The significance and reliability of the Mine Call Factor in gold mining using AI methods

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Abstract: The significance of the Mine Call Factor (MCF) has been discussed and debated for several years, with much of the debate being centred around whether the use of the MCF is still relevant in determining the actual performance of the mine. In theory, the Mine Call Factor was designed to be 100%, but when practicality now becomes a concern, evidence shows several ore loss occurrences within the Mine value chain consequently leading to a decrease in the accuracy of the Mine Call Factor. Over the last decade, there has been a significant decrease in the Mine Call Factor to approximately 60%, and the question that begs is whether the Mine Call Factor is still relevant in South African gold mining. This paper reviews the application of AI methods to help better understand metal reconciliation.

INTRODUCTION

The Mine Call Factor (MCF) reconciles the amount of metal produced with the amount of metal sold. Storrar (1981) defined the MCF as the ratio of the total weight of the ore extracted from the mine to the weight of the ore or material sent to the processing plant. However, discrepancies between the two values can occur, leading to significant financial losses for mining companies. Over the last decade, in South African gold mining, there has been a significant decrease in the MCF from approximately 100% to ranges of 45% to 60%, (Mpofu, 2018), and the decrease usually occurs at the stopes (poor blasting and cleaning practices), during tramming as well as on the surface (during transportation to the plant). This paper focuses on the advantages associated with the use of the MCF, its significance, as well as the effects it has on the mine performance. The study reviews the application of AI methods to understand the significance of the MCF. The MCF appears to no longer be an effective and accurate measure of determining the mine's performance, therefore creating a need to improve its accuracy. Furthermore, other strategies are required to aid the accurate determination of a mine's operation performance, such as the production rates.

The study considered the gold mining industry, which contributes 8% to the South African economy. The study reviews the MCF and its significance in gold mining. In addition, a gold mine case study was used to support the systematic review where the Mine Call Factor data from 2018 to 2022 were collected to map out the trend and compare it with the MCF data from 2000 to 2010. The significance of this research is that it has the potential to highlight areas that require improvement in the MCF values, thus increasing efficiency and profitability of gold mining operations. By accurately measuring the amount of metal produced, mining companies can make informed decisions about their operations and avoid financial losses. The use of AI methods to understand the apparent metal discrepancy can also lead to the development of new strategies to improve the accuracy of the MCF.

AI has significantly impacted gold mining by revolutionising exploration, grade control, and resource/reserve estimation processes. In exploration, machine learning algorithms analyse vast geological and geophysical datasets, facilitating more efficient identification of potential gold deposits. This data-driven approach enhances the targeting of areas with higher probabilities of containing gold, streamlining the initial stages of mining operations which further allows for an accurate estimation of the gold grade hence improving the Mine Call factor.

In the realm of grade control, AI technologies offer real-time monitoring capabilities. Sensors and cameras collect data during the mining process, and machine learning algorithms analyse this information to provide insights into the quality of extracted ore. The AI technologies leverage sensors and cameras to gather real-time data throughout the mining process. These devices capture information about the composition and quality of the extracted ore. Machine learning algorithms are then employed to analyse this data, identifying patterns and correlations that might be challenging for traditional methods (Schofield, Carswell, 2013). The algorithms can recognize features indicative of ore quality, allowing for timely adjustments and informed decision-making to optimise the extraction process. Moreover, AI-driven sorting systems such as automated optical sorting or x-ray transmission sorting systems, automate the separation of ore based on its grade, optimising the extraction process by directing higher-grade material to processing plants and lower-grade material to waste piles (Rossi, Camacho, 2000).

Resource and reserve estimation benefit from AI's predictive modelling capabilities. Machine learning models, trained on historical data, predict the size and quality of gold deposits more accurately. This integration of multiple data sources, including geological surveys and drilling results, contributes to a comprehensive understanding of a deposit's potential. The application of AI in gold mining, plays a pivotal role in influencing the Mine Call Factor. By improving exploration accuracy, AI technologies contribute to a more precise understanding of gold deposits, directly impacting the reliability of initial ore grade estimates.

In the context of grade control, where AI enables real-time monitoring and automated sorting, the Mine Call Factor is positively influenced by aligning predicted and realised ore grades this minimises discrepancies. Accurate data on the quality of extracted ore, provided by AI algorithms during the mining process, ensures that the actual grades align closely with the estimated grades (Topal, Umit, 2020).

Additionally, AI's role in resource and reserve estimation further ties into the Mine Call Factor. The predictive modelling capabilities of AI contribute to more accurate assessments of deposit size and quality. This, in turn, improves the reliability of initial estimates, positively impacting the Mine Call Factor by minimising the variance between expected and actual outcomes in terms of ore quantity and quality. In essence, the integration of AI technologies in gold mining operations contributes to optimising the Mine Call Factor through enhanced accuracy in exploration, grade control, and resource/reserve estimation processes through real time data analysis and automation. (Carswell, 2011)

Mine Call Factor (MCF) in gold mining faces challenges primarily rooted in sampling errors, geological variability, inadequate mineralogical information, operational inefficiencies, and environmental constraints. Sampling errors can arise due to the diverse nature of ore bodies and suboptimal sampling techniques. Geological variability introduces uncertainties in predicting the distribution and grade of gold deposits, leading to disparities between estimated and actual extraction outcomes. Incomplete mineralogical information hampers the understanding of ore composition, impacting grade estimates and potentially contributing to gold losses (Amoako, Al-Hassan, 2015). Operational inefficiencies, including suboptimal mining and processing practices, as well as equipment inefficiencies, can further affect the overall Mine Call Factor.

To address these challenges, AI emerges as a valuable tool in the gold mining industry. AI applications such as computer vision systems, machine learning algorithms and statistical models can enhance sampling accuracy by analysing historical data and identifying patterns in ore distribution, leading to improved representativeness of samples. Machine learning algorithms can analyse complex geological data to identify trends and patterns, refining resource models and enhancing the accuracy of grade predictions. Real-time mineralogical information provided by AI technologies, such as machine vision and spectroscopy, aids in mitigating the impact of inadequate mineralogical information on grade estimates. AI (machine learning and predictive analytics can optimise mining and processing operations by predicting equipment failures, automating sorting processes, and improving overall efficiency, contributing to higher ore recovery rates, and minimising gold losses (Fourie, Minnitt, 2016). Moreover, AI supports the development of sustainable and safe mining practices by optimizing processes, reducing waste, and ensuring compliance with regulations, thereby addressing environmental and safety concerns ((Xingwana, 2016).

LITERATURE REVIEW

The literature review focuses on the significance of the Mine Call Factor (MCF) in gold mining operations, particularly when leveraging artificial intelligence (AI) to comprehend apparent metal discrepancies. Furthermore, it highlights the importance of the MCF in assessing the efficiency and profitability of gold mining processes. The literature review emphasises the limitations of traditional methods of sampling, which can lead to overestimation or underestimation of the actual grade values. Poor sampling further introduces inaccuracies in ore grade estimates, thus causing divergence between the predicted and actual grades. The review suggests that AI methods have the potential to overcome these limitations and provide more accurate results.

(Abuntori, 2021) discusses the benefits of using AI methods, such as k-nearest neighbour (kNN) and artificial neural networks (ANN), machine learning algorithms and data analytics, to optimise gold mining processes, reduce losses, and increase overall production. AI can analyse massive datasets containing geological data, processing parameters, and historical MCF values to identify hidden connections and deliver actionable insights for process improvement (Cawood, 2003). Furthermore, (Jung, Yooso, 2021) did a systematic review of machine learning applications in mining. In this review, he states that machine learning can assist in improving recovery rates by efficiently using the AI in predictive analysis and real time monitoring, therefore, assisting in accurately determining the performance of a mine.

Machine learning can help optimise mineral processing operations and improve recovery rates by analysing large amounts of data from various sources through the implementation of predictive analysis of the ore grade, real time monitoring as well as accurate estimation of the ore resource. It can identify patterns and correlations in the data that are difficult for humans to detect and use this information to make predictions and recommendations for process optimisation (Saboor, 2017). For example, it can predict the quality of ore feed and adjust processing parameters accordingly or detect anomalies in the process that may indicate equipment failure or suboptimal performance. By improving process efficiency and reducing waste, machine learning can ultimately lead to higher recovery rates and lower operating costs.

Accurately predicting mineral grades is a crucial step in mining projects. (Topal, Umit, 2020), presents a new approach to ore grade estimation using machine learning algorithms. In this paper, a hybrid model that combines k-nearest neighbour and neural networks to estimate grades based on sample locations, lithological features, and alteration levels is used. The proposed method does not require complicated mathematical knowledge or deep assumptions, making it easily applicable to other mining resources. The aim is to overcome the limitations of current methods that often require assumptions on input variables and can make accurate grade estimation challenging.

The literature shows the application of AI in gold mining thus helping in understanding apparent metal discrepancy as well as appreciating that the use of AI may potentially assist in improving the Mine Call Factor. In this review, 35 main publications were sources for both Scopus and Web of Science data bases, including Academia and Springer. The authors of note are, amongst others (Abuntori, 2021), and (De Jager, 1996). The authors main thrust was to apply AI technology in the mining process to ensure that there is increased profitability. By leveraging AI methods, gold mining companies can optimise their processes, reduce losses, and increase overall production, leading to improved efficiency and profitability, ultimately leading to a more sustainable and secure future in the gold mining sector.

METHODS

To achieve this, a systematic review of literature was conducted to recognise and map knowledge domains by identifying prevailing research trends. The study exclusively relied on information extracted from past publications available in the Scopus and Web of Science databases. These are recognised as a prominent database encompassing various scientific disciplines and are widely utilised by researchers for literature retrieval. The exploration for pertinent literature concentrated on published journal articles and conference proceedings within the study areas associated with mining. The decision to prioritise journal articles was based on the perception that such articles are regarded as more dependable sources of knowledge as they undergo a peer review process, providing a greater level of precision. Furthermore (Watson, 2002) previously acknowledged the significance of conference proceedings as credible sources for literature reviews, justifying their inclusion in this study.

The chosen search criteria for this study included the terms, “Application of AI to improve MCF”,”MCF significance in gold mining” and ‘’MCF reliability in gold mining’’. Documents containing these keywords in their titles, abstracts, and keywords were selected for analysis. The temporal scope of the study spanned a 20-year period from 2003 to 2023, aimed at gaining insights into the most recent AI-related issues within the study domain. The initial search yielded 1 273 papers with the specified keywords. Due to the broad spectrum covered by the initial extraction, which encompassed various fields unrelated to mining, a meticulous refinement process was undertaken. This refinement involved filtering based on mining-related content, language of publication (restricted to English), and publication type (limited to published journal articles and conference proceedings). Following a thorough refinement process, a final set of 68 articles was identified for analysis. The presentation of results is structured around several key metrics, including the annual distribution of publications, the geographical distribution of publications per country, notable documents with high citation counts, the distribution of publications across various document sources, the frequency of publications per author, insights into co-authorship patterns, and the exploration of keyword co-occurrence networks.

To supplement the review, a case study was done. The case study focused on the Mine Call Factor trends for the last 10 years, a survey and interviews were also carried out at the mine. The interviews and survey targeted upper management personnel such as the mine overseers, surveyors and ore reserves managers. These individuals were targeted as they are part of upper management and have a better understanding of the Mine Call Factor and its implications for the efficiency of the mining process.

RESULTS

This section discusses a gold mine case study used to understand the reliability and significance of MCF and the application of AI. Mine X is the name given to the mine site which is used as a case study in this paper. Figure 1 presents the MCF from 2019 to date.

The trend of the Mine Call Factor (MCF) for Mine X shows a consistent and significant decline in the MCF over the five-year period from 2019 to 2023.Figure 2 shows the root causes of this decline, which are further discussed in the following. The MCF is a crucial metric in gold mining operations as it measures the accuracy of the ore grade estimation and the efficiency of the mining process. The decline in the MCF is because of factors, such as changes in the geological conditions of the mine, changes in the mining process, or errors in the ore grade estimation. The decline in the MCF has significant implications for the profitability and efficiency of the mining operation. A lower MCF means that the mine is losing more gold than expected, which can lead

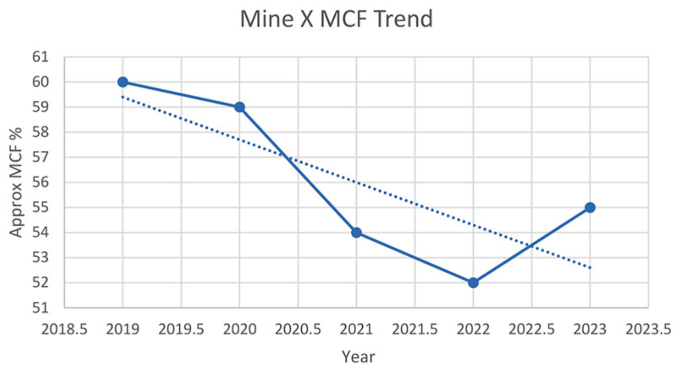

Figure 1: 5-Year Mine Call Factor trend at Mine X (2019–2023). This figure shows the consistent decline in MCF, attributed to operational inefficiencies and ore grade misestimations

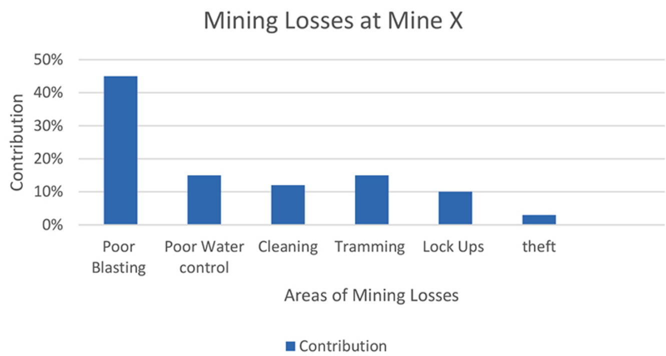

Figure 2: Root causes of poor Mine Call Factor at Mine X. Derived from survey and interview data showing key contributing factors such as blasting inefficiencies, water control issues, and cleaning delays

to reduced profitability and as in this case study, a loss of approximately R1,4 billion in profits over the last seven-year period. Additionally, a lower MCF can indicate that the mining process is not as efficient as it could be, leading to increased costs and reduced productivity. To address the decline in the MCF, the use of the trend analysis to identify potential issues and take action to optimise their processes is essential. For example, reviewing the ore grade estimation methods, adjust the mining processes, or implement new technologies to improve the accuracy of the MCF.

Figure 2 presents the causes of a poor MCF at Mine X The information shown in Figure 2 was summarised from the interviews and survey conducted at Mine X.

Root causes of poor or a decline MCF

According to upper management, poor blasting practices at Mine X, constitute 45% of the total mining losses. This is primarily linked to the use of explosives with high detonation rates resulting in excessive fine fragmentation of the rock, leading to inefficiencies in gold extraction. The finer fragments trap valuable gold particles, reducing overall recovery rates. Moreover, poor blasting not only causes gold losses but also leads to inefficient resource use, increased processing costs, and poses safety risks due to unstable rock conditions.

Water control, accounting for 15% of total mining losses, involves the seepage of water into the mine, disrupting operations and creating adverse conditions. Water can dilute ore grades, impacting gold concentration in the extracted material by mixing with extracted material. The water therefore reduces concentration of gold thus dilution further occurs. Additionally, water seepage can damage equipment, affecting its efficiency and contributing to downtime. The presence of water in the mining process creates safety hazards, impacting operational efficiency and potentially causing gold losses due to suboptimal processing conditions.

The contribution of cleaning conditions to mining losses (12%) highlights challenges related to the removal of impurities from the ore. Inadequate cleaning processes may result in the retention of undesired materials, reducing overall ore quality and impacting gold recovery rates during processing. Efficient cleaning is essential to ensuring that the extracted ore is free from contaminants that could otherwise lead to gold losses.

Tramming conditions, contributing 15% to total mining losses, relate to the transportation of ore within the mine. Suboptimal tramming practices such as inadequate loading and poor route planning, can lead to spillage and ore loss during transit, impacting the overall recovery of gold. Efficient tramming is crucial for minimising ore spillage and ensuring that the maximum amount of valuable material reaches the processing plant.

Theft, comprising 3% of total mining losses, involves the unlawful removal of valuable materials either by illegal miners or even other mining personnel, including gold-bearing ore. This unauthorised removal directly results in a loss of gold from the mining operation. Implementing robust security measures is crucial to mitigating theft-related gold losses and ensuring the integrity of the entire ore extraction and processing chain.

The following section reviews data from literature on the performance of AI and ordinary kriging in grade estimation.

The aforementioned information by Abuntori (2021) provides a comprehensive review of the use of Artificial Intelligence (AI) techniques in ore grade estimation, and how they have outperformed other techniques like kriging. AI techniques have been employed in diverse ore deposit types for the past two decades and have proven to provide comparable or better results than those estimated with classical methods like kriging. The graph in Figure 3 shows the performance of AI and ordinary kriging (OK) in estimating ore grade.

Figure 3 displays the percentage of cases where AI outperforms OK, OK outperforms AI, AI and OK perform equally, AI performs well alone, and OK performs well alone (Abuntori, 2021) The figure shows that AI techniques such as k-nearest neighbour and artificial neural networks have the highest performance of all the techniques present. Specifically, AI outperforms OK in 41% of cases, while OK outperforms AI in only 7% of cases. AI and OK perform equally in 17% of cases, while AI performs well alone in 24% of cases and OK performs well alone in 10% of cases. The implications of these findings are significant for the accuracy and reliability of ore grade estimation in the mining industry. The results suggest that AI techniques, such as k-nearest neighbour and artificial neural networks have a higher probability of providing accurate estimates of ore grade compared to traditional methods such as OK. By using AI-driven solutions, mining companies can improve the accuracy and reliability of their ore grade estimates, leading to more efficient and profitable operations. In conclusion, Figure 3 shows that AI techniques such as k-nearest neighbour and artificial neural networks have a higher performance in estimating ore grade compared to traditional methods such as OK.

The higher probability of accurate ore grade estimates with AI techniques implies a potential improvement in the reliability of MCF through advanced data analysis and machine learning algorithms, which enhance the precision of ore grade predictions during extraction and processing. If AI-driven solutions, known for their effectiveness in ore grade estimation, are adopted by mining companies, there is a likelihood of minimising discrepancies between predicted and actual metal content during extraction and these discrepancies are minimised the accurate and precise knowledge of the predicted ore grade which will be almost the same as the actual ore grade, will increase the percentage value of the MCF.

Therefore, the findings suggest that the adoption of AI techniques can have positive implications for the accuracy and reliability of ore grade estimates, which, in turn, may enhance the precision of the Mine Call Factor. Having accurate ore grade estimates ensures that the ration of the gold accounted for, and gold called for, is almost the same, thus leading to a higher MCF given that all other factors in the mine value chain such as blasting are carried out with highest efficiency. The advanced capabilities of AI in ore grade estimation offer a pathway for mining companies to optimise their operations, reduce gold losses, and achieve a more reliable Mine Call Factor, ultimately leading to more efficient and profitable mining endeavours. Accurate ore grade estimates facilitated by AI technologies minimise the variance between predicted and actual grades in mining. This alignment enhances the reliability of the MCF.A more precise estimation of ore grades contributes to improved decision making, efficient resource management and minimise operational losses, collectively optimising the MCF.

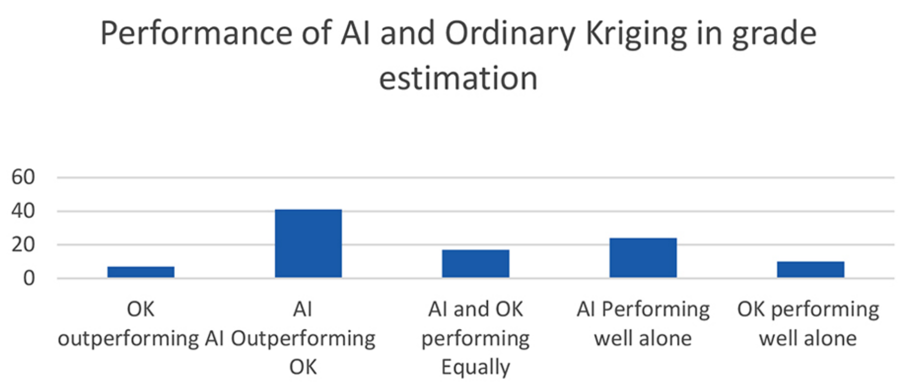

Figure 3: Comparison of AI vs. Ordinary Kriging (OK) in Ore Grade Estimation. This chart from Abuntori (2021) illustrates the higher predictive accuracy of AI models, particularly kNN and ANN, over OK

CONCLUSION

The Mine Call Factor (MCF) is a pivotal parameter crucial for the accurate reconciliation process between the mine and the mill. The study identifies various factors that influence the MCF, encompassing considerations such as ore type, mining and processing methods, and the precision of the sampling and assaying processes. Furthermore, the study underscores the transformative potential of AI methods, particularly k-nearest neighbour (KNN) and artificial neural networks (ANN), in enhancing the precision of the MCF. Notably, AI methods, reviewed from literature, exhibit a heightened likelihood of delivering accurate estimates of ore grade when compared to conventional approaches like ordinary kriging (OK) in gold mining.

Through the utilisation of AI-driven solutions and data-driven optimisation techniques, mining companies can not only refine the MCF, but also reduce gold losses, ultimately augmenting the overall profitability of mining endeavours. Identifying contributing factors to mining losses at Mine X, the study points out suboptimal practices in blasting, water control, cleaning, tramming, lockups, and theft. Addressing these factors is a viable strategy to curtail mining losses and, consequently, increases profitability.

Moreover, continuous refinement of AI models and collaborative efforts between mining companies and industry experts is essential. This partnership aims to optimise processes, diminish losses, and enhance profitability, underscoring the significance of ongoing collaboration and technological advancement in the mining sector.

In conclusion, the study highlights the significance of the Mine Call Factor in the gold mining industry and the potential of AI methods in improving its accuracy.

The study aimed to determine if the Mine Call Factor is still a relevant measure of a mine's efficiency and to explore the use of AI methods in improving the understanding of metal discrepancies. The paper reviews literature on the Mine Call Factor, apparent metal discrepancies, mine to mill reconciliation, factors affecting mining efficiency, production rates, ore grade estimation, and the accuracy of conventional sampling methods compared to AI methods. Furthermore, a case study was used to support the reviewed literature. The case study included data collection through questionnaires and interviews, followed by data analysis using thematic analysis and qualitative data analysis methods. The findings highlight the significance of the Mine Call Factor, the factors contributing to gold losses, the advantages of AI methods in addressing metal discrepancies, and the need for accurate ore grade estimation.

The conclusions emphasise the implementation of AI methods for grade estimation, and continuous monitoring and improvement of the Mine Call Factor. The paper provides recommendations for addressing gold losses, improving grade control, and optimizing the ore accounting process. Additionally, it suggests further research on the use of AI methods in mining and the accuracy of ore grade estimation.

RECOMMENDATIONS

Gold losses continue to be an issue as they are not adequately accounted for and therefore to try and increase the mine call factor at mine X, the following issues must be addressed.

- The roll-out of emulsions for blasting to curb the issue of poor blasting emulsions provide better fragmentations thus ensuring that less gold is lost in the extra fine fragments usually produced by the magnum explosives previously used.
- Incentivise workers working on the higher-grade reefs. This will assist the miners to mine accurately and efficiently, thus bring out ore that will provide a higher mine output. The incentives will work as a mode for motivation, therefore assist in increasing the Mine Call Factor.
- Education and training of the workers at the stope on what the Mine Call Factor is and the implications of a very low mine call factor. Once the workers are educated on the implications of the low mine call factor and the need for efficient mining, the Mine Call Factor will increase, due to the improved mining operations or process.
- Make use of AI methods such as KNN and ANN for grade estimation as well as make use of its prediction capabilities. These AI methods will assist in increasing the Mine Call Factor as they predict all the necessary areas where losses are occurring in real time thus assisting in reducing the gold losses.
- Most of the gold is also lost because of long tramming distances therefore, the long distances are a factor. To remedy this issue, it is recommended that the ore should be trammed for shorter distances from the face thus reducing the probability of the gold being lost.
- Furthermore, it is recommended that the cleaning rate should be increased to approximately 400tm/hr to 600tm/hr. This will assist the mine in ensuring that the ore does not remain underground for longer than necessary periods, thus reducing the probability of ore loss due to stockpiled ore.
- Make use of AI algorithms to account for the gold at the stope, before tramming, during tramming, and at the plant through predictive analysis. This will assist in accurate gold accounting, thus actually identifying if there was gold unaccounted for in the first place.

To be investigated in depth:

- The relationship between accurate ore grade estimation and a high Mine Call Factor needs to be further investigated.
- An overview of commonly used kriging methods and AI techniques.
- Accuracy of convectional sampling methods vs Artificial intelligence methods.
- Practical analysis using AI methods such as KNN and AN.
- Planning and scheduling.

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