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Production Monitoring and Machine Tracking in Underground Mines Based on a Collision Avoidance System: A Case Study

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In the era of Industry 4.0, one of the key challenges facing underground mines is the real-time tracking of both the production process and machinery movements. Significant emphasis is placed on comprehensive monitoring to achieve situational awareness to ensure informational continuity of operations in dispersed organizations. This knowledge is fundamental for safe and efficient extraction, current production reconciliation, and all operational and planning activities, particularly when considering specialized simulation environments for production optimization. So far, implementations of such solutions on an industrial scale have primarily been encountered in open-pit mines or smaller underground mines. This article presents a solution for machine monitoring and tracking based on data from a collision avoidance system, specifically designed for multi-site underground mining enterprises, where the scale of implementation is incomparably more challenging. This anti-collision system was originally designed for detecting machine-to-machine or machine-to-worker collisions. Consequently, the development of validation algorithms, including error correction and adaptive filtering, was imperative. This also required integration with enterprise resource planning (ERP) systems. Moreover, it was also essential to enhance the system infrastructure with additional sensors to enable the registration of machine localization in specified mining zones (e.g., heavy machinery chamber, mining area, loading and unloading point). As part of this study, several analytical models (enhanced by machine learning techniques) were developed to identify movement patterns and cooperation among wheeled transport machinery, as well as the entire course of ore logistics within the mining area. Finally, the process of implementing the system in the target environment is presented, along with a description of the user interface, which features manager dashboards for production visualization.

Keywords: Industry 4.0, real-time monitoring, underground mining, load-haul-dump (LHD), machine learning, anti-collision system, production optimization, efficiency analysis.

1. Introduction

In the modern mining landscape, achieving real-time awareness of the production process and machinery movement is crucial for maintaining operational continuity and maximizing productivity. Traditional monitoring methods often fall short of providing timely and comprehensive insights into the dynamic nature of underground mining environments. Therefore, there is a growing need for advanced monitoring solutions that are capable of capturing real-time data, facilitating informed decision-making, and being, at the same time, reliable and easy to maintain.

Access to a multidimensional characterization of ore logistics processes is crucial for developing DSS-class systems or so-called digital twins. Otherwise, management will be based on a classical approach where analytical models are fuelled by catalogue data or generally accepted statistics, without considering the diversity of machinery, local operational conditions, or random events. Due to the highly unpredictable nature of transportation processes, it is difficult to guarantee the accuracy of such an approach. Therefore, access to data measured under real-world conditions becomes an important element, as well as the ability to track the flow of ore in the transport network over time and space, with an awareness of operational contexts. The breakthrough in underground mining was not the emergence of control-measurement equipment, but the possibility of building broadband teletransmission networks based on fiber optic technology, which initiated full information exchange between the underground and the surface of the mine. Obtaining partial information about the operation of haulage machines 10–15 years ago would have required a large number of manual measurements. Even with significant human resources involved, it would have been difficult to achieve results comparable to those currently available in real-time through operational technology.

In underground mines, operations are conducted under highly dynamic and challenging conditions. Both mine personnel and a diverse array of mining equipment, including stationary and mobile machinery, are dispersed throughout various sections of the mine. While the width of the workings typically spans a few meters, the length of the underground excavations can extend for hundreds of kilometres [1]. The underground mining environment is full of various adverse factors that hinder reliable communication and monitoring systems, such as uneven structure, poor visibility, dust and gas concentration, humidity, as well as the presence of numerous other sources of interference or mechanical damage [2]. Communication in underground mining represents one of the key elements of mine operation, ensuring safety, increased productivity, reduced operational costs, as well as the protection of the work environment. The need for access to real-time data also applies to teleoperation of mining assets, particularly in exceptionally hazardous conditions [3, 4]. As indicated in [5], current trends in the digitization of the mining industry are moving towards real-time processing and big data, artificial intelligence (AI), automation and robotics, the Internet of Things (IoT), and simulation modeling.

The effectiveness assessment of the production process reveals the significant role of tracking the operation of wheel loaders and haul trucks. Recently, significant advancements have been made in systems for acquiring operational parameters, as well as in cycle detection algorithms. Typically, dozens of parameters are recorded in the monitoring scope, offering great potential for the development of predictive maintenance. However, maintaining such systems at full scale poses significant technical and cost challenges [6–9]. In [10], an analysis of the operating time of automatic long-haul-dump machine (LHD) in an underground mine in Sweden was presented. Particular emphasis was placed on the impact of total machine downtime. This study also applied the fault tree analysis (FTA) to analyze the total operating time. The issue of estimating the remaining machine life, with particular emphasis on changes in operating modes, based on a homogeneous Markov process, was further proposed in [11]. The authors of [12] conducted a review of the most popular key performance indicators (KPIs) used to select optimal (in terms of maintaining the net present value (NPV) of assets) machine maintenance strategies. Article [13] reviewed the literature on measures of efficiency in the process of ore selection, loading, and transportation in the mining industry. Article [14] presented a method to increase equipment utilization efficiency by reducing ineffective machine operating time. In [15], the author presented an analytical model identifying factors inhibiting the productivity of haul trucks used in the Conzal mine. The results of the study allowed for the development of recommendations aimed at eliminating these factors and optimizing production, particularly by improving worker cooperation, reducing haulage distances, maintaining road surfaces properly, and decreasing machine downtime due to breakdowns. A similar factor analysis was presented in [16].

Methods for assessing the utilization of wheel machines found in the literature yield satisfactory results, but their applicability in localizing machines in the mining corridor has not been noted. In extensive mines, the situational awareness of such solutions is therefore limited. As given by the authors in [17], one of the most reliable localization systems for underground mines is tagging technology. Moving machinery or personnel can be tracked by a local radio-frequency identification (RFID) reader at a distance of a few meters for passive tags and several tens of meters for active tags. On the other hand, a moving vehicle can track its position in the mining corridor through passive or active RFID reader identification (with known coordinates) defined as reference points.

Tagging technology is currently also being used to track ore logistics in continuous transport systems [18]. In the literature, one can find many applications of such solutions in industry [19]. Such solutions, in combination with hyperspectral cameras, allow for the tracking of ore flow in the transport network and its mixing, especially if the ore deposit structure is non-heterogeneous [20]. However, their primary application in the production process is found in safety systems. In this regard, collision avoidance systems (CASs) are very popular, as they inform the machine operator about the possibility of a collision with another machine or a pedestrian during machine operation and stationary phases. Many solutions also send warning signals to workers near machines [21, 22]. An overview of available anti-collision systems is presented in [23]. RFID technology has also found various other applications in the production process over the years. For example, authors [24–27] present solutions for tracking personnel and vehicles, tracing detonators and boosters, monitoring ore and the deposit boundary, and providing navigation.

As mentioned earlier, the optimal solution toward which modern underground mining is heading is the IoT technology. However, infrastructural constraints in communication, data management, and storage are the main reasons that prevent mines from achieving fully integrated, automated systems deployed on a large scale. Nevertheless, the literature reveals numerous applications of IoT sensors. For instance, the work of [28] presents an electronic solution integrated into a bracelet for collecting and processing worker's vital parameter data to minimize the physical strain on miners. The acquired data is transmitted via Bluetooth. Additionally, sensors for monitoring gas concentration and miner location within the mine workings, with wireless communication capabilities, are embedded in mining lamps. A similar solution was presented in [29]. Essentially, many operational, technical, and economic factors influence the operation of LHDs and haul trucks. Many of these factors have a random nature [30], which can be unravelled through the use of IoT sensors that provide access to data on various operational contexts crucial for optimizing the production process. An example of this is the use of a cost-effective and non-invasive IoT inertial sensor for multidimensional assessment of dynamic overloads acting on the machine, with factor analysis considering the operational regime (loading, full-load driving, unloading, empty-load driving), road conditions, shape and length of the road, operator driving style, etc. [31]. Other applications of this sensor include tracking machine manoeuvres [32], localization [33], or detecting damages to structural elements (joints) [34]. In [35], the authors conceptually presented the use of IoT platforms employing RFID technology for the localization and tracking of machines and miners in an underground mine.

Decision-making under uncertainty is inherent to the mining industry. Maximizing an organization's operational potential requires the development of specialized computational, engineering, analytical, and simulation environments, as well as optimization-support systems for existing processes and planning operations based on accurate and reliable information. This reduces intuitive decision-making to a minimum. The authors of [36] presented the results of a case study on a safety management system in a mine, utilizing a simulation model of mining truck transport operations, based on the example of an underground limestone mine in Danyang, South Korea. Data from three months of truck operation were analyzed. The model predicted parameters such as ore hauling time, cycle count, production volume, and delay times under various boundary conditions. Article [37] addressed the issue of modeling the heterogeneous ore flow from the mining field to the extraction shaft via conveyor transport in an underground copper mine. The authors utilized the dedicated FlexSim environment to construct a simulation model of underground transport for tracking ore logistics, incorporating functionality for estimating the qualitative and quantitative parameters of the ore. In [38], the author also utilized the FlexSim environment to develop a simulation model of the logistical system in an underground coal mine. The simulation and analysis of coal transportation, along with auxiliary operations, demonstrated the potential for a 30% increase in efficiency through the use of current support technologies and faster coal transportation.

In conclusion, the issues of monitoring production processes, tracking ore logistics, and optimizing the operation of transport machinery are well recognized in the literature. However, most methods described in the literature focus on relatively small mines, case studies, or research and development projects. Many studies do not present ready-made systems based on real-time monitored data. It is common for studies to rely on several months of historical data samples. Additionally, many studies do not focus on underground mines, or their research conditions differ from those of a typical underground mine. There is a lack of clear guidelines on how to obtain reliable information about operational parameters and haulage statistics in a dependable and cost-effective way. Additionally, exploring how to automate the entire process of data fusion from different sources and its validation is essential for further development of methods that support both operational and managerial processes.

This paper presents an analytical system based on data from an anti-collision system integrated into self-propelled machines. The system was tested at KGHM, a multi-plant mining company, offering an incomparably larger research scope, diversity, and volume of collected data.

The article first describes (in the following section) the anti-collision system used and the data obtained from it, the necessary data cleaning and fusion procedures, as well as three separate algorithms proposed for efficiency analysis. These algorithms consider the detection of operator working time, machine working time, and the detection of ore haulage cycles for haul trucks and loaders. Section 3 presents the output of the system in forms of reports created in cooperation with plant engineers (end-users). Finally, the article ends with our conclusions.

2. Materials and methods

The research presented in this article was conducted using a custom-made collision avoidance detection system installed in one of the KGHM Polska Miedź S.A. copper mines in Poland. Previously, the mine has been using this system to improve overall safety in all mine areas. However, as the informational potential of the data became increasingly valuable, the company decided to explore it further, thus leading to this research project. Consequently, several procedures for data cleaning and fusion, along with advanced algorithms for efficiency analysis, were developed. These are presented in detail in the following part of this section.

2.1. Collision avoidance system

The main idea behind the collision avoidance system (CAS) implemented in the studied mine was to utilize radio-based devices already mounted on all machines. Therefore, most components of the CAS were custom-made to meet that specific needs of the mine. For this reason, the entire machinery park was made system-compatible with little to no additional work. For worker equipment, each mining lamp required modification; however, after the initial setup period, the system was fully operational online.

The CAS consists of three main components: the active unit, the passive unit, and the gate (all presented in Fig. 1). At the time of this research, more than one hundred active units, nearly a thousand of passive units, and around a dozen gates were installed. The characteristics of each following device are as follows:

- Active unit – similar to RFID technology, it is used for both receiving and transmitting radio signals. One unit is mounted on each mining machine, and its main task is to inform the machine operator about the number of nearby unprotected workers (i.e., those not seated in other machines). The active unit also records every contact between the machine and other active and passive units, and transmits this data to storage whenever the machine is close to a system transmitting gate. The main power source of the active unit is the machine itself; therefore, and the active unit does not record any data when the machine is turned off.
- Passive unit – mounted on both worker equipment and machinery. This unit does not emit any signals, and can only be detected by an active unit. Passive tags do not require an active power source and can operate for

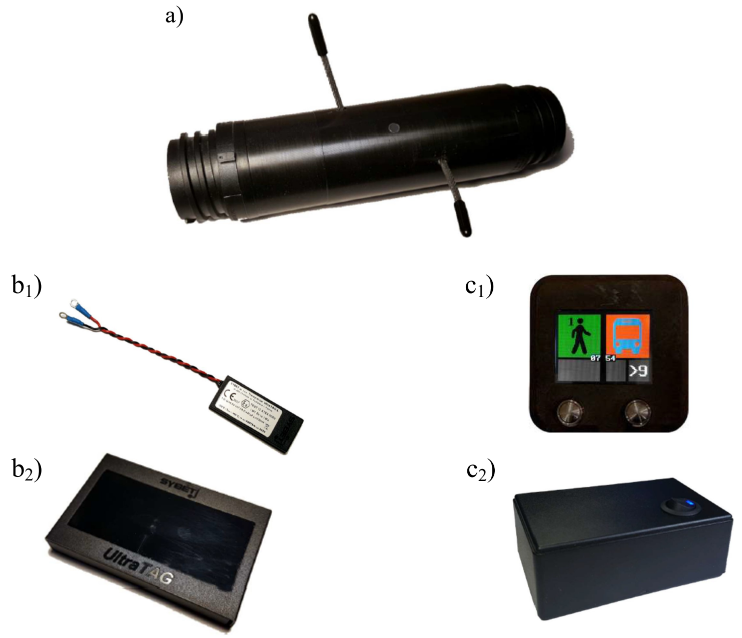

Fig. 1. Devices used in the CAS that was utilized in the studied mine: a) gate for data transmission, b) passive units (b_1 – mounted in workers' mining lamps, b_2 – mounted at other locations), c) active units (c_1 – display for the machine operator, c_2 – active device mounted on machines).

years on a battery pack. The purpose of mounting passive units on machines is to ensure they remain detectable when not in operation (i.e., when their active units are off). For the research presented in this paper, passive units were also mounted at locations to detect specific work operations.

- Gate – this device is used to establish contact with nearby active units and transmit all recorded data from machines to the centralized data storage of the system. Gates should be mounted in locations most frequently visited by machines to maximize online data availability. For this purpose, fueling chambers were selected, as each machine tank is refueled at least once within a three-day window (usually on a daily basis). In addition, the fueling time was deemed to be optimal for the data transfer to be successful.

The entire CAS works on the principle of establishing contact between active and other active or passive units. Whenever another unit comes within range of an active device, a contact event is generated and maintained until the other unit leaves the detection area. At any given moment, the operator of a machine equipped with an active unit is informed, using a display, as presented in Fig. 1c, of the number of contacts currently established by their machine.

The system has several additional features specifically applicable to mining operations. First, the system takes into account situations where a worker (with a passive unit) can travel on another machine (which has both an active and passive unit). In such scenarios, the system enables the option to hide (or cover) the passive unit that is closest to the active unit. This action can be repeated, resulting in multiple passive units being hidden. Units that are hidden remain visible to other units; however, those units see them as "safe" and therefore do not inform operators about additional people in the area – because they are traveling on machines. The "hide" status can be removed by either of two factors: (1) the machine operator terminates the "hide" status for all units or (2) the hidden unit moves away from the active unit, and the contact is ended.

Table 1. Events supported by the CAS and their descriptions.

Event name	Event category	Event description
START	Startup	The first row saved at startup, indicating the active unit's startup time.
IDENTIFICATION	Startup	Self-identification of the active unit performed at each startup. This row records the active and passive IDs visible to other machines.
DATA DUMP	Data transfer	The active unit contacts the gate and begins data transfer. The transfer lasts as long as the gate is within range, sending events from oldest to newest.
CONTACT (MACHINE)	Contact start	The active unit has made contact with another active unit (mounted on another mining machine).
CONTACT (PERSON)	Contact start	The active unit has made contact with a passive unit assigned to a worker.
CONTACT (OTHER)	Contact start	The active unit has made contact with a passive unit assigned to other tasks, e.g., locations of interest.
CONTACT (PARKING)	Contact start	The active unit has made contact with a passive unit mounted on a machine whose active unit is turned off (parking mode).
END OF CONTACT	Contact end	End of contact with another unit, applies to all contacts.
HIDE CONTACT	Hiding	The operator has pressed the hide button, causing the active unit to hide the closest passive unit.
HIDEN	Hiding	The active unit has contacted a passive unit that was hidden by another active unit.
END OF HIDE	Hiding	The hiding status ends either manually by the operator or when the hidden unit leaves the active units' range.

Data from the CAS comes in a .csv file format, where one file is created for each active unit. Information about established contacts is in a row-based format with five main columns: system ID for the second unit, type of event (one row per event), date, time, and description (standardized name and type of machine or worker involved in the contact). The system supports 11 different event types, and their descriptions are presented in Table 1. As the entire system operates in Polish, the names of events were translated into the best English equivalents.

Events are registered by the CAS active units in real time as they occur in the mine. These events are temporarily stored on the machines until the vehicle reaches a gate unit, at which point the data are transferred to the central event repository of CAS for the entire mine. The delay between event recording and its appearance in the global repository depends on the machine's operational pattern – some machines operate near gate units, while others access them only once per shift. This process could be made closer to real-time by equipping machines with long-range wireless communication technologies, such as long-term evolution (LTE) networks. Currently, the CAS system does not perform any on-site data processing. All data stored in the central repository are raw and include errors typical of the system's operation. Data cleaning and preparation are carried out by the algorithms described later in this paper.

The CAS's main role is to increase safety by informing operators of possible collisions. However, efforts are also underway to increase the system's usability, for example, by using it to locate underground personnel during rescue operations. One such application involves using system data for efficiency analysis of mining operations, which is presented in the following chapters.

2.2. Additional passive units

The CAS can be very useful on its own; however, it can be further enhanced, especially for efficiency monitoring, by mounting additional passive units. These units can be installed in areas of interest to gather information and calculate KPIs for various parts of the mining processes. During initial consultations with mining experts, several locations were established as possible targets for the initial stage:

- Dumping zone – The most basic form of ore transport in mines is handled by haul trucks and loaders. During each work cycle, the haul truck is loaded by the loader at the mining face, and then travels to the dumping zone (common in larger enterprises) where the ore is unloaded. The work cycle ends with the haul truck returning to the loader to begin the next work cycle. The basic CAS functionality allows for monitoring contacts between haul trucks and loaders, thus providing some basic KPIs, such as their cycle duration. However, by adding another sensor mounted at the dumping zone, a complete picture of the work cycle can be established. Monitoring both loading and unloading phases, a cycle can be broken down into its individual components, allowing for more detailed efficiency analysis.

- Heavy machinery chamber (HMC) – In the monitored mine, the work is organized into four shifts. At the beginning of the first and third shifts, machines are dispatched from the HMC to their respective work sites. Machines return to the HMC after completing two work shifts – at the end of the second and fourth shift. By mounting a sensor at each HMC, one can begin monitoring the total time machines spend at their workplaces. This data can be further combined with information on the first contact between machines and their operators, as well as cycle timestamps to further enhance time-based KPIs.

In compliance with expert recommendations, a total of 50 passive units were installed, mostly at dumping zones, with a smaller number placed in heavy machinery chambers.

2.3. Data cleaning and fusion

In an ideal situation, contact events related to a specific object should follow several predictable sequences. The most basic case is where an active unit detects other units, and after some time, contact ends due to loss of range. In this case, only two events are generated:

$$\text{CONTACT (MACHINE, PERSON, OTHER, PARKING)} \\ \rightarrow \text{END CONTACT.} \quad (1)$$

Another basic situation is when the active unit detects a passive one that was previously hidden by another active unit. In this situation, only two events are recorded:

$$\text{HIDEN} \rightarrow \text{END CONTACT.} \quad (2)$$

The situation becomes a little bit more complex if the hidden status is terminated before the contact ends. If this happens, a contact event is created to indicate that the given worker is no longer actively hidden:

$$\text{HIDEN} \rightarrow \text{CONTACT (PERSON)} \rightarrow \text{END CONTACT.} \quad (3)$$

Finally, the most complex situation is when an active unit hides another passive unit. In such a situation, one event is generated when the hiding operation starts and another when the hiding is completed, regardless of whether the hiding was completed by the operator or by the unit exiting the active unit range.

$$\text{CONTACT (PERSON)} \rightarrow \text{HIDE CONTACT} \\ \rightarrow \text{END OF HIDE} \rightarrow \text{END CONTACT}. \quad (4)$$

However, during initial research, it was found that processing the hidden status is not really helpful in efficiency analysis, but instead, it can help correct some of the data processing inconsistencies. Therefore, all HIDEN and HIDE CONTACT statuses were replaced with CONTACT (PERSON), and END OF HIDE was replaced with END CONTACT.

The CAS is based on radio waves, which naturally leads to some errors, such as contact breaks occurring at the edge of the communication range. In underground mines, these disturbances in radio-based communication are further naturally amplified; however, the data cleaning and processing methods developed and described below have allowed us to minimize this negative impact. The three most common problems found in the data were:

- Hanged contacts – sequences of events that start with CONTACT (MACHINE, PERSON, OTHER, PARKING) but lack a corresponding END CONTACT event. This results in an incorrect order of events, as if the machines meet again, a new star event will be logged without the previous contact being properly closed.
- Contacts broken into multiple pieces – most probably because of the characteristics of radio technology, all contacts (even the closest ones) can be broken into multiple parts. This results in a start event occurring right after (even at the same time with) an end event.
- Data latency – because data flow, there is a possibility for some machines that the data will be transferred with some latency. This is a problem of machines that do not need frequent visits to fueling stations. To address this, it was decided that with each data processing, the algorithms recalculate data going back up to three days (i.e., that is for day X, data from X-3 onward are reprocessed) in order to refresh incomplete KPIs for machines with latency.

To fix the aforementioned problems, a cleaning procedure was implemented that runs separately for each unique pair of a machine and another object, processing only the start and end of contacts (with hiding events treated as contacts as well). This procedure iteratively analyzes events, one after another, and when an event is repeated multiple times, one of two actions is performed. First, if the repeated events occur within 15 minutes of each other, the procedure marks the earlier event as valid for contact starts or the later event as valid for contact ends. Second, if the gap between repeated events is longer than 15 minutes, the procedure inserts an artificial event to either start or end the contact (depending on which is missing) with the same timestamp. This action results in the creation of contacts with a duration of 0 s, which symbolizes data loss, but still provides useful information for subsequent algorithms. After fixing the event order, the original row-oriented data can be transformed into column-oriented data and cleaned again. In this new format, there are no events, and each row represents one contact with the following parameters: start and end time, duration, information about the machine (an active unit that recorded such a contact), and information about the contacted object. The second cleaning removes duplicated rows (which sometimes occurs) and then merges all contacts separated by less than 30 s.

Finally, a fusion with other systems operating in mines is performed in order to further enhance subsequent analyses. The most important system to connect is the human resources (HR) system, which allows linking operators to their machines and associating machines that have worked in the same area. This linkage also allows for shortcuts in data processing, as only selected parts of machines are being taken into account (ones that have an ore haulage work assigned in HR).

Each day, over 600 000 events are reported by the CAS units. These events are stored in a central database in raw format and later processed by the algorithms described in this paper to generate reports. After cleaning, approximately 200 000 unique contact events – with defined start and end times – are identified (by the cleaning methods). These contacts form the foundation for the reporting process described in the following section. Data from the CAS system are collected in the central repository independently from other systems, as they are retrieved from machines via gate units. At specified time intervals, algorithms are executed to clean the data and generate reports. Currently, the process of data cleaning and report generation is carried out twice daily; however, it can be configured for more frequent runs – such as once per shift or even hourly. The current schedule reflects the specific requirements of the mining enterprise.

2.4. Algorithms for efficiency analysis

The objective of processing CAS data was to establish KPIs related to time management and ore haulage parameters. To achieve this target, three algorithms were designed: one for detecting operator working time, one for detecting machine working time, and one for detecting work cycles. Each algorithm processes data on a daily basis rather than by individual work shifts. This approach was chosen because overtime work by both operators and machines was quite common in the studied mine. All three algorithms were designed to operate independently; however, results from time detection algorithms were used to support the cycle detection algorithm, as this will be discussed in more detail later.

2.4.1. Detection of operator work time. The main purpose of operator work time detection was to select all contacts between an operator and their machine, thereby establishing the total work time of the operator. As a secondary purpose, these contacts can be used for disciplinary action, as operators are prohibited from leaving their vehicles for safety reasons. The detailed procedure for detecting operator work time is presented in Fig. 2. Initially, operators are matched to their respective machines using data from the HR system. Under normal conditions, the CAS records some short contacts between the operator and their machine at the start of a shift, where the necessary inspection and other formalities take place. Then, after leaving the heavy machinery chamber, the operator is expected to maintain one long contact until the end of the shift. The exception to this pattern occurs with machines such as drilling jumbos, where operators need to leave the machine in order to connect the necessary power and water supply.

Unfortunately, during the research, it was found that operators have a habit of shutting down machine power supplies when returning to heavy machinery chambers (mainly at the end of the second and fourth shifts). This action causes the active CAS unit to stop working, without properly ending all contacts, thus resulting in "hanged" contacts. In a situation where the operator maintained uninterrupted contact with the machine throughout the shift, this action results in eliminating the contact, leaving a zero-second contact as an indication of something missing. Unfortunately, no solution was found to recover this lost contact ending. Instead, an alternative was designed using contact interpolation. As this situation usually happens whenever machines are returning to HMCs, the contact's end time is interpolated to match the time the operator's passive CAS unit meets the sensor mounted in the HMC. This interpolation is quite accurate because usually only a few minutes elapse between meeting the sensor and the operator finishing work.

In large mining enterprises, it is relatively common for the HR records not to fully match the actual situation. Once every few days, operators may change machines (either through shift changes or replacements), and sometimes these modifications are not updated in the HR system. On such occasions, the following solution was implemented: when there are too few contacts with the assigned operator, the algorithm checks contacts with other personnel. If it identifies a worker with one long contact that lasts for hours, it assumes that such a situation happened, and algorithms note the change of operators. However, for safety reasons, this contact needs to be uninterrupted to avoid misinterpret-

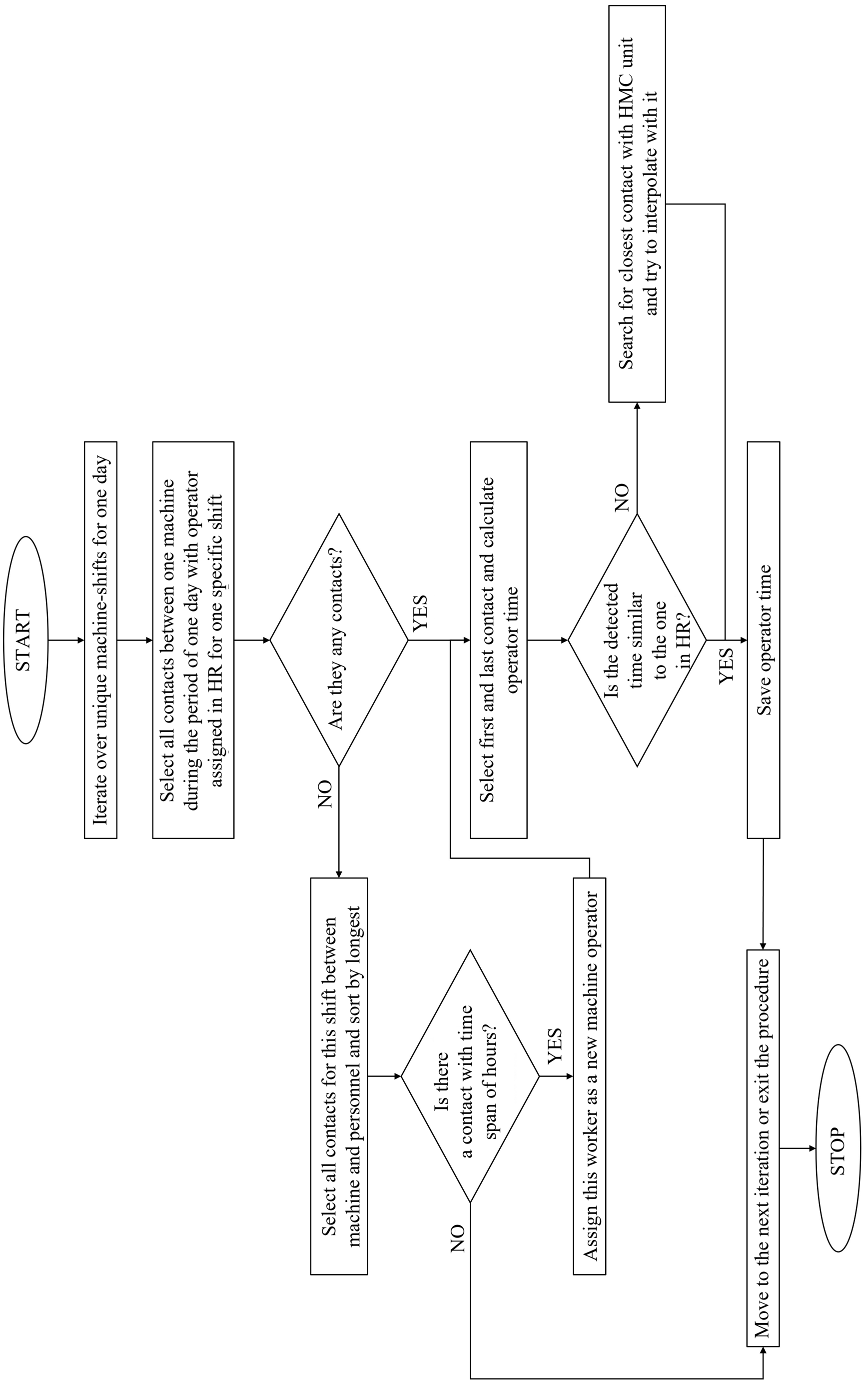

Fig. 2. Simplified diagram of the procedure for detecting machine operator work time using data from the CAS system.

ing situations where two machines collaborate during a shift and generate large combined contact times.

The overall result of this detection is the estimation of each operator's start and end of work, as well as confirmation of who actually operated the machine. In addition, all selected machine-operator contacts are visible in reports, enabling mining foremen to better enforce health and safety policies. The topic of reporting is further extended in Sec. 3.

2.4.2. Detection of machine work time. Machine work time detection is a task very similar to operator work time detection. The main goal here is to establish the actual times when a machine leaves and returns to the HMC (heading to and returning from work). This seemingly simple task is, in reality, more complicated due to various exceptions and noise in the data. Commonly, the machine comes into contact with the passive unit mounted at the HMC during regular work operations. There is also a common practice of leaving the machine at the workplace after the second and fourth shifts. For this reason, an algorithm (shown in Fig. 3) was designed to detect machine working time and then adjust it based on input from the HR system.

The function begins by iteration over the unique shifts of each machine. For each shift, all contacts with the HMC sensor are selected; the earliest contact within the first half of the shift is estimated as the "going to work" time, while the latest contact within the second half is considered the "return from work" time. In cases where one of these two times is missing, the corresponding shift boundary is used as an estimate. This basic detection is later verified and corrected using data from the HR system. Each detected work time is then reanalyzed, and if a corresponding HR entry is found (documenting that the machine did in fact operate during that shift), the detection is classified as successful. In situations where only a "return from work" event is detected and there is no HR entry for the selected shift but there is one for the following shift, the algorithm assumes that the machine began working earlier (prior to the current shift boundary). In analogical situations where only "going to work" event is found and there is no HR entry for the selected shift but there is one for the previous shift, the algorithm assumes that the machine remained at the workplace, working overtime. In both situations, contacts, interpreted as either "returning from work" and "going to work" are reversed, and the entries are merged with adjacent shifts (either next or previous shifts).

2.4.3. Detection of ore haulage cycles. The core of ore haulage cycle detection lies in the parametrization of work cycles performed by both the haul truck and the loaders. From this action, one can derive a set of the following KPIs: cycle duration and its components, the number of loaded haul

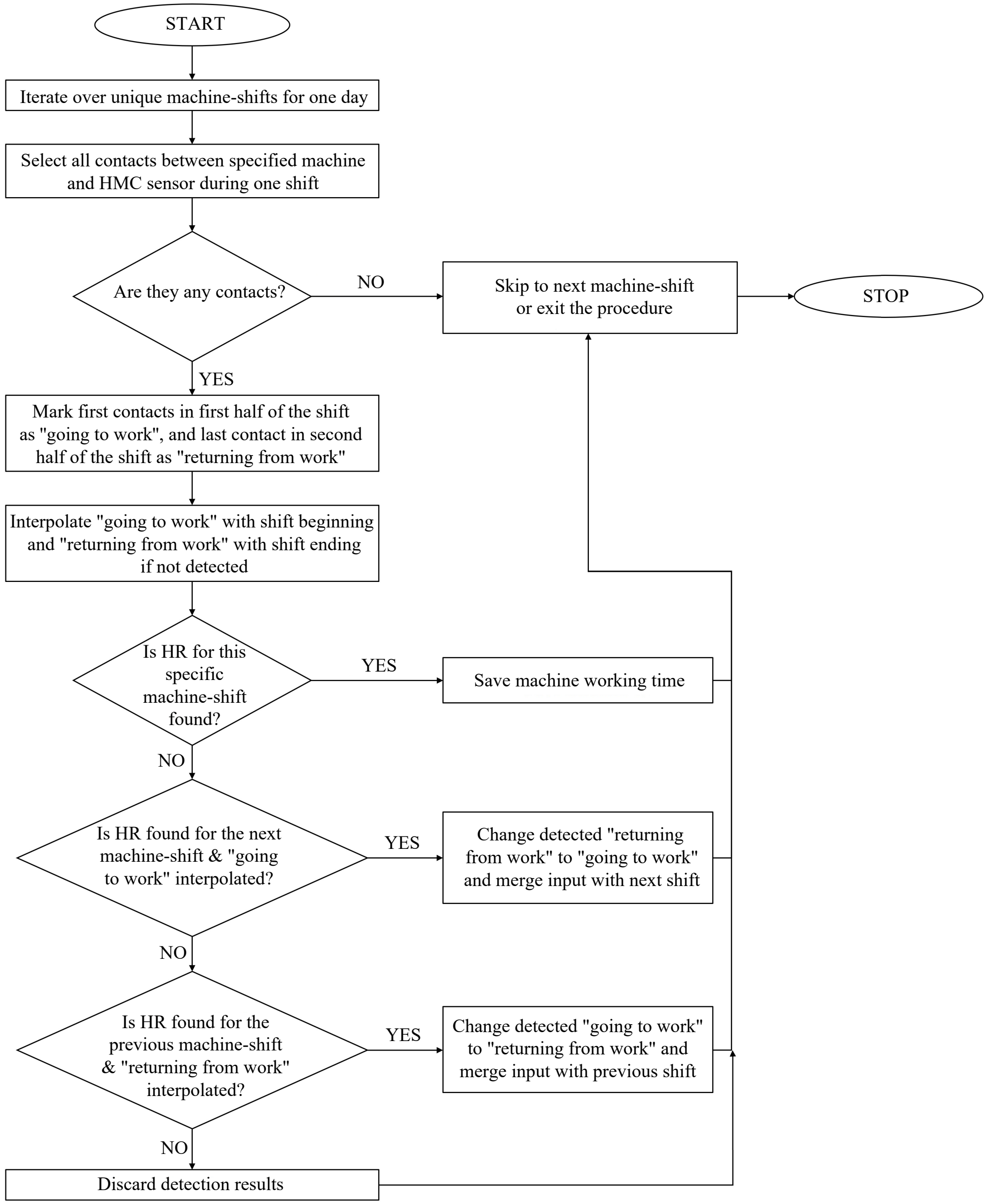

Fig. 3. Simplified diagram of the procedure for detecting machine work time using data from the CAS system.

trucks (for loaders), and the number of completed cycles. The latter is of great importance for mining operations, as, in most cases, this fundamental metric is recorded based on the operator's verbal statement. In many situations and different environments, it has been proven that falsifying this value is difficult to detect (without specialized computer aid) and can negatively impact subsequent stages of the process. The CAS is an ideal computer-assisted aid for this specific task; therefore, ore haulage detection was chosen as the primary focus of this research.

Generally, in mines, there are two ways in which wheeled transport for ore haulage can be conducted. The ore can be transported either by the loader alone or through a cooperation of a loader and a haul truck. In the second case, the loader stays at the mining face and loads every truck (usually more than one) that arrives. In smaller mines, the ore is transported by the haul truck directly to the surface through the portal. However, in larger mines, the truck transports the ore to the next processing point, the dumping zone, at which the ore is broken down using a rock breaker and loaded onto the next means of transport, usually a belt conveyor or underground train.

When machines perform ore haulage at the dumping zone, a CAS passive unit can be mounted at the rock breaker location. This allows one to detect repeated cyclical contacts of machines (trucks or loaders) with the dumping zone. In the case of haul trucks, specific contacts between the truck and the loader can also be filtered, thus providing further insight into actual operations. Both of these situations are visualized in Fig. 4.

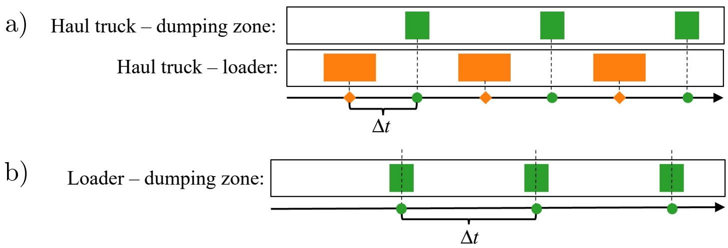

Fig. 4. Diagram of the work cycles as seen from the CAS for a) cooperation between the haul truck and the loader, and b) standalone operation of the loader. Contacts between the dumping zone and loaders or haul trucks are marked with green rectangles, while contacts between haul trucks and loaders are marked with orange ones.

The environment of a real-life underground mine is very complex and full of exceptional situations that do not follow the patterns specified above. During research, dozens of such exceptions were found and dealt with through continuous and iterative improvements to the cycle detection algorithm. The following list summarizes the most common problems found in the data from CAS:

- In general, a direct connection between one loader and one haul truck cannot be established because, in larger mining faces, multiple loaders work in close proximity. In such situations, it is common for loaders to switch and load the trucks that are available, causing frequent alternations of loaders from the haul truck's perspective.

- A direct connection between one machine and a single dumping zone for shift cannot also be made, as sometimes two or more dumping zones are used during one machine-shift (as per the mining plan).
- Each haul truck (usually) is loaded with three loader buckets. In the CAS data, this action appears as three separate contacts, a smaller number of contacts with varying durations, or one long contact that spans the entire operation.
- Malfunction of CAS active units sometimes happens, causing loss of data from a single contact point (e.g., haul truck being loaded by a missing loader). To deal with this specific problem, a procedure for reversing missing contacts was implemented, allowing the algorithms to fix around 90% of such cases.
- A haul truck or loader may have contacts with a dumping zone different from the one where unloading actually took place. This sometimes happens when other dumping zones are located close to the machine's path, resulting sometimes in a contact being recorded.
- Most dumping zones were equipped with passive CAS units; however, some remain undetectable by the system. In such cases, cycle detection relies solely on analyzing contacts between haul trucks and loaders. If ore haulage is done exclusively by loaders – detection is impossible.
- It is quite common for machines to operate for more than one shift. Operators quite often take overtime, working up to 1.5 times the length of a normal shift. This is one of the main reasons why the algorithms process data on a daily basis rather than by individual shifts.

The task of cycle detection in an underground mine is complicated because of all the above-mentioned exceptions. Therefore, to utilize CAS data in the best possible way and extract all achievable information about the process, a complex multi-layered procedure was developed (shown in Fig. 5).

The detection begins by filtering all data to retain only contacts that are potentially related to ore haulage. Usually, there are hundreds of thousands of contacts recorded daily by CAS. Because the system operates bidirectionally (meaning contacts between two machines should be recorded by both of them), it was decided that cycle detection is primarily focused on haul trucks and loaders that do not cooperate with haul trucks (i.e., contacts between the loader and the dumping zone). Analyzing every single contact would be a very tedious task; therefore, only a selected subset of the data is initially filtered to be taken into account in the analysis. Contacts that meet at least one of the below-mentioned criteria are initially labeled as parts of ore haulage and used as samples for subsequent procedures:

- The contact occurs between a haul truck or loader and the dumping zone passive CAS unit.

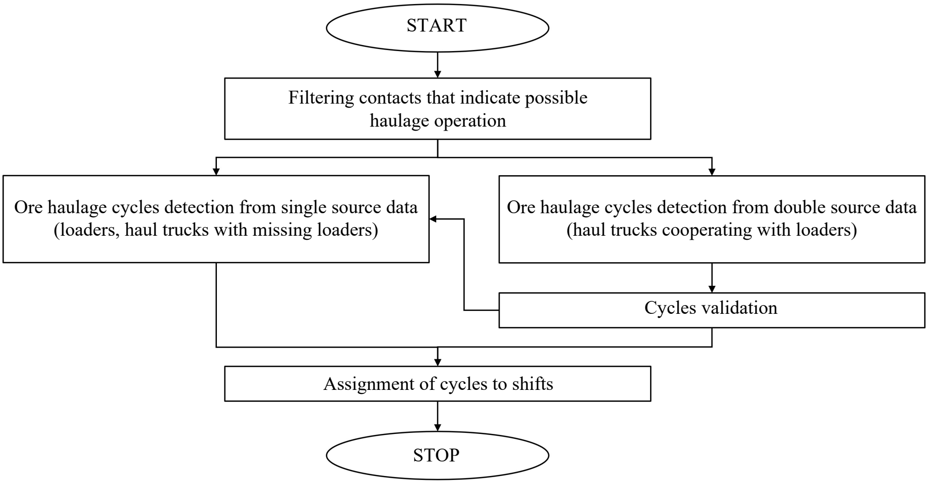

FIG. 5. High-level scheme of the procedure for ore haulage cycle detection.

- The contact occurs between a haul truck and a loader, and the HR information for both machines indicates ore haulage, and the same information indicates a similar workplace.

The initial filter for contacts reduces the overall daily sample to only a few thousand events for all machines. From that point, data from one machine day is selected and undergoes one of two possible flows. The simpler flow (detection from single-source data) is designed to detect cycles based only on contacts with the dumping zone (without involving a second machine). The entire procedure consists of the following five steps:

1. Contacts with each unique CAS object are transformed into a normalized binary vector sampled every 1 s. The vector length is 86 400 (seconds in 24 hours), with contact time with the object being marked by ones and zeros indicating no contact.
2. On every vector, an autocorrelation is performed to check whether contacts are repetitive. Only vectors that meet the autocorrelation threshold proceed to the next steps; however, this criterion is really low in order to also account for occasional visits to the dumping zone.
3. An addition operation is performed on every vector that successfully passes the autocorrelation check. This action creates one integer vector in which each second represents the number of dumping zones, the machine had contact with (usually one, but up to two in rare cases).
4. The vector is divided at moments when the machine loses contact with the dumping zone sensor, and each individual fragment is measured in length. The duration of all fragments is then collected into a single array

and cleaned using the 1.5 IQR rule to remove shifts in beginnings and endings (usually visibly longer). Finally, after cleaning, the mean duration is established.

5. The mean duration is used to determine whether given fragments qualify as cycles. If a fragment's duration x_i is close to the mean $\overline{x}$ ($0.5\overline{x} \leq x_i \leq 1.5\overline{x}$), it is detected as a work cycle.

When contacts with both the dumping zone and the loader (strictly for haul trucks) are recorded during the day, a different detection procedure is used. The simplified flow of the algorithm for double-source detection is presented in Fig. 6. The start of the procedure is similar to the single-source method; all unique contacts of the truck with loaders and dumping zones are vectorized (marked on a binary vector of length 86 400). In the double-source approach, the algorithm skips the autocorrelation criterion, as it is not compatible with the contact signals from loaders. Instead, all possible contacts are initially taken into account, and problems are later fixed during the cycle validation procedure. In the second step, both vector groups (vectors of contacts with loaders and vectors of contacts with dumping zones) are summed along the vertical axis within each group. This action creates two vectors that describe the number of loaders and dumping zones seen at every second of the haul truck's operation. Then, all endings of dumping zone contacts are identified (moments when the amount of visible dumping zones drops from a positive value to zero), and their indices are saved. These points are then used to divide the loader signal into fragments, each of which could be a possible cycle. The decision on whether each fragment is actually a cycle is made by a random forest model that uses a set of five statistics from each fragment.

During research, many different forms of algorithms were tested to carry out cycle detection. Initially, the work was focused on creating a single model that would take input signals from the CAS and return the number of cycles. The main problem found during this procedure was the lack of a source that accurately recorded how many cycles the machine actually completed. Mine statistics were made based on operator's verbal reports, which were susceptible to fraud; there is no other system for such detection, and the CAS itself sometimes has problems or noise in the data. Consequently, the global approach failed, as none of the tested architectures (ranging from standard classifiers and deep learning models to various data handling and cleaning strategies with different inputs and outputs) returned satisfactory results. Instead, a random forest classifier was trained for the subtask of binary classification. The main task of this model was to process a set of input statistics (derived from the contact vector with loaders) and determine whether a loading operation actually occurred. As fragments are separated by the dumping zone signal (indicating possible unloading), each time the model declares loading operations, the process estimates

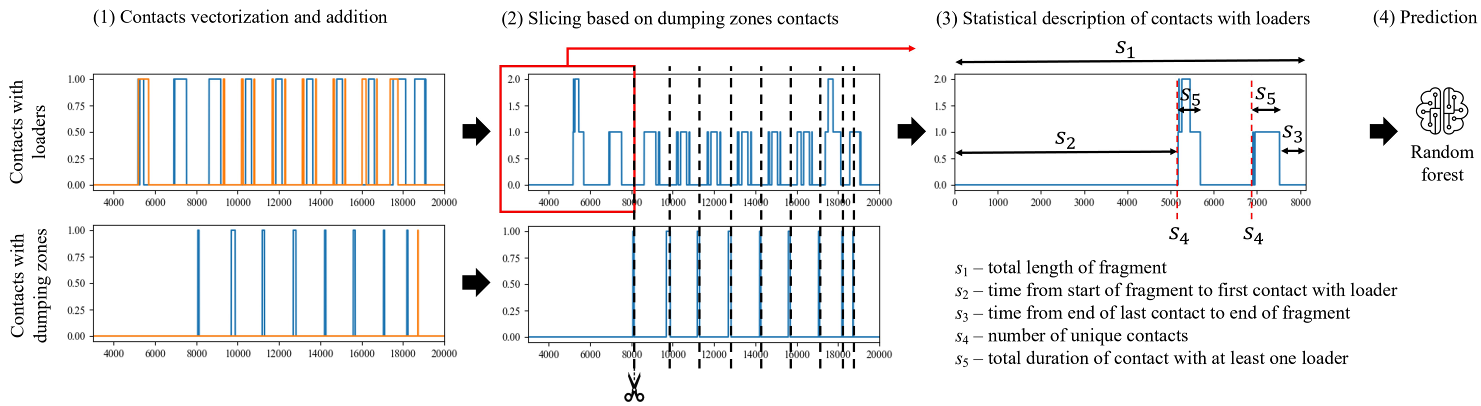

FIG. 6. Procedure for detecting ore haulage cycles from double-sourced contacts using a random forest classifier.

that a haulage cycle occurred during this fragment. The model input consists of a set of five statistics chosen after initial reconnaissance:

- Total length of the fragment (duration of the full haulage cycle).
- Time from the start of the fragment to the first contact with the loader (duration of haul truck's travel with an empty box from the dumping zone to the loading site).
- Time from the end of last contact to the end of the fragment (duration of haul truck's travel with full box from the loading site to the dumping zone, including unloading time).
- Number of unique contacts (number of buckets that the haul truck was filled with).
- Total time of contact with at least one loader (total time of the loading operation).

Model training was carried out with a test sample manually created by one of the authors. Samples and statistics were generated from a few days of work by several haul trucks, with each fragment assigned a category of 1 – a cycle, or 0 – not a cycle, depending on the context and the author's current knowledge. A total of 485 fragments were assessed and then used for model training. Finally, the random forest model achieved an accuracy of 95.8% in matching the human-labeled detections.

The above-described procedure enables the detection of most cycles. However, there are some quite common exceptions that require additional work. For this reason, a separate validation algorithm was designed to improve overall results. In this function, three frequent issues: rejected fragments that are too long, rejected fragments that are too short, and empty fragments where no loader signal was detected, were found. For the latter one, validation is done using a single-source algorithm without any additional modifications. As for the non-empty fragments, two separate procedures are designed, depending on their duration, as shown in Fig. 7.

Fragments (f_i) of long duration are defined as those greater or equal to three times the mean duration ($\overline{x}$) of all positively detected cycles ($f_i \geq 3\overline{x}$). Such cases naturally occur at the beginning of each first and third shift, where machines need to travel from the HMC to the workplace, which increases the duration of the cycle. This can also potentially happen when trucks change workplaces or perform a cycle in a dumping zone that is not supported. In all these situations, only the last part of the fragment is a real cycle; therefore, the procedure takes a segment from the right side of length equal to one mean duration ($\overline{x}$) and loads it into the model to check whether the cycle is really there. If the model makes a positive prediction, the fragment is separated into waste (left side) and a newly detected cycle (right side). This approach is presented in Fig. 7a.

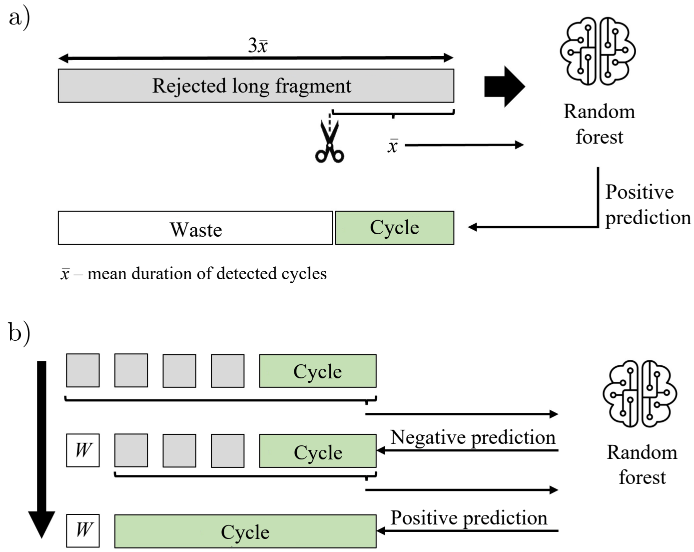

Fig. 7. Symbolic representation of the validation procedure for initially rejected fragments that are: a) too long, or b) too short.

Fragments (f_i) of short duration are defined as those smaller than 80% of the mean duration $(\bar{x})$ of all positively detected cycles $(f_i < 0.8\bar{x})$. These fragments occur when other dumping zones are present in close proximity to the machine's travel route or when a truck is maneuvering (or performing other operations) near the dumping zone CAS unit. When short fragments appear, there are usually three or more of them. Dealing with short fragments is a little bit trickier and depends on their surroundings. If a series of short fragments is followed by a cycle, then the main action is to attempt to merge them into that cycle. To do this, the algorithm considers the fragments together with the subsequent cycle and verifies the prediction using a random forest model. If the prediction is successful, all fragments and the cycle are merged and classified as a single cycle. In the case of a negative prediction, the left-most fragment is declared a waste, and the procedure is repeated. This process continues until the model returns a positive prediction for some combination or all short fragments are declared a waste. This approach is presented in Fig. 7b. If merging the short fragments with a cycle is unsuccessful or if the next fragment after a series of short fragments is not a cycle, another approach is applied. In such situations, the algorithm tries to create a completely new cycle by merging all short fragments t and performing predictions with a random forest model. This action follows the same iterative process, where in cases of negative prediction, the left-most fragment is declared a waste until a cycle is found or all fragments are declared.

Finally, after cycle detection (regardless of the algorithm used), shift assignment must be performed. Trucks and loaders usually work overtime, which causes at least a few cycles occurring after the shift ends. Each of these cycles needs to be assigned to the previous shift, as this information is linked to the operator driving the machine. The simplest way to perform this task is to verify cycles against the detected operator work time. For a specific machine shift that was detected, each cycle that is performed between the operator's start and endpoints is assigned to that operator In rare cases when no operator time is detected, cycles are first sorted using shift hours and then verified (going from latest to earliest) to see whether any given cycle is closer to the previous one or the next shift. In cases where a cycle is closer in time to the end of the previous shift but is currently assigned to the next shift, its assignment is adjusted to match the previous operator's shift. This process will continue until all cycles have been verified.

Additionally, the proposed detection method enables not only the estimation of the number, duration, and structure of haulage cycles, but, when combined with machine type information obtained through data fusion, it also enables estimation of ore mass movement. This is possible because machines of the same type typically transport similar amounts of ore per cycle.

2.4.4. Detection of truck-loading cycles. The ore haulage detection described in the previous chapter is used to generate KPIs for trucks and loaders that transport ore from the mining face to the dumping zone. However, a small modification can be made to the algorithm to also detect some metrics for the loaders that load ore onto trucks. After successfully detecting truck cycles, each cycle can be analyzed to extract the loader that performed the loading operation. Because more than one loader may have contact with the truck during a cycle, the most prominent one is chosen as the one performing work. The most prominent loader is understood as the one with the longest contact duration with the haul truck during one cycle, with the exception that the contact cannot last for the entire duration of the cycle. As one loader usually loads more than one truck, the results of this detection need to be aggregated, as shown in Fig. 8.

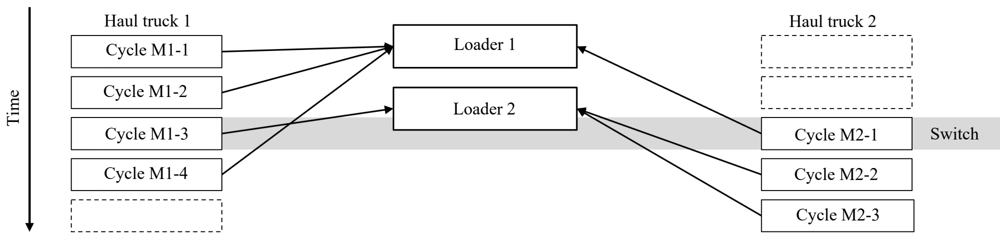

Fig. 8. Loader cooperation at a shared workplace during truck-loading cycles.

Essentially, loader detection enables establishing a very similar set of reports and KPIs to the one used for ore haulage cycle detection. However, as the mine was not really interested in this particular subject, only aggregated reports include the results obtained during detection (the overall number of cycles detected compared to the HR statement).

3. Results

In the course of this research, several reports in two distinct categories were developed to meet the mine's needs. Each report went through a development cycle involving regular discussions (held biweekly) with end users (mine managers and foremen). During this process, it was decided that two kinds of reports would be launched: aggregated and detailed. The purpose of the aggregated reports is to present key process KPIs to the end user. If any of the values appear questionable, the detailed reports can be used to see what happened during that specific shift.

Due to the experimental nature of the work, the reports were run in a temporary environment. Every single day, algorithms written in Python processed the CAS data, and the results were exported to a shared folder on the mine's network. Aggregated reports were saved in Excel format, while detailed ones were exported as images in .png file format. As of the writing this article, interest in reports among mine workers has grown significantly. As a result, special efforts have been launched to integrate the results of this research into the mine's existing business intelligence environment.

3.1. Aggregated reports

Three aggregated reports were launched, one for each of the main detection results (operator time, machine time, and cycles). The main purpose of these reports was to show, in a simple manner, the general results of detections and, when possible, compare them to information from the HR systems. It was decided that the best way to present such data is through a multilayer matrix structure (an example of such a report is presented in Fig. 9). The following reports were created in this category:

- Operators time – presents the detected work time for each machine operator. All cells are grouped by heavy machinery chambers and machines. Each cell shows a value representing the detected time using data from CAS and a color on a green-to-red (good-to-bad) scale that is scaled individually for each machine.
- Machines work time – presents the time machines go to and return from work for every machine. The grouping is the same as for operator time; however, each cell contains two values instead of one. Both values are

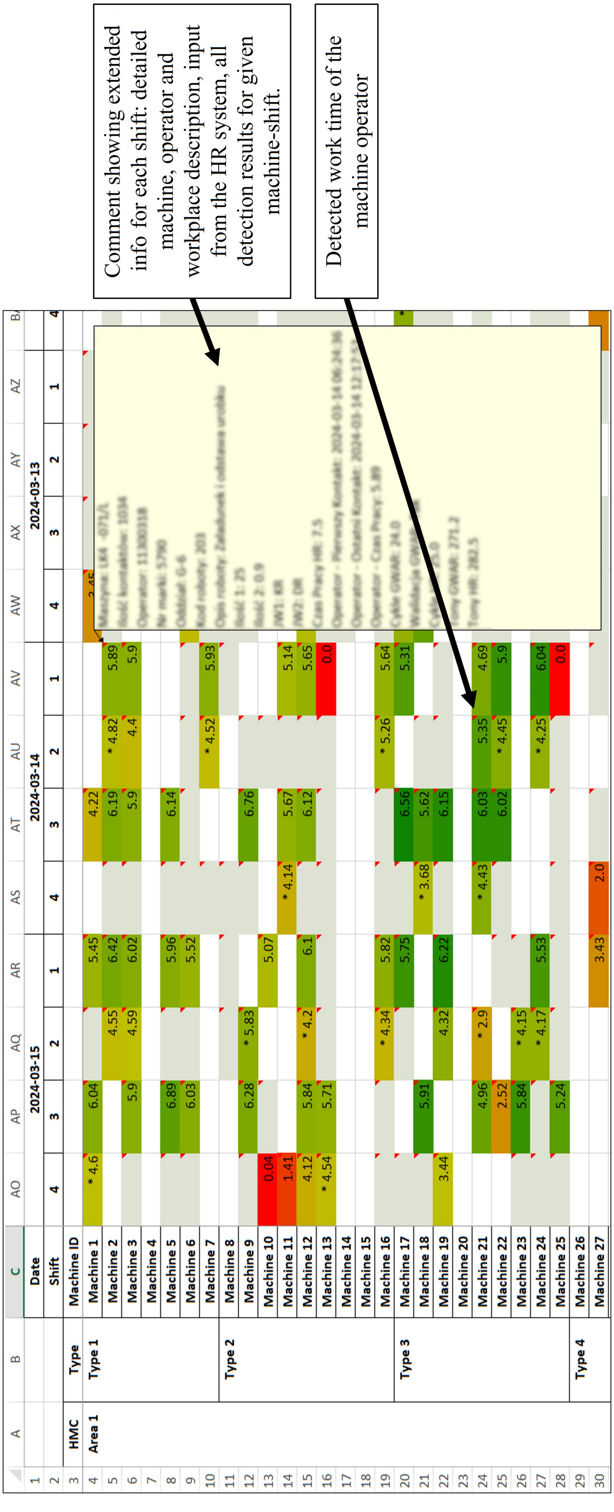

Fig. 9. Example of an aggregated interactive Excel report, shown here for detected operator time (details regarding machine operations have been intentionally obscured at the request of the mining enterprise).

in hh:mm format, and the first one indicates the detected time of the machine leaving the HMC (going to work), while the second one indicates the machine returning to the HMC (returning from work).

- Work cycles – present the number of performed cycles (for ore haulage) or loaded vehicles (for loading haul trucks). The format of this report corresponds to the style of the previous ones, with cell ordering and formatting. However, each cell contains multiple values, depending on the operation performed. For standard ore haulage or truck loading, each cell contains the number of cycles detected using CAS and the number that was reported in HR. In cases where machines perform other cyclic work that is not detected by CAS (such as stone haulage), this value is also reported to give end users a better understanding of the work carried out.

Each of the above-mentioned reports is fully interactive. All non-empty cells have a comment that appears whenever the mouse hovers over them. In this section, all of the information is inserted: machine, operator, and workplace description, work record from HR, and the detection results from all algorithms. In addition, each cell is also a hyperlink that, when clicked, opens the detailed report for that specific shift.

Currently, all aggregated reports have been successfully integrated into the business intelligence environment while preserving all functionalities. Unfortunately, due to security concerns at the mine site, these reports cannot be shared in their new form.

3.2. Detailed reports

All detailed reports follow a consistent format, similar to a timetable or bar plot. In these reports, contacts are usually plotted as rectangles, with the width equal to their duration. As the data are processed within a daily window, reports cover one day, with the plot space divided into four parts: shifts in chronological order arranged from the earliest on the left to the most recent on the right, I–IV). Every report also contains additional information extracted from the HR system; however, because of data privacy concerns, this information is blurred out.

An exemplary, detailed report of operator working time is presented in Fig. 10. One of such reports is created on a daily basis for each heavy machinery chamber and usually contains up to 25 machines. Each “row” of bars represents one machine, and each bar within this row is a contact between the machine and its operator. As operators change frequently, the color of contacts for every second and fourth operator alternates from green to red. Each box also contains information from HR, mainly about the operator and the types of work performed during their shift. A corresponding report of machine working time is presented in Fig. 11. It is structured in a very similar way to the operator work-

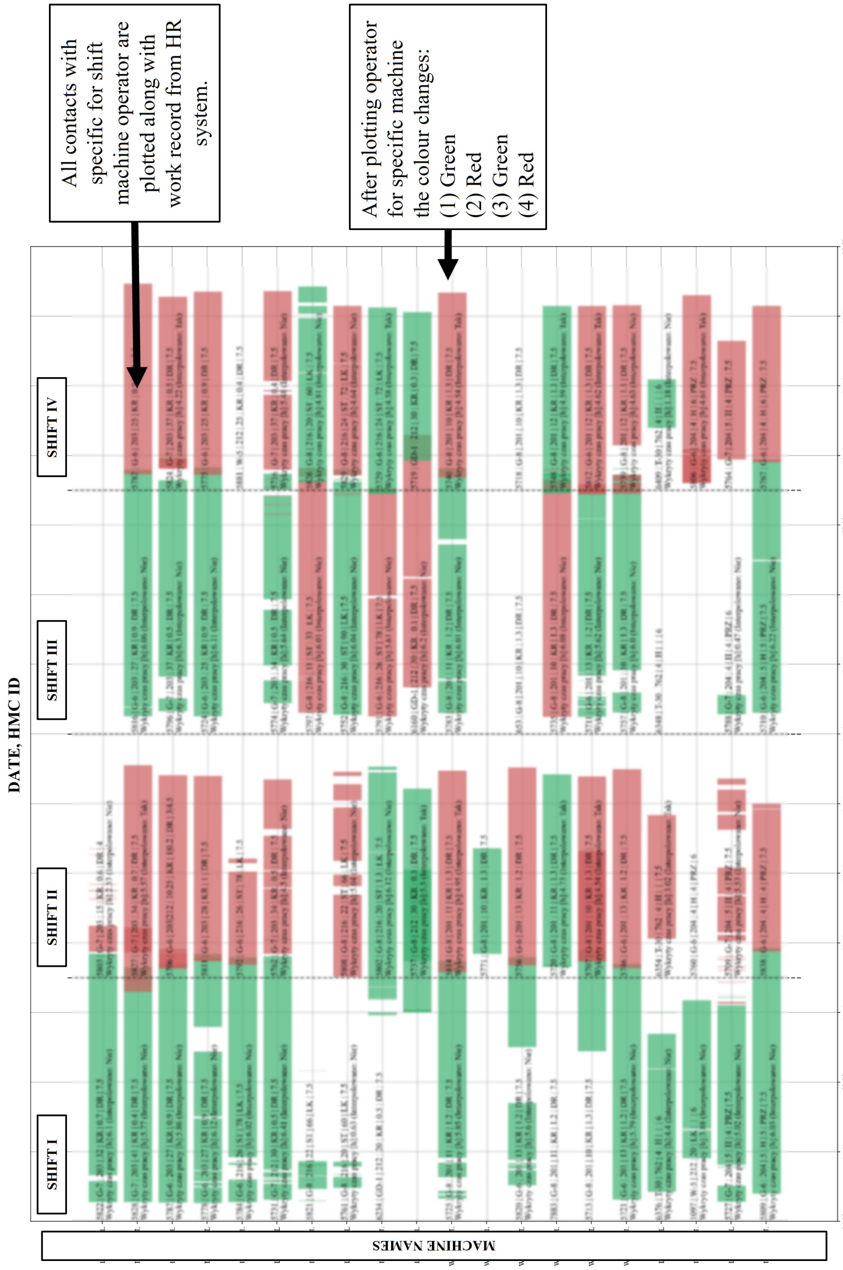

Fig. 10. Example of a report on operator working time (details regarding machine operations have been intentionally obscured at the request of the mining enterprise).

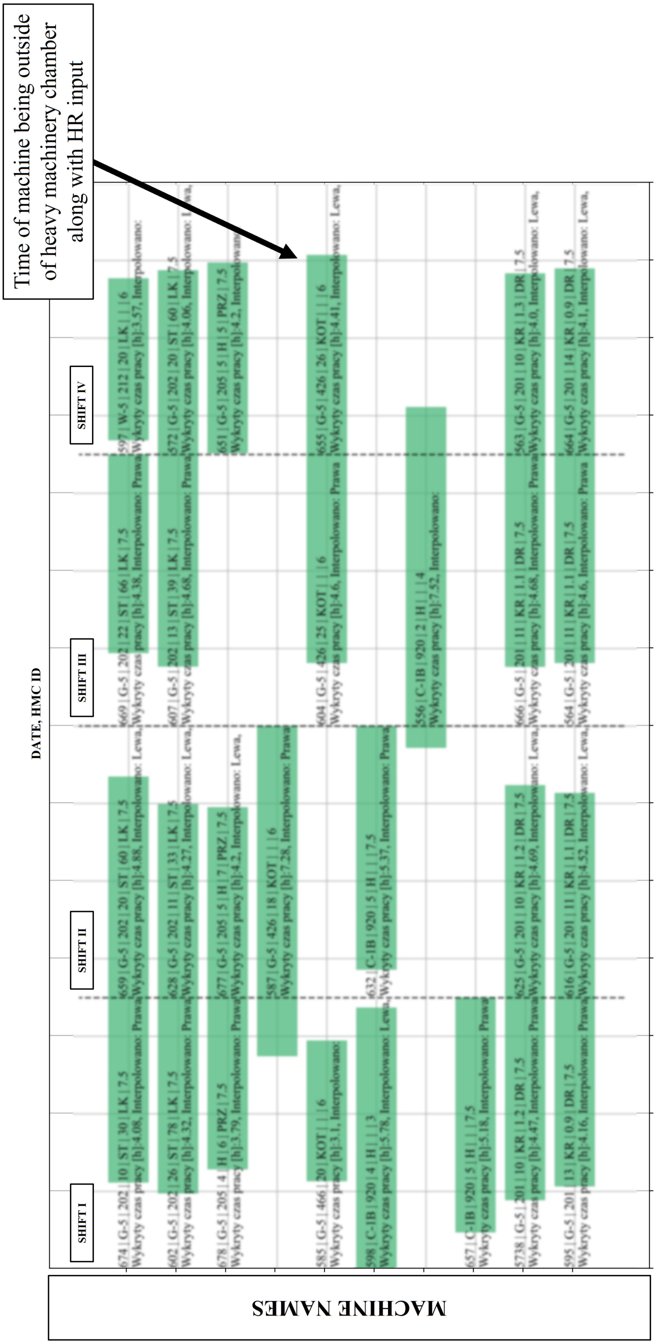

Fig. 11. Example of a report on machines' working time (details regarding machine operations have been intentionally obscured at the request of the mining enterprise).

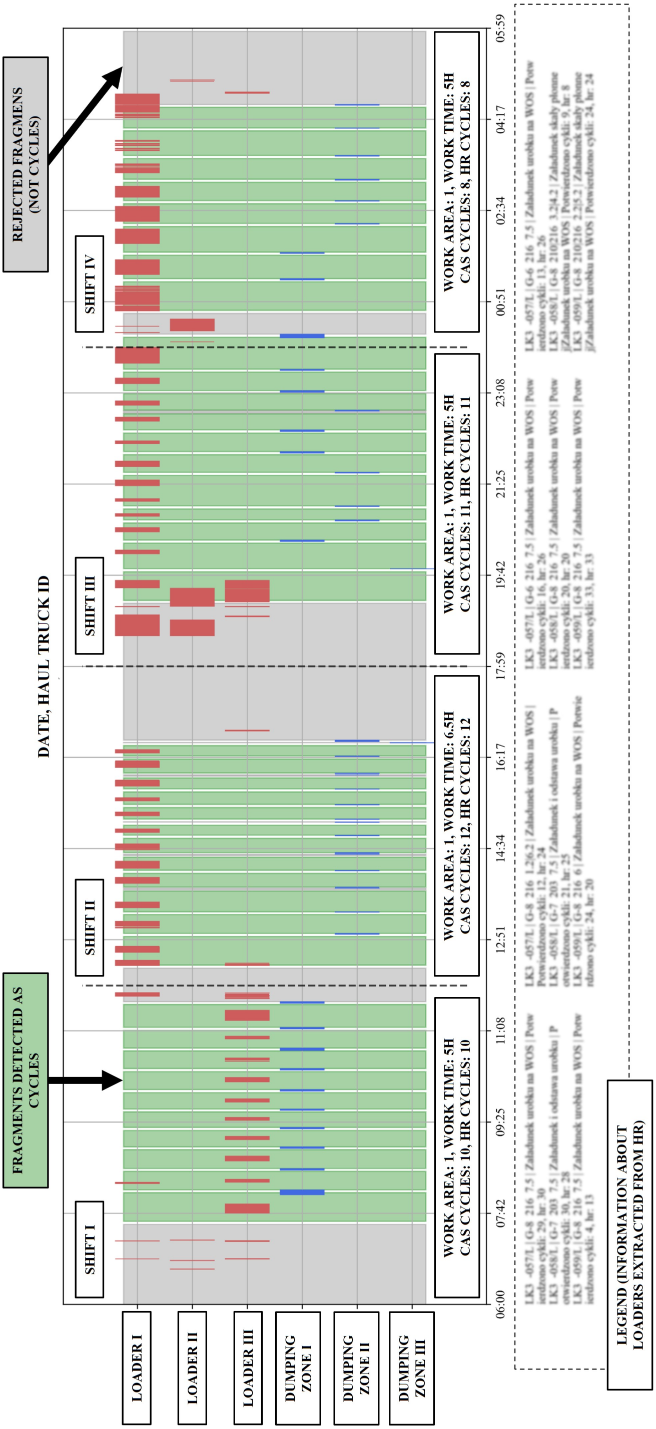

Fig. 12. . Example of a report on ore haulage cycle detection from a haul truck perspective (details regarding machine operations have been intentionally obscured at the request of the mining enterprise).

ing time report. The only difference is that the bars do not represent contacts between machines and the HMC sensor, but rather graphically present detection results – the times when machines leave and return to the HMC.

Finally, the most unique report of ore haulage cycle detection is presented in Fig. 12. Similar to previous reports, in every row there are plotted contacts with one unique object (i.e., loaders and dumping zones for haul trucks and only dumping zones for loaders). The colors of the contacts depend on the object being plotted: red is used for loaders and blue for dumping zones. The entire plot is divided into fragments (as it was done during the detection procedure), and all fragments that are cycles are colored green, as opposed to all other fragments that are grayed out (non-cycles). At the bottom of the plotting area, there is information about detection results compared to HR statements for each shift. In addition, below the plot itself, there is a legend where all necessary information from HR about loader's work is shown.

All of the above-mentioned reports are currently being transferred to the target mine environment. Once this process is completed, they will be generated automatically as needed. Until then, the plots are generated in a fixed image format and shared in a common environment.

4. Conclusions

The necessity for efficient and safe extraction drives ongoing research aimed at monitoring the movement of mining processes. This facilitates the development of performance analyses crucial for supporting effective production planning. One of the important parameters to track is the movement of wheeled underground machinery. This article demonstrated the feasibility of utilizing existing CAS for that purpose, revealing an additional application. The research was based on data from KGHM Polska Miedź S.A. copper mines in Poland. The use of data based on three detection methods was presented. The first method involved tracking operator's working time by analyzing operator-machine contacts. In turn, the second one enabled tracking machine operating time by detecting the moment when machines leave and return to the HMC. The third and most intricate method focused on detecting ore haulage cycles of haul trucks and loaders, utilizing loading and unloading points as key markers. The procedures also account for possible data incompleteness and various types of exceptions identified during the research. It was also necessary to develop multiple data-cleaning procedures to maximize result accuracy. The algorithms rely primarily on data coming directly from the mine's existing system used to support safety, an additional advantage of the presented methods is the low financial cost of implementation. However, it was necessary to install additional passive tags to detect key locations of machine operations, such as the unloading points or the

HMC. The developed methods facilitated the creation of tailored managerial reports that enable comprehensive monitoring of production processes. Final visualizations, as well as the entire work process, were continuously consulted with the end users to ensure the reports aligned with their operational needs.

Near-future plans include implementing the proposed methods and visualizations into the mine's programming environments for automatic and on-demand user access. During this work, three possible research directions were established for future investigation. First is the long-term analysis of the aggregated data from the algorithms and its comparison with other metrics commonly used in mines. Second is the potential for automatic detection of operator actions that violate health and safety standards, such as exiting a machine while it is in operation, or entering out-of-use excavations. Finally, the third area is monitoring refueling stations. It is quite common for queues to form near fuel distributors during rush hours, and CAS can be used to provide insights and help in reducing the machinery idle time. In addition, expanding the proposed system implementation to other underground mining sites is also under consideration.

A significantly broader application of the proposed solution is anticipated in the long term, as the methods described in this paper can contribute to the development of a digital twin of an underground mining facility. The system could potentially provide insights into the full range of interactions within the mine. However, in our view, an additional localization source is required to accurately reconstruct the mining environment, as the CAS system offers only limited localization capabilities – both in terms of spatial resolution and the scope of equipment it covers.

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