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An IoT-enabled dispatch framework for dynamic ore grade lending in open-pit mines: a simulation-based performance analysis

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Abstract

In open-pit mines, traditional truck dispatching systems typically make it hard to balance the demand for regular ore grade blending with the need for operating efficiency. Some people have suggested that intelligent, IoT-enabled systems could be a solution, but there is not always a thorough, controlled evaluation of how well they work compared to traditional baselines. This study fills in the gaps by creating a discrete-event simulation framework that lets you compare a traditional, proximity-based dispatching strategy with a new IoT-enabled method in a quantitative way. The suggested algorithm uses a closed-loop feedback system that works in real time to make judgments about how to blend ore dynamically, always bringing the stockpile back to the goal grade. We tested the two systems in the same way and looked at important performance indicators like grade consistency, manufacturing throughput, and equipment use. The simulation results show that the IoT-enabled system is much better since it can keep the target ore grade with great consistency and stability. These metallurgical improvements were accomplished with almost no effect on total production throughput (< 0.3% difference), and they made the workload of the excavator much more even, which means that operations are more sustainable. This study gives strong, quantitative proof that a smart, grade-aware dispatching system can improve both metallurgical quality and operational efficiency at the same time. The simulation framework shown here is a useful model for reducing risk and measuring the effects of IoT and AI technologies. This will help Mining 4.0 operations become more productive and sustainable.

Keywords: Open-pit mining, Truck Dispatching System (TDS), Ore blending, Grade control, Internet of Things (IoT), Discrete-event simulation

Introduction

Open-pit mining is the first step in many industrial value chains, and it is very vital for the world to get important raw materials. The most essential portion of operational costs in these difficult activities is the haulage cycle, which is the process of loading and conveying ore and rock [1]. It can be more than half of the total cost of production. Because of this, research and development has been focused on upgrading truck and shovel fleets

for a long time [2]. Ore grade management is a key but often conflicting goal in this optimization challenge. When you feed downstream processing machines, also known as concentrators, material with a steady and known elemental grade, they perform optimally [3–5]. If the target grade is too far off, it can have a large effect on metallurgical recovery, use up more chemicals, and make the end product less valuable and less profitable [6]. Thus, the development of effective algorithms for managing mineral resources is a critical area of research for maximizing the economic output of a deposit [7]. This management directly impacts downstream processes, as the dynamics of grinding and separation are highly sensitive to the consistency of the feedstock [8]. Industry reports indicate that haulage operations can represent over 50% of the total costs associated with mining, and inefficiencies in dispatching may lead to a reduction in fleet productivity of as much as 15% [9]. This underscores a crucial interconnection, wherein the particular geological and spatial attributes of a quarry directly affect the performance metrics of its technical transport fleet [10]. Similarly, fluctuations in ore grade can lead to metallurgical recovery losses that surpass 10%, while also considerably raising the consumption of reagents [11]. The statistics highlight the vital necessity of effectively managing both haulage efficiency and grade consistency, which drives the demand for intelligent, data-informed dispatch systems.

The major purpose of truck dispatching systems (TDS) has always been to save money by making operations as efficient as possible. To save time and travel, the customary method to do things is to send the closest truck to the closest shovel [12, 13]. This approach does move more tons per hour, but it goes against the basic needs of metallurgy. These systems can give you the wrong material a lot of the time since they do not look at the real-time ore grade at each excavator face. This can make a stockpile that is significantly different from the blend that the processing plant needs [14].

Static, pre-shift blending plans are one way to fill this gap [15]. These plans tell dispatchers where to get materials from different places based on a set recipe. But these static plans are known to be quite weak and often do not work with the changing and unexpected nature of a live mining site [16]. Unexpected equipment failures, changes in ore grade at the digging face, or stoppages of downstream crushers can all cause operational problems that make a pre-made plan useless [17, 18]. The requirement for real-time operational intelligence is made clear by the ability to deal with these kinds of problems. This is a challenge that also includes automatic fault detection and cause identification throughout the mining process [19]. This means that people have to go back to making decisions on the fly, which is less efficient. This shows how important it is to have a dispatching system that is not only fast but also smart, adaptable, and able to make decisions based on real-time grading information [20].

These “smart” dispatching systems are now conceivable because of new digital technologies like the Internet of Things (IoT), high-precision GPS location (like Beidou), and high-bandwidth wireless networks (4G/5G) [21, 22]. The effectiveness of this system depends a lot on how well these wireless networks work and how well they are optimized, since fast data transfer is necessary for real-time decision-making [23]. With an IoT-enabled framework, you can see everything that is going on in real time, including where each truck is, what it is doing, and what it is carrying, as well as the live grade of the material at each excavator [24–26]. This study looks into how advantageous it would

be to have a system that uses this information to make judgments about how to mix ore. The major purpose of this smart system is not only to find the best travel time but also to keep an eye on the stockpile's overall grade and send trucks to certain excavators to rectify any problems with the goal grade.

Even while the idea and use of these systems in the actual world are becoming more common, there is not always a thorough, quantitative, and comparative study of how their immediate benefits compare to those of traditional approaches. To fix this, our study uses a performance analysis based on simulation. Simulation provides us a controlled, repeatable setting to thoroughly test and compare how well an advanced, IoT-enabled dispatch plan works against a traditional, efficiency-focused strategy in the same operating situations. We can segregate and properly measure how the intelligent dispatching logic affects key performance measures using this way.

This study's main contributions are threefold:

- A comparative simulation framework: we create and show a discrete-event simulation model that lets us measure and compare the performance of traditional and IoT-enabled dispatch algorithms in a realistic open-pit mining setting.
- Measuring the improvement of grade control: we show and measure the large gains in stockpile grade consistency, stability, and precision that the IoT-enabled system brings about, which is unambiguous proof of its metallurgical benefits.
- Analysis of operational trade-offs: our performance analysis looks at more than just grade control; it also looks at the effects on key operational metrics like total production and equipment utilization. This shows the full trade-offs of each dispatching strategy.
- The rest of this paper is set up like this: first, we will look at some studies that are relevant to ore blending and truck dispatching. Next, we will explain how we did our simulations, show and analyze the results of our experiments, and finally, we will talk about what the results mean for the mining industry.

Review of relevant studies

A well-known area of academic and industrial research is improving haulage operations in open-pit mines. This is important for both economic and metallurgical performance. There are a few main themes that connect the literature in this field: the overall, strategic vision of Real-Time Mining (RTM) and Mining 4.0, which call for operations that are data-driven and adaptable; the creation of smart frameworks that use IoT and AI for different monitoring tasks; and the specific improvements in Truck Dispatching Systems (TDS) that try to solve difficult, multi-objective problems. This section looks at major research in various fields to explain how our work using simulations fits in and how it is different from other studies.

Mining 4.0 and Real-Time Mining are two notions that highlight how crucial it is for mining to update its tools. Hazrathosseini and Afrapoli's [27] review looks at the challenges and trends that come up when you try to employ Artificial Intelligence-based Fleet Management Systems (FMS) in the Mining 4.0 paradigm. They explain why we need smart solutions that integrate autonomy, interoperability, and interconnectedness, and they show how typical FMS does not work. Anvari and Benndorf's in-depth

review [28] of Real-Time Mining also sees this transition as a necessary response to challenges that come with modern life, such as decreasing ore grades and increased energy expenses. Their research is all about how to leverage current internet sensors, data analytics, and AI to keep an eye on the entire mining value chain and make decisions that can be changed as needed. All of these assessments agree on one thing: the future of mining is in smart, data-driven frameworks that can change with the way things are done.

This new set of technologies is very adaptable because it may be utilized to solve many different challenges in the mining industry. It uses IoT, smart sensors, and machine learning all at once. Yu et al. [29] present a fantastic example of a Digital Twin (DT) system that employs IoT and Deep Learning to keep an eye on the safety of geological cracks in open-pit coal mines in real time. By merging real-time sensor data with a virtual model, their technology allows you undertake preventive maintenance and lower geotechnical hazards. The study's focus area (safety) is different from ours (production and grade control), but it is still important because it shows that a similar IoT and AI-based technology stack can be used successfully for complex, real-time monitoring and decision-making in the difficult open-pit environment.

In the area of Truck Dispatching Systems, new research has moved past simple, cost-focused aims to tackle harder optimization problems that have more than one purpose. Kazemi Ashtiani's work [30] is an excellent example because it built a framework for truck dispatching that combines simulation and optimization and focuses on improving the environment. His idea seeks to accomplish production targets and cut down on the time that equipment is not being used, as well as cut down on fuel use and greenhouse gas emissions. The case study, which witnessed a big decline in fuel use of up to 6%, clearly supports the use of simulation as a way to optimize for important but non-traditional goals. The overarching difficulty of assessing and enhancing the production efficiency of loading and haulage equipment is a recurring theme in the literature, underscoring the necessity for analytical frameworks capable of modeling these intricate operational dynamics [31].

As Hou et al. [32] show with their model for the multistage dynamic optimization of ore flow in an underground mine, the problem of combining ore mixing with dispatching logistics is a common one. This challenge is important for many various mining processes because their work also tries to keep transportation costs as low as possible while taking ore grade limits into account. But the operational restrictions of an underground mine are very different from those of an open-pit mine. For example, transportation networks are fixed and access to stopes is limited. This means that domain-specific solutions are needed, which makes research that focuses just on the unique dynamics of open-pit haulage networks even more important. While the haulage dynamics differ, the core challenge of process optimization is universal, with related research focusing on areas such as the development of efficient blasting designs for underground mines [33].

The research of Yao et al. [34] on an "Open-Pit Mine Truck Dispatching System Based on Dynamic Ore Blending Decisions" is the most direct example of what we are doing. This study looks directly at the major issue with traditional, cost-based dispatching and the need to blend ore in real time. The authors explain about how a smart TDS that works with the Internet of Things was effectively used in a big mine in the real world.

They used high-precision location and 4G/5G to make decisions on how to mix ingredients in real time. Their year-long case study demonstrates that transportation is 5.5% more efficient, which is strong evidence that these technologies might operate and be useful in real life.

When you put all of this information together, it produces a clear picture. Smart, real-time mining has a clear strategic purpose. The technologies that make it feasible, such as IoT and AI, have been proved to function well for intricate monitoring jobs. There are real-life examples of how grade-aware dispatch systems can work, and simulation is a proven approach to improve specific dispatch goals. But there is still a specific gap: Yao et al.'s work is merely a case study of one implementation, even though it is the first of its kind. There is not a detailed, quantitative, and controlled comparison in the literature that looks at the exact consequences of an intelligent, grade-focused dispatch algorithm compared to a standard one in the same situations that can be repeated.

Our study is meant to fill this precise gap. We can get rid of the noise from outside operational elements and do a direct, “apples-to-apples” comparison of the two dispatching systems by using a discrete-event simulation method. This method allows us accurately weigh the merits and downsides of deploying an IoT-enabled system for dynamic ore grade control. It gives us strong, data-driven substantiation that adds to existing strategic reviews and real-world case studies.

As discussed earlier, a summary of the relevant studies has been provided in Table 1, offering a concise overview for reference.

The assessment of past studies found that while existing research uses advanced ideas like Real-Time Mining, IoT, AI, and simulation–optimization in mining operations, these methods have major flaws when it comes to our unique research subject. A lot of research looks at other optimization goals, such as saving money or making fuel more efficient, but they do not pay enough attention to the necessity for dynamic, real-time ore grade control. Research is also often particular to other locations, such as underground mines, and models that do not work for the peculiar haulage dynamics of open-pit operations. Most crucially, real-world case studies of grade-aware dispatch systems are very useful for showing that they work in practice, but they do not have the controlled, comparative study needed to accurately measure the benefits of an intelligent system versus a standard baseline [35].

This work proposes a discrete-event simulation framework to fill in these gaps. Unlike single-objective optimizations or real-world case studies, our simulation lets us compare traditional and IoT-enabled dispatch algorithms in a controlled way that is “apples-to-apples.” By putting the problem in a simulation, we can see how the dispatching logic affects several important performance measures, such as grade consistency, total productivity, and resource use. This method lets us give the hard, measurable proof we need to show that a dynamic, grade-aware dispatching system has operational and metallurgical benefits.

Methods

This study uses a quantitative, simulation-based method to compare the performance of an IoT-enabled ore blending and dispatching system to that of a traditional system. In Python, we created a discrete-event simulation model that makes a digital twin of

Table 1 Critical analysis of the relevant studies

Ref	Research issue	Methodology	Advantages	Limitations
[34]	Conflict between traditional cost-focused dispatch and the need for real-time ore blending	Real-world case study of an implemented IoT-enabled dispatch system at a large-scale mine	Provides invaluable proof of concept and demonstrates quantifiable real-world efficiency gains (5.5%)	As a case study, it lacks a controlled, side-by-side comparison with a traditional system under identical conditions
[28]	The need for a strategic shift in mining towards data-driven, adaptive operations	Comprehensive literature review on Real-Time Mining (RTM) concepts, technologies, and frameworks	Establishes the high-level strategic vision and technological feasibility for intelligent mining systems	As a review, it does not present a specific model or a quantitative analysis of any single component
[27]	The need to justify and understand the trend towards AI-based Fleet Management Systems (FMS)	Literature review and SWOT analysis of AI-based FMS in the context of Mining 4.0	Provides a strong strategic justification for the adoption of intelligent FMS and outlines the associated challenges and opportunities	Does not propose or validate a specific computational model or simulation framework
[29]	The need for proactive safety monitoring (crack detection) in open-pit mines	A Digital Twin framework using IoT sensors and a Deep Learning model for real-time crack detection	Demonstrates the successful application of an IoT/AI technology stack for a complex, real-time monitoring task in a mine	The application is focused on geotechnical safety, not on the operational and metallurgical problem of production/grade control
[30]	High fuel consumption and environmental impact of haulage operations	An integrated simulation and multi-objective optimization framework for truck dispatching	Validates the use of simulation for optimizing for non-traditional objectives; achieves significant fuel reduction	The primary optimization objective is fuel efficiency, not the dynamic, real-time control of stockpile ore grade
[32]	The universal challenge of integrating ore blending with transportation logistics in mining	A multistage dynamic optimization model for ore flow and blending	Addresses the core problem of integrated blending and dispatching, showing its broad relevance	The model and constraints are specific to underground mining and are not directly transferable to open-pit dynamics

a simple open-pit mining operation. We picked this method because it lets us create a controlled, repeatable experimental setting where we can directly compare dispatching tactics without the cost, risk, and complexity of a live-field trial. This approach is common in logistics and supply chain analysis, where innovative simulation models are frequently used to analyze the effects of various events, such as disruptions, on system performance [36].

Simulation environment and model setup

We used Python 3 to make the simulation environment. We used NumPy for math, Pandas for logging and manipulating data, and Matplotlib/Seaborn for showing data. The model has both static parts that show the mine's physical architecture and dynamic parts that show the operational fleet.

Mine layout and geological model

For any high-fidelity simulation, it is very important to make a “digital twin” of the system that accurately represents its most important spatial and physical attributes. Before simulating any moving parts, like loading cycles or truck movements, it is crucial to accurately define the simulation's static “world.” This includes finding the real-world locations of major buildings and, most crucially, simulating how resources are spread out in that space. This first setup supplies the essential facts and restrictions that all future choices and actions will be based on. We built a simple but realistic open-pit mine structure, depicted in Fig. 1, to use as the static canvas for our comparison experiment.

Figure 1 shows a two-dimensional Cartesian coordinate system that reflects the simulated mining environment. Each axis displays how far away it is in meters. This spatial framework lets you figure out exactly how far it is between any two places. There are two

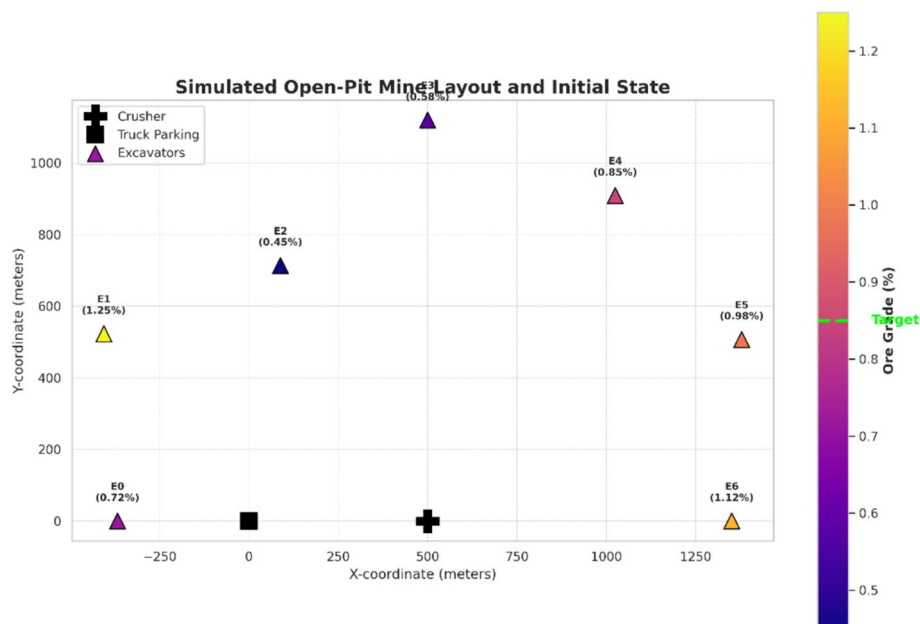


Fig. 1 The layout and initial state of the simulated open-pit mine environment

main static facilities in the haulage network, which are displayed as black squares. The first is a single Crusher at (500, 0), which is where all the ore goes. The second is a central Truck Parking area at (0, 0), which is where the trucks start and end their trips. The seven active digging faces, shown by colored triangles, are arranged in a semi-circular arc that looks like a typical multi-bench layout in an open-pit mine in real life. This setup purposely makes the haulage distances from each digging face to the central crusher different, which adds an important variable to the dispatching optimization problem.

Figure 1 shows not just the geometry of the space but also the geological model of the simulation. The color of each excavator's triangle emblem and its label show the particular and unchanging ore grade of the material in that area, as seen by the color bar on the right. This simulates data that would usually come from a geological block model in a real mine. It was planned ahead of time that these grades would be spread out in this way as part of the experiment. There are a few low-grade sources (E2 at 0.45%), a high-grade source (E1 at 1.25%), and sources with grades near the goal (E4 at 0.85%). This intended variety is very crucial to the study because it makes sure that the proper raw materials are constantly on hand for blending and that the dispatching algorithm always has to make wise decisions. It is important to note that in this geological model, the ore grades were deliberately kept constant throughout the entire simulation period. This assumption was embraced to establish a consistent and reliable foundation for the experiments. However, in reality, ore grades vary in different locations and can change over time across different levels. Adding in grade variability through stochastic or block-model approaches will be a significant enhancement to this framework.

The key rationale for employing this exact, visually defined simulation environment was to set a controlled, stable, and repeatable baseline for the experiment. There are a number of things that can go wrong when mining, such as bad weather, bad operators, bad roads, and equipment that breaks down without warning. This makes it practically impossible to compare two different strategies in a way that is truly “apples to apples.” Our simulation-based solution gets rid of these outside sources of noise by creating a static and deterministic digital counterpart of the mine. This method helps us focus on the major independent variable in our investigation, which is the dispatching algorithm.

By testing both the “Traditional” and “IoT-Enabled” techniques against the same set of spatial and geological challenges, we can be sure that any differences in performance are due to the logic of the dispatching algorithm itself. This level of control is needed to precisely and scientifically measure the exact effects of an intelligent, grade-aware dispatching system, which is the purpose of the study. We can acquire a level of analytical purity from a virtual setting that we cannot get from a real-world case study. This makes our results more valid.

The fact that this simulation setting can successfully produce the main operational conflict that this study is trying to look into—the trade-off between haulage efficiency (proximity) and metallurgical quality (grade)—proves that it works. Figure 1 shows that putting excavators with different grades at different distances from the crusher is not an easy optimization problem. The highest-grade ore (E1) is at one of the farthest spots, while a closer excavator (E0) has a grade that is lower than the target. This design makes sure that a simple, proximity-based algorithm and a grade-aware algorithm will act and generate results that are clearly different.

This well-planned disagreement worked really well because it created the right conditions to test the main idea of the study. If a simulation environment did not make this trade-off (for example, if all of the high-quality sources were also the nearest), it would not have been able to tell the two techniques apart in a meaningful way. So, the decision to construct the mine layout in this way was not only intentional but also crucial to the experiment's overall validity and success, as it made sure that the IoT-enabled system's smart capabilities were thoroughly evaluated.

Equipment fleet configuration

Now that we know what the mine's static environment looks like, the next important step in making our digital twin is to add the moving parts that keep it running. The equipment fleet is the operational heart of any open-pit mine's haulage system. It has a fleet of haul trucks that transfer things and a fleet of excavators that load them. The number of units in this fleet, how much each one can hold, and how similar they are to each other are all key parts of the model. These things have a direct effect on how much the simulation can handle, how hard it is to set up, and how well the complete system performs. While this study focuses on the system-level performance of the haulage fleet, parallel research focuses on optimizing the design of individual components, such as drilling tools, to improve their standalone efficiency [37]. A lot of care went into developing a fleet that looks like a real operation and makes it easier to understand what happened during the experiment.

The simulation can haul things since it has a fleet of 10 similar haul vehicles. All of the trucks (T_i) could carry up to 100 tons and moved at the same speed all the time. We made the experimental variable space easier to understand by building a fleet of identical trucks on purpose. Adding a fleet of trucks that are all different sizes, speeds, or fuel efficiency would make the dispatching problem considerably harder. The decision to assume a uniform fleet was a thoughtful methodological approach aimed at highlighting the effects of dispatching logic without the interference of varying factors like truck capacity, speed, or fuel efficiency. In practice, fleets in the real world often consist of a mix of different types. By broadening the framework to encompass a variety of truck types, we can gain more authentic insights into how IoT-enabled dispatching strategies perform in real-world scenarios. In this situation, the algorithm would have to think about more than just the slope and distance. It would also have to think about what each vehicle is good at. By making sure that the haulage units are all the same, we can be sure that any differences in performance between the traditional and IoT-enabled strategies are only due to the intelligence of the dispatching logic and not because a "better" or "worse" truck was randomly assigned to a certain haul cycle.

The simulation has seven excavators, which are the same number as the seven active digging faces in the geological model. One important assumption that made things easier was that each excavator would have enough loading capacity to service a truck without becoming a major operational bottleneck itself. This means that we did not think about factors that are unique to excavators, such the size of the bucket, how long it takes to swing, or when the machine breaks down. The fundamental reason for this simplification is to keep the simulation focused on the decision to send the vehicle. By always having a shovel ready to load, we make the truck the most crucial thing to improve. A

fixed loading_time, which is the length of time it takes to fill a 100-ton truck, is the most essential operational parameter for the excavators.

In short, we made sure that the equipment we used for our simulation was similar to what would be used in a small to medium-sized mining operation, while also making sure that the configuration was easy to understand. The setup of ten identical trucks and seven non-bottleneck excavators makes for a balanced system. The primary problem is still how to smartly distribute hauling resources to meet a changing blending aim. The study's main goal is to find and measure the precise effects of the dispatching algorithm on performance. These intentional design choices are essential to that goal.

Simulation dynamics and core mechanics

Now that we have set up the static parts of the simulation environment—the physical mine layout and the equipment fleet—let us look at the dynamic rules that control how they work over time. The simulation takes place as a discrete-event process, moving forward in 1-min intervals for a total of 480 min, which is the length of a normal 8-h production shift. A set of core mechanics controls how each dynamic agent, especially the haul trucks, acts. These mechanics include the set times for important operational tasks and a formal state machine that keeps track of each truck's lifecycle as it moves from one task to the next. Together, these rules make up the engine of the simulation, which makes sure that the modeled operation goes on in a logical and consistent way.

Movement and process durations

The time it takes to finish each step of the haulage cycle is what controls the flow of material through the simulated mine. We set a group of constant parameters for travel, loading, and dumping activities to model this.

Travel Time is an important factor. We figured out how long it would take for a truck to get from one location to another in the 2D environment by looking at the straight-line Euclidean distance between their coordinates. For example, we looked at how long it would take for a vehicle to get from the parking lot to an excavator. Then, the distance was divided by a constant average truck speed of 30 km/h, which is the same as 500 m per minute. This is a methodological simplification that assumes perfect and steady travel circumstances and leaves out more complicated factors like the slopes of haul roads, traffic jams, and how quickly trucks speed up and slow down. We made this approach so that the simulation would stay focused on the high-level strategic impact of the dispatching logic instead of becoming a complicated traffic micro-simulation.

It is important to note that using Euclidean distances is a conscious choice to make things easier. This abstraction gets rid of the geometric and operational problems that come with haul road networks, like slopes, curves, and possible traffic jams. It was used to study the effects of dispatching logic in a very controlled setting. Future developments of this work will integrate a realistic depiction of the haul road network to enhance the fidelity and external validity of the simulation results.

In addition to the time it took to travel, set times were given for the main loading and dumping processes. The Loading Time was always set to 5 min. This is the entire amount of time that has passed from when a truck pulls up to an available excavator to when it is fully loaded and ready to leave. The Dumping Time at the crusher

was also adjusted to a steady 2 min. Another way to make things easier on purpose is to utilize fixed, deterministic times for these processes. It assumes that operations would be very consistent and gets rid of the randomness that could happen in real life because of changes in operator expertise, how easy it is to dig up materials, or small delays in the crusher. By keeping the process times, the same for both the traditional and IoT-enabled simulation runs, we make sure that the only thing that affects system performance is the order in which dispatch choices are made. This is the main variable we are looking into.

Choosing to have fixed loading and dumping times is another intentional step towards making things simpler. This assumption removes the unpredictability that can come from factors like equipment delays, differences among operators, or changing digging conditions. By doing so, we can focus on understanding the strategic impacts of our dispatching logic more clearly. However, in real-world situations, such times are naturally unpredictable. In the future, we plan to enhance the framework by incorporating probabilistic distributions for these processes. This will allow us to conduct more realistic sensitivity analyses.

Haul truck state machine

We set up a formal state machine to handle the complicated lifespan of each haul vehicle in a strong and logical way. This is a common computational model used in simulation research. It outlines a limited number of states that an object can be in and the factors that cause it to go from one state to another. This method makes sure that each truck in our fleet is always in one, and only one, well-defined state. This gives the simulation's logic a strong and error-free engine.

We represent the whole hauling cycle for each truck as a series of seven different states. At the central parking area, a truck starts in the Idle state, waiting for a new job. At this point, the dispatching algorithm steps in and makes a difference. After a dispatch decision is made, the truck goes into the Traveling to Excavator state. If the allocated excavator is already working on another truck when it arrives, it goes into a Queuing at Excavator state. The truck moves to Loading once the excavator is free. The completely loaded truck goes into the Traveling to Crusher state when the 5-min loading operation is over. When it gets to the crusher, it changes to Dumping. Finally, after its 2-min dump cycle, the truck, which is now empty, goes into the Traveling to Parking state. It then completes the loop by going back to the parking area, where it becomes Idle and ready for its next job.

This clearly specified state machine is very important to the validity of the experimental design. It is the main engine behind our discrete-event simulation, making sure that the flow of materials through the system is handled in a way that makes sense and is consistent. Its design is important because it limits the moment of decision-making to one transition point: the move from the Idle state. At this point, the experimental variable -the option between the Traditional and the IoT-Enabled dispatching algorithm- affects how the system works. This makes sure that our next comparison is based on a clear and unambiguous difference in strategic reasoning, which confirms the experiment's outcomes.

Dispatching algorithms: the experimental variable

Now that we have set up the simulation system and its main operational dynamics, we can get to the heart of the research: comparing two very different dispatching algorithms. The dispatching logic is the “brain” of the haulage system because it decides where to send a truck that is not working. This choice, which is made hundreds of times during a shift, ultimately determines how well the operation runs. The dispatching algorithm is the only independent variable in our study. We can separate and assess the effect of this decision-making intelligence by using two different tactics in the same simulated environment. The next few parts explain how the baseline traditional plan works and how our IoT-enabled strategy works.

The main focus of this study is to compare two different dispatching methods. These algorithms are not just separate sets of rules for how things should be done; they are two very different ways of thinking about how to run the mine that affect how materials move through it. The first, a classic method, puts simplicity and quick results at the top of the list. The second technique, which uses the Internet of Things (IoT), is a more complicated, data-driven method that aims to optimize several goals. Before going into the details of how each algorithm works in the next sections, it is helpful to have a general idea of what they are, what they want to do, and what trade-offs they have to make. Figure 2 is an infographic that gives a visual, qualitative summary of these two opposing ideas. It sets the stage for the main idea of our simulation study.

The left half of the infographic in Fig. 2 shows the main ideas behind the traditional dispatching philosophy. Its main benefits are that it is “Simple to Use” and “Minimal Travel Time.” This shows a technique that is simple to put into action and keep track of, based on one simple rule: proximity. The goal is to get the haulage fleet moving as quickly as possible by cutting down on the distance that empty trucks have to travel, which is a direct measure of operational cost. But there are also big problems with this simplicity, which are also pointed out. The system only has “Basic Grade Control” because it does not care about the metallurgical qualities of the material being moved. A direct and harmful result of this single-minded concentration on efficiency is an “Uneven Workload,” where excavators that are closer to the crusher or parking areas are overworked while those that are farther away may sit idle. This leads to wasteful use of capital equipment and possible bottlenecks.

The infographic’s right side shows how the suggested IoT-enabled dispatching philosophy takes into account several different goals. This plan uses real-time data to go beyond basic heuristics and get better results. “Precision in Blending” and “Stable Grade Output” are the main benefits listed, which shows that the main goal is to achieve the quality standards of the processing plant. This is done by “Optimized Resource Use,” which means smartly distributing the whole fleet. This smart distribution leads to a “Balanced Workload,” which means that the system spreads work more evenly among all the available excavators to reach its blending goals. The scale in the infographic shows the main point: the IoT-enabled strategy achieves a better balance between many, competing goals, resulting in a better overall output, even though the old technique is easier.

It is very important for teaching purposes that this conceptual visualization is included in the methods section. It connects the broad research question posed in the beginning to the more specific, step-by-step explanations of the algorithms that come next. By

Comparing Dispatch Strategies in Mining Operations

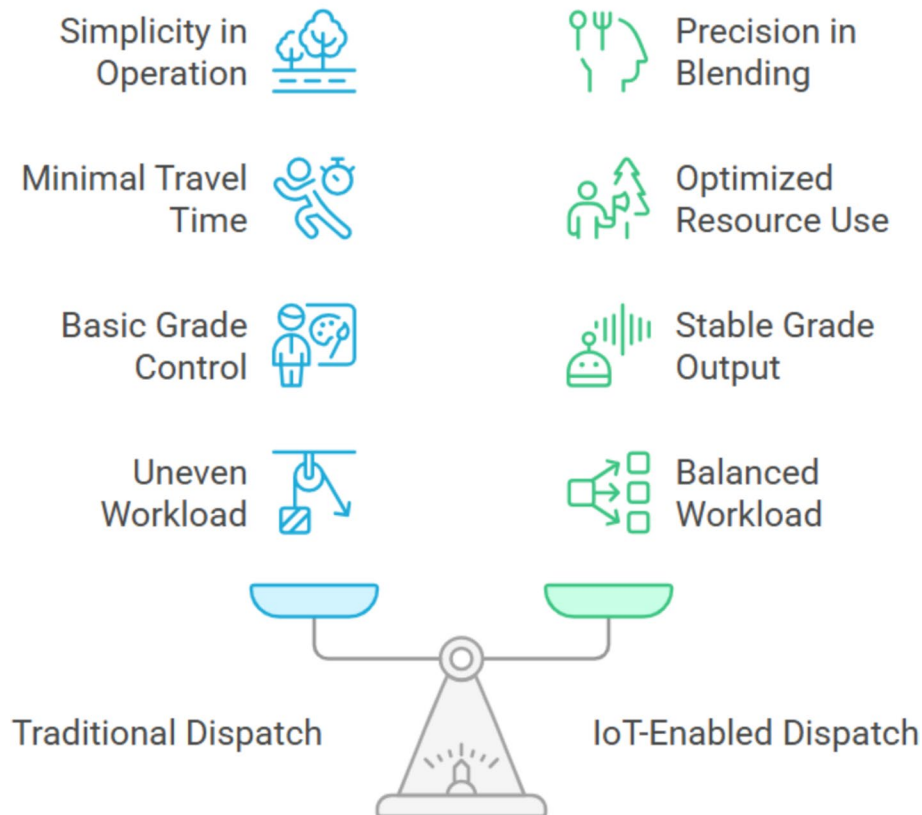


Fig. 2 A conceptual comparison of traditional vs. IoT-enabled dispatch strategies

showing the two competing methods as different ways of doing things with clear, qualitative trade-offs, we give the reader a strong conceptual foundation. This picture makes it much easier to understand what the next, more technical parts are about. It puts the whole experiment in the context of a quantitative examination of two very different ways to run a mine, not just a comparison of two pieces of code. This way of framing concepts is very important for making sure that the bigger picture of our technical work is clear and easy to understand.

This infographic is a very useful methodological tool because it turns the complicated, multi-faceted topic of dispatch optimization into a simple and easy-to-understand visual metaphor: a balancing scale. It does a good job of getting across the main tension of the research (for example, simplicity vs. precision, unequal vs. balanced workload) to a wide range of people, even those who may not be specialists in simulation or mining logistics. This clear conceptual foundation at the start of the section on algorithms makes the whole methodology clearer and more powerful. It gives the “why” before the “how,” which makes the more in-depth look at each algorithm’s reasoning that comes next more interesting and relevant for the reader. This makes sure that the basic ideas behind our study are clear before we show how they were tested with numbers.

Baseline strategy: traditional closest-available dispatch

To provide a robust benchmark for comparison, our first algorithm represents the “control group” in our experiment. It is designed to model a common, non-optimized industry practice where operational decisions are driven primarily by the goal of maximizing immediate efficiency, often measured by minimizing travel time. This strategy is computationally simple and does not require any real-time grade information, reflecting a more traditional approach to fleet management.

The logic of this “Closest-Available” algorithm is straightforward. When a truck enters the Idle state, the system performs the following steps:

1. It scans for all excavators that are currently available (i.e., not currently loading another truck or already assigned a truck that is en route).
2. It calculates the Euclidean distance from the idle truck’s current position (the central parking area) to each of these available excavators.
3. The truck is dispatched to the excavator with the minimum calculated distance.

The underlying rationale for this strategy is the optimization of asset utilization. By minimizing the travel time of empty trucks, the system aims to reduce the overall cycle time for each haulage unit, thereby maximizing the potential number of trips that can be completed within a shift. However, the critical weakness of this approach is its complete agnosticism to ore grade. The algorithm treats a ton of low-grade ore, high-grade ore, or waste rock as entirely interchangeable. Its decision-making is purely spatial, answering the question, “What is the fastest way to move the next load?” without any consideration for the more strategic metallurgical question, “What is the best load to move next to meet our quality target?”

Proposed strategy: IoT-enabled blending dispatch

In direct contrast to the baseline, our second algorithm represents the “experimental group.” It models the proposed intelligent system, which operates within a simulated IoT-enabled environment. This environment provides the dispatching logic with access to two critical, real-time data streams that are unavailable to the traditional system: (1) the specific, live ore grade at each active excavator, and (2) the up-to-the-minute cumulative history of all deliveries made to the crusher. The fundamental objective of this algorithm is therefore different: it does not seek to minimize travel time but rather to actively minimize the deviation of the cumulative stockpile grade from the global target.

The decision logic of the IoT-enabled system is based on a dynamic, closed-loop feedback mechanism. This kind of dynamic control logic, which is meant to stop unwanted states, is similar in idea to control strategies used in other mining processes, including tracking prevention during drilling operations [38]. When a truck becomes Idle, the algorithm executes a “what-if” analysis to make a forward-looking, corrective decision:

It first queries the crusher delivery log to calculate the current total tonnage and the current weighted-average grade of the entire stockpile.

It identifies all excavators that are currently available.

For each available excavator, the algorithm simulates the outcome of a potential dispatch, predicting what the new stockpile average grade would be if one 100-ton truckload from that excavator were to be added.

A “cost” is calculated for each potential dispatch, defined as the absolute difference between the predicted new stockpile grade and the global target grade (0.85%).

The truck is dispatched to the excavator that yields the *minimum cost*, thereby selecting the single action that most effectively moves the stockpile grade closer to its target.

While the textual description above outlines the procedural steps of the algorithm, a visual representation is essential for fully appreciating its dynamic, goal-oriented behavior in practice. The scatter plot in Fig. 3 provides an empirical visualization of the algorithm’s decisions over the course of the simulation, plotting its choices (the grade of the dispatched truckload) against the state of the system at the moment of each decision. This plot effectively serves as a map of the algorithm’s “brain,” revealing the clear, corrective patterns that govern its operation.

The scatter plot in Fig. 3 gives a clear and strong look at how the intelligent agent makes decisions. The y -axis shows what the algorithm did, which was to pick the truckload with the right mineral grade. The x -axis shows what was going on in the system that made the operation necessary: the cumulative stockpile grade was below the 0.85% threshold before the dispatch. Each point on the plot is a single dispatch choice. The vertical dashed line shows a flawless stockpile (no variance), while the horizontal dashed line shows a truckload that was shipped out with the precise target grade. Each point’s color shows how far off the stockpile is from the target. Red means the grade is too low, and blue means the grade is too high. This adds additional layer of visual information.

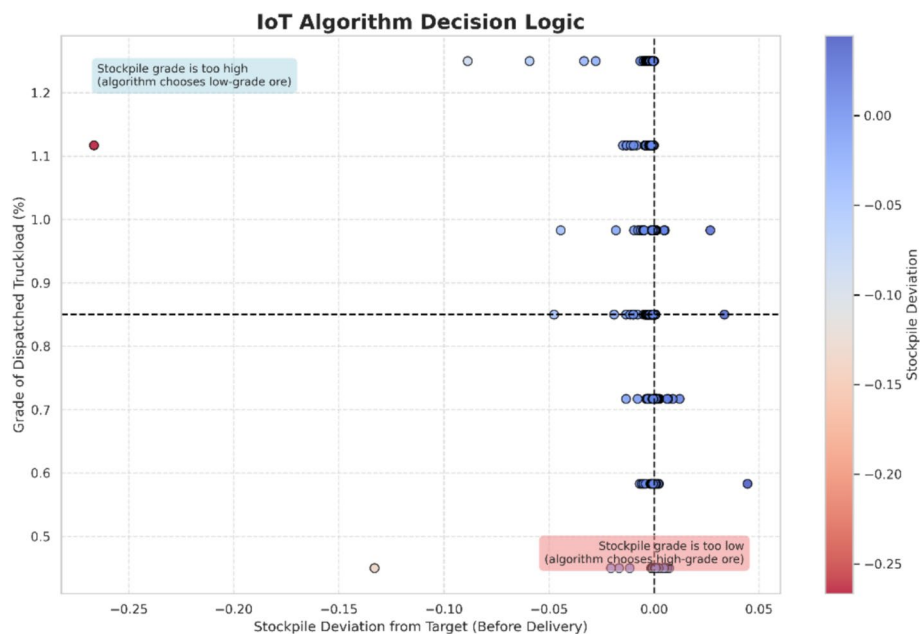


Fig. 3 Visualization of the IoT-enabled algorithm’s decision logic

This depiction makes it very evident that there are three separate and logical areas for making decisions. First, when the stockpile grade is too high (the data points to the left of the zero-deviation line and are blue), the algorithm always and accurately sends trucks from low-grade excavators (those with a grade below the 0.85% target line). The group of points in the upper-left quadrant shows this corrective action. Second, when the stockpile grade is too low (spots with red coloration), the algorithm does the exact opposite of what it should do: it sends trucks to high-quality sources (those above the target line) to raise the average, as shown in the lower-left quadrant. Third, when the stockpile is already extremely close to the target (the dense cluster of points around the vertical zero-deviation line), the algorithm correctly prioritizes stability by predominantly selecting material from excavators whose grade is near the target.

The main reason we made and looked at this visualization as part of our process is to show clearly and with real data that the algorithm behaves in a logical and goal-oriented way. This figure makes it evident that the simulated intelligent agent is working on a principle that is explicit and right, unlike a “black-box” model where the internal logic is not clear. It proves that our implementation of the suggested technique is proper and that the algorithm is working exactly as it should. Our phase is very important for making sure that our experiment is internally legitimate and that the performance results we see are indeed the consequence of our smart, closed-loop logic.

This visualization method works well because it makes the main idea of a feedback control system so plain. The plot does a good job of turning the algorithm’s abstract, step-by-step instructions into a clear pattern of action and reaction. It shows that the system is not just picking things at random; it is always measuring, predicting, and correcting. This validation is very important to the whole study. If there was not proof that the proposed algorithm was working correctly and rationally, any comparison of its performance to the baseline would be pointless. This visualization is an important link between the algorithm’s conceptual design and the real-world results of the simulation. It gives us the confidence we need to move forward with the comparative analysis.

Data collection and performance metrics

A whole data collecting and performance measurement framework was set up to make it easier to do a strict, quantitative, and multi-faceted comparison of the two competing dispatching systems. A complete event log with time stamps was created for each 480-min simulation run to record all important operational operations. A delivery log for crushers was the main source of raw data for our investigation. Every time a haul cycle was finished, a new entry was made. This entry included the time of delivery, the truck’s ID, the source excavator’s ID, the tonnage delivered (always 100 tons), and the precise ore grade of the load. We used this detailed, high-resolution data to figure out a set of high-level Key Performance Indicators (KPIs). The chosen KPIs were meant to give a complete picture of how well each method worked, looking at both the main goal of improving metallurgical quality and the important side effects on production efficiency and resource use.

Key performance indicator: ore grade accuracy

Ore Grade Accuracy is the first and most important KPI. It is the final weighted-average grade of the entire stockpile at the end of the 480-min shift. This indicator tells you how well the ore mixing approach worked in the end. It gives a clear, bottom-line answer to the question, “How well did the dispatching system meet the metallurgical target of 0.85% after a full 8-h shift?” A final grade that is closer to this goal means that the blending algorithm is smarter and works better. This KPI is the main way to monitor how well the system is meeting its quality-focused aim. Any variation from the target means that the downstream processing plant is losing money or not working as efficiently as it could be.

Key performance indicator: production throughput

Grade control is the most important thing to think about, but you also need to look at how productive a dispatching plan is as a whole. So, our second key performance indicator (KPI) is production throughput, which is the total number of tons of ore supplied to the crusher throughout the entire shift. This number tells you how well the haulage business is working at its most basic level. An intelligent dispatching system that sends out flawless grade but at a very low production rate would not be able to make money. This KPI is very important for figuring out the possible operational trade-offs of the IoT-enabled approach. It lets us answer the important question: “What, if any, is the cost to productivity of putting grade control ahead of simple proximity-based dispatching?”

Key performance indicator: grade consistency

The constancy of the ore feed during the shift is just as important as getting the ultimate target grade for the smooth running of a processing plant. Grade Consistency is our third KPI. It is the standard deviation of the cumulative stockpile grade, which we calculate at every delivery during the simulation. A high standard deviation would mean that the stockpile grade changed a lot during the shift and then maybe settled around the target, which is very bad for the plant. On the other hand, a lower standard deviation means that the blending process is smoother, more stable, and easier to predict. So, this KPI is a very important way to monitor process control. Lower values mean that the blending method is better and more reliable.

Key performance indicator: workload balance

Finally, a good dispatching system should use its resources in a way that is both sustainable and balanced. Our fourth key performance indicator (KPI) is Workload Balance, which we analyze by looking at the standard deviation of the utilization percentages across the seven excavators. To find out how much each excavator is being used, divide the total time it spent in the Loading state by the total length of the simulation. If the standard deviation is high, it means that the system is using a small number of excavators too much (perhaps the ones that are closest or have a certain grade), while leaving others sitting around for long periods of time. This might cause equipment to wear out unevenly and cause bottlenecks in certain areas. A lower standard deviation means that

the workload is more evenly spread out, which is an indication of a more balanced and stronger operational plan. This KPI is a way to measure how well resources are being used.

Our method lets us directly, quantitatively, and comprehensively evaluate the effect of each dispatching strategy on operational quality, efficiency, stability, and sustainability by systematically comparing these four different KPIs throughout the two simulation runs. The next chapter shows the outcomes of this comparison.

Experimental results

This section presents the quantitative and qualitative outcomes of the comparative simulation study. The Traditional (baseline) and IoT-Enabled (proposed) dispatching strategies were each simulated for a full 8-h (480-min) shift under the identical environmental and fleet conditions detailed in the previous chapter. By analyzing the detailed event logs generated during each simulation run, we can now present a direct, data-driven comparison of their performance. The analysis is structured thematically to first address the primary objective of the study—ore grade control and consistency—followed by an evaluation of the secondary, but equally important, operational impacts on production throughput and resource utilization.

Primary objective: ore grade control and consistency

The basic idea behind this study is that a smart, IoT-enabled dispatching system may do a much better job of keeping a consistent stockpile grade than a traditional, proximity-based method. Being able to reliably supply an ore blend that meets specifications to the processing plant is a major factor in mining operations' value, since it directly affects metallurgical recovery and profits. To see if this idea is true, we start our research with the most obvious and straightforward way to quantify how well each system worked: the change in the total stockpile grade throughout the course of the simulation. This time-series visualization tells a clear story about how well each strategy was able to reach and keep the worldwide metallurgical objective of 0.85%. It also gives a big picture view of how well they blended from the start to the end of the shift.

Figure 4 shows a time-series graphic that tells a very clear story about how well the two competing dispatching strategies worked over the course of the 480-min simulation. The x -axis shows the number of minutes that have passed in the simulation, while the y -axis shows the cumulative weighted-average grade of the central stockpile. The dashed line at 0.85% shows the target grade that both systems were supposed to reach. It is always there to help you see it. The blue line shows how well the suggested IoT-Enabled, grade-aware method works, whereas the orange line shows how well the Traditional, closest-available dispatch strategy works. The first 50 min of the simulation are very unstable for both systems. This is a normal result of starting the simulation with an empty stockpile, where the first few truckloads have a bigger effect on the overall average grade than the rest.

After this first period of stability, it becomes very evident that the two techniques are performing very differently and will continue to do so. The blue line, which shows the IoT-Enabled system, acts like a well-tuned control system. It quickly moves toward the 0.85% target line and then stays on a very stable path, swinging snugly around this target

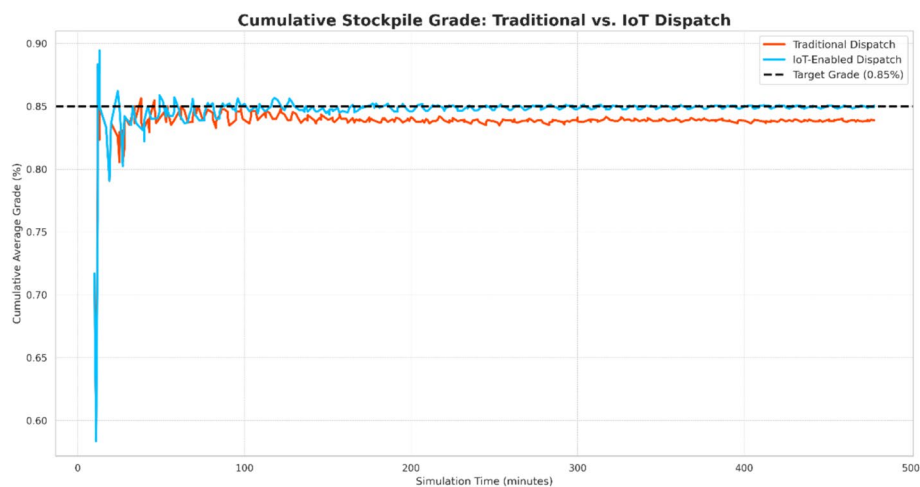


Fig. 4 Time-series comparison of cumulative stockpile grade for traditional vs. IoT dispatch

for the rest of the 8-h shift. The orange line, which stands for the Traditional method, on the other hand, moves in an unregulated, drifting way. After the early fluctuations, its cumulative grade does not reach the target; instead, it settles at a level far below what is needed. This result is a clear and expected result of its basic reasoning. By putting proximity ahead of quality, it probably used the closer, lower-grade excavators too much, which led to a final stockpile that does not match the metallurgical standards.

The main reason to use this type of comparative time-series visualization is that it may show performance in a way that goes beyond a single, static endpoint number. A basic bar chart that merely shows the final stockpile grade would suggest that the IoT system worked better, but this plot shows how and why. It shows the idea of “process control” in a way that makes it evident how the IoT system is always making changes to stay on target, while the old system is just letting things drift without any control. So, this way of visualizing is very important for showing not only the better result, but also the better operational behavior and intelligence of the proposed algorithm during the whole production shift.

This analytical strategy worked quite well to give clear proof of our main hypothesis. Figure 4 shows clearly and convincingly that the IoT-enabled dispatch method is far better at reaching and keeping a target ore grade than a traditional approach that focuses on efficiency. The graph is a strong and easy-to-understand example of the main benefit of making decisions based on real-time, data-driven, and grade-aware information. This one finding strongly supports the use of these smart technologies since being able to dependably deliver on-spec material to the processing plant is a key factor in the value and efficiency of any contemporary mining operation. This visualization does a good job of turning a complicated set of algorithmic decisions into a simple and easy-to-understand story about performance.

The cumulative grade plot gives a general idea of the system’s stability and control performance, but looking at the running error, or the absolute difference between the stockpile grade and its objective over time, gives a more accurate picture. This method lets us look at more than just the overall grade; it lets us look at how much the system is wrong

from moment to moment. A fully stable system should not only be accurate on average, but it should also quickly correct any mistakes that happen. Figure 5 shows a time-series plot that was made to show and compare this part of control performance. It is a more thorough test of each system's stability.

Figure 5 shows the absolute difference between the cumulative stockpile grade and the 0.85% objective at all times for both the Traditional (orange) and IoT-Enabled (blue) systems. The first big jump in deviation at the start of the simulation is caused by the empty stockpile. The first truckload of goods causes a huge difference from the target. But just after this, the graph makes it very evident how the two systems have different control properties. The blue line, which stands for the IoT-Enabled system, indicates that the deviation is quickly and strongly suppressed. During the first 100 min of the shift, the error settles into a very low and narrow range, which means that the smart algorithm is actively and successfully keeping any major deviations from the objective in check.

The way the old system works is really different. The orange line, on the other hand, stays at a far higher level of absolute error, even though its deviation also goes down from the first spike. This shows that the proximity-based algorithm cannot fix a long-term, systemic departure from the target. After the 100-min mark, the blue and orange lines' consistent error bands create a visible and persistent gap that shows how much better the IoT-enabled method controls things. Not only does it get a superior final grade, but it also stays more accurate over the entire operational term.

It is common in control systems engineering to look at and graph the running absolute deviation. Plotting the error term directly is a very sensitive way to check how stable and responsive a control system is. The cumulative grade plot (Fig. 4) provides the final outcome, but the deviation plot (Fig. 5) demonstrates how the control works behind the scenes. We chose this method because it would give us a more rigorous and quantitative look at the promises of "stability" and "consistency." Instead of just describing them qualitatively, we would be able to directly quantify how well the process control worked over time.

This way of looking at things worked very well to show how much better the control logic is in the IoT-enabled system. It shows that the smart algorithm is not only more accurate in the end, but it is also more stable and predictable from moment to moment.

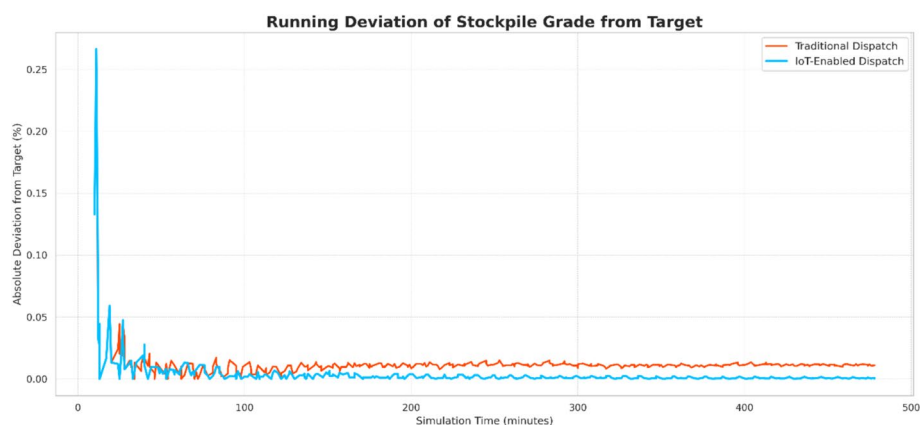


Fig. 5 Time-series comparison of the running absolute deviation of stockpile grade from target

This consistency is a very important operational benefit for a downstream processing plant. A steady and regular ore feed lets the plant be fine-tuned for the best performance, which leads to better metallurgical recovery and lower costs. This plot shows that the IoT system's benefits go beyond just accuracy. They also include better process stability, which is a critical factor in the value of an integrated mining and processing operation.

To finish our study of grade control, we need to change from looking at the process as a whole over time to looking at it in smaller, more specific statistical terms. The stockpile's final consistency depends on how consistent each truckload that is brought to it is. A method that gets the right average grade by switching between truckloads with very high and very low grades is still causing a lot of short-term problems for the processing plant. We looked at the distribution of grade deviation on a per-truckload basis for both systems to find out more. We chose the violin plot for this job because it is a complex way to show data that gives us a far better idea of how the data is spread out than simple summary statistics like the mean or median.

Figure 6 shows violin plots that compare the probability density of the absolute grade deviation for each truckload delivered under the two dispatch options. You might think of a violin plot as a mix of a box plot (the black-and-white figure inside each “violin”) and a kernel density plot, where the width of the form at any level shows how many data points are at that value. There is a big difference between the two distributions when you look at them. The plot for the Traditional dispatch (orange, left) is much wider and has a number of big “bulges” at higher deviation levels, such as 0.15%, 0.27%, and 0.4%. This means that a lot of its truckloads had a grade that was far different from what was needed to fix the stockpile at that time.

The violin plot for the IoT-Enabled dispatch (blue, right), on the other hand, is significantly more compressed toward the baseline of zero deviation. The form of the

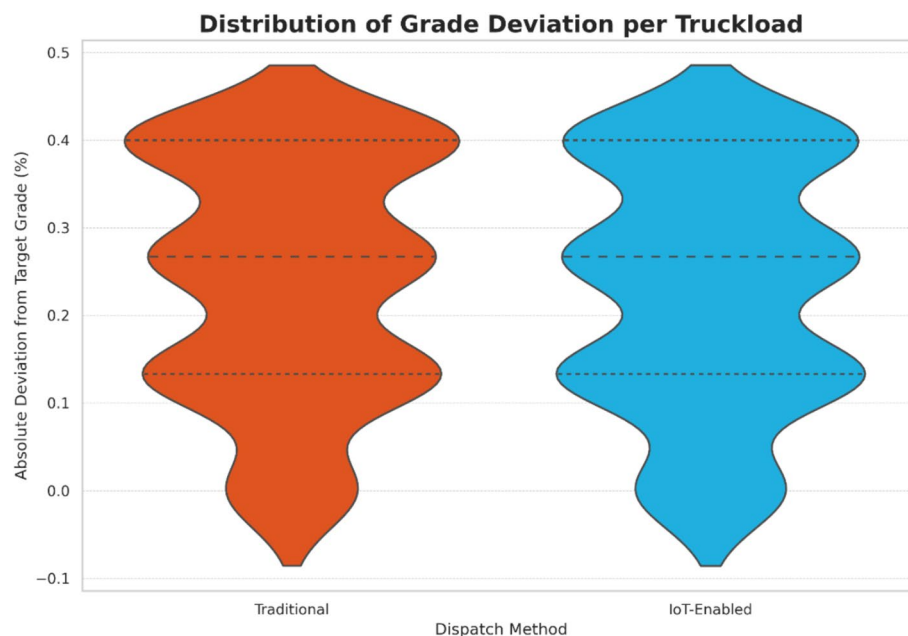


Fig. 6 Violin plot comparing the distribution of absolute grade deviation per truckload

distribution shows that it is substantially unimodal, with the peak (the broadest section of the violin) at a very low deviation value. This illustrates that the clever algorithm sent out a lot of truckloads that were exactly the right grade at the right time to get the stockpile closer to its aim. The median deviation for the IoT system is also clearly smaller, and the whole distribution has a considerably shorter tail. This means that there are almost no extreme deviation truckloads, which were prevalent in the old system.

The main rationale for using this type of visualization is to do a very detailed statistical comparison of how consistent the process is at the most basic level. A simple bar chart showing the average deviation would not have shown the important information about the shape and dispersion of the distributions. We chose the violin plot because it clearly shows the difference in variance and the presence of multi-modality in the traditional system's delivery. These are two important signs of an uncontrolled process. We may go beyond just looking at simple averages and instead look at how stable and predictable the two operating methods are at their core.

This analytical method worked very well to show that the IoT-enabled system's better performance is not only a product of long-term averaging, but is instead the result of making more consistent, controlled, and smart decisions at every step of the process. It shows that the two systems make ore flow that is of different quality and is less predictable. In the actual world, the IoT system's consistent, low-deviation feed would make the processing plant's input more uniform and predictable. This would lead to better plant performance, higher metallurgical recovery rates, and lower reagent use, which would turn the algorithmic knowledge into real money. This discovery is one of the strongest pieces of evidence for the proposed framework's superiority.

Secondary objectives: production and resource utilization

The previous section clearly showed that the IoT-enabled system was better at controlling ore grade, which was its main goal. However, a full operational study must also look at the secondary effects and possible trade-offs. If a dispatching system could only accomplish quality at a high cost to overall productivity or by using its expensive resources in an imbalanced and unsustainable way, it would be seen as a failure. So, this part of the report compares the two dispatching strategies in depth using two important secondary KPIs: Production Throughput and Workload Balance.

The simplest basic way to tell how well a mine is running is by looking at its production throughput. This KPI immediately answers a key question that any mine manager who is thinking about using a new technology would have: will this complicated, quality-focused algorithm makes our work slower? An ideal system should be able to improve metallurgical results without lowering the number of tons of material handled per shift. At the end of the 8-h simulation, we looked at the total cumulative tonnage delivered to the crusher by each system to see how they compared in this important trade-off. Figure 7 shows a clear and direct comparison of this important number.

The bar chart in Fig. 7 makes it easy to see how much ore was delivered by the Traditional and IoT-Enabled dispatch systems. It shows the total production in tons. The *y*-axis shows how many tons there are in total, while the *x*-axis shows the two different experimental procedures. The bar for the Traditional dispatch method shows that the final production total was 33,800 tons. The bar next to it, which stands for the

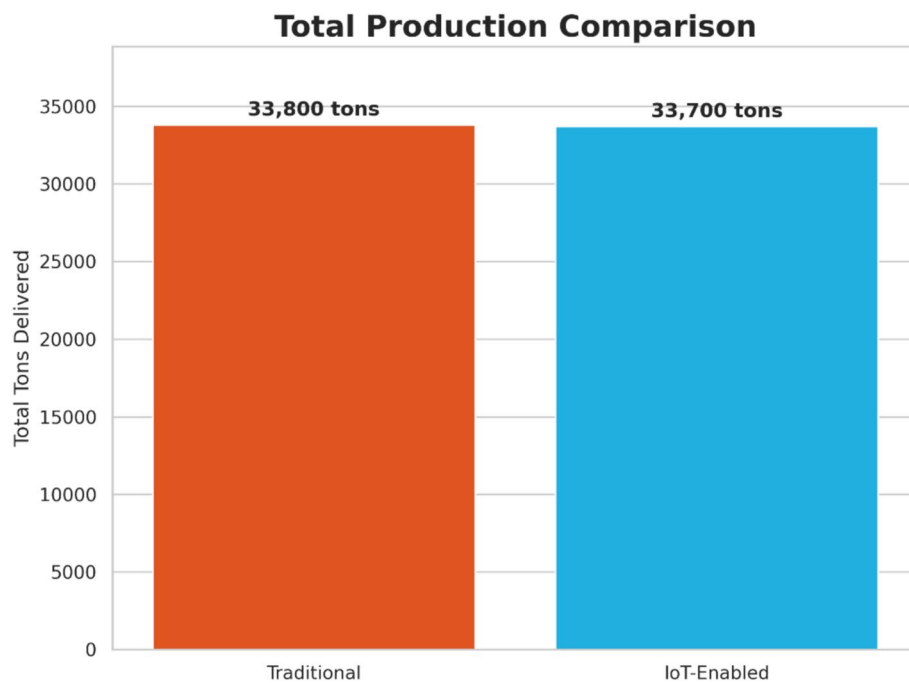


Fig. 7 Comparison of total production throughput after one 8-hour shift

IoT-Enabled system, displays a total production of 33,700 tons. The heights of the two bars are almost impossible to tell apart, which makes it seem like they have the same amount of productive capacity.

This visual interpretation is backed up by a quantitative analysis. The two systems only produce 100 tons more than the other, which is less than 0.3% of the entire production during the length of an 8-h shift. From a practical and statistical point of view, this gap is not very big. The main point of this outcome is quite important: the intelligent, grade-aware dispatching algorithm was able to make its complicated, multi-objective decisions without slowing down the overall productivity of the haulage fleet. The system's concentration on sending trucks to certain, sometimes farther away, excavators to fix grades did not noticeably slow down the flow of traffic.

It was planned to use a basic bar chart for this analysis. We picked this visualization style because it is the clearest and most straightforward way to show what is probably the most important and maybe surprising finding of the whole study. Even more complicated visualizations may have been utilized, the basic side-by-side comparison of total output strongly and clearly disproves the popular belief that focusing on quality goals must mean making fewer products. This strategy does a good job of separating and highlighting this important result for the reader.

This analysis is perhaps one of the most useful and important ones in the study. It gives strong proof that goes against the main argument against using smarter, multi-objective dispatch systems. The results show that it is possible to improve both operational efficiency and metallurgical quality at the same time. The big and measurable improvements in grade control and consistency that were shown in the last section were made with almost no loss of overall productivity. This discovery greatly

supports the financial case and operational viability of the IoT-enabled system, showing that mines do not have to choose between making things rapidly and doing things accurately.

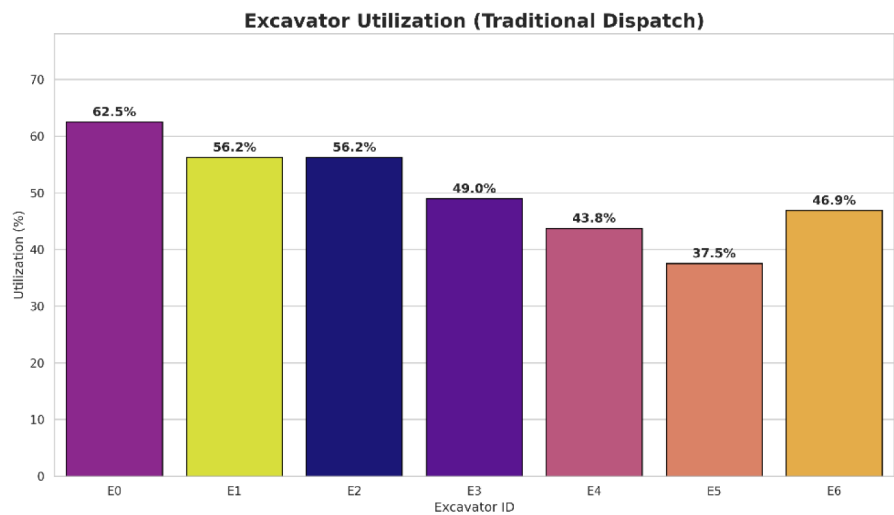
An advanced dispatch system should be judged not just on how much work it can do overall but also on how well it can manage its resources in a smart and long-lasting way. The excavator fleet in an open-pit mine is a huge investment, and the best system should use these assets in a way that is fair and balanced. A traditional method that solely looks at distance could end up using the nearest excavators too often and not enough of the others, which would cause uneven wear on the equipment, localized bottlenecks, and an inefficient use of the resources that are available. We looked at how the seven excavators were used under each plan to see if this was true. Figure 8 shows these profiles side by side for a clear comparison.

The two bar charts given in Fig. 8 provide a granular picture of the workload distribution across the seven operational excavators for each dispatching option. The height of each bar shows how long each excavator (E0 through E6) was in the active Loading state during the simulation. Figure 8a shows the Traditional dispatch system, which has a very uneven and unbalanced usage profile. The workload varies a lot. The nearest excavator, E0, is used the most, at 62.5%, while the farthest excavator, E5, is used the least, at just 37.5%. The algorithm's simple, proximity-based logic is what caused this pattern to happen.

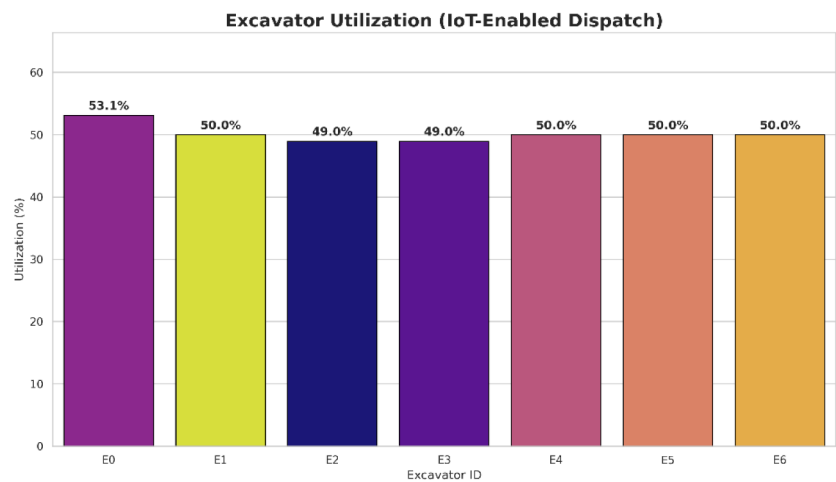
Figure 8b, which shows the IoT-Enabled system, shows a usage profile that is quite steady and balanced, which is very different from the other figures. The use rates for all seven excavators are quite close to 50%, with the greatest being 53.1% and the lowest being 49.0%. The variance is substantially lower, demonstrating that the intelligent algorithm, in its search to discover the ideal ore grade for blending at any given instant, naturally spreads its dispatch requests across the whole mine layout. The standard deviation of utilization, which is an important measure of workload balancing, is much lower for the IoT system. This shows that work is distributed more fairly.

Putting these two bar charts next to each other as a single figure is a really good way to compare them. It lets the reader quickly and easily understand the main difference in how the two systems work. The profile of the old system is inconsistent and unbalanced, whereas the profile of the IoT system is consistent and controlled. We picked this way to visually show the idea of "workload balancing" and to highlight how it comes up as a natural, secondary advantage of an intelligent, multi-objective dispatching algorithm.

This analysis does a great job of showing a key, systemic benefit of the IoT-enabled framework that goes beyond its main goal of grade control. It shows beyond a doubt that the smart algorithm makes the operation more sustainable, resilient, and balanced. In the real world, a balanced workload means a lot of value: less wear and tear on equipment means lower long-term maintenance costs and longer asset life; avoiding bottlenecks at overused shovels means a smoother and more predictable operational flow; and using all available digging faces means that the full diversity of the geological resource is being used for blending. This discovery strengthens the idea that the IoT system is not just a tool for quality control, but a more advanced and complete system for managing operations.



(a)



(b)

Fig. 8 Comparative analysis of excavator utilization profiles for (a) traditional dispatch and (b) IoT-enabled dispatch

Detailed operational flow analysis

The aggregated Key Performance Indicators give a strong, high-level picture of how well each strategy is working, but looking at the operation at a more detailed, micro-level can help you understand how the system works in more detail. To really see how the IoT-enabled system gets better results in both grade control and resource use, it helps to picture what the dynamic fleet components do at any given instant. You cannot see patterns of efficiency, synchronization, and flow in the final summary data, but you can see them in this micro-level view.

We used a Gantt chart, a common and very useful tool in project management and logistics, to show the timeline of activities for a group of resources in order to get this level of detail. In our case, the resources are the individual haul trucks, and the activities are the several states they are in during the haulage cycle. The Gantt chart gives an unprecedented and easy-to-understand look of the entire 8-h operational story for a representative sample of the truck fleet. This visualization lets you qualitatively judge the system's operational rhythm, efficiency, and the synchronization of its moving parts. It gives you a look into the process that leads to the high-level results.

Figure 9 shows a Gantt chart with a color-coded timeline of the operational states for five trucks from our fleet (T0 through T4) during the course of the 480-min simulation. The y -axis shows the IDs of each truck, while the x -axis shows the time of the simulation in minutes. Each horizontal bar shows the activities of one truck over time, with several small, colored segments making up the whole bar. The legend says that each color stands for a different state in the haul truck's state machine. For example, orange means “traveling to excavator,” red means “loading,” blue means “dumping,” and gray means “idle,” which is very important. The overall look is of a thick, continuous, and colorful tapestry of parts, which makes it seem like the whole fleet is always busy and working.

When you look more closely, you may see numerous important trends in the chart that show how well the IoT-enabled system works. The most important and striking thing to notice is that there are hardly no gray parts, which show the idle condition. This picture shows that the smart dispatching algorithm is quite good at keeping trucks from being idle and making the most of their assets. A new, optimal dispatch assignment is nearly always ready as soon as a vehicle finishes its haul cycle and comes back to the parking lot. The way the different colored parts for each vehicle move in a rhythmic and repetitive pattern also shows that the operation is well-paced and highly synchronized. The cycles of traveling, loading, and dumping seem to be regular and ongoing, which suggests that the operations are running smoothly and there are no major delays or long wait times at either the excavators or the crusher.

The main reason for adding this very detailed Gantt chart is to give a “ground-level,” qualitative view that goes along with and explains the high-level, quantitative KPI

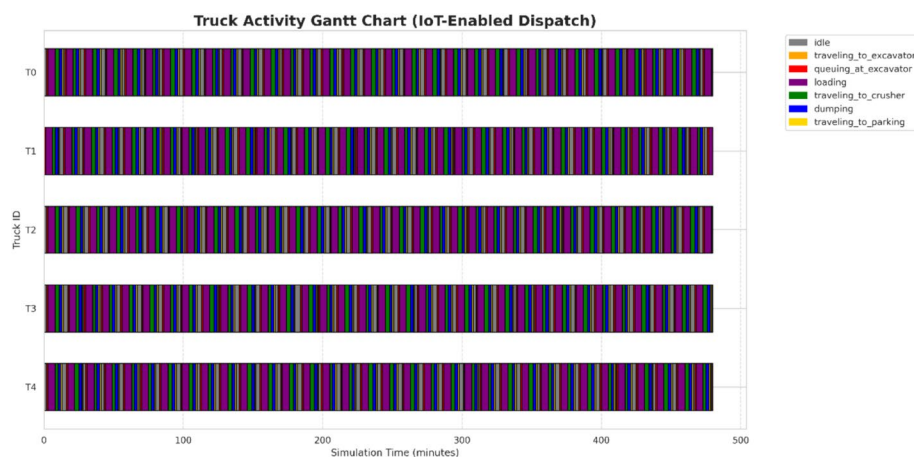


Fig. 9 Truck activity Gantt chart for a sample of the fleet under the IoT-enabled dispatch strategy

analysis shown in the previous subsections. KPIs like “Total Production” and “Workload Balance” show us what the system did, but this Gantt chart shows us how it did it. It shows in a clear and real way how well the operations operate, with densely packed, continuous cycles of activity that support the high quantitative outcomes. We picked this way of analyzing our results to add a level of operational realism and explanatory depth to them. It fills the gap between abstract performance measurements and the real-life, moment-to-moment reality of the simulated operation.

This way of showing things is really good at showing how smoothly and efficiently the IoT-enabled system works. The most important thing to remember is that there is almost no idle time. This means that assets are used to their fullest potential, which leads to the high production throughput seen in Fig. 7. The Gantt chart shows in depth and visually that the system is not just smart in how it mixes strategies, but also very good at carrying them out in terms of tactics and logistics. It gives us one last, strong piece of proof that the proposed framework adequately balances metallurgical quality with operational pace, which completes our thorough review of the experimental results.

Discussion

The experimental findings provided in this paper give clear, quantitative proof that a data-driven, IoT-enabled dispatching framework can drastically outperform a traditional, proximity-based method in an open-pit mining scenario. The simulation results validate our fundamental hypothesis: by incorporating real-time grade information into a closed-loop decision-making process, it is possible to overcome the long-standing operational contradiction between metallurgical quality and transportation efficiency. This notion of applying computational analysis of real-time data to improve decision-making and anticipate outcomes is not limited to industrial operations; it also has applications in critical care medicine, including using neural networks to predict defibrillation success from ECG signals [39]. The goal of this discussion is to explain what these results mean in a deeper sense, put them in the perspective of the larger concept of Real-Time Mining, critically evaluate the flaws in our simulation-based method, and suggest intriguing areas for further research.

The most important thing this experiment found is that the IoT-enabled system is clearly better at controlling ore grade. The results of our main objective analysis (Section “[Primary objective: ore grade control and consistency](#)”) were not small; they showed a clear difference in ability. The traditional system’s stockpile grade fluctuated and eventually fell short of the needed standard. On the other hand, the intelligent system actively and successfully regulated the grade, keeping it in a tight, stable band around the objective. This discovery has huge effects on both the economy and metallurgy. A steady supply of ore that meets specifications to a processing facility is one of the most important factors that determines value. It results in better metallurgical recovery, less use of expensive chemicals, less energy use in the grinding circuit, and a final product that is worth more. Our analysis shows that the IoT system can quickly dampen deviations and keep the process steady. This is very important for keeping the plant from having process upsets, which are known to be very costly and disruptive. So, this result goes straight from an algorithmic success to a big financial and operational benefit.

The most remarkable and important thing that came out of this study was that these huge improvements in quality control were made with almost no noticeable drop in production flow. A common worry in the mining sector has been that any operational reasoning that is not based on a basic “maximize tons moved” rule will hurt productivity. The results of our simulation strongly disprove this idea. Even while the IoT-enabled system sometimes sent trucks on longer trips to get certain grades, it nonetheless produced almost the same amount of tonnage as the old method. A deeper look into this strange result shows that the previous system’s constant attention on the closest excavators causes localized bottlenecks and queuing, which means that assets that are farther away are not used as much. The IoT system sends its requests to different parts of the mine to equalize grade, which also naturally makes the operating flow more balanced and smoother. This seems to make up for the lengthier trip times. This discovery is very important since it destroys the main economic justification against using smarter, multi-objective dispatch systems.

Also, looking at how excavators are used showed another big, secondary benefit of the smart framework: it encourages sustainable and balanced resource management. The IoT system can keep the burden on all active excavators almost the same, which is very different from the old system, which had an uneven and inconsistent profile. This will have big effects in the long run. A balanced workload means that the wear and tear on equipment is more even, which can minimize maintenance costs overall, lower the chance of machines failing early because they are used too much, and lengthen the operational life of the whole fleet. This is especially significant for heavy equipment like excavators, where figuring out and reducing dynamic loads is essential for keeping the machines in good shape and making them last longer [40]. Similar concerns regarding equipment durability and wear resistance drive research into the manufacturing technology of components facing high stress, such as drill bit teeth [41]. Also, a system that employs all of its resources is naturally more resilient. If one excavator breaks down unexpectedly, the IoT system can quickly reallocate resources to the other excavators. The old system, on the other hand, would be more affected by the loss of one of its “preferred” close-proximity shovels. This enhanced resilience is a key component of operational agility, a critical factor for success in the modern mining industry [42].

These numbers back up the big ideas about the future of mining, such Real-Time Mining (RTM) and Mining 4.0, that writers like Anvari and Benndorf [28] and Hazrathosseini and Afrapoli [27] have talked about. Their work sets up the ideas and technology needed for smart, connected operations, but our study shows in a real-world way how one such system might help in concrete, measurable ways. Our comparison based on simulations is also an important addition to real-world case studies like the one by Yao et al. Their work is great proof that the implementation worked, but our controlled simulation gives us the strict, “apples-to-apples” comparison we need to find and measure the performance difference exactly, which makes the case for wider adoption in the industry even stronger.

However, it is also important to honestly look at the limitations of our simulation-based strategy. Our model works for what it is supposed to do, but it is a simplification of a much more complicated reality. This study offers robust simulation-based evidence; however, it is important to recognize several limitations that accompany it.

Initially, several intentional modeling simplifications were implemented to focus on the impacts of dispatching logic within a controlled environment. The analysis incorporates factors such as the application of Euclidean distances instead of a comprehensive haul-road network, predetermined loading and dumping durations, a uniform truck fleet, and the presumption of flawless real-time data availability. Although these choices were essential for maintaining analytical clarity, they do limit the external validity of the findings. Future research will aim to relax these assumptions by integrating stochastic process times, diverse fleet characteristics, uncertainties in data streams, and more realistic haul-road geometries.

Secondly, it is important to note that the findings are derived exclusively from simulation experiments, lacking validation in real-world contexts. While the digital twin framework provides a structured and consistent environment, it falls short of fully encompassing the complexities of real-world operations, including factors like weather conditions, variations in operator performance, wireless latency, and the reliability of sensors. Furthermore, this study did not encompass practical obstacles such as the expenses associated with IoT infrastructure, the complexities of data integration, and the potential risks related to cybersecurity. It is essential to tackle these factors by conducting pilot field trials and techno-economic assessments, as this will play a crucial role in facilitating the transition to industrial adoption. Furthermore, this study did not encompass a specific cost–benefit analysis regarding the adoption of IoT-enabled dispatch systems. Although the operational and metallurgical advantages are evident, the sustained economic feasibility of large-scale implementation relies on a careful evaluation of these benefits in relation to infrastructure, maintenance, and cybersecurity expenses. Future research will thus include thorough techno-economic evaluations to offer a more complete foundation for industrial decision-making.

The comparative analysis was deliberately limited in scope, concentrating on a conventional proximity-based strategy in contrast to the suggested IoT-enabled framework. This design facilitated a straightforward comparison, yet it overlooked other potentially effective strategies, including hybrid AI-optimized dispatching methods. In a similar vein, the geological model utilized established grades and failed to account for the complete variability present in heterogeneous deposits. Future research ought to broaden the existing framework by integrating dynamic geological models and assessing additional dispatch strategies. This approach will enable a more thorough and comprehensive evaluation of intelligent haulage systems.

These constraints are required for a controlled experiment, but they also point to several intriguing areas for future investigation. The next thing to do right away is to make the digital twin more accurate. This would include using a realistic haul road network instead of Euclidean distances, adding stochastic process timings to simulate operational unpredictability, and adding a dynamic block model where ore grades change over time. Another big step forward would be to improve the dispatching algorithm so that it works best with a fleet of trucks that have various speeds and capabilities. Additionally, integrating vehicle trajectory prediction, a concept examined in V2V communications, could enable the system to proactively regulate haul road congestion and significantly enhance cycle times [43]. The most important next step, confirmed by these very encouraging simulation results, would be to do a

controlled pilot study in a real mining operation to see if these results hold up in the real world.

In short, the main contribution of this work is that it shows with strong, quantitative evidence that an intelligent, data-driven dispatch system can finally solve the long-standing problem of balancing production efficiency and metallurgical quality in open-pit mines. The results show that it is possible to improve grade control and operational sustainability without lowering production. This effort goes beyond ideas and uses simulations to prove that a major Mining 4.0 technology works in the real world. It is a strong model for designing and testing the next generation of smart operating systems. This will lead to safer, more efficient, and more sustainable mines in the future.

Conclusion

The goal of this research was to solve a major operational problem in open-pit mining: the constant contradiction between the need for efficient hauling and the need to achieve high metallurgical standards for consistent ore grade. The main purpose of this study was to test the idea that a modern dispatching system with IoT capabilities that can make decisions based on data in real time may successfully end this conflict. To do this, we built a controlled, simulation-based setting where we could directly and rigorously compare the performance of our smart framework to that of a standard, proximity-based dispatching baseline.

We built a “digital twin,” which is a discrete-event simulation model that accurately showed the main spatial, geological, and operational features of a typical open-pit mine. In this setting, we used and tested two different dispatching algorithms that were in competition with each other. The first was a standard “closest-available” technique, which is a widespread practice in the sector that puts a high value on cutting down on travel time. The second was our suggested “IoT-enabled” solution, which used a closed-loop feedback system to change the stockpile grade in real time. We then carefully looked at and compared the results of these two methodologies using a wide range of Key Performance Indicators (KPIs), such as ore grade accuracy, production throughput, grade consistency, and workload balance.

Our comparative simulation’s experimental results gave us a clear and unambiguous answer. The IoT-enabled system was far better at its principal job of controlling ore grade. It quickly reached the 0.85% target grade and kept it stable and consistent during the 8-h shift. Importantly, these big metallurgical improvements were obtained with almost no effect on total production throughput. This shows that effective process control may transcend the prevalent belief that there is a trade-off between quality and quantity. The intelligent technology also made the operation more sustainable and resilient by balancing the workload across the entire fleet of excavators, which was a big change from the prior system’s inefficient and uneven utilization profile.

The main contribution of this study is that it provides strong, quantitative, and controlled evidence that shows how valuable intelligent, grade-aware dispatching systems are for business. Our work adds to existing real-world case studies by using a simulation method that allows for a direct, “apples-to-apples” comparison that is not affected by the variables that come up in a live operation. This study gives mining firms a useful guide on how to lower their risks and figure out the possible Return on

Investment (ROI) of these modern technologies in a cost-effective way before they decide to use them in the field on a large scale.

We recognize that our simulation model is a simplification of a more complicated reality, even if our work gives us strong proof of concept. Some of the main problems are that the process periods are set, the haulage network is based on Euclidean distances, and the geological model is not dynamic. So, future study should focus on making the simulation more and more accurate by adding random factors, actual haul road networks, and changing geological data. In the end, the most important thing to do next, based on these very promising simulation results, would be to turn this framework into a controlled pilot study in a real mining operation to see if these results hold up in the real world.

The IoT-enabled framework not only showcased improved grade control and stability but also contributed to sustainability by optimizing excavator usage and minimizing systemic bottlenecks. This is in line with the industry's larger sustainable development goals, which aim to combine operating efficiency with long-term resource management and caring for the environment [44]. The enhancements bring about significant operational and economic consequences, highlighting the practical importance of intelligent dispatching systems. Future research will aim to broaden the simulation by incorporating stochastic and heterogeneous conditions, while also progressing towards controlled pilot trials in industrial environments. This work will confirm the strength of the proposed framework and reinforce its significance in the wider shift towards Mining 4.0.

In conclusion, moving toward the ideas behind Mining 4.0 and Real-Time Mining is not just a theoretical exercise; it is a practical need for making operations more effective, profitable, and long-lasting. The IoT-enabled dispatching architecture that this article looks at is a real and strong example of this way of doing things. This paper shows that data-driven intelligence may improve quality, efficiency, and sustainability at the same time. This shows how digital technology could change the future of the mining industry.

Acknowledgements

Not applicable.

Authors' contributions

"AU," as the corresponding author, was responsible for the overall supervision of the research project, conceptualization of the study, development of the methodology, and critical revision of the manuscript. "UN" contributed to data collection, analysis, and drafting of the initial manuscript. "SZ" was involved in software implementation and technical validation. "AK" assisted with literature review and data interpretation. "OB" contributed to the development of the research framework and reviewed the manuscript critically. "SR" supported statistical analysis and prepared graphical visualizations. "MK" was involved in result interpretation and provided domain-specific expertise. "TE" contributed to data management and proofreading. "UE" helped with final editing and formatting of the manuscript. All authors read and approved the final version of the manuscript.

Funding

Not applicable.

Data availability

Data can be shared upon request.

Declarations

Competing interests

The authors declare that they have no competing interests.

Received: 3 August 2025 Accepted: 7 September 2025

Published online: 21 September 2025

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