Real-time Forecasting and Operational Control of Perceivable Induced Seismicity in Geo-Energies

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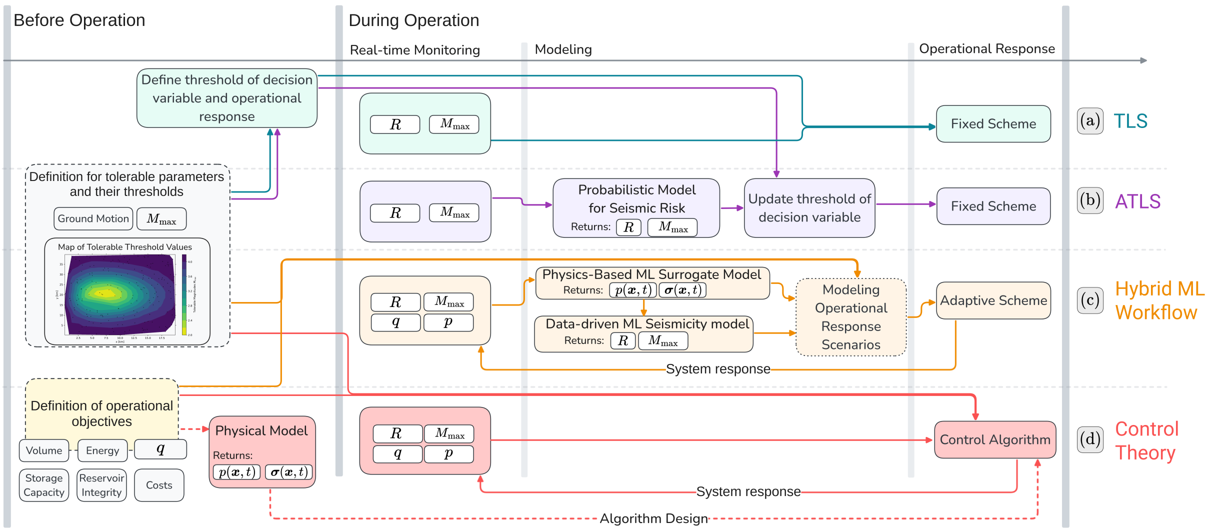
Abstract

Geo-energies, including enhanced geothermal systems, geological carbon storage, and underground hydrogen storage, are essential for decarbonizing the energy and heavy industry sectors. However, their widespread implementation is hindered by the risk of perceivable induced seismicity. This review begins by evaluating existing seismic hazard mitigation schemes, particularly the traffic light system (TLS) and its advanced variants. While these schemes are practical, they have proven unreliable in fault-dominated reservoirs, as demonstrated by the shutdown of the Pohang EGS following a M_{w} 5.4 event. Building on these lessons, we propose a paradigm shift: The next generation of induced seismic hazard management schemes has to fully integrate data processing, probabilistic physics-based reservoir models, and operational response schemes into a single workflow. To this end, we review machine learning (ML) techniques for creating surrogate models trained on physics-based simulations and discuss how linking these models to observed seismicity enables near real-time forecasting. Such hybrid workflows would empower geo-energy operators to make informed, scenario-based decisions, balancing seismic risk with economic profitability. Additionally, we examine recent advances in applying control theory to geo-energy operations, aiming to prevent induced seismicity while maximizing production. These integrated workflows hold the potential for active operational control and possibly full mitigation of perceivable induced seismicity, paving the way for large-scale, socially acceptable deployment of geo-energies.

Graphical Abstract



Comparison of Workflows for Seismic Hazard Mitigation

Highlights

1. Geo-energies support decarbonization, yet induced seismicity hinders their expansion.
2. Existing workflows to mitigate induced seismicity fail in complex reservoir domains.
3. Machine learning links probabilistic seismicity models and physical reservoir models.
4. Control algorithms simultaneously minimize seismicity while optimizing production.

List of Acronyms

ATLS Adaptive Traffic Light System

EGS Enhanced Geothermal System

GCS Geological Carbon Storage

PINNs Physics-Informed Neural Networks

TLS Traffic Light System

1 Introduction

Geo-energies have the potential to significantly contribute to reduce carbon emissions to mitigate the climate emergency through (1) clean and reliable geothermal energy [70], (2) geologic carbon storage and utilization to eliminate emissions from hard-to-abate industries [96] and (3) subsurface energy storage like underground hydrogen storage and utilization [16]. These geo-energies imply injecting and extracting fluids, which alter the *in situ* conditions in the subsurface and eventually destabilize faults, inducing earthquakes.

The safe management and mitigation of felt induced seismicity remains one of the major challenges in geo-energy applications. In fact, it is a decisive factor for geo-energy projects to scale up by two orders of magnitude by the mid of the century to reach the Paris Agreement's objective of net-zero emissions [164]. This objective requires (1) to provide sufficient renewable energy through geothermal sources (from the current 16 GWe to more than 200 GWe), (2) to permanently store CO_2 deep underground at rates of gigatonnes per year (currently around 40 Mt/year), and (3) to store large amounts of energy (e.g. hundreds of km^3/year of hydrogen storage is estimated to be required) [72, 28, 16]. This significant demand is confronted with the reality that the existing traditional approach to manage injection-induced seismicity in geo-energy projects, known as the traffic light system (TLS), repeatedly failed to mitigate unexpected perceivable events. Notable examples are the magnitude $M_L\,3.4$ induced earthquake in the enhanced geothermal system (EGS) at Basel (Switzerland) [65], the $M_w\,4.1$ in the Castor Underground Gas Storage (Spain) [171], and of $M_w\,5.4$ in the EGS at Pohang (Republic of Korea) [48]. The cancellation of these projects implied multimillion-dollar losses and a severe damage of public trust in the safety of geo-energy operations, hindering their future implementation, at least in the regions where these earthquakes were induced.

The objective of this review is to highlight current practices and to present state of the art methods that could significantly reduce or ultimately eliminate perceivable seismicity associated with production and injection operations of geo-energies.

For this purpose, we evaluate in Section 2 existing and already applied techniques by considering the practical outcomes from nearly two decades of implementation of TLS and its improved versions such as the adaptive traffic light system (ATLS). Although their focus on minimizing seismic hazard remains the most viable option for managing seismic risk, we argue based on multiple historical examples that these management schemes lack the necessary physical complexity to achieve their objective. In addition, we find that the growing demand for geo-energies and the still unresolved control of seismic hazard demonstrate how economic objectives and risk management are inherently coupled and, therefore, should be ideally optimized simultaneously within geo-energy operations. To address this, we identify and combine in Section 3 emerging technologies that have the potential to serve as building blocks for more reliable workflows for meeting both objectives, thus paving the way toward a more trustworthy technology. Specifically, we discuss the latest developments in real-time data processing, continuous forecasting of induced seismicity, and the simulation of operational response scenarios, with a special focus on proposed machine-learning frameworks. The review concludes in Section 4 with recent advances of automating geo-energy operations by adopting control theory. In particular, we showcase the design of application-specific workflows, and how they simultaneously optimize multiple operational objectives, such as operation demands and references of seismic variables, demonstrating a very promising pathway towards fully integrated strategies for seismic hazard management.

2 Existing Strategies for Managing Induced Seismicity

2.1 Traffic Light Systems (TLS)

Mitigation of induced seismicity in geo-energy applications has been traditionally approached by a traffic light method [110]. The traffic light system (TLS) was conceived as a real-time risk management, adapting injection and production operations in response to thresholds of decision variables such as peak ground velocity and/or magnitude of monitored seismicity; thresholds gradually defined by the colors from green to red [19, 144, 167]. The TLS is configured before the injection start and gives directions to the operations when certain thresholds are reached. In general, the green light indicates that operations can proceed as planned. But once the yellow/orange threshold is reached, a decrease of injection rate or duration can be applied instantly or for the next injection cycle, depending on the predefined TLS threshold values and responses. The red light category leads to the cessation of the injection, and sometimes a bleed-off of the well, until an expert assessment considers it safe to re-initiate the operations.

The concept of the TLS is based on the hypothesis that large-magnitude earthquakes are preceded by smaller earthquakes, which should be considered as indicators for reacting and adapting operations in order to minimize induced seismicity in the project; assuming the delay between operations and reservoir responses is sufficiently small [13, 167, 192, 43]. The design of a robust decision-based scheme of operational responses is key for the framework of this approach. TLS are developed jointly by operational and expert committees in coordination with local authorities, depending on the project's type, location, and goals, to anticipate and manage site-specific risks in future operations [18, 51, 169, 192]. As indicated in Figure 1, the first step in the setup of a TLS involves a seismic hazard analysis (SHA) that quantifies the tolerable levels of ground motions for local infrastructure and population and sets the thresholds of peak ground velocity and/or magnitude and the required operational responses of the TLS [73, 167]. The expected maximum magnitude M_{max} during and after the operations is estimated as a function of the objectives of the project, usually based on the target net fluid volume [47, 166, 115].

The TLS framework in geo-energy applications has been meticulously presented by many recent works [20, 143, 142], and for EGS specifically [192]. The first TLS was deployed in 2003 at the EGS of Berlín (El Salvador) [19, 97]. Subsequently, the framework was applied to different geo-energy applications, such as wastewater disposals (e.g., shale gas operations in Alberta (Canada) [21]), long-term gas production (e.g., Groningen (Netherlands) [27, 37]) and geothermal systems (e.g., Cooper and Paralana Basins (Australia) [4, 14]; Otaniemi (Finland) [99]; Landau and Insheim (Germany) [56]; Newberry, Blue Mountain and Utah FORGE (USA) [34, 93, 122, 128]), reported detailed in Table 1 of Baisch et al. [13]. The TLS was generally presented as an efficient protocol to mitigate induced seismicity. However, perceivable seismicity occurred despite the usage of TLS at numerous projects of fluid injection, such as wastewater disposal, underground gas storage, and geothermal projects, exposing the limitations of this approach. These failures of the TLS led to severe consequences, including the interruption and cancellation of the respective projects. The case of wastewater disposal in Oklahoma (USA) illustrates the effects of long-term injections on large-magnitude earthquakes, when the Fairview and Prague earthquakes of magnitude $M_{\mathrm{w}} > 5$ were triggered after years of injections through multiple wells in the area. Subsequent operational decisions led to the reduction of injection rates for several wells and the termination of injection activities for others [15, 53].

Certainly, mitigating induced seismicity poses considerable challenges, as increasing fluid pressure in the reservoir decreases effective stresses and may lead to reactivation of local faults and fractures [85, 52, 22]. In the context of EGS, managing induced seismicity is in particular challenging because fractures are intentionally sheared to enhance permeability, which induces seismicity. The basic assumption of TLS of inferring the expected M_{max} from the target net volume solely assumes isotropic fluid pressure diffusion as triggering mechanism and does therefore not apply to fault dominated reservoirs. This assertion is supported by the experience of numerous projects that have been canceled due to large-magnitude earthquakes that exceeded the TLS thresholds, such as the EGS projects in Basel (Switzerland) [65], Pohang (Republic of Korea) [48] and Strasbourg (France) [140]. The $M_w\,5.4$ Pohang earthquake, the largest magnitude attributed to induced seismicity in EGS, exceeded the maximum TLS threshold by two orders of magnitude two months after the stop of the fifth hydraulic stimulation [48, 54]. Such post-injection seismicity underscores the limited applicability of TLS, as it is unable to anticipate large-magnitude earthquakes occurring after the stop of injection.

Additionally, the case of the Pohang EGS demonstrates why the fixed operational TLS thresholds are far from ideal. Hofmann et al. [69] describe transparently the project's specific TLS implementation and the applied cyclic soft stimulation. They mention that a $M_w 1.8$ event was incorrectly estimated, which was then posteriorly corrected as a $M_w 1.9$ event. However, since the TLS maximum threshold was $M_w\,2$, operations continued as planned and the opportunity to potentially mitigate a large-magnitude event in time was missed. This example illustrates the limitation of rigid thresholds that do not account for uncertainties in the decision variables.

Overall, although the TLS has proven effective in mitigating induced seismicity in various geo-energy projects, such as in Berlín [19, 97] and Otaniemi [99], it cannot be considered a fully reliable mitigation method due to its repeated failures. As mentioned above, perceived seismicity led to the cancellation of numerous projects, resulting in negative public perception and substantial economic losses. For example, the cessation of the Pohang EGS project led to total costs of 300 million dollars [103], while the shutdown of the Castor gas storage project (Spain) will cost Spanish taxpayers a total of 4.7 billion euros [127]. The cases of Oklahoma waste water disposal and Pohang demonstrated the inability of the TLS to forecast and mitigate large-magnitude seismicity particularly during long-term operations, exceeding the scope of prior seismic hazard assessments. A key limitation lies in the reliance of the TLS on the 'maximum volume' postulate, which assumes that the magnitude of induced earthquakes will inevitably increase with continued injection time [115, 13, 20, 167]. Hence, the TLS does not consider the risk of post-injection seismicity within the spectrum of operational responses, making it an unreliable strategy for both ongoing and future projects. This shortcoming is especially critical in the context of large-scale implementation of geo-energies in less favorable geological settings. Moreover, the risk-oriented versions of TLS focus on mitigating induced seismicity rather than operational objectives such as production. This can result in unsuccessful enhancement of permeability, as has happened at the Otaniemi EGS [99, 3]. With no doubt, induced seismicity is triggered by complex coupled mechanisms that are intrinsically challenging to identify and anticipate [85, 52]. To address this complex problem in a practical way, the introduction of the TLS concept was a valuable starting point to reduce seismic hazard. However, it is significantly limited by (1) ambiguously defined thresholds, often grounded in expert judgment, (2) disregard for observed seismicity patterns and propagation during operations, and (3) uncertainty in interpreting event magnitudes. These limitations lead to inadequate operational responses and underscore the urgent need for new tools and methodologies to support the sustainable development of geo-energy applications.

2.2 Advancements of the TLS

Since its initial implementation by Bommer et al. [19], a major advance of the TLS is the adaptive traffic light system (ATLS) [182, 117]. ATLS is a decision scheme for seismic hazard mitigation that defines the threshold values for decision variables based on a quantitative risk assessment, rather than relying solely on regulatory authorities and expert knowledge prior to operations. As shown in Figure 1, ATLS continuously updates the traffic light thresholds, such as ground motion or M_{max} during the operations, as new insights unfold that contribute to a better understanding of the system. The ATLS is forward-looking, using a probabilistic model to determine the adaptation of the flow rate [182]. For example, Mignan et al. [118] proposed an ATLS that can receive inputs from multiple models and weigh them in an ensemble approach, where the weight for each model is chosen based on the confidence in the data. Another early adaptation was the ATLS proposed by Douglas and Aochi [45], which uses the previous 6 h window of observed seismicity in combination with the ground motion curve to compute the current seismic hazard. Moreover, ATLS has the capability to incorporate time series of various parameters as input. For instance, an estimated forecast of the b-value can be derived from the model by Bachmann et al. [11], which associates it with pore pressure diffusion. Subsequently, Langenbruch et al. [100] utilized the progression of the b-value to compute a variable called 'values at induced risk' (VaIR) for estimating potential economic losses in a retrospective analysis of the Pohang induced seismic event. Building upon this research, Ritz et al. [133] propose using the temporal evolution of the b-value as a broad indicator for seismic hazard assessment in EGS projects.

In general, the concept of ATLS receives certain resonance in the scientific community. For example, Templeton et al. [162] proposed the deployment of ATLS for safe operations in geological carbon storage (GCS) projects and Király-Proag et al. [88] evaluated seismic risk for the datasets of the EGS projects of Basel and Soultz-sous-Forêt (France) with an ATLS based on diffusion of the pore pressure. Apart from retrospective analyses, the ATLS has been tested in several subsurface applications, such as in the Bedretto Underground Laboratory for Geosciences and Geoenergies (BULGG) (Switzerland) during hydraulic fracturing and circulation experiments [67], wastewater injection in Oklahoma (USA) [55], at the (re-)stimulation of the Geldinganes (Finland) deep geothermal project [26], and at the Utah FORGE project (USA) [101].

Despite the advantages of being real-time ready, risk oriented and adapting to observed seismicity during project operations, the proposed versions of the ATLS have one major shortcoming: they exclusively consider of the output of probabilistic models, whereas the physical mechanisms that govern induced seismicity are often limited to isotropic fluid pressure diffusion (see further discussion in Section 3.2). The latter assumption limits the applicability of the ATLS forecast to relatively homogeneous reservoir conditions without dominant fault zones [117]. This shortcoming also limits the ability to simulate operational scenarios. As a result, the ATLS fails to offer meaningful operational scenarios to the operator in complex reservoir settings, alternatives that are essential for ensuring the success and economic profitability of geo-energy operations (see Section 1). In conclusion, the ATLS inherited the sole focus on hazard mitigation from TLS, without incorporating operational optimization into its framework (see Figure 1).

We acknowledge both the simplicity and risk-oriented focus of the ATLS, as well as its substantial advancements over the traditional, static TLS (Section 2.1). At the same time, its limitations motivate the following section, which reviews existing research across the key components of seismic hazard mitigation. This body of work suggests a potential paradigm shift: the incorporation of advanced, physics-based models into probabilistic, real-time workflows, as well as the systematic application of control theory. Such frameworks offer significant promise for enabling informed, adaptive operational responses that not only enhance seismic hazard mitigation but also support production optimization.

3 Towards Real-Time Forecasting Based Risk Management of Induced Seismicity in Geo-Energy Operations

Future developments of real-time operational management schemes for geo-energies should consider a paradigm shift toward simultaneous optimization of both minimizing seismic hazard while maximizing operational objectives, including economic benefits [111]. Therefore, we advocate for a stronger integration of physical mechanisms within forecasting workflows, going beyond the mere representation of fluid pressure in isotropic reservoirs. Although prohibitive computational costs were a reasonable argument for mainly deploying analytical probabilistic models for real-time applications [117], novel developments in scientific computing offer an immense increase in scalable parallel computing via CPUs and GPUs. In addition, advances in (physics-based) machine learning and reduced order modeling promise the possibility of uniting the demands of data-driven probabilistic models and interpretable physical models. This development is not a guaranteed success, on the contrary: it poses many new challenges. By providing a visual comparison in Figure 1 between the current mitigation schemes and potential future developments, we contribute to the discussion of prospective innovations for seismic hazard control. Figure 1a and Figure 1b illustrate the workflows of the TLS and the ATLS, respectively, with regard to the objectives and decisions prior to operations versus the real-time processing steps during operations. Additionally, Figure 1c shows a 'Hybrid machine learning (ML) workflow' that combines all the recent developments in the field of real-time modeling with physics-based and data-driven machine learning and the simulation of operational response scenarios. Moreover, Figure 1d exemplifies the steps of a fully automatic operational control scheme based on control theory. The essential components for both workflows in Figure 1c and Figure 1d will be examined in the following.

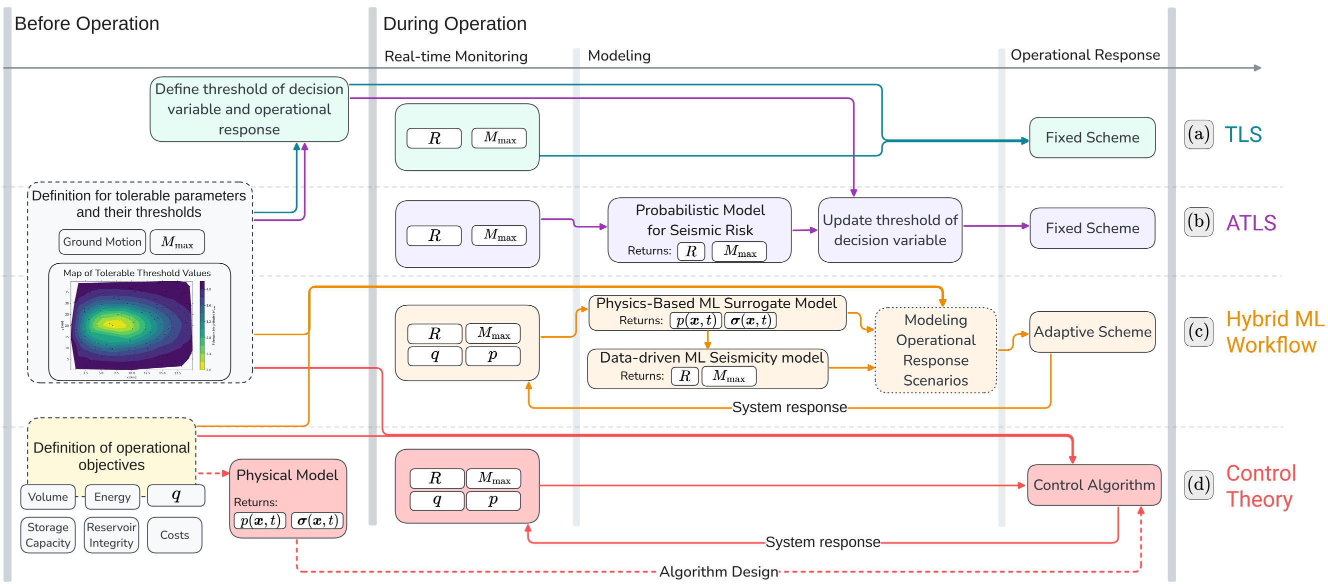


Figure 1 Comparison of Workflows for Seismic Hazard Mitigation. (a) Within the TLS, operators take operational decisions based on pre-defined thresholds of decision variables and operational response variables, namely flow rate. (b) The ATLS adapts the thresholds of the decision variables in real-time during the operations based on the output of a probabilistic model for seismic risk assessment. (c) The proposed hybrid workflow considers operational variables in addition to the seismic catalog as inputs. It creates a physics-based machine learning surrogate model for the state variables. These parameters are linked to the seismicity with a data-driven probabilistic seismicity model. In a subsequent step, the combination of these two models provides a timely forecast for operational scenarios that are used for decision making, in accordance to the operational objectives and the predefined thresholds of tolerable parameters. (d) Other than the hybrid workflow, the workflow based on the control theory automatically enforces both objectives, an optimal production/injection and a controlled seismic risk through automated operational control.

3.1 Real-time Data Processing through Machine Learning

The workflows for real-time mitigation of seismic hazard in Figure 1c rely on on-the-fly data acquisition and processing. Within the industry, the state-of-the-art for the post-processing of seismic data is still mainly performed by manual or semi-manual phase picking [183]. Although phase picking algorithms existed in this field already before the advent of machine learning [145], the latest advances with these cutting-edge algorithms are elevating phase picking to another level. Major innovations in the data processing of natural earthquakes via machine learning are paving the way for real-time processing of seismic catalogs that could be applied in geo-energy projects [94]. An early famous breakthrough example is 'PhaseNet' by Zhu and Beroza [193], which brought unprecedented accuracy in phase picking. In addition to phase picking, Lee et al. [102] were able to compute the earthquake magnitude in real-time for the natural 2019 Ridgecrest earthquake in California (USA). Wang et al. [178] achieved another major step by additionally determining the location of the seismic events, enabling fully automated catalog generation based on the work of Zhang et al. [189] and Waldhauser [173]. In addition to method development, these emerging algorithms are tested for a variety of applications and datasets, such as their effectiveness in detecting microseismic events [114] or assessing ground motion. One major testing site for these emerging technologies is the Utah Forge EGS project (USA) [128]. These developments give rise to the hope that this new generation of machine-learning algorithms will soon be industry-ready products that become a standard to produce real-time seismic catalogs as inputs to forecasting models.

Apart from real-time catalogs, other data crucial for modeling are operational parameters such as the volumetric flow rate q and the injection pressure p_{well}, especially for physics-based models. While measurements of q are usually available at the well head and are measured by the pump itself, wellhead pressures are not always seamlessly monitored, and especially downhole pressures are rather difficult to obtain as long-term time series [184]. However, at least one measurement for q and ideally a few spatially distributed observation points of p would be required as input variables for real-time forecasting models that are based on physics.

3.2 Modeling and Forecasting of Induced Seismicity in Real-Time

Assuming seismic data and operational parameters are available in real-time, we discuss the existing modeling schemes and potential future developments to forecast induced seismicity (see block 'Physics-Based ML Surrogate Model' in Figure 1c). Historically, the induced seismicity modeling domain is shared by two main communities: the seismologic community (from the data perspective), which mainly uses and advocates for the use of probabilistic models, and the community of civil engineering and geomechanics that uses deterministic models based on physical principles such as coupled thermo-hydro-mechanical-chemical-seismic processes [51].

As far as probabilistic models are concerned, a major advantage of them is that they can be computed on-the-fly (recall Section 2.2). An approach suggested for statistical models is to associate the seismic hazard to the flow rate q or to the maximum injected volume V [12, 115], which has already been implemented in several projects among various domains, such as EGS [98] and shale gas extraction [35]. Associated with this assumption, a main movement follows the work of Shapiro et al. [149] considering the fluid pressure variation as the main mechanism triggering induced seismicity. According to this theory, the seismic rate and M_{max} could be inferred from pore pressure changes using the Seismogenic Index [148, 147]. In fact, these models are a simple form of hybrid modeling, since they consider fluid pressure diffusion as a physical mechanism [121]. An example of the applicability of this concept in certain reservoir conditions is provided by Taeho and Avouac [157] who used a convolutional kernel for fluid pressure diffusion and combined it with a rate-and-state friction model to approximate the seismic rate at the Otaniemi EGS [42, 146]. Given homogeneous and isotropic reservoirs, such probabilistic models based on analytical solutions are applicable in near real-time as they require only few computational resources and little computation time. As a result, these models are more practical to apply for industry operators. For similar reservoir conditions, Verdon and Eisner [168] apply the extreme value theory to determine M_{max}, which is a product that can be easily implemented at geo-energy project sites.

However, the validity range of these models is usually exceeded in geological conditions where large fault zones are prevalent and where the assumed radially symmetric diffusion of p as the main triggering mechanism is no longer applicable. In such fault-dominated regimes, the size of the fault and the role of the stress regime determine the seismic hazard [171, 142].

Since probabilistic models do not yield explainable regression results for these reservoir types, more complex multi-physically coupled models are used to infer the dominant processes. In particular, hydro-mechanical effects play an important role in the scale of days to years [170], while thermal effects come into effect in long-term injection [91, 10, 129]. Usually applied failure criteria that accurately describe fault slip are the poroelastic Mohr-Coulomb criterion [133] and plastic slip weakening [9, 23]. Physics-based models are also used for the detailed evaluation of observations at various scales, where the laboratory scale and the underground laboratory scale allow for a more detailed analysis of the physical mechanisms behind induced seismicity [165, 29]. In the field scale, physical models were used in retrospective modeling to investigate the dominant mechanisms of induced seismicity at the EGS sites in Soultz-sous-Forêts (France) [92], Basel [23, 133, 87], and Blue Mountain [93].

As these complex physics-based numerical models solely return deterministic fields of state variables, we consider the hybrid integration of both physics-based and probabilistic models the most promising approach for real-time forecasting and control of induced seismicity. This is illustrated in Figure 1c, where a physics-based model computes the spatio-temporal distribution of the continuous state variables p, stress σ, and temperature T. A probabilistic model then evaluates the relationship between these state variables and the occurrence of seismicity, typically through empirical relationships such as the Gutenberg–Richter law. Such hybrid approaches have been implemented by Luu et al. [109] for the GCS site of the Illinois Basin Decatur Project (IBDP, USA) and by Acosta et al. [2] within the *Flow2Quake* framework, which was tested for the Groningen gas field, the IBDP, and the Quest GCS site. Both studies link the seismicity rate to the computed change in Coulomb failure stress using the rate-and-state friction model [42, 146]. For the Basel EGS dataset, Ritz et al. [133] related σ to the b-value through the relationship of Scholz [141] in their near real-time hydraulic reservoir model. For the same dataset, Boyet et al. [25] utilize a fully hydro-mechanically coupled model of sufficient complexity, yet its runtime remains incompatible with real-time applications. Some of these hybrid workflows include a sophisticated scheme for reservoir characterization and seismicity forecasting in long-term projects, such as the Groningen gas field in the Netherlands, where major fault zones are yet identified [40]. Beyond exemplary case studies, the scientific community has already developed ready-to-use workflows for earthquake simulation [43, 68, 79]. A recent example is the open-source software 'ORION' by Kroll and Sherman [95], which accommodates a wide range of input data, from radially symmetric fluid pressure diffusion to state variables of coupled reservoir models. These state variables can be linked to a seismic catalog by ensembling the outputs of multiple probabilistic seismicity models. For new exploration sites with poor knowledge of the geological features, reservoir characterization and forward modeling of operational scenarios becomes prohibitively computationally expensive for the majority of fully coupled physics-based models. These limitations highlight the need for a new generation of seismic hazard control workflows, which require (1) near real-time reservoir characterization, including fault identification, (2) high-performance reservoir models, and (3) adaptive probabilistic models that link state variables with seismicity.

Recent developments in parallel computing offer solutions to the bottleneck of long computation times of physics-based numerical models [30]. For example, Alkhimenkov et al. [7] present a near real-time solver for fully-coupled reservoir models, including seismic wave propagation, executable on the GPU of a desktop computer. Apart from the computational aspect, deterministic models are also limited in their ability to infer material parameters, as each new set of material property fields requires a separate simulation. Machine learning-based surrogate models address this challenge by interpolating state variables across a wide range of input parameters, by being trained on multiple parameter realizations from data of a numerical reservoir simulator. This makes them ideal for inverse modeling tasks such as history matching [179]. Surrogate modeling is a rapidly growing field in subsurface sciences, with applications ranging from natural convection [172] to single- and two-phase flow, with a major effort in the oil and gas industry [186, 159, 112, 158, 179, 75]. Beyond fossil fuel utilization, these models are increasingly used in GCS applications [180, 181, 76], EGS [39, 33, 57], and hydrogen storage [113]. For example, Tang et al. [158] introduced a machine-learning model that assimilates InSAR displacement data in real time to infer subsurface pressure fields and return probabilistic permeability and porosity maps. While most surrogate models to date rely on synthetic datasets, their integration with real-time data assimilation would mark a significant advancement for continuous seismic hazard forecasting.

With respect to EGS, another crucial feature is the incorporation of fractures into surrogate models. Ju et al. [76] addressed this necessity by using graph neural networks to model two-phase flow in fractured systems. In addition to a fractured reservoir, Chen et al. [33] presented a real-time optimization framework where a low-fidelity model guides the training of a high-resolution surrogate. This workflow could be combined with approaches like the one of Wang and Sun [174], in which recurrent neural networks learn stress–strain relations within hybrid finite element models. Regarding thermo-hydro-mechanical coupling, existing surrogate models for fractured reservoirs do not yet fully explore the space of material parameters, but instead focus on modeling operational scenarios [57]. However, they provide a strong foundation for future developments in which ranges of hydraulic and mechanical material parameters could be explored.

As an alternative to data-driven surrogate models, physics-based machine learning (PBML) introduces an alternative approach by simultaneously incorporating observational data and physical laws during model training [83, 150, 185]. The most common PBML framework are physics-informed neural networks (PINNs)[132], which embed the residuals of the governing partial differential equations (PDE), computed by automatic differentiation, into the loss function [17]. Past studies on PINNs could provide a highly promising opportunity for sparse data regimes like subsurface process models. However, PINNs face implementation challenges that data-driven surrogate models do not encounter, as the latter are trained on synthetic datasets from already fully developed numerical models. Recent studies have tackled these obstacles in PINNs, such as multiphysics coupling [63, 8], two-phase flow [64], and sharp material transitions [104, 139]. Inverse modeling using hydraulic PINNs has shown promise, often taking advantage of the Karhunen-Loéve expansion to generate permeability fields [106, 175].

Despite these advances, model simplifications are required in nearly all studies, such as assumptions of homogeneity [63], stationary flow [104], simplified well representations [36, 153, 191, 163, 71, 108], and the need for dense observational grids [161, 106, 177]. These simplifications clearly reflect the persistent challenges in adapting PINNs for practical reservoir modeling. As stated in Karniadakis et al. [83], PINNs can exploit their full potential when a minimum number of data is available where the physical relationship is used to bridge the space between the data points. For multi-scale problems like fractures, the only viable solution so far is domain decomposition and training a distinct PINN for each subdomain [151]. For example, Abbasi et al. [1] used pressure field data derived from a CT scan to infer the two-phase flow in a fractured core, using domain decomposition to distinguish between matrix and fractures. Although such data are not available on the reservoir scale, one future perspective is to include surface uplift as a displacement measure [126] or the microseismic cloud for fracture identification within a PINN workflow. While PINNs are very suitable for interpolation of data within the same scale, their weak extrapolation performance makes them less applicable for time-series forecasting of state variables. Therefore, several studies adapted the concept of unidirectional discretization of the time domain similar to numerical models [135]. One promising approach is the use of convolutional encoder-decoder neural networks, where the space dimensions serve as regular gridded input variables [187, 176]. In such a workflow, small-scale features such as fractures can be integrated through the efficient discrete-fracture model [187, 78]. While PINNs for now did not conveniently solve the previously described limitations for multi-scale and multi-physics modeling, Xu et al. [186] present a convenient hybrid approach, by training on synthetic data from a numerical solver while simultaneously constraining the training by minimizing the residual of a PDE. This handling of complementing sparse observations with synthetic data and simultaneously enforcing physical constraints during training is expected to lead to more robust models and higher modeling accuracy [44, 186]. An advanced example is NVIDIA's 'PhysicsNeMo' framework [49, 124], which uses a physics-informed neural operator to conduct 3D reservoir characterization in hours [107]. Although these models currently leverage less multi-physical coupling than surrogates trained on synthetic data [57], the pace of development as well as the high investment from companies like NVIDIA suggests that this gap will close soon. Simultaneously, a growing trend is to integrate numerical solvers and physics-based machine learning and, combining the computational efficiency of the former with the data handling capabilities of the latter [152, 190].

While surrogate modeling already provides continuous fields of state variables, another field of investigation is the linking of field observations and synthetic data from surrogate models with the actually occurring induced seismicity (see Figure 1c). Empirical models such as rate-and-state seismicity model [42] and the b-value–stress relationship [141] are still dominant, in addition to more physics-based deterministic models that consider the fault geometry itself [125, 77, 105]. Recent contributions to the field mainly explore data-driven machine learning, linking available measured data to match the seismic rate R and the maximum seismic magnitude $M_{\max}$. Seismic laboratory experiments provide spatio-temporal data in controlled environments that allow to predict the preparatory time before failure [134, 82], while giving novel insights about which features have the highest predictive relevance, such as acoustic emission rate, correlation integral, event proximity and focal mechanisms [80]. In addition, they allow for physical interpretation by correlating data with the generally known slip stages [82]. Similarly to the lab scale, studies use data from different origins to match observed seismicity through machine-learning algorithms, applying it to both natural seismicity [41, 137] and induced seismicity [131, 188, 130, 194, 120].

The main difference among studies is that some consider only operational state variables, such as flow rate and well pressure, as input features [131, 188], while others also consider the seismic catalog [50, 119]. Here, we find that studies that incorporate seismic features as input limit their forecasting capabilities to one window length [137, 194], which is inherent to the chosen data binning structure. Another discrepancy regarding the input features is that the observations of state variables are usually sparsely sampled over space. Therefore, purely data-driven workflows use only time-series data without spatio-temporal discrimination [188, 119, 50, 194, 81]. However, this handling might result in a less accurate performance, compared to models that are also discretized over space [131, 137], since the spatiotemporal evolution of state variables in combination with fault zones explains several triggering mechanisms of induced earthquakes [52, 171], which is especially relevant for long-term injection [109]. Therefore, the next generation of machine learning-based seismicity forecasting might need to include the spatio-temporal evolution of all state variables into the forecasting models. Due to the sparsity of direct observations, we suggest the deployment of a surrogate model to provide continuous fields of state variables (Figure 1c). Similarly to Millevoi et al. [120], the output of our proposed surrogate is fed into a data-driven seismicity model, learning the relationship of the state variables and the observed induced seismicity. This approach allows for flexible forecasting horizons and long-term simulations. Once the seismicity model is trained on the reservoir surrogate model, we let the surrogate return a long-term prediction of the state variables, and obtain a probabilistic seismicity map for R and $M_{\max}$ as output of the seismicity model. The real-time capabilities of both models also enable efficient parameter studies to assess uncertainty in seismic hazard forecasts.

3.3 Simulating Operational Control Scenarios

According to the suggested new paradigm, controlling seismic hazard implies to forecast the maximum expected ground motion or $M_{\max}$, as outlined in Section 3.2, and adjusting the operational response, typically the pumping rate q, accordingly. Traditional mitigation schemes such as TLS and ATLS define operational control protocols prior to injection (see Figure 1a and Figure 1b). One reason for this static approach is that, in the past, physics-based models were too computationally expensive and their material parameters are difficult to determine, which impaired their suitability for real-time hazard management. As a result, induced seismicity control has often relied on oversimplified models, based, for instance, on the postulate that seismicity scales with absolute injection volume, or on generalized pre-injection plans derived from physics-based modeling. The former assumes that $M_{\max}$ scales with the injected volume [115], a relationship that is applicable in several cases, particularly in rather homogeneous reservoirs where fluid pressure diffusion is the dominant triggering mechanism of seismicity [99, 138, 121, 136, 148]. However, in fault-dominated systems, where stress conditions, fault structure and induced poromechanical stress control seismicity, this approach is not valid [52]. In such cases, high-magnitude events are often retrospectively analyzed using physics-based models to understand triggering mechanisms and propose customized mitigation strategies [171, 23, 5]. While these case studies shed light on triggering mechanism and improved the understanding of unexpected induced seismicity, they rarely yield broadly applicable operational guidelines. For instance, Alghannam and Juanes [6] recommended step-rate injection to minimize $M_{\max}$ in single-fracture scenarios, whereas Boyet et al. [25], forecasting induced seismicity on a discrete-faulted model of Basel EGS, find that step-rate injection was the only stimulation protocol, in contrast to constant-rate and cycling injection, that would have induced a large seismic magnitude event after the stop of injection. Next to the active operation scheme, the protocol that defines the operations after the stop of injection also affects the post-injection seismicity. In complex faulted systems, Boyet et al. [24] found for the dataset of the Basel EGS, that bleed-off leads to sudden relaxation of poromechanical normal stress on faults, resulting in a larger seismic hazard, whereas shut-in leads to smoother redistribution of poroelastic stress. Similarly, Kivi et al. [89] suggested that bleed-off is only effective when faults are hydraulically well connected to the wellbore. Both single-fracture models [160] and multi-fracture models [24] underscore the reservoir-specific efficiency of various operational scenarios, mainly based on the specific orientation and connectivity of fractures and faults, and the location of the injection well towards the fauls. Generalized statements of operational mitigation scenarios need to be handled with care, as demonstrated by the example of the cyclic injection scheme. Promoted as an effective mitigation strategy [69, 84, 74], cyclic injection appeared to successfully reduce seismic hazard at the Otaniemi EGS, albeit at the expense of an insufficient permeability enhancement [99]. However, it is believed to have contributed to the large earthquake in Pohang, the severest seismic incident linked to any EGS project so far [69]. For the latter case, a retrospective hydro-mechanical model by Alcolea et al. [5] revealed that controlling overpressure would have been a more effective way to limit fault reactivation. Similar conclusions were drawn for hydraulic stimulation experiments at the Bedretto laboratory (BULGG) [165]. These findings suggest that generalized injection strategies are useful as a starting point, but their effectiveness must be tested against the specific *in situ* conditions and operational objectives. The evaluation of these experiences concludes with the suggestion of a conceptual shift toward scenario-based simulations that are accompanied by continuous reservoir characterization.

Recent developments in EGS may seem to reduce this demand, as the focus shifts from stimulating mature fault zones toward creating controllable engineered fractures, approaches already successfully tested at sites like Utah FORGE [116, 46, 70] and Fervo Winnemucca EGS (USA) [123]. Although this strategy may limit seismicity during stimulation, operational scenario models remain essential for the production phase. Long-term injection can destabilize faults in the far-field beyond the reach of real-time controls [90]. Moreover, geological complexity may only become apparent during the drilling operations or during reservoir stimulation. In addition, even though EGS provides a prominent use case, we argue that operational scenario modeling is equally critical for large-scale GCS and underground hydrogen storage, especially in light of past failures such as the Castor gas storage project. We therefore propose the adaptive workflow shown in Figure 1c, where an up-to-date reservoir surrogate model is used to simulate operational scenarios, while a seismicity model forecasts the associated seismic response. These simulations can be performed with previously discussed methods, many of which have already been developed and tested for oil and gas applications. For example, Chang and Evensen [32] introduced a closed-loop probabilistic reservoir management framework. Recent studies are also extending these workflows to EGS contexts, including the surrogate modeling work by Gudala and Yan [57]. Future research should explore the extent to which fully-coupled reservoir surrogate models can infer parameter ranges, potentially through knowledge transfer between low- and high-fidelity surrogates [33] and continuous data assimilation, as demonstrated by Tang et al. [158]. However, a particularly compelling question remains: Can operational control be automated based on the real-time seismic response of the reservoir? We address this in the following subsection.

4 From Mitigation to Control: A Feedback-Based Framework for Preventing Induced Seismicity and Maximizing Production

Recently, control theory has been suggested as a systematic framework for solving the problem of induced seismicity [154]. Control theory enables the automatic regulation of complex dynamical systems across a range of engineering applications. The approach relies on rigorous mathematical proofs (and not on trial and error) to drive a dynamical system toward a desired state. This can be performed even without detailed information of the system parameters and under the presence of uncertainties (see also Figure 1d).

Control theory can be applied to induced seismicity by regulating the pressures or the fluxes at the wells, and consequently, the effective stress changes which trigger seismic slip. The control of induced seismicity involves the design of a controller, which takes into account desired operational targets (e.g., injected volume and duration, flow rate, pressure increase) and seismicity limits (e.g., keeping the seismicity rate constant or below a given threshold). A notable advantage of this approach is that it does not require detailed knowledge of key physical parameters that are typically needed in conventional and previously developed methods, such as fault and reservoir geometries and properties, reservoir permeability, rheology etc. Instead, it relies on real-time observations of induced seismicity and approximated reservoir properties.

Currently, applications of this approach include two categories: (a) slip control of large mature faults, and (b) prevention of induced seismicity in geological reservoirs where the exact faulting network is not determined a priori. In the first class of applications, a fault, critically oriented for slip, is regulated by adjacent fluid injections. Different works have shown theoretically, numerically and experimentally, through analog experiments, that it is possible to stabilize a fault and induce controlled slow slip to release the locked energy aseismically [62, 61, 154, 156]. This was achieved without exact knowledge of the friction rheology of the fault and other parameters of the system.

The second class of applications is more focused on preventing induced seismicity and maximizing production in geological reservoirs. Based on the pioneer work of Dieterich [42], the seismicity rate can be estimated throughout the reservoir domain (see also [146]). Coupled with the diffusion equation for calculating poromechanical stress changes resulting from operations, the Dieterich model gives estimates about the expected seismicity rate at each point of the reservoir (e.g., [25, 31, 66, 109, 38]). In Gutiérrez-Oribio and Stefanou [59, 60], the authors developed a robust controller capable of regulating the regional seismicity rate and the pressures over specific regions to follow the desired references. This control theoretical framework was applied to real geo-energy scenarios. In particular, the numerical simulations of Gutiérrez-Oribio and Stefanou [60] showed how the same amount of gas in the Groningen gas reservoir could have been extracted with negligible induced seismicity. It should be noted that the Groningen project was terminated in 2024 as a result of induced seismicity caused by the operations.

In the context of geothermal projects, a significant challenge involves the use of just one injection well to stimulate the reservoir (e.g., increase in pressure) while simultaneously avoiding induced seismicity. Apparently, these are contradictory objectives, which justifies the challenging nature of the problem. To address this issue, control theory was applied, following the objective of maximizing pressure buildup while maintaining the seismicity rate below a certain threshold. This threshold was determined based on the probability of exceedance of a given magnitude earthquake event, which is of paramount importance in applications. This theoretical framework was applied to the Otaniemi geothermal project, Finland [86] with promising results. In such applications, physics-based modeling can aid in the design of more optimal controllers.

Finally, the control framework is adaptable to combinations with artificial intelligence. In recent works, Gutiérrez-Oribio et al. [58] and Stefanou and Darve [155] have optimized the control effort using reinforcement learning. These works open further perspectives for safe and optimal operations of geo-energy projects.

5 Conclusions: Next Steps for the Paradigm Shift of Controlling Induced Seismicity

The large-scale deployment of geo-energy technologies, such as geothermal energy, geological carbon storage, and underground hydrogen storage, is essential for decarbonizing the energy and industry sector. However, their widespread adoption relies on our ability to reliably control induced seismic hazards while ensuring economic profitability. These two goals are inherently interdependent and must be addressed simultaneously through integrated, adaptive workflows (Figure 1c and Figure 1d). To date, existing mitigation approaches, such as the TLS and its adaptive variant ATLS, have only been partially effective, preventing high-magnitude events under mostly favorable reservoir conditions. However, notable failures have undermined public trust and damaged the reputation of the entire geo-energy sector, especially EGS and underground gas storage. From another perspective, these frameworks were designed solely for seismic hazard mitigation, with limited attention to operational feasibility or economic profitability.

This paper identifies critical limitations of TLS and ATLS, which rely predominantly on statistical approaches and oversimplified physics. Historically, more complex physics-based models have been avoided because of computational demands and the difficulty in characterizing subsurface parameters. However, recent advances have opened new possibilities: machine learning now enables the integration of physics-based simulations with real-time data analysis. Therefore, our review proposes a paradigm shift by combining these elements into a novel generation of seismic hazard mitigation workflows. Central to this workflow is a surrogate reservoir model that continuously estimates relevant state variables, updated in real time with operational and seismic data. A machine learning-based seismicity model links the evolving state variables to the observed seismicity. This workflow enables real-time forecasting of probabilistic seismicity maps for a range of operational scenarios, allowing operators to select the most appropriate course of action based on these forecasts. To manage seismic hazard, the framework facilitates informed decision-making by aligning operational plans with forecasted seismicity relative to tolerable impact thresholds, such as ground motion or expected $M_{\max}$. Ultimately, such a workflow should be capable of addressing practical 'what-if' questions encountered in the field, for example: What if the injection rate is doubled? What if injection is suddenly stopped? In the long term, this approach could support the development of a feasible digital twin for geo-energy projects.

Building on this, we introduce a second fully-automated workflow that simultaneously optimizes the operations on both previously defined objectives, namely production and seismic hazard control. Rooted in control theory, this approach enables dynamic, feedback-driven optimization and control of geo-energy operations.

Ultimately, the current state-of-the-art for mitigating induced seismicity calls for a paradigm shift: from reactive hazard mitigation to proactive, integrated management strategies. This shift is not only necessary, but it is also technically feasible. However, achieving this development will require stronger collaboration across disciplines and a move beyond proprietary thinking of single geoscientific domains. By mapping and evaluating latest advances from both data-driven, physics-based and control theory approaches, this review outlines a clear and actionable pathway toward a safer, a more trustworty, and economically feasible deployment of geo-energies.

6 CRediT authorship contribution statement

Linus Walter: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Auregan Boyet**: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Ioannis Stefanou**: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Víctor Vilarrasa**: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing.

7 Conflicts of Interest

The authors declare that they have no conflicts of interest to disclose regarding this manuscript.

8 Data Availability

No new data were generated or analyzed and no additional software was used in the preparation of this review article.

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