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Numerical Simulation and Neural Network Prediction the Cold Bending Spring back for Ship Hull Plate

Shaojuan Su[1,2,*], Yong Hu[2] and Wang C. Fang[2]

[1]*Transportation Equipments and Ocean Engineering College, Dalian Maritime University, Dalian, Liaoning, 116026*

[2]*School of Transportation, Wuhan University of Technology, Wuhan, Hubei, China, 430063*

Abstract: The accurate prediction of the spring back has great significance to the cold bending of plates. Based on the analysis of the square non pressure head CNC bending machine forming principle, the finite element model of the cold forming of the hull plate surface was established using the ANSYS/LS-DYNA finite element software. And the spring back computing research was done on the thickness of 8 mm to 16 mm. The influence rule of the thickness to spring back was analyzed. And the numerical simulation and experimental results of spring back comparison verified the reliability of finite element simulation. Then the prediction model of the plate thickness and the spring back was established using neural network which is based on nonlinear dynamic system and the test sample spring back was predicted. The results of simulation show that the BP neural network can predict the spring back transformation trend very well by comparison with the results of numerical simulation and provides a reliable basis for spring back control. A new idea was proposed for the ship hull plate CNC forming by the application of neural network.

Keywords: Neural network, spring back prediction, Numerical Simulation, cold forming, CNC.

1. INTRODUCTION

Plate spring back is the cumulative effect of the forming history, and is closely related to many factors, it is difficult to study the plate spring back by the pure theoretical analysis method and with the complexity of the forming program it is difficult to get any breakthrough. With the development of the elastic-plastic theory, the computer technology and the continuous improvement of the finite element theory, the research of plate spring back by numerical simulation technology is becoming mature, it has became an important means of plate spring back prediction and plate forming optimization. According to the structure and forming method by the CNC bending machine of the ship hull 3D surface plate, this paper establishes the finite element model of cold bending and studies the key technologies of numerical simulation.

Neural network system is a computing system of nonlinear dynamics system. There are many types of neural network model: BP network, RBF network, Hopfield network, Kohonen network and BAM network etc. They have often been widely applied to prediction and use the combination of numerical simulation technology and neural network in the accurate and fast prediction of spring back of the ship's hull plate forming.

2. COLD BENDING FORMING PRINCIPLE

The overall structure of the CNC bending machine of ship hull plate is shown in Fig. (**1**). The work area size of workbench is 840 mm*840 mm, the upper model is composed of 14*14 square pressure head, the lower die is composed of 15*15 square pressure head, the upper model and the lower die in longitudinal and transverse directions are staggered, the relative distance of the center line of press head is half of a pressure head length. The work area size of pressure head is 58 mm*58 mm, the separation distance of adjacent heads is 2mm, square pressure head is a combination of rectangular blocks and hemisphere and it can swing freely within the cone at 45° around the center of sphere [1].

Square pressure heads adjustable die forming method of plate surface is a new forming method for curved surface of ship hull forming which belongs to a new flexible forming technique without a mold [2]. Its principle is that the traditional mould is discretized into a series of highly adjustable and regular arrangement of the square pressure heads. Depending on the shape of the target surface, the height of the support body is adjusted and quickly forms an adjustable die surface that is dense, with small square head and has the pressing area almost over the entire plate. In the cold pressing process, the staggered square pressure head of upper and lower moulds support each other. When upper and lower molds clamps the plate, each pressure head of the upper mold is supported by four adjacent pressure heads of the lower die, whereas each pressure head of the lower die is supported by four adjacent pressure heads of the upper mold. Forcing the square pressure heads to deflect on their spheres

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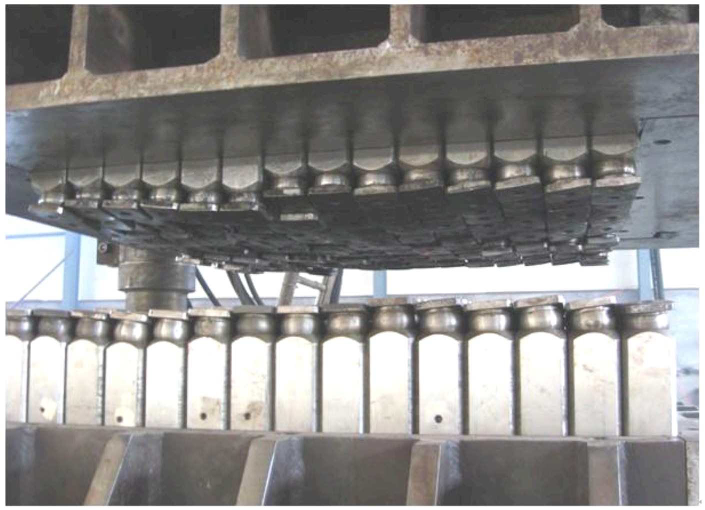

Fig. (1). SKWB-400 CNC bending machine.

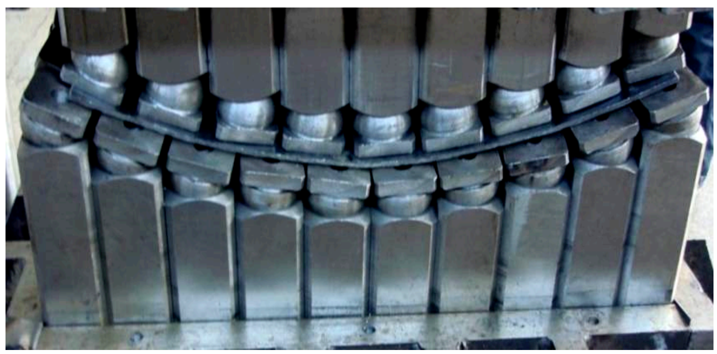

Fig. (2). SKWB-400 CNC bending machine work area.

according to the shape of the plate. Each die is raised and lowered independently from the lower and upper support bodies, respectively to bend the plate sandwiched between them, as shown in Fig. (**2**).

3 FINITE ELEMENT NUMERICAL SIMULATION

The finite element 3D model on non pressure multi heads cold bending forming device was built under the guidance of elastic plastic theory analysis. The key technologies such as treatment of constitutive relations of materials, the selection of unit type, meshing, constraint handling etc were studied. And through the dynamic display conversion algorithm and static implicit algorithm the spring back numerical simulation was realized. And the results were compared with the experimental results, which can calculate the spring back accurately. Because of space restrictions, only model establishment and material constitutive relation were described in the paper.

3.1. The Finite Element Three-Dimensional Model

Non pressure square head adjustable flexible die forming device numerical model consists of three main parts: the upper die body group, the lower die body group and the gap in between. In order to simplify and consider the symmetry of the problem, only 1/4 model was established in the paper. Namely the upper die body number are 7*7, the lower die body number are 8*8. The 1/2 head model is established in XOZ, YOZ symmetry plane and 1/4 head model is set up at the symmetry center [3, 4]. The simple model was shown as in Fig. (**3**). Then the finite element model was shown as in Fig. (**4**).

3.2. Constitutive Relations

Linear strengthening elastic-plastic model was adopted in the paper. The use of bilinear fits the real stress strain

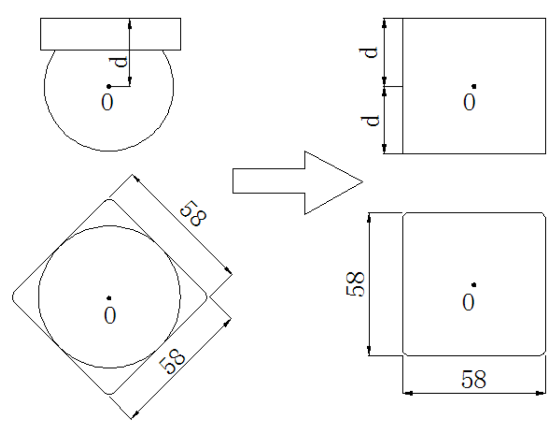

Fig. (3). The equivalent model.

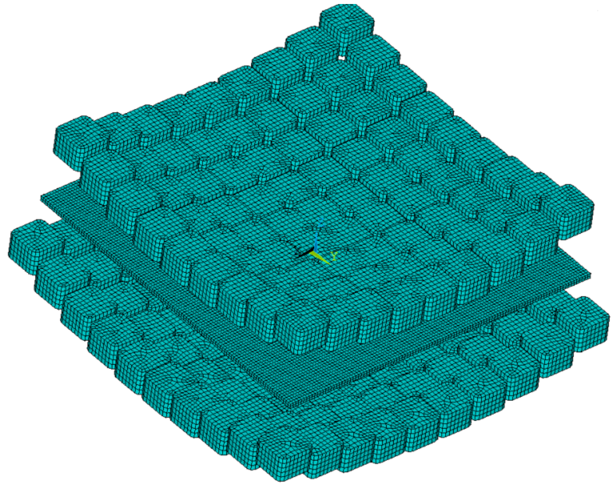

Fig. (4). Three-dimensional model.

Table 1 Sheet material parameters.

Modulus of Elasticity E_0/MPa	Tangent Modulus E_t/MPa	Yield Stress σ_y/MPa	Poisson's Ratio μ	Density ρ/kg·m^{-3}
2.06×10^5	2.0×10^4	355	0.3	7.85×10^3

Table 2. The maximum spring back for different thickness.

Thickness/mm	6	7	8	9	10	11
Spring back/mm	13.14	12.53	11.98	11.50	11.08	10.72
thickness/mm	12	13	14	15	16	
Spring back/mm	10.41	10.16	9.97	9.83	9.61	

curve. In the simplified model, tangent modulus Et and yield strength σy becomes the most important parameters that affect the performance of materials. The ability to resist deformation is enhanced with Et and σy increase. The components of elastic deformation will add under the same deformation. The spring back will increase which is released by the elastic deformation after unloading [5, 6].

The material parameters are shown according to test and calculation showed in Table **1** [7-9].

3.3. Calculation Results

The spring back simulation analysis was done from the thickness 6 mm to 16 mm for the spherical forming bending with the circular Φ800 mm, curvature radius R=1814 mm shown in Table **2**. The calculation results are shown in Fig. (**5**).

3.4. Experimental Verification

In order to test accuracy of finite element numerical simulation, the plate bending forming test was done by SKWB-800 type of ship hull plate CNC bending machine. Φ 800 × 10 mm and Q345 material was selected. In order to study the effect of deformation to spring back, the lower die was adjusted to a continuous spherical surface, die face diagonal center height is 100 mm i.e. curvature radius R= 1814 mm. Cold pressure forming was performed and the dies retracted. The center point spring back is measured by laser measuring instrument. The spring back measured value is 11.2 mm. The error is only 1.1 % with the finite element numerical simulation. The result shows that the numerical model is reasonable.

4. NEURAL NETWORK PREDICTION MODEL

Artificial neural network has the following characteristics: 1). Adaptive self-learning ability. Learning ability is the important manifestation that neural network has intelligence, by training the main features of the training sample can be abstracted and it shows a strong adaptive ability. Artificial neural network can gain weight and structure of the internet through training and learning, shows a strong self-learning ability and adaptability to the environment. 2). A high degree of parallelism. Artificial neural network is generally formed by many similar simple processing units, the function of each unit is simple, but a lot of sample parallel activities of handling units give it a strong ability to handle information. 3). Highly nonlinear. Neural network achieves the non-linear mapping from input space to output space. Therefore, the

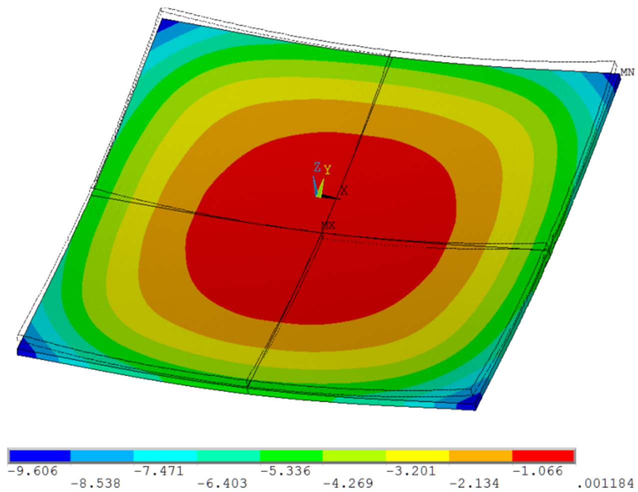

Fig. (5). spring back distribution of 16 mm thickness plate.

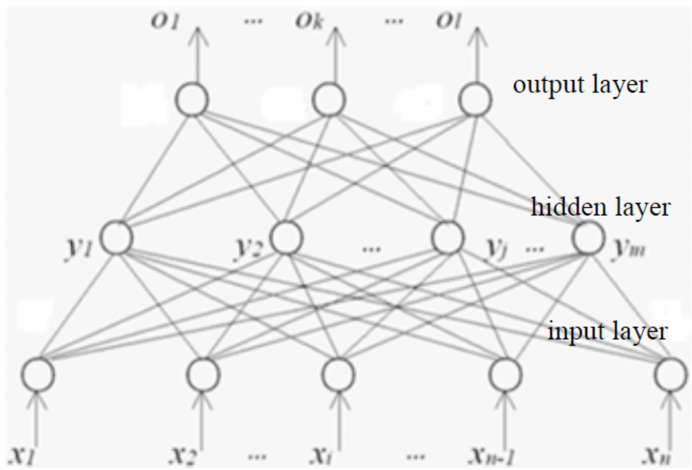

Fig. (6). The structure model of neural network.

neural network has become an important tool for the nonlinear system research. 4). Fault tolerance and associative memory function is good. Artificial neural network can achieve the information memory through the network structure by itself, but the information of memory is stored in the connection weights between the neurons, and from a single weight cannot see the stored information distributed storage way which makes the neural network have good fault tolerance. It can carry on the pattern information processing work such as the clustering analysis, feature extraction and memory recovery and is suitable for pattern classification, pattern association and other pattern recognition works [10].

The purpose of neural network learning is to generate reaction which is close to ideality. When network is training, it constantly compares the output data and the ideal data of network, and changes the weight according to learning specifications, until the comparison error of the output data with all the training data and ideal output data is within the error range [11].

Typical neural net work models are as shown in Fig. (**6**).

Assume the input vector of the network is $x=(x_1,x_2,\ldots x_n)^T$. There are m neurons in the hidden layer, $y=(y_1,y_2,\ldots y_m)^T$. There are n neurons in the output layer, $o=(o_1,o_2,\ldots o_l)^T$. The weight between input layer and hidden layer is W_{ij}, threshold is θ_j, the weight between hidden layer and output layer is W'_{jk}, threshold is θ'_k. According to the principle of BP neural network, the output of neurons in each layer can be expressed as Eq. 1.

$$\begin{cases} o_k = f(\sum_{j=1}^{n} w'_{jk} y_j - \theta'_k) & k=1,2\ldots l \\ y_j = f(\sum_{i=1}^{m} w_{ij} x_i - \theta_j) & j=1,2\ldots m \end{cases} \tag{1}$$

The formula: $f(x)=\dfrac{1}{1+e^{-x}}$

According to the output error adjust the network weight. Assume the total error as the objective function $E_j=\dfrac{1}{2}\sum_{p1=1}^{p}\sum_{k=1}^{l}(t_k^{p1}-o_k^{p1})^2$.

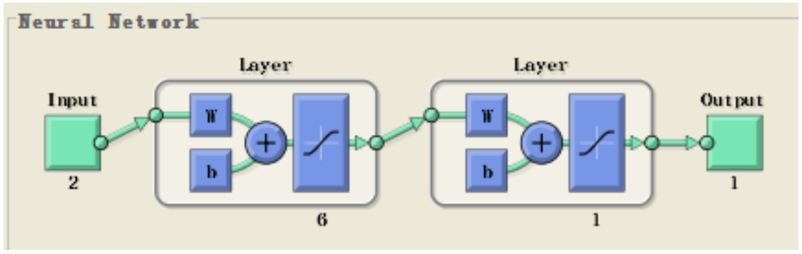

Fig. (7). Network topological structure.

E: nonlinear error function associated with the connection weights.

The weight of the output layer and hidden layer can be obtained by the gradient iteration:

$$w'_{jk}(n0+1) = w'_{jk}(n0) + \eta \sum_{p1=1}^{p} \delta_{jk}^{p1} y_j^{p1}$$
$$w_{ij}(n0+1) = w_{ij}(n0) + \eta \sum_{p1=1}^{p} \delta_{ik}^{p1} y_i^{p1} \tag{2}$$

η -the length of iteration step ; $n0$ -the length of iteration step

In the forward propagation process, the input information was handled from input layer to hidden layer and was transmitted to the output layer. The state of each layer neuron only affects the state of the next layer neuron. If the expected output was not obtained from the output layer then it changes to back propagation, returns the error signal along the original connection path, by modifying the weights of each layer of neurons and minimizes the error signal. The process continues alternately and repeatedly until it meets the iteration stopping criterion.

5. SPRING BACK PREDICTION MODEL

BP neural network model about sping back is realized in Matlab neural network toolbox which includes the following main points.

1) Sample collection. The sample consists of input and output data. Select circular plate with Φ800 mm, the target radius of curvature k=1814 mm. Spring back analysis for the forming spherical parts of the thickness from 6 mm to 16 mm was done and obtained the bending spring back data to predict research as shown in Table **2**.

2) Pretreatment of sample data. The input data was normalized to enable all the network weights within a not too large range so as to alleviate the difficulty of network training. The normalized formula is shown in Eq. 3.

$$P = (p - p_{\min}) / (p_{\max} - p_{\min}) \tag{3}$$

In the formula: Pmax and Pmin are the maximum and minimum values of sample before normalization, P: value of sample of normalization. When the value of normalization using trained neural network prediction is obtained, then we need to use the anti-normalization formula: $p = P * (p_{\max} - p_{\min}) + p_{\min}$

3) The design network topological structure. How to determine the number of input layers, the hidden layer and output is important. The network structure shown in Fig. (**7**) was used in the paper.

Network training: Formula of traingdx adapted learning rate and momentum gradient descent back propagation algorithm, combined with the gradient descent algorithm and adaptive learning rate gradient descent algorithm, improved the training speed and the training stability of network space usage of memory space is small, suitable for the requirement of this paper.

The technology route for the whole paper was shown in Fig. (**8**).

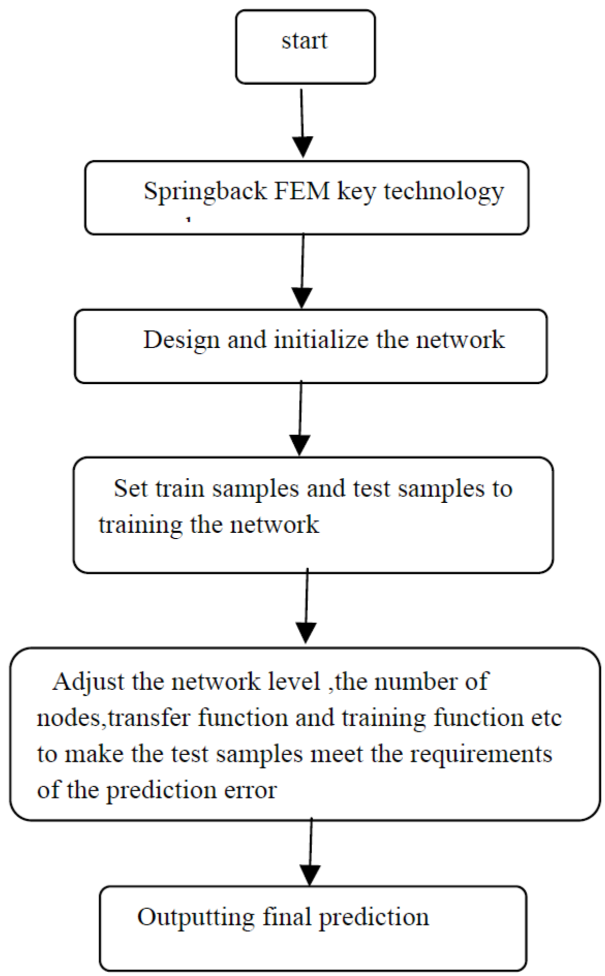

Fig. (8). Technology route.

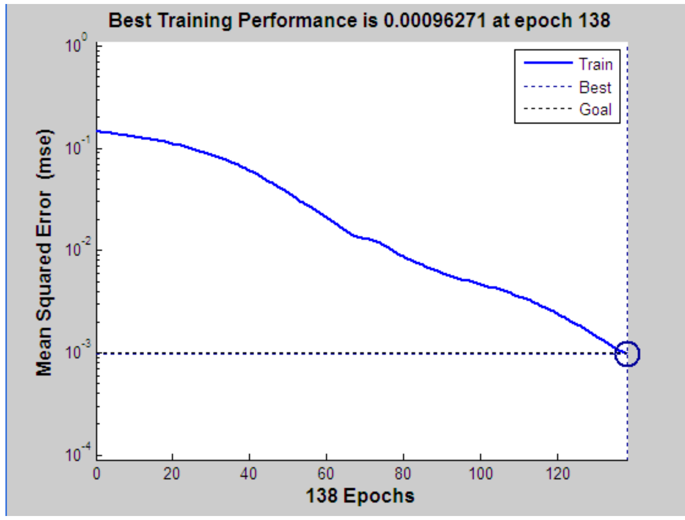

Fig. (**9**). Approximation diagram of neural network training error and target error.

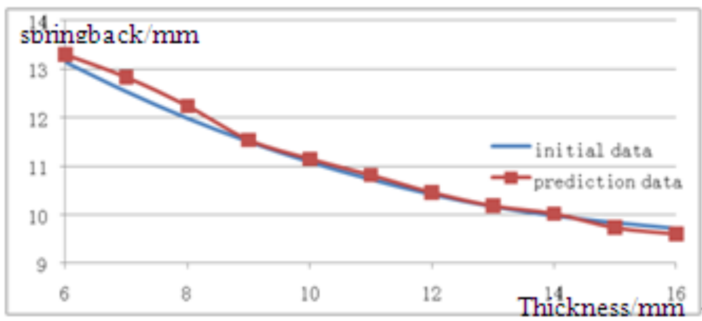

Fig. (**10**). The results comparative analysis.

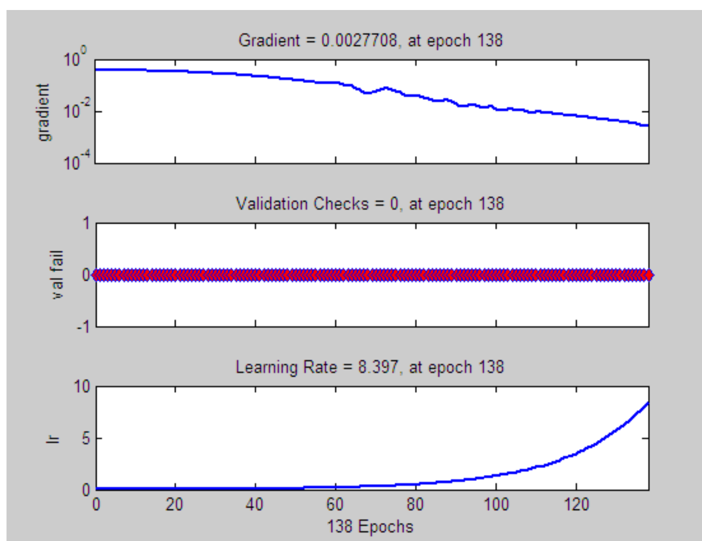

Fig. (**11**). The simulation after 138 times iterations.

5) Analysis of the prediction results

A neural network model of spring back prediction was established by the selected parameter above, which is used in the network training process is the Matlab 7.0 for Windows. The BP neural network training uses the Neural Networks Toolbox for Matlab. The training error convergence as shown in Fig. (**9**).

The Artificial neural network prediction results were compared with the spring back data from the finite element numerical simulation as shown in Fig. (**10**).

The sample achieved the goal error curve after 138 trainings as shown in Fig. (**11**). So far, we have set up a neural network prediction model of plate thickness and the amount of spring back. After, we will examine the reliability of the model and the prediction precision.

In order to verify its effectiveness, this paper takes prediction research on the plate of 18mm thickness, the spring back amount is 9.95, after a bending plate test of 18mm thickness plate, the spring back amount is 9.58 and errors are 3.3%. Error analysis after fitting shows that maximum spring back after the curve fitting calculated is close to the actual values which are consistent with the requirements.

CONCLUSION

This paper established nonlinear model of plate parameters and spring back amount based on BP neural network, tested the reliability of the model, and the error with the actual spring back is only 3.3%, and predicted the spring back of test sample. Conclusion: the prediction effect of the overall BP network for spring back amount is good, but after many experiments have revealed that it may appear local minimum and instability has yet to be improved.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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REFERENCES

[1] W. Chengfeng, J. Hutong, and H. Yong, *Square pressure head adjustable die plate forming device*: China ZL200910014794.6.

[2] W. Fang, H. Yong, and L. Jixian, "A novel forming method for 3d ship hull forming", *Journal of Wuhan University of Technology (Transportation Science & Engineering)*, vol. 34, no. 3, pp. 431-434, 2010.

[3] A.P. Karafillis, and M.C. Boyce, "Tooling design in sheet metal forming using spring back calculation", *The International Journal of Mechanical Sciences,* vol. 34, pp. 113-131, 1992.

[4] L. Shuang-yin, *Study of spring back for ship hull plate in cold forming*. Wuhan: Wuhan University of Technology, 2011.

[5] S.U. Shaojuan, H.U. Yong, W. Chengfang and L.I.U. Bo. Square Head Adjustable Die Device Research on Ship 3D CNC Forming Machine. *Applied Mechanics and Materials*, vol. 395-396, pp. 920-92, 2013.

[6] V. Marko, H. Miroslav, S. Bojan, and S. Boris, "Modelling of spring back in sheet metal forming", *International Journal of Material Forming*, vol. 2, no. 1, pp. 825-828, Dec. 2009.

[7] Z. Chuan-Min, F.U. Wen-Zhi, and L.I. Ming-Zhe, "Suppression of dimples in digital multi-point stretching process", *Journal of Jilin University (Engineering and Technology Edition),* vol. 39, no. 1, pp. 83-87, 2009.

[8] J.O. Hallquist, "*LS-DYNA 3D Theoretical Manual*. LSTC, Livemore, 1991.

[9] Z.H. Zhang, *Finite element Procedures for Contact-Impact problems*. Oxford: Oxford University Press, 1993.

[10] R. Stein, "Preprocessing date for data for neural network", *AI Expert*, vol. 25, no. 2, pp. 69-78, 2001.

[11] Y.I.N Chengqun, K. Lifeng, "Short-term load forcast based on combination of wavelet transform and hybrid neural network", *Electric power automation equipment*, vol. 27, no.5, pp. 40-44, 2007.

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