Efficient Fault Interpretation Using Machine Learning Technique in the Gulf of Thailand

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Abstract

The Thai government has launched the Petroleum Bidding Round in the Gulf of Thailand, offering the right to explore and produce petroleum in three exploration blocks. Valeura Energy holds an operated working interest in four shallow water offshore licences in the Gulf of Thailand (acquired from Mubadala Energy and Kris Energy), which are in close proximity to the new concessions on offer. One factor to evaluate the petroleum field for a new concession block in the Gulf of Thailand is the fault structure. The major fault locations should be identified within a minimal time to evaluate the field and its potential. The machine learning fault assisted interpretation is capable of identifying obvious faults, and in some other cases, it also identifies minor faults. The faults identification in the Jasmine field using ML fault assisted interpretation generates the results as it is capable of identifying tightly spaced faults and fault linkage. Fault-controlled closures are a primary hydrocarbon trap type in the Pattani Basin of the Gulf of Thailand. Accurate fault interpretation is therefore critical for both exploration and development in this basin, including prospect identification, risk assessment, volume estimation and well placement. Valeura's Jasmine field has demonstrated success on all of these fronts, and like other fields in the Gulf of Thailand, has hundreds of faults. This study is primarily focused on minimizing seismic fault interpretation turnaround time using a new technique known as Machine Learning (ML). ML is a type of artificial intelligence in which computers are trained to recognize patterns without being explicitly programmed. After a model has been suitably trained, it can then be used to predict similar patterns in data it has never seen before. The ML model used for fault prediction in this study was trained from a variety of geological basins around the world. The ML model can be run without any interpreter input or alternatively, the interpreter can participate by providing fault training labels as input. Both workflows were conducted on the Jasmine field's 3D seismic dataset for fault identification.

Keywords: machine learning, seismic, fault, interpretation, prediction