Prediction of Optimum Sheet Metal Blanking Clearance for IS513CR Steel Using Artificial Neural Network

Pradip P. Patil, Vijaya P. Patil, and R. Ramaswamy

Abstract In a quest for higher productivity, sheet metal manufacturing industry is undergoing significant development in the field of sensing and automation. One of the sheet metal operations is blanking, which is affected by an uneven crack which leads to a loss in productivity. In present work, an experiment is carried using the uni-punch tool on power press for varied punch penetration, to observe crack initiation and to find optimum clearance for IS 513 cold-rolled steel. The crack initiation is measured using shear angle, fracture angle and punch penetration. As the blanking process is complex and nonlinear, artificial neural network (ANN) is employed to predict clearance for input parameters. The predicted values are well within the experimental values.

Keywords Sheet metal blanking · Optimum punch–die clearance · Artificial neural network

1 Introduction

The metal-forming industry has been undergoing the requirement for an automated manufacturing system. One of the metal-forming processes is sheet metal blanking, which needs an accurate assessment of the parameters. In perspective on the advancement in the field of robotized fabricating, it is discovered that the present modern status is experiencing quick advancement in detecting framework equipped for recognizing and consequently replacing broken or worn segments, and absence

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of sufficient procedure model fits for discussing the multifaceted nature of the assembling framework. In any case, this advancement is seen through adaptable assembling frameworks, direct numerical control, shrewd assembling frameworks and PC incorporated assembling.

ANN modelling has been employed in developing an intelligent system in the field of machining for enhanced accuracy of prediction [1, 2]. Maiti et al. [3] modelled the sheet metal blanking and studied mechanical and geometrical parameters which include the wear state of the tool, thickness of the sheet and blanking clearance.

The aim of this work is to build up a predictive model for the optimum sheet metal blanking conditions. A feed-forward back propagation ANN system model is utilized for developing a prediction model. As customarily embraced means are frequently intelligent and compelling, the answer for the multifaceted nature of blanking parameter requires ANN modelling. A portion of the springiness and capacity of the human brain can be mirrored by the premise of ANN. The role of ANN is coming into the picture when the nonlinear plotting from inputs to outputs and the other way is not achievable by the conventional and regression methods. The following section explains literature review followed by result and analysis. The conclusion is presented at the end.

2 Literature Review

2.1 Blanking Process

In blanking processes, punch penetrates the sheet metal pressed by the blank holder as shown in Fig. 1. The process separates blank from sheet metal.

The quality of sheared edge of the cut workpiece/blank is defined by geometrical attributes (fracture depth, burr height, roll-over depth and smooth-sheared depth) through the blanking operation for a given material as shown in Fig. 2.

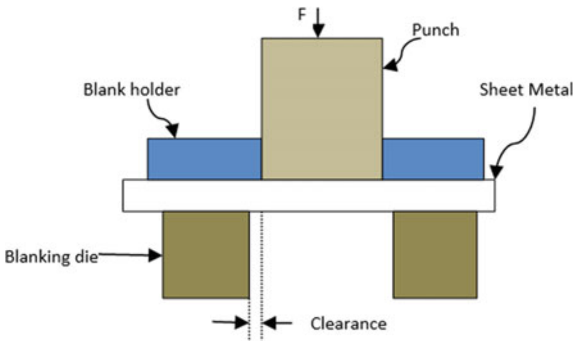


Fig. 1 Sheet metal blanking operation

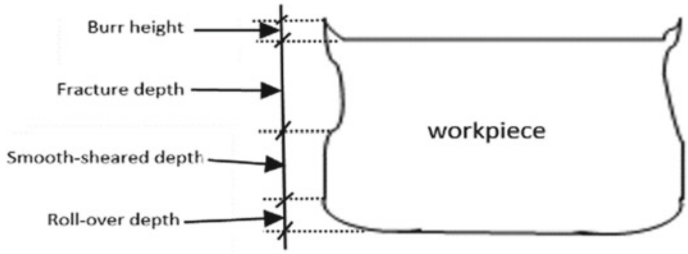


Fig. 2 Parameters of sheet metal blanking

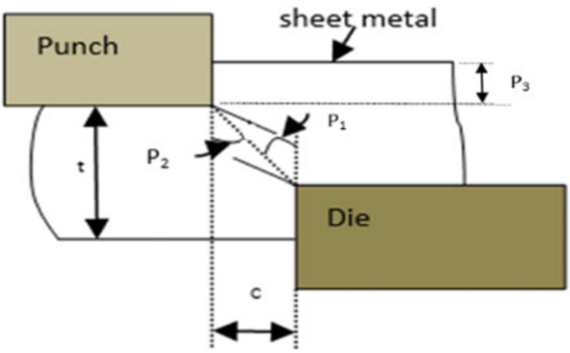


Fig. 3 Process of crack propagation

The process of finding optimum clearance is expressed by shear diagonal angle (P1), fracture angle (P2) and punch penetration (P3) when crack initiates, as illustrated in Fig. 3. The quality of sheared edge will be optimum when a crack propagates along diagonal line joining the punch and die corners. However, the clearance of the process is expressed as c.

$$c = 100\frac{D_{\mathrm{m}} - D_{\mathrm{p}}}{2t}\,(\%)$$

where t, D_{m} and D_{p}, and are, respectively, sheet thickness, the die diameter and the punch diameter. Since the primary material variable illustrating the fracture at beginning and propagation conditions is the strain at the crack, the fracture angles which is the input data for the ANN is determined by material elongation. The networks are utilized as digital devices for switching the experimental values required for the optimum clearance.

2.2 *State of Art*

Fang et al. [4] applied the Cockcroft and Latham fracture criterion and finite element method (FEM) to optimize clearance values for specified sheet material and thickness. They have established a shearing mechanism by mimicking the blanking operation of an aluminium alloy 2024. Faura et al. [5] propositioned a method to find optimum punch–die clearance for sheet material and thickness, applying the FEM. The diagonal angle and crack propagation angle for various clearances were calculated to uncover the optimum clearance. The effect of clearance on an angle of crack propagation and a diagonal angle is monitored. The diagonal angle and the clearance are directly proportional, whereas the tendency of crack propagation stays almost invariable. The clean surface forms when line emanating from punch and die coincide as shown in Fig. 2. This process leads the optimum clearance and punch incursion increases as per the ratio increases of clearance to metal thickness.

Hambli and Guerin [6] illustrated the blanking process and blanked surfaces shaped by the tooling (tool geometry and clearance) and properties of the workpiece material (mechanical properties, blank thickness and microstructure). For a specified material, tool geometry and the clearance configurations essential parameters, the simulation of an axisymmetric blanking process with Abaqus–Explicit software for particular sheet material. A Lemaitre-type damage model is deployed to describe crack initiation and propagation into the sheet. They explored that the material elongation is inversely proportional to the optimum clearance.

Hambli [7] proposed a methodology with the FEM and NN simulation to envisage the optimal punch–die clearance through sheet metal blanking. A damage model is employed to explain propagation and crack initiation into the sheet. The propositioned approach combines finite projecting element and NN modelling of the principal blanking parameters. As researched by previous researchers, the ANN is a powerful means for dealing with the complicated nature of the turning process [8]. Thus, the ANN was preferred to develop a predictive model to foresee optimum punch–die clearance. A backpropagation NN depleted in the prediction of optimum clearance with the help of backpropagation NN modelling [2, 9–11]. They carried out the experimentation on four materials with discrete ductility. The data of investigational fracture angles were operated to train the established simulation environment built on backpropagation NN modelling. The established prediction system achieved the capability of accurate clearance classification for the trained range. Mucha and Tutak [12] experimented the influences of the clearance on the deflection, initial values of burr and the bending radius of the hook and measured influence the wear of the punch on the geometric values of the cut. The outcome shows proper selection clearance and new tool materials.

The material selected for this work is 'IS 513 CR', suitable for stamping operations which includes a variety of processes, such as punching, blanking, embossing, bending, flanging and coining. The applications involve forming precision tubes, railway coaches, corrosion resistance applications, industrial storage systems, drum and barrel. Variety of shapes are developed (simple or complex) with high tooling and equipment costs at high production rates with low labour cost.

2.3 Artificial Neural Network

NN is made out of straightforward components working in parallel which are propelled by organic sensory systems. As in nature, the system work is acquired by the associations between parts. We can prepare a NN to play out capacity by adjusting the estimations of the associations (loads) between elements. By and large, NN is balanced or trained with the goal that information prompts the specific objective yield. The log-sigmoid capacity is utilized to standardize the information as shown in Fig. 4.

This transfer function takes the input (which may have any value between plus and minus infinity) and squashes the output in the range 0–1 according to the expression.

$$a = \frac{1}{1+e^{-n}}$$

This shows the neuron with R inputs and a single output, so it is called multiple input neurons, as shown in Fig. 5.

$$n = Wp + b$$

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \cdots + w_{1,R}p_R + b$$

Fig. 4 Log-sigmoid transfer function

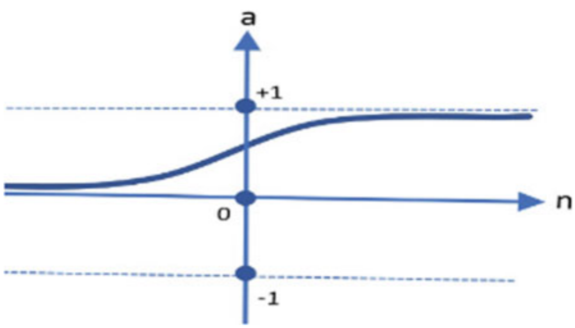
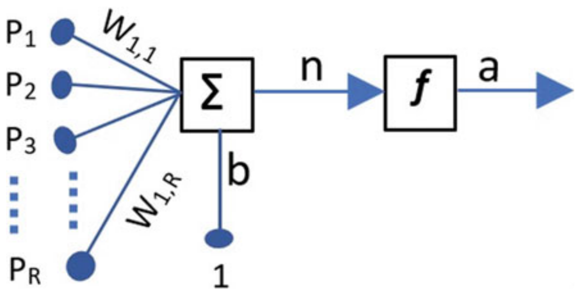


Fig. 5 Neural network model



where R = inputs, W = weight matrix.

The backpropagation algorithm with Levenberg–Marquardt training is used to train the neural network [13].

3 Result and Analysis

Experiments are carried out using the power press of 100-ton capacity for blanking operation. The uni-punch tooling system is used, and tonnage varies from 10 to 100 tons. The blank holder on the machine table holds the sheet and sheet is subjected to blanking. The material properties and input parameters for the experiment of 'IS 513 Cold Rolled' are shown in Table 1.

Experimentally, the values for engineering strain, true strain, optimum clearance C_0 and punch penetration are obtained [14].

Engineering strain $e_f = 7.16$, true strain $\varepsilon_f = (e_f + 1) = 2.1$

$$\frac{t}{C_0} = 1.36 \times e^{\varepsilon_f}\left[\frac{2.3\times e^{(\varepsilon_f)}-1}{2\times e^{(\varepsilon_f)}-1}\right]$$

$$\frac{t}{C_0} = 1.36 \times e^{1.75}\left[\frac{2.3\times e^{(1.75)}-1}{2\times e^{(1.75)}-1}\right]$$

Theoretical optimum value, $C_0 = \frac{2}{12.88} = 0.155\,\text{mm}$, from experimental study, optimum clearance, $C_0 = 3 \times \frac{6.1}{100} = 0.122\,\text{mm}$. Also, punch penetration to clear slug theoretical optimum value given as

$$\frac{\Delta + C_0}{t} = \frac{1}{2.45}\left[\frac{1.9\times e^{(\varepsilon_f)}-1}{2.56\times e^{(\varepsilon_f)}-1}\right]$$

Table 1 Mechanical properties of IS 513 cold rolled

Material	Material properties	Thickness (mm)	Clearance (mm)	Percent clearance (% of sheet thickness)
IS 513 cold rolled steel	Yield stress = 195 N/mm^2 Tensile strength = 321 N/mm^2 Material elongation (%) = 49.25 Reduction area (%) = 62.64 Engineering strain = 7.16 True strain = 2.1	0.8	0.2	25
		1.5	0.2	13.33
		2.0	0.2	10

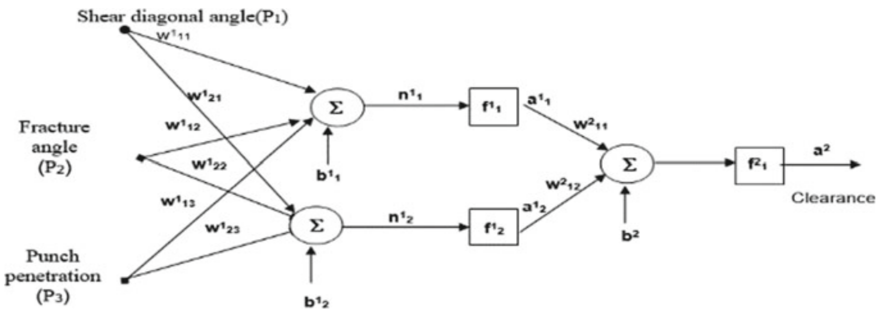


Fig. 6 Neural network for predicting optimum clearance

Punch penetration, $\Delta + C_0 = 0.28 \times t = 0.28 \times 2 = 0.58\,\text{mm}$.

Punch penetration from experimentation when crack initiates at Up = 0.31 mm.

The input to the network as shown in Fig. 6 is shear diagonal angle, fracture angle, punch penetration and output is clearance. The angles are determined from slug removed by the blanking process. The network uses three neurons and corresponding three transfer functions (2-log sigmoid and 1-purelin) Weights and biases are selected randomly at the beginning. A set of known parameters from experiments is selected for error minimization. At the beginning was calculated as $e = 0.075281$, which is brought down to $e = -0.0004325$ and took 4 iterations at a learning rate of $\alpha = 0.4$. Backpropagation iterations: following steps are followed in combination with LM training to solve the neural network (Fig. 7).

Results of the simulation are shown in Table 2 and the plot of input versus output and goal versus training error, as shown in Fig. 8. The graph shows improvement in approximation as shown in the graphs.

The inference of optimum clearance is derived where the line of shear diagonal angle intersects with the fracture angle. Theoretically, the shear line and fracture line shall lie on one line to avoid secondary fracture. The variation of fracture and shear angle verses per cent clearance and optimum clearance is observed to be 7% as shown in Fig. 7, and this outcome is confirmed by following earlier work [10]. The intersection of these two linear fitting of angles denotes the optimum clearance for IS513CR. The results of the simulation are plotted for input versus output and goal versus training error graph shows improvement in approximation.

The results of the simulation are validated using the analytical methodology of the neural network.

4 Conclusion and Future Scope

The purpose of this work is to find optimum clearance for IS 513 CR steel. The experimental values are validated by ANN simulation. The plot of the intersection of shear angle and fracture angle shows optimum clearance. The optimum clearance

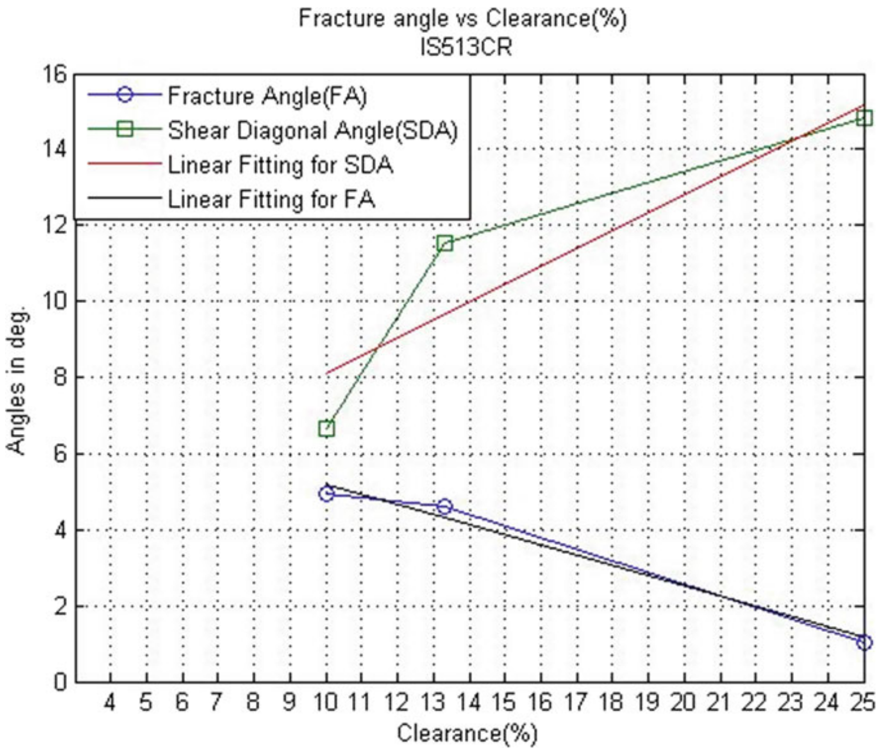


Fig. 7 Plot of angles vs clearance for IS513CR

Table 2 Results of neural network simulation for IS513CR for 2 mm sheet

S. No.	Punch penetration (mm)	Fracture angle	Shear angle	Clearance
1	0.004	0.7162	14.74	0.13
2	0.005	0.7162	14.74	0.15
3	0.004	0.7162	14.74	0.15
4	0.34	5.57	6.87	0.14
5	0.34	4.86	6.87	0.13
6	0.34	5.28	6.87	0.14
7	0.52	6.4659	11.76	0.16
8	0.52	6.4659	11.30	0.15
9	0.52	6.4659	11.53	0.14

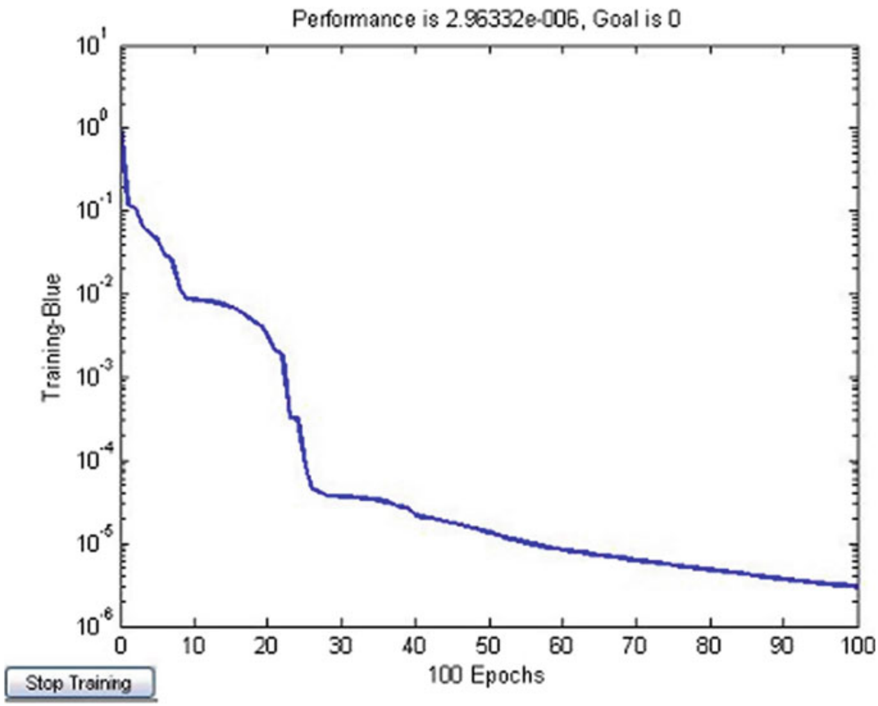


Fig. 8 Error graph

for IS513CR experimentally is found to be 6.1% of sheet thickness. The simulation using the neural network result gives optimum clearance of 7%. The backpropagation algorithm with LM training is used to solve the network. The backpropagation algorithm is an extension of least mean square algorithm that can be used to train the multilayer network. The backpropagation is an approximate steepest descent algorithm that minimizes squared error. After the four iterations performed, the error in the desired target and obtained value by the neural network approached to zero (0.0004428). The corresponding system is the optimum network and used to verify the clearance for different input conditions. However, the accuracy of prediction can be improved by considering more layers.

This study demonstrates the optimum clearance for IS513CR, a widely used material for a variety of in industrial applications.

The punch-load penetration, tool and die wear characteristics, sheet metal surface roughness will improve modelling of blanking process. The variation of clearance influences punch load because strains are larger when applying smaller clearance, and the stresses are also higher. The little difference in experimental and numerical results could be caused by other factors such as wear state of the tool and the thickness of the sheet.

References

1. Malakooti B, Raman V (2000) An interactive multi-objective artificial neural network approach for machine setup optimization. J Intell Manuf 11(1):41–50
2. Zuperl U, Cus F, Mursec B, Ploj T (2004) A hybrid analytical-neural network approach to the determination of optimal cutting conditions. J Mater Process Technol 157:82–90
3. Maiti SK, Ambekar AA, Singh UP, Date PP, Narasimhan K (2000) Assessment of influence of some process parameters on sheet metal blanking. J Mater Process Technol 102(1–3):249–256
4. Fang G, Zeng P, Lou L (2002) Finite element simulation of the effect of clearance on the forming quality in the blanking process. J Mater Process Technol 122(2–3):249–254
5. Faura F, Lopez J, Sanes J (1997) Criterion for tool wear limitation on blanking 18-8 stainless steel strips. Rev Metal 33(5):304–310
6. Hambli R, Guerin F (2003) Application of a neural network for optimum clearance prediction in sheet metal blanking processes. Finite Elem Anal Des 39(11):1039–1052
7. Hambli R (2005) Optimization of blanking processes using neural network simulation. Arab J Sci Eng 30(1):3–16
8. Wong SV, Hamouda AMS (2003) Machinability data representation with artificial neural network. J Mater Process Technol 138(1–3):538–544
9. Jiaa CL, Dornfeld DA (1998) A self-organizing approach to the prediction and detection of tool wear. ISA Trans 37(4):239–255
10. Patil VP, Patil PP, Ingale NE (2019) Experimental investigations of optimum sheet metal blanking clearance for IS2062 HR steel using artificial neural network (ANN). In: 2019 9th annual information technology, electromechanical engineering and microelectronics conference (IEMECON), Jaipur, India, pp 12–16
11. Özel T, Nadgir A (2002) Prediction of flank wear by using back propagation neural network modeling when cutting hardened H-13 steel with chamfered and honed CBN tools. Int J Mach Tools Manuf 42(2):287–297
12. Mucha J, Tutak J (2019) Analysis of the influence of blanking clearance on the wear of the punch, the change of the burr size and the geometry of the hook blanked in the hardened steel sheet. Materials 12(8):1261
13. Hagan MT, Demuth HB, Beale MH, De Jesús O (1996) Neural network design, vol 20. PWS Pub, Boston
14. Ghosh A, Mallik Manufacturing science. IIT Kanpur, pp 148–156