.

on Intel Core i7-1260p CPU. When properly designed and trained, an ANN can significantly reduce the time required for repetitive tasks, such as manually calculating pressure drops under various conditions.

3. Conclusions

ANN is tested for predicting the pressure drop during sudden expansion beyond that in the circular pipe [7]. It successfully reproduces the friction coefficient under these conditions. If various scenarios are properly modeled and trained under supervised learning, the ANN has the potential to significantly reduce the time required for repetitive calculations.

ACKNOWLEDGEMENT

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

REFERENCES

[1] J. H. Lee and I. S. Park, Robust technique using magnetohydrodynamics for safety improvement in sodium-cooled fast reactor, Nuclear Engineering and Technology, Vol.54, p. 565, 2022.

[2] J. H. Lee and I. S. Park, Magnetohydrodynamic stabilizer suppressing gas entrainment for safety improvement in a sodium-cooled fast reactor, International Journal of Energy Research, Vol. 46, p. 23595, 2022.

[3] K. K. Kim, W. Lee, S. Choi, H. R. Kim, and J. Ha, SMART: The First Licensed Advanced Integral Reactor, Journal of Energy and Power Engineering, Vol. 8, p. 94, 2014

[4] I. E. Idelchik, Handbook of hydraulic resistance 3rd edition, Begell house, Connecticut, 1996.

[5] J. –H. Song and Y. –J. Kim, Artificial intelligence-based aeroacoustic theories and research trends, Transactions of Korean Society of Mechanical Engineers B, Vol. 46, p. 481, 2022.

[6] S. Shin, J. Lee, T. Kim, H. Choi, and S. Lee, Physics-informed neural network studies through the analysis of unsteady laminar flow around a circular cylinder, KSME spring meeting, May. 18-21, 2022, Busan, Republic of Korea.

[7] J. H. Lee, G. Lee, S. B. Pak, J. H. Oh, C. B. Chang, Y. Bae, and S. Ryu, Pressure Loss Prediction in Circular Pipe using Artificial Neural Network, KNS Autumn meeting, October. 24-25, 2024, Changwon, Republic of Korea

[8] A. Paszke, S. Gross, S. Chintala, and G. Chanan, Pytorch documentation, “pytorch.org”.

[9] W. McKinney, Pandas documentation, “pandas.pydata.org”.