A Retrospective-Prospective Survey on the Introduction of Digital Twins to Mining Industry

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ABSTRACT

Digital Twin as a key enabler of Mining 4.0 is a sensational topic nowadays, characterized with intelligent decision-making and real-time data flow. Conventional methods are overshadowed by this disruptive technology since they fall short in fulfilling complex needs of modern systems. This research attempts to conduct a retrospective overview on the applications of simulation, optimization and machine learning in the surface mining concept to elicit their merits and demerits. Then, the twining technology is proposed as a mechanism to fill the gap. Lastly, a six-layer Digital-Twin-based architecture is developed to be applied as a roadmap in the mineral industry.

1. Introduction

Bottlenecks in surface mining such as optimization, decision-making and real-time supervision seem to be directly or indirectly tractable by resorting to novel technologies such as artificial intelligence, digital twins and cloud computing. In addition, profitable and intelligent mining known as Mining 4.0 entails mines to adopt these disruptive methods. The fourth industrial revolution, known as Industry 4.0 is a new movement in which virtual and physical systems of production interact flexibly on a global scale (Schwab, 2017). In other words, cyber-physical systems (CPSs) will communicate with one another using Internet of Things (IoT) (Sipsas et al., 2016). The year 2015 is deemed to be the beginning of this era (Munirathinam, 2020). Industry 4.0 is established on nine pillars including simulation, internet of things (IoT), cyber security, cloud computing, augmented reality, autonomy, machine learning, and real-time data (Rüßmann et al., 2015; Munirathinam, 2020). As it is obvious, Industry 4.0 holds the key to all bottlenecks in Mining 4.0, whose main enabler is Digital Twin (DT).

In simple terms, a DT is a dynamic digital representation of an asset/system and imitates its real-world behavior (Lu et al., 2020). The twinning technology has the potential to capture desirable features such as dynamicity and automation found to be scarce in conventional methods. The present study endeavors to conduct a retrospective overview on simulation, optimization and machine learning approaches in an attempt to find pros and cons associated with them in Section 2. Results will direct us towards the fact that the lack of an integrated solution like DT is really felt within surface mining. Then, an exemplary architecture inspired by forerunning industries is illustrated in the third section. Finally, discussion and conclusion are put forward.

2. Retrospection

Herein, applications of simulation, optimization and machine learning in surface mines are generally explored to identify merits and demerits required to be taken into account in the development of novel approaches such as DT.

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2.1. Simulation

Simulation is the process of imitating a real system and conducting experiments to understand the behavior of the system and/or evaluate various strategies (Shannon, 1998). Discrete-event simulation (DES) paradigm is referred to as the simulation model possessing a state at any point in time, and only if an event occurs does the state undergo a change (Hollocks, 2006; Law, 2007). Having a discrete sequence of time-ordered events (namely drilling, blasting, loading, hauling and dumping), mining is capable of preparing the foundation for DES (Blouin et al., 2007). Monte Carlo Simulation (MCS) model forms the basis of DES (Sturgul, 1999). The first credit for simulating a mine is given to Rist (1961) for emulating a haulage problem in an underground mine. Main efforts of simulation in surface mines are classified into two general categories of production scheduling and equipment management. Scholars have incorporated simulation in production scheduling for a variety of objectives, namely uncertainties related to geology and price, risk analysis, and block sequencing. The year 2020 was prolific in research projects for geological uncertainties (Chatterjee and Dimitrakopoulos, 2020; Gilani et al., 2020; Maleki et al., 2020; Quigley and Dimitrakopoulos, 2020). Simulation in price uncertainties was applied by Alipour et al. (2022) where they availed a stochastic differential equations simulation-based dynamic block value technique to an open-pit production-scheduling problem in order to consider the variation of commodity price in mine planning. In the field of simulation-based production scheduling, Shishvan and Benndorf (2019) ran alternatingly a deterministic optimization model and a stochastic simulation model to find the best extraction sequence between spreaders and excavators in an opencast coal mine employing a transportation problem and a job-shop scheduling problem. There are other worthwhile efforts, too (Fytas et al., 1993; Frimpong et al., 1998; Askari-Nasab et al., 2007; Askari-Nasab and Szymanski, 2007; Manríquez et al., 2019). Reliability and risk analysis have also been on the radar in mine planning every now and then (Huang and Espley, 2005; de Carvalho Junior et al., 2012; Kumral and Sari, 2017; Ugurlu and Kumral, 2020). Ugurlu and Kumral (2020) proposed an approach for determining the number of bits required in a given period and the number of holes to be drilled in drilling operations through reliability analysis and DES under uncertainty.

Madge (1964) was one of the first researchers employing simulation in truck management in an open pit mine to decide the optimum fleet size. In the 1960s and 1970s, simulation-based fleet management was at earlier stages, and the computer language used was primarily Fortran. Elbrond and Soumis (1987) tested their real-time dispatching procedure with the help of a simulation model fed with Erlang distributions, resulting in production increase and reduction in truck waiting times. Overall, the 1980s witnessed a substantial rise in the applications of computer techniques in truck haulage systems. Jacobsen et al. (1995) used GPSS/H for the simulation model of a waste handling system and PROOF for the animation. The most brilliant advancement appears to be the advent of animation over the 1990s. In the third millennium, Awuah-Offei et al. (2003) used a SIMAN-based simulation technique to forecast truck-shovel requirements for a gold mine over four years. Simulation-based fleet management in the 2000s was not as prevalent as it was in the 1980s, at least in the academic context. Askari-Nasab et al. (2014) integrated a mixed integer linear goal-programming model with a DES to upgrade fleet management systems (FMSs). Their mathematical model aimed to allow for four objectives of production, grade control, processing plant feed rates, and operating costs. Moradi-Afrapoli et al. (2019) formulated a multiple objective mixed integer linear programming model, with the truck fleet size being 13% less than the required number of trucks suggested by a benchmark tool. Mohtasham et al. (2022) presented a DES-based optimization method to evaluate the optimal number of trucks in their multi-stage approach. In the 2010s and later, simulation was included into the center of mathematical and heuristic techniques for multistage dispatching strategy. There are also more attempts in simulation-based FMSs over the last decade (Chanda and Gardiner, 2010; Nageshwaraniyer et al., 2013; Chęciński and Witt, 2015; Dindarloo et al., 2015; Hashemi and Sattarvand, 2015; Tabesh et al., 2016; Tan and Takakuwa, 2016; Chaowasakoo et al., 2017; Upadhyay and Askari-Nasab, 2018; Moradi-Afrapoli and Askari-Nasab, 2019; Ozdemir and Kumral, 2019; Moradi-Afrapoli et al., 2021; Tapia et al., 2021; Yeganejou et al., 2022). However, some demerits are mooted including 1) Expensiveness of simulation tools, 2) Requiring special training and experience, 3) Dependence to statistical methods, 4) Incapability to optimize the system alone, entailing combination with other techniques (Pegden et al., 1995).

2.2. Optimization

An optimization algorithm is generally categorized as classical (e.g. operations research (OR)) and advanced algorithms (e.g. metaheuristics). OR has been used in mining primarily for development and exploitation stages (Newman et al., 2010), and applied in a variety of problems including production scheduling and equipment management. Production scheduling is an optimization problem of realizing the most profitable sequence of blocks bounded by various constraints. Johnson (1969) is a pioneer in applying a linear programing (LP) model in open pit mine planning. Nevertheless, the algorithm shows flaws in scheduling of underlying blocks. Hence, integer variables are introduced to resolve the issue of mining partial blocks. Integer programming (IP) has other expansions, namely mixed integer programming (MIP), mixed integer linear programming (MILP) and stochastic integer programming (SIP). Gershon (1983) added additional decision variables to Johnson's LP model and created a MIP model. However, current commercial packages fail to solve a large number of zero – one variables. Some techniques are proposed to resolve this pitfall such as Lagrangian relaxation (Akaike and Dagdelen, 1999), clustering approach (Ramazan et al., 2005), branch-and-cut approach (Caccetta and Hill, 2003), and definition of some variables as linear and creation of an MIP model (Ramazan and Dimitrakopoulos, 2004). Some researchers have adopted dynamic programming (DP), in which the main problem is divided into sub-problems to find an optimal solution for each (Dowd and Onur, 1992). Uncertainty was considered in IP as well (Benndorf and Dimitrakopoulos, 2013). Zhang et al. (1993) emphasized on the application of goal programming (GP) and its effectiveness compared to linear programming. Given the complexity of the problem, several researchers have invoked metaheuristics such as simulated annealing (SA) (Kumral, 2013), tabu search (TS) (Lamghari and Dimitrakopoulos, 2012), variable neighborhood descent (VND) (Lamghari et al., 2014), genetic algorithm (GA) (Alipour et al., 2020), particle swarm algorithm (PSA) (Khan and Niemann-Delius, 2015), and ant colony optimization (ACO) (Gilani and Sattarvand, 2016).

FMS is a multistage optimization consisting of three sub-stages of finding the shortest path, the upper stage, and the lower stage (Moradi-Afrapoli and Askari-Nasab, 2019). Among multitude algorithms developed, Dijkstra (Dijkstra, 1959) is more prevalent in mining systems for the shortest path problem due to its simplicity, and also seen in commercial packages. Regarding the upper stage, other OR techniques have been implemented. Koenigsberg (1960) modeled a surface mine haulage system whose runtime increased proportionally by the number of trucks using queuing theory. LP and MILP approaches are prevalent in the upper stage problem. The first application of LP in truck- shovel hauling system returns to 1970s (Gurgur et al., 2011). White and Olson (1986) and White et al. (1993) introduced a two segment LP model to make optimal decisions on production requirements. While the first segment tries to ascertain shovels' digging rates, the second part allocates a minimum number of trucks to each active route to meet the routes' productivity rate. A pitfall of LP-based models is that to consider the limitations of the operation, such as the stripping ratio and required feed grade, the models have to define an acceptable range, pushing the operation far behind optimality (Moradi-Afrapoli, 2019). Elbrond and Soumis (1987), and Munirathinam and Yingling (1994) argue that the use of a nonlinear model at the upper stage instead of a linear one is preferable since truck waiting time does not follow a linear function, and NLP models search for the optimum solution over the entire feasible region instead of corners merely. Mohtasham et al. (2021) proposed a mixed-integer non-linear programming model for equipment sizing. Another OR method called Transportation modelling approach has also been applied in the upper stage by researchers like Li (1990) for homogeneous fleet. On account of numerous goals involved in the mining operation optimization, Temeng et al. (1997) formulated a GP model to enhance shovel production considering ore grade, shovel dig rate, dumping capacity and stripping ratio requirement.

The dynamic allocation of empty trucks is expressed as dispatching problem minding different criteria—e.g. production rate, as well as obeying a rule such as minimizing truck waiting time. This optimization problem is solvable by single-stage or multi-stage approaches. The multi-stage approach is more efficient in that a variety of constraints have been addressed at the upper stage (Alarie and Gamache, 2002). Despite the tremendous published models on the upper stage, the quota of the lower stage has been limited. Notable early works on the multi-stage form of dispatching are listed as White and Olson (1986), Soumis et al. (1989), Li (1990), White et al. (1993), and Temeng et al. (1997). Then, the problem kept a low profile for nearly twenty years. Ahangaran et al. (2012) used an MILP model for dynamic truck assignments by minimizing the total cost of loading and transportation in their two-stage algorithm without considering traffic over the routes. Moradi-Afrapoli (2019) compared a benchmark model used in DISPATCH® with three simulation-integrated models for real-time dispatching, namely a multiple objective goal programming model, a stochastic mixed integer linear programming model, and a fuzzy linear programming model. Another group of authors have resorted to heuristics such as GA (He et al., 2010), VND (Souza et al., 2010), imperialist competitive algorithm (Dabbagh and Bagherpour, 2019), ACO (Dabbagh and Bagherpour, 2019), and TS (Zhang et al., 2021).

Notwithstanding, optimization techniques are not flawless. OR methods run into difficulty for large-size production scheduling in terms of complexity and runtime. Another vital aspect is uncertainty which is absent in most OR techniques. In addition, deterministic approaches often lead to non-optimal results. Metaheuristics are exploited to rectify the downsides, yet they deal with their own demerits such as enormous diversity, hyper-parameters adjustments and being problem-specific (Lamghari, 2017).

2.3. Machine learning

Artificial Intelligence (AI) refers to something with the ability to think on its own. Machine learning (ML) is a part of AI allowing the system to learn without explicitly being programmed and is categorized into three learning strategies: supervised learning, unsupervised learning, and reinforcement learning (RL). Common ML techniques include linear and nonlinear discriminant analysis (LDA), decision trees, random forests (RF), k-nearest neighbors (kNN), support vector machines (SVMs), artificial neural networks (ANNs), linear regression, principal component analysis (PCA), and Q-learning (QL). One of the most substantial sub-fields of ML is deep learning (DL), in which feature extracting of input data is carried out without human interventions. Gartner Inc. placed DL and ML at the peak of inflated expectations in their hype cycle for emerging technologies in 2017 (Gartner Inc., 2017). A recent trend analysis indicates that ANNs and RL may become consolidated choices in due time (Noriega and Pourrahimian, 2022). A systematic review of studies in the 2010s indicates that SVM, and after that, DL were the most prevalent ML techniques in exploration, exploitation, and reclamation phases (Jung and Choi, 2021). In the exploitation stage of mining, ML applications can be chiefly classified as production scheduling, drilling/blasting, and equipment management. With regard to mine planning, Askari-Nasab and Szymanski (2007) introduced an intelligent open pit optimal production simulator, in which an agent interacts within an open pit environment through simulation and uses Q-learning algorithm to maximize the NPV of the mining operation. Regarding ore delineation, Beretta et al. (2019) used unmanned aerial vehicles to photograph and classify lithology of mining benches by kNN, SVM and tree-based methods. There are some articles focusing on capital cost prediction (Nourali and Osanloo, 2019; Zhang et al., 2020; Guo et al., 2021). With respect to drilling and blasting, Dirkx and Dimitrakopoulos (2018) applied a multi-armed bandit framework to select the best infill drilling pattern amongst a set of patterns. Khandelwal and Monjezi (2013) predicted backbreak in blasting operations by incorporating rock properties and blast design parameters using the SVM method. Guo et al. (2021) applied an advanced version of ANNs for prediction of flyrock induced by blasting, as well as implementing the whale optimization algorithm to find a suitable blasting pattern. K-means clustering algorithm and ANNs were considered by Nguyen et al. (2020) for predicting blast-caused ground vibration in open-pit mines.

In the scope of equipment management, Choi et al. (2021) compared six ML techniques for predicting ore production through truck haulage, with the SVM model outperforming others. In agent-based truck dispatching problems, trucks are considered individual agents interacting with the mining system to optimize a goal. Bastos et al. (2011) presented a single-dependent agent approach based on time-dependent Markov Decision Processes to model the dispatching problem. Their model outperformed two common dispatching heuristics. Zhang et al. (2020) proposed a multiple-agent and experience-sharing Deep Q Network for heterogeneous fleet dispatching. Their algorithm outdid two heuristics in terms of productivity. Fuel consumption prediction using ANNs has also been targeted in some studies (Siami-Irdemoosa and Dindarloo, 2015; Soofastaei et al., 2016; Alamdari et al., 2022). With regard to autonomous trucks, Ali and Frimpong (2021) developed a framework consisting of convolutional neural networks for object recognition ability, and an RL-based algorithm for the steering action decision making ability.

2.4. Recapitulation

Simulation was born with manual applications, and evolved by 3D-animated gadgets. Yet, a review of previous works demonstrates that the simulation applied suffers from four main shortages such as 1) Being online (real-time and bidirectional data flow), 2) Being intelligent (capable of learning in the course of time), 3) Integration with optimization tools, i.e., simulation is unable to optimize problems per se and should be integrated with other tools, 4) Being inclusive of the mining value chain. Exact techniques run into trouble in complex and large-size occasions, as well as ignoring dynamic behaviors. Metaheuristics have their own fraction of demerits. AI is disrupting all the industries, and mining is no exception. The new solution exclusive of the aforementioned drawbacks must show prerequisites such as dynamicity and self-dependency. DT seems to be the technology pushing all the right buttons. In the ensuing section, this phenomenon is explained thoroughly and an exemplary architecture is proposed.

3. Digital Twin

DT owns it existence to NASA efforts in the 1970s, when a similar concept named mirroring technology was applied to test some failure scenarios. Grieves (2002) proposed a conceptual model consisting of real space, virtual space, and a link for data flow between the two elements. After changing a few names, the term “Digital Twin” was coined in a NASA report (Piascik et al., 2010). A DT can be defined as a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision-making (Rasheed et al., 2020). A DT model is comprised of three main elements of physical twin (physical asset), digital twin (virtual asset), and digital thread (exchange of data and information between twins) (Grieves, 2022). Kritzinger et al. (2018) distinguished three types of digital model, digital shadow and DT based on manual, one-way and bidirectional data flow between the real and digital worlds, respectively. In another classification, DTs are categorized according to five maturity levels (Evans et al., 2019). Intelligent Digital Twins involve four main characteristics of being active, online, goal seeking, and anticipatory (Grieves, 2022). Gartner’s hype cycle for emerging technologies in 2018 placed DT at the peak of inflated expectations, with needing 5 to 10 years to reach the plateau of productivity (Gartner Inc., 2018). Other industries have pioneered in synthesizing DT into their systems. Table 1 lists some exemplary works in non-mining fields with potential usage in the mining concept. Manufacturing, agriculture, healthcare, automotive, and smart cities are able to provide fruitful guidelines for the mining industry, especially in terms of fleet systems/processing plants, rehabilitation, health/safety concerns, autonomous trucks, and water/electricity conservation.

Table 1. Exemplary Digital Twin works in other sectors.

No.	Domain	Authors	Focused area	Application in mining
1	Manufacturing	Redelinghuys et al. (2020)	Catalytic converter assembly lines	Emulation of fleet systems and processing plants.
		Zhou et al. (2020)	Manufacturing cells	
		Polini and Corrado (2020)	Composite assembly manufacturing process	
2	Agriculture	Alves et al. (2019)	Smart farming	Rehabilitation and land restoration (e.g. vegetation) during exploitation and mine closure phases.
		Chaux et al. (2021)	Climate and crop management	
		Verdouw et al. (2021)	Smart farming	
3	Healthcare	Liu et al. (2019)	Health management of elderly patients	Health and safety of miners. Occupational hazards identification. Risk assessment.
		Laamarti et al. (2020)	Health and well-being	
		Elayan et al. (2021)	Diagnosing heart conditions	
4	Automotive	Al-Ali et al. (2020)	Supervision on vehicles	Emulation of equipment such as trucks, shovels, etc. Development of autonomous trucks.
		Almeaibed et al. (2021)	Safety and security in autonomous vehicles	
		Martínez-Gutiérrez et al. (2021)	Automatic guided vehicles	
5	Smart cities	Conejos Fuertes et al. (2020)	Water distribution system	Utility management in mines. Designing smart mines.
		Tomin et al. (2020)	Electricity networks and power grids	
		Schrotter and Hürzeler (2020)	Urban Planning	

Ever-increasing attentions on DT have induced many companies to come up with software and hardware infrastructures for implementation of the twinning technology. Azure Digital Twins®, Ansys Twin Builder®, and Siemens NX® are among key players providing solutions for a variety of industries. Particularly-designed platforms for mining also exist. FORESTALL® provides predictive algorithms and maintenance, and health monitoring (Petra Co., 2022). TIMining Aware® promises real-time mine visualization, live mine plan compliance, and hauling speed improvement tools (TIMining Co., 2022). Centralized data with remote access and hyper-connected planning are claimed by MineLife® (LlamaZOO Co., 2022).

A CPS consists of several layers for exchange of data and information between physical and virtual spaces. In contrast, a DT is a layer in the structure of a CPS. Lee et al. (2015) unveiled a 5–level CPS structure known as the 5-C architecture as a guideline for manufacturing (Fig. 1). At the smart connection level, data might be directly acquired by sensors or obtained from controllers. At the second level, meaningful information is inferred from the data. The cyber level acts as a central information hub in this architecture, where visualization is achieved through digital twinning. Optimization and decision making are carried out at the cognition level to issue commands for the configuration layer which acts as a supervisory control unit through complying with corrective and preventive decisions.

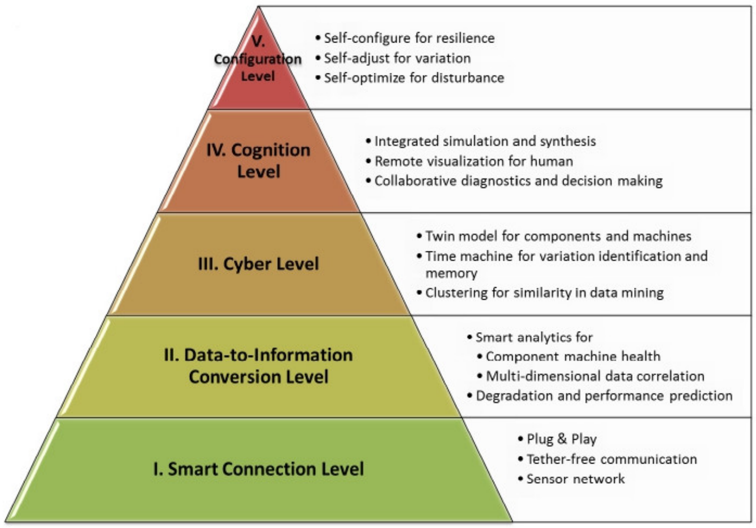

Figure. 1. The 5C architecture for implementation of a CPS (adopted from (Lee et al., 2015)).

Research efforts developing a DT structure in surface mining are few. Elbazi et al. (2022) proposed a four-level architecture for mining industry. On the first layer, all the necessary data is collected from physical assets. On the second layer, the raw data is preprocessed by cleaning, integration and reduction, and then fed onto the edge computing layer for the real-time update of the DT. The last layer is the residence of cloud databases receiving data from the previous layer for both storage and implementation of predictive production, maintenance scheduling and process optimization. Peña-Graf et al. (2022) integrated a machine learning technique, DES, and a DT to capture geological uncertainties in gold mineral processing performance. Nonetheless, the architecture was more of a digital shadow than a DT due to general offline data flow. With respect to lessons taken from some industrial frameworks (Al-Ali et al., 2020; Laamarti et al., 2020; Redelinghuys et al., 2020; Chaux et al., 2021), it can be envisaged that a decent DT-based architecture for the mining sector should incorporate approximately six layers, namely 1) Physical space layer (physical assets), 2) IoT gateway layer (the network of sensors, controllers and actuators), 3) Cloud repository layer (storing data and information), 4) Virtual space layer (DT), 5) Cognition layer (prediction, optimization, and decision-making using AI and optimization techniques), and 6) Briefing layer (issuance of analytical reports), as developed and depicted in Fig. 2. Firewalls and cybersecurity measure must be in action on all layers.

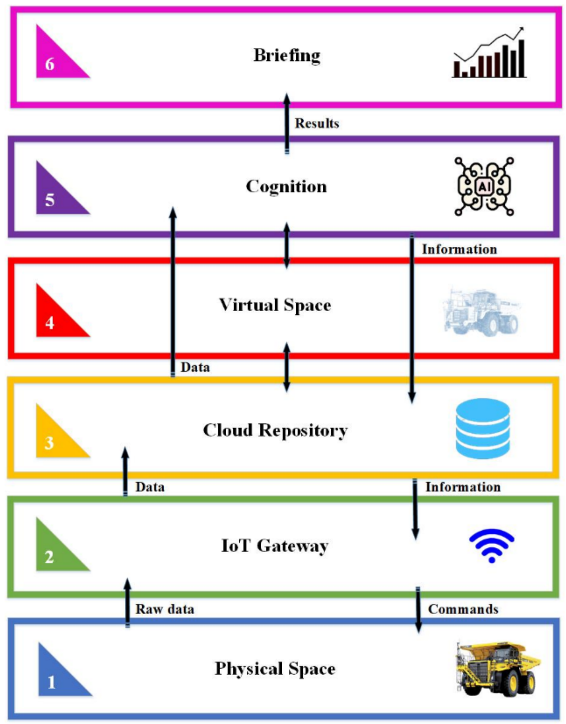

Figure 2. The proposed DT-based architecture for mining in this study.

4. Discussion

This misconception should be dispelled that DT will replace OR, metaheuristic and simulation techniques. Despite being consumed with some drawbacks, conventional methods still play an incumbent role in CPSs. The more complicated systems become in the future, the more needy they get for DT incorporation. This theory corresponds with an opinion survey indicating that DTs and simulation will achieve high accuracy and reliability by 2030 (Siemens Co., 2020). Genuine case studies carried out by some companies at some surface mines uncover striking improvements in fleet production, cycle delays, throughput of a mine refinery, and ore extraction (General Electric Co., 2018; Du Preez, 2021). DT paves the way for opportunities such as increasing productivity, early detection of hazards, teleworking, and predictive maintenance. However, there are some challenges as well, including the need for creating new business models, training the staff, stablishing prerequisite infrastructure, and persuasion of traditionally-minded managers. These challenges are tractable through precise planning and management. DT will gain more recognition and reliance in the course of time. The proposed architecture is just a paradigm for DT integrations. More details are required to be added during the implementation process. We are on the edge of the fourth industrial revolution in mining and it seems to be inevitable.

5. Conclusions

The retrospective overview highlighted the fact DT is the cure for the existent demerits in conventional solutions over the already-begun era of Industry 4.0. Nevertheless, exact, heuristic and simulation techniques are still essential in the structure of CPSs, but they act under the supervision of AI and DT. A paradigmatic six-layer architecture for surface mining was developed through scrutinizing frameworks presented in pioneering sectors. Like any growing technology, DT is encountered with some minor challenges addressable with appropriate measures. It wouldn't be absurd to say "Its time has finally arrived."

6. References

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