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Prediction of deformations of steel plate by artificial neural network in forming process with induction heating †

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Abstract

To control a heat source easily in the forming process of steel plate with heating, the electro-magnetic induction process has been used as a substitute of the flame heating process. However, only few studies have analyzed the deformation of a workpiece in the induction heating process by using a mathematical model. This is mainly due to the difficulty of modeling the heat flux from the inductor traveling on the conductive plate during the induction process. In this study, the heat flux distribution over a steel plate during the induction process is first analyzed by a numerical method with the assumption that the process is in a quasi-stationary state around the inductor and also that the heat flux itself greatly depends on the temperature of the workpiece. With the heat flux, heat flow and thermo-mechanical analyses on the plate to obtain deformations during the heating process are then performed with a commercial FEM program for 34 combinations of heating parameters. An artificial neural network is proposed to build a simplified relationship between deformations and heating parameters that can be easily utilized to predict deformations of steel plate with a wide range of heating parameters in the heating process. After its architecture is optimized, the artificial neural network is trained with the deformations obtained from the FEM analyses as outputs and the related heating parameters as inputs. The predicted outputs from the neural network are compared with those of the experiments and the numerical results. They are in good agreement.

Keywords: Plate forming; Electro-magnetic induction; Thermo-mechanical analysis; Deformation; FEM; Artificial neural network

1. Introduction

The steel forming process in a shipyard is an important stage with respect to productivity and precision of curved plates. The forming process to make steel plates of the desired curvature is performed mainly with the oxy-propane gas flame and depends exactly on the skill of experienced workers to control the deformation to produce a curvature within an allowable range. To control the deformation precisely during the process, it is easy to control the heat flux from the oxy-propane mixed gas because of the heat generation characteristics resulting from the reaction of the gases. Meanwhile, because the hull dimension needs to be controlled more precisely for high-performance ships, the oxy-propane process may be limited in various applications. An alternative heat source of electro-magnetic induction has been suggested as a substitute for the gas flame heating for such applications. The induction heating process is known to produce controllable heat on a conductive workpiece. When the induction heating process is applied in association with automatic inductor-handling equipment and a heating

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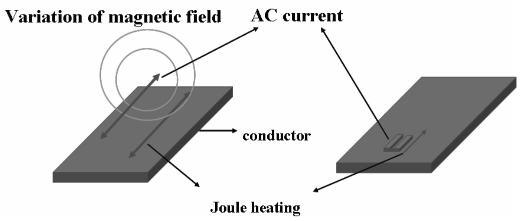


Fig. 1. Schematic model of induction heating process.

line generation algorithm, the productivity of the curved plate forming process is expected to be improved greatly. Especially, the heating line generation algorithm on how and where to heat a workpiece requires one to understand the relationship between the desired curvature of the plate and the heating parameters [1]. For the derivation of the relationship, the induction heating process should be in advance precisely modeled to evaluate its feasibility in plate forming. Meanwhile, only a few studies on plate forming with the induction heating process have ever been reported. The 2-dimensional temperature distribution during high-frequency induction heating has been the main subject in most of these studies [2-6], and the 3-dimensional deformation behavior of a steel plate has been modeled by an analytical method [7]. Nevertheless, the previous study gives finite element method (FEM) models for analysis of the heat-flux, heat-flow, and thermo-mechanical behaviors in the steel forming process with induction heating [8]. The study takes account of the thermo-mechanical and magnetic material properties of the heating process, which all depend on the temperature of the material. Furthermore, it also models travel of the inductor over a workpiece for simulation of an actual induction process. However, the calculation procedure of the coupled problem associated with magnetic, thermal, and mechanical phenomena consumes much time and cost. Therefore, to predict the deformations with a wide range of heating parameters easily, a more simplified approach is needed.

In this study, to easily predict deformations of steel plate during the forming process with input heating parameters, an artificial neural network (ANN) is proposed using a database including deformations and their related heating parameters. To build the database in advance for the ANN, the heat flux, heat flow and thermal deformation analyses on the heating process are firstly performed with heating parameters. To obtain the heat flux from the inductor over a workpiece, an FEM program for electro-magnetic field analysis of

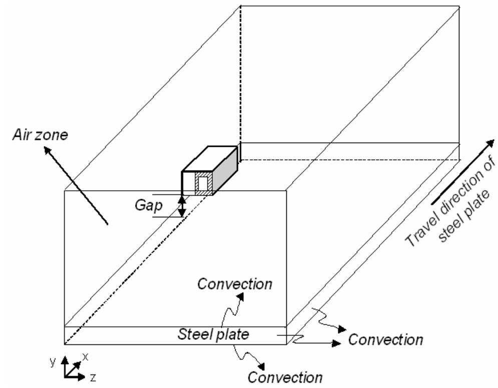


Fig. 2. Three-dimensional half model for FEM analysis of induction heating.

the heating process is developed under the assumption that the process is a quasi-stationary state process with a moving coordinate. In the analysis, the nonlinear characteristics of the material properties and the travel of the inductor during the heating process are taken into account simultaneously. The heat flow and thermo-mechanical deformation analyses for the workpiece are then followed with a commercial package program of Msc.MARC that uses the heat flux obtained from the electro-magnetic analysis. Angular distortion and transverse shrinkage of steel plate are calculated with the thermo-mechanical analysis for each of 34 combinations of heating parameters. ANN is composed of densely interconnected adaptive simple processing elements, called artificial neurons that are capable of executing massively parallel computations for data processing and knowledge representation. The advantage of ANN stems from the remarkable information processing characteristics of the biological system such as nonlinearity, high parallelism, fault, and failure tolerance and learning [9]. The ANN model can effectively reduce not only the time required to solve the problem to predict deformation, it also helps to define predictive values of deformation with more than two parameters as velocity and thickness for more complex cases, in which statistical methods or other ones will meet the difficulties. Therefore, the proposed ANN model in this paper can be used to predict the deformations instead of the statistical method in the steel forming process with induction heating. The architecture of the ANN model is optimized with a trial and error method, and the model is then trained by using both the results of the FEM analyses and the input heating parameters. The proposed network is tested and its results are compared

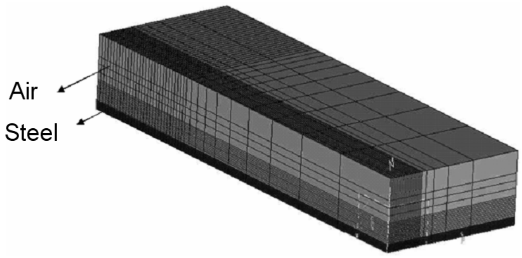


Fig. 3. Mesh generation for heat flux and thermal analysis of induction heating.

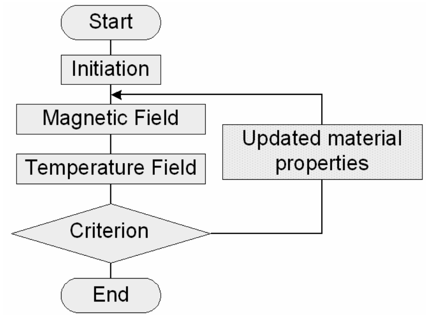


Fig. 4. Calculation procedure for heat flux and heat flow analyses.

with those of the experiments and the numerical analyses to reveal its feasibility to predict the deformation of steel plate in the forming process with induction heating.

2. Heat generation in the induction heating process

When high-frequency current flows through an inductor located over a conductor of a steel plate as shown in Fig. 1, a bundle of magnetic fluxes pass through the plate underneath, which is just to be coaxial coil, and consequently, eddy current is induced at the surface of the plate. The induced current generates electric-resistance heat in the plate, which can be used to bend the plate. The governing equation for the eddy current distribution in the induction heating process can be derived from Maxwell equations [10]. When the magnetic vector potential of the governing equation is analyzed, eddy current and heat-flux distribution can be calculated.

In this study, the governing equation is formulated for the finite element method (FEM) to analyze the electro-magnetic problem. The electro-magnetic field analysis to describe heat flux distribution over a steel plate requires exact material properties such as permeability, electric conductivity, etc., of the solution domain, which depend significantly on the temperature of the material. Therefore, the analysis to simulate the induction process becomes a coupled problem between electro-magnetic and heat flow analyses in the solution domain at the same time. To handle this coupled problem, we introduced the following procedure: Heat-flux distribution is obtained first by the analysis of the electro-magnetic field with the material properties at the initial temperature. Subsequently, a heat flow analysis through the steel plate is then performed to obtain the temperature distribution of the plate, which is used to determine the material properties for the following analysis of the electro-magnetic field to obtain the heat flux distribution. This procedure continues until convergence to a solution within an allowable range.

To perform the electro-magnetic and heat flow analysis to obtain the heat-flux and temperature distributions of a steel plate with FEM, a solution domain consisting of the steel plate, air and inductor is modeled as shown in Fig. 2. Meanwhile, as the inductor travels on the steel plate, the position of the inductor in the domain changes constantly. A part of air element changes to the inductor, whereas the previous inductor becomes air. To handle this constant change, a quasi-stationary state to the traveling direction of the inductor is assumed for the heat flux and heat flow analyses. Then, the heat-flux generation and heat flow can be modeled with a moving coordinate system, which has the origin at the position of the inductor.

The governing equation of heat flow in the moving coordinates is formulated for the FEM and the formulated equation is then implemented to a FORTRAN program to obtain a temperature distribution in the steel plate during the induction heating process [8]. The mesh division for the analysis is shown in Fig. 3, which consists of 3-dimensional 8-node elements. In the developed program, heating speed, current and frequency are set as the input parameters.

Fig. 4 illustrates the procedure for analyzing the electro-magnetic field and heat flow. In the analyses, iterations are carried out at each step with updated material properties until the convergence limit by comparing the temperature distributions of subsequent iteration steps. The comparisons finally produce a heat flux at each node from the inductor. The heat flux obtained is then used as the heat input onto the plate in the following transient heat flow and

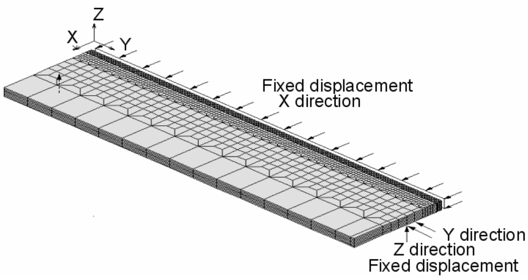


Fig. 5. Mesh generation for thermal and mechanical analysis.

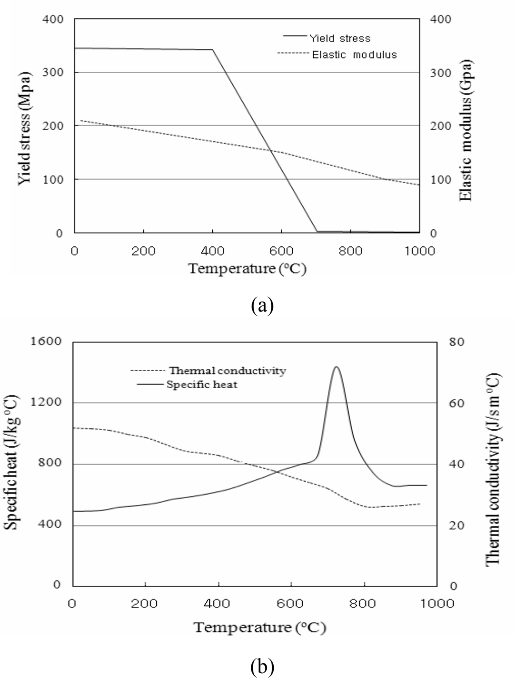


Fig. 6. Temperature dependent materials properties of AH32 steel: (a) Mechanical properties and (b) Thermal properties.

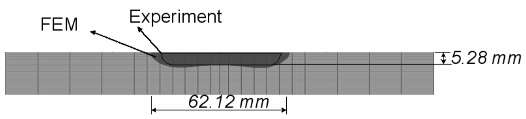


Fig. 7. Comparison of HAZ sizes obtained by analysis and experiment.

thermal deformation analyses.

3. Heat flow and thermal deformation in the induction heating process

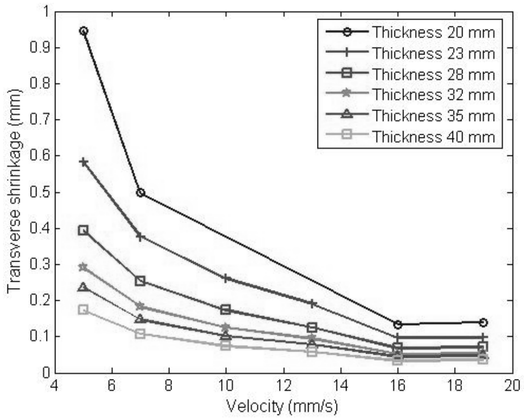
3.1 Analyses of heat flow and thermal deformation

To analyze the thermal deformation of a steel plate in the induction heating process, a transient heat flow analysis is required first. By using the heat flux obtained in the electro-magnetic analysis as the heat input onto the steel plate, the heat flow analysis is conducted with a commercial FEM package program of Msc.MARC. The magnitude of heat input being distributed around the inductor depends on the distance from the current position of the inductor.

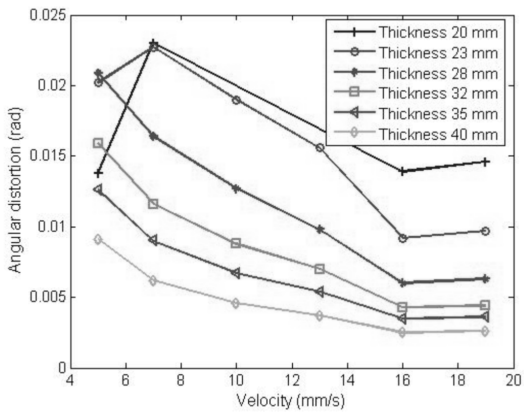
Fig. 5 shows the mesh shape of the steel plate used for the analysis. The steel plate has a length of 1000 mm, a width of 500 mm and the material properties of the AH32 steel, which are shown in Fig. 6. The solution domain is divided into 50,000 hexahedral elements with eight nodes, which are generally used in the thermo-elasto-plastic analysis. The finer elements, which have a minimum length of 1mm and a maximum length of 2.5mm, are used in the vicinity of the heating line to capture the thermal gradients accurately, whereas the elements located far away from the heating line are somewhat coarse to have a minimum length of 1mm and a maximum length of 82.5mm. In the analysis, the steel plate is assumed to be heated one pass by the inductor along the center line at a constant speed in the lengthwise direction. Because of the symmetric condition of the geometry around the heat source, half of the plate is selected to be a solution domain. Heating parameters are selected within the working conditions relevant to practical applications: Heating speeds are 5~19 mm/s, plate thicknesses are 20~40 mm and current is set to 3750 A. Thermal deformation analysis is then followed with the program of Msc.MARC by using the results of the heat flow analysis as the thermal load, where the same solution domain and material are used as those of the heat flow analysis. The boundary condition is as follows: lateral movements are fixed at the center, axial movement is fixed at two positions at one end and height movement is fixed at the position of 1/4 width of the plate at each end.

3.2 Results of analysis of heat flow and thermal deformation

Transient temperature distribution in the steel plate during induction heating could be obtained by heat flow analysis. To verify the validity of the analysis, the size of the heat-affected zone (HAZ) of the heated plate in the experiment is compared with the contour line of 723^{0}C obtained from the analysis. Fig. 7 illustrates the size of HAZ obtained from the experiment,



(a)



(b)

Fig. 8. Results of thermal deformation analysis for induction heating (a) transverse shrinkage and (b) angular distortion.

which was performed at a heating speed of 10 *mm/s*, and this size is compared with the result of the analysis performed at the same heating conditions. The two results are in fairly good agreement in both width and depth. This indicates that the heat flow model with the heat flux from the electro-magnetic analysis proposed in this study is relevant for the simulation of the induction heating process.

Fig. 8 represents the results of the deformation analysis for the prediction of the angular distortion and transverse shrinkage with the heating parameters of speed, plate thickness and electrical current of 3750A. The results show that as the velocity of the heating and the thickness of the plate decrease, the thermal deformations tend to increase. This is explained by the enlarged thermal load with lower velocity and the reduced stiffness with thinner plate.

4. Artificial neural network model to predict deformations

The deformation analysis in the forming process requires much time and cost with the calculation procedure of the coupled problem associated with magnetic, thermal, mechanical phenomena. To predict the deformations with a wide range of heating parameters, an artificial neural network is proposed using the results of the previous numerical analyses on the forming process.

Artificial neural networks (ANN) are revolutionary computing paradigms that try to mimic the biological brain. These ANNs are modeling techniques that are especially useful to address problems where solutions are clearly formulated or where the relationships between inputs and outputs are not sufficiently known. ANNs have the ability to learn by example so that patterns in a set of input and output data as training cases are recognized. A part of the training data can then be used by the ANN to predict unknown output values for a set of input values.

The type of ANN used in this study is a multilayer feed-forward architecture that is trained with the Levenberg–Marquardt method [11], which is selected as the training algorithm due to the convergence speed and the performance of the network to find a better solution. A comprehensive description of this type is beyond the scope of this paper and can be found in many publications [12-14]. The typical structure of a multilayer feed-forward neural network consists of a number of processing elements of neurons that are fully or partially linked via connection weights. These processing neurons are usually arranged in layers: an input layer, an output layer, and one or more hidden layers.

The network structure has a significant effect on the predicted results. However, the optimal number of hidden layers and the optimal number of nodes in each layer depend on the specific problem to be handled, and there is no straightforward method for determining them. Several previous researches showed that the Levenberg–Marquardt training method with one hidden layer and sufficiently large neurons can map any input to each output to an arbitrary degree of accuracy [11-14].

In this study, an ANN model is developed using the relationship between heating parameters and deformations of plate, which are accumulated with the numerical analysis of the induction heating process. A

Table 1. Statistical criteria for evaluation of ANN model for predicting deformations.

Structure of ANNs models	MSE	RMS of training		RMS of test	
		Transverse shrinkage	Angular distortion	Transverse shrinkage	Angular distortion
2 – 4 – 2	0.000333	6.5201	94.1293	8.0628	90.23
2 – 5 – 2	0.000474	6.5201	94.1293	8.0628	90.23
2 – 6 – 2	0.000101	9.7496	18.9845	10.8869	21.4624
2 – 7 – 2	0.0000382	8.0503	13.6974	8.7712	16.8659
2 – 8 – 2	**0.0000011**	0.8120	8.9370	0.5154	6.4733
2 – 9 – 2	0.0000024	1.3137	9.9682	1.4046	10.9935
2 – 10 – 2	0.000101	6.5201	94.1293	8.0628	98.923

Note: Bold values show the selected ANN architecture.

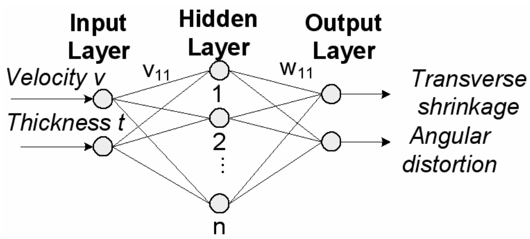


Fig. 9. Proposed ANN model for predicting transverse shrinkage and angular distortion.

standard feed-forward network with one hidden layer with *n* neurons is employed. The input layer includes velocity *v* and thickness *t,* whereas the output layer has the transverse shrinkage and angular distortion. To find the optimal architecture, a number of networks with different number of neurons in the hidden layer are considered and errors for each network are then calculated. Fig. 9 shows a schematic representation of the neural network architecture employed in this study, which can predict transverse shrinkage and angular distortion from input variables of velocity and thickness. The network layers are fully interconnected by weights. The input layer neurons receive information from the outside environment and transmit them to the neurons of the hidden layer without performing any calculation. The hidden layer neurons then process the incoming information and extract useful features to reconstruct the mapping from the input space. Lastly, the output layer neurons produce the network predictions to the outside world.

The relationships of 34 combinations between the angular distortion and transverse shrinkage and the heating parameters shown in Fig. 8 are used as the training and testing data, and they are randomly divided into two statistically consistent sets: training and testing. In total, 26 data are used for training and 8 for testing. Another important factor in ANN design is the type of transfer functions. The sigmoid function as follows is selected for all neurons because of its better prediction performance than other transfer functions.

$$output = \frac{1}{1+e^{-x}} \tag{1}$$

Where x is weighted sum of the input depending on values of thickness and velocity.

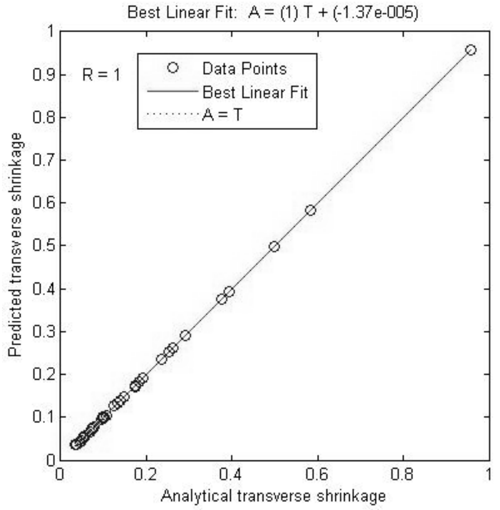
A computer program is devised using Matlab based on the Levenberg–Marquardt algorithm for implementing the ANN model. To determine the optimal network architecture of the proposed ANN, a trial and error approach is used. In this study, the best architecture of the network is obtained by trying different number of neurons for 1 hidden layer. To determine the optimal structure of the ANN model, mean absolute percentage error (MAPE) and mean squared error (MSE) are used as follows, respectively:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - O_i}{A_i}\right| \tag{2}$$

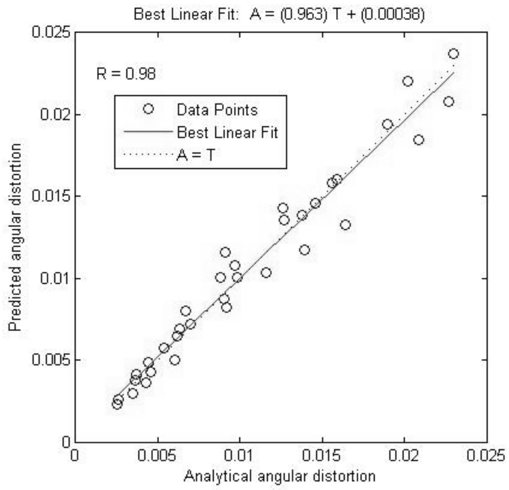
$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(A_i - O_i\right)^2 \tag{3}$$

Where A_i is the actual output at the output neuron *I,* and O_i is the desired output at the neuron *i*, and *n* is the total number of neurons in the output layer of the ANN model. The criterion of MSE is used to terminate the training process so that the MSE between the actual and predicted values is monitored until no significant improvement in the error occurs. This is achieved at approximately 1000 training cycles (epochs).

In this study, the structures containing neurons of between 4 and 10 in the hidden layer are investigated. The trial starts with 4 neurons, and the accuracy of the predicted values is checked before the optimal structure of ANN is selected. The goal is to maximize



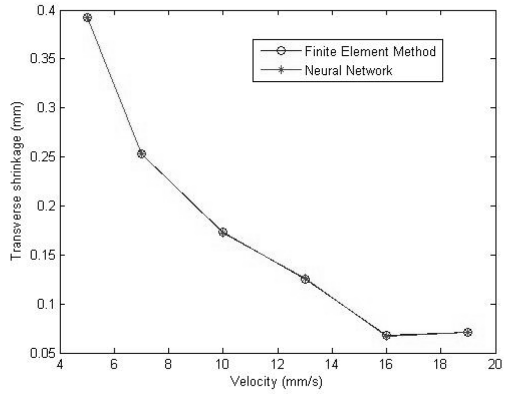
(a)



(b)

Fig. 10. Correlation between predicted deformations and analytic solutions: (a) transverse shrinkage (b) angular distortion.

accuracy to obtain a network with the best generalization. Seven different network models are tried and their errors are calculated. Results of corresponding errors to these trials are shown in Table 1. According to the table, increasing the number of neurons used in the hidden layer did not improve the performance of network. The highest accuracy for predicting the transverse shrinkage and angular distortion was obtained at a network which has 8 neurons. Based on this analysis, the optimal architecture of the ANN was constructed as 2-8-2 presenting the number of inputs, neurons in hidden layers, and the number of outputs,



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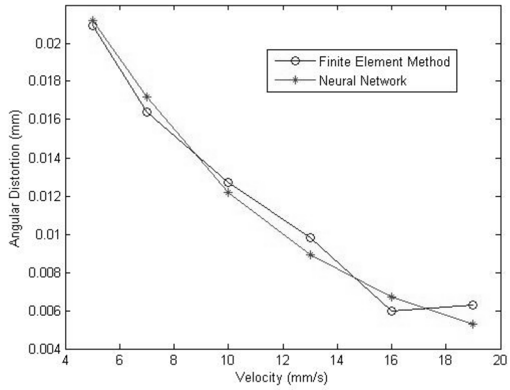


(b)

Fig. 11. Effect of velocity parameter on (a) transverse shrinkage, and (b) angular distortion.

respectively. Another important factor that affects the performance of networks is the selection of the initial weights. In this work, the Nguyen–Widrow algorithm [15] was used to initialize the weights of layers and biases.

The performance of the ANN model for predicting transverse shrinkage and angular distortion is confirmed by the correlation between the deformations predicted with the model and those calculated with the analytic solution as shown Fig. 10(a) and 10(b), respectively. It can be seen from Fig 10(a) that the prediction of transverse shrinkage has a high coefficient of correlation r of 1.0 in both the training and testing sets, and Fig 10(b) shows that prediction of angular distortion has also high r of 0.98 in the training and testing sets. Fig. 10(b) also demonstrates that there is a little scatter around line of equality between the analytical and predicted values of deformations in training and testing sets.

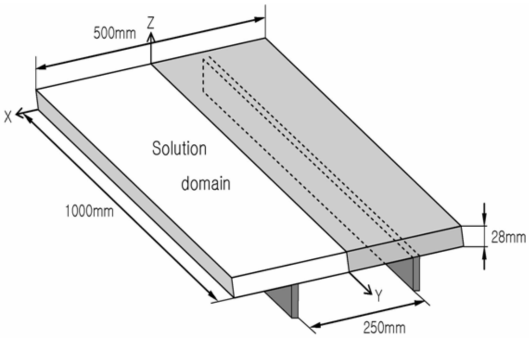
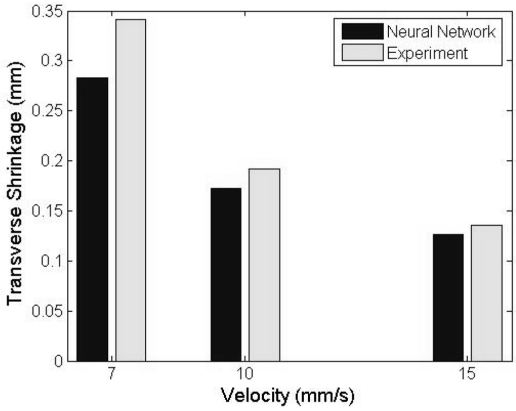


Fig. 12. Steel plate and supporting condition.

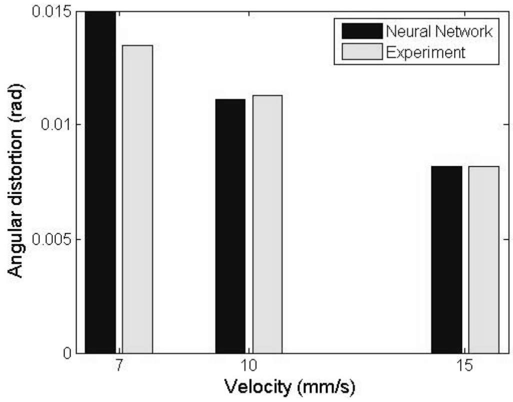
Fig. 13. Photograph of inductor.

The ANN model developed in this study is used to predict the transverse shrinkage and angular distortion of an AH32 steel plate in the induction heating process. The performance of the proposed ANN model is plotted in Fig. 11(a) and 11(b) for shrinkage and distortion, respectively. They show the relations between the velocity of inductor and transverse shrinkage as well as angular distortion obtained by both the analysis and the ANN model at a constant thickness of 28 mm. The relations are in good agreement with one another to show very similar deformations, which means that the proposed ANN model in this study can be used to predict the deformations instead of the numerical analysis in the steel forming process with induction heating.

To confirm the credibility of the ANN model for the induction heating process by an experimental method, a steel plate is heated along the center line at a constant speed in the lengthwise direction by the induction heating equipment, and the deformations of angular distortion and transverse shrinkage of the heated plate are then measured after cooling the plate in air. The plate in the experiment has the same length and width with a thickness of 28 *mm* and supporting conditions as the plate used in the thermal deformation analysis does as shown in Fig. 12. Fig. 13 shows the inductor used for the heating equipment, which is controlled to have travel speed of 7, 10 and 15 *mm/s* and a current of 3750 *A*. The deformations are measured with a 3-dimensional coordinate measuring machine.



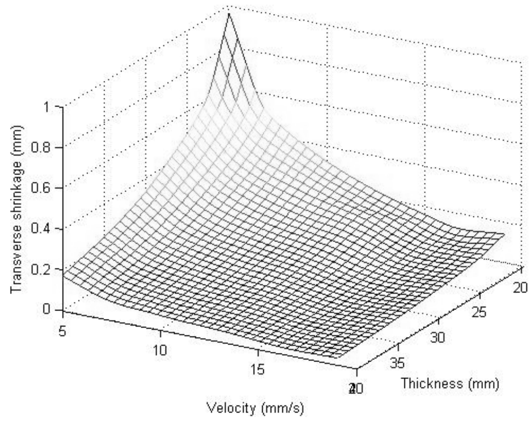
(a)



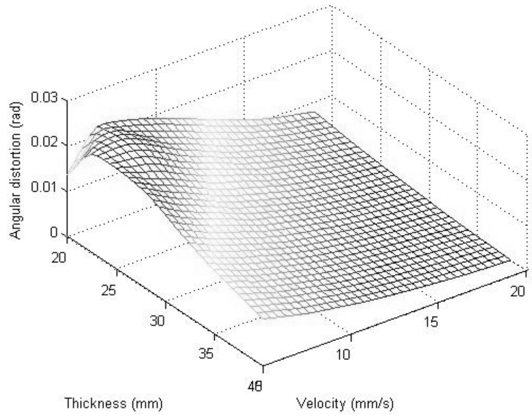
(b)

Fig. 14. Results of experiments and predictions (a) transverse shrinkage and (b) angular distortion by ANN model for induction heating.

The results predicted by the ANN model with inputs of the same heating parameters as those of the experiment are compared with the deformations measured in the induction heating experiment in Fig. 14. There are some relatively remarkable errors between results of ANN model and experimental results. However the relations are in close agreement with one another to show similar deformations, which means that the proposed ANN model in this study can



(a)



(b)

Fig. 15. Generalization performance of optimal ANN with effect of thickness and velocity on (a) transverse shrinkage and (b) angular distortion.

be used to predict the deformations instead of analysis in steel forming process with induction heating. They also demonstrate that the ANN model was quite successful in learning the relationship between the input parameters and outputs values.

The developed network is then used to predict shrinkage and distortion for different inputs in the domain of training data. In Fig. 15(a) and 15(b), transverse shrinkage and angular distortion are plotted versus heating parameters of velocity and thickness in 3D plots, respectively. As can be seen, the generalization performances of the 2-8-2 network show no oscillations and this confirms the excellent prediction performance of the ANN model.

5. Conclusions

To easily predict deformations of steel plate in the forming process with induction heating, an artificial neural network is developed. The training and testing data for the network are obtained from the results of the thermal deformation analyses with the FEM for a steel plate in the heating process. The deformation analysis required the heat-flux and heat flow analyses for the plate during the process in advance. Heat input for the analyses of the process during the travel of the inductor was assumed to be quasi-stationary and was obtained by a developed FEM program, which considered the change of material properties with temperature. A series of the heat-flux, heat flow and thermal deformation analyses were performed for the heating parameters. The architecture of the neural network is optimized with the trial-and-error method to have 1 hidden layer which has 8 neurons; therefore, a set of 34 training data combinations is enough to predict the deformations of steel plate. The back-propagation algorithm is used for the network to learn the training data of deformations resulting from the numerical analyses for the steel plate. The ANN model was tested to predict the transverse shrinkage and angular distortion with inputs of heating speed and plate thickness. A series of tests were performed and the results were then compared with both those of the experiments and those of the numerical analyses to reveal that the developed model could not only quite well predict the deformations of steel plate in the forming process with induction heating but also significantly reduce time and cost for the analyses.

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