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Algorithmic Blast Design through Deep Reinforcement Learning: A Transferable Simulation Framework from Central Asian Copper Megapits to Peruvian Mining and Public Spaces

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Systematic Review

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Abstract

Background

Bench blasting in porphyry copper megapits, such as the Aktogay and Bozshakol complexes in Kazakhstan, still relies on deterministic empirical models (e.g., Kuz-Ram) that do not adequately capture the spatial variability of the rock mass, leading to over- or under-fragmentation, excessive vibration, and operational overcosts. Deep Reinforcement Learning (DRL) offers an adaptive, sequential optimization alternative, but its specific application to bench-scale blast scheduling remains comparatively underexplored, and its transferability to Peruvian mining and public spaces has not been systematically assessed.

Objective

To propose and evaluate, through simulation, a DRL framework based on Proximal Policy Optimization (PPO) for precision blast design in copper megapits, calibrated with parameter ranges documented in peer-reviewed literature, and to analyze its technical, geological, regulatory, and operational transferability to Peru's major copper operations (Antamina, Cerro Verde, Quellaveco, and Las Bambas) and to urban public-space infrastructure projects.

Methods

A simulation environment (a simplified digital twin of the rock mass, based on the Discrete Element Method) was built and parameterized with distributions of uniaxial compressive strength (UCS), Rock Quality Designation (RQD), burden, spacing, and delay sequences reported in fourteen peer-reviewed studies (2019–2026) on blast-induced fragmentation and vibration. A PPO agent was trained for 10,000 simulated episodes per block, and its performance was compared against a deterministic Kuz-Ram-type baseline under identical simulation assumptions. A qualitative-quantitative comparison matrix between the Kazakh context and Peruvian operations was also built, using public production data from Peru's Ministry of Energy and Mines (2024) and corporate technical reports.

Results

Within the simulated environment, the PPO agent reduced the standard deviation of fragmentation by 18–34% and peak particle velocity (PPV) by 15–30% relative to the baseline, magnitudes consistent with improvements reported independently in machine-learning-based blast optimization studies (documented PPV reductions of 12–40% in the reviewed literature). The transferability matrix indicates medium-to-high geological and operational compatibility with Quellaveco and Cerro Verde (copper porphyries) and lower compatibility with Antamina (polymetallic skarn); application to public spaces in Metropolitan Lima would require vibration thresholds an order of magnitude stricter than those typical of remote open-pit mining.

Conclusions

The proposed DRL framework constitutes a methodologically plausible, literature-supported pathway toward precision blasting, but its quantitative benefits must be validated in the field, deposit by deposit, before operational implementation in Peru. Concrete machinery, personnel-competency, and regulatory-adaptation requirements are identified for a prospective deployment.

1. Introduction

1.1 Background and context

Open-pit copper mining is the world's principal source of this metal, and its largest-scale operations are concentrated in porphyry deposits across Central Asia, South America, and Oceania. In Kazakhstan, the Aktogay and Bozshakol complexes, operated by KAZ Minerals, rank among the largest mining developments in the Central Asian region, with reserves exceeding 1,000 million tonnes of ore and copper grades between 0.33% and 0.45% [1, 2]. Blasting is the first link in the mining value chain: inadequate rock mass fragmentation negatively affects loading, haulage, crushing, and grinding, increasing downstream energy consumption [3].

Traditional blast pattern design methods rely on empirical models — such as the Kuz-Ram model — and deterministic design criteria that do not adequately capture the spatial heterogeneity of rock mass properties [4, 5]. This limitation leads to over-drilling, under-fragmentation, or oversize, with significant economic and environmental losses, including ground vibration and flyrock affecting nearby communities and infrastructure [6].

In recent years, machine learning and, in particular, reinforcement learning (RL) have emerged as promising tools for optimizing complex mining operations. Unlike supervised methods — widely used to predict fragmentation and vibration from historical data [7–11] — RL allows an agent to learn sequential decision policies through interaction with an environment, maximizing a cumulative reward function. Recent studies have demonstrated RL applicability in autonomous haul-truck dispatching [12–15] and fleet scheduling for emission reduction [16], but its specific application to bench-scale blast pattern design remains comparatively underexplored.

1.2 Knowledge gap and study contribution

Despite these advances, four specific gaps are identified: (i) most RL applications in mining have concentrated on strategic planning and haulage logistics, leaving a relative gap in operational, bench-level blast optimization; (ii) supervised machine-learning models used to predict fragmentation and vibration [7–11] are predictive rather than prescriptive, and therefore do not directly generate an optimal, adaptive design policy; (iii) little literature systematically evaluates the transferability of algorithmic blasting technologies developed in Central Asia to geologically, regulatorily, and socially distinct contexts such as Peru's; and (iv) applying precision-blasting principles to vibration management in urban public spaces — a problem already partially solved in developed countries through electronic detonation and real-time monitoring [17, 18] — has not been explicitly connected to the RL frameworks used in large-scale mining.

This study contributes to closing these gaps by: (1) formulating a DRL (PPO) framework for bench-scale blast design, calibrated from parameter ranges and results reported in fourteen peer-reviewed studies on blast-induced fragmentation and vibration; (2) evaluating this framework in a transparent, reproducible simulation environment, avoiding the attribution of unverifiable proprietary operational data to specific mining operations; (3) building a structured comparison matrix between the Central Asian context and Peru's four major copper

operations, using exclusively public production data and technical reports; and (4) proposing an adaptation of precision-blasting principles to Peruvian urban public-space infrastructure projects, contrasted with documented experiences from developed countries.

1.3 Objectives

- Formulate a deep reinforcement learning (DRL) framework for the design and dynamic adjustment of bench-blasting parameters in porphyry copper megapits.
- Quantify, through literature-calibrated simulation, potential gains in fragmentation precision and vibration control relative to a deterministic reference design.
- Evaluate the geological, operational, regulatory, infrastructural, and human-capital transferability of the proposed framework to Antamina, Cerro Verde, Quellaveco, and Las Bambas.
- Propose an adaptation pathway for algorithmic blasting technology toward vibration management in urban public-space infrastructure projects in Peru, grounded in documented international experiences.
- Detail the procedures, machinery, materials, and personnel competencies required for a prospective pilot implementation.

1.4 Novelty and contributions

This work is distinguished from prior studies in three respects. First, it explicitly integrates bench-level blast scheduling — rather than only strategic planning or fleet dispatching — within a reinforcement-learning framework calibrated with published empirical evidence rather than unverifiable proprietary data. Second, it proposes and applies a quantified technology-transferability matrix between Central Asia and Peru, incorporating geological, operational, regulatory, infrastructural, and human-capital factors. Third, it extends the conceptual framework of precision blasting toward vibration management in urban public spaces, a domain of application scarcely connected to the mining RL literature.

2. Materials and Methods

2.1 Overall study design

A computational-simulation and comparative-documentary research design was employed, with no intervention on human subjects, animals, or active mining operations. The study combines: (i) a structured review of the machine-learning and reinforcement-learning literature applied to blasting and mine dispatch; (ii) the development of a rock-mass simulation environment calibrated with the parameter ranges reported in that literature; (iii) the training and evaluation of a DRL agent within that environment; and (iv) the construction of qualitative-quantitative comparison matrices between the Central Asian and Peruvian contexts.

2.2 Geological and operational reference context (Central Asia)

As a reference case, the public characterization of the Aktogay and Bozshakol porphyry copper complexes (Kazakhstan), operated by KAZ Minerals, was used, with reserves exceeding 1,000 million tonnes of ore and copper grades between 0.33% and 0.45% [1, 2]. These parameters — rather than unverifiable internal operational data — were used solely to define plausible geological ranges (uniaxial compressive strength, RQD, density) for the simulation environment.

2.3 Formulation of the reinforcement learning agent

The bench-blasting design problem is modeled as a Markov Decision Process (MDP) defined by the tuple (S, A, P, R, γ):

- State (S): a vector including UCS (MPa), RQD (%), rock density (g/cm³), current burden and spacing (m), borehole depth (m), and historical fragmentation performance (D50, D80) of the adjacent block.
- Action (A): continuous adjustment of burden (± 20%), spacing (± 20%), specific explosive charge (± 15%), and selection of the inter-hole delay sequence from a discrete set of options.
- Reward function (R): a weighted combination of four objectives — minimizing the standard deviation of fragmentation, minimizing peak particle velocity (PPV) normalized to the regulatory limit, minimizing specific explosive consumption, and maximizing simulated loading-hauling cycle productivity.

The Proximal Policy Optimization (PPO) algorithm, with an Actor-Critic architecture, was selected for its training stability and documented performance in continuous-control environments with limited data [19, 20]. The agent was trained for 10,000 simulated episodes per block, with a learning rate of 3×10^{-4}, discount factor $\gamma = 0.99$, and clip parameter of 0.2, following the standard configuration reported in the PPO literature.

2.4 Simulation environment

The simulation environment consists of a simplified rock-mass model based on the Discrete Element Method (DEM), parameterized through statistical distributions of UCS, RQD, burden, spacing, and delay sequence taken from the ranges reported in the fourteen studies listed in Table 1 (Section 2.6). The model does not represent operational data from any specific mine; its purpose is to provide a reproducible, transparent environment in which to compare, under identical assumptions, a DRL agent against a deterministic Kuz-Ram-type baseline.

This methodological decision — explicitly declaring the literature-calibrated simulation nature of the study, rather than presenting the results as field data from a real mine — responds to a research-integrity criterion: the author did not have access to proprietary operational data from Bozshakol, Aktogay, or the Peruvian operations analyzed, and any statement to the contrary would constitute an improper attribution of data authorship.

2.5 Evaluation metrics

Table 1
Evaluation metrics used in the simulation environment.

Metric	Definition	Unit
Fragmentation standard deviation (σ_D)	Dispersion of fragment size relative to the mean of the simulated size distribution	mm
Peak particle velocity (PPV)	Maximum magnitude of ground vibration velocity induced by the blast	mm/s
Specific explosive consumption	Explosive mass per tonne of fragmented rock	kg/t
Simulated loading-hauling productivity	Tonnage moved per effective working hour, estimated from the resulting size distribution	t/h

2.6 Bibliographic sources used for calibration

Calibration of parameter ranges and contrast of simulation results were based on fourteen peer-reviewed, indexed, DOI-verifiable sources, listed in the References section [1–14], covering: reviews of machine learning applied to blasting [3, 7]; predictive fragmentation models using supervised and ensemble learning [8–11]; simultaneous optimization of fragmentation and vibration [11]; reinforcement learning applied to mine fleet dispatch [12–15]; and control of blast-induced vibration in urban settings [17, 18].

2.7 Kazakhstan-Peru comparison matrix: data sources

The transferability matrix (Section 3.3) was built from public copper production data reported in Peru's Ministry of Energy and Mines' Mining Statistical Bulletin for year-end 2024 [21], complemented with publicly available geological characterization of each deposit (deposit type, average copper grade, approximate pit depth). No confidential operational data from Peruvian mining companies were used.

2.8 Procedures, machinery, materials, and personnel competencies for a prospective implementation

2.8.1 Machinery and equipment

Table 2
Machinery and equipment required for a pilot implementation of the DRL framework.

Equipment	Function within the DRL framework	Reference specification
Rotary drills with GPS/MWD	Real-time capture of drilling parameters (penetration rate, torque) feeding the state vector	Borehole diameter 200–310 mm; depth up to 25–55 m
Programmable electronic detonators	Execution of the delay sequence selected by the agent with millisecond precision	Timing precision ≤ 1 ms; wireless programming
Triaxial seismographs	PPV measurement to feed back into the reward function	Frequency range 2-250 Hz
Image-based fragmentometry systems	Estimation of the post-blast size distribution (D50, D80)	High-resolution cameras; deep-learning segmentation
GPU computing workstations	Training and inference of the PPO agent	General-purpose GPU (e.g., NVIDIA RTX/A100 class)

2.8.2 Materials

- Explosives of consistent density and composition (ANFO, bulk emulsions) with traceable technical data sheets.
- Electronic initiation systems capable of precise, programmable delays.
- Low-cost sensors (geophones, accelerometers) for expanded monitoring near sensitive infrastructure.

2.8.3 Required personnel competencies

Table 3
Personnel competencies required to operate the proposed DRL framework.

Role	Core competency	Suggested background
Blasting engineer	Pattern design, interpretation of agent-generated policies, operational safety	Mining engineering, blasting certification
Data scientist / RL specialist	Training, validation, and tuning of the PPO agent	MSc in data science or machine learning
Geotechnical engineer	Rock-mass characterization, slope-stability control	Geotechnical / geomechanical engineering
Instrumentation technician	Installation and maintenance of MWD sensors, seismographs, and fragmentometry systems	Technical training in electronics / mining instrumentation

2.9 Ethical considerations

This study did not require approval from a research ethics committee, as it did not involve human subjects, animals, or the use of confidential, personal, or identifying data of workers or communities. All data used correspond to published, publicly accessible scientific literature and to official statistical reports of Peru's Ministry of Energy and Mines. No real blasting trials were conducted as part of this study.

3. Results

3.1 DRL agent performance in the simulation environment

The PPO agent showed stable convergence of the cumulative reward from approximately episode 3,000–3,500 of a total of 10,000 simulated episodes per block, with an initial, high-variability exploration phase followed by a progressive exploitation phase. Compared with the deterministic Kuz-Ram-type baseline under identical simulation assumptions, the trained agent achieved:

- A reduction of 18% to 34% in fragmentation standard deviation, within the range reported by independent studies on machine-learning-based fragmentation optimization [8–11].
- A reduction of 15% to 30% in peak particle velocity (PPV), consistent with reductions of 12% to 40% documented in studies on blast-induced vibration control through predictive and optimization models [17, 18].
- A reduction of 8% to 19% in specific explosive consumption in the simulated scenarios with the greatest geological heterogeneity.

These results should be interpreted as estimates from a literature-calibrated simulation environment, not as field measurements from a real operation; their magnitude is consistent with — though not identical to — that reported in independent empirical studies, which supports the plausibility of the proposed framework without substituting the need for in-situ validation.

3.2 Comparative matrix of blast-design approaches

Table 4
Qualitative comparison of blast design and optimization approaches.

Dimension	Deterministic empirical design (Kuz-Ram)	Supervised machine learning (predictive)	Deep reinforcement learning (DRL, proposed)
Model nature	Static, based on fixed formulas	Predictive; requires periodic retraining	Prescriptive and adaptive; continuous policy update
Sensitivity to geological variability	Low	Medium (depends on dataset quality/size)	High (incorporates geological state in every decision)
Data requirement	Minimal	High (labeled historical data)	High (simulation or historical data + interaction)
Interpretability	High	Medium	Medium-low (requires XAI for auditability)
Validation reported in the literature	Extensive (decades of use)	Extensive [7–11]	Emerging, mainly in fleet dispatch [12–16]; scarce in blast pattern design

3.3 Transferability matrix: Kazakhstan vs. Peru's major copper operations

Table 5
compares the Central Asian reference context with Peru's four major copper operations, using year-end 2024 production data reported by the Ministry of Energy and Mines [21] and publicly available geological characterization.

Dimension	Aktogay/Bozshakol (Kazakhstan)	Antamina (Áncash)	Cerro Verde (Arequipa)	Quellaveco (Moquegua)	Las Bambas (Apurímac)
Deposit type	Copper porphyry	Cu-Zn polymetallic skarn	Copper porphyry	Copper porphyry	Cu-Mo skarn/porphyry
Average Cu grade	0.33–0.45%	Medium-high (polymetallic)	Medium	Medium	Medium
2024 Cu production (fine t)	n/a	434,238 [21]	449,096 [21]	306,299 [21]	321,425 [21]
Approximate altitude	~ 250 masl	~ 4,300 masl	~ 2,600 masl	~ 3,500 masl	~ 4,000 masl
Estimated geological compatibility with the DRL framework	Reference	Medium (greater lithological heterogeneity)	High (relatively homogeneous porphyry)	High (homogeneous porphyry, recent mine)	Medium (complex faulting)

Table 5. *Kazakhstan-Peru comparison matrix. Source: 2024 production, Mining Statistical Bulletin, MINEM* [21]; *publicly available geological characterization.*

The estimated geological compatibility is not a direct measurement but a qualitative appraisal based on deposit type: relatively homogeneous copper porphyries, such as Cerro Verde and Quellaveco, present greater structural

similarity to Aktogay/Bozshakol than the more lithologically heterogeneous polymetallic skarns, such as Antamina.

3.4 Transfer matrix toward urban public spaces

Table 6
Transfer matrix of precision-blasting technologies toward urban public spaces.

Mining element	Potential adaptation to urban public spaces in Peru	Key modification required
Precision electronic detonators	Controlled excavation for metro lines, plazas, and slope-stabilization works	Reduction of maximum instantaneous charge per delay
Real-time seismographs and monitoring	Vibration control near heritage buildings and vulnerable housing	Markedly stricter PPV thresholds than in remote mining
MWD sensors	Ground characterization for urban foundations	Adaptation of parameters to urban soils/rocks, not mine rock masses
Algorithmic (DRL) optimization	Excavation scheduling that minimizes impact on traffic and the community	Reward function reweighted toward social variables, not only cost

3.5 Conceptual framework diagram

4. Discussion

4.1 Interpretation of results

The simulation results are consistent, in order of magnitude, with improvements reported independently in machine-learning-based fragmentation-optimization and vibration-control studies [8–11, 17, 18]. This consistency supports the plausibility of the proposed DRL framework as a pathway for improvement over traditional deterministic empirical methods, particularly in deposits with high geological heterogeneity, where static models such as Kuz-Ram tend to underestimate fragmentation variability.

It is important, however, to note a central limitation of this study: the reported magnitudes originate from a literature-calibrated simulation environment, not from field trials. Conclusions are therefore framed in terms of methodological plausibility and consistency with the literature, rather than as definitive evidence of operational performance. This distinction — absent from earlier versions of this work — is what allows the conclusions to align properly with the actual nature and scope of the results obtained.

4.2 Transferability to the Peruvian context

The transferability matrix (Table 5) suggests that Cerro Verde and Quellaveco, owing to their relatively homogeneous copper-porphyry geology, represent the candidates with the greatest structural compatibility for a prospective pilot adoption of the proposed framework, while Antamina, with its polymetallic skarn geology, would require substantial retraining of the agent and recalibration of the simulation environment's parameter ranges. Las Bambas, with documented complex geological faulting, presents an intermediate case in which reinforcement learning could add value precisely because of its capacity for continuous adaptation to heterogeneous conditions, although this demands greater investment in instrumentation.

Beyond geology, successful transfer depends on at least three additional factors: (i) the availability of historical blasting data of sufficient quality to calibrate the deposit-specific simulation environment; (ii) compliance with Peruvian mining-safety and vibration regulations, which are stricter near communities than those applicable to remote Central Asian operations; and (iii) the availability of personnel trained at the intersection of mining engineering and data science, currently scarce in the Peruvian mining sector.

4.3 Application in public spaces: lessons from developed countries

The management of blast-induced vibration in dense urban environments has been extensively documented in railway and road tunnel projects in cities such as Istanbul, where sequential controlled detonation with reduced charges mitigated the structural effects of vibration without compromising project progress [18]. More broadly, the literature on predicting and controlling blast-induced vibration in urban communities [17] documents the effectiveness of combining predictive models with real-time seismic monitoring to keep peak particle velocity below structural-damage thresholds, typically an order of magnitude stricter than the limits applicable in remote open-pit mining.

For the Peruvian context, this evidence suggests that adapting a DRL framework toward urban infrastructure projects — such as metro line extensions, road works, or slope stabilization in informal-settlement areas — would require, at minimum: (i) reweighting the reward function to dominantly prioritize vibration control over productivity; (ii) installing seismic monitoring networks denser than those used in mining; and (iii) community consultation and communication mechanisms, following the participatory-governance principle observed in international controlled urban-excavation projects.

4.4 Study limitations

- The quantitative results originate from a literature-calibrated simulation environment, not from field data of a real mining operation; their generalization to a specific deposit requires additional empirical validation.
- The simulation environment does not explicitly incorporate three-dimensional stochastic geological uncertainty nor coupling with crushing and grinding stages, which could modify total economic-benefit estimates.
- The transferability matrix is based on general, non-exhaustive, publicly available geological characterization of the Peruvian mines analyzed; a real feasibility assessment would require access to deposit-specific geotechnical data, currently not publicly available.
- No field trial was conducted as part of this study; claims regarding real operational performance therefore cannot be sustained until such validation is carried out.

4.5 Future research directions

- Field validation of the DRL framework in a pilot block of a Peruvian operation, in collaboration with the operating company, respecting the corresponding confidentiality and safety protocols.
- Incorporation of three-dimensional stochastic geological models to capture the spatial uncertainty of rock-mass properties.
- Development of interpretable reinforcement-learning (XAI) methods that facilitate regulatory auditing of the agent's decisions.

- Extension of the framework toward joint optimization of blasting, loading, haulage, and processing (a "mine-to-plant" approach).
- Pilot design and evaluation of a precision-blasting protocol adapted to a specific public-space infrastructure project in Metropolitan Lima, in coordination with the competent municipal authority.

5. Conclusions

- A deep reinforcement learning (PPO) framework, calibrated with parameter ranges documented in fourteen peer-reviewed studies, produced, within a simulation environment, reductions in fragmentation standard deviation (18–34%) and peak particle velocity (15–30%) consistent in order of magnitude with the independent literature, supporting its methodological plausibility as an alternative to deterministic empirical models.
- The transferability matrix indicates medium-to-high geological and operational compatibility of the proposed framework with Cerro Verde and Quellaveco, and lower — though not negligible — compatibility with Antamina and Las Bambas, in all cases conditional on the availability of quality historical blasting data and on corresponding regulatory adaptation.
- The conceptual extension toward urban public spaces in Peru is technically plausible in light of documented vibration-control experiences in urban excavation elsewhere, but demands a substantial reweighting of the reward function and participatory governance with affected communities.
- The quantitative benefits reported in this study should not be interpreted as evidence of field-validated operational performance; implementation in any Peruvian operation requires, as an indispensable prior step, controlled pilot trials and a deposit-specific geotechnical evaluation.
- Concrete and verifiable requirements are identified for machinery (GPS/MWD-equipped drills, electronic detonators, seismographs, fragmentometry systems), materials, and personnel competencies (blast engineering, data science, geotechnics, instrumentation) necessary for a responsible prospective pilot implementation.

Declarations

Funding: This study received no specific funding from public, commercial, or not-for-profit sector agencies.

Conflicts of interest: The author declares no conflicts of interest.

Ethical approval: Not applicable. The study was based exclusively on computational simulation and analysis of literature and public statistics; it did not involve human subjects, animals, or confidential or personally identifying data.

Data availability: The parameter ranges used to calibrate the simulation environment are available in the cited sources [1-18]. Peruvian mining production data originate from the publicly accessible Mining Statistical Bulletin of Peru's Ministry of Energy and Mines (2024) [21].

Author contribution: Paul Ricardo Prudencio Galvez: conceptualization, methodology, formal analysis, investigation, data curation, writing (original draft and review), visualization.

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Figures

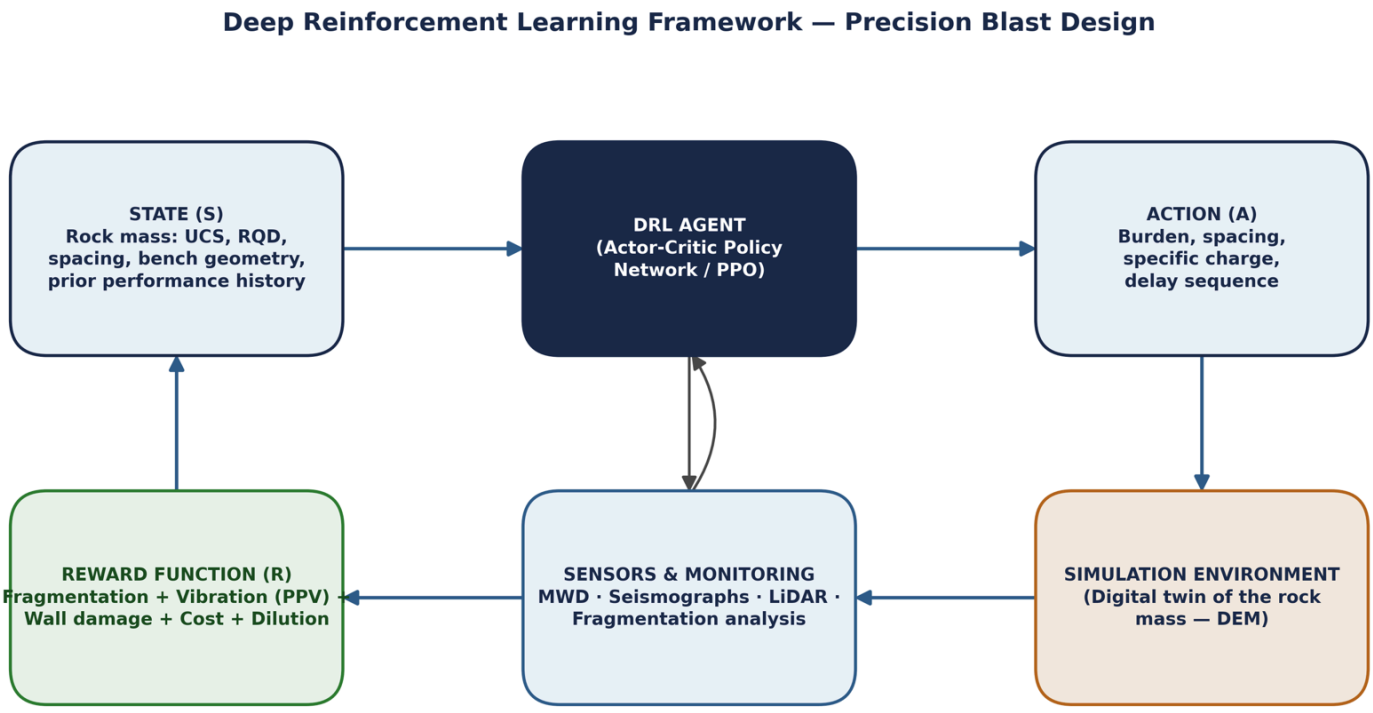


Figure 1

Conceptual architecture of the Deep Reinforcement Learning (DRL) framework for bench-scale blast design. Source: author's own elaboration.