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Residual Stress Evaluation for Dissimilar Metals Welding Using Deep Fuzzy Neural Networks with Rule-Dropout

Ji Hun Park, Hye Seon Jo, Man Gyun Na*
Department of Nuclear Engineering, Chosun Univ., 309 Pilmun-daero, Dong-gu, Gwangju, Korea 61452
**Corresponding author: magyna@chosun.ac.kr*

1. Introduction

Nuclear power plants (NPPs) consist of numerous components and pipes, and many welding processes are performed to connect them. As NPPs age, there are many reports of reactor coolant leaks due to cracks occurring in these welding areas. This is due to the occurrence of primary water stress corrosion cracking (PWSCC). It is known that such PWSCC occurs when 1) sensitive material, 2) corrosive environment, and 3) residual stress exist simultaneously. NPPs satisfy all of the above conditions for the following reasons. First, an Inconel-based welding material called Alloy 82 or Alloy 182 was commonly used for the cracked welding areas [1]. These welding materials are known to be sensitive materials. Second, NPPs are corrosive according to the extreme environment of high temperature, high pressure, and high radiation. Finally, welding residual stress is generated according to the local heating and cooling that occurs during welding; here, residual stress is evaluated as a very important factor that causes PWSCC when it is difficult to improve the material corrosiveness of components and the environment under the operating conditions of NPPs.

In general, residual stress is evaluated for a reliable evaluation of the structural integrity of welded parts of NPPs; that is, residual stress evaluation is performed to evaluate fitness-for-service (FFS) [2]. There are several methods for evaluating residual stress. The residual stress evaluation methods are largely divided into 1) local destructive technology, 2) non-destructive technology, and 3) finite element analysis. First, the local destructive technique includes hole drilling, sectioning, contour method, etc. Second, the non-destructive technique includes x-ray diffraction, neutron diffraction, ultrasonic technique, etc. The previous two residual stress evaluation methods have disadvantages such as large dispersion of measured values, space constraints, surface-oriented measurement, and relatively excessive time and cost. Finally, the finite element analysis method is a technique to evaluate the residual stress numerically, unlike the previous methods. The finite element analysis method is being actively applied to derive the welding residual stress distribution in terms of FFS evaluation because of the shortcomings of the previous two methods. Nevertheless, the finite element analysis method is technically and computationally difficult. Also, there are limitations in that simplification and idealization of shapes, material behavior, and process parameter is inevitable.

Therefore, in this paper, unlike the existing methods, we try to predict the welding residual stress using artificial intelligence (AI) technology, which has recently been in the spotlight with the advent of the 4th industrial revolution. Specifically, the prediction of welding residual stress is attempted using a deep fuzzy neural networks (DFNN) where the rule-dropout technique is applied. ABAQUS, a finite element analysis code, was used to build data for AI training; here, for modeling, 1) the shape of the pipeline, 2) the welding heat input, 3) the yield strength of the welding base material, and 4) the constraint of the end of the pipeline were considered. As a result, 6300 welding residual stress data were obtained from 150 analysis conditions. The rule-dropout technique and genetic algorithm were applied to optimize the welding residual stress prediction model. A root mean square (RMS) error and relative error were used to evaluate the performance.

2. Deep Fuzzy Neural Networks with Rule-Dropout

This section describes the DFNN with rule-dropout method used to develop the welding residual stress prediction model. In addition, the genetic algorithm and rule-dropout technique used to optimize the welding residual stress prediction model is explained.

2.1 Deep Fuzzy Neural Network

The DFNN method is an extension of the fuzzy neural networks (FNN) method. In general, deep learning has the effect of improving performance as the number of layers increases; here, the DFNN method treats the FNN as one layer. In other words, performance improvement can be induced by configuring and deploying the FNN as a single module.

The FNN method can be described as a combination of fuzzy inference and artificial neural networks. Fuzzy inference is the process of mapping a given input to an output using fuzzy set theory. In this paper, a Gaussian membership function is used to construct a fuzzy set. The Gaussian membership function is expressed as Eq. (1); here, it is important to optimize the parameters c_{ij} and s_{ij} that determine the distribution of Gaussian membership [3].

$$\varphi_{ij}(x_j(k)) = e^{-(x_j(k)-c_{ij})^2/2s_{ij}^2} \quad (1)$$

Once the Gaussian membership function is determined, the inputs are assigned according to the fuzzy set. After that, the training proceeds by calculating the weights using the artificial neural network structure.

Fig. 1 shows the structure of the FNN method, which consists of six layers. The layer related to fuzzy inference described earlier is the second layer. After that, the third to fifth layers simulate the artificial neural network structure.

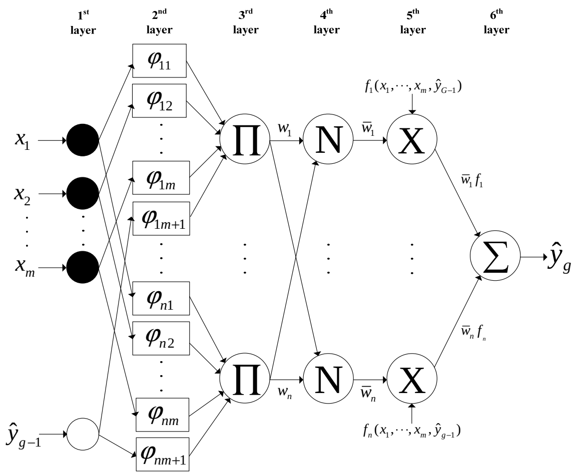

Fig. 1. The structure of FNN method (FNN module).

The DFNN method is constructed by deeply deploying this FNN method as one module. Fig. 2 shows the structure of the DFNN method, characterized in that the results of previous FNN module are input to the directly connected next FNN module.

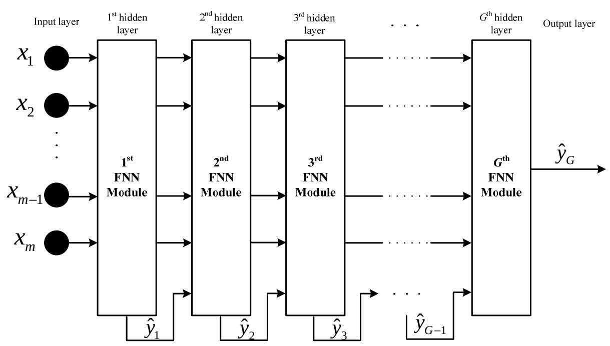

Fig. 2. The structure of DFNN method.

The performance of the DFNN method is closely related to the structure of the DFNN method. Since the DFNN method is a combination of fuzzy inference and artificial neural networks, each feature can determine its performance. For fuzzy inference, this is the Gaussian membership function and fuzzy rules. In the case of artificial neural networks, the number of FNN modules corresponds to this.

2.2 Optimization technique of DFNN method

The optimization of the DFNN method includes a genetic algorithm for parameter optimization and a rule-dropout technique for training optimization.

The genetic algorithm is responsible for optimizing the parameters that determine the performance of the DFNN with rule-dropout method. The genetic algorithm is the process of finding the optimal parameter by selecting, crossing, and mutating the candidate groups of each variable in general. In the DFNN method, the genetic algorithm optimizes for 1) Gaussian membership function (c_{ij} and s_{ij}), 2) fuzzy rule number, and 3) FNN module number.

The rule-dropout technique applied to the DFNN method is similar to the dropout technique commonly used in deep learning [4]. The purpose of applying the rule-dropout technique is to prevent overfitting problems that may occur during AI training. The overfitting problem means that the performance on the training data used for AI training is high, but the performance on the test data used for AI evaluation is low; that is, it suggests that the generalization performance of AI is lowered. The rule-dropout technique adjusts the number of network nodes that affect fuzzy inference performance to optimize training. Specifically, it prevents over-adaptation of neurons by artificially disabling the number of nodes in the layer that exists between the input layer and the output layer.

In general, DFNN methods tend to improve in performance as the number of FNN modules and fuzzy rules increases. On the other hand, as the network structure becomes more complex, there is a risk of overfitting. The rule-dropout technique receives inactive node candidates determined from the genetic algorithm and deactivates some of the nodes in the initially configured network. This process is repeated whenever an FNN module is added, and the optimal number of fuzzy rules is determined. Because of this optimization process, each FNN module has the same or different optimal number of fuzzy rules. In other words, the genetic algorithm and rule-dropout technique are combined to optimize the number of fuzzy rules. The rule-dropout technique helps prevent overfitting by disabling some nodes in a complex network structure.

3. Data Acquisition

In this section, ABAQUS, a finite element analysis code, was used for data acquisition. In addition, 150 analysis conditions were utilized to build a database of welding residual stress from various welding conditions. The 6300 constructed data is divided into training, verification, and testing data for AI training and assessment.

3.1 Finite Element Analysis

ABAQUS, a finite element analysis code, was used to obtain welding residual stress data [5]. A dissimilar weld joint between the nozzle and the pipe was simulated for ABAQUS modeling. For the detailed material structure, SA508 ferritic steel and TP316 austenitic stainless steel were applied to the nozzle and pipe, respectively. In addition, Alloy 82 and Alloy 182 were used as welding base materials for the weld joint between the nozzle and the pipe. The detailed modeling structure is expressed in Fig. 3.

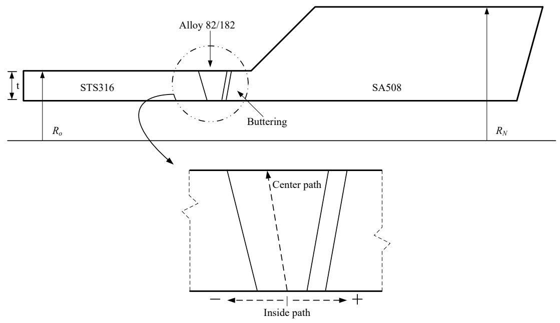

Fig. 3. Welding part of dissimilar metals and estimation paths in welding area for data acquisition [5].

The following parameters were selected to simulate material behavior; the parameters are 1) shape of the pipeline, 2) end section constraint, 3) welding heat input, and 4) yield stress of weld metal. Table I shows the conditions for each parameter.

Table I: Conditions for analyzing welding residual stress

Shape of the pipeline	R_o (mm)	R_N (mm)	R_o/t
	205.6	300.10	4.8778
	205.6	271.75	6.8763
	205.6	256.80	8.8735
End section constraint	Restrained		Free
Welding heat input, H (kJ/s)	Pass 1		others
	0.49764		1.2690
	0.55985		1.4277
	0.62205		1.5863
	0.68426		1.7449
	0.74646		1.9036
Yield stress of weld metal, σ_{ys} (MPa)	192.33		
	203.06		
	213.70		
	224.38		
	235.07		

3.2 Data Composition for AI training

According to the previous material behavior conditions, 150 analysis conditions were applied using ABAQUS. In addition, a total of 6300 datasets were obtained using these analysis conditions. The obtained data is used for training and evaluation of the AI model. The detailed data composition is shown in Table II.

Earlier, it was mentioned that simplification and idealization of shape are inevitable in finite element analysis. However, this paper focused on the prediction of welding residual stress using the DFNN with rule-dropout method. It is assumed that the obtained finite element analysis results are accurate.

According to each condition, 1250 training data, 260 validation data, and 65 test data are divided. The training data is used to train the DFNN model, and the validation data is used to check whether the training is working well (overfitting evaluation). In general, training and validation data are collectively defined as development data. The test data is used to evaluate the performance of DFNN model developed as data independent of these development data.

Table II: Data composition according to each condition

Path	End section constraint	Data type	No. of data point
Inside path	Restrained	Train	1,250
		Validation	260
		Test	65
	Free	Train	1,250
		Validation	260
		Test	65
Center path	Restrained	Train	1,250
		Validation	260
		Test	65
	Free	Train	1,250
		Validation	260
		Test	65
No. of total data point			6,300

4. Evaluation Result of Residual Stress

The results of the welding residual stress prediction model developed using the DFNN with rule-dropout method were evaluated using the RMS error and the maximum relative error. The performance of the DFNN model according to the estimation paths (inside path and center path) is shown in Tables III and IV, respectively. When the end section constraint condition in the inside path is restrained, the result evaluated with the test data has an RMS error of 1.004%. When the end section constraint condition is free, the result evaluated with test data shows the RMS error of 1.736%. The evaluation result of the center path is 1.041% and 0.537% as a result of evaluation with test data when the end section constraint conditions are restrained and free, respectively. Overall, the DFNN model developed by showing the RMS error within 2% is judged to be sufficient for evaluating the welding residual stress.

Table III: Performance of the DFNN with rule-dropout model (inside path)

End section constraint	Data type	RMS error (%)	Relative max. error (%)
Restrained	Train	0.808	4.958
	Validation	0.888	3.680
	Test	1.004	3.455
Free	Train	1.807	8.803
	Validation	1.967	8.900
	Test	1.736	7.469

Table IV: Performance of the DFNN with rule-dropout model (center path)

End section constraint	Data type	RMS error (%)	Relative max. error (%)
Restrained	Train	0.682	3.115
	Validation	0.744	3.394
	Test	1.041	3.940
Free	Train	0.417	2.007
	Validation	0.454	2.178
	Test	0.537	2.028

Figs. 4-6 shows the results of plotting the actual (blue 'o' mark) and predicted (red 'x' mark) values under the center path and free conditions.

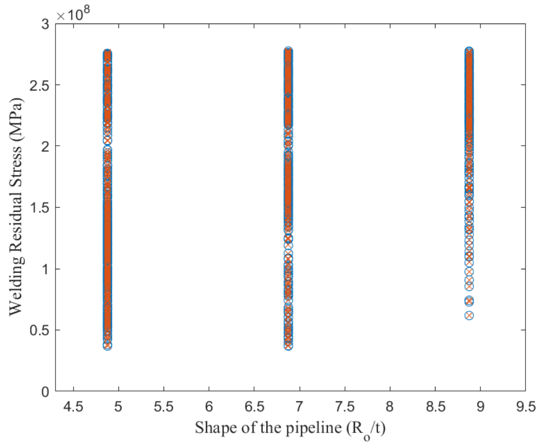

Fig. 4. Performance evaluation result of DFNN with rule-dropout model based on shape of the pipeline.

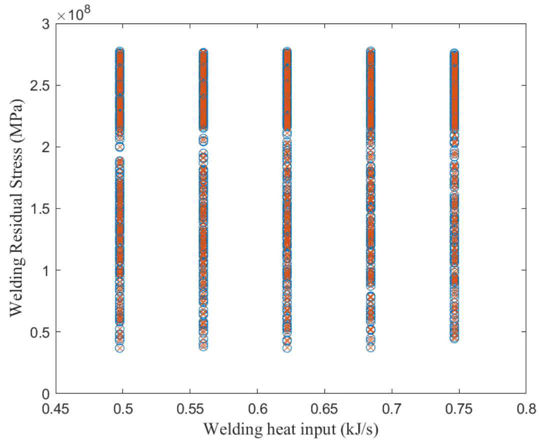

Fig. 5. Performance evaluation result of DFNN with rule-dropout model based on welding heat input.

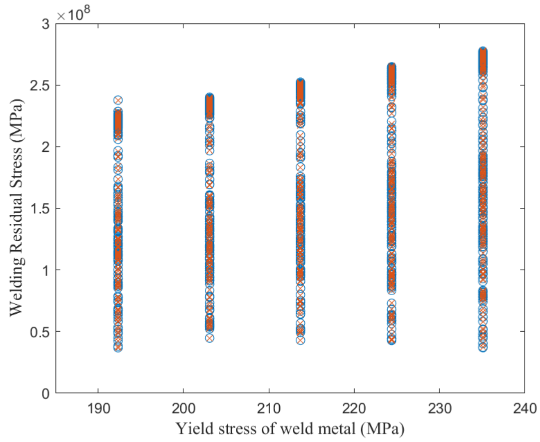

Fig. 6. Performance evaluation result of DFNN with rule-dropout model based on yield stress of weld metal.

5. Conclusions

In this paper, we used artificial intelligence (AI) to predict welding residual stress. For AI training, 6300 datasets obtained by using ABAQUS were used. Based on the data, the model was developed using the deep fuzzy neural network (DFNN) with rule-dropout method. The developed DFNN model with rule-dropout method shows good performance within 2% of root mean square error. It is judged that it will be possible to predict the welding residual stress well enough using the DFNN model. The predicted welding residual stress is sufficient to evaluate the integrity of dissimilar metals welding.

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