Investigation of Quality of Clean-Cut Surface for Sheet Metal Blanking Using Decision Tree

Pradip Patil and Vijaya Patil

Abstract In case of sheet metal blanking, inadequate trimmed condition of such a blanked material may produce fit concerns in the assembly. Cracks may form due to uneven surfaces, leading to a loss of exterior smoothing and improved efficacy. Four underlying parameters are selected after punching: shear angle, punch penetration, burr height, fracture angle as decision-making input parameters to measure quality of clean-cut surface. The fracture depth is determined by gradually increasing the punch penetration. Experiments are conducted with uni-punch tool on the power press, and sheet metal material is IS277GI. This research aims to assess the cut surface quality using surface roughness value, which is categorized into three groups. To measure the efficiency of the cut surface, a classification model is developed adopting the machine learning decision tree classifier technique. The model's reliability is 93% of the Gini and Entropy index.

Keywords Quality of clean-cut surface · Decision tree classifier · Sheet metal blanking

1 Introduction

The metal forming business is facing challenges worldwide due to new materials and processing processes. Because the process necessitates the employment of several resources, a computerized method for assessing the blanking procedure is required. Improved approaches for studying the behavior of the sheet metal forming sector are in high demand.

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Automation is required to increase production. Given the automation level, deploying software applications in the sheet metal processing industry is advantageous. Different sensing techniques for fault diagnosis and the re-use of damaged component replace systems rapidly appearing as automation develops. However, a suitable process model is required to manage the complexity of sheet metal.

The next industrial revolution is being ushered in by advancements in automation. There has been growing research in sensing systems for defect detection and identifying significant parameters. The intricacy of the sheet metal working method, on the other hand, makes building a self-learning model challenging. With advent of mechanization, the industrial positioning in assessing defect is rapidly moving toward developing self-sustained systems. However, a suitable process model is required to manage the complexity of sheet metal processing.

While studying the process parameters in machining, research is conducted utilizing ANN modeling to increase the precision of intellectual structures [14, 21, 23] and as well as sheet metal blanking [11, 16, 17, 19]. The approach has been influenced by sheet thickness and tool wear [6, 7].

Classification model is proposed using decision tree modeling in current work, for IS277GI material for predicting fracture surface quality.

2 Literature Review

2.1 Blanking Process Setup

The process model of blanking consists of blanking die, sheet metal, blank holder, and punch as shown in Fig. 1. Suitable clearance is selected between blank and punch for obtaining smooth fracture surface. A punch with velocity shears the work-piece placed between blank holder and die. In this way, a slug, called blank, separates from the work-piece.

Figure 2 depicts blank part after shearing and the clean-cut surface. Strain at rupture is the most crucial element in determining when a fracture will begin and the propagation circumstances. From the inside die corner to the punch corner, a fracture line develops as a result of shearing. As per literature, the clearance is defined in terms of percentage of sheet thickness. Figure 3 shows mechanism of metal fracture at punch and die. Smooth sheared surface is obtained when the crack path joins the fracture line.

The previous studies on clearance identification for sheet metal employed FEM [9, 11] and FEM simulation findings were consistent with experimental investigations. They concluded that surface roughness improves when the cracks beginning at the punch and die coincides [9]. However, punch velocity and heat production during processing have a significant role on metal behavior [16]. Investigations were done into how the punch geometry affected the features of the cut surface and the cutting forces [21].

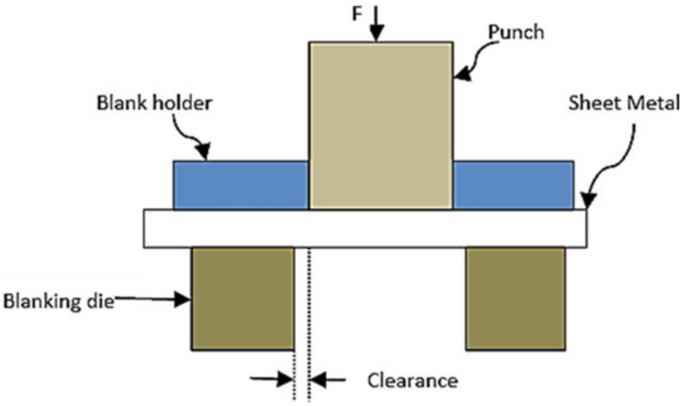


Fig. 1 Blanking procedure system [18]

Fig. 2 Slug work-piece [18]

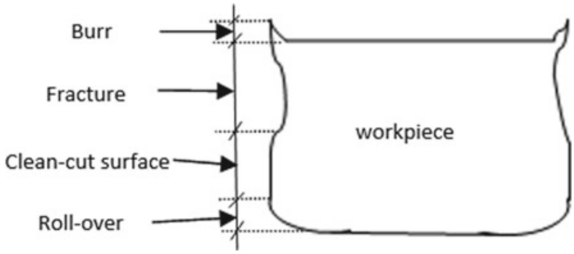
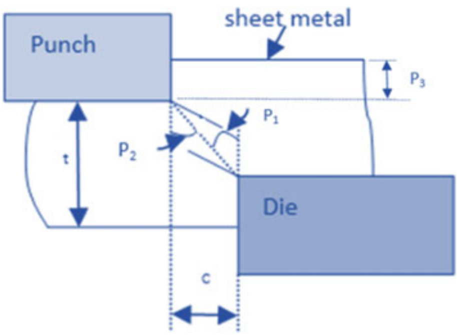


Fig. 3 Diagonal fracture line diagram [16]



$$c = 100\frac{D_m - D_p}{2t}(\%) \tag{1}$$

where D_m—die diameter, D_p—punch diameter, t—sheet thickness.

ANN is powerful methodology for studying the behavior of the turning process [12, 23], as well as the bending of sheet metal [3, 23]. The simulated system uses an algorithm that replaces the conventional judgment system. The NN is chosen to construct suitable model for predicting optimal punch-die clearance. A backpropagation neural network was used for the prediction of optimal clearance [16–18]. The data on experimental fracture angles was utilized to train the algorithm, and model is developed for a given data. While assessing the defects in sheet metal forming, [5] uses a CART, MLP, SVM, RF techniques for predicting the coil back, and utmost thinning result achieved the accurateness varying from 87.39 to 94.98%.

2.2 Decision Tree Classifier (DTC)

The decision tree (DT) algorithm is a supervised machine learning technique to solve classification and regression problems. This approach aims to develop a model that predicts the value of a targeted variable; for that, the decision tree solves the issue using the tree representation, where the leaf node belongs to a class label, and characteristics are expressed on the inner node of the tree. A classification strategy continually separates data using decision rules. Data is classified at each node for optimization of decision-making for information gain:

$$\text{Gain} = \sum_{j=1}^{m} \frac{n_j}{N_j} H\left(D_j\right)$$

where N represents the total number of data points for node j, n represents the number of data points for node j of the expected class, D represents node values, and H represents impurities [5]. The formula for impurity Gini Index is as follows:

$$I_{\mathrm{G}} = 1 - \sum_{i=1}^{C} p_i^2$$

where p_i share of sample for node.

$$I_{\mathrm{H}} = -\sum_{i=1}^{C} p_i \log_2(p_i)$$

where p_i—the proportion node fitting to a class [2]. If all node samples are of the same kind, then entropy is zero. This step is followed until the same label remains in a sample from each terminating node. A stop condition can also be established to avoid over fitting.

3 Methodology

For investigating the quality of surface, decision tree classifier is employed. The independent factors dependent, and categorical variable is chosen. Figure 4 depicts a correlation analysis using Python code to investigate the association between the independent variables through heat map generation.

The control factors are derived though literature and total of 140 data points (training and testing) and 42 (validation) data points. This study develops a DTC model by splitting data: 70% for training and 30% for testing. An estimator with a variable maximum depth is used to train the resulting model, while parameter adjustment is applied. At the depth of 5, we obtained highest accuracy for accuracy measurements in terms of training and testing, recall, precision, f1-score, and confusion matrix. At each node, we employed Gini and Entropy as impurity indices, with a maximum depth of 5 and minimum sample leaf 5. The research flowchart is shown in Fig. 5.

During training phase, progressive categorization of samples and visualization of the decision tree is developed using Python code for the detailed functioning of the Gini and progressive calculation Entropy indexes.

Figure 6 shows gradual classification of samples based on Gini index, and Fig. 7 shows iterative steps till samples are classified based on entropy.

The outcome of classification is approved if the validation (experimental) provides consistent results; the findings are directed to the DTC model training and testing for parametric optimization.

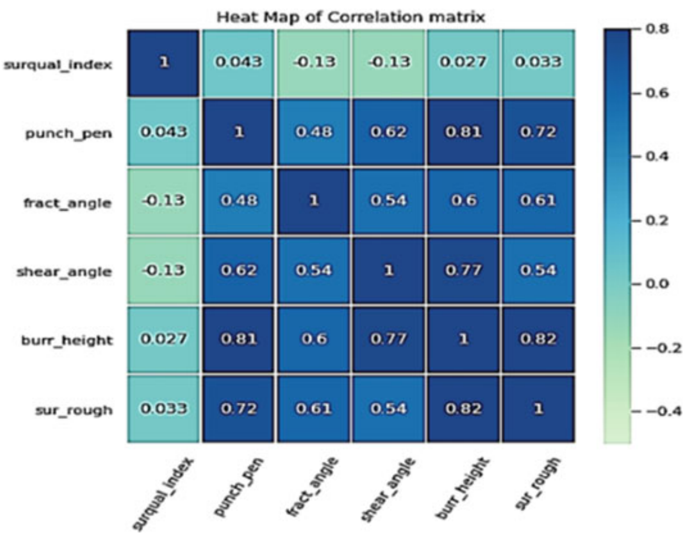


Fig. 4 Analysis of correlation

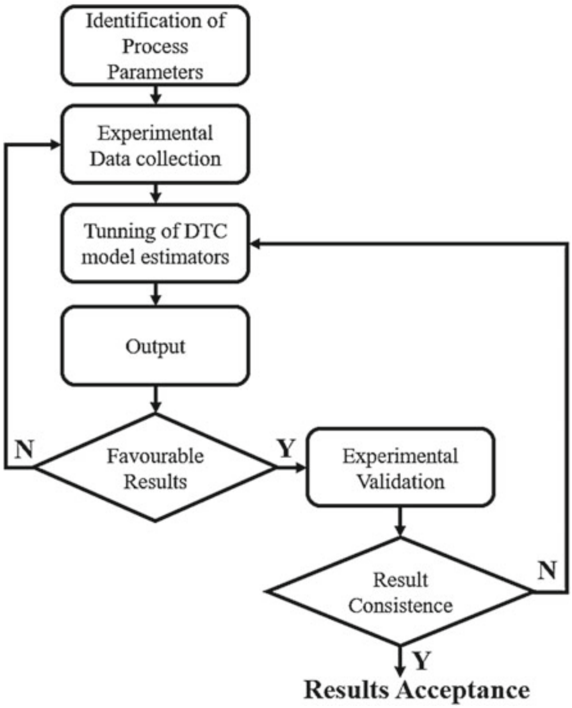


Fig. 5 Research chart

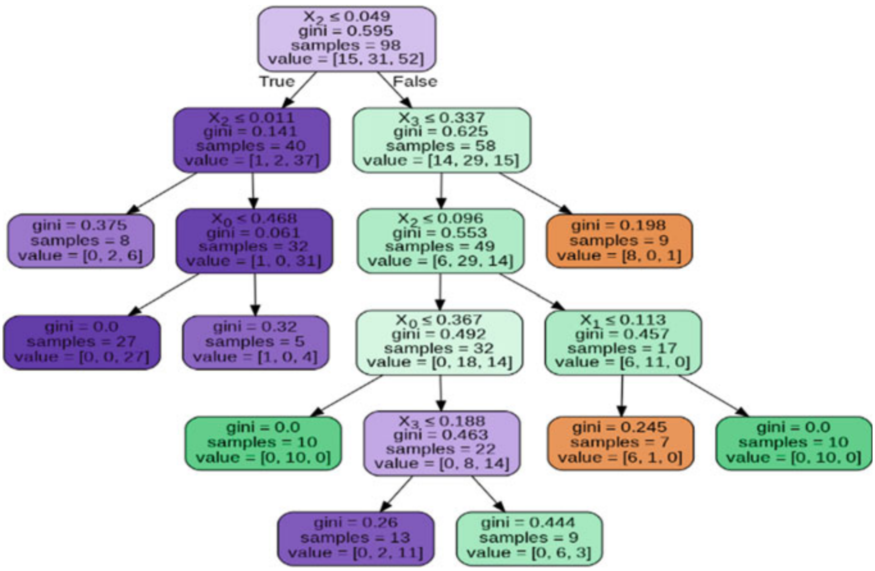


Fig. 6 Functioning of Gini index visualization

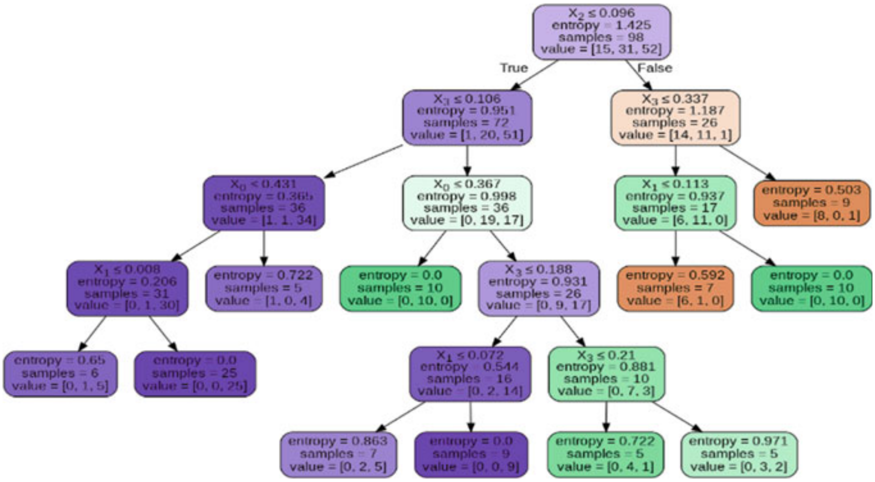


Fig. 7 Functioning of Entropy index visualization

4 Discussion and Result

Experiments are carried out for blanking operation using power press with a punch (hallow circular). Table 1 displays the input parameter and properties of 'IS277GI' for the experiment. Engineering strain and real strain are calculated using material characteristics [5].

We trained the DTC model using the Gini and Entropy index of impurity criterion, and both models obtained 93% accuracy. Figure 8 depicts a comparison of prediction performance with various classes.

Confusion matrix is an another approach employed for measuring the accuracy of model as shown in Fig. 9, to validate the performance of DTC model. During the testing phase, class 3 has all of its sample points properly identified; however, classes have a deviance of sample points (one and two).

One more performance measure for the model is receiver operating characteristic (ROC), which presents graphically performance of classification. Two variations are

Table 1 'IS277GI' mechanical properties

Properties	Percent clearance (% of sheet thickness)	Clearance (mm)	Thickness (mm)
Material elongation (%) = 48.19 Tensile strength = 301.46 True strain = 2.3 Engineering strain = 6.025 Reduction area (%) = 49.43 Yield stress = 315.43	20	0.2	1.0
	13.33	0.2	1.5

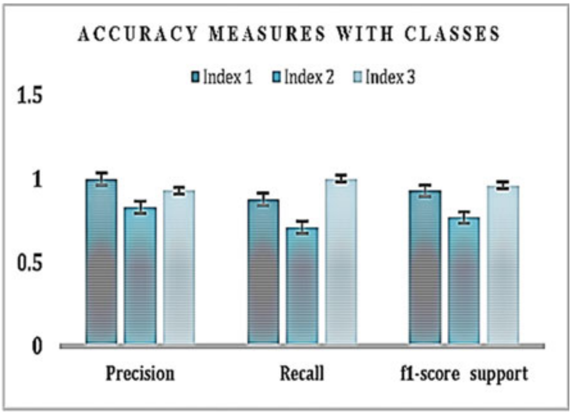


Fig. 8 Accuracy measures for different classes

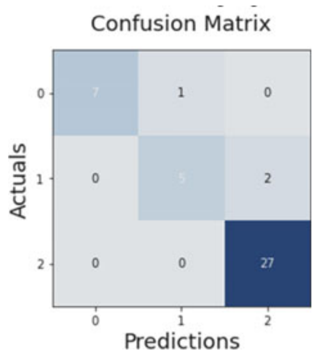


Fig. 9 Confusion matrix

plotted: the true positive rate (TPR) and the false positive rate (FPR), as shown in Fig. 10. The probability for the ROC curve of class 2 is 0.85, which is less than the probability for classes 1 and 3, which are 0.93 and 0.92, respectively.

5 Conclusion

The machine learning approach (decision tree classifier method) is used to estimate quality of the fracture surface. The result shows that punch penetration has a direct impact on burr height creation and surface roughness. When employing DTC, we discovered that both the Gini as well as Entropy index impurities provide precise model correctness for the training, testing, and validation sets. The precision metric for class one is 1, whereas the recall measure for class two is 1. With k-fold cross-validation, additional sample points would imply greater model accuracy. Other classification models, such as support vector machines and random forest, can also be investigated using the significant data points.

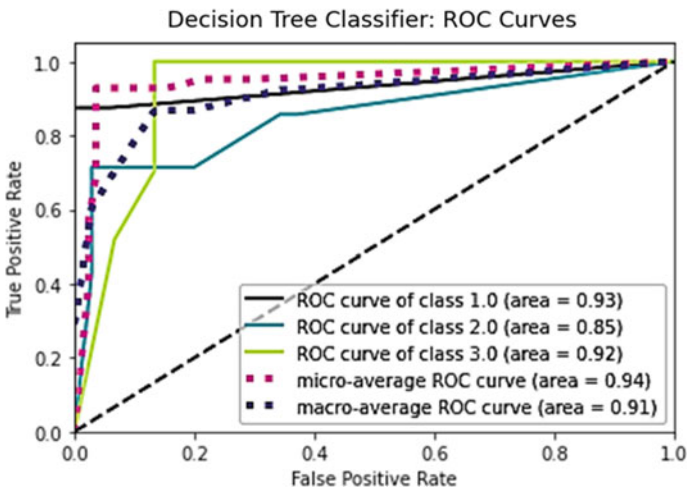


Fig. 10 ROC curve

Current study provides sheet metal production engineers with a decision-making solution for selecting the underlying factors for calculating precision for right fit requirement for processing IS277GI.

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