

# Research Proposal

XXXVIII Ph.D. Cycle in Earth Sciences

Università Degli Studi di Roma La Sapienza

Application of Deep Learning Techniques for the Detection and  
Localization of Laboratory Earthquakes

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# 1 Introduction and State of the Art

Since its foundation as a scientific discipline earthquake prediction has been recognized as one of the main objectives of seismology [1]. Although throughout its history this goal has been repeatedly deemed as unfeasible [2] if a major innovation can be related to earthquake understanding, it is often readily used for predicting purpose [2][3]; this is the case for the evergrowing Machine Learning (henceforth ML) applications in the field [4]. This research proposal aims to bend this powerful automation tool to provide physically explicable predictions under controlled laboratory conditions.

Earthquake prediction may be loosely defined as the ability to correlate recognizable precursor phenomena to major seismic events. Still, strict criteria are needed to cast the problem in a testable hypothesis. In particular, it is acknowledged that the precursors *should have a relation to stress, strain, or some mechanism leading to earthquakes* [5] and that must be clear *the physical model relating the precursor to the main shock, and the amplitude-distance variation of the anomaly associated with the precursor* [6]. Since earthquakes are the release of elastic energy due to slips along the surfaces of a fractured media, a preferred class of candidates for such a task is the one that shares with earthquakes the same physical framework of continuum mechanics: seismic waves and the attributes from wavefield patterns and variations that can be linked, through constitutive laws, to the internal state and dynamics of the fault zone [7].

Own to the vastity of the physical, chemical, and tectonic boundary conditions and the intrinsic lack of measurements at a depth where earthquakes nucleate, the unambiguous determination of the source mechanism from wavefield features is an underdetermined problem [8]. The result is that sound geological and physical assumptions are needed to constrain the model. In this respect, the role of fluid-induced earthquakes, related to anthropogenic activities of underground fluid injection, has emerged in recent years as a specific context where the variation of seismic attributes as compressional over shear velocity ratio can be related to the internal state of the fault and fluid migrations, providing a promising tool for predictions [9][10].

Laboratory frictional experiments, instrumented with sensors recording acoustic emissions, are of paramount importance to investigate the hydromechanical coupling processes that link fault internal structural variations to a seismic event: they provide reproducibility, while the recognized self-similarity nature of most of the laws governing seismicity are promising for the up-scaling of the results [11]. Embedding the dynamic interaction of structural, frictional, and fluid flow properties in a quantitative description of fault zone dynamic is challenging in many respects, from modeling to monitoring; however, this strive has already shed light on phenomenology hardly explicable before, such as slow slip events [12].

The tackling of technical limitations on reproducing geometrical, pressure, and temperature conditions of natural fault zones is an ongoing endeavor to which the application of ML techniques is adding its increasingly predictive capability [13][14]. Still, there are significant doubts regarding the possibility of generalizing such results to natural faults, given the obscure relationship between the features used by such AI applications to make a prediction, and the pre-slip processes that must occur in the region identifiable as the earthquake hypocenter, for the prediction to be possible at all [15].

## 2 Research objectives

**General objective** Reliable predictions of fluid-induced fault reactivation.

**Specific objectives** An Artificial intelligence algorithm that predicts the occurrence of a fluid-induced laboratory earthquake, using acoustic emission attributes uniquely localized as the signature of pre-slip processes happening at the fault shear stress zone.

## 3 Implications and applications

This work will enhance the laboratory earthquake experiments' ability to shed light on fluid-induced fault reactivation. Although the prediction of an impending earthquake in broad areas of complex tectonic evolution (e.g. subduction zones) may still be considered overambitious, the short-term forecasting of fluid-induced seismicity, which generally occurs in localized, more controlled, and increasingly better-monitored environments, will become a more realistic target.

## 4 Work plan

The Ph.D. research project exploits the unconventional experimental instrumentation at the Sapienza Earthquake Physics and Mechanics Lab disposal to carry out reproducible experiments that can closely mimic, in the laboratory, the geological conditions of crustal faulting under hydromechanical forcing. In particular, the newly developed biaxial shear apparatus BRAVA 2 allows up to 100 MPa of confining pressure and 70 MPa of pore fluid pressure, so from hydrostatic to near lithostatic fluid pressure conditions, and up to 250 C temperature. The ultimate goal is to predict the stress drop on double shear experiments and the consequent acoustic emission (i.e. the "laboratory main shock")

**November 2023 - September 2024** The initial step will be to instrument the apparatus with an Acoustic Emission network (i.e. variously polarized piezoelectric transducers with up to 8 MHz central frequency) to illuminate the fault, simulating

at the same time a cross-borehole tomography and a dense seismic monitoring one. Preliminary double shear experiments using dry fault gouge of quartz will assess the ability of the system to uniquely locate the acoustic emissions, relying on the retrieved evolution of amplitude, compressional ( $V_p$ ), and shear velocity ( $V_s$ ) during the "silent" parts of the experiments.

Moving then to the first session of fluid-injection experiments, the first main achievement of the work is to automate the detection of the features and the location of the laboratory earthquakes, through a combination of waveform stacking and ML algorithms.

**October 2024 - July 2025** The second part of my Ph.D. will be devoted to building a database of acoustic attributes time series for relevant and diverse stress P-T boundary conditions and fault slip behaviors. Specifically, I will focus on those that have already shown consistent variation throughout the seismic cycle and are ready proxy for fault internal physical changes (acoustic amplitude variation) and fluid flow distribution ( $V_p/V_s$  ratio). The crucial data analysis moment here will aim to constrain the information about the fault carried from a lab quake waveform using the active source attributes. In other words, the idea is to use the Green Theorem [7] to separate the seismic source contribution from the media one.

**August 2025 - July 2026** This rich ensemble of time series attributes will be the training data for supervised ML algorithms directly or as the backbone for generating a synthetic ensemble. Choosing as the ML algorithm an Artificial Neural Network (ANN), the supervised training procedure aims to map the current collection of input features selected (the acoustic attributes) into the correct future prediction (the shear stress on the fault and the time-to-failure experimentally determined) through a recursive adjusting of the parameters that identify the operational units (the neurons), whose composition ultimately determines the ANN outcome. If trained on a large enough database with all the essential qualitative physical features, the ANN should be able to output the correct prediction on unseen data. The goodness of the AI prediction algorithm will be tested on a last set of fluid-injection experiments.

## 5 Milestones

Simultaneous active and passive acoustic emission acquisition system for the detection and localization of laboratory earthquake precursors (September 2024).

A database of acoustic emissions attributes under relatively broad conditions of temperature, fluid, and confined pressure (July 2025).

Physical-based Artificial Intelligence algorithm for the real-time prediction of time to failure laboratory fault induced by fluid injection (July 2026).

## 6 Dissemination plan

The Ph.D. will result in the publication of one scientific paper in an ISI journal for each of the milestones and the dissemination of the result through presentations and posters at national and international conferences (i.e. GNGTS, EGU, SSA, IUGG, NeurIPS).

## 7 List of training activities

During my Ph.D, I will attend the courses provided by the Earth Sciences PhD course of La Sapienza University, and courses on AI, numerical modeling, and parallel programming from the Computer Science Department. I will keep on attending ERC Tectonics seminars and the relative annual workshop.

## 8 Details of mobility abroad

While working at the AE attributes database, I will spend three months at the Penn State (USA) rock mechanics laboratory, which has a sound tradition.

## 9 Time schedule

Years	2023												2024												2025												2026													
Month	n	d	j	f	m	a	m	j	j	a	s	o	n	d	j	f	m	a	m	j	j	a	s	o	n	d	j	f	m	a	m	j	j	a	s	o	n	d	j	f	m	a	m	j	j	a	s	o	n	d
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Acoustic Emission Network													█																																					
Detector													█																																					
Dry Experiments													█												█												█													
Fluid Experiments													█												█												█													
Data Analysis													█												█												█													
AE Attributes Dataset													█												█												█													
Prediction Algorithm													█												█												█													
International mobility													█												█												█													
Dissemination	█												█												█												█													
Training	█												█												█												█													
Final Dissertation	█												█												█												█													

## References

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