Analysis of a Mining Process Performance in a Longwall Face – Visualization Proposals

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http://doi.org/10.29227/IM-2019-02-41
Submission date: *05-07-2019* | Review date: *01-08-2019*

Abstract

Analysis of multi-sourced data sets for process improvement purposes requires the selection of relevant techniques enabling data visualisation. There are two main approaches in this scope. The first is based on a raw data and requires from the user determination of properties or patterns while the second one is based on computation of aggregate properties and presentation of the derived data. In the paper we propose to visualize aggregated data in relation to spatial dimension for gaining additional knowledge about process performance. We present an example of performance analysis of machinery used in specific kind of industrial process, namely longwall mining. Our proposals extend range of visualisations that can be used in mining process analysis as well as can be applied in longwall monitoring dashboards and for reporting purposes.

Keywords: mining process, longwall face, data visualisation, process analysis

Introduction

Process improvement is one of the main goals for modern companies. At present, new possibilities of supporting these activities have emerged through more accurate measurement of the process by various sensor systems. Sensors are now the standard elements used in companies i.e. for monitoring of the machinery operation in various industrial processes.

Data coming from sensors can be analysed with data mining techniques, characterised by different degree of sophistication, depending on selected data mining task. The first, and the most intuitive, choice for data analysis is their exploration with visualisation and statistical tools. Sensor data can be easily illustrated as time series (TS) and can be further mined with data mining techniques. However, sometimes raw data illustrated as linear chart and mined as TS type can miss an important information about process performance. Sometimes raw data aggregation is needed for more advanced visualisation purposes and further process analysis.

In the paper we present our proposals in this scope for analysis of machinery operation used in longwall mining.

Our contribution includes providing process space-oriented visualisation of time series data and introduction SPC-like charts in the spatial context of a mining process as well.

Visualisation of time series data

Visualizations can support analysis with two separated approaches. The first (a) is based on raw data and requires from the user determination of properties or patterns while the second one (b) is based on computation of aggregate properties and presentation of the derived data (Albers et al.2014).

The most common visualisation charts are presented in the table 1.

The most popular visualization charts for time series analysis, especially for high-volume data sets, are (Jugel et al. 2014): line charts (Fig. 1), scatter plots (Fig. 2) and space filling visualization (Fig. 3).

In (Weber et al. 2001) as the most important visualization techniques for time series data are pointed: sequence charts, point charts, bar charts, line graphs and circle graphs. In this cited paper also spiral charts were introduced.

The mentioned above techniques are mostly used for raw data visualization. However, for process analysis this kind of visualizations might be insufficient and misleading. For more advance visualization aggregated data can be used. In the (Albers 2014) the following charts are investigated that can be used in (b) visualization approach: modified stock charts, box plots (Fig. 4), composite graphs or coloured charts (Fig. 5).

Other proposals include: calendar view (Van Vijk, Van Selow 1999), viz-tree chart (Lin et al. 2004), time-series bit map (Kumar, Lolla 2005), fan chart, distance chart, bump chart (Schardong et al. 2018).

In this paper we would like to extend the set mentioned above with SPC-like charts as a specific form of visualization of aggregated data regarding to process performance based on time series data.

The main application for SPC (Statistical process control) charts is quality control and process improvement in a manufacturing domain. However, many applications outside of the conventional production systems can be found (MacCarthy, Wasusri 2002).

The control chart is a visualisation of quality characteristic that has been measured or computed from a sample versus sample number or time (Montgomery 2009). Control charts enable detection whether process is working under normal conditions (in-control) or not (out-of-control) (Kadri et al., 2016).

Numerous control charts have been developed to visualize changes of analysed variable mean over time i.e.: Shewhart (Shewhart 1931), CUSUM - cumulative sum (cusum) control (Hawkings, Olwel; 1998) or EWMA - exponentially weighted moving average (Lucas, Saccucci 1990).

Tab. 1. Main elements of data visualisation systems. * – treated as special kind of the bar chart. Source: based on: (Jugel, 2017)
Tab. 1. Główne elementy systemów wizualizacji danych. * – traktowany jako specjalny rodzaj wykresu słupkowego. Źródło: na podstawie: (Jugel, 2017)

Category	Chart type	Marks	Numerical data	Categorical data
line charts	continuous line discrete line	line line	2 1	- 1
bar charts	aligned bars side-by-side bars stacked bars histogram measure bars space-filling vis.	bar bar bar bar bar bar*	1 1 1 1 2 1	- 1 2 - 1 -
2D plots	scatter plot circle charts Gantt charts	shape shape Gantt	2 1 2	- 1 1
2D grids	text table heat map highlight table	text bar* bar+text	1/0 1 1	0/1 1 1
chart matrix	scatter matrix	shape	3	-

The example of SPC chart visualization is presented in Fig.6.

The typical control chart contains the following elements: the center line representing an average value of measured variable, upper control limit (UCL) and lower control limit (LCL).

Typically for classic SPC charts the normal distribution of data samples (with μ and σ) and their independency is assumed. Very often, the assumption of uncorrelated or independent observations is not even satisfied in some manufacturing processes. When autocorrelation of data occurs the various methods of pre-processing and data aggregation can be applied (Montgomery 2009): based on model-based approaches (i.e. ARIMA model, EMWA model) or model-free approaches (i.e. Batch Means Control Chart).

Regarding the proposed visualization methods for aggregated data we propose to visualize TS data in the spatial context of the process to enable detection of potential problematic places in the process execution in relation to specific location. It is especially important if during process realisation the place of operation is changed. An example of this type of process is a mining process. In our work we focus on longwall mining which is a cyclic process conducted in space. Its characteristic is presented in the next section.

Mining process and longwall shearer operation characteristic

In Polish hard coal mines, mining of coal is most often carried out in the longwall faces, which are equipped with a longwall complex. The longwall complex is a set of machines and devices appropriately selected in terms of efficiency and mutual cooperation.

The mining process can be defined as a cyclical implementation of a set of operations (activities) repeated in a specific order and time in a longwall face (Snopkowski, Napieraj 2012). The set of these activities depends on the used technology, equipment and work organization, however, most often (i.e. in the technology of two-way mining with a shearer) it covers (Napieraj 2012):

- cleaning with use of the shearer,
- cutting with use of the shearer,
- slotting with use of the shearer,
- turning conveyor,
- turning support,
- turning drive station replacement,
- turning reverse drive replacement.

Moving the support and conveyor follows the working shearer. Drive station and reverse drive shifts are performed at both ends of the excavation. These activities are illustrated in Fig. 7.

Longwall shearers are the most commonly used mining machines in the Polish hard coal mining industry. They are part of a mechanized longwall complex, a shearer – conveyor – support.

The shearer consists of two mining heads (cutter drums), placed on the arms, power train, electric motors and a block of electrical equipment. The feed speed of the shearer is usually considered for the following operations: slotting, cutting (mining) and cleaning (manoeuvring). The load of mining heads (cutter drums) is not constant and depends on the type of operation performed as well as on the changeable geological conditions. Differences in loads can be observed i.e. during coal cutting and cutting of some harder types of rocks.

Described process has a logistical and specific character because the place of the process execution changes in time and space. The approach presented in this paper can be used to identify problems in the process, which may include i.e. undesirable overloading of the shearer parts in relation to the spatial structure of the mining process as well as geological or mining conditions.

Proposals of data visualisations for analysis of longwall shearer operation

There are two main groups of visualizations used in basic analysis of a mining process in a longwall face. The first group comprises classic line charts for selected variables from longwall monitoring systems (in a form of time series) like: currents, location (i.e. Stecula et al. 2017), methane con-

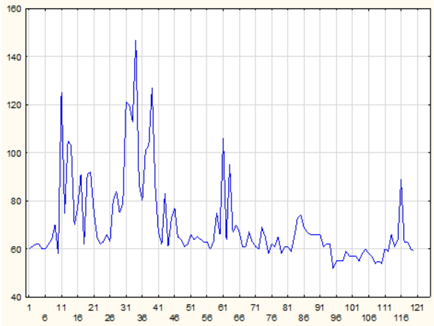


Fig. 1. An example line chart
Rys. 1. Przykładowy wykres liniowy

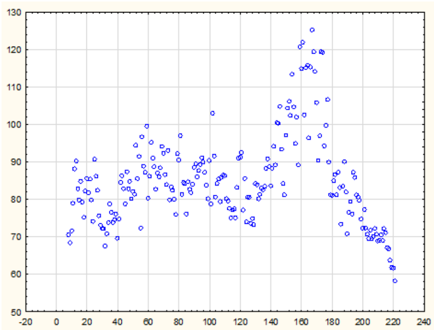
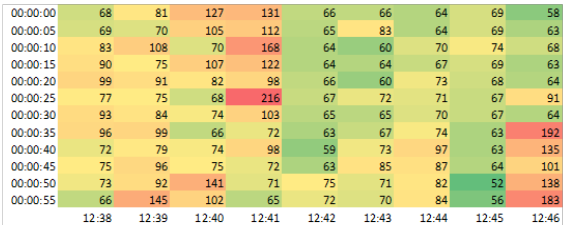


Fig. 2. An example scatter plot
Rys. 2. Przykładowy wykres rozproszenia



00:00:00	68	81	127	131	66	66	64	69	58
00:00:05	69	70	105	112	65	83	64	69	63
00:00:10	83	108	70	168	64	60	70	74	68
00:00:15	90	75	107	122	64	64	67	69	63
00:00:20	99	91	82	98	66	60	73	68	64
00:00:25	77	75	68	216	67	72	71	67	91
00:00:30	93	84	74	103	65	65	70	67	64
00:00:35	96	99	66	72	63	67	74	63	192
00:00:40	72	79	74	98	59	73	97	63	135
00:00:45	75	96	75	72	63	85	87	64	101
00:00:50	73	92	141	71	75	71	82	52	138
00:00:55	66	145	102	65	72	70	84	56	183
	12:38	12:39	12:40	12:41	12:42	12:43	12:44	12:45	12:46

Fig. 3. An example space filling visualization
Rys. 3. Przykładowa wizualizacja wypełnienia przestrzeni

centrations (i.e. Sikora, Sikora 2012), mechanized roof support leg pressure (i.e. Li et al. 2018) or aligned bar charts of selected features(i.e. Szurgacz, Brodny 2018). The second group comprises coloured charts (heat maps) mainly for visualization of roof supports' leg pressure with spatial context – location of roof supports (Jasiulek 2018).

In this section we propose selected visualisations for a longwall shearer operation analysis based on aggregated data, regarding spatial characteristic of the mining process.

In figure 8 and 9 visualisations of current of the shearer's right cutter drum and location of the shearer in the longwall A as time-ordered sequences are presented (note: because of anonymisation requirements - time is expressed in 5 seconds units).

In the Fig. 8 we can observe overloading of the cutter drum (>300A), however further analysis of process performance in the spatial context cannot be easily performed.

Thus, we propose to aggregate and visualize data in relation to space dimensions for support detection of problematic places in excavation which have impact on mining process realisation.

The first visualizations (Fig. 10,11) show box plots including basic statistical measures for current of the right cutter drum in the longwall A, on x-axis shearer location in the longwall face is presented. In Fig. 10 quartiles (include median), minimum and maximum values of cutter drum current are included while in Fig. 11 mean values and standard deviation of variable can be observed.

These charts visualize the same data as presented in Fig. 8 and Fig. 9, but in this case problematic places in process related to shearer location in excavation can be identified easily. Such visualisation can support analysis of daily work progress monitoring and decision-making process as well as prediction of shearer performance in time window (assumed for statistical aggregation). Usage of aggregated data enables observation of places in which problem often occurs and it is not biased by single (i.e. maximal) sensor reading. In analysed excavation we can observe that abnormal high values of cutter drum current occurred between 160m and 176m of the longwall face. Such information can be used for further investigation of causes of such phenomena (i.e. changes in seam geology, organizational or technological problems).

Similarly, aggregated data can be used for creation of SPC-type charts. In case of SPC-type charts, we propose to apply at x-axis spatial dimension of the process (instead of

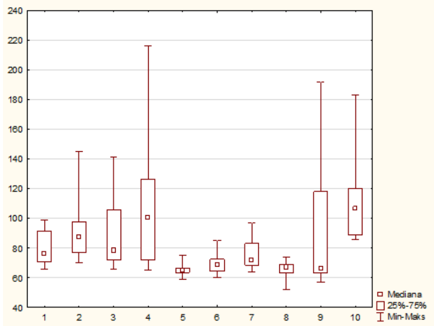


Fig. 4. An example box plot (square encodes median value, box encodes percentiles (25% and 75%), lines with dash encodes minimum and maximum values)
Rys. 4. Przykładowy wykres pudełkowy (kwadrat koduje wartość mediany, pole koduje percentyle (25% i 75%), linie z myślnikiem kodują wartości minimalne i maksymalne)

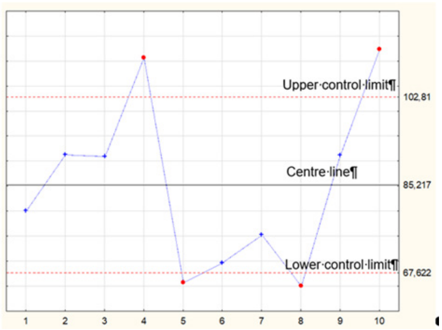


Fig. 6. An example control chart
Rys. 6. Przykładowa tabela kontrolna

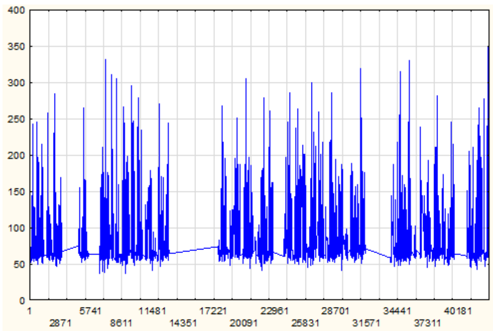


Fig. 8. Current of the right cutter drum in time [A]
Rys. 8. Prąd prawego bębna tnącego w czasie [A]

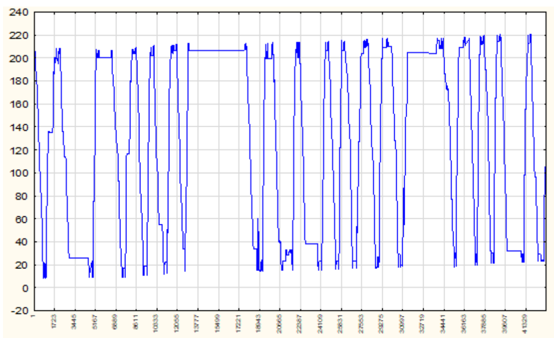


Fig. 9. Location of the shearer in time [m]
Rys. 9. Lokalizacja kombajnu w czasie [m]

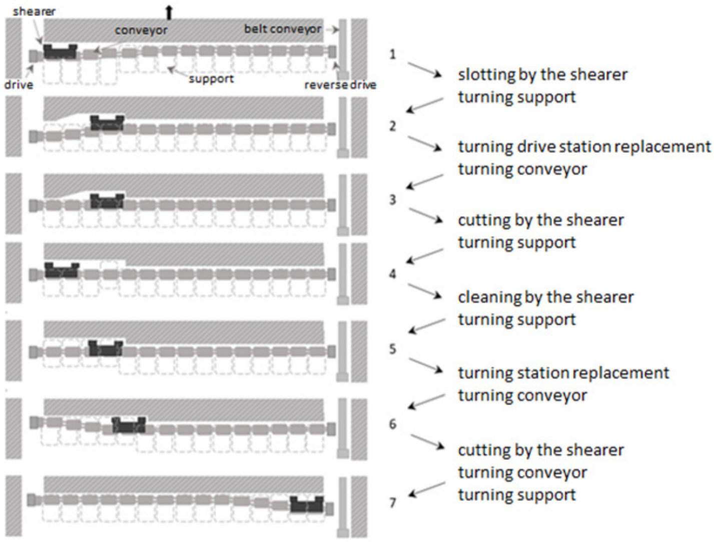


Fig. 7. The general scheme of activities carried out in a longwall face. Source: (Brzychczy, Napieraj 2018)
Rys. 7. Ogólny schemat czynności wykonywanych na ścianie

99	145	141	216	75	85
80	91	91	111	66	70
66	70	66	65	59	60
12:38	12:39	12:40	12:41	12:42	12:43

Fig. 5. An example coloured chart (each minute has 3 colour blocks: the top encodes maximum, middle is the mean, bottom – minimum) adopted from (Albers et al.2014)
Rys. 5. Przykładowa tabela w kolorze (każda minuta ma 3 kolorowe bloki: góra koduje maksimum, środek to średnia, dół – minimum)

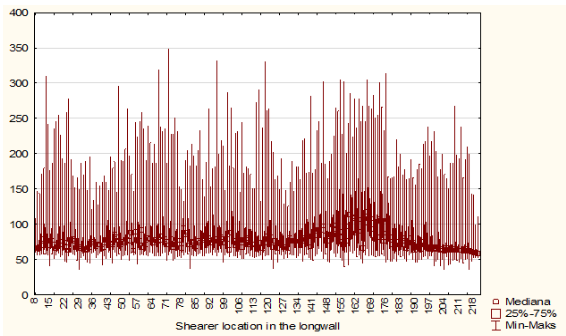


Fig. 10. Box plot 1 for basic statistics of right cutter drum current in relation to shearer location
Rys. 10. Wykres pudełkowy 1 dla podstawowych statystyk prądu bębna prawego noża w odniesieniu do położenia kombajnu

samples number) and selected statistical measure at y-axis. There is also possibility to indicate the "alarm" limits for too high or low values of statistical measure for analysed variable.

In the Fig. 12 mean values of cutter drum current are presented. In the Fig. 13 values are smoothed with exponentially-weighted moving average. In both charts problematic places can be easily identified. SPC-type chart additionally provides information about "visual" distance of measured values to settled alarm limits.

Modified SPC charts have been applied in mining domain, mainly for roadway's cross-section convergence analysis (Duży 2007, Ulaszek 2013).

The last proposal of shearer data visualisation in the spatial context is a heat map enabling detection of anomaly values with detail information related to time dimension (Fig. 14).

In the heat map colours indicate diversified mean values of analysed variable aggregated daily. Depending on user requirements colour scale can be adjusted. In the heat map, changes of aggregated measures in time can be observed, providing wider perspective for space-oriented analysis of the process.

Conclusions

Nowadays, in the era of big data, it is very important to select relevant techniques and methods for analysis and interpretation of multi-sourced data sets for process improvement purposes. Huge volume of data can be found in every enterprise applying the Industry 4.0 solutions based on sensor data. Time series visualizations in process analysis, especially in case of changeable processes in space, can be insufficient.

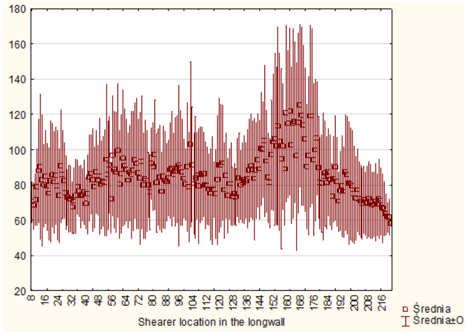


Fig. 11. Box plot 2 for basic statistics of right cutter drum current in relation to shearer location
Rys. 11. Wykres pudełkowy 2 dla podstawowych statystyk prądu bębna prawego noża w odniesieniu do położenia kombajnu

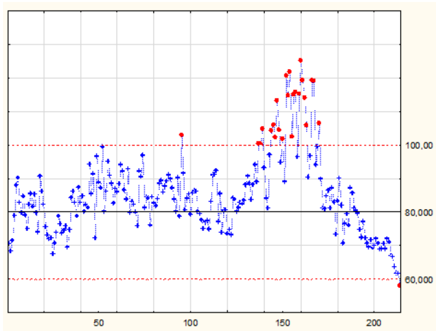


Fig. 12. SPC-type chart with mean value of cutter drum current
Rys. 12. Tabela typu SPC ze średnią wartością prądu bębna tnącego

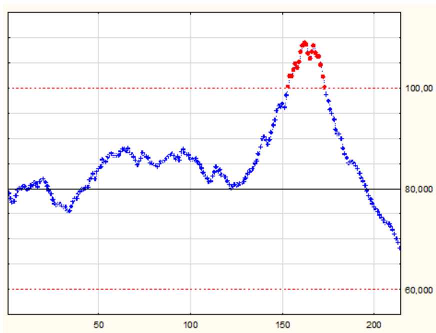


Fig. 13. SPC-type chart with EMWA for cutter drum current
Rys. 13. Tabela typu SPC z EMWA dla prądu bębna tnącego

	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86
day1	107,82	126,22	127,50	107,56	90,56	97,75	100,92	159,60	143,07	152,50	145,25	127,07	111,40	131,70	113,27	148,36
day2	78,26	85,10	80,07	75,79	78,56	82,11	77,86	96,57	84,18	87,93	88,52	74,51	76,44	70,93	73,70	76,19
day3	90,69	100,80	106,33	85,73	95,60	74,62	71,82	73,36	84,32	90,50	87,31	84,50	79,20	69,12	79,47	65,36
day4	70,39	78,21	78,88	74,17	68,72	75,00	76,52	68,94	89,78	87,56	87,82	74,09	77,79	80,21	85,04	78,81
day5	96,81	75,83	90,39	77,01	91,22	81,42	77,65	65,95	90,23	84,94	104,95	86,33	77,07	89,86	75,49	84,85
day6	94,53	119,19	101,60	99,13	107,35	87,91	81,92	95,26	97,20	89,38	92,29	92,35	92,78	83,91	73,76	89,10

Fig. 14. Heat map of right organ current with spatial dimension
Rys. 14. Mapa cieplna prądu prawego organu tnącego

In our work we proposed to use visualisations of aggregated data in relation to spatial dimension for gaining additional knowledge about process performance. Use case presented in the paper regards to mining process conducted in the longwall face.

Selected visualisations take into account specific nature of this process and enable identification of problematic places in the process execution. Provided information can be in-depth investigated taking into account the context data regarding seam geology, organizational or technological issues.

We think that our proposals extend range of visualisations that can be used in mining process analysis as well as can be applied in longwall monitoring dashboards and for reporting purposes.

Acknowledgements

This activity has been funded as a part of research work no.16.16.100.215 at AGH University of Science and Technology

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Analiza wydajności procesu wydobycia systemem ścianowym – propozycje wizualizacji

Analiza danych w celu usprawnienia procesu wymaga między innymi wyboru odpowiednich technik wizualizacji danych. Istnieją dwa główne podejścia w tym zakresie. Pierwsze opiera się na wykorzystaniu surowych danych i wymaga od użytkownika określenia właściwości lub wzorców dla wizualizacji. Drugie natomiast opiera się na wartościach zagregowanych i prezentacji przekształconych danych. W artykule, w celu uzyskania dodatkowej wiedzy na temat realizacji procesu wydobywczego w wyrobisku ścianowym, zaproponowano wizualizację zagregowanych danych w odniesieniu do wymiaru przestrzennego realizowanego procesu. Jako przykład przedstawiono wizualizację obciążenia organu kombajnu ścianowego w odniesieniu do położenia w ścianie. Przedstawione propozycje rozszerzają zakres wizualizacji, które mogą być wykorzystane w analizie procesu wydobywczego. Mogą również znaleźć zastosowanie w pulpitach menedżerskich (dyspozytorskich).

Słowa kluczowe: proces wydobywczy, wyrobisko ścianowe, wizualizacja danych, analiza procesu