Drill bit state-oriented drilling process classification with time-series data for wheeled drilling rigs

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Abstract. This paper represents an analysis of the wheeled drilling rig’s drilling process. Thanks to data from the onboard measurement unit of the machine, the characteristics of the drilling process regarding state of the drill bit are identified and calculated. The aim of the work is to provide a comparison between different drill qualities and process classification using Threshold-based segmentation with feed pressure levels and duration of single hole drilling. Second methodology is hierarchical clustering to create cluster analysis. Thanks to these approaches, it is possible to detect the time when the drill bit should be changed. The obtained results state that the average drill time for a new drill bit is shorter approximately by 50\% than for the worn-out bit in terms of average drilling duration. Moreover, these changes are visible in the subsystem pressure level of the machine under specific drilling regimes.

1. Introduction

For the vast majority of underground copper mines perform their mining activities in a room and pillar system. The first part of copper extraction from the deposit is to prepare a blast-hole mesh before the execution of blasting. Hole quality performance is crucial, because improper performance causes an appropriate blasting off the rock and creating a tunnel of the appropriate shape \cite{1}. Moreover, if this process is executed in an inefficient way it directly implies the volume of ore extracted. Thus, a proper description of drilling and process parametrization is significantly important and it is needed to create solutions to implement methods for improving this process and enhancing safety \cite{2, 3}.

Wheeled drilling rigs are complex machines, and it is not a trivial problem to determine the quality of drilling. Hence, the most reliable approach is to compute it statistically and identify the regimes of heavy duty mining mobile machines \cite{4}. It is a common practice to use several parameters for cycle classification for underground machines and their overall condition, because it has an enormous influence - state of the machine- on the drilling process performance. Thus, the engine overheating problem \cite{5}, analysis of the failure rate of hydraulic systems \cite{6}, pressure signal hydraulic cylinder \cite{7}, or load reduction during drilling \cite{8, 9} is as important as a direct signal describing the progress of drilling or the duration of single hole drilling. In \cite{10} is presented a multidimensional signal analysis for technical conditions, operation and understanding deeply the heavy duty mining machines, such as wheeled drilling rigs. Thanks to that, it is possible to improve the quality of data segmentation due to access process performance and help to obtain...
insight into how to improve the management of underground machinery fleet thanks to data taken from cycle classification and quality analysis for improving drill bit management within the mining company[11-13].

2. Problem description
A machine operation monitoring system, called SYNAPSA, is implemented in all self-propelled mining machinery, also in wheeled drilling rig [14]. The aim of this paper is performing the drilling process classification for wheeled drilling rigs using time-series data taken from the abovementioned system. In Fig.1 is presented wheeled drilling rig used in the polish copper mines. The problem of cycle diagnostics is essential regarding performing the analysis of drilling assessment and further analysis in the next phases of copper ore extraction and processing. Usage of some parameters taken from this system helps to determine different working cycles for other machines, such as: dump truck [15], load-haul machines (LHD) [16] based on pressure or temperature from several machine’s subsystems. It enables long-term diagnostic of underground machine condition monitoring [17].

Figure 1: The drilling rig used in KGHM S.A.

Onboard monitoring system for wheeled drilling machines consists of 33 parameters describing different machine subsystem parameters. Each of them is sampled with 1 Hz. Nevertheless, taken into account, there are just only 4, the most populated and useful among others for drilling progress monitoring:

- ’KLDSMG SWW 181LDR PROGR I m’ - drilling progress, [m],
- ’KLDSMG SWW 181LHYDDFEDP AMPa’ - pressure in the drill feed system [MPa],

In addition, each row of data has a timestamp of measurements, what significantly enhances data preprocessing. The information describing state of the drill bit is obtained From Computerised Maintenance Management System (CMMS).
3. Methodology

3.1. Threshold-based segmentation

To determine an signal segmentation where data do not change over time in reliable and efficient manner the threshold-based segmentation is used. Thanks to expert-knowledge it is competently possible to define the machine’s subsystem pressures for drilling, pre-boring and idle state.

A required signal \( X = \{x_1, \ldots, x_N\} \) of length \( N \) with a predefined group of thresholds \( T \) of size \( K \), the class indicator \( c_n \) is assigned to each data element based on the regime (scope of values between two following thresholds) it belongs to.

Thresholds vector should be padded on both sides applying dataset extremes - minimum and maximum values. Thus, several regime is characterized by upper and lower boundary:

\[
T = \{\text{min}(X), t_1, \ldots, t_K, \text{max}(X)\}
\]  

(1)

Based on the aforementioned, the new vector \( C = \{c_1, \ldots, c_N\} \) of length \( N \) is organized such as:

\[
\forall n \in \{1:N\} \exists k \in \{1:K+1\} c_n = k \quad \text{for} \quad t_k \leq x_n < t_{k+1}
\]  

(2)

This way, for each sample from the signal \( X \) there is a value in vector \( C \) that holds its regime number.

Thusly, corresponding part of signal \( X \) with value in vector \( C \) that has its regime number. Given the signal prepossed in such a way, the most convenient way to calculate the actual segmentation using derivative of the vector \( C \), where non-zero values represent point of regime change. Moreover, the next sample value indicates the class that a taken part of signal belongs to.

3.2. Hierarchical clustering

Second part of data preprocessing is using hierarchical cluster analysis [18], where an approach to cluster class of segments with a common properties to determine machine state is presented. In [19], hierarchical method is used to build a hierarchy of clusters. There are two major strategies that could be performed in this case:

- **Agglomerative:** in the beginning every observation constitutes a separate as its cluster.
  
  In the next steps, algorithm process the closest pair of clusters and merges them into larger clusters.

- **Divisive:** algorithm splits recursively from one cluster, where all observations belong, into smaller clusters.

In this case, the authors used the agglomerative strategy, because of deterministic characteristics of signal used. On one hand, the divisive approach usually needs to utilize other heuristics (i.e. k-means) to correctly define splits. On the other hand, as a result of agglomerative approach, a dendrogram can be obtained that depict all connections between clusters and how they are merged. To sum up, it is possible to select the precision level of clustering what is performed as a desired amount of clusters after completing the merging algorithm. In [18], as a metric for distance, Euclidean metric and Ward linkage criterion is used.

4. Results

First part of data preparation from the wheeled drilling machine’s onboard monitoring and CMMS system is ingestion from multiple sources. Subsequently, data cleaning is performed, particularly deletion of corrupted data and smoothing data using rolling window was made. Next step is finding the local maxima and minima to determine cycles and calculation of each
duration. Execution of all aforementioned actions on the signal provides a prepared time-series data describing three states of drilling due to state of the drill bit, taken from CMMS:

- Worn out drill bit
- Worn out bit with increased feed pressure
- New drill bit

Figure 2: Comparison of drill bit state - worn out, worn out bit with increased feed pressure, and new drill

In Fig. 2 is presented a comparison of these states using hole depth [m] and tool feed pressure [MPa]. It is clearly detectable that the quality of the drill bit significantly influence on the duration of each hole drilling. For label ‘worn out drill bit’ it can be distinguished the state when the machine’s operator influences on the tool feed subsystem with nearly 16% higher pressure. Chosen time-series data last about 10 minutes for each state of the drill to make it straightforward to analyze and compare between classes.

In Fig. 3 results of drilling cycle identification and regime classification for worn-out drill bit are presented. 7 cycles of drilling are classified as worn out, and for this state of the drill, the average drilling time equals 73 seconds.

In Fig. 4 analysis for the subgroup of worn out with higher level of pressure in the drill feed system is shown. This group is extracted in a deliberately manner, because this state of the process - with increased pressure level during the drilling, is unfavorable due to not only for the bit that is already worn, but for the rest of the machine. The optimal pressure range of tool feed for wheeled drilling is 5-6 MPa, but for this bit state - it comes to a value of 7 MPa. In this manner, 9 cycles of drilling are classified, and the average drilling time equals 53 seconds.

Cycle identification and regime classification for the new drill can be seen in Fig. 5. In comparison with worn out drill bit, the pressure of tool feed is quite the same and stands for the optimal machine operating point. This regime consists of 12 cycles of drilling with an average drilling time of 35 seconds, what does mean that it is half the drilling time for a worn out.
To summarize the abovementioned results, they are presented in Fig. 6. The main focus is taken to highlight the difference between the average of drilling time for each class of drill bit state. It is clearly visible that hole drilling with different states of the drill bit is significantly fluctuating. The length of uninterrupted operation for particular classes is roughly the same and lasts approximately 10-12 minutes.

Based on mathematical formula in 3.1, providing set of rules to perform segmentation for corresponding drilling holes, the dendrogram shows that three independent group are clearly highlighted. The hole samples are not in order, because they are grouped based on their similarity to subgroups. In this case, these subgroups confirm the convergence with the drill used.

Undoubtedly, one-dimensional analysis is insufficient for such complex objects. Due to that fact, an additional analysis is undertaken to compare the obtained results. Thus, for each captured cycle, the feed pressure level and hole duration are presented in Fig. 8.

Figure 3: Cycles identification and regime classification for worn out drill bit

Figure 4: Cycles identification and regime classification for worn out drill bit with increased feed pressure
Figure 5: Cycles identification and regime classification for new drill

Figure 6: Comparison of drill bit state and its influence on the performance of the drilling process

dimensional representation of hole parameters is fitted to Gaussian mixture contours. Centres of every centroids represent the distribution of the three abovementioned states of the drill bit. Moreover, the parameter space is divided into three clasess, what can be used for futher analysis or other drilling datasets.
5. Conclusions

Data unification from onboard measurement system from wheeled drilling rigs and information related to drill bit state from CMMS system allows to process classification algorithms successfully. Analysis based on threshold segmentation and hierarchical clustering enables distinguishing three states of machine performance strongly coinciding with the changes in the tool management system. The obtained results state that the average drill time for a new drill bit is shorter approximately by 50% than for the worn-out bit in terms of average drilling duration. Moreover, these changes are visible in the subsystem pressure level of the machine under specific drilling regimes.

Summarizing, a proper cycle identification and classification based on technical condition of the drill bit has a significant value for the optimal drilling process management. Classification analysis shows that it is a promising approach to enable performing the tool management in the most efficient way.
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