Pressure Loss Prediction in Circular pipe using ChatGPT

Jong Hui Lee [a*%], Gyeongseop Lee [b%], Seungyeob Ryu [a], Hun Sik Han [a], Kwanghyun Ahn [a]
[a]*Korea Atomic Energy Research Institute, 111 Daedeok-daero 989beon-gil, Yuseong-gu, Daejeon, 34057*
[b]*Department of Engineering Practice, Seoul National Univiersity, 1 Gwanak-ro, Gwanak-gu, Seoul, 08826*
[*]*Corresponding author: jonghuilee@kaeri.re.kr*
[%]*Jong Hui Lee and Gyeongseop Lee have equally contributed to this article*

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

1. Introduction

Small modular reactors (SMRs), which can be coupled with renewable sources such as solar, wind, or hydro power, are drawing attention as alternatives to fossil-fuel-based plants in the era of climate crisis [1, 2].

In 2012, the Korea Atomic Energy Research Institute (KAERI) achieved a milestone by developing the system-integrated modular advanced reactor (SMART), which became the world's first SMR to receive standard design approval (SDA) [3]. Based on this foundation, KAERI proposed SMART100, a fully passive version with enhanced engineered safety features (ESFs) designed in response to lessons from the Fukushima accident, and the reactor also received SDA in 2024. Recently, "Team Korea," led by Korea Hydro & Nuclear Power (KHNP), has launched the development of an innovative SMR (i-SMR) aimed at positioning Korea as a global leader in the future nuclear market.

KAERI also participated in the i-SMR consortium, contributing to the overall reactor design at the basic design stage, including mechanical and hydraulic aspects of the reactor internals. The hydraulic analysis involved estimating overall pressure drops by considering events such as channel contractions and pipe friction losses [4]. These evaluations required iterative adjustments until the hydraulic performance met the mechanical design requirements. Lee et al. [5] suggested that artificial intelligence (AI) could support engineers by automating such repetitive evaluation processes. Their studies demonstrated that artificial neural networks can successfully replicate pressure losses in cases such as circular pipes [5] and sudden expansions [6].

This study extends previous work by exploring the use of large language models (LLMs) to predict hydraulic pressure losses instead of conventional multilayer perceptrons, with a particular focus on ChatGPT, which has recently attracted global attention.

2. Methods and Results

This section outlines the data generation process, the configuration of artificial neural network (ANN), and the results of predicting pressure drop in a circular pipe

2.1 Empirical correlation

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

1. laminar regime (Re ≤ 2000)

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

2. Transition regime (2000 ≤ Re ≤ 4000)

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

3. Turbulent regime (low) ($4000 \leq \mathrm{Re} \leq 10^5$)

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

4. Turbulent regime (high) ($\mathrm{Re} \geq 10^5$)

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

The friction factor is a dimensionless parameter defined as the ratio of pressure drop to dynamic pressure. Once the friction factor is determined, the calculation of pressure drop becomes straightforward.

2.2 ANN modeling

Supervised training was performed using the Pytorch (ver. 2.3.1) [7] and pandas (ver. 2.2.2) [8] libraries in Python (Fig. 1). The Reynolds number was used as the input variable, while friction factor served as the output. Hidden layers fully connected input and output nodes, and ReLU function was applied as activation function.

Training data were generated across the laminar, transitional, and turbulent regimes. Logarithmic scaling was applied to Re within the range of 500 to 10^8. The dataset was divided into training (80%), validation (10%), and testing (10%) sets. A batch size of 5 and 3000 epochs were used, with early stopping applied if the average validation loss fell below 10^{-7}. The mean squared error (MSE) was adopted as the loss function, and the Adam algorithm was employed as the optimizer.

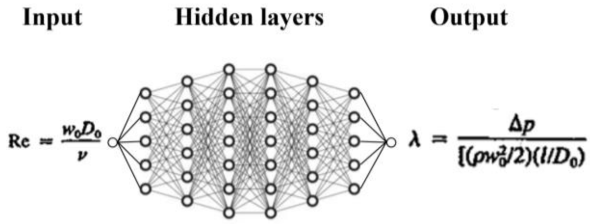

Fig. 1. ANN of supervised learning for prediction pressure loss in circular pipe.

Fig. 2. Example of ChatGPT interface.

2.3 large language model

A large language model (LLM) is an artificial intelligence model pre-trained on massive amounts of text data, capable of performing a wide range of language-based tasks. Recently, LLMs have also been applied to simple code generation and mathematical calculations. Here, pressure loss predictions were obtained using OpenAI's GPT-4-turbo, a conversational prompt-based LLM, through the following two approaches:

1. Constructing a prompt to output friction factor predictions by training a multilayer perceptron (MLP) with the dataset obtained from the flow pattern.
2. Constructing a prompt to output friction factor predictions using well-known empirical correlations.

Fig. 2 presents an example of the ChatGPT interface.

2.4 Results

Fig. 3 presents the friction loss coefficient as a function of the logarithm of the Reynolds number, predicted using both ANN and GPT. Laminar, transitional, turbulent regions are classified from 0 to 3.3, from 3.3 to 3.6, from 3.6 to 8 of log(Re), respectively. Four MLP structures (5-10-5-10-5, 10-20-10-20-10, 30-50-30-40, and 20-30-20-30-20-65) are used for predicting pressure loss in circular pipe. The ANN predictions show good agreement across all flow regimes, except in the case of the deficient-node configuration (5-10-5-10-5); in particular, low prediction accuracy is observed near 3.7 and 5.2 of log(Re).

The GPT results, obtained using an MLP-based structure (GPT-ANN) and correlation reproduction (GPT-correlation), also demonstrate good agreement with the ground truth. The same dataset and residual criterion used in ANN modeling was identically adopted for an output of GPT-ANN. The results for laminar, transition, and turbulent regimes were obtained by respective inquiries because of the token limitation

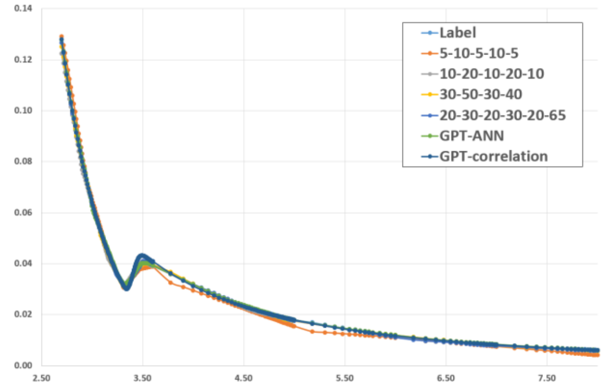

Fig. 3. Pressure loss prediction using ANN and GPT.

in ChatGPT. On the other hand, the GPT-correlation that predicts the friction factor based on the empirical correlation shows quite different gradient especially in transition region.

Table 1 summarizes the MSE of friction factor prediction from both ANN and GPT. The ANN with deficient-node configuration (5-10-5-10-5) doesn't satisfy the convergence criterion. Also, GPT-correlation also shows a slightly large value of MSE. The difference is expected to be caused by the inherent discrepancy for raw data.

Table 1. MSE of friction factor prediction.

CASE	Structure	MSE
ANN	1-5-10-5-10-5-1	3.201×10^{-6}
	1-10-20-10-20-10-1	8.856×10^{-7}
	1-30-50-30-40-1	2.307×10^{-7}
	1-20-30-20-30-20-65-1	1.877×10^{-7}
GPT	ANN regression	1.781×10^{-7}
	Correlation reproduction	1.763×10^{-6}

3. Conclusions

This study demonstrated that large language models, such as ChatGPT, can be applied to predict pressure losses with accuracy comparable to conventional ANN approaches. The GPT-correlation approach reproduced classical formulas almost exactly, while GPT-ANN showed reasonable agreement with some sensitivity in transitional regime.

These results highlight GPT's potential as an accessible design aid, reducing the need for coding or dataset preparation. However, prompt dependence and lack of physical guarantees remain challenges, requiring careful validation in practical applications.

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. 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.
[6] J. H. Lee, G. Lee, S. B. Pak, J. H. Oh, C. B. Chang, Y. Bae, and S. Ryu, Pressure Loss Prediction during Sudden Expansion using Artificial Neural Network, KNS Spring meeting, May. 22-23, 2025, Jeju, Republic of Korea.
[7] A. Paszke, S. Gross, S. Chintala, and G. Chanan, Pytorch documentation, “pytorch.org”.
[8] W. McKinney, pandas documentation, “pandas.pydata.org”.