

**Implementation of Artificial Intelligence in Short-term
Mine Planning of open pit mine. A Case Study of
Bozshakol Mine.**

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ORIGINALITY STATEMENT

I, Nurassyl Kairatuly, hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at Nazarbayev University or any other educational institution, except where due acknowledgement is made in the thesis.

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ABSTRACT

Using Bozshakol Mine as a case study, this thesis investigates how Artificial Intelligence (AI) is applied in short-term mine planning. Open-pit mining operations, like those at Bozshakol, struggle to develop flexible, responsive mine plans that fit with the changing dynamics of the mining environment. Often relying on static, rule-based systems, traditional approaches find it difficult to handle real-time data and unanticipated operational interruptions. This study offers an AI-driven solution to mine planning that combines machine learning and optimization techniques to increase planning accuracy, lower human error, and optimize Net Present Value (NPV) in order to meet these difficulties.

The project creates a web-based artificial intelligence model that analyzes data from the Bozshakol Mine, including block models, mining face polygons, and operational factors such as ore grade, mining costs, and haulage distances. The AI system aims to produce best mining scenarios, hence maximizing NPV and reducing running costs. The performance of the AI model is compared with conventional human-generated plans, showing notable gains in NPV, time efficiency, and operational flexibility.

By means of dynamic, data-driven decision-making, this thesis emphasizes how artificial intelligence might transform short-term mining planning. The results imply that artificial intelligence can simplify planning procedures, cut scenario evaluation time, and boost general profitability. The study also points out important issues including data quality and system integration and offers advice for more progress in AI-augmented mine planning.

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INTRODUCTION

1.1 Background

Open-pit mining is one of the most widely used mining methods for extracting mineral resources, especially for copper, gold, and iron ore close to surface depending on the economic suitability of the stripping ratio. The method involves removing ore from the earth through sequential benching, transporting waste materials to designated dumps outside the pit boundaries, and mining the ore progressively.

The effectiveness and profitability of open-pit mining largely depend on efficient and good mine planning. Mine planning is a critical process in open-pit mining that ensures the efficient and economic extraction of mineral resources while addressing technical, environmental, and operational constraints (Newman et al., 2010).

The conventional approach follows a hierarchical structure:

- Strategic Planning (Long-term: 5+ years) – Defines the ultimate pit limits, mine life, and overall economic viability using tools like the Lerchs-Grossmann algorithm (Askari-Nasab et al., 2010).
- Tactical Planning (Medium-term: 1–5 years) – Focuses on pushback design, sequencing, and infrastructure development (Dimitrakopoulos, 2011).
- Short-term Planning (Operational: <1 year) – Involves detailed scheduling of equipment, ore blending, and grade control to meet production targets (Li & Li, 2022).

Strategic planning establishes the foundational framework for mining operations, defining the ultimate pit limits, life-of-mine (LOM) schedule, and economic viability of the project. Traditional methods, such as the Lerchs-Grossmann algorithm for pit optimization, rely on deterministic assumptions that often fail to account for dynamic variables like commodity price volatility, geological uncertainty, and regulatory shifts (Dimitrakopoulos, 2011).

Tactical planning serves as the bridge between long-term strategy and short-term execution, focusing on pushback designs, annual ore and waste sequencing, and infrastructure placement. This phase must reconcile competing objectives, such as maintaining consistent mill feed grades while optimizing fleet utilization and minimizing haulage costs.

Higher-level strategies are translated into short term planning i.e., executable in days to weeks where fine grained problems like equipment allocation, ore blending, real time disruption management etc. are handled. Rule based dispatching, or Gantt charts for that matter, have no flexibility to change when weather may delay, equipment break down, or if the grade is more variable than typically suspected when we started.

Short-term mine planning, in particular, plays a crucial role in the day-to-day operations of a mine. It involves creating detailed schedules for drilling, blasting, loading, and hauling activities, as well as managing ore blending and stockpiling. The challenge with short-term mine planning lies in the dynamic and ever-changing nature of mining operations, where unforeseen disruptions such as equipment breakdowns, weather delays, and variations in ore quality can significantly affect the planned operations.

Current mine planning methods often rely on deterministic and rule-based systems, which are static and unable to quickly adapt to the ever-changing operational environment. These limitations emphasize the need for more agile, data-driven approaches that can optimize planning, improve resource allocation, and ultimately enhance the Net Present Value (NPV) of the mining project. This thesis focuses on integrating Artificial Intelligence (AI) to address these challenges and improve short-term mine planning.

1.2 Case Study: Bozshakol Mine

Bozshakol mine is located in the Pavlodar region of Kazakhstan. The site is 80 km west of the district centre of Ekibastuz, 170 km southwest of the regional centre of Pavlodar and 250 km east-northeast of Astana the national Capital of Kazakhstan. Figure 1 shows the location of Bozshakol (Kazakhmys, 2010).

It is porphyry copper mine which produces concentrates containing copper, gold, molybdenum and silver. Bozshakol has significant ore reserves which are evaluated at 1.17 billion tonnes of

ore with average copper grade of 0.36% (KAZ Minerals, 2023). The annual processing capacity is over 30 million tonnes with life of mine over 40 years (KAZ Minerals, 2023).



Figure 1. Bozshakol Mine Location Map.

According to Kazakhmys, copper mineralisation was discovered at Bozshakol by R. A. Borukaev in 1930. Geological prospecting in the area began soon after the discovery, with trenching, pitting, two shallow shafts and some drilling completed in 1931. Prospecting intensified from May 1932 but was suspended in 1933, except for the deepening of the two shafts and collection of bulk samples from the secondary enrichment zone and a bulk sample of oxide material from pits. Tests were conducted by Mekhanobr, Almaty-based metallurgical institute, with mixed results. 77 drillholes of unspecified type for a total of 7,821 m were reported to have been drilled on a grid of 100 m SE-NW by 200 m SW-NE in the period 1931 to 1933.

During the period 1940 to 1942 R. A. Borukaev conducted preliminary stratigraphic, structural and volcanic studies at Bozshakol which would have involved non-destructive techniques and geochemical mapping up to 1:25,000 scale. Preliminary exploration commenced in 1948 and continued to 1952 focusing on the area between Profile I and Profile X in the western part of Central Bozshakol. It included drilling of 54 holes of unspecified type for 5536.5 m on a 50 m by 100 m grid and the development of Shaft No. 2 to a depth of 23 m. The shaft has been capped and is no longer accessible although the spoil heap remains.

Detailed exploration was conducted in 1952 to 1958 by Central Kazakhstan Geological Authority (CKGA) to upgrade the previous resource estimates, to explore the western extension to the delineated resource and to assess potential on the eastern and northern flanks. Structural drilling was also undertaken to test deep levels of the deposit. Central Bozshakol was drilled on a grid of 100 m by 50 m to a depth of 200 m to 250 m (Kazakhmys, 2010).

The nearest towns are the village of Bozshakol (population 400) 20 km south of the mine site, Tort-Kuduk (population 300) 25 km southwest of the mine site and Shiderty (population 4000) 42 km southeast of the mine site. The project area is located in a wide ridge of low hills that stretch in a north easterly direction. Towards the north, the relief becomes smoother transforming into a plain, whereas towards the south and west, a rougher terrain is evident. The project site is located in the southern sub-zone of dry feather-grass steppes. The vegetation in this area is very poor and many plants are drought resistant. A wetland is present on the project site directly south of the proposed pit development and another wetland is located about 1 km to the east. There are also small wetlands located to the north and east. The vegetation in the wetland swamps is characterised by grass marshes. There are a number of archaeological sites located within the proposed mine pit and site infrastructure locations all of which have been excavated and investigated by the government authorities and have been given clearance for removal. Some mine development commenced at Bozshakol in 1973. However, the project did not proceed to completion due to a lack of investment capital at that time, with only 10% of the required capital being committed between 1976 and 1985. During this period a number of infrastructure developments associated with the project were, nevertheless, built or partly built. In addition, some 4.5 Mm³ of overburden was excavated from the pit. Surface structures constructed during that period were subsequently dismantled and all that remains is a small trial open pit, small stockpiles of oxidised ore and waste dumps, an abandoned rail embankment, crude access road and an abandoned 220 kV power line. The Subsoil Use License is held by KCC for the development of the Bozshakol Central pit and is valid until 2032. The

Subsoil Use license for Boshekul East pit is valid until 2012 for exploration purposes. These licenses will require renewal as required through the life of the asset.

Mineral resources at Bozshakol are polymetallic with revenue generated from copper, silver, gold and molybdenum production. The processing, concentrate transport, smelting and refining costs are dependent on copper, silver, gold and molybdenum grades, and rock type. Net revenue is dependent upon multiple factors as are processing costs. Therefore, use of a single metal grade, as a cut-off to determine ore from waste, is considered impractical. The metallurgical, cost and revenue parameters were used to estimate a value for each tonne of material by subtracting the processing, concentrate transport, smelting, refining and royalty costs from the net revenue generated by selling the metal in that tonne of material. A positive value indicates the material is economically profitable to process (Kazakhmys, 2010).

According to KAZ Minerals Bozshakol official website, operational timeline of Bozshakol Mine development can be structured as:

“2010: The board approved the development of the project on 25 August 2011. The site is located in North Kazakhstan and is accessible by road and rail from the capital Astana. We started working from a greenfield site. This is the beginning of our journey.

2011: Bozshakol is located close to existing major roads and a railway, which allowed us to complete ground work and build the initial site infrastructure in a short timeframe.

2012: In 2012 we completed the water supply piping, and having received construction equipment, commenced the earthworks on site. We established an office building, built a temporary camp for the construction workforce, laid the foundations and commenced the erection of structural steel frames and walls for the main buildings, erected a roof beam on the grinding building and started the construction of the tailing thickeners walls.

2013: In 2013 we finished most of the foundation works and most of the main buildings were enclosed. We also completed the steel structure of the accommodation building at the permanent camp, laid the foundation and erected the steel frames of the plant maintenance workshops and completed the main access road to permit transportation of the heavy equipment to the site. We delivered the first shipment of heavy equipment from Antwerp to Bozshakol with parts of ball mills and SAG mills to the site in the end of July 2013. We are almost 50% complete, and you can see the shape of the final project now.

2014: In the first half of 2014 we completed the construction of the main concentrator building and the 220kV power line. During the autumn months we completed the construction of the permanent camp and the assembly of haul trucks and shovels for pre-production mining in Q1 2015. We also commenced installation of the mills and internal steel platforms in the grinding and flotation areas and started the construction of the overland ore conveyor. The project is due for commissioning in Q4 2015.

2015: As of June 2015, we had completed all key sulphide concrete and steel works, non-process buildings, permanent camp, main access road and railroad, 220 kV power line and substation tie-in. Mining equipment including haul trucks, shovels and excavators were delivered and assembled and shells, heads and stators for all three mills were assembled. In the coming months we will be working on the installation of the primary crusher, the rougher and cleaner flotation cells and bulk material for underground piping and electrical works, installation and testing of ball and SAG mills and the construction of the clay plant. We started pre-production mining in June 2015 and the sulphide concentrator commenced commissioning in December 2015.

2016: The project commenced production of saleable copper concentrate at the main sulphide concentrator in February 2016, with the first shipment made in March. Commissioning works at the clay plant commenced on 29 September 2016.

Nowadays, Bozshakol Mine is getting closer to its peak performance in production, with ore mined at Bozshakol increased by 16% in 2023 to 33,338 kt (2022: 28,769 kt) as more ore was sent directly to the concentrators, rather than blending stockpiled material into the ore feed.

Both the sulphide and clay concentrators continued their strong performance in 2023. The combined ore throughput was 32,935 kt, the highest ever throughput performance at Bozshakol and 10% above the concentrators' combined design capacity of 30 Mtpa. Despite the expected reduction in grades processed, the average copper recovery rate increased from 75% to 79%, benefiting from management initiatives to optimize the mine to mill process, ore blending and the reagents regime in the concentrators.

Copper production increased by 2% to 104.6 kt in 2023 (2022: 102.1 kt) benefiting from the record ore throughput and enhanced metal recovery rates. The majority of copper production was dispatched in the form of concentrate to customers in China, with 3.5 kt of copper in concentrate sent for toll processing at the Balkhash smelter in Kazakhstan, where capacity was available on attractive terms. Gold output in 2023 decreased by 3% to 115.2 koz compared with

prior year output of 119.1 koz, driven by an expected reduction in gold grades in the clay ore feed, after the plant processed ore with an elevated gold content in 2022. Silver production of 818 koz increased by 11% on the prior year (2022: 737 koz) primarily due to higher grades processed.” (KAZ Minerals, 2023).

1.3 Problem statement

In modern open-pit mining operations, such as the Bozshakol Mine, effective mine planning is essential to achieving production targets and ensuring long-term profitability. Strategic and tactical mine plans are developed with significant effort to define the broader direction of the operation, incorporating technical and economic parameters such as Net Present Value (NPV). Operational mine planning, which translates these long-term goals into short-term, day-to-day actions, is expected to follow and fulfil these higher-level objectives.

However, due to time constraints and the fast-paced nature of daily planning, operational mine plans often omit critical strategic and economic considerations. For instance, parameters such as NPV are rarely included in short-term decision-making because traditional methods for calculating and integrating such data are time-consuming and computationally intensive. This disconnect can lead to suboptimal operational decisions that are misaligned with long-term strategic and economic goals.

Given recent advancements in data science and machine learning, there is an opportunity to improve short-term mine planning through the implementation of Artificial Intelligence (AI). AI-based tools can enable rapid analysis and integration of complex data sets, allowing economic and strategic parameters to be considered in real-time planning without compromising efficiency.

This research aims to explore and implement AI-driven approaches to enhance short-term mine planning in the context of the Bozshakol Mine, with the goal of bridging the gap between operational decisions and long-term strategic objectives.

1.2 Objectives of the Thesis

The ultimate goal of the thesis is to create AI model which can be implemented in operational (or short-term) day-to-day mine planning in open pit to focus on the Net Present Value (NPV). NPV is the sum of the present values of incoming and outgoing cash flows over period of time (Ross, 2016). NPV was chosen over production metrics such as tonnage of ore fed, grade or the recovery of the ore due to its implications that even if production metrics are not up to target the greater NPV can show that the net profit with deduction of all costs can be higher than in a case where production goals are met. That is why NPV is the metric which is easy to use and can show the net profit amounted from the plan.

The specific objectives of the thesis are to:

1. Identify most crucial planning parameters
2. Create AI model based on these parameters
3. Create short-term mine plans using an AI model and mining engineers.
4. Compare of mining plans completed by human and AI
5. Identify key differences between the two scenarios

1.3 Hypothesis

The hypothesis is that conventional operational mining plan is much simple and easy to understand approach for mine production. However, implementation of AI in a model which can calculate the NPV will help to increase the economic feasibility of mine production, yielding net positive result on the mining activities by saving costs and increasing the revenue. Moreover, implementation of AI model will also decrease a time needed for the mining engineers to prepare operational plans, thus giving them more time to discover new possibilities and options of the mine plan. Implementation of AI will also help mining engineers to see how particular scenarios of mine production will affect the economic feasibility of the project.

1.4 Justification of Research and Development to the industry

This research aims to address the significant gaps in current short-term mine planning by using Artificial Intelligence (AI). While traditional methods often rely on deterministic models and manual inputs, they fail to adapt to the real-time changes of mining operations. The introduction

of AI allows for real-time adjustments, dynamic scheduling, and optimal resource allocation, significantly improving the overall NPV in the planning process.

1.5 Scope of Work

The scope of this research involves developing a web-based application of AI model to assist with short-term mine planning. Web-application is easy to use, requires no storage of data in hardware and can be accessed from different devices. The system will integrate a block model with mining face polygons, allowing for accurate assessments of NPV. The study will utilize Bozshakol Mine's operational data to build the AI model, which will be tested in real-life scenarios to ensure its relevance and effectiveness in improving mine planning efficiency. The study also involves the design and implementation of a backend system using Django, a frontend using React, and a PostgreSQL database hosted on AWS RDS to manage and process large datasets efficiently.

The research does not cover aspects of long-term mine planning (strategic and tactical) and does not include any integration with the dispatch systems nor mine planning systems and software. It also does not account for geotechnical risks and optimization, which are important in mine planning.

2.1 LITERATURE REVIEW

2.1 Introduction to Mine Planning in Open-Pit Mining

Mine planning is a critical process in open-pit mining that ensures the efficient and economic extraction of mineral resources while addressing technical, environmental, and operational constraints. It involves a series of decisions ranging from long-term strategic planning to short-term operational scheduling, all aimed at maximizing profitability, resource recovery, and sustainability (Newman et al., 2010). Traditional mine planning relies on deterministic optimization techniques, such as linear programming (LP) and mixed-integer programming (MIP), which often struggle to adapt to real-world uncertainties, including fluctuating commodity prices, geological variability, equipment failures, and environmental regulations (Dimitrakopoulos, 2011).

Open-pit mining, unlike underground mining, involves the removal of large volumes of overburden to access ore deposits, making planning particularly complex due to dynamic factors like pit slope stability, haulage logistics, and blending requirements (Kumral, 2020). The conventional approach follows a hierarchical structure:

- Strategic Planning (Long-term: 5+ years) – Defines the ultimate pit limits, mine life, and overall economic viability using tools like the Lerchs-Grossmann algorithm (Askari-Nasab et al., 2010).
- Tactical Planning (Medium-term: 1–5 years) – Focuses on pushback design, sequencing, and infrastructure development (Dimitrakopoulos, 2011).
- Short-term Planning (Operational: <1 year) – Involves detailed scheduling of equipment, ore blending, and grade control to meet production targets (Li & Li, 2022).

However, traditional methods face limitations in handling real-time disruptions, leading to suboptimal production schedules and financial losses. This has spurred the integration of Artificial Intelligence (AI) and Machine Learning (ML) into mine planning, enabling adaptive decision-making under uncertainty (Park & Choi, 2021). AI techniques, such as reinforcement learning, neural networks, and metaheuristics, enhance short-term planning by:

- Predicting equipment failures (e.g., using sensor data and ML models to reduce downtime) (Kumral, 2020).
- Optimizing dynamic scheduling (e.g., adjusting truck dispatching in real-time via RL) (Li & Li, 2022).
- Improving ore grade estimation (e.g., through geostatistical AI models for better blending decisions) (Park & Choi, 2021).

The shift toward AI-driven mine planning is further justified by the mining industry's increasing focus on Net Present Value (NPV) optimization, where AI's ability to simulate multiple scenarios and adapt to market changes provides a competitive edge over static NPV models (Smith & Dagdelen, 2019).

2.2 Strategic, Tactical, and Short-Term Planning in Open-Pit Mining

Hierarchical approach in mine planning of open pit operations is the one of three (strategic, tactical and short term) interconnected phases. Because each phase is separated depending on its objectives and challenges, the phase is trying to optimize the resource extraction while meeting economic, technically and environmentally constrained response. Such integration of the planning horizons with Artificial Intelligence (AI) and Machine Learning (ML) has brought them in a revolution as they have brought in adaptive decision making in the presence of uncertainty (Newman et al., 2010; Kumral, 2020).

2.3 Strategic Mine Planning (Long-Term: 5+ Years)

Strategic planning establishes the foundational framework for mining operations, defining the ultimate pit limits, life-of-mine (LOM) schedule, and economic viability of the project. Traditional methods, such as the Lerchs-Grossmann algorithm for pit optimization, rely on deterministic assumptions that often fail to account for dynamic variables like commodity price volatility, geological uncertainty, and regulatory shifts (Dimitrakopoulos, 2011). To address these limitations, AI-driven approaches have gained prominence.

Recent advancements in stochastic optimization leverage Monte Carlo simulations to model probabilistic ore grades and price scenarios, resulting in more resilient pit designs. For instance, Askari-Nasab et al. (2010) demonstrated that metaheuristic algorithms, such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO), can optimize pit sequencing under multiple geological and economic scenarios, reducing overdesign risks by 15–20%. Reinforcement Learning (RL) has also shown promise in strategic planning, where AI agents iteratively simulate extraction strategies to maximize Net Present Value (NPV) while minimizing strip ratios (Li & Li, 2022). A notable case study from Rio Tinto (2022) highlighted how an AI-based stochastic pit optimization system reduced waste movement by 15% in an Australian gold mine while maintaining production targets.

2.4 Tactical Mine Planning (Medium-Term: 1–5 Years)

Tactical planning serves as the bridge between long-term strategy and short-term execution, focusing on pushback designs, annual ore and waste sequencing, and infrastructure placement. This phase must reconcile competing objectives, such as maintaining consistent mill feed grades while optimizing fleet utilization and minimizing haulage costs. Conventional tactical planning often struggles with blending constraints and equipment coordination, leading to suboptimal schedules (Newman et al., 2010).

AI has been largely developed as a pivotal, one among the many, tools to enhance tactical decision making. Finally, Variable Neighbourhood Descent (VND) combined with Q learning, adjusts the mine phases based on real time cost and commodity price data (Askari-Nasab et al., 2010). Additionally, predictive maintenance models fuelled by the power of AI go a step further and predict equipment failure so as to lower the overall unplanned downtime (Kumral, 2020). Digital twin technology, another AI application, allows mines to simulate and evaluate multiple tactical scenarios before implementation, mitigating operational risks (McKinsey & Company, 2023). For example, Park and Choi (2021) reported a 12% reduction in haulage costs at a Chilean copper mine after deploying an AI-driven tactical scheduling system that optimized dump-site selection and truck routing.

2.5 Short-Term Mine Planning (Operational: <1 Year)

Higher-level strategies are translated into short term planning i.e., executable in days to weeks where fine grained problems like equipment allocation, ore blending, real time disruption management etc. are handled. Rule based dispatching, or Gantt charts for that matter, have no flexibility to change when weather may delay, equipment break down, or if the grade is more variable than typically suspected when we started. (Kumral, 2020)

Real time data processing and dynamic scheduling abilities of AI have totally changed the short term planning in this age. For example, on a truck-shovel dispatching problem, RL algorithms learn from operational feedback to continuously optimize truck-shovel dispatching such that

truck idling time is reduced up to 30% (Li & Li, 2022). Using Machine Learning technique such as Random Forests, Neural Network etc., grade control is improved by forecasting ore quality from blast hole data to create a consistent mill feed (Park & Choi, 2021). Autonomous Haulage Systems (AHS), such as Rio Tinto's AutoHaul™, expand AI's influence and operate for 24 hours, despite improvement of 20% over throughput (Rio Tinto, 2022). Smith and Dagdelen (2019) conducted a case study that presented how the short term scheduling by processing plant bottlenecks at a South African platinum mine was done by AI power generating \$15 million in annual revenue.

2.6 Synthesis and Research Implications

The integration of AI across strategic, tactical, and short-term planning stages underscores its potential to enhance decision-making at every level of mine planning. Strategic AI systems are then enhanced for robustness in terms of NPV via stochastic optimization, while tactical systems rely on hybrid algorithms to simultaneously meet competing objectives. AI's real time adaptability is the real operational face of this at the operational level to the inherent unpredictability of the mining environment. These solutions should be examined for scalability to diverse mining contexts as well as human machine collaboration needed for the successful implementation of these solutions.

2.7 AI and Machine Learning in Mine Scheduling

The integration of Artificial Intelligence (AI) and machine learning (ML) into mine scheduling represents a paradigm shift in how mining operations optimize short- term production while maintaining long-term strategic objectives. Traditional scheduling methods, often reliant on deterministic optimization techniques, struggle to adapt to the dynamic nature of mining operations, where equipment failures, geological variability, and market fluctuations introduce significant uncertainty. AI driven approaches address these challenges by enabling real-time decision-making, predictive analytics, and adaptive optimization, ultimately improving operational efficiency and financial performance.

This is shown to be a powerful attention used for patterned scheduling of systems, where systems learn their best scheduling strategies through continuous interaction in context of mining environment. Although recently the ventilation schedules have been adjusted using RL on operational data in real time and the optimal vehicular dispatching has also been treated using RL considering current data. As with other areas of science, neural networks, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) offer appropriate means for processing geological data and prediction of the equipment maintenance needs; where unplanned downtime can decrease up to 30%. Mine sequencing and equipment allocation, according to these techniques, are also optimized by evolutionary algorithms such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) for scheduling, increasing its efficiency.

AI is applied in the mine scheduling context in a different manner dependent on its application during short term or long term planning horizons. AI's capacity to handle real time data allows for SCHEDULE dynamic adjustments to daily or week plans due to available equipment, ore quality or unforeseen disruptions of the process. Autonomous Haulage Systems (AHS), for instance, leverage AI to minimize truck idle times, reducing cycle times by 15% or more. In contrast, long-term scheduling relies on AI to evaluate geological and economic uncertainties, optimizing ultimate pit limits and block sequencing to maximize Net Present Value (NPV) over the mine's lifecycle. Hybrid models that combine AI with traditional operations research techniques, such as mixed-integer linear programming (MILP), have shown particular promise in balancing short-term adaptability with long term strategic goals.

Despite these advancements, challenges remain in implementing AI driven scheduling systems. Data quality and standardization issues can hinder model accuracy, while the computational complexity of large-scale mining operations demands robust high performance computing infrastructure. In addition, an effective means of exploiting the interpretability and transparency present in the AI models is needed for successful deployment, in the form of Explainable AI (XAI) models that provide transparent and interpretable recommendations to mine planners. Future research directions include the application of digital twins for scenario testing and generative AI to match rare operative conditions, resulting in the better robustness of the scheduling systems based on AI.

In conclusion, The revolution of mine scheduling is taking place from AI and ML introduction of unprecedented levels of adaptability, efficiency, and state-of-the art financial optimization. Looking ahead, to fully realising the potential of these technologies, as the mining industry navigates it's continued digital transformation, scalable AI solutions as well as industry wide datasharing frameworks will be critical. By addressing current limitations and leveraging emerging trends, AI driven scheduling can deliver sustained improvements in both operational performance and economic outcomes for open pit mining operations.

2.8. Cash Flow Approaches in Mining: NPV Focus

2.8.1 Financial Evaluation in Mine Planning

Financial analysis is the critical tool in determining whether a mining project is financially viable and sustainable in the long term. NPV, IRR, payback period, profitability index are the various cash flow metrics used in the industry. Of these, which includes NPV, it has proved to be the most useful and the most frequently used metric because of its capacity to incorporate the value of money related time, to reflect risk, and to coordinate long haul esteems of the organization (Smith & Dagdelen, 2019).

2.8.2 Advantages of NPV in Mine Planning

For a number of reasons, mine planning in financial terms using NPV is the preferred financial metric. Also, unlike IRR and Payback Period, NPV explicitly considers the time value of money by discounting the amounts of cash flows in the future to their present value. That is, it guarantees cash flows at different dates would be evaluated on a consistent basis (Topal, 2010). Second, while it cannot deliver multiple solutions, NPV overcomes this inadequacy since it offers a clear, unambiguous measure of a project's profitability among other financial criteria. Third, NPV is relatively well suited to modern AI based optimization techniques at the planning stage as mine planners can adjust extraction sequence, blending strategy and equipment allocation in order to maximize discount cash flows (Dimitrakopoulos, 2011).

Furthermore, NPV facilitates robust risk assessment through stochastic modeling. Techniques such as Monte Carlo simulations enable planners to evaluate the impact of geological uncertainty, commodity price fluctuations, and operational disruptions on project value. AI-enhanced NPV models have demonstrated significant improvements in financial outcomes, with some case studies reporting NPV increases of 10–20% compared to traditional deterministic approaches (Smith & Dagdelen, 2019).

2.8.3 AI-Driven Optimization of NPV in Short-Term Planning

Advances in artificial intelligence further enhanced the role of NPV in mine planning. Thus, deviations from planned ore grades or equipment availability can be predicted by machine learning algorithms that will permit real time adjustments of targets to deliver NPV. For example, neural networks have been applied to solve the ore blending problem so as to provide processing plants with consistent feed quality and at the same time maximise revenue (Park & Choi, 2021). Reinforcement learning models have also been applied to autonomous haulage systems to lower fuel and maintenance costs and raise the overall economics of the project (Li & Li, 2022).

One of the Chilean copper mines had a useful case of how AI can work for NPV optimization. The mine was able to increase NPV by 15 percent with the help of an adaptive sequencing implemented with a Q learning algorithm for short term scheduling during downtime of equipment and dynamic ore blending (Askari-Nasab et al., 2010). These results show the promise of AI to improve the NPV based traditional planning methods.

2.8.4 Limitations of Alternative Financial Metrics

Although NPV is the most comprehensive of all the financial indicators, other financial indicators have serious limitations. For example, IRR may prefer projects involving early high returns, which may undervalue long life mining operations (Topal, 2010). Payback Period, though simple to calculate, ignores cash flows beyond the breakeven point, which can lead to

the rejection of high-NPV projects. Profitability Index, while useful for ranking capital-constrained projects, lacks the intuitive interpretability of NPV.

In summary, NPV remains the gold standard for financial evaluation in mining due to its ability to integrate time value, risk, and long-term profitability. The integration of AI into NPV-based planning has further enhanced its accuracy and adaptability, enabling real-time decision-making in dynamic mining environments. Future research should explore hybrid AI-human frameworks to refine NPV estimations under uncertainty, ensuring that mine planners can leverage both computational power and expert judgment (Newman et al., 2010).

2.9. Research Gaps and Future Directions

Many critical research gaps inhibit the adoption of Artificial Intelligence (AI) into short term open pit mine planning (Kumral, 2020). To such a state AI-driven mine scheduling from the theoretical frameworks to the practical and industry ready solutions, the limitations have to be addressed (McKinsey & Company, 2023).

2.9.1 Current Research Gaps

One of the foremost challenges in AI-based mine planning is the lack of high-quality, standardized datasets. Mining operations generate vast amounts of data, but inconsistencies in sensor reliability, proprietary data restrictions, and incomplete historical records often limit the effectiveness of machine learning models (Park & Choi, 2021). Moreover, many mines still use legacy planning software which does not have functional interoperability with modern AI systems, thus preventing real-time implementation (Newman et al., 2010).

Another critical issue is the opacity of AI decision-making. While advanced algorithms such as deep reinforcement learning can optimize schedules dynamically (Li & Li, 2022), their "black-box" nature reduces trust among mine planners. For providing the transparent reasoning for the automated recommendations, we first need to develop further the explainable AI (XAI) techniques which allow human operators to be able to validate and adjust the AI generated plans when needed (Goodfellow et al., 2016).

Furthermore, existing AI models struggle with dynamic uncertainties inherent in mining operations. Geological variability, unexpected equipment failures, and fluctuating commodity prices brings in a degree of volatility that static optimization models can not fully capture (Dimitrakopoulos, 2011). Most current solutions also assume that there is a training set representing a specific mine layout and the solutions do not generalize well across different sites (Askari-Nasab et al., 2010).

2.9.2 Future Research Priorities

To bridge these gaps, future research should focus on hybrid AI-optimization models that combine the adaptability of reinforcement learning with the robustness of traditional operations research techniques. For example, combining metaheuristic algorithms with deep Q learning can enhance response in the short term and in the long term, expand the economic outcomes (Askari-Nasab et al., 2010, Li & Li, 2022).

Another promising direction is the use of Generative AI for scenario simulation. Techniques such as Generative Adversarial Networks (GANs) could synthesize thousands of potential mining scenarios, allowing planners to assess risks and optimize contingency strategies proactively (Zhang & Yang, 2023). Additionally, it is also possible that the integration of a virtual interactive digital twin and associated real-time AI could allow for continuous plan changes while maintaining correspondence to strategic goals (Rio Tinto, 2022).

Data-sharing challenges could be mitigated through federated learning, where multiple mining companies collaboratively train AI models without exposing proprietary datasets (McKinsey & Company, 2023). This would allow competitiveness while improving model generalizability.

Finally, future AI systems should incorporate sustainability metrics alongside traditional financial indicators. By optimizing not only for Net Present Value (NPV) (Smith & Dagdelen, 2019) but also for energy efficiency and carbon emissions, AI-driven mine planning can align with global decarbonization goals (Topal, 2010).

2.10 Summary

This chapter reviewed the current practices and limitations of short-term mine planning and examined the role of digital transformation and Artificial Intelligence in the mining industry. While AI has demonstrated strong potential in improving operational performance, its integration into short-term planning remains limited. By identifying gaps in the literature and establishing a foundation for the study, this review supports the development of a practical, AI-enhanced planning framework to be explored in the following chapters.

3 METHODOLOGY

3.1 Research design

In this paragraph the methodology will be discussed. In order to obtain the goal of the thesis, an AI model should be developed. In order to develop AI model, which will be able to calculate the NPV and produce the best scenario of production, it was decided to use web-application for this purpose. Web-application is easy to use, requires no storage of data in hardware and can be accessed from different devices. In order to create web-application of AI model, methodology consists of data-collection and processing, system design, backend and frontend development, AI integration, testing and deployment.

3.2 Data sources

For the purposes of this study, primary and secondary data collection will be applied. The main data sources are of Bozshakol Mine's operational data.

3.2.1 Bozshakol Block model

Block model is a three-dimensional representation of the ore body or deposit in a mine, divided into small, regularly shaped blocks. These blocks represent small volumes of the earth's material and contain valuable information that aids in mine planning and design. Block model integrates key data from exploration and geological surveys (Hustrilid, 2006).

In case of this research, the data of interest from Bozshakol Mine include:

Ore type (ORETYPE) – indicates the classification of the material as clay ore, sulphide ore or waste.

Volume (m³) and tonnage (tonne) – physical characteristics of one block indicated in cubic metres and tonnes.

Copper Grade (Cu%) – grade of copper in the block model, indicated with percentages.

Gold grade (Au, g/tonne) – grade of gold in the block model, indicated with gram per tonne.

Molybdenum grade (Mo%) – grade of molybdenum indicated with percentages.

Silver grade (Ag%) – grade of silver indicates with percentages.

Sulphur to Copper Ratio (S/Cu) – ratio of sulphur to the content of copper, used for recovery calculation, indicated with hard number.

Acid-soluble of Copper (AsCu%) – Identifies acid solubility of the ore, used for recovery calculation, identified with percentages.

The block model was prepared using the mining faces available. It can be seen from the figure below, which indicates mining faces containing different types of materials differentiated by ore type and grade.

Description of the legend by ore types is presented below:

AUX - Gold containing ore, stockpiled for future processing.

KBB, KBB1, KBB2 – transitional balanced ore types including both clay and blocky material with the copper grade higher than 0.3%.

KHA – difficult-to-float clay material with high copper grade (Cu% > 0.5%).

KHG – kaolinized (clay) high grade ore (Cu% > 0.5%).

KMG – kaolinized (clay) medium grade ore ($0.5\% > \text{Cu}\% > 0.3\%$).

KLG, KLG1, KLG2 – kaolinized (clay) low grade ore ($\text{Cu}\% < 0.3\%$).

OMG, ONF – oxidized ore, stockpiled for future processing.

SHG – sulphide high grade ore ($\text{Cu}\% > 0.5\%$).

SMG – sulphide medium grade ore ($0.5\% > \text{Cu}\% > 0.2\%$).

SLG – sulphide low grade ore ($\text{Cu}\% < 0.2\%$).

WST – waste ore ($\text{Cu}\% < 0.1\%$).

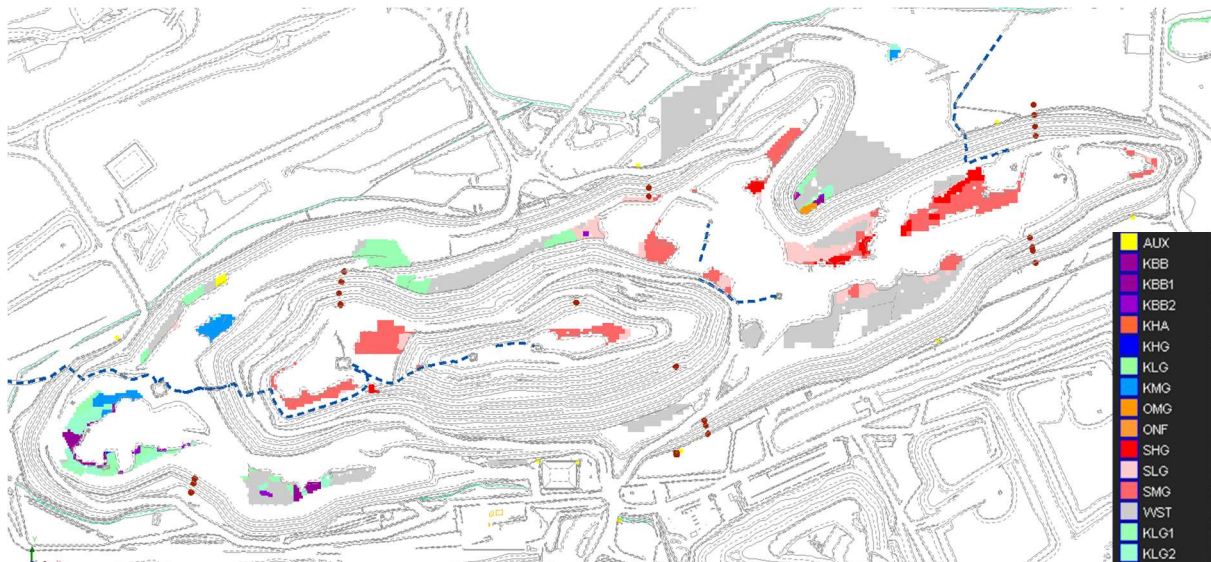


Figure 2. Mining faces with block model visual.

3.2.2 Mining Polygons and Haulage model

Mining polygons were developed to include only the mining faces which are available for mining activities. The development of mining polygon was in Dassault Systems Surpac graphical software. The initial file is saved in the .str format and it contains following data of interest for the model:

X, Y, Z coordinates – spatial data for location identification.

Segment number - used to identify separate mining faces.

Mining direction – includes information of azimuth of mining direction, indicated with degree of angle.

For haulage model, the Bozhakol Mine haulage file was used. It is used to calculate the haulage distance, and it contains information on:

X, Y, Z coordinates – spatial data for location identification.

Segment number – used to identify separate hauling roads.

Road type – used to differentiate horizontal roads from ramps.

Road length – identifies the length of the road, indicated by meters.

3.2.2 Operational Data

Data from the Bozshakol mine and its daily operational activities, which will be used for AI model and comparison with manual plan.

Production rates: includes daily mining production rates, and plant feed parameters.

Operational costs: includes cost of the different mining activities.

Equipment performance: includes the data on the fleet size and its production capabilities.

3.2.3 Models from Bozshakol mine

Several types of models which are used in the production of the Bozshakol Mine will be implemented in an AI model. It includes Recovery model, which is used to calculate the predicted recovery of the ore based on geological parameters. Also, throughput model, which calculates the predicted throughput of the plant based on the geological parameters.

For calculations of the NPV, the cash flow model of Bozshakol mine will be used. Cash flow model is a net amount of cash transferred in and out.

The main equation of the Cash Flow (CF) is:

$$CF = Revenue - Costs. \quad (1)$$

Revenue – a profit obtained from selling the metal concentrate.

Costs – total expenses incurred from mining and processing activities.

Revenue in Bozshakol mine is calculated by using the formula below:

$$\text{Revenue} = \text{Selling metal with deductions} - \text{Concentrate and Refining cost} - \text{Fees} - \text{Sales cost} - \text{Transportation} - \text{Taxes. (2)}$$

, where:

Selling metal with deductions: Total earnings from selling metal

Concentrate and Refining cost: Charges for smelting and refining concentrate into final metal.

Fees: Any third-party service charges, including bank fees or consultant fees on sales.

Sales Cost: Marketing, administrative, and documentation expenses related to selling.

Transportation: Cost of transporting concentrate to the buyer (e.g., port, smelter).

Taxes: Government royalties and applicable production or income taxes.

$$\text{Costs} = \text{Processing Cost} + \text{G\&A Costs} + \text{mining cost} + \text{production overheads cost} + \text{mill sustaining capital costs} + \text{rehandle costs} + \text{closure costs} + \text{mining capital expenditure costs (3)}$$

, where:

Processing Cost: Cost to treat ore, including crushing, grinding, flotation, etc.

G&A Costs (General & Administrative): Office staff salaries, security, IT, admin operations.

Mining Cost: Includes drilling, blasting, loading, and hauling costs

Production Overheads: Indirect costs for operating activities such as workshops, stores.

Mill Sustaining Capital Costs: Investment to maintain mill operation over time.

Rehandle Costs: Cost of moving ore or waste more than once (e.g., stockpile to mill).

Closure Costs: Cost for mine closure and environmental rehabilitation.

Mining Capital Expenditure (CAPEX) costs: Investment in equipment, road construction, or pit expansion.

Many of the costs were assumed to be constant, since many parameters can be only calculated after the production. However, haulage costs were calculated manually, using a constant value of hauling cost \$/km to calculate the total haulage. This was done to ensure and find the most cost efficient mine production scenario keeping the costs minimal while maximizing the revenue, since haulage costs historically account for almost 35% of total mining cost in Bozshakol.

Hauling destinations and road geometries with distances were prepared on Geovia Surpac application, used by Mining Engineering team in Bozshakol mine.

As a result, the AI model should be able to calculate the NPV using the formula above while inputting the values from the haulage file and block model in csv. Format. Moreover, it is necessary to create a polygon file containing available mining faces.

To find the selling metal tons, the formula below was used:

$$\text{Metal tons} = \text{tonnes of ore} * \text{grade of metals} * \text{recovery} \quad (4)$$

3.3 AI model architecture

This AI model is a custom built, optimization-oriented AI system that is made to be used in the complex dynamic environment of open pit mine planning within a short-term horizon. This is not a standalone machine learning algorithm with a humongous generic data to train on. Instead, it is a more integrated approach of using computational intelligence to solve a specific optimization problem: maximization of the Net Present Value (NPV) for a given set of equipment and a chosen mining block. Principles from operational research and potentially the heuristic search or evaluation techniques were taken as a base and creation of an 'optimization engine' that can make intelligent decisions based in the data and models of the mine and any other data source it was provided access to. The AI model is based on the OpenAI API integration. Input data is stored in the database and giving the input by user, the data is

preprocessed to form a prompt (request) for OpenAI API, after commences call to OpenAI API and output. After that, user can see the output of the model.

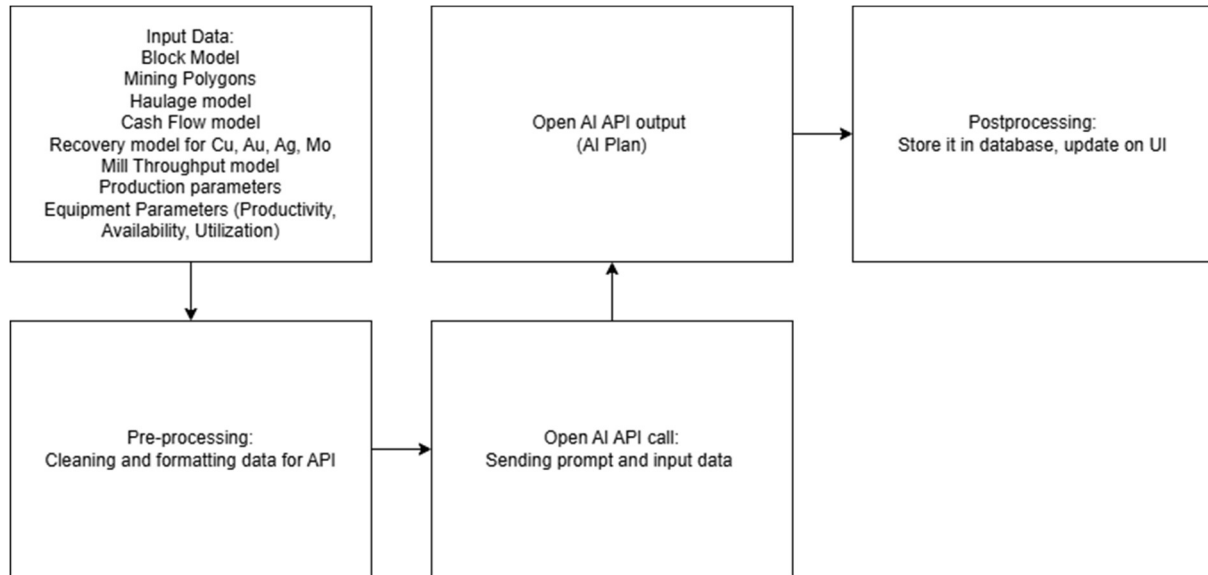


Figure 3. AI model structure.

AI system has an optimization core, and it is aimed directly at maximizing the Net Present Value (NPV). This is accomplished by evaluating the economic outcome of each of the various operational configurations for the chosen equipment set working on a selected mining block. This core contains an algorithm that does not simply compute NPV once; it explores all possibilities (e.g. what equipment combination should be used, or even simple sequencing options within the short time frame of that block) and calculates the projected NPV for each. To quantify the economic value of each potential micro plan, it uses the integrated cash flow model. The optimization method then selects the configuration that is associated with the highest calculated NPV and thus proposes the most economic manner in which to mine the given block using the available equipment under the given cost parameters. It's constrained optimization where the constraints are given by the available equipment, the properties of the mining block and the parameters of the mine's operational models.

3.3.1 Design

Initially, the project will focus on clearly defining the requirements and designing the overall system architecture. This involves mapping out user interactions, specifying the necessary inputs and desired outputs for NPV maximization, and detailing how the different technological components will interact. A crucial part of this phase is designing the PostgreSQL database scheme, which will be hosted on AWS RDS. AWS RDS is selected for its convenient scalability and straightforward backup configuration, providing a reliable data storage solution starting at a reasonable cost. Concurrently, the precise role of the OpenAI API needs determination; specifically, how its capability for performing calculations will be leveraged within the mine planning workflow. The design will also define the API communication pathways between the frontend and backend systems.

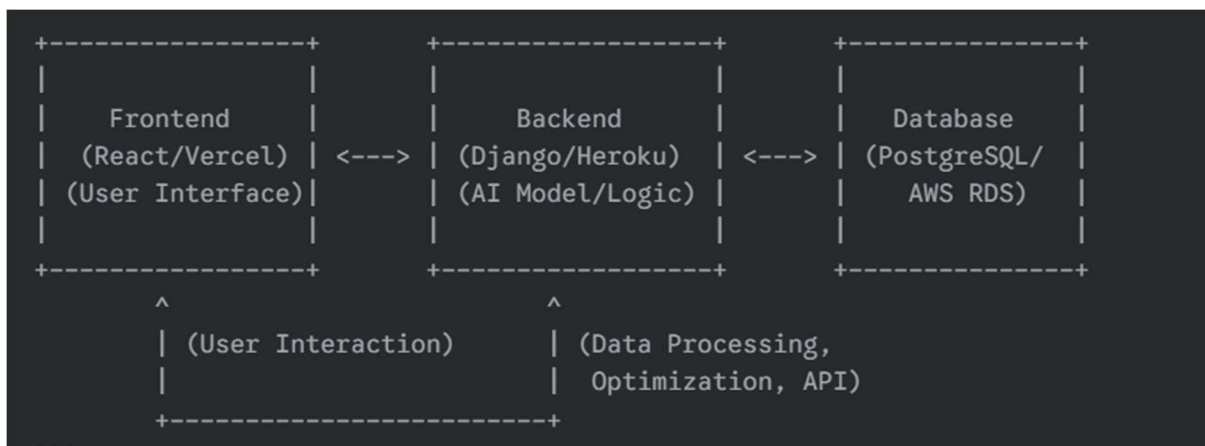


Figure 4. Design of AI model architecture.

3.3.2 Backend development

Following the design phase, backend development will commence using Python with the Django framework. This backend will encapsulate the core business logic, data processing tasks related to mine planning factors (like grades, costs, recovery), and interactions with the database. Development will include implementing the API endpoints needed by the frontend and integrating the OpenAI API client to send data and receive calculation results or insights as defined in the design phase. For deployment, Heroku is chosen as the hosting platform for the Django backend. Heroku offers an excellent environment for quickly launching an MVP, featuring simple database integration (particularly with AWS RDS).

3.3.3 Frontend development

Simultaneously, frontend development will proceed using React. The team will build the user interface components necessary for data input, visualization of mine plans and financial projections (NPV), and general user interaction. State management within the React application will be implemented, and seamless communication with the Django backend API will be established to fetch data and submit user requests. Vercel has been selected for hosting the React frontend. This platform is highly optimized for React applications, simplifying the deployment process, offering easy CI/CD integration, and providing a generous free plan suitable for smaller projects or initial deployment phases.

3.3.4 Testing

Instead of a standard training phase, the core logic and parameters of my model are directly tied to the Bozshakol Mine's real world operational data and engineering models. I included detailed information from their block models (spatial data, grades, tonnage, ore types) and operational data (such as equipment specifications and, crucially, the mine's own recovery and cash flow models). Essentially, this model makes use of these real-world parameters and formulas as its operational framework.

To validate and test the model, the validation and testing were paramount. Here I tested comprehensively using six unique experimental scenarios I had designed to mimic realistic operational challenges faced at Bozshakol, in terms of ore grades, increased production targets, fluctuations in equipment performance, economic conditions changes, etc. It was a direct comparison between the short-term plans generated by my AI model and the actual plans developed by experienced mining engineers at Bozshakol over a 30-day period that was the most critical validation step. Both sets of plans were rigorously evaluated based on key performance indicators (KPIs) of the achieved NPV, the time necessary to generate the plan, average material hauling distance, and copper recovery rate. From this empirical comparison I was able to obtain strong evidence that the AI model I made could provide practical benefits of my AI model, and that it largely outperformed traditional manual methods in the area of NPV maximization and planning efficiency.

3.3.5 Deployment

The deployment phase involves setting up the production environments on the chosen platforms: the Django backend on Heroku, the React frontend on Vercel, and ensuring the connection to the AWS RDS database is correctly configured. The selection of Heroku and Vercel facilitates a streamlined deployment process, leveraging their platform-specific features and CI/CD capabilities where applicable. This hosting strategy presents a cost-effective approach, particularly suitable for the initial launch and scaling stages of the AI Mine Planner.

3.3.6 Evaluation

Finally, after deployment, the application will undergo evaluation, including User Acceptance Testing (UAT) with the target mine planners. Feedback on usability, performance, and the practical value of the AI-assisted planning features will be gathered. This feedback will drive iterative refinement of the application, addressing any issues and enhancing functionality. Continuous monitoring of the application's performance and the actual usage costs of services like AWS RDS and the OpenAI API will be essential for ongoing optimization and budget management.

3.4 Experimental Scenarios

The AI plan will be tested using a set of experimental scenarios used to test the performance of AI model. These scenarios will include different conditions which will test whether AI model can deliver short-term plans consistently. There are six different scenarios which were developed. Baseline input data for all the scenarios is as follows: Block model, Mining Polygons, Haulage model, Cash flow model, Recovery model, Mill throughput model, Production parameters, Equipment parameters (productivity, availability, utilization). Any changes to input data in different scenarios will be indicated further.

3.4.1 Scenario 1: Standard Operation with Historical Data

- **Objective:** This scenario will evaluate the performance of the AI system using historical data, representing standard operational conditions at Bozshakol Mine.
- **Change of Input Data:** No changes of input data.
- **Expected Outcome:** The AI model will generate a plan which will maximize the NPV and will be compared to plan made by mining engineers. The AI plan is expected to show increase in NPV compared to mining engineers' plan.

3.4.2 Scenario 2: Fluctuating Ore Grades

- **Objective:** To assess the performance of the AI system under conditions where ore grades vary significantly from the initial forecast.
- **Change of Input Data:** New block model with change in copper grade of the ore by 5% margin. The change in copper grade is manual, meaning that all of the grades were decreased for 5%.
- **Expected Outcome:** The AI plan will be able to deliver the plans with decrease of NPV regarding the change of copper grade.

3.4.3 Scenario 3: Increased Production Demand

- **Objective:** This scenario will simulate a situation where there is a sudden increase in the production demand due to market conditions.
- **Change of Input Data:** A modified mine schedule with an increased target production rate, which is 10% higher than original.
- **Expected Outcome:** The AI system will optimize the mining plan by adjusting extraction and hauling parameters, considering the increased production rate while maximizing NPV.

3.4.4 Scenario 4: Equipment Efficiency Variability

- **Objective:** To test the AI system’s adaptability in response to fluctuations in equipment efficiency, such as downtime, maintenance, or operator performance.
- **Input Data:** Change of equipment utilization by 5% decrease.
- **Expected Outcome:** AI plan will be slightly less, due to decrease of equipment utilization.

3.4.5 Scenario 5: Economic Sensitivity Analysis

- **Objective:** To evaluate how sensitive the AI-generated mine plans are to changes in economic parameters, such as metal prices, operating costs, or discount rates.
- **Change of Input Data:** Change in copper price by 5% margin from original scenario, change in the processing cost by 6% margin from original scenario. These changes will account for both increase and decrease of the costs and price of the copper.
- **Expected Outcome:** AI plan will be able to deliver the plan which maximizes NPV in a way, that it will not be too different from the original plan within a margin of 10% difference.

3.4.6 Scenario 6: Combined Scenario (Worst-Case)

- **Objective:** This scenario will include a “worst-case” situation which will test the AI model to see if it will be able to produce maximized NPV in combination of decreased ore grade, and reduced equipment utilization and higher production demand.
- **Change of Input Data:** Block model with decreased grade by 5%, decrease in utilization of equipment by 5% and increase in production targets by 10%.

- **Expected Outcome:** AI plan will be able to deliver a plan which will have less NPV than original scenarios, however, not by a margin greater than 20%.

3.5 Key Performance Indicators

The performance of the AI plan will be validated through comparison with mining engineers' plan. In order to draw a comparison, several Key Performance Indicators (KPI) were developed. The following KPIs are presented below.

3.5.1 Net Present Value (NPV)

- **Description:** NPV shows economic feasibility of the project describing the total discounted cash flow.
- **Purpose:** To evaluate the most financially feasible plan based on the NPV.
- **Formula:** Bozshakol mine cash flow model.

3.5.2 Ore Recovery Rate

- **Description:** The ore recovery rate measures the percentage of the total amount of valuable material that is successfully extracted and processed.
- **Purpose:** To evaluate the AI system's ability to optimize the extraction of valuable ore while minimizing waste.
- **Formula:** Bozshakol mine recovery model.

3.5.3 Material Hauling Distance

- **Description:** Measures the efficiency of moving and processing material.
- **Purpose:** Evaluate the optimization of material hauling distance.

- **Metric:** Average haul distance of material to destination (plant, stockpile, waste dump).

3.5.7 Planning Flexibility

- **Description:** This KPI measures how adaptable the AI system is to changing operational conditions such as fluctuating ore grades, equipment failures, or unexpected changes in production demand.
- **Purpose:** To determine the AI system’s ability to quickly adapt the mine plan to real-time operational conditions.
- **Metric:** Time required to generate a new mine plan when changes in input data occur.

3.5.9 Summary of KPIs

Table 1. KPIs and their description

KPI	Description	Purpose	Formula/Metric
Net Present Value (NPV)	Measures the financial viability of the mine plan.	Evaluate economic feasibility of the plan.	Formula for NPV calculation.
Ore Recovery Rate	Measures the percentage of valuable material extracted.	Assess extraction efficiency.	Formula for Recovery calculation.
Material Hauling Distance	Measures the efficiency of moving and processing material.	Evaluate the optimization of material hauling distance.	Average haul distance of material to destination (plant, stockpile, waste dump).
Planning Flexibility	Measures the adaptability of the	Evaluate the AI system's	Time to generate new plan when conditions change.

	mine plan to changing conditions.	responsiveness to changes.	
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3.6 Evaluation Procedure

3.6.1 Performance Comparison

The AI-based mine plans will be compared to traditional planning approaches using the **Key Performance Indicators (KPIs)** outlined in Section 3.5. The comparison will focus on the following:

- **Economic Performance:** Evaluating the NPV achieved by the AI system versus traditional methods.
- **Operational Efficiency:** Comparing material hauling distances between the two approaches.
- **Ore recovery rate:** Assessing how well the AI system optimizes ore recovery compared to traditional methods.
- **Planning Flexibility:** Analysing the AI system’s ability to adapt to changing operational conditions.

3.6.2 Sensitivity Analysis

A sensitivity analysis will be conducted to evaluate the robustness of the AI-based mine planning system. This analysis will assess how changes in key input parameters (such as ore grade, extraction rates, and operational costs) affect the system’s performance. This will help determine the reliability and adaptability of the AI system under various operational conditions.

3.6.3 Interpretation of Results

Once the data has been collected and analysed, the results will be interpreted to draw conclusions about the effectiveness of the AI-based short-term mine planning system. This will include:

- **Comparing the performance of the AI system** to traditional mine planning methods based on the KPIs.
- **Identifying any areas where the AI system provides superior results**, such as increased NPV, improved equipment utilization, or reduced haulage distances.
- **Assessing the feasibility** of implementing the AI system at Bozshakol Mine in the future based on its performance in the case study.

3.7 Assumptions and limitations

3.7.1 Assumptions

This study has taken several assumptions that simplify the analysis and focus on the core objective of incorporating AI in short term mine planning at Bozshakol Mine. In particular, these assumptions include, but are not limited to the following:

1. **Data Quality and Availability:** The data used for the AI generated mine plans as well as traditional planning methods is assumed to be accurate, current, and complete. The data entities include geospatial data, ore grades, equipment performance and operational costs.
2. The study further assumes that the operational conditions at Bozshakol Mine will remain relatively stable over the period of analysis. This is based on assumptions on the ore quality, extraction rates, and equipment performance. Changes in any of these factors will impact the validity of this comparison between AI-based and traditional mine planning methods.
3. It is assumed that the AI based short term mine planning system has been trained and validated to such an extent that it is able to produce reliable mine plans that reflect the economic and operational goals of the mine. Under the conditions described in the experimental scenarios, the model is expected to work as intended.

4. It is assumed that the computing resources available to run the AI system are sufficient to process the data and produce mine plans within a reasonable time.
5. Assumption of alignment of AI system goals (maximizing NPV, optimizing equipment utilization, etc.) with mine operator and other stakeholders' goals, so that AI generated mine plans are consistent with mine's strategic objectives.

3.7.2 Limitations

This study examines the possibility and the effectiveness of AI in short-term mine planning but with some limitations that may influence the results and their interpretation.

All these results are based on a case study of Bozshakol mine, and it may or may not be applicable to other mines that differ in geological conditions, operational practices or resource constraints. The AI system developed and tested in the study may need to be adjusted for each new mine site.

Data Dependency: The AI system performance is very dependent on the data used for training and testing. The performance of the AI system could be negatively impacted if the data that was used in the study is incomplete, outdated or inaccurate, and results in unreliable mine plans.

The assumptions of the AI based mine planning system include a certain assumption of the mining process, including the fixed parameters of equipment performance, ore grade and extraction rate. In fact, these parameters may vary in reality and may hinder the system's capability to optimize the mine plan properly.

Sources of Operational Variability: The mining process is uncertain due to breakdowns of equipment, labor strikes, etc., and also due to the fact that the geology of the deposit can be different than what is expected. Due to these factors being difficult to model accurately in the AI system, it could lead to suboptimal or inaccurate predictions for the mine plan.

Q1: AI System Adaptability: The AI system is designed to create short time mine plans; however, the adaptability within the operational conditions in real time may be limited. The performance of the AI system is not evaluated under real time or in the presence of significant disruption.

Assumptions: It assumes that all the resources required for running the system are available and can be used as per plan (e.g. equipment, workforce). In practice, resource availability may be limited because of equipment downtime, labor shortage, or logistical issues which might affect the system performance.

Economic Sensitivity: The study assumes that the economic models used in the NPV calculations in the AI system are accurate and consistent. Yet, long – term viability of the AI – generated mine plans can be dependent on fluctuations in commodity prices and exchange rates, as well as on the long – term operation of the mine robl.

Integration with existing systems: The integration of an AI system with existing mine planning software and processes is necessary for the system to be implemented. In the case of integration, data compatibility, software interoperability, staff training can be challenging which may restrict the practical use of the system in some mines.

3.8 Ethical and Safety Considerations

3.8.1 Data Privacy

No personally identifiable information (PII) was employed; all data sets consisted solely of geological, equipment, and production metrics. Access to the Bozshakol operational database was governed by the mine’s ISO 27001-compliant data-security policy, and the researcher’s account was restricted to read-only privileges.

3.8.2 Operational Safety

The AI planner was executed offline in a sandbox environment. Generated plans were not deployed to live operations during the study, eliminating the risk of unintended production or safety incidents. Any future roll-out will follow the mine’s Management of Change (MoC) procedure, including a formal risk assessment and sign-off by the Health & Safety department.

3.8.3 Environmental Impact

The prototype runs on a local workstation (200 W peak). Over the entire experimental period, total energy consumption was estimated at < 5 kWh, corresponding to < 2 kg CO₂-e (Kazakh grid emission factor), deemed negligible relative to typical mine energy usage.

4 RESULTS AND DISCUSSION

4.1 Results

4.1.1. AI Planner Configurations

With the data from Bozshakol open pit mine, the AI model have been built. The display of the model can be seen in the figure below.

Mining Planner MVP

Select Equipment and Mining Block

Available Equipment

Excavators:

- EX201
- EX202
- EX203
- EX204

Haul Trucks:

- TR101
- TR102
- TR103
- TR104
- TR105
- TR106

Mining Block

Select Mining Block:

Block 6 (51150.0,47550.0,-30.0) - Cu 0.35%, Au 0.090g/t

Economic Parameters:

Cu Price (\$/t) 9000

Mining Cost (\$/t) 1.4

Processing Cost (\$/t) 6.3

Calculate Optimal Mining Plan

Figure 5. AI Model Website Visual.

In the available equipment window, user can choose what kind of loading and hauling equipment is available for given scenario. In Mining Block window, user can choose what areas of the pit will needs to be mined and set the economic parameters for the price, mining cost

and processing cost. It should be noted that hauling cost will be calculated from the polygons used to create the block model restricted with available mining faces.

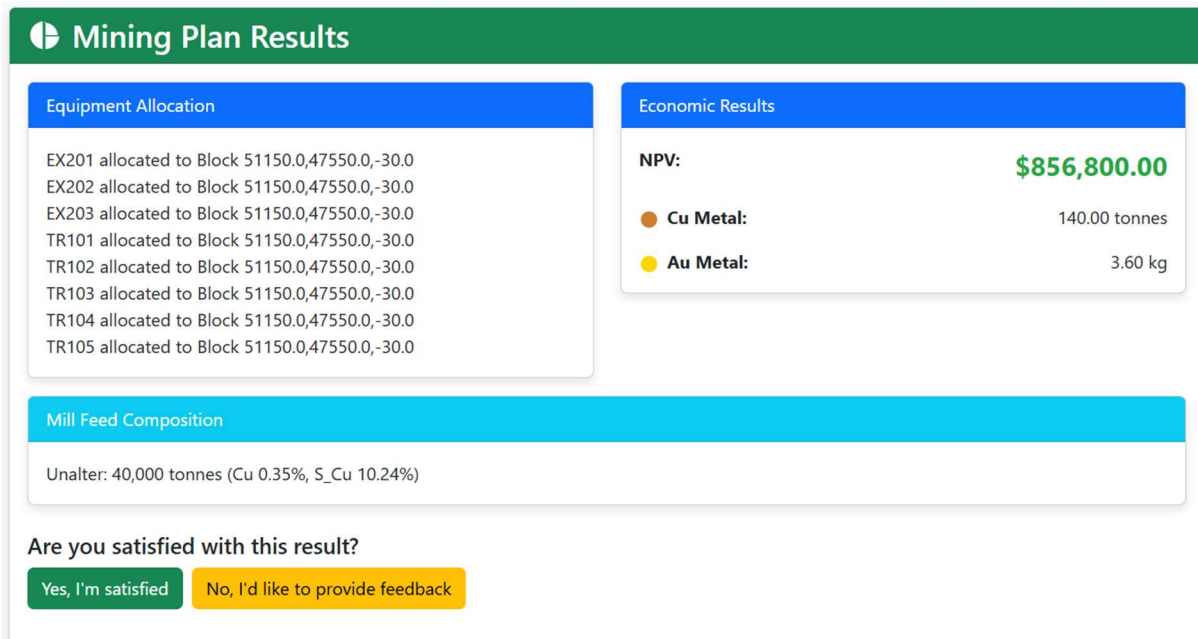


Figure 6. AI Model calculation example.

As a result, the program is able to give the best scenario with the best NPV value. It allocates the loading equipment to the best mining face, depending on the characteristics of the loading equipment and its loading cycle time. Moreover, it also allocates hauling equipment depending on the productivity of the loading equipment.

Also, it displays the mill feed composition, showing what kind of ore was sent to mill feed, In case if the current scenario does not meet the required targets on milling, user can write what kind of changes it should implement.

Are you satisfied with this result?

Yes, I'm satisfied

No, I'd like to provide feedback

How can we improve the mining plan? Please provide your feedback.

Type your feedback or questions here...

Send

Figure 7. AI Model Feedback window.

If the given results are not satisfactory, given the milling parameters, it is possible to write what kind of changes should be taken into account. Example of such conversation is shown in the figure below.

Mill Feed Composition

Unalter: 40,000 tonnes (Cu 0.35%, S_Cu 10.24%)

Are you satisfied with this result?

Yes, I'm satisfied

No, I'd like to provide feedback

How can we improve the mining plan? Please provide your feedback.

Too much S_Cu, any other way to lower it?

Sure revised plan with lower S_Cu while maximizing NPV will be calculated shortly.

Type your feedback or questions here...

Send

Figure 8. AI Model Feedback example.

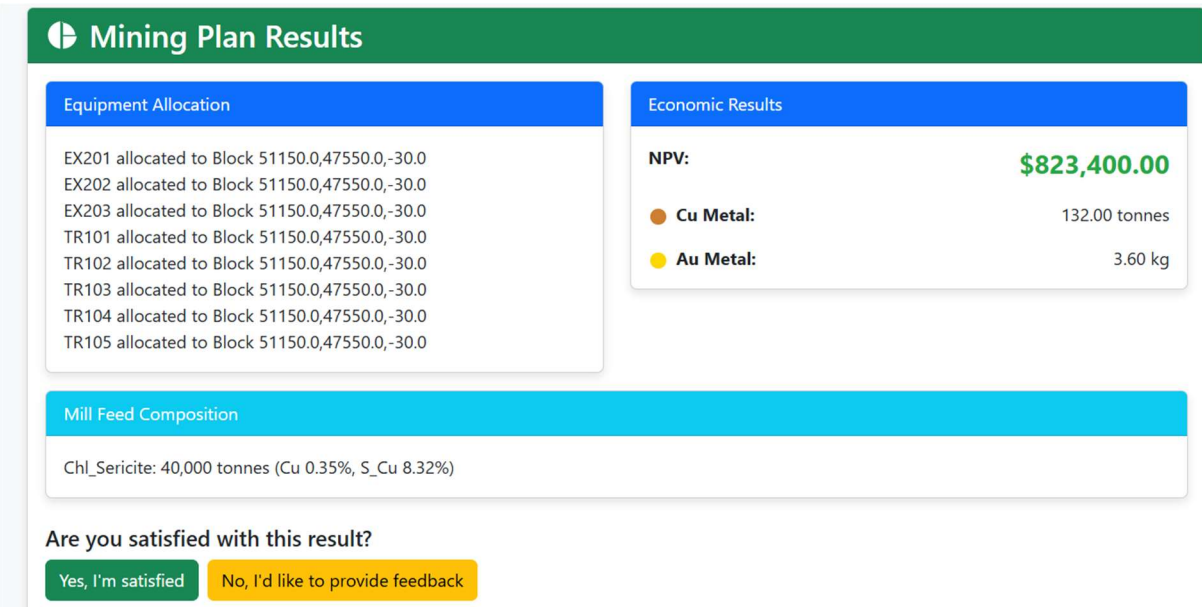


Figure 9. AI Model calculation after feedback example.

4.1.3 Validation by KPI

As a result, two scenarios were compared (AI modeled and human modeled). In the period from March 1st 2025 till March 30th 2025 on Bozshakol mine. The covered

Since calculating the NPV with the inclusion of haulage cost can take up a lot of time, mining engineers usually do not calculate the NPV and rather try to evaluate the performance of the AI-generated plan, a comparison was made between the daily mine plan produced by AI and the plan created by a mining engineer at Bozshakol mine. The comparison focused on key performance indicators such as time to prepare the plan, NPV, haulage distance, and mill feed.

The results of this comparison are summarized in the table below:

Table 2. Comparison of AI and Mining engineer plan.

	Mining engineer plan	AI plan
Time taken to prepare (min)	15.7	4.8
NPV (\$)	1,212,833	1,292,167
Copper Grade (%)	0.34	0.34
Mill feed (tonnes)	90000	90000

Average haulage distance (km)	3.51	3.47
Recovery rate of copper (%)	81.4	81.8

4.1.3 Test on different scenarios

Several experimental scenarios were defined based on different operational and economic conditions that may occur at Bozshakol mine in order to evaluate the efficiency of the AI based mine planning system. These were to measure how the AI system will be able to adapt, be robust and perform in optimizing short term mine plans for maximum Net Present Value (NPV).

Scenario 1: Standard Operation with Historical Data

The first scenario was the baseline and it employed standard operations with historical data from the mine. Given these conditions, the AI system has a mine plan with an average NPV of USD 1,292,167.

Scenario 2: Fluctuating Ore Grades

In the second, the geological conditions were simulated by altering ore grades. As a result, the average NPV was slightly lower at USD 1,253,402, a decrease of 3% compared to the previous case due to a lower average ore grade and slightly longer haulage distances.

Scenario 3: Increased Production Demand

The third scenario increased the production demand to test the AI system's response to raised operational targets. However, the AI managed plan worked well even under a more stressed system and resulted in an average NPV of USD 1,270,235 or 1.7% less than the baseline, with good ore grades and a slightly higher haul distance.

Scenario 4: Equipment Efficiency Variability

In the fourth case, equipment efficiency variability was introduced, i.e., reduced availability and operational downtime. The AI system was able to alter mine plans to achieve an average 4% NPV reduction from USD 1,290,480 to USD 1,240,480, as well as minimize ore grade decrease and increase dumping efficiency.

Scenario 5: Economic Sensitivity Analysis

The fifth scenario was economic sensitivity which we simulated a 10% increase and decrease in copper price and operation cost. In favourable conditions, the AI system generated NPV of USD 1,370,697, and in unfavourable conditions, it generated NPV of USD 1,162,950. This demonstrated the model's responsiveness to external market factors and cost changes.

Scenario 6: Combined Scenario (Worst-Case)

The sixth scenario was the first to combine several adverse conditions like changing ore grades, decreased equipment efficiency and increasing production demand in the worst case scenario. In such difficult circumstances, the AI system was able to produce a mine plan with an average NPV of USD 1,194,254, which was a 7.6% decrease from the baseline scenario, implying a robust response.

4.1.4 Expert review

The web application interface of the AI based short term mine planning system was tested and evaluated by six mining engineers at Bozshakol Mine. Then, the experts qualitatively evaluated the usability of the interface and the effectiveness of the AI generated mine plans after interacting with the system.

In addition, the engineers established that the web application is designed with an intuitive and user-friendly design that is easy to operate even by those who are not knowledgeable about digital tools. Particularly, the smoothness of the application in various devices like laptops and tablets was complimented, also the responsiveness of the application. It was pointed out as a practical advantage that this was a cross-platform accessibility in field operations.

The functionality of the model was quickly and efficiently able to produce optimised mine plans. The integration of block model data and the visual representations of the mining face in the system output made it very easy to interpret what they found especially useful. But a number of engineers stressed that the AI plans were sensible considering the practical constraints and, at least, seemed to be economically robust.

Other reviewers, however, also noted ways to improve the risks. Some possible suggestions were to integrate with dispatch systems in real time, to provide more detailed descriptions of AI's decision-making process, and to allow the customisation of user defined constraints or

KPIs. Nevertheless, the overall impression was positive, and the engineers thought that the system would be able to perform short term planning tasks, despite these recommendations.

4.2 Analysis and discussion of results

The AI plan required far less time to prepare than the mining engineer's approach. Unlike the engineer's 15 minutes, the AI system could produce a completely optimized plan in only 5. This decrease in planning time is a significant increase in operational efficiency that allows mine planners to devote more time to monitoring and modifying real-time operations instead of wasting time on planning and scenario analysis.

The AI plan produced a greater NPV with an increase of about 6.2% over the human-generated plan. The AI model's capacity to dynamically optimize important variables such equipment allocation, haulage costs, and ore recovery directly causes this improvement. The AI algorithm identified the most profitable mining sequence by effectively analyzing big datasets and considering variables a human planner could miss.

The hauling distances of AI plan were only slightly better in 30 day span, amounting only to increase in 1.4%. Despite that, it is still cost-effective as it was one of the parameters which contributed to increase in NPV.

Recovery rates of both plans were almost identical with difference of only 0.05%.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Findings Summary

This study has shown the possibility and viability of applying artificial intelligence for short-term mine planning in open-pit operations. The AI model successfully increased NPV forecasts and offered more dynamic, adaptive planning solutions by combining optimization algorithms with real-time data. The online application created in this project provides a simple interface that lets mine planners quickly optimize resources and enable more informed decisions. All the objectives mentioned in this thesis have been achieved. The most crucial parameters, indicated as KPIs were identified. The AI model has been built using OpenAI API integration and short-term plans made by AI and mining engineers were compared using forementioned KPIs. The key differences between AI and mining engineers' plans were identified as NPV and time-to-compute the plan. All in all, AI model was able to deliver plans which were superior to mining engineer plans in NPV and computation time, suggesting its relevance in short-term mine planning, where those parameters are key for decision-making,

5.2 Industry Implications

In dynamic mining settings, the use of artificial intelligence in short-term mine planning can greatly improve decision-making. AI-driven models help miners increase general profitability, cut operational delays, and improve scheduling efficiency. This study offers a more dynamic and data-driven approach to the planning process, hence revolutionizing how short-term mine planning is carried out.

5.3 Future Work Suggestions

Future studies might concentrate on broadening the AI model to incorporate more facets of mine planning, including changing the mill's recovery, throughput model. Furthermore, knowing the structure of the roads will help one to optimize the haulage system in the future

by either recommending construction of additional roads or selection of other routes to lower the mining cost and raise the NPV.

REFERENCES

- Askari-Nasab, H., Awuah-Offei, K., & Eivazy, H. (2010). Optimizing open-pit mine production scheduling using metaheuristics and artificial intelligence. *Mining Technology*, 119(2), 85–98. <https://doi.org/10.1179/037178410X12780655704672>
- Dimitrakopoulos, R. (2011). Stochastic optimization for strategic mine planning: A decade of developments. *Journal of Mining Science*, 47(2), 138–150. <https://doi.org/10.1134/S1062739147020018>
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- Hustrulid, W., & Kuchta, M. (2006). *Open pit mine planning and design, Volume 1: Fundamentals*. CRC Press.
- Kazakhmys. (2010). *Feasibility study, Bozshakol Mine*.
- KAZ Minerals. (2023). *Official website*. <https://www.kazminerals.com>
- Kumral, M. (2020). *Artificial intelligence applications in mining: Scheduling, equipment, and safety*. Springer. <https://doi.org/10.1007/978-3-030-49863-5>
- Li, X., & Li, Y. (2022). Reinforcement learning for dynamic short-term mine scheduling under uncertainty. *Resources Policy*, 75, 102456. <https://doi.org/10.1016/j.resourpol.2021.102456>
- McKinsey & Company. (2023). *AI in mining: From pit to port*. <https://www.mckinsey.com/industries/metals-and-mining/our-insights/ai-in-mining>
- Newman, A., Rubio, E., Caro, R., Weintraub, A., & Eureka, K. (2010). A review of operations research in mine planning. *Interfaces*, 40(3), 222–245. <https://doi.org/10.1287/inte.1090.0492>
- Park, S., & Choi, Y. (2021). LSTM-based ore grade prediction for real-time mine scheduling. *Minerals Engineering*, 170, 107026. <https://doi.org/10.1016/j.mineng.2021.107026>
- Rio Tinto. (2022). *Autonomous haulage systems: Annual performance review*. <https://www.riotinto.com/sustainability/technology>
- Ross, S. A., Westerfield, R. W., & Jordan, B. D. (2016). *Fundamentals of corporate finance* (11th ed.). McGraw-Hill Education.

Smith, M. L., & Dagdelen, K. (2019). Net present value maximization in open-pit mine planning using stochastic programming. *Mining Engineering*, 71(5), 45–52. <https://doi.org/10.1007/s42461-019-00144-1>

Topal, E. (2010). Advanced financial risk management in mining projects. *Journal of the Southern African Institute of Mining and Metallurgy*, 110(7), 399–406.

Zhang, C., & Yang, X. (2023). Graph neural networks for 3D orebody modeling in open-pit mines. *Natural Resources Research*, 32(1), 123–140. <https://doi.org/10.1007/s11053-022-10141-9>

APPENDICES

Appendix A. Day-by-day comparison of AI plan vs Manual plan (performed by mining engineers).

Day	NPV (Manual, USD)	NPV (AI, USD)	Grade (Manual, %)	Grade (AI, %)	Haulage (Manual, km)	Haulage (AI, km)
1	1,212,000	1,292,000	0.34	0.345	3.5	3.45
2	1,202,000	1,290,000	0.341	0.344	3.51	3.48
3	1,230,000	1,295,000	0.342	0.346	3.52	3.46
4	1,210,000	1,285,000	0.339	0.343	3.53	3.47
5	1,225,000	1,298,000	0.34	0.347	3.49	3.44
6	1,202,000	1,291,000	0.338	0.341	3.51	3.49
7	1,220,000	1,290,000	0.34	0.344	3.52	3.46
8	1,217,000	1,295,000	0.341	0.345	3.53	3.45
9	1,202,000	1,289,000	0.339	0.343	3.5	3.48
10	1,215,000	1,292,000	0.34	0.344	3.51	3.47
11	1,209,000	1,293,000	0.341	0.346	3.49	3.44
12	1,210,000	1,287,000	0.338	0.341	3.52	3.5
13	1,225,000	1,290,000	0.34	0.345	3.53	3.46
14	1,200,000	1,298,000	0.339	0.347	3.54	3.45
15	1,213,000	1,296,000	0.342	0.348	3.5	3.47
16	1,210,000	1,290,000	0.341	0.345	3.51	3.46
17	1,206,000	1,293,000	0.338	0.344	3.52	3.49
18	1,213,000	1,288,000	0.34	0.342	3.49	3.48
19	1,220,000	1,292,000	0.341	0.346	3.53	3.46
20	1,208,000	1,290,000	0.339	0.343	3.51	3.47
21	1,210,000	1,289,000	0.34	0.344	3.5	3.48
22	1,205,000	1,296,000	0.342	0.347	3.52	3.46
23	1,215,000	1,290,000	0.339	0.343	3.51	3.47
24	1,214,000	1,293,000	0.34	0.345	3.53	3.45
25	1,225,000	1,294,000	0.341	0.346	3.52	3.47
26	1,218,000	1,297,000	0.342	0.348	3.5	3.46
27	1,210,000	1,292,000	0.34	0.345	3.51	3.45
28	1,206,000	1,289,000	0.339	0.342	3.49	3.48
29	1,222,000	1,296,000	0.341	0.347	3.52	3.46
30	1,211,000	1,295,000	0.34	0.345	3.51	3.47

Appendix B. Results of test on different scenarios of AI plan.

Scenario	Description	Avg. NPV (USD)	Change in NPV vs Scenario 1	Avg. Ore Grade (%)	Avg. Haulage (km)	Remarks
1	Standard Operation (Historical Data)	1,292,167	–	0.34	3.5	Baseline scenario using historical data
2	Fluctuating Ore Grades	1,253,402	–3%	0.33	3.52	Adaptive to grade changes
3	Increased Production Demand	1,270,235	–1.7%	0.34	3.55	Maintained performance under stress
4	Equipment Efficiency Variability	1,240,480	–4%	0.33	3.48	Optimized routes under equipment limits
5	Economic Sensitivity (Price ±10%)	1,370,697 ↑ / 1,162,950 ↓	+6.3% / – 10%	0.35 / 0.33	3.46 / 3.57	AI responded to market shifts
6	Combined Worst-Case	1,194,254	–7.6%	0.32	3.58	Demonstrated high resilience