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Influence of Material Randomness on Welding Residual Stress in Dissimilar Metal Welded Joints of Nuclear Power Plants

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Abstract: *The welding residual stress is one of the main factors that lead to Stress Corrosion Cracking (SCC) in dissimilar metal welded (DMW) joints of the safe-end in nuclear power plants. Based on ABAQUS software, a thermal-elastic plastic finite element method is developed to simulate residual stress for DMW joints of the safe-end. Considering the randomness of material parameters of the welding metal, the neural network response surface method is applied to calculate the change of welding residual stress distribution. Meanwhile, to improve the efficiency of numerical analysis, MATLAB is employed in the secondary development for ABAQUS. With the help of existing experimental data, the effect of random parameters of the welding metal on the residual stress in DMW joints is simulated and analyzed in this study. The results show that the residual stress distribution of the DMW joints is significantly affected by the random parameters. Among the parameters, the randomness of Yield strength and Module of Elasticity has the most significant influence on the uncertainty of the distribution of welding residual stress.*

Keywords: *Dissimilar metal welded joint; Residual stress; Randomness; Response surface method*

1. Introduction

The dissimilar metal welded (DMW) joint in the safe-end is the critical component and structure of nuclear power plants. In recent years, the occurrence of primary water stress corrosion cracking (PWSCC) in welding region of the safe-end has increased, and one of the critical factors of the welded joint failure is the welding residual stress produced in the welding process of the safe-end. In order to evaluate the crack propagation of PWSCC, it is required to estimate stress distribution including residual stress. Much effort has been put into researching residual stress measurement and evaluation[1-4].

Some residual stress test models were produced using the same fabrication process of Pressurized Water Reactor, and some important conclusions about residual stress distribution were obtained on the base of the experimental data[5,6]. As is well known, the welding residual stress is affected by many factors and varied complicated, and it is very expensive and time-consuming to investigate the welding residual stress, and sometime is impossible[7]. Therefore, welding residual stress simulation using finite element method (FEM) analysis has become increasingly common in crack analysis combined with experiments[8,9]. It has been found that the distribution of welding residual stress depends on several main factors such as structural dimensions, material properties, restraint conditions, heat input, number of welding pass and welding sequence[10]. Additionally, the uncertainty of welding residual stress measurements and modeling predictions is not well understood[11]. At present, the effect of randomness on the residual stress distribution has rarely been investigated. In practical engineering, the geometrical and physical random variables of structure, such as material property strongly influence the residual stress distribution. Hence, these parameters should be considered as random variables and then the result of research for residual stress will be more reasonable. In view of the complexity of the calculation of residual stress distribution and the long-time running model, adopting by analytic method is very difficult considering all the parameters as random variables. Due to its good curve fitting characteristics, neural network response surface method is primarily intending for using with long-running models [12]. However, the report on the uncertainty of the residual stress distribution using this method has rarely appeared yet currently.

The main purposes of the research are to explore the uncertainty of the residual stress distribution and the corresponding influence factors based on the thermal elastic-plastic finite element and neural network response surface method, which provides a foundation to improve the crack evaluation and crack propagation prediction accuracy of the safe-end in the nuclear plants.

2. Materials and Methods

2.1. Geometric and Material Model

The basic geometric shape of the DMW joint of the safe-end in the Pressurized Water Reactor is shown in Figure. 1, which is used in the following calculation and analysis. In this model, a low alloy steel nozzle forging with 304 stainless steel cladding is buttered with the Alloy 132 welding metal, then a safe-end consisting of a short 316 stainless steel pipe is welded to the nozzle with the Alloy 132 welding metal. An axisymmetric model is created to simplify the analysis process, and the geometry size is shown in Figure. 2. It is shown that the outside diameter of the pipe is 883mm.

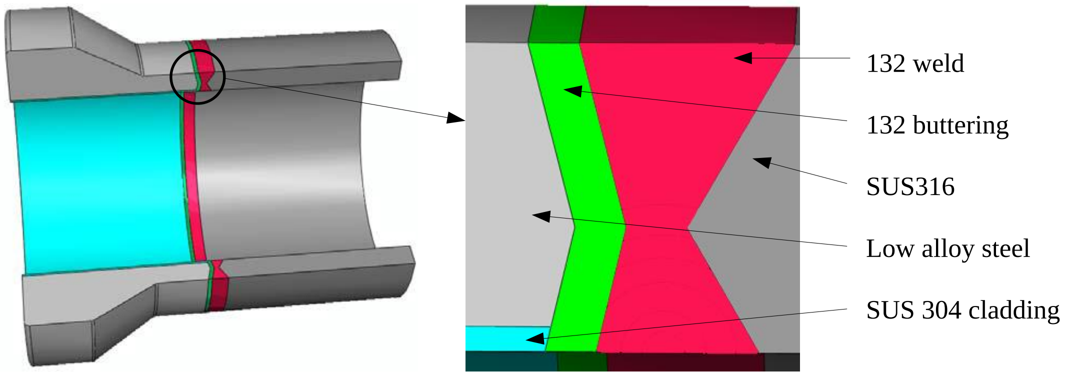
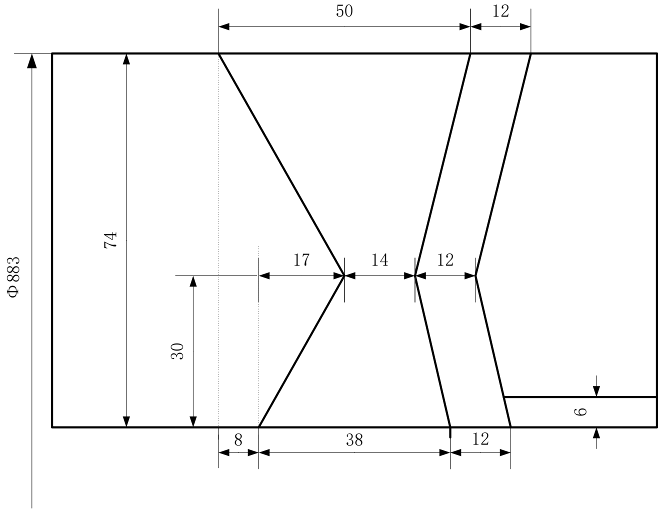


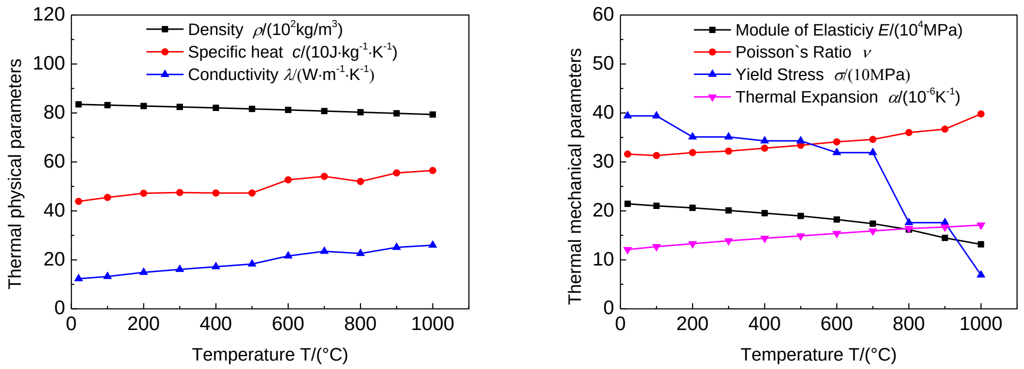
Figure 1: Geometric Shape of DMW joint in the safe end.



Unit: mm

Figure 2: Geometry size of DMW joint in the safe-end.

The welding process is a highly nonlinear thermodynamic coupling process, and thermophysical properties of metallic materials vary with temperature, such as Specific Heat, Thermal Conductivity, Density, Coefficient of Thermal Expansion, Yield Stress, Module Elasticity, Poisson's Ratio. Based on the measured data[5], linear interpolation method was used to deal with the material properties parameters determined within a certain temperature range, and linear extrapolation method was used to obtain the high-temperature properties of materials near and above the melting point. Residual stress measurement results indicate that there is larger residual stress in the welding zone, so it is important to understand the distribution of residual stress in this zone. The material properties of Alloy 132 welding metal are shown in Figure.3. Other material properties such as 316 stainless steel, 304 stainless steel and 508 low-alloy steel can derive from reference 5.



(a) *(b)*

Figure 3: Material property of Alloy 132 welding metal: (a) Thermal physical properties (b) Thermal mechanical properties.

To investigate the randomness on the residual stress distribution in the welding zone, some important parameters such as Density, Module of Elasticity, Poisson’s Ratio and Yield Strength of Alloy 132 are described as normal distribution parameters. For simplicity, the variable coefficients of all the random variables are assumed as 0.01 and all the random variables are mutually independent.

A simple isopycnic heat source is selected, and the temperature distribution in the welding zone is assumed to be uniform. The temperature is set at 1000°C. The setting of welding condition includes two steps: welding and cooling. Firstly, the equal density heat source is applied for 2s to simulate the welding heating process, and then the DMW joint is cooled in the cooling step until it is cooled to room temperature which is set at 20°C. The welding pass sequences of Alloy 132 welding region are shown in Figure.4. The test model has 10 welding layers and 100 passes. However, all passes for each layer were welded at once which is called grouping technique to reduce analysis time for the analysis model, except for two or three layers on the inner and outer surface.

A commercial FEM code ABAQUS is used in this simulated analysis. Mesh of the partial model is shown in Figure.5, where a 4-node thermally coupled axisymmetric quadrilateral element is adopted as the element type. The mesh in the vicinity of the welding zone is observably refined in order to improve the calculation accuracy of residual stress distribution. Other zones with less meshing make use of the meshing transition technology. X axis is along the radial direction, and Y axis is along the axis direction in the coordinate system.

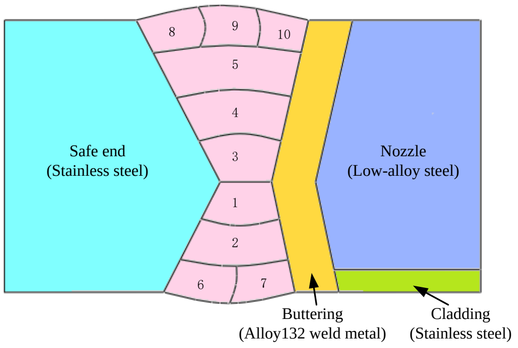


Figure 4: Welding pass sequence of Alloy 132.

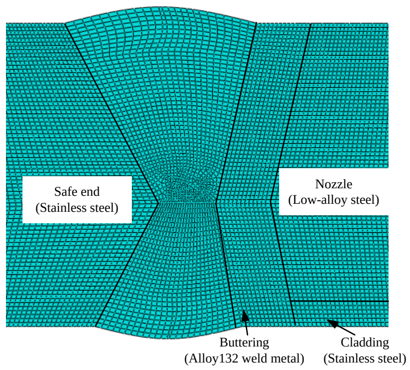


Figure 5: Mesh of the partial model.

2.2. Network Response Surface Method.

The back propagation neural network algorithm is a multi-layer feedforward network trained according to error back propagation algorithm, and it is one of the most widely applied neural network models[12]. It usually consists of input layer with multiple nodes, a hidden layer, and an output layer of multiple or one output node. Its learning process can be divided into two stages. The forward Propagation process of information and the Back Propagation process of error. The external input signal is processed layer by layer by the neurons in the input layer and the hidden layer, then it propagates forward to the output layer to give the results. If the desired output cannot be obtained in the output layer, it will be transferred into the reverse propagation process, and the error between the actual value and the network output will be returned along the original connection path. The error will be reduced by modifying the connection weight of neurons in each layer, then transferred into the forward propagation process and repeated iterations until the error is less than the given value. The topology of the four-layer forward neural network which is an input layer,an output layer and two hidden layers is shown in Fig.6

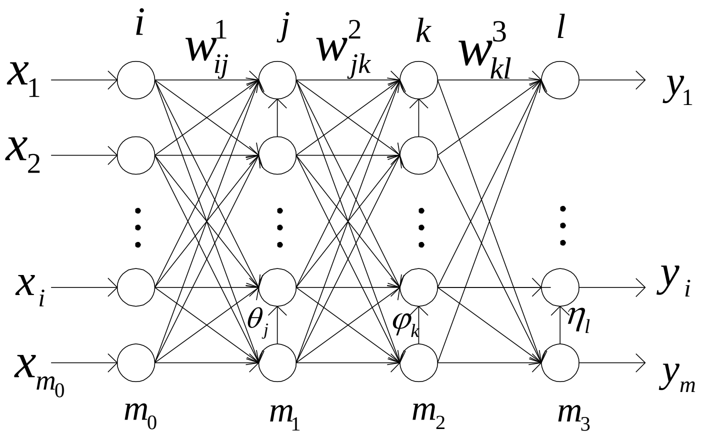


Figure 6: Network structural model with two hidden layers.

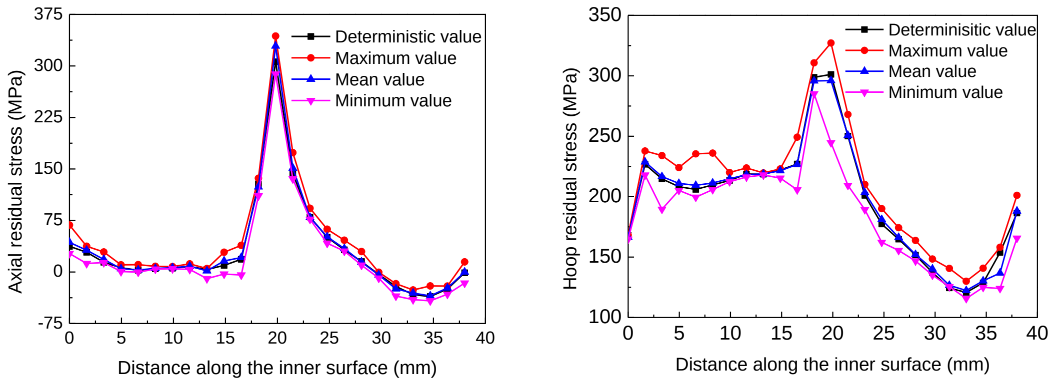
$x_i\ (i=1,2,\cdots,m_0)$ is the node of an input layer, which corresponds to a sample point of a random variable, w_{ij}^1 and $\theta_j\ (j=1,2,\cdots,m_0)$ are the connection weight and threshold between the ith node of the input layer and the ith node of the first hidden layer, $y_i\ (i=1,2,\cdots,m)$ is the number of output nodes which corresponds to a simulation result. Then, based on learning from 50 sample points of the welding residual stress simulation, the neural network toolbox in MATLAB is used to realize the prediction of 5000 sample points.

MATLAB is powerful mathematical software for scientific and engineering calculation, and it has the characteristics of simple and intuitive programming and strong openness. Considering that the random analysis with neural network response surface method needs multiple samplings, MATLAB is employed to develop pre-processing and post-processing to improve the effectiveness of simulation with ABAQUS. The development process of ABAQUS with MATLAB software is as follows: (1) Determine the statistic characteristic of each random variable; (2) Generate random sampling with simple random sampling; (3) Program with MATLAB, realize the replacement of random variables in the ABAQUS program; (4) Calculation and analysis with ABAQUS, and return the calculated value of response quantity in result file .dat to MATLAB; (5) Obtain the statistical characteristics of the welding residual stress.

3. Results and discussion

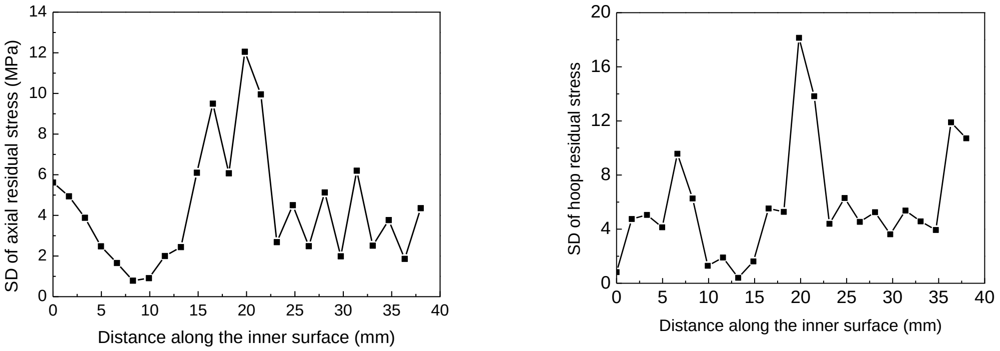
It is considered that the inner surface of welding zone is one of the main areas where cracks occur. Axial and hoop residual stress distribution changes along the inner surface are shown in Fig.7(a) and Fig.7(b), respectively. It can be seen that the deterministic result is a certain value in the random result and close to the mean result, which can`t completely describe the law of residual stress distribution. Axial and hoop residual stress along the inner surface are mainly tensile stress, and the maximum stress value appears in the middle of the inner surface, which implies that crack propagation in the direction should pay more attention. The maximum axial residual stress is about 400MPa, which is basically the same as its in reference 5. Therefore, it indicates that the analysis procedure using axisymmetric models and group technique is reasonable.

Fig.8(a) and Fig.8(b) show the standard deviation (SD) of axial and hoop residual stress distribution change along the inner surface, respectively. The maximum dispersion of axial and hoop residual stress appears near the center of the inner surface, which implies that the calculation deviation caused by random factors in this region is larger than other directions.



(a) *(b)*

Figure 7: (a) Axial residual stress distribution change along the inner surface (b) Hoop residual stress distribution change along the inner surface.



(a) *(b)*

Figure 8: (a) SD of axial residual stress distribution change along the inner surface (b) SD of hoop residual stress distribution change along the inner surface.

To investigate a single random factor effect on the residual stress distribution near the center of the inner surface, the randomness of Module of Elasticity, Poisson's ratio, Yield strength and Density of Alloy 132 are separately considered. Table 1 is shown the contribution of each random variable to SD of axial residual stress and hoop residual stress. From the results in Table 1, we can observe that the uncertainty of Yield strength has the greatest influence on the uncertainty of SD of axial and hoop residual stress, Poisson's ratio of oxide film has the lowest effect.

Table 1: Contribution of each random variable to SD of residual stress.

Random variable	E [MPa]	v [-]	σ_0 [Pa]	ρ [Kg/m^3]
SD of axial residual stress [MPa]	6.794	0.203	7.137	1.385
SD of hoop residual stress [MPa]	2.291	0.545	11.937	1.676

4. Conclusions

1) Based on the neural network response surface method, the program of welding residual stress distribution for DMW joints of the safe-end calculated using MATLAB and ABAQUS is complied, and the proposed method has certain rationality. The analysis procedure using axisymmetric models and group technique is reasonable, and the maximum axial and hoop residual stress appears near the center of the inner surface in the welding zone, which indicates that this region should be paid sufficient attention to the study of residual stress evaluation.

2) Compared with conventional sampling method, the neural network response surface method can greatly reduce the simulation time. Due to the uncertainties of Module of Elasticity, Poisson's ratio, Yield strength and Density, they should be regarded as random variables in establishing the FEM model. The deterministic result which is a definite value among random values can`t completely describe the law of the residual stress distribution.

3) Comparing the influence of each random variable on the SD of residual stress distribution, Yield

strength and Module of Elasticity has more significant effect on the residual stress uncertainty, and Poisson's ratio of material affects little.

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