Identification of Optimum Parameters of Deep Drawing of a Cylindrical Workpiece using Neural Network and Genetic Algorithm

D. Singh, R. Yousefi and M. Boroushaki

***Abstract*—**Intelligent deep-drawing is an instrumental research field in sheet metal forming. A set of 28 different experimental data have been employed in this paper, investigating the roles of die radius, punch radius, friction coefficients and drawing ratios for axisymmetric workpieces deep drawing. This paper focuses an evolutionary neural network, specifically, error back propagation in collaboration with genetic algorithm. The neural network encompasses a number of different functional nodes defined through the established principles. The input parameters, i.e., punch radii, die radii, friction coefficients and drawing ratios are set to the network; thereafter, the material outputs at two critical points are accurately calculated. The output of the network is used to establish the best parameters leading to the most uniform thickness in the product via the genetic algorithm. This research achieved satisfactory results based on demonstration of neural networks.

***Keywords*—**Deep-drawing; Neural network; Genetic algorithm; Sheet metal forming

I. Introduction

DEEP drawing is one of the most imperative processes used in industries for metal shell forming. The cylindrical product drawing is a complex art. Hence, in order to survive in the ever increasing competition in market, artificial intelligence technology is applied to the metal shell forming. The use of neural network based researches on metal shell forming has been increased tremendously since 1980's. In the early developments, the main focus was on V-type bending [1], [2] rather than deep drawing [3], [4]. The reason is that the deep drawing process is much more complicated than bending.There are many factors influencing the formability of cylindrical products including; the material of the work piece, the lubrication condition of the material, the velocity of the hydrodynamics, the radius of punch, the radius of die, the pressure on the blanket and the pressure of the hydrodynamics. These factors are of central importance in determining the result of the deep drawing workpiece. Therefore, in order to fulfill the specifications of the target product, a highly experienced die-design engineer is required. While the poor performance of the engineer will certainly lead to drastic losses of money and time. Meanwhile, in traditional factories, still the metal sheet forming processes are still controlled and designed manually by process engineers using the trail-and-error techniques.

The deep drawing of the sheet metal parts are governed by the limitations of wrinkling (buckling) and tearing. These limiting factors are measured by the drawability of the workpiece and is determined by the factor called 'limiting drawing ratio' or LDR defined by the ratio of the original material radius, R_1 to the final perfect product radius of R_2. There is a direct relation between LDR and that of the material of the material employed in the work piece, the process parameters and tool design. Theoretically, for an optimal design determining the material stress and strain distribution considering LDR parameters is indispensible.

Whitely [5] made vast researches on the importance of the anisotropy in correlation with LDR. Hu's [6] proposed r-value anisotropy theory. Ruminski [7] investigated the strain distribution of dies of different shapes by finite element method using simulation as well as experimental technique taking in account the hardness measurement. Lin [8] and you-Min [9] established the importance of clearance that is inevitably important existing between the die and punch on the formability in the cup-drawing process. Zhao [10] employed neural networks to establish the real-time identification of the friction and coefficients used in deep drawings. Zhao [11], also determined the critical parameters via conventional curve fitting. Their work focused of an axisymmtric work piece. Yet there have been no or very few optimization techniques employing genetic algorithm in collaboration with neural network in this field.

As a matter of fact, this study, takes even one step ahead of the previous articles by utilizing an established intelligent computational techniques determine the optimum parameters. This technique which is getting more attention in these days is neural network (NN) model. The EBP-NN model in correlation with the GA-NN model is utilized to identify of the certain parameters influencing the deep drawing product's thickness uniformity. The target is to achieve the most uniform thickness in the product. It includes considering the role of

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different die and punch radii considering different LDRs and lubricating conditions. A set 28 data has been derived through the experiments in the workshop.

II. EXPERIMENTAL PROCEDURE

All experiments were conducted on st-14 steel plates with initial uniform thickness of 1mm. Fig.1, Fig.2 and Fig.3 shows the schematic view of the experiment apparatus, experimental room and the some of the final products respectively. The equipments used in the test are hydraulic press, control unit, monitor and a printer. The experiment was conducted as follow;

1. Cutting circular plates of different diameters from the initial plate.
2. Measurement and registration of diameters of matrix and die, the active tolerances and the holder pressure.
3. Adjustment of the circular plate.
4. Application of the lubricant.
5. Fine-tuning the speed of the matrix.
6. Registration of the required forces.

In order to study the effect of zinc-stearate and press oil, plates of different diameters with a matrix with die arc of 8mm was employed. In order to find the limiting dying ratio diameter of the plate was increased from 80mm with an increment of 10 mm and after reaching 100mm this increment was changed to 5mm. After the estimation of the approximate dimension the increment was further reduced to 1mm. LDR was obtained based on diameter where rupture occurred. Different parameters were tested by fixing all parameters but the on being considered.

Fig. 4 shows the amount of punch travel versus the punch load for the test with Zinc-strearate lubricant. It clearly indicates the point where the rupture occurs. Fig.5 also depicts the amount of punch travel versus punch load in applying press oil and Zinc-stearate. It is clear that zinc-stearate consumes less energy. This fact highlights the stability quality of zinc-strearate in high pressure in respect to press oil. Note that Fig.4 and Fig.5 have been derived via the experimental control system.

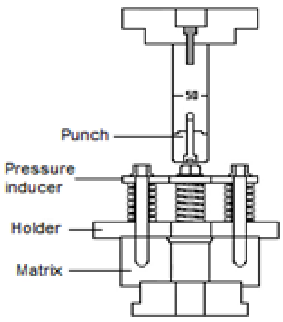

Fig. 1 Schematic view of the experimental apparatus

Fig. 2 Experimental apparatus and its control system

Fig. 3 Specimen that have been successfully drawn

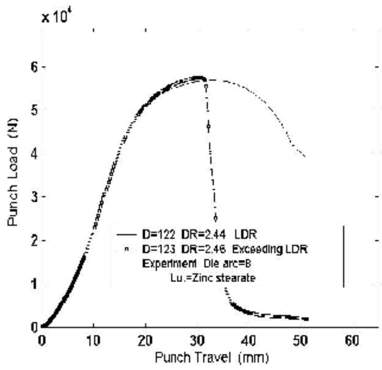

Fig. 4 The magnitude of punch traveled versus the applied load in a test to determine the rupture limit

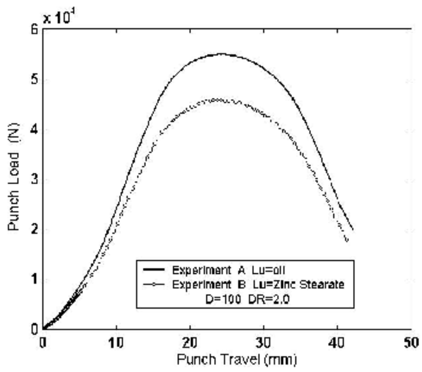

Fig. 5 The magnitude of punch travel versus the punch load in a test for a different lubricant oils

III. ARCHITECTURE OF NEURAL MODEL

1. Design OF INPUT and output layers

Fig. 6 shows the schematic geometry of a typical work piece before and after drawing. For the simulation of such processes, there have been several hypotheses are used. Such hypothesis include: straight generatix, constant area, and quasi- straight beam bending. The materials are usually modeled by the strain hardening law;

$$\sigma = B\varepsilon^{n} \tag{1}$$

The generalized expression for the thickness is

$$T = f\left(R_d, R_p, \mu, Dr, n, B, r\right) \tag{2}$$

where T represents the thickness, R_d is the die radius, R_p is the punch radius, μ represents the friction coefficient, Dr represents the drawing ratio, n the strain hardening exponent, B the material strength coefficient, and r the normal anisotropy. All these parameter are obtained prior to the design, while μ is obtained by generating a correlation between the simulation and the experimental data of different lubricants. Fig. 7 shows the architecture of the neural network used in this work. The metal sheet used for the drawing is St-16. The fact that the material is same in all the experiential data established in the workshop, was all the same dictating the fact that there was no need to include the strain hardening coefficients. Fig. 7 shows a typical geometry of network used in this paper to predict the cost function defined afore. It is evident that there exist 4 input parameters and 2 output parameters existing in the network so designed.

2. Gathering and Processing of Sample Data

The sample data is categorized in two basic parts in neural network: the input data and the output data. In this paper, the input data consists of die radius, punch radius, the friction coefficient and the drawing ratio, established in the

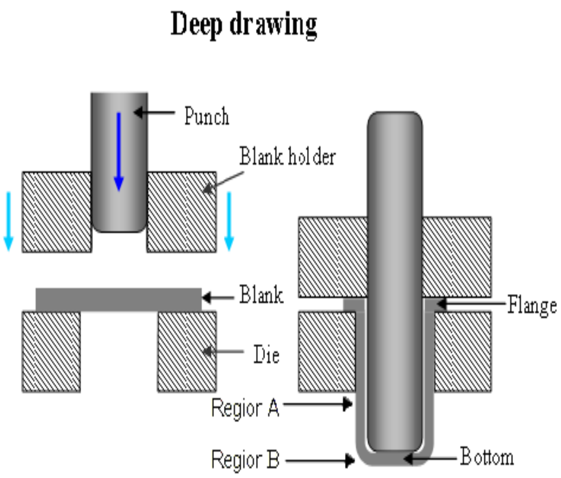

Fig. 6 The schematic geometry of workpiece before and after drawing

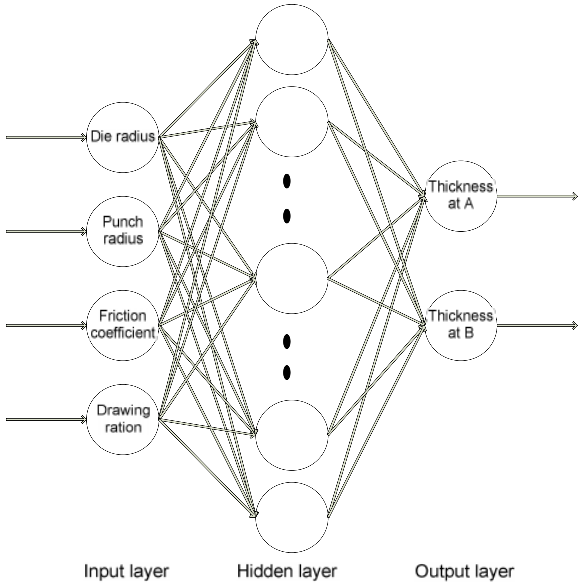

Fig. 7 Feed-forward neural network model

TABLE I
SAMPLE DATA

No.	R_d	R_p	μ	Dr	T_A	T_B
1	4	8	0.1	2	0.811	0.832
2	6	8	0.1	2	0.852	0.835
3	8	8	0.1	2	0.875	0.839
4	10	8	0.1	2	0.881	0.841
5	12	8	0.1	2	0.905	0.846
6	14	8	0.1	2	0917	0.852
7	8	8	0.1	1.6	0.880	0.841
8	8	8	0.1	1.8	0.878	0.840
9	8	8	0.1	2.1	0.873	0.837
10	8	8	0.1	2.2	0.871	0.835
11	8	8	0.1	2.3	0.866	0.830
12	8	4	0.1	2	0.895	0.821
13	8	6	0.1	2	0.883	0.840
14	8	10	0.1	2	0.866	0.861
15	8	12	0.1	2	0.865	0.862
16	8	14	0.1	2	0.863	0.862
17	4	8	0.01	2	0.853	0.883
18	6	8	0.01	2	0.896	0.888
19	8	8	0.01	2	0.905	0.872
20	10	8	0.01	2	0.906	0.874
21	12	8	0.01	2	0.912	0.879
22	14	8	0.01	2	0.914	0.886
23	8	8	0.01	1.6	0.905	0.882
24	8	8	0.01	1.8	0.910	0.885
25	8	8	0.01	2.2	0.888	0.864
26	8	8	0.01	2.28	0.872	0.855
27	8	8	0.01	2.36	0.821	0.760
28	8	8	0.01	2.44	0.770	0.679

There was no need to normalize the thicknesses since they were 1cmm.

workshop. The output of the designed neural network consists of thickness at two different parts of the product. The variation of thickness after the deep drawing is established in the workshop. The punch and die radii vary from 4mm to 14mm, since these two numbers form the practical boundaries of the die design. The higher radii than 14mm lead to “spring back” while the smaller radii than lead to the rupture. The test was conducted using St-14. The radii of the specimen were initially taken to be 100mm.

The value of the friction coefficient was obtained in the experiment and thereby, by using the FEM simulation and comparing the results with that of the experiment data obtained in the workshop. Consequently, it was assumed that common press oil represents the coefficient of 0.1 while zinc stereat represented that of 0.01. Different drawing ratios ranging from 1.6 to 2.44 for μ=0.01form the limiting drawing ratio established in the workshop. The value of limiting drawing ratio has a direct relation with the value of friction coefficient of lubricant.

The output nodes of the neural network nodes predict the thickness of two critical regions of the product in deep drawing. The first point is the value of thickness at point A (see Fig. 4) while the second point is the thickness at region B the values of which is in Table I, in columns 6 and 7 respectively.

It is important to note that point B lies at the edge of punched flat part of the workpiece made from direct contact of the flat edge of punch’s flat circular surface to the plate sheet. Point A lies on the beginning of the cylindrical region of the workpiece. The region A is more critical. Therefore, the output cost function is chosen in a way that 80% of the output cost is dedicated to the thickness at point B while due to the lesser significance of the critical point at B; it weighs 20% of the output cost.

The sample sheets had a thickness of 1mm. Therefore, the value of the thickness of the final product easily shows the percent reduction in thickness. In the workshop it was established that the after the plate reaches the value of 67.9% of its initial thickness, the necking starts and consequently the rupture starts. Hence, the more uniform the thickness and the closer to the initial thickness. Hence, the chance of fracture under static and dynamic loads will be lesser.

It is important to note that many a times there exists a large difference in the magnitude of the variables. This fact results in the formation of large number of singularities and consequently local maxima/minima. Such data lead to the poor convergence capability of the costs functions and thereby, have a direct influence on the time for global search. Hence, the sample data are conventionally normalized before training the network. In this paper, the magnitude of the data was relatively close to each other. Hence no normalization has been done.

3. Number of Hidden Layers And Hidden Nodes

As a matter of fact, it is a well known there is a relation between the numbers of hidden layer to the overall error of the network. Hence, it can be concluded that addition of hidden layers may decrease the network error. Therefore, accuracy of the result is increased. This act also has the drawback of increase in the topology of the network. Hence, the training time for finding the values of the network weights gets increased tremendously. There is another way which is widely used to reach the desired precision that is by increasing the number of nodes in the hidden layer. The neural network is a mean to map the input data to the output data. There are some relations between the hidden layer nodes and, input and output nodes. In general there is no particular rule, but in most of the papers in this matter, the number of the hidden layer nodes is assumed to be a number around;

$$N = 2n + 1 \quad (3)$$

Where N is the number of the hidden layer nodes while, n is the number of input parameters. Therefore, a sum of 11 nodes for the input may have even more satisfactory result while satisfying the condition more or less.

4. Training and Testing of Data

A total number of 5 sets were made, each set containing 22 items for training the network while 6 were kept aside to test the convergence of the network. Table II shows the given set of data. The data for testing the convergence were chosen on the random basis. While testing the network, it was found that set number 5 had the least error for predicting the unknown 6 items. The sixth item had the largest number of epochs for the convergence. The criteria for convergence test were an rms error of 0.055. Table II shows different number of epochs required to reach the specified error. For the prediction test it was found that set number 5 had an rms error of 0.037 which was the least among the 5 randomly chosen sets.

Consecutively, the weights of set number 5 were chosen as the best weights being able to realize the space of the sample data.

TABLE II
RESULTS OBTAIN FOR TESTING EACH SET OF DATA

Case	Order	Error	Epochs	Test rms error
1	5-7-13-18-21-26	0.05	5384	0.0038
2	3-8-15-18-24-27	0.05	158	0.0132
3	2-6-10-16-20-25	0.05	673	0.0057
4	3-9-17-21-23-26	0.05	437	0.0154
5	4-11-14-18-20-26	0.05	14293	0.0035

As a result, these weights were used for predicting some unknown values within the space of the sample data, and also to be used in GA to determine the best diameter for die and punch for getting the highest and the most uniform thickness in the deep drawing product. As a result, the values of thickness of the deep drawing product are determined for equal punch and die radii ranging from 4mm to 14mm given in the tabe3 and Table 4 with friction coefficients 0.1 and 0.01 respectively.

5. Training and Testing Of Data

Error back propagation is one of the most qualified neural network being widely used. In special cases where there exists large number of data covering a large space with several local extremums with comparatively wide range of parameter space, neural network is modified to highly qualified algorithms like simulated annealing. The biggest drawbacks of such algorithms are that they are rather time consuming. Taking account the domain of the data, there was no need to complicate the algorithm. Since the present algorithm was enough satisfactory and have proved itself in this paper as well as in many other researches, we found no need for overdesigning our network.

The algorithms so defined for the determination of the optimum parameters in deep drawing process were based on genetic algorithm. The algorithm was so design that maximum cost as well as the mean cost of the population was monotonically increasing if not being stationary for some generation. The population was chosen comparatively large, that is, a number of 800 initial populations were chosen in order to increase the chance of searching the outer space at each evolutionary stage. Therefore, there were 100 pair of population reproducing at each generation.The mutation rate was chosen to be 20%.

The strategy to reach the target in this paper can be seen in the Fig.8. The theory of genetic algorithm shows that the crossover operators as well as the selective operators have no obvious effect on evolution [12]. At the same time, the mutation operators have great potentials for increasing the searching space. Thereby, the chance for sudden approach to the desired cost function increases. Usually the neural net programs are written, using C, VB, or C++ languages. Here, the programs are written with the help of MATLAB but, no tool box has been used.

IV. RESULTS AND DISCUSSIONS

The error dynamic convergence process is be observed and error goals are set at any time to any arbitrarily number for reaching convergence with a certain precision. It is frequently seen that as long as the action function is appropriate, convergence steps are enough and the topology of the network can approximate arbitrarily a nonlinear system to any degree of precision. As a result, in order to test the generality of the neural network, a set of five elements have been made, from which the last set had the least error for prediction of the unknown data. Fig. 9 shows the number of epochs required to reach the training error to a value of only 0.05, the assumed value. As tabulated in Table III, case 2 had the list number of epochs to reach the required error for training the network.

At the same time it has relatively higher prediction error. Instead, case 5 which had the maximum number of epochs had the least error for the prediction of the unknown data for the neural network. Therefore, case 5 had realized he space of the data best and its weights our criteria. The test error for the prediction of the conserved data was 0.0035 in case 5 which are calculated on the r.m.s. error calculation criteria.

This value is guaranteeing the correct prediction of the further data. The next step was to predict certain values especially the thickness of workpiece for different die and punch radii, and different friction coefficients. The values obtained are tabulated in Table IV. The next task of this paper was to find the best parameters that lead to the highest cost function where the cost function was defined by

$$T_{cf} = 0.2 * T_B + 0.8 * T_A \tag{4}$$

where T_{cf} is the cost function, having the dimension of thickness, T_B the least thickness of the region *B* and T_A the least thickness of the region *A*.

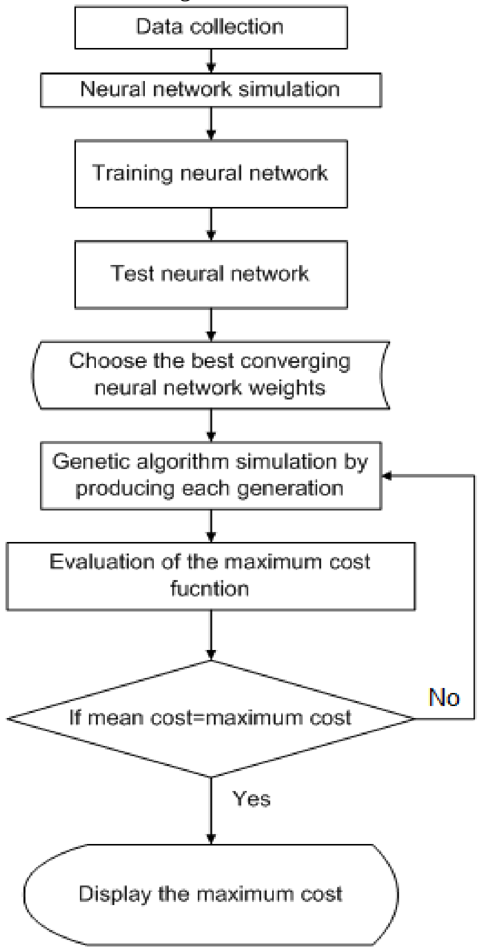

Fig. 8 The optimization strategy

The values so found are tabulated in table five given in the following page. For this test, different drawing ratios are taken into consideration to find the best value serving the cost function. It was found that for all the drawing ratios maximum cost function is the one with die and punch arc radii of 14mm. since, the values more the 14mm lead to spring backing of the workpiece special measures need to be taken in the design of such specimens.

Consecutively, the aim was to find the values that lead to the maximum cost function among all the cost in the entire parameter of the defined space. The result was the case one of the Table IV which was expected to be so.

The interesting point is that all the friction coefficients are the least possible ones, i.e., 0.01. Fig. 10 shows the convergence of the mean cost and the maximum cost to the same value which occurs at around generation 18 of the randomly selected population satisfying the boundary conditions so defined in the problem. The red line shows the maximum cost function at each generation while, the blue one shows the mean cost function.

In Fig. 10, it is easily noticed that each generation is either better or equal to the last generation. This fact highlights the role of the sequences employed in the genetic algorithm. Since these values are the predicted values, there is a chance of deviation from the exact values by a small amount. Still, the sequence is enough precise.

Fig. 11 depicts the thickness of different items used in testing the accuracy of case 5.

TABLE III
PREDICTED VALUES OF WORKPIECE THICKNESS AFTER DEEP DRAWING FOR DIFFERENT DIE AND PUNCH RADII, AND DRAWING RATIO EQUAL TO TWO

punch and die radii	Friction coefficient= 0.1		Friction coefficient= 0.01	
	Region A	Region B	Region A	Region B
Rp=Rd=4	0.8145	0.7801	0.8164	0.7811
Rp=Rd=6	0.8619	0.8293	0.8628	0.8295
Rp=Rd=8	0.88	0.8508	0.8804	0.8509
Rp=Rd=10	0.8874	0.8616	0.8877	0.8616
Rp=Rd=12	0.8906	0.8678	0.8908	0.8679
Rp=Rd=14	0.8921	0.872	0.8922	0.8721

TABLE IV
PREDICTED VALUES OF WORKPIECE THICKNESS AFTER DEEP DRAWING FOR DIFFERENT DIE AND PUNCH RADII, AND DRAWING RATIO EQUAL TO TWO

Dr	R_p	R_d	μ	T_A	T_B	T_{cf}
1.6	14	14	0.01	0.8928	0.8731	0.8770
1.7	14	14	0.01	0.8927	0.8729	0.8768
1.8	14	14	0.01	0.8926	0.8726	0.8766
1.9	14	14	0.01	0.8925	0.8723	0.8764
2.0	14	14	0.01	0.8924	0.8721	0.8761
2.1	14	14	0.01	0.8923	0.8718	0.8759
2.2	14	14	0.01	0.8921	0.8715	0.8756
2.3	14	14	0.01	0.8920	0.8712	0.8754
2.4	14	14	0.01	0.8919	0.8709	0.8751

In Fig. 11, N.N.B stands for neural network output corresponding to the thickness at region "B" while, E.R.A stands for the experimental records at point "A". In most of the similar paper, the output dimensions are normalized but here since the maximum amount of the cost function is 1, such a procedure is unnecessary.

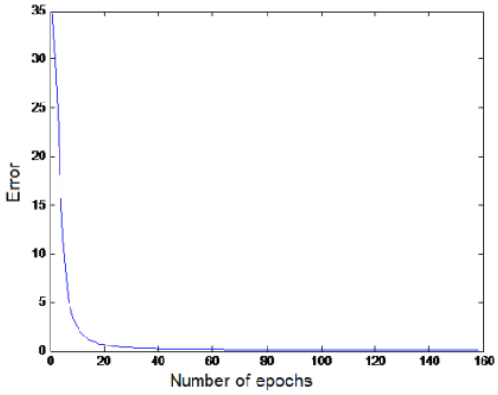

Fig. 9 Training errors versus the number of errors in case 2

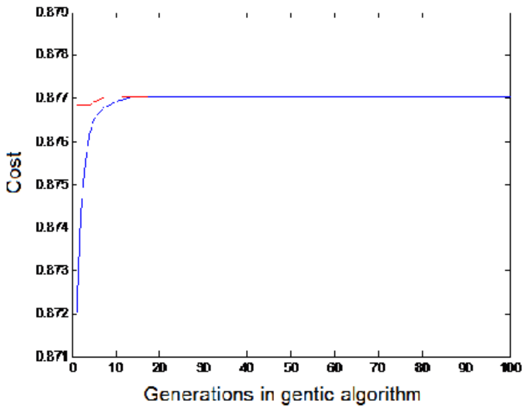

Fig. 10 Convergence of the mean cost to the maximum cost

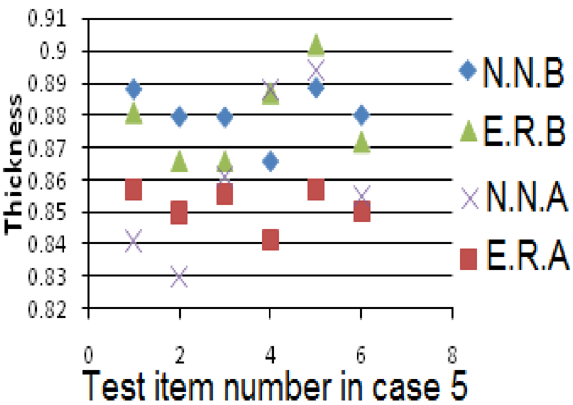

Fig. 11 Results obtained in different test items in case 5 versus the thickness at different regions of the product

V. Conclusion and Summery

This paper illustrates a neural network approach for modeling and predicting the cylindrical products deep drawing parameter. These parameters included die and punch radii, friction coefficient and drawing ratios which are qualified by the thickness values of the output, in search of the most uniform and closer to the initial thickness.In this paper a good model to realize the parameter space was obtained.

Meanwhile, the optimum values for different punch and die radii were found. Consecutively, it was established that punch and die radii of 14mm produce the best quality products in this experimental data. Therefore, the rapidity and the efficiency of determining deep drawing designing parameter for cylindrical piece can successful improved. It also to note that the values obtained via neural network has certain errors. This error depends on the density of the relative distribution of the training data. Hence, it may found that certain values do not produce expected results due to the presence of low density data around the required region.

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