



APPLICATION OF ARTIFICIAL NEURAL NETWORK AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEMS FOR PREDICTION OF LIFE OF STRIPPER

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Abstract: Predicting the life of stripper is one of the major concerns in the design of compound dies. Finite element analysis is performed to determine the maximum and minimum principal stresses through which fatigue limit of stripper is estimated. The factors affecting the life of stripper are examined and a mathematical model is established using artificial neural network (ANN) and adaptive neuro fuzzy inference systems (ANFIS). The developed model is utilized to evaluate the life of stripper for varied load conditions. Comparative evaluation of ANN and ANFIS results suggested that the later model is superior in predicting the life of stripper and it can be effectively utilized in machine tool applications.

Key words: Stripper, Compound Die, Finite Element Analysis, ANN, ANFIS

1. INTRODUCTION

Compound dies are extremely useful to produce fine sheet metal parts in stamping industries because of the following: high dimensional accuracy, superior surface finish, adequate structural integrity and reduction in material wastage. However, design of compound dies are considered to be challenging task due to the involvement of various components such as punches, die block, stripper, knockout bar, die gage, die-set, etc. in stamping industries to meet the functional requirement. Current market (stamping industries) demands that the stripper of compound die should produce more accurate sheet metal parts without any internal or external defects. Estimating the life of stripper is an important aspect in sheet metal die design. The stripper life of compound die is mainly depends on sheet thickness and stripping force. Generally, life of stripper is predicted by experienced die designers with its performance characteristics and it can cause severe penalty when misjudgment occurs. Last two decades, researchers have realized that ANN and ANFIS are most reliable techniques to provide viable solutions in sheet stamping. Di and Thomson, (1997) employed ANN model for identification of wrinkling behavior of

formed sheet metal parts. Greska et al., (1997) used neural networks and Fourier descriptors to identify various categories of sheet metal parts. Inamdar et al., (2000) developed an ANN model to study the behavior of bending parts and prediction of springback. Djurisc and Manic, (2003) proposed trained neural network for shape recognition of sheet metal parts. Yilbas et al., (2006) formulated an ANN model for study of formed kerf surface of laser cutting corners in sheet metal parts. In order to obtain optimal process parameters and tool geometry with a springback of cylindrical deep drawing process (Crina, 2006) constructed an ANN model. De and Klingenberg, (2008) used a combination of neural network and expert system for the detection of tool wear and blanking force measurement in sheet metal forming process. Babu et al., (2010) conjugation of ANN and expert system for prediction of behavior of welded blanks materials (steel and aluminum alloy) of deep drawing sheet metal parts. ANFIS and FEM method (Yeh et al., 2012) is utilized to arrive an optimal shape of sheet metal bending die. Lin et al., (2013) formulated ANFIS algorithm to measure the springback angle of sheet metal bending parts. Ashhab et al., (2014) investigated the combination of deep drawing and extrusion processes using an ANN model. Liu et al., (2015) evaluated the bending radius of sheet metal parts through back propagation ANN strategy. Zhou et al., (2016) proposed convolutional neural network (CNN) to examine the surface defects of sheet metal parts. Yaghoobi et al., (2016) combined ANFIS and genetic algorithm to optimize the hydroforming process of cylindrical-spherical sheet parts. Radial Basis Function (RBF) neural network are effectively utilized by Wang et al., (2016) to predict and optimize the location layout of sheet metal fixtures. Panthi et al., (2016) estimated the velocity of spring back using a backpropagation ANN model in straight flanging process. Naranje et al., (2016) estimated the life of deep drawing die with an ANN model. Dilan et al., (2017) examined the springback effect of sheet metal bending process through an ANN strategy. Aleyasin, (2017) proposed

ANFIS algorithm to determine forming limit diagram (FLD) of sheet metals. It is evident from the review of literature that, estimating the life of stripper is not yet investigated. In particular, the development of ANFIS and ANN algorithms is useful to predict the life of stripper in compound die effortlessly with less human intervention to save time and cost.

2. PROPOSED ANALYTICAL MODEL FOR STRIPPER

Initially, 3-D CAD model of stripper is designed in CATIA software. This 3D model is transformed into. IGES / STEP format for FE analysis. Further, ANSYS workbench tool is used for FE analysis of 3D CAD model of stripper. From the output of ANSYS results (maximum and minimum principal stress), S-N method is used to calculate number of mathematical cycles (one cycle means one parts can be manufactured). Mean stress (σ_m) and amplitude stress (σ_a) are an important equations to calculate number of mathematical cycles. The formula of (σ_m) and (σ_a) are given below.

$$\sigma_a = \frac{\sigma_{\max} - \sigma_{\min}}{2} \quad (1)$$

$$\sigma_m = \frac{\sigma_{\max} + \sigma_{\min}}{2} \quad (2)$$

Based on (σ_m) and (σ_a) values, Haigh diagram is used for calculate mathematical cycles of stripper. Utilizing these approximations, a generalized S-N curve can be drawn as shown in Figure 1. The endurance strength is calculate from following equation:

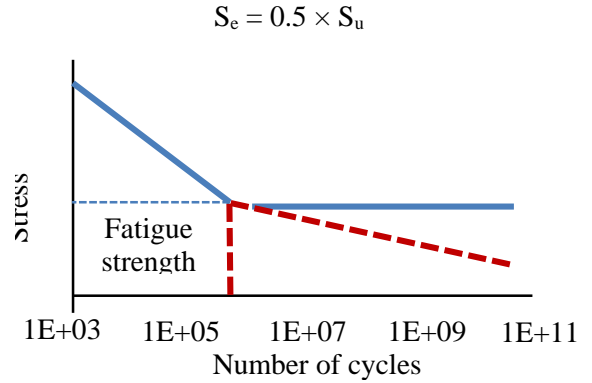


Fig. 1. S-N for tool steel (Kazymyrovych, 2010)

S-N curves for AISI 310 used for calculate number of cycles from equations (2) and (3) as given as under

$$N = \left(\frac{S_n}{S_e} \right)^{\frac{1}{b}} \times 10^6 \quad (4)$$

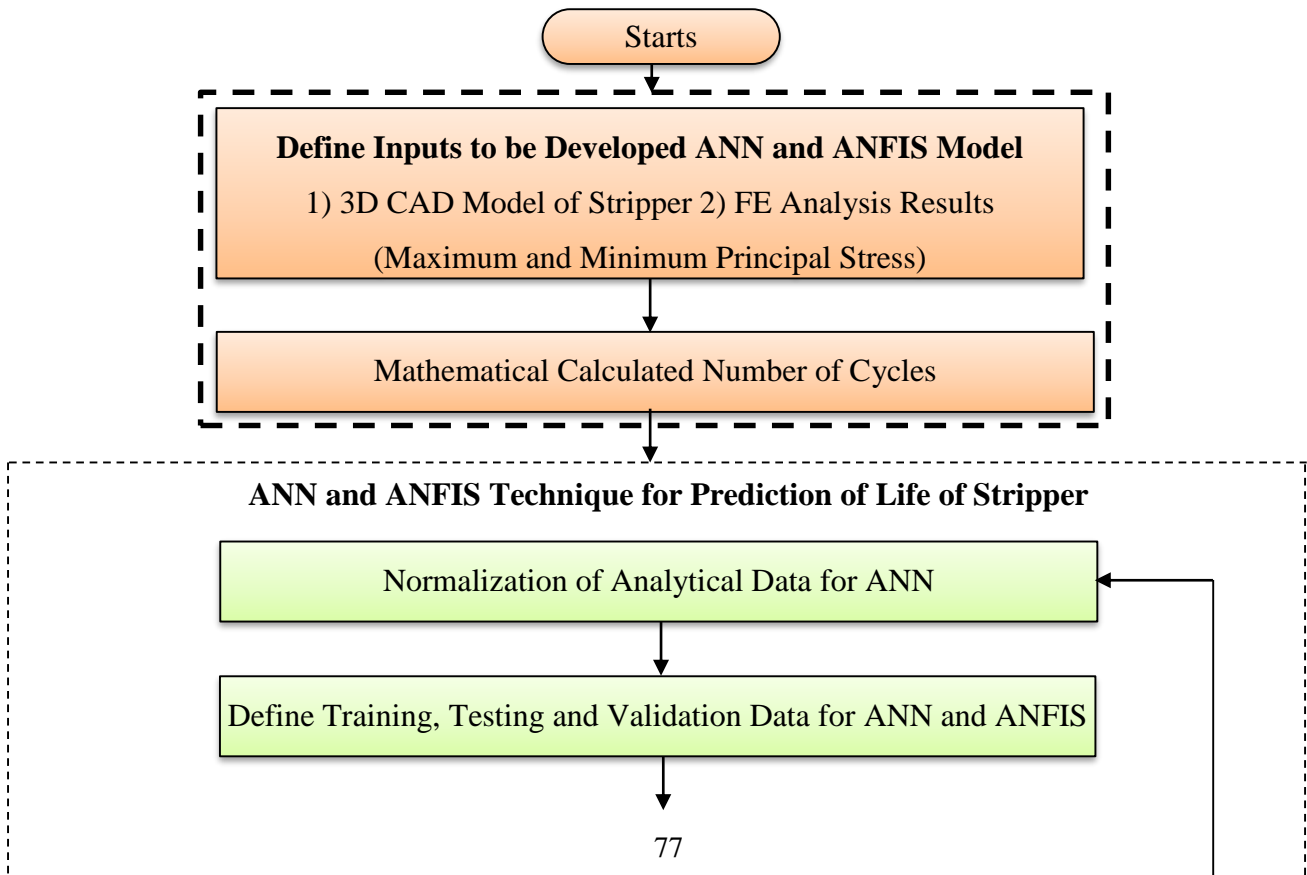
where, N = Number of cycles, S_n = Fatigue strength (from Goodman equation), S_e = Endurance strength

$$b = -\frac{1}{3} \log \left(\frac{\sigma_a}{S_e} \right) \quad (5)$$

Goodman equation as given as under

$$\left(\frac{\sigma_a}{S_n} \right) + \left(\frac{\sigma_m}{S_u} \right) = 1 \quad (6)$$

The empirical relations are utilized to construct the ANN and ANFIS model to determine the fatigue limit of stripper and Figure 2 depicts the framework of proposed ANN and ANFIS.



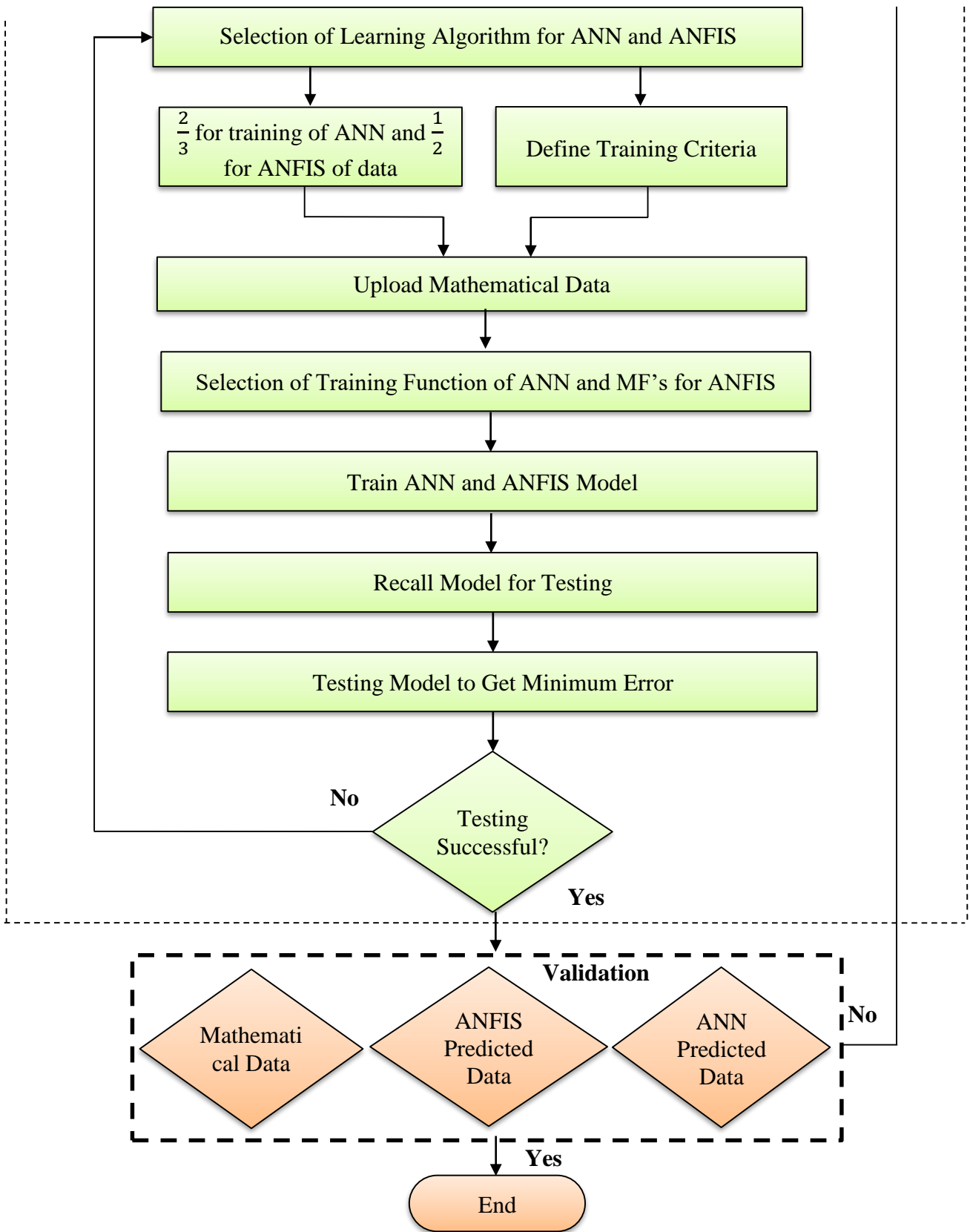


Fig. 2. Framework of proposed ANN and ANFIS model

3. PROPOSED ANN AND ANFIS MODELS FOR PREDICTION OF LIFE OF STRIPPER

The equations (4) to (6) are coded in Microsoft Excel sheet. Neural network toolbox in MATLAB™ is used for the development proposed ANN model. For ANN model the analytical data is divided into three sets 1) for training 60%; 2) for testing 20% and 3) for validation 20%. The weights of neural network are adjusting by set of training and testing data. Validation data is used to validate the ANN model. A supervised ANN, Lavenberg-Marquardt backpropagation is used to develop prediction model. In the present study, eight layers of neurons with four input parameters, three hidden layer and one output layer is used as shown in Figure 3.

The selection of input parameters and output parameters are affects the ANN framework and depends upon the types of problem. The input parameters of proposed

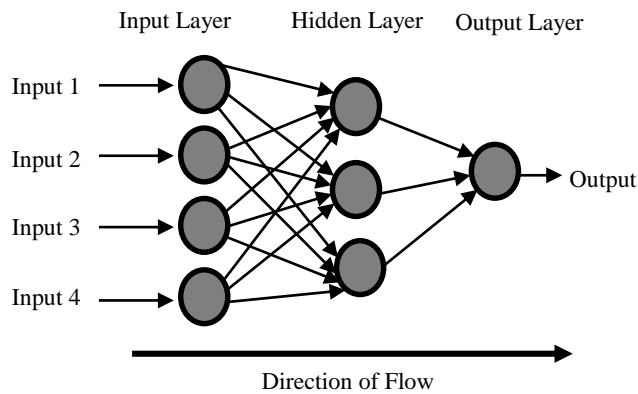


Fig. 3. Feed Forward Ann Structure

4. TESTING OF PROPOSED MODELS

The proposed ANN and ANFIS model were tested various stripper of compound dies. A sample of 3D model of stripper is depicted in Figure 5. The results of FEA are shown in Figures 6, 7 and summarized in table 1. Stripper of compound die is taken from stamping industry namely M/s Punchmahal Dies and Tools Pvt. Ltd. Vadodara, India.

5. RESULT AND DISCUSSION

After training and testing of ANN (Figure 8) and ANFIS model (Figure 10), for a typical loading conditions, life of the stripper is estimated as 308112 and 311864, respectively which is considerably higher than the manufacturer recommendation of about 300000.

ANN model are maximum and minimum principal stress, amplitude stress and mean stress. Similarly, the output parameter is number of mathematical calculated cycles. Based on input and output parameters of ANN, the neurons of hidden layer are chosen. The learning rate of proposed ANN model is set as 0.01. ANFIS is a combination of two technique neural network and fuzzy logic for a mapping relationship between inputs and outputs. The fuzzy inference system contains the fuzzy sets and membership functions, fuzzy implication operators and linguistic if-then rules for mapping the relationship between input and output parameters. There are several membership functions viz. Triangular (trimf), generalized bell (gbellmf), trapezoidal (trapmf), Gaussian (gaussmf), etc., used in fuzzy inference system.

The ANFIS model consists of five layers, and each layer is connected by several nodes. The structure of ANFIS model is shown in Figure 4.

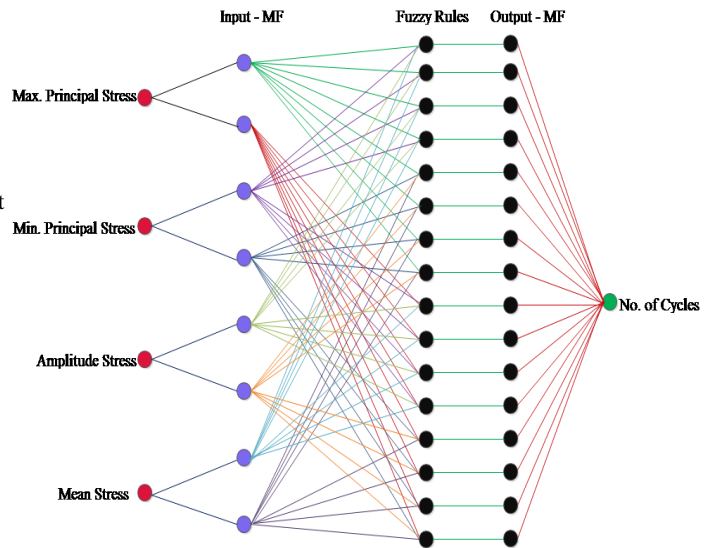


Fig. 4. Structure of ANFIS Model

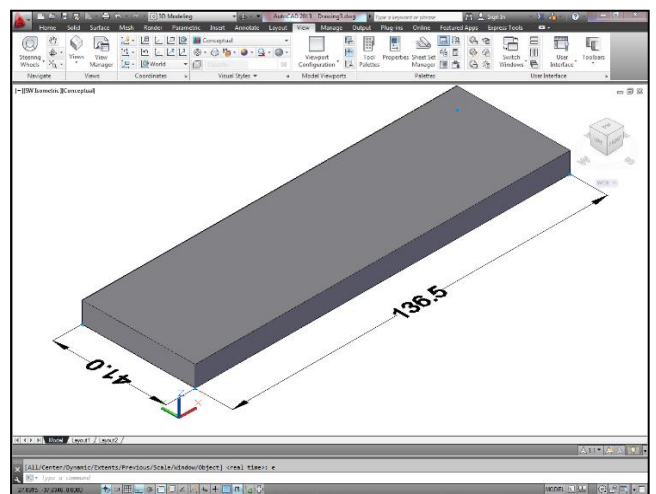


Fig. 5. CAD model of stripper

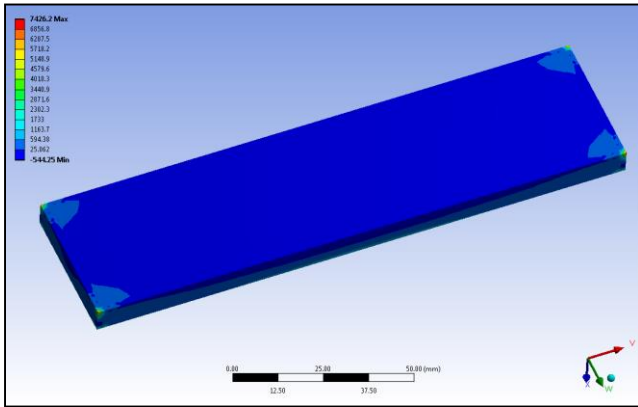


Fig. 6. Maximum principal stress

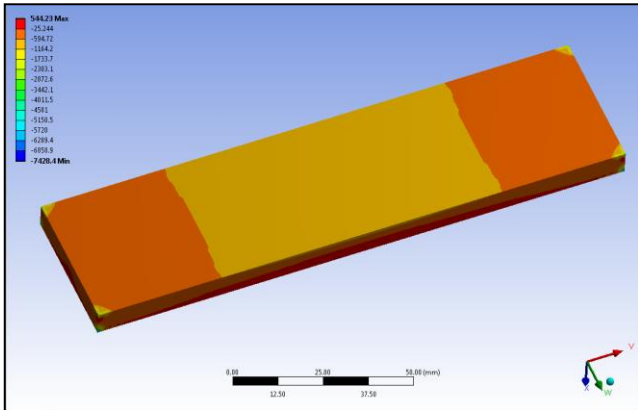


Fig. 7. Minimum principal stress

Figure 9 shows the results of trained, validated, tested and best performance of the ANN model. Prediction of life of stripper using ANFIS mainly consists of three stages: training, checking and testing. In this present study, 45 data set cited in analytical results

have been selected for training the ANFIS network with 300 epochs. Then the trained network has been tested by other 45 datasets which has not contributed in the training. Further, ANFIS model is divided into three phases for predict number of mathematical cycles effectively.

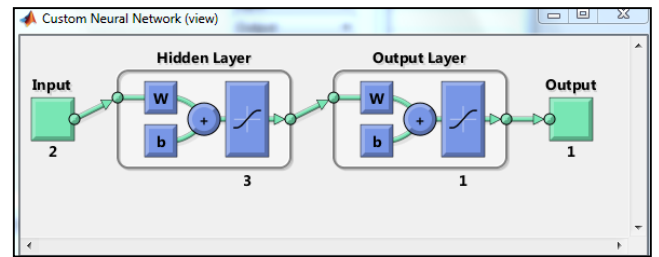


Fig. 8. Number of layers 2 and 3 neurons

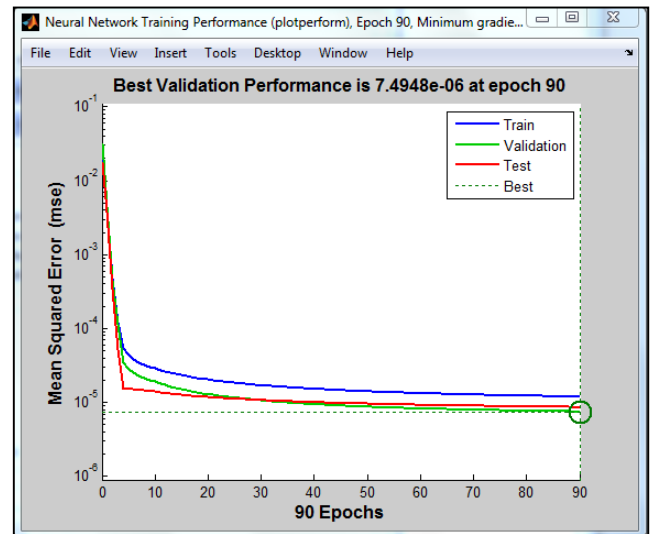


Fig. 9. Minimum error for 2 layers and 3 neurons

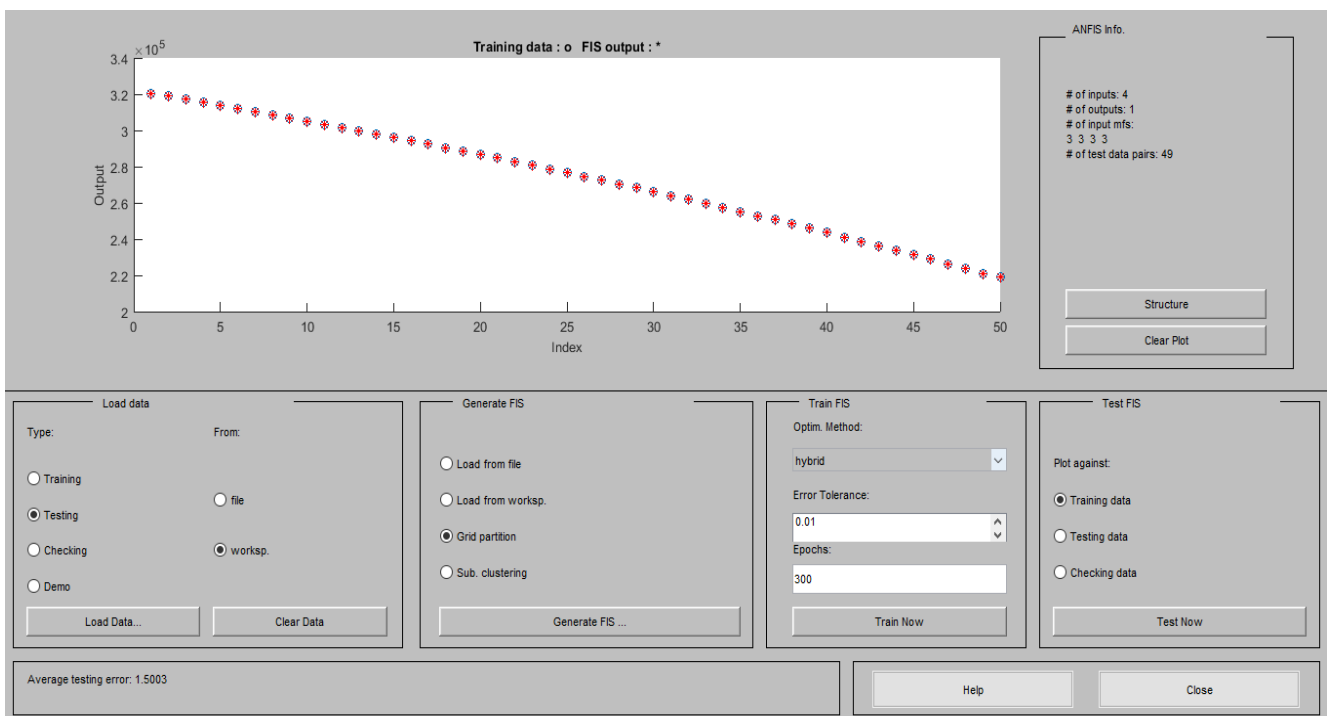


Fig. 10. Testing ANFIS model

The first phase is to define the type of fuzzy rules. Then the set of all fuzzy subsets of variables with membership functions (MFs) were formed. In the third phase, the appropriate number of MFs has been selected for prediction. Triangular membership (trimf) function has been selected due to its lesser mean square error (MSE) value compare than other MFs. The error tolerance during the training of ANFIS network is kept as 0.01 to obtain less error value in prediction. Based on trial and error method, the converged error of 0.4 is observed at 250 epochs which shows that there is no further error reduction is pertinent. In addition the trained ANFIS network is tested for validate the accuracy of prediction. Figure 10 shows the testing of response performance with an

average testing error of 1.5003, which shows the accuracy of prediction. A total number of 81 fuzzy rules were generated for the prediction of response, as shown in Figure 11. From the ANFIS rule, the first four columns indicate the input parameters and the last column represents the predictor variable. The ruler can move from minimum to maximum levels of selected variables to calculate the predictor variables. Finally, the ANN and ANFIS models predicted value were compared with analytical predicted values as depicted in Figure 12. From the figure it is observed that the error difference between the mathematical values with ANN and ANFIS predicted values are 4.6%, 3.2%, respectively.

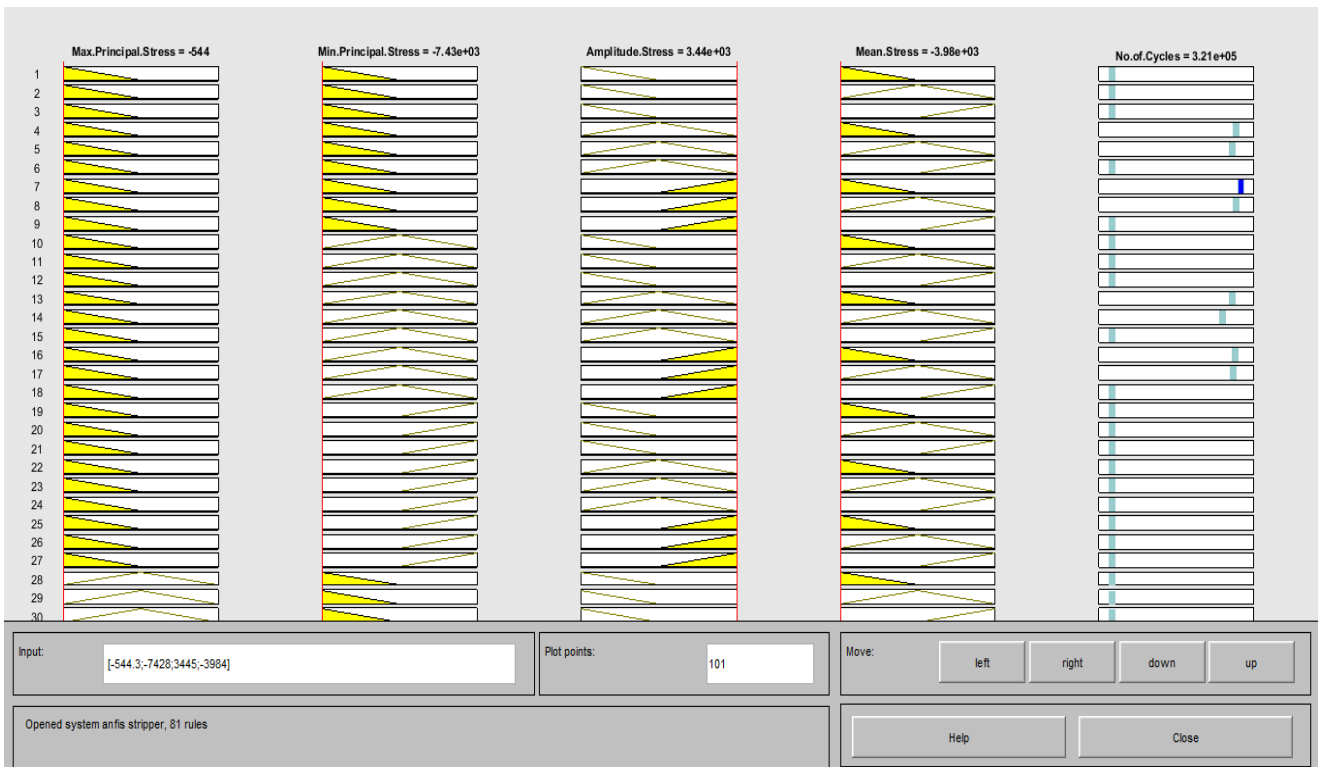


Fig. 11. Testing ANFIS model

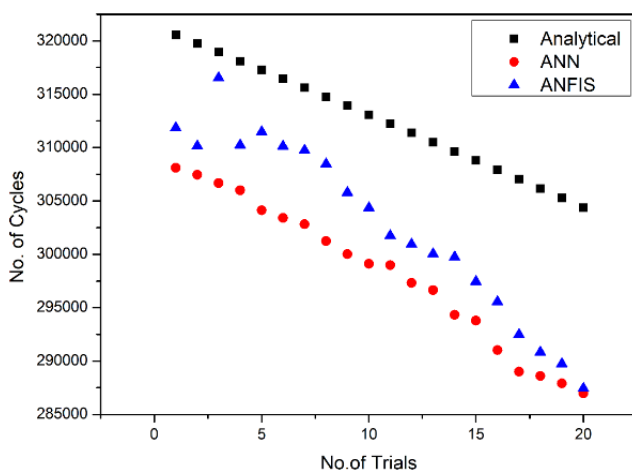


Fig. 12. Comparison of analytical result, ANN and ANFIS predicted

From the figure it is observed that the error difference between the mathematical values with ANN and ANFIS predicted values are 3.45%, 0.029%, respectively.

6. CONCLUSIONS

In this paper, ANN and ANFIS model has been developed for prediction of life of stripper of compound dies. The results of this developed model can be summarized as follows:

- The predicted results obtained from the ANFIS model showed a 96.8 % confidence level. In addition to that, the average percentage of error between the analytical calculated cycles and predicted ANFIS model was found to be 3.2 %, whereas ANN model produce an average error of 4.6 %.

- ANFIS predicted values demonstrate that the accuracy and robustness compared to mathematical calculated values. Hence, the proposed ANFIS model is effectively predict the life of stripper of compound

die compared to ANN model.

- These results indicate that the ANFIS technique is reliable for prediction of life of other dies such as bending die, progressive die, etc.

Table 1. A sample of FE analysis, analytical, ANN and ANFIS outputs of stripper

Stripper stresses, [MPa]							ANFIS Predicted [Cycles]
Sr. No.	Max. principal stress	Min. principal stress	Amplitude stress [σ_a]	Mean stress [σ_m]	Analytical results [Cycles]	ANN predicted results [Cycles]	
1	-544.25	-7428.4	3444.705	-3983.7	320567	308112	311864
2	-538.99	-7401.9	3434.085	-3967.82	319751	307459	310157
3	-533.73	-7375.4	3423.465	-3951.94	318931	306669	316532
4	-528.47	-7348.9	3412.845	-3936.06	318107	305997	310245
5	-523.21	-7322.4	3402.225	-3920.18	317279	304121	311483
6	-517.95	-7295.9	3391.605	-3904.3	316448	303421	310127
7	-512.69	-7269.4	3380.985	-3888.42	315613	302816	309753
8	-507.43	-7242.9	3370.365	-3872.54	314774	301239	308462
9	-502.17	-7216.4	3359.745	-3856.66	313930	300012	305786
10	-496.91	-7189.9	3349.125	-3840.78	313083	299121	304356
11	-491.65	-7163.4	3338.505	-3824.9	312233	298987	301756
12	-486.39	-7136.9	3327.885	-3809.02	311378	297326	300942
13	-481.13	-7110.4	3317.265	-3793.14	310519	296645	300043
14	-475.87	-7083.9	3306.645	-3777.26	309656	294336	299756
15	-470.61	-7057.4	3296.025	-3761.38	308789	293789	297452
16	-465.35	-7030.9	3285.405	-3745.5	307918	291026	295554
17	-460.09	-7004.4	3274.785	-3729.62	307043	289000	292475
18	-454.83	-6977.9	3264.165	-3713.74	306163	288612	290841
19	-449.57	-6951.4	3253.545	-3697.86	305280	287917	289742
20	-444.31	-6924.9	3462.45	-3462.45	304392	286987	287438

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