Application of Machine Learning in the Investigation of Residual Stress in Electron Beam Welding

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Abstract

Welding is one of the most common fabrication techniques for assembly metal parts. It is widely used in different industries such as nuclear, shipbuilding, aerospace and many other manufacturing industries due to its versatility, cost-effectiveness, high efficiency and ease of implementing automation. However, the quality of welding is not always guaranteed. Sometimes, undesired residual stress can be introduced to the welded joints since metal components usually undergoes severe and uneven internal temperature changes as well as phase changes at the welding site during welding process. Residual stress can lead to the flaws or even the ultimately failure of the welded components. Therefore, study the residual stress is a crucial step of the structural integrity investigation of welding especially for industries that highly emphasise structural integrity such as the nuclear industry.

The current approaches for investigating residual stresses in welded metal components involve finite element analysis (FEA) and experimental methods. In the case of traditional FEA and experimental methods, a clear understanding of material properties and the welding heat source is an indispensable prerequisite for obtaining reliable residual stress data which usually leads to high time and monetary costs. With the rise of artificial intelligence and its widespread application in engineering tasks, it is considered to have the potential to become an auxiliary or even substitute for traditional FEA to increase simulation efficiency. Therefore, this study focuses on the application of machine learning in the investigation of welding residual stress.

For traditional welding methods, the use of filler material is usually unavoidable which adds considerable complication to study the residual stress. Currently, power-beam welding techniques are attractive since they are autogenous and the heat affected zone is generally narrower than traditional welding methods. The most typical power-beam welding techniques are laser-beam welding and electron-beam welding. This study currently focuses on the electron-beam welded 316L steel pipe provided by CEA as indicated in Fig. 1. Besides investigating the residual stress in the current specimen, an inverse prediction method is sought to predict the appropriate thermal parameters of the electron beam for the desired residual stress profile in the pipe. This could be challenging for the traditional FEA or experimental method. Since machine learning is a kind of data-driven technique, there is no need for a precise understanding of the relationship between electron-beam thermal parameters and the generated residual stress. Hence, it has been considered as a feasible way in this work.

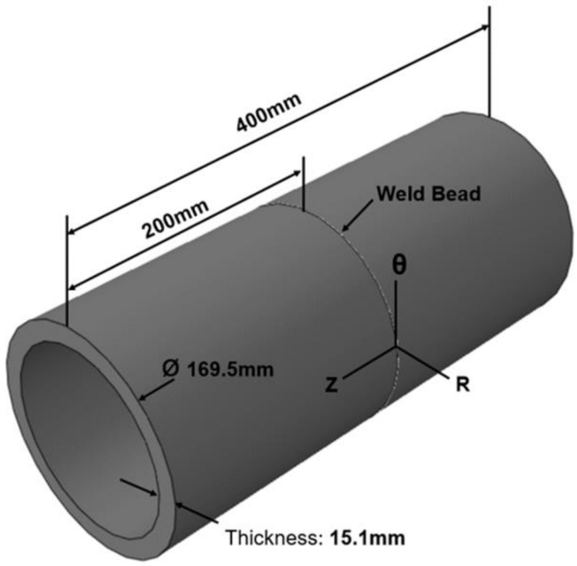

Figure 1: The Electron-Beam Welded 316L Steel Pipe from CEA

As machine learning is a data-driven algorithm, a sufficient database is a prerequisite for utilising this technique. The FEA model was thought to be a good source of the training database. Therefore, the inversely prediction methodology in this study was based on the combined use of machine learning and FEA. CEA was interested in the electron-beam welded 316L steel pipe. However, it is too expensive to investigate the residual stress profile by generate various similar specimens. Therefore, an alternative low-cost experiment has been placed by CEA to reproduce the residual stress field in the electron-beam welded pipe. The alternative experiment is heating a 304 steel pipe with an induction coil at middle and then cooling it with flowing water on the inner side of the pipe as shown in Fig. 2.

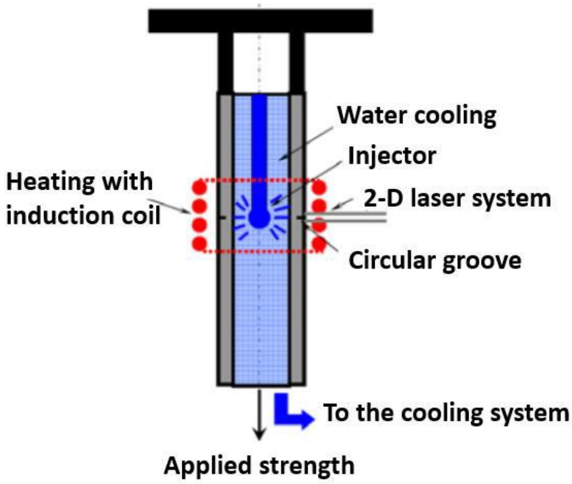

Figure 2: CEA Induction Heating Experiment Setting

The 2D axisymmetric FEA model was built based on this induction heating pipe experiment and residual stress data was extracted from the heating area surrounded by the induction coil. For finding the relationship between electron-beam thermal parameters and welding residual stress, artificial neural networks (ANN) were chosen from different machine learning techniques as they are proven to be capable of learning linear or non-linear relationships between input and output. To be more specific, the most common ANN architecture Multi-layer Perceptron (MLP) network was used in this work where the structure is shown by Fig. 3. For training the network, 120 sets of training data were generated with different combinations of welding thermal parameters for the MLP network. In the data set, 80% were used to training the network and the rest were used to estimate the accuracy of predictions made by the trained network. Besides, the Incremental Deep Hole Drilling measurement of the residual stress in the electron-beam welded 316L steel pipe was also used to estimate the performance of the inverse predicting model built in this work.

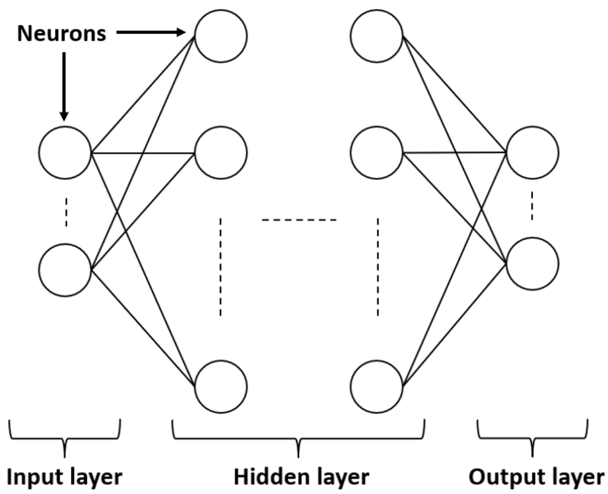

Figure 3: Architecture of Multi-layer Perceptron Network