Abstract

Earthquakes are among the most devastating natural hazards worldwide. Accurate earthquake prediction can significantly reduce disaster losses, yet seismic precursor identification remains one of the most challenging scientific problems of our time. Earthquakes result from macroscopic rock fracture in the Earth's crust, and their preparation process shares profound physical homology with the cross-scale damage evolution in materials, from microcrack initiation and propagation to macroscopic instability. Acoustic emission (AE), as stress waves generated by the release of strain energy during rock microfracturing, offers the potential to capture direct physical effects of earthquake preparation and to explore physics-based earthquake precursor identification. However, existing research faces challenges such as unclear precursor mechanisms, high false-alarm rates of single methods, and difficulties in unifying laboratory and field observation scales. Addressing these issues, this study takes fracture mechanics as the theoretical foundation, adopts the novel Method of Critical Fluctuations-Based (MCF-B) analysis as the core approach, and leverages AE technique to conduct cross-scale precursor identification research spanning laboratory experiments and field measurements, while integrating multi-source data and deep learning techniques to construct an intelligent precursor warning framework. The main research work and conclusions are as follows:

(1) An AE signal analysis method based on the critical fluctuation (MCF-B) approach is proposed. Traditional *b*-value analysis has limitations in describing nonlinear amplitude distributions. Grounded in critical fluctuation theory, the MCF-B method is introduced, incorporating a power-law decay exponent (p_2) and an exponential decay exponent (p_3). Its potential for cross-scale application, from material fracture to earthquake preparation, is demonstrated. It quantifies deviations of amplitude distributions from ideal power-law behavior and captures crossover

phenomena (p_2 decrease, p_3 increase) as systems approach instability, providing a more physically meaningful and sensitive statistical criterion for precursor identification.

(2) A series of experiments were conducted, including compression tests on steel fiber-reinforced concrete (SFRC), size effect tests on ultra-high performance concrete (UHPC), flexural tests on UHPC-strengthened beams, field monitoring of cracks in steel-UHPC composite decks, and flexural tests on glass fiber-reinforced polymer (GFRP) bar-reinforced concrete beams. Results indicate: AE parameters (*b*-value, RA-AF, etc.) effectively characterize damage evolution and cracking mode transitions; AE energy follows a fractal scaling law, with fiber toughening increasing the fractal dimension of the damage domain; Natural time (NT) analysis can serve as an earlier warning indicator than the *b*-value method. In the GFRP beam tests, the MCF-B method, through the synergistic evolution of its parameters, tracked the entire process from critical state to instability more robustly and persistently than the traditional *b*-value method. Its identification results were consistent with NT analysis and AE information entropy analysis, validating the effectiveness and superiority of the MCF-B method in identifying failure precursors across scales.

(3) Synchronous monitoring of AE and seismicity was conducted in a granite mountain tunnel. Significant correlations were found between intense AE bursts and regional earthquakes. AE characteristic parameters, *b*-value, and NT analysis effectively identified pre-seismic anomalies. Multimodal statistical analysis showed that temporal variations in AE distribution precede those of seismicity, serving as earthquake precursors capable of identifying seismic events approximately 17 hours in advance. The MCF-B method was applied to field AE data, revealing significant synergistic anomalies in p_2 and p_3 parameters before earthquakes. Simultaneous electromagnetic emission (EME) monitoring cross-validated the reliability of AE precursors, revealing a strict temporal sequence of "EME precursor first, AE precursor second" before earthquakes, with signal strength positively correlated with subsequent magnitude.

(4) A physics-data driven deep learning model for earthquake precursor identification was constructed, achieving real-time warning with high accuracy. Based

on fundamental features (AE count, count rate, frequency, amplitude), a deep neural network model was designed. Through cross-validation and hyperparameter optimization, the baseline model achieved 97.6% accuracy on the test set, significantly outperforming traditional machine learning methods. Validation using 180-day long-term time-series data showed an average warning lead time of 20.5 hours for four major seismic events, with 97.1% accuracy and 97.8% recall, indicating good generalization ability and stability in long-term practical applications. By further incorporating higher-order physical features, namely MCF-B parameters (p_2, p_3) and NT variance (κ_1), into the model, a physics-data hybrid-driven framework was constructed, improving accuracy and extending warning lead time. SHAP analysis confirmed the key contribution of these physical feature parameters (p_2, p_3, κ_1) to model decisions, demonstrating the effectiveness of the physics-data synergistic-driven approach.

In summary, through theoretical innovation, methodological development, and multi-scale empirical validation, this study establishes a set of theories and methods for cross-scale precursor identification, from microfracture to macro-earthquake. The research findings can provide new scientific basis and technical pathways for earthquake early warning.