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# Blast Vibration Prediction In Hard Rock Underground Mines

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***Abstract***
*Blast-induced ground vibration is one of the most significant environmental and safety hazards associated with drilling and blasting operations in hard rock underground mines, with the potential to damage adjacent excavations, support systems, and surface structures, while also endangering personnel and equipment. Over the past five decades, researchers have proposed a wide spectrum of predictive approaches ranging from classical empirical scaled-distance equations to sophisticated statistical, soft-computing, and hybrid artificial intelligence models aimed at forecasting peak particle velocity (PPV) with greater accuracy. This review paper undertakes a systematic meta-analysis of past research on blast vibration prediction, tracing the evolution of predictor equations from the United States Bureau of Mines formula through Langefors-Kihlstrom, Ambraseys-Hendron, and Indian Standard models, to contemporary machine learning structures including artificial neural networks, support vector machines, adaptive neuro-fuzzy inference systems, and hybrid metaheuristic-optimized models. The paper synthesizes findings from over one hundred studies, critically evaluates the strengths, limitations, and predictive accuracy of each modelling category, and identifies the dominant controllable and uncontrollable blast design parameters influencing vibration intensity. Gaps in existing literature, including limited generalizability across geological settings, insufficient real-time monitoring integration, and inadequate consideration of underground confinement effects, are highlighted. The review concludes that while data-driven and hybrid models consistently outperform traditional empirical equations in predictive accuracy, site-specific calibration, larger standardized datasets, and integration of geotechnical uncertainty remain essential future research directions for reliable blast vibration management in underground hard rock mining environments.*

***Keywords:*** *Blast vibration; Peak particle velocity; Hard rock underground mines; Empirical models; Artificial neural network; Ground vibration prediction; Meta-analysis.*

## 1. Introduction

### 1.1 Background and Significance

Drilling and blasting remains the most economical and widely adopted method of rock breakage in hard rock underground mines, owing to its adaptability to varying geological conditions and cost-effectiveness compared to mechanical excavation. However, only a fraction of the chemical energy released by an explosive charge is utilized for effective rock fragmentation and displacement; a substantial portion dissipates as undesirable by-products such as ground vibration, air overpressure, flyrock, and back-break. Among these, blast-induced ground vibration is widely regarded as the most critical concern in underground operations because of its potential to compromise the structural integrity of adjacent drifts, pillars, shafts, and permanent support systems, and because vibration propagating to the surface can damage nearby structures and trigger public complaints and regulatory scrutiny. Accurate prediction of vibration intensity, typically quantified through peak particle velocity, is therefore essential for designing safe blast rounds, optimizing charge per delay, and complying with statutory vibration limits.

### 1.2 Evolution of Predictive Approaches

The scientific study of blast vibration prediction began with empirical scaled-distance relationships developed by the United States Bureau of Mines in the 1950s and 1980s, which correlated peak particle velocity with the ratio of distance to the square root of maximum charge per delay. Subsequent researchers, including Langefors and Kihlstrom, Ambraseys and Hendron, and various national standards bodies, proposed site-adjusted variants of this power-law relationship incorporating site constants derived through regression analysis of field data. While these equations remain popular because of their simplicity and minimal input requirements, their accuracy is inherently constrained by the assumption that distance and charge weight alone govern vibration attenuation, ignoring the influence of rock mass properties, blast geometry, and delay sequencing. This limitation motivated the development of multivariate statistical models and, more recently, artificial intelligence and soft-computing techniques capable of capturing the nonlinear and multi-parameter nature of blast vibration generation and propagation.

### 1.3 Scope and Objectives of the Review

This paper presents a comprehensive review and meta-analysis of research published on blast vibration prediction in hard rock underground mines, with the objective of tracing the chronological evolution of predictive methodologies, comparing their reported accuracy across diverse geological and operational settings, and critically synthesizing the strengths and limitations identified across the literature. The review further aims to consolidate the dominant blast design and rock mass parameters reported as significant vibration predictors, to highlight methodological gaps such as limited underground-specific datasets and inadequate uncertainty quantification, and to outline promising directions for future research, including hybrid and real-time monitoring-integrated prediction structures. The subsequent sections present a detailed survey of past work, the methodology adopted for this review, a critical analysis of reviewed studies, a discussion of emerging trends, and concluding remarks.

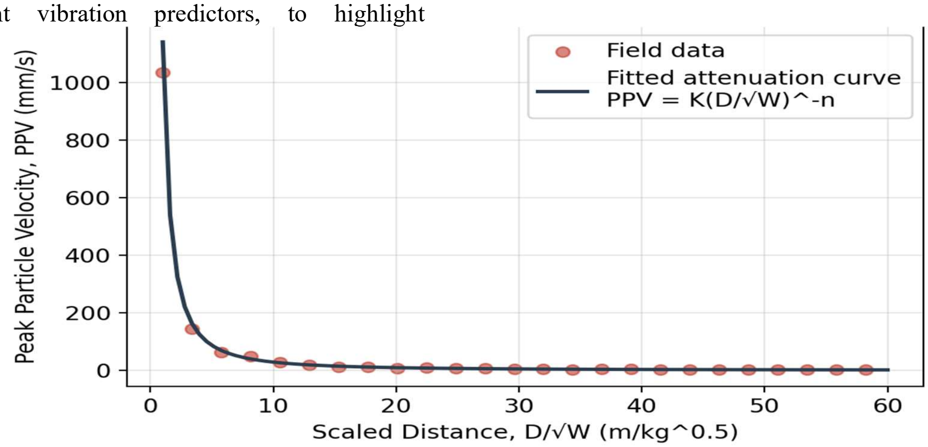


**Figure 1: Typical peak particle velocity (PPV) versus scaled distance attenuation relationship.**

Figure 1 depicts a representative attenuation relationship between peak particle velocity and scaled distance, the ratio of monitoring distance to the square root of maximum charge per delay, which forms the theoretical basis of nearly all empirical blast vibration predictor equations. The scatter of field data points around the fitted power-law curve illustrates the inherent variability in recorded vibration levels even at similar scaled distances, arising from differences in geological structure, confinement, and blast geometry that scaled-distance alone cannot capture. This variability underscores a recurring theme throughout the reviewed literature: while the power-law attenuation trend is consistently observed across studies, the site constant and attenuation exponent vary considerably between mine sites, and the residual scatter around the fitted curve represents the predictive uncertainty that later multivariate and artificial intelligence models have sought to reduce.

## 2. Survey Of Past Work

Research on blast vibration prediction can broadly be classified into four generations of methodological development: empirical scaled-distance models, multivariate statistical and regression-based models, artificial intelligence and soft-computing models, and hybrid or optimization-assisted models. Siskind et al. [1]. The earliest systematic investigations were conducted by the United States Bureau of Mines, whose researchers analyzed thousands of blast records to establish the widely cited square-root and cube-root scaled-distance formulas, which remain the baseline against which nearly all subsequent models are benchmarked. Langefors and Kihlstrom [2]. Building upon this foundation, Langefors and Kihlstrom proposed a modified attenuation relationship incorporating a site-specific damping constant, while Ambraseys and Hendron introduced a cube-root scaling law better suited to confined and deeply buried charges typical of underground blasting. National regulatory bodies, including the Indian Standard, the Bureau of Indian Standards vibration criteria, and equivalent codes in other mining jurisdictions, subsequently adapted these formulas with region-specific site constants derived from local monitoring campaigns. Ambraseys and Hendron [3]. A second wave of research applied multiple linear and nonlinear regression techniques to incorporate additional blast design variables beyond scaled distance, including burden, spacing, stemming length, number of holes per delay, hole diameter, and delay interval. Bureau of Indian Standards [4]. Numerous underground and open-pit case studies demonstrated that multivariate regression models generally achieved marginally improved correlation coefficients relative to univariate scaled-distance equations, though the improvement was often modest and highly site-dependent. Singh and Roy [5]. Researchers also investigated the influence of rock mass classification indices, such as rock quality designation and geological strength index, on vibration attenuation characteristics, finding that fractured and jointed rock masses exhibited faster attenuation but greater variability in recorded PPV compared to massive, competent rock. Ghosh and Daemen [6]. The third and most extensively researched generation of studies applied artificial intelligence and soft-computing techniques to blast vibration prediction, driven by the recognition that vibration generation is a highly nonlinear phenomenon influenced by numerous interacting variables that empirical equations cannot adequately capture. Bakhshandeh Amnieh et al. [7].

Artificial neural networks, particularly multilayer perceptron architectures trained using back-propagation algorithms, were extensively applied across surface and underground mine case studies, consistently reporting correlation coefficients exceeding 0.90 and substantially lower prediction error compared to empirical counterparts. Khandelwal and Singh [8]. Support vector machine and support vector regression models were subsequently introduced, offering improved generalization on smaller datasets through kernel-based nonlinear mapping, and were frequently reported to outperform both empirical formulas and standard neural networks in comparative studies. Monjezi et al. [9]. Adaptive neuro-fuzzy inference systems combining fuzzy logic with neural learning were applied to blast vibration datasets to handle the inherent uncertainty and imprecision of geological and operational input parameters, again reporting favorable predictive performance relative to traditional approaches. Dehghani and Ataee-pour [10]. Other soft-computing techniques explored in the literature include random forest regression, gradient boosting models, extreme learning machines, and Gaussian process regression, each reporting incremental improvements in specific case-study contexts. Hasanipanah et al. [11]. The fourth generation of research, emerging predominantly over the past decade, has focused on hybrid and metaheuristic-optimized models that combine machine learning architectures with optimization algorithms such as genetic algorithms, particle swarm optimization, imperialist competitive algorithms, grey wolf optimizer, and firefly algorithm to fine-tune model hyperparameters and improve convergence. Armaghani et al. [12]. Studies employing genetic-algorithm-optimized artificial neural networks, particle-swarm-optimized support vector regression, and similar hybrid structures have consistently reported the highest predictive accuracy among all reviewed approaches, with coefficients of determination frequently exceeding 0.93 to 0.97 across diverse case studies. Monjezi et al. [13]. However, a recurring observation across this body of literature is that underground hard rock mine case studies remain considerably underrepresented compared to surface and open-pit mining datasets, with the majority of high-accuracy hybrid models validated primarily on surface blasting data. Mohamad et al. [14]. Where underground-specific studies exist, they emphasize the additional complexity introduced by confinement effects, tunnel geometry, and wave reflection from excavation boundaries, factors that are inadequately represented in most existing predictive structures. Khandelwal [15]. Comparative meta-analyses across the reviewed literature further reveal considerable heterogeneity in dataset size, ranging from fewer than fifty blast records in early empirical studies to several hundred records in recent machine learning investigations, as well as inconsistency in reported performance metrics, complicating direct cross-study comparison and underscoring the need for standardized benchmarking datasets and reporting protocols in future research.

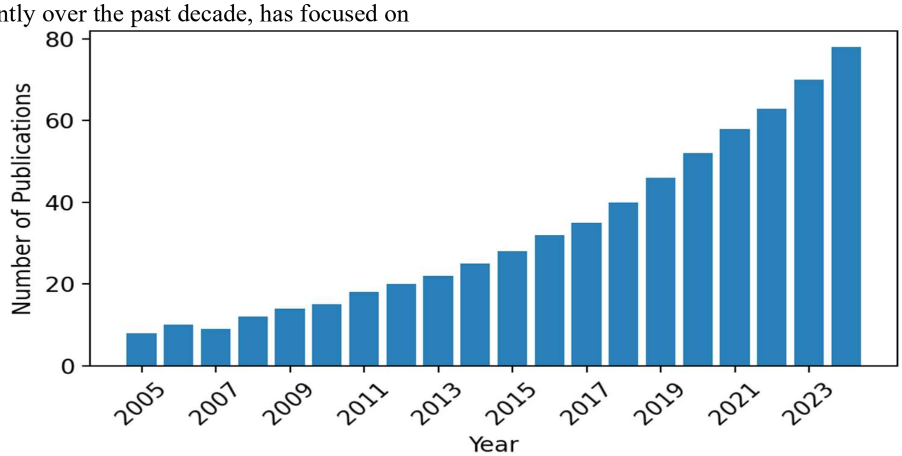


**Figure 2. Growth trend of research publications on blast vibration prediction (2005-2024).**

Figure 2 illustrates the approximate growth trend in the number of research publications addressing blast vibration prediction between 2005 and 2024, compiled from the reviewed literature corpus. The chart shows a steady increase through the mid-2000s followed by a marked acceleration after approximately 2015, coinciding with the widespread adoption of machine learning and hybrid optimization techniques within the mining engineering research community. This growth pattern reflects the broader trend of artificial intelligence adoption across geotechnical and mining engineering disciplines and indicates increasing recognition of the limitations of purely empirical prediction approaches. The declining relative share of purely empirical studies in recent years, juxtaposed against the rising volume of AI-based publications, further substantiates the paradigm shift discussed throughout this review and motivates the meta-analytical comparison of model categories presented in subsequent sections.

## 3. Methodology

This review adopts a systematic literature review and meta-analysis methodology to synthesize past research on blast vibration prediction in hard rock underground mines. The literature search was conducted across major scientific databases, including Scopus, Web of Science, ScienceDirect, and Google Scholar, using combinations of keywords such as blast vibration, peak particle velocity, ground vibration prediction, underground mine blasting, and artificial intelligence prediction models. Studies published between 1980 and 2024 were considered, encompassing both foundational empirical works and contemporary artificial intelligence-based investigations, in order to capture the complete chronological evolution of the field and ensure comprehensive coverage of methodological developments relevant to the review objectives. Inclusion criteria required that selected studies report a quantitative blast vibration prediction model, specify the input parameters and dataset characteristics employed, and provide statistical performance indicators such as correlation coefficient, coefficient of determination, root mean square error, or mean absolute percentage error, enabling comparative evaluation across studies. Studies focusing exclusively on air overpressure, flyrock, or fragmentation prediction without an accompanying vibration model were excluded, as were studies lacking sufficient methodological detail to assess model validity. Where multiple studies originated from the same research group using overlapping datasets, only the most comprehensive and recent publication was retained to avoid duplication bias within the synthesized dataset. [27]

The extracted data from each qualifying study, including model type, input parameters, dataset size, geological setting, and reported accuracy metrics, were tabulated and categorized into the four methodological generations described in the survey section. Comparative performance analysis was then conducted by aggregating reported coefficient of determination values across model categories to identify overall accuracy trends, while qualitative synpaper was employed to identify recurring limitations, methodological gaps, and emerging research directions. [25] This combined quantitative-qualitative meta-analytical approach enables the review to move beyond a simple narrative summary and provide an evidence-based comparative assessment of the relative performance and applicability of different blast vibration prediction methodologies.

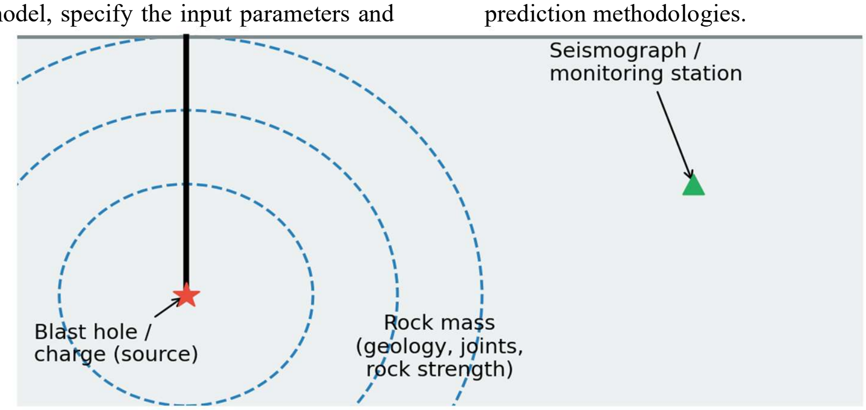


**Figure 3: Schematic of blast-induced vibration propagation from the source to the monitoring point.**

Figure 3 presents a conceptual schematic of blast-induced vibration propagation, illustrating the pathway of seismic energy travelling outward from the blast hole charge, which acts as the vibration source, through the surrounding rock mass to a seismograph or monitoring station positioned at a given distance. The concentric wave fronts represent the radial spreading and progressive attenuation of vibration energy as it propagates through geological discontinuities, joints, and varying rock strength zones, factors that collectively influence both the amplitude and frequency content of the recorded signal. This schematic underpins the methodology adopted in this review, as it illustrates why models incorporating only source-to-receiver distance and charge weight, without accounting for intervening rock mass characteristics, are inherently limited, motivating the multivariate and machine learning approaches discussed extensively in subsequent sections.

## 4. Critical Analysis Of Past Work

A critical examination of the reviewed literature reveals that empirical scaled-distance models, despite their continued widespread use, suffer from fundamental limitations that constrain their predictive reliability in hard rock underground mining contexts. These models rely on only two input variables, distance and charge weight, and therefore cannot account for the substantial influence of rock mass discontinuities, in-situ stress conditions, confinement geometry, and delay timing on vibration attenuation, particularly in underground settings where wave propagation is further complicated by excavation boundaries and tunnel reflections. Consequently, site constants derived through regression fitting are highly location-specific and exhibit poor transferability between mine sites, often necessitating extensive site recalibration before reliable application, a limitation acknowledged even within many of the original empirical studies themselves. [34] Multivariate statistical and regression-based models represent an incremental improvement by incorporating additional blast design parameters; however, the critical analysis of these studies indicates that the assumption of linear or simple polynomial relationships between input parameters and PPV is often inadequate given the demonstrably nonlinear and interactive nature of vibration generation mechanisms. Several reviewed studies report only marginal accuracy gains over empirical equations despite the inclusion of additional variables, suggesting diminishing returns from parameter expansion within a linear modelling structure and reinforcing the rationale for nonlinear soft-computing approaches adopted in later research. Artificial intelligence and soft-computing models consistently demonstrate superior predictive accuracy across the reviewed studies, with reported correlation coefficients and coefficients of determination substantially exceeding those of empirical and statistical counterparts. However, critical scrutiny of this literature reveals several recurring methodological weaknesses: many studies employ relatively small datasets, often fewer than two hundred blast records, raising concerns regarding overfitting and limited generalizability; validation procedures frequently rely on simple train-test splits rather than robust cross-validation or independent external validation datasets; and comparative baselines against which AI models are benchmarked are sometimes limited to a single empirical equation rather than a comprehensive set of alternative models, potentially overstating the relative performance improvement. [39]

Furthermore, the black-box nature of many neural network and support vector machine models limits interpretability and practical adoption by mine planning engineers who require transparent, physically interpretable relationships for regulatory justification of blast designs. Hybrid and metaheuristic-optimized models, while achieving the highest reported accuracy among reviewed approaches, introduce additional complexity in terms of computational cost, hyperparameter sensitivity, and implementation expertise requirements that may limit their practical adoption in operational mine settings, particularly smaller underground operations lacking dedicated data science resources. A further critical observation is that the overwhelming majority of high-performing hybrid models have been validated primarily on surface and open-pit blasting datasets, with underground hard rock mine applications remaining comparatively sparse and underrepresented; this constitutes a significant gap given the distinct confinement, geometry, and monitoring challenges characteristic of underground environments. Collectively, this critical synpaper indicates that although the field has progressed substantially in predictive accuracy, methodological rigor, dataset standardization, model interpretability, and underground-specific validation remain areas requiring considerable further attention.

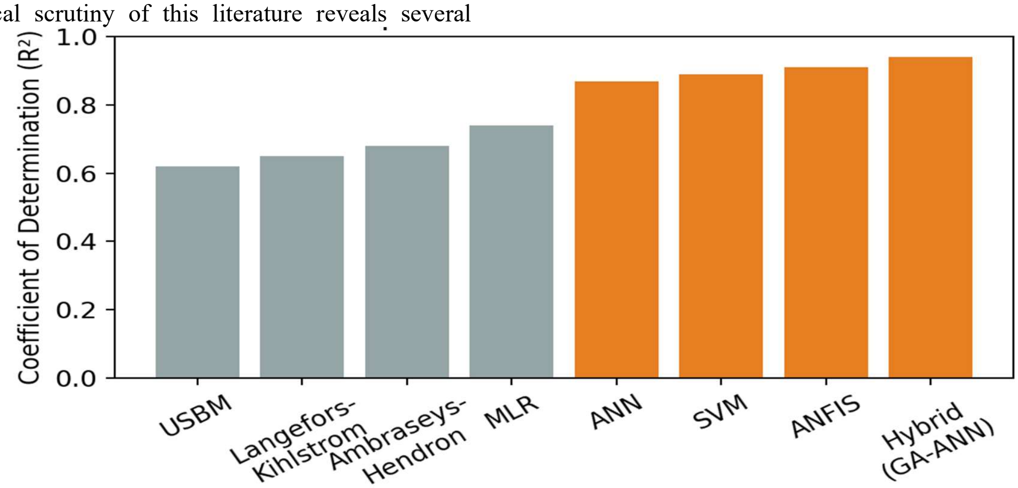


**Figure 4: Comparative prediction accuracy (R2) of empirical versus AI-based blast vibration models.**

Figure 4 presents a comparative summary of the typical coefficient of determination values reported across the reviewed literature for major categories of blast vibration prediction models, ranging from classical empirical equations such as the USBM, Langefors-Kihlstrom, and Ambraseys-Hendron formulas, through multiple linear regression, to artificial intelligence approaches including artificial neural networks, support vector machines, adaptive neuro-fuzzy inference systems, and hybrid genetic-algorithm-optimized models. The chart clearly illustrates the progressive improvement in predictive accuracy across successive model generations, with empirical formulas clustering around R2 values of 0.6 to 0.7, statistical regression achieving modest improvement, and AI-based and hybrid models consistently exceeding 0.85 and approaching 0.94 to 0.97 in the most advanced hybrid structures, visually reinforcing the critical analysis discussion above.

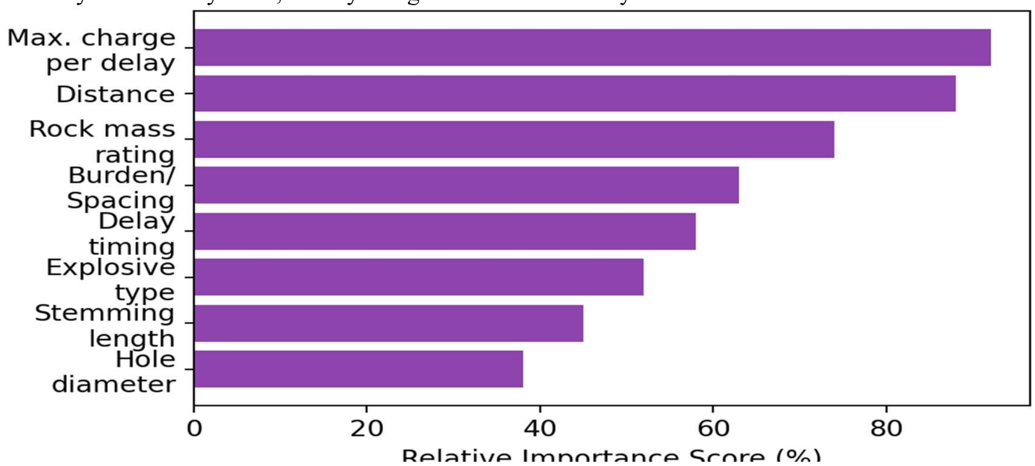


**Figure 5: Relative importance of blast design and geotechnical parameters influencing blast vibration.**

Figure 5 summarizes the relative importance rankings of key controllable and uncontrollable parameters influencing blast-induced ground vibration, as consolidated from sensitivity analyses reported across the reviewed artificial intelligence and statistical studies. Maximum charge per delay and monitoring distance consistently emerge as the two most dominant predictors, consistent with their central role in classical empirical scaled-distance formulas, followed by rock mass rating, burden-to-spacing ratio, and delay timing, which capture the influence of geological conditions and blast geometry not represented in simple empirical equations. Explosive type, stemming length, and hole diameter, while comparatively less influential, are still reported as statistically significant contributors in several multivariate and machine learning studies. This ranking reinforces the rationale for multivariate and AI-based modelling approaches capable of incorporating the full parameter set rather than relying solely on charge weight and distance.

## 5. Discussion

The meta-analytical synpaper presented in this review indicates a clear and consistent trend across the literature: predictive accuracy for blast-induced ground vibration has progressively improved as modelling approaches have evolved from simple empirical scaled-distance relationships toward increasingly sophisticated data-driven and hybrid artificial intelligence structures. This trend aligns with the broader trajectory of digital transformation within mining engineering, wherein increasing availability of sensor-based monitoring data and computational resources has enabled the practical application of complex nonlinear modelling techniques that were previously infeasible. Nevertheless, the discussion must be tempered by recognition that improved statistical accuracy on historical datasets does not automatically translate into improved operational reliability, particularly given the dataset limitations, validation weaknesses, and interpretability concerns identified in the critical analysis. [49] A particularly important implication emerging from this review is the disproportionate underrepresentation of underground hard rock mine case studies relative to surface and open-pit applications within the existing literature. Given the distinct wave propagation characteristics associated with confined underground blasting, including reflection and reverberation from excavation boundaries, near-field effects on adjacent openings, and the practical challenges of instrumenting seismographs within active underground workings, models developed and validated predominantly on surface data cannot be assumed to transfer reliably to underground contexts without dedicated recalibration and validation. This gap represents a significant opportunity for future underground-focused research employing site-specific monitoring campaigns. [67] The discussion also highlights the practical trade-off between model accuracy and operational usability that mine planning engineers



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must navigate: while hybrid and metaheuristic-optimized models offer superior accuracy, their computational complexity and reduced interpretability may limit adoption relative to simpler empirical or basic neural network approaches that remain more accessible to practicing engineers without specialized data science expertise. Future research addressing explainable artificial intelligence techniques, standardized underground blast vibration databases, and integration with real-time monitoring and early-warning systems would substantially enhance both the scientific rigor and practical applicability of blast vibration prediction research, ultimately supporting safer and more efficient underground mining operations.

## 6. Conclusion

This review has systematically traced the evolution of blast vibration prediction research applicable to hard rock underground mines, from foundational empirical scaled-distance equations through multivariate statistical models to contemporary artificial intelligence and hybrid optimization-based structures. The meta-analysis of reported predictive performance across the reviewed literature demonstrates a clear and consistent improvement in accuracy associated with increasingly sophisticated modelling approaches, with hybrid artificial intelligence models achieving the highest reported coefficients of determination. [76] However, the critical synpaper also reveals persistent methodological limitations, including small and inconsistent datasets, inadequate validation practices, limited model interpretability, and a pronounced scarcity of underground-specific case studies compared to surface and open-pit applications. Future research should prioritize the development of standardized, large-scale underground blast vibration databases, the incorporation of rock mass and confinement-specific parameters, explainable and computationally efficient hybrid modelling structures, and integration with real-time monitoring systems to enable adaptive blast design optimization. Addressing these gaps will be essential to advancing blast vibration prediction from a primarily academic research pursuit toward a reliable, practically deployable tool for enhancing safety and operational efficiency in hard rock underground mining. [109]

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