Machine Activity Recognition Using Clustering Method

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Abstract

Machine activity recognition is important for benchmarking and analysing the performance of individual machine, machine maintenance needs and automated monitoring of work progress. Additionally, it can be the basis for optimizing manufacturing processes. This article presents an attempt to use object clustering algorithms for recognizing the type of activity in the production complex. For this purpose, data from the production process and the k-means algorithm were used. The most common object clustering algorithms were also discussed. The results and the presented analysis approach demonstrate that this method can be successfully utilized in practice.

Keywords: *Machine Activity Recognition, clustering, process mining, performance of individual machines, operational efficiency*

1. INTRODUCTION

In mining production, significant financial and human resources are involved. How these resources are utilized in the actual production process often determines the profitability of production. Data from the production process, collected through sensors installed in machines, allows for monitoring the performance of production systems. This enables calculating the utilization of machines and tracking the progress in line with the adopted schedule. Proper data analysis can also lead to the optimization of the production process, which is often far from the ideal model due to real-world conditions.

Such analyses are conducted within the framework of a process known as Process Mining, whose aim is to identify potential issues occurring in the production process and find areas for improvement. In the current context of process automation, achieving this goal requires having an appropriate set of data. In addition to data from automatic measurement systems, information about the type of machine activity (e.g., transit, operation, downtime) is essential. Such information is not measurable and is not part of the sensor data stream recorded in the database. Comparing the actual sequence of activities performed in the production process with the adopted model process allows for identifying bottlenecks, identifying unnecessary repetitions of activities, and determining the causes of downtime and failures. If you do not have the appropriate event log, then the solution is MAR (Machine Activity Recognition). Methods of this kind involve recognizing the activities performed by machines based on the analysis of multiple parameters of their operation recorded at the same time. In the literature, there is a growing number of examples of such approaches, mainly in the construction industry. It most commonly concerns excavators [4, 10, 11, 12], loaders [5, 12, 13], or compactors [8]. In the mining industry, such analyses primarily pertain to the operation of loaders (open-pit mining) or shearers [6, 16].

Most commonly, machine activity recognition is accomplished using supervised machine learning methods based on labelling, where observed machine states are assigned to recorded machine operation parameters. In the majority of cases described in the literature, this involves observing video recordings of machine activities along with timestamps of their start and end times. For this purpose, supervised classification methods are employed, with neural networks being the most commonly used. However, conditions suitable for video camera operation are not always present, and the nature of activities may not be identifiable through this approach. In such situations, unsupervised classification methods become the solution. In the following part of the study, an example of activity recognition in a mining complex will be presented, based on the recorded current intensities flowing through motors driving its elements.

2. METODY GRUPOWANIA OBIEKTÓW

Object clustering methods, often referred to as clustering or cluster analysis, aim to identify groups/clusters of objects that are similar to each other within the group but dissimilar to objects in other groups. The most popular methods include:

K-means algorithm – is one of the simplest and most popular clustering algorithms. This algorithm involves dividing the dataset into k clusters, where k is a predetermined number. Each cluster is represented by its mean values, called centroids. In each step of the algorithm, each object is assigned to the class whose centroid is the closest. Then, new centroids for each class are calculated as the average value of all objects in that class. This process is repeated iteratively until the objects achieve a stable assignment to the clusters or a stopping condition is met. [3]

K-medoids algorithm – is similar to k-means, but instead of using mean values as cluster representatives, it selects one of the objects from the cluster, which is called a medoid. A medoid is a point that is closest to the other objects in the cluster. The main advantage of k-medoids is its greater robustness to outliers, as the medoid is not sensitive to extreme values in the cluster. The k-medoids algorithm is iterative and

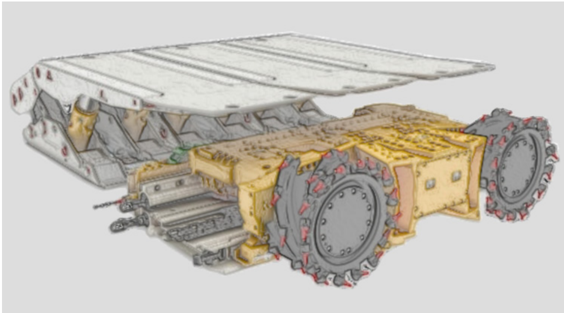

Fig. 1. “Mikrus” longwall system [17]
Rys. 1. System ścianowy “Mikrus”

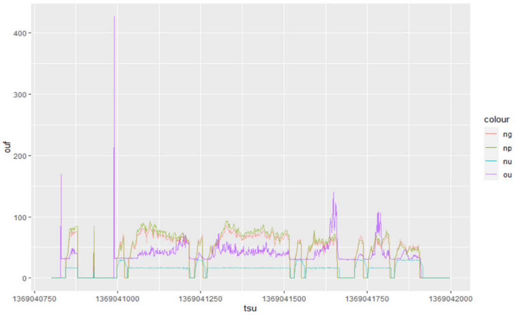

Fig. 2. A plot of the variation of recorded current intensities as a function of time. Source: own study
Rys. 2. Wyres przebiegu zmienności rejestrowanych natężeń prądów w funkcji czasu

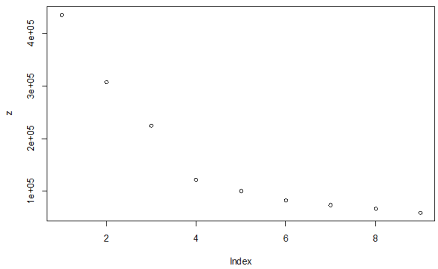

Fig. 3. Elbow rule plot. Source: own study
Rys. 3. Wykres reguły “łokcia”

relies on assigning objects to the nearest medoid and updating the medoids in each iteration. The iterative process is repeated until the objects achieve a stable assignment to the clusters, and the difference between the medoids in consecutive iterations is small .[7]

Hierarchical Clustering – is a family of clustering methods that create a hierarchical tree or dendrogram of objects, where each level of the tree represents a different level of grouping. It can be categorized into two main types: agglomerative (starting with individual objects and merging the most similar clusters) and divisive (starting with a single large cluster and recursively dividing it into smaller ones). The hierarchical clustering process continues until all objects are assigned to their individual clusters or until a stopping criterion is met. This method is useful for exploring the structure of the data at different scales, as it provides a visual representation of the nested relationships between clusters. [14]

DBSCAN – is a density-based clustering method that groups together objects based on their spatial density. It classifies objects into three categories: core points, border points, and noise points. Core points are densely surrounded by other points within a specified radius (epsilon) and are used as seeds to form clusters. Border points are within the epsilon neighborhood of a core point but are not core points themselves, and noise points have no core points within their epsilon neighborhood. DBSCAN efficiently discovers clusters of arbitrary shapes and is robust to outliers, as they are treated as noise points. The algorithm starts with an arbitrary point, finds its epsilon neighborhood, and recursively expands the cluster by adding reachable core and border points. The process continues until all points are assigned to clusters or marked as noise. [7]

The Expectation-Maximization (EM) algorithm – is a probabilistic clustering method that assumes data are generated by an underlying statistical model with latent (unobserved) variables. EM is an iterative process that alternates between two steps: the E-step (Expectation step) and the M-step (Maximization step). In the E-step, it estimates the probabilities of the latent variables given the observed data and the current model parameters. In the M-step, it updates the model parameters by maximizing the expected log-likelihood of the complete data. The EM algorithm converges to a

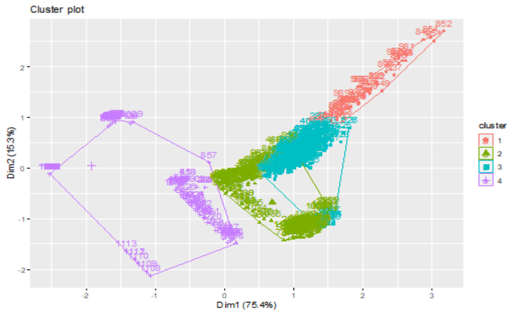

Fig. 4. Cluster plot. Source: own study
Rys. 4. Wykres grupowania

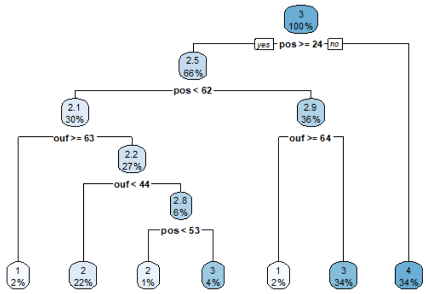

Fig. 5. Decision tree obtained after clustering process. Source: own study
Rys. 5. Drzewo decyzyjne pogrupowanych danych

local maximum of the likelihood function and is often used to find maximum likelihood estimates for models with missing data or unobserved variables. It has wide applications in various fields, including data clustering, image processing, and statistical modeling. [1]

The Fuzzy C-Means (FCM) algorithm – is a variation of the traditional k-means clustering method that allows objects to be assigned to multiple clusters with different degrees of membership. In FCM, each object is characterized by a set of membership values, indicating the likelihood of belonging to each cluster. Unlike k-means, where an object is rigidly assigned to the nearest cluster, FCM softens the assignment by using fuzzy logic. The algorithm iteratively updates the membership values and the cluster centers until a certain convergence criterion is met. FCM is particularly useful when an object can belong to more than one group simultaneously or when there is ambiguity in assigning objects to distinct clusters. It has applications in various fields, including image segmentation, pattern recognition, and decision-making systems. [2]

In the example presented below, the k-means algorithm was used due to its fast convergence, scalability, simplicity, and efficiency.

3. PRACTICAL EXAMPLE

The results presented below concern the "Mikrus" longwall complex, during the period when the complex was tested under real conditions. The "Mikrus" longwall complex is designed for extracting thin coal seams with a thickness of 1.1–1.5 meters. It is equipped with the GUŁ-500 cutting-loading head, which is moved along the coal face by a longwall conveyor. The movement of the head is carried out using a traction system of cutting elements beneath mechanized housing sections (Fig. 1). The exploitation of this complex is associated with an innovative mining technology using perpendicular caving, enabling the completion of a full shearing cycle in approximately 1 minute. [https://famur.com/urzadzenia-dla-gornictwa-podziemnego/kompleks-mikrus/]

The control of the complex is carried out by an operator utilizing a central control panel located in the goaf. The traction system of cutting elements is powered by electric motors supplied from frequency converters placed in the drivages. [17].

The original data format contained information about changes in current intensities, the time of their occurrence, and the engine code to which the change pertained. The investigated dataset contained columns with the following parameters:

tsu – time of observation (unix timestamp),
ouf – current intensity of the cutting element motor [A],
ngf – current intensity of the main drive motor [A],
npf – current intensity of the auxiliary drive motor [A],
nuf – current intensity of the cable layer motor [A].

The decision to register changes in current intensity effectively reduced the amount of transmitted and stored data, but for their analysis, it was necessary to reconstruct their original arrangement. This was achieved by using appropriate functions in the R programming language. This has been further elaborated in the work [9].

The operation of the main drive and auxiliary motors did not differ significantly. The values of the currents they consumed varied within a small range. This is illustrated in Figure 2, which shows a section of the recorded data.

In Figure 2, both the working and idle periods of the harvester can be observed. The current intensity values of the cutting element motor (ouf) are represented in the violet co-

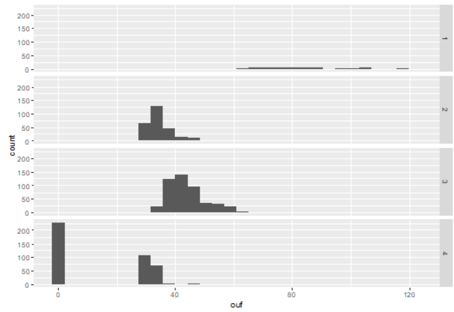

Fig. 6. Histogram of cutting head drive motor current with division into determined groups. Source: own study
Rys. 6. Histogramy natężeń prądów głowicy urabiającej z podziałem na wyodrębnione grupy

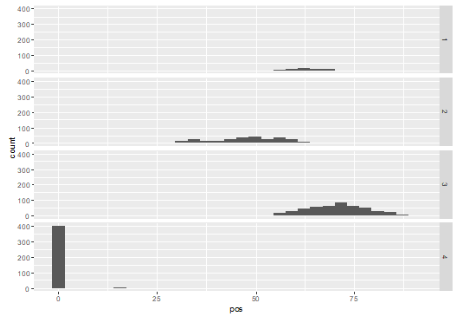

Fig. 7. Histogram of feed drive motor current with division into determined groups. Source: own study
Rys. 7. Histogramy natężeń prądów silników posuwu z podziałem na wyodrębnione grupy

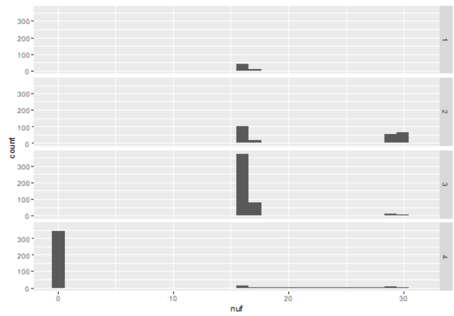

Fig. 8. Histogram of cable laying drive motor current with division into determined groups. Source: own study
Rys. 8. Histogramy natężeń prądów silnika układaka z podziałem na wyodrębnione grupy

lour. During the depicted time period, a peak reaching values exceeding 400 [A] is visible, associated with the start-up of this motor. This is confirmed by simultaneous increases in the current values flowing through the other motors. This figure well illustrates the mutual similarity of the current intensity values in both advancing drive motors and the relatively constant current intensity values in the conveyor drive motor. Due to the similar values of both advancing drive motors, which would result in repetitive information, the average of their values was used in the further analysis.

In the next stage, outliers were removed from the dataset, which, like the aforementioned peak, could disrupt the clustering process. To determine the boundaries beyond which outliers lie, a method based on the interquartile range was adopted The IQR * 1.5 rule, also known as the Tukey rule [15], is a statistical technique used for detecting and handling outliers in data. It involves calculating the interquartile range (IQR), which is the range between the 75th percentile (Q3) and the 25th percentile (Q1) of the data. The IQR represents the spread of the middle 50% of the data. According to the rule, data points that fall below Q1 - (IQR * 1.5) or above Q3 + (IQR * 1.5) are considered outliers and can be potentially removed or treated separately. This rule is especially useful in robust statistics, where it helps in identifying and dealing with extreme values that could adversely affect the results of statistical analysis.

The next step in the conducted analysis was to determine the number of clusters to which the observations could be assigned. The elbow rule was used for this purpose.

The Elbow Rule is a heuristic method used to determine the optimal number of clusters in a clustering algorithm, such as k-means. It involves plotting the variance explained (or another clustering performance metric) against the number of clusters, and looking for an 'elbow point' in the graph. The elbow point is the value of k at which the explained variance starts to level off significantly. The idea is that the optimal number of clusters is often located at this point, as adding more clusters beyond the elbow may not lead to significant improvement in the clustering quality. The Elbow Rule is a useful visual aid for selecting an appropriate number of clus-

Tab. 1. Activity identification. Source: own study
Tab. 1. Identyfikacja czynności

Group	Activity	Premise
1	maneuvering	occasional high values of feeding motor current, occasional high values of cutting element motor current
2	engaging	occasional high values of feeding motor current, high values of cutting element motor current
3	cutting	high values of feeding motor current, the highest values of cutting element motor current
4	idle	zero values of feeding motors current, zero values of cutting element motor current

ters when conducting clustering analysis. In this way, the graph presented in Figure 3 was obtained.

Based on the graph in Figure 3, it was determined that the optimal number of clusters is four. The clustering process was carried out using the k-means function available in the R language after loading the stats library. As a result, a list is generated, containing the cluster numbers to which the consecutive observations in the analysed data were assigned. Figure 4 presents the observations assigned to clusters in a coordinate system reduced to two principal components.

The clustering process conducted, however, does not provide answers to the fundamental question: what characterizes the separated groups of observations, or in other words, which machine operating states have been assigned to the resulting clusters? The answer to this question can be obtained by using a decision tree method, which generates decision rules. Figure 5 presents the decision tree generated using the rpart function available in R. It operates based on the CART (Classification and Regression Trees) algorithm, which involves recursively partitioning the dataset into subsets, based on feature analysis aimed at minimizing the entropy in the partition nodes.

The decision tree from Figure 5 displays the boundary values of the parameters ouf and pos in its nodes, which are used to assign measurements to the corresponding groups. The decision rules generated based on the tree are presented below:

```
cluster
 1 when pos is 24 to 62 & ouf >= 63
 1 when pos >= 62 & ouf >= 64
 2 when pos is 24 to 53 & ouf is 44 to 63
 2 when pos is 24 to 62 & ouf < 44
 3 when pos is 53 to 62 & ouf is 44 to 63
 3 when pos >= 62 & ouf < 64
 4 when pos < 24
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As can be observed, the parameter associated with the conveyor drive does not have an impact on the assignment to the resulting groups. Based on the generated decision rules, the current operation of the harvester can be attributed to the identified clusters. These groups correspond to specific machine activities, and the analysis of the obtained rules often allows for the identification of these activities. Additional assistance in this identification can be provided by histograms of the analysed parameters with division into groups. They are presented in figures 6, 7, and 8.

Simultaneous interpretation of decision rules and histograms allows for the following group assignments:

The extracted activities and rules for assigning observations of machine operating parameters can be used to determine the current machine's activities, but they can also be utilized for analyzing historical data stored in databases.

4. CONCLUSION

The presented method can be applied to a wide range of machines and devices. The widespread use of various sensors enables detailed control over the executed production processes. The results presented in this article are of an indicative nature, but conducting a similar analysis on a larger dataset would significantly enhance their credibility. Utilizing a larger amount of data would likely allow for the identification of a greater number of machine activities/states.

A significant advantage of the presented approach is the absence of the need for event logs, from which information about the occurrence times of specific activities could be obtained. However, if such event logs were available, neural networks could be successfully employed for activity recognition. The conducted analysis allows for the assignment of activities performed by the machine based on measured parameters of its operation. Further work should be conducted to verify the correctness of the recognized sequence of activities to detect deviations from the model sequence of activities envisaged for this production process.

Rozpoznawanie czynności maszyn z użyciem metody grupowania

Rozpoznawanie czynności realizowanych przez maszyny jest bardzo istotne dla porównywania i analizy wydajności poszczególnych maszyn, potrzeb konserwacji maszyn oraz automatycznego monitorowania postępu prac. Dodatkowo, może być ono podstawą do optymalizacji realizowanych procesów produkcyjnych. W niniejszym artykule przedstawiono próbę wykorzystania algorytmów grupowania obiektów do rozpoznawania rodzaju aktywności kompleksu urabiającego. Do tego celu użyto danych pochodzących z procesu produkcyjnego oraz algorytmu k-means. Przybliżono także najpowszechniejsze algorytmy grupowania obiektów. Wyniki oraz zaprezentowany sposób przeprowazania analizy pokazują, że taki sposób postępowania może być z powodzeniem wykorzystywany w praktyce.

Słowa kluczowe: *rozpoznawanie czynności maszyn, grupowanie, process mining, stopień wykorzystania maszyn, wydajność operacyjna*

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