Application of BPANN and regression for prediction of bowing defect in roll-forming of symmetric channel section

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Abstract: In this paper both back-propagation artificial neural network (BPANN) and regression analysis are employed to predict the maximum downward deflection of the exit profile in roll-forming of symmetric channel section. To prepare a training set for BPANN, some finite element simulations were carried out. Sheet thickness, flange width, fold angle and friction coefficient were used as the input data and the maximum downward deflection as the specified output used in the training of neural network. As a result of the specified parameters, the program will be able to estimate the maximum downward deflection of the exit profile for any new given condition. Comparing FEA and BPANN results, an acceptable correlation was found.

Key words: Roll-Forming, Channel Section, Bowing Defect, Artificial Neural Network, Regression.

1 INTRODUCTION

In roll-forming processes, a long metal strip is progressively deformed through a series of rolls in order to achieve a required cross-section. Since the final cross-section cannot be achieved in one stage, the process must be completed in several stages or stations. The final cross-section is therefore produced via a series of incremental deformation processes. As excessive deformation in any of the stages may lead to some form of geometric defect in the final product there is a limit to the allowable deformation and so the change in cross-section must be controlled in order to avoid the formation of such a defect. Therefore numerical simulation of defects occurrence in this process can provide and develop scientific bases of designing a roll-forming mill. Among previous researches, only a few reports have dealt specifically with modelling defects in this process. Interested readers can refer to Wen and Pick [1], Toyooka [2], Farzin et. al. [3] and Salmani Tehrani et. al. [4,5,6]. 'Local edge buckling' is known as a common defect in roll-forming processes which cause the increment of deformation in a single stage to be very limited [5]. As demonstrated in [5], the tendency of the strip to turn down (bowing) is the essential reason of 'local edge buckling' occurrence. The bowing shape of the exit profile can be well quantified by the downward deflection Δ of the leading edge, as illustrated in figure 1. In this paper both BPANN and regression methods are employed to predict the deflection Δ, in roll-forming of symmetric channel section, instead of time consuming for repeating the simulations for new conditions.

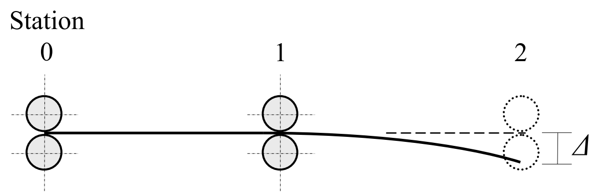

Fig. 1. Schematic illustration of bowing of the exit profile.

BPANN, is a relatively new computational tool that has found extensive utilization in solving many complex problems in plastic working domain [7,8], such as predicting flow stress [9], forecasting rolling force [10], optimizing the irregular shape rolling process [11], predicting springback in metal forming [12], predicting fatigue life of carbon steel [13], predicting fracture toughness in microalloy steel [14]. To prepare a training set, some finite element simulations were carried out. The effects of sheet thickness, flange width, fold angle and friction coefficient on the deflection Δ are to be investigated. Therefore in the training of neural network, sheet thickness, flange width, fold angle and friction coefficient have been used as the input data. The deflection Δ is the specified output used in the training of the program, which was determined from the FE simulations. As a result of the specified parameters, the program will be able to estimate the deflection Δ for any new given condition.

2 FINITE ELEMENT SIMULATIONS

2.1 Experimental Details

The channel section considered in this investigation was used in the experimental work of Bhattacharyya and Smith [15]. Experiments were conducted on an industrial roll-forming machine with stations spaced at 145 mm. All rolls had the same base diameter of 106 mm. The lower rolls were shaped to give the fold angle, while the upper rolls were flat faced. The material formed was a mild steel strip of 0.6 (thickness) × 40 (width) × 1200 (length) mm. The initially flat strips were formed into a symmetrical channel section having a nominal web width of 20 mm. The experiment was repeated for four fold angles 20˚, 30˚, 40˚ and 50˚.

2.2 Finite Element Model

A finite element simulation of Bhattacharyya and Smith experiment [15] was presented and validated in [5]. Here, the same basic data of the mill and the same simulation methodology as adopted in [5] are used to set up the finite element model. Considering the symmetry of the section, a work piece of 300 (length) × 20 (width) mm was modelled using S4R shell elements from the ABAQUS element library. A uniform mesh of 150 (longitudinal) × 20 (transversal) elements was created. Three stations of rigid rolls were included. Each simulation involves two steps. Step 1: Vertical closure of the rolls at station 1, by translating the bottom roll vertically up. Step 2: Rotation of the rolls at station 1; both top and bottom rolls were driven to move the strip leading edge towards and past the location of roll station 2. Rolls at zero station were modelled as frictionless surfaces and were fixed during simulation. While a frictional contact was defined between the strip and the rolls of stations 1 and 2.
To study the effects of sheet thickness, flange width, fold angle and friction coefficient on the deflection Δ, the FE simulations were repeated for different input parameter values, as summarized in table 1.

3 NEURAL NETWORK APPROACH

An artificial neural network is a parallel-distributed information processing system. It stores the samples with distributed coding, thus forming a trainable nonlinear system. The main idea behind a neural network approach resembles the human brain functioning. Given the inputs and the expected outputs, the program is self-adaptive to the environment so as to respond to different inputs rationally [16]. The objective of this paper is to investigate the prediction downward deflection Δ of the strip, after exiting from the first station, by training a BPANN. The neuron can be classified into three types: input, output, hidden neurons. Input neurons are the ones that receive input from the environment, such as sheet thickness, flange width, fold angle and friction coefficient in this study.

Table1. Summary of FE simulation conditions and numbering

Simulation Condition		Input Parameter Value ***(Increment)***			
Sequence Number	Variable Parameter	θ (º)	t (mm)	w_w (mm)	μ
1 to 8	Fold Angle	*15-50 (5)*	0.6	10	0.2
9 to 19	Thickness	30	*0.4-1.5 (0.1)*	10	0.2
20 to 28	Web Width	30	0.6	*8-17 (1)*	0.2
29 to 38	Friction Coefficient	30	0.6	10	*0.1-0.3 (0.02)*

Output neurons are those that send the signals out of the system, like downward deflection Δ. Neurons which have inputs and outputs within the system, are called hidden neurons. As the activation function, tangent hyperbolic activation function has been used, which is a continuous, nonlinear, monotonic non-decreasing and S-shaped function (equation 1).

$$f(x)=\frac{1-e^{(-x)}}{1+e^{(x)}} \tag{1}$$

In this study, the back propagation, which is a widely used algorithm, is used in the training step. This method is a feed forward network with one or more hidden layers and can map non-linear processes. Back propagation is a systematic method for training multilayer artificial neural networks. It has a strong mathematical foundation based on gradient descent learning. The elementary architecture of the back propagation network has three layers. There are no constraints about the number of hidden layers. Too many hidden layers not only lead to slow learning, but results in over fitting and poor generalization of the network. A four-layer feed forward BP network can approximate any arbitrary continuous nonlinear function to any degree of accuracy, so for the prediction of maximum downward deflection, in this Study a multilayer perceptron consisting of an input, two hidden layers and an output layer was used as shown in figure 2. It is shown generally that when the number of nodes in the hidden layer is as two times or so as the number of nodes in the input layer, the network can be more compatible in terms of the capacity and training time. Therefore, the structure of the network is as shown in figure 2 where fold angle, sheet thickness, flange width and friction are inputs and the downward deflection Δ is the output. Multi-layer Perceptron (MLP) trained using the back propagation algorithm was found to be successful in this study.

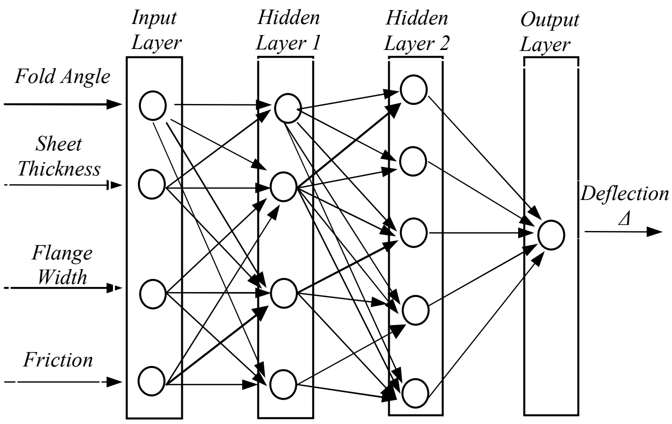

Fig. 2. The structure of the designed neural network.

Learning in an MLP model involves using an iterative gradient descent algorithm to minimize the mean square error between the actual outputs of the network and the desired outputs in response to given inputs. Training in an MLP network is performed by forward and backward operations. The network produces its actual outputs for a certain input pattern using the current connection weights. Subsequently, the backward operation is carried out to alter the weights to decrease the error between the actual and desired outputs. The alteration of weights is affected by two parameters, namely learning rate and momentum coefficient. The learning rate defines the range of changes in the connection weights. The momentum coefficient is introduced to improve the learning process and it works by adding a term to the weight adjustment that is proportional to the previous weight change. The error is computed using equations 2 and 3 known as average squared error.

$$e_k(n) = t_k(n) - y_k(n) \tag{2}$$

$$e_{av} = \frac{1}{2N} \sum_{n=1}^{N} \sum_{k \in C} e_k^2(n) \tag{3}$$

In equations 2 and 3, N denotes the total number of samples in the training set, the set C includes all the neurons in the output layer of the network, $t_k(n)$ are the magnitudes of outputs which are obtained from finite element simulations and $y_k(n)$ are the magnitudes of ANN outputs.

In training of BPANN, 38 input and output vector sets are generated from the simulations. 34 of these data points were used as the learning set, and the remaining four were used for testing the developed network. Due to the characteristic of tangent hyperbolic activation function, the training set is scaled between -1 and 1. Learning rate and the momentum rate are experimentally chosen as 0.6 and 0.6, respectively. Four layers BPANN, 4-4-5-1, are used in this study. The training process has been completed in approximately 24366 iterations. Training of the network is stopped when error e_{av} in equation 3 reaches 0.0001 and error e_{av} is not reduced appreciably for further iterations. The results obtained from BPANN predicted are compared with FE simulations in figure 3 for the all 38 simulation sets. For the 4 test cases the maximum relative error is less than 4. 5% and the average relative error is less than 4%. These results imply the reliability of the developed network for prediction the downward deflection Δ.

4 REGRESSION ANALYSIS

In this section regression analysis is used to fit the best linear model on response variable. Here fold angle (θ), sheet thickness and its square (t,t^2), flange width and its square (w,w^2) and friction coefficient (μ) are independent variables while downward deflection (Δ) is the response variable. Backward method was used to eliminate the variables with negligible effect on the response variable in regression analysis. Using this method, it was found that μ can be removed from the model Therefore it can be omitted from the model. The final model was derived as the following:

$$\Delta = 0.273\theta + 55.13t - 2.827w - 27.74t^2 + 0.064w^2 \tag{4}$$

R square of the model is 0.995 and the more robust statistics against the number of variables, adjusted R square, is 0.994. The coefficients in equation 4 show that Δ increases as t, θ and w^2 increase and decreases as w and t^2 increase. Also the effect of thickness, t, on response variable. Figure 3 shows the predicted values of all methods that used in this article This statistics analysis shows that linear model can be well fitted on data.

5 CONCLUSIONS

Maximum downward deflection of the exit profile, is important in “local edge buckling” occurrence, in cold roll-forming process. In this paper, both

BPANN and regression methods were employed to predict the downward deflection Δ of the exit profile, instead of time consuming for repeating simulation for each new conditions. The training set was obtained from finite element simulations. The effect of sheet thickness, flange width, fold angle and friction coefficient on deflection Δ were investigated. Comparing the BPANN and regression analyses with FEA results implies the validity and reliability of the both methods. Moreover it was found that this method was suitable for this interest but the BPANN results are more accurate than those of regression.

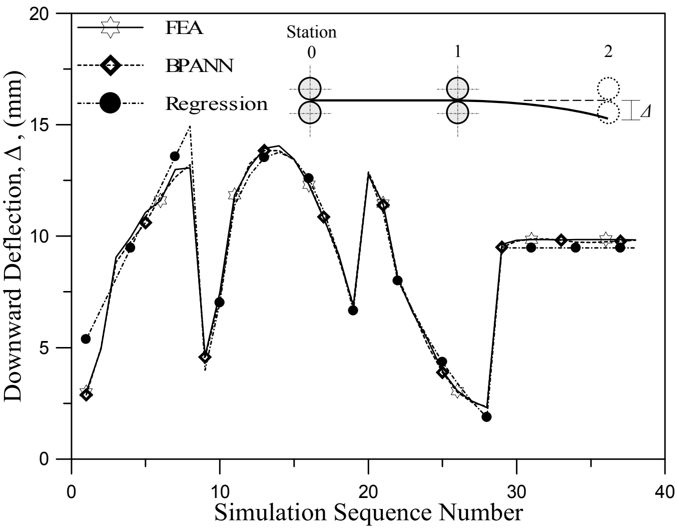

Fig. 3. Comparison between BPANN and Regression prediction with FEA results.

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