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Review

Review of Transition from Mining 4.0 to Mining 5.0 Innovative Technologies

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Abstract: The sustainable provision of mankind with energy and mineral raw materials is associated with an increase not only in industrial but also in the ecological and economic development of the raw material sector. Expanding demand for energy, metals, building and chemical raw materials on the one hand, and the deterioration of the living environment along with a growth of raw materials extraction on the other, put the human-centric development of mining at the forefront. This forms a transition trend from Mining 4.0 technologies such as artificial intelligence, big data, smart sensors and robots, machine vision, etc., to Mining 5.0, presented with collaborative robots and deserted enterprises, bioextraction of useful minerals, postmining, and revitalization of mining areas. This "bridge" is formed by the technological convergence of information, cognitive, and biochemical technologies with traditional geotechnology, which should radically change the role of the resource sector in the economy and society of the 21st century. The transition from Mining 3.0 to 4.0 cannot be considered complete. However, at the same time, the foundation is already being laid for the transition to Mining 5.0, inspired, on the one hand, by an unprecedented gain in productivity, labor safety, and predictability of commodity markets, on the other hand, by the upcoming onset of Industry 5.0. This review provides a multilateral observation of the conditions, processes, and features of the current transition to Mining 4.0 and the upcoming transformation on the Mining 5.0 platform, highlighting its core and prospects for replacing humans with collaborated robots and artificial intelligence. In addition, the main limitations of the transition to Mining 5.0 are discussed, the overcoming of which is associated with the development of green mining and ESG (environment, social, and governance) investment.

Keywords: artificial intelligence; Mining 5.0; cyber-physical systems; postmining; cloud computing; big data; green mining

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1. Introduction

Currently, the mining industry is going through two stages of technological transformation simultaneously—the transition to the Mining 4.0 platform with the formation of the platform of the future—Mining 5.0. Both of these platforms are associated with the transition from the IVth to the Vth Industrial Revolution. It means that Mining 4.0 can be considered the platform of Industry 4.0 in basic sectors. In fact, the formation of the digital "core" of Mining 4.0—application of Industry 4.0 technologies in the mining sector. Due to this, end-to-end technologies, such as artificial intelligence, the Internet of Things, and cobots, have changed the global trend of the industry's technological development (Figure 1 [1]).

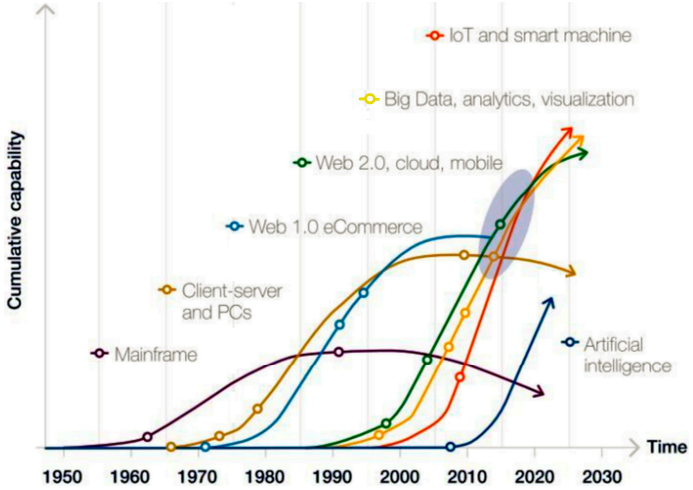


Figure 1. The trends in industrial digital information technologies in basic industries (Reprinted from Ref. [1]).

The oval shading in Figure 1 means the intersection of the above-mentioned digital development trends in the basic industries by the mid-2010s, which created the basis for a broad transition to Industry 4.0, enhanced by artificial intelligence.

The transition from Mining 3.0 to 4.0 and further to 5.0 is a natural process of key innovation diffusion from various fields of science and technology to geotechnology (Table 1 [2]).

Table 1. Main technological innovations and achievements of Mining 5.0 (Adapted from Ref. [2]).

The Ladders of Industrial Development	Achievements	Main Technological Innovations	Ladder of Geotechnology Development	Specific Innovations in Mining Industry
Industry 1.0 End of the 17th–first half of the 19th centuries	The first high-performance machines	Steam engines, coke producing, first machines	Mining 1.0	Replacement of manual labor by machines in secondary processes
Industry 2.0 End of the 19th century–beginning of 20th centuries	Creation of production complexes based on electrified equipment	Electrification, strong steels and alloys, conveyor production, petrochemistry, automobiles	Mining 2.0	Replacement of manual labor by machines in primary processes
Industry 3.0 1970–1990th	Robotization of individual processes	Automation, analog computing, and control systems	Mining 3.0	High-specific productivity equipment, analog telemetry
Industry 4.0 2000th–present time	Replacing human intelligence with “artificial one” in a number of areas	Deep digitalization, Internet of Things, artificial intelligence, convergent technologies	Mining 4.0	Unmanned technologies, remote process control, digital simulation
Industry 5.0 2050th (estimated time of expansion)	Synergy between humans and autonomous machines	Artificial intelligence as a main mean of production, Internet of Everything, cyber-physical systems, data mining, o-bots, ubiquitous augmented reality	Mining 5.0	Unmanned mining by collaborative robots, blockchain in control and management, postmining, ESG, digital tweens, machine learning

It follows from Table 1 that the trend of diffusion of the Fourth Industrial Revolution achievements into raw materials extraction (Mining 4.0) creates radical differences for traditional mining (3.0). It means that the process of automation will be replaced by the connection of man and machine using digital technologies. In fact, human intelligence is supplemented by machine intelligence, which makes it possible to remove the burden of analyzing large amounts of data from engineers for timely and adequate decision-making. It is in this way that Germany, a pioneer in the implementation of Industry 4.0 in basic industries, provided technological leadership in them [3].

Some researchers expect the replacement of Mining 4.0 with 5.0 from 2050th, not as a spontaneous process but as a gradual turn to human-centric production [4] and an increase in digital maturity of raw materials extraction (its saturation with modern digital technologies, such as artificial intelligence, digital twins, etc.) [5]. Another important difference between Mining 4.0 and 5.0 is the priority of health care and labor safety, as well as mining territories' restoration. However, the limiting factor of the transition to Mining 4.0 and further to 5.0 is insufficient digital maturity of raw material extraction (Figure 2 [6]).

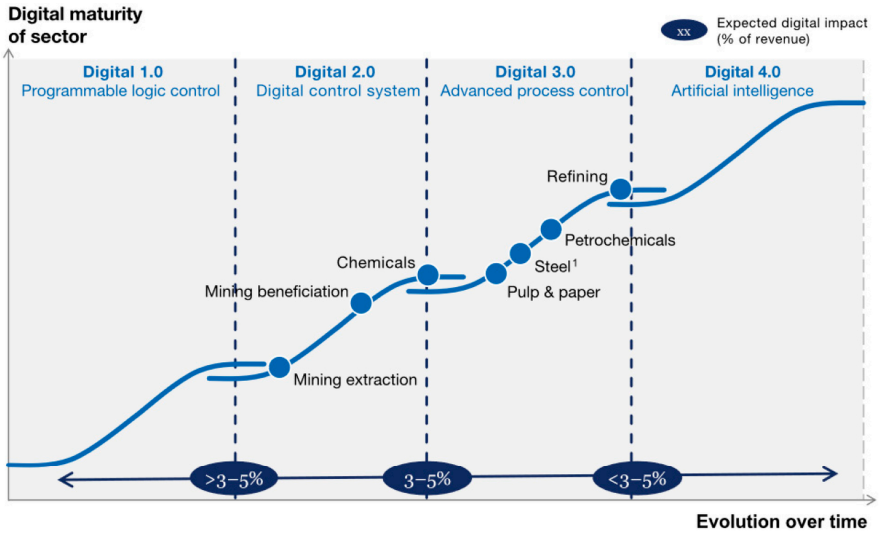


Figure 2. Comparison of digital maturity of mining and other industries, Steel[1] is used for example of non-extractive industry (Reprinted from Ref. [6]).

In turn, expectations of increasing digital maturity in the mining sector are associated with new ecosystems of basic industries, forming on the end-to-end platform of Industry 4.0 digital technologies. Therefore, it will be possible to talk about the transition to Mining 5.0 when the digital age in the extraction of minerals reaches the highest possible level—Digital 4.0 [7]. The transition to Mining 5.0 also means less impact on the environment [8] due to the lean production of green mining under the control of the Internet of Everything, which allows collecting and analyzing data on national and global energy consumption in real time to optimize the production of energy carriers [9]. Together with this, another component of Mining 5.0—big data mining (replacing human intuition with a machine one with a lack of operational information)—allows the implementation of a transition strategy to green mining thanks to an ultra-accurate analysis of the interindustry balance in the consumption of natural sources and energy generation [10].

Advancing mining on the path of the Fifth Industrial Revolution Evolution is associated with the development of machine vision and learning technologies, due to which modern autonomous machines (smart robots) will be replaced by collaborative robots (cobots) with powerful artificial intelligence, primarily in the most harmful and hazardous segments of mining (underground mines and processing plants) [11]. It is expected that Mining 5.0 technologies will go beyond geoengineering and will allow smoothing fluctuations in commodity markets through the widespread use of smart contracts [12,13].

Some authors consider the possibility of advanced development of digital technologies Mining 5.0 over the evolution of traditional geotechnology (i.e., reaching the limit of their development) [14], although there is an opposite opinion [15,16].

We attribute this divergence of opinions to the fact that when studying the perspectives of Mining 5.0, its core innovations are understood as a new step in information technology development, as opposed to geotechnology. This research gap is noted by a number of authors [17,18]. In our review, we rely on the fact that the transition to Mining 4.0 and further to 5.0 is, of course, associated with the diffusion of fundamentally new digital technologies of Industry 4.0 and 5.0, which can significantly improve geotechnology, but cannot replace it, so we are talking more about their convergence.

2. Methodology

This review comprises the major part of the publications made by the international cohort of Mining 4.0 and 5.0 researchers, investigating the application of the Fourth and Fifth Industrial Revolutions in basic branches, ecology, and society. The aim of their observation is to analyze the transition from digital technologies that make up the Mining 4.0 platform to converged technologies of Mining 5.0, taking into account the effectiveness in basic industries for contribution to the further development of research. The main tasks of the review include, first, performing comprehensive analysis, classification, and summarizing the concepts, ideas, and innovations put forward by various authors and international research teams in the field of technological development of the mining sector. Second, an important task is analyzing the successes and obstacles to the implementation of Mining 4.0 and 5.0 technologies and, thereby, identifying promising areas and segments of future research in this area. Individual obstacles should be generalized for defining towardly ways of mineral extraction in the 21st century.

In accordance with the assigned tasks, we set the following sections in the review.

The Introduction reflects the general state of research in the field of Mining 4.0 and 5.0, the level of digital maturity of the mineral resource sector.

The Methodology section shows the strategy of investigation, which determines the way it is carried out and the methods used.

The review of the transition from Mining 3.0 to 4.0 section provides an overview of scientific papers on the transition from Mining 3.0 to 4.0 during the mass expansion of Industry 4.0 technologies.

The Perspective of Transition from Mining 4.0 to 5.0 section is devoted to conditions and prerequisites of this process in the context of the core of Industry 5.0 technologies.

The Conclusions and Prospects section is devoted to the generalization of the considered approaches, and scientific works were made, conclusions were drawn.

The main part of the articles observed in this review is devoted to the digital technologies of the Mining 4.0 core (artificial intelligence and neural networks, Internet of Everything, augmented reality, 3D visualization, cloud computing, etc.), and Mining 5.0 (postmining, convergent biochemical, information and cognitive technologies, and ESG investment).

3. Review of the Transition from Mining 3.0 to 4.0

We consider the result of a systemic transformation of subsoil mining and primary processing technologies up to the Industry 4.0 level (Mining 4.0) in all the variety of intertwining technological and social and economic platforms [19]. The transition between platforms Mining 3.0 and 4.0 reflects the objective evolution of technology. It began in the 19th century, with coal mining for steam engines and coke production (Mining 1.0); then, manual labor was replaced by machines in primary processes at the beginning of the 20th century (Mining 2.0); and then there was a shift toward widespread automation and complex mechanization (Mining 3.0) [20]. Today, the defining stage is Mining 4.0 (digital computing and control systems that replace humans in a number of processes), which prepares the basis for the upcoming transition to Mining 5.0 as a more perfect optimization of production, with a characteristic symbiosis of humans and smart machines [21].

The transition of mining technological platforms "Mining 3.0–4.0–5.0" does not occur linearly but in steps (as the potential of digital and convergent technologies accumulates), resulting in overlapping and interweaving of old and new technologies. Examples of such transitional technologies are the following:

- In the transition from Mining 3.0 to 4.0: the use of artificial intelligence to control machines and their operators without replacing human intelligence with an artificial one (control of fatigue of dump truck drivers [22] and intelligent monitoring of machines for energy consumption optimization [23]); wearable smart sensors for monitoring the mine atmosphere and equipment operation [24]); using big data to control but not to manage the state of the rock array [25]; application of machine vision and learning to improve the quality of ore processing on existing flotation equipment [11].
- In the transition from Mining 4.0 to 5.0, a combination of postmining technologies is already observed today. It included 3D modeling of reclamation and the use of neural networks to analyze environmental damage, filling the restored ecosystem in surface mining clusters with genetically modified organisms, and installing renewable wind and solar energy facilities [26,27]. Further, the technologies of underground mining and chemical extraction of coal are combined in its underground gasification [28].

In general, the intersection and overlapping of old and new technologies (Industries 3.0 and 4.0) are quite rare; the most frequently observed picture is their coexistence and gradual displacement. In more detail, new technologies, the expansion of which marks technological transitions in mining, will be discussed below.

The defining component of Mining 4.0 is associated with human-cyber-physical systems (HCPSs) [22–24], which are currently actively evolving in the industry (Figure 3 [29]) from HPS (human-physical systems) to HPS 2.0. The second generation of such systems, on the basis of which Mining 5.0 will be formed, should turn the current operators of partially robotic devices into operators of intelligent machines, thereby freeing themselves not only from manual but also intellectual labor, moving on to pure engineering creativity.

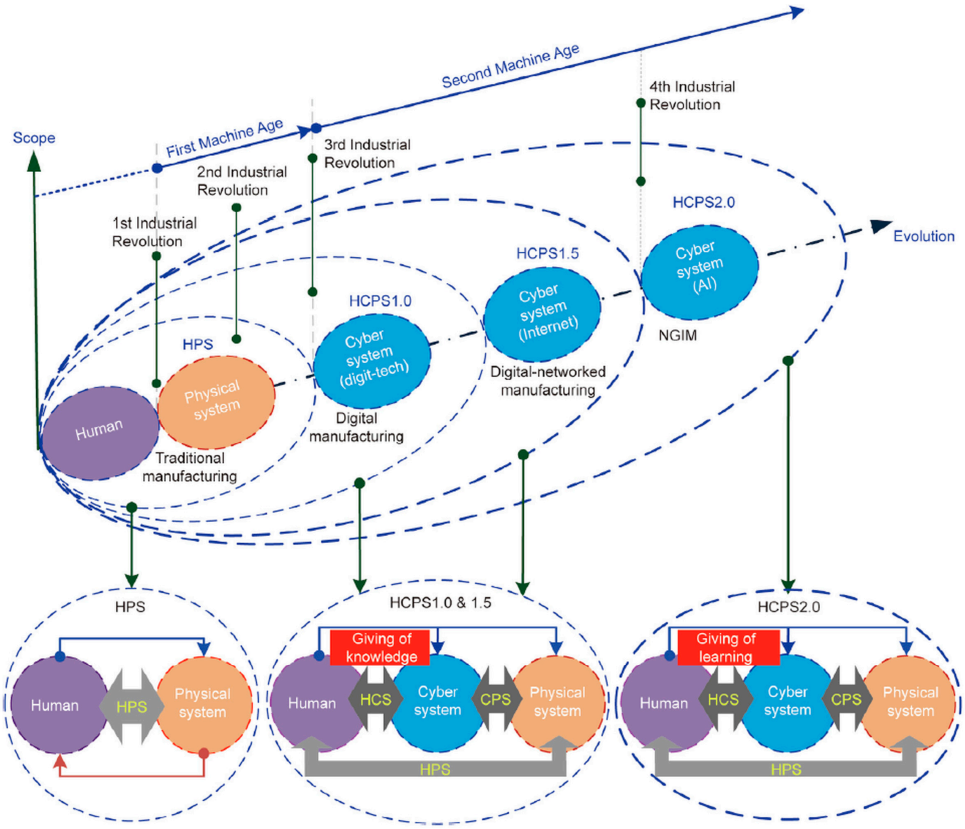


Figure 3. Intelligent manufacturing evolution (Reprinted from Ref. [29]).

3.1. Artificial Intelligence and Neural Networks in Mining 4.0

The basis of modern cyber-physical systems is artificial intelligence and neural networks, which allow for bringing energy efficiency and performance to a new level of optimization [30,31]. An interesting decision in this area is associated with the parametric graph closure algorithm, which allows the compounding of resources, followed by branching and pruning [32,33]. For example, an artificial neural network used for the discrete event simulation can accommodate all processes in refractory gold mining and enrichment, with the processing of large amounts of information using a swarm of sensors, which have proven themselves especially well in depleted deposits [34,35]. In addition, neural networks proved their efficiency in advancing the maintenance of mining equipment [36,37], as well as for complicated decision-making in the area of the environment [38].

Another area of the neural network application is to improve labor safety in mines. Thus, the recurrent neural network allows precise prediction of gas formation (nonlinear) in underground workings long before mining progress, based on retrospective and current data [39]. Artificial intelligence recognition systems based on such networks as support vector machines and wavelet scattering decomposition made it possible to create a seismic event recognition model in intensive mining clusters, taking into account petrographic and geological conditions, methods, and parameters of mining [40]. Causal modeling of mining operations using artificial intelligence is especially effective when based on semisynthetic (current and forecast) data [41].

Application of neural networks in rock blasting design at underground and surface mines is especially successful since it is aimed at increasing the blast efficiency (only 30% of its energy is channelized to the rock array) by optimizing all drilling and blasting parameters [42]. Multilayered artificial neural networks became more efficient when based on the Keras Python library (the result of using the sequential design strategy—Bayesian optimization), and the performance of the explosion was significantly improved [43].

3.2. Virtual Reality in Mining 4.0

Cyber-physical systems (industrial core of Mining 4.0) consist of two pillars—artificial intelligence and virtual reality. Such systems already widen the limits of efficiency of training for the mining industry, including using game methods. Simpler systems allow visualizing virtual reality reflecting the processes in mine workings with human participation [44].

The use of virtual gaming simulation of training emergencies has proven itself especially positive when using bots controlled by artificial intelligence. These bots play the role of partners who violate safety regulations or rescuers, or faulty equipment (Figure 4 [45,46]).

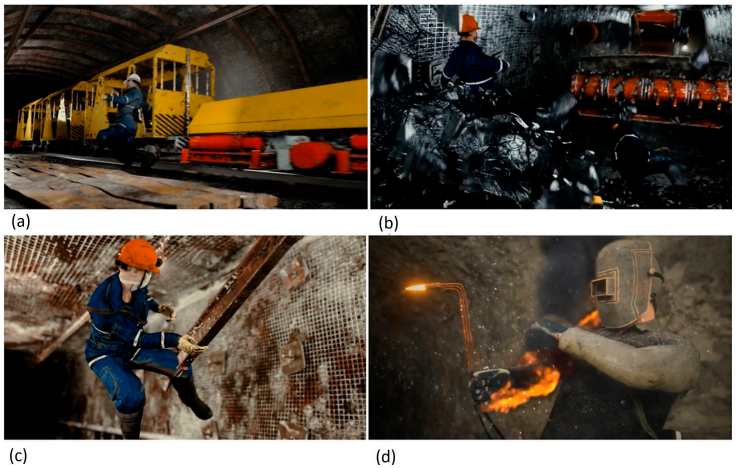


Figure 4. Models of mine accidents modeled on game virtual 3D ProExpVR platform: (**a**) trolley hooking; (**b**) roof collapse; (**c**) fall from a height; (**d**) ignition during welding (Adapted from Refs. [45,46]).

Mining virtual reality gaming technologies can also be based on the widespread Microsoft Xbox and Kinect platforms. AutoCAD software was used to create the virtual mine topology, which was then processed by Blender software and stored in the FireBird database; the PhysX game engine was used for rendering. Body positioning data are read through the driver and OpenNI library. The process of 3D simulation is shown in Figure 5 [47,48].

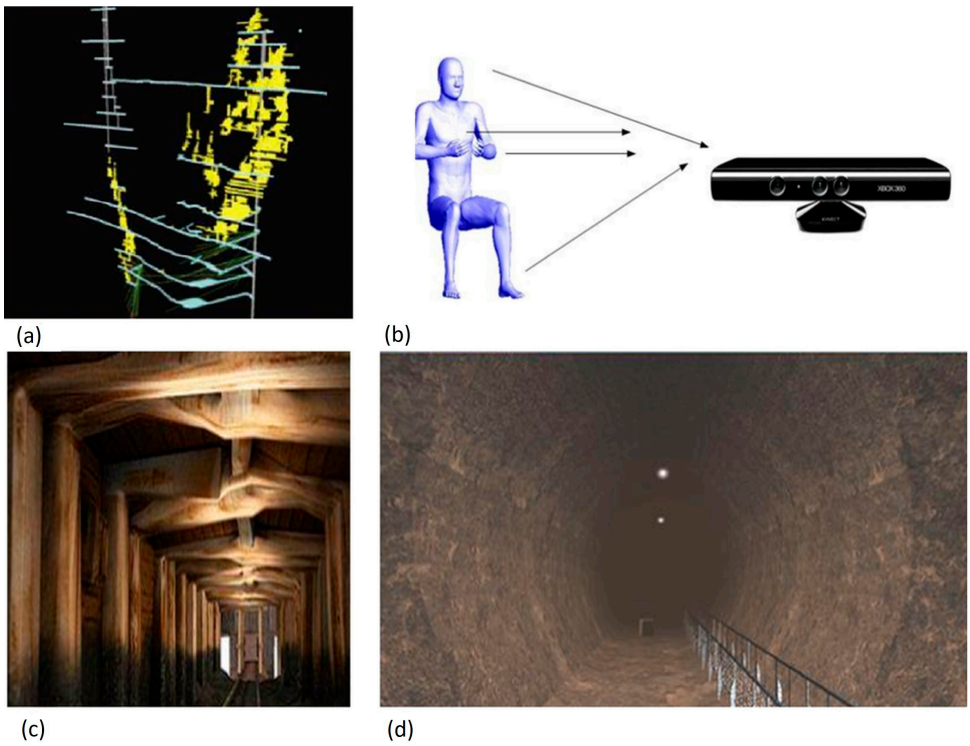


Figure 5. Three-dimensional virtual mine modeling using Microsoft Xbox and Kinect for (**a**) three-dimensional model of a mine working in AutoCAD format; (**b**) transferring digital avatar control gestures using Kinect; (**c**) game visualization of the mine working model after Blender processing; (**d**) an example of driving through a mine working based on the PhysX game engine (Adapted from Refs. [47,48]).

Another example of a virtual reality complex for the gamification of training future engineers, including miners, is the use of the Godot engine at the University of Žilina. The hardware component is represented by a headset made by HTC (Vive Pro model) [49].

At the forefront of Mining 4.0, computer-integrated mining is concerned with real-time control of dynamic polycomponent objects (dump trucks, excavators, drilling machines, harvesters, etc.) using fuzzy logic and flight control language [50].

3.3. Internet of Things in Mining 4.0

The Internet of Things is a "kernel" technology for cyber-physical systems; therefore, its importance for Mining 4.0 cannot be underestimated.

Such systems integrate various achievements of Industry 4.0—smart sensors, the Internet of Things, and machine learning—to replace humans with robots in difficult conditions. Cyber-physical systems operate based on their own recognition of environmental (including gas pollution, dustiness, and radiation), mining, geological, production, and technical conditions [9]. It is the introduction of cyber-physical systems in Mining 4.0 that allows not only to control of the operation and performance of equipment complexes without human intervention but also to improve labor safety unprecedentedly, as well as significantly reduce energy consumption due to the optimization of a load of all production systems (which correlates with the Energy Internet) [51,52]. The so-called "Digital Mine" is

a quintessence of Mining 4.0, comprising the digitalization of all the links in the chain of minerals mining and primary processing (Figure 6 [53]).

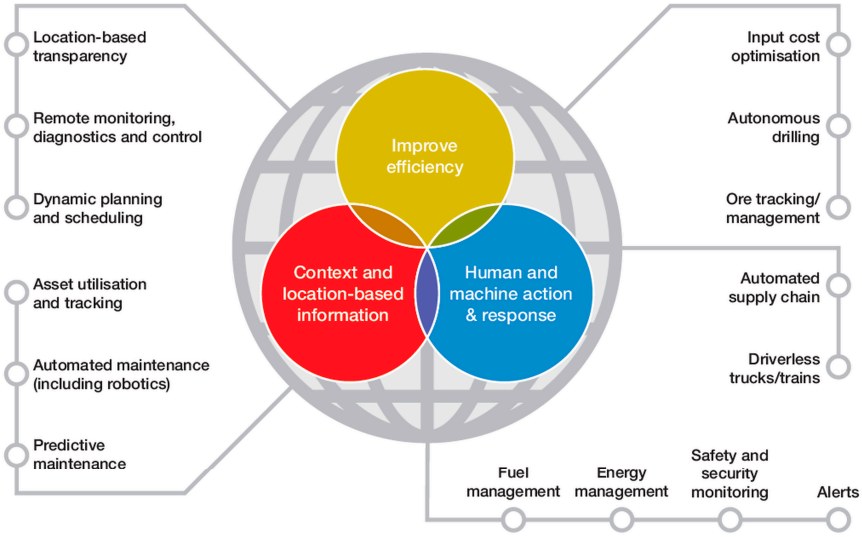


Figure 6. Internet-connected things in mining (Reprinted from Ref. [53]).

Mining 4.0 involves the widespread digital technologies for control of data flows, which cyclically comes from built-in sensors through different data storages to consoles (this is actually called the Internet of Things). After that, analyzed, summarized, and classified information comes to end users (control subsystems), which send it back to the machines in the form of commands.

The digital ecosystem of mining companies allows the integration of various platforms under the Internet of Things. It leads to more efficient decision-making due to the instant analysis of incoming data and the transfer of control action to technical systems (Figure 7 [54]).

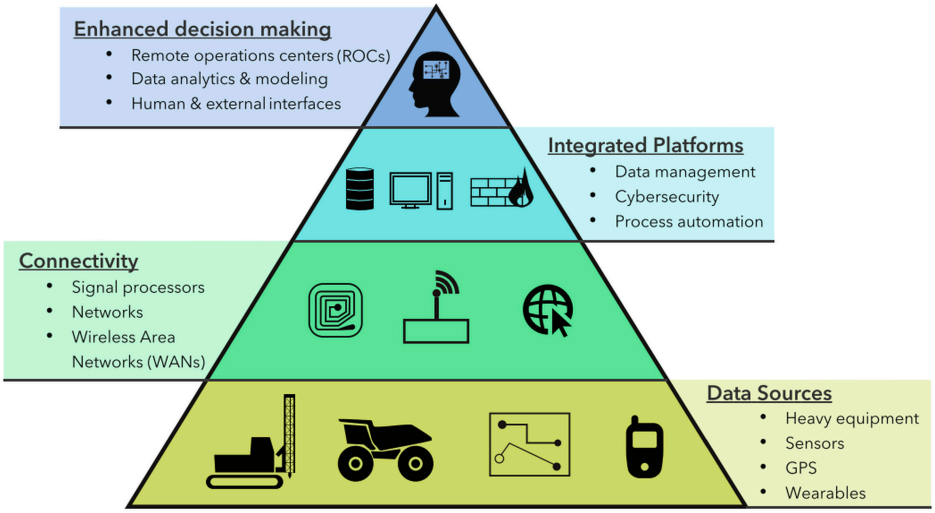


Figure 7. Digital ecosystem of mining company (Reprinted from Ref. [54]).

Data mining is a special part of the digital core of Mining 4.0, which helps to recognize data loss and gaps. For that purpose, a promising engine Apache Spark shows the utmost results in accelerating the calculations and balancing the input and output data, SWEclat algorithm [55].

3.4. Digital Twins in Mining 4.0

Digital twins, as well as artificial intelligence, are an immanent part of mine's digital ecosystem [56], changing the role of humans in processes management, from the driver of automated machines (Operator 3.0 of remote control of partially robotic equipment) and further to Operator 5.0 ("miner of the future") [57], which uses biomechanical support, interact with collaborative robots, relies on augmented reality for the assistance of machinery engineers [58]. In general, the digital ecosystem of Operator 4.0 activity corresponds to the maturity of Digital 3.0 and, in perspective, 4.0 [59].

We highlight the difficulties in the unification and system integration of software made by many companies around the world as the limitation of digital twinning processes of mining. These difficulties are connected with the incomplete compatibility of software products developed by different vendors and composing the digital ecosystem of the modern mining enterprise. For example, widespread software—production solutions made by ABB, OSIsoft data integrators, asset management by IBM Maximo, cloud data management by Microsoft Azure, customer management by Microsoft Dynamics 365, and business analytics by Microsoft Power BI—communicate with each other using Microsoft Excel sheets only. It reduces the overall efficiency of the digital ecosystem of the enterprise [60]. In turn, we see overcoming the difficulties of integrating software into a single ecosystem in the formation of a unified approach to software compatibility by the majority of developers.

In addition to cyber-physical systems, Mining 4.0 includes computer-integrated mining and smart mining, which quintessence is the use of integrated systems for design, management, equipment capacity, mining safety, and product quality monitoring [61]. The most important elements of digital ecosystems are smart sensors and digital twins. The latter is designed to balance the performance, synchronize data processing, and improve interface compatibility of various digital systems of mines—mobile devices, personal computers, and controllers [62]. Using digital twins of mining equipment and processes, different users (smart machines and humans) can stay connected and respond to unpredictable situations to avoid accidents (Figure 8) [63].

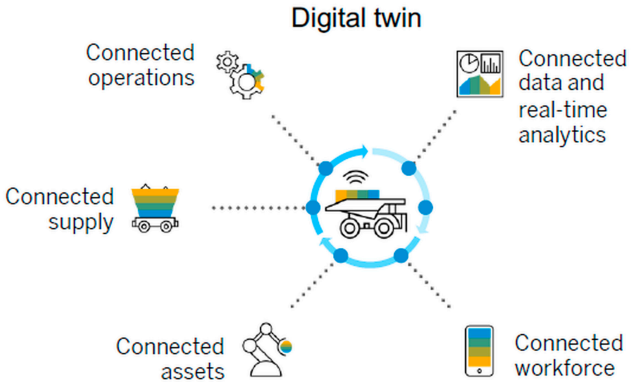


Figure 8. The use of a digital twin in Mining 4.0 (Reprinted from Ref. [63]).

The digital twin also makes it possible to solve the problem of incompatibility of digital avatars of processes, requiring large and fast calculations [64], to reduce the number of physical prototypes [65]. Due to this, digital twins are used in mining and geological engineering process design by connecting all users to the enterprise information system [66]. Expanding the participation of digital twins in displaying results of big data analysis is possible using the BERT-BiLSTM CRF (conditional random field) neural network, which accelerates the recognition of problems with mining equipment more accurately and faster than autonomous smart sensors [67]. In general, the use of neural networks together with digital twins makes it possible to create digital clones of mining processes as close to reality as possible, during continuous self-learning of networks, for example, for optimizing resource and energy consumption [68].

In parallel with digital twins, the valuable part of Mining 4.0—a blockchain—is transforming into a cross-chain ecosystem that integrates information from different participants of subsoils mining and processing (extractive companies, electricity and heat producing firms [69], government regulatory authorities, insurance companies, and investors [70]).

Distributed computing technologies (the basis of the blockchain) are used in forecasting methane appearance in coal mines. For that purpose, an autoregressive integrated moving average model is used along with the Spark Streaming framework for streaming data processing (in batches) with an ultra-accurate prediction of gas concentration in real-time (with the help of a support vector machine) [71].

3.5. Smart Sensors in Mining 4.0

It is impossible to analyze the transition to Mining 4.0 without considering the examples of smart sensor implementation in the areas of accurate and timely diagnostics and finding engineering solutions [72]. Successful examples of using smart sensors in mining are the following:

- Belt 4.0—underground and surface mine conveyor condition and loading control system based on artificial intelligence, which makes it possible to eliminate sudden stops due to breakdowns completely [73];
- Air flow visualization system connected to mine ventilation equipment to radically increase the accuracy of modeling [74];
- LiDAR (light identification detection and ranging) systems integrated with GPS (global positioning system) when creating a 3D cloud to predict sudden movements of rock mass [75];
- Land area subsidence prediction in clusters with high concentration of underground mining using differential interferometric synthetic aperture radar [76];
- Integration of InSAR (interferometric synthetic aperture radar) and LiDAR data with analysis of photographs made by aerial drones to predict soil deformations [77];
- Remote creation of predictive maps of surface subsidence and collapse over working mine longwalls using differential radar interferometry with an accuracy of 4 cm [78], using the GrabCut method to create high-precision scalable visual attention models—the first step towards full robotization of deserted mines [79];
- Integration of data from geoscanners with information from global navigation satellite system devices to achieve the highest accuracy of 3D modeling of underground mine workings, sufficient for unmanned control of processes in underground mines (with time synchronization using pulse per second) [80]. At the same time, ground-penetrating radars are also developing in the direction of increasing the accuracy of determining the deformation of mine workings, already in the submillimeter range. For surface mines, we should note the effectiveness of such smart sensors as ground-based synthetic aperture radar, which operation is based on the frequency-modulated continuous wave [81];
- Application of the method of persistent scatterer interferometry for increasing the accuracy of forecasting man-made earthquakes by 35.2% (based on refined external model-based decomposition of deformation). Moreover, SAR single-look complex was effective for sequential analysis of surface images, followed by analysis of the spatial distribution of the interferogram [82];
- Complex application of various smart sensors integrated with drones, cameras, and equipment controllers, proved to be very useful for advanced decision-making and perspective planning based on 3D virtual models (an example of Rio Tinto, Australia—Figure 9 [83]).

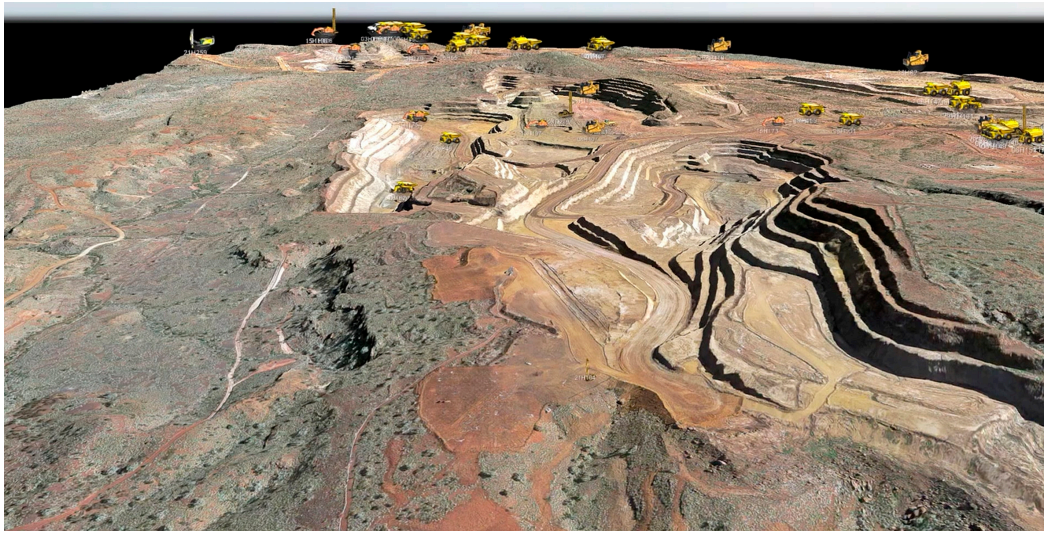


Figure 9. Visualization of open pit mining using a 3D model built using smart sensors in real-time (Reprinted from Ref. [83]).

3.6. Big Data in Smart Mining (Mining 4.0)

The transition to Mining 5.0 will mean the displacement of a person by smart machines from intellectual work to engineering creativity, for which the concept of smart mining is already being implemented in Mining 4.0 today. It combines artificial intelligence capable of solving complex operational problems, modern telecommunication systems (means of storage and transmission of big data), and means of their ultrafast processing [84].

In turn, the digital basis of smart mining is an analysis of big data, which allows for creating new knowledge without human intervention [85], integrating engineering, logistic, and economic information for managing the business cycle of minerals mining and processing [86], and adapting production volumes to changes in the world market of raw materials [87]. With regard to the operation of mining machines, cloud computing in the field of big data processing allows for optimizing their work with an increase in productivity of up to 30% [88].

Analysis of big data helps to move to subsoils intelligent geological exploration. It significantly reduces the loss of minerals due to improved accuracy of geological mapping [89], which is critically important for the development of deep deposits, especially with occurrence anomalies [90]. For modeling future underground mine workings on other planets in the course of space exploration, big data analytics can help with the integration of knowledge and data obtained on Earth [91]. It can also be translated to the modeling of mining workings under the seabed, penetrated with autonomous underwater robots (for that purpose, the computational fluid dynamics method is recommended, along with using Tracsim and OrcaFlex digital instruments [92]. Relying on computational fluid dynamics model cells gave positive results in the analysis of methane inflow from coal array pores to workings to radically improve the effectiveness of mine ventilation [93].

Big data in 3D modeling implementation in underground mine working design is based on point clouds obtained from various sources (ground penetrating radars, LiDAR scanners, etc.) and is of high relevance today (for example, digital speckle correlation is effective for predicting the strength characteristics of rocks in the composite roof in deep mines [94]). Virtual simulation with the construction of a fully functional interactive 3D model is successfully used in the analysis of the reliability of mineshaft structures [95].

The combination of laser scanning technologies, big data analysis, and 3D modeling allows controlling unmanned vehicles in underground mine workings, avoiding accidents and collisions [96]. This, using machine vision, allows for creating adaptive 3D models of mine workings [97], including using simultaneous location and mapping (the precision of displaying details reaches 0.01 m) [98]. In turn, the Hermite radial basis function with

spatial interpolation used for 3D modeling of ore deposits can significantly improve the accuracy of the calculation of mineral reserves [99] due to integrating geological maps, multispectral images, and magnetic surveys from drones [100].

3.7. Machine Vision and Learning in Mining 4.0

Another digital technology domain emerging from the transition from Mining 3.0 to 4.0 is machine vision and learning, as well as robots and drones. Machine vision provides new opportunities for the robotization of mining processes, distributing engineering decisions making between people and machines (including autonomous and collaborative robots), which can be considered a bridge to Mining 5.0 [11].

The expansion of deep machine learning based on artificial intelligence in mining gives a chance to equipment service companies, which can rely on machine-made decisions and knowledge due to the real-time collection and analysis of data required for independent decision-making by machines [101].

Along with machine knowledge [102], machine vision has significant potential for the identification of disturbances and cracks in the rock array, using a convolutional neural network with an accuracy of prediction model of more than 85% [103]. There is also a positive experience of implementation of a random forest model of artificial intelligence for early detection of prerequisites of coal dust explosions [104].

Another example of machine vision implementation is hyperspectral analysis of coal preparation processes using a self-control module, which made it possible to automate the process of identifying the host rock [105]. The fourth generation of flotation systems based on machine learning proved to be effective for calculating the content of a valuable component (precious minerals) in the concentrate for its complete recovery using the watershed segmentation technique for bubbles recognition, as shown in Figure 10 [106].

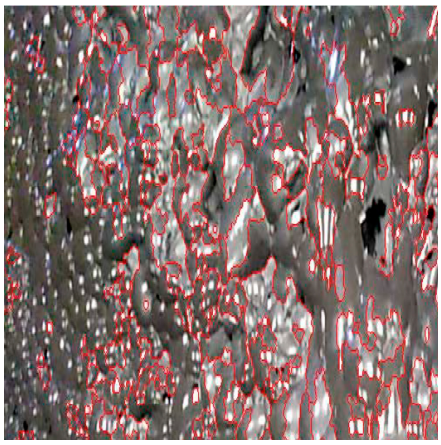


Figure 10. Example of segmentation results using watershed algorithm (Reprinted from Ref. [106]).

Unmanned (fully robotic) equipment is a new frontier of mining machinery development [107]. Integrating data from LiDAR sensors and machine vision for processing by geometric matching algorithm allows for successfully recognizing the traffic signs in underground mines by unmanned robotic transport (979.14 matches from 1000), ensuring accident-free movement along the planned route without human intervention [108]. Monitoring of mine mechanical systems with the help of machine vision is developing towards the use of robo-inspectors that independently collect and analyze heterogeneous information (RGB (red–green–blue)-image, noise, presence and level of gases, vibrations, gamma radiation, etc.) [109]. An example of an autonomous inspector robot is shown in Figure 11 [110].



Figure 11. Conveyor Inspection Robot (Reprinted from Ref. [110]).

The introduction of autonomous robotic control of mine equipment will make it possible to organize monitoring of areas near working mining equipment and diagnose it in coal and ore underground and surface mines using inspector robots. Their prototypes are made in the form of a walking and jumping ground bot equipped with various sensors (Figure 12 [111]).



Figure 12. ANYmal legged mine inspection robot by ANYbotics (Reprinted from Ref. [112]).

Aerial drone inspectors by DJI Matrice, Mavic, Phantom, etc. are promising for monitoring drilling and blasting operations in quarries, conducting preliminary, blasting, and postblast monitoring [112], as well as for the state of coal storages, dumps, and tailings, a magnetic survey of ore bodies [113,114], and geodetic survey [115]. Drones are also used for monitoring underground mining operations—monitoring the mine atmosphere, the state of mine pillars, and the operation of equipment [116]. Along with this, the use of drones, complete with augmented reality, allows expanding your vision [117].

3.8. Cloud Mining as a Path Digital Technology from Mining 4.0 to 5.0

Finally, the core digital technology, which determines the path of transition to Mining 5.0, is cloud mining, which allows using artificial intelligence not only to manage individual processes and even enterprises but entire industrial clusters, integrating digital data, technologies, talents, cloud computing parameters of cooperative ties between companies [118]. Reliance on multicriteria decision-making allows for combining the financial and marketing strategies of enterprises, designed with the help of a fuzzy cognitive map, for advance planning of nature restoration activities [119].

Cloud mining plays a special role in complete subsoil extraction, including byproducts of large deposits, as well as in the development of poor deposits and extraction of secondary raw materials. All this requires multicriteria development and decision-making modeling, for which it is advisable to use the analytical hierarchical process (AHP) and Python [120]. In turn, a deep analysis of a large number of factors of accidents at mining enterprises and industrial injuries is most effective when combining cloud computing and machine learning algorithms such as DAFW, ANN, and MSE, as well as data mining—synthetic data augmentation—to solve the problem of their imbalance that limits the effectiveness of cloud analysis [121].

4. Perspective of Transition from Mining 4.0 to 5.0

Transition to Mining 5.0 is associated with the expansion of the Industry 5.0 platform, in which digital technologies in the mining industry give a place to convergent ones, as well as to human-centric production. The latter is characterized by the priority of protecting the health and restoring disturbed natural ecosystems. Today, an understanding is gradually emerging that the transition from Mining 4.0 to 5.0 should be carried out as a synchronous development of geotechnology and convergent technologies—nano-biochemical and information-cognitive [27].

To perceive the global values of human-centered and environmentally friendly mining, the national strategies for the transition to Industry 5.0, such as "Made in China 2025" and Japanese "Society 5.0", were established [21]. In specific segments of the extraction of mineral resources, the material basis of the Mining 5.0 digital platform includes collaborative robots—entities, the replacement of which will allow people not only to protect the latter from hard, noncreative work and dangerous conditions but also to provide an economic opportunity to mine under any prices in the global commodity market [122,123].

4.1. Industry 5.0 and Society 5.0 as the Platforms of Transition to Mining 5.0

In general, material production technological development to Industry 5.0 with a characteristic human-centered society is objective and reflects the growth of social needs for minerals, regulated by digital technologies (Society 5.0, Figure 13 [124]).

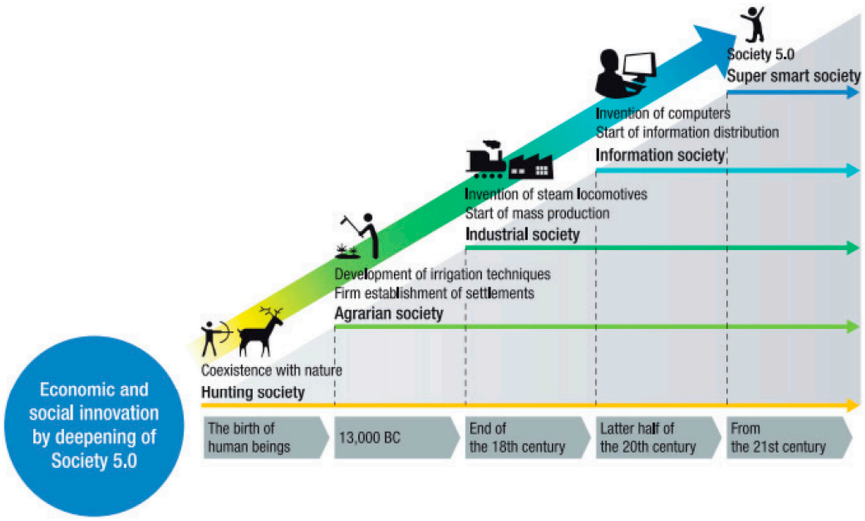


Figure 13. The Evolution of Society 5.0 (Reprinted from Ref. [124]).

Industry 5.0 serves as a platform for the development of a new aspect of mineral resource extraction—a closed cycle of using water and fossil fuels to reduce greenhouse gas emissions through the creation of new water treatment and desalination systems, energy generation from the combustion of associated coal dust and methane [28]. When designing such systems, artificial intelligence and big data are actively used [125].

4.2. PostMining and Green Mining as a Specific Feature of Mining 5.0

Recycling of natural and mineral resources as a component of Mining 5.0 is a part of postmining—the change in resource usage from natural ecosystems disturbed during mining to a new prosperity of resource clusters [126]. This, on the one hand, fits into the concept of human-centric Industry 5.0; on the other hand, it should be based on its breakthrough technologies that form Mining 5.0 (advanced neural networks, cloud computing for analyzing large amounts of data for comprehensive environmental and production-economic monitoring) [127]. Advanced digital technologies such as neural networks play an important role in the development of postmining, as well as in the advanced prediction of mining equipment failure. In particular, the lightweight convolutional neural network has been actively developing recently, proving its efficiency as a digital tool for the prediction of damages to mining equipment (such as conveyor belts). Such neural links have high-speed processing of a large number of images (for joined Yolov4 and MobileNet links—more than 70 fps with more than 90% accuracy) [36]. The application of a convolutional neural network to prevent rig failure gives an accuracy of 88.7% [37]. More advanced self-learning networks make it possible to successfully generate solutions to environmental problems in mining clusters, which is illustrated by the example of using Kohonen's network to adjust the strategy "The European Green Deal" based on the analysis of numerous environmental changes caused by underground and surface mining in Europe [38].

An important place in postmining is the restoration of biodiversity in places of intensive mining after closing the enterprises. Research in this area affects the convergence of geotechnology and microbiology in terms of the accelerated restoration of forest cover on lands occupied by mine and quarry fields and dumps [128]. It also concerns the selection of plants with the most successful vegetation in difficult physical and chemical conditions of zones of intensive mining [129] and the selection of biochemical compositions in areas of intensive reclamation for accelerated restoration of the ecosystem [130]. The concept of a new ecosystem on the site of a wasteland formed during the cessation of mining is being implemented in studies of the correlation between biota restoration and ecosystem development on the former coalmine sites [131].

As part of postmining, a new approach to environmental engineering is being developed in the transition from reclamation to revitalization in order to create the most sustainable and useful for humans and nature new ecosystem in mining clusters [132], reshaping the economy of old industrial regions upon completion of mining (for example, through the development of tourism) [133]. The European experience of postmining is associated with the production of electrical and thermal energy from secondary raw materials and wastes of extraction and primary processing of minerals, as well as with the study and implementation of alternative land-use planning scenarios (TRIM4PostMining), which actively involve virtual digital technologies [134].

Much attention in postmining research is paid to neural network applications for investigation in satellite images of residential areas and infrastructure, mining facilities, and water and forest resources, with the assistance of artificial intelligence, in order to plan nature restoration work optimally [134], as well as to analyze the dynamic factors of the transition from energy production from fossil fuels to hydropower [135]. The attention of researchers is also drawn to the formation of water reservoirs in former quarry fields and areas of large subsidence of mine fields [136] and the formation of recreational, tourist, and fish-breeding centers there [137].

The current incarnation of the upcoming Mining 5.0 is green mining, which is changing the ecological and economic landscape of the industry due to the new technological architecture of digital transformation and the perception of the global business community as the "gold standard" for sustainable resource and environmental investment [138]. It is important that if the territories systematically go through reclamation upon completion of mining, then it is possible to additionally obtain investment areas that contribute to the development of the region [139].

The transition from fossil energy sources to alternative ones in old coal mining clusters requires the implementation of a public initiative (within the framework of Society 5.0), which should ensure a gradual transition from an economy "tied" to mining to an economy of consumer and high-tech services and green energy (Figure 14 [140]).

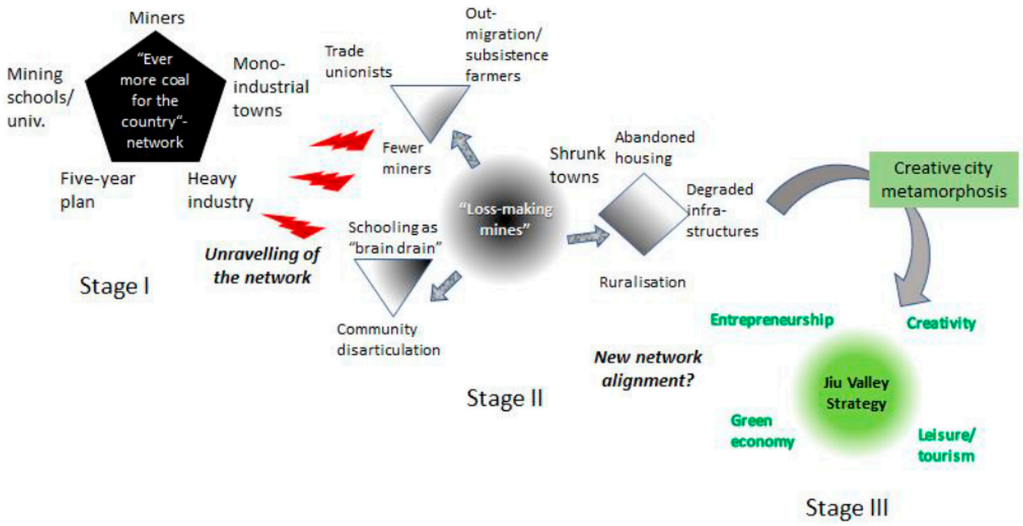


Figure 14. Stages of strategizing the development of Jiu Valley territory (Romania) after ending coal mining activity (Reprinted from Ref. [140]).

4.3. Biochemical Mining as a Convergent Technology of Mining 5.0

Reducing the anthropogenic impact on the environment in the Mining 5.0 system is seen by many authors as possible by expanding the place of bioextraction of minerals from the subsoil, which is consistent with reliance on ESG investing in the long-term transformation of the extractive sector in the Society 5.0 paradigm [141].

The biochemical method of mining, as a promising segment of convergent technologies, is largely based on the cultivation of certain microorganisms that can quickly absorb the valuable components of ores. For example, the future mining of pyrite (sulfur-containing chemical raw material) can be conducted with bio-oxidation, for which the RNA (ribonucleic acid)-modified chemolithotrophic acidophile bacteria is used. It will be a certain step towards the transition from geotechnology to biochemical technology [142]. There are studies of enriched iron-reducing bacteria cultures [143] and the biosorption of toxic metals from mine waters (in particular, during the extraction and processing of phosphate ores) [144], since traditional methods of mining and processing ore can cause irreparable harm to the environment and use a large amount of water for washing and flotation.

4.4. ESG Investment as a Main Finance Instrument for Mining 5.0

In general, it is expected that ESG (environment, social, and governance) investment, characteristic of Mining 4.0, will move to Mining 5.0 as the main form of green investment—the financial basis of green mining [145]. Further, it is possible to analyze energy consumption in the region and country in real-time and adapt energy production using breach-through digital technologies [10]. Moreover, the core technologies of Mining 4.0, critically needed for its expansion—industrial Internet of Things, autonomous robots provided with machine learning, unmanned equipment, etc.—are increasingly associated with the imperatives of Mining 5.0 (recycling of nonrenewable resources, full extraction and careful use of fossil fuels, replacing humans with collaborative robots and complete biodiversity restoration) [146]. In particular, the expected Internet of Everything (part of the Industry 5.0 platform) makes it possible to overcome the technological limitations of the transition from Mining 4.0 to 5.0 [147]. As a result of that, the concepts of lean and human-centric production, the adaptation of mining to global demand for them [148],

and increasing the digital maturity of the resource sector to the level of Digital 3.0 will be developed as part of a single convergent technology platform [149].

5. Conclusions and Prospects

This review examined a group of research in the development of mining technologies up to the level of Industry 4.0 and 5.0 (Mining 4.0 and 5.0, respectively). It was found that their technological platforms (Mining 4.0 and 5.0) integrate end-to-end digital technologies that are changing both mining and energy sectors and carry unprecedented opportunities to increase labor productivity and safety, reduce environmental damage in mining clusters and restoration of biodiversity, flexible management of enterprises, depending on the situation in the commodity markets.

The very process of transition from Mining 3.0 to 4.0 is mediated by such processes as digitalization and the introduction of cyber-physical systems into traditional geotechnology (surface and underground), as well as into the management of mining enterprises. The prerequisite for such a transition is the stabilization of the mining of minerals in the conditions of fluctuations in raw materials markets, the widespread introduction of lean production, and the expansion of renewable energy.

Today, we can see transitional technologies such as "assistants" of operators and engineers with artificial intelligence, portable wearable smart sensors, machine vision and learning on separate equipment, etc.

In turn, the expected transition from Mining 4.0 to 5.0 is due to the predicted dominance of the circular economy and renewable energy, as well as the emergence of a human-centric industry. Therefore, the processes accompanying the transition to Mining 5.0 include the widespread replacement of humans with collaborative robots, the artificial intellectualization of mining enterprises management in integrated systems of minerals extraction and processing, the introduction of biochemical technologies for the extraction and restoration of biodiversity, the final transition to ESG and green investments.

Transitional technologies of "Mining of the Future" (5.0) are being laid today and include the virtual design of reclamation and the use of neural networks to assess its capabilities, biochemical extraction of substandard ore deposits and underground coal gasification, and lean production (saving resources by mining companies).

The very process of transition from Mining 3.0 to 4.0 and further to 5.0 takes the form of the coexistence of new and old technologies with the gradual displacement of the latter; their overlap and intersection (transitional forms) are quite rare.

The issue of the transition from Mining 3.0 to 4.0 is being discussed in light of industry 4.0 expansion (artificial intelligence and neural networks, Internet of Things and smart sensors, drones and autonomous robots, digital twins, blockchain, big data, machine learning, and 3D visualization). Researchers are interested in the practice of using virtual gaming reality to train mining engineers, the Internet of Things ecosystem for the development of unmanned processes, and in the future—unmanned mines.

In turn, the transition from Mining 4.0 to 5.0 is considered by authors exploring the creation and application of the Internet of Everything and collaborative robots, recycling of natural and mineral resources, postmining and restoration of biodiversity, and convergence of geotechnology and microbiology for bioextraction of minerals. Already today, the use of break-through digital technologies is widespread for planning the revitalization of resource clusters. A specific transitional platform from Mining 4.0 to 5.0 is seen by some authors as green mining, the information architecture of which should correspond to the Digital 3.0 level, and the financial basis should be formed by green and ESG investments.

The existing limitations of the transition to Mining 4.0 include, first of all, the observed insufficient digital maturity of the mining sector (the coexistence of digital technologies of different generations, often within the same enterprise), the lack of political will to tighten labor safety and environmental requirements, the slow progress of technological convergence in terms of combining biochemical, information, and cognitive technologies.

We see the expansion of horizons of future modernization of mining in the convergence of geotechnology, digital, biochemical, and environmental technologies in the context of the expected transformation of Mining 4.0 into 5.0.

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