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Review

Development of Surface Mining 4.0 in Terms of Technological Shock in Energy Transition: A Review

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Abstract: The expansion of end-to-end Industry 4.0 technologies in various industries has caused a technological shock in the mineral resource sector, wherein itsdigital maturity is lower than in the manufacturing sector. As a result of the shock, the productivity and profitability of raw materials extraction has begun to lag behind the industries of its deep processing, which, in the conditions of volatile raw materials markets, can provoke sectoral crises. The diffusion of Industry 4.0 technologies in the mining sector (Mining 4.0) can prevent a technological shock if they are implemented in all segments, including quarrying (Surface Mining 4.0). The Surface Mining 4.0 technological platform would connect the advanced achievements of the Fourth Industrial Revolution (end-to-end digital artificial intelligence technologies, cyber-physical systems and unmanned production with traditional geotechnology) without canceling them, but instead bringing them to a new level of productivity, resource consumption, and environmental friendliness. In the future, the development of Surface Mining 4.0 will provide a response to the technological shock associated with the acceleration of the digital modernization of the mining sector and the increase in labor productivity, which are reducing the operating costs of raw materials extraction. In this regard, the given review is an attempt to analyze the surface mining digital transformation over the course of the diffusion of Industry 4.0 technologies covered in scientific publications. The authors tried to show the core and frontiers of Surface Mining 4.0 development to determine the production, economic, and social effect of replacing humans with digital and cyber-physical systems in the processes of mineral extraction. Particular attention was paid to the review of research on the role of Surface Mining 4.0 in achieving sustainable development goals.

Keywords: Surface Mining 4.0; Industry 4.0; technological shock; Internet of Things; artificial intelligence; unmanned equipment

Citation: Zhironkin, S.; Taran, E. Development of Surface Mining 4.0 in Terms of Technological Shock in Energy Transition: A Review. *Energies* **2023**, *16*, 3639. https://doi.org/10.3390/en16093639

Academic Editors: Abdul-Ghani Olabi, Krzysztof Skrzypkowski and Wen-Hsien Tsai

Received: 4 March 2023
Revised: 18 March 2023
Accepted: 21 April 2023
Published: 24 April 2023

1. Introduction

1.1. The Role of Surface Mining Digitalization in Energy Production in 21st Century

Fossil fuels perform a key role in the production of electricity and heat in Poland, the European Union (EU), and the world [1]. This review attempts to show a wide range of discussions about the role of the digitalization of surface mining in the global energy supply while taking into account the technological shocks that arise with the expansion of Industry 4.0 technologies in the mining sector (Mining 4.0). This role is significant, and is explained, on the one hand, by the connections of Mining 4.0 with the digital revolution in the energy industry [2], which have been built around end-to-end digital technologies (artificial intelligence, Internet of Things, machine vision, digital twins, etc.). On the other hand, the energy transition has caused shocks in the energy sources and electricity markets, which can destabilize power consumption in the medium term. In this regard, it is important to ensure the accelerated modernization of fossil energy production (more productive, environmentally friendly, and complementary to renewable energy) on a new digital basis.

A significant portion of fossil fuels (hard and brown coal, oil-bearing sand) is mined using surface methods. For example, A. Duda, G. Fidalgo Valverde wrote: "Coking coal has been on the European list of critical raw materials since 2014 due to its high economic importance and high supply risk" [3]. Therefore, the energy transition with a characteristic increase in the share of renewable energy, in which Industry 4.0 technologies are widely used, cannot be separated from the synchronous modernization of mining [4].

In the era of the Fourth Industrial Revolution, this makes the fuel energy industry dependent on the success of the transition to Surface Mining 4.0: " ... the hard coal sector worsened the eco-efficiency because of the lack of investment in technology of manufacturing in production and consumption. This situation is typical for many countries of the European Union and the world" [1]. The direct connection of the fossil fuels mining sector with ensuring energy security is understood by the public in countries with a developed resource complex (for example, in Poland [5]).

The transition from fuel to renewable energy can take some time; therefore, to avoid shocks in the energy market, it is important to ensure the innovative development of surface mining to level 4.0, with its characteristic full fossil extraction, high productivity and reduced negative environmental impact. Thus, the energy transition is largely associated with electric vehicles running on lithium batteries [6]; at the same time, a significant portion of lithium-containing rocks (spodumene, amblygonite, etc.) is mined by surface methods [7].

The coexistence of renewable and fuel power producing is made possible with the parity development of the basic technologies of Industry 4.0 (artificial intelligence and neural networks, Big Data, digital twins, drones, machine learning, etc.) for the surface mining of fossil fuels [8,9].

The innovative development of fossil energy source surface mining to the 4.0 level is of paramount importance for developing countries, wherein the transition from fossil fuels to renewable energy will take longer [10].

1.2. Surface Mining 4.0 as a Form of Industry 4.0 Implementation in Fossil Energy Resources Supply

Since the beginning of the 21st century, surface mining has been going through a technological transformation of being saturated with digital technologies, cyber-physical systems, and artificial intelligence. Since the mid-2000s crises of the world commodity market, the demand for raw materials became fluctuative, and the economic requirements for mining efficiency tightened. This process has been superimposed by an unprecedented increase in requirements for labor safety and a reduction in harmful effects on the environment [11]. Under such conditions, mining enterprises have a great chance to maintain profitability through the introduction of intelligent mining systems developing on the Industry 4.0 platform (Mining 4.0). There are such advantages to surface mining, upgraded to the level of Mining 4.0, as the possibility of the complete robotization of equipment with ultra-high specific productivity, the relatively easy access of artificial intelligence devices with smart sensors to the places of operation of the equipment, and the possibility of the prompt correction of virtual 3D models of surface mine workings [12]. All these advantages are summed up in the new technology platform Surface Mining 4.0.

Despite the rarity of the term Surface Mining 4.0, we see the possibility to consider it as a separate component of the Mining 4.0 technological platform, and we will try to prove its expediency in this review. The qualitative sign of Surface Mining 4.0 is its development on the Industry 4.0 technology platform with greater intensity than in underground mining. We see such a "window of opportunity" in the emergence of optimal conditions for the diffusion of end-to-end Industry 4.0 digital technologies into surface mining that results from an increase in investments by the largest manufacturers of quarry equipment in advanced R&D [13]. Examples include the Internet of Things, smart sensors, 3D visualization, artificial intelligence and neural networks, digital twins, and unmanned equipment with machine vision and learning.

The digital transformation of the mineral resource sector has reached the boundary of the convergence of human and machine labor [14]. It makes it possible to launch a new control system for the main processes of open-pit mining based on Surface Mining 4.0, in which the impact of humans on technological processes tends to zero. This is especially important for the development of Surface Mining 4.0 in countries that are “catching up” in technological development, in which the demand for modern mining engineers is not satisfied despite the fact that new equipment is constantly being put into operation [15].

In fact, in the expansion of Industry 4.0, the key technologies that allow for creating industrial cyber-systems radically increase labor productivity. This causes a technological shock for the raw materials sector, in which the saturation with digital technologies, and the added value created, is much lower than in the manufacturing sector of the economy. As a result, the profitability of raw materials extraction, the profits of mining companies, and their attractiveness for investors are reduced in the long term [16], and, under the conditions of volatility in prices for raw materials, future crises in the commodity markets cannot be ruled out.

The reason for the technological shock for the mining industry, arising in the process of Industry 4.0 technologies expansion, should be found in the heterogeneity of its implementation in the mining and manufacturing sectors of the economy, as evidenced by the outstripping demand of the latter for end-to-end digital technologies, such as product lifecycle management, SMART factories, and software interoperability [17]. Therefore, at present, when in such industries as software, electronics and machines production, and communications, there is a dramatic increase in productivity, the conditions for this process in the mining sector just begin to form by reducing the consumption of energy and materials. As a result, the gap in the productivity of the most widely used technologies in the manufacturing and minerals extractive sectors of the economy is growing, and the ratio of their effectiveness is changing not in favor of the latter. This enhances the impact of the technological shock on the mining sector, thereby forcing companies to look for ways to accelerate the implementation of Mining 4.0 technologies, as well as for researchers to reconsider approaches to the development of surface geotechnology in the context of total digitalization and robotization (Surface Mining 4.0).

In general, overcoming the technological shock is possible if the quarrying is upgraded to the level of Surface Mining 4.0. This means that the following requirements are met: ubiquitous coverage by Industry 4.0 technologies of all processes of surface mining operations (drilling and blasting, excavation, transport, dumping, logistics, design, and management), as well as the development of a digital ecosystem for the extraction and primary processing of minerals.

The Surface Mining 4.0 digital ecosystem reflects the opportunities provided by Industry 4.0 technologies, which stimulate the transition from centralized decision making to autonomous smart robots and self-learning cyber-physical systems. In this model of quarrying organization, the goal of development is to achieve a new high level of labor safety with a radical increase in productivity [16]. The digital essence of Surface Mining 4.0 is also manifested in solving the cybersecurity problems facing enterprises in the context of digitalization, which includesecure data exchange, protection against cyber attacks, sharing of cloud computing resources [18].

Expanding the boundaries of the technological efficiency of surface mining calls for gaining control over the main processes in real time, more precise control of product quality, monitoring the operating performance and condition of mining machines, safety, and the well-being of workers. The technological platform for such development—Surface Mining 4.0—is the result of the convergence of cyber-physical production systems (machine vision and learning, smart robots, and drones), the industrial Internet of Things, and the latest achievements in the field of mechanics and hydraulics, as well as digital controllers, which are embodied in modern quarry equipment [19]. Prospects for the development of the Surface Mining 4.0 technological platform as an important segment of Industry 4.0 have been confirmed by the success of the initial stage of digitalization of mining enterprises in a number of countries in the 2010s. The number of accidents was reduced by 20–25%, the loss of mineral raw materials decreased by up to 15%, and costs were reduced by 10% [20]. Taking into account the forecast about the share of Mining 4.0 in world mining by 2050 at 80–90%, in surface mining clusters, the integration of digital technologies and unmanned equipment will transform these territories, thereby solving many urgent environmental and social problems [21].

Therefore, it is worth highlighting those studies that consider the implementation of the Industry 4.0 concept in mining as a multi-sectoral task, for which its solution goes far beyond the development of digital technologies and cyber-physical systems. This task is connected with the formation of a technological and social-and-economic platform for sustainable development in the context of growing demand for minerals (in the last 40 years, the volume of coal and non-ferrous metals production around the world has doubled [22]). An important role in this is given to surface mining, wherein its volume has increased by 30% in the world over the past three decades [23]. This is quite consistent with the transitional stage for the mining industry as a whole from Mining 3.0 to 4.0 (Table 1 [24]).

Table 1. Relationship between the stages of industrial development, geotechnology, and the evolution of Mining 4.0 [24].

Century	Stages of Industrial Development	Key Innovations	Stages of Development of Geotechnology	Mining Innovations
First half of the 19th century	Industry 1.0	Coal and coke, steam engines	Mining 1.0	Mechanization of auxiliary processes
Second half of the 19th—early 20th centuries	Industry 2.0	Electricity, in-line production, oil and gas production, internal combustion engines	Mining 2.0	Mechanization of the main processes
Second half of the 20h century	Industry 3.0	Automation, analog computing and control systems	Mining 3.0	High capacity equipment, analog telemetry
Beginning of the 21st century	Industry 4.0	Digitalization, Internet of Things, Artificial Intelligence, Machine Vision, Blockchain	Mining 4.0	Unmanned technologies, remote process control, smart robots

Despite almost two hundred years of geotechnology evolution from Mining 1.0 to 4.0, surface mining has only been developing in its modern form since the beginning of the 20th century (starting from Industry 2.0 and Mining 2.0). In fact, only with the full-scale spread of electric machines (1930s) did the construction of quarries with an annual productivity comparable to the modern one begin [25]. At the same time, the specificity of the transition to from Surface Mining 3.0 to 4.0 lies in the faster development of surface mining compared to underground mining, which is largely due to the need to simultaneously automate and robotize both the main and auxiliary processes in quarries.

2. Methodology

Surface Mining 4.0 is based on the requirements for overcoming technology shocks in the industry, which are associated with the development of the following domains (“application points” of end-to-end digital technologies):

- Artificial intelligence and neural networks, which allow for the development of machine vision and learning, as well as decision making without human intervention;
- The access of engineers, designers, government control representatives to Big Data in the form of digital twins using appropriate mobile devices;
- Augmented reality that combines virtual models of mine workings and machines with their physical prototypes;
- Advanced 3D modeling technologies that are based on distributed and cloud computing.

The thematic range of research papers analyzed in this review is connected to both the expansion of break-through end-to-end technologies of Industry 4.0 in surface mining, as well as the problems and obstacles for their implementation. Therefore, this review contains a critical, but constructive, analysis of a significant body of publications in the field of Industry 4.0, Mining 4.0, and Surface Mining 4.0, which is aimed at identifying problems and prospects for future research in the field of the technological modernization of surface mining.

The purpose of this review is a multilateral analysis and generalization of innovative ideas of various authors in the field of surface mining development using Industry 4.0 technologies in accordance with their structure, which will make it possible to outline a new technological platform—Surface Mining 4.0—and highlight the key trends in its development. To achieve this goal, the article consists of six sections: the introduction (a brief description of the current area of research); the methodology (analysis of the range of scientific publications on the topic); a review of the end-to-end technologies of Industry 4.0 in Surface Mining 4.0 (overview of trends and areas of digitalization of various surface mining processes); a review of machine vision and learning for unmanned systems in Surface Mining 4.0 (achievements and prospects for the implementation of machine vision and learning systems, autonomous equipment, and drones); a review of intelligent decision-making systems in Surface Mining 4.0 (analysis of research in the field of new mining business models); a review of green techniques and post-mining in Surface Mining 4.0 (trends in ecosystem restoration, social and business activity in surface mining clusters, development of ESG investment); and the conclusions section (summarizing and generalizations).

The review was compiled on the basis of scientific articles indexed from the scientometric databases Web of Science, Scopus, Google Scholar, Science Direct, Springer Link, etc. using keywords such as Surface Mining 4.0, Mining 4.0, Industry 4.0, Internet of Things, digital twins, neural network, artificial intelligence, Big Data, blockchain, cloud computing, machine vision and learning, smart mining, autonomous machines, drones, 3D visualization, post-mining, and ESG.

According to their content, the considered articles were distributed as follows: technologies of virtual and augmented reality—5; Internet of Things—13; digital twins—5; simulation modeling—4; Big Data and cloud computing—12; smart sensors—20; blockchain—6; neural networks and artificial intelligence—23; machine vision and learning—29; drones and autonomous equipment—9.

3. Review of End-to-End Technologies of Industry 4.0 in Surface Mining 4.0

The main difference between the current trend of surface mining digitalization within Industry 4.0 and the previous round of automation (Industry 3.0) lies in the addition of human intelligence with digital (machine) intelligence, in which engineering and management decision making are transferred to cybernetic systems. Previously, it was a connection of man and machines with the help of intermediary devices—controllers [26]. As a result, in the last decade, there has been a steady increase in labor productivity in quarries around the world [27].

The key end-to-end technology that is changing the digital landscape of surface mining is Computer Integrated Mining (CIM), which represents a new frontier of digital maturity for companies engaged in open pit mining [28]. This technology combines surface mine design, planning and management, equipment control, safety, and product quality. CIM is, in fact, an end-to-end information technology that opens up the transformation of traditional geotechnology into Surface Mining 4.0 by eliminating the “gray” areas in which Industry 4.0 technologies do not find their application.

The digitalization of surface mining is being formed not only as digital automation and robotization tools are developed and implemented, but also as new competencies are being formed among workers, which, in total, yield “digital maturity”—the key criterion for Surface Mining 4.0 [29]. It is characterized by a transition from the fragmented implementation of programmable controllers to artificial intelligence, digital twins, etc., which together lead to the creation of a Smart Surface Mine where processes are controlled with the assistance of artificial intelligence, and minerals are mined in the required volumes and in the required time.

The Surface Mining 4.0 digital ecosystem meets the conditions of scalability and adaptability to various surface mining systems and types of minerals, and consists of interactive information systems for mining processes (drilling and blasting, excavation, transportation, dumping, and primary processing of raw materials) that are recombined using 3D visualization, multi-interface digital twins, and smart self-learning robots [30].

The advanced end-to-end technology of Surface Mining 4.0 includes augmented reality [31], which makes it possible to radically transforming the role of a person in the control of mining machines and mechanisms—from Operator 3.0 to 4.0.

Unlike an employee—Operator 3.0—who receives large flows of information from controllers and sensors installed on complex high-performance equipment, an Operator 4.0 employee integrates physical digital reality (for example, through interactive VR glasses, biomechanical systems, wearable sensors fixing the state of health, etc.) and obtains the opportunity for rapid self-learning, interaction with other operators, and collaboration with robots [32,33].

At the same time, the transformation of digital technologies into end-to-end systems for surface mining is hindered by the fragmentation of software from different manufacturers designed for individual technological processes, as well as the complexity of system integration resulting from their domain structure. Deep digitalization of mining processes involves software products from different vendors, such as IBM (Maximo is a product for managing business assets of enterprises), ABB (a family of software products for industry, including mining), Microsoft (Azure—programs for cloud computing, Dynamics 365—management of client databases and relationships, Power BI—integrated business analysis, etc.), and OSIsoft (data integration systems), etc. [34]. These and similar tools for data processing and analysis are based on the technology stack and data formats. Therefore, they have a rigid corporate binding in terms of the effectiveness of inter-software interaction. The data exchange between programs from different manufacturers is very limited in terms of functionality (for example, exchange through MS Excel spreadsheets, which violates the principle of a single digital eco-system Surface Mining 4.0) (Figure 1 [34]).

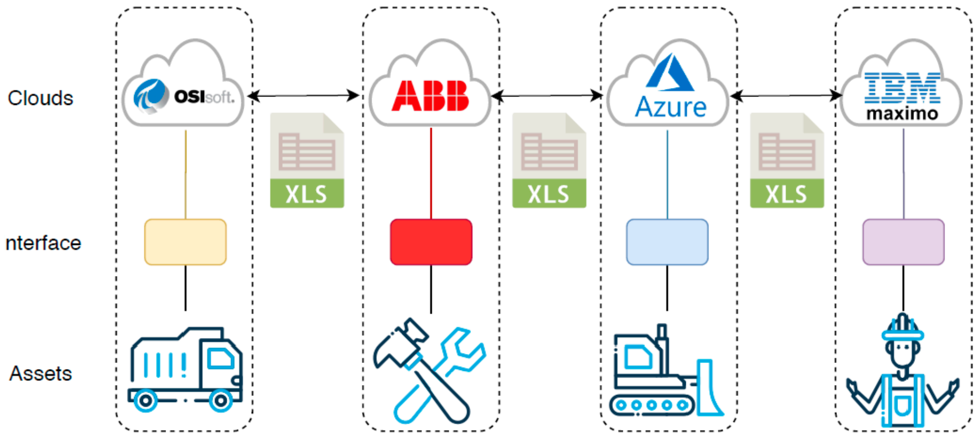

Figure 1. An example of a simple data exchange format between products of software manufacturers for Surface Mining 4.0 [34].

The issue of the integration of disparate information systems for the deep digitalization of surface mining is also related to the need for artificial intelligence systems to control the main processes (preparation and excavation of rocks, transportation and dumping), which control dynamic multi-loop and multi-component objects in real time. The greatest success regarding the integration of artificial intelligence components has been demonstrated by the use of controllers based on methods of fuzzy logic using the Flight Control Language

(FCL) [35]. With its help, each variable is assigned not only a quantitative, but also a qualitative value, which can significantly improve the process of making engineering decisions using artificial intelligence.

Another end-to-end digital technology that constitutes Surface Mining 4.0 is the Internet of Things (IoT), which excludes people from managing auxiliary processes in the operation of mining machines and equipment, which, thereby, reduces the impact of harmful and dangerous conditions on workers. Smart sensors for temperature, humidity, light, speed, and infrared radiation represent the frontier of the Internet of Things in Surface Mining 4.0 [36]. The core of the Internet of Things technologies, as applied to surface mining, is connected with the management of the power supply of equipment with high productivity using the principles of plug-and-play, full feedback from energy consumers, involvement of renewable energy sources in the power supply processes of quarries, and machine-to-machine interactions [27,37]. The real-time monitoring of the technical condition and performance of mining equipment with the introduction of Internet of Things technologies can obtain the maximum efficiency [38].

In general, the Internet of Things in Surface Mining 4.0 makes it possible to not only integrate production, but also integrate economic and stuff management processes, as well as manage the control and supervision of mining operations. Built on the IoT platform, a digital surface mine integrates dynamic planning and scheduling, automated supply chains, equipment predictive maintenance, assets visualization, the use of unmanned equipment, etc. [39] (Figure 2).

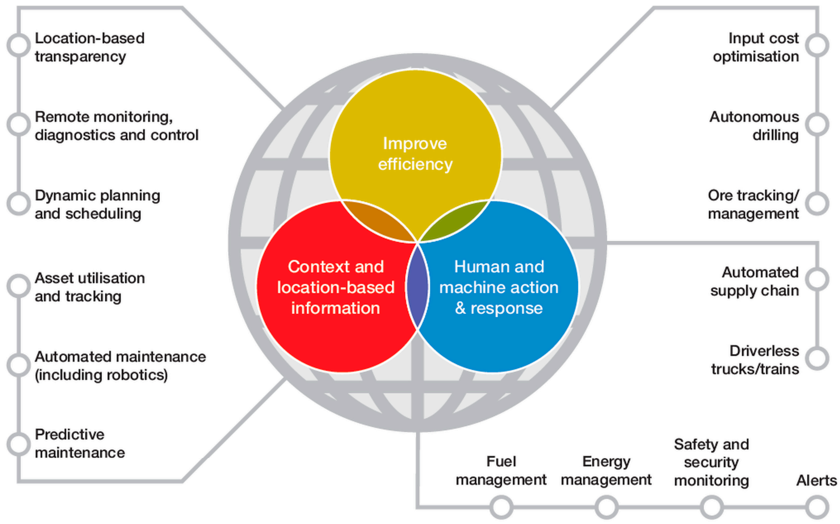

Figure 2. Connecting surface mining processes using the Internet of Things [39].

The integration of various equipment complexes based on the Internet of Things requires the processing of incomparably larger amounts of information than that generated by individual devices, which is intended to be facilitated by the use of the Distributed Frequent Itemset Mining Algorithm [40]. It makes it possible to fill in the missing data in the flow of digital information coming from smart sensors without failures in the operation of its analysis systems based on the reliable extraction of key data from the general array (Data Mining [41]). An example of the use of such technologies in Surface Mining 4.0 is Apache Spark, which successfully uses the SWEclat algorithm to accelerate and parallel data scaling and the balanced loading of information analysis systems [42].

Digital twins as an end-to-end technology for Surface Mining 4.0 are subordinate to the Internet of Things and Computer Integrated Mining. At the same time, digital clones with asynchronous requirements for the software interface make it possible to connect various users (machine operators, mining engineers, state mining inspectors) with artificial intelligence systems that process information from smart sensors and mining equipment of various types [43]. Digital twins—complex cyber-physical systems—can significantly increase the annual productivity of mining machines and labor safety by overcoming the "bottlenecks" of unequal transmission and the data processing rates of various information systems and equipment controllers [44]. Digital twins, by processing and visualizing large amounts of data about real physical processes asynchronously and on different devices, transform linear production chains into digital networks that allow "plugged" users to take part in management and control (Figure 3).

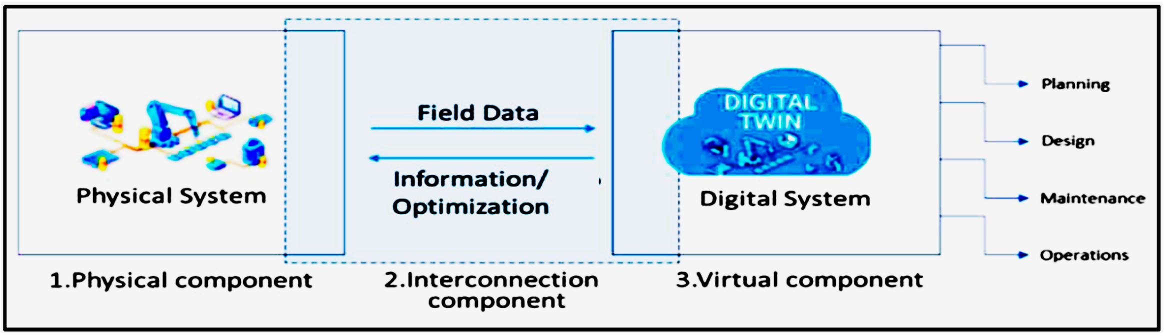

Figure 3. The components of a digital twin in surface mining [45].

Large amounts of information about the entire complex of technological processes that form surface mining require the simplification of its flows for adequate display without "overloading the picture" and replacement of the understanding of real phenomena with its digital models [46]. This actualizes the use of virtual reality to reduce the number of physical processes taken to make managerial decisions [47].

Simulation modeling of surface mining processes with the display of results using digital twins allows for moving from autonomous assistance in making engineering decisions using artificial intelligence systems to network systems with more verified information. An example of simulation modeling based on Big Data obtained using the Internet of Things is the creation of a knowledge graph for the maintenance of mining equipment using the BERT-BiLSTM-CRF neural network [48], which recognizes and classifies problems more quickly compared to modeling based on data from autonomous sensors.

In general, neural networks occupy a special place in the platform of end-to-end digital technologies for Surface Mining 4.0. They allow for managing the transfer of information about the state of mining processes in real time on a multi-channel and multi-user basis, thus organizing the creation of high-precision digital clones of processes and their continuous additional training [49], which is especially important for assessing the possibilities to reduce energy and resource consumption in quarries.

Big Data and cloud computing form the basis for the key Surface Mining 4.0 technology of advanced geographic information systems (GISs), which are changing the digital landscape of mining and creating "application points" for machine vision and learning [50]. Along with this, fast Big Data analytics make it possible to fully taking into account changes in global markets while considering the gradual transition to alternative energy sources in strategic and operational planning [51]. It is important to note that the recalculation of the load of equipment, the operation of individual units, and the entire fleet of mining machines are not available when relying on autonomous computing centers of mining companies. On the contrary, Cloud Computing Services (CCS) make it possible to increase the performance of quarry equipment by 25–30% [52].

Big Data analytics also have a significant effect on the development of intelligent geological exploration, which begins to rely on conceptual models of big spatial data that allow for moving on to ultra accurate geological and mine surveying documentation to improve the quality of a mineral and reduce its losses during extraction. This is of particular importance in the development of complex structural mineral deposits [53]. The physical sources of information that form Big Data are represented by smart sensors—these define modern means of monitoring the operation of quarry machines and equipment, natural and man-made rock arrays, and the state of health and working productivity of employees. In particular, smart sensors for the in-depth analysis of mine and quarry conveyors (belts, flights, and drives—Belt 4.0) allow for avoiding unscheduled stops and optimizing the load, thereby increasing it by 11–12% [54].

In surface mining, smart sensors make it possible to form an almost complete picture of the sustainability of bench slopes, dump tiers, quarry roads, and the impact of equipment on rock arrays. This is achieved by connecting LiDAR and GPS systems, which jointly generate saturated 3D point clouds, based on which virtual digital models of benches, quarry sides, and dumps are formed; they make it possible to predict screes, landslides, and collapses in an ultra-quick manner, as well as to take additional measures, thereby increasing the stability of rock arrays at the design stage [55].

In coal clusters with a high concentration of surface mining, frequent displacements of blocks of the Earth's surface are observed, which are initiated by massive explosions. The use of smart sensors such as D-InSAR (Differential Interferometric Synthetic Aperture Radar) makes it possible to create saturated point clouds that form realistic digital models that are used to predict surface disturbances near quarry fields and man-made earthquakes, thereby taking into account the lead angles and distribution of residual deformation along various axes [56]. Moreover, InSAR (Interferometric Synthetic Aperture Radar) technology, which was originally used to predict the reverse effect of the displacement of rock blocks on the quarry, makes it possible to determine the risks of benches, pit walls, and internal dump stability loss during natural earthquakes [57]. DSAR (Differential Radar Interferometry) smart sensors make it possible to combine satellite photographs and geoscanning data with an accuracy of 0.04 m [58].

The real-time scalability of digital quarry models, which is a hallmark of Surface Mining 4.0, is based, firstly, on the use of a large number of smart sensors of various kinds, as well as on the creation of visual attention models using the GrabCut method for processing large volumes of remote sensing data [59]. In fact, the use of online scalable models makes it possible to switch to fully automated excavator and dump truck systems that operate without a person due to the ultra precise positioning of not only equipment, but also the mining front. Great prospects in this segment of the Surface Mining 4.0 technological platform include the connection of mining geo-scanners for the local positioning of fragments of rock arrays that are subject to excavation (collapse of blasted rocks, quaternary deposits) with GNSS (Global Navigation Satellite System) receivers, and a PPS (Pulse Per Second) time synchronizer. The resulting modeling accuracy was sufficient to exclude a person from the process of managing mining equipment [60]. Improving the accuracy of geo-scanning in surface mining was made possible by modeling the spatial distribution of the bands of the interferogram created by a Single Look Complex SAR using the EMDD-PSI (External Model-based Deformation Decomposition of Persistent Scatterer Interferometry) method. As a result, the accuracy of digital modeling increased by 35% [61].

The next step in the smart sensors development in surface mining is the combination of flying drones and ground geo-scanners into multisensor aircrafts, which make it possible to integrate photo images with magnetometer data. As a result, it became possible to geologically map land plots for the construction of first-stage quarries in places covered with dense forests or in the glacial part of the Arctic [62].

The evolution of surface mining geo-scanners has been associated with an increase in the accuracy of scanning for the deformation of bench slopes to the submillimeter range of the displacement of rock particles by improving the data processing algorithms from Doppler range scanning. A certain stage in geo-scanners as smart sensors evolution in Surface Mining 4.0 can be considered as the development of a new type of Frequency Modulated Continuous Wave Ground-Based Synthetic Aperture Radar (FMCW-GBSAR) by the North China University of Technology (Beijing), which is shown in Figure 4 [63].

Figure 4. New FMCW-GBSA Radar developed by North China University of Technology in the quarry [63].

The development of 3D modeling of objects in a quarry field in the context of unmanned processes (the most advanced segment of Surface Mining 4.0) has one significant limitation. It is the heterogeneity of rock arrays, which requires a constant adjustment of the parameters of the mining method. For its accuracy, it is important to take into account changes in the properties of the host rocks as the mining front moves. Increasing the accuracy of considering the physical and technical parameters of rocks (strength, fracturing, density, abrasiveness, etc.) has been possible with nano-indexing using methods such as the Differential Effective Medium, Mori–Tanaka, Self-Consistent Scheme methods, and 3D printing of rock samples [64]. In addition, the modeling of rock properties using the Digital Speckle Correlation Method in the study of uniaxial compressive strength, performed for different ratios of elevations, made it possible to predict the deformations of complex coal-and-rock benches, landslides, and collapses in coal-saturated zones with high accuracy [65]. Moreover, the use of 3D laser scanning and CAD/MBS modeling technologies in designing objects for placing unmanned equipment will eliminate the collision of robotic dump trucks and other equipment [66].

Improving the display of real objects in virtual interactive 3D models has been possible with the use of Lidar SLAM laser scanning methods, processing of the received SegMatch and Simultaneous Location and Mapping point clouds, and LeGO-LOAM feedback reproduction. As a result, the accuracy of modeling increased by 5%, and the detail of the display of volumetric rotated objects in static drawings was 1 cm [67]. Dynamic 3D models of mining equipment can take into account vibration (a factor harmful to human health) by modeling the transmission of vibrations between individual units and machine nodes at the design stage [68].

In surface mining areas that develop ore deposits, traditional methods of modeling complex concurrent ore bodies are based on the interpolation of data from exploration wells, which is not distinguished by the high accuracy required for 3D modeling in Surface Mining 4.0. It is possible to increase the accuracy of 3D models of ore bodies by building a model of the body with spatial interpolation using the Hermite Radial Basis Function technology. It is also expedient to combine heterogeneous changes in the underlying ore bodies—this includes data from magnetometric surveys, geological observations, and multispectral images [69].

The implementation of 3D models in the management of quarry cargo flows using unmanned equipment requires a radical increase in the coordination of its work. The analysis of geo-location sensor data for mining machines and equipment using Fresnel three-dimensional indices, provided that the mining field is covered with wireless communication, makes it possible to take a new step in robotization—that is, control from a single source (Figure 5) [70].

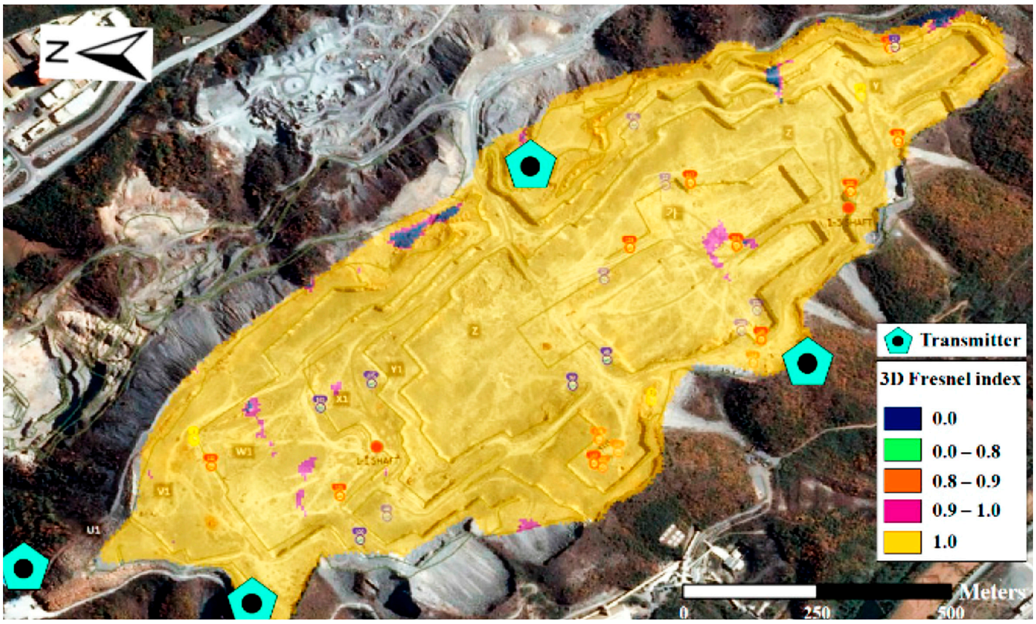

Figure 5. 3D Fresnel index overlay map for the four transmitters in the surface mine [70].

An important information technology for the Surface Mining 4.0 platform is the blockchain, which makes it possible to create conditions for reliable and confidential data exchange. This is especially in demand in the organization and conduct of mining and environmental inspections, as well as in the analysis and investigation of man-made accidents and natural disasters. Blockchain integration with digital twins of open-pit mining processes and individual equipment displayed on devices of various types (laptops, desktops, tablets, smartphones) with different software interfaces (MS Windows, Android, IOS, etc.) makes it possible to create an inter-sectoral "cross-chain" digital ecosystem [71]. With its help, information about various processes can be transferred to other participants in the extraction and processing of minerals, which not only include equipment manufacturers, mechanics, electricians, environmentalists, etc., but also company owners. The high level of blockchain and Internet of Things integration makes it possible to connect the capabilities of digital peripherals, cloud computing, mobile devices, and applications (Figure 6) [72].

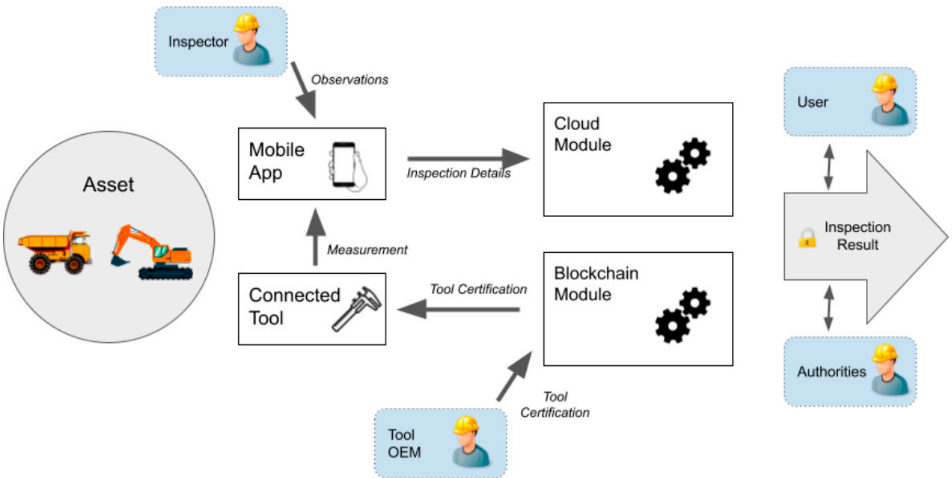

Figure 6. High-level architecture of a blockchain for a mining inspection system [72].

Blockchain technologies are also in demand for the analysis of labor safety threats using distributed computing. For example, it is expedient to analyze and predict the accumulation of hazards in the atmosphere of deep quarry fields using the SPARS forecasting infrastructure due to the accelerated processing of a large number of data streams. In particular, the Spark Streaming framework, Autoregressive Integrated Moving Average (ARIMA) model, and Support Vector Machine (SVM) [73] have proven themselves positively. At the same time, all the movement of information in distributed nodes of the blockchain network guarantees the safety of information and cybersecurity of surface mining [74].

The basis of artificial intelligence technologies, which, along with the Internet of Things, build the future frontier for Surface Mining 4.0, is represented by neural networks [75,76]. Their developing cognitive abilities extend far beyond managing individual mining processes without human intervention. With the help of neural networks, it is possible to transfer the management of entire quarries to artificial intelligence in the face of increasing uncertainty and fluctuations in the raw material market, thereby solving mixed-integer linear programming problems in two stages. The first stage is an iterative selection of combinations of mineral production volumes and prices in the markets of different countries (including the terms of supply and insurance); the second stage is the use of a parametric graph closure algorithm to obtain the final solution [77].

Modern computational methods underlying neural networks include discrete event simulation, which has made it possible, based on the sensors' swarm, to coordinate processes in the development of depleted gold deposits with a relatively low metal content and profitability compared to rich gold deposits [78]. Furthermore, deep learning based on lightweight convolutional neural networks allowed for the timely detection of the damage of machines and equipment by analyzing a large number of images (up to 100) every second with a test accuracy of 93.22% when integrating MobileNet and Yolov4 networks [79]. The use of a convolutional neural network (1D CNN) to analyze the causes of breakdowns in drilling equipment made it possible to use artificial intelligence to eliminate the human factor and search for technical and mining sources of breakdowns with an accuracy of 88.7% [80]. To eliminate the human factor and the subjectivity and bias in the planning of mining operations, as well as limit the soil, water, and air pollution by quarries and find the most effective solutions for reclamation, Kohonen's neural network has proven itself well. Based on the results of its application, promising directions for the adjustment of "The European Green Deal" (modern climate strategy) were identified [81].

3.1. Mining Machines Intelligent Monitoring

The intelligent monitoring of machines plays an important role in the development of the Surface Mining 4.0 platform, which constitutes an applied aspect of the application of smart sensors, neural networks, and artificial intelligence. The interest of researchers in intelligent monitoring is primarily related to the optimization of machine energy consumption (for example, using ARM7 to control from a remote location) [82]. Remote intelligent monitoring for mining safety providing is of unsurpassed importance, as was proven in China, which suffers the worst coal mine disasters in the world. To improve the safety of miners, research into the promotion of intelligent coal mining to coal mine safety was conducted, and a model of visual remote intervention was introduced (Figure 7) [83].

The intelligent monitoring of rotary machines is important for ensuring smooth operation and increasing labor productivity in connection with the original two-step method that was proposed. It consists, firstly, of checking two signals, the monitored one and the referential one (they must have the same distribution), and, secondly, of measuring the dynamics reflecting changes in the nature of the incompatibilities of the given signal and the referential ones [84]. Advanced three stages method includes multi-reference preliminary analysis, auto reference preliminary analysis, and probabilistic analysis of the signals [85]. In addition, industrial MEMS-based accelerometers have proven their perceptiveness for the intelligent monitoring of mining equipment [86].

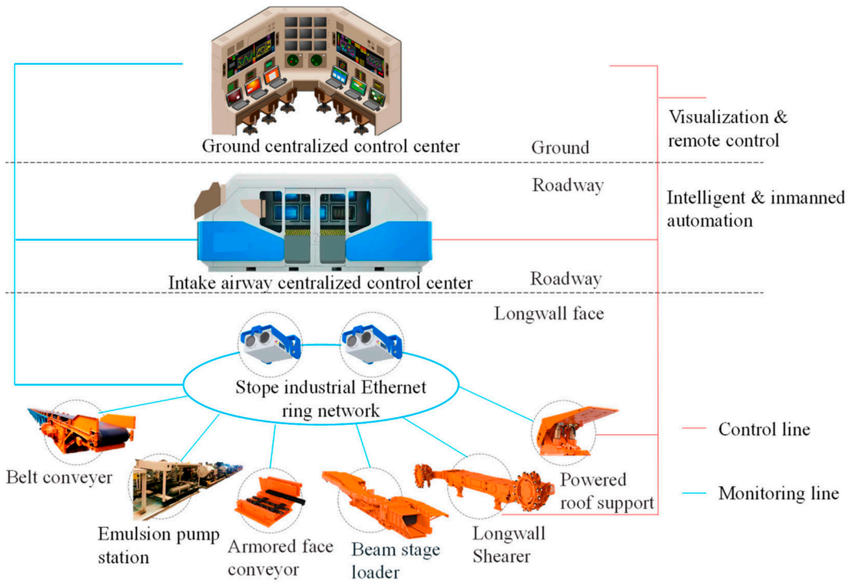

Figure 7. Technical framework of visual remote intervention mining.

To achieve real-time intelligent analysis for coal mine surveillance videos, the Channel-Attention-Based Pruning YOLO and Adaptive Image Enhancement Parameter Selection Module were proposed [87]. Another advanced intelligent monitoring system comprises a video acquiring unit, a working face dip angle detection unit, and a coal seam geological detecting instrument [88]. Such systems can be successfully used for large quarry shovels and dump trucks complexes for safe and productive dispatching [89]. For a similar purpose, the "Diagnoprzem" and "HELMOS" computer-knowledge-based expert systems have been used for fault diagnostics and the detailed monitoring of mine haulage and hoisting equipment [90].

Recently, the operational monitoring of tunnel boring machines is becoming increasingly perfect [91], so it is becoming possible to even use it in space missions [92].

3.2. Neural Networks in Mining Safety

Despite the fact that labor safety in surface mining is a priori higher than in underground mining, neural networks, as a way to ensure accident-free operation of enterprises, are reflected in Surface Mining 4.0. Neural networks such as Long Short-Term Memory, the Recurrent Neural Network, and the Gated Recurrent Unit make it possible to simultaneously process a large amount of retrospective and current data, compare them, and find the most effective solution based on both experience and forecasts (deep learning) [93].

An important aspect of surface mining safety is the accurate and long-term prediction of seismic events, both natural and those caused by the mining operations themselves. At the moment, such neural networks as the Wavelet Scattering Decomposition and Support Vector Machine make it possible to form artificial intelligence recognition models for the intelligent recognition of seismic phenomena with the highest possible accuracy that is sufficient to completely avoid the impact on coal seams. The BP Neural Network Model makes it possible to avoid rock bumps in areas with a high concentration of disjunctive disturbances [94]. This means reducing the uncertainty that accompanies the development of geo-technics and geo-technology due to a detailed understanding of the physical and mechanical properties of rocks in all zones of a quarry field, wherein the training by a neural network will make it possible to connect current and forecast data for production planning [95].

Neural networks as the basis of artificial intelligence play a special role in drilling and blasting work, which are physical processes in which formation, distribution, and the use of explosion energy have not yet been completely studied. In this regard, the task of increasing the share of energy directed to crushing and moving exploded rock masses is entrusted to neural networks. Today, energy losses during mass explosions in quarries are close to 70%. With the help of a neural network, it is possible to optimize the parameters of drilling and blasting operations, increase the share of energy directed to the rock mass, improve the quality of crushing, reduce the cost of rock loading and transportation, and improve labor safety [96] (Figure 8).

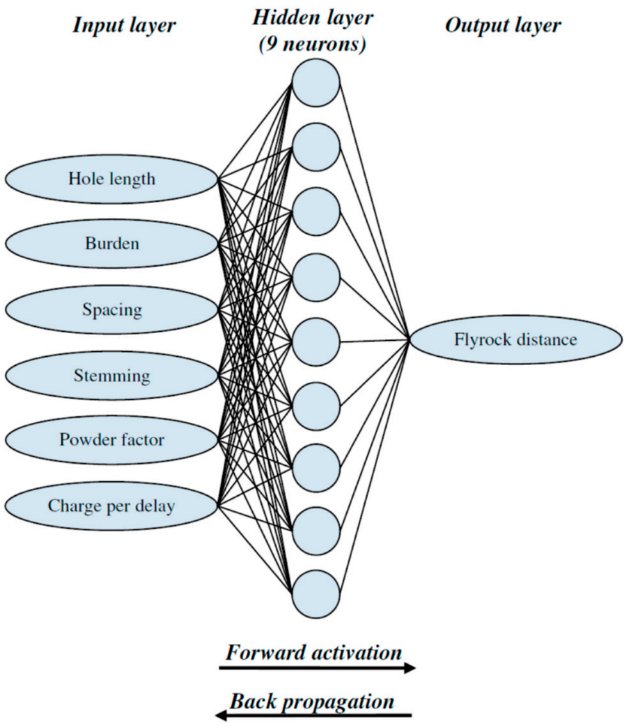

Figure 8. General view of neural network for optimization of drilling and blasting operations in surface mining [96].

It is important to note that the use of neural networks in the analysis of drilling and blasting operations is necessary for the implementation of machine learning algorithms in excavation and loading operations to provide excavators with high-quality crushing and a given granulometric composition of the blasted rock mass necessary to achieve maximum productivity. In particular, the use of network technologies such as support vector regression and Bayesian optimization in the Keras Python library in machine learning has significantly increased the performance of both the explosion and excavators when extracting rock mass [97]. More details on machine vision and learning in Surface Mining 4.0 are given in Section 4.

4. Machine Vision and Learning, Unmanned Systems in Surface Mining 4.0

The great role of vision and learning of machines, connected by the Internet of Things, in Surface Mining 4.0 makes it possible to move to a deep integration of drilling and blasting, excavation and loading, and transportation processes among themselves, as well as planning and management systems. It gives a chance to optimize the sequence of preparatory, overburdened, and mineral extraction operations in the dangerous and harmful zones performed in unmanned mode [98,99].

Machine vision technologies give mining machines a complete picture of the state of the environment, which opens up unprecedented opportunities for robotic mining in the course of connecting human and machine decision making as an optimization tool. Surface mining is an almost ideal testing ground for the introduction of autonomous and collaborative robots that are safe for people and replace them in unmanned equipment systems. At the same time, the full disclosure of the potential of machine vision and learning is expected in the second half of the 21st century when they, in cooperation with artificial intelligence and smart sensors, will completely displace humans from mining (this is now being discussed as Mining 5.0 [100]; we call it Surface Mining 5.0).

4.1. Machine Scene Analysis and Scene Understanding

Scene analysis by machines is one of the actively used areas of machine vision [101], which has significant prospects in mining as a part of the cyber-physical systems of Surface Mining 4.0 [102]. This is due to the fact that, in relation to quarrying (surface workings, faces and stopses, equipment of high specific capacity), we are talking about macro objects. Therefore, we can say with confidence that scene analysis and scene understanding are at the core of machine vision applications in surface mining. The latter is a more difficult task than the studied object recognition, since the scene is a more complex and less formalized concept; it is more difficult to identify qualitative features, even when using modern neural networks.

Perspective scenarios of scene analysis include flying robot tasks (to find the object in a real environment), bitmap pictures representing the scene provided in the form of previously prepared data, obtaining vector data representing object shapes, taking several pictures of the area using robots and vectoring them (Figure 9), calculating neighborhood graphs is for each of them, and using syntactic algorithms for searching for marked objects [103].

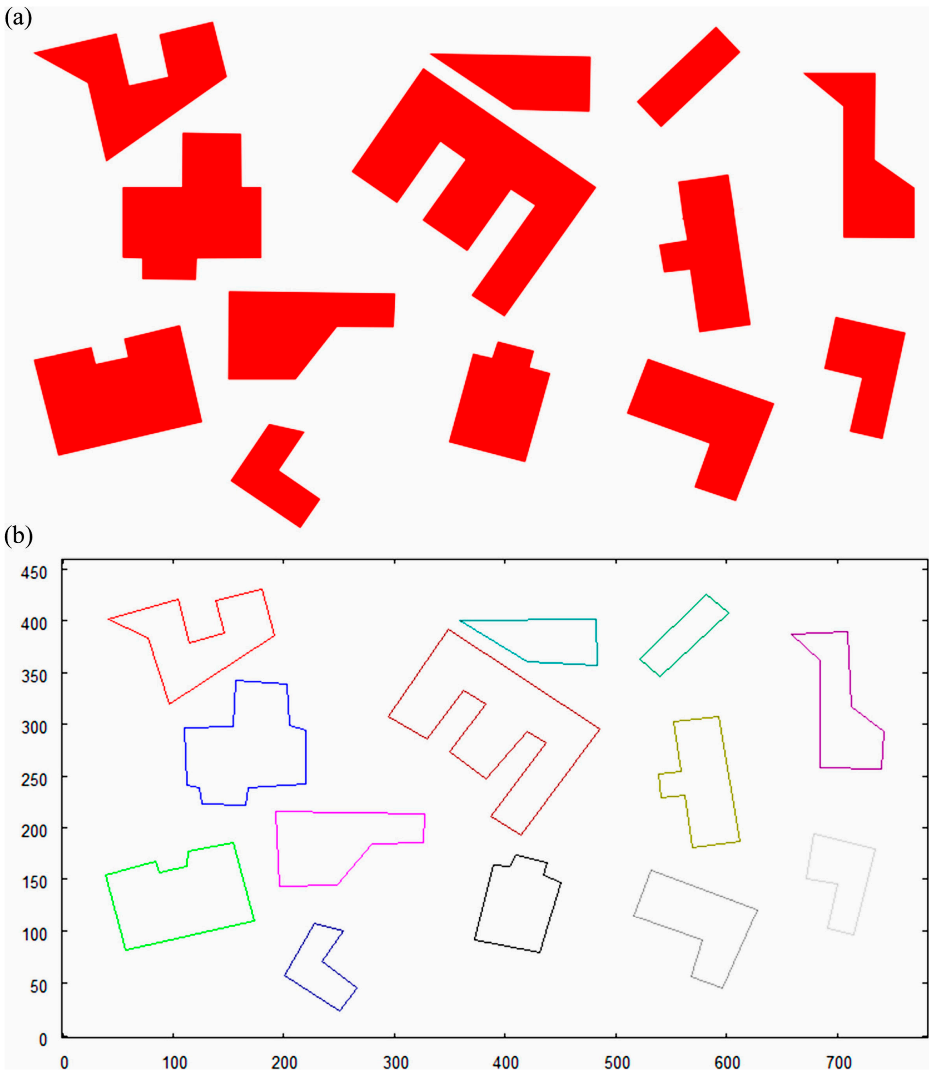

Figure 9. (**a**) Input for vectorization; (**b**) vectorization result. Coordinates calculated with respect to the bottom left corner of the picture.

Research on feature extraction for pattern recognition and multiple machine learning models for image categorization using the intel image classification dataset can be considered as a perspective area of scene understanding [104]. Convolutional neural networks are recognized as a perspective base for scene analysis and understanding [105].

For complicated scene images (objects in the mines refer to such ones), metric learning can be very useful to improve the performance of a distance-dependent classifier [106]. Some authors have investigated the obstacles for vision-based obstacle detection for a mobile robot, which primarily includes the detection of obstacles in front of the robot within a corridor, and they have proposed algorithms for obstacle detection using image processing techniques [107].

The use of scene analysis and scene understanding in mining is described in a relatively small number of scientific papers. So, in relation to the autonomous mobile drilling robot, scene analysis is considered as supplementing information about the environment by adding three-dimensional object representations [108]. The original application of scene analysis in the mining industry has involved the analysis of situations of unsafe behavior of workers [109]. Scene analysis for geological data entry recognition models has been applied to extract entities from the massive quantity of data in order to discover connections between them [110].

Already today, machine learning is the key to the steady operation of mining equipment, which is especially important for surface mining robots, where equipment with high specific productivity is used. With the development of deep machine learning, equipment diagnostics are moving under the control of unmanned self-learning systems that receive information from smart sensors and use neural networks for analysis and decision making [111]. This forms a system of machine vision; however, machine knowledge technologies are already being formed today, which have been accumulated and improved without human participation, thus increasing the adequacy of decisions made by machines [112]. An example is the positive experience of partially replacing the functions of an operator of a mining wheel loader with a machine vision and learning system that integrated GPS signals, as well as the analytical networks CART, DBSCAN, and C5.0, which helped to cluster and classify data to control the movement of the machine in a quarry [113]. Machine learning based on FLAC3D finite difference software has allowed for the convergence (merging) of various data—geological, technical, and operational—in order to accurately predict the impact of changes in the parameters of the occurrence of mineral bodies on productivity during the operation of mining equipment [114].

The use of machine vision and learning systems is especially valuable for preventing the risks of spontaneous coal combustion, which are relevant not only for underground mines, but also for surface mines, thermal power plants, and warehouses where significant coal piles are sometimes formed. Despite the lack of research in this field, we noted the positive experience of using the Random Forest Artificial Intellect model for coal ignition and coal dust explosions using the Shapley Additive exPlanations method [115].

4.2. Drones and Robot Inspectors

The material embodiment of digital machine vision and learning technologies takes the form of unmanned robotic equipment and drones. One of the contexts in which robotic surface mining machines have been considered was to increase the accuracy of their operations (drilling, excavation, transport, primary mineral processing) to reduce environmental damage and energy consumption, as well as increase productivity [116]. It is expected in the near future that autonomous unmanned quarry transport equipment will be provided with machine vision and robotic control systems based on high-precision traffic sign recognition devices (using LiDAR sensors with a recognition accuracy of 97.9% [117]). That innovation will allow cyclic quarry transport (dump trucks, trains, loaders) to move independently in the network of quarry roads, as well as approach the excavators in the faces, dumps, and coal warehouses for unloading.

Autonomous robotic inspectors of mining equipment are another promising direction in the development of machine vision and learning in the Surface Mining 4.0 system. Currently, there are no problems in scaling small-scale unmanned devices for the multifunctional control of equipment (not only flying drones [118], but also conveyors, mechanized mine support, and combine harvesters) for diagnosing quarry equipment (excavators, drilling rigs, dump trucks, etc.) [119]. An example of a small-scale inspection robot for mining equipment that perceives, processes, and analyzes information in the RVIZ visualization environment obtained from optical RGB and infrared cameras, sound, vibration, and gas sensors is an unmanned device for complete control over the state of the conveyor [120]. The machine vision of this inspector robot allows for the mapping of interactive 3D point clouds (Figure 10 [121]).

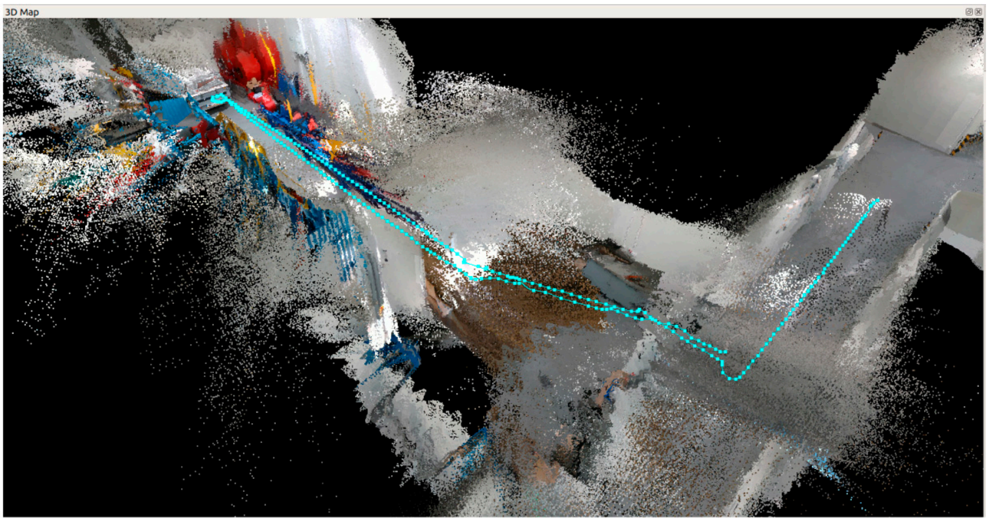

Figure 10. 3D map made during the autonomous driving with the robot's path [121].

The Surface Mining 4.0 platform includes the widespread use of flying drones in quarries for the following procedures: geological exploration; surface mine surveying and mapping; benches; dumps; mineral storage; tailings stability monitoring; drilling and blasting operations control; etc. Structurally, the drones used in surface mining are also diverse—they include winged and copters, open (Figure 11) and encased (Figure 12), and those made by different manufacturers [122].

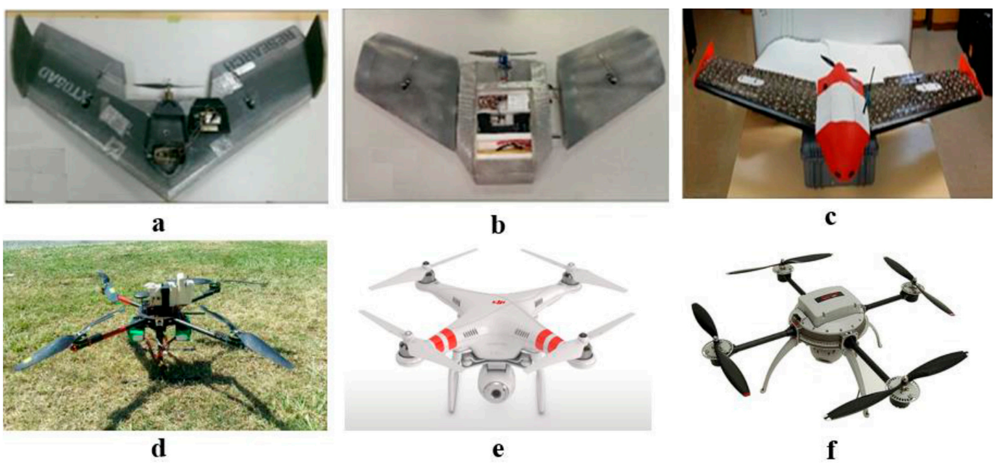

Figure 11. Views of some open drones used in surface mining: (**a**) Teklite, (**b**) GoSurv, (**c**) Swamp Fox, (**d**) Quadcopter, (**e**) Phantom 2 Vision+, (**f**) Aeryon Scout [122].

Figure 12. View of encased drones: (**a**) Fleye Racer, (**b**) Fleye Helmet, (**c**) Fleye Ducted, (**d**) Flybotix dron, and (**e**) Elios 2 [122].

An important point of application of robotic inspectors in quarries is the use of flying drones to control drilling and blasting operations in ore and coal mines. The personnel of the drilling and blasting sites that control the main parameters of explosions (the average diameter of natural blocks, the proportion of oversized pieces of the exploded rock mass, etc.) are exposed to harmful and dangerous factors. In contrast, robotic inspector drones allow for pre-explosive, explosive, and post-explosive monitoring.

Drones such as hexacopters with a backup control system of the DJI Matrice family (300 Pro and 600 Pro, made by SZ DJI Technology Co., Ltd. in Shenzhen, Guangdong Province, China) are widely used to monitor blasting operations in quarries around the world. The optical equipment is represented by DJI Zenmuse X5 and X5S cameras with a DJI 15 mm f/1.7 ASPH lens (16.0 megapixels) and an Olympus M.Zuiko 45 mm f/1.8 lens (20.8 megapixels) [90]. For the purpose of preliminary control of the drilling and blasting works, cheaper quadrocopters such as the DJI Matrice 300 Pro and Luftera LQ-4 are used (Figures 13 and 14 [123]).

Figure 13. Preliminary control of drilling operations using the Matrice 300 Pro quadcopter (photo by authors).

Figure 14. Post-blasting control of the collapse of the exploded rock mass using the Luftera LQ-4 quadrocopter [123].

Along with enabling the visual control of drilled blocks and collapses of the exploded rock mass with the help of flying drones, their participation in the development of the Surface Mining 4.0 platform is associated with the aerial geological mapping of hard-to-reach land areas over deposits, with dense vegetation, mountains, or wetlands. With regard to iron ore deposits, excellent results have been obtained by surveying the magnetic field, which is illustrated by the example of the use of a Matrice 600 Pro Hexacopter drone (SZ DJI Technology Co., Ltd.) at the Don Jacobo iron ore deposit (Betic Cordillera, Spain). The drone passed 24 parallel profiles at a speed of 5 m/s across the strike of the deposit, which made it possible to obtain magnetic data, analyze them, and contour two remanent ore bodies (A and B) (Figure 15) [124].

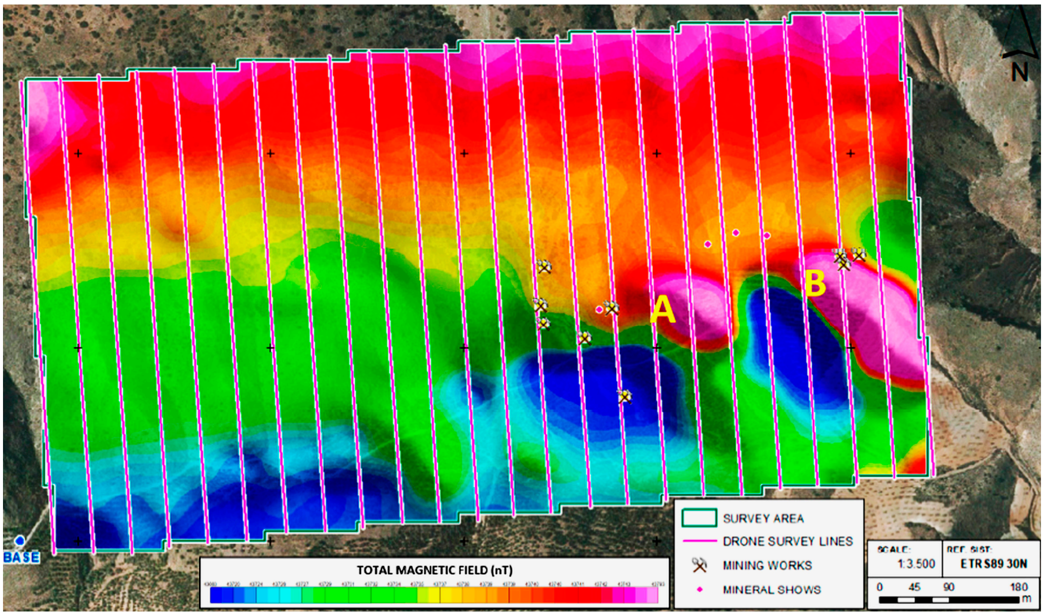

Figure 15. Total magnetic field marked on the map. The location of mineralization in aerial RGB image of geological cartography [124].

In the development of autonomous mining machines and equipment, a certain transitional stage can be the distancing of a person from direct control and turning him into a remote operator in difficult situations when the risk of errors of autonomous controllers of mining equipment increases. Thus, Orlaco EMOS cameras (Orlaco Products. B.V., Barneveld, the Netherlands), Delphi ESR radars (Delphi Technologies, Pittsburg, the USA), and GPS positioning sensors were used for the unmanned control of a BelAZ-7513R (PSC BelAZ, Belarus) mining dump truck. In risky conditions, a remote driver can simultaneously control several vehicles at once manually. For manual control, 11 video cameras were installed on the dump truck (Figure 16) [125].

An example of the most successful implementation of unmanned quarry equipment is the Australian company "Rio Tinto Group", which operates a large fleet of fully robotic dump trucks (80 from 400 in total) at its surface mines. The reduction in operating costs due to carpool robotization reached $80 million, with an additional $500 million in revenue expected from 2022 [126].

In general, when analyzing the prospects for the development of unmanned and robotized quarries, it is necessary to note the gradual nature of excluding a person from surface mining processes by replacing him with artificial intelligence. In particular, the zoning of a quarry field according to the access of a person to direct control of the equipment and technological processes includes the following zones [127]:

- Zone I—conditionally unmanned zone (with zero entrance, ZEPA).
- Zone II—places of a person's presence in the quarry field as needed to maintain machines and mechanisms.

- Zone III—places of a permanent person's presence.

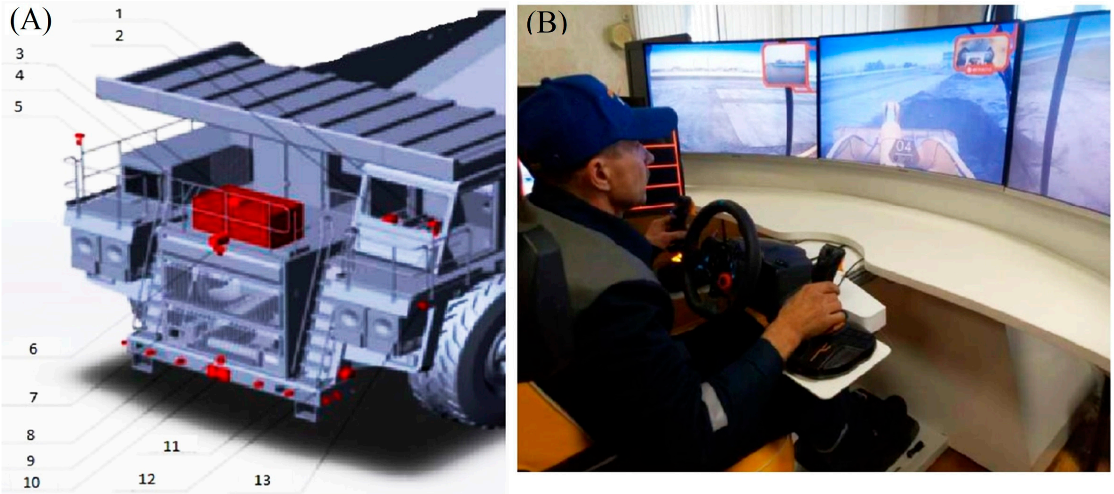

Figure 16. (**A**) The main elements of an autonomous control system of the dump truck movement (BELAZ7513R): (1) GPS receiver; (2) information panel; (3) power box monitoring unit; (4) power box; (5) GPS receiver; (6) camera; (7) motion sensor; (8) parctronic; (9) radar; (10) LiDAR; (11) parctronic; (12) camera; (13) round-view camera. (**B**) Remote driver workplace [125].

In all these zones, the presence of people is combined with robotic equipment, which raises the question of adjusting security requirements as Zone III expands, while Zones I and II shrink (Figure 17).

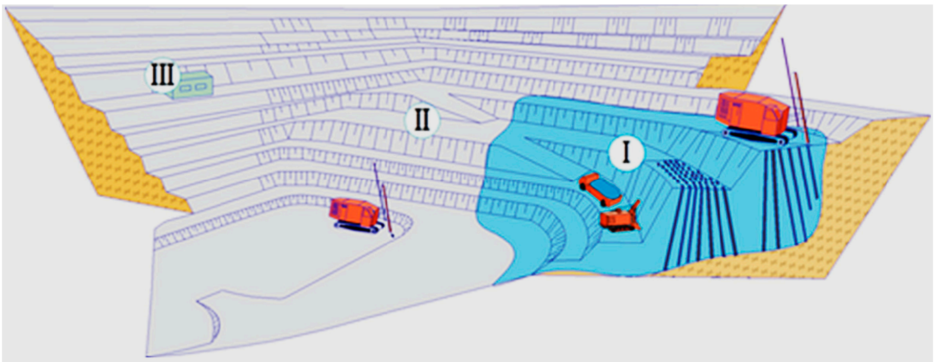

Figure 17. Zoning of a mining engineering system with the use of industrial excavating and transport robots [127].

5. Decision-Making Systems in Surface Mining 4.0

The development of the Surface Mining 4.0 technology platform affects not only the physical processes of mining, but also penetrates into the quarry management system.

First of all, Smart Quarries are the main elements of surface mining of the future, as all participants in the global mineral market are moving into a digital economic environment [128].

A Smart Quarry is based on the selection and prioritization of financial and market strategies, on multi-criteria decision-making systems (for example, the joining of the Z-number theory and fuzzy weighted VIKOR technique with a fuzzy cognitive map [129]). Furthermore, a Smart Quarry is characterized by advanced business models for optimizing production processes (lean production, waste recycling, blockchain finance, etc.), which are typical for the Industry 4.0 [130]. It is also specified by a flexible management methodology that unites social innovation and ESG investment [131] in the process of integrating mining companies, the state, civil society, and universities in a spiral innovative development (a penta helix) [132].

An important digital technology of Surface Mining 4.0—Cloud Mining—is a combination of production, financial, market, and management processes that unite the five sectors of the digital environment: data, technology, talents, cloud business, and cloud connections between mining enterprises and individual processes. The cloud mining system should implement continuous sequential modeling of the geology of the deposit and its assessment while taking into account current market prices, designing mining operations, and planning the transportation of mined raw materials, their sales, and their profits [133].

The use of Surface Mining 4.0 digital technologies (cloud computing, Big Data, neural networks, virtual interactive models) is especially important for the full extraction of minerals from deposits with a low concentration of a useful component and valuable associated raw materials. Multi-criteria decision-making models, such as the Analytical Hierarchical Process and Python, allow for the visualization of the production and economic potential of poor and secondary deposits to visually determine the prospects for their development in the context of a long-term increase in raw material prices, as well as enable their discussion with stakeholders to make an investment decision [134].

Labor safety management in quarries is also a promising field for the introduction of Surface Mining 4.0 technologies. In particular, such machine learning models as DAFW(Days Absent from Work – indicator of injury severity), ANN (Artificual Neural Network), and MSE (Mean Squared Error) [135] have proven themselves for in-depth analysis of the causes and modeling of injury factors for workers at mining enterprises. At the same time, DAFW makes it possible to predict the need to replace workers in the case of accidents, as well as the need to attract additional personnel. The traditional lack of data in the analysis of the causes of specific occupational injuries may well be filled with the use of data mining technology (the detection of previously unknown, non-trivial interpretations of the data are obtained) [136].

6. Energy 4.0 Achievements in Surface Mining 4.0

Like Surface Mining 4.0, Energy 4.0 is the scope of the digital technologies of the Fourth Industrial Revolution, which are discussed in this review, as well as new achievements in the field of production, storage, and the distribution of energy [137]. Surface Mining, as an area not only for the production of fossil fuels, but also for energy consumption, is proving to be receptive to the achievements of Energy 4.0.

In particular, smart energy management systems based on artificial intelligence are gradually being introduced at surface mines, which make it possible to optimize the energy consumption of mining equipment and significantly reduce it by analyzing the incoming data in real time (Figure 18) [138].

Microgrid clusters, which are being actively used at surface mines, are also managed by Smart Energy Management Systems with the assistance of cloud and machine learning [139]. In addition, for Smart Energy Management Systems being implemented at surface mines, cyber-physical energy system security is relevant, which is associated with ensuring the uninterrupted operation of electrical equipment under conditions of optimizing energy consumption [140].

Furthermore, the rapid development of electric propulsion systems and solid batteries for intelligent autonomous electric vehicles [141] has led to the gradual replacement of fuel dump trucks with electric ones, thus producing zero emissions [142].

Along with this, modern data centers of surface mines should ensure the uninterrupted operation of the Internet of Things and machine learning servers, computers with artificial intelligence and digital clones, blockchain nodes, etc. In this regard, one of the achievements of Energy 4.0—the industrial power supply systems with static or dynamic uninterruptible power sources—is being increasingly used at surface mines [143].

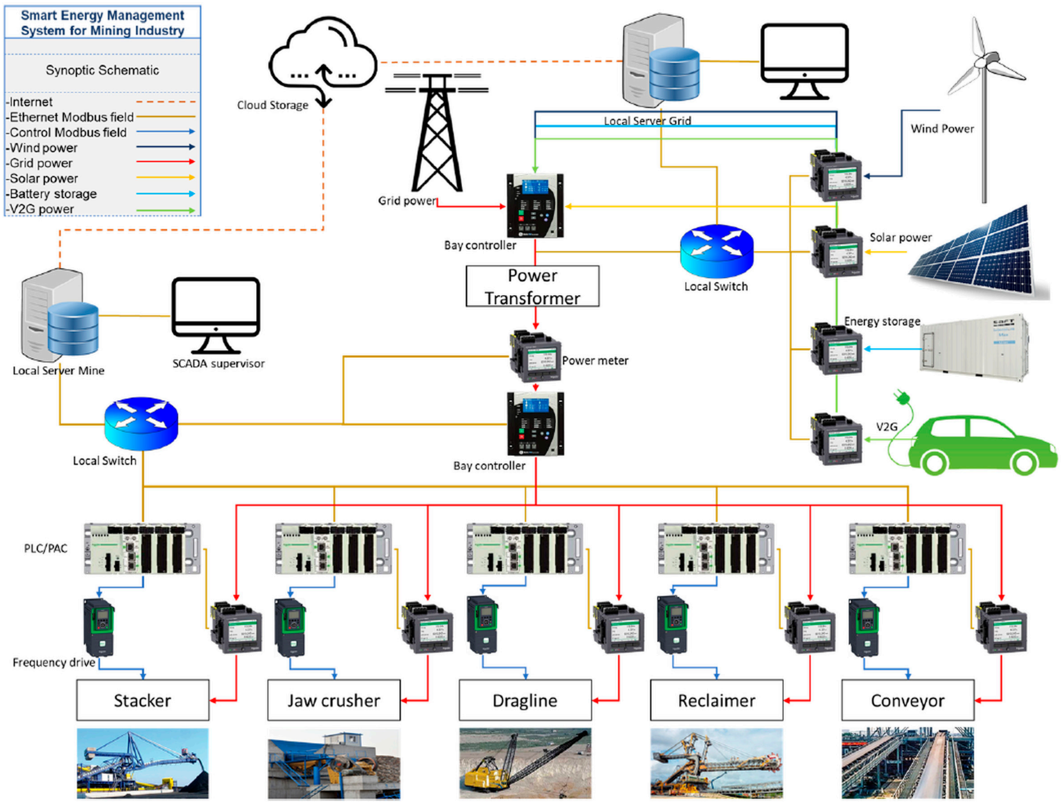

Figure 18. Scheme of the energy and data flow in surface mine in frames of Smart Energy Management Systems [138].

7. Green Mining and Post-Mining in Surface Mining 4.0

The development of open pit mining throughout the world should be subject to the achievement of the Sustainable Development Goals set by United Nations in 2015, which, in particular, include clean water and sanitation, affordable and clean energy, and life on land ("Protect, restore and promote sustainable use of terrestrial ecosystems") [144]. Therefore, the concepts of Lean Manufacturing, Recycling, Green Mining and Post-Mining should be considered as the results of the convergence of individual technologies on the Surface Mining 4.0 platform [145].

Green Surface Mining will take its place in the future human-centric economy (Industry 5.0, expected in the second half of the 21st century), with an emphasis on reducing the anthropogenic impact on the environment and protecting the health of workers [146]. There are five components of Green Surface Mining [146]:

- Advancing the introduction of environmentally friendly and resource-saving technologies in comparison with technologies that increase the productivity of surface mining enterprises;
- Transition to recycling scarce natural resources (such as fresh water and fertile land) with surface mining expansion in mineral resource clusters;
- The priority of ESG and green investments in the total amount of investments in quarrying;
- The restoration of surface mining clusters to the level of full economic use (transition from brownfields and blackfields to greenfields [147]);
- The achievement of a zero level of workers with serious injuries in areas of open pit mining.

7.1. Restoration of Post-Mining Areas

Post-Mining in a broad sense is the transition from natural ecosystems that have been disturbed during mining to a new prosperity of resource clusters [148]. The restoration of terrain from surface mining is influenced by many factors and processes; therefore, the automation of the decision making is desirable, i.e., with a fuzzy decision support system [149].

The attention of researchers in the restoration of Post-Mining areas has been drawn to digital 3D modeling of water reservoirs in former quarry fields [150], including using the "high conductivity cell" method [151].

Along with this, it is argued that the use of artificial intelligence and Big Data analysis to revitalize the area of surface mining creates investment opportunities that provide a new impetus to develop old industrial regions [152].

7.2. Green Surface Mining

Green Surface Mining is associated, first of all, with the reduction of greenhouse gas emissions, in which the use of neural networks can be of great help in designing a complex of environmental processes in quarries. They include the capture and burning of coal dust and methane from coal seams for power production, the deep purification of waste quarry water, and the use of overburdens as a building material [153]. Big Data, neural networks and the Internet of Things make it possible to receive and analyze real-time energy consumption in the country and the world, as well as define the demand in raw materials markets for the flexible management of the processes of extraction and processing of minerals, i.e., they actually integrate surface mining into a lean production system [154].

A promising aspect of Green Surface Mining is the use of a biochemical method for extracting raw materials from overburden dumps containing valuable associated components in a low concentrated form. An example is pyrite bio-oxidation by chemolithotrophic acidophile bacteria, whose RNA modification makes it possible to completely extract useful components from the subsoils [155].

Post-Mining, as a part of Surface Mining 4.0, is replacing traditional reclamation (technological and biological), wherein the task is to stop dust emission from overburden dumps and the likely transference of the part of disturbed lands to agricultural ones. Post-Mining (restoration of economic activity of clusters with a high concentration of surface mining after the completion of quarrying) requires a deep analysis of the state of damaged land, as well as the chemical composition of the water and soil. This requires the use of various Surface Mining 4.0 technologies—which include neural networks and cloud computing, drones and inspector robots, and smart sensors [156].

7.3. ESG Investment and Risk Management

The use of Surface Mining 4.0 as a tool for achieving sustainable development goals in mining clusters calls for the ESG optimization of investment and business operations thattake into account closed water use, improved energy efficiency and labor safety, and the generation of energy from the waste of coal mining and processing [156]. A number of projects in the EU countries are dedicated to this, and they have included developing alternative scenarios for land use planning, as well as the development of agricultural infrastructure in clusters of intensive open-pit mining (TRIM4Post-Mining as part of the H2020/RFCS initiative). These scenarios are based on interactive data embedding in the Transition Information Modeling System based on virtual reality [157].

An important analysis of the risk behavior of industrial systems from the point of view of cybernetic analysis of the system must first take into consideration its controllability [158]. The human factor as a source of risk for industrial ESG investment is considered critical for ESG investment [159]. The need for forming an investment risk management system in surface mining is to encourage the expansion of environment-saving funding. For risk assessment, the Monte Carlo simulation method has some advantages [160]. The presence of a sustainable development framework in the surface mining sector should be considered during risk evaluation for mining projects in order to mitigate risk exposure [161], as well as for national strategies of mining sector development as a whole [162].

We expect that the future research of Surface Mining 4.0 will touch upon such an important aspect as the cybersecurity of digital production systems, especially since there are currently few research articles in this area, with some exceptions [163–165].

Another perspective area of future research for Surface Mining 4.0 is the rise of digital maturity of this segment of the mining industry. Presently, the digital maturity of existing surface mining enterprises is significantly lower than that of other elements of the value production chain (energy, processing, metallurgical enterprises, etc.), and it corresponds to the Digital 2.0 level, compared to the target Digital 4.0 level [165,166]. One of promising ways to improve the digital maturity of mining is using virtual reality and the gamification of miners' training [167–169].

8. Conclusions

This review is aimed at drawing the scientific community's attention to the possibilities of Surface Mining 4.0 in the adoption of national energy transition strategies, especially in developing countries where the reduction of conventional fuel power producing can cause a supply shock in energy markets.

This review covered the results of the research of surface mining technological modernization in recent years and in the future, thereby giving a better understanding of the Surface Mining 4.0 technology platform. Along with this, the end-to-end technologies of Industry 4.0 were discussed, which cause technological shocks in the form of a radical increase in productivity in industries with high technological saturation. As a result, the world mineral resource sector in the next decade may experience an investment shock and a destabilization of the global raw material market. As a long-term countermeasure against technological shocks in the quarrying segment, the authors see the development of Surface Mining 4.0 as a platform for the accelerated modernization of the entire sector to the level of Industry 4.0.

The key domain areas of Surface Mining 4.0 being observed include the following: the Internet of Things, digital twins, Big Data and cloud computing, smart sensors, 3D visualization, blockchain, neural networks and artificial intelligence, machine vision and learning, and unmanned mining equipment and drones.

A review of scientific publications in the field of end-to-end digital technologies Surface Mining 4.0 made it possible to determine the steady interest of researchers in the expansion of core domain technologies. It allows us to conclude that physical systems are gradually being replaced by cyber-physical ones; the prospects reliably predict the negative impact on the environment and plan measures to prevent it, as well as establish control over mining equipment operation to achieve an unprecedented level of reliability and safety.

A review of the Surface Mining 4.0 domain, represented by drones, autonomous mining machines, and robots inspectors, led to the conclusion that a person will be significantly replaced from managing the processes of quarrying in the prospect of moving to Mining 5.0 by the middle of the 21st century, when unmanned technologies will dominate in surface mining.

Research in the field of digitalization and the intellectualization of the management of enterprises engaged in open-pit mining makes it possible to judge the possibility of the break-even development of deposits, including depleted ones, with significant fluctuations in demand and prices in the commodity markets due to the deep optimization of decision-making processes based on neural networks and cloud computing.

The development of Post-Mining and ESG investment as the most important contributions of Surface Mining 4.0 to the achievement of sustainable development goals also meets a certain interest of researchers, but to a lesser extent than issues of digital transformation of quarrying. Therefore, we see the horizons for the further innovative development of open geotechnology in the convergence of digital, production, and management technologies in the context of the expected transformation of Mining 4.0 into 5.0 (the platform of the upcoming Fifth Technological Revolution), which can bring new shocks to the mineral resource sector.

Author Contributions: Conceptualization, methodology, supervision, S.Z.; formal analysis, investigation, writing—review and editing, E.T. All authors have read and agreed to the published version of the manuscript.

Funding: The study was supported by the Russian Science Foundation grant No. 23-28-01423, https://rscf.ru/en/project/23-28-01423/.

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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