AL-QADISIYAH JOURNAL FOR ENGINEERING SCIENCES

Vol. 10 , No. 2

ISSN: 1998-4456

SPRING BACK PREDICTION IN V-DIE BENDING PROCESS USING ARTIFICIAL NEURAL NETWORK (ANN)

Mostafa Adel Abdullah,

Department of Production Engineering and Metallurgy University of Technology , Baghdad. Iraq

Email: mostafa_ad_87@yahoo.com

Received on 30 November 2016 *Accepted on 4 April 2017*

Abstract: *The Bending process is the critical operation in the sheet forming, there are large parameters influence on operation. Spring back is considering large influential indication to specify the quality of product parts. The basic parameters which are takes to study in this paper are: speed of punch, time of hold and thickness of plate. Experiment use L16 array with four levels for every parameters using V-bending die with 90^0, with different thickness of (0.5,1,1.5,2) mm ,hold time (0,5,10,15) min and punch speed(10,20,50,100)mm/min, for (1050) Al –alloy having employed as the work pieces. Spring back value prediction use Artificial Neural Network with conventional configuration. The results show that the thickness of plate is the large influential parameter effect in spring back by 77.29%, then punch speed by 10.51% and hold time by 3.36%. The predict result using Artificial Neural Network shown a best accuracy with (99.35%) in spring back compared to the measured value.*

Keywords: Spring back, Bending process, Artificial Neural Network(ANN),Prediction.

1. INTRODUCTION

Spring-back is a general event that happens in sheet metal when bend it after remove load apply because elastic recover. When the bending process removes elastic power stay in the bending plate cause it to repair part to begin shape and this is called spring back. spring-back ratio (KS) mean(the ratio between the die angle and final bending angle). The experiment worked for various shapes, and processes and material condition [1]. Large of the studies focus on V- die bending operation. Leu, D-K [2008][2] study the spring-back in V-bending was effectived by the bend radius, punch speed and punch load and also a few important literatures are briefly discussed here. Yoshida[2005] [3], studied a forming process to minimize springback for steel sheet part made with large strength. Yanagimoto,j.Oyamada[2006] [4],studied the effect of many parameters on spring back phenomenon at worm and hot condition and study the effect of hold time on this condition, and founded that the spring back decreases with an increase of hold time. Zhu L, Beaudoin[2004] [5], presents outline of a simple bending test to study stress levels the evolution of stress and development of plastic strain with time are assessed easy analysis of spring back process and the micro plastic that causes distortion of the bent metal which a model developed by Garmestani and Hart.In recent research has been considered the different parameters which affected on spring back phenomenon. Ali Ghoddosian[2015][6] prediction and reduce the responses of the sheet metal bending process using Artificial Neural Network (ANN) and Genetic Algorithm(GA). Gawade Sharad[2014][7] used easy Neural Network is used for prediction the springback from finite element analysis. The results get by finite element analysis simulations compared with Neural Network and found in large agreement.

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2. BASIC THEORIES OF SPRING BACK

Materials divided for two deformation, zones first the elasticity and then the plastic zone . In bend process, this recovery of elasticity called spring back, Spring back phenomenon is shown in Figure.(1) the larger bent radius change with after than before bending process. Spring-back happen in flat sheets , plate, rod and bar with different cross-section [8]. Spring back, mean as the increase in the angle of the bent part proportional to the included angle of the forming tool after the tool removes. This is illustrated in Figure. 1 :

$$\text{Spring back} = \alpha f - \alpha b \ , \ Ks = \alpha b / \alpha f$$

Where :-
αf = angle after spring back(degee)
αb = angle of bending tool (degee)
Ks = spring back ratio

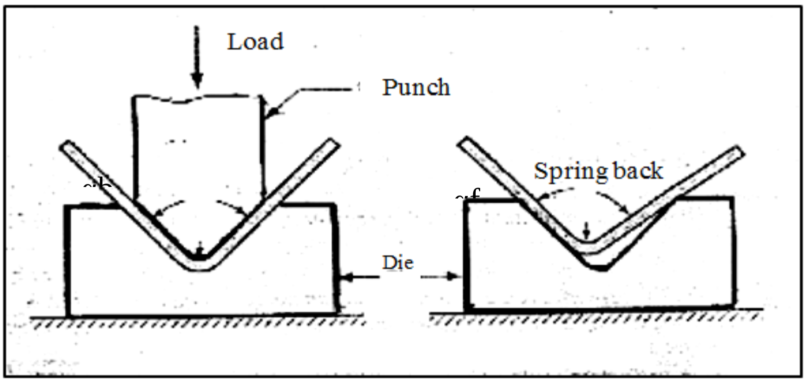

Figure 1. Spring-back in bending process [6].

3. THEORY OF TAGUCHI METHOD

Taguchi method is a powerful tool for the design of high quality systems. It provides systematic approach, simple and efficient to optimize designs for cost, quality and performance .To determine the good design it requires the use of a strategically designed experiment for choices parameter level [10].

4. EXPERIMENTAL WORK

4.1. MACHINE USED

A WDW model (200E)electro mechanical load frame (200KN) shown in Figure 2. Experimental work for the specimens in bending die used in as show in the Figure 3.

4.2. MATERIAL USED

The specimens for spring back test were manufactured these specimens must fit the die and punch with a suitable clearance about (1mm) with a V-die. A rectangular sheet of 50 mm of width and 100 mm. Aluminum alloy 1050 which the chemical composition is listed below in Table 1. is used as a work piece with (0.5,1,1.5,2) mm thickness.

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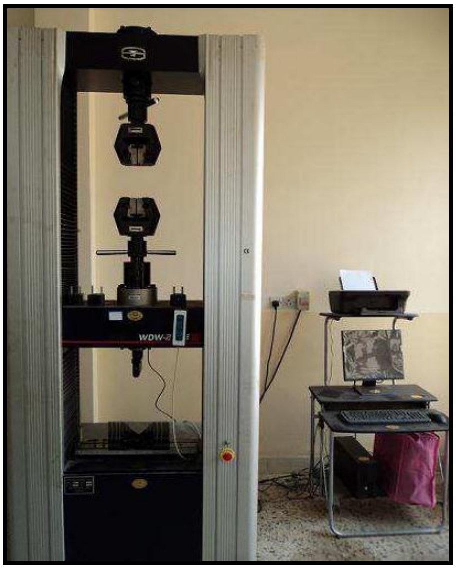

Figure 2. Uniaxial Tensile Testing

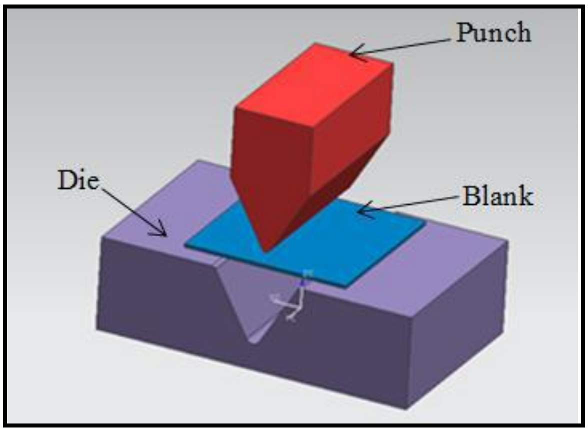

Figure 3. The V-die bending use.

Table 1. Chemical composition of AL- alloy (1050).

Material thickness	Element %								
	Si	Fe	Cu	Mn	Mg	Zn	Ti	Al	other
0.5 mm	0.25	0.40	0.05	0.05	0.05	0.07	0.05	99.4	0.030
1 mm	0.21	0.32	0.03	0.04	0.05	0.07	0.04	99.3	0.042
1.5 mm	0.24	0.38	0.03	0.03	0.04	0.06	0.03	99.1	0.045
2 mm	0.19	0.30	0.02	0.04	0.05	0.06	0.05	99.3	0.041

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4.3. DESIGN OF CUTTING CONDATION

The good design of cutting condition important part on the numeral of work to occur low cost and good output with minimum sample. The all numeral of cutting condition is (64 sample) based on four levels three parameters. a partial factor design was done use (16 sample) to obtain spring back values at room temperature. The parameters were T, s, t_h the levels and units of condition are listed below in the Table 2.

Table 2. condition level used in work

No	Parameter	symbol	Level 1	Level 2	Level 3	Level 4	Units
1	Thickness	T	0.5	1	1.5	2	mm
2	Punch speed	S	10	20	50	100	mm/min
3	Hold time	t_h	0	5	10	15	min

4.4. SPRING BACK TEST

A 90^0 (Vee- bending die) is applied to action the bending operation . The die is comparison load with (200) KN used A WDW model (200E), work piece dimension use(100*50)mm as shown step in Figure.4 and spring back measure for Al-alloy as shown in Figure.5.

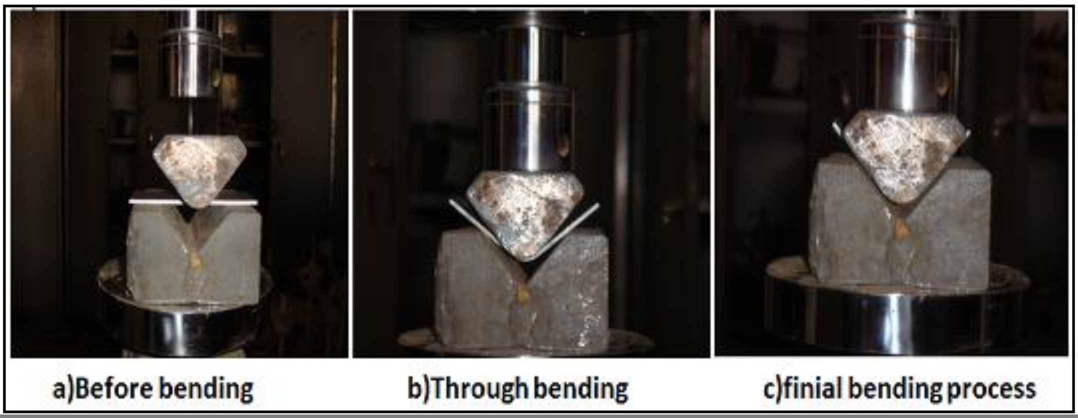

Figure .4 The experimental setup step of V-bending process

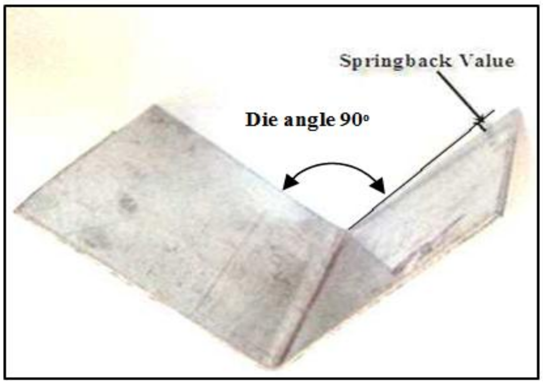

Figure .5 Spring back measures for Al-alloy work

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The final distribution of the experiments sample as listed below in Table .3 with using Taguchi Method and Design in MINITAB16 software as follows step:

START → DOE → Taguchi → Create Taguchi Design

Table .3 Experimental design for the work

No	Thickness (mm)	Punch speed (mm/min)	Hold time (min)	Spring- back measure (degree)
1	0.5	10	0	12.5
2	0.5	20	5	10.6
3	0.5	50	10	8.5
4	0.5	100	15	7.8
5	1	10	5	10.5
6	1	20	0	8.2
7	1	50	15	9.1
8	1	100	10	7.1
9	1.5	10	10	8.3
10	1.5	20	15	5.8
11	1.5	50	0	6
12	1.5	100	5	4
13	2	10	15	2.3
14	2	20	10	3
15	2	50	5	3.5
16	2	100	0	4.1

5. ARTIFICIAL NEURAL NETWORK MODELING

ANN is a multi layered method putting between the input layers and output layers with included many operation part call with neurons [11]:

$$net_j = \sum_{j=0}^{N} w_{ij} x_i \qquad \text{... .... (1)}$$

Where
net_j : input net
N :No of inputs
w_{ij} is the weighing of the connection
x_i : input of the layers
out_j :output network [12]**:**

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$$out_j = f(net_j) = \frac{1-e^{-net_j}}{1+e^{-net_j}} \quad \ldots\ldots.(2)$$

The designed using MATLAB Neural Network Toolbox with three inputs parameter and one output parameter using as shown in Figure.6 . The divide of cutting condition to 16 groups a 12 groups or 75% as training and 4 groups or 25% as testing data. The final sequence design used with 3-5-1 .

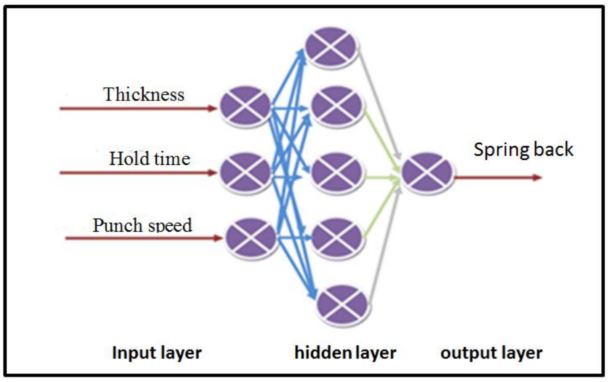

Figure .6 sequence design used.

To find the accuracy of the predict (ANN) percentages errors Φ_i and average percentages errors $\overline{\Phi}$ [13]**:**

$$\Phi_i = \frac{|R_{aie}-R_{aip}|}{R_{aie}} \times 100\% \quad \ldots\ldots (3)$$

Where:

φi= Percentages errors.

R_{aie}=measuring spring back.

R_{aip}= Predicting spring back.

$$\overline{\Phi} = \frac{\sum_{i=1}^{m} \Phi_i}{m} \quad \ldots \ldots (4)$$

Where

$\overline{\Phi}$= average percentages errors.

m= No of e measuring.

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6. RESULTS & DISCUSSION

ANALYSIS OF VARIANCE:

The ANOVA of spring back are shown in Table .3 for work. The F ratio value of 5.9933 for the thickness of plate which greater than other parameters. So, the large affect parameter is the thickness of plate with (77.29%) than the hold time and punch speed**.**

Figure .7 shows the main effect parameter in spring back with increases (Thickness, Punch speed and Hold time) lead to decreases spring back. The minimum spring back was: Thickness at level-4 (2 mm), Punch speed at level-4(100 mm/min), and Hold time at level-4(15 min).

Figure .8 shows the effect of the thickness of the plate and punch speed on spring back at a fixed hold time. It showed the decrease in spring back with increase the thickness of plate and increase punch speed.

Table .3 ANOVA for spring back.

Source of variance	Degree	Sum of squares	Variance	F ratio	P(%)
Thickness (mm)	3	105.17	35.06	5.9933	77.29
Punch speed(mm/min)	3	14.3	4.8	0.7890	10.51
Hold time(min)	3	4.6	1.5	0.2493	3.36
Error ,e	3	12.03	4.01	---	8.83
Total	16	136.1	---	---	100

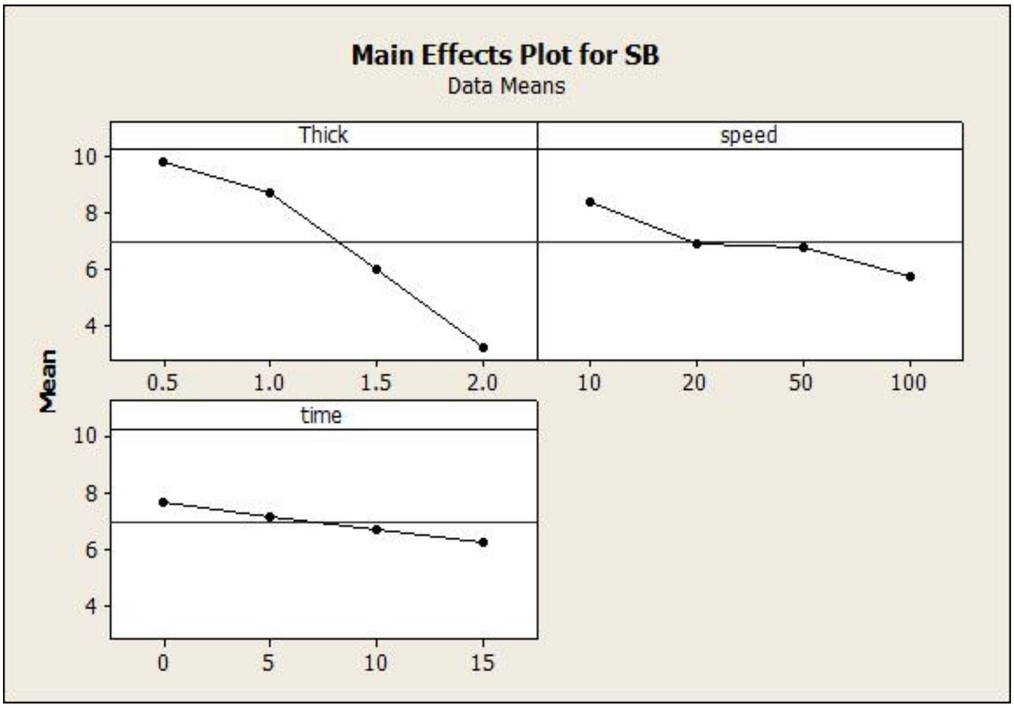

Figure .7 Mean effects plot for spring back.

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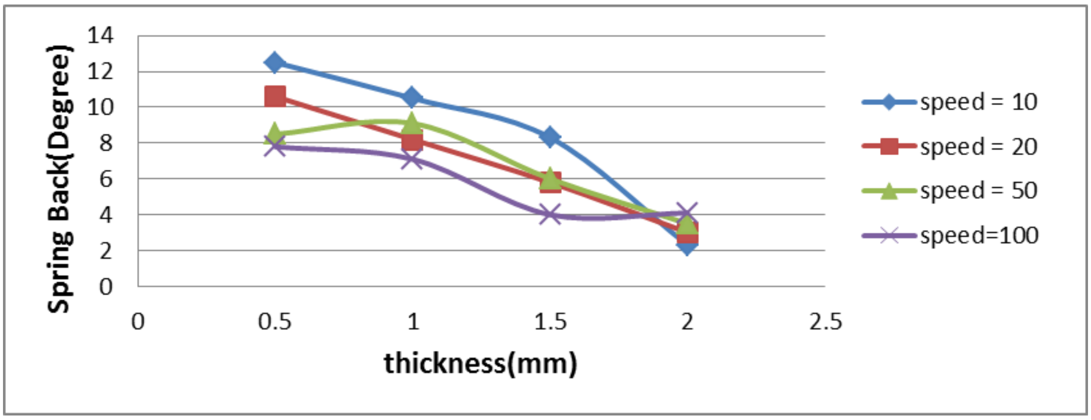

Figure .8 effect of thickness of plate and punch speed on the value of spring back at a constant hold time.

Figure. 9 shows the effect of thickness of plate and hold time on spring back at a fixed punch speed. It shown decrease in spring back with increase the thickness of plate and increase hold time .

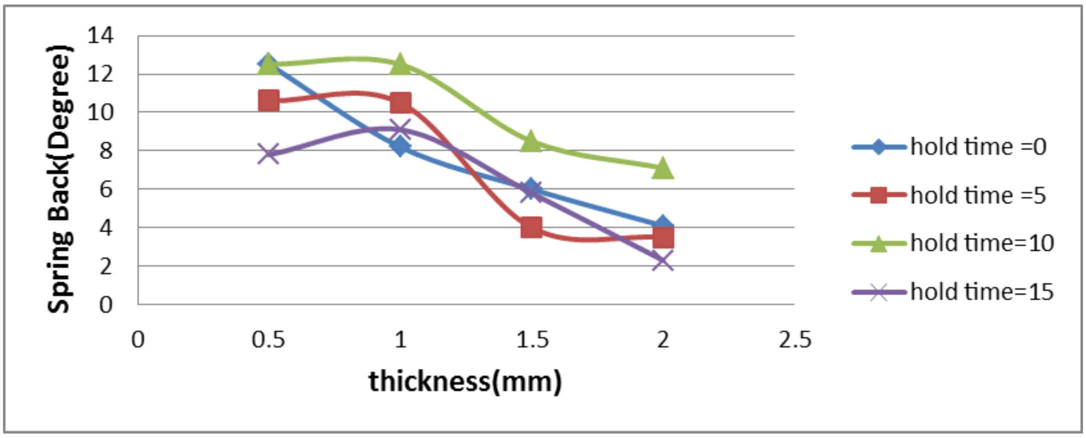

Figure .9 effect of thickness of plate and hold Time on spring back at a constant punch speed.

The results shown in Table .4 . These results are developed to predict spring back using Artificial Neural Network (ANN). Using a given three input (thickness of plate, punch speed and hold time) and output (spring back) data set. Training data depend of 12 as listed below in Table .4 and test data depend 4 of data as listed below show in Table .5 . The training error for predicting spring back value must be lower than (0.008) at 12 , as shown in Figure .10 and Figure.12 and shown error value in Figure .11 .

Table .4 compare for result work measure and (ANN) results for the spring back, respectively. The ANN predicted spring back shown a perfect correlation with the experimenter, (mean square error =0. 0058). And show the methods using to predict the spring back in a minimum error rate for bending process.

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Table .4 The experimental training results.

No	Thickness (mm)	Punch speed (mm/min)	hold time (min)	Spring- back measure (degree)	Spring- back Prediction (degree)
1	0.5	10	0	12.5	12.49
3	0.5	50	10	8.5	9.38
4	0.5	100	15	7.8	7.79
5	1	10	5	10.5	10.49
7	1	50	15	9.1	9.09
8	1	100	10	7.1	7.10
9	1.5	10	10	8.3	8.29
11	1.5	50	0	6	5.99
12	1.5	100	5	4	4.17
13	2	10	15	2.3	2.66
15	2	50	5	3.5	3.77
16	2	100	0	4.1	4.10

Table (5) correlation of neural network predict with experiment measure using test set data.

<table>
<tr><th rowspan="2">No</th><th rowspan="2">Thickness (mm)</th><th rowspan="2">Punch speed (mm/min)</th><th rowspan="2">hold time (min)</th><th colspan="2">Spring- back (degree)</th><th rowspan="2">Error</th><th colspan="3">ANN result</th></tr>
<tr><th>Measure</th><th>Prediction</th><th>$\overline{\phi}$</th><th>MSE</th><th>accuracy</th></tr>
<tr><td>2</td><td>0.5</td><td>20</td><td>5</td><td>10.6</td><td>10.61</td><td>0.09</td><td rowspan="4">0.65</td><td rowspan="4">0.0058</td><td rowspan="4">99.35%</td></tr>
<tr><td>6</td><td>1</td><td>20</td><td>0</td><td>8.2</td><td>8.35</td><td>1.83</td></tr>
<tr><td>10</td><td>1.5</td><td>20</td><td>15</td><td>5.8</td><td>5.78</td><td>0.34</td></tr>
<tr><td>14</td><td>2</td><td>20</td><td>10</td><td>3</td><td>2.99</td><td>0.33</td></tr>
</table>

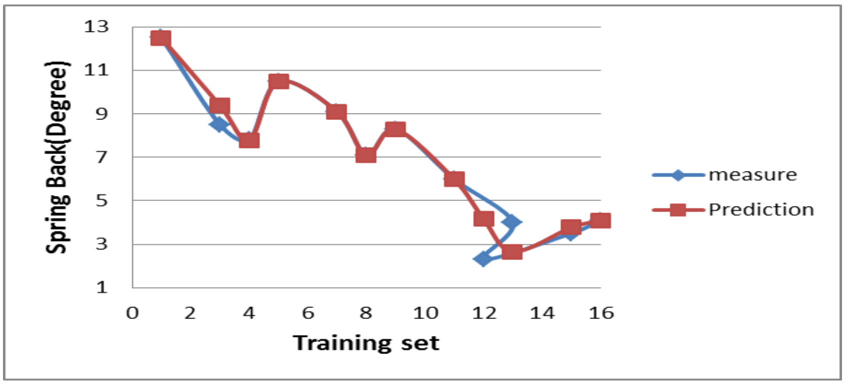

Figure .10 The correlation between the measure with the prediction of Spring back for train set data.

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(a) Regression coefficient of learning data.
(b) Regression coefficient of validation data.
(c) Regression coefficient of test data.
(d) Regression coefficient of all data.

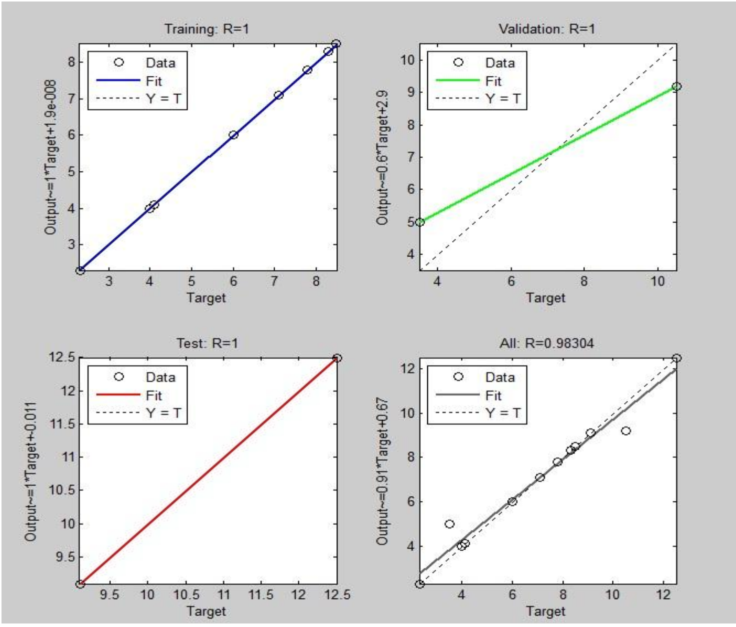

Figure .11 Regression graphs to model.

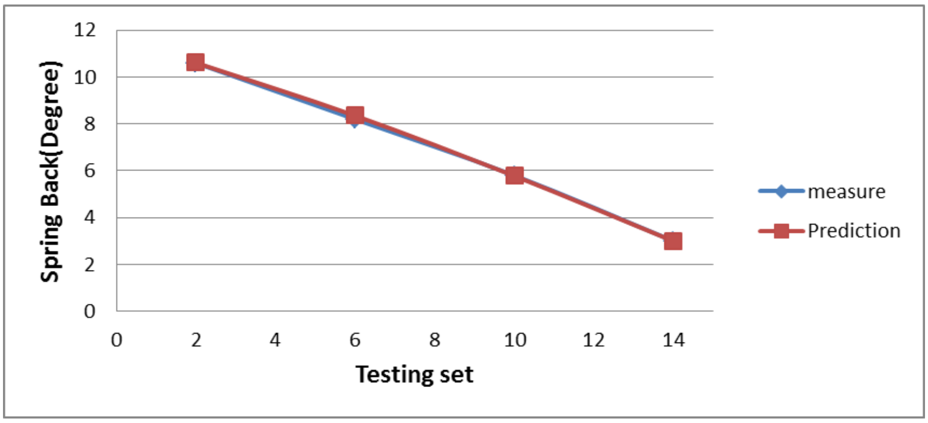

Figure .12 The correlation between the measures and the prediction of Spring back for test set data.

7. CONCLUSIONS

In this study, the effect of various bending parameters (thickness of plate, punch speed and hold time) on spring back as a result of application (1050) Al- alloy and predicting the values of spring back using of ANN. Figure .10 shows the correlation between experiment and predicted given accuracy with (99.35%) for spring back using data for training purpose. The ANN is represent a good simple design and fasting method for the bending process production.

From ANOVA results, it can be achieve that thickness of plate is the most importantly parameters effecting spring back by 77.29%, then punch speed with 10.51% and hold time with 3.36%. The combination of conditions and their levels (punch speed 100 mm/min, thickness of plate 2 mm and hold time 15 min) are recommended to obtain a lowest spring back for V- die bending aluminum sheet 1050 alloy.

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