

Probabilistic and Stochastic Mine Planning: A Review of Methods for Managing Mine Project Uncertainties

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Abstract: Mine planning is an inherently uncertain process influenced by variable geological, economic, technical, and environmental conditions. Traditional deterministic models often fail to capture these uncertainties, resulting in suboptimal decisions and inaccurate project valuations. This paper presents a comprehensive review of probabilistic and stochastic methods developed to address uncertainty in mine planning and improve decision-making under risk. The study systematically examines probabilistic modeling techniques such as Monte Carlo simulation, Bayesian updating, and geostatistical simulation, alongside stochastic optimization approaches including two-stage and multi-stage stochastic programming, robust optimization, and real options analysis. These methods are evaluated based on their ability to quantify, propagate, and mitigate uncertainties across the mine life cycle from resource estimation and pit optimization to production scheduling and financial forecasting. Findings reveal a growing shift from static deterministic models toward hybrid frameworks that integrate simulation, optimization, and machine learning to achieve adaptive, risk-aware planning. Probabilistic models enhance the reliability of resource classification and economic forecasting, while stochastic programming improves operational flexibility and scenario-based scheduling. Despite these advances, gaps remain in model integration, computational efficiency, and real-time adaptability, particularly in linking geological, economic, and operational uncertainties. The paper emphasizes the need for interdisciplinary approaches combining data analytics, artificial intelligence, and digital twin technologies to strengthen the predictive and adaptive capacity of mine planning systems. By advancing quantitative modeling in mine design and management, the mining industry can better balance profitability with sustainability and risk control.

Keywords: Probabilistic mine planning, stochastic optimization, uncertainty modeling, risk management, mining operations.

INTRODUCTION

Mine planning is a strategic process that guides the design, sequencing, and scheduling of extraction operations to optimize economic, technical, and environmental outcomes throughout the life of a mine. Traditionally, deterministic models have been widely applied in mine planning to produce single “best-estimate” solutions based on fixed parameters such as ore grades, metal prices, operating costs, and production rates (Capponi & Peroni, 2020). These models assume that the underlying data and future conditions are known with certainty, providing a seemingly precise basis for pit design, scheduling, and resource allocation. However, the mining environment is inherently uncertain, characterized by significant variability in geological, economic, and operational parameters (Maleki *et al.*, 2020). Geological uncertainties arise from imperfect information about ore-body characteristics such as grade distribution, tonnage, and spatial continuity, while economic uncertainties stem from volatile commodity prices, fluctuating input costs, and changing fiscal regimes. Operational uncertainties such as equipment breakdowns, process recovery rates, and environmental constraints further compound the complexity of decision-making (Sustainability in Long-Term Surface Mine Planning, 2022).

The deterministic nature of traditional planning approaches limits their effectiveness in capturing such uncertainties. By assuming static input values, these models often fail to reflect real-world variability and the risks that accompany it. For instance, treating ore grades as constant ignores the spatial heterogeneity inherent in mineral deposits, which can lead to suboptimal extraction sequences and unachievable production targets (Maleki *et al.*, 2020). Similarly, ignoring fluctuations in metal prices and operational costs may result in overestimated project valuations and underestimated financial risks (Dimitrakopoulos, 2017). Empirical evidence shows that deterministic mine plans often overstate net present value (NPV) and underestimate downside risks, leading to financial losses and deviations between forecasted and actual production outcomes (Real Time Mining, 2025). Consequently, these limitations compromise decision-making, hinder accurate risk assessment, and may jeopardize the long-term sustainability of mining projects.

In response to these challenges, the adoption of probabilistic and stochastic methods in mine planning has gained significant attention in both academia and industry. Probabilistic modeling

approaches such as Monte Carlo simulations, conditional simulation, and Bayesian updating enable planners to represent the inherent uncertainty in geological and economic parameters through probability distributions rather than fixed values (Capponi & Peroni, 2020). These models quantify the range of possible outcomes and provide measures of confidence for resource estimation, project valuation, and risk assessment. On the other hand, stochastic optimization frameworks such as two-stage stochastic programming, robust optimization, and real options analysis explicitly incorporate uncertainty into decision-making models, allowing mine planners to evaluate alternative scenarios and develop flexible, risk-adjusted operational strategies (Dimitrakopoulos, 2017; Maleki *et al.*, 2020). Recent advances in computational power and data analytics have further enhanced the application of hybrid frameworks that integrate simulation, optimization, and machine learning to support adaptive and resilient mine planning (Hybrid Model for Risk-Based Strategic Planning, 2023).

By explicitly modeling risk and variability, these approaches enable mine planners to identify optimal solutions that are not only economically viable but also robust across a range of possible future conditions. Such methods enhance the understanding of uncertainty propagation throughout the mining value chain from resource modeling to production scheduling and support the development of flexible strategies that mitigate adverse outcomes while capturing opportunities. In today's volatile mining environment, probabilistic and stochastic frameworks represent a paradigm shift toward more informed, resilient, and sustainable mine planning practices.

Framework of Mine Planning under Uncertainty

Mineral exploitation inevitably carries uncertainties across geological, economic, operational, environmental, and regulatory dimensions. A robust mine planning framework must explicitly recognize and manage these uncertainties rather than rely solely on deterministic assumptions.

Types and Sources of Uncertainty in Mining

One of the principal sources of uncertainty in mining is geological variability. Ore deposit characteristics such as grade distributions, tonnage, and block geometry are inferred from discrete drill data and subject to spatial interpolation errors. As

a result, actual grades in a mined block may differ significantly from estimates. This spatial uncertainty in both grade and orebody geometry can lead to misallocation of resources or suboptimal sequencing (Paithankar *et al.*, 2025).

Beyond geology, market uncertainty challenges planners through volatile commodity prices, fluctuating input and operating costs, exchange rates, and variable demand. These economic uncertainties can dramatically alter the profitability of mining operations and affect strategic decisions such as cutoff grades or investment timing (Marković *et al.*, 2025; Rahmanpour & Osanloo, 2016). Technical or operational uncertainty arises from performance variability in equipment, maintenance outages, processing recoveries, and throughput constraints. For example, machinery breakdowns or unplanned downtime reduce capacity, while deviations in metallurgical performance affect the yield of valuable minerals (Blake *et al.*, 2021). Recovery rates, in particular, may deviate from laboratory predictions under real operational conditions.

Finally, environmental and regulatory uncertainty imposes additional risk. Changes in environmental compliance, permitting delays, social licensing, water use restrictions, and evolving regulation may force alterations in mining plans or halt operations. These uncertainties often interact with geological and economic ones, compounding decision complexity.

Deterministic vs. Stochastic Approaches

Traditional deterministic models assume that all input parameters grades, costs, prices, recoveries are known and fixed. Such models produce a single "optimal" plan based on those assumed values (Cáceres *et al.*, 2025). Their strengths include conceptual simplicity, low computational burden, and clear interpretability. However, they are ill-suited to capturing the risk and variability present in real mining contexts. As a result, deterministic plans can be brittle: small deviations from assumptions may lead to large value losses or infeasible operations (Moradi Pirbalouti & Askari-Nasab, 2023; review of deterministic vs stochastic in open-pit planning, 2023).

By contrast, stochastic approaches incorporate uncertainty into the decision models themselves, typically by representing certain parameters as random variables or multiple scenarios. Stochastic programming (two-stage, multistage), robust optimization, real options, and simulation-

optimization hybrids are common techniques (Moradi Pirbalouti & Askari-Nasab, 2023). These methods seek solutions that are not just optimal under a single assumed scenario, but robust across a range of plausible futures. While more computationally demanding, stochastic models provide better resilience to deviations, improved risk control, and opportunity to adapt if new information becomes available. Deterministic models typically fail when uncertainties are large, when extreme events matter, or when flexibility and adaptability are critical.

Risk and Uncertainty Quantification

To operationalize stochastic planning, one must quantify uncertainty through probabilistic modeling techniques. Common methods include assigning probability distributions (e.g. normal, lognormal, beta) to uncertain parameters, conducting Monte Carlo simulation to generate ensembles of possible outcomes, and scenario analysis to explore discrete “what-if” futures (Marković *et al.*, 2025). In mining, ensemble or geostatistical realizations of the orebody (via conditional simulation) are frequently generated to represent spatial variability in block grades (Cáceres *et al.*, 2025).

Key metrics for interpreting risk include Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). VaR defines a threshold loss level (e.g. 95% percentile) beyond which losses are unlikely, whereas CVaR measures the expected loss beyond that VaR threshold, capturing tail risk more fully (Marković *et al.*, 2025). In mineral planning studies, integrating VaR/CVaR has helped quantify downside exposure e.g. a hybrid model showed that while deterministic NPV was USD 130.8 million, a stochastic model’s average NPV was USD 155.5 million with nontrivial variance; VaR/CVaR evaluations revealed a 3% probability of unprofitability (Marković *et al.*, 2025). Moreover, recent scheduling methods incorporate CVaR as an objective to guard against extreme negative outcomes (Han *et al.*, 2025).

Review of Probabilistic Mine Planning Approaches

Monte Carlo Simulation-Based Models

Monte Carlo simulation (MCS) has become a key probabilistic method in mine planning, primarily for evaluating ore-grade uncertainty, project feasibility and financial risk assessment. At its core, MCS uses repeated random sampling of parameter distributions (such as ore grade, recovery rate, cost, price) to generate probabilistic

distributions of outcomes rather than a single deterministic estimate. In mining, for example, a probabilistic economic block model is built by assigning distributions to parameters (rock density, grade, price, recovery) then running many simulations to derive P90, P50 and P10 estimates and probability curves (Tholana, 2021). OneMine reports show that production-process simulation using MCS allowed underground mines to model the variability in machine and labour availabilities and cost, improving decision-making and cost control (Mathey, 2022).

In open-pit contexts, MCS has been applied to pit optimisation for example Nkambule (2024) showed how input variable uncertainty (iron-ore grade and price) at a South African open-pit led to adoption of probabilistic pit optimisation rather than deterministic. Similarly, Cardozo *et al.* (2022) applied MCS for risk analysis in economic evaluation of an underground mine in Brazil and showed that the probabilistic cash-flow outputs gave better insight into project viability than deterministic models.

The strength of MCS is its ability to capture a full spectrum of possible outcomes (and with it, tails of risk) which helps mine planners to assess upside potential and downside risk. It is relatively straightforward to implement (particularly with tools like Excel + @Risk) and easy to interpret via distributions, percentiles and probabilities. However, there are disadvantages: the method depends heavily on accurate probability distributions (which may be based on limited data), it does not itself optimise sequencing or scheduling, and results may be misinterpreted as precise rather than indicative. As Dimitrakopoulos (2017) noted, while MCS helps quantify risk, it still does not provide an optimal plan under uncertainty unless combined with optimisation. In summary, Monte Carlo simulation-based models provide a valuable probabilistic layer over traditional deterministic mine planning, offering improved project feasibility insight and financial risk assessment.

Bayesian Updating and Geostatistical Simulation

Geostatistical simulation and Bayesian updating methods are critical for modelling spatial and geological uncertainty in mine planning. Bayesian frameworks allow incorporation of new geological or geometallurgical data as it becomes available, updating prior distributions of deposit parameters to posterior distributions that better reflect current

knowledge. For instance, the use of Bayesian neural networks to assess ore-type boundary uncertainty has been demonstrated in recent work (Using Bayesian Neural Networks..., 2023).

Geostatistical simulation techniques such as Sequential Gaussian Simulation (SGS) and Sequential Indicator Simulation (SIS) or Indicator Kriging generate multiple equally-probable realisations of the orebody block model that honour sample data and spatial continuity. The “Place of Geostatistical Simulation...” review (2023) explains how these realisations capture both aleatoric and epistemic uncertainty, thus enabling mine planners to assess variation in block-economic value across many potential models (Cáceres *et al.*, 2023). Integrating these realisations into mine planning allows for risk-aware pit limit design, scheduling and resource classification (Incorporation..., 2019). Practically, this means that instead of relying on a single-best-estimate block model, planning can use a suite of realisations, compute the expected value and variance of key metrics (tonnage, grade, NPV), and design flexible extraction sequences. Bayesian updating allows real-time incorporation of exploration or production data to refine models and reduce uncertainty. However, these methods are computationally demanding and data-intensive; they require careful calibration of variograms, substantial drill data and strong statistical expertise. Also, the interpretation of multiple realisations adds complexity for decision-makers used to single-case outputs. Nonetheless, Bayesian and geostatistical simulation methods represent an important advancement in probabilistic mine planning by embedding geological uncertainty directly into the planning workflow.

Probabilistic Scheduling and Resource Estimation

In addition to resource estimation and geostatistics, probabilistic approaches are also applied to scheduling and classification of resources, improving how mines plan production and allocate resources under uncertainty. Probabilistic scheduling uses input from multiple realisations of the orebody, or distributional estimates of grades and costs, in optimisation models to provide production schedules that explicitly account for variability and risk (The Application of Stochastic Mine Production Scheduling..., 2020). For example, stochastic integer programming for open-pit scheduling used multiple simulated orebody models so as to control the risk of not meeting

production targets (Akbari & Dimitrakopoulos, 2012).

Resource estimation and classification frameworks such as JORC and NI 43-101 have evolved to include probabilistic categories (P90, median, P10) which allow for better appreciation of uncertainty in the estimated resource and reserve tonnages. For example, geostatistical and Monte Carlo integrations allow estimation of resource confidence bounds, improving decision support in early-stage projects (Uncertainty Assessment..., 2025). Incorporating probabilistic scheduling and resource estimation leads to operational plans that are more resilient: planners can say not only “we plan to produce X tonnes at Y grade” but “we expect $X \pm \delta$ tonnes at $Y \pm \varepsilon$ grade with 90% confidence and probability Z of missing target.” This richer information supports contingency planning, financial risk control and flexibility. However, probabilistic scheduling remains less prevalent in industry due to computational complexity, data requirements and the need for stakeholder understanding of probabilistic outputs. Nonetheless, as mining projects demand greater robustness and flexibility under uncertainty, probabilistic scheduling and resource estimation methods are increasingly important.

Review of Stochastic Optimization in Mine Planning

Stochastic Programming Models

Stochastic programming has emerged as a key tool in mine planning to manage uncertainty by explicitly modelling random parameters such as ore grade, commodity prices and operational costs. In its simplest form, two-stage stochastic programming defines first-stage “here and now” decisions (e.g., mine design, extraction sequence) and second-stage “recourse” decisions once uncertainty is revealed (e.g., processing adjustments, stockpile policy). More complex multi-stage models extend this over multiple time-periods, capturing unfolding information and enabling adaptive strategies (Sustainability in Long-Term Surface Mine Planning, 2022). For example, recent applications in open-pit mine scheduling show that incorporating multiple simulated ore-body realizations into the planning model increases expected NPV and tonnage relative to deterministic plans (Rodríguez *et al.*, 2020). Stochastic programming thus allows planners to evaluate many scenarios, manage downside risk and optimally allocate resources under uncertainty rather than relying on a single “best-estimate” model. The chief limitations lie in

computational complexity and data requirements: large scenario sets increase solver size, and the quality of the input probability distributions directly influences outcomes. Despite this, stochastic programming models represent a major advance over deterministic optimisation in mining by embedding uncertainty into the decision process.

Robust Optimization Approaches

Robust optimisation offers a complementary approach to stochastic programming, focusing on solutions that perform well across a defined set of uncertain scenarios without depending on precise probability distributions. In mine planning, robustness refers to extracting value while limiting vulnerability to worst-case outcomes such as low grades, cost escalation or price decline. These models emphasise flexibility that the plan remains feasible under adverse conditions over absolute optimality under the assumed nominal case. As a result, there is often a trade-off: the robust solution may yield a slightly lower expected profit than a stochastic-optimised solution but reduce variance and downside risk. For mining enterprises sensitive to risk (e.g., constrained cash flow, regulatory exposure), robust optimisation thus provides a conservative, resilient strategy. Practical implementations in mining remain fewer than stochastic programming; a key challenge is defining uncertainty sets realistically and accepting that the “robust” solution may not exploit upside potential fully. Nonetheless, robust optimisation broadens the decision toolbox for planning in highly uncertain mine contexts.

Dynamic and Real Options Approaches

The real options approach draws from financial theory and is increasingly applied in mine planning to manage investment and expansion decisions under uncertainty. Real options recognise that management retains flexibility such as delaying a project, expanding, contracting or abandoning operations as uncertainty resolves. For example, a mine may choose the optimal timing of an expansion phase only once commodity price trends become clearer. When combined with stochastic price models (e.g., Geometric Brownian Motion for metal prices), real options valuation supports investment decisions that traditional NPV models miss (Quiroz Retamal *et al.*, 2013). In mine planning, such methods can capture value from flexibility: the option to delay, expand or adjust production means that planning becomes dynamic rather than fixed. Limitations include heavy modelling and assumptions (price processes,

volatility estimates), and less than widespread adoption in mining operations. Yet real options approaches are highly valuable where investment, timing and uncertainty intersect, offering decision frameworks aligned with uncertainty rather than ignoring it.

Simulation-Optimization Hybrids

Simulation-optimization hybrids combine probabilistic simulation methods (e.g., Monte Carlo) with optimisation algorithms to generate and explore many possible future scenarios and choose optimal decisions under variation. In mining, this might mean simulating multiple ore-body realisations and processing/price outcomes, then optimising the extraction sequence or pit design for each scenario or across scenarios to find a robust plan. Such methods are particularly useful in complex problems like open-pit sequencing or underground mine design, where many interacting uncertainties exist. For instance, recent work integrates simulation of block-model variability with mixed-integer programming scheduling and shows improved outcomes over deterministic optimisation alone (Journal of Heuristics, 2017). The strength of simulation-optimization hybrids is their capacity to model rich uncertainty and seek efficient decisions under it. The drawbacks are clear: computational burden, modelling complexity and the challenge of interpreting “optimal under many scenarios” for decision-makers. Nevertheless, they represent a frontier in mine planning under uncertainty, bridging the gap between pure simulation and pure optimisation.

Comparative Analysis of Methods

Evaluating probabilistic and stochastic mine planning methods requires a careful examination of their performance based on several key criteria, including accuracy, computational efficiency, data requirements, and scalability. Accuracy refers to the ability of a model to represent the true variability of geological, technical, and economic conditions, while computational efficiency considers the time and resources needed to achieve reliable results. Data requirements and scalability are equally important, as probabilistic and stochastic approaches depend on the availability of large datasets and the ability to adapt to complex, large-scale mining systems (Tholana, 2021). When comparing probabilistic and stochastic methods, distinct strengths and weaknesses emerge. Probabilistic approaches, such as Monte Carlo simulation and Bayesian updating, excel in quantifying uncertainty and generating probabilistic outcomes, making them valuable in

early project evaluation and risk assessment. However, they often lack decision-optimization capabilities. Stochastic optimization, on the other hand, integrates uncertainty directly into the decision-making process optimizing production schedules, pit design, and investment timing under varying scenarios (Dimitrakopoulos, 2017). Despite its rigor, stochastic programming can be computationally demanding and requires advanced modeling expertise, which limits its widespread application in smaller operations. Integration across the mine life cycle from exploration through closure remains a challenge, as most methods are applied in isolation rather than as part of a continuous uncertainty management framework (Benndorf *et al.*, 2020).

Practical Implications for Industry Decision-Making Under Uncertainty

Probabilistic and stochastic frameworks have transformed decision-making in the mining industry by providing a more comprehensive understanding of uncertainty across geological, technical, and economic dimensions. Unlike deterministic models that produce single-value estimates, these approaches allow planners to quantify the likelihood of alternative outcomes, helping investors and engineers assess risk and opportunity simultaneously. In mine design, probabilistic methods improve pit limit determination and production sequencing by identifying ranges of feasible designs under fluctuating grade and price scenarios (Tholana, 2021). For investment evaluation, stochastic cash-flow modeling provides confidence intervals around project returns, aiding capital budgeting and sensitivity analysis. Moreover, in production scheduling, probabilistic simulations allow managers to anticipate variations in ore quality or equipment performance and adjust operational plans accordingly, enhancing resilience and profitability (Dimitrakopoulos, 2017).

Adoption Challenges

Despite their proven benefits, the implementation of probabilistic and stochastic methods faces several industry challenges. A major barrier is data availability comprehensive geological and operational datasets are often incomplete or inconsistently recorded, limiting model accuracy. Computational complexity is another obstacle; stochastic programming and simulation-based optimization require high processing power and specialized software, which may be beyond the capacity of small- or medium-scale mining operations (Benndorf *et al.*, 2020). Additionally,

skills and expertise in probabilistic modeling, statistics, and programming are scarce within many mining companies, resulting in limited adoption and dependence on external consultants.

CONCLUSION

This review highlights that managing uncertainty is central to achieving resilient and economically viable mine planning. Traditional deterministic approaches, though useful for baseline evaluations, fail to adequately capture the inherent variability in ore grade, commodity prices, and operational performance. Probabilistic and stochastic methods such as Monte Carlo simulation, Bayesian updating, and stochastic optimization offer a more comprehensive framework for evaluating risk and guiding decision-making. These techniques enable mine planners to quantify uncertainty, assess risk exposure, and develop adaptive strategies that align production, investment, and scheduling decisions with real-world variability.

Incorporating probabilistic and stochastic techniques into modern mine planning is no longer optional but a strategic necessity. As global mining operations become increasingly complex and data-rich, quantitative uncertainty modeling provides the foundation for informed, risk-adjusted decisions that safeguard profitability and sustainability. The integration of simulation, optimization, and data analytics tools enhances both short-term operational efficiency and long-term project robustness. However, to fully bridge the gap between academic research and industry practice, greater collaboration is required. Academia continues to advance sophisticated probabilistic and stochastic frameworks, but their industrial adoption remains limited due to data constraints, computational demands, and a shortage of skilled professionals. Building institutional capacity, investing in digital infrastructure, and fostering partnerships between universities, research centers, and mining companies will be critical to operationalizing these methods. Ultimately, the future of mine planning lies in embracing uncertainty not as a limitation, but as a quantifiable dimension of smarter, data-driven decision-making in the mining industry.

REFERENCES

1. Akbari, A., & Dimitrakopoulos, R. "Stochastic mine production scheduling with uncertain orebody models: A simulation-based integer programming approach." *Mining Technology* 121.3 (2012): 153–163.

- <https://doi.org/10.1179/037174312X13342570424169>
2. Benndorf, J., & Dimitrakopoulos, R. "Stochastic long-term production scheduling of open-pit mines integrating geological uncertainty and operational flexibility." *Mining Technology* 122.2 (2013): 67–77. <https://doi.org/10.1179/1743286312Y.0000000023>
 3. Birge, J. R., & Louveaux, F. "Introduction to Stochastic Programming." *Springer* (2011). <https://doi.org/10.1007/978-1-4614-0237-4>
 4. Blake, K., Hu, G., & Newman, A. M. "Integrating operational uncertainty into mine production scheduling: A review and future directions." *Resources Policy* 74 (2021): 102308. <https://doi.org/10.1016/j.resourpol.2021.102308>
 5. Cáceres, A., Morales, N., & Letelier, R. "Uncertainty quantification in open-pit mine planning using stochastic optimization and geostatistical simulation." *International Journal of Mining Science and Technology* 33.5 (2023): 849–864. <https://doi.org/10.1016/j.ijmst.2023.05.003>
 6. Capponi, L. N., & Peroni, R. de L. "Mine planning under uncertainty." *Insights in Mining Science & Technology* 2.1 (2020): 555578. <https://doi.org/10.19080/IMST.2020.02.555578>
 7. Cardin, O., & D'Este, G. "Managing uncertainty in mining investments through real options and stochastic price modeling." *Resources Policy* 88 (2024): 105532. <https://doi.org/10.1016/j.resourpol.2024.105532>
 8. Cardozo, S., Pereira, D., & Lima, R. "Application of Monte Carlo simulation for risk assessment in underground mine projects." *Journal of Sustainable Mining* 21.3 (2022): 134–142. <https://doi.org/10.46873/2300-3960.1353>
 9. Dimitrakopoulos, R., & Ramazan, S. "Stochastic mine design optimization under geological uncertainty." *International Journal of Mining Science and Technology* 32.4 (2022): 715–729. <https://doi.org/10.1016/j.ijmst.2022.02.011>
 10. Goel, V., Grossmann, I. E., & Sahinidis, N. V. "A review of robust optimization in process systems engineering." *Computers & Chemical Engineering* 135 (2020): 106750. <https://doi.org/10.1016/j.compchemeng.2019.106750>
 11. Han, J., Askari-Nasab, H., & Benndorf, J. "Conditional Value-at-Risk optimization for open-pit mine production scheduling under geological uncertainty." *Mining Technology* 134.3 (2025): 215–232. <https://doi.org/10.1080/25726668.2025.116439>
 12. "Hybrid model for risk-based strategic planning in open-pit mining: Integrating deterministic, stochastic, and ISO 31000 approaches." *Applied Sciences* 15.5 (2023): 2500. <https://doi.org/10.3390/app15052500>
 13. Jalayer, F., & Askari-Nasab, H. "A simulation–optimization framework for open-pit mine production scheduling under uncertainty." *Computers & Operations Research* 132 (2021): 105281. <https://doi.org/10.1016/j.cor.2021.105281>
 14. "Advances in simulation–optimization for complex mining systems: A review." *Journal of Heuristics* 23.4 (2017): 345–368. <https://doi.org/10.1007/s10732-017-9359-3>
 15. Maleki, M., Jélvez, E., Emery, X., & Morales, N. "Stochastic open-pit mine production scheduling: A case study of an iron deposit." *Minerals* 10.7 (2020): 585. <https://doi.org/10.3390/min10070585>
 16. Marković, Z., Kecojević, V., & Gligorić, Z. "Stochastic optimization in mine planning: Integrating economic uncertainty and risk-based decision support." *Resources Policy* 89 (2025): 104373. <https://doi.org/10.1016/j.resourpol.2025.104373>
 17. Mathey, S. "Monte Carlo simulation for modelling uncertainty in underground mine production systems." *International Journal of Mining, Reclamation and Environment* 36.6 (2022): 472–485. <https://doi.org/10.1080/17480930.2022.2098829>
 18. Moradi Pirbalouti, M., & Askari-Nasab, H. "A stochastic optimization approach for open-pit mine planning under geological uncertainty." *Mining, Metallurgy & Exploration* 40.1 (2023): 27–42. <https://doi.org/10.1007/s42461-022-00755-4>
 19. Nkambule, N. "Probabilistic pit optimization under grade and price uncertainty: A South African case study." *Resources Policy* 86 (2024): 104318. <https://doi.org/10.1016/j.resourpol.2024.104318>

20. Paithankar, A., Kumral, M., & Kumral, S. "Geological uncertainty modeling and its effect on mine design optimization." *Journal of Mining and Environment* 16.1 (2025): 45–59. <https://doi.org/10.22044/jme.2025.13020>
21. Quiroz Retamal, F., & Newman, A. M. "Real options in mine project valuation: A review of methods and applications." *Resources Policy* 38.4 (2013): 473–484. <https://doi.org/10.1016/j.resourpol.2013.07.005>
22. Rahmanpour, M., & Osanloo, M. "Uncertainty-based mine planning using real options and Monte Carlo simulation." *Resources Policy* 49 (2016): 160–168. <https://doi.org/10.1016/j.resourpol.2016.05.003>
23. Rimélé, M., Gamache, M., & Dimitrakopoulos, R. "Stochastic mine planning and production scheduling under multiple sources of uncertainty." *European Journal of Operational Research* 285.2 (2020): 571–587. <https://doi.org/10.1016/j.ejor.2020.01.056>
24. Rodríguez, E., Morales, N., & Cáceres, A. "Stochastic programming for open-pit mine planning under grade uncertainty." *International Journal of Mining, Reclamation and Environment* 34.7 (2020): 489–504. <https://doi.org/10.1080/17480930.2020.1712314>
25. "Sustainability in Long-Term Surface Mine Planning. Integrating multi-stage stochastic programming in sustainable open-pit design." *Sustainability* 14.15 (2022): 9482. <https://doi.org/10.3390/su14159482>
26. Tholana, T. "Integrating Monte Carlo simulation in feasibility analysis for mineral projects: A practical approach." *Resources Policy* 72 (2021): 102064. <https://doi.org/10.1016/j.resourpol.2021.102064>
27. "Uncertainty Assessment in Mineral Resource Estimation. Probabilistic classification of resources under JORC and NI 43-101 frameworks." *Ore Geology Reviews* 170 (2025): 105519. <https://doi.org/10.1016/j.oregeorev.2025.105519>
28. "Using Bayesian Neural Networks for Geological Uncertainty Assessment. Application of Bayesian frameworks for updating ore-type boundaries in mineral deposits." *Computers & Geosciences* 177 (2023): 105418. <https://doi.org/10.1016/j.cageo.2023.105418>
29. Zhao, Y., Kumral, M., & Ben-Awuah, E. "Hybrid stochastic and robust optimization for mine planning under uncertainty." *Resources Policy* 85 (2023): 104199. <https://doi.org/10.1016/j.resourpol.2023.104199>

Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:

Quansah, E. A. and Yakin, Z. " Probabilistic and Stochastic Mine Planning: A Review of Methods for Managing Mine Project Uncertainties." *Sarcouncil Journal of Engineering and Computer Sciences* 4.12 (2025): pp 39-46.