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Automated measurement systems in mine water management and mine workings – A review of potential methods

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ABSTRACT

There is limited research on the application of digital technologies at mine sites for treating and managing polluted mine water. This review will identify underlying models, theories and frameworks applied to the mines, and used to “smartly” treat and manage mine water. The aim is to provide informed details about these technologies in order to move the mine water management sector to the Industrial-Internet of Things (IIoT).

The Internet of Things (IoT), Wireless Sensor Networks (WSN), artificial intelligence, swarming drones and automation are the most widely used smart technologies in current industries, especially the mining industry. In recent years, automation has seen substantial growth in the mines, for example, self-driving trucks. In addition, a lot of work that usually was done by humans can be performed better and safer by machines and drones. WSN are used for automated measurement systems, especially for collecting flow data and physico-chemical parameters for managing and treating mine water. All of these are operated through the main smart technology which is the IoT. It is expected that these technologies will positively affect the mining industry in the long run, making it possible for the mines to reach their expected full-scale production more easily. In this study, latest digital technologies to optimise mine water management and state-of-the-art mines are reviewed and described. In addition, the advantages of using these digital technologies are investigated.

1. Introduction and background

Industry is moving from the third industrial revolution (Industry 3.0) to the fourth industrial revolution (Industry 4.0), and this implementation of disruptive technologies will vastly influence the mining sector, especially mine water management. Nanda [2] describes the importance of integrating Industry 4.0 technologies in mines to improve production and increase profits. In order to survive in the competitive market, smart mining is imperative. This will see technologies such as Big Data, Internet of Things (IoT), Machine to Machine (M2M), data analytics, sensor networks, drones, robotics increase efficiency in critical mining activities such as

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mine water management, drilling, surveying, processing and transportation [2,3]. The aging technology in some mines needs to be improved, which means that the mining departments need to be modernised to prevent premature mine closures, job losses and persisting mine water contamination by potentially harmful metals on the mine site [4–9]. Hopwood and Deloitte Touche Tohmatsu Limited [10] emphasised this issue accurately: "With each passing year, water has become a more critical issue for the mining sector" and because of the many changes that the mining industry encounters, "mining companies must enhance their approach to water management". Integrating these digital technologies will reduce the barriers that impede fully optimised production in the mines through optimised water management. These latest digital technologies include Wireless Sensor Networks (WSN) (e.g. [11–13]), fast speed networks such as the fifth generation of wireless network communication, the 5G network (e.g. [14–16]), robots [17] or cloud computing (e.g. [18,19]).

Only a few mines are currently utilising these digital technologies, and their experience showed that they are profiting substantially from these innovations. These mines include the Hull Rust (United States, Minnesota), Garzweiler (Germany, North Rhine-Westphalia), Escondida (Chile, Antofagasta Region), Bingham Canyon (United States, Utah), Berkeley Pit mines (United States, Montana) [20], Rio Tinto Pilbara iron ore (Perth, Australia: "Mine of the Future") [2], BHP Billiton's "Next Generation Mining" project [3], the Donghuai Mine in China's Guangxi Province [21] or Newtrax Technologies (Canada), who also implemented artificial intelligence systems [22]. All of them have in common that they use state-of-the-art technologies and software, ensuring that they maximise their profit without having to cut off their employees [23,24]. In reviewing the most innovative mines using ground-breaking technologies and software, this article will prove that the Industrial-Internet of Things (IIoT) [25–31] for mine sites (sometimes called Mine Internet of Things: MIoT) is the future for optimising mine water management.

Industry 4.0, in simple terms, refers to the IIoT [25,26], while the IoT refers to a system of physical things and technologies which consists of software, electronics, sensors and connectivity to ensure that the performance is enhanced by sending information or data to other connected devices and vice versa [32–35]. However, IoT is not as well received in industry yet, as compared to the consumer world. One of the reasons is that the IoT in the industry comes with a number of disadvantages such as the types and levels of security and a potential production disruption due to maintenance failures of the technologies [25,26]. Overcoming these barriers results in the IIoT. These technology systems can be applied in many sectors such as mining, water, energy and even the building industry. It comes with several advantages such as saving costs, increased production and flexibility in the workplace [32].

The relationship of sensor network with IIoT is critically important, i.e. the IIoT system yields good results when a WSN is applied as opposed to cabled systems [12,36]. With WSN, applications and companies can strategically place a large number of sensors in the area of interest to gather large quantities of information (e.g. [37]), which is not possible with cabled sensors. Therefore, by using WSN, the costs of installation and maintenance are dramatically reduced.

An additional advantage of Industry 4.0 applications in the mine water sector is its contribution to Integrated Mine Water Management Plans (IMWMP) as outlined by Chahbandour [38]. An IMWMP also requires that all mine departments cooperate; mine water management is incorporated into the overall mine plan, on-site and off-site risks relating to mine water are understood and internal and external commitments of the mine are supported at all times [38].

This article describes several disruptive technologies that can contribute to optimising future mine water treatment and will bring water management into the technological age of Industry 4.0. Examples from the mining industry, where some of these technologies

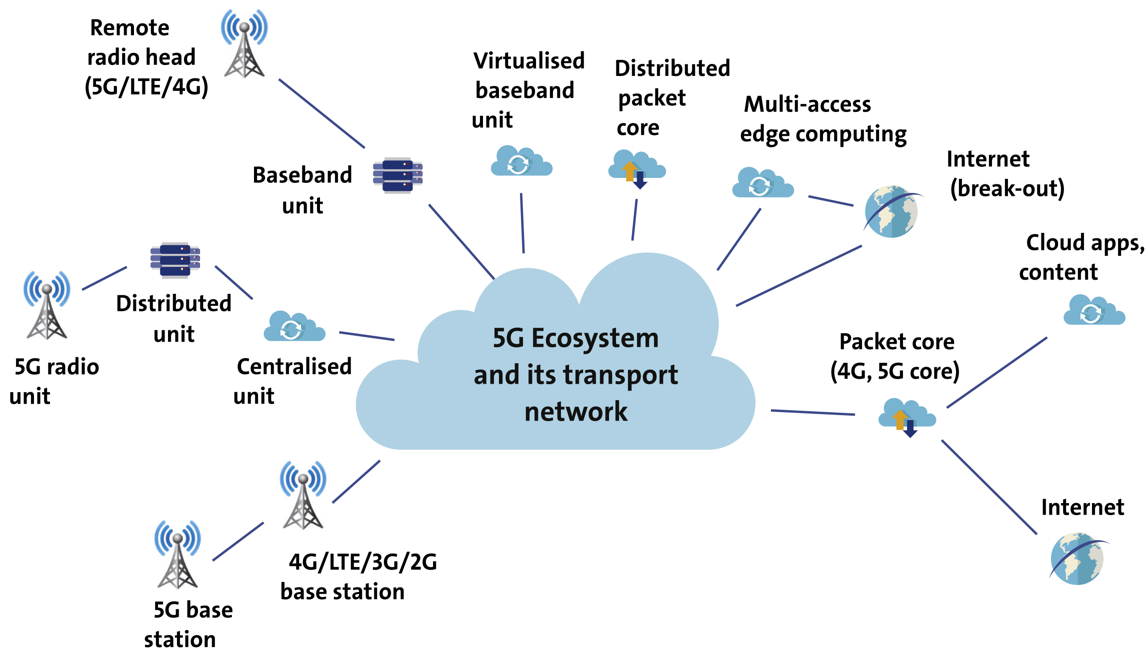

Fig. 1. The 5G ecosystem.

are already in use, will be presented and examples from other industries, where some of these technologies are already standard will be described. In the discussion and conclusions, these technologies will be used to outline future mine water management strategies based on these interruptive technologies.

2. Problem statement and definitions

Many mining companies are reluctant to fully adopt Industry 4.0 or are waiting to implement the technology. However, efforts are being made at several mining companies that already use automation options [39,40]. This is a first step to qualify mines into the fourth industrial revolution, yet more efforts might be needed [41]. The sluggish advancement of this technology sees the mines slowing down in production compared to those that implement state-of-the-art technologies, and others affecting nearby community water sources, which can be considered a severe concern in some areas. In South Africa, one of the largest iron ore mines prides itself as the most technologically advanced mine and is already well advanced in the production of Industry 4.0 [42,43]. This mine is dominated by robotics systems, similarly to many other mines worldwide (e.g. [39,40]), therefore, it might be safe to mention that approximately 95% of the world's mines are still moving from the second industrial revolution to the third.

Usage of electricity for mass production can be classified as the second industrial revolution as mentioned by Yin et al. [44], while Industry 3.0 can be defined as automated production using electronics, IT systems, robotics as well as programmable logic controllers [44,45]. The main limitation blocking most of the mines to smoothly move to Industry 4.0 is basically the type of network they use. Highly recommended for this transition is the 5G network (Fig. 1), because of its fast speed [46,47] and it will help fuel the rise of IoT technology and provide the infrastructure needed to carry out Big Data processing [14,48]. This network will add vital contributions to the industry, such as transferring or moving Big Data with greater speed [48], increase the responsiveness of connected devices such as WNSs and other smart devices as its now with Verizon 5G tests in Chicago, U.S.A [11,14,16,49,50].

3. Methodological approaches

3.1. Dynamic mine water management

A dynamic system approach for treating mine water is slowly becoming a norm with modelling software such as GoldSim, MATLAB Simulink, Geochemists Workbench and PHREEQC being favoured over the normal spreadsheet-based approach. Dynamic modelling is highly useful when the aim is to predict the mine water quality and quantity over time, which helps to predict the future of mine water management. Nowadays, it is recommended to use dynamic and probabilistic methods when designing mine water management systems, which will require a dynamic system modelling package (e.g. GoldSim, MATLAB Simulink, STELLA, Vensim) that can integrate all

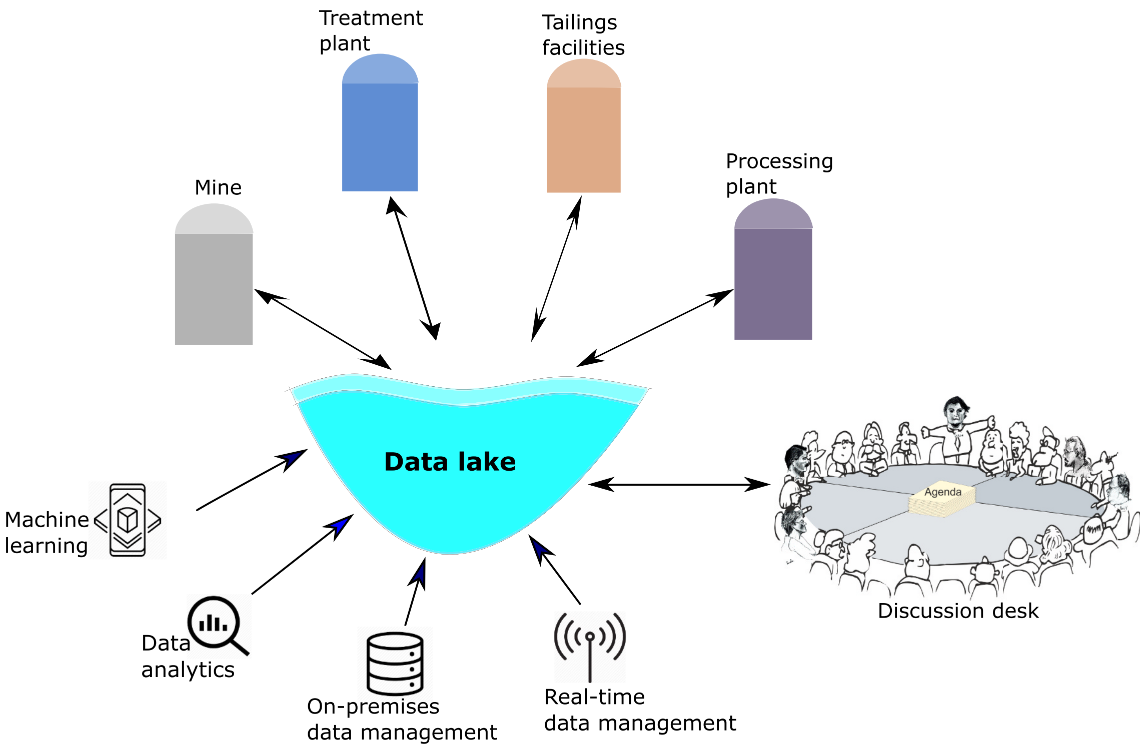

Fig. 2. Data Lake development on the mine site for free flow of data.

possible factors that might affect mine water management [51,52].

Applying these water software technologies results in a good mine water balance development for the whole mine site [53]. With the wide range of dynamic software, GoldSim is the most used in generating mine water balance models, mainly because of its flexibility. Though dynamic models are not new and have been around for a long time, they are not utilised in mine water management to a degree that would be possible. Dynamic water balance calculations include all the mine site departments; therefore, this approach provides a highly qualitative tool which can be used to track the system's performance. Dynamic system modelling is helpful because it includes all possible factors contributing to the mine water quality and quantity. Shift to this approach will be vital for operating future mines and such consideration will also become important in the wider industrial sector as Kunz and Moran [54] have shown.

3.2. Data silos

Currently, many industries, including the mining industry, work through "data silos". A data silo can be considered as a group of raw data that can only be administered or controlled by one department and is isolated from the rest of the organisation or other departments [55], often to keep secrets or exclude others from getting overall insights [56]. Figuratively speaking, data silos are the electronic safes of modern times and are, therefore, preventing efficient development on site. For example, a mine site consists of various departments (e.g. the mine, processing plant, treatment plant, tailings facilities), which are not always communicating with each other in terms of data sharing, resulting in a data silo style of data management. Data silos come with many disadvantages such as difficulties in analysing the data, i.e. data may sometimes be stored in formats that are inconsistent with one another resulting in time consuming standardisation of data and compilation into appropriate formats before it can be used [55,57]. Varying levels of security and data duplication is also caused by data silos [55,57,58]. Therefore, this data handling practice needs to be broken down and a free flow of data and communication across the mine site departments implemented instead. With the emerging digital technologies, some of the mines are moving into more comprehensive solutions for data management, i.e. all the mine site departments will now transfer the data into a single data retrieving and management system (e.g. [59]). This is known as either "Data Warehouse" or "Data Lake", which is a big data storage facility for the company on which multiple functions can be performed on such as real-time data management, on-premises data management, data analytics and also goes as far as using the data for machine learning (Fig. 2; [56,60]). Simplified, a Data Warehouse stores, processes and analyses data in an organised structure, while a Data Lake holds raw or unstructured data of various types, and processes and analyses this data at the time of usage [56]. One of the first integrated mine management systems having been invented was Al.Vis from the German company Wismut GmbH in 2003/2004 ([61], pers. comm. M. Haase). This resulted in an easier data management on their mine sites and helped to improve the effectiveness of the water and site management processes.

3.3. Sensor network-based mines

A commonly used approach being followed by mines nowadays is data collection through a variety of sensors. Mines are developing sensor network-based online monitoring systems consisting of data monitoring sensor nodes, base stations and monitoring centres [62,

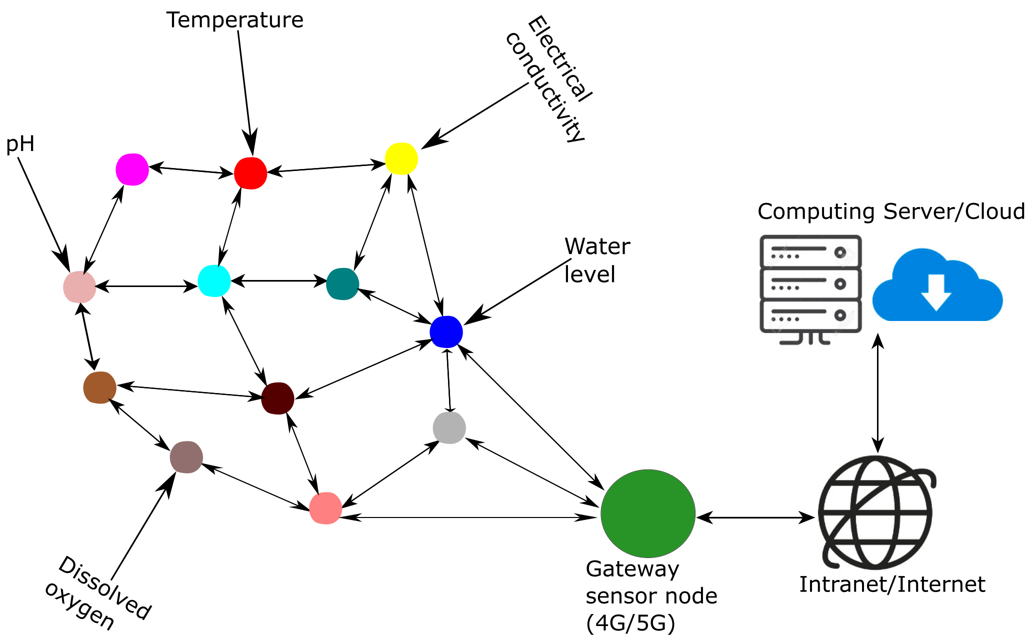

Fig. 3. Wireless sensor network (WSN) deployment on the mine site.

63]. Wireless Sensor Networks are strategically placed on the mine site to collect relevant data and it is imperative that these sensors need to be suitable for the rough mining environment, requiring ruggedized sensors [3]. In the mine water management division, these sensors collect flow data and physico-chemical parameters such as pH, electrical conductivity, temperature, dissolved oxygen, turbidity, biological oxygen demand, chemical oxygen demand or redox potential (Fig. 3). This information is then transferred to the Data Lake via the available network on the mine site [11,49,50,62,63]. Compared to the existing network infrastructure, a 5G network will be more efficient for transferring these data from the sensors to the Data Warehouse or Data Lake [11,14,64].

4. Models or theories

Effective treatment of mine water has often proven to be an illusion, with a number of mines, especially abandoned ones, contributing severely to water pollution. The current models used in treating mine water are not ideal as they treat mine water based on the compositions and volumes of water entering the plant (Fig. 4 left). This simply means that the plant needs to react instantly when the volumes or chemistry of mine water changes. In most cases, there is no interaction between the precipitation, water inflow into the mine, technological changes within the mine, water analyses of the plant and the outflow of the treated water [1,52,65–68]. Application of digital technologies will allow for this interaction to happen and, therefore, proving the need for the mines to move to IIoT. In consequence, WSN collecting and transferring this data to the server will lead to improved water balance and chemical modelling due to the frequent and reliable data that will be recorded.

Based on the literature and information review about the mentioned topic, the following summary can be given: all the reference lists of the included papers, information gathering from consultants, electronic database and grey literature searches, reveal that mines are widely using the traditional or "old style" of mine water treatment and management (e.g. [1,52,65,66]). However, some research attempts to move into the fourth industrial revolution in the mining sector (e.g. [39,40]). By introducing these digital technologies, e.g. IoT [19,32,40], WSN [11,49,50,62,63] or the 5G network [14,16] at the mine sites would ensure that all parameters that need to be known for an optimised mine water process will be collected and used to predict the water chemistry and treat mine water effectively. This, for example, is currently being practiced in Ghanaian mines (pers. comm. Ricky Bonner, Miwatek); however, instead of using WSN, they are using cabled sensors. Therefore, this forces them to implement these digital technologies on a smaller scale [12,36,50,69,70].

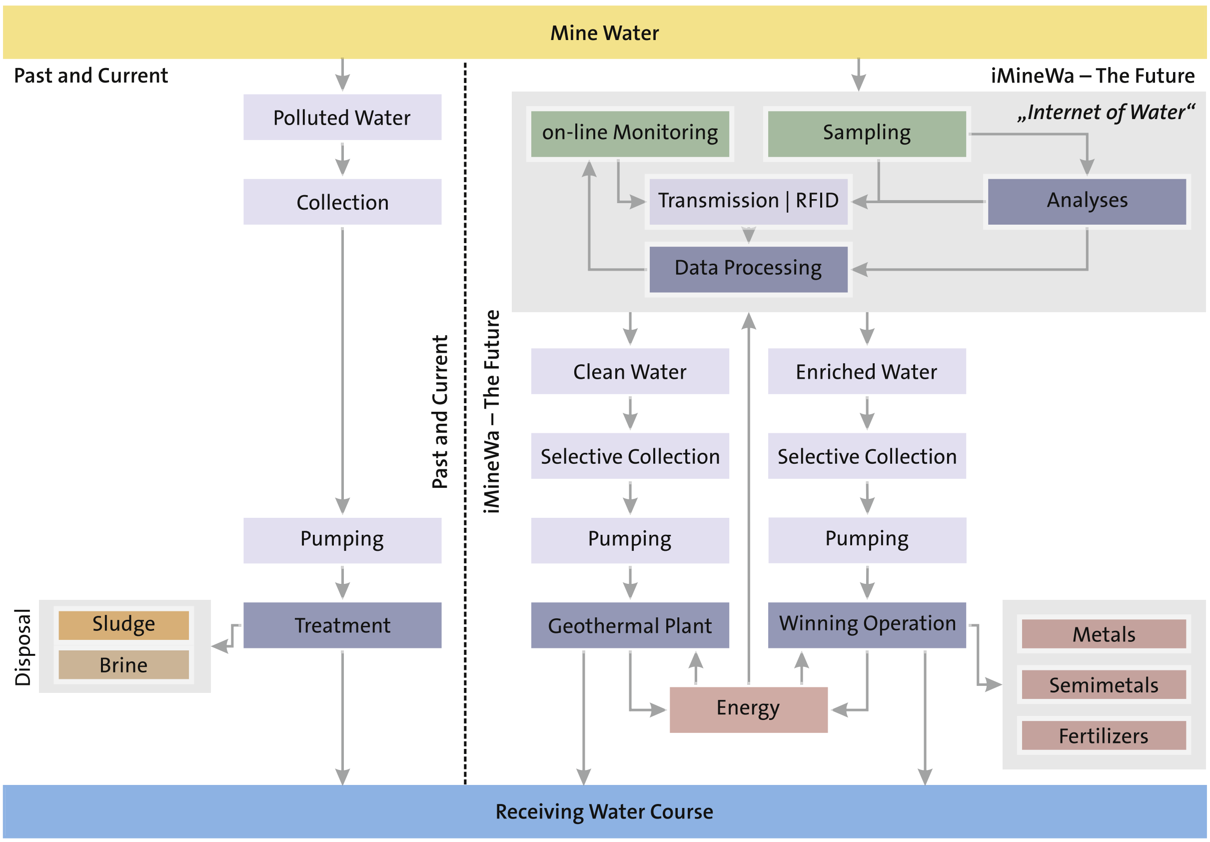

Fig. 4. Comparison of past and current mine water treatment (left) with future mine water treatment plant using elements of iMineWa (right).

5. Related work

5.1. Introduction

The most recent technologies in mining show a convincing industry shift towards sustainability [4,41]. These digital technologies make it possible for the mines to reach optimised production, and tackle problems such as acid mine drainage much faster. Yet, there is little progress of implementing these technologies for mine water management, though other departments in mines and certain industries are experiencing good technology advancement such as implementation of artificial intelligence (e.g. [26,39,40,71–73]), swarming drones (e.g. [71,74–77]), RFID and NFC [78–82], as well as WSN (e.g. [11,12,36,37,49,50,83,84]).

5.2. Artificial intelligence

Artificial intelligence (AI) presently drives the decision-making in a lot of industries [85,86]. They utilise smart data and machine learning to enhance the efficiency in operations [73,87], safety at the mine sites [88,89] and workflow in production [73,87,90]. Using digital technology in mine sites for data collection and feeding the AI systems with this data will ensure that AI supported software learns automatically from features in the data. In addition, this will ensure that data is collected and processed faster and smarter than the previously used data collection and processing methods. As the mining industry changes and grows daily, AI and machine learning influences the future choices of today's mines. For example, AI is used in economic geology, to optimise the mineral exploration process [73]. It is also used in machine autonomous vehicles, e.g. in narrow mine tunnels where self-driving trucks require AI technology for easy navigation (e.g. [40]). AI technology also helps to ensure the safety of the miners and improves the safety of mining workplaces and the environment in general, e.g. it can be used to predict slope failure in open-pit mines [89]. Lilić et al. [88] also describes using AI methods to identify hazardous places in surface mining environments. Introducing this technology in mine water management should be in the form of computational modelling – the knowledge driven algorithms based on computer programs that utilises expert systems and fuzzy concepts to make decisions (e.g. [85,86,91,92]). The main tool used in machine learning to predict mine water quality are artificial neural networks (ANN) which are computational models consisting of a lot of processing elements which receives input data and immediately produces a single output. For instance, Maier et al. [93] used ANN to model and eventually predict the residual aluminium concentrations in southern Australian surface waters.

5.3. Swarming drones and drones

Swarming drones are a fleet of drones that operate together and can make decisions based on information gathered by one, many or all the drones contributing to the swarm [94]. They originate from military research seeking to reduce the loss of soldiers and equipment in warfare [95]. Several mines belonging to one of the biggest mining companies now use swarming drones to gather large quantities of data. Swarming drones are a technique that makes it possible to evaluate collective problem solving without having any centralised control [71]. Aerial photography, surveillance, site mapping and infrastructure inspection are some of the areas, where swarming drones are already incorporated [74–76]. This data collection method is now highly preferred as compared to collecting data by using helicopters, because these swarming drones are cheaper to use, faster, can collect data in large quantities, and meanwhile, are highly reliable [75]. Some areas at a mine site might even not be accessible with self-driving trucks, and therefore, mining companies use drones in such areas to gather data. Another key point with drones is that they have cameras and they can take images and videos while collecting data. This camera feature enables specialised software to create 3D models of the mine sites, their infrastructure and open pits [74–76]. Therefore, drones and swarming drones substantially contribute to time saving and costs cutting as opposed to creating 3D models using ground-based lasers or surveyors. Some of the drones are even operating with embedded sensors and these are utilised for mine water management, e.g. at Century Mine in northern Queensland, Australia, where sensor embedded drones were used to identify pyrite oxidation in subsurface rocks [75]. At the Hannukainen mining development site, Northern Finland, Rautio et al. [96] used unmanned aerial vehicles (UAVs) and thermal infrared (TIR) to investigate groundwater-surface water interactions that might be relevant for the final mine design. The same technique was used to support the mine development of the Sakatti mine site, also in Northern Finland (pers. comm. Veli-Pekka Salonen).

5.4. Wireless Sensor Networks (WSN)

Deployment of WSN for data collection is also becoming fashionable in mining environments. In most cases, the mines use water quality sensors to manage mine water [37,84]. This can be considered an automated data collection and control system, i.e. data is collected, processed, stored and transmitted to the monitoring server for analyses (Fig. 3). Data is communicated through the available network on the mine site. Therefore, this data allows for a better business decision making, and avoids instant reaction when mine water quality changes [1,11,12,36,37,50,83,84]. Tuna et al. [97] describes a theoretical approach, where continuous water monitoring was modelled with MATLAB using autonomous buoys and mini boats on the Kirklareli Baraji Dam (Turkey), collecting data, which was transmitted via a wireless network. Their proposed autonomous mini boat measured temperature, electrical conductivity and nitrate concentrations. A real system was designed, installed and tested by Sun et al. [98] in a lake near Lamar University, Beaumont (Texas, U.S.A.). They monitored water temperature, dissolved oxygen and pH values in real-time using STORM 3 data loggers, and they used a wireless network to transmit the data from the loggers to the server. Based on their studies, they conclude that choosing the locations for the network are imperative for a well-functioning system. These problems with choosing a good location were also eminent when a mine water monitoring station (temperature, electrical conductivity, pressure) at the Nikolaus-Bader-Schacht in Tyrol (Austria) was installed by the second authors' research group. Though the provider's maps show a good cell phone connection, trees and a narrow valley made finding an appropriate location for the antenna tedious.

5.5. RFID and NFC (radio frequency identification and near field communication)

Radio Frequency Identification (RFID) is a technology that identifies and tracks items by using radiated and reflected radio frequency power. Usually, an ordinary RFID system comprises of a reader and a tag [78,80–82]. An RFID reader is made up of at least one antenna, a radio frequency transmitter and a radio frequency receiver [99], while an RFID tag is an electronic tag consisting of an antenna and a microchip [80–82]. Both, the tag and reader communicate with each other via backscattering, which simply means the reflection of waves back to their original place [80,100,101], and they utilise ultra-high frequencies (UHF) from 860 MHz to 960 MHz [102].

RFID tags consist of a small microchip, which can store not more than two KB of data [103,104]. Information from these tags can be read from a wide range of distances, e.g. toll roads use an electronic toll collection process, and the reading distance there is more than 3 m. Toll roads or cloth stores use RFID technology incorporating car or cloth embedded tags, while the reading system is near or above the road or the store's exit location. Data is exchanged between the reader and electronic tag attached to the car or cloth through UHF radio waves [78,80,102,105]. Mining work clothing are also incorporated with RFID tags to track employee locations and ensure that they are safe [2].

RFID systems have been successfully applied in a wide range of areas such as healthcare, transportation, logistics, agriculture, manufacturing, and many other services [79,82,106,107]. There are a wide range of uses for the RFID technology, but mainly it is used for tracking and identification purposes. It can also be used to store important information for products or in biometric, electronic passports [108]. In agriculture, RFID tags have already been used for tagging vine rootstocks to identify various hybrids for scientific investigations [107], and the second author developed an RFID tag for the tracking of a tracer injection probe. A future technology, which is presently being developed by the first two authors, is the application in mine water sampling. Currently, sample bottles are labelled at the sampling location and this is then recorded in the field book. However, sometimes sample bottles get wet during the process and it is difficult to write on them. In addition, the process is time-consuming and during transport the marking or a sticker may

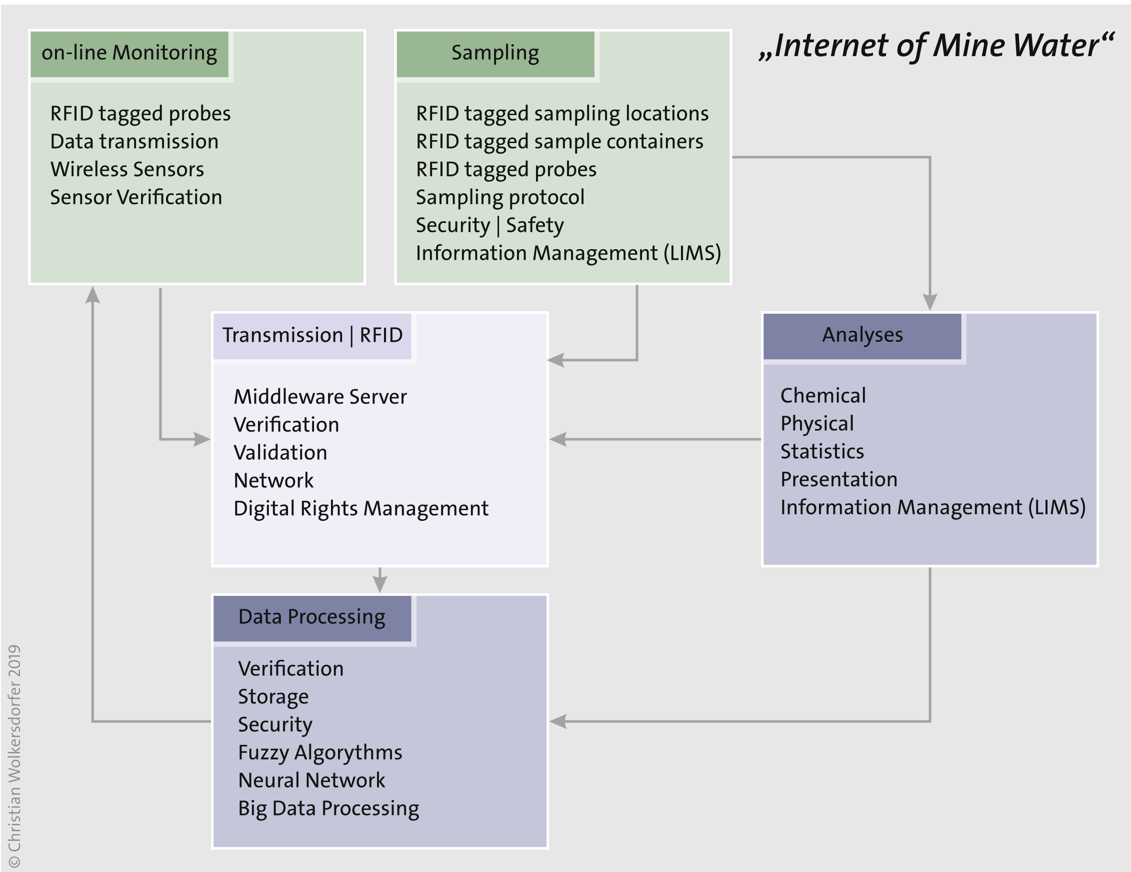

Fig. 5. Relevant steps and their connection in the "Internet of Mine Water" (from [45])

smear or scratch. With water sample bottles equipped with RFID technology, the extraction of mine water can be faster and smoother. A microchip incorporated in the plastic bottle can store relevant information such as sampling location, time and date, or it can just be a simple tag. In the analytical lab, this information can later be downloaded from a server or data lake. In other means, this is a 3-way technology development which involves electronic identification tags (eTag), web application (eApplication) and storage location (eStorage), unlike the current method which only uses eTags for tracking and identification. In addition, this will close a gap between the sampler, laboratory and end-user of the results by embedding an eTag in the sample containers and communicating the sampling times, sampling parameters and results between the parties involved in the process.

6. The Internet of mine water (IoMW)

Usage of disruptive technologies in mines will result in "smart" mines and, relating to mine water management, into the technological age [109], when the "Internet of Mine Water (IoMW)" [45] becomes implemented on a broader scale (Fig. 5). The term "Internet of Mine Water (IoMW)" is derived from the term "The Internet of Things (IoT)", which very likely was first mentioned in 2000 by the RFID community [33]. The IoT now is referred to all "things" that are somehow tangible and, theoretically, could be reached by an internet address. Yet, the IoMW can be more than just referring to "things" – it can also include data and the results of data processing coming from common statistical procedures or the procedures involved to analyse "Big Data". Those non-touchable objects are commonly referred to as digital objects and they can be referenced by persistent identifiers, such as digital object identifiers (DOI) or uniform resource names (URN).

This IoMW can easily incorporate smart technologies to improve the current processes and ultimately would result in intelligent mine water management (iMineWa). Parameters that can be measured and processed by these emerging technologies include: online monitoring of flow and physico-chemical parameters, results of sampling campaigns, RFID controlled sample management, results of chemical analyses of the mine water and data processing (e.g. statistics or stochastics of various scales). Because of the large volumes of data that might be collected, Big Data analysis used in the process can include expert systems, fuzzy based decision mechanisms (e.g. [67]) or neural networks [87,90]. Therefore, this eventually evolves to developed techniques in "Big Data" processing (e.g. [48]), as the amount of data to control a large mine water management scheme will continuously expand as has been shown in the previous sections of this paper.

In this concept, all water pathways into, through and out of the mine must be monitored and used to feed the IoMW with relevant data. To avoid unauthorised access, a digital rights management approach is imperative, which includes managing different access levels of the various users. Because of the problems related to wireless sensors in a real situation environment, not all sensors might become wireless in the first place. Yet, the current technology development might be able to provide innovative sensor technology which is able to overcome those problems and other problems encountered in water related sensor technology (e.g. [37]). Methods that can be included are data processing, statistical methods and simulation (e.g. GoldSim) into an expert system based decision process [68].

Recent discussions in public and scientific journals revealed that the "Internet of Things" is also connected with severe security issues [26,27,110,111]. To overcome those issues, all devices and servers need a thorough digital rights management. Some of those procedures have already been developed in Laboratory Information Management Systems (LIMS) or Scientific Data Management System (SDMS), can be part of the IoMW [112] and can generally be based on ASTM E1578 ([113]; http://limswiki.org).

Quality management must also be an integrative part of the IoMW. Users shall be able to track the source of the data and standards need to be developed to store, process and retrieve the data obtained in the IoMW. It is also essential to distinguish between raw data and processed data. With the help of meta-data, the source of the data and potential data manipulations can be traceable and the guidelines outlined in ISO 9000:2005 can then be employed [114]. To ensure proper use of data, a database management system (DBMS) can also be installed, which needs to be scalable so that other sites can profit from the IoMW. A solution to the before mentioned issues might be the implementation of the Open Platform Communications Unified Architecture (OPC UA) protocol developed for the industrial automatization under a GPL 2.0 licence. It allows, besides communication between equipment and infrastructure on a cross-platform basis also security functionality for authentication, authorization, integrity and confidentiality of the data and the communication and has already been used in around 600 water plants and wastewater plants [115,116].

Another issue that might be resolved is the management of fuzzy data and how to include fuzzy data in the decision process. Not in all cases, a mathematical or physical relationship between a parameter and the control mechanisms might exist. In those cases, fuzzy decision mechanisms need to be studied and included in the control software or model as well. Some of the fuzzy data can be estimations of flow (low, high, medium), colours (greenish, reddish) for non-sensor-based observations. In addition, it might be necessary to conduct fuzzy algorithm processing with properly measured data, especially when it comes to special analyses [117] or quality evaluation with indicator methods, as proposed by Liu et al. [118].

Finally, the data processing within the framework of "Big Data" needs to be considered and employed, to identify patterns in the dataset that might be useful for the optimization of the mine water treatment and finally a potential "winning" plant, where the metals in the mine water could be extracted on a commercial basis.

Above all, the IoMW can help in separating the water streams in a mine so that the amount of polluted water that needs treatment can be minimised. Techniques to separate different water streams in surface or underground mines are known but usually not used, because practical reasons and costs might interfere with the management of various water streams.

7. Discussion

The mining industry is currently confronted with many challenges such as low commodity prices, increasing cost of electricity and production or pressures from NGOs to provide fast and useful monitoring data. These are driving the mining sector to Industry 4.0, as it brings the industrial transformation. The implementation of these digital technologies drives an increase in skills demand, i.e. more jobs are and will still be created [119]. As much as these technologies will not change basic mining principles, using electricity and mechanics, the mine workers will communicate with their equipment through the IoT [32,120,121], and some might call themselves IT experts in the future. This paper wants to emphasise that upgrading mines to Industry 4.0 will positively affect organisations as their employees will be forced to learn new skills [122]. This will create jobs; many of the employees will be needing higher qualifications and requesting a better education. Some of these adjustments can already be seen in mines in Ghana ([6], pers. comm. Ricky Bonner, Miwatek), Chile, USA, Finland (pers. comm. Veli-Pekka Salonen) or Australia.

The mine water treatment branches in the mines must start embracing the advantages that come with Industry 4.0. These technologies will allow "smooth" reactions to changing water quality or quantity conditions in the mine, and it enables the mine to not only know that the pump has stopped, but to also know why, meaning that the pump, its control systems and motor will have to be connected to a network that will allow the operator to know everything [121,123–125]. In an ideal situation, the system will even predict when the pump is going to stop. The new skills that will be brought by this interruptive improvement includes configuring wireless devices, setting up networks or knowledge on internet protocols; therefore, this technological advancement will benefit the mining sector as a whole [126]. In this context, Industry 4.0 is defined as IIoT [25–27] with the influence of cloud computing or cloud-based systems [18,19]. It will increase the safety and security on the mine site, will enable the mines to reach full production [26] and optimise mine water management. With a data lake in the picture, communication between all the compartments in the mine that deal with water becomes faster, easier and more reliable [48,55,127].

The falling productivity in some areas of the mining sector is highly notable, partly due to lower commodity prices and lower grade ore deposits, and this can be prevented with the adaptation of Industry 4.0. A combination of technologies, production, communication and information that already can be seen in some of the mines (e.g. [5,6]) is what the rest of the mines should be investing in, i.e. investing in the future of their mines. It is important to have real-time data in modern mine water management to ensure that good and valuable business decision making becomes normality [120] in a world where water management becomes increasingly important.

8. Conclusions

This study presented an overview of smart technologies being applied in mines, their advantages and how to overcome barriers making it difficult for free flow of water related data on the mine site. It also introduced multiple approaches to embrace the use of the Industry 4.0 technologies at production level. Having an automated measurement systems or real-time data monitoring (e.g. WSN), Data Warehouse or Data Lake and improving machine learning, full scale production in the mines can be achieved by optimising the water management on site and costs can be reduced drastically. These latest digital, partly interruptive technologies are slowly being introduced in the mining environment. However, so far, polluted mine water is not the primary issue for the introduction of these technologies. They are introduced as part of IIoT and MIoT, therefore, focusing on optimising the mining process and security issues. Proper integration of the before described smart technologies will allow great improvements in dealing with structural and environmental issues, management of mine water as well as safety and security issues on the mine site. Continued advancement in IIoT technologies, and implementing them in the mine water management, will reduce the cost of adaptation and making the transition more attractive for future operations.

Outdated ways of mining, which were used for decades if not centuries without any change, are now proving to be costly with sharp decline in productivity. Therefore, "intelligent" ways of mining need to be explored and this can be possible through continuous data collection, more automation, machine to machine communication and increased data analysis. Underlying geology in mines is critically important to better manage mine water. Therefore, the use of sensor technology, 3D modelling and advanced robotics to detect harmful metals in underlying rocks could be helpful in this regard. Smart mining needs to explicitly explore interconnected communication of data in real time in all spheres of production. More future research is needed in Big Data analytics across mining processes. In mine water processes, dynamic modelling approach are critical and can yield improved mine water balance if prioritised as soon as possible.

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CRediT author contribution statement

Kagiso S. More: Literature Review, Writing - original draft. **Christian Wolkersdorfer:** Conceptualization, Supervision, Literature Review, Writing - review & editing. **Ning Kang:** Literature Review. **Adel S. Elmaghraby:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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