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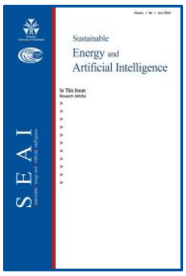

Prediction of Structural Steel Strength with Lap Joint Welds Using Artificial Neural Networks and Finite Element Simulation

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Abstract

Welding is a critical and sensitive technique for joining parts in industry. It has numerous applications and, in some cases, is irreplaceable. Therefore, it's essential to examine components produced by welding to determine the tolerable strength of welded sections for design and manufacturing purposes.

This study utilized thermo-elasto-plastic finite element analysis to examine the thermomechanical behavior that emerges from the arc welding of overlapping 37St steel sheets. The welding process was simulated in two stages using ANSYS software. The weld strength was measured through two independent analyses: thermal and mechanical. To simulate the heat source during welding, the element "birth and death" feature was utilized. Due to the high temperature gradient in the weld zone, the material's thermophysical and mechanical properties were considered temperature-dependent.

The calculation of weld strength is of great importance. Given that experimental methods are time-consuming and costly, the provision of fast and economical methods is significant. In this article, weld strength has been calculated using two methods: simulation with ANSYS software and artificial neural networks with MATLAB software. Finally, the results obtained from these two methods (numerical simulation and artificial neural networks) have been compared with experimental results.

Keywords: Welding, Lap Joint, Strength, Artificial Neural Network, Weld Simulation.

1. Introduction

Analyzing the welding process to measure weld strength involves a thermo-mechanical analysis. This analysis is performed separately within ANSYS software and comprises two distinct stages.

The first stage is the thermal analysis, which focuses on the heat conduction problem. This is conducted independently of the mechanical analysis to obtain the temperature distribution resulting from welding over time. Additionally, a coupled analysis approach is used for the thermal equations [1].

In the second stage, the temperature history of each node is applied as a thermal load. Here, mechanical analysis is employed, and through this process, the values of thermal stresses are obtained.

Properties of the materials are temperature-dependent and vary during welding. The heat generated during the welding arc follows a complex thermal cycle, causing changes in the microstructure of the heat-affected zones. This leads to time-dependent thermal stress and strain in the metal, as well as residual stress and distortion in the final product. To analyze such problems, the heat flow during welding must first be analyzed, and then the strength is measured by applying a mechanical load.

The material chosen for modeling in ANSYS software is St37, and its properties, according to the following graphs, have been applied as input to the simulation software [2]. Also, the density (7870g/cm³) is considered constant.

2. Experimental Investigation of Weld Strength

To measure the weld strength, some specimens made of St37 mild steel strips with an overlapping lap joint were welded using electric arc welding. The specimens were then subjected to notching (grooving) operations using a spark machine and subsequently underwent uniaxial tensile testing using an Instron servo-hydraulic machine.

Details regarding the geometric specifications of the test specimens are provided in the tables below. Welding parameters are presented in Table 1, and the geometric characteristics of the test specimens are detailed in Table 2.

Fig. 3 displays one of the experimental specimens and Schematic of sample.

Among the tested specimens, some samples failed in the notched region, and another failed a few millimeters away from the notched region. Localized necking was observed in both samples prior to fracture. The fracture in these samples was of the ductile type, attributed to the occurrence of necking and the 45-degree angle of the fracture surface relative to the transverse cross-section.

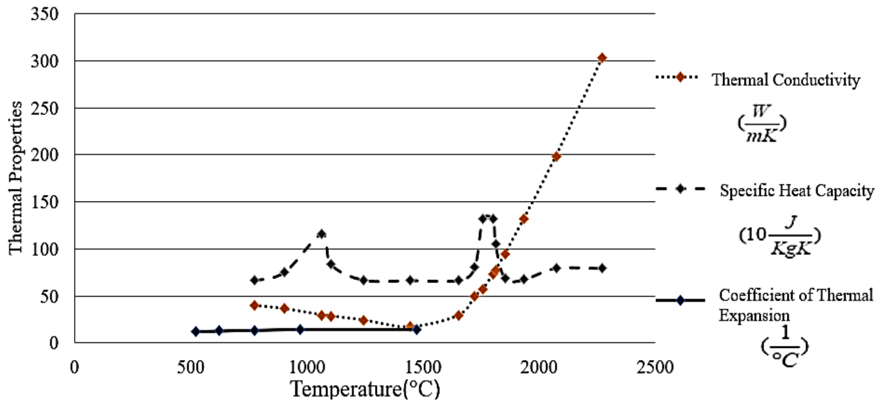


Fig. 1. Thermal properties of St37 as a function of pemperature [2]

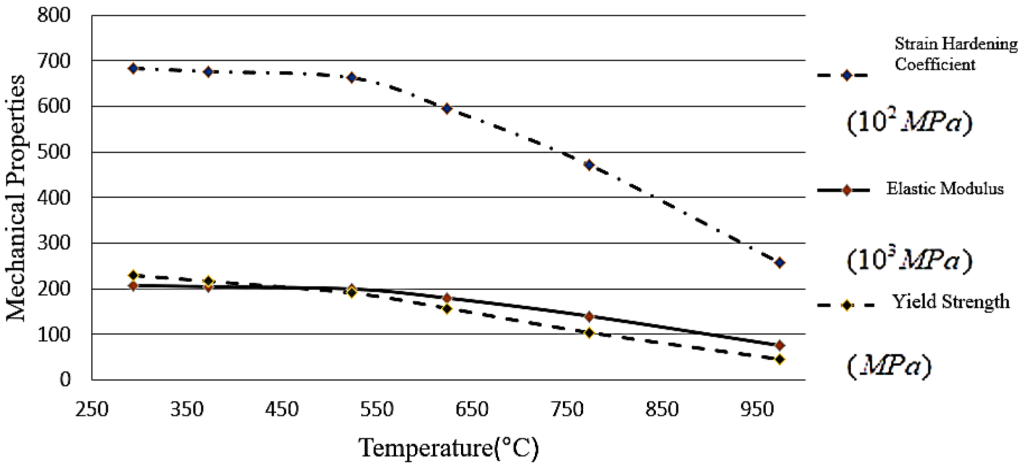


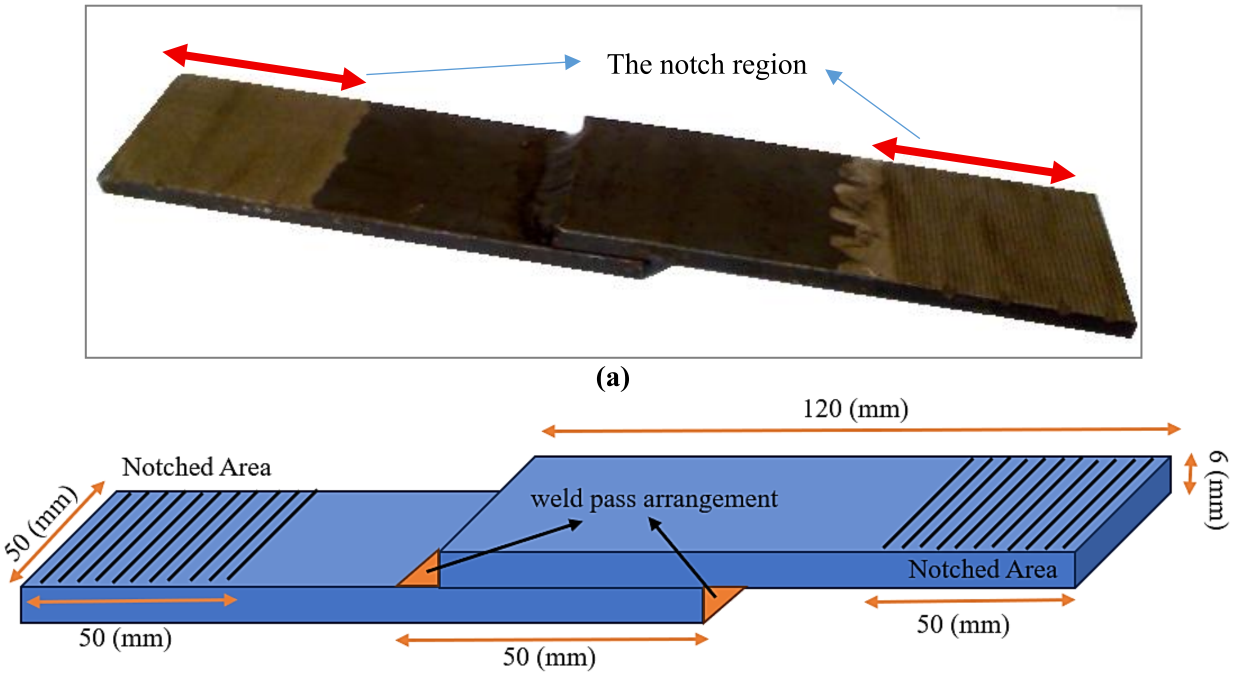
Fig. 2. Mechanical properties of St37 as a function of temperature [2]

Table 1. Welding specifications of test specimens

Welding Speed (mm/min)	Voltage (Volt)	Amperage (Amper)	Electrode Diameter (mm)	Electrode Type	Number of Weld Passes
200	220	100	2	E6013	2

Table 2. Geometric specifications of test specimens

Length (mm)	Width (mm)	Height (mm)	Number of Samples	Weld Distance from Adjacent End (mm)	Notch Length from End (mm)
120	50	6	5	50	50



(a)

(b)

Fig. 3. (a) Experimental sample. (b) Schematic of sample

Table 3. Maximum applied force values for specimens

Specimen Number	Maximum Elongation (mm)	Strain	Maximum Stress (GPa)	Maximum Force (N)
1	47.13	0.3571	0.399	99749.74
2	107.86	0.0686	0.375	93838.51
3	35.56	0.0144	0.146	36448.18
4	73.63	0.0657	0.357	89193.05
5	69.64	0.0179	0.271	67812.03
6	50.61	0.1543	0.338	846

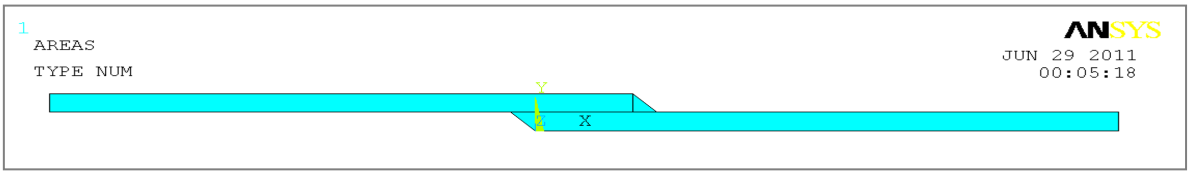


Fig. 4. Sample model in ANSYS software

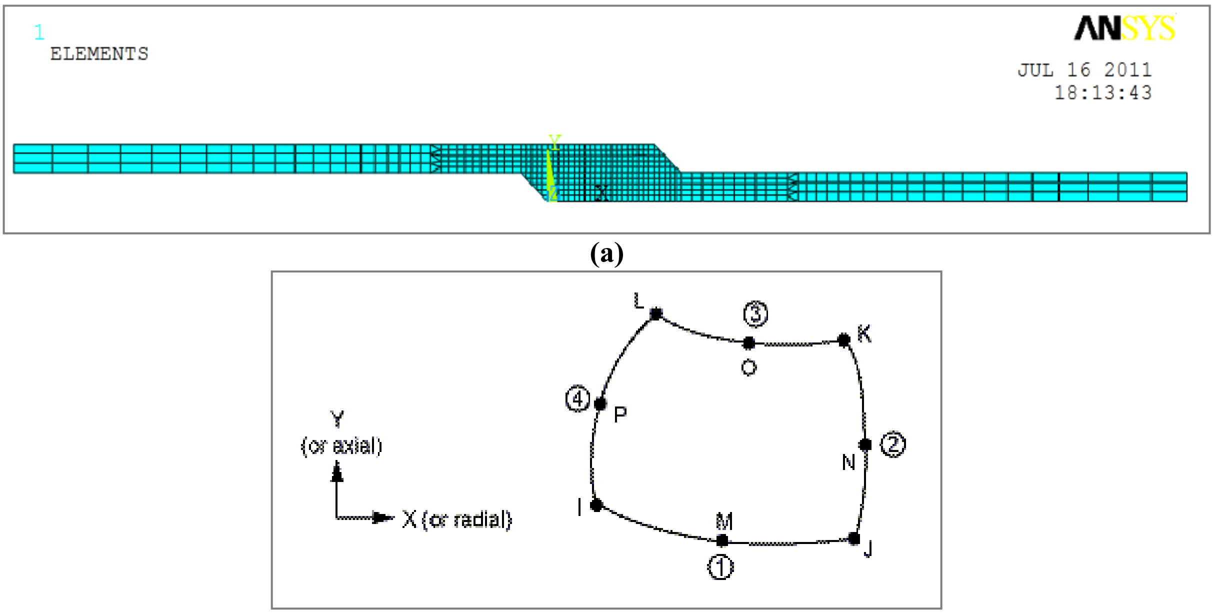
Some specimens slipped out of the grips due to excessive deformation and thinning of the section within the grips. The maximum applied force, maximum elongation, and strain for each specimen are presented in Table 3.

3. Simulation of Lap Joint Weld in ANSYS

The modeling of two steel strips and their lap joint weld was performed in 2D. In this model, two rectangular parts represent the St37 sheets, and two triangular parts at the corners of the rectangular surfaces are modeled as the first and second weld passes.

After modeling, all parts of the model were meshed. The meshing strategy involves using a finer mesh near the weld line (where the thermal gradient is significantly larger than in other parts of the model). This fine meshing is crucial because sufficiently small elements greatly contribute to the solution's accuracy.

Conversely, making all elements extremely small would drastically increase analysis time. Therefore, as shown in the figure, the meshing is finer in regions closer to the weld line and gradually becomes coarser further away from it. This approach optimizes computational efficiency while maintaining accuracy in critical areas. The plane 77 element is used for thermal analysis. This element is two-dimensional and has 8 nodes, and each node has one thermal degree of freedom. Fig. 5(b) Geometry and degrees of freedom of the Plane 77 element. The model consists of 1693 nodes and 519 elements.



(a)

(b)

Fig. 5. (a) Sample Meshing in ANSYS Software. (b) Geometry and degrees of freedom of the Plane77 element

3-1. Element Birth and Death Technique in ANSYS Simulation

One crucial aspect of weld simulation is modeling the filler material deposition over time during the welding process. Key methods for this include the element birth and death technique, silent elements, and element movement methods. Among these three, only the element birth and death capability are available in ANSYS software, so this section introduces that method.

Since the welding process involves adding material to the model and it's not possible to create or delete elements during the solution time, all elements must be initially generated. Therefore, for modeling multi-pass welding, we utilize the element birth and death feature.

This method employs "dying" elements instead of actually removing elements that the electrode hasn't yet passed over. To "kill" elements, a reduction factor is multiplied by their stiffness. Although the force vector of a "dead" element becomes zero, it still appears in the element force vector. Additionally, mass, heat capacity, and other effects are reduced to near zero. This way, the mass and energy of "dead" elements are not calculated in the total mass and energy of the model.

Similarly, instead of adding elements as the electrode passes over them, the element "birth" capability is used in this method. For "birthing" elements, their stiffness, mass, element force, and other coefficients are returned to their original values. coefficients are returned to their original values.

3-2. Thermal Analysis of Weld in ANSYS Software

In this article, the thermal loading is applied as follows:

- Initial Conditions: The entire model is subjected to an initial temperature of 25 degrees Celsius.
- Heat Flux Application: The heat flux generated during the welding process, which represents the heat created in the workpiece due to the welding heat source, can be calculated using the following Equation [3]:

$$Df_i = \frac{\eta v_i I_i t_{wi}}{u_i t_s} \qquad (1)$$

Where the parameters are:

$Df_i =$ Heat flux due to welding

$\eta =$ Welding efficiency, assumed to be 70%

$V_i =$ Welding voltage, set to 220 Volts

$I_i =$ Welding current, set to 100 Amperes

$t_{wi} =$ Welding time, averaging 7.5 seconds per pass

$t_s =$ Simulation time for welding in the software, which is 5 seconds per pass

$u_i =$ Volume of the weld area, considered to be 625 square millimeters per weld pass

It's worth noting that according to reference [3], the effect of varying the heat source distance from the weld line is neglected, and the heat flux distribution is assumed to be constant.

- Convective Heat Transfer to Environment: Convective heat transfer is applied to surfaces exposed to the environment. The ambient temperature is 25 degrees Celsius, and the variable heat transfer coefficient, accounting for radiation effects, is given by the following relationship [4]:

$$\begin{cases} \alpha_h = 0.0668T \_\_\_\_(w/m^2)\_\_\_\_ 0 < T < 500^0 c \\ \alpha_h = 0.231T - 82.1\_(w/m^2)\_\_\_\_\_\_ 500^0 c < T \end{cases} \quad (2)$$

Where the parameters used are:

T= Temperature of the weld zone at any given moment

α_h=Convective heat transfer coefficient

- Element Birth and Death Technique: This technique is utilized to simulate the welding process.

The thermal loading in this analysis consists of three stages:

- ✓ Placing the second weld pass in a "dead" state and applying thermal loading to the first weld pass.
- ✓ "Birthing" the second weld pass and applying load to it.
- ✓ Removing the thermal loading from the workpiece and weld passes, allowing the model to reach thermal equilibrium.

3-3. Mechanical Analysis of Weld in ANSYS Software

In the second stage of the analysis, the results from the thermal analysis, which provide the temperature distribution in the sheet over different times, are used as an applied load for the structural problem. The mechanical solution steps are precisely similar to the thermal solution. That is, initially, the elements of the second pass are set to a "dead" state, and then, with the "death" of the first pass elements, the second pass elements are "born." The boundary conditions used in the mechanical analysis are as follows:

- Zero displacement is assumed at two nodes located in the middle of the model.
- A uniform tensile load is applied to the end lines of the modeled shape (both ends of the sheet).

The mechanical solution is carried out in two phases:

- Applying the results of the thermal solution as input for the mechanical solution.
- Applying a tensile load to both ends of the part.

4. Artificial Neural Network Modeling

An artificial neural network (ANN) is a mathematical or computational model that has been inspired by the structure or functional aspects of biological neural networks [5]. Inspired by biological neural systems, ANNs process information [6]. ANNs have emerged as powerful computational tools for modeling complex material behavior, demonstrating remarkable capability in capturing nonlinear relationships between mechanical inputs and outputs [7]. Inspired by biological neural systems, ANNs process information through interconnected layers of artificial neurons, with performance governed by three key parameters [8]:

- Network Architecture: Interconnection patterns between neural layers
- Learning Algorithm: Weight optimization methodology (e.g., backpropagation)
- Activation Functions: Mathematical transformations of neuron inputs

An Artificial Neural Network (ANN), leveraging the learning process [9] and utilizing processing units called neurons, endeavors to establish a mapping between the input space (input layer) and the desired space (output layer) by identifying the inherent relationships within data. The **hidden layer(s)** process the information received from the input layer and then make it available to the output layer. Each network is trained by being presented with examples.

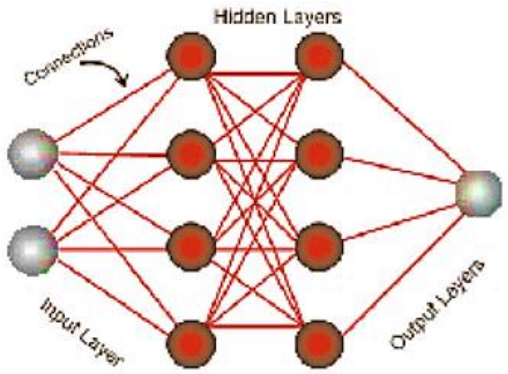


Fig. 6. Neural Network layers

Fig. 6. shows the input, hidden, and output layers with connections between neurons. Training is a process that ultimately leads to learning. Network learning occurs when the connection weights between layers change such that the difference between predicted and calculated values is within an acceptable range. Once these conditions are met, the learning process is achieved. These weights represent the network's memory and knowledge.

A trained neural network can be used to predict outputs corresponding to a new dataset [10]. Given the structure of an artificial neural network, its major features include high processing speed, the ability to learn patterns through pattern recognition, the ability to generalize knowledge after learning, flexibility against unintended errors, and the absence of significant disruption if an issue occurs in a part of the connections due to the distribution of network weights [11]. In this article, an MLP (Multi-Layer Perceptron) network has been used.

4-1. Multi-Layer Perceptron (MLP) Network

This network consists of an input layer, one or more hidden layers, and an output layer. The backpropagation (BP) algorithm [12] is typically used to train this network. During MLP network training with the aid of the BP learning algorithm, computations are first performed from the network input towards the network output. Then, the calculated error values are propagated back to the preceding layers. Initially, output calculation is performed layer by layer, and the output of each layer becomes the input for the next layer. In the backpropagation phase, the output layers are adjusted first, because for each neuron in the output layer, there is a desired value, and with their help and updating rules, the weights can be adjusted. The steps for training using this algorithm are [9,10]:

a) Assigning a random weight matrix to each connection.
b) Selecting an input vector and its corresponding output.
c) Calculating the neuron's output in each layer and, consequently, calculating the output of neurons in the output layer.
d) Updating weights using the network error backpropagation method to previous layers, which is the error resulting from the difference between the actual output and the calculated output.
e) Evaluating the performance of the trained network.

5. Prediction Results

5-1. Prediction Results of simulation by ANSYS

In the Thermo-mechanical loading of the weld, under a plane strain condition and with a tensile force applied to both ends of the specimen, the following results for principal stresses are extracted from the numerical simulation.

Table 4. ANSYS simulation results

Applied Tensile Force (KN)	Maximum Stresses (MPa)
30	234
40	240
50	255
60	261
70	270
80	274
90	284
100	300
120	314
130	321
140	338
150	353

5-2. Prediction Results of Artificial Neural Network

To train the Artificial Neural Network (ANN), data obtained from experiments was utilized and a portion of test data was used to train the neural network The training data are presented in Table 5.

Table 5. Neural Network training data

Applied Tensile Force (KN)	Maximum Stresses (MPa)
35	315
45	327
55	335
65	346
75	356
85	372
95	380
105	387
115	392
125	396
135	401
145	407

After designing and implementing the network, the prediction results from the neural network are shown in Table 6.

Table 6. Neural Network results

Applied tensile force (KN)	Maximum stresses (MPa)
30	234
40	246
50	263
60	275
70	290
80	277
90	295
100	316
110	333
120	345
130	382
140	402

According to Fig. 7, the results obtained from the Artificial Neural Network (ANN) prediction and the results from the simulation are compared with the experimental test data.

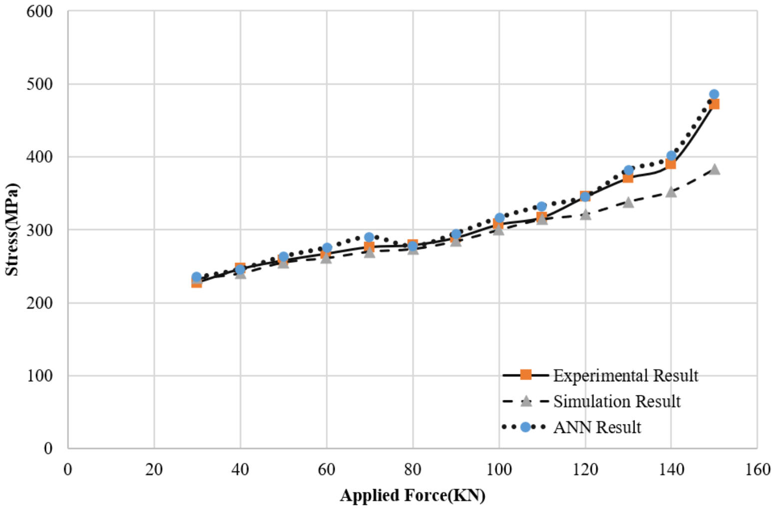


Fig. 7. Comparison of Stress-Force output from neural Network and numerical simulation

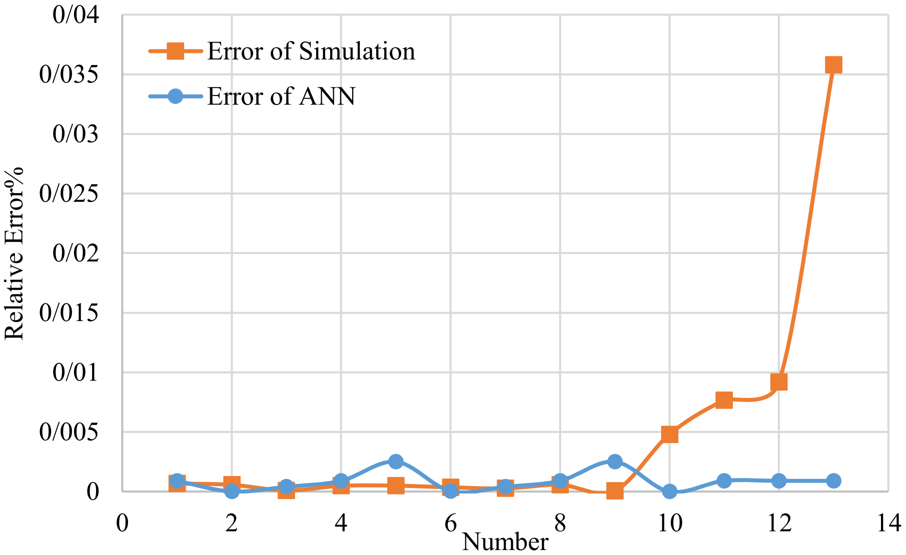


Fig. 8. The relative error of neural Network and numerical simulation

As evident from the results, the predictions from the Artificial Neural Network and the simulation show good agreement with the experimental data. Some existing differences in the trend and results of the simulation can be attributed to the simplifying assumptions made during the simulation process. For a more precise comparison of the results, the relative error criterion has been used, and the error graph versus data number is shown in Fig. 8.

Furthermore, since the neural network has been trained based on actual values obtained from experimental tests, it exhibits a closer resemblance to the test data at first glance, and the limitations of simplifying assumptions do not affect its results. However, it might incur errors when extrapolating results outside its training range.

6. Conclusion

Two methods were investigated for determining the maximum stress resulting from loading and providing a suitable criterion for measuring weld strength in a lap joint weld model. By observing the results obtained from both methods, it can be concluded that predicting weld strength using an Artificial Neural Network (ANN) offers advantages over numerical simulation for several reasons, including:

- **Parallel Processing:** Artificial neural networks can respond to a set of inputs in parallel, whereas numerical simulation requires completing all steps for each individual loading condition.
- **Error Tolerance:** There is a possibility of overlooking minor errors due to the parallel operation inherent in neural networks.
- **Reduced Data Requirement:** For predicting strength with an ANN, there is less need for extensive problem characteristics; only the input data for training the network is required.

- **Significant Time Reduction:** Using a neural network dramatically reduces the time required to complete the task.
- **Ignoring simplifying assumptions in the neural network prediction process:** Unlike predictions made through simulation, which are made with assumptions such as homogeneity and purity of the material, the neural network provides more accurate and acceptable results since it follows the actual behavior of the material based on test data.

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Biography

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