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The Concept of an Intelligent Decision Support System for Ore Transportation in Underground Mine

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Abstract

The management of in-mine ore transportation systems is a crucial challenge due to the constant development of underground mines. The transport network's stability and efficiency directly affect enterprise profits and growth. Managing key areas such as transportation asset maintenance, object control, and ore extraction planning is essential to ensuring high transportation standards. For larger, multi-site enterprises, transportation supervision is divided among many managers. To address short-term production planning and management support during unplanned events, a decision support system is proposed in this article to meet the expectations of both lower and higher-level managers. The proposed concept is based on the simulation deployed from real-time operational data from mine, in which an agent is placed and taught through reinforcement learning. The simulation as well as agent possible actions have a block structure, where each means of ore transport is a separate add-on. In addition, it is assumed that the solution will be further improved by the implementation of various algorithms found in the literature (e.g. early fault detection algorithms). When created and implemented, such a system will bring improvements in multiple levels of operation, such as the safety of employees, overall machine health, cost reduction, energy efficiency, etc. As a result of this work, a conception of an intelligent decision-support system is presented, along with the specification of areas of its influence and a description of tasks and algorithms proposed to be incorporated within the system itself.

Keywords: Underground Mine; Ore Transport; Decision Support System; Belt Conveyor; Wheeled Haulage; Rail Haulage; Shaft Transport

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1. Introduction

Underground mines are subject to constant growth. Many of them are already incredibly large, and they are still expanding. This process causes the continuous development of in-mine ore transportation systems in both size and efficiency. The progressive expansion of the mine over time makes it gradually harder to monitor and control at every management level. Most mines are already dealing with such a problem by introducing more monitoring and supporting systems [1]. Such solutions are designed to improve management team decisions by giving them more precise information. However, in many examples, such systems are focused on specific use cases or dedicated process parts. Eventually, this leads to a situation where there are so many secluded solutions (even for a group of employees or a specific mining area) that the decision-maker cannot possibly use all of them. The solution for such a situation could be a DSS (Decision Support System) that will merge all of the relevant knowledge into an easy-to-operate, user-friendly environment. DSS will help to make correct decisions that will improve transport processes in many ways, like reducing energy used, improving workers' safety, extending the service life of machine elements, reducing the number of unexpected events, improving ore transport efficiency, reducing general overall costs, etc.

When it comes to the mines, there are some approaches to decision support systems for different purposes presented in the literature. The authors of [2] propose using one for the selection of mining method. An DSS for underground mine fire level prediction was introduced by [3]. In [4], the influence of the underground mine on air quality was examined, and a DSS system was created to mitigate air pollution in mining excavations. General aspects and tools used to build a DSS system for large-scale underground mines were presented in [5]. DSS based on fuzzy logic for ventilation operators was researched in [6], which main task was the dynamic interpretation and processing of gas images. Another DSS was shown in [7], where it dealt with the problem of coal mine exploitation disposition. A general conception of DSS along with a more detailed algorithm for random event handling in underground ore wheeled transport was presented in [8]. Issues of building a DSS for support of large-scale belt conveyor systems in terms of predictive maintenance were raised by [9]. The system presents information on the technical condition of conveyor drives in a large, extensive machine park (over 80 km of conveyor routes) based on vibration monitoring and designated methods of diagnostic reasoning [10]. The authors of [11] describe some key concepts, problems, and technologies for the creation of a digital twin for an underground mine. Another simulation is presented in [12], where the authors tried to mirror the transportation network (of wheeled vehicles) for management support. An DSS for synchronizing maintenance events was proposed in [13].

The above mentioned systems were developed to optimize some specific part of the process instead of the whole system. This shows that there is a gap when it comes to an DSS that will concern the whole transportation network, including various interconnected means of transport in underground mining (LHDs, conveyors, rail transport, and shaft transport). To meet the current expectations of the mining transport area, an international consortium was formed, and the NetHelix project (Intelligent digital toolbox towards more sustainable and safer extraction of mineral resources) was launched. One of the project goals is the optimization of mining operations in a broad view to improve cost efficiency, facilitate energy savings, improve health and safety issues, and minimize the environmental impact of the mining process. As part of the task, it is planned to develop predictive maintenance tools, optimization algorithms, and a DSS system for day-to-day operational efficiency in underground mines. Mine transportation networks are complex, heterogeneous systems that are hard to handle using standard programming methods used to build DSSs. A solution to this problem can come with the use of an Intelligent DSS, a subgenre of DSS created for solving sophisticated problems. Such systems incorporate AI (Artificial Intelligence) techniques and are therefore more flexible (one of the most important factors in mine transport). A technique especially well-suited to logistic-like problems is reinforcement learning, where latterly emphasis is put on Q-learning [14]. One example of such a system in an on-ground environment is presented in [15], where the authors present the architecture and working principles of a DSS working on a data-driven discrete-event simulation model. A similar approach that was adapted to underground mine environments is presented in this article. Unfortunately, mine environments are unique; therefore, each solution created can be generalized only to some extent. The approach shown in this article tries to maximize the generalization factor by dividing the whole system into blocks. Each individual block is a group of data, algorithms, techniques, decisions, and variables concerning one specific means of transportation. Although the literature is full of specific methods created for almost every aspect of mine, the authors would like to present some of the possible approaches and areas that can be incorporated into Intelligent DSS.

The article structure is as follows: Chapter 2 describes the ore haulage process; in Chapter 3, the concept of a DSS system is presented along with areas that such a system should cover and research work applicable. Finally, chapter 4 presents our conclusions and discusses future works.

2. Process of Ore Haulage

Ore haulage can be performed with the use of four main transportation means: tire machines, belt conveyors , railways, and shafts. The combination that will be used in the mine is an individual matter and depends mainly on the scale of extraction, the quality of corridors and roads, planned mine expansion, frequency of route use, and many others. Regardless of the combination, the main goal of any such transport network is to extract and transport the ore from the mining face to on-ground facilities for further processing (such as enrichment plants in the case of copper ore), which are usually integrally located on the surface [16]. In the case of small-scale extraction [17], only tire machinery, more specifically self-propelled haul trucks loaded by bucket loaders, is used. This method is by far the most flexible of all, as it does not require any additional infrastructure apart from a corridor of sufficient width and fresh air. However, these machines are also applicable at higher excavation rates as part of a larger ore transportation network. In such cases, they are often used in cooperation with belt conveyors or railways, where they usually perform the first part of the overall transport process. In such situations, their task is to move the excavated material from the extraction site (mining face) to the nearest pre-loading point for the conveyor or railway. Conveyors are often used as an efficient, damage-resistant, and safe alternative. In the majority of cases, the conveyors are linked to form a network that enables practically continuous transport. To such networks, amortization with the use of bunkers is additionally added. The railway, on the other hand, was, in most cases, the main ore haulage system until the 1970s, after which technological progress in other forms of transportation suppressed it. Recent advancements in this field have made the railway once again a viable mode of transport [18]. However, nowadays, it is hard to use it because in most mines, ore haulage architecture is already developed using other transportation means. Finally, regardless of the beginning and middle of the transportation process, the ore should always be brought to the surface. For this purpose, both conveyors and self-propelled machines can be used; however, in the case of high-performance mining enterprises, specially adapted mining shafts are used [19]. As high-performance mines (that can actually benefit from using the shaft for ore transport), we understand those facilities with a depth exceeding 250m and an extraction rate exceeding 300,000 tons per year [20].

3. The Concept of Intelligent Decision Support System

In the early years of the 21st century, mines were the subject of the digital revolution. As a result, most mines possess multiple sources of data concerning almost every part of the enterprise. From the DSS perspective, some are more crucial than others. Especially important are the real-time data from sensors used in machine monitoring systems, as they give a straight peek into the mine operation. In the case of multi-site mining enterprises, the gradual digitization process results in a variety of IT solutions used for the same purpose. This gives rise to certain challenges in the development of analytics, as presented in the paper [21]. Also important in terms of predictive maintenance are data concerning previous malfunctions, repairs, scheduled maintenance, etc. Most mines also log the parameters of operation, like the work place of machines and operators or work time. This information, correlated with economic indicators describing factors like production costs or sales revenue, can be used to estimate (with strong conviction) the general mine operation. However, if more detailed data from automation systems is fused with a general estimation of operation and put on the predefined transportation network, the outcome will be a data-driven continuous-time simulation. In the presented approach, into this simulation is embedded a reinforcement learning agent that will be the kernel of the proposed DSS.

The architecture of the proposed solution is presented in Figure 1. The data generated in the mine can take a variety of possible types and shapes. Therefore, the best way to store them is with unstructured data storage. From data storage, raw data can take one of four possible routes, each finally ending in the simulation. The first two routes assume the flow of raw or clean data straight to the simulations, while the other two routes use this data to fuel algorithms whose output will be passed into the simulation. Currently, there is an abundance of algorithms that can be implemented. However, later in the article, possible areas and examples of application are presented that can be involved in this block. The mine simulation is used to present the current state to the agent as well as to calculate important metrics and KPIs (Key Performance Indicators) to be presented to the user. The agent evaluates the current environment situation and selects one of the possible actions from the separate action bank. This ensures generalization, as different mines can not only use different means of transportation but also face unique challenges. Finally, the agent returns the policy to the user to show not only the decision taken but also others considered. In agent training, decisions will be extracted from the policy and applied to the mine simulation. In the final solution, however, the policy will only inform the user, who will decide in the end.

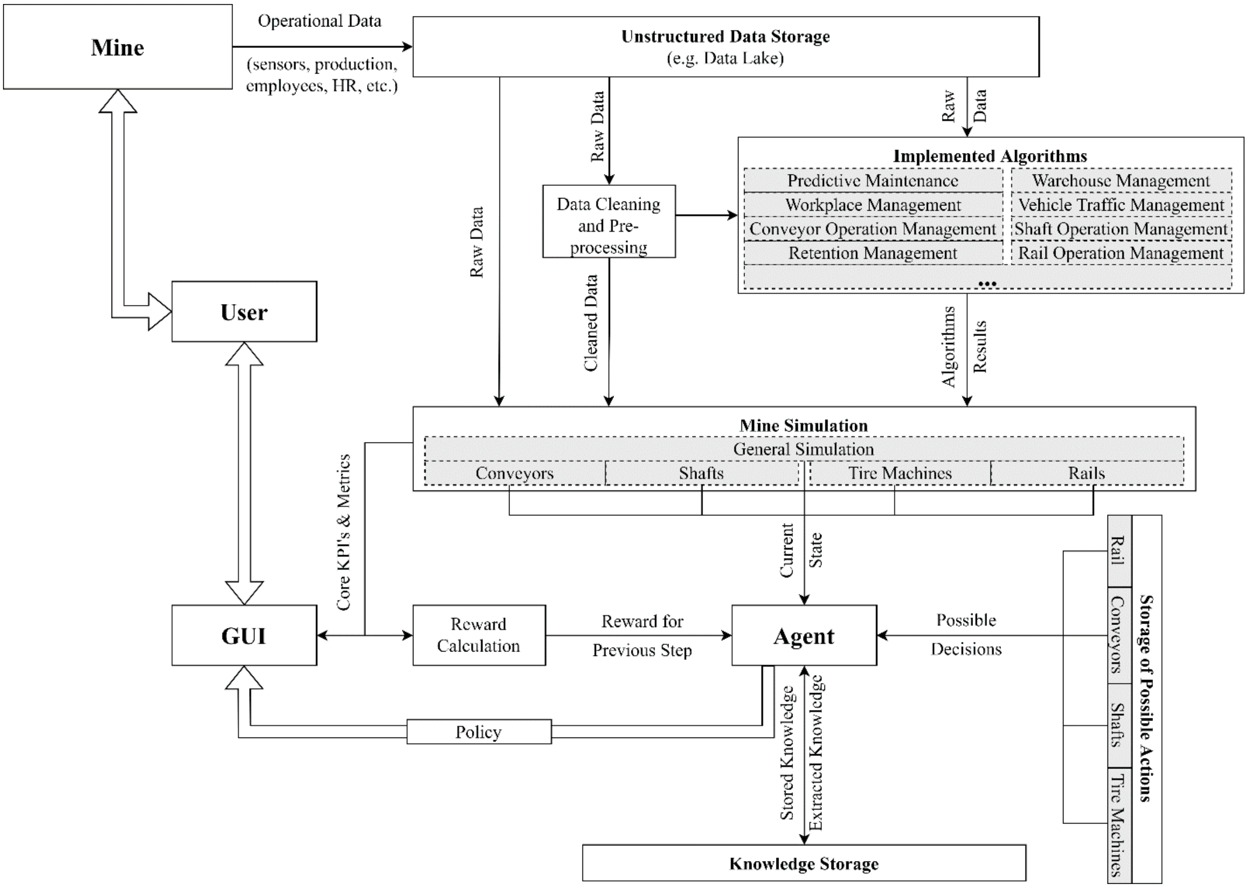

Figure 1 Proposed DSS architecture for underground mine ore transportation

This article will not delve into the particular details of the implementation of this proposed concept. Research project, of which this article is a part, assumes the construction of a similar system in the coming years. Therefore, rather than contemplating the what-ifs of construction, the authors want to propose general areas and solutions that such a system can include and implement. Such solutions are divided into four main means of transportation used in mines and described in later subsections.

3.1. Tire Haulage

The decision support module for tire transport should focus on several important aspects. First, it should assess the condition of machines on an ongoing basis, try to predict breakdowns, and plan repair work (Predictive Maintenance). Based on that, it should also manage the inventory so that the repair parts shortage doesn't cause long-term downtime (Warehouse Management). This module should also consider employees and workplaces to maintain work at an optimal and safe level (Workplace Management). Ultimately, the traffic should be supervised and planned to achieve further benefits (vehicle traffic Management).

Predictive maintenance can be performed in several different ways, all of which utilize some form of data. The data gathered by on-board machine measurement systems can be used to assess the current state of the machine fleet and predict upcoming failures. In the majority of large enterprises, machines have been equipped with systems that measure several parameters, such as engine speed, oil temperature, hydraulic system pressure, temperature of the most important components, tire pressure, fuel consumption, movement speed, etc. Such measurement systems can send data in real-time; however, this is not practiced due to high operating costs. Instead, the data is aggregated and transferred to a server every time a specified activity takes place (e.g., refueling) [22]. This data is a valuable source of information about the current condition of machines and allows one to implement effective methods of failure prediction. Self-propelled machines have a strict maintenance schedule, but unexpected breakdowns still happen. Each of them poses a direct threat to the safety of workers and causes significant costs. In the event of a sudden failure, depending on the condition of the machine, several employees (and machines in the event of critical failures) are delegated to provide repairs, which translates into further costs. In the literature, several algorithms have been described for solving many specific problems related to tire machines: condition monitoring for wheel motors [23], methods for overheating engines [24], [25], lifetime analysis of machine engines [26], analysis of joint damage [27], and overall survival analysis [28].

The Workplace Management module relates to the management of machines, operators, and workplaces. The analysis of historical data on machine failures allows for the selection of machines with a greater susceptibility to failure. Vehicles of this type should not be dispatched to areas with poor road quality or driven by operators prone to exceed the generally accepted standards (high-speed driving, sharp turns, etc.). Both of these factors (the operator's driving style and road quality) can be classified when the machine's measuring system detects the vibration [29], [30]. It is possible to adjust the machines to the prevailing road conditions and drivers. As a result, the efficiency of the transport system and overall machine health and safety should improve. In cases where vibration measurement is not performed, it is possible to reference the data from repair records to the data from machine operations performed (as a general area, not an exact location). In such a situation, it is still possible to combine the machine, workplace, and operator; however, the results of such a method will be less reliable. Alternatively, it is possible to extract a similar category of knowledge by tracking the efficiency of working cycles (monitoring their duration) [31], e.g., using a signal from automation [32].

Warehouse management utilizes maintenance record data that is commonly stored by mines. Quite often, it is a source of hidden but very useful knowledge. Data analysis of this type allows one to optimize the inventory of parts available on site. This is extremely important because, in the event of a breakdown, each hour when the machine is unable to work brings a loss to the system's efficiency (mining machines are extremely expensive, so typically their quantity is barely meeting the demand). Usually, the company wants to repair it as quickly as possible, and this is only achievable when parts are available on-site. Otherwise, the mere waiting period for the necessary parts can last up to full weeks. This problem appears in enterprises from various industries, so there are plenty of articles about it [33].

Vehicle traffic management consists of optimizing the access route, i.e., selecting for each of the working machines the route it should take to perform the assumed transport. It is often performed in open-pit mines [34], but it is equally important in underground mines. The main reason for this type of optimization is the reduction in transport time and energy used for it. Algorithms solving this problem may consider several parameters, including: roads condition or the absence of ventilation. This is important because in an underground mine, especially in room and pillar mining, the number of possible roads is large (unfortunately, most of them are suboptimal). If the company's infrastructure allows for real-time tracking of the location of machines, the suggested route can be constantly updated, which will translate into further optimization.

3.2. Conveyor Haulage

Mining enterprises usually use several interconnected belt conveyors that form a network. Such a network can be compared to a directed graph, where each edge is a conveyor. Additionally, to such networks, an amortization is added in the form of bunkers. When one conveyor stops its operation, bunker allow for continuous production thanks to ore collection (if it is located ahead of the damaged conveyor) or release (if it is behind the damaged conveyor). We propose a 3-part module of conveyor haulage for DSS. The first part will be responsible for analysing the current state of machines, scheduling repair work, and detecting critical conditions (Predictive Maintenance). Because unexpected downtimes cannot be eliminated, proper load management for ore bunkers is needed, which will be implemented in the second part of the conveyor module (Bunkers Management). Finally, the third part will be performing real-time conveyor operation control concerning conveyor start-up moments and operation mode (e.g., transportation speed).

The main reason for the use of predictive maintenance in conveyor networks is the reduction of unexpected downtimes and the improvement of overall machinery condition. This is extremely important because even one failure has the potential to halt all transport. Such hazards usually focus on one tight-neck conveyor, through which, at a certain point, most of the material in the mine is transported. In a general diagnostic, conveyors can be separated into three main parts: a transportation belt, a belt support with idlers, and a drive unit. Diagnostics of such elements mainly consist of analysing conveyor automation signals (vibrations, temperature, and power consumption) or performing a measurement. Such action can be done with the use of separate measuring stations [35] or Unmanned Ground and Aerial Vehicles [36]. In the majority of cases, measurements of conveyors come down to the use of specialized cameras (spectral, thermovision). In the literature, several methods are described that can be combined to perform a complex state analysis of a belt conveyor. For the actual belt, there are methods concerning its overall wear state [37], tear detection [38], or even using it to estimate the conveyor speed [39]. For the belt support system, one analyses the idlers using acoustic-based methods [40] and thermovision methods [41]. Finally, when it comes to the conveyor drives, methods based on vibration measurement [42] or electrical current signal analysis [43] can be implemented. The general condition of the conveyor can also be diagnosed using its temperature signal [44].

The main goal of bunkers when it comes to ore transport is to ensure the continuous flow of transported material. However, bunkers can also be used to even out the transportation flow or store material before changing the means of transport [45]. Depending on the usage, the level of spoil that has been accumulated by the reservoir needs to be monitored and optimized to take full advantage of it [46].

Conveyor operation management is often introduced to improve their energy efficiency. This can be achieved through the management of conveyor belt speed and feed rate or the coordination of operational status and time [47]. In the literature, multiple methods of estimating conveyor optimal speed can be found [48]. However, the best ones tend to connect optimal speed with healthy dynamic behaviour [49]. The second practice, which manages operational status and time, is done by load shifting. This practice relies on lowering the total energy used during peak hours (when the energy price is the highest) by using a controller for smart conveyor network management. One of such algorithms was presented in [50] and allowed for a 49% reduction in energy costs.

3.3. Shaft Haulage

Mining shafts are of utmost importance in underground mines. They are used for transportation (of the equipment, workers, and materials); they provide access to electricity, water, and telecommunication; and above all, they are part of the mine ventilation system. They are also subject to constant deterioration forces like rock mass movements, local deposit tectonics, atmospheric conditions, and groundwater acting [51]. Therefore, mining shafts need to be under constant surveillance, which will cause quick and decisive actions after spotting the first appearance of damage symptoms (Predictive Maintenance). To further reduce the possibility of malfunctions while improving overall safety and efficiency, smart management methods can be implemented (Shaft Operation Management).

Damage to the shaft can manifest itself in various forms, like failure of the shaft lining, collapse of the filling material column, failure of the shaft head, ruptures (due to water or other geological forces), gas leaks, and many others [52]. Apart from the case, shaft failure is always a dangerous event for everything in its immediate vicinity and possibly the entire underground mine as well. For these reasons, shafts are particularly monitored and curated to avoid even the possibility of failure. For the predictive maintenance of shafts, one can use long-term, direct, and indirect monitoring methods along with field investigations [53]. Specific methods rely on photogrammetric observations [54], laser photogrammetry [55], shaft parameters combined with engineering measurements [56], and others like IMUs, 360° cameras, gas sensors, or power supply monitoring [57]. However, when it comes to predictive maintenance of mine shafts, there is also the hoisting system that needs to be taken into account. One can search for specific subsystem failures, like breaking system [58] or gearbox [59]. As an alternative, a more general analysis can be performed like the one that was presented in [60].

Most of the works in the literature that research the optimization problem of the hoisting process suggest changes in the overall system architecture or hoisting equipment. However, some modifications can be made in operation management to increase the overall efficiency of the hosting process. First, the hoisting schedule can be optimized to still achieve the hoist target but with the use of lowest possible energy [61]. Second, the hoisting parameters, like hoisting velocity or hoisting load, can be controlled. One of the reasons for such management is to avoid large-amplitude transverse vibrations that can cause catenary collisions [62].

3.4. Rail Haulage

The authors of [63] stated that rail transport is more convenient than its trackless counterparts; however, there are still some major problems waiting to be resolved. As such, one can list the transport efficiency problem, the real-time monitoring problem, and the rear-end collision problem. All of which could be eliminated using one efficient control system (Rail Operation Management). Such a solution would take care of all aspects of rail operation management and could be further supported using fault detection algorithms (Predictive Maintenance).

Most of the research regarding the management of underground mine rail transportation proposes the implementation of a modified CBTC system (Communication-Based Train Control). Such systems are popular in both on-ground and underground public transportation networks. The CBTC relies on three main modules, whose names are self-explanatory: the ATP (Automatic Train Protection), the ATO (Automatic Train Operation) and ATS (Automatic Train Supervision) [64]. To make the system efficient, all of the CBTC parts need to be modified to match the conditions prevailing in the underground mine. In the literature, one concept of such an operational system can be found [65]. The authors of which propose a set of possible solutions to the main problems of using the CBTC in underground mines (safety, efficiency, control, and management). Such propositions are based on multiple works in the literature concerning isolated parts of general problems such as the ATP system based on Dynamic Fault Tree analysis [66], fleet management [67], positioning system [68], and many others.

A fully operational CBTC, modified for use in underground mines, can be further improved with the predictive maintenance module. It is expected that train equipment will deteriorate faster than one used in public transport [69]. For these reasons, we propose to improve the ATP subsystem through the implementation of fault diagnostic methods found in the literature. These include condition monitoring of stock wheels and axle bearings [70], railway wheelset monitoring [71], detection of sliding railway wheels and hot bearings [72], track deterioration [73], and others [74].

4. Conclusions

Optimal decision-making is a key challenge in ensuring efficient underground mining operations. Especially in the case of the transportation process, which is directly correlated with enterprise profits. Unfortunately, most of the literature in this area presents a solution that enhances only a separate part of the whole process. Meaning, that there is a lack of holistic approaches that will optimize large underground, heterogeneous ore transportation networks. To fill this gap, we present the concept of an intelligent decision support system. The system is a simulation-based approach in which an agent taught by reinforcement learning is nested. The whole architecture is divisible into blocks corresponding to different means of transportation in the network to ensure flexibility and a holistic view of mine. In addition, system architecture is meant to implement a number of literature-provided algorithms. Apart from the general system architecture, this article presents a review of tasks and possible solutions to be implemented by the system, divided into four main means of transport. If constructed, such a system will allow for almost any kind of optimization, but the most commonly found in literature are energy efficiency, transport efficiency, and enterprise net value. Future works relating to this concept will include the study of decision processes that occur in mines, the creation of a general simulation and add-in simulation blocks for each means of transportation, the creation and training of an agent to learn and work in such an environment, and finally the validation of the system based on a real-world use case.

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References

[1] Hu, S., Tang, C., Yu, R., Liu, F., & Wang, X. (2013, November). Intelligent coal mine monitoring system based on the Internet of Things. In 2013 3rd International Conference on Consumer Electronics, Communications and Networks (pp. 380-384). IEEE.

[2] Alpay, S., & Yavuz, M. (2007, June). A decision support system for underground mining method selection. In International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems (pp. 334-343). Springer, Berlin, Heidelberg.

[3] Kamran, M., & Shahani, N. M. (2022). Decision support system for the prediction of mine fire levels in underground coal mining using machine learning approaches. Mining, Metallurgy & Exploration, 39(2), 591-601.

[4] Asif, Z., & Chen, Z. (2020). A Life Cycle Based Air Quality Modeling and Decision Support System (LCAQMS) for Sustainable Mining Management. Journal of Environmental Informatics, 35(2).

[5] Dessureault, S. (2004, June). Developing decision support systems at large-scale underground mines. In 2004 SME Annual Meeting Preprints.

[6] Insinga, I. V. L. R. C. (2003). DECISION SUPPORT SYSTEM FOR VENTILATION OPERATORS BASED ON FUZZY METHODS APPLIED TO IDENTIFICATION AND PROCESSING OF GAS–DYNAMIC IMAGES. Journal of Electrical Engineering, 54(9-10), 277-280.

[7] Zuo, X., Zhang, X., Wang, Y., Xu, Y., & Tao, W. (2020). Decision support system of coal mine exploitation disposition. In Computer Applications in the Mineral Industries (pp. 291-294). CRC Press.

[8] Nguyen, D. K., & Bui, X. N. (2015). A real-time regulation model in multi-agent decision support system for open pit mining. In Proceedings of the 12th International Symposium Continuous Surface Mining-Aachen 2014 (pp. 255-262). Springer International Publishing.

[9] Stefaniak, P., Wodecki, J., & Zimroz, R. (2018). Maintenance management of mining belt conveyor system based on data fusion and advanced analytics. In Advances in Technical Diagnostics: Proceedings of the 6th International Congress on Technical Diagnostic, ICDT2016, 12-16 September 2016, Gliwice, Poland 6 (pp. 465-476). Springer International Publishing.

[10] Stefaniak, P. K., Wyłomańska, A., Zimroz, R., Bartelmus, W., & Hardygóra, M. (2016). Diagnostic features modeling for decision boundaries calculation for maintenance of gearboxes used in belt conveyor system. In Advances in Condition Monitoring of Machinery in Non-Stationary Operations: Proceedings of the Fourth International Conference on Condition Monitoring of Machinery in Non-Stationary Operations, CMMNO'2014, Lyon, France December 15-17 (pp. 251-263). Springer International Publishing.

[11] Lin, H., Liu, P., Li, W., Zhang, L. P., & Ji, Y. Z. (2012). Construction of digital mine and key technologies. In Advanced Materials Research (Vol. 524, pp. 413-420). Trans Tech Publications Ltd.

[12] Upadhyay, S. P., Askari-Nasab, H., Tabesh, M., & Badiozamani, M. M. (2015, May). Simulation and optimization in open pit mining. In Proceedings of the Application of Computers and Operations Research in the Mineral Industry—Proceedings of the 37th International Symposium APCOM.

[13] Boland, N., McGowan, B., Mendes, A., & Rigterink, F. (2013, December). Modelling the capacity of the Hunter Valley coal chain to support capacity alignment of maintenance activities. In 20th International Congress on Modelling and Simulation. Adelaide, Australia (pp. 3302-3308).

[14] Singh, A., Wiktorsson, M., & Hauge, J. B. (2021). Trends in machine learning to solve problems in logistics. Procedia CIRP, 103, 67-72.

[15] Rabe, M., & Dross, F. (2015, December). A reinforcement learning approach for a decision support system for logistics networks. In 2015 Winter Simulation Conference (WSC) (pp. 2020-2032). IEEE.

[16] Jasiński, M., & Janik, S. (2015). Zabezpieczenie ciągłości transportu urobku pod ziemią–zarys problematyki. Zeszyty Naukowe Dolnośląskiej Wyższej Szkoły Przedsiębiorczości i Techniki. Studia z Nauk Technicznych.

[17] Antoniak, J. (2011). Problematyka transportu pionowego w kopalniach podziemnych o wydobyciu masowym. Mechanizacja i Automatyzacja Górnictwa, 49, 5-12.

[18] Dammers, M., Brudek, G., Pütz, M., & Merchiers, A. (2016). Opportunities and Challenges of Rail Haulage Systems in Current Mining Operations. Engineering and Mining Journal, 217(5), 42.

[19] Matsui, K. (2009). Underground mining transportation systems. Civil Engineering-Volume II, 5, 285.

[20] Gonen, A., Malli, T., & Kose, H. (2012). Selection of ore transport system for a metalliferous underground mine/Dobór systemu transportu rud w kopalni podziemnej rud metalu. Archives of Mining Sciences.

[21] Dudycz, H., Stefaniak, P., & Pyda, P. (2019). Advanced data analysis in multi-site enterprises. Basic problems and challenges related to the IT infrastructure. In Computational Collective Intelligence: 11th International Conference, ICCCI 2019, Hendaye, France, September 4–6, 2019, Proceedings, Part II 11 (pp. 383-393). Springer International Publishing.

[22] Zimroz, R., Wodecki, J., Król, R., Andrzejewski, M., Sliwinski, P., & Stefaniak, P. (2014). Self-propelled mining machine monitoring system–data validation, processing and analysis. In Mine planning and equipment selection (pp. 1285-1294). Springer, Cham.

[23] Jardine, A. K. S., Banjevic, D., Wiseman, M., Buck, S., & Joseph, T. (2001). Optimizing a mine haul truck wheel motors' condition monitoring program Use of proportional hazards modeling. Journal of quality in Maintenance Engineering.

[24] Wodecki, J., Stefaniak, P., Michalak, A., Wyłomańska, A., & Zimroz, R. (2018). Technical condition change detection using Anderson–Darling statistic approach for LHD machines–engine overheating problem. International Journal of Mining, Reclamation and Environment, 32(6), 392-400.

[25] Stefaniak, P., Śliwiński, P., Poczynek, P., Wyłomańska, A., & Zimroz, R. (2019). The automatic method of technical condition change detection for LHD machines-engine coolant temperature analysis. In Advances in Condition Monitoring of Machinery in Non-Stationary Operations: Proceedings of the 6th International Conference on Condition Monitoring of Machinery in Non-Stationary Operations, CMMNO'2018, 20-22 June 2018, Santander, Spain 06 (pp. 54-63). Springer International Publishing.

[26] Madhu, B.R., Santos, G., Ilham, M., Teguh, K., Dwi, Ali, F., Mayur, B., Antonio, E., Mcrae, M., & Cerilli, S. (2020, September). Predictive Maintenance of Mining Haul Truck Engines Using Oil Sampling and Telemetry Data. ISOR Journal of Engineerin, 10(9), 56-63.

[27] Stefaniak P, Koperska W, Skoczylas A, Stachowiak M. (2022). Application of Spectral Entropy in Haul Truck Joint Damage Detection. Sensors, 22(19):7358. https://doi.org/10.3390/s22197358

[28] Hochstein, A., Ahn, H. I., Leung, Y. T., & Denesuk, M. (2013, July). Survival analysis for HDLSS data with time dependent variables: Lessons from predictive maintenance at a mining service provider. In Proceedings of 2013 IEEE International Conference on Service Operations and Logistics, and Informatics (pp. 372-381). IEEE.

[29] Stefaniak, P., Gawelski, D., Anufriiev, S., & Śliwiński, P. (2020). Road-quality classification and motion tracking with inertial sensors in the deep underground mine. In Intelligent Information and Database Systems: 12th Asian Conference, ACIIDS 2020, Phuket, Thailand, March 23–26, 2020, Proceedings 12 (pp. 168-178). Springer Singapore.

[30] Skoczylas, A., Stefaniak, P., Anufriiev, S., & Jachnik, B. (2020, December). Road Quality Classification Adaptive to Vehicle Speed Based on Driving Data from Heavy Duty Mining Vehicles. In International Conference on Intelligent Computing & Optimization (pp. 777-787). Springer, Cham.

[31] Park, S., Jung, D., Nguyen, H., & Choi, Y. (2021). Diagnosis of problems in truck ore transport operations in underground mines using various machine learning models and data collected by internet of things systems. Minerals, 11(10), 1128.

[32] Polak, M., Stefaniak, P., Zimroz, R., Wyłomańska, A., Śliwiński, P., & Andrzejewski, M. (2016). Identification of loading process based on hydraulic pressure signal. International Multidisciplinary Scientific GeoConference: SGEM: Surveying Geology & mining Ecology Management, 2, 459-466.

[33] Boylan, J. E., & Syntetos, A. A. (2010). Spare parts management: a review of forecasting research and extensions. IMA journal of management mathematics, 21(3), 227-237.

[34] Liu, G., & Chai, S. (2019). Optimizing open-pit truck route based on minimization of time-varying transport energy consumption. Mathematical Problems in Engineering, 2019.

[35] Błażej, R., Jurdziak, L., Kozłowski, T., & Kirjanów, A. (2018). The use of magnetic sensors in monitoring the condition of the core in steel cord conveyor belts–Tests of the measuring probe and the design of the DiagBelt system. Measurement, 123, 48-53.

[36] Shiri, H., Wodecki, J., Ziętek, B., & Zimroz, R. (2021). Inspection Robotic UGV Platform and the Procedure for an Acoustic Signal-Based Fault Detection in Belt Conveyor Idler. Energies, 14(22), 7646.

[37] Webb, C., Sikorska, J., Khan, R. N., & Hodkiewicz, M. (2020). Developing and evaluating predictive conveyor belt wear models. Data-Centric Engineering, 1.

[38] Hou, C., Qiao, T., Zhang, H., Pang, Y., & Xiong, X. (2019). Multispectral visual detection method for conveyor belt longitudinal tear. Measurement, 143, 246-257.

[39] Dabek, P., Krot, P., Wodecki, J., Zimroz, P., Szrek, J., & Zimroz, R. (2022). Measurement of idlers rotation speed in belt conveyors based on image data analysis for diagnostic purposes. Measurement, 111869.

[40] Skoczylas, A., Stefaniak, P., Anufriiev, S., & Jachnik, B. (2021). Belt conveyors rollers diagnostics based on acoustic signal collected using autonomous legged inspection robot. Applied Sciences, 11(5), 2299.

[41] Dabek, P., Szrek, J., Zimroz, R., & Wodecki, J. (2022). An Automatic Procedure for Overheated Idler Detection in Belt Conveyors Using Fusion of Infrared and RGB Images Acquired during UGV Robot Inspection. Energies, 15(2), 601.

[42] Wodecki, J., Stefaniak, P., Obuchowski, J., Wylomanska, A., & Zimroz, R. (2016). Combination of principal component analysis and time-frequency representations of multichannel vibration data for gearbox fault detection. Journal of Vibroengineering, 18(4), 2167-2175.

[43] Kruczek, P., Sokołowski, J., Obuchowski, J., Sawicki, M., Wyłomańska, A., & Zimroz, R. (2017). Fault detection in belt conveyor drive unit via multiple source data. In Cyclostationarity: Theory and Methods III (pp. 173-186). Springer, Cham.

[44] Sawicki, M., Zimroz, R., Wyłomańsk, A., Obuchowski, J., Stefaniak, P., & Żak, G. (2015). An automatic procedure for multidimensional temperature signal analysis of a SCADA system with application to belt conveyor components. Procedia Earth and Planetary Science, 15, 781-790.

[45] Antoniak, J. (1990). Urządzenia i systemy transportu podziemnego w kopalniach. Wydawnictwo" Śląsk".

[46] Bardzinski, P. J., Walker, P., Krol, R., & Kawalec, W. (2018). Simulation of random tagged ore flow through the bunker in a belt conveying system. International Journal of Simulation Modelling, 17(4), 597-608.

[47] Zhang, S., & Xia, X. (2011). Modeling and energy efficiency optimization of belt conveyors. Applied energy, 88(9), 3061-3071.

[48] Hiltermann, J., Lodewijks, G., Schott, D. L., Rijsenbrij, J. C., Dekkers, J. A. J. M., & Pang, Y. (2011). A methodology to predict power savings of troughed belt conveyors by speed control. Particulate science and technology, 29(1), 14-27.

[49] He, D., Pang, Y., & Lodewijks, G. (2017). Green operations of belt conveyors by means of speed control. Applied Energy, 188, 330-341.

[50] Middelberg, A., Zhang, J., & Xia, X. (2009). An optimal control model for load shifting–with application in the energy management of a colliery. Applied energy, 86(7-8), 1266-1273.

[51] Kalinowski, P., Długosz, O., & Kamiński, P. (2021). Digital twin of the mining shaft and hoisting system as an opportunity to improve the management processes of shaft infrastructure diagnostics and monitoring. In Data science, data visualization, and digital twins. IntechOpen.

[52] Lecomte, A., Salmon, R., Marshall, A., Purvis, M., Prusek, S., Bock, S., ... & Niharra, A. M. (2012, April). Case studies and analysis of mine shafts incidents in Europe. In 3. International Conference on Shaft Design and Construction (SDC 2012) (p. NC).

[53] Sun, Q., Ma, F., Guo, J., Li, G., & Feng, X. (2020). Deformation failure mechanism of deep vertical shaft in Jinchuan mining area. Sustainability, 12(6), 2226.

[54] Fraštia, M., Plakinger, M., & Beck, J. (2011). Photogrammetric observation of deformation of the vertical mining shaft. Acta Montanistica Slovaca, 16(4), 276.

[55] Vala, D. V. D., Slanina, Z., & Walendziuk, W. (2016). Mining shaft inspection by laser photogrammetry. Elektronika ir Elektrotechnika, 22(1), 40-43.

[56] Chen, C., Zhou, J., Zhou, T., & Yong, W. (2021). Evaluation of vertical shaft stability in underground mines: comparison of three weight methods with uncertainty theory. Natural Hazards, 109(2), 1457-1479.

[57] Benecke, N., Hancock, P., & Weber, M. (2016, September). Latest developments for practice in shaft inspection. In Proceedings of the XVI Congress of the International Society of Mine Surveying (ISM), Brisbane, Australia.

[58] Juanjuan, L., Aiming, W., Guoying, M., Guangming, X., Shuai, W., Liang, H., & Yifan, J. (2017, September). Fault Diagnosis in Braking System of Mine Hoist Based on the Moment Characteristics. In CS & IT Conference Proceedings (Vol. 7, No. 12). CS & IT Conference Proceedings.

[59] Chang, Y. W., Wang, Y. C., Tao, L., & Wang, Z. J. (2008). Fault diagnosis of a mine hoist using PCA and SVM techniques. Journal of China University of Mining and Technology, 18(3), 327-331.

[60] Vayenas, N., & Peng, S. (2014). Reliability analysis of underground mining equipment using genetic algorithms: A case study of two mine hoists. Journal of Quality in Maintenance Engineering.

[61] Badenhorst, W., Zhang, J., & Xia, X. (2011). Optimal hoist scheduling of a deep level mine twin rock winder system for demand side management. Electric Power Systems Research, 81(5), 1088-1095.

[62] Yao, J., Deng, Y., & Xiao, X. (2017). Optimization of hoisting parameters in a multi-rope friction mine hoist based on the multi-source coupled vibration characteristics of hoisting catenaries. Advances in Mechanical Engineering, 9(3), 1687814017693216.

[63] Dash, A. K., Bhattcharjee, R. M., Paul, P. S., & Tikader, M. (2015). Study and analysis of accidents due to wheeled trackless transportation machinery in Indian coal mines–identification of gap in current investigation system. Procedia Earth and Planetary Science, 11, 539-547.

[64] Yu, H., Li, S., & Yu, J. (2021, March). Intelligent Monitoring and Control System for underground mine rail transportation based on communication-based train control (CBTC) system and AI computing. In 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE) (pp. 704-707). IEEE.

[65] Yu, H., & Li, S. (2021). The Function Design for the Communication-Based Train Control (CBTC) System: How to Solve the Problems in the Underground Mine Rail Transportation?. Applied System Innovation, 4(2), 31.

[66] Gao, P., Liu, C., Dong, H., & Zheng, W. (2020, September). A dynamic fault tree based CBTC onboard ATP system safety analysis method. In 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC) (pp. 1-7). IEEE.

[67] Gamache, M., Grimard, R., & Cohen, P. (2005). A shortest-path algorithm for solving the fleet management problem in underground mines. European journal of operational research, 166(2), 497-506.

[68] Xue, J., & Liming, W. (2012, June). Research on intelligent track positioning system to the mine accident rescue. In World Automation Congress 2012 (pp. 1-3). IEEE.

[69] Biały, W. (2019). Equipment/machinery failure rate in hard coal mines. New Trends in Production Engineering, 2.

[70] Papaelias, M., Amini, A., Huang, Z., Vallely, P., Dias, D. C., & Kerkyras, S. (2016). Online condition monitoring of rolling stock wheels and axle bearings. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 230(3), 709-723.

[71] Amini, A. (2016). Online condition monitoring of railway wheelsets (Doctoral dissertation, University of Birmingham).

[72] Deilamsalehy, H., Havens, T. C., Lautala, P., Medici, E., & Davis, J. (2017). An automatic method for detecting sliding railway wheels and hot bearings using thermal imagery. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 231(6), 690-700.

[73] Ghofrani, F. (2020). Data-driven railway track deterioration modeling for predictive maintenance (Doctoral dissertation, State University of New York at Buffalo).

[74] Ghofrani, F., He, Q., Goverde, R. M., & Liu, X. (2018). Recent applications of big data analytics in railway transportation systems: A survey. Transportation Research Part C: Emerging Technologies, 90, 226-246.