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Modelling the Forming Limit Diagram for Aluminium Alloy Sheets using ANN and ANFIS

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Abstract: In this work, it is planned to model the formability of various grades of aluminium sheet metals using ANN and optimization is done using ANFIS. Formability test is performed on aluminium sheet metals Al5052, Al6061 and Al8011 with thickness 0.8 mm, 1 mm and 1.2 mm. Forming limit diagrams are constructed using strain values obtained from the test. Tensile tests are conducted on the sheet samples and the important mechanical properties which affect the formability are measured and calculated. Using the forming limit strains at different states namely tension-tension, plane strain and tension-compression, modeling is done using ANN and optimization is performed using ANFIS. The architecture 7–14-14–9 is found to be the optimum and it is used in ANN modeling. Using the strain values predicted by ANN, FLD curves are constructed. The predicted strain values are compared with experimental strain values. Further optimized strain values are predicted using ANFIS. This work reveals that experimental FLD, ANN predicted FLD and ANFIS predicted FLD are in good agreement.

Keywords: Forming Limit Diagram; Artificial Neural Network; Adaptive Neuro-Fuzzy Inference System

1 Introduction

Sheet metal industries look for materials formed without necking, fracture and wrinkling. Many research works have been carried out to make use of various grades of sheet metals which results in the usage of aluminium sheet metals in military, marine, aeronautical and processing industries, which is mainly due to the excellent properties of aluminium alloys. The aluminium-magnesium or Al5052 sheet metals are being used for vehicle structures as they have attractive combination of strength, formability, weldability and corrosion resistance. The aluminium-magnesium silicon or Al6061 sheet metals are used for architectural, aircrafts, military bridges, boiler making, motor boats and extruded sections as they have moderate strength, weldability, formability and good corrosion resistance. The aluminium-lithium or Al8011 sheet metals are being used for aerospace applications as they have low density, high stiffness and moderate formability.

The important tool to identify the strain limit up to which sheet metals can be formed is the Forming Limit Diagram which is emphasized by [4] and [5]. A model has been proposed to predict the forming limits of sheet metals [6]. A model is proposed using artificial neural network by [1] to predict the forming limit of perforated commercial pure aluminium sheet metals. In their work, experiments were conducted by varying the width of the blanks and size of perforation. A finite element based model is developed for predicting the forming limit diagram of aluminium 5xxx series sheet metals [10]. The tensile properties of IF steel sheets are correlated with the formability of sheet metals [11].

An ANN is a set of processing elements or neurons and connections with adjustable weights. ANN can be used to create a model easily based on the given input and output. A design has been developed with three layer back propagation network and it is described with the help of flow diagram [2].

In this work, it is planned to find the optimum architecture for ANN modeling based on the correlation

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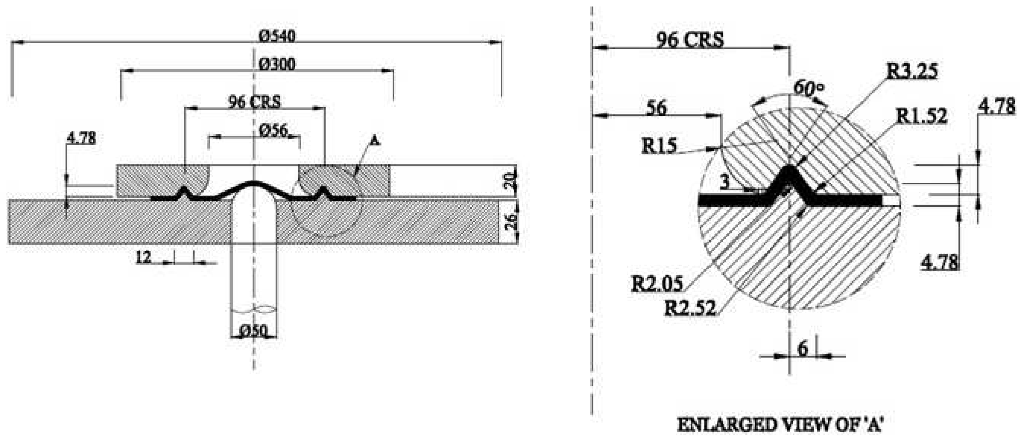

Fig. 1: A typical die punch setup.

coefficient. Using the optimum ANN architecture, the forming limit strains at different strain states are to be predicted. Optimization is to be done using ANFIS and the optimum limiting strains for all the nine sheet metals are to be predicted.

2 Experimental procedure

2.1 Material

The material chosen for the study are aluminium sheet metals Al5052, Al6061 and Al8011 with thickness 0.8 mm, 1 mm and 1.2 mm.

2.2 Tensile Test

The mechanical properties of materials play a vital role in the forming behaviour. Specimens are prepared from all the nine sheet metals as per the ASTM Standards and are cut along 0°, 45° and 90° to the rolling direction. Tensile test is performed on these specimens in a tensile testing machine. Using the true stress and true strain values obtained from the tensile test, strain hardening exponent (n-value) and strength coefficient (k-value) for all the sheet metals are calculated using the expression $\sigma = k\varepsilon^n$, where ε is the true strain and σ is the true stress as explained elsewhere [9].

The other mechanical properties such as strain rate sensitivity, normal anisotropy, ductility, yield strength and ultimate tensile strength (UTS) are found out using the procedure as explained elsewhere [8]. The tensile test values for all the sheet samples are shown in Table 1.

2.3 Forming Limit Diagram

Forming limit test is an important tool to identify the strain up to which a sheet metal can be formed without necking, wrinkling and fracture as explained elsewhere [4]. Aluminium sheet metals taken for study are to be prepared to do the formability test. Sheet specimen were sheared in a shearing machine to have dimensions of 110×110 mm, 110×100 mm, 110×90 mm, 110×80 mm, 110×70 mm, 110×60 mm, 110×50 mm, 110×40 mm, 110×30 mm and 110×20 mm. The variation in width results in different strain states of tension-tension, plane strain and tension-compression regions as explained elsewhere [7]. The formability test is performed on a double action hydraulic press of 30 ton capacity. All the specimen are laser marked with standard circular grid pattern of 2 mm on one side of the specimen. The specimen is placed in between the die and punch as shown in Fig. 1. The test is continued till the sheet sample is subjected to fracture. The circles are converted to ellipses. The major diameter and minor diameter of the ellipse is measured. Using these values, the major strain and minor strain along the necked region, safer region and fractured region are calculated using the formulae elsewhere [8].

$$\text{Major strain} = \ln\left[\frac{\text{major diameter of ellipse}}{\text{original diameter}}\right] \tag{1}$$

$$\text{Minor strain} = \ln\left[\frac{\text{minor diameter of ellipse}}{\text{original diameter}}\right]. \tag{2}$$

Forming limit diagram is constructed by joining the strain path along necked region, called forming limit curve. The forming limit diagrams for all the sheet metals are constructed. The limiting strains for all the nine sheet metals are shown in Table 2.

3 Modelling the formability by ANN

The Artificial Neural Network (ANN) has been processed by generalization of the mathematical model of the human brain's ability and neural biology [14, 15]. An ANN is a

Table 1: Tensile test values for various grades of aluminium sheet metals.

Sheet Metal thickness	Orientation relative to rolling direction	UTS (MPa)	Yield strength (MPa)	Elongation at break at non-proportional elongation	Strain hardening exponent (*n*-value)	Strength co-efficient (MPa)	Normal anisotropy (r)	Strain rate sensitivity (m)
Al5052 0.8 mm	0°	203	181.06	0.0553	0.10168	195.63907	0.1933	0.487
	45°	195	173.71	0.05998	0.15049	253.306	0.111	0.391
	90°	185	163.24	0.0683	0.139	290.618	0.1833	0.2718
Al5052 1.0 mm	0°	144	125.24	0.07984	0.3174	406.5362	0.1078	0.64
	45°	162	143.01	0.07284	0.01349	406.5362	0.1065	0.5929
	90°	336	302.13	0.06431	0.01349	306.0586	0.1555	0.4278
Al5052 1.2 mm	0°	145	121.1	0.0576	0.07351	194.09041	0.1403	0.305
	45°	135	119.81	0.0505	0.17315	264.6574	0.1825	0.29
	90°	136	117.09	0.0608	0.07726	183.347	0.2077	0.21
Al6061 0.8 mm	0°	535	438.37	0.049326	0.09256	750.001	0.1376	0.358
	45°	557	442.45	0.052824	0.15433	961.29455	0.151‘	0.2941
	90°	555	399.08	0.0599	0.04767	670.43712	0.294	0.22
Al6061 1.0 mm	0°	476	350.24	0.05606	0.1221	736.2963	0.3572	0.656
	45°	452	185.79	0.05042	0.10273	654.014	0.1235	0.273
	90°	482	281.11	0.0582772	0.16709	854.286	0.161	0.261
Al6061 1.2 mm	0°	444	282.42	0.06337	0.17065	789.8222	0.1635	0.45
	45°	439	296.89	0.0721	0.1692	776.4801	0.2132	0.33
	90°	246	168.84	0.0822	0.0796	335.08006	0.5252	0.254
Al8011 0.8 mm	0°	238	202.2	243650797.3	0.10497	363.42977	0.1117	0.497
	45°	249	232.55	253957998.7	0.06609	328.34062	0.4179	0.356
	90°	256	235.52	261673460.2	0.08972	372.1522	0.1355	0.294
Al8011 1.0 mm	0°	194	177.37	197902573	0.09749	291.23085	0.2629	0.671
	45°	208	184.38	211419563.3	0.11468	336.70546	0.3905	0.44
	90°	200	186.51	203641947.9	0.0818	284.25412	0.45	0.36
Al8011 1.2 mm	0°	191	168.73	195630542.2	0.08508	271.48172	0.1052	0.6471
	45°	185	173.62	187653430.3	0.08444	265.79323	0.1004	0.482
	90°	191	157.83	195168427	0.07219	258.41906	0.2588	0.35

Table 2: Limiting strain evaluated from experiment at different strain state.

Sheet Metal Thickness	Experimental Limiting Stain	Strain State				
		F_{TC}	F_{TC1}	F_P	F_{TT1}	F_{TT}
Al5052 0.8 mm	Minor Strain	−0.067	−0.0304	0	0.131	0.223
	Major Strain	0.148	0.1527	0.135	0.2029	0.227
Al5052 1 mm	Minor Strain	−0.05	−0.025	0	0.0907	0.161
	Major Strain	0.131	0.113	0.09	0.1441	0.166
Al5052 1.2 mm	Minor Strain	−0.025	−0.022	0	0.1171	0.231
	Major Strain	0.161	0.152	0.124	0.1988	0.243
Al6061 0.8 mm	Minor Strain	−0.025	−0.025	0	0.068	0.174
	Major Strain	0.135	0.1266	0.112	0.153	0.186
Al6061 1 mm	Minor Strain	−0.025	−0.02	0	0.081	0.135
	Major Strain	0.1354	0.1266	0.123	0.186	0.207
Al6061 1.2 mm	Minor Strain	−0.099	−0.046	0	0.025	0.169
	Major Strain	0.223	0.169	0.147	0.161	0.27
Al8011 0.8 mm	Minor Strain	−0.04	−0.0202	0	0.1088	0.161
	Major Strain	0.113	0.1	0.081	0.131	0.166
Al8011 1 mm	Minor Strain	−0.035	−0.0202	0	0.1133	0.194
	Major Strain	0.178	0.131	0.103	0.1655	0.199
Al8011 1.2 mm	Minor Strain	−0.051	−0.0036	0	0.0629	0.161
	Major Strain	0.1	0.104	0.081	0.131	0.166

F_{TT}, F_{TT1}—Forming limit strain at tension–tension region,
F_P—Forming limit strain at plane strain region,
F_{TC}, F_{TC1}—Forming limit strain at tension–compression region.

set of neurons and connections with adjustable weights. The biggest use of this neural network method is that a model can be created easily based on the given input and output [12, 13]. This approach is very much useful where complete understanding of the mechanism is difficult as in sheet metal forming process. In this work, two-third of the data is used for training and one-third of the data is used for testing. The neural network learns by using training data. The process is repeated until the network performs well on the training data.

3.1 Back Propagation (BP) Network

A model for FLD using ANN is developed by [1] where feed forward back propagation network design is used. There are many algorithms and architecture for developing a model using ANN. Most successful and powerful network is the feed forward back propagation network design. The network architecture consists of the input layer, hidden layers and the output layer. Each layer has several processing units called the neurons.

3.2 Model Description

In the process of creating a model, the mechanical properties which are responsible for the forming behavior of the sheet metals such as strain hardening index (n-value), normal anisotropy (r-value), strength coefficient (K), ductility (D), strain rate sensitivity (m-value), yield strength (Y), and ultimate tensile strength (UTS) are taken as input parameters. The limiting major strain and the limiting minor strain at different strain regions are taken as output parameters. The input and output dataset of the model is as shown in Fig. 2.

3.3 Neural network design

Initially it is essential to identify the optimum architecture which gives better performance for the output parameters. In this work feed forward back propagation network is designed with MATLAB 12.0 as explained elsewhere [1]. The network consists of three layers: the input layer, hidden layers and the output layer. The designed network has seven input neurons and nine output neurons. The performance of the network is evaluated by calculating the mean square error using the expression,

$$E_p = \sum_{p=1}^{p} \sum_{k=1}^{k} (d_{pk} - o_{pk})^2 \tag{3}$$

where d is the desired output, o is the calculated output, p is the total number of epochs and k is the number of neurons. To evaluate the predictability of the model, the error in the predicted output for each node is found by the following equation,

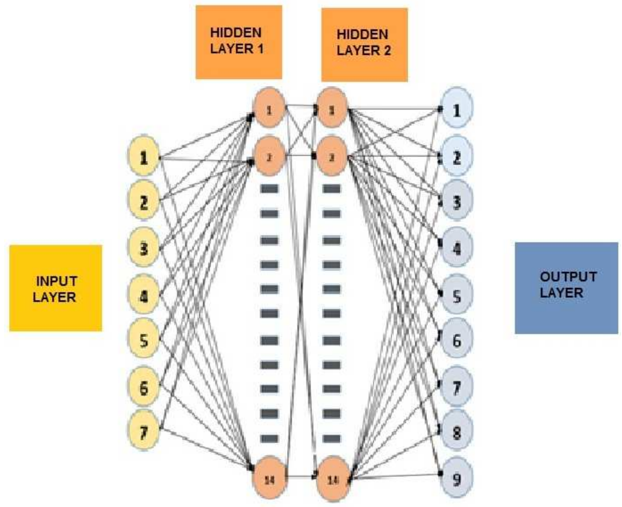

Fig. 2: Neural network model.

$$\%\text{Prediction error} = \frac{\text{Actual value} - \text{predicted value}}{\text{Actual value}} \times 100. \tag{4}$$

The architecture is changed by changing the hidden layer. The mean correlation (R) is noted down for each architecture. In the process of identifying the optimum architecture, 24 different networks with different hidden layers have been tested for various grades of sheet metals with different thickness and it is shown in Table 3 The identified optimum architecture is used to predict the limiting strain values at different strain states for all the nine sheet metals using Artificial Neural Network with Visual Gene Developer, a neural network toolbox and is as shown in the Table 4.

4 Optimization by ANFIS

The daptive Neuro-Fuzzy Inference System is used to identify the optimum limiting strains using the optimum values of the input parameters. This process is done using Neuro Fuzzy design of MATLAB 12.0. The tensile parameters for all the sheet metals are given as input and limiting strain at different strain state are given as output. In this work, out of different methods, sub clustering method is used to generate Fuzzy Information System. The input and output data are trained using feed forward back propagation design. The architecture 7–14-14–9 is used to predict the limiting strain at different strain state.

During the process, it is identified that there is a possibility to change the values of the seven input parameters from low to high, for which the output will be predicted. If the values of the input parameters are on the higher side, then the forming limiting strain increases.

Table 3: Mean Correlation between the experimental values and network predictions for different network of Al 5052 with thickness 0.8 mm.

Network Architecture	Data Set	Major true strain	Minor true strain	MSE	Mean Correlation	Mean Prediction Error
7–2-9	Test Data	0.22972	0.22345	1.3013E−04	0.85781	0.724788
7–4-9	Test Data	0.231	0.25064	1.8955 E−06	0.99305	7.00077
7–6-9	Test Data	0.223	0.22681	2.1671 E−06	0.99285	−0.04185
7–8-9	Test Data	0.22247	0.22896	4.3819 E−05	0.97971	0.312884
7–10-9	Test Data	0.2234	0.22838	9.6329 E−04	0.92616	0.393651
7–12-9	Test Data	0.22336	0.22519	7.3779 E−06	0.91821	−0.31796
7–14-9	Test Data	0.22296	0.2267	1.0057 E−07	0.9869	−0.07505
7–16-9	Test Data	0.224	0.22647	5.3051 E−05	0.92819	0.107475
7–18-9	Test Data	0.21926	0.22874	2.7131 E−05	0.97042	−0.45531
7–20-9	Test Data	0.22264	0.22111	1.0727 E−05	0.98989	−1.37807
7–22-9	Test Data	0.22309	0.22455	9.4114 E−06	0.99234	−0.51947
7–24-9	Test Data	0.21855	0.22389	1.6523 E−04	0.94025	−1.68278
7–2-2–9	Test Data	0.231	0.15665	7.3418 E−04	0.88349	−13.7019
7–4-4–9	Test Data	0.2208	0.23251	8.0453 E−06	0.93705	0.720383
7–6-6–9	Test Data	0.22552	0.23977	6.2525 E−04	0.95244	3.377798
7–8-8–9	Test Data	0.22954	0.24586	8.0937 E−05	0.98988	5.620553
7–10-10–9	Test Data	0.22526	0.22749	5.1001 E−05	0.98739	0.614656
7–12-12–9	Test Data	0.22313	0.22607	1.1154 E−05	0.99043	−0.1757
7–14-14–9	Test Data	0.22247	0.23673	4.6138 E−06	0.99812	2.024338
7–16-16–9	Test Data	0.22398	0.22691	8.4451 E−07	0.99375	0.199907
7–18-18–9	Test Data	0.2203	0.22742	6.5839 E−07	0.98526	−0.51287
7–20-20–9	Test Data	0.22353	0.24401	1.5851 E−05	0.94887	3.86553
7–22-22–9	Test Data	0.2203	0.24772	1.2998 E−04	0.93141	3.958495
7–24-24–9	Test Data	0.22353	0.24146	2.7497 E−05	0.97091	3.303856

Table 4: Limiting strain predicted by ANN at different strain states.

Sheet Metal Thickness	ANN Predicted Limiting Stain	Strain State				
		F_{TC}	F_{TC1}	F_P	F_{TT1}	F_{TT}
Al5052 0.8 mm	Minor Strain	−0.0528	−0.0426	0	0.1338	0.219
	Major Strain	0.1498	0.1535	0.13	0.199	0.225
Al5052 1 mm	Minor Strain	−0.05	−0.025	0	0.097	0.1596
	Major Strain	0.1277	0.11	0.09	0.1371	0.163
Al5052 1.2 mm	Minor Strain	−0.0247	0.0217	0	0.1205	0.231
	Major Strain	0.1549	0.1512	0.1234	0.194	0.2472
Al6061 0.8 mm	Minor Strain	−0.0376	−0.0312	0	0.0588	0.1362
	Major Strain	0.129	0.1225	0.1126	0.1476	0.1763
Al6061 1 mm	Minor Strain	−0.0249	−0.0201	0	0.0754	0.1322
	Major Strain	0.135	0.1235	0.1241	0.1733	0.2071
Al6061 1.2 mm	Minor Strain	−0.0982	−0.0454	0	0.0237	0.1559
	Major Strain	0.217	0.1685	0.1461	0.1621	0.2546
Al8011 0.8 mm	Minor Strain	−0.0375	−0.02	0	0.1005	0.147
	Major Strain	0.1088	0.0975	0.0815	0.1218	0.156
Al8011 1 mm	Minor Strain	−0.0329	−0.0199	0	0.0955	0.176
	Major Strain	0.1765	0.1318	0.0991	0.1659	0.1895
Al8011 1.2 mm	Minor Strain	−0.0485	−0.0365	0	0.0703	0.1556
	Major Strain	0.1012	0.1072	0.08	0.1251	0.1604

Table 5: Limiting strain predicted by ANFIS at different strain state,

Sheet Metal Thickness	ANFIS Predicted Limiting Stain	Strain State				
		F_{TC}	F_{TC1}	F_P	F_{TT1}	F_{TT}
Al5052 0.8 mm	Minor Strain	−0.0498	−0.0392	0	0.138	0.206
	Major Strain	0.134	0.142	0.129	0.199	0.214
Al5052 1 mm	Minor Strain	−0.0524	−0.0265	0	0.102	0.168
	Major Strain	0.139	0.12	0.0951	0.155	0.176
Al5052 1.2 mm	Minor Strain	−0.0226	−0.0199	0	0.126	0.179
	Major Strain	0.138	0.136	0.112	0.209	0.226
Al6061 0.8 mm	Minor Strain	−0.0227	−0.0229	0	0.0484	0.14
	Major Strain	0.113	0.11	0.1	0.138	0.16
Al6061 1 mm	Minor Strain	−0.0244	−0.0195	0	0.0792	0.132
	Major Strain	0.132	0.124	0.12	0.182	0.202
Al6061 1.2 mm	Minor Strain	−0.0355	−0.0776	0	0.0179	0.126
	Major Strain	0.126	0.16	0.109	0.119	0.187
Al8011 0.8 mm	Minor Strain	−0.0359	−0.0204	0	0.0857	0.159
	Major Strain	0.113	0.1	0.0811	0.12	0.138
Al8011 1 mm	Minor Strain	−0.0355	−0.0199	0	0.0971	0.184
	Major Strain	0.175	0.129	0.101	0.161	0.19
Al8011 1.2 mm	Minor Strain	−0.0499	−0.0351	0	0.0488	0.16
	Major Strain	0.0982	0.102	0.0794	0.128	0.163

Since in this work it is proposed to optimize the formability, the values of the seven input parameters are selected as optimum and hence the predicted output is optimum. The optimum limiting strain predicted by ANFIS at different strain state are as shown in Table 5.

5 Results and discussion

The main aim of this work is to analyse and model the formability of various grades of aluminium sheet metals using ANN. The correlation coefficient obtained for the 24 networks have been examined in order to decide the optimum architecture. From Table 3, it is evident that the network architecture with two hidden layers of fourteen neurons in each layer results in the best performance for each of the output parameters (7–14–14–9). The mean correlation coefficient for this architecture is 0.9983.

This optimum architecture (7–14–14–9) of ANN is used for all the sheet metals to predict the limiting major and limiting minor strains at various strain states. The strain values are tabulated in Table 4 for all the nine sheet metals. The predicted limiting strains by ANN are compared with the experimentally evaluated limiting strains.

The ANFIS predicted limiting strains using the optimum architecture (7–14–14–9) are tabulated in Table 5. Forming limit diagrams are constructed for all nine sheet metals using experimentally evaluated limiting strains, ANN predicted limiting strains and ANFIS predicted limiting strains and are as shown in Fig. 3. From Fig. 3, it is evident that there is a good agreement between experimental FLD, ANN predicted FLD and ANFIS predicted FLD.

From Fig. 3, it is evident that the forming limit curve in the tension-compression region, the experimental evaluation, ANN prediction and ANFIS prediction are almost in line with each other for all the nine sheet metals.

In the plane strain region, for the sheet metals Al5052 with 1.2 mm thickness and Al6061 with 0.8 mm thickness, the ANFIS prediction falls slightly lower when compared to the experimental evaluation. For all other sheet metals, the forming limit is almost same for experimental evaluation, ANN prediction and ANFIS prediction.

In the tension-tension region of the forming limit diagram, the forming limit curve for experiment and prediction traced the same path in the case of Al5052 with 0.8 mm thickness, Al6061 with 1 mm and 1.2 mm thickness, Al8011 with 1 mm and 1.2 mm thickness. In the case of Al5052 with 1 mm thickness, the ANFIS curve trace a higher value when compared with experimental output. In the case of Al5052 with 1.2 mm thickness, the ANFIS output curve is slightly lower than the experimental curve. For Al6061 with 0.8 mm thickness and Al8011 with 0.8 mm thickness, the forming limit curve for ANFIS slightly deviates from the experimental curve.

6 Conclusion

In this work, it is observed that *n*-value and *r*-value are the most influencing factors in determining the FLD. Upon training the 24 different ANN architecture, the

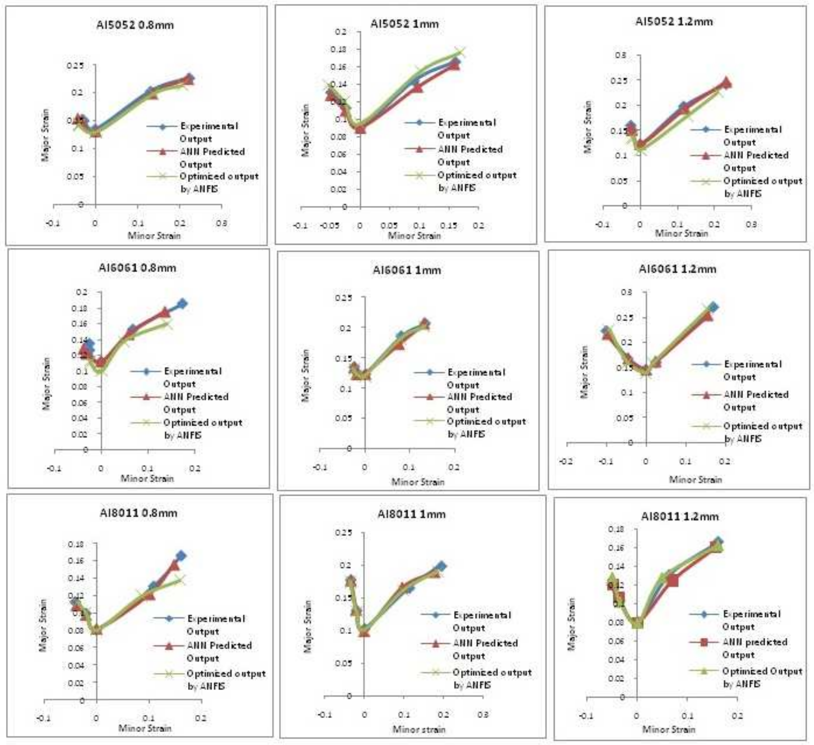

Fig. 3: Variation of experimental FLD, ANN predicted FLD and ANFIS predicted FLD for various grades of aluminium sheet metals.

correlation coefficient, mean square error and convergence obtained are analyzed using the experimental values and finally an optimum architecture is obtained. Among the different ANN architectures trained, the architecture with two hidden layers with fourteen neurons in each layer is identified as the optimized network model. In this optimized network model, the correlation coefficient, mean square error and the convergence perform well and lie within an acceptable range of error.

Using this architecture, the limiting strain at various strain states are predicted for all the nine sheet metals. Optimization is done using ANFIS and the optimum limiting strains at various strain states are predicted for the same. Experimental FLD, ANN predicted FLD and ANFIS predicted FLD for all the nine sheet metals are in good agreement.

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