Introduction

Methods of carbon capture and storage are suggested to reduce greenhouse gases. One candidate for a CO_2 storage site is the Smeaheia site within the Norwegian North Sea (Mulrooney et al., 2020), and is the focus of this study. The Alpha prospect identified for this site is located within a tilted fault block bound by a deep-seated basement fault: the Vette Fault Zone (VFZ), and hence a high fault sealing capacity with no reactivation potential is required to retain the injected CO_2. Both of these parameters hinge on generating an accurate geological model, performed using suitable picking strategies.

The process by which seismic is interpreted has developed significantly over the years. The ease and accuracy of seismic interpretation is continually increasing, associated with advanced geophysical and rock physics tools, as well as the increased use of automated technologies. While technology has progressed to allow user to quickly interpret horizons using facilities such as auto-tracking, the ability for machine learned algorithms for automated fault extraction has, until recently, been lacking. New technology has emerged that uses Deep Learning (i.e. Deep Neural Networks (DNN) inspired machine learning) to automatically extract faults from seismic, with minimal manual seismic fault interpretation. However, as with any new technology, it is crucial to understand any uncertainties when using these automated methods, and how they may impact any further fault analyses.

Methodology

We compare manual fault interpretation with that from supervised DNN fault extraction for the prospect-bounding VFZ. Further, we also compare differences between interpretations using varying line spacing, as this has proven to be crucial for in-depth fault analyses such as fault stability. Specifically, we have examined how the predicted dilation tendency varies when faults are picked on every line (25 m), every 2nd line (50 m), every 4th line (100 m), every 8th line (200 m), every 16th line (400 m) and every 32nd line (800 m). Dilation tendency is the relative probability of a plane to dilate within the current stress field (from Statoil 2016), taking into consideration the cohesion and frictional coefficient of the fault rock, which are set as 0.5 MPa and 0.45, respectively. Dilation tendency is a ratio between 0 and 1, where the higher the value, the more likely a fault will go into tensile failure.

Results: Manual Fault Interpretation

Although fault stability is influenced by external factors, specifically the in situ stress conditions, it is also heavily influenced by intrinsic fault attributes, namely strike and dip. Here, we show the variation in dilation tendency recorded with differing picking strategies, associated with the varying dip values.

Along fault-strike there are minor patches where the fault is more stable than the surrounding values and patches where the fault is less stable. These patches are most apparent when every line is picked on, with irregularity decreasing in severity until every 100 m to 200 m line spacing. Since the fault surface is smoothed with greater picking spacing, the results for fault stability are also smoothed, reducing the range of values of the predicted dilation tendency (Figure 1). Hence, interpretation of fault stability varies with picking strategy, and may in fact lead to incorrect fault stability assumptions. For example, areas where the fault is close to failure are only observed when a narrower line spacing picking strategy is used (Figure 1). However, if these irregular areas are not a product of human error or triangulation method, the overall stability would be overestimated within this location if a coarser line spacing was used. Therefore, a question is presented regarding optimum picking strategy that retains sufficient detail but remove any data that may be caused by human error and/or triangulation method. For the studied fault system, we propose an optimum picking strategy of every 100 m line spacing, incorporating inherent irregularities of the fault surface, while adding some smoothing to reduce the impact of human error. Best-practice is however likely to be case-dependent.

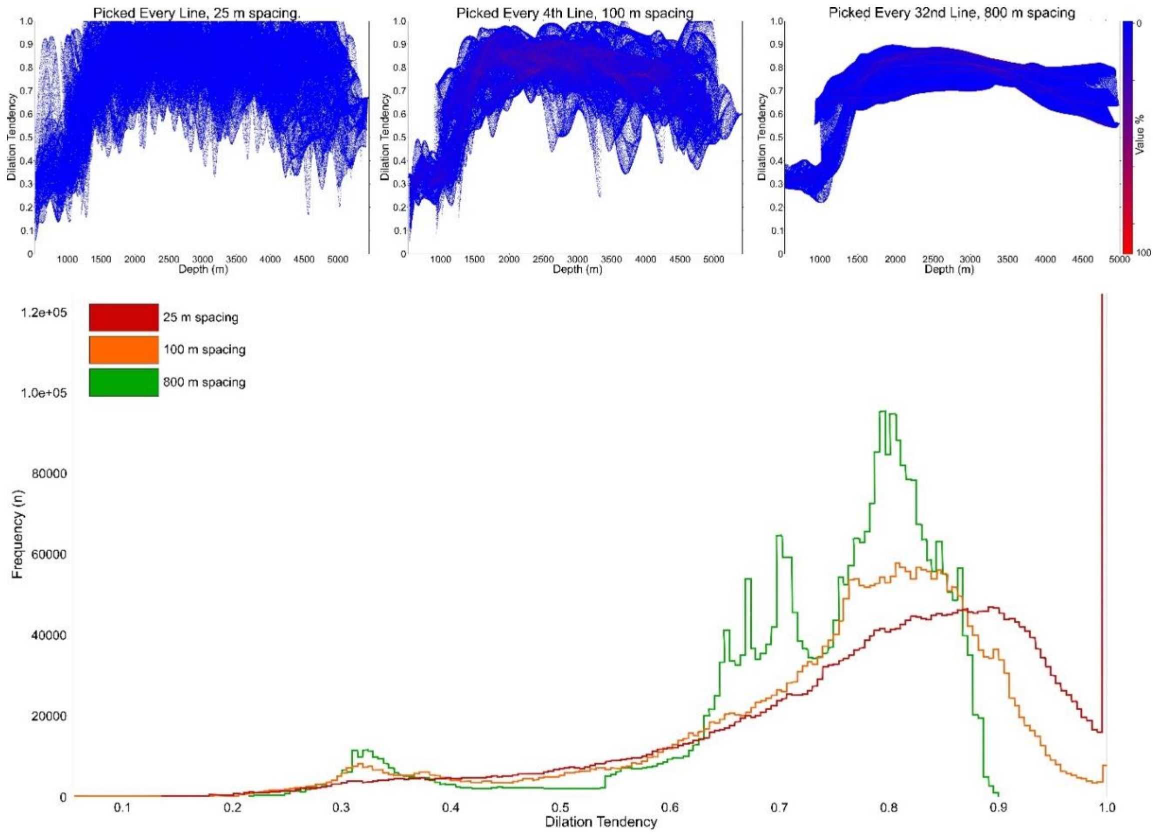

Figure 1. *Top: plots showing dilation tendency with depth, manually picked on every line (left), 4th line (middle) and 32nd line (right). Colour intensity reflects the frequency of those values, where blue is 1% and red is 100%. Bottom: Histogram showing frequency of dilation tendency for scenarios picked on every line (red), 4th lines (orange) and 32nd line (green). Dilation tendency values decrease (stability increases) as the spacing increases.*

Results: Deep Learning Fault Interpretation

For the DNN approach, we used supervised learning, where some fault picks are used for training with seismic full stack data. The trained DNN models are checked against input picked faults through confusion matrix and visual review. Comparisons have been made between fault surfaces picked using manual interpretation and machine learning techniques, at different picking intervals (every line, 4th line and 32nd line). We also describe how faults identified by different seismic quality influence the results from machine learned automated fault extraction. The VFZ has relatively poor seismic quality, with a wide fault zone shown by decreased seismic quality. Conversely, minor faults surrounding the VFZ show significantly improved seismic image quality.

VFZ poorly imaged fault:
There are distinct differences between the predicted dilation tendency of the VFZ with manual verses machine learned picking techniques. Regardless of picking strategy spacing, we can observe an increased predicted dilation tendency when machine learned techniques are employed over manual interpretation (Figure 2). Manual interpretation shows a gradual increase in predicted dilation tendency with a decrease in line spacing, where a fault is predicted to be at the failure envelope at 25 m line spacing, and further away from the failure envelope at 800 m line spacing. This trend of a decrease in fault stability with a decrease in line spacing is also observed when machine learned techniques are used. However, in all scenarios the fault is predicted to be at the failure envelope, regardless of line spacing used for fault surface generation. Specifically, all three scenarios (25 m, 100 m and 800 m line spacing) show areas on the fault where the dilation tendency is 1 or over. This means that any increase in pore fluid pressure, e.g. through CO_2 injection, is likely to be interpreted as causing the fault to fail (under these specific input parameters).

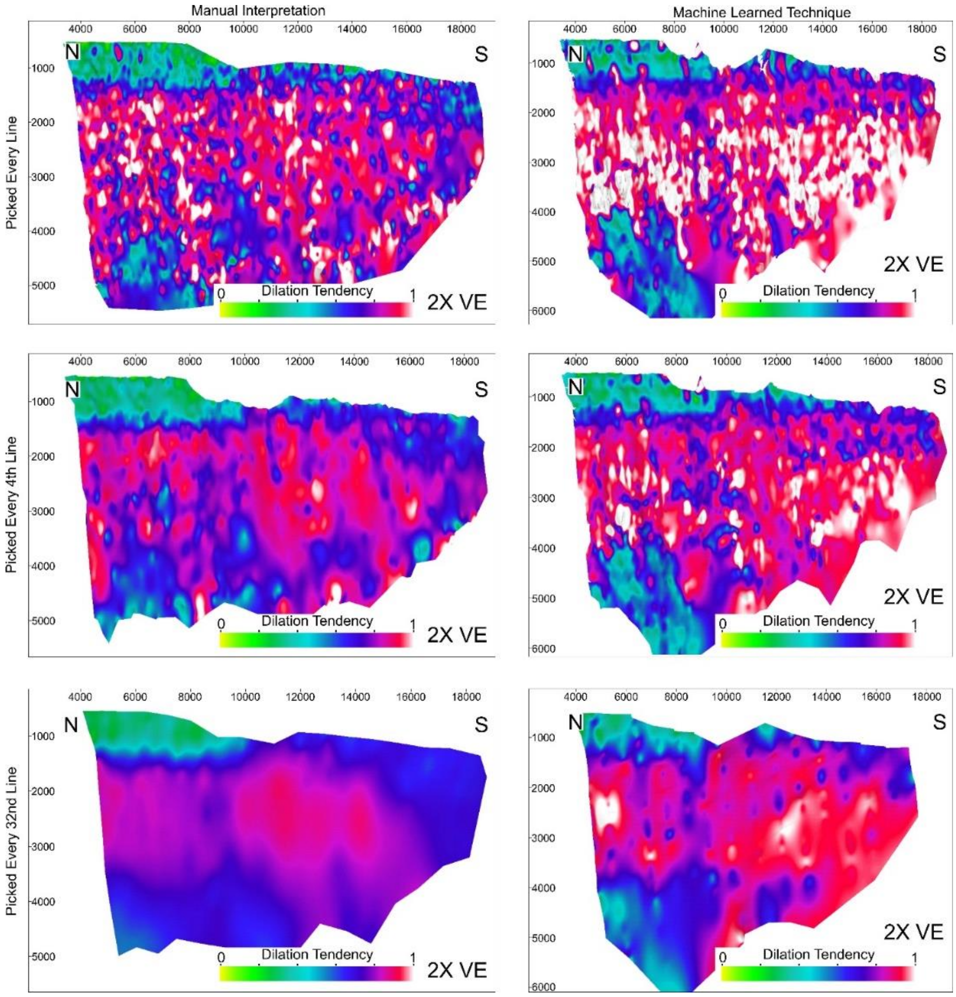

Figure 2. *Dilation tendency attribute displayed on the fault surfaces for manual interpretation verses machine learned techniques picking on every line, every 4th line and every 32nd line. Note that unconstrained triangulation is used for fault surface generation.*

Well imaged minor faults:
While machine learning techniques have shown to be challenging for areas of poor seismic quality such as the VFZ, other smaller faults that are better imaged show improved identification. Specifically, minor faults (up to 100 m displacement) within the footwall of the VFZ show accurate identification with reduced segmentation and similar irregularity to that when manually interpreted (Figure 3), despite in several places not showing any sharp cutoffs, but rather identified by subtle folding. To qualitatively and quantitatively assess this improved fault extraction of the minor faults, we compare calculated dilation tendency using machine learning techniques with manual interpretation for one fault within the footwall of the VFZ: fault 'FW 01' (see Mulrooney et al., 2020 for location details of this fault). We can observed that FW 01 has significantly less segmentation than those picked for the VFZ, and in fact, with the majority of lines picking only one segment. Moreover, the predicted dilation tendency is very similar between the machine learned and manual interpretation, which would lead to the same overall interpretation of fault stability (Figure 3). The only slight difference between machine learned and manual interpretation is the size of the fault: machine learned techniques do not extrapolate deeper than manual interpretation, which is simply a product of the poor seismic resolution at greater depths.

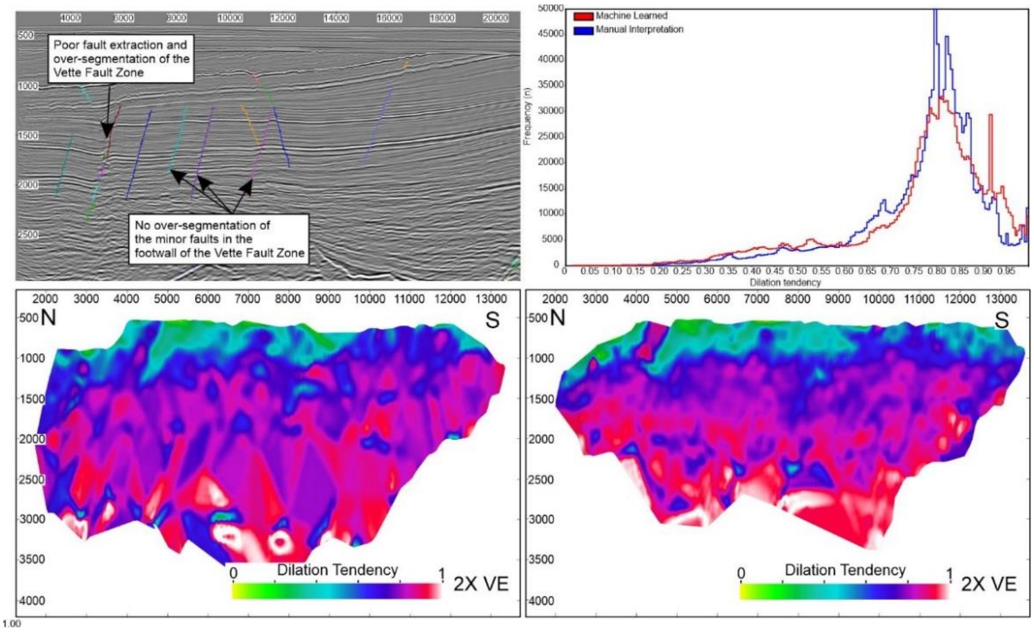

Figure 3. *Comparison of manual verses machine learned interpretation of a fault in the FW of the VFZ. Bottom left: manual interpretation. Bottom right: machine learning. Similar surfaces are produced from both techniques, with the interpretation of the fault stability being almost identical (top right).*

Conclusions

Line spacing chosen to pick fault segments will influence any subsequent analysis, e.g. fault stability. Manual interpretation using a wider line spacing creates a fault that is predicted to have an increased stability. Conversely, picking using every line creates a highly irregular fault such that the stability is predicted to be significantly reduced, and in fact will lead to the prediction of an unstable fault.

Automated methods of fault extraction is sensitive to the quality of seismic data. Poorer imaging of faults creates surfaces with increased irregularity when compared to manual interpretation, leading to higher predicted dilation tendency values in all line spacing scenarios. Fine tuning of hyperparameters, using other DNN networks, and fault label picks can potentially improve the results. On the contrary, picking of well-imaged, smaller faults show noticeable similarity in results between manual and automated methods.

Acknowledgements

This is a contribution of the FRISK project, supported by the Research Council of Norway (RCN# 295061). Support from the NCCS Centre is acknowledged, performed under the Norwegian research program Centres for Environment-friendly Energy Research (FME). The authors acknowledge the following partners for their contributions: Aker Solutions, Ansaldo Energia, CoorsTek Membrane Sciences, EMGS, Equinor, Gassco, Krohne, Larvik Shipping, Lundin, Norcem, Norwegian Oil and Gas, Quad Geometrics, Total, Vår Energi, and the Research Council of Norway (RCN# 257579/E20). Badley Geoscience Ltd. and Earth Science Analytics are thanked for their academic licenses of T7 and EarthNet, respectively.

References

Mulrooney, M.J., Osmond, J.L., Skurtveit, E., Faleide, J.I. and Braathen, A., 2020. Structural analysis of the Smeaheia fault block, a potential CO2 storage site, northern Horda Platform, North Sea. Marine and Petroleum Geology, p.104598.

Statoil, 2016. Subsurface Evaluation of Smeaheia as part of 2016 Feasibility study on CO2 storage in the Norwegian Continental Shelf. OED 15/1785. Document A – Underground report Smeaheia.