Self-propelled Mining Machine Monitoring System – Data Validation, Processing and Analysis

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Self-propelled Mining Machines constitute large group of basic machines in underground copper ore mining in Poland. Depends on their purpose and design there are several key parameters that (according to mining companies suggestions) should be monitored and processed in order to assess machine efficiency, its condition, proper operation (according to manufacturer recommendation), human factors influence and so on. Several studies have been done regarding selection of parameters, developing algorithms of data processing, data storage and management and finally reporting and visualization of knowledge extracted from measured data. Although serious efforts have been done in this field, there is still some work to do. In this paper, a new look on the problem will be presented including data acquisition process validation, importance of data quality for automatic processing and analysis. Finally new approach for signal analysis will be proposed and compared with already existing parameters. Also kind of target re-definition attempt will be discussed. All discussed issues will be illustrated using real data acquired during machine operation.

Keywords: Self-Propelled Mining Machine, Monitoring System, Data Processing, Data Analysis.

1 Introduction

Self-propelled mining machines are commonly used in the biggest mining company – KGHM Polish Copper. Their design and operation depends on machine type, basically one can classify them into three categories: i) machines and equipment for mining and preparation of mining faces (drilling and bolting

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C. Drebenstedt and R. Singhal (eds.), *Mine Planning and Equipment Selection*,
DOI: 10.1007/978-3-319-02678-7_124,

rigs, vehicles for ripping), ii) self-propelled machines for short distance haulage (loaders and haul trucks) and iii) machines for auxiliary works.

Machines from two first groups are the most important due to their number, role of their operation in production line and place of their work. The production process in the underground mine is complex process, which consists of preparing for mining operation (excavation), drilling-blasting, hauling, bolting etc. To effectively manage mining work, it is the necessary to introduce IT support for maintenance and operation management. It means that managing the process of mining production requires the acquisition of basic information about the processes. Monitoring the processes requires the installation in an underground mine a wide variety of sensors that control each sub-process components such as mobile machinery performance, efficiency of work they do, monitoring the technical condition of selected elements of machinery, etc.

There are some recent international initiatives in Europe (SMIFU, I2Mine [1,2]) that face up these challenges. This paper might be treated as introduction to the practical aspects of the problem. A key issue is to understand what kind of information is expected and what departments are interested in acquisition of such information. This step has been fully investigated by interdisciplinary team working for KGHM several years ago [3,4]. They proposed definitions of variety of indicators estimated based on online monitoring system. Now, investigation on practical implementation of these ideas, their validation and further extension are carried out in parallel by two collaborating teams, namely KGHM Cuprum R&D working in frame of *Work Package 1 of I2Mine project* and engineers in KGHM.

It should be said, that there are several good examples of successful work on similar issues, i.e. monitoring systems for mining machines [6-7,9-14,17]. Purpose of our research is to understand sub-processes included in mining production process, to define structure of monitoring system, to monitor these processes and finally to propose set of parameters appropriate for analysis the data and automatic identification of mentioned processes. The paper is organized as follows: **Section 2** provides brief description of example of machine (loader) and Monitoring System, structure of data acquired from the monitoring system and examples of raw signals. **Section 3** discusses signal processing issues: techniques for signal validation, basic features for signal understanding and finally advanced approaches for processing and analysis. Closing section will point out further work and concluding remarks.

2 Description of Machine and Monitoring System.

Understanding of design, operation, degradation processes, environmental and human factors influence to signals have been highlighted by Bartelmus [5] in the context of condition monitoring (CM) applications. Although here CM is not recognized as the most important issue (at least at this level of the project), for machine operation monitoring, mentioned factors seem to be still important. A key issue is to understand key components (or sub-systems) of machine (electric, hydraulic, transmission system, etc), and key processes that might appear during "normal" operation (loading, transporting the material to self-propelled haulage vehicle or directly to receiving container). Knowledge about the machine is associated with type of machine. It is obvious that loader will be described by other parameter than drilling or bolting machine [6,7]. However, there is a set of parameters that is common for each type of machine. It was decided to use loader as a basis for further discuss.

Fig. 1 General view on loader used in underground mine

Loader can be "decomposed" into several subsystems important from monitoring point of view, two of them, namely drive system (engine and transmission system) and hydraulic system for lifting and steering the bucket seem to be the most important. To get information about condition and operation of these subsystems one might partially take advantage of build-in (provided by engine manufacturer) data acquisition system, unfortunately, other components should be equipped in sensors and data acquisition tools. So, concept deployed in this project is to use as much as possible existing data streams, add extra sensors and data channels and finally integrate all into one output data stream.

2.1 Structure of Data Acquired from the Monitoring System

Data acquired from the monitoring system cover temperatures, pressures, rotational speeds (and estimated machine speed), torques, angles etc. Number and types of acquired variables depends on machine type. For loader analysed here, total number of output variables is more than 30 (depends on machine type). Among others, a key variables used for analysis are machine speed, engine torque, temperatures and pressures of oil in engine, gearbox, hydraulic system. As it was said above, the monitoring system consists of two part: devices acquiring set of variables related to engine operation (they are available via CAN data transmission protocol) and auxiliary monitoring system developed especially for this project that allows to acquire rest of required variables.

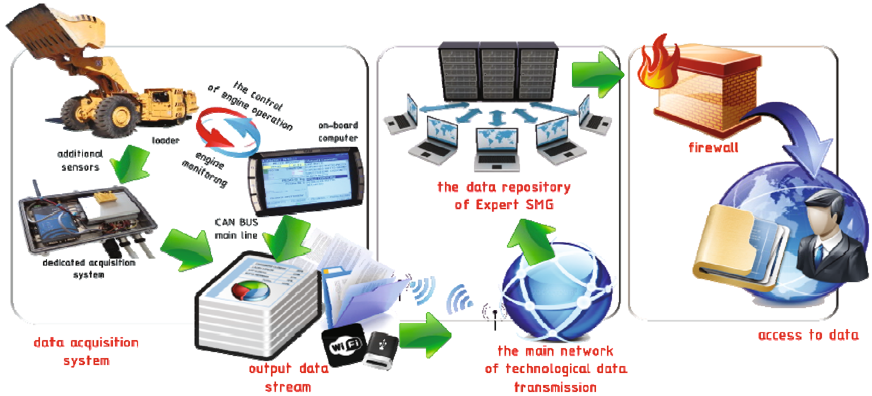

Fig. 2 The idea of used monitoring system

In general, one might group all acquired data into 4 main class of signals: i) variables related to engine operation (torque, rotational speed, instantaneous fuel consumption), ii) temperatures, iii) pressures and iv) others. Some auxiliary variables, as engine start/stop, total distance at given period, etc are secondary variables, calculated based on primary ones mentioned above. In the next section, some examples of acquired signals will be presented and discussed.

2.2 *Examples of Raw Signals. Raw Data Description*

As it could be expected, dynamics and variability of data related to different physical variables are different and require specific data analysis techniques. For example, engine operation as well as pressures are high frequency processes, while temperatures are changing slowly. Depending on variable, different tasks are defined. In general, required information covers, among others, period of time when machine was overloaded, and operated above allowed temperatures and pressures limits. Such information might be use to force drivers to minimize these periods and indirectly extend lifetime and reduce cost of service. It is also important to know how much time machine was not operated. More advanced problems are related to automatic segmentation of signals in order to find hidden periodicity (cyclic behavior of the process). In order to extract information existing in the signals or model data, it might be necessary to use signal validation and pre-processing to enhance signal (i.e. extract informative part).

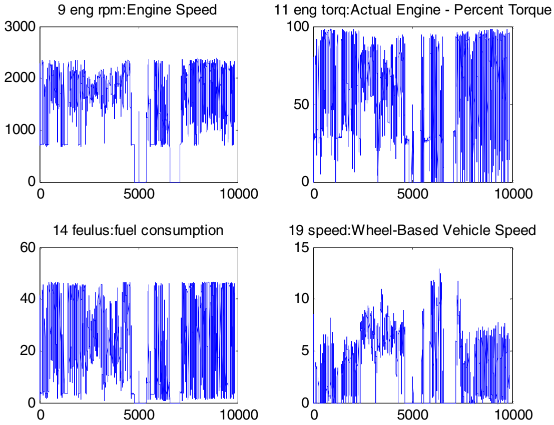

Fig. 3 Variables related to engine operation (X axis: [s],Y: 9:[rpm], 11:[%],14:[l/h], 19:[km/h])

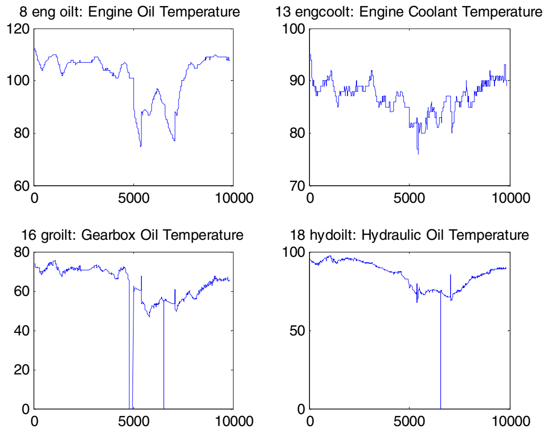

Fig. 4 Examples of acquired signals belonging to group "temperature" (*X axis [s], Y [°C])*

Due to harsh environment acquisition and pre-processing of these signals is challenging task [12,15-18]. Even for signals presented in this paper, before building the model of variability of the signal there is a need to remove for example idle segments, sudden jump to zero etc. Preliminary analysis shows that "de-trending" of temperature of pressure signal might be very helpful to discover information about machine behavior.

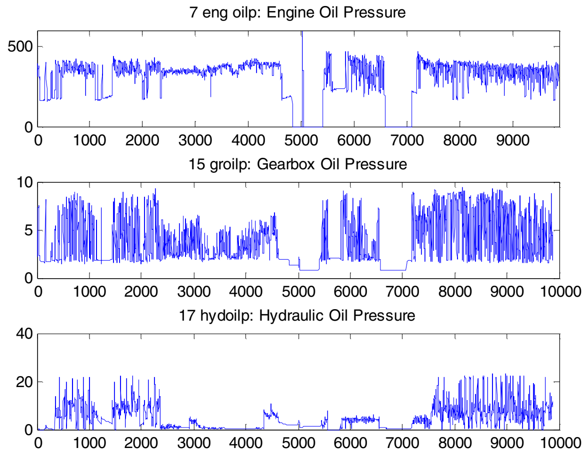

Fig. 5 Examples of acquired signals belonging to group "pressures" (*X axis [s], Y [kPa]*))

Searching for Idle and Overloading of the Machine

To assure effectiveness of production it is important to minimize situations where machine is not operating due to some reasons. It might be related to unexpected situation, machine damage, influence of operator etc. A key issue is to identify the problem and next step is to propose solutions. How to find this information? One might use signal segmentation technique. The task is defined as searching of values of rotational speed (variable eng. rpm) less than idle speed (around 700 [rpm]). Other important speed ranges are: normal operation (50-80%), intensive operation (80-105%) and overspeed (>105% of max allowed speed), see fig 5 . One should notice an important issue for idle speed searching. It might happen that idle speed will appear just for a second(s) due to releasing the accelerator pedal. In proposed procedure such very short event is not taken into account, we are searching for significant (longer than predefined threshold value) idle operation of machine. Such analysis is very useful and provide a lot of information regarding effectiveness of machine usage and risk related to machine damage due to overloading.

Searching for Hidden Cyclic Behavior of Data

In the underground copper ore mine loaders are used to transport copper ore from place A to place B. The distance should not exceed a few hundred meters. Such a cycle (loading at A, transporting, leaving the materials at B) should be repeated many times during one shift. By signals segmentation, it is possible to investigate what is a cycle, how many cycles have been done during one shift, average duration of cycle and –if exist- deviations from average cycle. Building the model

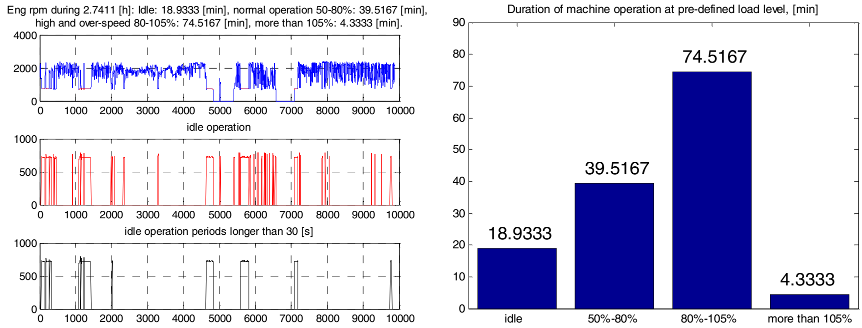

Fig. 6 Segmentation and analysis of speed signal

of cycle one might use many variables (multidimensional model) taking into account volume of material, duration of the cycle, effectiveness of loading procedure etc.

Obviously it can be easily seen that set of features describing behavior of signals will be redundant, i.e. will partially contains the same information. Signal redundancy in multichannel systems have been reported in [19].

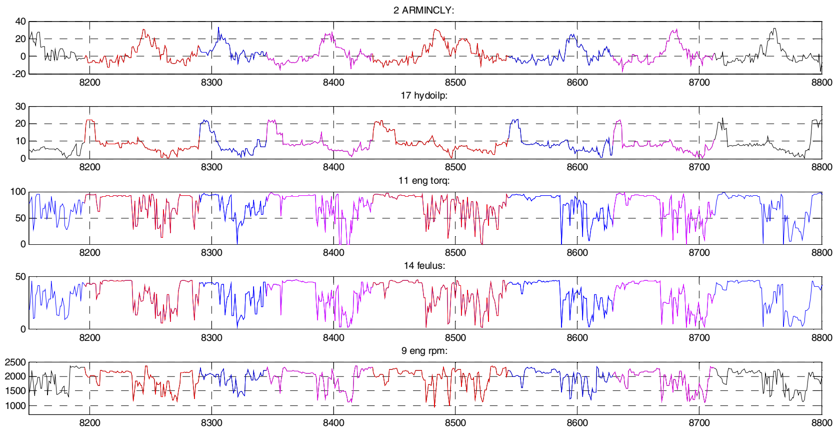

Fig. 7 Segmentation (cycle extraction) of signals according to hydraulic oil pressure variation

Examples of multi-dimensional data analysis, dimensionality reduction and feature selection in order to minimize size of the model have been reported for mining machines in [20-22]. Fig. 6 shows example of data segmentation. As a criterion of segment extraction variable no.17 (hydoilp - pressure of oil in hydraulic system) was used. Extracted cycles are marked by different colors. There is no doubt that such cyclic behavior exists for several variables.

Fig.7 presents comparison of extracted segments (for each variable separately) to investigate if they are similar to others. Till now there is no objective measure to compare segments, however it might be clearly seen that length of segment 2 is much shorter than other and segment 4 is longer that “average” segment length. It is obvious that there is a need to analyse these data with respect to real cycles that take place during machines operation. It is believed that for larger population of data describing an average cycle will be possible using statistical data analysis techniques.

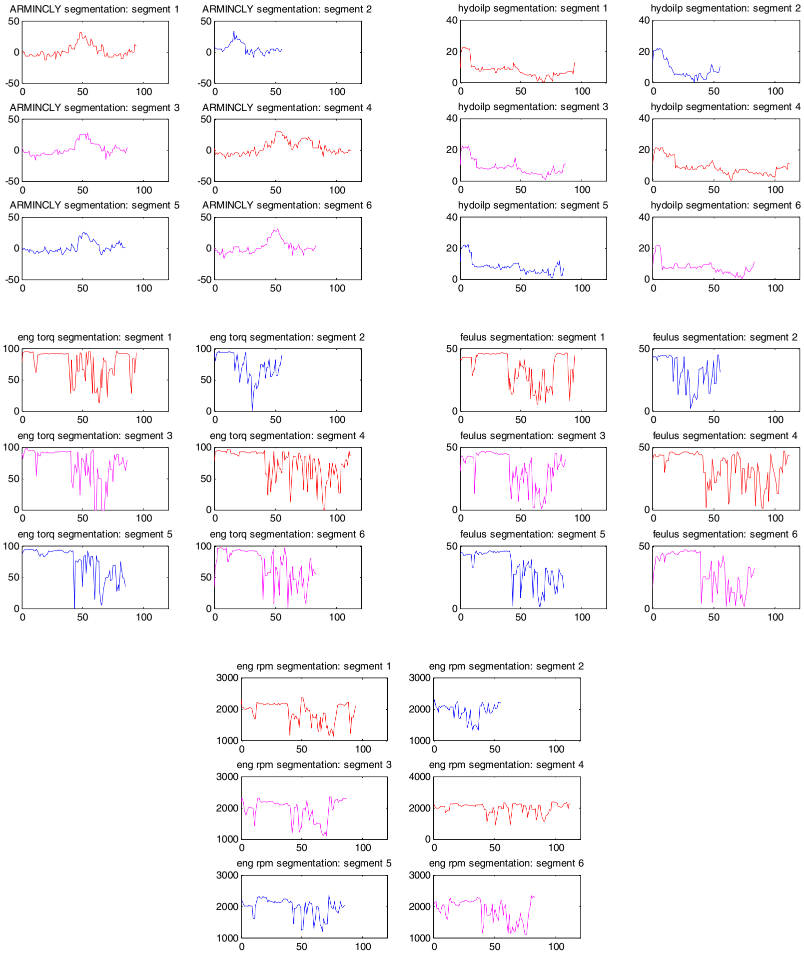

Fig. 8 Analysis of duration and shape of extracted cycles

3 Conclusions

In the paper an introduction to Self-propelled Mining Machine Monitoring is presented. First, in order to understand our motivation, brief description of the machine and the monitoring system is provided. Importance of data validation, processing and analysis are highlighted. Examples of raw data, i.e. real signals acquired by the system during normal operation of machine in the underground mine. Three main purposes of data processing were defined: i) analysis of idle and overloaded regimes, ii) searching of cyclicity of data and statistical analysis of extracted cycles and iii) monitoring of current machine condition. Finally some examples of results were provided. Based on signals segmentation and further statistical analysis one might get information about how much time machine was not operated, was overloaded, how much was used at advised load range. Tracking of temperature or pressure in the system might be used to prevent overheating or damage machine caused by increased pressure in hydraulic system. Extraction of cyclic processes might allow to assess operator skills and process efficiency. It should be highlighted, that more data should be processed to validate / prove conclusions defined based on data analysis.

Acknowledgment. The research work has been financially supported by EU I2Mine Project. The authors would like to aknowledge also colleagues from KGHM Cuprum R&D and KGHM P.M. .S.A. for their comments and help.

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