Charles University
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MICROEARTHQUAKES DETECTION BY SYNTHETIC TEMPLATE MATCHING

DETEKCE MIKROSEISMICKÝCH JEVŮ POMOCÍ KORELACE SE SYNTHETICKÝMI SEISMOGRAMY

Doctoral thesis

Supervisor: Prof. Tomáš Fischer

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Prohlašuji, že jsem tuto práci vypracovala samostatně a že jsem uvedla všechny použité zdroje a literaturu. Ani tato disertační práce, ani žádná její podstatná část, nebyla předložena k získání jiného nebo stejného akademického titulu. Pro úpravy textu a pomoc s kódováním byly použity nástroje umělé inteligence (ChatGPT).

I declare that I have independently prepared this thesis and that I have cited all the sources and literature used. Neither this thesis nor any substantial part of it has been submitted for the attainment of a different or the same academic degree. Artificial intelligence (ChatGPT) instruments were used to smooth the text and help with coding.

Praha, 23. 7. 2025 MSc Eva Káldy

I would like to express my sincere gratitude to my supervisor for his support of my scientific ideas and for his critical guidance during their development. I am also grateful to my colleagues and fellow PhD students — not only from our office — for their pleasant company, encouragement during challenging times, assistance with acquiring seismic data, valuable advice during code development, collaboration on our paper, and for standing by me in the battle with bureaucracy.

Abstract

This article-based dissertation focuses on monitoring local seismicity in regions without natural seismic activity, with an emphasis on potential induced seismicity linked to geothermal or other underground operations. It presents three case studies, of which I am the first author, that form a comprehensive framework for assessing seismic network sensitivity and the effectiveness of automatic detection algorithms. The first study introduces a novel computational approach to 3D sensitivity estimation for networks operating in aseismic environments, using real noise measurements and station geometry. The second study evaluates the performance of the automatic detector and locator PEPiN using realistic synthetic seismograms designed for the Litoměřice region. The third study extends detection capabilities through a synthetic template-matching routine, including focal mechanism estimation. The findings demonstrate that even in seismically quiet regions, effective monitoring of potential seismicity is achievable with appropriate methods, contributing to safer planning of deep subsurface projects and advancing detection methodologies under low-activity conditions.

Keywords

Microseismic monitoring, microseismic activity, template matching, synthetic seismograms, geothermal, induced seismicity, magnitude of completeness, network sensitivity, local magnitude, moment magnitude, West Bohemia, Vogtland, Litoměřice

Abstrakt

Tato kompilační disertační práce se zaměřuje na monitoring lokální seismicity v oblastech bez přirozené seismicity, zejména v souvislosti s možnou indukovanou seismicitou spojenou s geotermálními nebo jinými podzemními projekty. Práce obsahuje tři případové studie, jejichž jsem první autor, které společně tvoří ucelený rámec pro hodnocení citlivosti seismických sítí a efektivity automatických detekčních algoritmů. V první studii je představen nový výpočetní přístup k 3D odhadu citlivosti seismické sítě v oblastech bez zaznamenané seismicity, využívající reálná šumová data a geometrii stanic. Druhá studie testuje výkonnost automatického detektoru a lokátoru PEPiN pomocí realistických syntetických seismogramů pro oblast Litoměřic. Třetí studie rozšiřuje možnosti detekce pomocí rutiny založené na syntetických šablonách, včetně odhadu fokálních mechanismů. Výsledky ukazují, že i v seismicky tichých oblastech lze pomocí vhodných metod účinně sledovat potenciální seismicitu, čímž práce přispívá k bezpečnějšímu plánování hlubinných projektů a k vývoji detekčních metod v podmínkách nízké aktivity.

Klíčová slova

Mikro-seismická aktivita, detekce pomocí korelace, synthetické seismogramy, geotermální energie, indukovaná seismicita, magnitudo kompletnosti, citlivost seismické sítě, lokální vs. momentové magnitudo, oblast Západních Čech, oblast Litoměřic

List of Abbreviations

STM - Synthetic Template Matching - my new seismic detection method based on template matching
ANN - Artificial Neural Network - seismic detection method
CNN - Convolutional Neural Network - seismic detection method
STA/LTA - seismic detection method based on the ratio between Short-Time-Average and Long-Time-Average
PEPiN - Polarization based Earthquake PIcker for Networks - automated seismic detection and location algorithm operating both on GRSN and WEBNET
GRSN - local seismic network in Litoměřice region
WEBNET - local seismic network in West Bohemia
ELISE - Eger Large Seismic Experiment - temporal seismic network in West Bohemia
EGS - Enhanced Geothermal System
GF - Green's Function
xc - cross-correlation
Tp - P-wave arrival time
Ts - S-wave arrival time
M_L - local magnitude
M_W - moment magnitude
M_C - magnitude of completeness
M_m - minimal detectable magnitude
σ - standard deviation FM - Focal Mechanism
AI - Artificial Intelligence
PVGT-LT1 - identification of the exploration well for EGS project in Litoměřice region
RMS - Root-Mean-Square
PNR - (S-wave) Peak to Noise Ratio
t_{err} - maximal difference between simulated and real S-wave arrival time
REAL - Rapid Earthquake Association and Location (Zhang et al., 2019)
seismic event - earthquake

Contents

1 Summary of Publications

This article-based dissertation comprises three peer-reviewed research articles, published in open-access journals or currently under review, in which I am the first author. An article Káldy and Fischer (2023) is published in the international Journal of Seismology (impact factor 1.6), while two others Káldy and Fischer (2025); Káldy et al. (2025) appear in the Diamond Open Access journal Seismica, which is expected to receive its first impact factor in 2025. The first two publications Káldy and Fischer (2023, 2025) focus on assessing the sensitivity of local seismic networks, particularly in regions with low or absent seismicity. The third paper Káldy et al. (2025), currently under review, introduces and tests a newly developed detection methodology, *Synthetic Template Matching* (STM), which uses synthetic waveforms in matched-filter detection routines. In addition to these three main contributions, I was also a co-author of the article *Hydraulic injection tests in the pilot EGS borehole PVGT-LT1 in Litoměřice, Czechia* (Fischer et al., 2023).

1.1 Microseismic network sensitivity in case of no seismic activity. (Journal of Seismology, 2023)

In this article, the sensitivity of local networks is evaluated in the absence of detected seismic events. Using noise levels, geometry, station sensitivities, and algorithm settings, a method is developed to estimate 3D sensitivity maps. West Bohemia is used for validation; Litoměřice is assessed as the target. The framework supports early-operational planning and adjustment of seismic monitoring systems.

In terms of the author's contribution, I have co-designed the theory and fully implemented the network sensitivity evaluation mainly in MATLAB; also, I have determined the station's corrections for Litoměřice. All the text and figures of the article were provided by me and corrected by the supervisor.

In this article-based dissertation, this article is mentioned as Káldy and Fischer (2023); and the full article is attached in the Appendix (page I). Cite as:

Káldy, E. and Fischer, T. **Microseismic network sensitivity in case of no seismic activity.** *Journal of Seismology*, 27(4): 627–641, 2023. doi: 10.1007/s10950-023-10134-y

1.2 Hydraulic injection tests in the pilot EGS borehole PVGT-LT1 in Litoměřice, Czechia. (Geothermics, 2023)

This article reports on two water injection experiments that aim to create and characterize fractures in deep crystalline rock. The first injection (24 m^3) in January 2020 created a fracture at 880 m depth, while the second (202 m^3) confirmed its openness. Despite dense seismic monitoring and the application of three detection approaches (PEPiN, source scanning algorithm with multichannel cross-correlation, and visual examination), no induced seismicity was observed. Tests with synthetic seismograms overlayed on real records imply that no seismic event $M_L > -2.2$ occurred during hydraulic tests. The overall results support the feasibility of developing an Enhanced Geothermal System (EGS) in the Litoměřice area.

In terms of the author's contribution, mine was limited. First, I visually checked the seismograms recorded during the first stage of hydraulic injection, looking for any undetected earthquakes. Second, I created synthetic seismograms that were overlayed on the real records and used to test the source scanning detection algorithm. Third, it was the 1D velocity model for Litoměřice compiled by me that was used in this study.

In this article-based dissertation, this article is mentioned as Fischer et al. (2023); and the full article is attached in the Appendix (page III). Cite as:

T. Fischer, J. Vlček, P. Dědeček, J. Řihošek, G. Zimmermann, J. Holeček, M. Mazanec, L. Rukavičková, L. Janků, **E. Káldy**. **Hydraulic injection tests in the pilot EGS borehole PVGT-LT1 in Litoměřice, Czechia.** *Geothermics*, 115: 102805, 2023. doi: 10.1016/j.geothermics.2023.102805

1.3 Performance of an Automatic Detector & Locator Tested on Synthetic Seismograms: Case Study from Litoměřice in Czech Republic. (Seismica, 2025)

This paper validates the PEPiN detection abilities in Litoměřice region using synthetic events superimposed on real noise recorded by seismic stations. The simulation shows that PEPiN detects 82% of events above a magnitude of completeness $M_L = -0.5$, confirming its effectiveness in aseismic environments.

In terms of the author's contribution, I have created the velocity model(s) for Litoměřice region (based on Burda et al., 2008; Myslil et al., 2012, 2007; Bachura, 2017), calculated synthetic seismograms for Litoměřice using Pyrocko package (Heimann et al., 2017, 2020), superimposed it on the real noise recording of the seismograms and used PEPiN for event detection and location. I coded the evaluation mainly in MATLAB. The methodology is inspired by López-Comino et al. (2017). All the text and figures of the article were provided by me, except the section *Methodology: PEPiN - detection and location algorithm*, corrected by the supervisor.

In this article-based dissertation, this article is mentioned as Káldy and Fischer (2025); and the full article is attached in the Appendix (page V). Cite as:

Káldy, E. and Fischer, T. **Performance of Automatic Detector & Locator Tested on Synthetic Seismograms:** Case Study from Litoměřice in Czech Republic. *Seismica*, 4(1), Apr. 2025. doi: 10.26443/seismica.v4i1.1373

1.4 Local Seismicity: Matched Filter Detection Routine with Synthetic Templates using 1D velocity model (Seismica, currently under review)

This article presents the development and implementation of *Synthetic Template Matching* (STM) in the seismically active West Bohemia region using a grid of synthetic templates derived from a 1D velocity model. The grid of templates is built as no prior knowledge about seismicity was known, but depth. STM detection results are compared to detections by PEPiN and Artificial Neural Network. While STM does not outperform these methods in terms of magnitude completeness, it provides reliable focal mechanism estimates and robust event localization, demonstrating that STM can be a valuable tool, especially where no real templates are available.

In terms of the author's contribution, I have designed the methodology (inspired by Chamberlain and Townend (2018), calculated a grid of synthetic seismograms for West Bohemia using the Pyrocko package (Heimann et al., 2017, 2020), tested the implementation and interpretation of the focal mechanism, modified the ObsPy code for Template Matching, compared the detection by STM to the detection results assessed by the co-authors' software. All of the new code was coded in Python by me. The methodology is inspired by López-Comino et al. (2017). All the text and figures of the article were provided by me, except the section *Methodology: PEPiN - detection and location algorithm*, corrected by my co-authors.

In this article-based dissertation, this article is pointed to as Káldy et al. (2025);

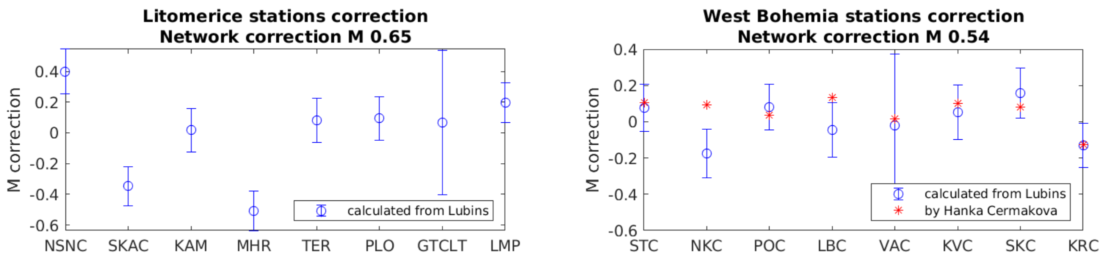
and the full article, as submitted to Seismica on 18*th* June 2025, is attached in the Appendix (page VII); a similar version is published as also as a preprint at EarthArXiv. Cite as:

Káldy, E., Fischer, T. and Doubravová, J. **Local Seismicity: Matched Filter Detection Routine with Synthetic Templates using 1D velocity model**. Preprint at *EarthArXiv*, Submitted to *Seismica*, 2025. doi: 10.31223/X5MQ88

1.5 Practical Outcomes

In addition to the published articles, several outcomes of this cumulative PhD study are expected to have practical applications:

- Derivation of **station corrections for the GRSN network** based on regional earthquakes from the Lubin area [Fig. 1a, Káldy and Fischer (2023), Tab. 2; Káldy and Fischer (2025), Tab. 3]. These corrections are essential for accurate magnitude estimation also during the monitoring of induced seismicity.



(a) (b)

Figure 1: Station and network corrections derived from regional Lubin (Poland) earthquakes by blue circles with error bars representing standard deviations σ. (a) GRSN – corresponding to Káldy and Fischer (2023), Tab. 2. (b) WEBNET – red stars are station corrections derived by Hanka Čermáková (Čermáková and Horálek, 2015).

- Validation of **station corrections for the WEBNET** network using regional events from the Lubin area (see Fig. 1b). A notable discrepancy was found in the correction values for the NKC and LBC stations - both located near the swarm activity - which may reflect the influence of the dominant focal mechanism on the station correction estimates when derived from local seismicity (Čermáková and Horálek, 2015).

- **Velocity model** for sedimentary layers in the Litoměřice region [(Káldy and Fischer, 2025) Tab. 1 and Fig. 2] — the developed 1D velocity model has already been used as an initial model in an active seismic survey conducted in the area.

- **Green's functions**, which can be converted to synthetic seismograms for Bohemian Cretaceous Basin (sedimentary area) in Litoměřice, are available at greens-mill.pyrocko.org (Káldy and Fischer, 2025).

- The **Python codes for** detection, location and focal mechanism estimation by **Synthetic Template Matching**, including an example usage, is publicly available at Google drive (All will be transferred to Zenodo when the article is approved by reviewers, Káldy et al., 2025).
- Method of network sensitivity from noise (Káldy and Fischer, 2023) applicable to other regions, especially regions where the amplitude-based detector is operating.
- The demonstrated detection capability of the local seismic network (**network sensitivity** in Litoměřice provides essential support for the seismic safety assessment of the planned EGS system (Káldy and Fischer, 2025, 2023).

2 Introduction

This dissertation focuses on the development and testing of a novel seismic detection method in the context of the Enhanced Geothermal System (EGS) project in Litoměřice (Šafanda et al., 2020; Fischer et al., 2023), Czech Republic. Over the years, the design of the planned geothermal well has evolved, with the proposed depths of the EGS varying between 5 km and 2 km. Regardless of these changes, continuous seismic monitoring remains a critical requirement due to the risk of induced seismicity associated with the future injection of subsurface fluid.

During several years of preliminary seismic monitoring, no natural seismicity was recorded in the vicinity of the planned EGS, nor within tens of kilometers around the Litoměřice site, nor was any induce seismicity detected during the hydraulic tests (Fischer et al., 2023). However, it is crucial to determine the minimum magnitude of seismic events that could be detected in the event that future EGS operations induce seismicity. Therefore, the sensitivity of the existing seismic network was assessed using two methods: The first method was based on evaluating the seismic noise levels at each station (Káldy and Fischer, 2023), while the second involved superimposing synthetic seismograms onto real noise records to simulate and assess the detectability of potentially induced earthquakes (Káldy and Fischer, 2025). Both of these approaches evaluate sensitivity in the context of the currently implemented automatic detection and location system, PEPiN (Fischer, 2003b; Káldy and Fischer, 2025).

Efforts to improve detection capabilities led to the development of a new detection methodology that constitutes the central theme of this dissertation. This method is based on the well-established template matching technique, which excels at detecting signals below the noise level but is inherently limited to identifying events similar to those already observed (Shelly et al., 2006; Janská and Eisner, 2012; Gibbons and Ringdal, 2006). In some circumstances, this limitation can be addressed by a linear combination of known templates (subspace detector, Harris, 1991), or by matching synthetic seismograms reflecting the real seismicity (Chamberlain and Townend, 2018; Rodgers et al., 2006). In contrast, the newly developed *Synthetic Template Matching* (STM) approach is designed specifically for aseismic regions. It generates artificial templates that simulate realistic seismic waveforms for a range of source locations and focal mechanisms within the monitoring network; these templates are independent of expected seismicity.

This thesis comprises four articles published as open-access (or currently under review) in peer-reviewed journals: one (Káldy and Fischer, 2023) in the international

Journal of Seismology (impact factor 1.6), another (Fischer et al., 2023) in the journal *Geothermics* (impact factor 3.5), and two (Káldy and Fischer, 2025; Káldy et al., 2025) in the Diamond Open Access journal *Seismica*, which is expected to receive its first impact factor in 2025. The first two articles (Káldy and Fischer, 2023, 2025), where I am the first author, focus on the assessment of the sensitivity of the seismic network. The third article (Káldy et al., 2025), currently under review, introduces and evaluates the newly developed *Synthetic Template Matching* (STM) method. The fourth article (Fischer et al., 2023), where I am the last author, reports on hydraulic stimulation tests and their seismic monitoring.

Most of the introduction to methods is presented through individual publications; in the following sections, I provide compilation and comparison of topics relevant for the whole thesis.

2.1 Monitoring induced seismicity

Induced and triggered seismicity refers to earthquakes that result from human activities, particularly those involving subsurface operations. Such seismic events are increasingly associated with industrial processes including hydraulic fracturing (fracking, Clarke et al., 2014; Schultz et al., 2020; Fischer et al., 2023), geothermal energy production (Deichmann and Giardini, 2009; Gaucher et al., 2015; Koirala et al., 2024; Káldy and Fischer, 2023, 2025), CO_2 storage (overview in Cheng et al., 2023), wastewater injection (Janská and Eisner, 2012), and mining (Kaláb et al., 2007). These activities alter the stress state and fluid pressure in the Earth's crust, potentially activating preexisting faults or fractures. In some cases, even small perturbations can trigger seismic events, especially in critically stressed regions. Although most of these events are of low magnitude and are not felt on the surface, a subset can exceed magnitude 3 or 4, posing potential risks to infrastructure and public safety [The list of significant induced earthquakes is in Zang et al. (2014), a plain summary of induced seismicity in the Introduction of Káldy and Fischer (2023)].

Monitoring of induced seismicity requires the deployment of local seismic networks designed with high sensitivity and tailored detection methodologies. The optimal interstation spacing depends on the expected depth of seismic events and the sensitivity of the instruments deployed. For shallow sources, such as those typically associated with enhanced geothermal systems or wastewater injection, it is generally recommended that the station spacing does not exceed twice the minimum target depth, in order to ensure adequate azimuthal coverage and reliable detection capability (Hallo, 2012). Since induced microseismic events often occur in the high frequency range (commonly between 1–20 Hz, my study), short-period seismometers are typically sufficient for detection purposes. However, broadband sensors are frequently included in network configurations to facilitate the broader applicability of recorded data. In addition, a receiver near the geothermal system or wastewater injection can increase the detection and location capacity of a network.

In some countries, national guidelines for monitoring EGS or other underground operations stipulate minimum sensitivity requirements (Kraft et al., 2020; Braun et al., 2020). The achievement of the prescribed sensitivity of seismic networks requires not only the proper geometry of the network, but also knowledge of the local noise environment and the instrumental response characteristics of the individual stations (Káldy and Fischer, 2023).

Note that unlike long-term security monitoring of induced seismicity discussed above, induced seismicity during hydraulic fracturing operations is often monitored using dense arrays composed of hundreds of single-component geophones arranged in a star-like (radial) pattern, supplemented by a few three-component stations and several borehole sensors. Its primary objective is high-resolution imaging of fracture growth for reservoir characterization and operational control (Anikiev et al., 2014). This type of monitoring is mentioned here only for completeness; it is not part of the research conducted or analyzed within the scope of this thesis.

2.2 Micro-seismic detection and location methods

Seismic detection methods can be broadly categorized into two main classes: waveform-based and pick-based approaches (Zhang et al., 2019; Grigoli et al., 2018). The waveform-based category encompasses techniques that utilize full waveform information, such as back-projection methods, which enable event detection and location independently of precise P- or S-phase picks. Although computationally demanding due to the processing of entire waveforms, energy traces, or envelopes, these methods generally exhibit superior detection performance compared to their pick-based counterparts (Grigoli et al., 2018; Perol et al., 2018; Grigoli et al., 2013).

In contrast, pick-based methods rely on the association of identified P and S arrivals with individual seismic events. These approaches are commonly employed in continuous monitoring, particularly in the context of induced seismicity. The most widely adopted techniques include the traditional Short-Term Average over Long-Term Average (STA/LTA) algorithms, matched-filter methods, and, more recently, machine learning-based frameworks. STA/LTA algorithms are computationally efficient and suited for real-time applications, but their performance degrades under high-noise conditions and often fails to detect events of low magnitude (Allen, 1978, 1982; Velasco et al., 2016). Enhancements using polarity filters can improve the accuracy of phase identification, particularly for P and S arrivals (Fischer, 2003a; Káldy and Fischer, 2025).

Matched-filter techniques, based on cross-correlation with pre-existing waveform templates, substantially improve detection sensitivity and are particularly effective for identifying repeating or similar events. However, they require a priori template databases and incur a significant computational cost (Gibbons and Ringdal, 2006; Janská and Eisner, 2012). Missing template events can be replaced by a combination of existing templates (Harris, 1991) or using synthetic waveforms for detection (Káldy et al., 2025; Chamberlain and Townend, 2018).

More recently, machine learning methods, including convolutional neural networks (CNN, Dokht et al., 2019; Perol et al., 2018; Zhang et al., 2020) and artificial neural networks (ANN, Doubravová and Horálek, 2019), have shown considerable promise for seismic detection, particularly in noisy or complex environments (Perol et al., 2018). These techniques can outperform traditional algorithms in terms of sensitivity to weak events but typically require large, labeled training datasets and may suffer from limited interpretability.

The selection of an appropriate detection methodology depends on factors such as the availability of prior seismic data, computational capacity, and specific monitoring objectives. Further discussion of detection approaches tailored to microseismic monitoring is provided in the introduction of Káldy and Fischer (2025), with a general overview of standard detection workflows presented in the following section. A comparative evaluation of three detection methods is detailed in Káldy et al. (2025).

2.2.1 Example procedures for seismic event detection and association

When pick-based detection and location method is applied, it's typical processing has structure as follows. It involves three stages: detection, association, and location (Grigoli et al., 2018).

The input consists of waveform recordings from all stations in a local network along with their coordinates. Each seismogram has three components: the vertical component is particularly important for detecting P waves, while the two horizontal components are essential for S-wave detection. The seismograms are commonly bandpass filtered to enhance signal over noise; conversion of the amplitudes to absolute values, or to envelopes by the Hilbert transform, or to polarization-based function might be beneficial.

Detection typically involves scanning the signal — sometimes separately for each component, though more often per station as a whole — using a sliding window algorithm or filter. This is done either through classical STA/LTA (Short-Term Average over Long-Term Average) methods or via cross-correlation with waveform templates. These operations transform raw seismograms into similarity functions: the so-called characteristic functions (Káldy and Fischer, 2023, Fig. 4) or the correlation similarity curves (Káldy et al., 2025, Fig. 4).

Values of these similarity functions that exceed a given threshold on a single station are interpreted as potential seismic arrivals and are referred to as triggers. In ideal cases, the trigger can also be classified as a P-wave or S-wave arrival, based on the component or polarization. The output of this first detection stage is a list of P and S triggers recorded at individual stations.

The second phase, known as association, involves grouping these triggers into individual event detections. The logic used to associate triggers depends on the specific association algorithm. The simplest form defines a fixed time window within which multiple station triggers are grouped into a single event. If several triggers from the same station fall within the window, the one with the highest amplitude or similarity is typically selected.

However, this naïve approach ignores the geometry of the source–station configuration within the network. Therefore, it is essential to ensure that the arrival times at the stations are physically consistent with a plausible earthquake location. This can be achieved by using the set of P and S triggers as input for a location procedure, which attempts to find a hypocenter that fits the observed arrival times. The quality of this location is then evaluated based on the RMS (Root Mean Square) of the arrival-time residuals, providing a quantitative measure of the fit between the data and the hypothesized source (Káldy and Fischer, 2025, Section 3 Methodology: PEPiN – Detection and Location Algorithm).

More sophisticated associators, such as REAL (Rapid Earthquake Association and Location, Zhang et al., 2019) or PhaseLink (Ross et al., 2019), use the delay and sum approach, probabilistic or machine learning techniques to improve association robustness, especially in dense or complex seismic networks.

The final stage of the seismic processing workflow, the location of events, involves minimizing the discrepancy between the observed arrival times of the P and S phases and their theoretical predictions based on a velocity model. This procedure can be carried out using either absolute or relative location techniques. In the absolute approach, each event is located independently based on observed arrivals, while relative location methods, such as the double-difference algorithm implemented in `HypoDD` (Waldhauser, 2001), optimize the relative positions of clustered events by minimizing residual travel-time differences across shared ray paths.

In some cases, particularly in high-throughput or template-based detection workflows, the location can be approximated by assigning the event the coordinates of the matched template. Alternatively, a preliminary location, such as one derived from a coarse-grid search used during initial association or clustering, may serve as the starting point or final assignment if computational efficiency is prioritized. The accuracy of the resulting locations strongly depends on the quality of the velocity model, the density and geometry of the seismic network, and the precision of the phase picks.

2.3 Seismic network sensitivity: Parameters

To characterize the performance of a seismic network in combination with the implemented detector, two key magnitude-based parameters were used: the *magnitude of completeness* (M_C) and the *minimal detectable magnitude* (M_m). These parameters reflect different aspects of the network's ability to detect seismic events and can be both used in mapping the sensitivity across space. The detector's performance can also be characterized by the false-event ratio and the accuracy of earthquake locations.

The **magnitude of completeness** (M_C) is defined as the lowest magnitude at which the catalog of detected seismic events can be considered complete, i.e., where the frequency-magnitude distribution starts to follow the expected Gutenberg–Richter law, determined using the maximum curvature method in these studies (Wiemer and Wyss, 2000; Leptokaropoulos and Gkarlaouni, 2016; Pavlenko and Zavyalov, 2022).

The **minimal detectable magnitude** (M_m) refers to the lowest possible magnitude that the network detects, providing a theoretical limit of sensitivity (Yang et al., 2021; Káldy and Fischer, 2023).

The detector's performance can also be characterized by the false event ratio, the accuracy of earthquake locations, and, when compared to other methods, also by the percentage of events missed at a certain magnitude.

2.4 Regional Focus: Litoměřice and West Bohemia

This dissertation focuses on two key regions in the Czech Republic (Europe): Litoměřice (GRSN seismic network) and West Bohemia (WEBNET seismic network). The town of Litoměřice, the main area of interest, is a target for EGS development but exhibits no natural seismicity, limiting direct testing opportunities. In contrast, West Bohemia experiences frequent natural seismic swarms and serves as a validation site for methods and concepts that cannot be initially applied in aseismic environments. The similarity of these networks is that the spacing between stations is approximately the minimal depth of (expected) seismic events: 2 km in Litoměřice, 6 km in West Bohemia. Although the geology of these regions is different (sedimentary basin in Litoměřice vs. metamorphic baserock in West Bohemia (Czech Geological Survey, 2025), an identical local magnitude (M_L) calculation is used, supported by records of regional seismicity from Lubin (Káldy and Fischer, 2023). See an overview map of the permanent seismic networks of GRSN and WEBNET in Káldy and Fischer (2023, Fig. 1).

The permanent network GRSN was temporally extended by 18 stations for a more detailed monitoring of hydraulic tests in 2020. An overview map can be found in Fischer et al. (2023, Fig. 5).

3 Methods

In the following, a brief summary of the key methods utilized or developed during Ph.D. studies is provided. A more detailed explanation of individual steps, assumptions, and validation is provided in the relevant chapters of the original articles (Káldy and Fischer, 2023, 2025; Káldy et al., 2025).

3.1 Seismic network sensitivity

The sensitivity of local seismic networks, primarily the GRSN in Litoměřice, was evaluated using two complementary approaches: (1) an analytical estimate based on ambient noise levels and network geometry and (2) a simulation-based method utilizing synthetic seismograms superimposed on real noise records.

The first method is a theoretical approach that estimates the minimum detectable S-wave amplitude at each station based on long-term RMS noise levels and empirical knowledge of the peak-to-noise ratio (PNR) required to detect the weakest earthquakes using the applied algorithm (PEPiN, in this case). By combining the relationship between S-wave amplitude, magnitude, and hypocentral distance (Čermáková and Horálek, 2015) with RMS noise values derived from 100 days of recordings, a 3D sensitivity volume was constructed. This method assumes that an event is detectable if the theoretical amplitude of the S-wave exceeds the noise level at a minimum of five stations, reflecting the configuration of the detection algorithm requiring trigger at four stations. The one additional station is required to register a theoretical S-wave above the noise level to account for amplitude variation due to focal mechanism radiation patterns. The resulting 3D maps represent the minimum detectable magnitude M_m within the monitored volume. The conversion from M_m to the more operationally relevant magnitude of completeness M_C is performed by requiring two additional stations (that is, seven in total) or by using a higher noise threshold, such as the 90^{th} percentile instead of the RMS. A detailed explanation of this methodology is provided in *Methodology* section of Káldy and Fischer (2023).

The second method offers a more realistic performance assessment by injecting synthetic seismic events - modeled using Green's functions and regional velocity models - into real background noise recordings. For the Litoměřice region, the synthetic seismograms were intentionally designed to be challenging for the detector, as they incorporate two different 1D velocity models, resulting in complex waveform characteristics (Káldy and Fischer, 2025, section Methodology: Synthetic seismograms). The synthetics were generated for a single focal mechanism and a single source location but span a range of magnitudes following the Gutenberg–Richter distribution. These hybrid records (synthetics superimposed on real noise) are then processed using the PEPiN detection algorithm, enabling the evaluation of detection rate, magnitude completeness, false positive rate, and location accuracy.

3.2 Detection by Synthetic Template Matching

Synthetic Template Matching (STM, Káldy et al., 2025) was developed as a waveform-based detection approach that can be used even in aseismic regions where no real templates are available. The method uses synthetic seismograms generated from a 1D velocity model to simulate a dense grid of potential (synthetic) earthquake sources with a limited set of fundamental focal mechanisms. These templates are cross-correlated with continuous seismic data to identify events with similar waveforms, even below the conventional noise level.

Due to discrepancies between the real velocity structure and the simplified 1D velocity model used for simulation, the relative arrival times of the real and synthetic waveforms differ. This arrival time error (maximum noted as t_{err}) prevents the use of standard template matching techniques, which assume consistent timing across stations (Káldy et al., 2025, see the middle bar in Fig. 4). However, the detection procedure can be adapted by smearing the station-wise similarity functions before summing them, thus compensating for timing mismatches (Káldy et al., 2025, see section *Match filter detection routine – Modification for Synthetic Templates*, Fig. 4). The smearing is applied over a window of $\pm 0.5\, t_{err}$, where t_{err} can be estimated based on the event–station geometry and the uncertainty of the velocity model (around 10% for the West Bohemia region, Málek et al., 2005). This smearing has potential also in the standard template matching.

Another key difference between standard template matching and the Synthetic Template Matching (STM) approach lies in the number of templates that detect a single event. While standard template matching typically relies on one or a few known templates, STM employs a dense grid of synthetic templates, often numbering in the thousands. As a result, thousands of templates may match a single event. In the resulting catalog, the location of the event is assigned according to the template with the highest similarity, while the focal mechanism is estimated by combining information from all matching templates with a similar location. Specifically, the focal mechanism is derived as a linear combination of the moment tensors of these templates, weighted by their similarity values, adjusted by subtracting the minimum similarity within the group of final location.

This modification of template matching allows the STM to be an automated detection, localization, and focal mechanism estimation of microearthquakes in regions lacking historical seismicity, offering a scalable and transferable method for early-stage seismic monitoring in induced or emerging seismic environments.

4 Review of Results

This section brings together the results of multiple case studies aimed at assessing the sensitivity of local seismic networks and the performance of various detection algorithms in both aseismic and seismically active regions. The focus is primarily on the Litoměřice area, where potential induced seismicity may occur in the future, and where detection capabilities were evaluated using two complementary sensitivity estimation methods combined with the PEPiN detection algorithm. For comparison and validation purposes, an established seismic region in West Bohemia was used to test a new Synthetic Template Matching (STM) method against existing detectors (PEPiN and ANN). The results provide a practical overview of the strengths and limitations of each approach, highlighting the influence of network geometry, geological conditions, noise environment, and algorithm design on overall seismic monitoring effectiveness.

4.1 Litoměřice aseismic region - network sensitivity

The sensitivity of the seismic network in Litoměřice was evaluated using two methods, both applied in combination with the detection algorithm PEPiN. The first method, which estimates detectability based on ambient noise levels, is more theoretical and required tuning and validation using data from the West Bohemia region. The outcome is a 3D network sensitivity map, illustrating the minimum detectable magnitude or the magnitude of completeness throughout the monitored volume (Káldy and Fischer, 2023, Fig. 8, 9, 10). The second method, based on superimposing synthetic seismograms onto real background noise, was utilized in two studies. In the study by Fischer et al. (2023), superimposed synthetics tested the ability of the source scanning algorithm to detect fracking-caused earthquakes at depth 0.9 km while using an extended network of 24 stations. In the study by Káldy and Fischer (2025), it tested the ability of PEPiN (Fischer, 2003b) to detect earthquakes at depth 2.0 km with only the permanent network. The second case study offers a more robust and realistic test as a result of the complexity of the waveforms. Although our approach is spatially limited to a single injection point, it enables an assessment of the precision of the location by PEPiN (Káldy and Fischer, 2025, detectability: Fig. 7, 9; and location accuracy: Fig. 11, 12). A simplified overview of GRSN sensitivity in terms of magnitude completeness M_C and minimal detectable magnitude M_m is presented in Tab. 1.

When comparing the sensitivity of the eight-station subset of the GRSN network, the estimated magnitude of completeness near the planned EGS well (assuming a

Stations for detection	Method	M_C	M_m
8 surface	PEPiN + noise level	-0.7	-1.0
8 surface	PEPiN + synthetic earthquakes	-0.5	-0.7
9 surface + 2 borehole	PEPiN + synthetic earthquakes	-0.7	-0.9
24 surface (6 permanent + 18 temporal)	source scanning algorithm + synthetics (depth 0.9 km)	-2.2	-2.5

Table 1: **GRSN network sensitivity** in terms of magnitude completeness M_C and minimal detectable magnitude M_m **at the EGS location, at 2 km depth** (beside the last row). By *Method* we understand method for Detection + method used for determining the sensitivity. For method *PEPiN + noise level*, M_C is from Fig. 10 in Káldy and Fischer (2023), M_m from Fig. 9 in Káldy and Fischer (2023). For method *PEPiN + synthetic earthquakes*, both M_C and M_m are from Fig. 7(9) for 8(11) stations in Káldy and Fischer (2025). The sensitivity of 24 station network, tested with synthetic sources at depth 0.9 km and detection method *source scanning algorithm* is described in Fischer et al. (2023).

source depth of 2 km, Tab. 1) is approximately $M_L = -0.7$ based on the noise analysis method and $M_L = -0.5$ based on the synthetic event injection approach (Tab. 1). The difference of 0.2 magnitude units is relatively small and lies within the uncertainty of magnitude estimation in West Bohemia, where this method for M_L originates (Čermáková and Horálek, 2015).

Superimposing synthetic earthquakes on real seismic recordings in Káldy and Fischer (2025) enabled two key evaluations: (1) an assessment of how many events are missed despite being above the estimated magnitude of completeness and (2) a comparison between the preliminary locations derived from PEPiN and the single known (simulated) event location. The results show that using eight GRSN surface stations with PEPiN, 82% of events with magnitudes above $M_L = -0.5$ were detected, while none above $M_L = 0.5$ were missed (Káldy and Fischer, 2025, Fig. 7). However, the preliminary location of the events deviated approximately 1 km from the known source, forming a linear pattern suggestive of a fault structure that was not part of the synthetic input (Káldy and Fischer, 2025, Fig. 11).

When using the complete GRSN configuration (9 surface + 2 borehole stations) with PEPiN, the detection rate was 78% for events greater than $M_L = -0.7$ (Tab. 1, Káldy and Fischer, 2025, Fig. 9). Notably, two strong events with magnitudes around $M_L \approx 1.5$ were unexpectedly missed. Additionally, the resulting preliminary locations split into two spatially distinct clusters approximately 1 km apart (Káldy and Fischer, 2025, Fig. 12). These results highlight both the capabilities and current limitations of the PEPiN detection and location system in complex network configurations.

Although it was not the main focus of the study by Fischer et al. (2023), the alternative of M_C and M_m was evaluated for the GRSN network, which at the time consisted of six permanent stations temporarily extended by an additional 16 stations (Tab. 1). The sensitivity was assessed specifically for a source depth of 880 m at the injection site, using a source-scanning algorithm based on multichannel cross-correlation.

When comparing the sensitivity of two local networks, the average of the magnitude completeness maps is compared in a small region (Káldy and Fischer, 2023, Fig. 7). The sensitivity of the GRSN seismic network surrounding the planned EGS site in Litoměřice is approximately $M_L = -0.6$ at a depth of 2 km. A comparable level of sensitivity is achieved in West Bohemia, but only at greater depths of around 7 km. This highlights that geological conditions and industrial noise levels have a more significant impact on network sensitivity than inter-station spacing alone. In other words, favorable site conditions in West Bohemia partially compensate for the sparser network configuration, whereas the shallower sources and higher ambient noise in Litoměřice limit sensitivity despite denser station coverage.

4.2 West Bohemia swarm region - evaluating new detection method

Although the thesis is focused on the aseismic region, suitable detection methods require testing in a seismically active and well-monitored region: West Bohemia in this case. In Tab. 2, the detection capacities of newly developed Synthetic Template Matching (STM) is compared with the methods established in West Bohemia: Artificial Neural Network (ANN) and PEPiN (Káldy et al., 2025) and with predicted network sensitivity (Káldy and Fischer, 2023). The magnitude completeness M_C and the minimal detectable magnitude M_m in Tab. 2 reflect the ability of the methods to detect natural seismicity both within and slightly outside the network, using a WEBNET subset of 8 stations.

Although STM does not outperform established methods in terms of magnitude completeness M_C and minimal detectable magnitude M_m (Tab. 2) it does provide two benefits: (1) automatic location which varies from manually determined epicenters 1.2 km, comparable to grid spacing 1.0 km (Káldy et al., 2025, Fig. 6 and section *4.3 Location by Synthetic Template Matching*); and (2) automatic estimate of focal mechanism, which mainly correlates with FM of the region by Vavryčuk et al. (2022), surprisingly, it correlated better for weaker events (Káldy et al., 2025, Fig. 10b).

Method	M_C	M_m
Synthetic Template Matching (STM), *xc 0.4*	-0.1	-0.65
Synthetic Template Matching (STM), *xc 0.35*	-0.3	-0.8
Artificial Neural Network (ANN)	-0.7	-1.2
PEPiN	-0.5	-1.2
PEPiN + sensitivity from noise level	-0.5	-1.1

Table 2: **WEBNET network sensitivity** in terms of magnitude completeness M_C and minimal detectable magnitude M_m during test day 18^{th} May 2018 (all the activity in the test region, not only a specific location). M_C is taken from Fig. 5a in Káldy et al. (2025), M_m is estimated from Fig. 5a, 7ab in Káldy et al. (2025) together with the corresponding detection catalogs, and reflecting the M_m in Fig. 7, Káldy and Fischer (2023). For the theoretical estimate of network sensitivity from noise level *PEPiN + sensitivity from noise level*, M_m and M_C are the average values for depth 6-10 km based on Fig. 7 in Káldy and Fischer (2023).

5 Discussion: Future Directions

During synthetic testing of seismic network sensitivity (Káldy and Fischer, 2025), a limitation was identified in the applicability of the PEPiN detection and association algorithm when used with the GRSN network, particularly in configurations where downhole sensors were deployed near existing surface stations. An initial attempt to adapt the associator component of PEPiN to accommodate this setup did not yield satisfactory results. Potential solutions include replacing the current associator with an alternative (such REAL by Zhang et al., 2019), treating the downhole receivers as standalone stations, or implementing an AI-based detection system such as Qseek (Isken et al., 2025). Preliminary Qseek tests on GRSN data have already been started (J. Vlček, personal communication).

Implementing the Synthetic Template Matching (STM) method within the GRSN network could serve as a complementary approach; however, PEPiN currently outperforms STM in terms of magnitude completeness, limiting the practical benefit of STM as a primary detection method.

Given that the EGS borehole operations are planned for 2026, it is critical that the GRSN network be fully optimized by the end of 2025. This includes resolving the integration and operational deployment of borehole sensors to ensure maximum detection sensitivity and reliable event association in the vicinity of the EGS site.

Additional potential applications of the methods presented in the published articles include: (1) estimating the sensitivity of a temporary seismic network comprising approximately 300 stations in West Bohemia, planned for deployment in autumn 2025 as part of the Eger Large Seismic Experiment (ELISE). This network will support regional seismic tomography, detection of weak seismic events, and Qseek tests. Sensitivity estimates will rely on ambient noise analysis and updated station correction factors; and (2) further testing of the Synthetic Template Matching (STM) method at other locations, with a particular focus on evaluating its accuracy in determining focal mechanisms for events occurring within the monitored area.

6 Conclusion

The article-based dissertation contributed to the field of local seismicity monitoring in regions without natural seismic activity, with a particular focus on areas with potential for induced seismicity. Although no seismic events were recorded in the Litoměřice area during the monitoring period, the methodologies developed and tested in this work provide significant insights into the capabilities of seismic networks to detect potential anthropogenic earthquakes.

The first study (Káldy and Fischer, 2023) introduced a novel workflow for estimating 3D network sensitivity in aseismic regions. This approach utilizes real noise levels and station geometry to calculate the minimum detectable earthquake magnitude, integrating it with the PEPiN detection algorithm based on the S-wave amplitude. The method is applicable even in the absence of seismic events and offers a quantifiable way to assess the performance of the network in real world conditions.

The second study (Káldy and Fischer, 2025) evaluated the performance of the PEPiN automatic detector and locator using realistic synthetic seismograms created for the Litoměřice region. The tests confirmed that even under real noise conditions, including daily variability, PEPiN successfully detected the majority of synthetic events with magnitudes greater than $M_L = -0.5$. These results validated previous sensitivity estimates and demonstrated the robustness of automated detection in areas with low seismicity.

The third part of the thesis (Káldy et al., 2025) extended the detection capabilities using a matched-filter routine based on synthetic waveform templates. Originally limited to regions with known seismicity, this method was successfully applied using synthetic waveforms generated from 1D velocity models and a small set of fundamental focal mechanisms. Despite the approximations involved, the method proved effective in estimating focal mechanisms and confirming event locality in real data.

The fourth, minor, part of this thesis (Fischer et al., 2023) monitors shallow hydraulic injection tests with no seismicity recorded down to $M_L = -2.2$.

In summary, this dissertation provides a comprehensive view of various approaches for assessing the ability to detect local seismicity in seismically quiet regions. The tools and methods developed, especially those that use synthetic data, contribute to improved preparedness for potential induced seismicity and support decision-making in the planning of deep geothermal or other subsurface projects.

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Appendix

Article 1:

Microseismic network sensitivity in case of no seismic activity

Káldy, E. and Fischer, T. Microseismic network sensitivity in case of no seismic activity. *Journal of Seismology*, 27(4): 627–641, 2023. doi: 10.1007/s10950-023-10134-y

Article 2:

Hydraulic injection tests in the pilot EGS borehole PVGT-LT1 in Litoměřice, Czechia

T. Fischer, J. Vlček, P. Dědeček, J. Řihošek, G. Zimmermann, J. Holeček, M. Mazanec, L. Rukavičková, L. Janků, E. Káldy Hydraulic injection tests in the pilot EGS borehole PVGT-LT1 in Litoměřice, Czechia. *Geothermics*,115: 102805, 2023. doi: 10.1016/j.geothermics.2023.102805

Article 3:

Performance of Automatic Detector & Locator Tested on Synthetic Seismograms: Case Study from Litoměřice in Czech Republic.

Káldy, E. and Fischer, T. Performance of Automatic Detector & Locator Tested on Synthetic Seismograms: Case Study from Litoměřice in Czech Republic. *Seismica*, 4(1), Apr. 2025. doi: 10.26443/seismica.v4i1.1373

Article 4:

Local Seismicity:
Matched Filter Detection Routine with Synthetic Templates using 1D velocity model

The following pdf version of the article was submitted to Seismica on 18*th* June 2025, a similar version is published as a preprint at EarthArXiv:

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