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A Programmatic Approach for the Prediction of Fatigue Life of Deep Drawing Die Using ANN

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The present work is concerned with fatigue life prediction of active components of deep drawing dies. Finite element Analysis is performed and S-N approach is used for evaluation of number of cycles of deep drawing die. Then based on the available evaluated data and mathematical formulae the ANN program is developed in the MATLAB, which is used to predict the fatigue life of deep drawing dies. The developed program achieved satisfactory results and verified based on a demonstration of an industrial sheet metal part

***Keywords*:** Deep Drawing Die, FE analysis, S-N approach, Artificial Neural Network, MATLAB

1. Introduction

Die design includes various activities such as manufacturability assessment, process planning, selection of die components, and die modeling. Another important aspect in die design, to predict the die service life and die performance and for this well trained and experienced die designers are required. Another way to find die life is through experimental studies, but it is time-consuming and costly. Artificial neural network (ANN) is one of the promising artificial intelligence tool to address the limitations of commercial software and experimental studies. In this study, ANN is used to predict fatigue life of deep drawing dies. In the present work, Firstly, the factors affecting deep drawing die life are identified and categorized into (1) Process parameters, (2) Geometrical parameters, and (3) Machine parameters. Then based on the application, the most influencing factors are found out and used for the finite element analysis. Afterwards FEA results are used to developed ANN program to predict the fatigue life of deep drawing dies.

In last 20-25 years, various researchers are working to improve the fatigue life of forming tools to achieved better accuracy and service life of die. Park and Colton [2] presents a fatigue failure analysis of V-bending dies used for sheet metal forming. Die life is predicted by using various fatigue failure criteria namely, maximum tensile principal stress, effective stress, Some researchers found different failure modes, like Arif et al. [3] uses 17 different die profiles & around 616 die failures were studied with an industrial setup. This paper presents results of an ongoing study about the relationship between die profile and modes of die failure. Lange et al. [4] presents an integrated approach to tool stress analysis and shows its possible application for a punch failure and further study experimentally investigates measures to reduce fatigue failure and so improvement of tool service life in cold forging. Geiger et al. [5] tried to improve the fatigue resistance of cold forging dies based on numerical simulation of forming process and computer aided design (CAD) of die shape design. Lee et al. [6] reformulated Archard's wear model as an incremental form, for calculating wear amount during cold forging and FE simulations empirical equations were obtained to estimate tool life. Klingenberg and Boer [7] presented a review and proposal for condition-based maintenance (CBM) in blanking of sheet metal. Initially statistical, AI and model based approaches are analyzed. Further they demonstrated how the signature of the force–displacement relation changes significantly with increasing tool wear in a typical configuration of sheet steel blanking. Kazan et al. [8] developed prediction model of spring-back in wipe-bending process of sheet metal using ANN approach. Aguir et al. [9] presented an inverse strategy coupled with an ANN model for identification of anisotropic parameters of cylindrical cup deep drawing. ANN model is trained by finite element simulations. Li et al. [10] used ANN and GA for optimization of sheet metal deep drawing parameters with variable blank holder force. Choi et al. [11] proposed a channel-type indirect blank holder to develop a high-strength centre pillar in form-type hot stamping, so that severe wrinkling at the flange can be reduced. Slope angle and corner radius of the channel are selected as the main shape parameters by FE analysis and ANN. Kashid and Kumar [12] presented prediction of life of punches of compound die using artificial neural network.

From the review of available literature on fatigue failure consideration for die life prediction it is found that the worldwide researchers have estimated the die life by considering fatigue failure criterion for forging dies, extrusion dies, V-bending dies, lap joints and stamping process. But no system is reported in the literature for prediction of life of deep drawing dies due to fatigue failure.

2. Methodology for Die Fatigue Life Prediction and Assessment

Initially a three-dimensional (3D) CAD model of active and passive components of deep drawing die are model using solid modeling software. This CAD model is then converted into IGES format for FE analysis. Static Structural analysis is performed on the active components of deep drawing dies. An important factor for FE analysis is drawing punch force. Some assumptions are generally taken to simplify calculation of punch force. One very simple and useful empirical relation to calculate an approximate punch force is as follows

Draw force or Punch force at each stage, $(F_{max})_i = (\pi \times Dp \times t \times Sut) \times \{Dr - 0.7\}$

Where, Diameter of punch (Dp) t = Thickness of the blank sheet. Sut = Ultimate tensile strength of Sheet Material, Dr= Draw ratio

Another force i.e the blankholder force is usually consider as about one-third the punch force.

$$\text{Blank Holder Force } (F_h)_i \text{ at Stage i} = \left(\frac{(F_{max})_i}{3}\right) (i = 1,2,3,\ldots..)$$

Finally, total punch force is calculated by adding maximum punch force for each stage and blank holder force at each stage. Total Force = $(F_{max})_i + (F_h)_i$ Then by applying total punch force, the finite element model is analyse to obtained maximum and minimum principal stresses. Based on this stress values the number of cycles is evaluated. The following equations are used for calculation of number of cycle [8].

$$N = \left(\frac{S_n}{S_e}\right)^{1/b} \times 10^x \qquad \text{eq. 1}$$

Where,

N = Number of cycles.Sn = Fatigue strength (as calculated from Goodman equation).

Se = Endurance limit of tool material =0.5×Su

Su = Ultimate tensile strength of Tool Material.

b = Constant = $\left\{-\frac{1}{3}\log_{10}\left(\frac{\sigma_a}{S_e}\right)\right\}$

σa = Amplitude stress = $\left\{\frac{\sigma_{max} - \sigma_{min}}{2}\right\}$

The value of 'x' in the term 10^xin eq. 1 is 9 which are obtained from S-N approximation curve [Fig. 1].

Goodman equation is given as follow [11] -: $\left(\frac{\sigma_a}{S_n}\right) + \left(\frac{\sigma_m}{S_u}\right) = 1$

σm = Mean stress = $\left\{\frac{\sigma_{max} + \sigma_{min}}{2}\right\}$ - - - - - - - - - - - - - - (9)

Therefore, the equation (4) becomes -: $N = \left(\frac{S_n}{S_e}\right)^{1/b} \times 10^9$

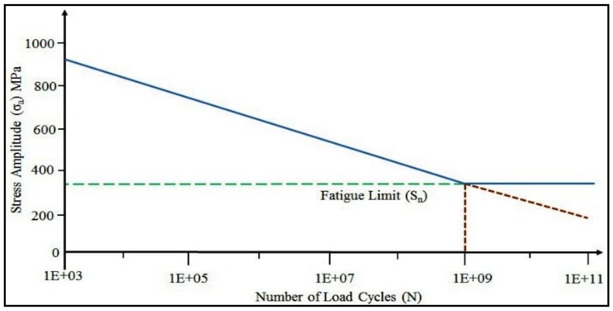


Fig. 1 S-N Curve Approximation for Tool Steel [8]

3. ANN module for deep drawing die fatigue life prediction

The ANN module is developed using MATLAB 2014R. Then the type of network is selected as feed- forward network. This is set by using 'fitnet' function in the program. The input to the ANN is data file of the FEM analysis results which includes maximum and minimum principle stress and the ultimate tensile strength of tool material. Initially for all examples results are founded for hidden layer size of 4, and thereafter size increases gradually until a very small variation in the FEM and ANN results are obtained. There are several transfer functions available to be use in ANN. Out of them Log-Sigmoid transfer function is chosen as an activation function in this study which is given as follows

$$\mathrm{Output(a)} = \mathrm{logsig\ (input)} = \frac{1}{1 + e^{-n}}$$

The neural network is supervised Train by using Levenberg-Marquardt Back Propagation training function. Error in the network performance is calculated by using mean square error technique. The learning rate is set as 0.5. The maximum epoch are set to 2000 to provide more iteration freedom to neural network and thus obtained more accurate results. Two-third data are selected for training and one-third data are selected for testing.

4. Sample run of the proposed system

The proposed ANN module has been validated and verified on a number of deep drawing die punches designed for manufacturing of wide variety of sheet metal parts. A sample run of this module on punches designed for producing an industrial sheet metal part (Fig.2) is demonstrated here.

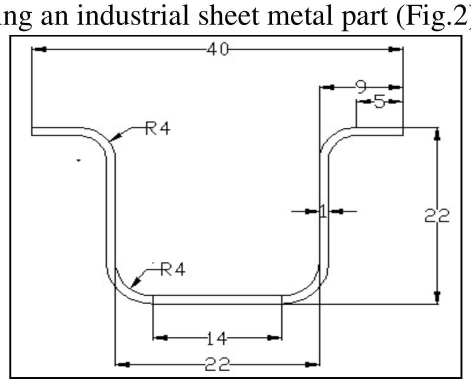


Fig. 2 Final Deep Drawn Component 2D Diagram

This drawing data is obtained from industry named M/s Fine Dies & Moulds Pvt. Ltd., Pune, India. According to the industrial deep drawing die expertise, the component gets manufactured in 4 stages of deep drawing. The component is manufactured for the application of Supporting Component in Automobile Electrical Systems. For drawing this component, the mechanical type of power press is used of 55 tonnes capacity. The forming velocity used for the production of specified component is around 55 to 65 mm/sec. The blank material is Mild Steel (DC06 Grade), the material for die is SVERKER 21(AISI D2), and the punch material is SVERKER 3 (AISI D3). A simple deep drawing die setup is used to manufacture this component. Blank are lubricated from both sides. Friction coefficient between blank & punch is 0.12 and that of between (blank and die block) and (blank and blank holder) is 0.15, as per industrial expertise. The scrap rate for the production of this component is around 4% to 5% as per industrial expertise. Using design data, 3-D model of punches of deep drawing die is prepared is shown in Fig. 3. Outputs of FE analysis of punch of stage 4 are shown in Fig.4 and summarized in table 1. Also the results obtained from developed ANN module are depicted in Fig.5

Table 1: Results obtained from developed ANN module

Max. Principal Stress in [MPa]	Min. Principal Stress in [MPa]	Amplitude Stress (σ_a)	Mean tress (σ_m)	Analytical Results (Number of Cycles)	ANN Predicted Results (Number of Cycles)
-25.40	-162.16	68.37	-93.78	824846.65	824836.51
-25.41	-162.17	68.37	-93.79	824832.50	824831.34
-25.41	-162.17	68.37	-93.79	824831.53	824829.06
-25.42	-162.17	68.37	-93.79	824829.29	824823.20
-25.42	-162.17	68.37	-93.79	824828.97	824822.31
-25.42	-162.18	68.37	-93.80	824815.46	824816.03
-25.42	-162.19	68.38	-93.80	824800.34	824803.21
-25.43	-162.2	68.38	-93.81	824784.90	824787.46
-25.43	-162.2	68.38	-93.81	824784.58	824786.27
-25.43	-162.2	68.38	-93.81	824784.58	824786.27
-25.44	-162.2	68.37	-93.82	824782.98	824780.42
-25.44	-162.21	68.38	-93.82	824769.79	824771.73
-25.44	-162.21	68.38	-93.82	824769.47	824770.54
-25.44	-162.22	68.38	-93.83	824755.95	824760.07
-25.44	-162.22	68.38	-93.83	824754.99	824756.51

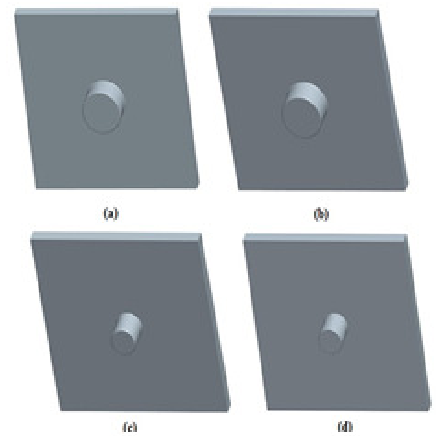
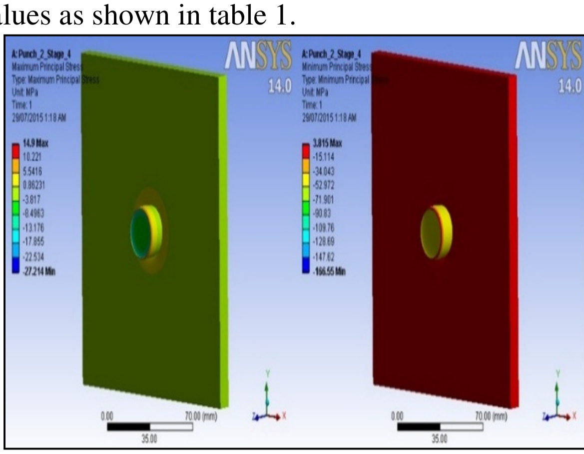


Fig. 3 3-D model of punches of deep drawing die

The proposed ANN module predicts fatigue life of punches of deep drawing die in terms of avg. number of cycles (means number of sheet metal parts that can be produced) as 7,29,270 which is very similar to the actual number of sheet metal parts produced in the said industry using these punches. Fig. 6shows the comparison of analytical result & ANN predicted result for max. Principal stress v/s number of cycles for punch of stage 4. The maximum error is 0.99 as calculated using the values as shown in table 1.



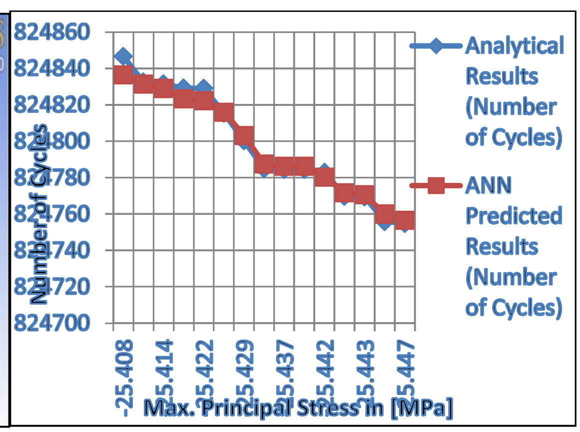


Fig. 4 Output of FE analysis of punch 4

Fig.5 Comparison of FEM and ANN results

5. Conclusions

In the current study, an ANN module has been developed for prediction of life of active components of deep drawing dies (which is punches here). The execution of proposed ANN module has been briefly described. A sample run on a typical deep drawing dies demonstrated the usefulness of proposed module. The results obtained from ANN module are compared with analytical evaluation to obtained maximum error between the two predictions. It is observed that, the difference between analytical evaluated results and ANN predicted results are very small which confirmed that an ANN has ability to accurately predict unseen data. Further, the comparison graphs shows that the prediction by ANN model closely follows the analytical evaluated results. Therefore, this comparison shows that the ANN model can be useful for prediction of life of deep drawing die. The proposed ANN module is capable of accomplishing the tedious and time-consuming task of prediction of life of deep drawing dies in a very short time period. The outcome of proposed ANN module is very useful for sheet metal industries to accomplish the above experience-based task. Also, the developed ANN module can be positively used to predict the fatigue life of blanking dies, bending dies, extrusion dies, compound dies, progressively dies etc.

6. Sample Code

```
File_Name = input('\n\nSpecify the Excel Workbook Sheet Name = ','s');
Data_Inputs = xlsread(File_Name);
Read_Data = input('\nEnter the Number of Data Points to be Read for Analysis from Excel Workbook Sheet = ');
UTS = input('\nEnter the Value of Ultimate Tensile Strength of Tool Material = ');
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.------------
ANN_to_Number_of_Cycles_Retrain(j)=(((Analytical_Number_of_Cycles(ND)-Analytical_Number_of_Cycles(1))*ANN_Predicted_Results_Retrain(j))+Analytical_Number_of_Cycles(1));
end
count = count+1;
k = 1;
i = i+1;
elseif (choice==2)
x = count+1;
```

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