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Review

Equipment and Operations Automation in Mining: A Review

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Abstract: The mining industry is undergoing a transformative shift driven by the rapid advancement and adoption of automation technologies. This paper provides a comprehensive overview of the current state of automation in mining, examining the technological advancements, their applications, and the prospects of automation in this critical industry. A key focus of this paper is the impact of automation on the safety and efficiency of mining operations. Highlighting the successful implementation of Automated Haul Truck Systems (AHSs) in surface mining. Additionally, this paper explores the development of automation in underground mining and its challenges, particularly limitations in communication and localization, which hinder the development and deployment of fully autonomous systems. It also provides an exploration of the challenges associated with widespread automation adoption in mining, including high initial investment costs, concerns about job displacement, and the need for specialized skills and training. Looking toward future advancements in enabling technologies will be critical for furthering automation in mining. Machine learning and AI will play an increasingly critical role in intelligent automation, enabling autonomous systems to adapt to dynamic environments, optimize processes, and make informed decisions. This paper provides a look into human–robot collaboration in the future of mining. As the industry transitions toward greater automation, it is essential to consider the evolving roles of human workers to foster a collaborative work environment. This involves prioritizing human safety, providing adequate training, and addressing concerns about job displacement to ensure a smooth transition toward a more automated future.

Keywords: mining automation; equipment automation; operations automation; robotic operations

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1. Introduction

Mining has experienced many significant leaps in technology over its long history. These periods of time can be classified into four distinct industrial revolutions. The first was the manual stage, which began in the 1700s. This period saw the advent of steam-powered machinery, early mechanization of production, and rail transport. These advancements drastically improved production and efficiency and lessened the reliance solely on human labor.

In the 1800s, the industry experienced another revolution in technology, which included the first use of electricity in mines with electrical pumps removing water from coal mines [1]. This stage saw the widespread implementation of mechanization. Coal mining machines such as continuous miners and longwalls were developed for performing the majority of the production work. For example, in West Virginia, mechanization started in coal mines in the 1920s, and by the 1970s, a majority of work was performed through mechanical means [2].

Haul trucks, loaders, shuttle cars, and conveyor belts replaced most of the in-mine rail networks allowing for more flexibility. This revolution in mining removed the need for large-scale labor forces and drastically improved efficiency while also drastically improving safety. This effect can be seen very clearly in the number of fatalities in the US: in 1911, there were 883 fatalities, 322 in 1941, and 164 in 1971 [3]. This incredible feat was in large part due to mechanization; instead of manual labor, miners used heavy machinery to do much of the heavy lifting and dangerous work. Miners were still required to operate these pieces of equipment, so exposure to hazards was still an issue. Following the revolution of mechanization, mining saw the introduction of automation, beginning a new technological revolution in mining.

In mining operations, autonomous systems are usually used for monotonous tasks that require precision and speed that humans cannot perform. Lynas and Horberry [4] detail early mining automation with unmanned rail carriages, remote control ore extraction machines, and automatic rock-bolting machines. This stage has also introduced the computerization of mining. Programmable logic controllers (PLCs) were first used in coal preparation plants to automate start-up and shut-down procedures [5].

One of the benefits of deploying these autonomous technologies in mining is that tasks can be executed faster with precision while simultaneously mitigating human risks by moving operators away from potentially hazardous working environments. Automated systems can enable more precise and efficient mining operations, minimizing waste and reducing the environmental footprint of mining activities.

According to McNab and Garcia-Vasquez [6], automation has been around for over 50 years in the mining sector: enhancing efficiency, removing operators from hazardous environments, and improving the accuracy and reliability of data collection. However, unlike the previous wave of mechanization, the revolution in automation is still not ubiquitous. There have been many issues with implementing automated mining technologies into the mining industry, which will be discussed in this review.

Very recently, a new revolution in mining technology has begun to impact the industry. The digitization of mining is the newest frontier of mining technology. Research and development are being applied to improve communication and wireless systems in mines. The potential for this could pave the way for zero-entry mining, where no humans are required to enter a mine site. Additionally, the popularization and development of artificial intelligence (AI), machine learning (ML), and large language models (LLM) have seen new research into their possible applications for mining. While automated mining is still being implemented throughout the mining industry, this new wave of smart digital mining is just beginning to take shape. As mining operations are declining in terms of quality reserves, mining companies are increasingly adopting the implementation of autonomous and remotely operated systems to improve efficiency and productivity, address labor shortages, and especially improve the health and safety conditions of mine workers. Likewise, the deployment of automation and remote operation systems has reduced risks associated with mining operations. According to McNab and Garcia-Vasquez [6], there is a notable improvement in control, accuracy, and efficiency when a remotely controlled system is integrated with other equipment (manned or autonomous). This paper aims to provide a comprehensive overview of the current state of automation in mining, examining the technological advancements, their applications, and the future prospects of automation in this critical industry.

2. Current State of Mining Automation:

The mining industry, in most cases, utilizes a mechanized workforce. Miners operate mobile equipment such as haul trucks, loaders, and drill rigs, which make up a large portion of the mine's labor. Jobs that require more involvement from the miner often have some form of mechanical assistance such as with roof bolting in underground coal mines. However, these jobs still require miners to be in the mines and operate equipment. This subjects them to hazards within the mine and the entire mine process to human error. As such, many companies are seeking practical technologies to increase automation in mining operations due to the higher safety and productivity rates of autonomous production systems [7]. Tubis et al. [8] suggested that the introduction of automated technologies could be the solution to the growing challenges facing mining operations. Unfortunately, the mining industry has traditionally been slow to accept this new technology [5]. This is especially true in countries that lack expertise in maintaining automated equipment. Despite the slow progress, many new automation technologies have been field tested to success and implemented.

2.1. Automated Haul Truck Systems

Automated haul truck systems (AHSs) are one of the key technologies that have transitioned from experimental phases to full-scale implementation in several mining operations worldwide. In Western Australia, Rio Tinto has successfully implemented autonomous haul trucks [9,10]. The haul trucks operate without being manned but are still monitored remotely by an operator. The haul trucks are given various commands and guidance by a main controller, such as the number of vehicles allocated and dumping points; however, the trucks themselves handle the routing and autonomous driving without needing additional input [10].

As a result, the mine operator, Rio Tinto, saw numerous benefits. Firstly, there was a marked increase in productivity. "On average, each autonomous truck was estimated to have operated about 700 h more than conventional haul trucks during 2017 and around 15% lower load and haul unit costs" [11]. The main advantage is that these automated haul trucks' limiting factors are now only fuel, maintenance, and environmental factors. Having automated haul trucks removes operator fatigue and inefficiencies [12]. This also removes many of the administrative delays or breaks that manually operated equipment sees [12].

AHSs often have a high capital cost as they require extensive infrastructure; however, long-term benefits become very attractive as AHSs result in reduced labor costs, lower fuel consumption, and decreased tire wear [12]. Overall, AHSs provide nearly continuous operation to the mine, allowing for optimization of pathing, timing, and acceleration [13].

In a simulation performed by Parreira 2013 [9], these exact improvements were modeled, showing that many of the predicted benefits can feasibly become a reality. However, most importantly, AHSs provide exceptional safety to miners due to many of the miners being removed from the hazardous work [12,14–17]. As a result, Rio Tinto in 2017 saw "zero injuries attributed to autonomous haul trucks since deployment, highlighting their significant safety advantages" [11].

Despite the noticeable impact of autonomous technologies, zero harm has not been attained in mining operations, and many miners still must work in many other roles, which expose them to the hazards of mining operations. A main benefit of Rio Tinto's application of AHSs is that the mines are located on the surface. This enables the use of global positioning systems (GPSs), which greatly aid in positional awareness [12], as opposed to underground locations, which cannot use these systems. Indeed, the majority of successfully implemented AHSs have been in surface operations. The reason for this is the geography and nature of surface operations. Surface operations are open to the sky, providing ready access to wireless infrastructure either by GPS, Cell, or Wi-Fi. These systems allow for other nearby autonomous trucks to relay their position. Using wireless connections, AHSs can continuously provide real-time updates, allowing for remote dispatchers to effectively monitor equipment health and performance [14].

Automated haul trucks are not the only surface automation technology seeing implementation. Another similar use is in automated water trucks [18], as water trucks are very similar to AHSs, allowing the same technology to be applied.

However, with the successful implementation of AHSs, the mining industry has been slow to adopt the new technology. There are several reasons for this, with the high initial implementation cost being chief among them. An AHS requires a large investment in infrastructure with each piece of equipment needing modification or new equipment altogether. New training and completely new positions are required to operate and maintain the new systems [16]. Furthermore, due to the low number of operations using AHSs, the available workforce is low causing troubles in acquiring the talent needed [10,12]. As such, this is a major barrier for mines with limited budgets or short lifespans [12]. While there are many examples of success for automated haul trucks, the technology is still very new for the mining industry.

Implementing automated processes and human-driven processes drastically changes the design of workflows [19]. This can cause growing pains within mining operations as a majority of mining personnel have little to no experience with the new workflow, calling into question the reliability and causing trust issues within management and operations [10,16]. While rare, incidents have occurred within mines utilizing an AHS [20].

Finally, there is the concern over job displacement. While automated technologies do not have to necessarily result in a workforce reduction, they often do, and as such, many miners are justifiably worried about their jobs. This causes friction in the implementation of the new technology, especially with unions. Despite this, AHSs highlight many of the benefits automated technologies can provide to the industry. While AHSs may still be developing, more and more mines are expected to adopt them. Draglines has also seen research into automation with remote monitoring and integration with an AHS. Connolly and Jessett [21] developed a system that can monitor draglines with the implementation of the MineWare integrated support center. Marshall et al. [22] designed an automated method to load materials using draglines and shovels.

2.2. Automated Drilling

Another critical area where automation is making significant strides is in drilling technologies. Drilling and drilling rigs serve many roles in all aspects of mining. Exploration drilling is the initial step in any mining project, used to locate and evaluate mineral deposits before full-scale operations commence. Geologists and drill operators traditionally use core drills to extract samples from the earth, which are then analyzed to determine the composition, grade, and extent of the ore body. This process is crucial for assessing the viability of a mining site and determining the potential profitability of extracting the minerals. The most important part of day-to-day operations is production drilling, which plays a central role in the extraction process itself. Drills create holes to be filled with explosive material, which allows for the economical liberation of hard rock resources such as limestone or metals. Drills are also used in tunnel boring for ventilation and access in underground mining, along with many other use cases. As such, drilling is essential to almost every mining operation [23].

Drill operators face different hazards depending on the specific drilling application, but ubiquitous hazards include noise, dust, and vibration. Due to the nature of drilling, these health hazards are extremely hard to eliminate or reduce. In a study by Edwards et al. [24], it was found that drill operators are consistently exposed to noise levels above 85 dBA, placing them at risk for a reduction in quality of life. Just as in the previous discussion on AHSs, automation has the potential to remove miners from the hazardous noise environment. This can allow drill rigs to operate in far more hazardous environments without the potential for human exposure [19,25].

The capability for drill rigs to operate remotely has been an extremely attractive benefit of autonomous drilling. In fact, there are many examples of autonomous drill rigs (ADRs) being developed and used throughout the mining industry [26–29]. Additionally, many companies see potential production benefits to implementing ADRs. ADRs can provide faster drilling cycles because they continuously monitor and optimize parameters in the drilling process, such as rotational speed or forces on the drill bit, to provide maximum penetration rates, leading to faster hole completion [25,30]. ADRs can provide a more streamlined process by minimizing delays; for instance, automated rod handling eliminates the downtime associated with manual rod trips and removes the need for human intervention [23,31]. Additionally, real-time monitoring allows for proactive maintenance, preventing major breakdowns that can significantly halt operations [32].

By minimizing the need for human intervention and streamlined processes, ADRs provide a more continuous operation than traditional methods [33]. Another benefit is increased accuracy and hole quality. Automation technologies like the Hole Navigation System (HNS) ensure precise drilling of blastholes, resulting in more uniform fragmentation and potentially improving the overall blasting efficiency [34,35]. Additionally, autonomous systems can detect and respond to changing rock conditions, optimizing drilling parameters for consistent hole quality [23,25,36]. ADRs can provide features like drill plan handling, void detection, and automatic collaring contributing to greater accuracy, lower deviation, and better drilling consumables economy [37]. The streamlined process for the human operators and remote-control capabilities moves miners from an operations role to a supervisory role, allowing for a small team of miners to manage multiple ADRs simultaneously. This reduces the workforce requirements and increases overall drill production, allowing multiple ADRs to operate in parallel. Locations that have implemented these ADRs have seen significant improvements in drilling efficiency [30]. This is another example of the impact that autonomous technologies can have on the mining industry. Many of the technologies enabling ADR are similar to the AHS, with new wireless systems, control systems, sensors, artificial intelligence, and software all contributing. The specific technological contributions and state of development will be explored below in a later section.

These two highlighted systems represent highly developed automated systems and their impact on the mining industry. Overall, there have been reported increases in efficiency and safety across the board. However, implementation has been slow due to high costs, labor displacement, lack of trust, and initial disruption to regular operations associated with adopting the technologies. Furthermore, both systems represent a trend in mining automation primarily used in surface mining operations rather than in underground settings.

AHSs and ADRs represent automation for mobile moving platforms. However, static haulage systems such as conveyor belts have seen greater automation. Lodewijks [38] explored the automated maintenance systems for conveyor belts, utilizing vibration analysis to monitor idler rolls and determine their health. Additionally, this lends itself well to providing predictive maintenance as using data other than the human experience can provide better warning for when a system may need maintenance. Jurdziak et al. [39] highlighted how conveyor belts are often the least sensor-monitored systems, but there is the potential for conveyors to be more centrally monitored and controlled. By installing more sensors, alarms, and triggers, systems of conveyors can be controlled remotely from a central location. Wang et al. [40] provided research for automatic control systems by using variable frequency drives to control the speed and torque of belt motors, leading to improved efficiency and reduced wear. Automated machine vision Tessier et al. [41] highlighted the potential for machine vision to automatically monitor and classify the ore composition of conveyor belts. This would allow for real-time monitoring of ore quality and allow for downstream processes to adapt.

3. Underground Mining Automation

Underground mining, as opposed to surface mining, faces many additional challenges. One of the main issues is that underground mining takes place below hundreds of feet of rock. This unavoidable fact limits communication and data transfer out of the mine. Most importantly, this prevents the use of GPSs, as satellite signals are unreachable underground [19,22,42–44]. The absence of satellites presents a challenge in accurately positioning and localizing both mine personnel and automated equipment. Several studies have proposed solutions to address these problems. The study by Billingsley and Brett [45] developed a method to measure the three-dimensional (3D) shearer path directly through an inertial navigation-based system. Similarly, Xu and Wang [46] applied a longwall shearer path system based on 3D position and dynamic-static fusion to collect dynamic data, static data from the shearer, and data from the hydraulic supports. Ruiz [47] highlighted the difficulty in collecting horizontal position data using inertial navigation systems because the measurement errors tend to increase with time. To address this, Fan et al. [48] created a wireless sensor network that results in a decrease in the position drift error. However, the study of Houshangi and Azizi [49] estimated the probabilistic distribution using a small range of numbers taken from specifically chosen test points using integrated robot positions and orientation using a fiber optic gyroscope and Unscented Kalman Filter (UKF). This research is critical to the development of underground mining automation because solving the positioning issue will enable many other forms of automation. Most notable is that of fully autonomous mobile equipment, as the developments in surface mining automation have heavily relied on GPSs and wireless technology.

3.1. Longwall Automation

Even with massive hurdles disrupting the development of autonomous technology for underground mines, new technologies have been appearing. Particularly that of underground longwall automation. Traditionally longwalls are large systems, stretching hundreds of meters in length. They are typically comprised of over 150 shields that support the mine roof while a shearer extracts the target resource, which is often coal. Longwall automation has been under development for an extended period of time. A study by Ralston et al. [50] describes the technical contribution (milestones) attained worldwide to develop longwall automation, which has influenced the direction and development of present-day longwall technology since its introduction in the 1960s. A review by Peng et al. [51] covers the advancement of automated longwall technology, separating it into three categories: shearer-initiated-shield advance (SISA), semi-automated longwall faces, and remote-controlled shearers. The SISA is an extremely common automation technology that has been in use since the 1990s. It uses sensors to determine the position of the longwall shearer, and as it passes longwall shields, it signals them to move forward. This reduces the number of miners required to advance the longwall and increases production. Semi-automated longwalls combine many systems, such as SISA, to automate a large portion of the longwall operation. Semi-automated longwalls are becoming more popular, as is the interest in remotely controlled longwalls. Remotely controlled longwalls are a relatively new advancement, with the first being employed in 2012. These longwalls further automate the longwall operation through the use of cameras, allowing an operator near the working face to control it remotely from a safer location underground. Unfortunately, fully remote operations from outside the mine are not yet a reality due to operations still requiring on-site personnel due to the limitations of sensors, the complexity of underground conditions, and the need for human oversight. Kelly et al. [52] successfully implemented an on-line 3D shearer positional information system allowing for improved face alignment and control of the longwall. Additionally, this project proved the feasibility of wireless ethernet communications as a method for face-wide communication, allowing for remote monitoring. As highlighted in the project, automation can perform well in ideal conditions, but when a more complex scenario is encountered, human intervention is needed. This is allowed through the developed communication systems allowing for operators to intervene when necessary. One of the pronounced advantages of longwall automation is that it has reduced miner exposure to respirable dust levels [53]. It is evident throughout this review that automation continues to provide excellent safety benefits because workers have a lower, or no, exposure time to the hazards of mining.

3.2. Automated Load Haul Dumps

Another area of underground automation has been that of load haul dump (LHD) machines. LHDs are very similar to wheel loaders with a bucket at the front. These machines are designed to load material and haul it an extended distance, with the bucket having a resting position for transit. Additionally, these machines are lower than traditional wheel loaders to accommodate the underground mining environment. These machines are often used in mines where it is unfeasible to load haul trucks due to the low mine height. Automation of these vehicles can be traced back to the 1960s, with original automation using reactive navigation; LHDs would be guided by wires and painted lines on the floor of the mine to guide the machine as it moved [54]. Since then, automation of LHDs has become more sophisticated, with research intensifying in the early 1990s [19,54]. The research focused on the localization issue of underground mining, which, as mentioned earlier, is difficult to achieve in an underground mine without extensive infrastructure. As such, solutions began to be tested, such as using simultaneous localization and mapping (SLAM), which has the LHD build the mine map as it operates. This allows the LHD to determine its location based on its map. There are issues with this method: SLAM is computationally intensive and needs powerful onboard computing. Additionally, it does not work well in dynamic environments as the LHD only updates its memory upon arriving at a location, meaning moving objects can pose a serious issue. Despite these challenges, Thrun et al. [55] and Nüchter [56] both achieved successful mappings in underground environments using SLAM.

Furthermore, Larsson et al. [57] proposed a fully automated navigation system for LHDs to navigate underground terrain. Advancements in PLCs have also been an enabling technology for LHD automation. PLCs have been used to enhance system controls on many different types of mobile equipment including LHDs [58], acting as an intermediary between high-level control functions and the LHD actuators. Research on the software of LHD automation has been performed by Tampier et al. [59] outlining an autonomous loading algorithm designed to handle the entire process of loading fragmented rocks from draw points, including rock pile identification, LHD positioning, charging, excavation, pullback, and payload weighing. Additional work has been performed on automatic loading conducted by Dasys et al. [60] who developed an algorithm using sensors to fill the bucket automatically. With research still ongoing, many attempts to implement autonomous LHDs have been made. Most notably, the El Teniente mine in Chile has implemented semi-autonomous LHDs in some block-caving mines beginning in 2004 [61]. These LHDs can autonomously navigate but also require remote monitoring and control from human operators. This offers a balance between the capabilities of automated systems and the need for human oversight and intervention in complex and dynamic mining environments. For example, in underground LHD machines, the use of tele-remote systems is being superseded by autonomous navigation while machine monitoring can still be performed remotely [62].

These two examples of underground automation, longwalls and LHDs, reveal a common issue in underground mining automation—the difficulty of communication in an underground environment. Many modern automation systems have easy access to localization and GPSs, which is key to self-navigation. Additionally, the complex dynamic nature of underground mining presents another challenge requiring human interaction for corrections and monitoring. Monitoring could be performed remotely, but having proper wireless connectivity out of the mine has proven to be difficult. As such, remote monitoring is still performed within the mine, but at a distance. Like surface mining, underground also faces the normal issues of automation in addition to unique ones such as operator acceptance and trust [61], a lack of trained workforce to maintain automated machines [63], and the initial integration growing pains [19]. However, operations have achieved substantial safety benefits by removing miners from performing potentially hazardous work along with the economic benefits of lower operating costs and the expansion of economical ore bodies [64,65]. These ore bodies are expanded as autonomous machines can operate in environments that designers and engineers would consider far too dangerous, allowing for operations in less geologically stable conditions or higher temperatures.

Another environment that has seen preliminary research is that of deep-sea mining. The main issue with human mining is the possibility of higher atmospheric pressure at deeper ocean depths, along with the difficulty of supplying oxygen. Autonomous vehicles can be designed to handle pressures and do not require breathable air. Examples of work conducted include Sartore et al. [66], who designed a perception and control framework for an autonomous underwater vehicle (AUV). This AUV concept was designed to provide mapping for underwater terrains and analysis of mineral content. Leng et al. [67] provided a review of the development of deep-sea mining vehicles, including progress on vehicles such as submarine drag bucket systems, shuttle vessel systems, and pipeline lift systems.

These systems are usually remotely operated as they are often infeasible to design for human occupancy. Additionally, conditions in lower depths are often very consistent, allowing for more focused designs. Automation in mining has the potential to not only provide new efficiency but also open up new mining environments.

Like conveyor systems, static systems have also been subject to research and development with respect to automation, particularly with skips, which are unique to underground mining operations. Skips are containers that are hoisted vertically through a shaft by one or more cables. Beus et al. [68] performed a study on automated hoist conveyance, creating a computer-based system that controls the hoisting system to cycle automatically. The system utilized switches, motor speed feedback, PLCs, and a Human–Machine Interface so that the skip system could operate without a need for constant human intervention. Biegaj [69] highlighted in their paper that automation in skip loading would lead to lower skip waiting time and better cycle times leading to increased efficiency and production. Northcote [70] covered new automated skip-loading systems, which, among others, included pre-loaded conveyor belts. The belts are measured to contain the right amount of material to fill a skip. Once the skip arrives at its loading position, the belt is set to high speed, leading to a faster skip loading time. Kempson [71] covered automated skip tipping at the surface, whereby the unloading process is sped up. Automation in mining is not only limited to mobile equipment but more static transportation systems as well.

Over the years, mining depths have increased and that has resulted in elevated temperatures in the mining environment. In response to that, mining operations have introduced cooling systems that allow humans to work at higher mining depths. As the degree of mining automation increases, more unit operations will eventually become fully automated. Nevertheless, it is envisioned that for the next few decades, humans will still be present in the underground environment, slowly transitioning from an operator role to a supervisory role. Hence, current ventilation systems (with or without cooling) will still need to be in place. These ventilation systems will also serve to control the operating temperatures of automated equipment. As automation progresses and equipment gains more autonomy, either dedicated cooling systems will need to be implemented or equipment that can function under elevated temperatures will need to be developed.

4. Enabling Technologies

4.1. The Transition from Manual to Autonomous Operations

The advancement of automation in the mining industry relies heavily on a variety of enabling technologies that support the transition from manual to autonomous operations. As discussed in previous sections, wireless networks are of extreme value for automated systems. Due to the difficulties in underground communication, underground wireless systems have seen new research. A study by Leinonen et al. [72] investigated the feasibility of using a 5G wireless network in an underground mine, finding multiple issues with implementation, particularly with the movement of large vehicles that could block signals. In a paper published in 2011 by Rusu et al. [73], a wireless system of RFID chips was proposed that would provide localization services in underground mining. Lasantha et al. [74] reviewed the potential for RFID sensors to provide the Internet of Things (IoT) to underground mining, finding that, while still an emerging technology, it shows promise as a localization and tracking technology. But there are still many issues, most notably limited range. Implementation of RFID would likely require extensive infrastructure. In a review by Seguel et al. [75], the issue with underground positioning is discussed, with the main issues being signal propagation, limited infrastructure, dynamic environments, and cost-effectiveness. Additionally, in a paper by Sreedharan et al. [76], a subterranean mesh networking solution based on the biomimicry of ant colonies was proposed to help an IoT for underground environments. The network is separated into three layers: central, zonal, and personal routers. With continuing research on underground wireless networking, further development is required before this technology can fully enable underground autonomous operations.

4.2. Intelligent Automation

Another emerging technology that has furthered the development of automated mining is ML and AI. ML and AI provide decision-making capabilities for autonomous operations. This is particularly important for areas that require intelligent automation. Unlike repetitive automation, which repeats similar tasks, intelligent automation can adapt and make decisions. This has been critical for the development of navigation for autonomous machines as they provide object detection, object tracking, and collision avoidance to autonomous vehicles [77]. This allows systems like AHSs or other automated equipment to adapt to a variety of situations. AI enables autonomous navigation, path planning, and obstacle avoidance for haul trucks, improving efficiency and safety in transporting materials [78–80].

However, there are far more uses for ML and AI than just navigation. Recently, intelligent automation has been used in the mapping, exploration, and planning of mines. In a paper by Schneider et al. [81], the authors highlight how AI systems can analyze hyperspectral imagery to detect and classify geological structures, creating detailed models of the mining environment. Leung et al. [16] detailed the use of AI in the Pilbara in geologic modeling and material tracking, along with use cases in automated equipment. Long et al. [82] highlight the potential of AI to automate mineral identification leading. AI has also been used in blasting, as detailed by Ali and Frimpong [83], optimizing blast designs with geologic and blast parameters, resulting in improved fragmentation and reduced vibrations.

ML and AI applications also have the potential for improved dispatching and monitoring in mining. Matsui et al. [13] provide a deep-learning model that can adapt to varying fleet sizes without requiring retraining, outperforming conventional mathematical optimization approaches. In a paper by Liu [84], the potential for automation in the mining supply chain is highlighted. Intelligent automation techniques can assist in the mine planning process by monitoring inventory, transportation, and processing models as ore grade fluctuates. Jämsä-Jounela [85] highlights the importance of data for the future of mining automation. With this, an Internet of Things can be created, allowing for machine learning to use collected data for process modeling, prediction, and optimization. Ramezani and Tafazoli [86] present an application of object detection for excavator buckets to monitor for wear patterns, material distribution, and missing teeth. However, one of the issues with ML and AI is preparing the correct parameters and objectives for them.

Li et al. [87] explored the potential for large language models (LLMs) to guide other automated processes, allowing humans to give regular language commands. While ML, LLMs, and AI are still at the forefront of research, their development will be critical for mining automation in the future. Moreover, there has been a continuous interest in improving the performance of manipulator control and functionality in automation. Having a proper interface for intelligent automation to mining equipment is important for system integration. Numerous scholars have conducted research on the progress of proportional-integral (PI) control by utilizing algorithms to attain optimal performance and improve tuning methods. This has been explored in studies by Nagaraj and Murugananth [88], Forley et al. [89], and Iqbal et al. [90]. These studies have been useful in developing robots to improve the performance of personnel in harsh working environments. For instance, Huh et al. [91] designed a tele-operated mining robot to replace mine workers in Korean coal mines. In another notable development, a study by Lu [92] demonstrates the conversion of a bucket wheel reclaimer to a robotic arm that can be controlled automatically.

5. Human–Robot Collaboration

5.1. Human–Robot Interaction

As more and more automation begins to be adopted, it is clear that the goal of zero entry cannot yet be fully achieved. As operations begin integrating automation, there will inevitably be a mix of both robotic and human workforces. During this transition, researchers and industry must consider the interaction between humans and robotics in a mining environment. With this being a new challenge for mining, it is useful to look at other industries, such as manufacturing, and see the effect of human–robot collaboration on efficiency and safety. Lynas and Horberry [4] listed the differences between robots used in mining and those in the manufacturing industry. The study stated that mining robots are required to move around to perform specific tasks, while the robots used in the manufacturing industry only assemble products and pass them to the next production phase.

The cooperation between robots and humans (human–robot interaction) must be considered during the design phase. Robot navigation in the presence of humans raises new issues for motion planning and control, as humans must be considered. Several studies concluded that for automation to be successful, the human factor needs to be considered during the design and development of autonomous equipment. Lynas and Horberry [4] reported that automated systems must consider the human element as a means of user-centered design and implementation. Over the years, there have been significant improvements in autonomous machines in the areas of safety, reliability, and economics of operations. Regardless, human judgment, logic, and foresight cannot be compared to that of a robot because the robot relies on human attributes in any complex system due to the unknowns, uncertainties, and complexities in mining operations [93]. Human involvement is fundamental to system design, development, installation, testing, and deployment of automated systems. However, humans have performance barriers, including fatigue, distractions, and biases, which can also lead to the poor design of systems or insufficient human operator inputs. Hence, the differences and interplay of automation design and human input are the keys to understanding flexible interaction, function allocation, and the level of automation to be applied in a dynamically changing environment to achieve maximum benefits [94].

5.2. Human–Robot Etiquette

Miller and Funk [95] listed rules for human–robot etiquette that can make automation behave more like a human collaborator. These include the ability to override an automated system, the robot's awareness of what the operator knows, the ability of the system to take instructions, the system's inability to repeat mistakes, and the system's ability to provide information about why it is performing the tasks. Considering these tasks during design, development, and integration will provide solutions to some of the unanticipated problems and failures that have been observed in the use of automated technologies. The goal is to combine robotic strength, endurance, and accuracy with human intelligence and flexibility [96]. Rosenthal and Veloso [97] and Fong, et al. [98] both have worked on a possible way to improve human safety while working with robots by developing algorithms that can enable the robot to ask for human help to reduce uncertainty. Similarly, the presence of humans in the robot's environment and the necessity to interact with them have been a concern for the robot's end users. Sisbot et al. [99] addressed this issue by developing a human-aware motion planner (HAMP) to provide solutions to safeguard humans working around robots.

Nowadays, the end user uses the robot's path algorithm planning approach to provide safety to the people working around the robot. Trajectory planning is one of the ways to interact with the robot while at the same time guaranteeing the safety of the operator. Robot path planning entails creating an optimum and safe path for the robot to follow while ensuring high precision and accuracy with other equipment in its surroundings.

6. Safety around Industrial Robots

6.1. Industrial Robots in Mining

Continuing to look at industrial automation and robotics to inform design processes, industrial robots have become an essential asset in production lines due to their attributes, such as modularity, scalability, agility, flexibility, and reconfigurability. It is expected that mining automated equipment will fill a similar role. Because of these attributes, robots are being deployed to perform more tasks. For instance, in automated production lines, robots perform tasks such as welding, handling, assembling, and coating. As a consequence, robots not only improve safety but also productivity. However, the dangers associated with robots limit the potential benefits of operator interaction [100]. The power and size of industrial robots show that they are capable of causing injuries and accidents if used in an unsafe manner. The robots are designed to interact with humans to increase both efficiency and precision while reducing operational costs. Robots were introduced to replace humans in working on dangerous, difficult, dull, monotonous, and dirty tasks [101]. The nature of tasks sometimes requires the operators to work near the robot while the robot actuators are being powered, leading to contact between humans and robots. Thus, great care must be taken to make an industrial robot safe for human interactions.

The latest trend in the robotic world is determining how to use the robots' strength, velocity, predictability, repeatability, and precision, as well as human intelligence and skills in a safe working environment. That is, the ability to use robot attributes to develop safety technologies for human–robot interaction (HRI) [102]. Perhaps the most important thing is to implement control, safety, and operator support strategies for humans to work safely with the robot. The end users are more concerned about the safety and security of the industrial robot as operators often are not robotics experts. The safety and security challenges must be addressed before deploying the robot into humans' everyday environments. Industrial robots are used to perform repetitive tasks with a high degree of precision and accuracy.

The advent of industrial robots has led to a reduction in factory footprint, thereby eliminating the need for human operators to carry out certain tasks within the installation area. Robots are now deployed to physically assist operators with difficult tasks, enhancing task ergonomics and reducing cycle times. Despite these immense benefits, there is a need to check the safety of humans working around these robots. According to Vasic and Billard [101], the sources of injuries when working around robots can be classified into three categories: engineering errors, human mistakes, and poor environmental conditions. The sources of errors in robotics can be ascribed to robot mechanics issues such as faulty electronics or sensors, failed controllers due to programming bugs, and loose parts. This error can lead to the robot working at an uncontrollable speed or robot failing to stop. Human errors in robots are controllable and are caused by human negligence, fatigue, and inadequate robot training. Environmental errors can be attributed to extreme weather conditions, such as extreme temperatures, that lead to an incorrect response from the robot. User guides specify the conditions where the robot can perform optimally. To prevent environmental errors, the user must ensure the robot is working according to the manufacturer's specifications.

6.2. Industrial Robotic Safety Measures

Earlier studies on robotics by Pervez and Ryu [103] and Heinzman and Zelinsky [104] classified industrial robot security into post-collision and pre-collision approaches. The post-collision approach detects collisions and uses exteroceptive sensors (force and torque sensors) to minimize the resulting damage. Rybski et al. [105] stated that there is a reduction in the use of the post-collision approach as the methods cannot prevent a collision. In contrast, pre-collision is a preventive collision technique that prevents collision by detecting them in advance. This approach uses a sensor mounted on the robot or robot environment, which allows the robot to stop or alter trajectory before a collision takes place. Examples of this method are used in ABB SafeMove, where sensors prevent collisions [100]. Other methods of preventing collision in industrial robots include the use of virtual barriers such as laser-based curtains [105], the mounting of a force torque sensor on the wrist of the robot to control robot motion [106], and the application of force or torque sensors with visual information [107].

In addition, the implementation of SafetyEye systems that employ stereo vision to detect mobile objects within the safety zone has resulted in a decrease in the reliance on physical barriers such as fencing. The use of multiple 3D imaging sensors of different modalities in the volumetric evidence grid by Rybski et al. [105] also forces the robot to stop until the problem is resolved. A recent development from KUKA introduces collaborative robots (cobots) that can interact with humans by sharing the same workspace without concern [108]. Similarly, ABB developed collaborative robots that can work side by side with humans safely and productively without barriers [109].

However, to make industrial robots safe for humans, certain industries have adopted formal standards and regulations in place based on best practices. The automotive industry works under the standard of ISO 26262 [110], while in robotic systems, there is ISO 13482 [111], which recognizes and guides hazards present in the use of industrial robots and systems. Tong and Lei [112] in their study stated that software development for safety standards can only address a few standards indirectly. However, those standards only present the requirements but do not provide guidance on their implementation. Ideally, humans should be safe working around the robot regardless of its failure mode or even misuse. It is necessary to guarantee higher safety standards for humans working with a robot in the same space by preventing unexpected collisions between humans and robots.

7. Conclusions

The mining industry is on the verge of a technological revolution with the advancement and adoption of automation technologies. As examined in this paper, the integration of robotics, artificial intelligence, and machine learning is transforming traditional mining practices, influencing various aspects of the mining value chain. While the mining industry has historically been slow to embrace new technologies, the potential for increased safety, efficiency, and productivity has spurred a growing interest in automation across the industry. One of the most significant impacts of mining automation is the potential to improve the health and safety of mine workers. By removing human operators from hazardous environments and enabling remote operation, automation technologies minimize the risk of accidents and exposure to harmful conditions. The successful implementation of an AHS in surface mining operations, as demonstrated by Rio Tinto, has shown a significant reduction in injuries and fatalities. However, it is crucial to acknowledge that achieving "zero harm" in mining operations requires a multifaceted approach that goes beyond technological solutions.

While automation offers substantial benefits, the widespread adoption of these technologies faces several challenges. The high initial investment costs, concerns about job displacement, the need for specialized skills and training, and the inherent complexity of integrating automation into existing workflows hinder the pace of implementation. The unique challenges of underground mining, particularly in terms of communication and localization, further complicate the development and deployment of fully autonomous systems. Research in these areas is ongoing but is not currently in a state for full integration into underground mines. The future of mining automation will rely heavily on addressing these challenges while harnessing the full potential of enabling technologies. Advancements in underground wireless networking are crucial for enabling real-time data transmission and remote operation in underground settings. Machine learning and AI will play an increasingly critical role in intelligent automation, enabling autonomous systems to adapt to dynamic environments, optimize processes, and make informed decisions.

As the mining industry transitions towards greater automation, it is essential to consider the evolving roles of human workers and foster a collaborative human–robot work environment. By prioritizing human safety, providing adequate training, and addressing concerns about job displacement, the mining industry can ensure a smooth transition toward a more automated future. Designing automation technologies with human–robot collaboration in mind, drawing inspiration from industries like manufacturing, will be crucial for achieving optimal efficiency and safety. The success of mining automation hinges not only on technological advancements but also on the industry's ability to adapt, innovate, and prioritize the well-being of its workforce.

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