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Research Article

Novel Method in Induction Heating for Complex Steel Plate Deformation Based on Artificial Neural Network

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The implementation of an artificial neural network for predicting induction heating region locations is proposed in this research. Steel plate deformations during the induction heating process are produced using an analytical solution derived from electromagnetic and plate theory. The plate transform following vertical displacements in each divided area was used as input of neural following desired shape of the steel plate and the specified heating areas for induction treatment as output parameters to predict and evaluate the model. A dataset used 90% for training and remaining 10% for testing to implement on the efficient models when changing hidden layer and its neurons relatively. The trial and error for analyzing and predicting heating-affected regions with the ANNs model reached the high average accuracy and lowest mean square error at 98.08% and 0.00913, respectively. Consequently, the feasibility test indicates that the developed approach may be well utilized to identify the heating positions by grid area in order to achieve the desired plate deformation. Moreover, the analysis of vertical displacement during induction heating and its response behaviour of steel plate based on thermo-mechanical are also addressed.

1. Introduction

Many researchers [1–3] are concerned about the deformation analysis of steel plates as a result of thermo-mechanical behaviour due to its complex distortion in space dimension that makes it hard to form precisely. Its application is now common in many fields, especially in manufacturing including ships, submarines, car shells, and even aerospace. The process of steel deformation in the shipbuilding industry is considered the most important stage to create efficiency and increase the accuracy of the curved surfaces of the paired steel plate. The process of steel sheet format in shipbuilding technology requires productivity and accuracy, assembling by millions of nonuniform parts of steel plate. The thermal deforming process can be divided into a few groups according to heat sources which are known as a gas torch [3], laser heating [4], welding arc [5], and induction heating [6]. The induction forming has numerable advantages compared with the other heat sources. First of all, induction heating not only meets the economical requirements for the shipbuilding industry but also allows manufacturers to configure rigidity and strength of material properties. Certainly, flame deformation by acetylene torch is rarely manufactured because it requires the seasoned experience of the worker. Moreover, the torch made from oxygen-acetylene gas is difficult to control the intensity of a mixing gas and heat distribution, and the reason why integration with complex control of robots or automatic systems could increase operating cost, the reason why induction and also laser heating can also implement automatically with robot mechanism. However, the cost of a laser is not only much higher than an inductor coil but also power, time and speed are limited [4]. Consequently, taking advantage of the residual stress of steel sheet and electromagnet, induction heating is produced not only efficiently and quickly but also easier and more precise which can be altered origin heat source from oxy-acetylene torch and welding arc. However, based on each parameter of induction heating required deforms complicated surface rises, and their placements are complex to predict, making analysis for calculating steel plate shape is more necessary than ever. In advance, the derivation from numerical and analytical methods has been proposed for the prediction of residual stress due to the induction heating process. The analysis of changing residual stress confirms that the induction heating process could be easily applied to the supervised learning artificial neural network to robustly predict and simplify the model allowed to perform thermal behaviour of steel plate with predicted heating region treatment.

In recent years, most of us are being surprised by the speed and accuracy of ANNs application by those wonderful advantages all the field of sciences issues. It was a robust and efficient role in simulating complicated hot deformation in real-life situations [7–9]. For example, the random neural network presented by Bi et al. is one of the deep learning methods to calculate the time and energy-efficient course of actions and routes for different types of road users within an urban road network in a real-time manner [10]. In their view, ANN has been implemented to predict the thermal-deformation behaviour in pearlitic steel based on its properties and hot compression test [11] or even supportively for machining hard-cut material with assisted laser and induction [12]. Moreover, a robust machine learning model with mathematical expressions of ML models could predict and evaluate the energy and exergy efficiencies of the parabolic dish concentrator box solar still fitted with thermoelectric condensing duct and antiseptic nanofluid [13]. Following the above problems, this study proposed an efficient method to get the desired form of steel plate with the assistance of an artificial neural network (ANN) on predicting induction heating positions and various parameters, in advance with the results of investigated effect factors like heating deform area and altitude of displacement based on the finite element method (FEM) at the plastic region of a plate. Application of ANN in induction forming is to give the heating region positions, which produce the desired curvature plate. The training and checking dataset is generated based on plate theory and plastic analysis of heating region treatment. Experiment and analysis are both achieved to approve the predicted results of induction deformation. The structure of this study presents in six parts; the methodology is described in the next section. Due to a large number of samples for the training dataset, the correlation between input parameters known as vertical displacement and its deformation is well analyzed and described thermomechanical analysis of steel plate theory. In the next section, based on the formula analyzed previously, hyper-parameter is being configured to optimize the training model. Finally, in the results, experiments are present with different complex shapes of steel plate supporting with ANN model when comparing analyzed and predicting model.

2. Methodology

Thermal deformation is important and a concerned problem in most steel design industries, especially in shipyards. Induction forming is not only the most economical and natural friendly but also effective to transform a plate of steel into a three-dimensional form without spending much labour. However, the power of the inductor and its properties affected the heating surface, and the desired form is considered to be analyzed. The advantage of greater power and distribution of inductor are easier to control than any other heat source. The deformations based on induction heating are being priority utilized. Hence, for reaching truthfulness efficiency and effectiveness, the mathematical model is in advance analyzed which is dedicated to the correlation between heating parameters, residual stress and heating deformation. All experimental studies of induction forming were produced on a steel plate which was being used for making ship hull due to its strength and its properties.

The structure of this research is divided into 3 main phases shown in Figure 1 explaining the step-by-step process of predicting plate deformation with ANN corresponding to distinct input parameters of displacement of heating position based on plate theory. In the first phase, the diagram explains the way of collecting data from induction heating analysis. Various factors could transform a horizontal steel sheet into the desired shape. These factors could be described as heat flow, heat flux and thermomechanical fixed with properties of considered material. Iterations with updated material characteristics are carried out at each stage in the analysis until the convergence at limited error is reached by comparing the temperature distributions of succeeding iteration phases. The inductor produces a heat flux at each area element as a result of the comparisons. The heat flux derived in this study will be used in the subsequent transient heat flow and evaluation of thermal deformation using a commercial finite element program, namely ABAQUS to analyze the effect of induction heating on the geometric material of steel. Training data, especially nonlinear data, have to divide the result as detailed as possible. A mathematical model was given important factors that affected the displacement of steel sheets. Therefore, in this stage, the finite element method (FEM) is being used to perform instead of induction experiment not only to carry out data due to the large sample data for training but also to indicate the relationship between electromagnetic and heating effected where its located on the plate's surface. Investigation on the plate with FEM could even easily collect the position of the grid area. Finally, the achievement of FEM to compare with final desire deforms could be efficiently and readily for precise evaluation with transform position based on inherent strain theory [14, 15]. It is an essential, manufacturing procedure that may be used to make a variety of curved thick plates. As a consequence, the induction heating treatment should be accurately shaped by some experiments in order to assess its suitability for plate deformation.

Secondly, the residual stress at the heating region is simulated and shown the relationship with its response to a vertical displacement form of a sheet which factors are considered as input parameters of ANN. In this stage, the training method is conducted with ANN to calculate the summation of several heated areas after both feed-forward and backpropagation processing. Backpropagation consists

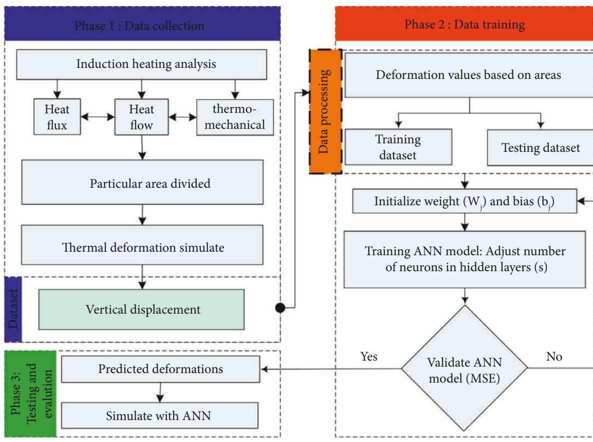


Figure 1: Flowchart of data collection from analysis of induction heating supported with ANN model.

of two processes over the network's layers: backward-propagation and forward-propagation. The input vector-vertical displacement is applied to the network's gridded area in the forward-propagation, its impact layer by layer until the network's precise response is acquired at the output which is defined as a predicted heat position causing response by its displacement. Changing the number of neurons in a single or multi-hidden layer is vital to choosing the most optimistic ANNs model with a trial-and-error method. Moreover, the bias is used to modify the synaptic weights during the forward pass which was created during the comparison between the target values and the network output values in the padding with the error checking to show how close the regression line is to reach the desired point known as Mean Square Error (MSE) in the final phase of the diagram. This error propagates backwards, adjusting synaptic weights and bringing the network's response closer to the expected response.

Finally testing and evaluation of predicted combining multiple areas based on initial deformation with ANN model in the final stage 3. The motivation of this study was to export data for predicting deform areas during induction heat not only the principle curvature but also the complex saddle, pillow shape, wavy shape, or even making to the desired deformation of the steel plate surface. Evaluation and comparison of the predicted deform plate with neural network and numerical analysis experiment would give the promised results with high applications on manufacture and fabrication field.

3. Thermo-Mechanical Analysis of the Steel Plate

Induction heating is characterized by the production of eddy currents which are generated in a magnetic field when the coil locates the nearby surface of the workpiece. The governing formulas for eddy current distribution during this process were derived from Maxwell as follows:

$$J_s = j\omega\sigma A - \frac{1}{\mu}\nabla^2 A, \tag{1}$$

where magnetic vector potential A is calculated by external current source, angular velocity and electric conductivity denotes as J_s, ω, σ respectively, which could be calculated heat flux distribution independently in Cartesian coordinate then vector composition. The currents have the same frequency as the coil while the flow of current is the opposite of that current in the coil causing heat resistance on the plate's surface. Following equation (1), the heat resistance in the surface could be derived following the density of eddy current denoted by Je shown:

$$J_e = \sigma\left(\frac{-\partial A}{\partial t}\right). \tag{2}$$

The amount of heat dispersed around the inductor is proportional to its distance from its present position. Therefore, the average heat flux is needed to be obtained by (3) in the analysis domain:

$$\overline{q} = \frac{1}{\tau}\int_0^\tau \mathrm{qdt} = \frac{1}{2}\left(\sigma\omega^2 A_x \overline{x} + \sigma\omega^2 A_y \overline{y}\right), \tag{3}$$

where $\overline{x}$ and $\overline{y}$ are complex numbers of A by Cartesian coordinate. During the induction process, the material properties of steel plates are required due to the significant change in material temperature. Following Zhang et al., numerical electromagnetic and thermal analyses dependent on material properties considering temperature-dependent material properties were implemented to calculate the heat generation rate (HGR) and temperature distribution at each moving step under induction heating [16]. Thus, for applied and analyzed transient thermo-mechanical behaviour, the AH32 and its properties were residual stress analyzed due to its common for ship hull construction. Particularly, during induction heating, workpiece surface softens and expands at the same time while the surrounding material has not yet lost any of its initial tensile strength. In the analysis, the steel plate is assumed to be heated one pass by the inductor on the area's surface at a constant time. Because of the symmetric condition of the geometry around the heat source, half of the plate is selected to be a solution domain which the plate will thicken slightly as the hot and soft steel yields. Consider an isotropic and homogeneous arbitrarily shaped inclusion contained in an elastic infinite plate. According to the superposition principle, an isotropic inclusion in an infinite plate may be deconstructed into three components: the original, mirror, and solution of normal stress distributed across the semi-infinite space's free surface. During the induction heating process, the material regains its strength after cooling, and the thermal shrinkage bends or shrinks the plate, this phenomenon is called plastic strain which follows the laminated plate's theory, expressed by the following formula:

$$\varepsilon^* = \alpha T_c - \sigma_{yl}\left(\frac{1}{aK} + \frac{1-\nu_1}{E_1}\right), \tag{4}$$

where σ_{yl} is described as the stress of boundary of the circular area and infinite plate and spring constrain of around analyzed region are defined as K. Deform plate with induction heating was taken advantage of residual stress and

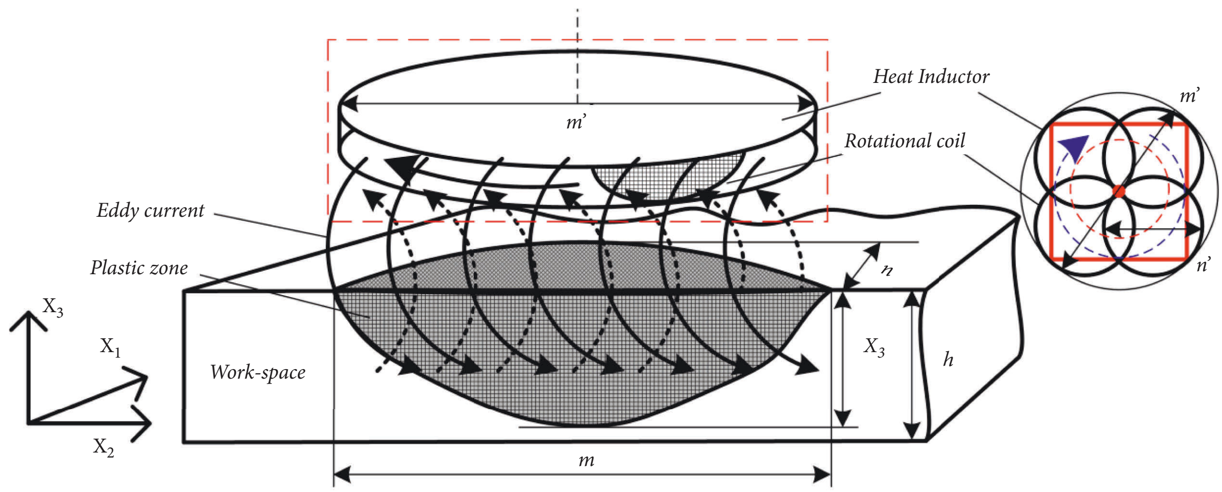


Figure 2: Approximation of induction heating plastic zone 3D Cartesian plane.

plastic strain method to transform initial flat into desired plate economic requirement of industries. Residual stress occurring such as shrinkage, distortion, or displacement has appeared in the process of deforming plates which formed steel sheets in a particular dimensional space such as horizontal, vertical, or curved deformation plate. Since the steel plate's thermo-mechanical behaviour was complex, assumptions of vertical displacements for the specific area are simply analyzed.

In this study, vertical displacement analysis was implemented as the input parameter for the ANN training process during the induction heating technique, the rotational coil inside the inductor is suggested to use to treat the workpiece in specific areas. Following Bae et al., his study investigated a two-dimensional rotational coil to study the triangle induction heating process, they also dedicated the relationship between the heating region in the triangle region of the workpiece and the rotation heating inductor, and their result showed the heated region size is not similar to the inductor size above [17]. Thus, the analyses of the heat-affected zone (HAZ) had shown the ability to calculate the vertical displacement in the space. Based on this appropriate result, the purpose of this study uses a heat zone on the workpiece as the initial size to divide the area gridded. Analysis of the model of thermo-mechanical with its behaviour is necessary to archive the homogeneous model which helps in regression of heating position to have the desired plate shape. First of all, the three-dimension plates (length x width x thickness) in mm for experiments are being analyzed. Each heated region is described by heat-affected zone generated by inductor. The heated region's location on above of the plate's surface is determined in accordance with the working trajectory of the inductor. With the assumption that the circular rotational coil has rotated inside the inductor with *n*' diameter following the centre of inductor which is much faster than the inductor moving from the heated region to the next one, the whole induction process is described to be a quasi-stationary. The rotational heat rotates several times following a round of heat inductor with a diameter of m' (mm) and its affected heat region which generated the concentrate plastic zone followed by the squared area on the surface of work-piece shown in the right corner of Figure 2. A simple and definite relation between the width of the plastic region and the inductor area parameters and the plate thickness is assumed to be in the form of the following exponential function:

$$n = k.s^{\alpha}.\,t^{\beta}, \tag{5}$$

where k, α, and β are constants which are synthetic from by HAZ analyzed, s is the inductor area, t is the thickness of the heated plate and b is the width of plastic region. The plastic zone length and the width made by induction process located in the workpiece are defined as m and n, respectively; meanwhile, the plastic zone's length and width correspond with the smaller than inductor size [17]. With the plastic region calculated above, the heated region is determined as unit of grid for evaluating the position of plate deformation. In this situation, the length of the heated region could be assumed as the same size as the width in the x_1x_2 plane. For the third dimension of plate deform caused by plastic strains, the heating height is denoted as $h(x_1, x_2)$. The plastic strains that dominate the vertical deformation considering a cuboidal inclusion with an eigenstrain followed Thinh et al. which express the vertical displacement of the plate treated by induction heat in terms of material properties [18], heat parameters, and plate thickness:

$$d_{x3} = -\frac{3d(1+\nu)}{4\pi\left(h^0\right)^3}\left(h^0 - \frac{d}{2}\right)\left[\alpha T_c - \sigma_{yl}\left(\frac{1}{Kb} + \frac{1-\nu}{E}\right)\right] \cdot \left[h(x_1, x_2) - h(0,0)\right]. \tag{6}$$

Here, properties of material known as Poisson's ratio and Young's modulus, coefficient of thermal expansion, minor axis of ellipsoid are denoted as ν, E, α and b, respectively. Critical temperature, yield stress of the plastic region, equivalent spring constant and radius of plastic region are defined as T_c, σ_{yl}, K and a, respectively.

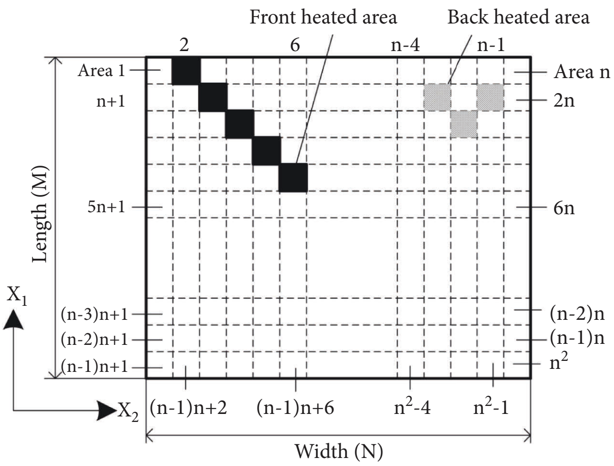


FIGURE 3: Discretization of area position using a uniform finite pixel meshing.

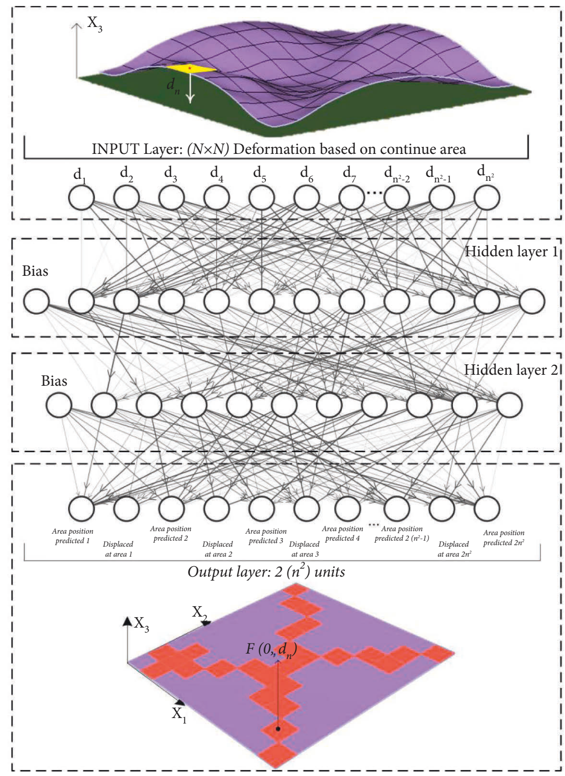


FIGURE 4: The concept of ANN for predicting areas heated with initial flat steel plate.

Notwithstanding, to readily predict the deformation of the steel surface, simple formulas are produced by incorporating the results of a series of plate deformations; the deformation regression is presented by ANN in the next section. Because of their versatility, thermo-mechanical behaviour of steel plate following multiple heating areas is being analyzed by the initial area using the inherent strain method and disc-spring model to simplify the complex phenomenon that offers several benefits.

4. Hot Forming with Induction Heating Based on Artificial Neural Network

4.1. Parameterization and Collecting Data. In the previous section, thermo-mechanical analysis was given the formulas of induction deforms, and vertical displacements are being easily calculated with analyzed parameters that were presented in the last section. The more complicated the required form, the more challenging the estimate of heating parameters, since the number of induction areas increases and they also have unplanned locations. The disadvantages of experimental and numerical models for predicting heating properties, including heating locations, and for getting a desired form of the plate are their length of time and high cost. Therefore, a neural network not only would be on behalf of custom configuration instantaneously but also an alternate numerical method for the most efficiency. An ANN model is created by accumulating the correlation between heating variables and plate deflections from the numerical investigation of the induction heat treatment. The broad problem of arbitrarily shaped inclusion is tended to be more commonly handled using the convenient and straightforward procedure of the heating effects by dividing a plate into continuous and separate small areas, each area being gridded appropriate with the heated zone which is being effective by inductor on the surface of the plate. Each of these areas would affect each other like a model of a plastic region, when combining these impact areas; it becomes a spread deformation effect on the whole plate. These results are being used to derive an analytical solution with a disc-spring model to estimate the vertical displacement to be sum as the distortion of surface as discussed.

As illustrated in Figure 3, the initial form is a flat plate with length × width dimension that is split into n^2 areas to provide displacements with identical distances from one area to another on a x_1x_2 planar plate. The arrangement for grid centre points was denoted by passing the area step by step once until the end. Heating deformation at the specific location of the plate is defined by its centre of the grid area and is standard for the performance of the displacement itinerary. Moreover, all the areas are subjected to homogeneous stress which is discretized by a uniform or square area grid. As shown in Figure 4, the vertical displacement in the position i of the divided grid area along the z-axis denotes as d_i. As a result, each vector contains n^2 units indicating the deformed plate's shape depicted as a pattern on an initial dimension grid of displacement's position. Obviously, the number and locations of plastic regions modify the deformed curvature of the plate during the induction heating process, thus heating area's position and summing of all nearest areas must be defined. In this discussion, an ANN has $2n_2$ units corresponding heated areas both 2 sides of the plate. The areas covering all positions of the plate are measured vertical displacement to be designated as input variables, several heated areas among whole plate are established as output variables. To simplify the model and increase the learning rate, the output layer is used as binary values which are 1 and 0. Simulated results yielded a number of induction heated areas with two binary values, with 1-black square representing the expected heated area and 0-

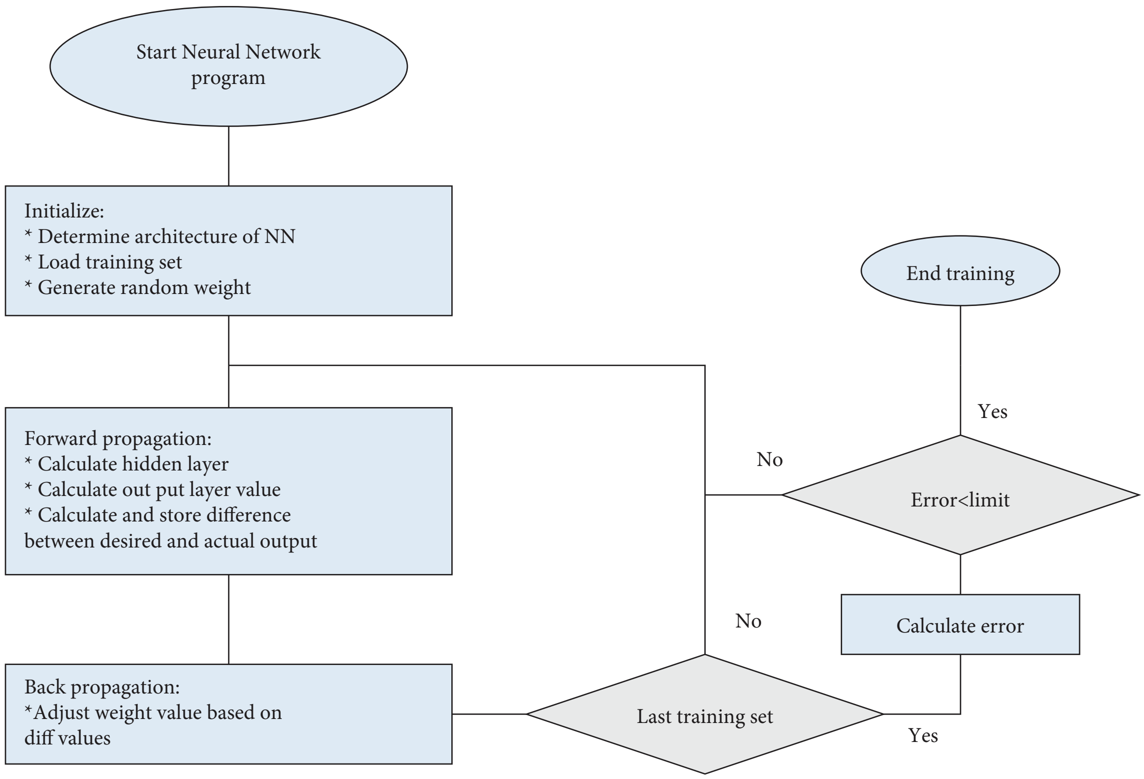


Figure 5: Flowchart of ANN back-propagation method.

white square representing no induction heating treatment as shown in Figure 3. For every induction heated region, ANN would predict with 3 output parameters. An active heating parameter is described with parameter 1 which binary value as 1 mean has heated treatment in the gridded unit area and the other value is 0 then no area to be heated. The second parameter is heating surface, which the 1-binary value described area heated in front surface and 0-binary is performed in back heated surface. The final parameter for induction heating process is various times affected on the steel plate's surface. The period of induction heating would change heated regions from elastoc to plastic to deform plate as desired. In this case, the analysis is concentrated on the uniformation deformation with a single type of material. The time parameter is set as constraining value as five seconds.

The proposed ANN is applied for the initial dimension of plate of $M \times N \times h$ (mm) in which h is the thickness of the steel plate. In this study, experiments analyzed are implemented on the plate with $500 \times 500 \times h$(mm) in dimension; the distance between 2 points of gridded along x_1 and x_2 for calculating displacements was 25 (mm). Therefore, the architecture of ANN was formulated with 400 input units from the divided plate area which included vertical displacement of its established as input variables. In the results, the prediction of induction heated among 2 surfaces (front and back) was represented as 2 binary values and corresponding 400 locate areas of the plate were established and evaluated as output variables shown in Figure 5.

4.2. ANN Configuration for Induction Region Heating. In advantage, ANN is made up of densely linked adaptable simple processing units known as artificial neurons or units, which can perform multithreaded computations for data acquisition and expert systems with both forward propagation and backpropagation shown in Figure 5. The ANN's benefit originates from the biological system's extraordinary data processing qualities such as highly parallel computing, nonlinearity, and fault tolerance. The primary goal of a computing-based ANN is to create complex algorithms that allow neural architecture to learn by simulating neural activity and discovery learning in the human brain. First of all, ANN has archived the results because it is difficult to accurately denote the relationship between induction heating conditions and process performance by means of mathematical expressions while limited to sample data for experiments. The general network contains three layers: input, output, and hidden layers. Neurons are the fundamental components of ANN, and they are linked together through synapses. There is a weight factor $(w_1, w_2, \ldots, w_{ij})$ associated with each synapse to connect the relative between the heated region and its deformation.

The simplified formula is used to easily predict heated locations and heating parameters from the goal curved surface which the neuron j can be written by the following pair of equations:

$$u_j(n) = \sum_{i=0}^{m} w_{ij}(n) y_i(n), \tag{7}$$

where m is the total number of inputs applied to the neuron j (excluding the bias). The adjustments of the weights are made in accordance with the respective errors computed for each training set element presented to the network. So the arithmetic average of these individual changes over the training set is therefore an estimate of the true change that would result from modifying the weights based on minimizing the cost function E_{average} over the entire training set. N is denoted as the number of patterns contained in the training set, the averaged squared error energy is obtained by summing $E(n)$ over all n, the number of iterations performed, and normalizing with respect to net set size N as shown by

$$E_{\text{average}} = \frac{1}{N}\sum_{n=1} E(n). \tag{8}$$

Both $E(n)$ and E_{average} are functions of the synaptic weights and bias levels known as the cost function. Secondly, with cost function and backpropagation, it might infer unknown associations on unseen data after learning from the initial inputs and relationship parameters, allowing the model to generalize and predict nonlinear data. Finally, ANN has superior advantages than other methods that have not imposed any restrictions on the input variables but for its distributed, for instance, in this study, vertical displacement considered as an input parameter is being analyzed with nonconstant variance of thermo-mechanical behaviour. Thus, ANN was provided with the capacity to discover hidden correlations in data and its densely networked adaptive fundamental processing components can perform parallel computing simulations for data acquisition based on expert systems.

The learning rate was set at 0.15, and the momentum coefficient was set to 0.8 in this circumstance. Training was carried out until 10,000 iterations and an error of 0.001 were achieved. The network was fed a series of training pairs at each epoch (iteration). The system then computed the sum of squared errors between the desired and actual outputs of the network. The network's input units are connected to the output layer through j hidden layers with p_j units. During the training phase, the transfer function is shown as an important key aspect in the ANN model for optimal configuration, to be known as input parameters are continuous values and output values are binary. Thus, due to its superior prediction ability over other transfer functions, a sigmoid function described in formula (9) is employed as the activation function for various layers.

$$\widehat{y} = \sigma(x) = \frac{1}{1+e^{-x}}. \tag{9}$$

One of the most significant advantage tasks in ANN development, a considerable impact on the expected results, determines the proper network configuration, which is strongly associated with the input, output neurons and hidden layer number in the network. However, the appropriate number of neurons of each hidden layer as well as the number of hidden layers in ANN are case-dependent which is difficult for determining. In most cases, the trial-and-error method is applied for determining the number of hidden layers of training patterns and the desired classification accuracy. The optimal neural network design was determined by experimenting with different numbers of 1-2 hidden layers and neurons. The experiments in the next section begin with one hidden layer of 200 neurons to 700 neurons and the final one is separated intentionally into two hidden layers, and the accuracy of model is tested 10 times in a row before deciding on the best ANN structure. The objective is to optimize accuracy in order to achieve the best generalization from the network. Many alternative network models were tested, and their biases and precisions are estimated for the minimum error of the output values and the network models with different hidden layers were evaluated by training and validation model accuracy and mean square error (MSE) of q models between the actual outputs (d_i) and predicted values ($\widehat{d}_i$) as follows:

$$\text{MSE} = \frac{1}{q}\sum_{i=1}^{q}\left(d_i - \widehat{d}_i\right)^2. \tag{10}$$

5. Experiments and Results

AH32 plate is material on the experiment of induction heating which is analyzed chosen by its properties. Application of ANN in predicting heated region in an area during induction process that used for analyzing a dataset from the simplified formula of vertical displacement shown in (6) to estimate the weights of different layers shows the expectative results. A neural network model was created to examine the relationship among various parameters affected by objective plate forms and induction heated zones. The goal of the model is to tackle the issues of finding the number of heated regions with all of its parameters during the induction process and also show the efficiency of ANN-based on predicting the identifying candidate heated locations. Combining the governing equations on analyzed plastic zone, the deformation of a metal sheet or flat steel plate in the induction heating using the location and area gridded technique is very significant for the production of desired plates based on determined heated regions. In this study, original effective evaluation of heated affected regions compared with line heating [8, 18] and triangle heating [14, 15, 17] is also mentioned. The simulations of deforming plates were performed with common square steel plate (500 mm in length and 500 mm in width) to verify predicted results for locations and their parameters of heated regions. Beside, the experimental plates for same conditions of simulating are carried out as set of experiment 1 of rectangle plate (500 mm in length and 400 mm in width) corresponding to 3 types of thickness of plate (10 mm; 20 mm; and 30 mm) shown in Table 1. At temperatures exceeding 723°C, yield stress and Young's modulus of mild steel become comparatively insignificant because the surrounding material is restrained throughout the induction heat treatment; the plastic process would form not just in surrounding areas with temperatures exceeding 723°C, but also in areas with

Table 1: Induction parameter for experiment and analysis and estimating form by ANN and experiment.

No	Material	AH32 mild steel
Induction parameter	Input power	40 kW, 45 kHz
	Current	3750A
	Inductor treated velocity	5 mm per second
	Critical temperature	≥723°C
Experiment 1	Wavy shape induction thermo-bending with multiple diagonal heating regions	$500 \times 500 \times 20$ (mm) $500 \times 400 \times 10$ (mm)
Experiment 2	Require curvature of thick plate with surface heating regions	$500 \times 500 \times 30$ (mm)
Experiment 3	Saddle plate induction thermo-bending with circular heating regions	$500 \times 500 \times 10$ (mm)

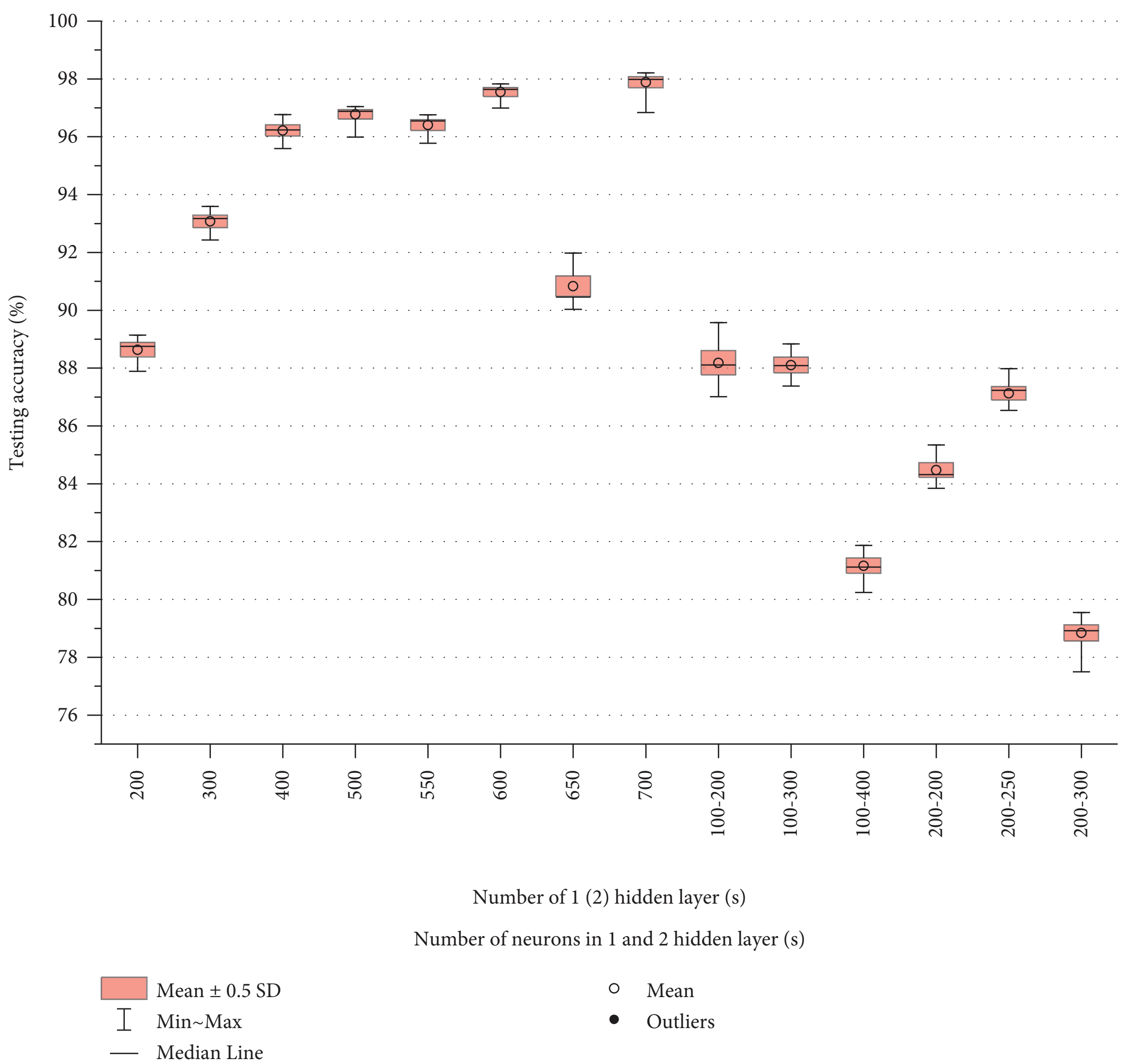


Figure 6: Predicted induction heating area position accuracy (%).

lower temperatures. These parameters correspond to an inductor speed of 5 mm/s and experiments for adjusting the hidden layer (s) and bias validation was carried out under the same conditions of induction parameter explained.

With specific experiments for measuring the truthfulness of models, 3 complex forms of sheet deform, known as wavy shape, upper (lower) curvature and saddle shape, have been considered as relevant transformations to definite the accuracy of models with multiple time and architecture of ANNs. The trial-and-error method is applied to optimistic the neural model, experiments for predicting the position of deformation and its surfaces had been surveyed the efficiency with 14 neural architectures in both one hidden layer and multi-hidden layers (shown in Figure 6 and Figure 7)

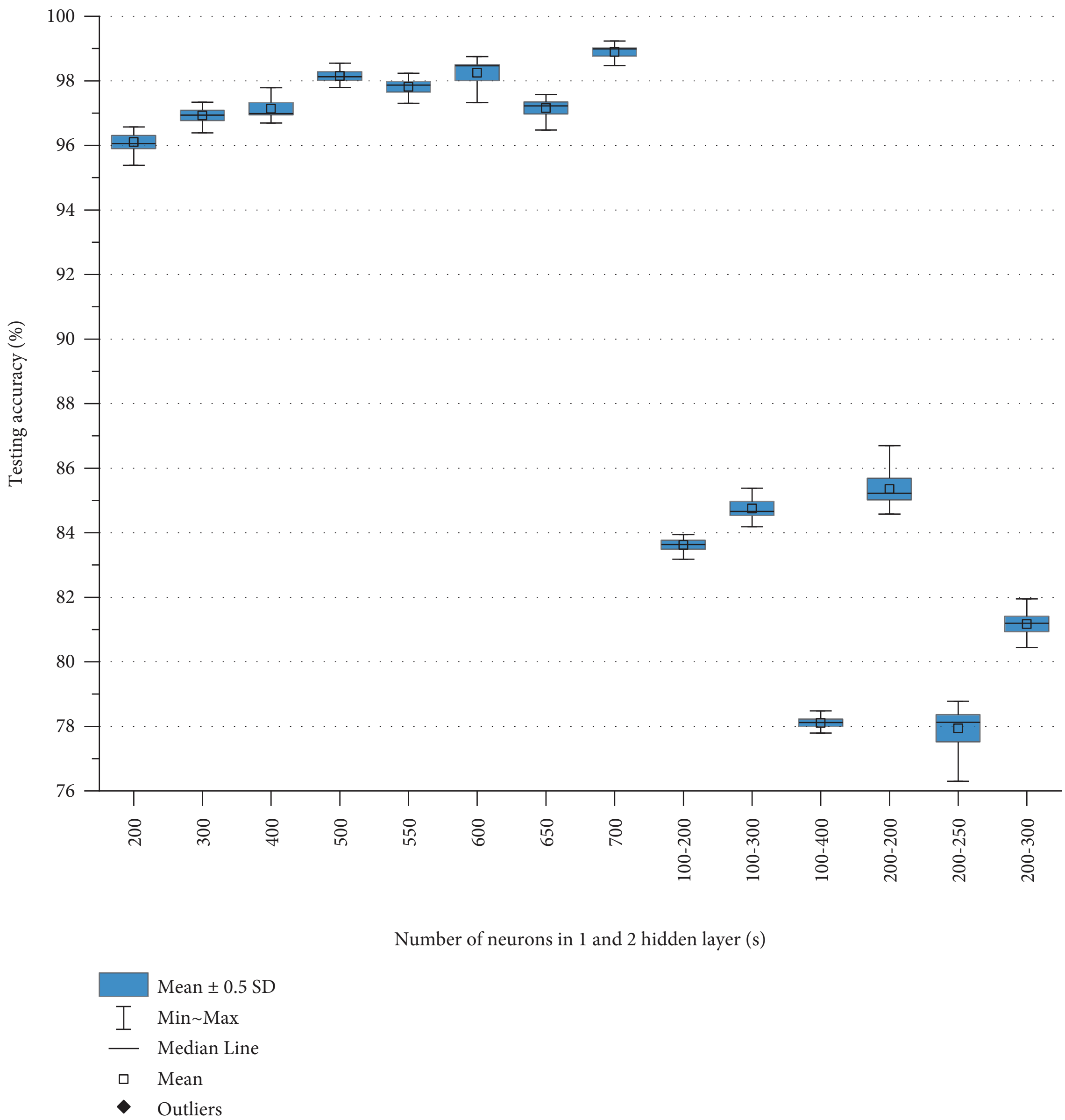
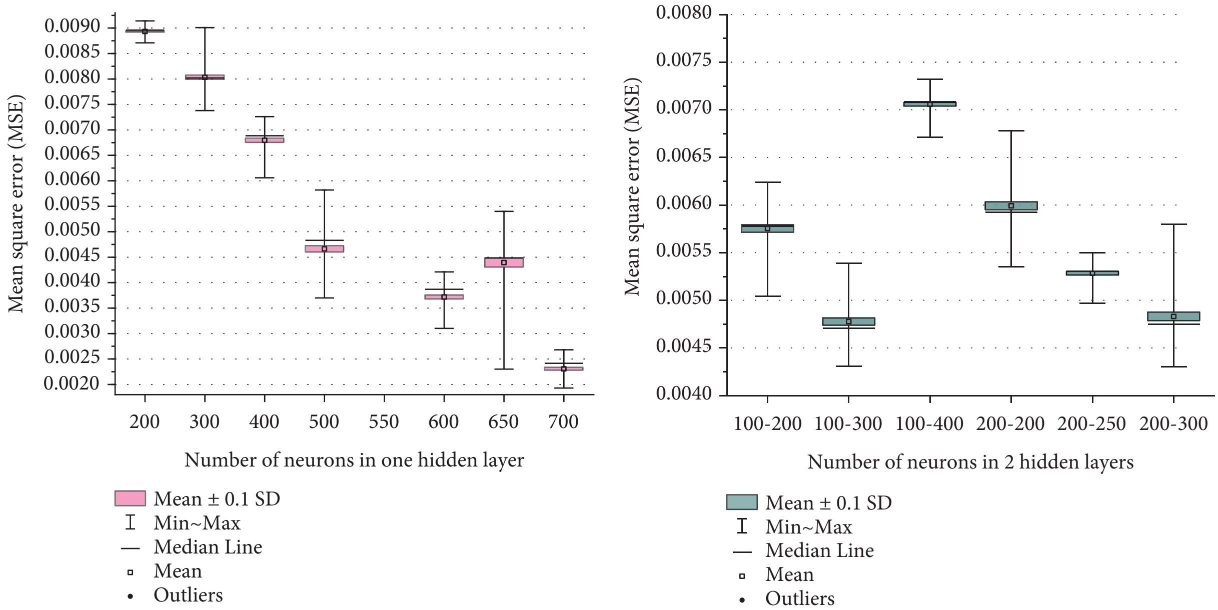


FIGURE 7: Predicted induction heating surface accuracy (%).

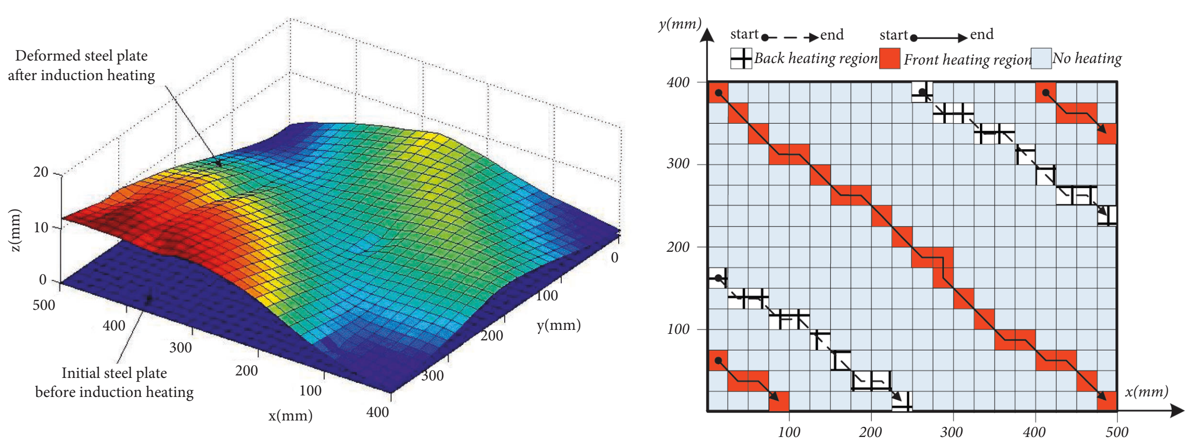
and evaluated with MSE index. Based on the simulations in the previous section, the plastic region approximately 585.46 mm^2 performed heating region corresponding to gridded size on the surface of the steel plate (shown in Figure 2). The induction heating treatment is located at the centre of the grid area on the upper or lower surface. The inherent strains can be modelled easily by increasing the width and depth of the region continuously along its heating regions when the heating inductor is carried out from the starting point to the endpoint over a steel plate. The FEM model calculates the temperature distribution first and then the size of the eigenstrain domain is estimated as explained in the preceding section calculated in (6).

Figures 6 and 7 demonstrate the impact of ANN model configuration on predicting induction areas and their transformation, indicating that increasing the number of neurons in the hidden layers has no influence on network performance. It was discovered that single hidden layers can provide more convergence in the predicted heated region model than two hidden layers. As can be noticed in all of the following pictures, models with densely packed neurons in several hidden layers demonstrated the influence of two distinct degrees of precision on desired heating zones on plate deformation. ANN models with one hidden layer pointed out the effective accuracy assessment on the position of plastic regions at 92.98% average values while considering on predicting of the treated surface had been reached the average precise at 97.21%. Meanwhile, two hidden layers do not reach the highest accurateness over 90%. Thus, the best ANN design was built with the 400 number of inputs, a network with one hidden layer and 700 neurons, the result in 402 outputs of heated position and where induction heating



(a) (b)

FIGURE 8: Regression loss evaluation from 3 individual shape experiments on number of neurons in one hidden layer (a) two hidden layers, and (b) ANN models.

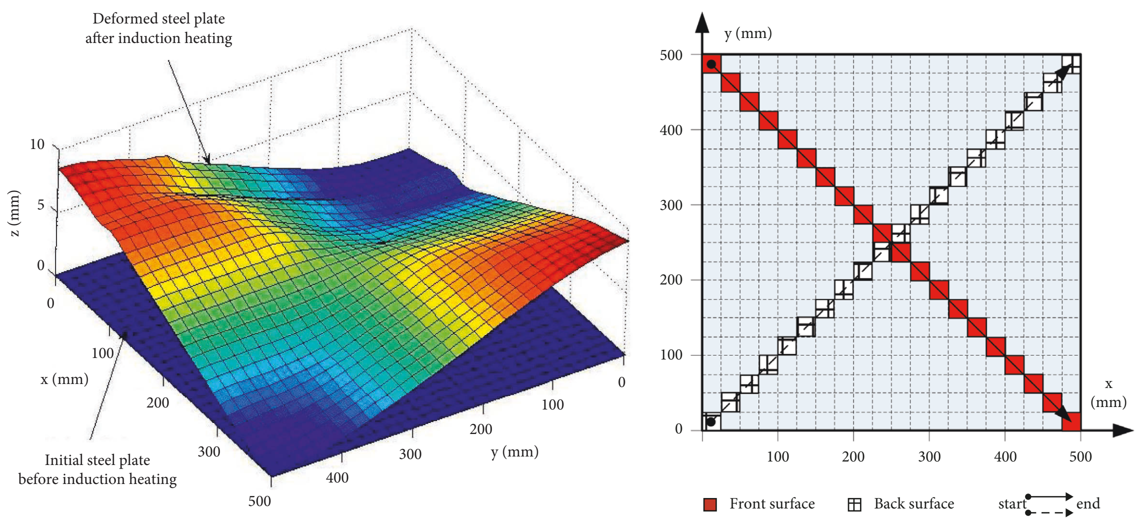


(a) (b)

FIGURE 9: Measurement results: (a) wavy transformation on nonsymmetric steel plate and (b) predicted regions and its relative surface.

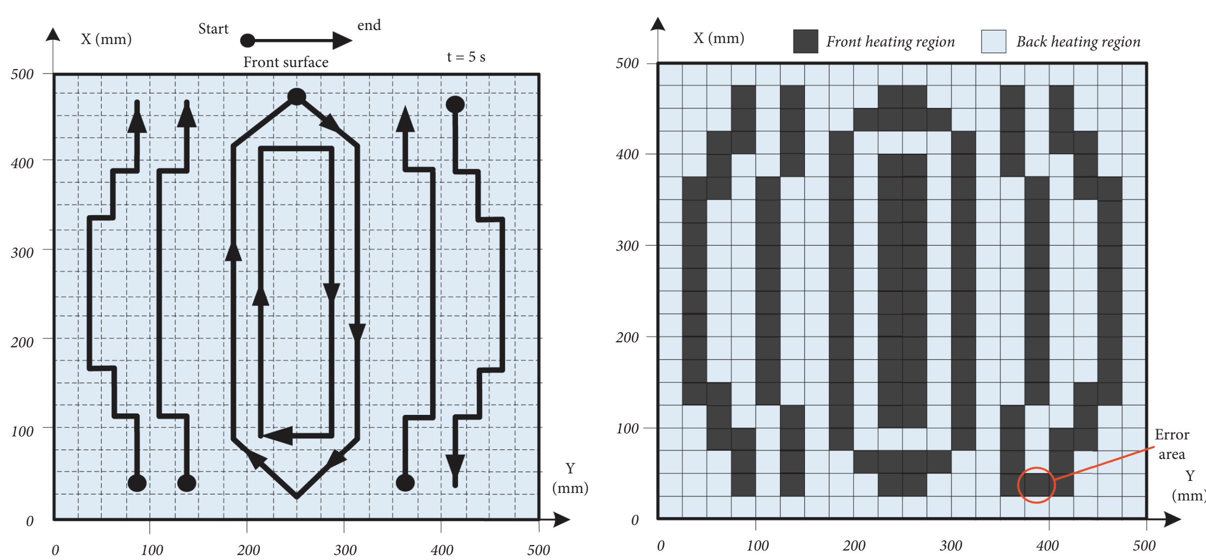
was applied, respectively. The best accuracy for estimating induction heated region was achieved at 98.08% to find the location of transform regions and at 99.03% accuracy to get the precise surface of induction treated expanding that the number of hidden nodes does not guarantee a reduction in typical training process error or increased accuracy. MSE (shown in Figure 8) is considered as vital values to reach the converging of error result at the limited of experiments which is clearly illustrated. The accuracies of testing and training are performed for evaluating designed model to predict heated regions with their surface and location. The position of induction heating region is highly recommended not only to impact in specific zone but also to affect on the whole deforming plate. After determining the precise range of the model in tests with three different transforms of steel plates, this study segregated the MSE values findings from a hidden layer and two hidden layers at the same time and displayed them in two separated Figures 8(a) and 8(b). Overall, all MSEs using ANN for 1 or 2 hidden layers pointed out the precise models in predicting induction heat impact. One hidden layer and 700 neurons error now reached the lowest values from approximately 0.0027 down to just upper 0.0019 in MSE.

For simulating the idea of plate deformation, at the outset, the study tests have been implemented at this stage to examine the desired treatment on the deformation plate with measuring results. First of all, with induction thermo-bending for wavy form, the ANN model indicated the 2



(a) (b)

Figure 10: Measurement results: (a) wavy transformation on square plate and (b) predicted regions and its relative surface.



(a) (b)

Figure 11: (a) Desire trajectories landing for heat inductor and (b) predicted regions error.

types of expected values for shear of ship part and hull bottom which showed by numerous diagonal heating zones and intersecting diagonal heated zones. The heated position influenced by its deformation had been investigating the thermo-mechanical behaviour applied to a thin rectangle plate with dimensions $500 \times 400 \times 10$ (shown in Figure 9) and a fine square plate of $500 \times 500 \times 20$ (shown in Figure 10). Heat treatment in shipyards is entirely automated which means that the use of a robot system will make it simpler to manage restricted distances since the inductor can only travel on a parallel plate with a steel surface. The z-displacement of the changing shape was measured and assessed along the next prospective route, after one pass of forming with the estimated data. The provided data curve was then utilized to calculate the remaining distance of the next deflection. The specimen is secured in one perpendicular corner, and after heating on one side, the steel plate is flipped over and heated on the other surface. The result shows a symmetrical shape for plate transform and the predictive position following the uniform as in the previous investigation. The error wavy shape of the plate (as Figures 9(a) and 10(a)) is relative to the desired heating position regions on the top and bottom surface (as Figures 9(b) and 10(b)). However, with the shape of the original survey of a thin rectangular, the diagonal survey indicated the deviation of position of predicted area that patterns shift poured towards at the end of the nonsymmetrical plate.

In the second experiment, the thick plate AH32 structural steel ($500 \times 500 \times 30$) was chosen as the specimen to

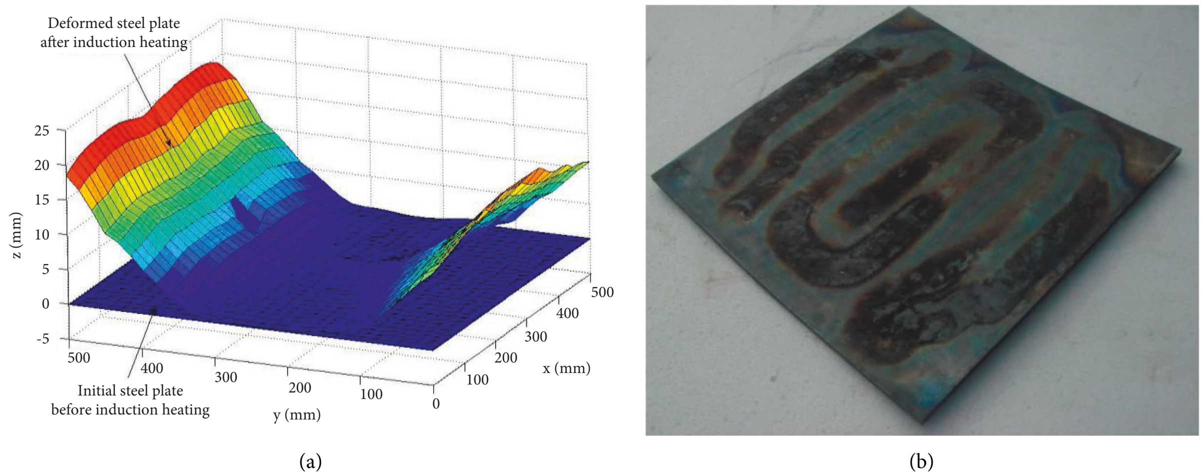


FIGURE 12: Measurement results: (a) target curvature transformation with the symmetric steel plate and (b) experiment on the real sample.

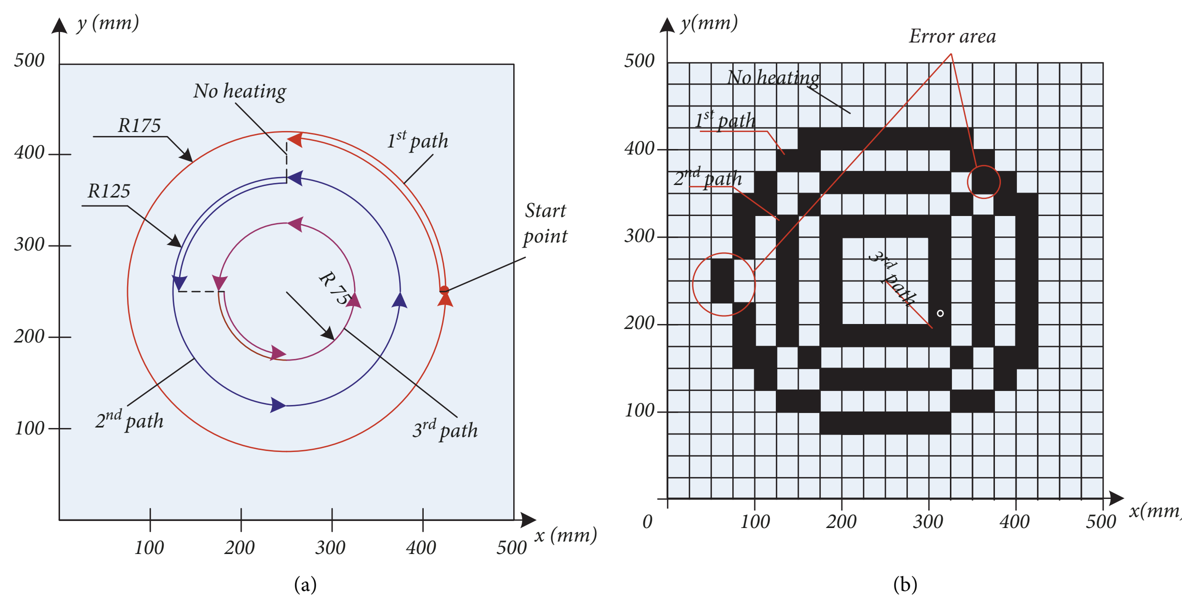
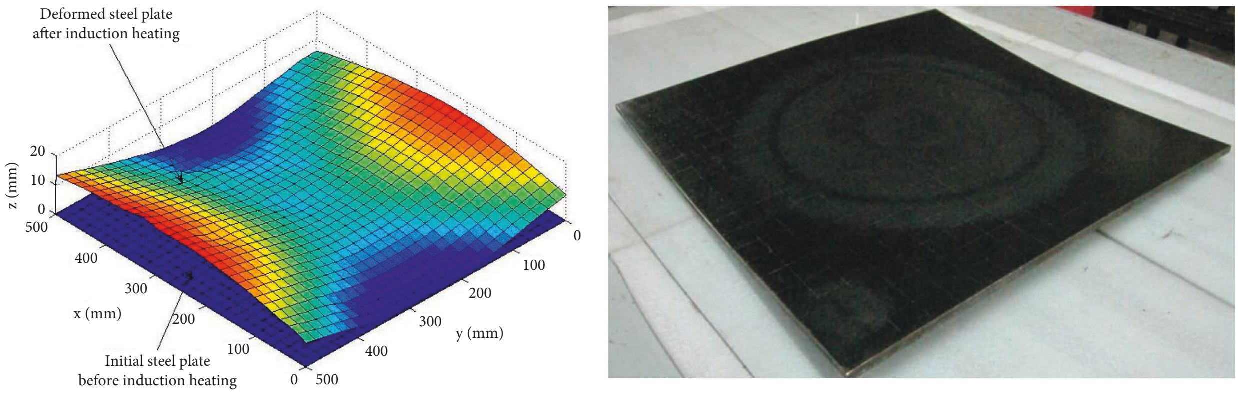


FIGURE 13: (a) Target trajectories of the heat inductor and (b) predicted heating regions errors by ANN.

simulate the required curvature and predict the induction impact. Following the region heating experiment, the z-displacement of a deformed steel plate was meticulously examined using displacement sensors. Under the premise of isotropic material characteristics, a commercial ABAQUS application was employed for FEM simulation. In time, the plastic strain and residual stress problems were solved consecutively. Induction heating source models have been proposed for heat transfer studies in order to predict V-curvature transformation. Figure 11(a) shows the desired route for induction area passing, and Figure 11(b) shows the result of the ANN model predicted, although it appears to be created precisely to the working surface, flaws do exist. However, the error of 0.0076 is not much of concern in this experiment due to the precise reach at 98.23%. FEM analysis and sample in Figures 12(a) and 12(b), respectively, showed the result of curvature bending with high truthfulness which explains why longitudinal distortion happens along the x-axis in the opposite direction of the inductor pass; it is combined with the deformation following the subsequent heating area on the opposite surface.

Finally, saddle deforms of the plate using induction thermo-bending with ANN model had been predicted with multi-circular heating regions shown in Figures 13 and 14, which is the most complex transform shape due to its geometrical approach. In fact, there were 2 ways to fabricate saddle shape that were spiral irradiating technique and multiple crossing parallel heat treat on both sides technique. These are adopted with several efficient fabricates and also geometrical approaches in many research [4, 19]. Heat treatment, in particular, is widely used in practically all applications; in this study, not only is an induction source used but a beneficial route is also generated using a neural network to increase economic



(a) (b)

Figure 14: Measurement results: (a) saddle transformation with the symmetric steel plate and (b) experiment on the specimen with its relative surface.

manufacturing. Saddle shape is described as in perpendicular angles of planes, but the saddle form has distinct curvatures, and the manufacturer faces an anti-clastic curvature. For forming saddle shape, an experiment was chosen to 500×500 and with a thickness of 10 mm. Z-displacement of formed shape was carefully measured after one pass circular forming route. The product of saddle form using the induction heating technique is examined with high accuracy as presented above.

When the circular treat heat pitched is reduced forward to centre, the deformation of the saddle-shaped surface increases considerably. It is also demonstrated that the spiral border to centre route movement pattern (like in Figure 13(a) numbered circular order) results in bigger deformations than the spiral centre to border route movement pattern. Furthermore, three concentric heated circles are created by induction heating with different diameters creating a saddle-shaped curved plate. Figure 13(b) illustrates an error of the ANN model generated which could be explained by the edge effect, in which the degree of deformation changes along the edges, as well as the restriction condition near both the inlet and outlet edges. FEM and experiment on a specimen (shown in Figure 14) have proved the truth of predicted values and the above explanation. The z-displacement with a setup parameter was successfully generated, although the further corner of the plate slightly increased the edge altitude following archived data from ANN models.

6. Conclusion

An artificial neural network applying plate deformation with induction heating solved the problem of transforming the specific and complex shape of steel plates. Normally, the plastic deformation depends on the heating route and setting the parameter of inductor, plate transform investigated not only by divided induction regions but also implemented on ANN for analyzed complex and distinct forms were proposed the novel method with highly precise. The equations for vertical deformation were considered with a cuboidal inclusion with an eigenstrain used to adjust the weight and the bias in ANN which illustrated 99.03% accuracy and 0.0091 with a coefficient of determination MSE. Many experiments with large steel complex-shaped surfaces were successfully fabricated by archived data and schemes generated by ANN. The vertical displacement of specimens investigated in a wide range and the experiment errors were less than 1.8 mm. For enhancing the accuracy of transforming the complex shape, the edge effect and longitudinal distortion of deformation need to be concerned.

Data Availability

Supplementary materials and techniques for training support are provided by Ho Chi Minh City University of Technology and Education. Data and computer codes are available in the following link: https://github.com/Ryannguye/Supplemental-Files-ANN_Novel-Method-in-Induction-Heating-git.

Conflicts of Interest

All authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

Supplementary materials and technical techniques for training support are provided by Ho Chi Minh City University of Technology and Education. Data and computer codes are available at Git following link: https://github.com/Ryannguye/Supplemental-Files-ANN_Novel-Method-in-Induction-Heating-git. (*Supplementary Materials*)

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