ON DIAGNOSIS OF LONGWALL SYSTEMS

Marcin Michalak, Magdalena Lachor

Institute of Informatics, Silesian University of Technology, Gliwice, Poland
{Marcin.Michalak,Magdalena.Lachor}@polsl.pl

ABSTRACT

Nowadays we can observe the change of the structure of energy resources, which leads to the increasing fraction of a renewable energy sources. Traditional underground coal mining loses its significance in a total but there are countries, including Poland, which economy is still coal based. A decreasing coal resources imply an exploitation a becoming harder accessible coal beds what is connected with the increase of the safety of the operation. One of the most important technical factor of the safety of underground coal mining is the diagnostic state o a longwall powered roof support. It consists of dozen (or hundreds) of units working in a row. The diagnostic state of a powered roof supports depends on the diagnostic state of all units. This paper describes the possibility of unit diagnostic state analysis based on the biclustering methods.

KEYWORDS

Biclustering, Longwall Systems, Machine Diagnosis.

1. INTRODUCTION

In a coal mining industry – similarly as in the case of other industry branches – the growth of monitoring systems application. Initially, monitoring systems were designed just for the purpose of data acquisition and presentation. Over time, their abilities were extended in the direction of simple dangerous situations recognition and finally – to the advanced machine diagnostic status analysis and its prediction for the nearest future.

Longwall systems are the basis of the coal mining, because the longwall is the place in the process of mining from which we can say about the output. Mechanised longwall systems consist of longwall shearer (which tears off the output from the rock), longwall conveyor (transports the output from the longwall to the heading) and units of powered roof support (prop the roof after mining the output).

Longwall systems are very interesting objects from the collected data point of view. Its most important part is a power roof support. Its primary task is to protect the other elements of the longwall system, especially the coal shearer which is an essential part as of a coal mining process. Power roof support consists of units. In a particular moments of time – after shearer takes the another part of the longwall output – each unit has to move in the direction of the whole longwall face advance (treading), protecting the rock material, exposed by the shearer, from collapsing.
Unequal propping can be caused by leaks in the hydraulic system (pipes, valves) or leaks in legs of the unit. To long times of treading can point the wrong diagnostic state of the unit or be caused by the wrong usage (so called: moving with the contact of roof-bar with the roof). It is also dangerous to perform the treading too long as the roof is not propped. So it can be stated that the

David C. Wyld et al. (Eds) : ITCS, CST, JSE, SIP, ARIA, DMS - 2015
pp. 63–70, 2015. DOI : 10.5121/csit.2015.50107

safety of coal mining is determined by the diagnostic state of all parts of the longwall mining system, including the diagnostic state of all units of power roof support.

In this article the ability of adaptation of biclustering method for the purpose of the analysis the data from longwall monitoring systems is presented. The paper is organized as follows: it starts from the brief description of monitoring systems with a special consideration of underground coal mining monitoring system is presented. Than the description of a construction, the role and a working cycle of a powered roof support is presented together with the proposed monitored (and extracted) parameters. Next part presents a wide group om continuous and binary data biclustering methods. The paper ends with a perspective of application of these methods in the longwall monitoring systems.

2. MONITORING SYSTEMS

Nowadays, software producers and monitoring systems users point the need of analysis of the data, collected in repositories of these systems. In particular, the definition of diagnostic models of monitored devices can be a goal of this analysis [1][10][19]. The process of a diagnostic model identification can be carried out by planned experiments or on the basis of a data from the past device operation.

The problem of a monitoring and diagnosing of a coal mine industry devices was raised recently in [1][6][8][16][17][19]. These topics are presented widely and review in [1][19]. In these works also new methods of extraction and processing of new diagnostic features in new diagnostic relations discovering are presented. Especially in [1] the diagnostic of conveyor belts is described. In [17] a current consumption and a temperature of roadheader cutting head. On the basis of these parameters three roadheader working states were defined. Two of them described different but correct underground mining conditions. In this paper also the parameter reflecting the roadheader cooling system efficiency was defined.

Longwall conveyors diagnostic was an aim of the following works [6][8][16][4][5][12]. In [6] the way of conveyor chute failures detection on the bottom side of a conveyor was presented. On the basis of the conveyor engines power consumption analysis the failure was detected with an accuracy to the one unit. In [8] the complex subassemblies management system was proposed, which allows to generate operational and analytical reports as well as summary statements.
In [16] the analysis of the motor driving the conveyor power consumption is described. As the result summary reports are presented and an association rules-based description of the motor operating parameters are described.

3. POWERED ROOF SUPPORT

The safety of underground coal mining depends on many of natural and technical factors, also including the human factor. From the technical factors the diagnostic state of powered roof support units must be acknowledged. It becomes more understandable when the construction and the working cycle of single unit is known. In this section the basics of the powered roof support unit structure and its working cycle description are presented.

3.1. Unit Structure

An unit consists of one or more hydraulic prop (legs), holding up an upper part of the unit (roof-bar). It also has and hydraulic shifting system that is responsible for shifting the unit with the longwall advance simultaneously. The unit should prop the roof, assuring the safety of mining. From time to time – after the shearer passage – the unit must prop the newly bared roof.

Fig. 1 Single unit of powered roof support (www.joy.com).

3.1. Working cycle

A typical unit working cycle can be described from the moment of treading, when the pressure in the leg decreases. A 6000 second long leg pressure series is presented on the Fig. 2.

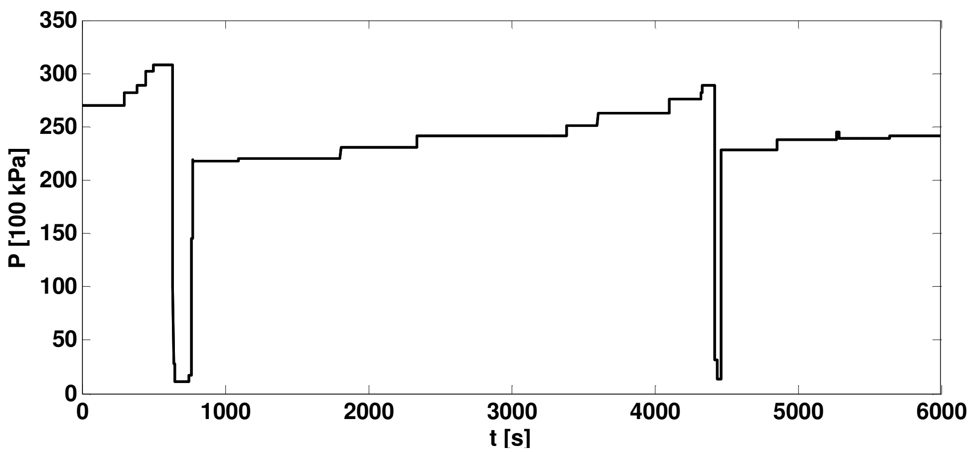

Fig. 2. A real time series of pressure in the unit leg.

It is typical to decrease the pressure as long as the roof-bar has the contact with the roof. This phase is very short – takes only several seconds – and is characterised by the rapid decrease of the pressure (light grey field between 635th and 648th second on the Fig. 3.). Then the phase of treading is performed (between 649th and 751st second on the Fig. 3.). It is characterised by the very low level of the pressure in the leg. Usually the time of treading should be constant as the wall web by shearer is also almost constant. But it happens that the duration of this phase increases with the malfunction of hydraulic system (the pressure in the leg remains on the low level) or due to the treading with the roof-bar touching the roof (treading with contact). The second situation is present with the rather high pressure in the leg (several or more times higher than in the treading without a contact). Next, the spragging – an initial, rather fast, pressure increase of the leg – is performed in order to assure the contact with the roof (dark grey field between 752nd and 772nd second on the Fig. 3.) and then as a result of roof work the slow increase of a pressure in the leg follows.

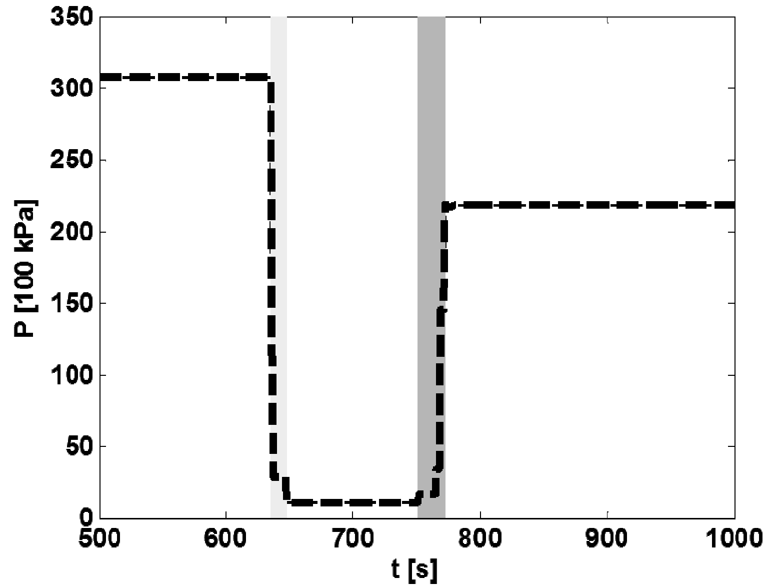

Fig.3. Phases of unit working cycle.

3. POWERED ROOF SUPPORT MONITORING

The most important element of powered roof support monitoring is the measuring legs pressures in each unit. This helps to determine the working cycle phase of unit. Following also the durations of all cycle phases can be calculated, including the treading time. For units equipped with more than one leg also the effective roof propping strength can be determined. Unequal roof-bar propping may have negative consequences influencing on the unit diagnostic state.

On the basis of measured pressures in all units in the longwall the detailed analysis of each unit work and even each leg in the unit work during the exploitation can be performed, including the following aspects:

- Durations of unit working cycle phases,
- Pressure statistics aggregated in time intervals (max, min, std)
- Inequality of propping (for units with two or more legs)
- Statistics of treads (durations, pressure level)

As all characteristics are time dependent (values are varying in the time) and all units can be treated as objects from the same population, every characteristic for the powered roof support can be present as the twodimensional matrix. A sample matrix is presented on the Fig. 3. It is intuitive that the time axis is the X axis we will assumed that following sections are rows and the column represents the state of all units at the selected time in the past.

This matrix can be interpreted as the image in the further analysis, but this assumption implies that two distant units which behave in the same inappropriate way should be considered separately. In our feeling this does not reflect the nature of the process. The other way of twodimensional data analysis is searching of subsets of rows which behave in the similar way on the subset of columns. This way of data analysis is called biclustering.

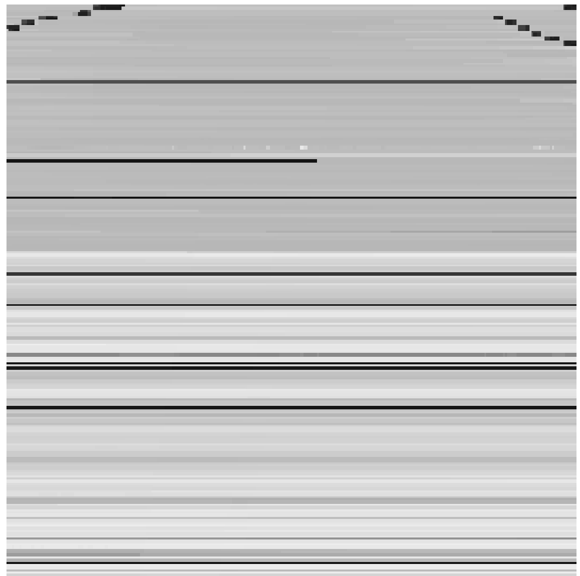

Fig. 3 Matrix representing a series of legs pressures in the powered roof support.

3. BICLUSTERING

Biclustering is the problem of unsupervised data analysis, where we are grouping scalars from the two-dimensional matrix. It called also as co-clustering, two-dimensional clustering or two mode clustering. This approach has been started in 70's in the last century [7] and is successfully applied in bioinformatics [5][14][19] or text mining [5]. The illustration of the main idea of biclustering is presented on Fig. 1.

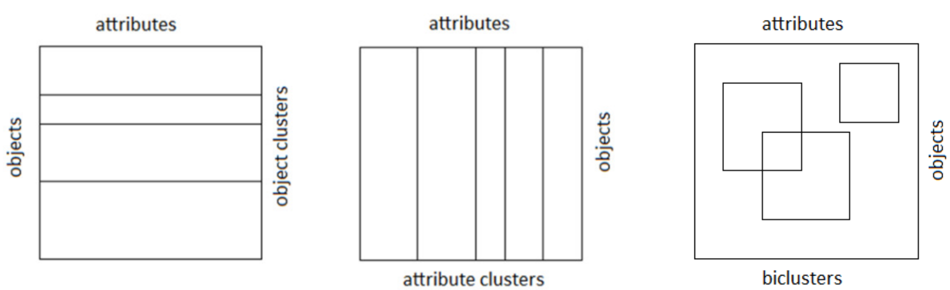

Fig. 4 Schematic representation of clustering (left, centre) and biclustering (right) [1].

In the literature there are a lot of algorithms of biclusters induction. In [5] authors define bicluster as a subset of rows under subset of columns, for which calculated parameter (mean squared residue score) is below threshold defined by the user. The minimum value of the considered parameter is 0. The algorithm consists of two steps. Initially the rows and columns are removed from input dataset, until the value of mean squared residue score is below assumed level. Then rows and columns, which were removed during the first step, are added to obtained in the previous step submatrix until its score fulfils the criterion of being bicluster. After each iteration, the founded bicluster has been hidden with random values. The extension of this algorithm proposed in [20] allows to avoid noise among input dataset, which was a consequence of masking discovered biclusters. The Order Preserving Submatrix Algorithm was presented in [3]. The bicluster was defined as subset of rows, which preserves linear ordering across subset of conditions. The set of valid biclusters is identifying by algorithm based on stochastic model. This idea was also evolved in [9].

The algorithm X-Motif is dedicated to the extraction of conserved gene expression motifs from gene expression data and has been proposed in [13]. Bicluster is defined as subset of genes, which expression level belong to the same state across subset of conditions. The states are assigned to genes during preprocessing step. In order to find multiple biclusters an algorithm is running in an iterative way. Each iteration starts from different initial sets.

There exists also methods of biclustering dedicated for matrices with the binary values. Bimax [15] uses a simple divide-and-conquer approach for finding all inclusive maximal biclusters for a given minimal number of rows and columns. Bicluster, which is maximal in the sense of inclusion is defined as not entirely contained in any other bicluster. Such assumption allows to exclude from analysis individual cells equal to one, which can be considered as a single biclusters, however they provide no important information.

BicBin [18] is an algorithm dedicated for binary sparse matrices. It consists of three main components: the score function to evaluate a submatrix, the search algorithm to restrict the search space of all possible submatrices and an algorithm used to extract all biclusters in an ordered way from a dataset. BicBin is dedicated for finding inexact biclusters. Each run of BicBin may give different results, because algorithm finds set of random biclusters, which fulfil its restrictions and cover all ones in dataset.

A novel approach of the binary matrix biclustering is based on the rough sets theory [11], where non-exact biclusters are defined as the ordered pair of biclusters called a lower and an upper approximation. The lower approximation is the exact submatrix of the given one and the upper approximation is non-exact matrix that is the superset of a given one. The algorithm is hierarchic similarly as the Ward clustering algorithm. In every step two rough biclusters can be joined if the intersection of their lower approximations is nonempty. The generalisation of the data description allows to limit the number of final biclusters assuring the assumed level of the description accuracy.

The analogical hierarchical strategy can be also applied for classical biclusters (not considered as the rough bicluster) and was presented in [11].

4. PERSPECTIVES OF LONGWALL SYSTEMS MONITORING

As presented above it is very important to determine the diagnostic state of powered roof supports units. Due to the nature of units behaviour, which can be different in the close neighbourhood and similar for the distant ones, biclustering methods seem to be appropriate tools for detection of subsets of units behaving similarly in the same period of time.

A single measured value – the pressure level of leg (or legs) in the unit – can bring a lot of diagnostic features, which can describe a diagnostic state of a particular unit. Apart from the units diagnostic state of, also the level of proper longwall system operation quality can be measured.

All mentioned analysis requires data in two aspects. The first one aspect means the raw data, coming from the monitoring systems, which should help in the process of detection of unit working cycle phases. The second aspect means the technical expert knowledge, necessary for the purpose of a raw data interpretation.

ACKNOWLEDGEMENTS

This work was supported by the Ministry of Science and Higher Education – internal grant signature: BK 266/RAu2/2014.

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AUTHORS

Marcin Michalak was born in Poland in 1981. He received his M.Sc. Eng. in computer science from the Silesian University of Technology in 2005 and Ph.D. degree in 2009 from the same university. His scientific interests is in machine learning, data mining, rough sets and biclustering. He is an author and coauthor of over 50 scientific papers.

Magdalena Lachor - received the B.Sc. and M.Sc. diploma in Biotechnology (Bioinformatics) from The Silesian University Of Technology, Gliwice, Poland in 2010. Currently she is a PhD student in the Silesian University Of Technology. Her research interests include data mining methods (in particular biclustering) and application of motion capture technology in medicine.