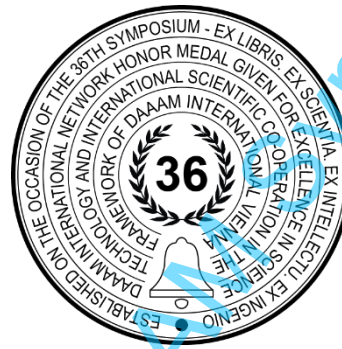


ACOUSTIC EMISSION AMPLITUDE AND SPECTRAL RESPONSES TO FEED AND CUTTING SPEED IN DRILLING

Michal Straka



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Abstract

This study examines how feed and cutting speed change acoustic emission during small diameter interrupted drilling. Seven recordings formed two series with four process levels and one shared condition. Four reviewed holes per recording were divided into four kinematically defined cutting segments. Features were calculated in overlapping 25 ms windows after filtering from 40 to 400 kHz. Direct comparisons based on hole medians were combined with descriptive feature sensitivity, XGBoost classification and feature group ablation. Acoustic emission amplitude increased with both parameters. Amplitude features were more informative for cutting speed than for feed. Band sensitivity and band RMS profiles showed stronger separation by cutting speed from 70 to 150 kHz and by feed in much of the region above 150 kHz within the investigated ranges. A model without individual band powers or shares reached balanced accuracy of 0.880 for feed and 0.957 for cutting speed. Adding these features changed the scores to 0.851 and 0.987. The results show overlapping but distinguishable amplitude and spectral responses within the measured recordings.

Keywords: acoustic emission; drilling; feed; cutting speed; process monitoring; machine learning

1. Introduction

Reliable monitoring of drilling is important because tool wear, edge damage and unstable chip formation can reduce hole quality before the change is visible. Acoustic emission captures elastic waves generated by deformation, fracture and friction. It is therefore widely used as an indirect signal for machining and tool condition monitoring [1], [2]. Recent studies have used AE for tool-condition monitoring in small-hole drilling [3], [4]. Related studies have examined feed and depth-of-cut effects on chip shape in turning [5] and used decision trees to analyse material, cutting-parameter and tool-geometry effects on drilling torque [6]. Machine states in turning have also been classified using features from structure-borne AE and microphone signals [7]. Povolny et al. [8] discussed the influence of the transmission path and sensor placement on AE measurements.

This sensitivity creates a practical problem. A feature intended to indicate tool wear can also change when feed or cutting speed is adjusted. Early drilling research already showed that acoustic emission responds to the cutting process [9]. AE monitoring studies describe changes in signal amplitude, waveform shape and frequency content under different operating and measurement conditions [1], [7]. A high classification score alone cannot reveal which of these changes carries the useful information.

The objective is to determine how feed and cutting speed differ in their effects on acoustic emission during small diameter interrupted drilling. The analysis first compares amplitude and spectra directly. It then tests whether amplitude, temporal shape, absolute band power or relative spectral shape is needed to separate the investigated process levels. The intended contribution is a compact comparison of the two process parameters on the same measured quantity. Two questions guide the study. First, how does acoustic-emission amplitude change with feed and cutting speed? Second, which frequency regions respond more strongly to each parameter?

2. Materials and Methods

2.1. Experimental design and acquisition

Experiments were performed on a DMU 40 eVo linear machining centre. The main workpieces were untreated DIN 1.2379 cold work tool steel with an approximate reported hardness of 250 HB. The nominal grade composition is C 1.55 percent, Si 0.30 percent, Mn 0.30 percent, Cr 11.30 percent, Mo 0.75 percent and V 0.75 percent [10]. These values describe the steel grade and are not a batch specific chemical analysis.

The workpiece was attached from below to a fixture plate with four screws and the plate was clamped to the machine table. A passive DAKEL IDK-14 acoustic emission sensor remained at one fixed position on the same plate adjacent to the workpiece. Silicone grease was applied at the interfaces between the workpiece and plate and between the sensor and plate. The nominal transmission path and sensor position were therefore constant within the experiment, although coupling and tool state may still have varied between recordings.

The measurement chain consisted of the IDK-14 sensor, a DAKEL PreAmp One external preamplifier and 32 dB gain, a TiePie Engineering Handyscope HS6 DIFF and a computer. One channel was recorded at 1 MHz with AC coupling and 14-bit resolution. Six recordings used a 4 V input range, while the 180 m/min recording used a 2 V input range. The acquired signals were stored as NumPy arrays.

A drill with a diameter of 2.5 mm produced holes 10 mm deep. The cycle contained four consecutive cutting segments of 2.5 mm. Cooling pressure was 52 bar and a Schunk Hydro 20 holder was used. Four feed levels were measured at a constant cutting speed of 130 m/min. Four cutting speed levels were measured at a constant feed of 0.06 mm/rev. The condition 130 m/min and 0.06 mm/rev was shared by both series. The design therefore contained seven recordings.

The two series were evaluated separately. Within the feed series, cutting speed was fixed so changes could be associated with feed. Within the cutting speed series, feed was fixed for the same reason. The shared condition connected both comparisons and provided a check that the amplitude and spectral summaries were calculated from the same operating point.

Series	Cutting speed v_c (m/min)	Feed f (mm/rev)
Feed	130	0.01, 0.02, 0.04, 0.06
Cutting speed	70, 100, 130, 180	0.06

Table 1. Experimental conditions

2.2. Segmentation and preprocessing

The expected duration of each 2.5 mm cutting segment was determined from cutting speed, feed and drill diameter. It ranged from approximately 109 to 906 ms.

The first four holes of every recording were analysed. Sixteen segment centres per recording were proposed automatically and reviewed in a graphical application that displayed the waveform, the RMS curve and machining probability. Every segment retained its kinematically calculated duration. The dataset comprised 28 analysed holes in total. Four cutting segments from each hole produced 112 confirmed segments.

Segment duration was allowed to change with feed and spindle speed because every segment represented the same axial travel. Slow conditions consequently produced more overlapping windows than fast conditions. This difference was retained during feature extraction because shortening all segments to a common time would remove a different fraction of the cutting path from each condition. It was addressed during analysis by balancing the number of windows for every process level and hole.

Each segment was filtered by a fourth-order zero-phase Butterworth filter from 40 to 400 kHz. A 5 ms extension was filtered on both sides and removed before analysis. Twelve percent of each segment was removed from both ends. Features were calculated in 25 ms windows with 50 percent overlap. The final dataset contained 2112 windows.

The targeted comparison used six amplitude descriptors, twelve temporal shape descriptors, 36 powers from consecutive 10 kHz bands, 36 relative band shares and five global spectral descriptors, giving 95 features in total. Mean absolute deviation (MAD) was calculated as the mean absolute difference from the window mean. The global spectral

descriptors were centroid, spread, entropy, flatness and the 85 percent rolloff frequency. A compact set without individual band powers or shares contained 23 descriptors.

2.3. Comparison and classification

Direct comparisons used medians of window values within each hole. RMS was summarized by the mean of four hole medians. Each hole median band power was converted to dBV as $10 \log_{10}$ of power relative to 1 V squared. Spectral curves show the mean of these four levels. Error bars and shading show plus or minus one sample standard deviation across holes. Relative band powers were normalized by total power from 40 to 400 kHz.

For every 10 kHz band power, sensitivity to the four feed levels and to the four cutting speed levels was quantified by one way ANOVA eta squared. The same number of windows was drawn without replacement for every process level and hole. Balanced sampling was repeated 1000 times. Eta squared is the fraction of observed feature variance associated with the process levels. The plotted contrast is the median of the 1000 differences between feed eta squared and cutting speed eta squared. Positive values indicate stronger descriptive separation by feed and negative values by cutting speed. Here, dominance refers only to separation within the investigated parameter ranges. Values near zero indicate similar sensitivity, which may be strong for both parameters.

Separate four class XGBoost models [11] classified feed and cutting speed. Missing values were replaced by medians calculated only from training data.

SHAP [12] and permutation importance [13] explained the 95-feature Combined models in Figure 4 using held out holes. SHAP importance averaged absolute values across validation windows and classes. Permutation importance averaged the decrease in balanced accuracy over 20 shuffles per feature and four folds. Each method was normalized to its maximum for display. Correlated features were interpreted by type and frequency region, without assigning unique physical sources.

Validation left out one hole index from every process level. The other three indices were used for training, with balanced windows per level and hole. Balanced accuracy and macro F1 were calculated in each of four folds. Models used amplitude, temporal shape, absolute bands, relative spectrum, the compact set without individual bands, or their complete combination.

Band ablations used absolute powers or relative shares alone. Unlike the relative-spectrum group in Figure 4, the relative-band ablation models did not include the five global spectral descriptors.

Imputation medians and training-window selection used training holes only. Reported scores are means and sample standard deviations across the four held out hole indices. This validation estimates repeatability across holes within the measured recordings, not performance on a new campaign.

3. Results

3.1. Amplitude response

RMS increased across the feed levels. The means of four hole medians were 0.064, 0.073, 0.084 and 0.105 V for feeds of 0.01, 0.02, 0.04 and 0.06 mm/rev. The corresponding values for cutting speeds of 70, 100, 130 and 180 m/min were 0.054, 0.103, 0.105 and 0.141 V. Figure 1 shows these means with error bars of plus or minus one sample standard deviation across the four holes.

The amplitude only model reached balanced accuracy of 0.645 for feed and 0.916 for cutting speed. Amplitude therefore contained information about both parameters but was much more useful for distinguishing cutting speed.

The shapes of the two curves were also different. Feed produced a gradual increase across all four levels. Cutting speed produced a large increase from 70 to 100 m/min, almost no change between 100 and 130 m/min, and another increase at 180 m/min. RMS is therefore a simple indicator of changing feed in this dataset, but its separation is small. For cutting speed it provides stronger class separation, although the close middle levels show why spectral and temporal information remains useful.

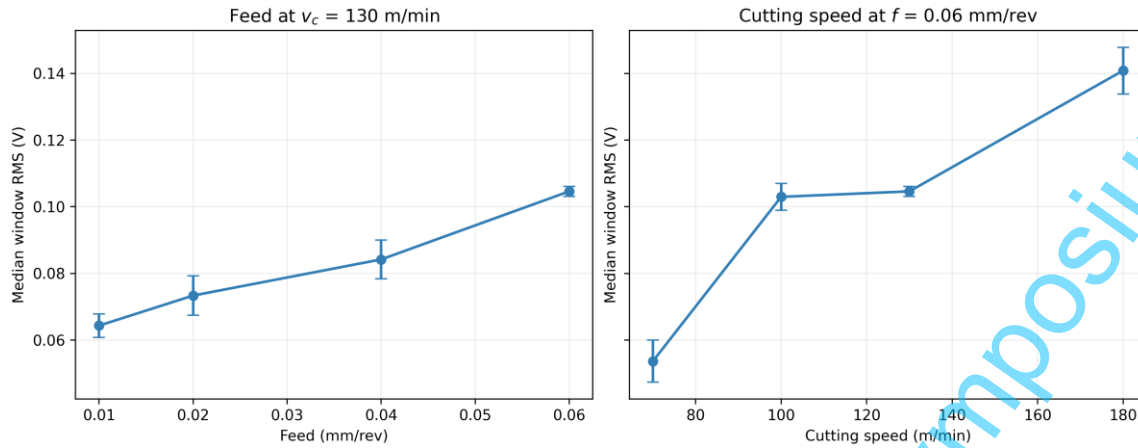


Fig. 1. Mean of four hole-median RMS values.

3.2. Differential sensitivity of frequency bands

Figure 2 compares the separation produced by feed and cutting speed in each 10 kHz band. It plots the median difference between feed eta squared and cutting-speed eta squared across 1000 balanced draws. Positive values indicate stronger separation by feed and negative values indicate stronger separation by cutting speed.

Cutting speed was dominant from 70 to 150 kHz. The largest contrast occurred in the 90 to 100 kHz band, where the median eta squared values were 0.034 for feed and 0.827 for cutting speed. The median contrast was minus 0.750 and was negative in every repeated draw. The neighbouring 70 to 90 kHz bands showed the same direction. This region therefore changed much more consistently across cutting speed levels than across feed levels in the investigated data.

The balance changed above 150 kHz. Feed had the larger effect in most bands from 150 to 250 kHz and in almost every band from 280 to 400 kHz. From 310 to 340 kHz, the median eta squared difference was 0.31 to 0.38 and remained positive in every repeated draw. Comparable feed dominance was observed in several bands from 370 to 400 kHz. These values must be read together with signal level. A feature can separate four levels consistently even when it contains only a small part of total signal energy.

Several bands were sensitive to both parameters and consequently lie near zero in Figure 2. The 50 to 60 kHz band is the clearest example. Its median eta squared values were 0.892 for feed and 0.816 for cutting speed, giving a median contrast of 0.076 despite strong separation in both experiments. A near zero bar therefore cannot be interpreted as absence of a process response.

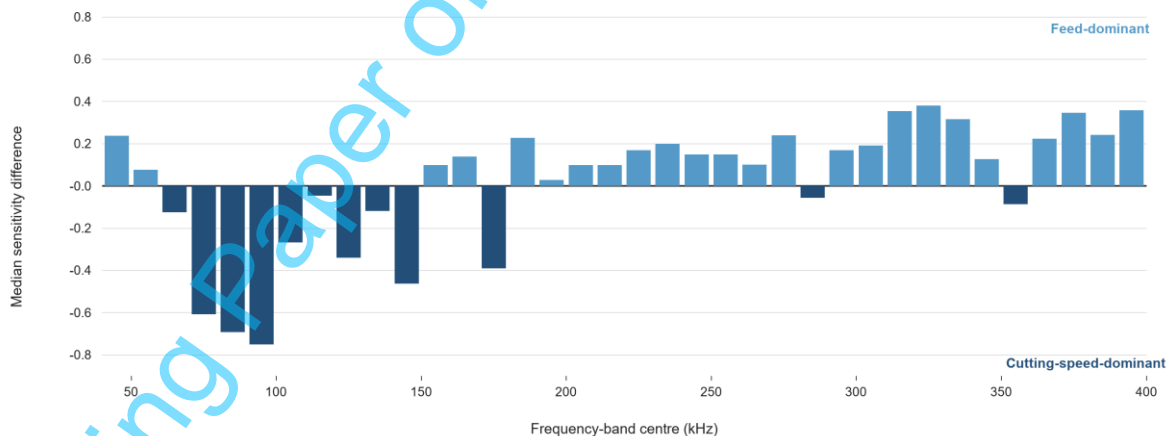


Fig. 2. Median difference between feed and cutting speed sensitivity of 10 kHz band energies.

3.3. Band RMS profiles

Figure 3 provides the signal level that is not visible in the sensitivity contrast. Each point is the mean of four hole levels in dBV, calculated from the median band power within each hole. Shading shows one standard deviation across holes. Less negative values indicate a larger band RMS. The dominant energy region for both experiments was

approximately 80 to 200 kHz. Signal level then decreased toward 250 kHz and remained much lower from 250 to 400 kHz.

For feed, the 0.01 and 0.02 mm/rev curves were close over much of the range. The 0.04 mm/rev curve became more clearly separated above about 150 kHz. The 0.06 mm/rev curve was generally the highest and its separation was largest in the upper half of the spectrum. This agrees with the positive sensitivity contrast above 150 kHz. The response was broad and smooth across neighbouring bands. It does not support the interpretation of one isolated feed frequency. For cutting speed, 70 m/min produced the lowest curve over nearly the whole frequency range. The curves for 100 and 130 m/min were similar, which explains why the global RMS values at these two speeds were also close. The 180 m/min curve was highest through most of the main energy region. The clearest ordering was between about 70 and 150 kHz, consistent with the negative bars in Figure 2. The pattern again covered several adjacent bands rather than one narrow peak.

The hole-median share of total power from 300 to 400 kHz ranged from 0.3 to 1.2 percent. The high feed sensitivity in this region therefore describes a consistent change in a weak spectral tail. Adding the region to a band power model changed balanced accuracy by minus 0.009 for feed and plus 0.006 for cutting speed. The measured response above 300 kHz is useful for describing spectral redistribution but contributed little additional classification information in this comparison.

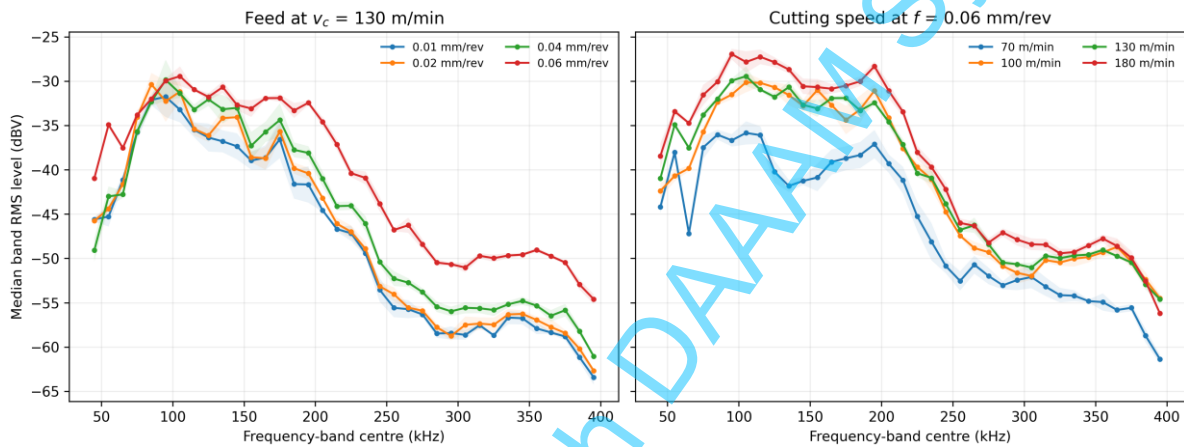


Fig. 3. Mean band levels from four hole medians.

3.4. Feature group comparison

Figure 4 compares the information carried by each feature family using the same XGBoost learner and the same leave one hole out validation. Bars show mean balanced accuracy and error bars show the standard deviation across four validation folds. Absolute and relative spectral features separated both parameters well. Temporal shape features were more useful for feed than amplitude alone. The opposite ordering was observed for cutting speed.

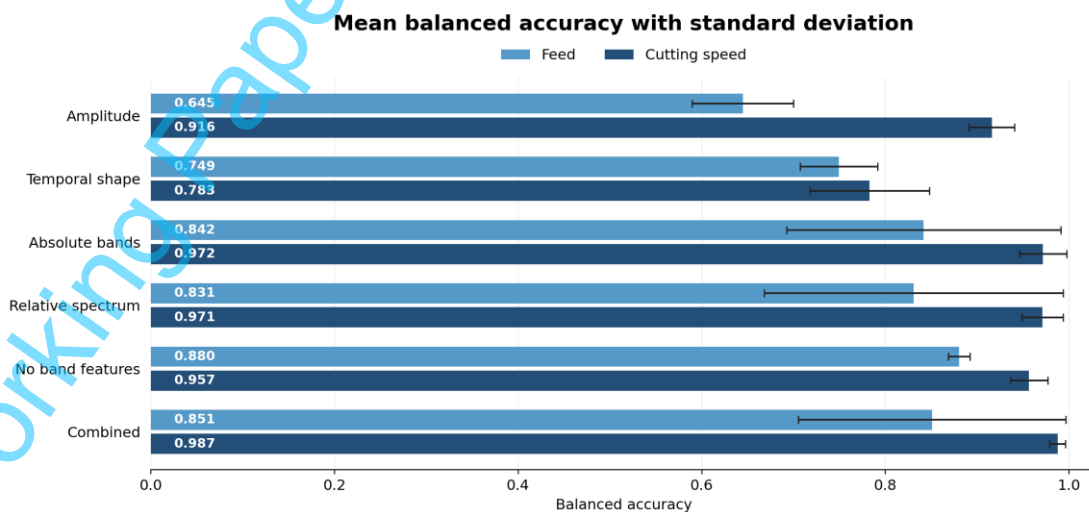


Fig. 4. Mean balanced accuracy across four folds; error bars show one standard deviation.

The 23-feature model without individual band powers or shares achieved balanced accuracy of 0.880 for feed and 0.957 for cutting speed. Its macro F1 values were 0.861 and 0.958. Adding all absolute and relative band features gave the 95-feature Combined model, with balanced accuracy of 0.851 for feed and 0.987 for cutting speed. The complete model was less stable for feed because performance varied strongly between validation holes.

Adding individual band powers and shares did not improve mean feed classification in this comparison, but increased cutting speed balanced accuracy by 0.031. Removing only the 90 to 100 kHz band did not reduce mean performance in the band-ablation tests. Removing the entire 100 to 200 kHz region reduced cutting speed performance in the relative-band model in all four folds, by 0.040 on average. This supports a contribution from a wider frequency region rather than one indispensable band.

Figure 5 explains the Combined models using the five highest ranked features from each method. For feed, SHAP and permutation importance selected the same five features: skewness and band powers at 40 to 60 kHz and 130 to 150 kHz. Their order differed, but both methods identified temporal shape and several spectral bands as useful. Skewness was treated as a classification feature rather than a monotonic indicator of feed. For cutting speed, both methods ranked mean absolute deviation first, followed by absolute power and relative power share at 50 to 60 kHz. Envelope mean also appeared in both top five lists. This combination indicates contributions from signal amplitude and spectral distribution. The 50 to 60 kHz band was sensitive to both parameters in Figure 2, so its usefulness does not make it specific to cutting speed. Lower permutation importance can be consistent with correlated features providing similar information.



Fig. 5. SHAP and permutation importance for the 95-feature.

4. Discussion

The results do not support a simple division in which one process parameter changes only amplitude and the other changes only frequency content. Both parameters changed both quantities. The difference was one of emphasis. Amplitude was considerably more informative for cutting speed. Feed was represented more strongly by temporal shape and global spectral distribution.

Figures 2 and 3 support a regional interpretation of the response. Adjacent bands followed similar curves and may provide overlapping information to a model. The contrast graph identifies regions that separate the investigated levels more strongly in one series. The band RMS graph shows whether this involves a broad increase, separation of one level or a change in a weak spectral tail. Together they give context to the model rankings.

The classification comparison supports this interpretation. The compact model retained good separation without individual band powers or shares. Adding these features reduced mean feed performance but improved cutting speed balanced accuracy by 0.031. Absolute and relative band groups also performed well on their own. Their information therefore overlaps with the amplitude, temporal shape and global spectral descriptors, although the benefit of combining them depends on the task and model.

The contrast between the low and high frequency regions is particularly useful for interpreting feed. The main spectral peak remained in approximately the same broad region, while separation between feed levels became larger toward higher frequencies. This means that feed did not simply multiply the complete spectrum by one constant factor. Its effect included a change in spectral shape. Cutting speed also changed spectral shape, but its strongest preferential sensitivity occurred around the main energy region below 150 kHz. This explains why amplitude alone was already effective for cutting speed and why spectral features could provide additional discrimination.

A practical monitoring system must therefore distinguish changes caused by the selected cutting condition from changes caused by tool condition. A rise in RMS cannot automatically be assigned to wear because both feed and cutting speed increased RMS here. Likewise, a change in one 10 kHz band is not sufficient evidence of a new signal source because neighbouring bands often changed together. Features that compare broader frequency regions and use the current process settings as model inputs are more defensible candidates for future tool monitoring.

The observed amplitude and spectral changes are consistent with AE monitoring studies describing sensitivity to operating conditions [1], machine state [7], and tool condition and adhesion [4]. The present comparison adds that the relative contribution of amplitude and frequency regions differs between feed and cutting speed under controlled drilling conditions. This distinction is relevant when features are later used for tool condition monitoring because a change in operating parameters could otherwise be mistaken for a change in tool state.

5. Conclusion

Within the investigated conditions, feed and cutting speed produced overlapping but distinguishable changes in acoustic emission. RMS increased with both parameters. Amplitude features distinguished cutting speed more successfully than feed. Band sensitivity showed stronger separation by cutting speed from about 70 to 150 kHz and by feed through much of the range above 150 kHz. Band RMS profiles showed responses distributed across neighbouring bands rather than confined to one narrow frequency. This study isolated the baseline sensitivity of acoustic emission to these cutting parameters using an unworn drill. Progressive tool wear was not included.

In this model comparison, adding individual band powers and shares did not improve mean feed classification and increased cutting speed balanced accuracy by 0.031. The main finding is the combined contribution of amplitude and spectral redistribution. The hole-median power share from 300 to 400 kHz was only 0.3 to 1.2 percent, and adding this region had little effect on classification in the band-power test. For practical monitoring, AE changes should therefore be interpreted together with the current feed and cutting speed before being attributed to tool wear. These findings establish a parameter-dependent baseline for separating operating-condition effects from wear-related AE changes. Future work will evaluate multi-variable models trained simultaneously on controlled feed and cutting-speed steps and progressive drill flank wear.

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