Transactions of the Korean Nuclear Society Autumn Meeting
Gyeongju, Korea, October 26-27, 2023

Development of CNN and DNN based Deep Learning Techniques for Predicting Heat Transfer Performance According to HX Fin Shape

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***Keywords** : pix2pix, image-to-image translation, TEG, deep learning, GAN, DNN, CFD

1. Introduction

Thermoelectric power generation is a technology that directly converts heat energy into electrical energy as internal charges move in response to a temperature difference across thermoelectric elements. By utilizing thermoelectric generation (TEG) systems, waste heat lost in a nuclear reactor system can be recovered to enhance the efficiency and safety features of the I&C system during a station blackout. To maximize the power generation output of thermoelectric systems, enhancing the performance of heat exchangers is crucial [1]. Optimization for various thermodynamic characteristics is essential in the design of TEG temperature contour. TEG designers base their designs on inlet pressure and hot side temperature, necessitating a rapid comprehension of TEG temperature contour CFD analysis results. However, CFD analysis imposes significant computational time and effort on designers. As a result, Deep Learning (DL) is being applied to predict TEG temperature contour. Convolutional Neural Networks (CNN) have been employed to parametrize TEG temperature contour images. Furthermore, Deep Neural Networks (DNN) have been used to predict inlet pressure and hot side temperature within the TEG system. Therefore, this study implements Generative Adversarial Network (GAN)-based pix2pix models [2] for predicting TEG temperature contour, leveraging the prompt utilization of CFD analysis results in TEG temperature contour design. Additionally, DNN-based performance prediction models are developed.

2. Methods

This section describes the deep-learning techniques used to predict the TEG system temperature contour and the data used to train the deep learning.

2.1 Generative Adversarial Network (GAN)

The Generative Adversarial Network (GAN) [3] represents a prominent generative model and remains an active area of research within the realm of deep learning [4]. Comprising a generator and a discriminator, the GAN architecture operates through adversarial training, yielding data generation. Specifically, the generator, denoted as G, fabricates synthetic data from a latent random vector, while the discriminator, labeled as D, distinguishes genuine data from fabricated counterparts. The training process entails honing the generator to craft data that is indistinguishable from authentic instances, concurrently training the discriminator to effectively differentiate between spurious and authentic data. The architectural depiction of the GAN can be depicted in Fig 1.

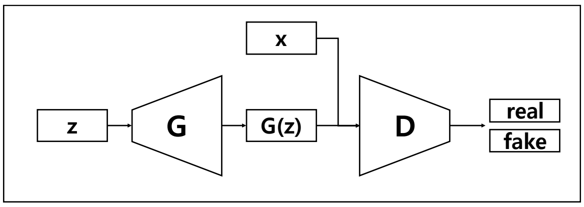

Fig. 1. The generative adversarial network (GAN)

2.2 Conditional Generative Adversarial Network (cGAN)

The conditional Generative Adversarial Network (cGAN) [5] stands as a GAN variant devised for the purpose of data generation under specific conditions [6]. The conditions for the cGAN can manifest in diverse formats, including noise vectors, images, and class labels. The cGAN's architectural configuration is visually depicted in Fig. 2, where the input denoted as z and the condition marked as c are fused and subsequently fed into the generator G. Furthermore, the input designated as x, directed towards the discriminator, is likewise harmonized with the condition c.

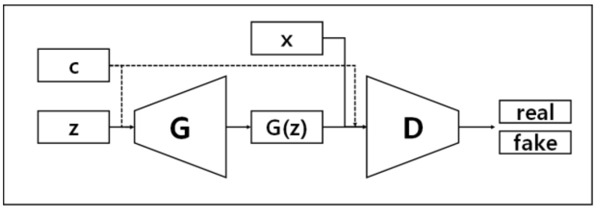

Fig. 2. Conditional generative adversarial network (cGAN).

2.3 Image-to-Image Translation with Conditional Adversarial Net (Pix2pix)

Pix2pix presents a versatile solution for addressing image-to-image translation challenges by leveraging conditional Generative Adversarial Networks (cGANs) [7]. The generator architecture in pix2pix adopts the U-Net framework, which is widely applied in image-to-image translation tasks. U-Net is a structural design that establishes a direct connection between the encoder and decoder layers through a "skip connection," allowing for more stable learning compared to a simplistic encoder–decoder architecture. The discriminator in the setup employs a convolutional PatchGAN classifier. This classifier assesses images based on patches of defined dimensions rather than evaluating the entire image area. Consequently, this approach trains the generator to yield images that exhibit enhanced realism.

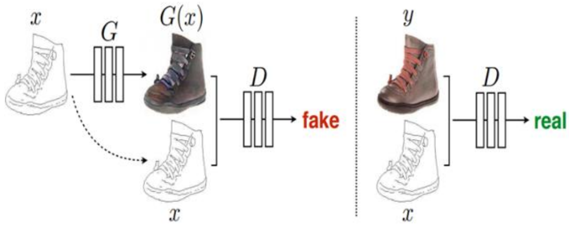

Fig. 3. Structure of pix2pix

2.4 Deep Neural Network (DNN)

A deep neural network (DNN) is a statistical learning technique that emulates the behavior of human neuron cells. It constitutes an artificial neural network with numerous hidden layers positioned between the input and output layers. Within each layer, nodes receive input (x) from nodes in the preceding layer, which are then multiplied by corresponding weights (w), added to a bias (b), and subsequently processed through an activation function to be propagated to the next layer, as depicted in Equation (1):

$$y_n = f\left(\sum_i w_i x_i + b\right) \tag{1}$$

Several activation functions exist, yet in this study, ReLU and leaky ReLU were employed as the activation functions. During training, the back-propagation algorithm iteratively refines the weights to minimize the loss function. The mean squared error (MSE) serves as the chosen loss function. The objective is to minimize the defined loss function, which takes the following form:

$$\mathrm{MSE} = \frac{1}{n}\sum_{1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

For

$$\begin{gathered}\mathrm{ReLU}: f(x) = \max(0, x) \\ \mathrm{Leaky\ ReLU}: f(x) = \max(0.01, x)\end{gathered} \tag{3}$$

As a result of training, the output value can converge to the actual value according to the optimization of the weights. The schematic diagram of the DNN is shown in Fig. 4.

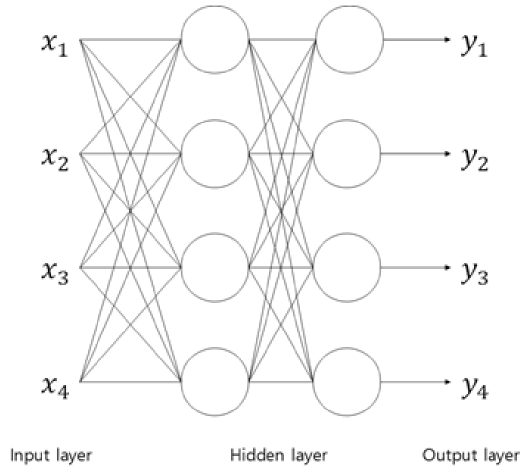

Fig. 4. Schematic diagram of the deep neural network (DNN).

2.5 Prediction of TEG temperature contour and Inlet pressure, Hot side temperature Using Pix2pix and the DNN

In this study, pix2pix was utilized for predicting the temperature contour of a Thermoelectric Generator (TEG). The input comprised 225 configurations of TEG temperature contour obtained through Computational Fluid Dynamics (CFD), serving as a database for TEG temperature contour profiles. Furthermore, the air velocity and fin height of the TEG were presented in textual format. The flowchart detailing the implementation of pix2pix for TEG temperature contour prediction is depicted in Fig. 5.

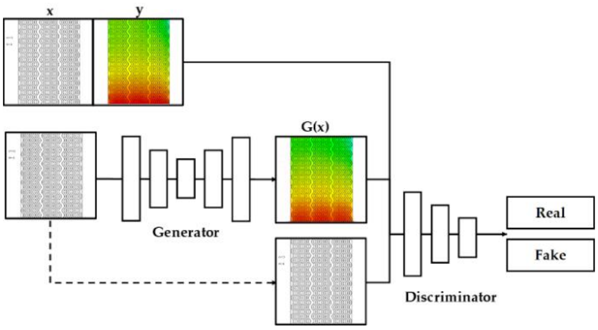

Fig. 5. The temperature chart for the use of pix2pix in TEG temperature contour prediction

The training objective function was formulated as depicted in Equation (4). LcGAN stands as the loss function associated with cGAN, designed to optimize the generator parameter for minimization and the discriminator parameter for maximization. Within LcGAN, the loss function corresponds to Equation (5). LL1 is optimized towards minimizing the difference between the actual value (y) and predicted value G(x). LL1 is the same as Equation (6). λ is the hyper-parameter that balances the LcGAN and LL1.

$$G^* = argminmaxL_{cGAN}(G, D) + \lambda L_{L1}(G) \tag{4}$$

$$L_{cGAN}(\mathrm{G}, \mathrm{D}) = \mathbb{E}_{x,y}[logD(x, y)] + \mathbb{E}_{x,z}\left[-D\left(x, G(x, z)\right)\right] \tag{5}$$

$$L_{L1}(G) = \mathbb{E}_{x,y,z}[\| \mathrm{y} - \mathrm{G}(\mathrm{x}, \mathrm{y}) \|] \tag{6}$$

In this study, two DNN models, TEG inlet pressure prediction DNN and hot side temperature prediction DNN, were established for predicting the pressure drop and heat transfer performance of the TEG system. They shared the common inputs of fin pitch, height, curvature radius, and velocity, while utilizing inlet pressure and hot side temperature as outputs. The data was divided into training, validation, and testing sets in a 4:1:1 ratio for learning. The TEG inlet pressure prediction DNN architecture consisted of an input layer that accepted the 4 inputs used for training, three hidden layers with 16 nodes each employing the leaky ReLU activation function, and an output layer with 1 node employing the linear activation function to predict the TEG inlet pressure. The schematic overview of the constructed TEG Inlet Pressure Prediction DNN architecture is depicted in Fig. 6.

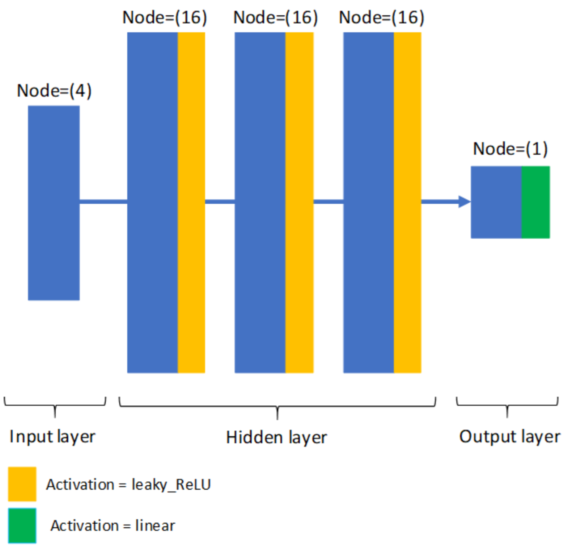

Fig. 6. The schematic diagram of the implemented DNN.

2.6 Dataset

Deep Learning (DL)-assisted optimization of fin shape design for pressure drop and heat transfer aspects was conducted through CFD on a thermoelectric power generation system with attached fins. The schematic shown in Fig. 7. illustrates a finned thermoelectric power generator system. The high-temperature fluid flows through the upper part of the module, while the coolant flows through the lower part, forming a heat exchanger system that supplies heat to the thermoelectric power generator system. The heat exchanger has a width of 288mm and a length of 414mm, with a duct size of 288*21mm. The thermoelectric power generator system consists of a total of nine fin-attached thermoelectric modules, as depicted in Fig. 8. Information regarding the design parameters of the fins can be found in Fig. 8. and Table 1(a). The thermoelectric module has a height of 10mm and is composed of eight fins, including four reference fins and four height-variable fins. Using ANSYS CFX, 225 databases were constructed by analyzing the heat transfer performance of 225 cases (comprising 5 height. 5 radius of curvature, 3 fin pitch, and 3 boundary conditions). The domain and boundary conditions of the thermoelectric module with attached pins used in the analysis are presented in Table 1(b). To enhance the reliability of computational analysis results, pressure drop in the TEG system was analyzed based on grid resolution. The results were obtained using a reference grid resolution of approximately 10 million cells, with the grid designed to maintain a y+ value of less than 5 through an ordered grid arrangement.

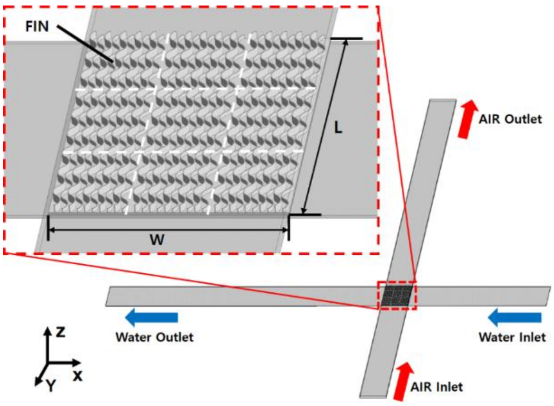

Fig. 7. Schematics of Thermo Electric Power Generator system

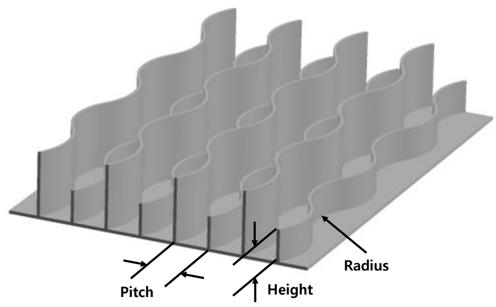

Fig. 8. Fin geometric parameter

Table 1. (a) Thermoelectric module pin shape variables

Parameter	Value
Fin Pitch	8, 10, 12
Height	5, 6, 7, 8, 9, 10
Radius	15, 17, 20, 25, 30
Inlet Velocity	10, 15, 20

Table 1. (b) Analysis boundary conditions

Parameter	Value
Y+	<5
Turbulence Model	SST
Air Inlet	200℃, 10m/s
Water Inlet	20℃, 1m/s
Fin, TEM Hot, TEM Cold	Cooper
TEM Conductor Conductivity	0.1W/mK

3. Results

3.1 The pix2pix implementation details

For the prediction of the temperature contour in the TEG system, pix2pix utilized a 512x512 image that incorporated velocity and height parameters into the fin layout of the thermoelectric power generation module. This image served as the input. Additionally, actual images of the temperature contour in the hot side, obtained through CFD analysis, were employed as the corresponding real images for discrimination. The input used for training was consistent with Fig. 8. The dataset was divided into training, validation, and testing sets in a 4:1:1 ratio for learning. The optimization function employed was Adam, with a learning rate of 0.00002. Training was conducted for 250 epochs using a batch size of 4. The loss functions employed were L1 loss and GAN loss. Following training, the predicted temperature contour results for the TEG system are depicted in Fig. 9.

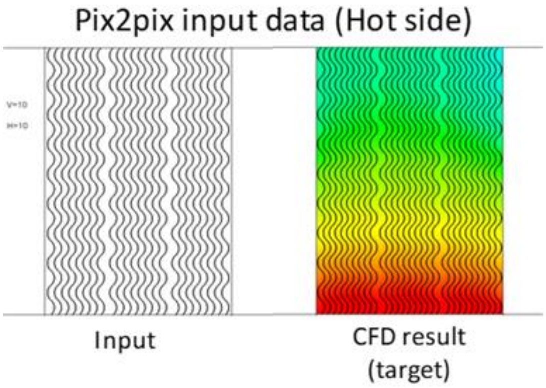

Fig. 8. TEG system hot side temperature contour prediction pix2pix input data

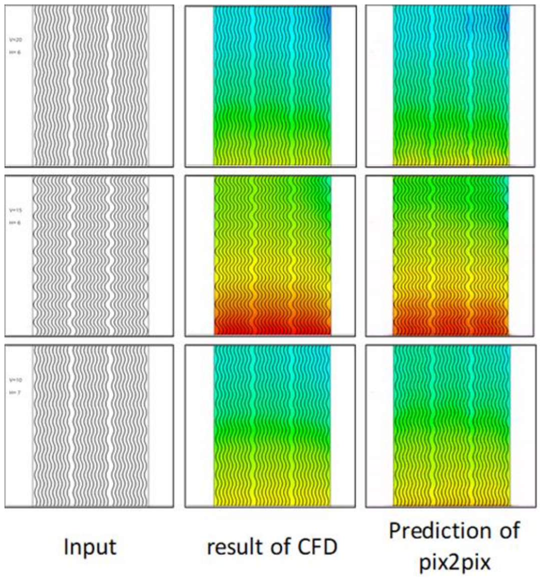

Fig. 9. TEG system hot side temperature contour prediction using pix2pix

3.2 The DNN implementation details

For the TEG inlet pressure prediction DNN training, the optimization function used was Adam, with a learning rate of 0.001. The training process was conducted over 1000 epochs with a batch size of 1. The loss function employed was the Mean Squared Error (MSE). After training the TEG inlet pressure prediction DNN, the Mean Absolute Percentage Error (MAPE) of the predicted results compared to the original data was 3.042%.

For the TEG hot side temperature prediction DNN training, the optimization function utilized was Adam, with a learning rate of 0.001. The training process was executed over 200 epochs with a batch size of 1. The loss function used was again the Mean Squared Error (MSE). After training the TEG fine part temperature prediction DNN, the Mean Absolute Percentage Error (MAPE) of the predicted results compared to the original data was 1.0562%

4. Conclusions

In this study, a dataset comprising 225 data points, including TEG system fin pitch, height, curvature radius, and velocity, was constructed. Using this dataset, pix2pix-based TEG temperature contour prediction model and DNN-based TEG performance prediction model were implemented. The results of model training confirmed the accurate prediction of TEG temperature contour, inlet pressure, and hot side temperature. In the future, we plan to further advance the deep learning models to predict temperature distributions and pressure fields based on the geometry of SFR (Sodium-cooled Fast Reactor) nuclear fuel assemblies. Additionally, we aim to utilize these models to predict Nusselt numbers and friction coefficients. Currently, we are in the process of constructing a CFD database using Thermal-

Hydraulic experimental data from various fuel assembly of SFR such as ORNL 19Pin, WARD 61Pin, and Toshiba 37Pin and so on.

ACKNOWLEDGMENTS

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (No. 2021M2E2A2081062), And also supported by Korea Institute of Energy Technology Evaluation and Planning(KETEP) grant funded by the Korea government(MOTIE) (20223030020070).

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