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Modelling On Wrinkling Behvaviour During Deep Drawing Of Different Grades Of Stainless Steel Sheets Using Artfifical Neural Network

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ABSTRACT:

Artificial neural networks are extremely useful in modelling of complex non-linear systems which are difficult to model using simple mathematical closed form equation. The wrinkling behaviour of a deep drawn sheet metal is an example of such a non-linear system, predicting the pattern manually is difficult. This project aims to employ artificial neural network to learn the pattern of wrinkling along different orientations and devise an algorithm based on the observation that can provide the results for new set of inputs. The validation of the artificial neural network is carried out on experimented deep drawing process on stainless steel of various grades. The construction of the artificial neural network is based on experimented deep drawing process on stainless steel of various grades such as **SS302, SS316, SS410, and SS430**. It is found that the obtained values using ANN and the experimental values are in good agreement with each other.

KEY WORDS: Artificial Neural Network, Wrinkling, Deep drawing, Stainless Steel

INTRODUCTION:

Deep drawing is a widely used forming process extensively in making beverage cans, kitchen sinks, bearings, sealing technologies, sensors and other appliance controls.Wrinkling is one of the main failure modes in deep drawing of sheet metals. In recent years, due to great usage of thin high strength sheet metals, this failure mode is more prevalent in stamping of various automotive parts. So, emphasis has been given on prediction, evaluation and prevention of wrinkling especially in final sheet metal parts [Ref. 3]. Wrinkling is a kind of local buckling of sheet metal which is formed by excessive compressive stress [Ref. 5].In other words, it is observed from instability under compressive stress.The phenomena of instability appearing at the forming of metal sheets lead to a decrease in the processing accuracy through the modification of the geometrical shape and the faulting of the surfaces. Wrinkling may be defined as the formation of waves on the surface to minimise the compression stresses [Ref. 5].Wrinkling defect generally occurs at the flange of the deep drawn cup. Wrinkling is a stochastic process and hence cannot be predicted easily with conventional mathematical equations. Artificial Neural Network (ANN)is one of the precise computing modelling techniques based on their statistical approach to model complex non-linear functions. S.Raghuraman, et.al studied the wrinkling behaviour of deep drawn stainless steel of different grades through experimentation [Ref 1] and in this project a neural network architecture is built based on the experimental observations for each grade.

NOMENCLATURE

D-	Average diameter of the cup in mm
Ravg-	Average Normal Anisotropy
Eavg-	Average Young's modulus of Elasticity in N/mm^2
%Df-	Percentage Draw Fraction
Tf0^0-	Thickness at 0 degrees in mm
Tf45^0-	Thickness at 45 degrees in mm
Tf90^0-	Thickness at 90 degrees in mm
1/σ(dσ/dε)-	Average normalized hardening rate
dσ/dε-	Average tangent modulus in N/mm^2
εy-	Hoop Strain
εr-	Radial Strain

LITERATURE REVIEW OF EXPERIMENT:

In the experiment performed by S.Raghuraman, et.alin "Wrinkling Behavior of SS 302, SS316, SS410, SS430 grade stainless steel of various diameters during deep drawing process ", conical die, hemispherical and flat bottom punch were employed to study the wrinkling pattern of stainless steel SS302, SS316, SS410, SS430. Different diameters 115, 120, 125, 130 in mm of blanks were drawn. It was well established that use of conical die eliminates the need of blank holder or clamping which also enhances the limiting drawing ratio compared to conventional drawing operation. However this increases the tendency of thin blanks to fail by wrinkling. It was proved that onset of wrinkling takes place when the plastic strain increment reaches a critical value. This experiment was aimed at predicting the onset of wrinkling in the partially drawn cups. Blanks of different diameters with electrochemically printed grid circles of 2.5mm diameter were cut and drawn through conical die of flat-bottom and hemispherical ended punches of 49mm diameter. The drawing is continued at dry lubrication condition until first stage of wrinkling appears on the flange surface of sheet metal. The top and bottom diameters of each partially drawn cup are measured and percentage draw fraction was calculated using the expression

$$Percentage\ Draw\ Fraction(\%DF) = \left(\frac{D_b - D_{avg}}{D_b - 55}\right) * 100$$

Where
D_b- Blank diameter;
D_{avg}- Average diameter at top and bottom of cup

Radial strain and circumferential strain were also calculated at various stages along 0^0, 45^0 and 90^0 to the rolling direction of the sheet.

Where
Radial strain = $\ln(d_{major}/Do)$
Circumferential strain = $\ln(Do/d_{minor})$

From the experiment Average diameter, Percentage draw fraction, Thickness along 0^0, 45^0 and 90^0 Radial strain, hoop strain was obtained.

Table 1 Chemical composition of Stainless Steel

Element	SS302	SS316	SS410	SS430
C	0.15	0.08	0.15	0.12
Mn	2	2	1	1
Si	1	1	1	1
Cr	17-19	16-18	11.5-13	16-18
P	0.045	0.045	0.04	0.04
S	0.03	0.03	0.03	0.03
Mo	0	2.0-3.0	0	0
Ni	8.0-10.0	10.0-14.0	0	0

Rest: Iron

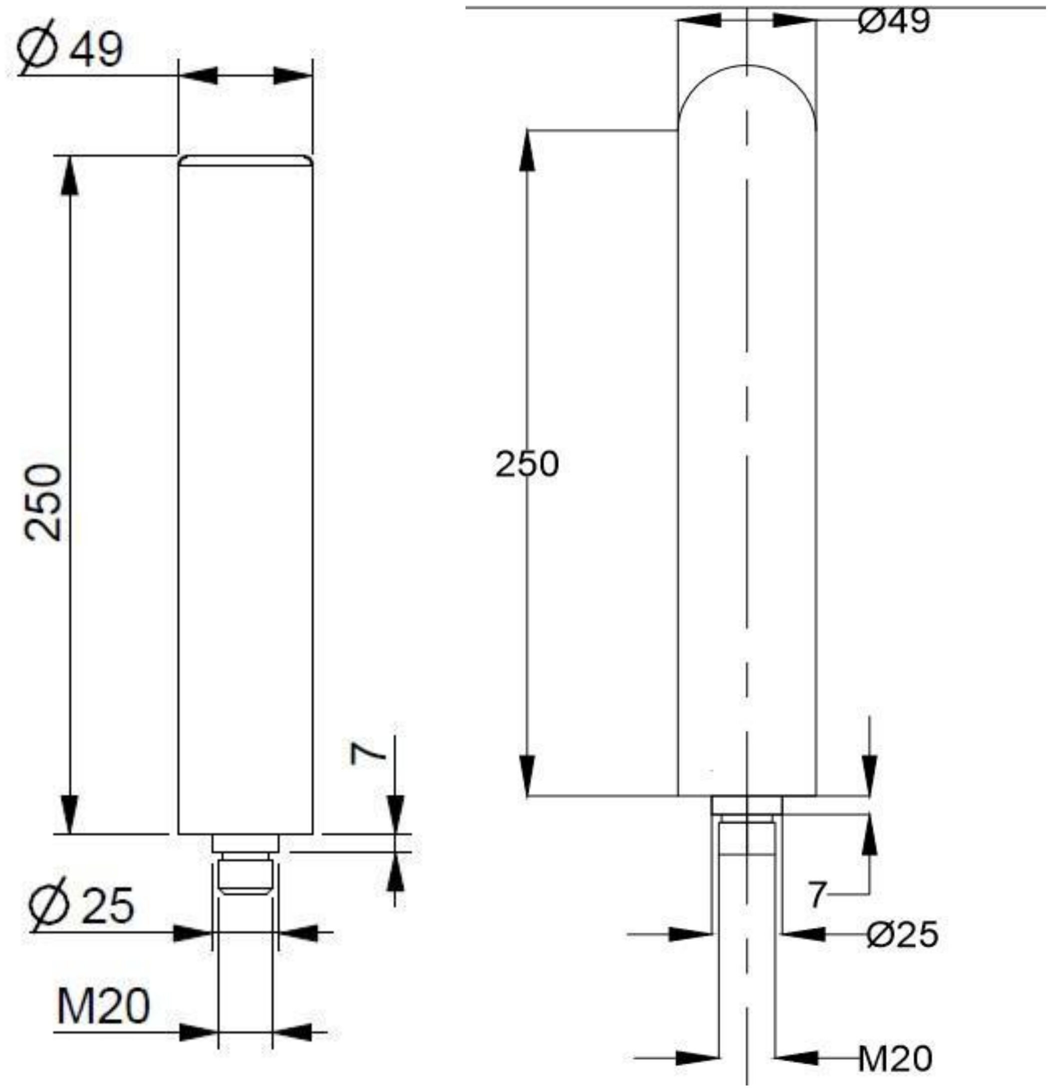

Figure 1: Flat bottom and Hemispherical bottomed punch

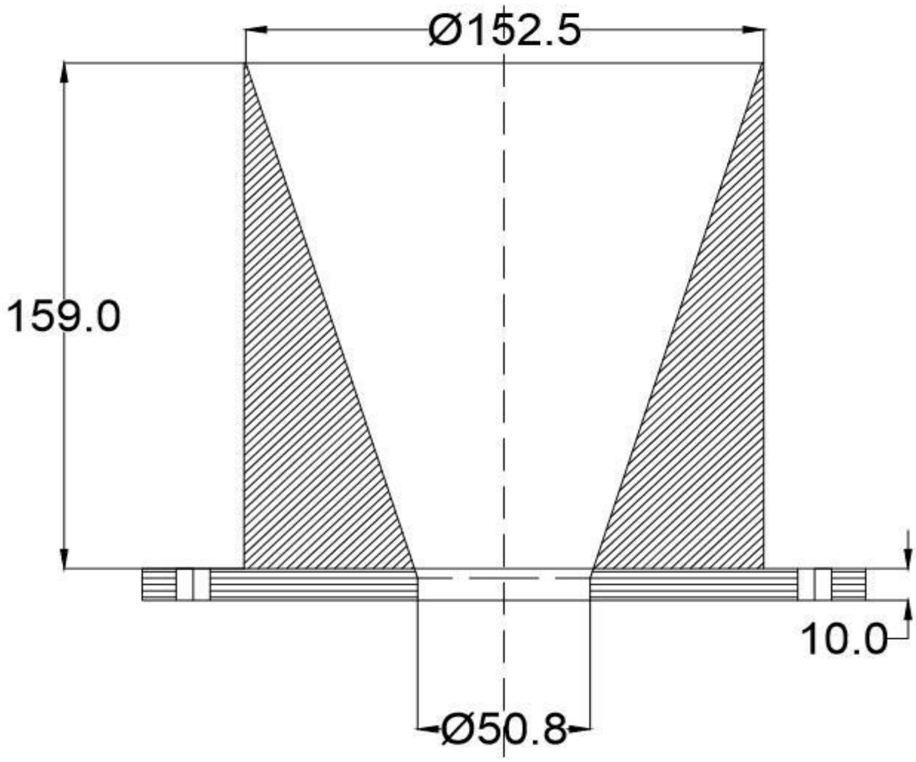

Figure 2: Conical Die

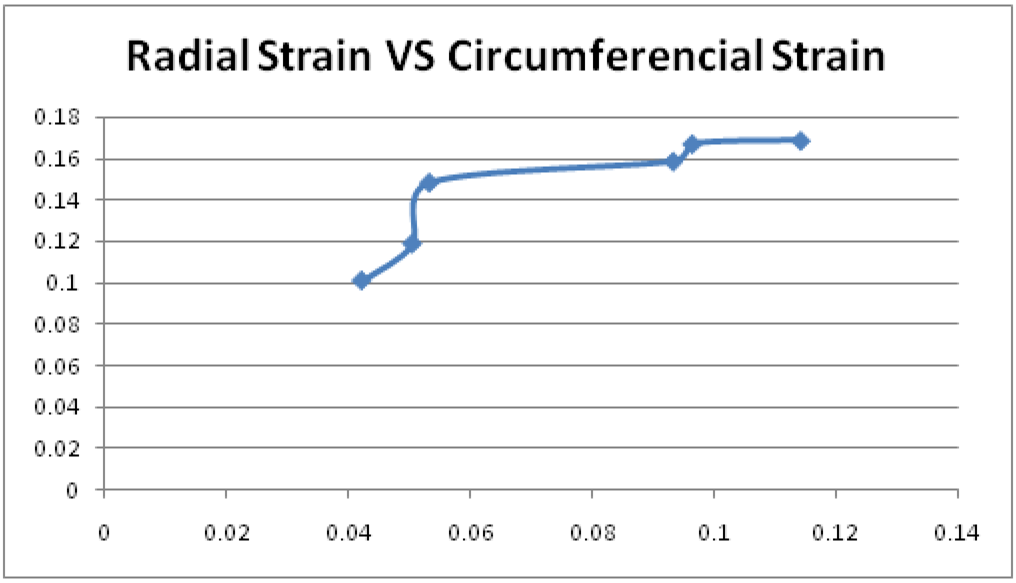

Figure 3: Wrinkling Behaviour of Stainless Steel SS410

Artificial Neural Network

Artificial neurons simulate the basic functions of biological neurons: input, processing, and output by passing information through interconnected neurons. Each input is given a weight to signify how important it is compared to other input. Neural networks are developed with the prime objective of modelling information processing emulating biological systems which we describe the basis of neural network models, it will be useful to think of the network as dynamic system as all the real time process parameters has its irregularities which exists due to many unknown natural phenomena,

EXPERIMENTAL PROCEDURES

Experimental Data Collection

Average anisotropy $\mathbf{R_{avg}}$= 0.25 (R_0+2R_{45}+R_{90})

R_0, R_{45}, R_{90} is calculated asε_w/ ε_t along 0^0,45^0 and 90^0.

Where

ε_w is width strain and ε_t is thickness strain

$\mathbf{E_{avg}}$ Average Young's Modulus is calculated as ratio of engineering stress to engineering strain in N/mm^2

1/σ (dσ/dε) Average normalized hardening rate is calculated as x_{avg}=0.25(x_0+2x_{45}+x_{90})

dσ/dε Averagetangent modulus (Slope of true stress- true strain data) is calculated as x_{avg}=0.25(x_0+2x_{45}+x_{90}) in N/mm^2[Ref. 2]

Table 2.1 Mechanical Properties of Stainless Steel SS302

S. No	Average anisotropy	Average Young's Modulus	Average tangent modulus	Average normalized hardening rate
1	0.363	112.9	387.32	1.25
2	0.285	141.54	570.15	1.104
3	0.2485	154.62	683.59	1.04
4	0.234	206.515	951.89	1.014
5	0.214	234.67	1145.69	0.976
6	0.2086	346.568	1720.59	0.964
7	0.20335	372.056	1881.63	0.954

Table 2.2 Mechanical Properties of Stainless Steel SS316

S. No	Average anisotropy	Average Young's Modulus	Average tangent modulus	Average normalized hardening rate
1	0.584	171.83	470.63	1.517
2	0.445	211.81	678.54	1.177
3	0.281	155.06	683.16	1.039
4	0.275	215.126	965.32	1.028
5	0.2407	229.95	1134.52	0.967

Table 2.3 Mechanical Properties of SS410

S. No	Average anisotropy	Average Young's Modulus	Average tangent modulus	Average normalized hardening rate
1	0.435	132.158	419.73	1.353
2	0.4177	210.436	678.06	1.313
3	0.3655	229.88	802.95	1.222
4	0.2697	229.36	989.06	1.053
5	0.2554	267.25	1203.08	1.025
6	0.1915	296.98	1624.88	0.911

Table 2.4 Mechanical Properties of SS430

S. No	Average anisotropy	Average Young's Modulus	Average tangent modulus	Average normalized hardening rate
1	0.527	163.008	443.09	1.428
2	0.4547	220.08	691.58	1.34
3	0.348	203.03	763.56	1.62
4	0.265	210.704	956.06	1.018
5	0.2325	224.3	1125.06	0.958
6	0.124	250.17	1495.56	0.838

BACKPROPOGATION NETWORK

The major benefit of using neural network is to train the network for predicting its process dynamics accurately by designing a model based on its given input and output. This technique is used in process where complete physical mechanism is complex to understand and comprehend in real time process like sheet metal forming. Neural network is a logical structure with multi-processing elements called neurons, which are interconnected through hidden layers each consisting of a particular weights. The interconnection is adjusted during the learning phase. Levenberg-Marquardt algorithm (Trainlm) is chosen among several available algorithms utilizing its fastest converging nature. The Levenberg-Marquardt algorithm is a very popular curve fitting algorithm used in many software applications for solving generic curve fitting problems. In many cases, trainlm is able to obtain lower mean square errors than any of the other algorithms tested. This BP network is a layer of the network architecture including the input layer, the hidden layer(s) and the output layer. In the network, the input layer receives information from external source and passes this information to the network for processing [Ref. 2]. The hidden layer receives information from the input layer, and does all processing. The output layer receives processed information from the network, and sends the results to an external receptor. The backpropogation algorithm is elucidated with the help of flow chart.

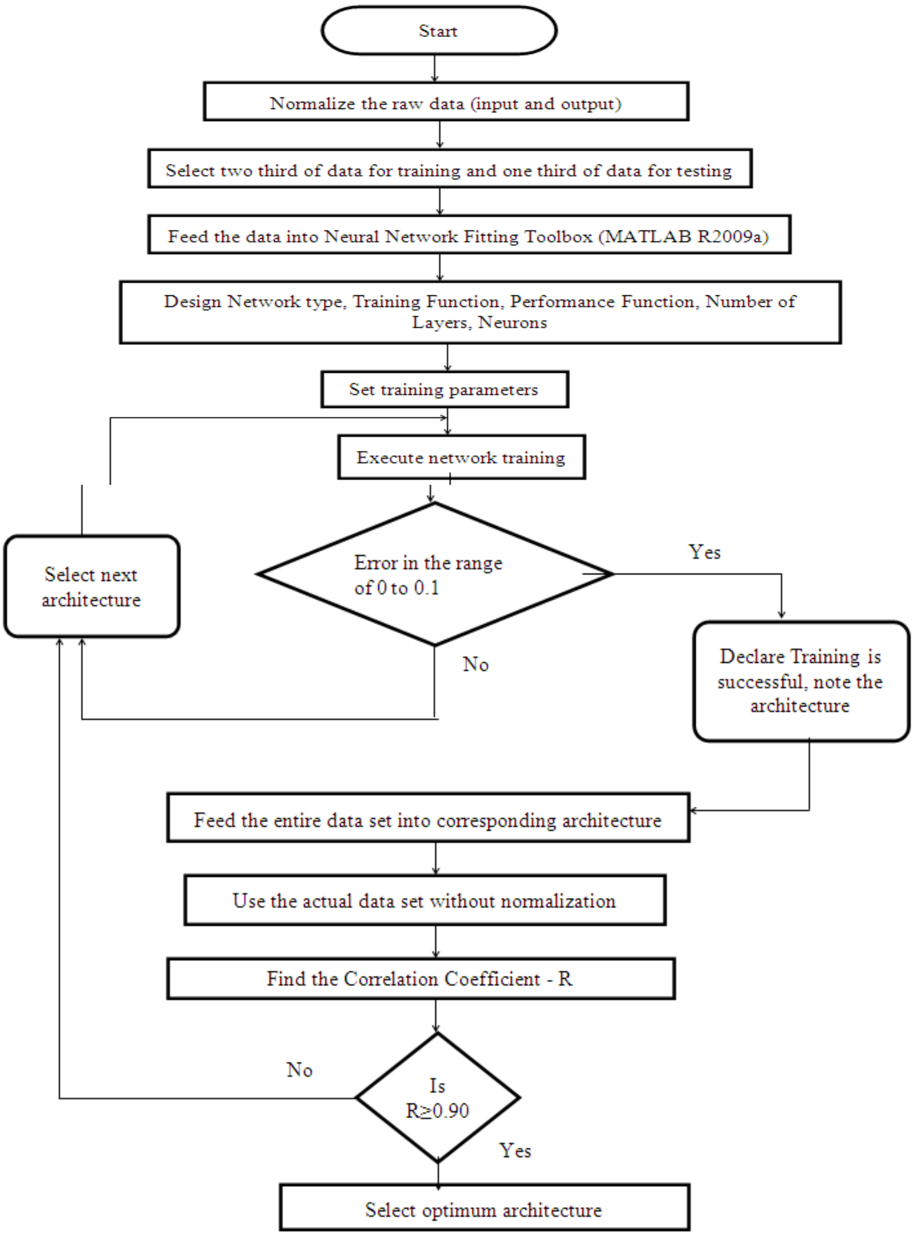

Fig. 4Flowchart

MODEL DESCRIPTION

In the formulation of a neural network model, several parameters regarding number of neurons in the input layer, number of hidden layers, number of neuron(s) in the hidden layers, and number of neurons in the output layer and optimum architectures have to be decided. Based on the experimental investigation by S.Raghuraman et. al in [Ref. 1], sheets are wrinkled or wrinkle free after 5-7 drawn which depend on mechanical properties and mechanical treatments at any different orientations (0^0,45^0 and 90^0). The results had shown that the values of $d\varepsilon_r/d\varepsilon_y$ obtained in SS302 and SS316 grades are greater than that of obtained in SS410 and SS430 grades. Also they have measured instantaneous diameter of cup and thickness of cup at different orientations in order to observe wrinkle or wrinkle free. Hence, mechanical properties of the sheets such as average normal anisotropy (R_{avg}), average Young's modulus of elasticity (Eavg), average tangent modulus ($d\sigma/d\varepsilon$), Average normalized hardening rate($1/\sigma(d\sigma/d\varepsilon)$), Percentage draw Fraction(%Df) are given as input parameters to ANN model. The output parameters are instantaneous diameter of the cup (D) after drawn, thickness of cup at different orientation ($Tf0^0$, $Tf45^0$, $Tf90^0$), radial strain (εr), and hoop strain (εy).

In the experiment performed by Sivasankaran S et. al [Ref. 2] additional input parameters such as soaking time, annealing temperature, number of times drawn till wrinkling,average yield stress and average ultimate stress, average strain hardening index, average strength coefficient where included. In this experiment for modelling in neural network, these parameters were assumed to be constant. The schematic representation of input and output parameters involved in the neural network model is shown in Figure 5. [Ref. 4]

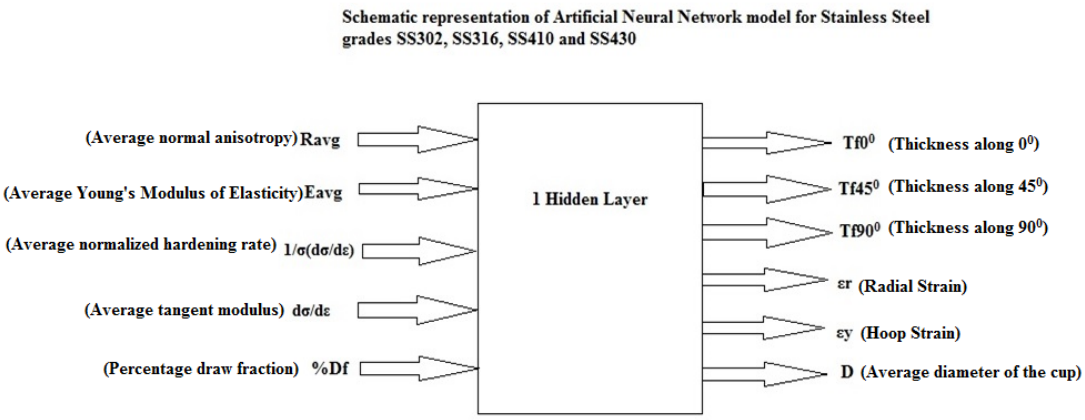

Fig 5: Schematic representation ANN model with input/ output parameters

Normalisation of Data

Higher magnitude input variables may tend to suppress the influence of smaller magnitude ones. To eliminate this problem, the neural network has been trained with the normalized input data [Ref. 2],directing the network to learn weights associated with the connections emanating from these inputs. The raw data are scaled in the range -1 to +1 for use by neural networks to minimize the effects of magnitudes between inputs and also to aid the Backpropogation learning algorithm. The normalized values (x_n) for each raw input/ output dataset (d_i) were calculated as:

$$x_n = (2 * \frac{d_i - d_{min}}{d_{max} - d_{min}}) - 1$$

Where d_{max} and d_{min} are the maximum and minimum values of the raw data.

Table 3.1 Normalized values for execution for grade SS302

S. No	Diameter of the cup	Thickness along 0^0	Thickness along 45^0	Thickness along 90^0	Radial Strain	Circumferential strain
1	1	-1	-1	-1	-1	-1
2	0.948912	-0.75	-0.11111	0.2	-0.78705	-0.86995
3	0.772942	0.25	0.333333	0.2	-0.73525	-0.62007
4	0.445601	0.375	0.444444	0.7	-0.97122	-0.5569
5	0.010407	0.875	0.777778	0.8	-0.42158	-0.06177
6	-0.61211	0.875	0.888889	1	0.951079	0.581979
7	-1	1	1	1	1	1

Table 3.2 Normalized values for execution for grade SS316

S. No	Diameter of the cup	Thickness along 0^0	Thickness along 45^0	Thickness along 90^0	Radial Strain	Circumferential strain
1	1	-1	-1	-1	-1	-1
2	0.871404	-0.36	-0.28571	-0.35714	-0.41803	-0.93103
3	0.269036	0.84	0.642857	0.428571	0.434426	-0.40948
4	-0.35364	1	0.642857	0.5	0.860656	0.536638
5	-1	1	1	1	1	1

Table 3.3 Normalized values for execution for grade SS410

S. No	Diameter of the cup	Thickness along 0^0	Thickness along 45^0	Thickness along 90^0	Radial Strain	Circumferential strain
1	1	-1	-1	-1	-1	-1
2	0.873057	-0.85714	-0.92	-0.90909	-0.7754	-0.71183
3	0.536269	-0.71429	-0.6	-0.45455	-0.06952	-0.1957
4	0.11658	0.285714	-0.04	0.272727	0.914439	0.169892
5	-0.51295	0.571429	0.04	0.363636	0.975045	0.905376
6	-1	1	1	1	1	1

Table 3.4 Normalized values for execution for grade SS430

S. No	Diameter of the cup	Thickness along 0^0	Thickness along 45^0	Thickness along 90^0	Radial Strain	Circumferential strain
1	1	-1	-1	-1	-1	-1
2	0.919954	-0.69697	-0.5	-0.62162	-0.47137	-0.76944
3	0.647059	-0.21212	-0.0625	-0.24324	0.400881	-0.69167
4	0.356401	-0.0303	0.5625	0.351351	0.703377	0.419444
5	-0.07728	0.575758	0.625	0.459459	0.95301	0.505556
6	-1	1	1	1	1	1

Neural Network Architecture and Testing

The formulation capability of the neural network necessarily depends on

1) Choice of appropriate input/output parameters of the system
2) Nature of the data set and
3) The format of feeding the data set into the network

The five input parameters used here are R_{avg},E_{avg},$1/\sigma(d\sigma/d\varepsilon)$, $d\sigma/d\varepsilon$, % Draw Fraction while the output parameters are instantaneous diameters of the cup (D) after drawn, thickness of cup at different orientation($T0^0$, $T45^0$ and $T90^0$), radial strain(ε_r), hoop strain(ε_y) in the ANN model. Two third of data was used for training and one third for testing. Before training the network the input / output dataset were normalized within the range of -1 to +1. The standard feedforward Backpropogation neural networks were designed with MATLAB R2009a neural network fitting toolbox. The network consists of three layers: the input, the hidden layer and the output layer. Now the designed network has five input neurons and six output neurons. A neuron in the network produces its input by processing the net input through an activation (transfer) function which is usually nonlinear [Ref. 2]. The chosen activation function is tan-sigmoid transfer function which is assigned in hidden layer(s) for processing the input as:

$$f(x) = \left(\frac{2}{1+e^{-x}}\right) - 1 \text{range } (-1,1)$$

Performance of the Network

The performance capability of each network is evaluated based on the correlation coefficient between the network predicted values and the experimental values using the dataset. It is observed that the increase in the number of neurons in the hidden layer had significant improvement on the performance of the networks. The architecture designed from the experiment has 5 input neurons and 6 output neurons for all the four grades. From the observations, it is identified that the network with one hidden layer with 25 neurons is used to predict output on SS302 for achieving good correlation. For SS 316, it is identified that the network with 20 neurons in one hidden layer produced best performance at 4 epochs. For SS410 and SS430 it is identified that 30 neurons and 15 neurons in one hidden layer at 4 and 5 epochs respectively predicted the output accurately. The results have shown 90% of the entire data set correlate and rest 10% are acceptable results. This demonstrated that the model has high accuracy for predicting the process parameters and found to have optimum neural network architecture. Performance features between the network predicted values and the experimental values using the dataset for different network and training parameters of Stainless Steel grade sheets of SS 302, SS 316, SS 410 and SS430 are:

Table 3.5: Network Training and Testing Performance

Stainless Steel Grade	Number of Hidden Layers	Hidden Neuron s	Number of epochs	Correlation Coefficient - R	Training network Mean Square Error- MSE
SS302	1	25	5	0.90273	4.87E-10
SS316	1	20	4	0.98484	3.31E-29
SS410	1	30	4	0.93568	6.05E-02
SS430	1	15	5	0.96821	2.03E-21

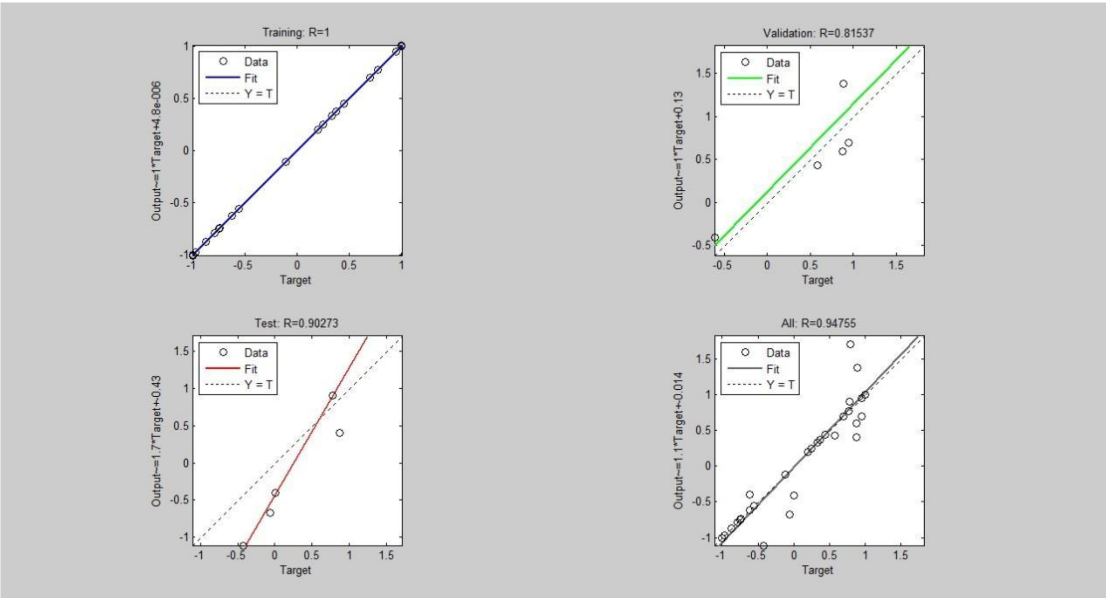

Fig. 6 Network Performance for Stainless Steel grade SS302

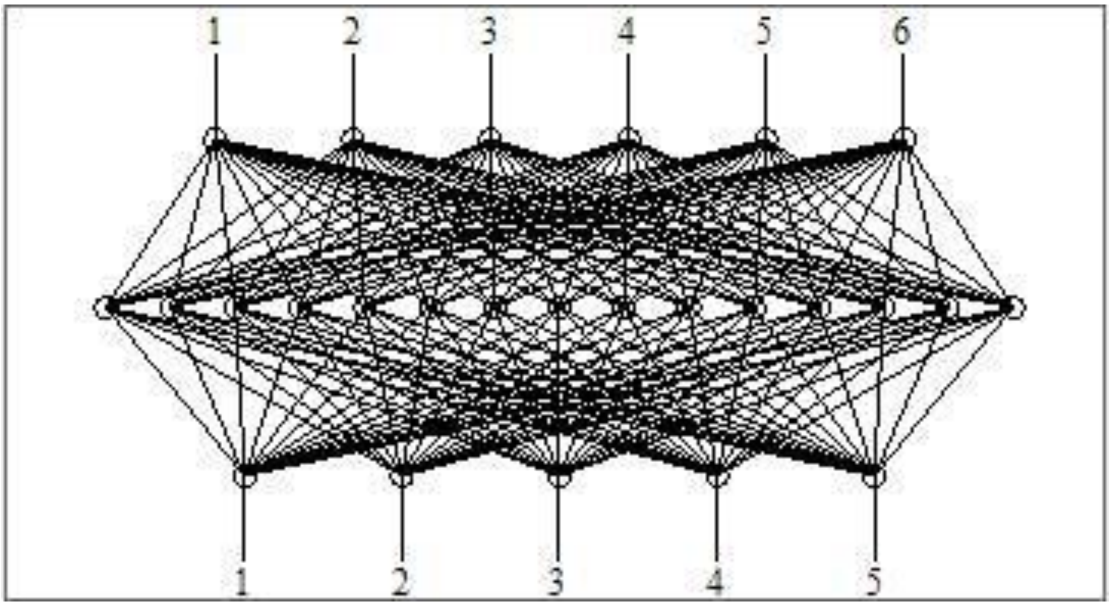

Fig. 7 Neural Network Architecture for Stainless Steel grade SS430

The above figure represents optimum architecture for stainless steel grade SS430 containing 5 input neurons, 6 output neurons and 15 hidden neurons.

RESULTS AND DISCUSSION

The wrinkling behaviour of various grades of stainless steel during deep drawing through a conical die was experimentally analysed using hemispherical and flat bottomed punches. The results have shown that wrinkling takes place when $d\varepsilon_r/d\varepsilon_y$ reaches a critical value. It is also observed the percentage change in thickness at the onset of wrinkling is different for different grades because of the change in chemical composition and crystal structure of the various grades of stainless steel as austenitic and ferritic grades. It was concluded that SS302 and SS316 grade stainless steels show better resistance to wrinkling compared to SS410 and SS430 grades. The prediction of wrinkling can be identified by a sudden change in the slope of $d\varepsilon_r/d\varepsilon_y$ curve. Based on optimised network parameters the ANN model has been developed to predict the deep drawn process parameters based on five input parameters and from the results a close agreement has been observed between predicted and experimental values for Stainless Steel SS302, SS316, SS410 and SS430 respectively.

CONCLUSIONS

1. The neural network with one hidden layer having 25 neurons, 20 neurons, 30 neurons, 15 neurons in the case of stainless steel sheets of grade SS302, SS316, SS410 and SS430 respectively, trained with Levenberg –Marquardt algorithm were found to be the optimum network model developed in this study.
2. A fine correlation coefficient between the predicted values and experimental values indicate the excellent accuracy of the neural network model.
3. The devised ANN modelcan be used to predict and study the wrinkling behaviour of stainless steel sheets of grades SS302, SS316, SS410 and SS430.

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