Artificial Neural Network Application for Parameter Prediction of Heat Induced Distortion

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Abstract. Heat induced distortion has been widely studied over the years, in order to provide reliable results, thermal elastic-plastic FEM analysis have been used to estimate the distortions produced by the heat source. However this type of analysis often involves long computational time and requires high degree of technical knowledge by the user, moreover it's mainly performed to specific regions that limit the scope of the analysis. In order to provide a tool for the prediction of the line heating phenomena, an artificial neural network (ANN) is used. ANN is a powerful tool to predict complex phenomena, and in addition, it is very attractive because of the relatively modest hardware requirements and fast computational time. In this paper, parameter prediction for the heat induced distortion as an inverse problem is performed by ANN, using, the inherent deformation from a gas heating FEM analysis and their heating conditions as the training data. Exploratory analysis of the data and the model were performed to accurately predict the heating conditions. The prediction of the necessary heating conditions to generate an arbitrary deformation in the plate is a step forward in the automation of the line heating forming process. The possibility of predicting arbitrary heat induced distortion problem by an ANN model is shown.

Keywords: Inverse problem · Neural networks · Heat induced distortion · Line heating

1 Introduction

For many decades line heating has been used as a method for forming three dimensional surfaces in the shipbuilding industry [1], however the procedure is often done manually depending on the skill of experienced workers. Therefore this dependency results in a low productivity rate for shipyards which leads to high cost. The prediction of the distortion produced by line heating have been studied for several years, however, it is a highly nonlinear problem consisting of many factors such as the amount of heat, the plate thickness, the speed of the heating source and secondary factors like the cooling method, residual stress, etc. [2, 3]. In order to analyze this phenomena it is required to have an appropriate mathematical tool dealing with all the variables involved in this problem. Finite element method (FEM), through a three dimensional

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thermal elastic plastic analysis, is the tool for it, but due to the complexity of the problem, it takes long computational time [4]. Final plate deformation have been successfully predicted by using an ANN model [5], however this ANN model is only able to predict the final deformation of a flat plate due to a line heating process. By this limitation, the ANN model cannot be used to predict the required heating conditions to produce an arbitrary deformation in the plate, which is often requested, in the shipbuilding industry. In this study, in order to improve this problem, another ANN model is proposed and discussed.

2 Gas Heating FEM Analysis

First of all, to understand heat induced distortion, thermal-elastic-plastic FEM is perform. In this code proposed by Osawa et al. [2], gas torch is regarded as the heating source. The process of forming a plate for a given heating conditions can be viewed as the process to deform a plate into a desired shape by giving the heating conditions, using the shrinkage and the angular distortion induced by the heating and cooling process [6]. Plate deformation by line heating can be described by four deformation components as is shown in Fig. 1. These deformation components (inherent deformation) are inherent longitudinal shrinkage, inherent transverse shrinkage, inherent longitudinal bending and inherent transverse bending respectively.

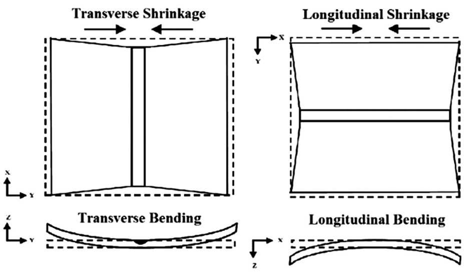

Fig. 1. Line heating distortion components

In this study the attention is focused in the process of deforming thick plates, where herein the term thick plate refers to those plates with thickness equal or greater than 10 mm, because it is more difficult to deform them by using the line heating technique. Therefore for this analysis, the plate thickness range from 10 to 50 mm and the heating speed range from 4 to 40 mm/s as shown in Table 1.

Table 1. Heating Conditions

Heating conditions	
Plate thickness [mm]	10, 20, 30, 40 & 50
Heating speed [mm/s]	4, 8, 12, 16, 20, 24, 28, 32, 36, 40

For better prediction of the inherent distortion, squared plate of 1200 mm (length) by 1200 mm (width) is selected as shown in the Fig. 2. Furthermore the effect of the plate thickness and the heating speed are evaluated. Once the model and the heating condition are defined, the thermal-elastic-plastic analysis is carried out. The analysis can be divided in two steps: the thermal analysis, where the heat source is applied to the model, and then the mechanical analysis where the deformation of the plate it's obtained. Later these results are used to train the ANN model to estimate the heating speed.

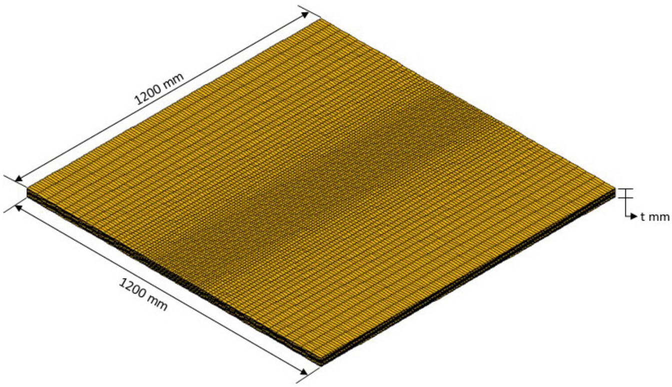

Fig. 2. Subject flat plate and its FEM model

From the thermal analysis the temperature distribution over the plate is obtained. Figure 3, show the maximum temperature in the plate with different heating speed. As a common practice in line heating process, the maximum temperature of the plate should be kept below 800 °C [7], in order to avoid material degradation,. Therefore the heating speed is restricted to a range over 12 mm/s.

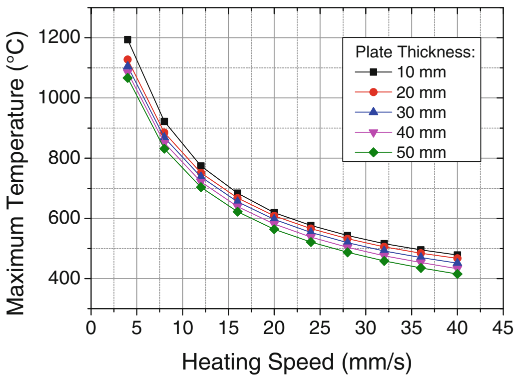

Fig. 3. Maximum temperature with heating speed and plate thickness (thermal analysis)

The transient temperature distribution obtained by the thermal analysis is employed as a thermal load in the subsequent mechanical analysis and finally the inherent distortion is obtained as shown in Fig. 4.

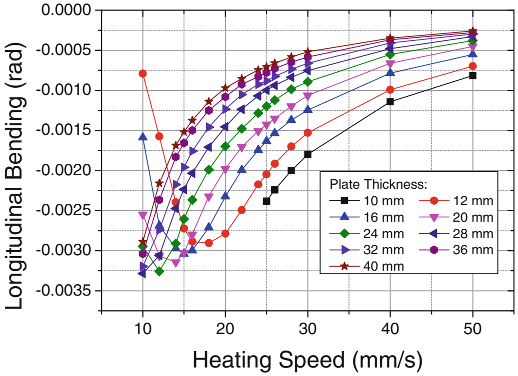

Fig. 4. Longitudinal bending distortion with plate thickness and heating speed (mechanical analysis)

Then the gas heating to a plate is simulated by FEM analysis with the given transient temperature distribution. The result is shown in Fig. 4. It can be noticed clear continuous relation between the plate thickness, the heating speed and the four inherent distortion components. On the other hand in the case of thinner plates with low heating speed, there exists slightly different behavior especially for the case of the longitudinal bending. This behavior is mainly because the heat distribution in the direction of the plate depth. At low speed the temperature at the top and the bottom of the plate are nearly similar.

2.1 Generation of the Training Data

In the case of the thermal-elastic-plastic FEM analysis, the model is able to predict the inherent distortion for a given plate thickness and heating speed. This type of problems, where the cause is given and the effect is determined is known as forward problem as it is presented in Fig. 5. In the other hand, the prediction of the heating speed by using the actual deformation of the plate and its thickness is an inverse problem where the effect is given and the cause is estimated.

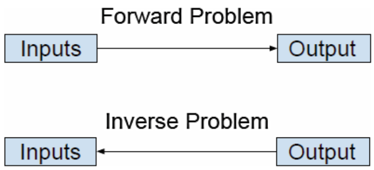

Fig. 5. Forward and inverse problems

Inverse problem is generally difficult, because it may not have a unique solution [8], furthermore inverse problem has a deductive nature rather than the inductive nature of forward problem. To overcome this situation ANN is used based on its ability to approximate unknown input-output mapping.

To perform the inverse problem analysis, the ANN model use the inherent distortion predicted in the forward problem as shown in the Fig. 6. From the figure, it can be seen that the plate thickness is taken as an input parameter since the plate thickness is known beforehand as well as the inherent deformation, then the ANN model will be able to predict the heating to deform the plate into the desired condition.

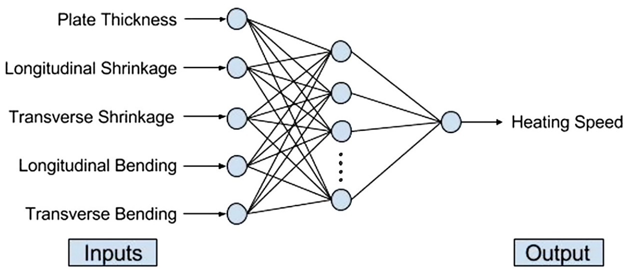

Fig. 6. Neural network model topology

The training data plays a key role in the development of the model. During the training stage of the ANN model, it was noticed that not only the size but also the quality of the data have a positive impact in the performance of the model.

3 Neural Network Development

In general terms, ANN can be seen as a tool that is designed to mimic the way in which the brains perform a specific task or function [9]. They are characterized by: the architecture, the training method and its activation function [10].

In this study, the development of the ANN model were performed using the neural network toolbox of MATLAB [11].

3.1 Neural Network Topology

Major advantages of ANN are that it is not necessary to presume any predetermined model nor coefficients and it copes with the cases not prepared as teaching data. In order to develop this feature, the topology of the network is quite important. The performance of the ANN model will depend on the chosen topology.

For simplicity of the ANN model, one hidden is selected as it is shown in Fig. 6, then the number of neurons in the hidden layer is evaluated so as to get the best performance of the ANN model, as shown in Fig. 7. From the figure it can be noticed that as the number of neurons in the hidden layer is increased, the MSE of the ANN

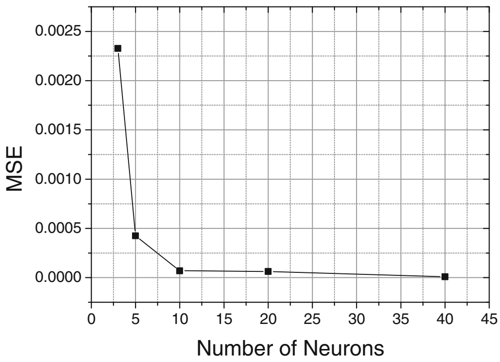

Fig. 7. Influence of number of hidden layers neurons in terms of MSE

model is improved. However, five neurons is selected for the hidden layer because further increase in the number of neurons does not improve the response of the ANN model drastically. Since the ANN model is used to perform an approximation task, a hyperbolic tangent sigmoid transfer function is selected for the hidden layer while a linear transfer function is used for the output layer.

The Levenberg-Marquardt optimization is chosen as the training algorithm for the backpropagation ANN model, as the ANN model present few hundred weights [12], while the Mean Squared Error (MSE) is used as the performance function.

Early stopping technique is used while monitoring the behaviour of the network, dividing the data into three subsets: 70 % for training, 15 % for test and the other 15 %, for validation, where the training data consist in 120 different cases taken from the gas torch FEM analysis. Furthermore another set of data is prepared for the purpose of testing the tolerance of the model, i.e. this set is not used to train the network, but to confirm the performance of the untaught cases.

4 Results

Once the training stage is finished, the performance of the ANN model during the training is evaluated as it is shown in Fig. 8. As different solutions were obtained even using the same model, the performance of each candidate was evaluated in order to select the best ANN model. From the figure, can be noticed that beyond 150 epochs the MSE is almost constant, then further training of the network will not improve the performance of the ANN model.

After the ANN model is selected, the response of the ANN model is tested with the training data and simultaneously is compared with the FEM results as shown in Fig. 9. In the figure, the relationship of the longitudinal bending and the heating speed for a plate of 10 mm thickness is presented, where the ANN model predicted the FEM results quite well, therefore the heating speed is accurately predicted by the ANN model.

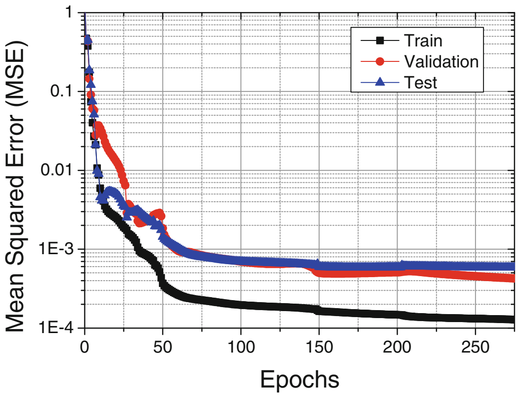

Fig. 8. ANN model training performance

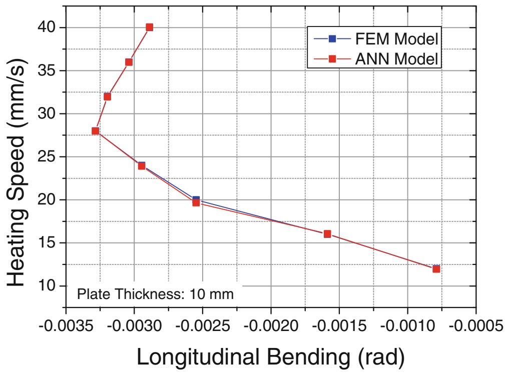

Fig. 9. FEM & ANN model comparison (Color figure online)

In order to have a wider view of the response of the ANN model, the error generated by predicting the training data is measured and plotted as shown in Fig. 10. From the figure is noticed that the error in the prediction is almost below 2 %, thus it proves the good performance for almost the given conditions.

Besides the response of the ANN model for data used during the training stage, the response of the ANN model for unseen data must be tested, as the prediction of the heating speed is performed using the plate thickness and the inherent distortion, they were taken in consideration for testing the response of the ANN model.

In Fig. 11, the relationship of the heating speed and the longitudinal bending for a 10 mm thickness plate is presented again, but the model is tested with conditions that were not used during the training stage. The response of the ANN model correctly matches with the FEM analysis.

Again in Fig. 12, the relationship of the heating speed with the longitudinal bending is presented but for an 11 mm plate thickness. Since the training data do not have any information for an 11 mm thickness plate, it can be noticed the good

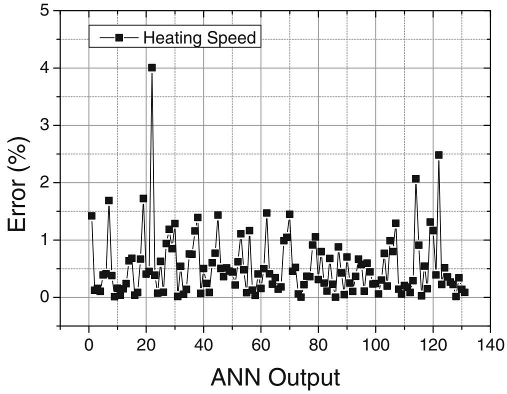

Fig. 10. ANN model response

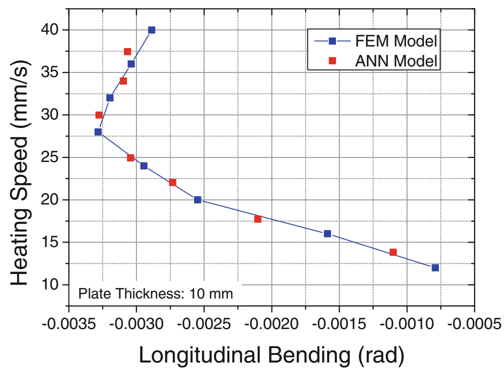

Fig. 11. ANN model prediction for longitudinal bending intermediate points

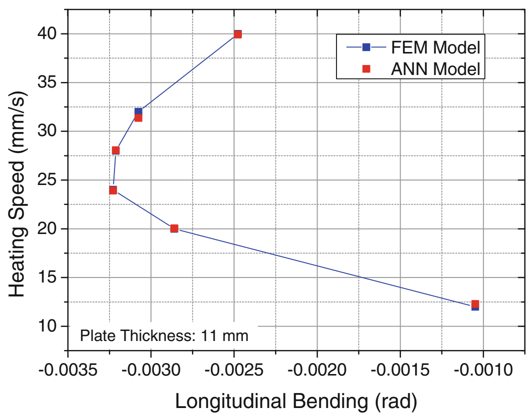

Fig. 12. ANN model prediction for plate thickness intermediate points

estimation of the ANN model for intermediate values of plate thickness. To confirm this results, several cases (blue square symbols) is calculated by the FEM model for an 11 mm thickness plate. The ANN model has a good capability to predict the heating speed even for untrained cases.

5 Conclusion

The heating speed for a given plate thickness with certain conditions by line heating process is accurately predicted using an ANN model. This model is capable to predict the heating speed by using the plate thickness and the four components of inherent distortion measured at the middle of the plate. Although this model is limited to a gas torch heating under the condition that the maximum temperature of the plate is kept below 800 °C to avoid material degradation, the following conclusions are drawn.

1. ANN models can successfully solve line heating distortion as an inverse problem.
2. The topology and the training data used in the ANN model have greatly affect the performance of the model, so they should be chose carefully.
3. The developed ANN model can successfully predict the heating speed to obtain certain distortion for a given steel plate even for conditions outside the training data making the ANN model an alternative tool for the heat induced distortion problem prediction.

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