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SPRINGBACK EFFECT PREDICTION IN WIPE BENDING PROCESS OF SHEET METAL: A GA-ANN APPROACH

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ABSTRACT

Sheet metal is one of the most important semi-finished products used in automobiles, domestic appliances, aircraft and other familiar products. Therefore sheet metal forming technology is an important engineering discipline in the area of mechanical engineering. In sheet metal forming, wipe bending process plays a major role in which the sheet metal tries to return to its original shape after release of the load by a punch, due to the elastic stresses. This phenomenon is called as springback and the angle between the target bend and the original after elastic release is called sprinback angle. Springback angle prediction is essential while engaging with such wipe bending processes. State of the art methods use Artificial Neural Network with conventional configuration for the prediction of springback angle. To improve the prediction efficacy, this paper exploits Genetic Algorithm to provide appropriate training to Artificial Neural Network. The experimental investigations show that the proposed ANN approach predicts more precisely compared to the conventional ANN approach.

Keywords: *Springback, Wipe Bending Process, Artificial Neural Network (ANN), Genetic Algorithm (GA), Prediction*

1. INTRODUCTION

Materials engineering encompasses the science and art involved in the conceptualisation, specification, design, analysis, fabrication and evaluation of generic materials in their various forms and in different operating conditions with the aim of developing materials for an application [16]. Among them, sheet-metal working processes have been related with mankind since the Iron Age, when human beings first discovered that metals, especially gold and silver, can be shaped in the cold state by repetitive hammering to form thin sheets for making bowls, plates, containers, decorative items, etc [2]. Sheet-metal forming is one of the most widely used manufacturing processes for the fabrication of a broad range of sheet metal products in many industries such as automotive appliances, aerospace, and others [1] [3] [5] [6] [10] [11]. The sheet metal forming has gained a lot of attention in modern technology because of ease with which metal may be formed into useful shapes by plastic deformation processes in which the volume and mass of the metal are preserved and metal is displaced from one place to another [3]. Sheet metal can be easily produced by rolling mills at low cost and the parts that are formed from sheet metal have the advantage that the material has a high elastic modulus and high yield strength, so that they can be both stiff and have a good strength-to-weight ratio [7].

In recent years, new technologies are expected to respond to new industrial demands, which are mostly seek to precise and accurate information concerning parts design and formability of metal sheet [4] [15]. While in sheet metal designing process, some uncertainties are caused due to uncontrollable conditions such as metal suppliers, forming conditions, and numerical errors which need to be taken into consideration in the design process [5].Throughout the years, technological advances have allowed the production of extremely complex parts [6]. However, in the case of complicated sheet metal deformation, improper design of process parameters may lead to defects. Thus it is necessary to select the most appropriate process conditions. However, it is still a very difficult problem to obtain the optimum result [10].

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Sheet metal forming simulation plays an indispensable role in integrating manufacturing necessities into the product design process at an early stage. In conjunction with concurrent engineering, sheet metal forming simulation is proving to be an important tool in linking design and manufacturing [4]. The numerical simulation of sheet metal forming processes is particularly attractive to reduce the waste of time and cost because of the process modelling for computer simulation by a virtual trial and error process [8]. As a result, rapid tooling technologies have made inroads into conventional die fabrication methods with the aim of reducing the lead time and investment costs of tooling development. One category of rapid tooling technology involves the application of advanced polymers and composite materials to fabricate sheet metal forming dies [6]. However, there are many variables which are unknown but which can control the forming processes in order to be able to solve the industrial problems [8]. Optimization theory provides an effective way for further studying the relations among the sheet metal forming quality influence factors and scientifically controlling them [9].

2. RELATED WORKS

Some of the recent literary works that deal with the optimization of sheet metal formation are discussed in this section.

In 2009, G.M. Kakandikar et al., [2] have discussed the application of evolutionary strategies to optimize the geometry parameters such as die design and punch design, process parameters such as forming load, blank holder pressure and coefficient of friction, the spring back, hammering sequence etc. Evolutionary algorithms offered many advantages over traditional methods. Those are widely used now days for sheet metal industry.

In 2009, Recep Kazan et al., [13] have discussed the prediction model of spring back in wipe-bending process of sheet metal was developed using artificial neural network (ANN) approach. In their work, several numerical simulations using finite element method (FEM) were performed to obtain the teaching data of neural network. The learned neural network was numerically tested and can be easily implemented spring back prediction for new cases.

In 2010, Mehmet Firat et al., [14] have proposed an approach based on numerical simulation of stamping processes by using explicit–incremental and implicit–iterative finite element techniques. The influence of the numeric model parameters were investigated with factor analysis and described with response surfaces obtained by multi-linear regression. A forming process lead to spring back-critic channel geometry was selected for the application of the proposed methodology. The effects of modelling parameters were determined by evaluating influences of the punch velocity and the element size, in order to obtain a numerically calibrated simulation model. Then the sensitivity of the spring back deformations to the contact interface friction and the blank holder force was predicted, and a set of response surfaces was generated. Comparisons with the experimental data have indicated the suitability of the proposed approach in spring back predictions. The proposed technique was employed in the stamping analysis of an engine suspension bracket made of high-strength steel. The process conditions were investigated in terms of draw bead penetration and blank holder force setting, and the predicted part shapes were compared with CMM measurements of the manufactured parts. An evaluation of computed spring back distortions have shown good correlation with experiment results and confirms the use of process parameters estimated with the proposed design.

In 2011, Mihael Volk et al., [12] have discussed about the FEM which was needed for reliable product development and stable production process. One of the most significant parameters in the sheet metal forming process was the blank holding force. In their work, the optimisation of the blank holding force was performed with the help of FEM analysis. For the optimisation the geometry and the structure of the blank holder was optimised. The best results were obtained with flexible, segmented blank holders, which enables wider technological window for good parts.

In 2011, Guangyong Sun et al., [1] have proposed a two-stage multi-fidelity method to better compromise the uses of low-fidelity and high-fidelity solutions. A correction response surface (RS) was first constructed based on the ratio or difference between high-fidelity and low-fidelity solutions at fewer sample points. Then the low-fidelity analysis was further replaced by a moving least square (MLS) approximation to enhance its accuracy. To demonstrate the present design procedure, multi objective optimization of draw-bead restraining forces for an automobile inner panel was exemplified. The results significantly improved the computational efficiency

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and accuracy of optimizing sheet-metal formability without wrinkle and fracture.

The literary works have dealt with the bending process of sheet metal forming process by focusing on the modelling of bending process. For instance, kazan et al [13], have focussed on deriving prediction model for springback angle in wipe-bending process. They have proposed an ANN approach for prediction model and compared the results with FEM method. In their method, they have exploited the basic configuration of ANN training algorithm that is not effectual in search of global solutions. As the work is suffering due to the problem, we focus on developing an ANN approach with effective error minimization process. The paper is organized as follows. Section 3 gives a brief introduction about the springback wipe bending process, Section 4 details the proposed ANN approach with required illustrations and mathematical formulations and Section 5 explains the error minimization procedure using GA. Section 6 discusses the results and Section 7 concludes the paper.

3. SPRINGBACK WIPE BENDING PROCESS

The wipe-bending process plays a major role in sheet metal forming industry [29]. In the bending process, after release of the load by withdrawal of the punch, the metal tries to return to its original shape because of the elastic stresses [30] [31] [32].Springback after proclamation is one of the problems of such bending process [19] [20]. Springback refers to the elastic recovery of deformed parts. Springback occurs because of the elastic relief from the bending moment imparted to the sheet metal during forming. The sheet metal bending is a composite elasto-plastic deformation process involving small to moderate deformation and large rotation [21].

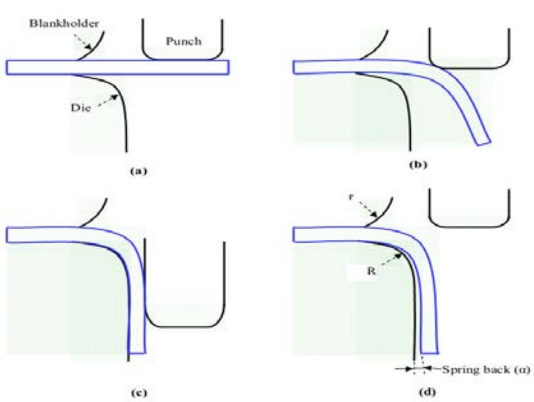
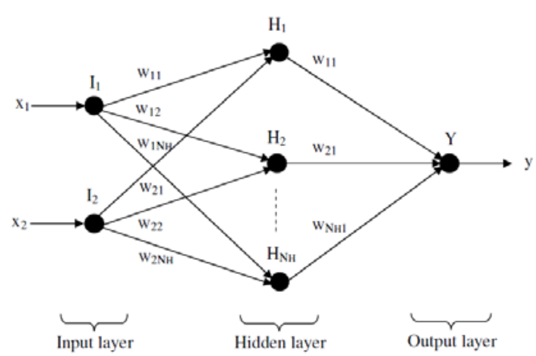


Figure 1: Springback Effect Of Wipe Bending In Sheet Metal Forming Process

In the past two decades, several mathematical models have been proposed to describe and predict springback for meek geometry. None of these have found wide acceptance, although some common characteristics are prominent [17]. For pure bending, springback has been reported to be approximately proportional to the bend ratio, the yield stress and contrariwise proportional to the elastic modulus [18]. The accuracy of the spring back prediction depends on the accuracy of constitutive equation and their equivalent material parameters [22]. It is also sensitive to range of materials and process parameters such as strain acclimatization evaluation of elastic properties elastic and plastic anisotropy and the presence of Bauschinger effect [23] [24]. On the other hand, curl occurs when the walls of a part away from the locally bent region, which ideally should remain straight, become curved [25] [26]. It is a complex corporal phenomenon which is mainly oversaw by the stress state obtained at the end of a deformation. Depending on the product geometry and deformation regime, there are several types of springback in sheet metal forming: bending, membrane, twisting and combined bending and membrane [27] [28].A general illustration of springback effect in a wipe bending process is depicted in Figure 1.

4. PROPOSED SPRINGBACKPREDICTION IN WIPE BENDING PROCESS

ANN is a generalized mathematical model of human brain structure and neural biology. Here, the neurons and its associated weights are modelled to ANN structure, which can be two layered (with input and output layers) or multi-layered (with input, output and hidden layers). In our method, we exploit multi-layered feed forward neural network for developing the prediction model for springback in wipe-bending process of sheet metal. The architectural view of the ANN model is given in Figure 2.



(a)

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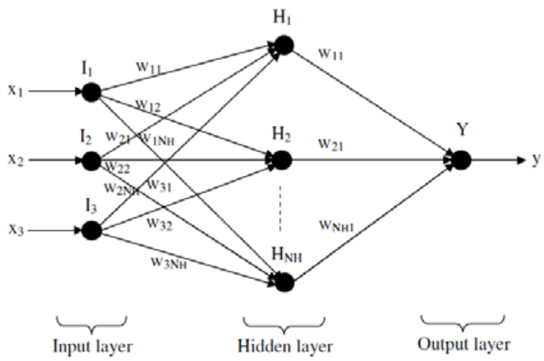

(b)

Figure 2: Proposed ANN Architecture For Springback Angle Prediction

Table I: Input And Output Parameters Of The Proposed ANN Architecture For Prediction Of Sprinback Angle In Wipe Bending Process

Architecture ID	Input			Output
	x_1	x_2	x_3	y
1	K-value	N-value	-	Springback angle
2	R	t	R/t	Springback angle

In Figure 2, two architectures are presented in which the first architecture takes two inputs (K-value and n-value) and the second takes three inputs (R, t and R/t) that are mentioned in Table I. This represents that the first ANN architecture is for prediction of FE simulation data given in Table II [13]. Both the architecture has N_H number of hidden neurons and an output neuron.

4.1. Derived Prediction Model

It is well known that the ANN is a mathematical model, which is comprised of a function of the input variables and the operation of input, hidden and output layers. Let $x_i : 1 \le i \le N$ be the generalized input variables and y be output of the model to be derived. The generalized model output can be

$$Y = f_y(h, w_{hy}) \tag{1}$$

$$H = f_h(x, w_{ih}) \tag{2}$$

where, $f_y(\cdot) : (y = 1)$ is the output layer output, which is the model output and $f_h(\cdot) : 1 \le h \le N_H$ is the hidden layer output that are given in Eq. (1) and (2), respectively, w_{ih} and w_{hy} are the weights of edges of input-hidden layer and edges of hidden-output layer, respectively.

$$f_h(x, w_h) = \frac{1}{1 + \exp\left(-\sum_{i=1}^{N} x_i w_{ih}\right)} \tag{3}$$

$$f_y(h, w_y) = \sum_{h=1}^{N_H} w_{hy} f_h(x, w_h) \tag{4}$$

5. ERROR MINIMIZATION USING GA

The previous Section describes the architecture and the mathematical model of ANN. In the model, it is essential to optimize the weights in such a way that the error between the model output and the actual output sought to be extreme minimum. Traditionally, Back propagation algorithm has been used in the literature in which the weights are optimized by propagating in the backwards direction. As the weights optimization is gradual in this method, achieving the objective of minimizing the error consumes more time and hence the computational complexity become more. Moreover, literature has asserted that back propagation algorithm can easily stick in local optima and hence the error minimization process gets saturated without accomplishing sought figure. Hence, our method exploits GA to minimize the error. The GA process optimizes all the weights at every instant of operation based on the obtained error, instead of gradual operation (propagating in backward direction in BP algorithm). The steps that covered in the GA-based error minimization is as follows

Step 1: Generate a population pool with the following attributes

$$x_{pq} : 0 \le p \le Np - 1,\ 0 \le q \le N_w - 1$$

such that,

$$N_w = (N \times N_H) + (N_H \times Ny) \tag{5}$$

where, $Np \rightarrow$ *population pool size*

Step 2: Determine fitness as follows

$$f_p = \frac{1}{1/2(y - y_T)^2} \tag{6}$$

Step 3: Select the $N_p/2$ best chromosomes which have maximum fitness

Step 4: Perform single point crossover at a crossover rate of C_r and hence obtain $N_p/2$ offspring. In every crossover operation,

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$N_w C_r$ genes are exchanged between the corresponding parents.

Step 5: Perform random mutation operation to obtain new $N_p/2$ offspring x^{new} at a mutation rate of M_r. In random mutation, the genes in arbitrary mutation points are replaced by randomly generated numbers within the limits.

Step 6: Replace the population pool chromosomes by the $N_p/2$ selected chromosomes and new $N_p/2$ offspring chromosomes

Step 7: Repeat the process until the termination criterionis met. Once the termination criterion is met, terminate the process and select the best of the chromosomes in the population pool.
The best optimized weights are determined from the aforesaid process and updated in the ANN model further evaluation phase.

5.1. Evaluation phase

In the evaluation phase of the method, the unknown R, t and R/t, and K-values and n-values is given to the learned ANN model. As the ANN model is already trained because of a huge training samples and the error gets minimized between the actual springback angle and the model springback angle. The ANN model is made correlated with the training data by updating the weights obtained at the end of every iterative process. At the end of the complete GA process, updating the optimal weights leads the ANN model to cope up closely with the training data with minimum error rate. This in turn, theoretically asserts that such trained ANN model is able to determine or estimate the output of any unknown data provided the data has to be in correlation with the training data.

6. SIMULATION RESULTS

The proposed ANN approach for prediction of springback in wipe-bending process is implemented in MATLAB (version 7.12) and the performance is evaluated for the FE simulation data given in Table II.K-fold cross validation method is used for reliable experimentation of the method performance. An extensive analysis is made on the impact of number of hidden neurons on the training performance. The experimental results are illustrated in Figure 3-7 in comparison with the conventional BP-ANN model [13] and the FEM data [13].

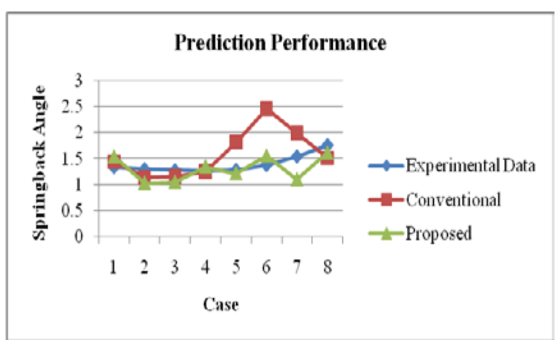
Table II: Springback Values Determined With FE Simulation With Various (I) Blank Thickness And Die Radius, And (Ii) K-Value And N-Value

(i)

Case	Blank thickness(t)	Die radius(R)	R/t	Springback angle(^{0})
G1.1	0.70	0.70	1.00	1.3457222619
G1.2	0.70	1.40	2.00	1.3025469163
G1.3	0.70	1.75	2.50	1.2808051320
G1.4	0.70	2.10	3.00	1.2671661138
G1.5	0.70	2.45	3.50	1.2878514318
G1.6	0.70	2.80	4.00	1.3830116887
G1.7	0.70	3.15	4.50	1.5489459690
G1.8	0.70	3.50	5.00	1.7670563422
G2.1	5.00	5.00	1.00	1.2246734021
G2.2	2.50	5.00	2.00	1.2694581256
G2.3	2.00	5.00	2.50	1.2754867869
G2.4	1.67	5.00	3.00	1.2601561700
G2.5	1.43	5.00	3.50	1.2860660196
G2.6	1.25	5.00	4.00	1.3819058959
G2.7	1.1	5.00	4.50	1.5399236150
G2.8	1.00	5.00	5.00	1.7637458645

(ii)

Case	K-value	n- value	Springback angle(^{o})
H1	430	0.2	0.7293352128
H2	640	0.1513	1.3272425067
H3	650	0.2	1.2715515135
H4	900	0.2	2.0692270082
H5	900	0.25	1.8672640872
H6	1100	0.25	2.4697249891
H7	547	0.226	0.9447464705
H8	554	0.249	0.9317873148
H9	716	0.1724	1.541976925



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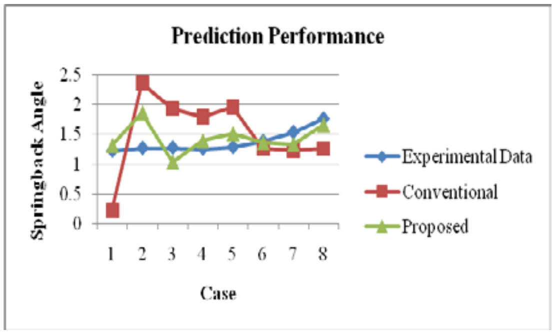

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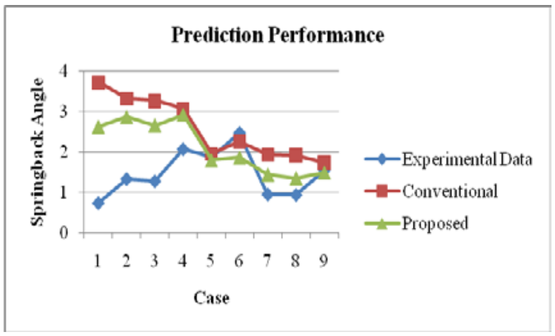
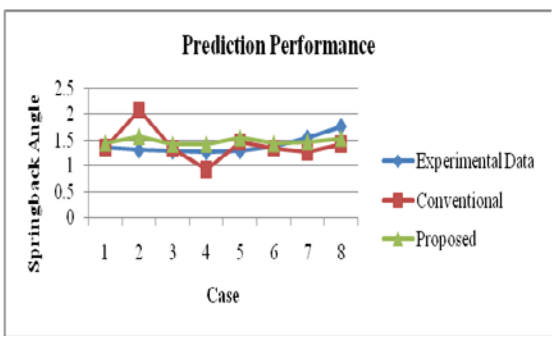


(iii)

Figure3:Comparison Graphs Between Predicted Springback Using Proposed And Conventional ANN Approach With Nh = 5,For (I) Case G1, (Ii) Case G2 And (Iii) Case H



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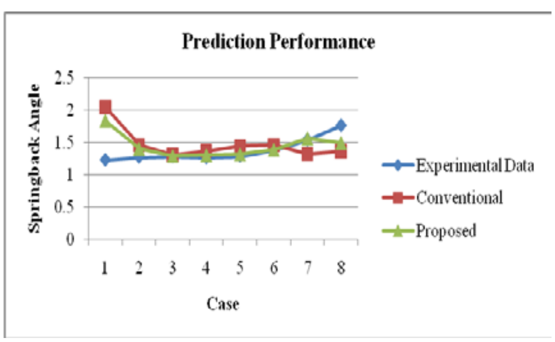

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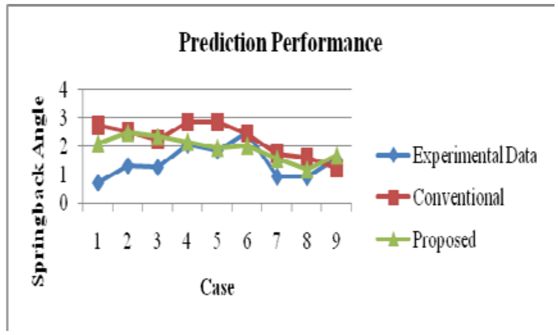

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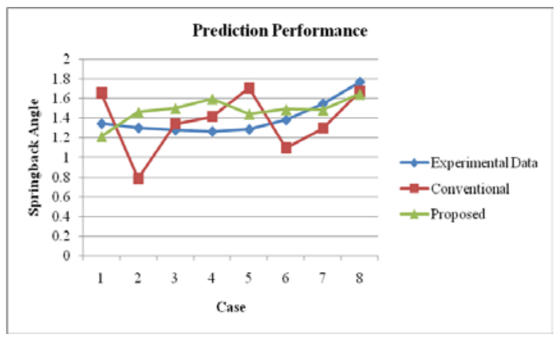
Figure 4: Comparison Graphs Between Predicted Springback Using Proposed And Conventional ANN Approach With Nh = 10, For (I) Case G1, (Ii) Case G2 And (Iii) Case H



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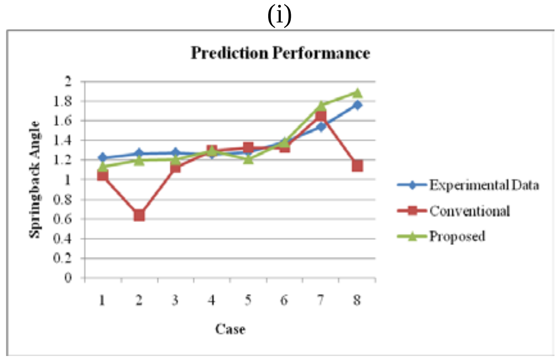

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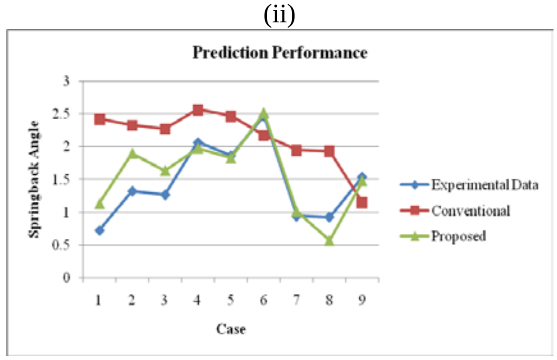

(iii)

Figure 5: Comparison Graphs Between Predicted Springback Using Proposed And Conventional ANN Approach With Nh = 5, For (I) Case G1, (Ii) Case G2 And (Iii) Case H

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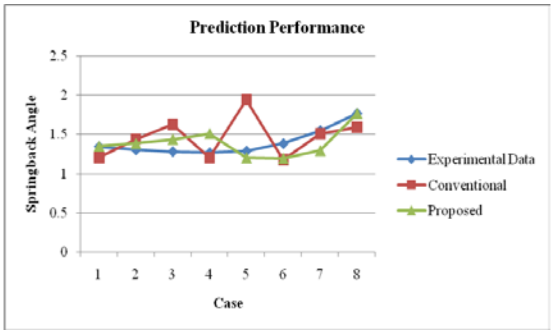

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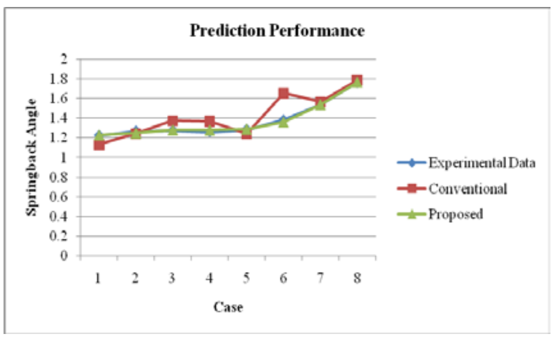

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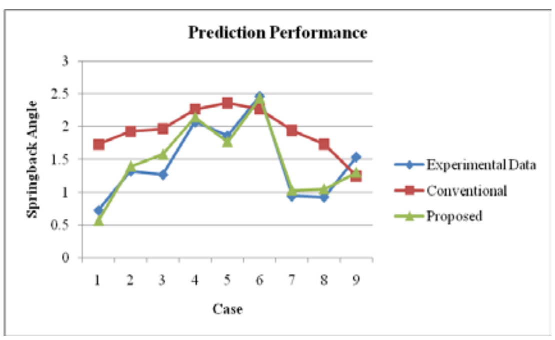
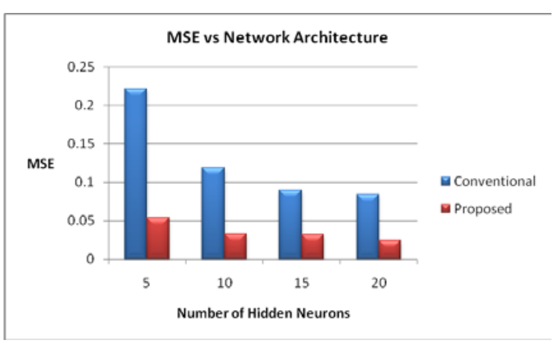


(iii)

Figure 6: Comparison Graphs Between Predicted Springback Using Proposed And Conventional ANN Approach With Nh = 5, For (I) Case G1, (Ii) Case G2 And (Iii) Case H



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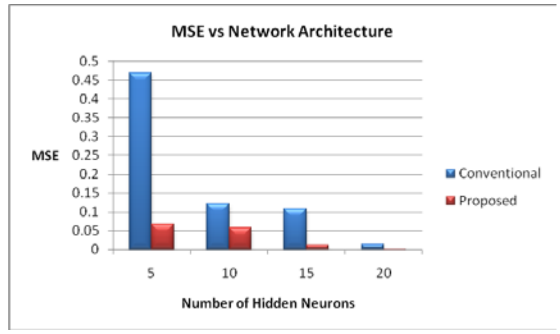

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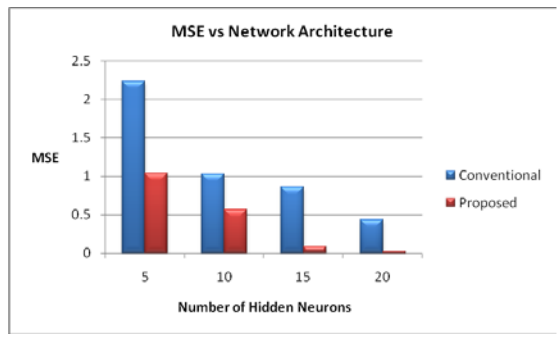

(iii)

Figure 7: MSE Comparison Between Proposed ANN And Conventional ANN With Various Hidden Neuron Configurations For (I) Case G1, (Ii) Case G2 And (Iii) Case H

6.1. Discussion

In Figure 3-7, experimental, conventional and proposed data represent of FE simulation data, BP-ANN [13] and proposed GA-ANN results, respectively. Figure 3, 4, 5 and 6 portray the predicted springback angle when the architecture is developed with hidden neurons 5, 10, 15 and 20, respectively for different cases G1, G2 and H. These predictions are performed through K-fold cross validation, as mentioned earlier. In the K-fold cross validation, the entire published simulation data [13] is segregated into K-folds (K = 8 in our case and it should not be confused the input K of Table II (ii)). Totally K experiments are conducted by alternatively giving K-1 folds of data for training and the remaining for testing. Hence, we obtain test results for 8 cases of data and they are plotted. From Figure 3 (i), it can be seen that the conventional ANN method copes up with the simulation data closer for the cases 2 and 3 and almost compete with the proposed method for the cases 1, 4 and 8, however the proposed ANN method outperforms for the remaining cases. Likely for the other cases, at certain instants, conventional ANN dominates over the proposed. For example,

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case 5 and 9 of Figure 3 (iii), case 3, 6 and 8 of Figure 4 (i), etc., however in an overview the proposed ANN approach more closely copes up with FE data when compared to the conventional ANN approach. This can be observed from Figure 7 using the illustration of Mean Squared Error (MSE). MSE of conventional approach represent the deviation between the predicted data using conventional ANN approach and the FE data. Similarly, MSE of the proposed approach represent the mean squared deviation between the predicted data using the proposed ANN approach and the FE data. It can be seen from Figure 7 that MSEs of proposed ANN approach are considerably lesser that the MSEs of conventional ANN approach. Moreover, the graphical illustrations show that increasing the number of hidden neurons leads to reduce the MSE, which in turn can be interpreted that the prediction is more likely to be precise while comparing with the FE simulation data.

7. CONCLUSION

This paper proposed an effective ANN approach to predict the springback angle of wipe bending in sheet metal forming process. The proposed approach exploited two ANN architectures, one with *K*-value and *n*-value as inputs (for case H) and the other with *R*, *t* and *R/t* as inputs (for case G). The architectural views were used for deriving the prediction model and prediction error was minimized by optimizing the weights using GA. The intention of using GA is to overcome the problems in conventional BP algorithm in such a way that the error was reduced to the minima compared to the conventional BP algorithm. Cross validation is conducted for the three different cases and the MSE if determined to determine the precision of the prediction. The validations results have showed that the proposed ANN approach outperformed the conventional ANN approach at remarkable. This in turn directs that the proposed ANN approach is more suitable for predicting the springback angle of wipe bending process.

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