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Implement the Concept of Artificial Neural Networks in Studying the Sheared Edge Defects at the Sheet Metal Blanking Processes

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ABSTRACT

The quality of cut blanks is influenced by several process parameters, such as cutting speed, punch–die clearance, and workpiece material. This study investigated the effects of these parameters on sheared edge quality in sheet metal blanking of medium-carbon steel and brass. The results showed that the material type is the most dominant factor affecting edge defects; however, the values are higher in brass compared to medium-carbon steel. Also, variations in clearance-to-thickness ratio (C/T) from 3.75% to 5% lead to obvious changes in the defect indices. Regarding the cutting speed, increasing its value has significantly improved the edge's quality by reducing the deformation time and enhancing the strain-rate effects. The best experimental conditions have been obtained by using medium-carbon steel, C/T 4.25%, and a cutting speed of 480 mm/s. Furthermore, an artificial neural network (ANN) model was developed for enhancing predictive capabilities. It includes training of a three-layer architecture with inputs of the cutting speeds, clearance, and type of material. Overall, the findings provide engineering guidance in terms of optimum blanking parameters and highlight the importance of simultaneous control of process variables and material selection to improve product quality and reduce post-processing requirements.

1. INTRODUCTION

Sheet metal blanking is one of the most widely used manufacturing processes in many industrial sectors due to its high productivity, dimensional repeatability, and suitability for mass production. Its applications range from small electronic components to large automotive and structural parts. Blanking is achieved through a shearing action in which a sheet is placed between a fixed die and a moving punch. The primary objective of the process is to separate the sheet by plastic deformation followed by crack initiation and crack propagation until complete fracture occurs [1]. Depending on the position of the sheared surface relative to the workpiece, several shearing operations are used, including blanking and piercing. Both are fundamentally similar operations, and the main difference lies in the useful product and scrap portion. In blanking, the punched-out part is the required product, whereas in piercing the removed portion is scrap [2, 3], as shown in Figure 1.

During the application of punching or blanking force, the induced shear stress exceeds the ultimate shear strength of the material, causing fracture and separation along the cutting contour. A small clearance should be calculated between the punch and die edges in order to control the crack initiation and propagation through the sheet thickness [4, 5]. Although blanking and piercing processes often produce parts that do not require another machining step, dimensional and geometric defects may still occur, such as doming, edge taper inclination degree (ETID), dishing, and poor edge integrity. These defects reduce the quality in terms of dimensional precision that may negatively affect subsequent forming operations or assembly performance. Figure 2 shows some of the mentioned defects.

Since the blanking process has industrial importance, many researchers have studied and analyzed the impact of the process parameters on the dimensional accuracy, sheared edge quality, and tool life via both experimental and numerical approaches. Choi et al. [6] investigated the effects of punch–die clearance and die inclined angle on the sheared edge characteristics of trimmed DP980 steel. It has been claimed that increasing the clearance value has reduced trimming load. However, a tensile-type burr is produced with excessive clearance, while a negative inclined angle reduced cutting load and improved edge quality. Patil and Kadlag [7] presented an optimization strategy of blanking parameters using finite element analysis and the Taguchi method. The study shows that proper selection of sheet thickness, clearance value, and material properties can improve edge quality and reduce tool load. Similarly, Rawali et al. [8] used CATIA and ANSYS Explicit Dynamics to analyze the effects of the clearance, material type, sheet thickness, and punch geometry on blanking process performance and edge quality.

Kurniawan et al. [9] examined the influence of punch velocity and claimed that an increasing of punch speed would increase the punch force and burnish height when working on pure titanium sheets. In contrast, Wang et al. [10] showed that increasing blanking speed can significantly improve the edge quality of phosphor bronze sheets. This is due to the combined effects of strain-rate hardening and thermal softening. Sahli et al. [11] presented a numerical investigation of steel fine blanking and confirmed that clearance value, punch geometry, and material properties significantly influence blanking force and cut-edge finish.

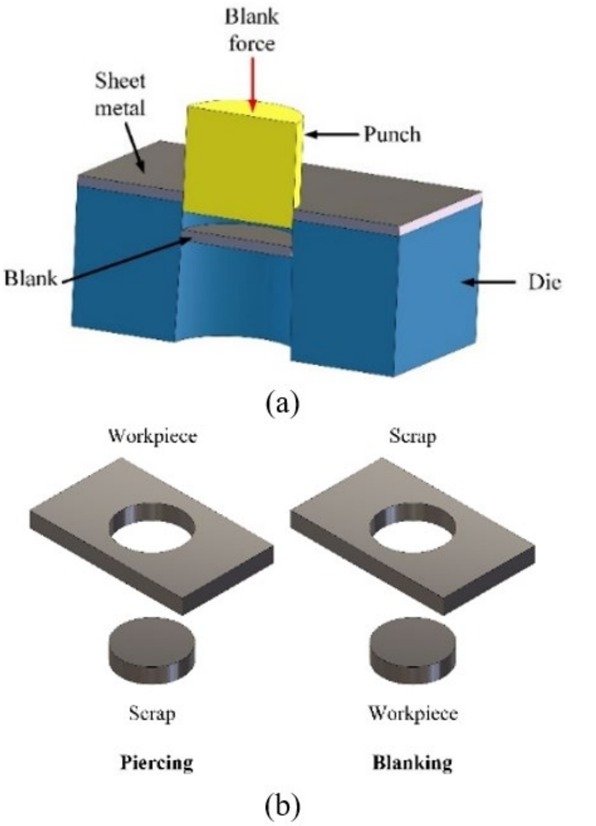


Figure 1. Sheet metal cutting (a) general process and (b) blanking and piercing

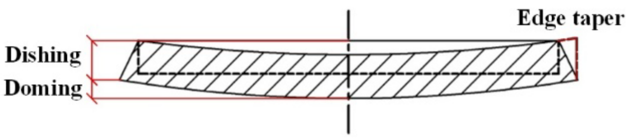


Figure 2. Three defects with a projection of an ideal dotted blank

Bohdal et al. [12] analyzed the cutting behavior in AA6111-T4 aluminum alloy sheets experimentally and numerically. The study showed that excessive knife clearance and cutting speed increased burr formation and deformation; whereas, optimized parameters produced smoother edges. Gu et al. [13] studied the effect of press speed on sheared edge formability. It was concluded that higher press speeds can reduce burrs and microcracks, while improving stretch flange ability of sheet metal components.

Lubis et al. [14] reported the impact of clearance value on sheared edge characteristics in punching of cranioplasty plates. While smaller clearances improved edge smoothness and reduced burr height, large clearances would produce irregular fracture surfaces. Lubis et al. [15] studied the combined effect of material type and thickness and found that thicker sheets required higher shearing forces and generated larger burrs. However, soft materials produced smoother edges in comparison with hard materials.

Winter et al. [16] investigated adiabatic blanking of hardened 22MnB5 steel. The authors claimed that small clearance and high cutting velocity promoted adiabatic shear band formation and improved cut-edge quality. Pätzold et al. [17] studied stainless steel blanking, where optimum clearance value provided a balance between high edge quality and lower cutting force. Whereas excessive clearance increased fracture depth and burr formation.

Bhoir et al. [18] presented experimental optimization of clearance in soft steel blanking. The authors identified a suitable clearance value range that minimized cutting force while simultaneously maintaining good edge quality. Yang et al. [19] examined the punching of ultra-high-strength steel sheets. It has been claimed that the punch geometry, corner radius, velocity, and clearance have an impact on maximum punching force and edge characteristics.

Shugailo et al. [20] proposed a mechanical model for straight cutting of thin sheets supported by an elastic foundation. The authors demonstrated the impact of elastic support on stress distribution, crack propagation, and cut surface quality. Rohaľ and Spišák [21] investigated the tool wear and its effect on burr formation. It has been confirmed that worn cutting edges strongly degrade dimensional accuracy and edge finish.

Tang et al. [22] investigated the influence of blanking clearance on sheared edge quality. The study included establishing a comprehensive multiscale framework to analyze the link between blanking clearance parameters and both microstructural characteristics and macroscopic responses. The results showed that increasing the blanking clearance reduced the surface roughness and fracture zone, whereas the rollover zone increased. Larour et al. [23] introduced advanced microscopy-based methods for evaluating cut-edge damage in high-strength sheet steels. According to the authors, it enables better detection of local deformation, burrs, and microcracks. Furthermore, Sandin et al. [24] demonstrated that cut-edge heterogeneity significantly affects edge cracking behavior in complex-phase steels, where irregular burrs and non-uniform burnish zones strongly reduce formability.

Recently, machine learning techniques have played an important role in manufacturing engineering due to their capability in establishing nonlinear relationships between process parameters and product quality. Among different techniques, artificial neural networks (ANNs), support vector machines (SVMs), random forest (RF), and gradient boosting algorithms have been effectively used for predicting machining performance, optimizing manufacturing processes, and improving product quality.

Liewald et al. [25] reviewed the application of data-driven and machine learning methods in metal forming and blanking processes. The research illustrated the potential of these techniques in improving process quality and productivity while emphasizing the necessity for reliable and explainable artificial intelligence (AI) models in manufacturing applications. Kubik et al. [26] presented a deep learning-based domain adaptation model that achieves real-time tool wear monitoring in sheet metal blanking processes. According to the authors, the system is able to achieve up to 95% classification accuracy. However, it detects only tool wear and does not address the prediction of sheared-edge quality or blanking defects. Schenek et al. [27] applied an ANN model to predict cutting surface quality in punching processes using tooling parameters and material characteristics. The model is able to capture the nonlinear relationships affecting cutting-edge quality, demonstrating the effectiveness of ANN for data-driven optimization of sheet metal cutting processes.

Tuninetti et al. [28] studied feed-forward backpropagation ANNs to detect the parameters of the Johnson–Cook constitutive model. The proposed framework achieves high prediction accuracy and illustrates that ANN models can effectively capture complex nonlinear material behavior. It also provides an efficient replacement to conventional parameter identification methods. Claver et al. [29] presented a model for optimizing the steel punching process via experimental tests and finite element simulations following the Johnson–Cook damage concept. The results showed that the clearance has greater influence on cut-edge quality in comparison to the punching speed. The lower clearance improves the burnish surface and reduces crack formation. The proposed method demonstrated effectiveness for predicting cut-edge characteristics and optimizing punching performance. Bhoir et al. [30] developed a hybrid Taguchi–regression method to optimize the punch–die clearance value and predict burr height in aluminum and brass blanking processes. The results showed that clearance was the dominant factor affecting burr formation, while the developed regression models accurately predicted burr height, demonstrating the effectiveness of data-driven optimization for improving blanking quality.

Although many research papers studied the influence of blanking parameters on sheared edge quality, they have focused on assessing individual edge characteristics, one type of workpiece material, or traditional statistical optimization techniques. Furthermore, most of the studies that employed ANNs have focused on predicting an individual response or machining-related output rather than simultaneously modeling multiple sheared-edge defects in sheet metal blanking. Hence, a clear gap still exists in developing a comprehensive predictive framework that can bridge process parameters with several critical edge-quality indicators for different engineering materials.

The novelty of the proposed work lies in the integration of practical experimental investigations with an ANN-based predictive model to simultaneously predict three essential sheared-edge defects (doming, edge taper, and dishing) under the combined influence of clearance, cutting speed, and material type. The purpose of using two materials (AISI 1048 steel and CuZn30 brass) in this study is to enable a better understanding of how different mechanical properties influence sheared-edge defect formation. Also, the developed ANN model represents a rapid and reliable prediction tool within the investigated processing window. While this model reduces the necessity for extensive experimental trials, it also assists in selecting suitable blanking parameters.

Regarding the blanks' defects, these were selected because they are considered major indicators of sheared-edge quality and dimensional accuracy. They also reflect the material flow behavior during the blanking process and significantly influence the subsequent manufacturing operations such as assembly, bending, and deep drawing. Thus, predicting these defects simultaneously provides a more complete validation of blanking quality than evaluating a single edge characteristic. Figure 3 shows the overall workflow of the proposed study. It highlights the relationship between all the research phases, including the objectives, the experimental investigation, the development of the ANN model, and the performance evaluation.

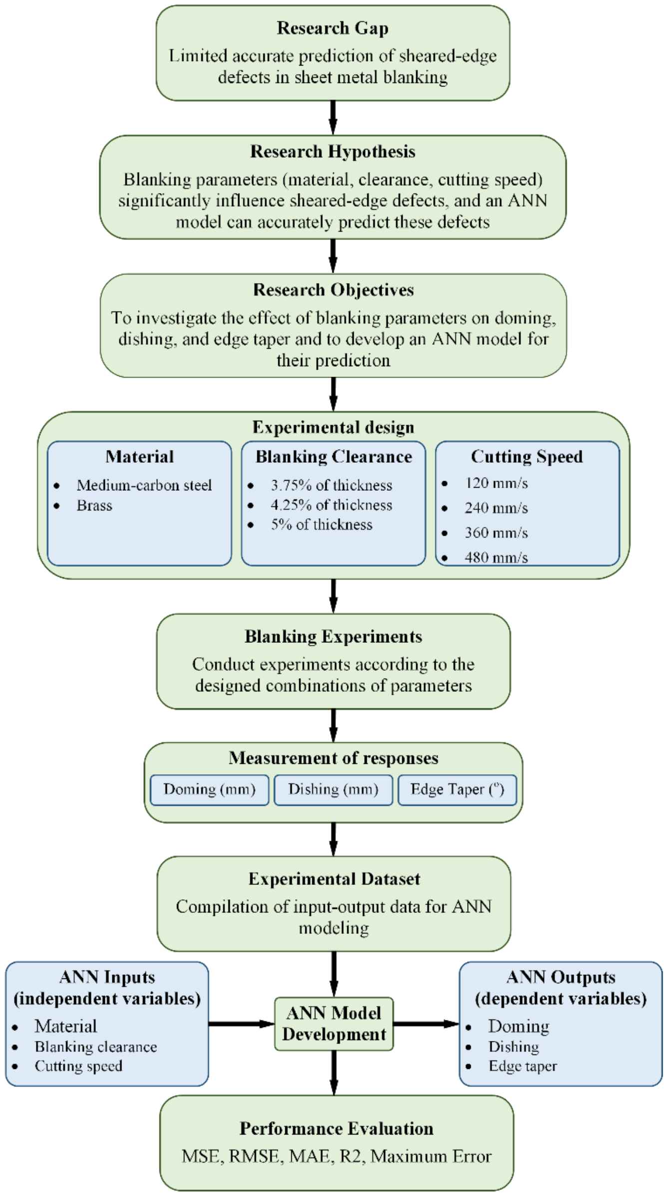


Figure 3. The general workflow of the proposed study

2. BLANKING PROCESS PHASES

The blanking operation can be divided into a number of sequential stages in which the sheet metal experiences deformation followed by complete separation [2, 5, 11], as illustrated in Figure 4.

a. Contact of punch: At the beginning of the operation, the punch contacts the steady sheet surface. At the moment of impact, a compressive stress is rapidly generated at the punch and a shock wave is transmitted through the tool.

b. Elastic and plastic deformation: When the punch moves down towards the sheet, an elastic deformation is formed at the material, followed by plastic deformation as the applied stress continues to rise.

c. Initiation and propagation of crack: Next the stress level becomes sufficiently high, shearing begins and cracks are initiated from both the punch side and the die side of the sheet.

d. Fracture of the sheet: When the cracks are formed due to the punch and die meeting, a complete separation of the material occurs. If the sheet is thick or possesses high strength, a greater blanking force is required. During fracture, compressive energy is stored in the tooling system. Once full separation takes place, this stored energy is suddenly released, producing a shock that may sometimes cause punch failure.

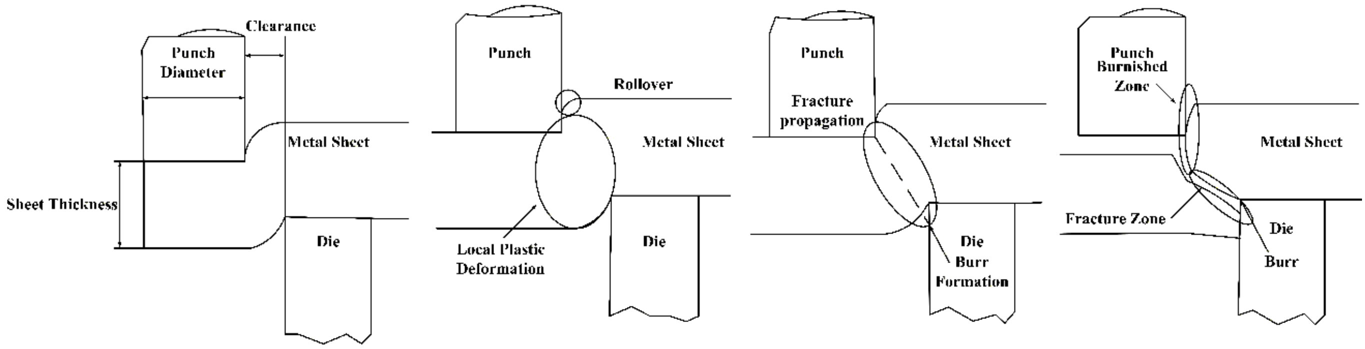


Figure 4. Schematic diagram of blanking: (a) punch contact with the sheet, (b) plastic deformation of the sheet, (c) initiation and propagation of crack, (d) fracture of the sheet [19]

3. CHARACTERISTICS OF PART EDGE

The edge of the blank is produced after the blanking operation is composed of several distinct regions formed as a result of material deformation and fracture during the cutting process [18]. These zones, together with their corresponding deformation modes, are illustrated in Figure 5.

•Roll over zone: a rounded region formed due to plastic deformation of the material at the initial stage of punch penetration.

•Shear zone: a smooth and bright surface generated during the actual shearing action of the material.

•Fracture/rupture zone: a rough region produced after crack initiation and propagation through the sheet thickness.

•Burr zone: a raised edge formed mainly because of plastic deformation near the final stage of separation.

•Secondary shear: occurs when the cracks from the punch side and die side do not meet properly, causing the material to be sheared again.

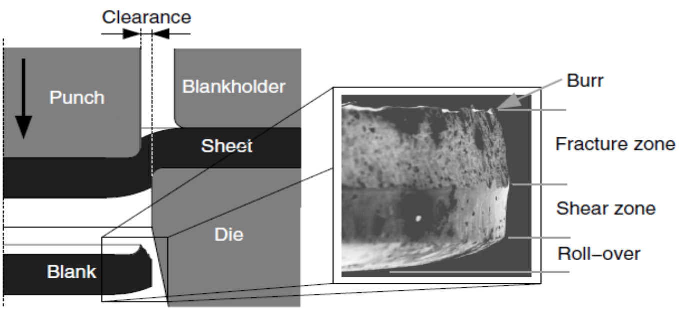


Figure 5. Zones of blank edge [18, 5]

4. PARAMETERS AFFECTING THE BLANKING PROCESS

Process variables have a major influence on the final geometry and quality of parts produced by blanking operations. The characteristics of the sheared edge are among the most important quality indicators in sheet metal cutting. These characteristics depend not only on the mechanical properties of the work material, but also on several operating parameters such as punch–die clearance, sharpness of the cutting edges, and punch speed. The principal factors affecting blanking and piercing processes are as follows:

4.1 Cutting clearance

Clearance *C* is defined as the gap per side between the punch and die, as illustrated in Figure 6. The clearance between punch and die is considered one of the most important design parameters because it strongly affects the condition of the sheared surface [14, 18]. In the case when the clearance is very small, extra layers of material should be sheared before complete separation occurs. Whereas a suitable clearance allows cracks to arise at both the punch and die edges in a controlled manner. These cracks then move toward each other until they meet and produce a cleaner fractured surface [5].

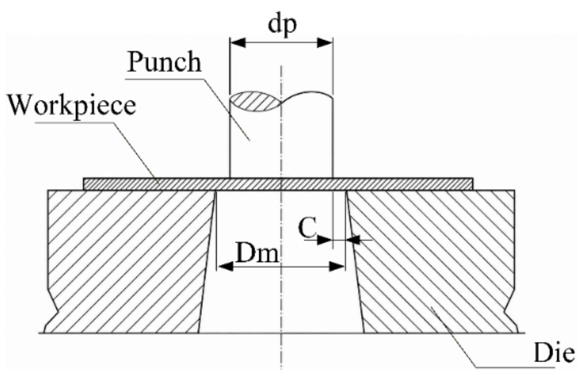


Figure 6. Clearance between punch and die

However, an excessive clearance can cause a tapered cut edge because the exit side of the material generally follows the die opening size after cutting [4, 5]. Clearance is commonly designed as a percentage of the sheet thickness. This value is approximately 10% of the sheet thickness, and for more precise calculation, it can be determined using Eq. (1) [4, 5, 14]:

$$C\% = \left(\frac{Dm - dp}{2t}\right) * 100 \qquad (1)$$

where, *Dm* is the die diameter, *dp* is the punch diameter, and *t* is the sheet thickness.

4.2 Material type and thickness

Material selection is considered an important factor in blanking because each material possesses different mechanical and chemical properties. Hence, it directly influences the cutting behavior and quality of the blanked part. To obtain good dimensional control, accuracy, and repeatability, the material type must be carefully considered. Different components require different materials according to service requirements; therefore, a variety of sheet metals are used in blanking operations [13].

Materials having high ductility, low yield strength, and homogeneous structure generally provide better edge quality, closer dimensional tolerances, and longer tool life [1]. Material properties also affect the clearance that should be selected. In addition, for a given material, the energy required for blanking is influenced by sheet thickness. Blanking energy decreases as the clearance-to-thickness ratio (C/T) increases, while it rises with increasing sheet thickness [5, 8].

4.3 Cutting speed

Blanking speed is one of the important technological parameters in the blanking process. It affects both the quality of the cut surface and the magnitude of the blanking force. Selection of punch velocity is not straightforward because its influence varies according to the material being cut [9].

The quality of the blanked edge improves noticeably with increasing blanking speed due to the combined effects of strain-rate hardening and thermal softening. For instance, the amount of the shear zone on the blanked edge increases when the cutting speed becomes higher [10].

5. MATERIALS AND EXPERIMENTAL PROCEDURES

5.1 Material selected

Material selection is an important factor in the blanking process because different materials possess different mechanical and chemical properties, which directly influence the cutting behavior and quality of the blanked parts. In the present study, the specimens were produced from AISI 1048 steel and CuZn30 (commercial grade) sheets with a thickness of 2 mm, as these materials are commonly used in industrial blanking applications. The chemical compositions of medium-carbon steel and brass are presented in Tables 1 and 2, respectively.

Table 1. Chemical composition of AISI 1048 steel

C%	Mn%	Cr%	Si%	S%	Ni%	Mo%	Fe%
0.48	0.74	0.85	0.35	0.02	0.03	0.001	other

By performing tensile tests, the mechanical characteristics of the blank can be determined. When uniaxial tensile testing is concerned, tensile specimens were tested by uniaxial tensile tests according to ASTM E8. Sections were made at 0° with regard to the rolling direction of the sheets. All tensile tests are performed with utilizing computerized general examination device (WDW-200E). The cross-head velocity is set to 0.2 mm/s; the mechanical properties for the two materials are shown in Table 3.

Table 2. Chemical composition of CuZn30

Cu	Zn	Fe	Pb	Sn	Al	Ni	Other
70	28.5	0.25	0.35	0.1	0.02	0.2	-

Table 3. Mechanical properties of AISI 1048 Steel and CuZn30

Material	Yield Strength (MPa)	Ultimate Tensile Strength (MPa)	Strain Hardening (n)	Total Elongation (%)
AISI 1048	370	610	0.18	21
CuZn30	205	410	0.45	35

5.2 Experimental procedures

A blanking die set was designed and manufactured to produce the required workpieces while allowing easy replacement of the effective components, as shown in Figure 7. The die was prepared to manufacture circular blanks of 30 mm diameter from sheets with a thickness of 2 mm. All punches and dies were fabricated from X12M die steel. The tooling components were heat treated by oil quenching from 1050 °C followed by tempering at 300 °C. Three flat-ended punches with different diameters (29.85, 29.83, and 29.80 mm) were employed to obtain different radial clearance ratios of 5.00%, 4.25%, and 3.75% (C/T), while the die diameter was kept constant at 30 mm.

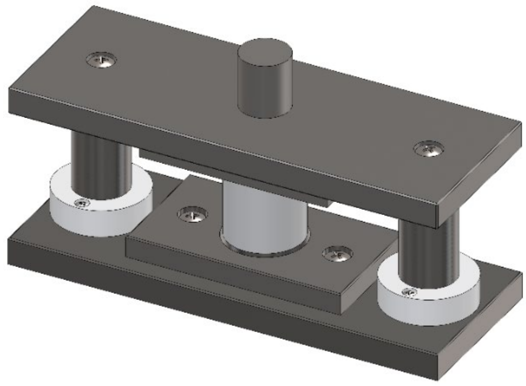


Figure 7. The construction of the used tool set

The blanking tests were carried out using a 15-ton mechanical press equipped with variable cutting speed capability. Four punch speeds of 120, 240, 360, and 480 mm/s were used. The experimental work was performed in two stages. The first one includes the use of varied punch diameters to get different radial clearances while keeping a constant die profile diameter. Whereas the punch velocity was changed at the second stage for the purpose of studying the influence of cutting speed.

The punch was operated under a constant downward motion throughout all the experiments with the prespecified cutting speed during each blanking stroke. Also, all process parameters, except the investigated variables, were kept fixed to remove their influence on edge quality. However, this also requires performing the experiments under dry conditions without any lubrication. In order to study the wear effect, the punch and die were inspected before and after the experimental campaign. As a result, there was no noticeable wear or edge damage at the punch and the die during the conducted experiments. Hence, it is suggested that the tool wear has a negligible influence on the obtained results.

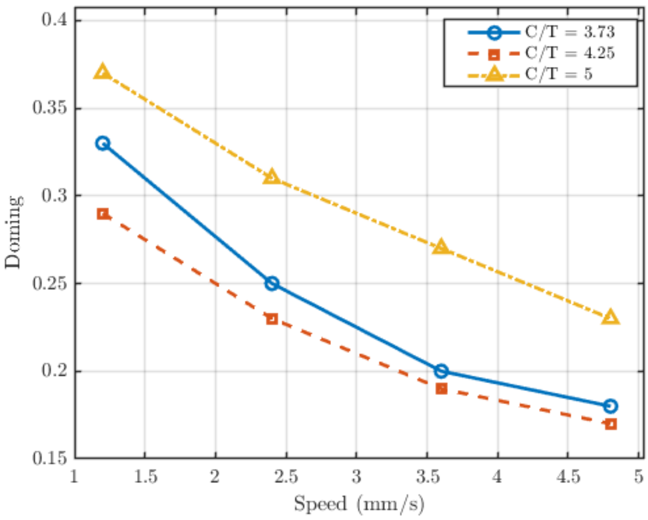
In order to evaluate the dimensional accuracy and edge quality of the produced blanks, the values of dishing, doming, and edge taper on sectioned, polished, and mounted specimens were measured. This is achieved using a PT300 profile projector at a magnification of X10. Three samples were examined for each experimental condition. Then, the average value was stated to ensure measurement reliability. The projector enabled precise determination of both profile deviations and edge geometry resulting from the blanking process.

6. PRACTICAL RESULTS

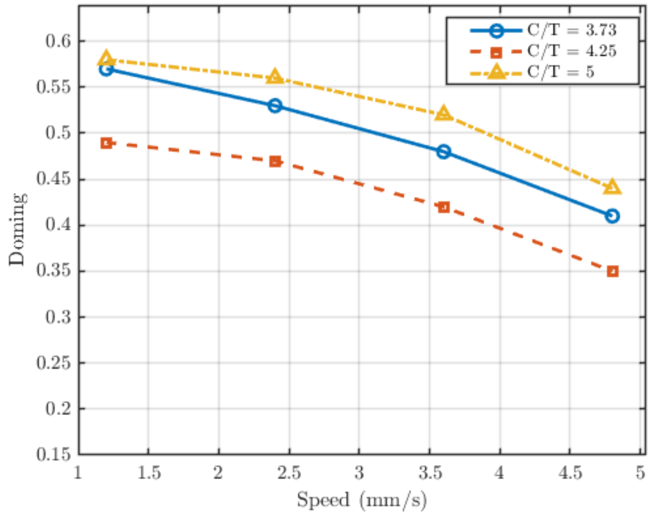
The quality of the sheared edge is considered one of the most important criteria in the blanking processes. It can be affected by the material characteristics and the process parameters. In this research, the effect of some blanking process' parameters was studied. The parameters include the cutting speed, shearing clearance, and material type, the studied criteria are the amount of doming, dishing and edge taper.

6.1 Influence of cutting speed

In order to analyze the effect of the cutting speed on the blanking process, four different cutting speeds were considered (1.2, 2.4, 3.6, 4.8) mm/sec simultaneously with various percentages of radial clearance (3.75%, 4.25%, and 5%). This is achieved for two materials, medium-carbon steel and brass, to study the doming defect, as shown in Figure 8(a) and (b), respectively. A quick glance at this figure shows that the doming value decreases inversely with increasing cutting speed for both materials. This result can be attributed to the fact that higher cutting speeds reduce the deformation time during the blanking process. Also, when the cutting speed increases, the fracture occurs more rapidly. Hence, it limits the plastic deformation, material flow, and localized bending around the cutting zone. Furthermore, it has been noticed that the values of doming for brass material are higher in comparison with the value for steel, due to the higher ductility and lower yield strength of brass.

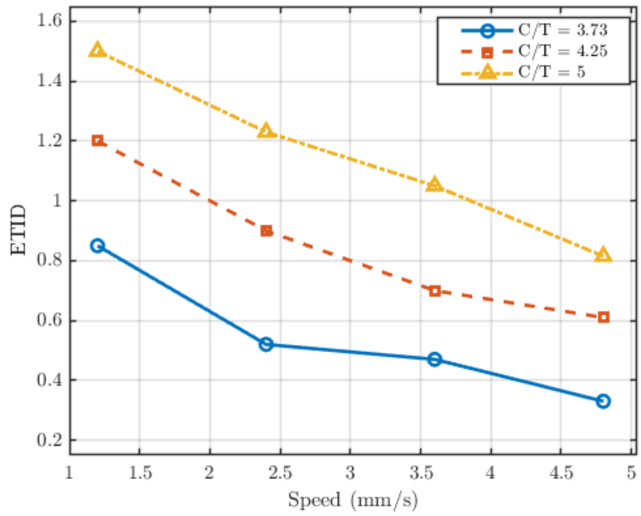


(a)

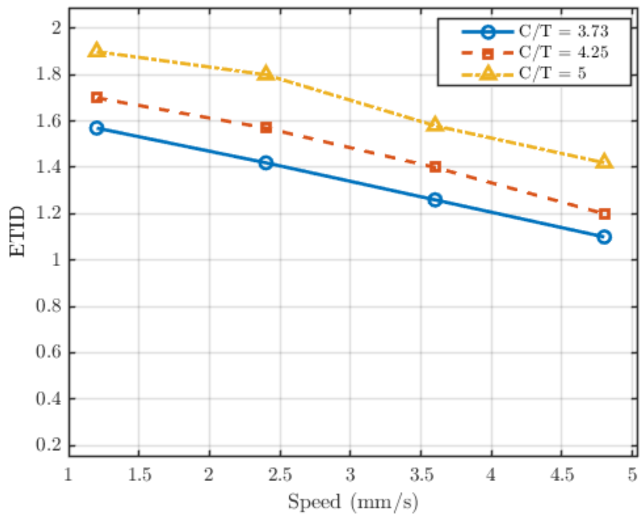


(b)

Figure 8. The effect of cutting speed on the doming defect (a) AISI 1048 (b) brass



(a)



(b)

Figure 9. The effect of cutting speed on the edge taper inclination degree (ETID) (a) AISI 1048 (b) brass

Figure 9 illustrates the effect of the cutting speed on the edge taper of the blank. It can be noticed from the figures that the edge taper, which is a defect, decreased as the cutting speed increased. However, during the blanking process, the brass material is exposed to high plastic deformation and material flow before fracture. Consequently, it causes higher edge distortion and a more tapered edge profile.

The effect of the cutting speed on the dishing is presented in Figure 10 following the same previous conditions. The results show that at higher cutting speeds, the interaction time between the tool and workpiece decreases; hence, this limits material deformation and reduces the dishing defect. However, the dishing values of brass remain higher in comparison with steel due to its higher ductility and greater tendency for plastic flow.

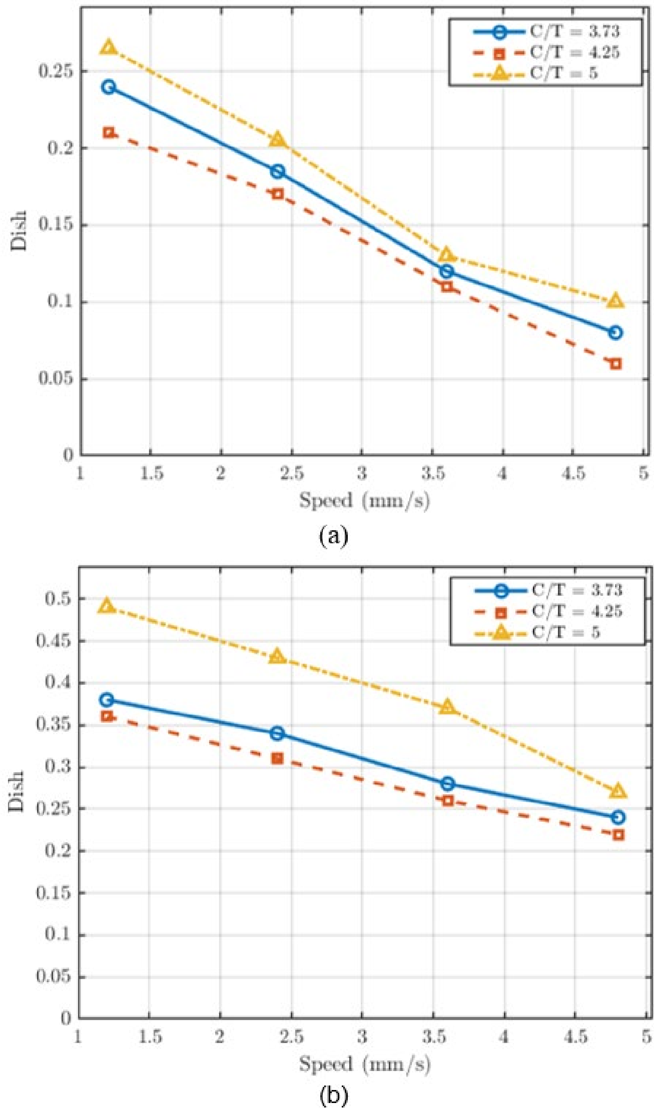


Figure 10. The effect of cutting speed on the dishing (a) AISI 1048 (b) brass

The sheared-edge defects of AISI 1048 steel and CuZn30 brass exhibit different characteristics. This can be explained by their deformation and fracture mechanisms during the blanking process. Since AISI 1048 steel has a higher yield strength and lower ductility in comparison with CuZn30 brass, it shows a limit to excessive plastic deformation before fracture. Thus, it is possible to notice crack initiation after a relatively smaller amount of localized plastic flow, and the generated cracks grow directly toward each other. Such a behavior produces a more uniform sheared edge with lower doming, dishing, and edge taper.

In contrast, CuZn30 brass has a larger strain-hardening exponent and higher ductility, which enables the material to withstand greater plastic deformation before fracture initiation. This attitude promotes larger doming and dishing defects, while the extended plastic deformation alters the crack propagation path, leading to greater edge taper and reducing the dimensional accuracy.

6.2 Influence of the clearance percent

Three flat-ended punches with different diameters of 29.85 mm, 29.83 mm, and 29.80 mm were manufactured for the purpose of investigating the effect of the clearance between the punch and die. This was provided with radial clearance percentages of 3.75%, 4.25%, and 5%, respectively.

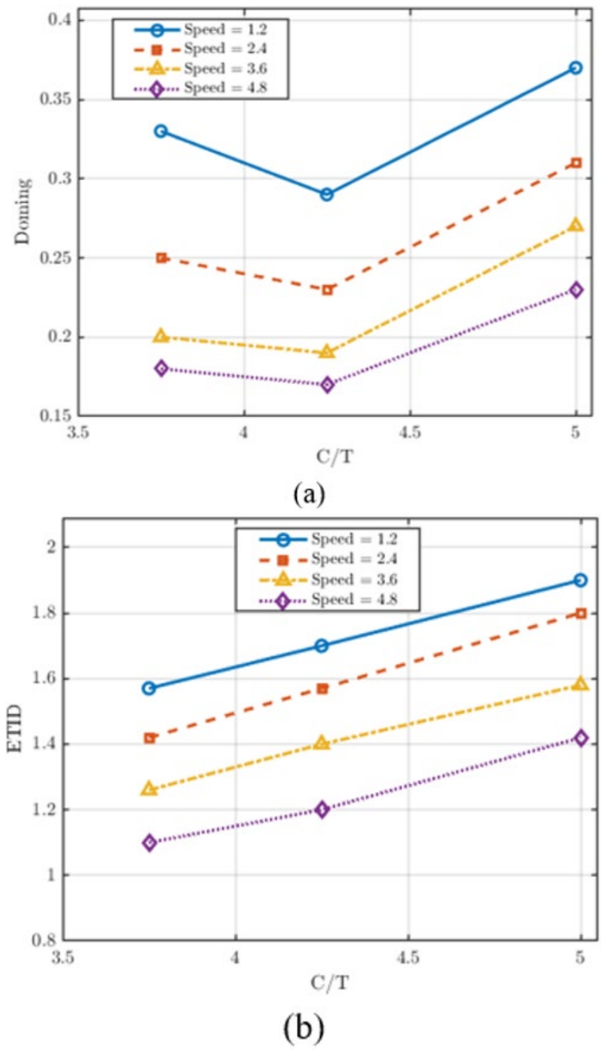


Figure 11. The effect of clearance-to-thickness ratio (C/T) on the doming (a) AISI 1048 (b) brass

Figure 11 shows the effect of the radial clearance percentage on the doming defect. It clearly indicates that the lower values of doming occur at a clearance percentage equal to 4.25% because this value of clearance performs the optimum shearing condition between the punch and die. Moreover, the stress distribution during the blanking process becomes more uniform at this value of clearance. This consequently produces smoother crack propagation and lower plastic deformation around the cutting zone.

The relationship between the radial percentage and the edge taper in the blank for the medium-carbon steel and brass is shown in Figure 12, respectively. A smaller clearance value provides better support for the material during the blanking process. Hence, it reduces side material flow and minimizes bending deformation near the cutting edge. As a result, the cut edge becomes straighter and more uniform, which leads to lower edge taper values for both materials. However, when the radial clearance increases, the unsupported gap between the punch and die becomes larger, causing greater plastic deformation and material bending even before fracture occurs. This increases the inclination of the cut edge and consequently increases the defect of edge taper.

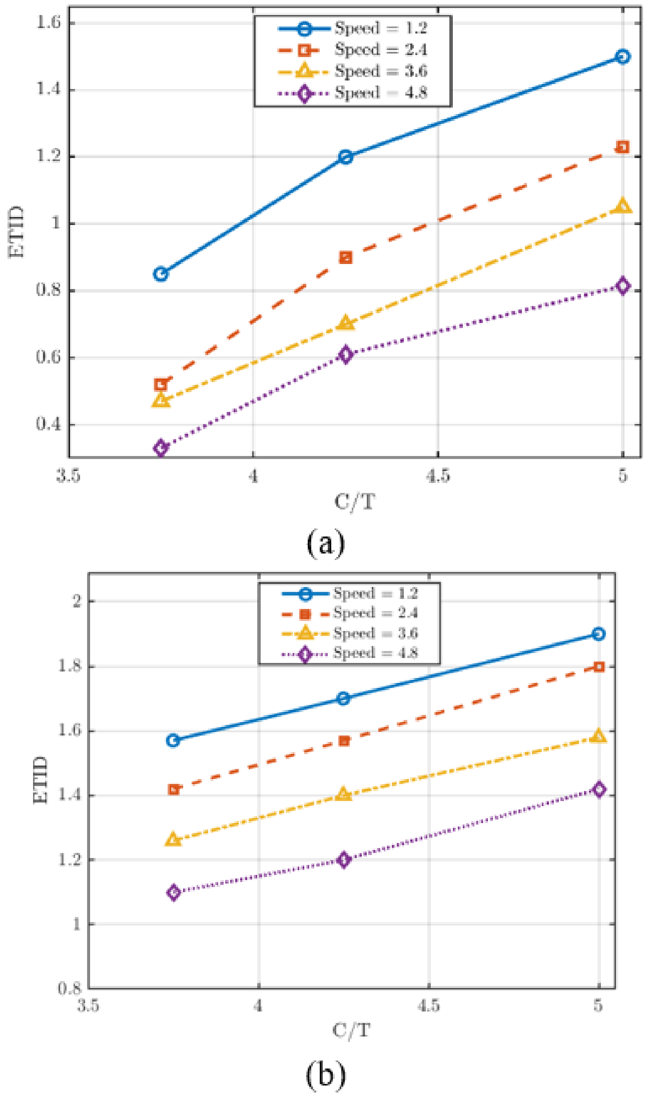


Figure 12. The effect of clearance-to-thickness ratio (C/T) on the edge taper inclination degree (ETID) (a) AISI 1048 (b) brass

Finally, the effect of the radial clearance percentage on the dishing defect is illustrated in Figure 13. It can be observed that the lower dishing value occurred at a clearance percentage equal to 4.25% for all the tested speeds. This statement holds true for the two materials used. At this clearance value, the stress distribution between the punch and die appears more uniform; hence, it promotes smoother crack initiation and propagation while at the same time minimizing excessive bending and drawing deformation around the cutting zone.

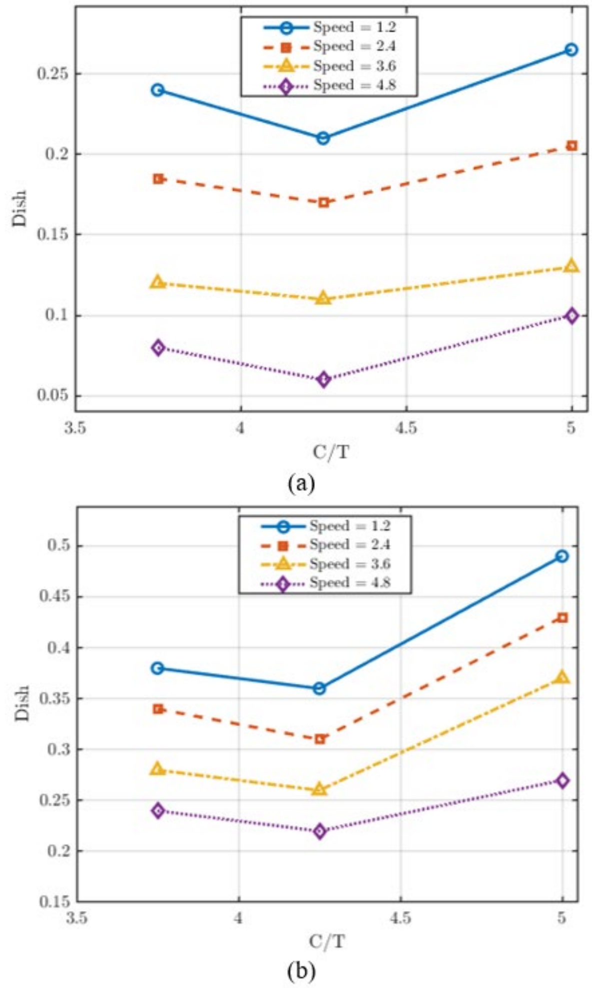


Figure 13. The effect of clearance-to-thickness ratio (C/T) on the dishing (a) AISI 1048 (b) brass

7. ARTIFICIAL NEURAL NETWORK

After completing the shape defect measurements, an ANN tool has been applied for learning-based information processing to cover pattern recognition, data classification, and application-based problems. The neural network (NN) involves three layers commonly called: input, hidden, and output. The input layer consists of three input neurons: material type, cutting speed, and clearance. The measurement task comprises three separate output parameters; each one needs 24 trials; hence, the input matrix has been built as 3 × 24. To account for various response variables in each criterion, the output matrix was set to 3 × 24. The performance of the hidden layer is determined by the relationship between the inputs and the weights applied to its components. However, MATLAB's default initialization procedure was used to automatically initialize the biases and initial weights. The preliminary trials were conducted using ANN architectures 15 and then 10 hidden neurons. Then, the architecture containing 10 hidden neurons was selected since it achieved comparable predictive performance while maintaining a simpler network structure, thereby reducing unnecessary model complexity. It is essential to mention that the developed ANN model works as a process-specific predictive model, which is precisely suited for the analyzed manufacturing domain. The experimental dataset was created based on a 24-case Full Factorial Design of Experiments (DoE). Consequently, it ensures a systematic coverage of all investigated combinations of material, cutting speed, and C/T within the selected operating domain. Hence, the predictive capability of the proposed ANN is intentionally limited to the investigated parameter ranges (speed: 1.2-4.8, C/T: 3.75%-5%) rather than being presented as a universally generalizable model. Furthermore, model development incorporated a separate validation stage and early stopping during training in order to reduce the possible overfitting, while the reported performance metrics were gained from independent testing data within the investigated experimental domain. In this study, the NN model utilizes the back-propagation technique for learning in order to modify these weights, successfully detecting and adopting input correlations. The procedure begins with sending various sets of input data to the network. Then, the algorithm progressively updates the weight values based on the errors found since it compares the predicted results to the actual outcomes. The output layer uses a single neuron to represent the doming, ETID, and dishing values for each table based on practical computations. The values are presented as a 1 × 24 matrix. Figure 14 illustrates the NN design.

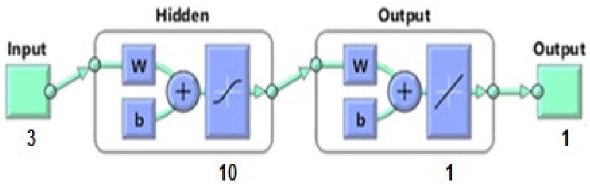


Figure 14. An illustration of the used neural network (NN) architecture

Table 4. The output response observation

Network Configuration	3-10-1
Training Algorithm	Levenberg-Marquardt (trainlm)
The transfer function type	Tansig
Number of epochs	2000
The learning rate factor (α)	0.01
Size of neuron	10

The purpose of using ANN in this research is to predict outcomes and then compare them with data from actual tests, which were also employed to train the NN. Three classifications compose the model's data: 70% training, 15% validation, and 15% testing. Since this research includes many experiments and a lot of data in terms of inputs and outputs, these are classified into three sectors based on the type of defect as an output in the ANN: doming, ETID, and dishing. However, each sector has the same inputs, which are: type of material, cutting speed, and C/T. Also, for all three sectors, the Levenberg-Marquardt method generated extremely accurate results, showing a high degree of agreement between the ANN predictions and the experimental data. Regardless the output data, the three sectors share the same typical response, as demonstrated in Table 4.

7.1 Artificial neural network training performance

The performance of the NN model in terms of mean squared error (MSE) for the training, validation, and testing datasets, including epochs for the three sectors of doming, ETID, and dishing, is shown in Figure 15, respectively. The three sectors' highest validation performance was found at various phases of training, suggesting that the models successfully specialized to the validation data. The first sector's performance peak at epoch 1 with an MSE of 0.00028756, whereas the second sector reached its peak with an MSE of 0.00019621 at epoch 0. Finally, the third sector reached its peak with an MSE of 2.2604^{e-13}.

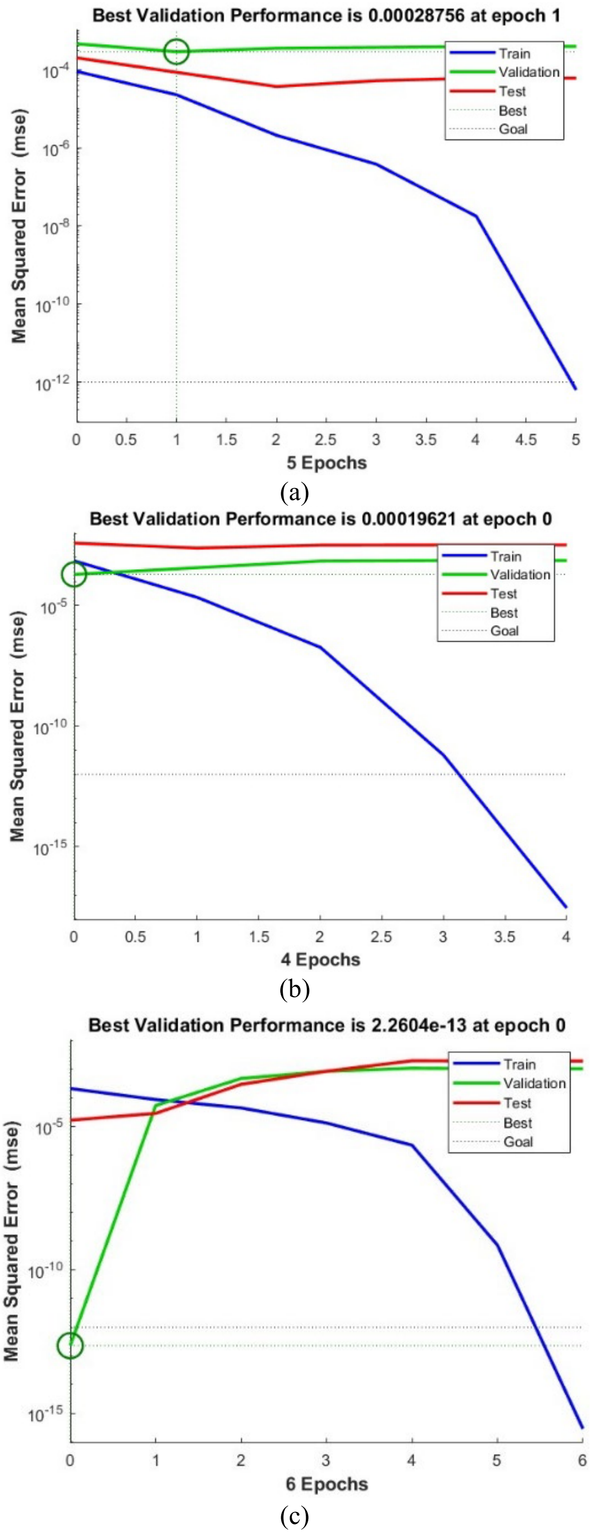
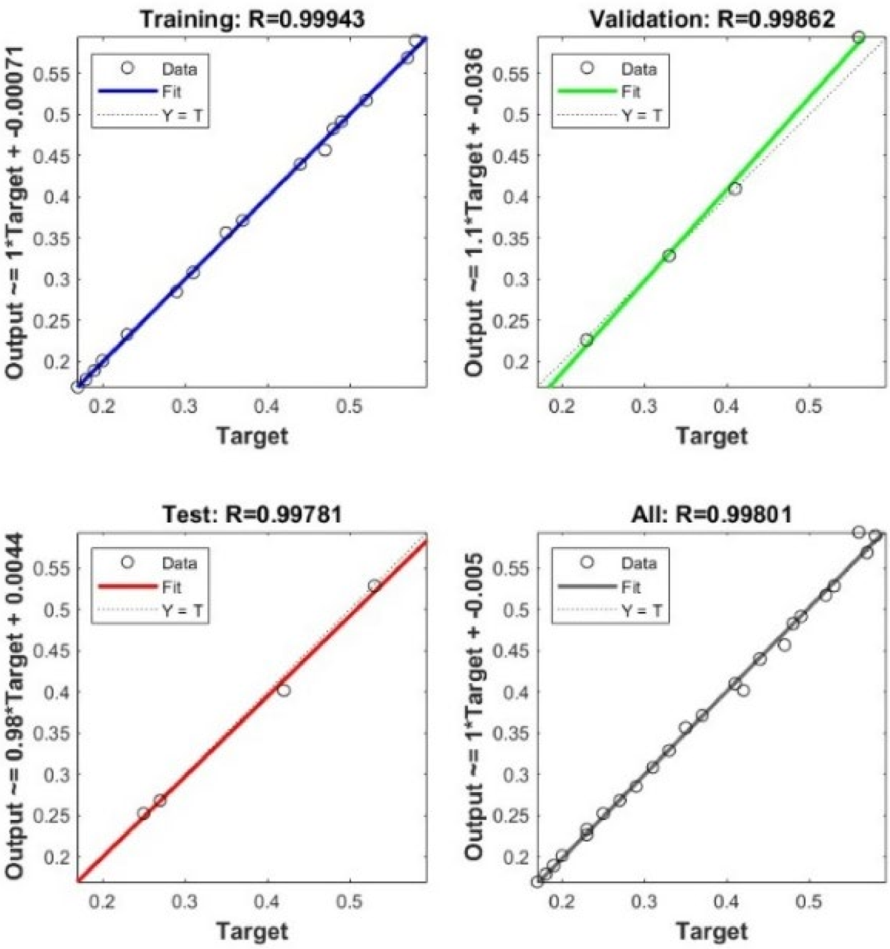
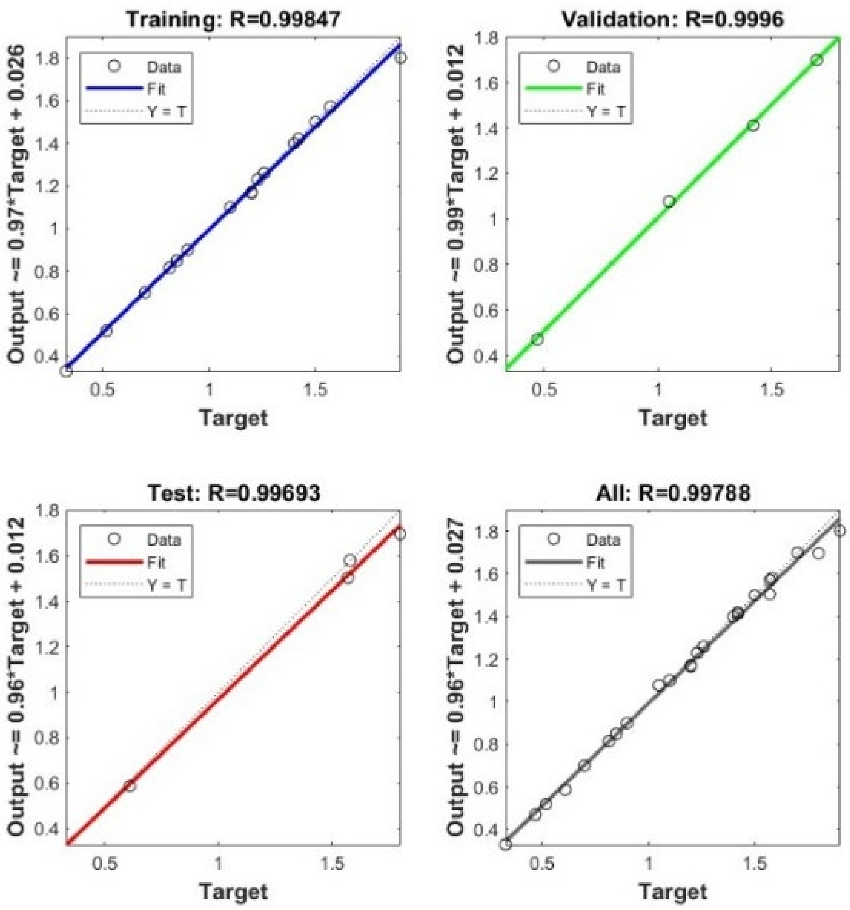


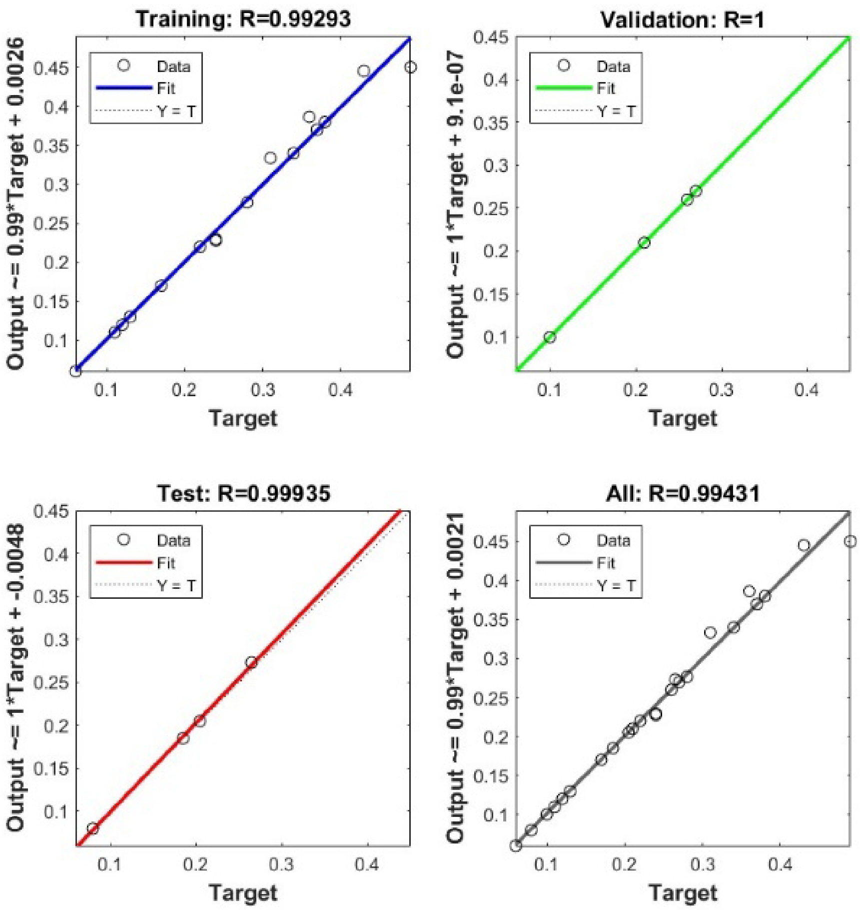
Figure 15. Performance plot of three sectors (a) doming (b) edge taper inclination degree (ETID) (c) dishing


Training: R=0.99943
Output ~= 1*Target + -0.00071
Target
Data
Fit
Y = T
Validation: R=0.99862
Output ~= 1.1*Target + -0.036
Target
Data
Fit
Y = T
Test: R=0.99781
Output ~= 0.98*Target + 0.0044
Target
Data
Fit
Y = T
All: R=0.99801
Output ~= 1*Target + -0.005
Target
Data
Fit
Y = T

(a)


Training: R=0.99847
Output ~= 0.97*Target + 0.026
Target
Data
Fit
Y = T
Validation: R=0.9996
Output ~= 0.99*Target + 0.012
Target
Data
Fit
Y = T
Test: R=0.99693
Output ~= 0.96*Target + 0.012
Target
Data
Fit
Y = T
All: R=0.99788
Output ~= 0.96*Target + 0.027
Target
Data
Fit
Y = T

(b)



(c)

Figure 16. The connection between predicted outputs and actual target values (a) doming (b) edge taper inclination degree (ETID) (c) dishing

Regarding the regression analysis, the correlation coefficients (R) are determined for the training, validation, testing, and overall correlation. This process is achieved throughout each of the three sectors of doming, ETID, and dishing as shown in Table 5 and Figure 16, respectively. The sub-figures provide information about the models' performance by assessing their accuracy and generality for the specified experiment.

Table 5. Correlation coefficients (R) of the developed artificial neural network (ANN) model for predicting the investigated blanking defects

Output Variable	Training (R)	Validation (R)	Testing (R)	Overall (R)
Doming	0.99943	0.99862	0.99781	0.99801
ETID	0.99847	0.9996	0.99693	0.99788
Dishing	0.99293	1	0.99935	0.99431

Note: Edge taper inclination degree (ETID).

7.2 Prediction performance

Different statistical error metrics were calculated by comparing the predicted values with the corresponding experimental measurements to assess the predictive performance accuracy of all the developed ANN models. The calculations include the MSE, root mean squared error (RMSE), mean absolute error (MAE), percentage error (% Error), and maximum prediction error.

$$MSE = \frac{1}{N}\sum_{t=1}^{N}(measured\ value - predicted\ value)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(measured\ value - predicted\ value)^2} \quad (3)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\|measured\ value - predicted\ value\| \quad (4)$$

$$Error\% = \left|\left(\frac{(measured\ value - predict\ value)}{measured\ value}\right) * 100\right| \quad (5)$$

$$Max\ Error = (\|measured\ value - predicted\ value\|) \quad (6)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(measured\ value - predicted\ value)^2}{\sum_{i=1}^{N}(measured\ value - \bar{y}_{measured})^2} \quad (7)$$

$$\bar{y}_{measured} = \frac{\sum_{i=1}^{n} measured\ value}{number\ of\ experiments}$$

The ANN-predicted values for the three sectors of doming, ETID, and dishing are represented in Tables 6, 7, and 8, respectively. These include Eq. (5), which is used to determine the % error for each data point. The results show small errors in each case, indicating a high degree of agreement between the experimental and predicted values.

Table 6. The artificial neural network (ANN) prediction values of doming

No.	Material	Speed	C/T	Doming	Prediction	Error%
1	1048 steel	1.2	3.75	0.33	0.3340	1.20
2	1048 steel	2.4	3.75	0.25	0.2575	3.00
3	1048 steel	3.6	3.75	0.2	0.2056	2.8
4	1048 steel	4.8	3.75	0.18	0.1796	0.22
5	1048 steel	1.2	4.25	0.29	0.2846	1.86
6	1048 steel	2.4	4.25	0.23	0.2349	2.13
7	1048 steel	3.6	4.25	0.19	0.1928	1.47
8	1048 steel	4.8	4.25	0.17	0.1722	1.29
9	1048 steel	1.2	5	0.37	0.3701	0.03
10	1048 steel	2.4	5	0.31	0.3108	0.26
11	1048 steel	3.6	5	0.27	0.2703	0.11
12	1048 steel	4.8	5	0.23	0.2227	3.17
13	CuZn30	1.2	3.75	0.57	0.5707	0.12
14	CuZn30	2.4	3.75	0.53	0.5298	0.04
15	CuZn30	3.6	3.75	0.48	0.4811	0.23
16	CuZn30	4.8	3.75	0.41	0.4092	0.2
17	CuZn30	1.2	4.25	0.49	0.4899	0.02
18	CuZn30	2.4	4.25	0.47	0.4469	4.91
19	CuZn30	3.6	4.25	0.42	0.3927	6.50
20	CuZn30	4.8	4.25	0.35	0.3502	0.06
21	CuZn30	1.2	5	0.58	0.6085	4.91
22	CuZn30	2.4	5	0.56	0.6020	7.50
23	CuZn30	3.6	5	0.52	0.5200	0
24	CuZn30	4.8	5	0.44	0.4400	0

Table 7. The artificial neural network (ANN) prediction values of edge taper inclination degree (ETID)

No.	Material	Speed	C/T	ETID	Prediction	Error%
1	1048 steel	1.2	3.75	0.85	0.8500	0
2	1048 steel	2.4	3.75	0.52	0.5200	0
3	1048 steel	3.6	3.75	0.47	0.4700	0
4	1048 steel	4.8	3.75	0.33	0.3300	0
5	1048 steel	1.2	4.25	1.2	1.1663	2.81
6	1048 steel	2.4	4.25	0.9	0.9000	0
7	1048 steel	3.6	4.25	0.7	0.7000	0
8	1048 steel	4.8	4.25	0.61	0.5870	3.77
9	1048 steel	1.2	5	1.5	1.5000	0
10	1048 steel	2.4	5	1.23	1.2300	0
11	1048 steel	3.6	5	1.05	1.0768	2.56
12	1048 steel	4.8	5	0.815	0.8150	0
13	CuZn30	1.2	3.75	1.57	1.5700	0
14	CuZn30	2.4	3.75	1.42	1.4120	0.56
15	CuZn30	3.6	3.75	1.26	1.2600	0
16	CuZn30	4.8	3.75	1.1	1.1000	0
17	CuZn30	1.2	4.25	1.7	1.7000	0
18	CuZn30	2.4	4.25	1.57	1.5044	4.18
19	CuZn30	3.6	4.25	1.4	1.4000	0
20	CuZn30	4.8	4.25	1.2	1.1707	2.44
21	CuZn30	1.2	5	1.9	1.8023	5.14
22	CuZn30	2.4	5	1.8	1.6964	5.76
23	CuZn30	3.6	5	1.58	1.5800	0
24	CuZn30	4.8	5	1.42	1.4200	0

Table 8. The artificial neural network (ANN) prediction values of dishing

No.	Material	Speed	C/T	Dishing	Prediction	Error%
1	1048 steel	1.2	3.75	0.24	0.2297	4.29
2	1048 steel	2.4	3.75	0.185	0.1850	0
3	1048 steel	3.6	3.75	0.12	0.1200	0
4	1048 steel	4.8	3.75	0.08	0.0800	0
5	1048 steel	1.2	4.25	0.21	0.2100	0
6	1048 steel	2.4	4.25	0.17	0.1700	0
7	1048 steel	3.6	4.25	0.11	0.1100	0
8	1048 steel	4.8	4.25	0.06	0.0600	0

9	1048 steel	1.2	5	0.265	0.2731	3.06
10	1048 steel	2.4	5	0.205	0.2050	0
11	1048 steel	3.6	5	0.13	0.1300	0
12	1048 steel	4.8	5	0.1	0.1000	0
13	CuZn30	1.2	3.75	0.38	0.3800	0
14	CuZn30	2.4	3.75	0.34	0.3400	0
15	CuZn30	3.6	3.75	0.28	0.2768	1.14
16	CuZn30	4.8	3.75	0.24	0.2276	5.17
17	CuZn30	1.2	4.25	0.36	0.3864	7.33
18	CuZn30	2.4	4.25	0.31	0.3335	7.58
19	CuZn30	3.6	4.25	0.26	0.2600	0
20	CuZn30	4.8	4.25	0.22	0.2200	0
21	CuZn30	1.2	5	0.49	0.4503	8.10
22	CuZn30	2.4	5	0.43	0.4454	3.58
23	CuZn30	3.6	5	0.37	0.3700	0
24	CuZn30	4.8	5	0.27	0.2700	0

To evaluate the generalization capability of the developed ANN models, the MSE, RMSE, MAE, R^2, and maximum error metrics presented in Table 9 were calculated precisely using the independent testing dataset, which was not utilized during network training or weight optimization. Hence, these metrics provide a reliable evaluation of the models' predictive capability on previously unseen data within the investigated experimental domain.

The developed ANN models achieve high coefficients of determination (R^2), together with low values of MSE, RMSE, MAE, and Maximum Prediction Error. This indicates good agreement between the predicted and experimental values. However, it should be considered that these results are applicable only within the investigated ranges of material, cutting speed, and C/T, and should not be counted as evidence of comprehensive predictive capability beyond the experimental domain considered in this research.

Table 9. Statistical performance metrics of the artificial neural network (ANN) models

Performance Metric	Doming	ETID	Dishing
Testing MAE	0.008837	0.048046	0.002025
Testing MSE	0.000201	0.003890	0.000016
Testing RMSE	0.014168	0.062372	0.004049
Testing R^2	0.9847	0.9816	0.9963
Testing Maximum Prediction Error	0.027321	0.103601	0.008098

Note: Edge taper inclination degree (ETID), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE).

8. CONCLUSION

Based on the experimental investigation, enhanced by ANN prediction, of the effect of punch–die clearance, cutting speed, and material type on edge quality and dimensional accuracy in sheet metal blanking, the following conclusions are drawn:

•Material type significantly affects edge quality, where brass displays higher levels of doming, ETID, and dishing compared to medium-carbon steel due to its lower yield strength and higher ductility, which promote greater plastic deformation prior to fracture.

•Based on the results, the punch–die clearance is considered as a critical parameter affecting edge quality. While the defect values vary with clearance, the relationship between each defect and the clearance is not strictly linear. The best edge quality was found at a clearance of about 4.25%, where the defect indices reached their lowest values.

•Cutting speed has an inverse effect on defect formation. Increasing speed from 120 to 480 mm/s reduces doming, ETID, and dishing. The improvement in sheared-edge quality observed at higher cutting speeds may be associated with strain-rate effects and possible localized thermal softening, as reported in previous studies. However, since the strain rate and temperature have not been directly measured in this research, these are considered sensible explanations rather than experimentally verified phenomena.

•The interaction effects confirm that process parameters are interdependent. Brass is more sensitive to variations in clearance and speed than steel, while higher cutting speeds partially reduce the adverse effects of large clearances.

•Among the investigated experimental conditions, AISI 1048 steel with a clearance ratio of 4.25% and a cutting speed of 480 mm/s showed the best overall edge quality in terms of reducing doming, dishing, and edge taper.

•Furthermore, an ANN model was developed to predict doming, ETID, and dishing values based on the experimental data. The ANN confirmed excellent predictive accuracy, with a regression coefficient (R) of 0.99862, 0.9996, and 1 for the three trials, respectively.

•Among all test cases of the ANN, the maximum prediction error observed was 8.1%, while the average prediction error was about 1.52%. This indicates good overall agreement between the experimental and predicted values.

•Overall, the study demonstrates that proper control of material selection and process parameters is essential for improving blanking performance and achieving high-quality sheet metal components in industrial applications.

9. LIMITATIONS AND FUTURE WORK

One of the important issues at the future work includes presenting a more comprehensive statistical analysis of the experimental measurements. This is by reporting standard deviations and uncertainty estimates based on repeated experiments, to provide a quantitative assessment of experimental repeatability. Also, the proposed ANN model proved effective estimation capability to predict doming, dishing, and edge taper defects under the specified blanking parameters. However, like many other data-driven modeling methods, the prediction capability is inherently affected by the range and diversity of the collected experimental data. In this research, the ANN model was developed using an experimental dataset consisting of 24 samples covering the combined effects of clearance and cutting speed values, as well as the material type. Hence, the model provides a reliable prediction framework within the investigated processing window, while expanding the database would enable wider applicability under additional specific circumstances. For example, it is possible to add other types of materials, different thicknesses, and processing conditions in future work to further enhance the robustness and generalization capability of the developed ANN model. However, to assess the proposed ANN model's prediction accuracy and applicability to sheared-edge defect prediction, future work may include a comparative evaluation with conventional predictive approaches, such as regression analysis and response surface methodology (RSM).

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