Performance evaluation of a real-time induced seismicity management tool

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Summary

Minimizing risk of seismic activity induced by hydraulic fracturing is a high priority for oil and gas operations. The majority of the regulatory traffic light protocols introduced to date is reactive and based on staged magnitude thresholds. The operators are required to establish operational protocols designed to minimize the likelihood of the occurrence of large magnitude events and are in some instances mandated to implement high-resolution seismic monitoring arrays. The ultimate goal of these seismic networks and their data products, beyond simple regulatory compliance, is to provide operators with a near real-time measure of the induced seismicity (IS) risk and an indication of the implemented mitigation protocol effectiveness. One such approach includes using high-resolution seismic data products to derive maximum magnitude (Mmax) and seismicity forecasting models in near real-time, allowing for adjustments in operational parameters to reduce the probability of a felt or damaging event.

In this study, we present the learnings from a practical implementation of model-based ricks management systems using three forecasting methodologies for hydraulic fracture operations. The performance of this system to predict seismicity is validated via real-time monitoring and playback in over 50 diverse datasets. The results show that the estimated seismicity agrees well with observed seismicity in majority of cases, multiple models produce very similar results and injected volume has limited impact on seismicity forecasts. The study also highlights the limitations of this approach when a large event occurs early in the sequence. One of the most important takeaways is the impact that the quality of seismic data has on the system performance. A high-quality data recorded by a local array combined with advanced processing techniques designed to generate "research grade" seismic catalogues automatically in near real-time is a key requirement. This development also serves as an excellent example of collaboration between industry (data acquisition and array deployment), academia (model development), and service providers (data processing advancements and implementation) to understand and manage induced seismicity phenomenon.

Method

The majority of the regulatory traffic light protocols introduced to date are based on staged magnitude thresholds, which increases the need for a better estimation of the largest possible magnitude event that is related to oil and gas operations. Forecasting maximum magnitude in real-time is a subject of significant interest to many operators. Prior knowledge of the largest possible event in real-time allows operators to optimize and adjust their stimulation plans accordingly to prevent events that would trigger regulation-driven operational shutdowns.

A large body of work has been published on forecasting maximum magnitude (Mmax) related to fluid injection in a given area. The performance of these models has been assessed in several studies (Eaton and Igonin 2018. Shultz et al. 2018, Kiraly-Poag et al. 2016) using available datasets to identify the benefits and challenges of each method.

Shapiro et al. (2010) introduce a parameter called ‘seismogenic index’ which represents the tectonic feature of a given location and is independent of injection parameters. Using this index, cumulative injected volume, and an estimated b-value, one can calculate the number of events within a specific magnitude range and consequently determine the probability of events occurring that have a magnitude larger than the threshold magnitude that results during fluid injection (referred to hereafter as SH_{10}). The result from this method is valid during active fluid injection.

Shapiro et al. (2011) state that the minimum principal stress axis of the fluid-stimulated rock volume is one of the main factors limiting the probability of large magnitude events. This model essentially relates the fluid-injected Mmax with geometrical characteristics of the simulated volume (i.e., the microseismic cloud). This method suggests real-time monitoring of the spatial growth of seismicity during rock stimulation to estimate expected Mmax and consequently to mitigate the seismicity risk.

McGarr (2014) develops a simple relationship between the cumulative volume of injected fluid and the largest seismic moment. This model is developed based on some assumptions, including a fully saturated, brittle rock mass with a b-value of 1.0.

Van Der Elst et al. (2016) demonstrates that the size of the strongest events from seismic activities related to fluid injection is consistent with the sampling statistics of the Gutenberg-Richter distribution for tectonic events. They conclude that injection controls the nucleation but that earthquake magnitude is controlled by tectonic processes. They introduce a model based on this hypothesis (referred to hereafter as VDE_{16Seis}). They further link their model to total injected volume and seismogenic index (referred to hereafter as $VDE_{16SI\text{-}V}$).

Eaton and Igonin (2018) add a tapered Gutenberg-Richter relationship to VDE16Seis, to introduce a limit to the size of the maximum magnitude event.

In this paper, we calculate the seismicity for regular time intervals (e.g., Kiraly-Proag et al. (2016)) utilizing the SH_{10}, VDE_{16Seis} and $VDE_{16SI\text{-}V}$ models to illustrate how well the techniques forecast Mmax and number of events in near real-time based on recorded seismicity and treatment data. Other than the three models used in this study, we investigate three other published methods and decided not to use them in the forecasts. Shapiro et al. (2011) does not account for the far-field triggering due to poroelastic stress effect and neglects nucleation of an event in the stimulated volume while the fault continues out of the events cloud. Our analyses show that McGarr (2014) overestimates Mmax compared to the observations. Furthermore, this model is developed based on assumptions including a constant b-value of 1. Eaton and Igonin (2018) limit upper magnitude level in the real-time application which we did not prefer.

In order to improve the practicality of seismicity forecasts, all observations and estimations are presented in an interactive dashboard environment with the objective of providing effective real-time operational risk mitigation feedback.

Results and Conclusions

In this study, we evaluated the performance of the approach proposed by Shapiro et al. (2010) and two models from Van Der Elst et al. (2016) for estimation of Mmax and number of events in dashboard format as part of a real-time feedback loop to the operational risk mitigation protocols.

It is worth noting that the three forecasting models used in this study have been developed based on moment magnitude, consequently prior to applying the models, the seismicity catalog should be homogenized by converting all magnitude types to moment magnitude.

Figure 1 illustrates an example of the dashboard related to a local surface seismic monitoring array located in North America. The results from this case study are typical and represent the majority of the real-time and playback datasets where a rich and accurate catalog was collected using either a local array or a near-regional array with advanced processing. Figure 1a shows the Gutenberg-Richter distribution on top and the normalized probability density function from SH_{10} (green line) and VDE_{16Seis} (blue line) on the bottom. The vertical dashed line is the mode of the VDE_{16Seis} probability density function and the dotted lines denote 90% confidence bounds of the distribution. Figure 1b illustrates probability of exceeding four magnitude thresholds that are matched to configurable operations tiers and subsequent actions. The 3D events distribution is displayed in Figure 1c.

We calculate seismicity parameters including b-value and Mc at regular time intervals from the cumulative seismicity data. We use these parameters to estimate the expected Mmax and the number of events that exceed a threshold magnitude at each time step and compare them to the recorded seismicity. It should be noted that the estimated Mmax is the mode of the probability density function (Figure 1a). The symbols in Figures 1d show results at 12-hour intervals over the stimulation period. On the top plot, the recorded (red squares) and estimated Mmax (green and blue lines) are shown over time.

The middle plot of Figure 1d presents the recorded number of events that are larger than the threshold magnitude of ML1.2. The bottom plot in this figure shows the time-varying estimation of b-value and Mc. In this example, we observe a very good agreement between the recorded and estimated seismicity including Mmax and the number of events.

Our analysis confirms that the estimated seismicity agrees well with the observed largest magnitude and recorded events in most cases. However, we observe some scenarios in which a strong event occurred in early stages of the HF operations, resulting in under-prediction of Mmax.

The sample size hypothesis holds that each event in the sequence has the same probability of occurrence and the order of occurrence of the largest earthquake is random within the sequence (Van Der Elst et al. (2016)). In other words, induced earthquake magnitudes are drawn independently from a Gutenberg-Richter distribution rather than being physically determined by increasing injection volumes. This highlights the limitations of forecasting models using statistical approaches when a large event occurs early in operation.

The results of our investigation on the impact of cumulative injection volume data on the forecasted seismicity parameters show that estimations of maximum magnitude and the number of events lose their sensitivity to the variation of cumulative injection volume over time.

We observe that the quality of the seismicity catalog has a significant effect on the outcome of the forecasting model. A high resolution local or near-regional seismic monitoring array along with advanced seismic data processing techniques is required to generate data sets that are rich and accurate enough to be used as inputs into real-time seismicity forecasting models. However, the seismicity catalog must be extended with small magnitude events well below the regulation threshold in order to accurately compute catalog-level data products (such as b-value or seismicity rate variations). Additionally, the event locations should be highly accurate in order to enable delineation of activated structures.

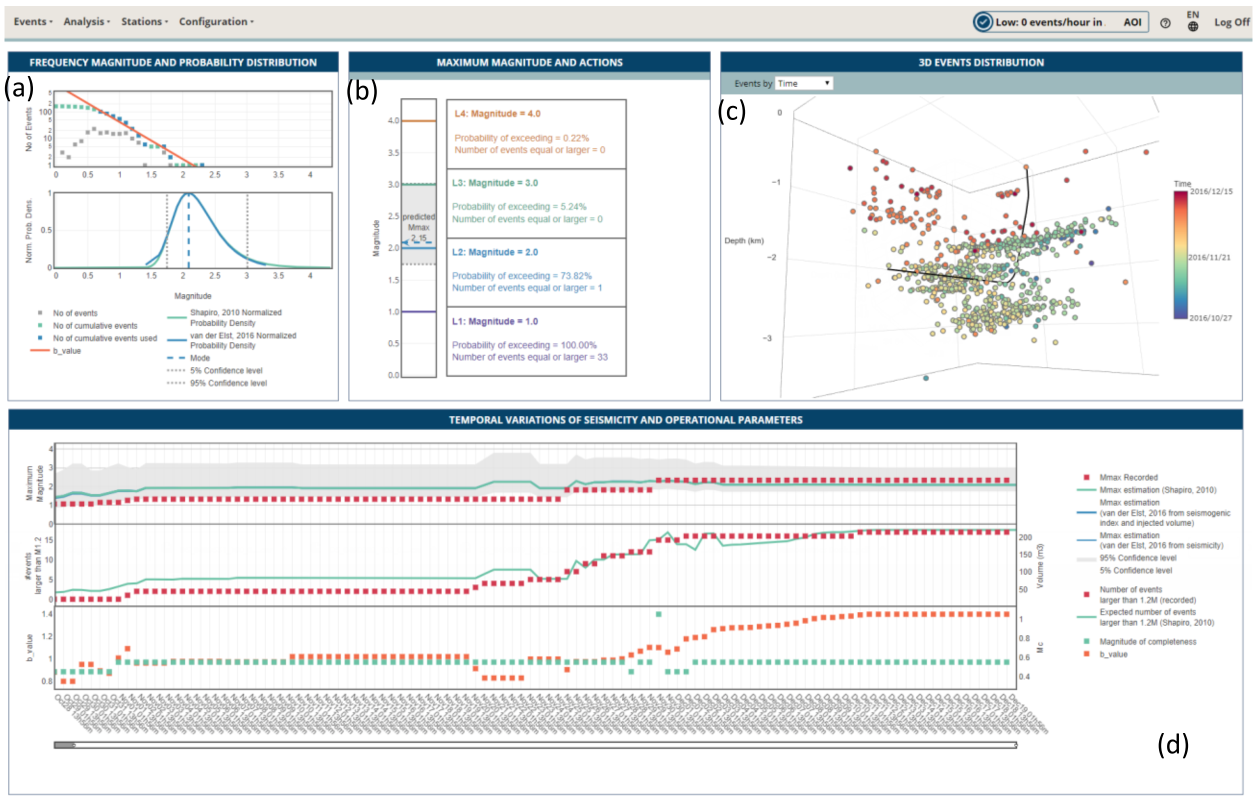

Figure 1. Seismicity Management Dashboard for a local surface seismic monitoring array located in North America. (a) Top: Gutenberg-Richter distribution, Bottom: Normalized probability density functions. (b) Maximum magnitudes and action items (c) 3D view of event distribution, (d) Temporal variation of recorded and estimated seismicity. Top: Recorded Mmax (red squares), estimated Mmax (green dark and light blue lines), the 90% confidence bounds of the estimations (shaded gray area). Middle: Number of recorded events larger than M_L1.2 (red squares) and the estimated values (green line). Bottom: b-value (orange squares) and Mc estimations (green squares).

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