Prediction of burr height formation in sheet metal trimming processes using acoustic signals and an artificial neural network

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Abstract: Sheet metal trimming is an important manufacturing process in various industries. In trimmed components, burr formation is a significant defect, and the burr height is a key determinant of product quality. Punch wear and punch-die clearance are the two main factors affecting burr formation. An online burr height prediction system is required to improve the productivity of the process. In this research, the human hearing system was imitated for burr height prediction during trimming. Firstly, a discrete wavelet transform with the mel-frequency cepstral coefficients was employed to extract features from an acoustic signal. Subsequently, a feed-forward back-propagation artificial neural network was trained to determine the changes in the sheet metal thickness and punch wear state and to predict the burr height using the signal features. The proposed online burr height prediction system can improve productivity by mitigating defective production, reducing inspection time, and enabling timely regrinding of components.

Keywords: sheet metal trimming; mel-frequency cepstral coefficients; ANN; artificial neural network; acoustic emission; condition monitoring.

Reference to this paper should be made as follows: Badgujar, T.Y. and Wani, V.P. (2023) 'Prediction of burr height formation in sheet metal trimming processes using acoustic signals and an artificial neural network', *Int. J. Mechatronics and Manufacturing Systems*, Vol. 16, No. 1, pp.22–36.

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1 Introduction

The manufacturing of components using stamping machines is a highly specialised and knowledge-intensive process. The sheet metal industry has been facing a shortage of experienced operators and affordable process monitoring systems necessary to maintain productivity (Raftopoulos and Vosniakos, 2020; Lorenz et al., 2019). Sheet metal trimming is an important process that is performed using a stamping machine to remove excess material from components. Recent research on the mechanical and geometric characteristics of trimmed edges has revealed strong associations between trimmed edge quality and punch-die clearance, punch wear states, and sheet metal thickness (Hambli et al., 2003; Cavusoglu and Gurun, 2016, 2017; Kwak et al., 2002; Lorenz and Netland, 2019). The required punch-die clearance depends on the shear strength of the material and sheet thickness. Furthermore, the punch-die clearance significantly affects the burr height, punch life, and edge quality (Husson et al., 2008; Subramonian et al., 2013; Mucha and Tutak, 2019). Researchers have used the condition monitoring technique to determine the process performance, and most studies have focused on monitoring the punch wear using sensor data. However, from an industrial perspective, the burr height is a key criterion for punch regrinding and component acceptance. Therefore, for the production of high-quality components, it is important to evaluate the height of the burr on the trimmed edge.

Typically, the manufacturing process related parameters are evaluated using direct/offline or indirect/online methods. The direct method monitors the actual parameters, whereas the indirect method monitors auxiliary quantities and estimates the parameters using an empirical correlation without interrupting any ongoing processes. Offline monitoring, however, delays the corrective decisions. Researchers have proposed several online monitoring methods using vibration, strain, and acoustic signals to determine the variations in the sheet thickness and punch wear states. However, few have focused on monitoring the trimming/punching/blanking processes (Sari et al., 2017; Ge et al., 2008).

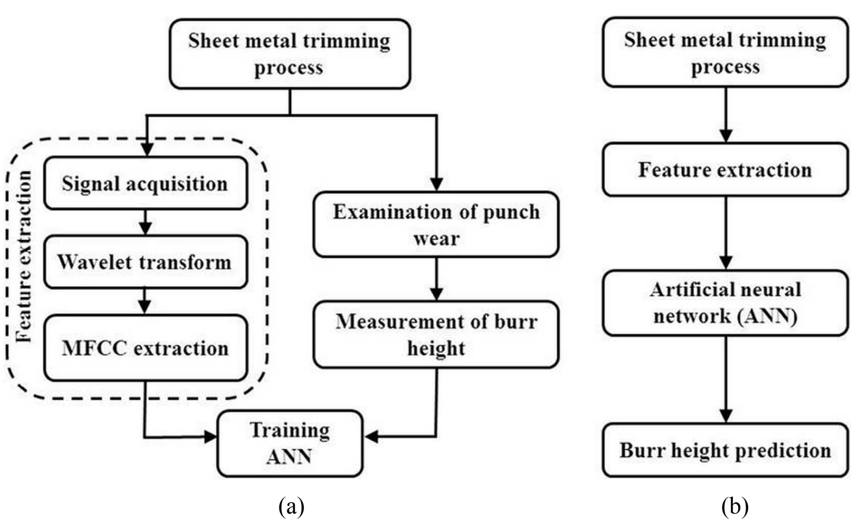
The aforementioned studies have demonstrated the advantages of acoustic signals, such as the use of inexpensive instruments and the ability to capture the dynamic properties of the process. Acoustic signal analysis may be performed in the time, frequency, or time–frequency domains. Recently, time–frequency domain signal analysis has received considerable attention, and wavelet transform (WT) based approaches have been developed to study time–frequency data (Peng and Chu, 2004; Zhu et al., 2009). The Hilbert–Huang transform (HHT) is another useful method for extracting features from sound signals to perform fault diagnosis. However, the HHT experiences deficiency–ripple phenomena at approximated frequencies (Ge et al., 2008). Various algorithms have been developed by researchers for feature classification. Examples include the artificial neural network (ANN) and support vector machine (SVM) based approaches (Sun et al., 2004; Roth et al., 2010; Saravanan and Ramachandran, 2010; Saeidi et al., 2016; Deng et al., 2020). However, SVM provides fewer details about the priority ranking of features. In comparison, ANNs are versatile and can be used for parameter design, optimisation, classification, and prediction (Satheeshkumar et al., 2017). The training of an ANN model involves a set of known inputs and outputs for learning and generalisation. The random forest algorithm has been used in some studies to extract features from the acoustic field model. The mel-frequency cepstral coefficients (MFCCs) can facilitate successful modelling of the human auditory system; hence, the range of frequencies audible by humans was used. However, the use of acoustic emission with MFCCs to monitor the height of the burrs formed during sheet metal trimming has not yet been explored. The proposed system may be able to provide an alternative to manual burr height measurement. This study helps in addressing this gap in the existing literature. The MFCCs are robust features for speech recognition and use the time–frequency domain (Frigieri et al., 2016; Liu et al., 2020).

The main objective of this study was to investigate the utility of the MFCCs as features and ANNs as classifiers to detect variations in the sheet metal thickness and punch wear for accurately predicting burr height during the sheet metal trimming process. The use of a WT in the initial stage for signal denoising improved the performance of the MFCCs during feature extraction. The 24 MFCCs extracted from the sound signal in the form of an acoustic spectrum were identified as features, and a new burr height diagnostic methodology based on a feed-forward back-propagation ANN was developed. Several parameter levels were determined by comparing features for effective burr height prediction.

2 Methods

The burr heights and feature values at various parameter levels are necessary for reliable ANN model training. Therefore, sheet metal trimming experiments were conducted on extra-deep drawn steel, acoustic signals were recorded, and burr heights were measured. Figure 1 illustrates the methodology of the study.

Figure 1 Methodology for burr height prediction: (a) MFCC-ANN model training and (b) MFCC-ANN model implementation



Twenty-seven experimental conditions were identified, and corresponding experiments were performed. Figure 1(a) illustrates the method of training the model. Firstly, the acoustic signals were recorded under various experimental conditions. Thereafter, a discrete wavelet transform was used to decompose the acoustic signals, and the 24 MFCCs of an individual acoustic signal were evaluated as the signal features. The 27 extracted features under 27 experimental conditions, along with the measured burr height, were used for ANN model training. Later, the trained model was used to predict the burr height of the sheet metal trimming process, as shown in Figure 1(b). The methodology is further discussed in Sections 2.1, 2.2, and 2.3.

2.1 Signal denoising

The acoustic emission signal generated during trimming is a dynamic signal. Denoising using the wavelet decomposition method can help achieve a smooth signal. In this study, the Symmlet wavelet was used to represent the acoustic signal up to eight levels, considering its usefulness in denoising similar signals. The energy distribution of the reconstructed wavelet coefficients were based on the distribution of the multiresolution frequency bands and used as an input for MFCC evaluation.

2.2 MFCC extraction

Initially, the energy corresponding to higher frequencies was boosted using a pre-emphasis filter, making information in higher formants accessible for further analysis. Subsequently, the signal was sliced into short time windows. The slicing of the signal could lead to a sudden drop in the amplitude and the addition of noise. The overlap of adjacent frames control the abrupt changes in the parameters to some extent. The Hamming window was used for windowing with 50% overlap to reduce the spectral distortion. The windowing can be expressed as follows:

$$w(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{F-1}\right), \quad 0 \le n \le F-1 \tag{1}$$

where F is the frame size.

The energy spectrum of the signal was evaluated using the discrete Fourier transform and can be expressed as

$$X_k = \sum_{n=0}^{N-1} \tilde{X}_k(n) e^{2\pi kn/N} \tag{2}$$

$$S_k = |X_k|^2, \tag{3}$$

where X_k represents the discrete Fourier transform, S_k is the spectral energy, and N is the number of fast Fourier transform (FFT) points.

The spectrum contained useful information. The mel-scale power spectrum was estimated using the mel-scale filter bank. The power spectrum of the signal represents the energies of various frequency bands of the signal. Lastly, the MFCCs of the feature were extracted using the discrete cosine transform (DCT):

$$C_k(m) = \sum_{l=0}^{L-1} \log\left(\tilde{S}_k(l)\right) \cos\left(\frac{\pi m}{2L}(2l+1)\right), \quad \forall k = 1, ..., K, \tag{4}$$

where m = 1, 2, …, C, and C denotes the number of desired coefficients.

2.3 ANN

An ANN is a popular classifier capable of mapping input to output without knowledge of the prior relationship. It consists of a parallel processing architecture and numerous interconnected processing neurons. The weight of the internal connection is adjusted while training an ANN model to reduce the difference between the model output and target output. The general structure of an ANN consists of interconnected neurons; the rules that determine whether a neuron executes a transfer function, and the training laws modify the connection weights. In this study, a feed-forward back-propagation neural network was used with Tansig as the input transfer function and Purelin as the output transfer function. The 24 MFCCs of the signal were input into the network. The output layer of the network consists of one processing element, which exemplifies the punch wear state, sheet thickness, and burr height.

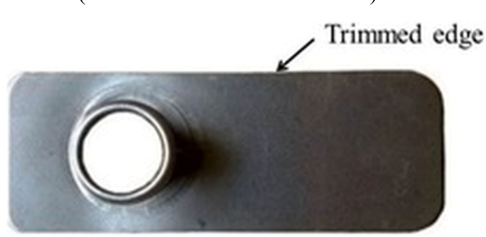
3 Experimental outline

This section presents the experimental outline. Firstly, the experimental object and stamping press are discussed. Then, the use of the proposed methodology for extracting the features from the acoustic signal is discussed, and the ANN training is explained.

3.1 Experimental setup

A tyre valve protector is a sheet metal component used in heavy-duty vehicles such as trucks and tractors. Considering the market demand, tyre valve protectors are produced in large quantities. Figure 2 shows an actual image of the component. During manufacturing, the tyre valve protector goes through various stamping processes, and finally, the sheet metal trimming process is applied to give it the final shape.

Figure 2 Tyre valve protector (see online version for colours)



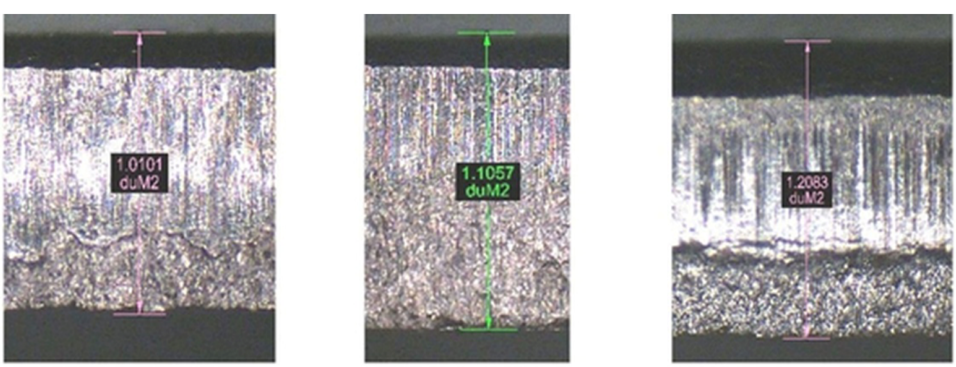
In this investigation, experiments were conducted on a 20-ton mechanical power press (Rajesh Machines, Rajkot, India). Table 1 gives the details of the experimental parameters for the sheet metal trimming process.

Table 1 Experimental parameters

S. No.	*Description*	*Details*
1	Material type	Cold-rolled close annealed (extra deep drawn (EDD))
2	Designed sheet thickness	1.00 mm
3	Tensile strength	350 MPa (Max.) (Bureau of Indian Standard, 2008)
4	Punch die clearance for 1.00 mm sheet thickness	5% of sheet thickness
5	Sheet thicknesses (mm)	0.8, 0.9, 0.93, 0.97, 1.00, 1.03, 1.05, 1.10, and 1.20
6	Punch wear states	1 Freshly ground punch (S)
		2 Partially worn punch (i.e., when the burr height reaches 10% for a sheet thickness of 1.00 mm) (P)
		3 Blunt punch (i.e., when the burr height reaches up to approximately 15% for a sheet thickness of 1.00 mm) (B)

The key faults experienced in tyre valve production are burr formation, fracture, and wrinkling. The punch and die dimensions were determined based on a 5% clearance for 1.00-mm sheet thickness. Thereafter, the punch and die dimensions were unchanged throughout the trials. Along with three punch wear states, nine sheet thicknesses were identified based on the required clearance for trials (Table 1). A proximity sensor-based triggering circuit was used to record the interval signal. Trials were conducted for 27 combinations, and each trial run was replicated 20 times to ensure the statistical reliability of the experiments. During the experiments, it was confirmed that no other machining operation was performed in the vicinity, to avoid the interference of acoustic signals. A Zoom H1/MB microphone was placed at 150 mm from the punch to record the signal during the trimming process. The cross-section of the trimmed edge consisted of the following zones: rollover zone (Z_r), shear zone (Z_S), fracture zone (Z_f), and burr zone (Z_b). Figure 3 shows images of the 1.00-mm thick sheet metal trimmed edges under the three punch conditions.

Figure 3 Trimmed edge for a 1.00-mm thick sheet when using a (a) freshly ground punch, (b) partially worn punch and (c) fully worn punch (see online version for colours)



(a) (b) (c)

The burr height of an individual component was estimated using the following equation:

$$\text{Burr zone } (Z_b) \text{ or Burr height} = Z_r + Z_s + Z_f + Z_b - t \quad (5)$$

where t is the sheet thickness. The burr heights of the components were evaluated using a vision measuring system (VMS) (Rapid-I, Customised Technologies (P) Ltd., Bengaluru, India). The VMS is a contactless device; it magnifies images at 67× and measures the sum of Z_r, Z_s, Z_f, and Z_b.

3.2 Feature extraction

The recorded acoustic signals were processed using MATLAB 2020a with the prepared code. Initially, Symmlet wavelets were utilised to decompose the acoustic signal up to eight levels for denoising. After pre-emphasis, the signals were sliced into small intervals using a Hamming window with 50% overlap. Next, the FFT of the signal was calculated, and the mel-scale power spectrum was estimated by employing 13 linear and 18 log band pass triangular filters. The triangular band pass filter maps measured frequencies with respect to the mel-frequency scale. Subsequently, the mel scale filter bank is utilised to obtain the mel scale power spectrum. The output of the mel scale power spectrum represents the energy of various frequency bands. In the last stage, the DCT is applied to the first 24 frequency bands to extract the 24 MFCCs. These 24 MFCC values define a feature for a particular parameter combination, which implies that there are 27 distinct features for 27 experimental conditions. The MFCCs extracted from the signal identify the signal features.

3.3 ANN training

Based on the obtained features, training, validation, and testing sets were prepared. The training set contained 70% of the data, whereas the validation and testing sets contained 15% data each. The training set was used to train the ANN, which consisted of four layers: an input layer, an output, and two hidden layers. The first hidden layer consisted of 20 neurons, whereas the second hidden layer included one neuron. The 24 MFCC values for the 27 experimental conditions with known burr heights were used to train the neural network. The Tansig transfer function was employed as the input function, whereas the Purelin transfer function was utilised to convert the input signals into output signals. The Levenberg–Marquardt training algorithm was used, and the mean-squared error was employed to stop the training. The networks for the sheet thickness and punch wear state converged in 1000 epochs with mean-squared errors of 0.90875 and 8.1571×10^{-8} and R values of 0.91631 and 1.00, respectively.

4 Results and discussion

This section presents and discusses the evaluation results of the developed approach. The effectiveness of this method was evaluated based on various factors, and the results indicate that this approach can accurately predict the burr height and punch wear state using acoustic signals and can potentially be used in industrial facilities for real-time monitoring.

4.1 Burr height measurement

Table 2 presents the percentage clearance variations and burr heights for various sheet thicknesses. The burr height increases with decreasing sheet thickness. The effect of clearance variation in burr height is nominal when the punch is freshly ground, but it becomes more noticeable as the punch wears.

Table 2 Average burr height

				Burr height (% of sheet thickness)		
S. No.	*Thickness* (mm)	*Required clearance* (%)	*Actual clearance* (%)	*Freshly ground punch*	*Partially worn punch*	*Blunt punch*
1	0.80	4.0	6.25	6.847	13.500	20.137
2	0.90	4.5	5.56	3.189	13.418	17.683
3	0.93	4.7	5.38	1.619	13.041	17.352
4	0.97	4.9	5.15	1.529	13.123	17.250
5	1.00	5.0	5.00	1.352	10.823	16.850
6	1.03	5.2	4.85	1.262	9.791	12.846
7	1.05	5.3	4.76	1.381	9.383	10.641
8	1.10	5.5	4.55	0.916	10.250	11.283
9	1.20	6.0	4.17	0.617	9.736	12.001

4.2 Features of acoustic signal

The proposed methodology was used to extract the features of the recorded acoustic signal. Figures 4–6 illustrate the features for 27 different parameter combinations. The MFCCs of the features show clear differences for various experimental setups.

Figure 4 Features of signals for freshly ground punch (see online version for colours)

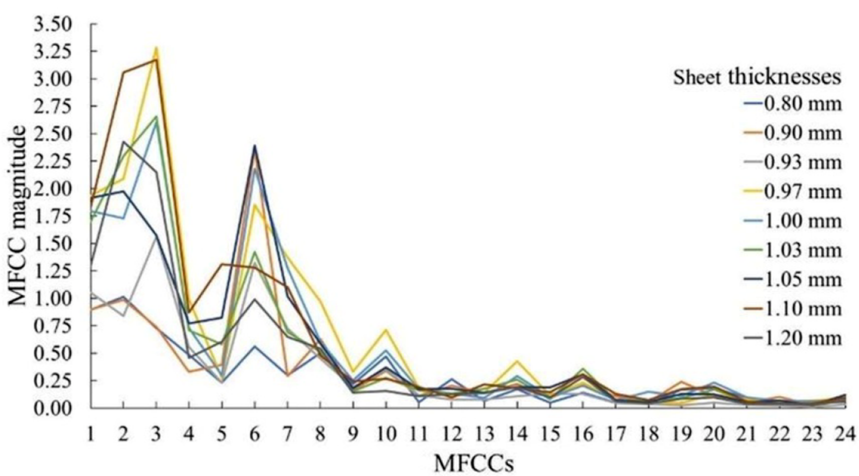


Figure 5 Features of signals for partially worn punch (see online version for colours)

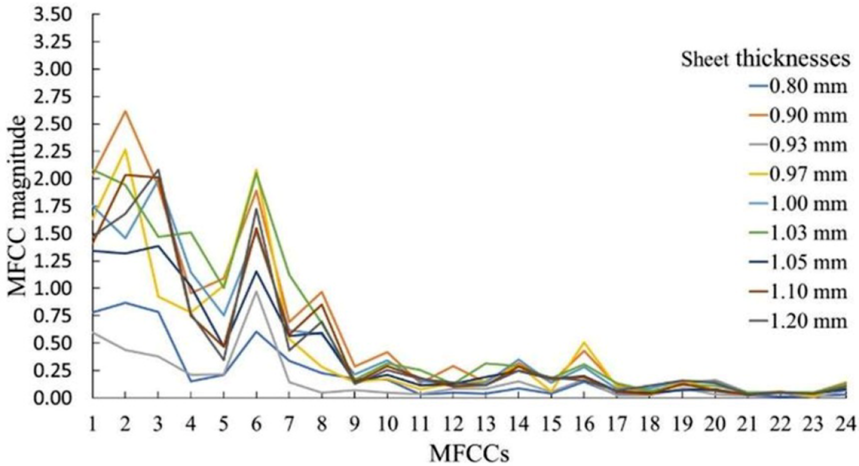
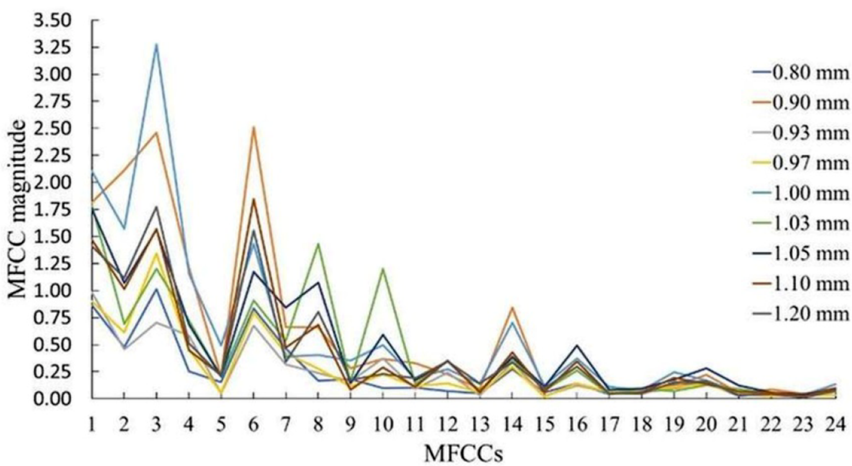


Figure 6 Features of signals for blunt punch (see online version for colours)



A correlation analysis was performed to determine the relationships between the MFCC magnitude and the burr height and sheet thickness. The results of Pearson's correlation test between MFCC energy and burr height is shown in Table 3.

The correlation results reveal that MFCCs M_1, M_2, M_3, M_7, M_{12}, M_{15}, and M_{16}, for the newly ground punch; MFCCs M_4, M_{11}, and M_{15} for the partially worn punch; and MFCCs M_8, M_{12}, M_{16}, and M_{21} for the blunt punch show strong relationships with the burr height. Since more than one MFCC demonstrates a correlation with burr height, all 24 MFCCs of the acoustic signal were used as characteristics of the machining setup to estimate the burr height.

Figures 7–9 illustrate the training performance, regression results, and mean-squared error, respectively, for the sheet thickness classification.

Table 3 Results of correlation analysis between MFCCs and burr height

Punch type	*Freshly ground punch*							*Partially worn punch*			*Blunt punch*			
MFCC No./Sheet thickness (mm)	M_1	M_2	M_3	M_7	M_{12}	M_{15}	M_{16}	M_4	M_{11}	M_{15}	M_8	M_{12}	M_{16}	M_{21}
0.80	0.8944	1.0153	0.7297	0.3002	0.2633	0.0492	0.1414	0.1525	0.0343	0.0396	0.1643	0.0693	0.1429	0.0264
0.90	0.9000	0.9838	0.7402	0.2894	0.2057	0.0914	0.2065	0.9560	0.1340	0.1389	0.6591	0.2264	0.2978	0.0540
0.93	1.0542	0.8373	1.5630	0.7248	0.0758	0.1298	0.1274	0.2125	0.0370	0.0564	0.2387	0.2405	0.1232	0.0397
0.97	1.9358	2.0898	3.2812	1.3689	0.1071	0.1163	0.2309	0.7792	0.0819	0.0588	0.2759	0.1434	0.1405	0.0408
1.00	1.7969	1.7289	2.6066	1.2771	0.1314	0.1015	0.2032	1.1480	0.1560	0.1379	0.4067	0.2720	0.3738	0.0611
1.03	1.6957	2.2941	2.6564	0.6908	0.1319	0.0825	0.3590	1.5079	0.2558	0.1786	1.4310	0.3450	0.2628	0.0886
1.05	1.9131	1.9740	1.5717	1.0179	0.1762	0.1884	0.3068	1.0195	0.1153	0.1746	1.0732	0.3507	0.4940	0.1227
1.10	1.8262	3.0567	3.1715	1.1003	0.0969	0.1460	0.3073	0.7505	0.1835	0.1723	0.6831	0.3532	0.3434	0.0650
1.20	1.2942	2.4243	2.1491	0.6502	0.1283	0.0982	0.2845	0.7705	0.1770	0.1863	0.8026	0.3470	0.2956	0.0355
r =	−0.6373	−0.6218	−0.6904	−0.6229	0.8406	−0.6052	−0.5833	−0.6139	−0.7355	−0.8675	−0.7650	−0.9089	−0.6905	−0.6716
P =	0.0649	0.0738	0.0395	0.0732	0.0045	0.0842	0.0992	0.0786	0.0239	0.0024	0.0163	0.0007	0.0395	0.0476

M_1, M_2, …, M_{21} denote the mel-frequency cepstral coefficients (MFCCs), and a *P*-value < 10% is considered significant for two-tailed tests.

Figure 7 Training performance at epoch 1000 (see online version for colours)

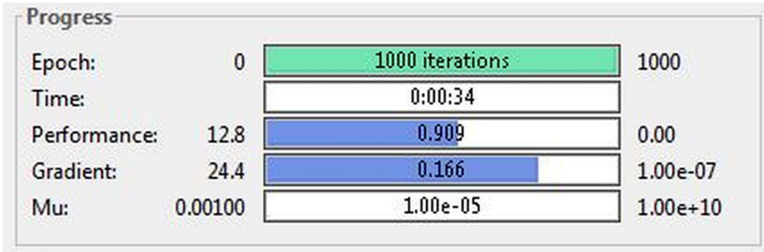


Figure 8 Regression results (see online version for colours)

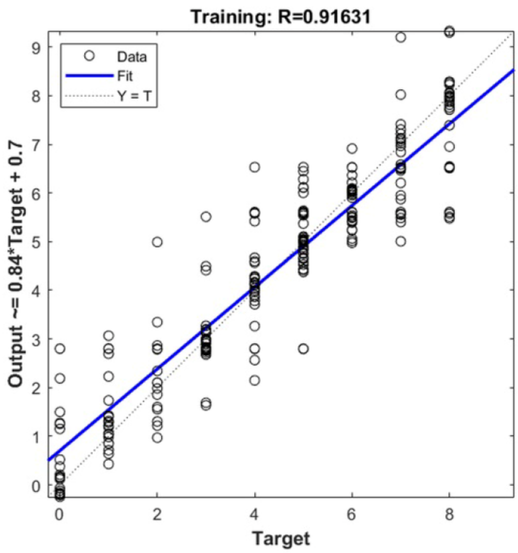
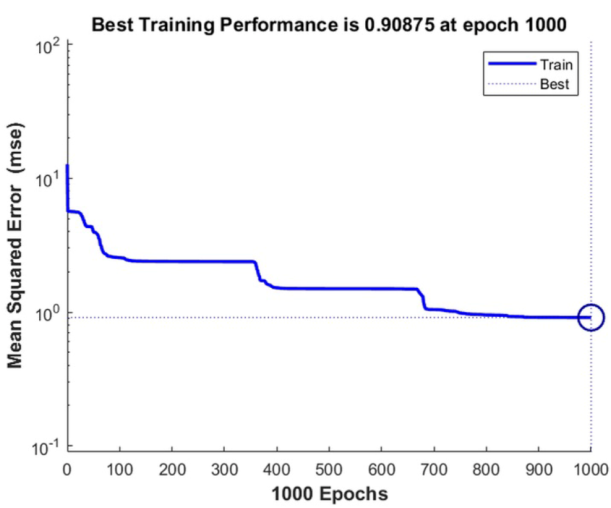


Figure 9 Mean-squared error over 1000 epochs (see online version for colours)



Figures 10–12 show the classification results of the punch wear states when the curves in Figures 9 and 12 stabilise after 1000 training cycles.

Figure 10 Training performance at epoch 1000 (see online version for colours)

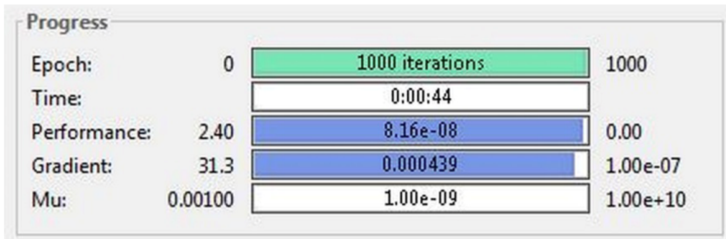


Figure 11 Regression results (see online version for colours)

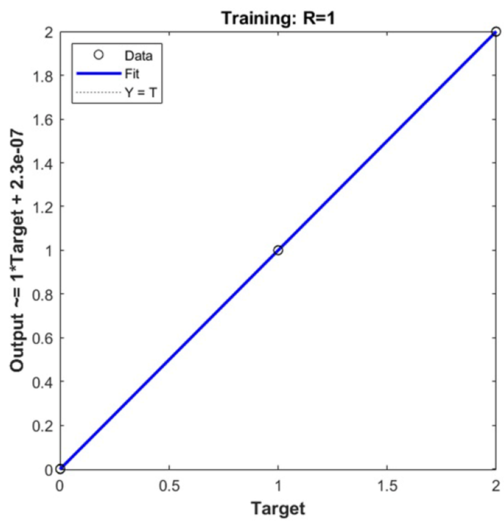
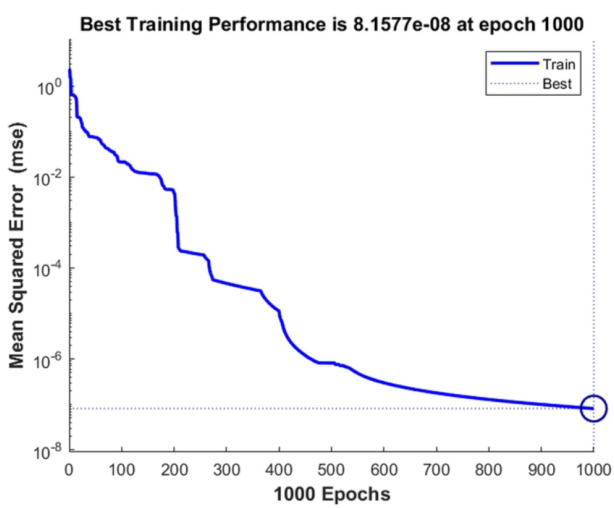
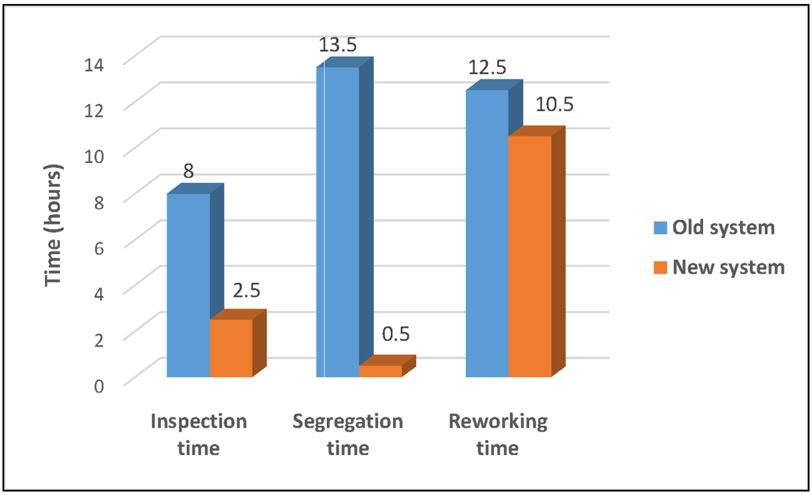


Figure 12 Mean-squared error over 1000 epochs (see online version for colours)



The MFCC–ANN algorithm was implemented in MATLAB for burr height estimation. While testing the model with pre-recorded acoustic emission signals, the model estimated the burr height with an accuracy of 95.01%. When the developed system was tested for the production of 270 trimmed parts, its accuracy was 88.05%. Previously, the number of components produced during 30 days, i.e., two consecutive grindings of the punch, was 150,000. After implementation of the proposed system, the overall production during the same period was 164,650. Thus, an overall production increase of 9.8% was achieved through a saving of 20.5 h between two consecutive grindings of the punch, as shown in Figure 13.

Figure 13 Times required by old and new systems (see online version for colours)



5 Conclusions

Sheet metal trimming is an important process in the manufacturing of mechanical parts. Therefore, improving its performance is crucial. In this study, a trained feed-forward back-propagation neural network algorithm was used to estimate the height of burrs formed on trimmed parts in terms of sheet thickness and punch wear state. Initially, the MFCC-based features were extracted for signals under different trimming conditions. The feed-forward back-propagation neural network model was trained using the MFCC values of the signals and measured burr height. The WT–MFCC–ANN model was employed as a substitute to obtain the actual burr height for the burr height prediction of the trimmed part. The proposed model predicted the burr height with an accuracy of 95.01% for the recorded signal and 88.05% for the actual online monitoring of the trimming process. With the implementation of the proposed system, the times for inspection, component segregation for deburring, and reworking were reduced by 81.4%, 96.0%, and 15.0%, respectively, and the overall productivity of the process was improved by 9.8%. A comparison of the simulation results with the experimental results confirmed the reliability of the proposed system in predicting burr height formation. Moreover, this methodology can be used for stamping processes, such as blanking, punching, and trimming, which involves the use of shearing to produce components. However, in actual industrial setups, several machines operate simultaneously, which inhibits the capturing of individual process signals. The signal-to-noise ratio may be improved by using short-throw, unidirectional microphones and sound isolation between machines.

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