Use of Machine Learning to Estimate Sonic Data for Seismic Well Ties*

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Abstract

Bongkot is a Miocene siliciclastic gas field located in the Gulf of Thailand, producing from hundreds of sand layers. More than 700 wells have been drilled on the Bongkot Gas Field giving us a very large dataset to work on and learn from. Seismic well tie is a critical process to verify accuracy of time-depth relationship. This process requires sonic transit time data which was acquired in most exploration and delineation wells. However, there are a number of wells where sonic and/or density these logs are not available due to either cost saving, unfavorable well path, or other operational issues. Attempts to generate synthetic sonic logs by Gardner equation, porosity correlation, or depth correlation did not provide the required accuracy. Consequently, well ties lacked accuracy.

In 2017, PTTEP implemented machine learning techniques to generate artificial sonic data over the sand reservoirs for sand management purposes. The input data required were a few wells for each individual platform, with sonic data to train the Neural Network, as well as the main logs, GR, density, neutron, resistivity and depth. The resulting sonic from blind tests showed a very good match of computed sonic with the acquired sonic. Those excellent results in sand management led the geophysics team to extend the method and not only generate sonic over the gas sands to be put in production but over the whole well interval. This added an extra complexity, as the sonic log estimation would be done not only over gas sands, but also water sands, shales, organic shales and coals. Lithology from petrophysical evaluation was added to the input data. Then, blind tests were performed by comparing correlation coefficient and time shift of synthetic seismogram versus seismic. The results revealed that synthetic seismogram generated by actual well logs and synthetic well logs are very similar. According to these results, synthetic seismograms were generated and all wells were tied using the computed sonic logs.

To summarize, based on the large amount of data available in Bongkot, machine learning has allowed us to compute sonic data in well that did not have sonic logs for synthetic seismogram. Testing shows the computed log is very similar to the real logs. This provided three major benefits: (1) To determine probability of sanding risk from the reservoirs, (2) to generate synthetic seismogram and tie the wells to the seismic for wells that did not have sonic data, and (3) to reduce the number sonic data acquisition, directly saving time and money but also reducing the risk of getting the long logging string stuck in the hole with possible fishing operations and its associated cost.

Use of Machine Learning to Estimate Sonic Data for Seismic Well Ties

Thanapong Ketmalee

PTTEP

Outline

- Objective.
- Bongkot Field.
- Challenges.
- Project Background.
- Project Workflow.
- Result Discussion.
- Conclusion.

Objective

- To generate synthetic sonic logs using Machine Learning (ML) for seismic well ties.

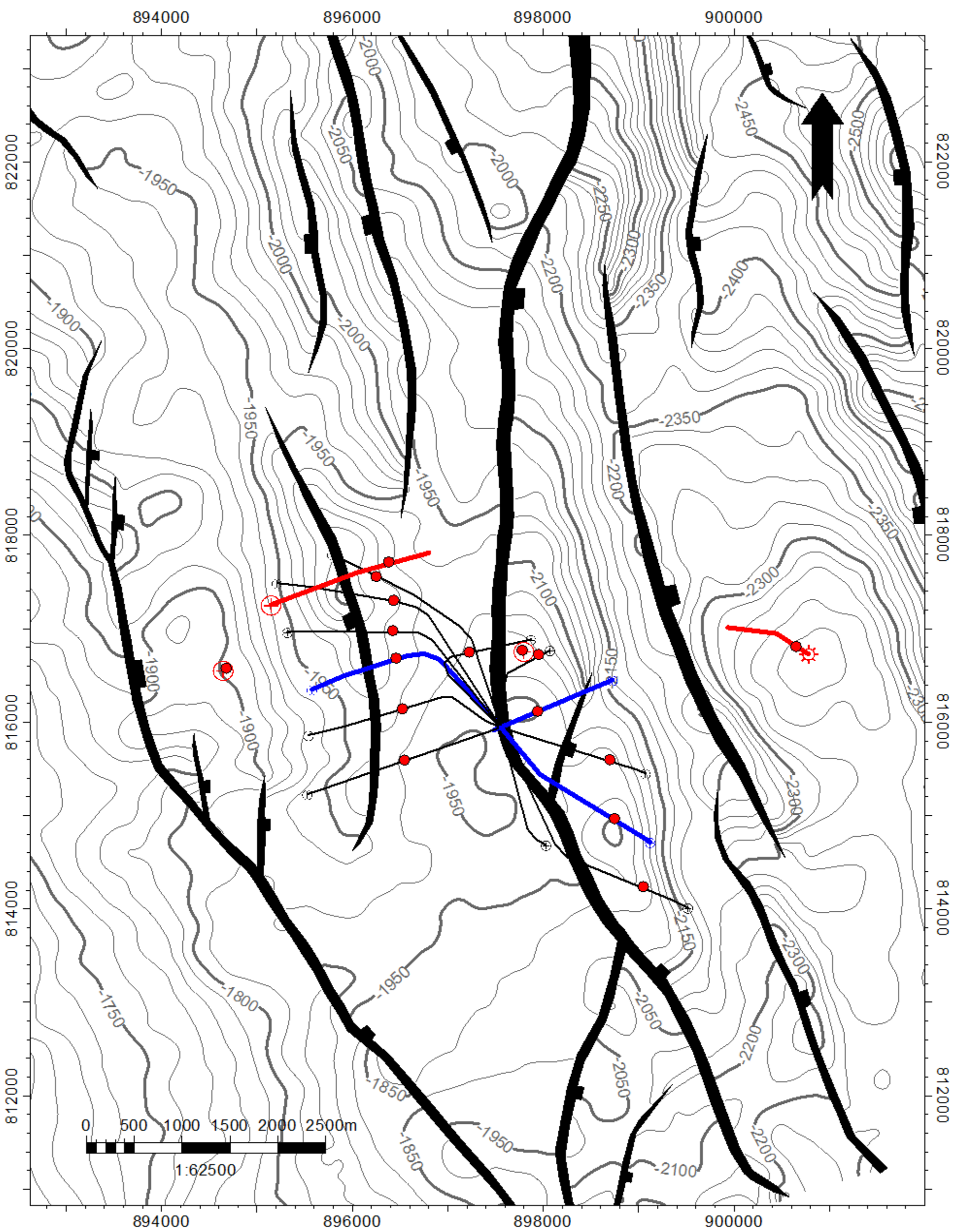
- To reduce sonic data acquisition and cost.

Bongkot Field

- Offshore Thailand.
    - Water depth around 70 m.
- Gas and condensate field.
- North Malay basin.
- Early to middle Miocene fluvio-deltaic.
- Production startup in 1993.

Platform A Infill Project

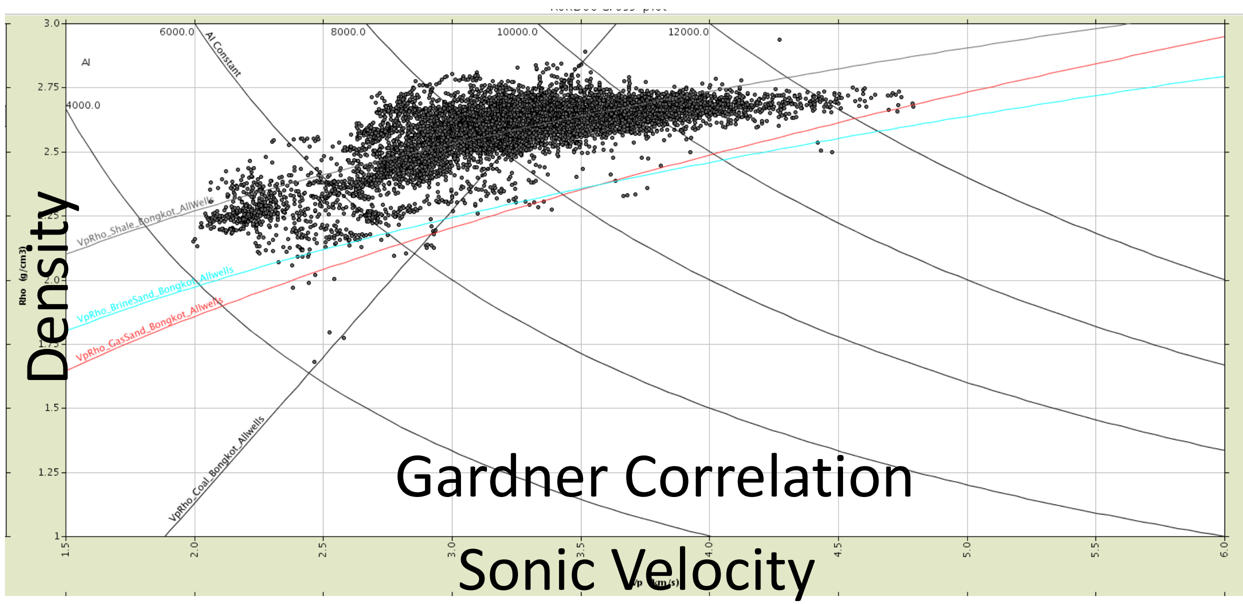
- 16 wells in the area
  - 4 Delineation wells, all with sonic log
  - 3 Development wells with sonic log
  - 9 Development wells without sonic log
- Identified as an infill candidate.
- Challenging to run sonic log.
  - Slim-hole monobore.
  - High deviation: 40 – 65 deg.
  - Difficult well path.
  - Depleted zones together with overpressure zones.
  - Cost saving.



Conventional Solutions

- Gardner Correlation.
- Constant velocity.
- And other correlations.
- All are not accurate.

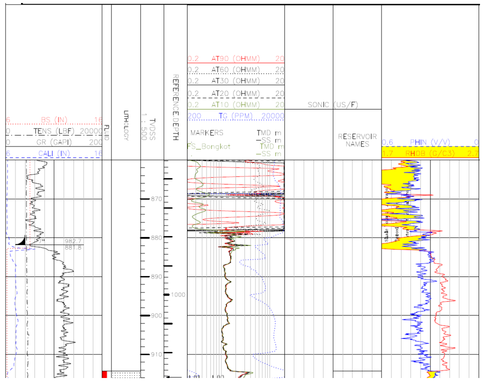
- Aim to improve quality for seismic well ties.
- Thus, to test concept of ML DT for seismic well tie in platform A.

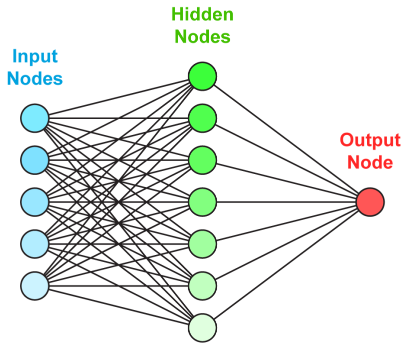


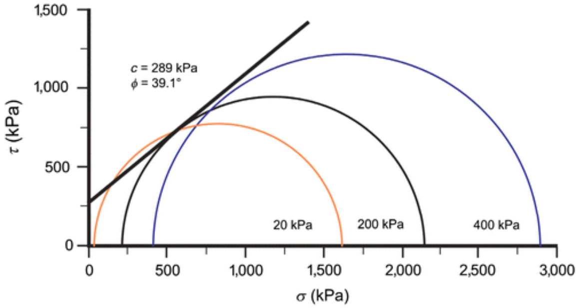
Project Background: Log Synthetic Using ML

- Ketmalee and Bandyopadhyay (2018) used ML to synthetic sonic for sand reservoir failure prediction.

Relevant Logs → ANN Predicts Acoustic/Density Value → Sand Model based on Synthetic Values







- To extend to other lithologies: Shale, coal, organic shale.
- Handle abnormal pressure.

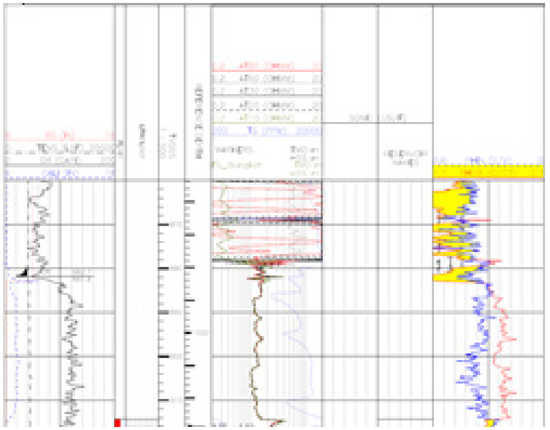
Project Workflow

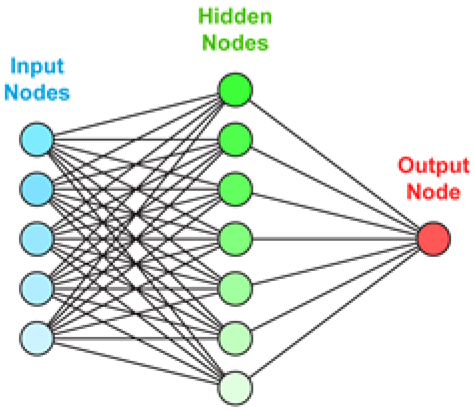
Relevant Logs and Data

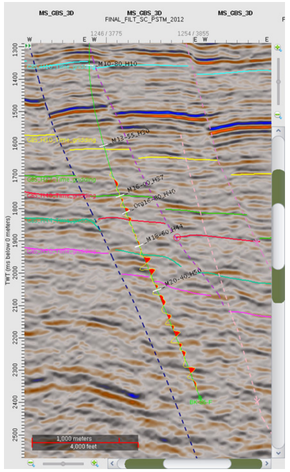
ML Predict Acoustic Transit Time (DT)

Generate Acoustic Impedance and Seismogram

Seismic Well Tie and Comparison Scenarios



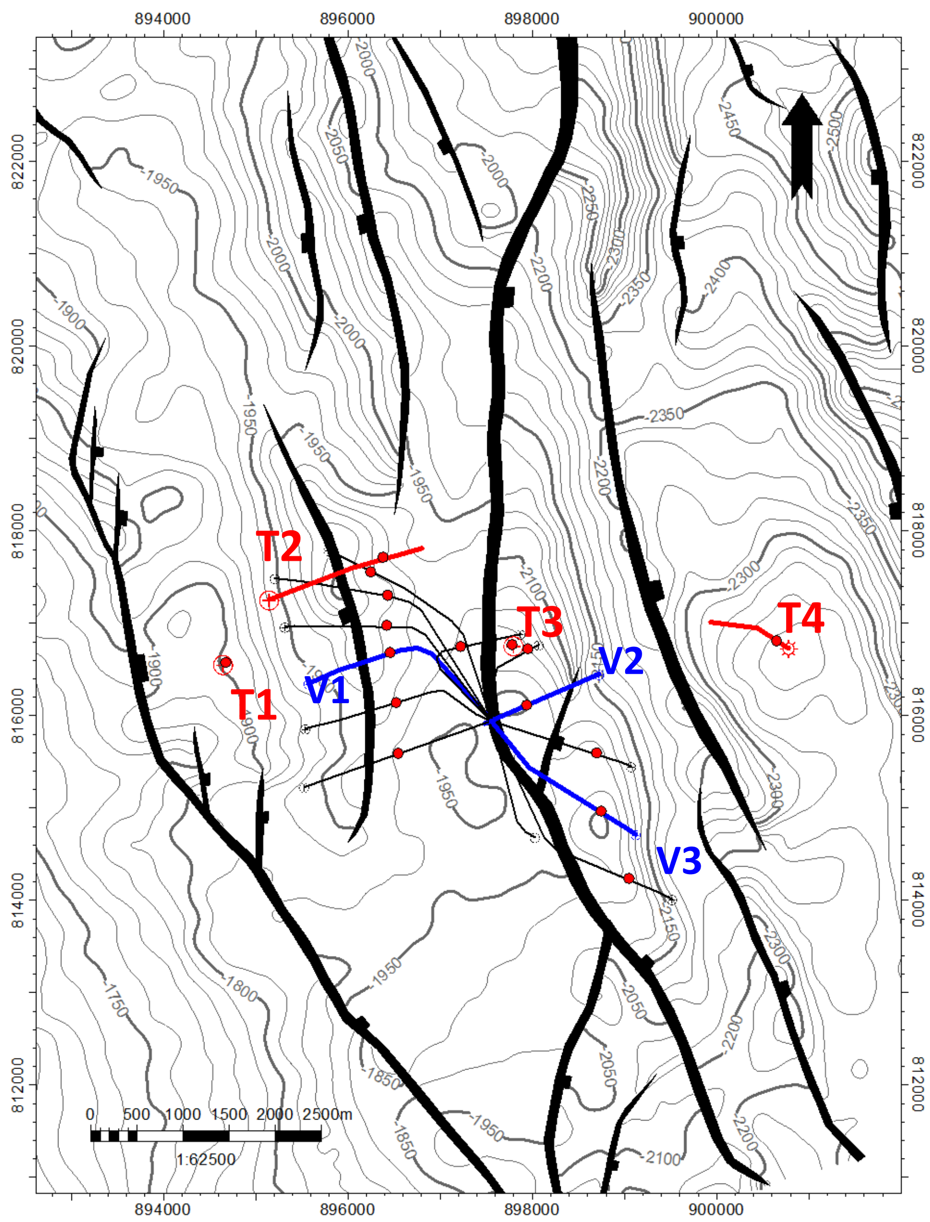




Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → Seismic Well Tie

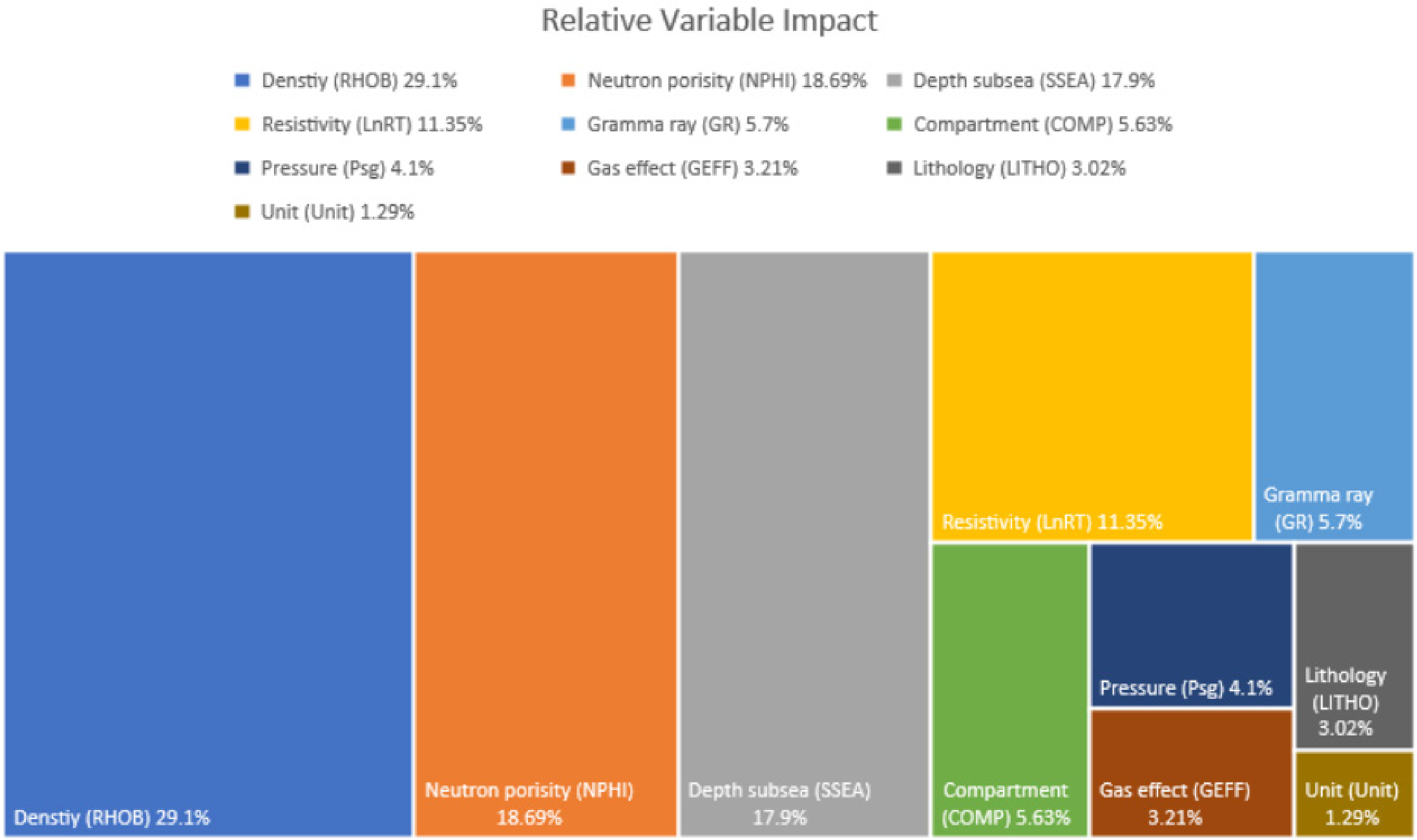
Input Preparation

- **Training Wells: 4**
  - T1
  - T2
  - T3
  - T4
- **Validating Wells: 3**
  - V1
  - V2
  - V3



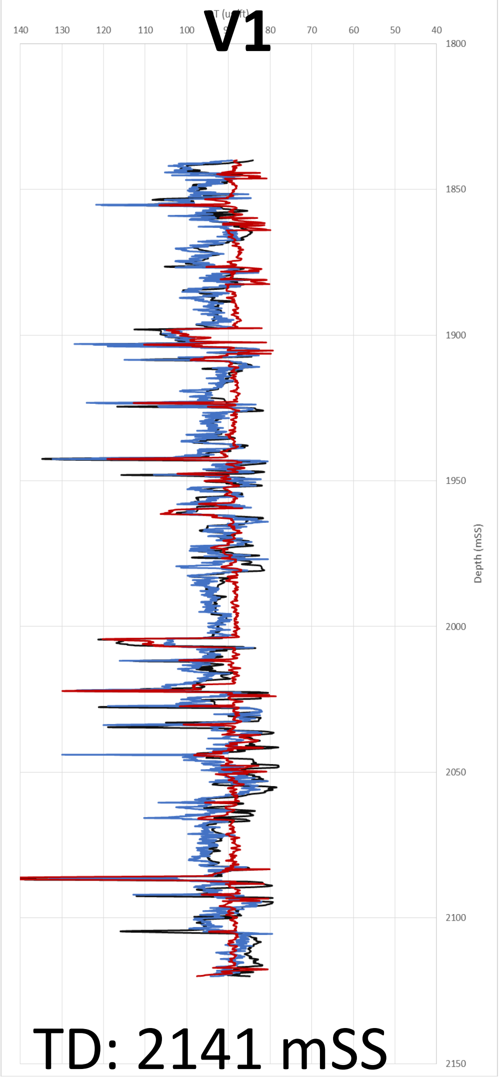
Model Training

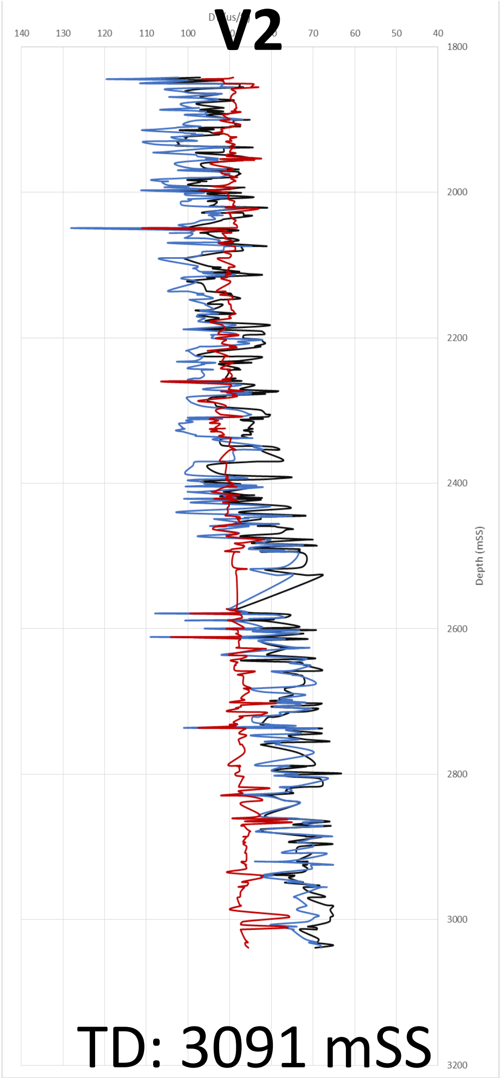
- Input variables,
  - Wireline / LWD logs,
    - Vertical depth subsea.
    - Gamma ray.
    - Resistivity.
    - Density.
    - Neutron porosity.
  - Formation pressure.
  - Geological information,
    - Compartment.
    - Reservoir unit.
    - Lithology.

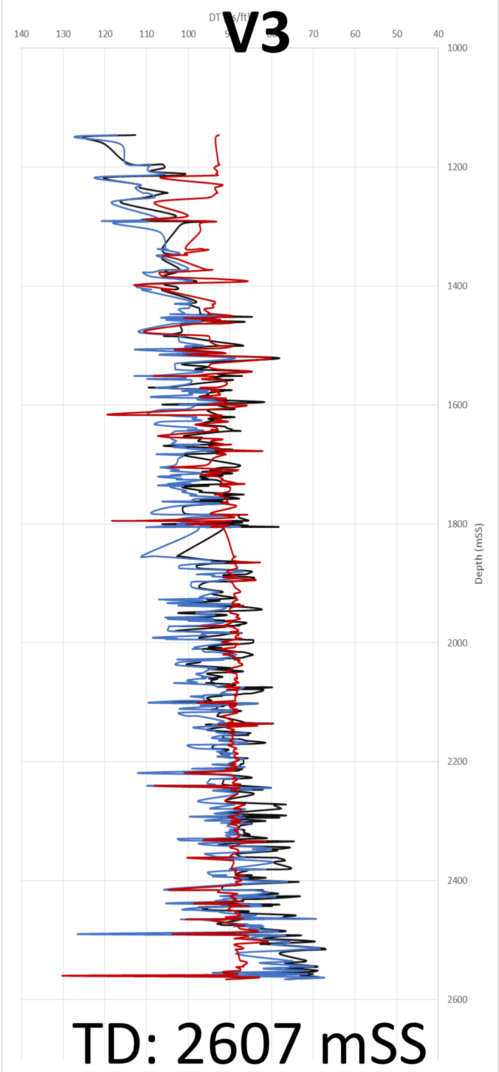


Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → Seismic Well Tie

DT Comparison in Validating Wells



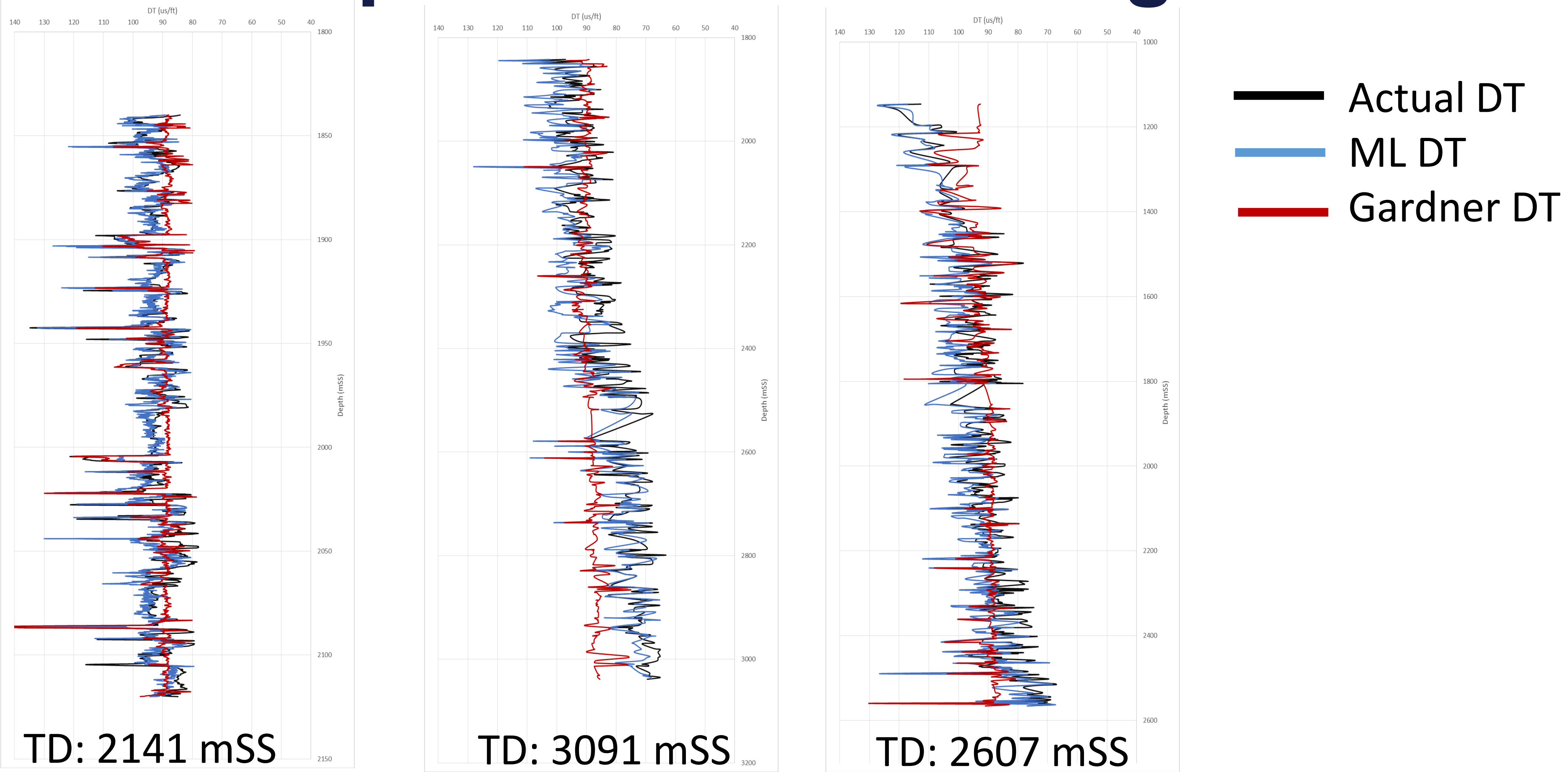




Actual DT
ML DT
Gardner DT

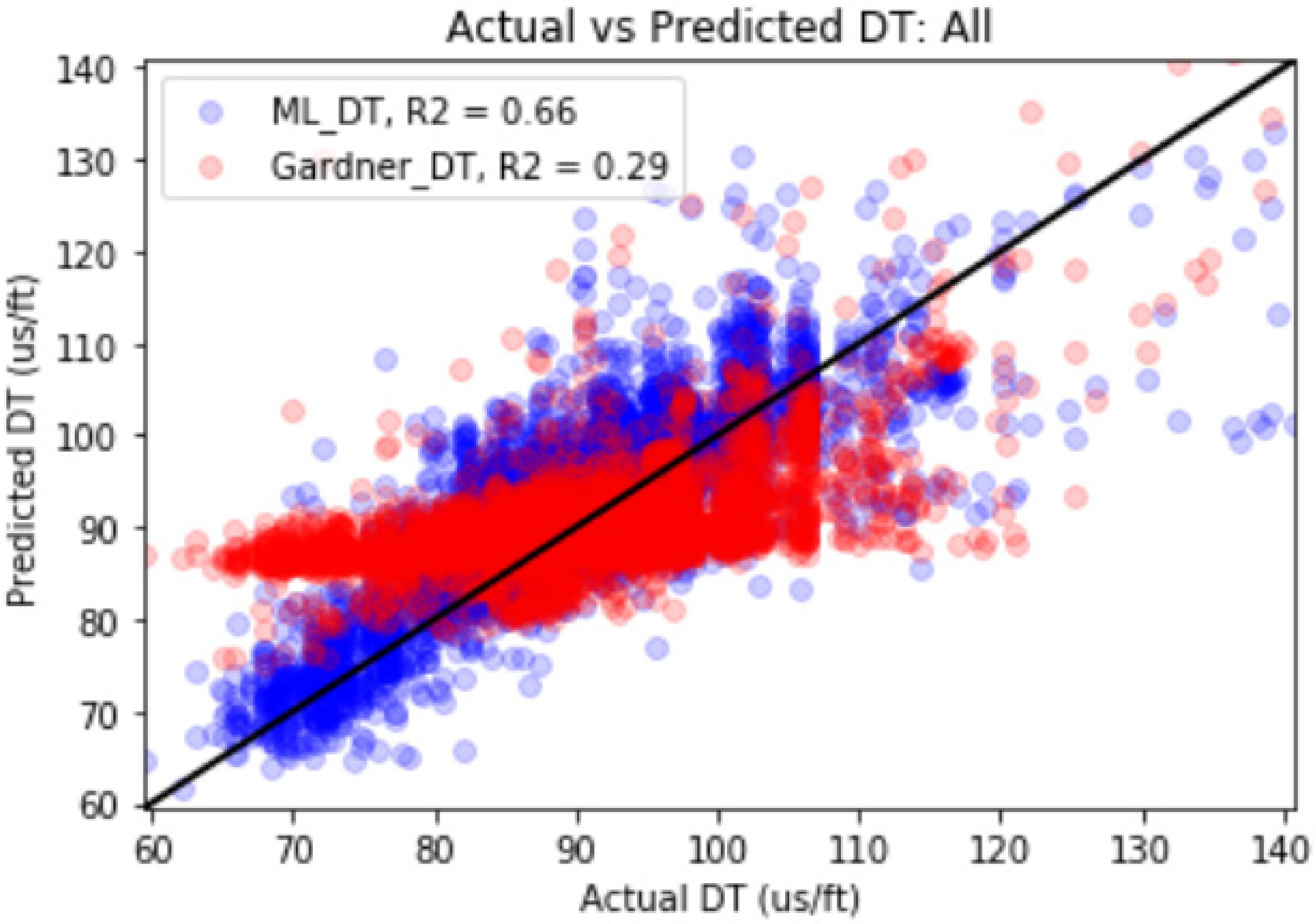
Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → Seismic Well Tie

DT Comparison in Validating Wells



Relevant Logs
ML Predict Acoustic Transit Time (DT)
Generate Acoustic Impedance and Seismogram
Seismic Well Tie

DT Comparison in Validating Wells



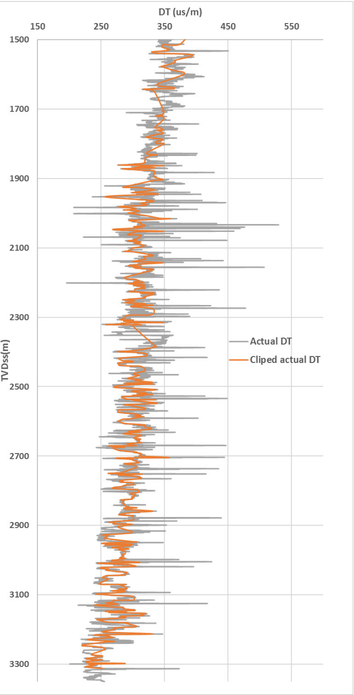
Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → Seismic Well Tie

Well Tie Work Flow

Import Data Well Log QC & Editing

Input

- DT log
- Density log
- Checkshot or VSP

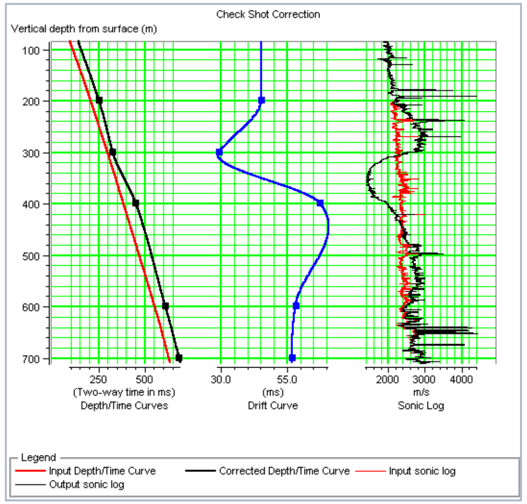


Actual DT

Filter DT

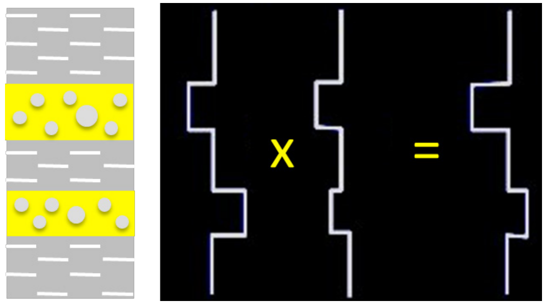
Casing
Bad hole condition
Spike

Sonic Calibration



Synthetic Generation

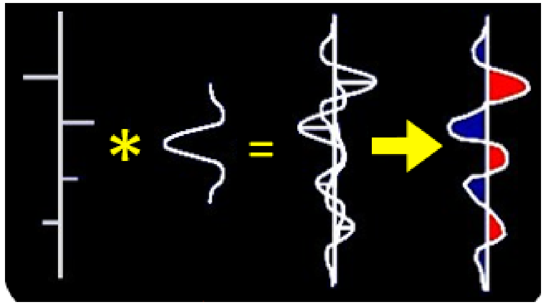
Acoustic Property



Lithology **Density log** **DT log** **AI**

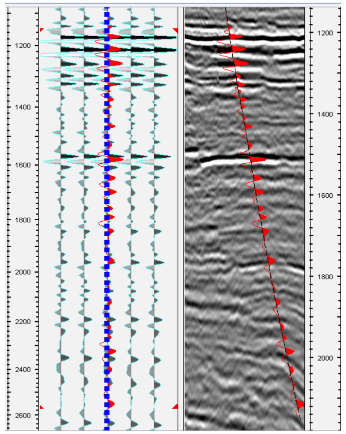
Computed

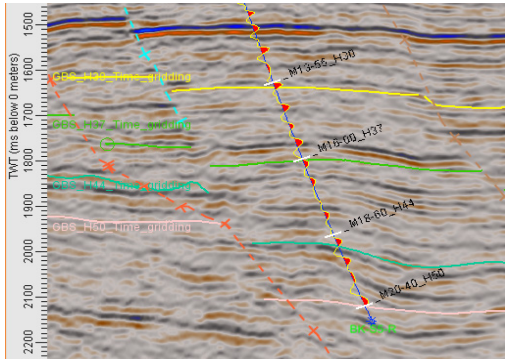
Convolutional Model



RC * Wavelet **Synthetic Seismogram**

Well Tie





Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → **Seismic Well Tie**

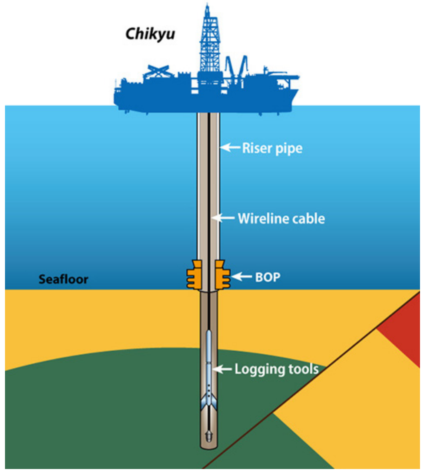
Comparison Scenarios

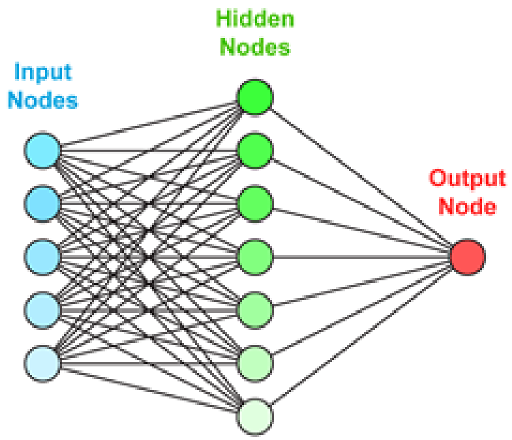
Actual DT

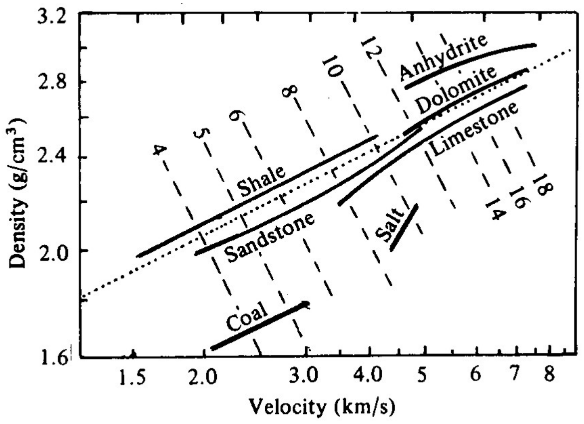
ML Synthetic DT

Gardner Synthetic DT

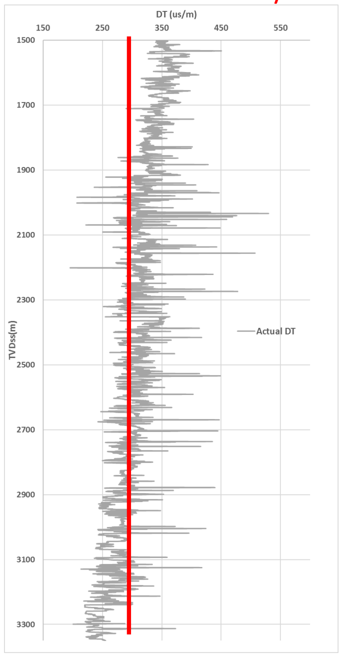
Constant DT





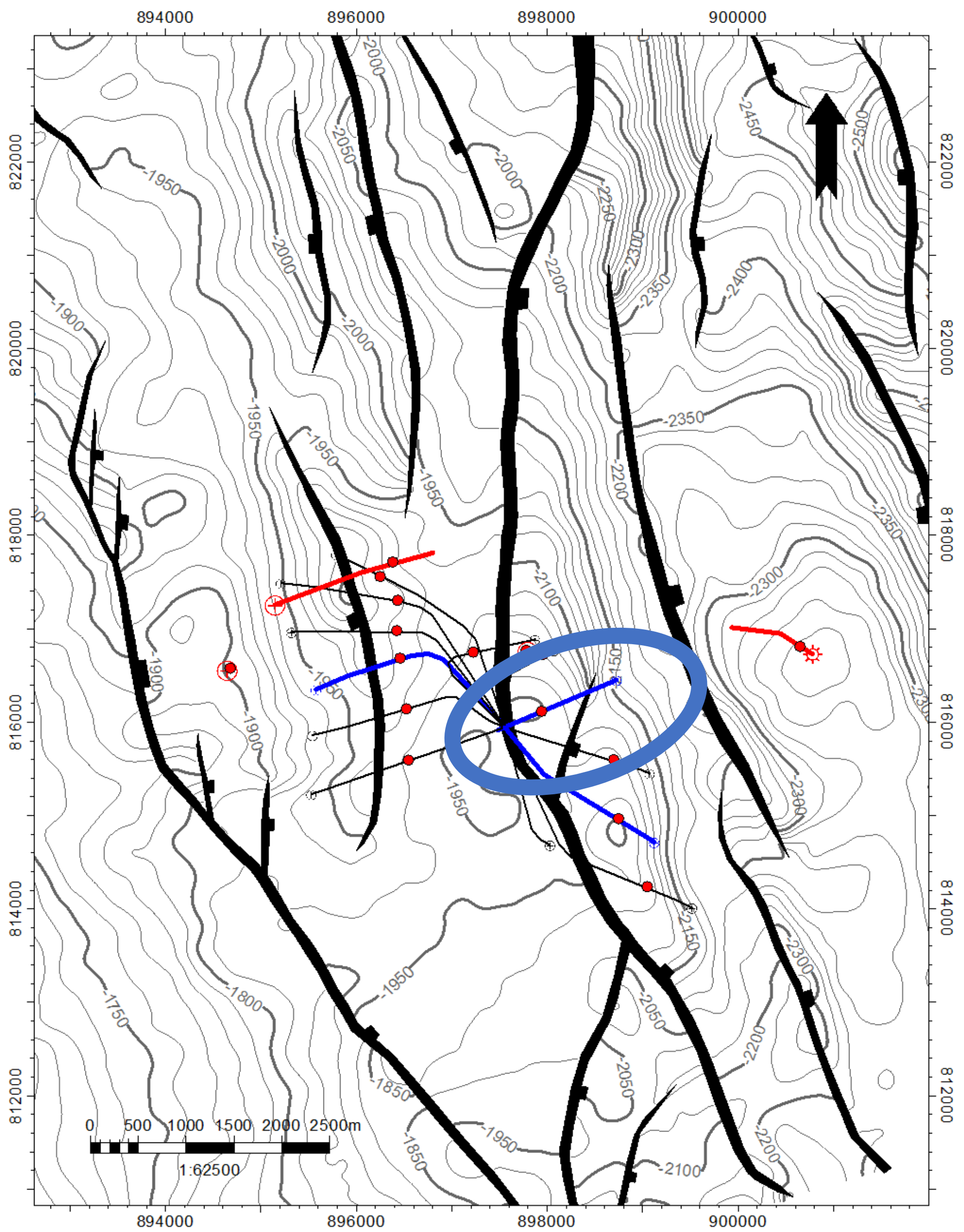


Constant DT 300 us/m



Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → **Seismic Well Tie**

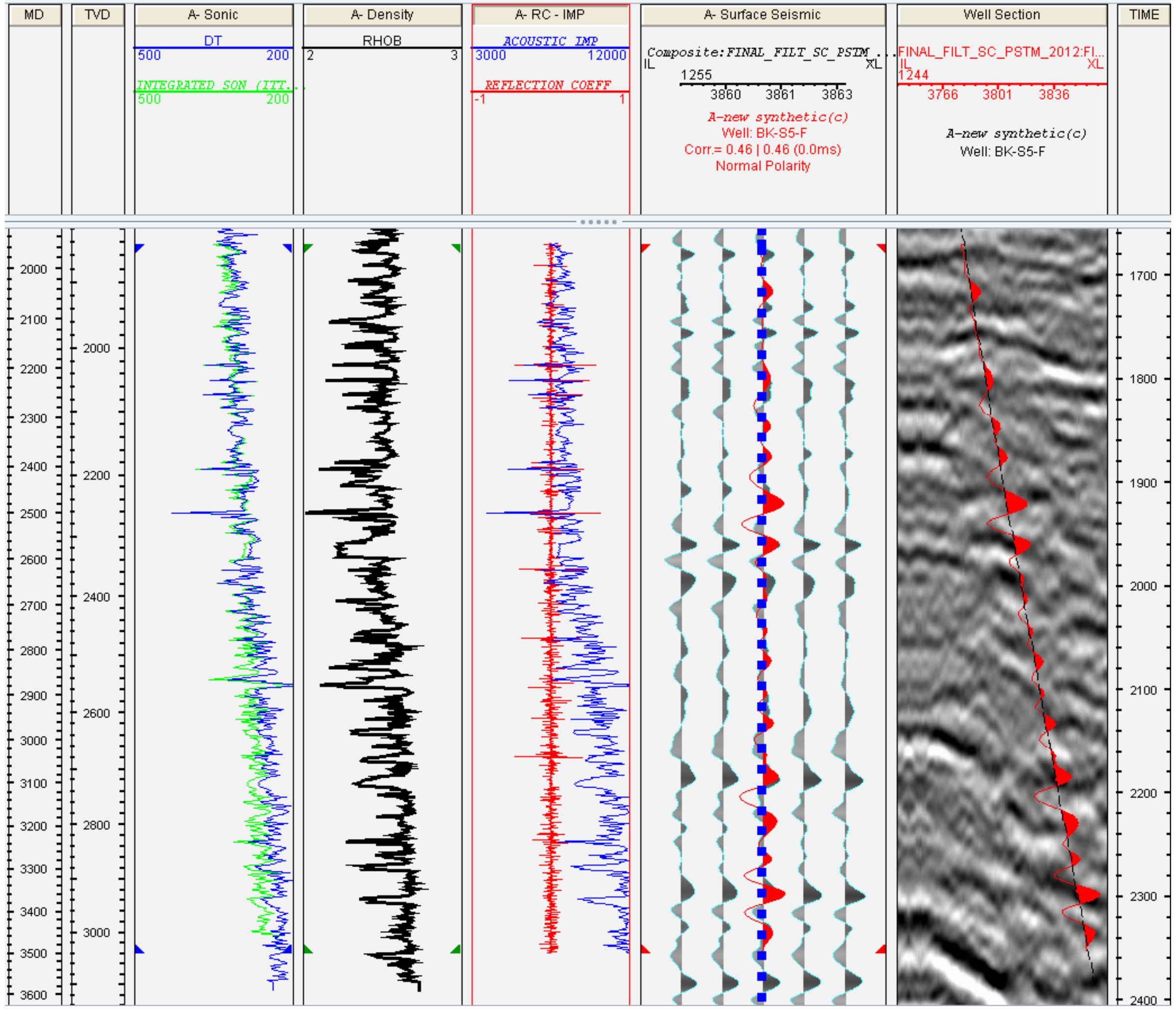
V2 Blind Well Test

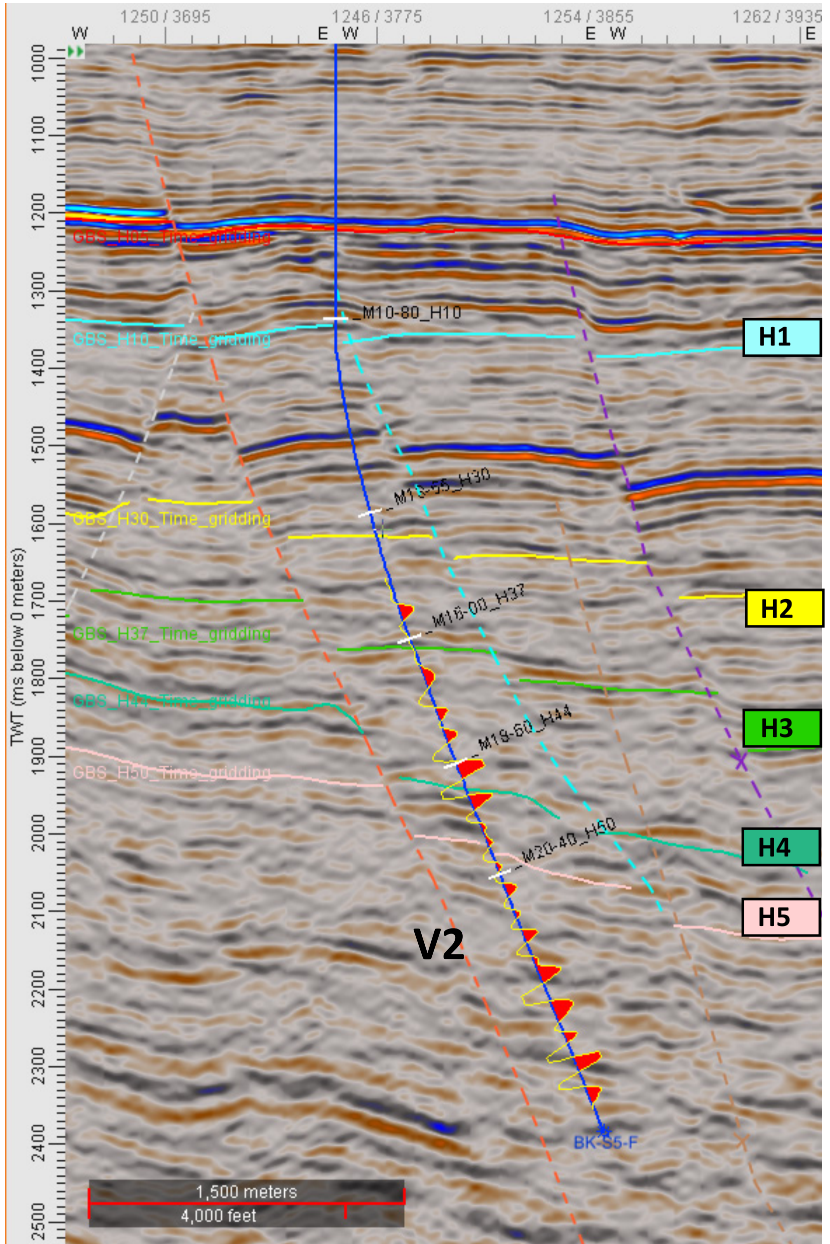


Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → **Seismic Well Tie**

Actual DT

Corr. Coefficient: 0.40
Time shift: -2.8 ms





Relevant Logs

ML Predict Acoustic Transit Time (DT)

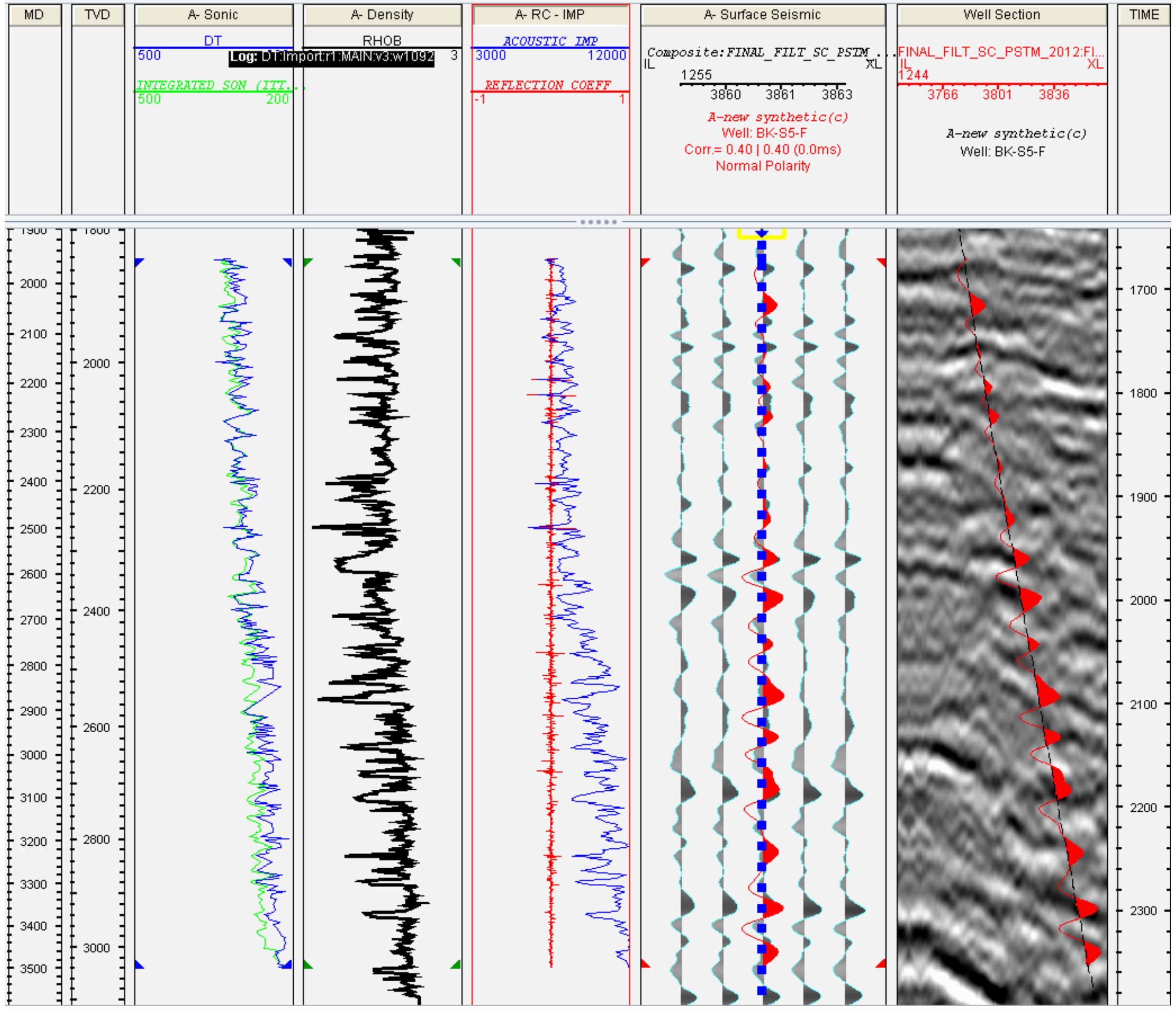
Generate Acoustic Impedance and Seismogram

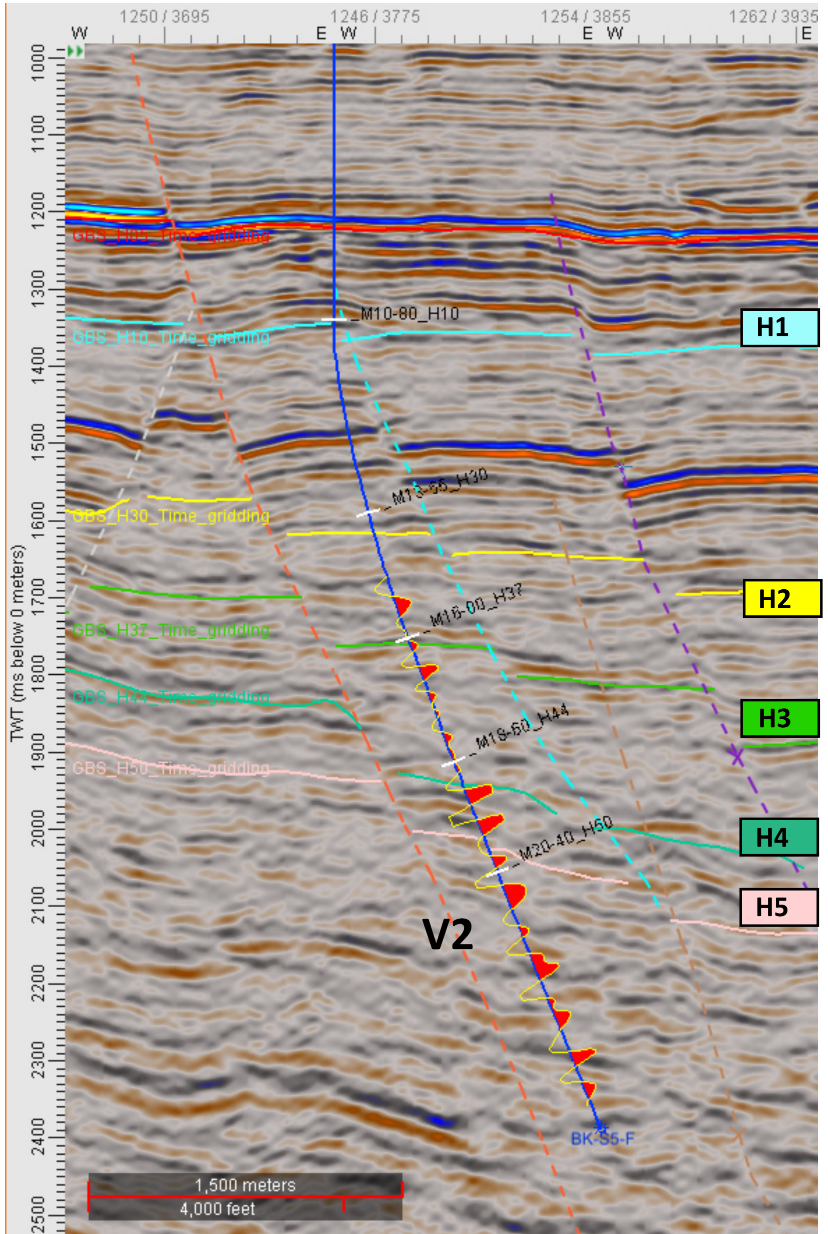
Seismic Well Tie

ML DT

Corr. Coefficient: 0.42

Time shift: 0.2 ms



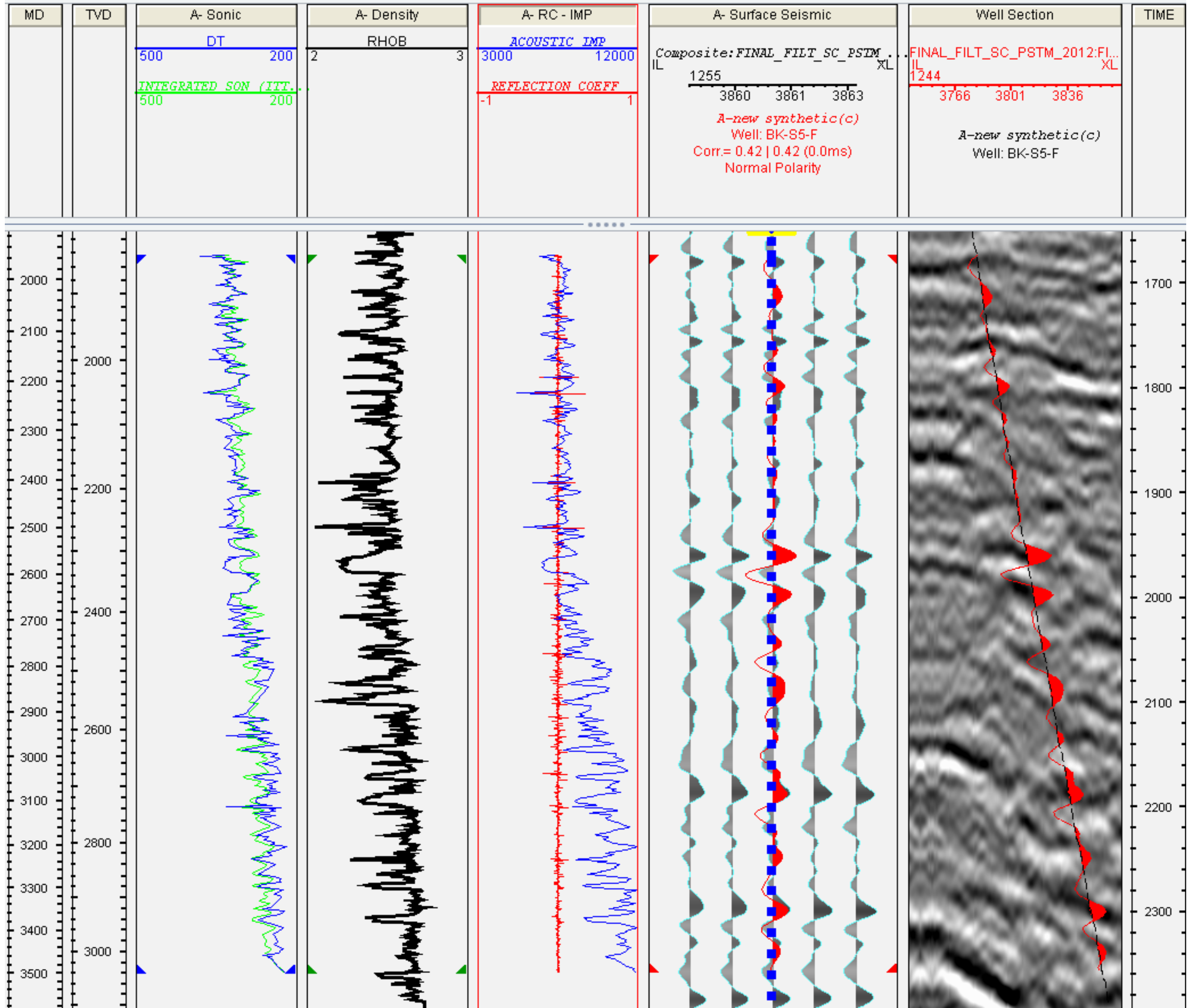


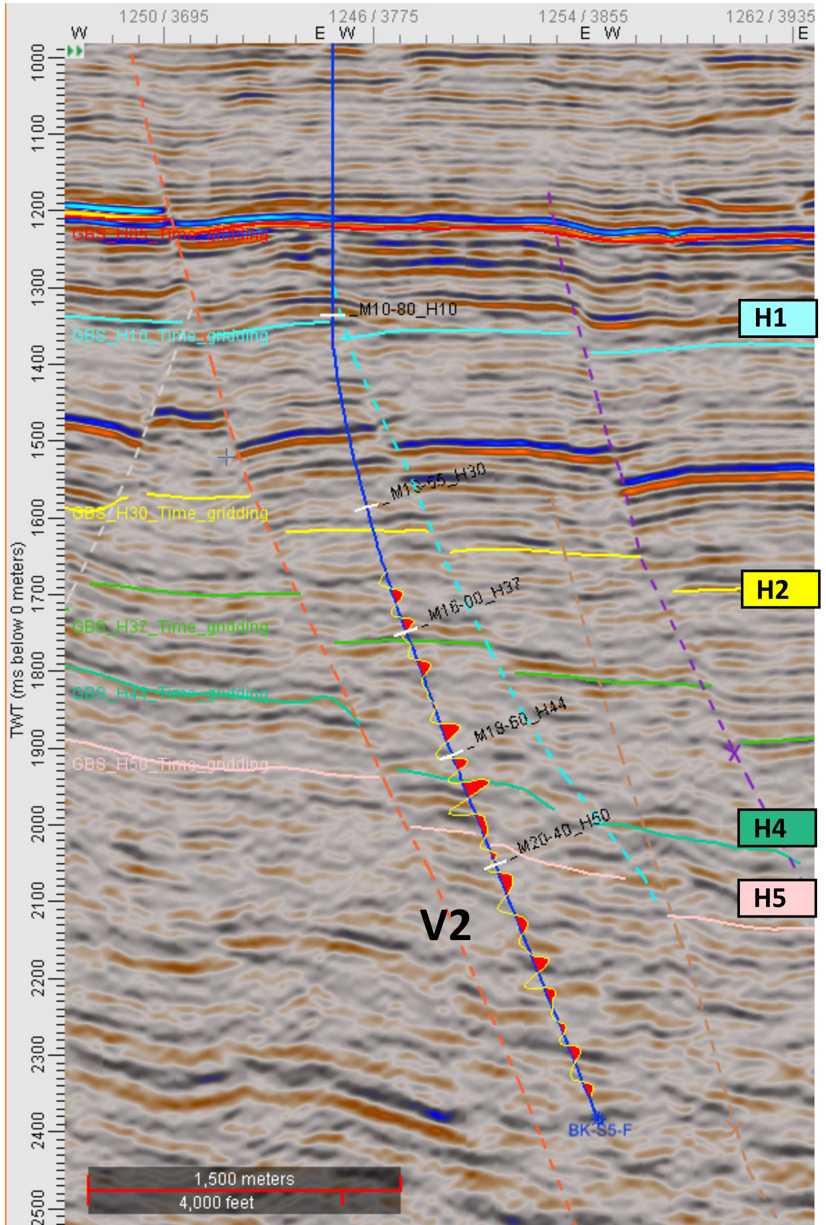
Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → Seismic Well Tie

Gardner DT

Corr. Coefficient: 0.25

Time shift: 21.4 ms



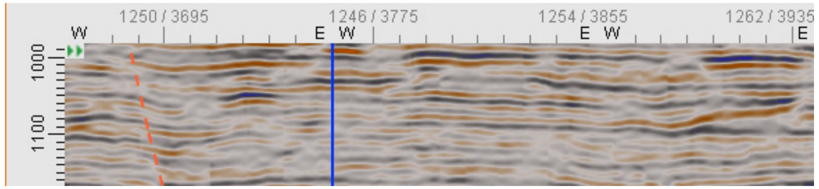


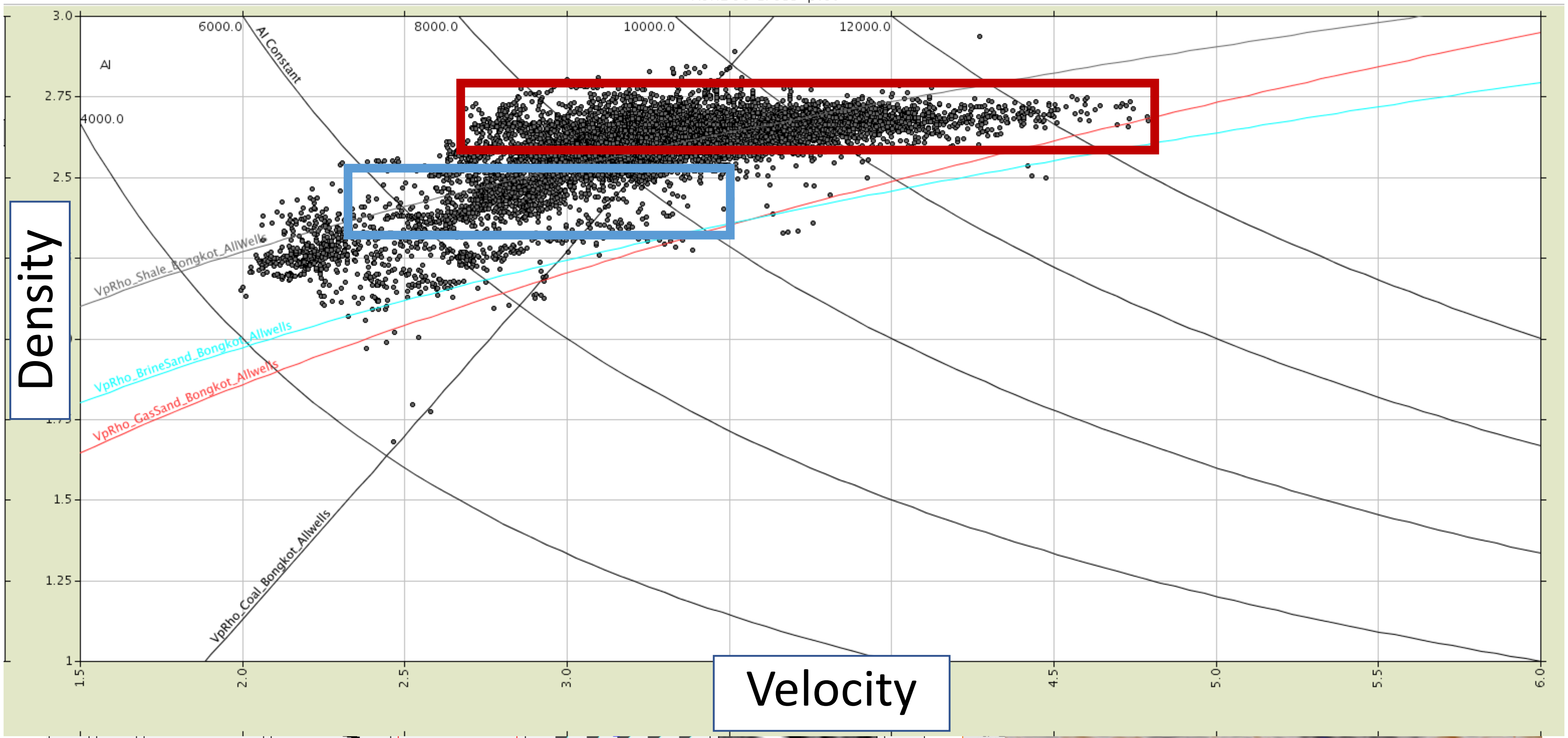
Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → Seismic Well Tie

Gardner DT

Corr. Coefficient: 0.25

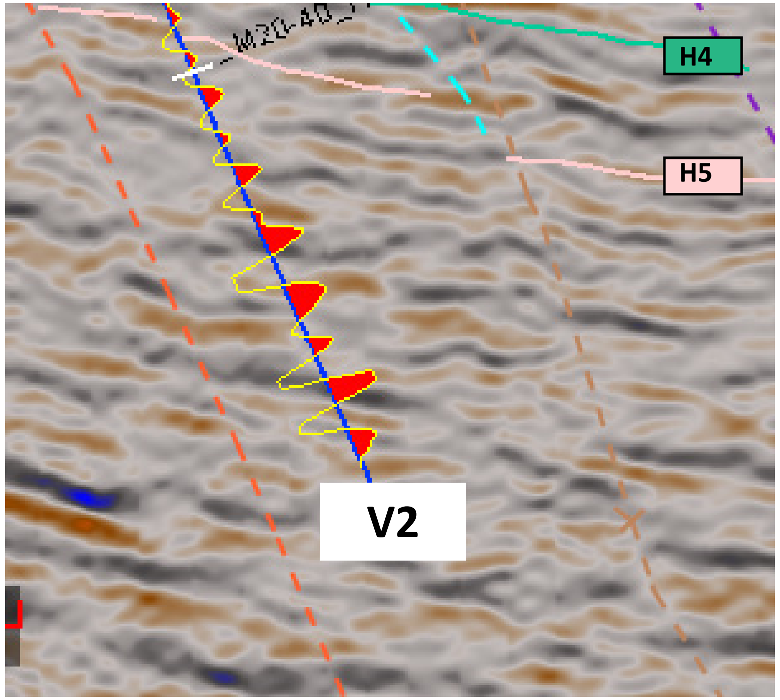
Time shift: 21.4 ms

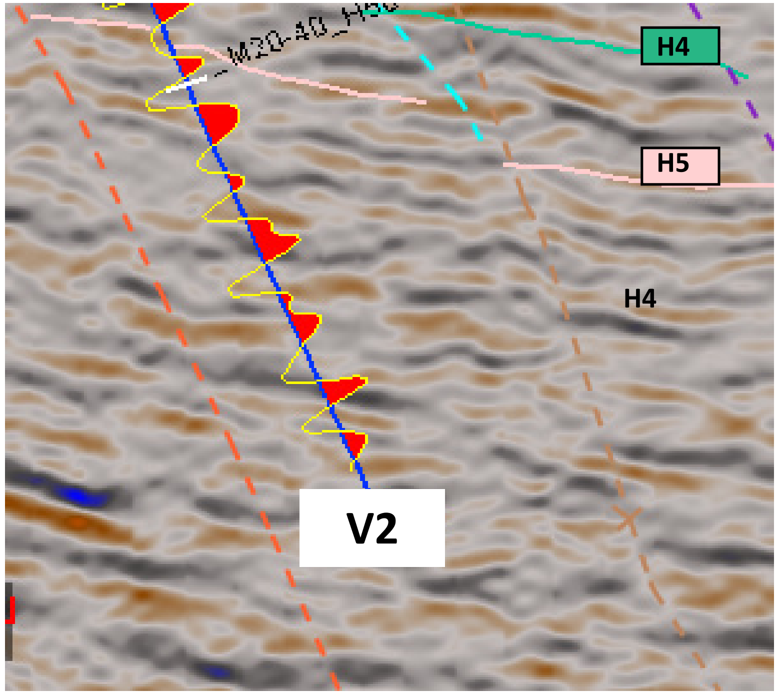


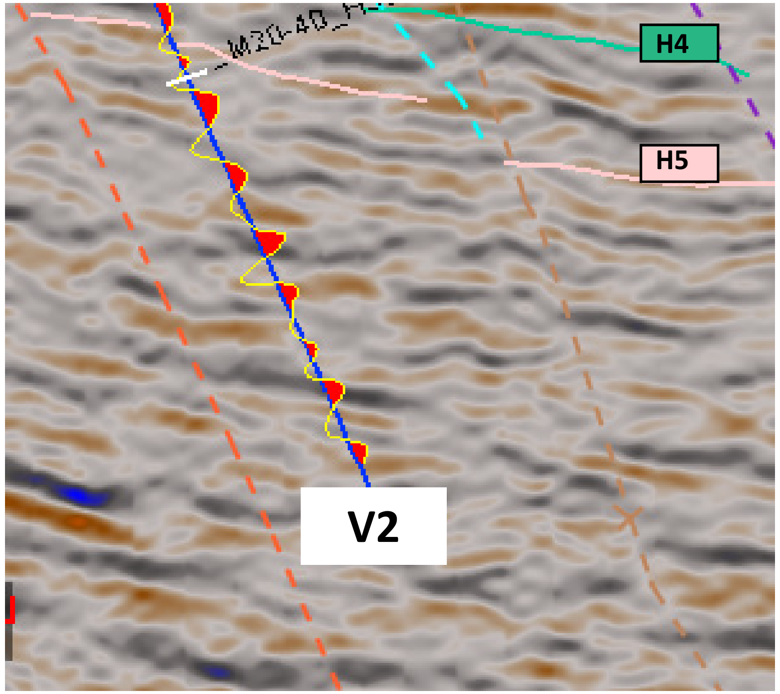


Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → **Seismic Well Tie**

Actual DT	ML Synthetic DT	Gardner Synthetic DT



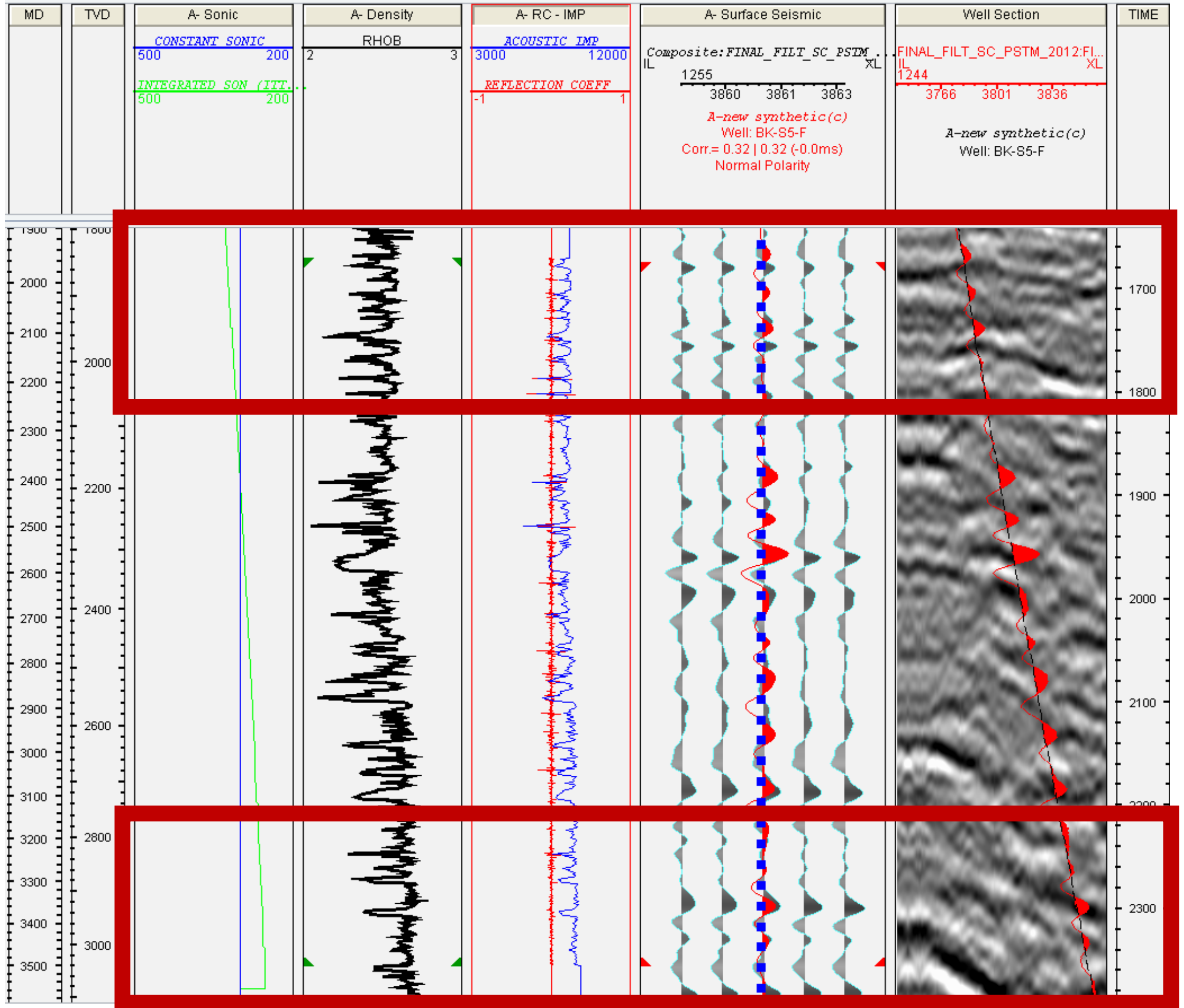


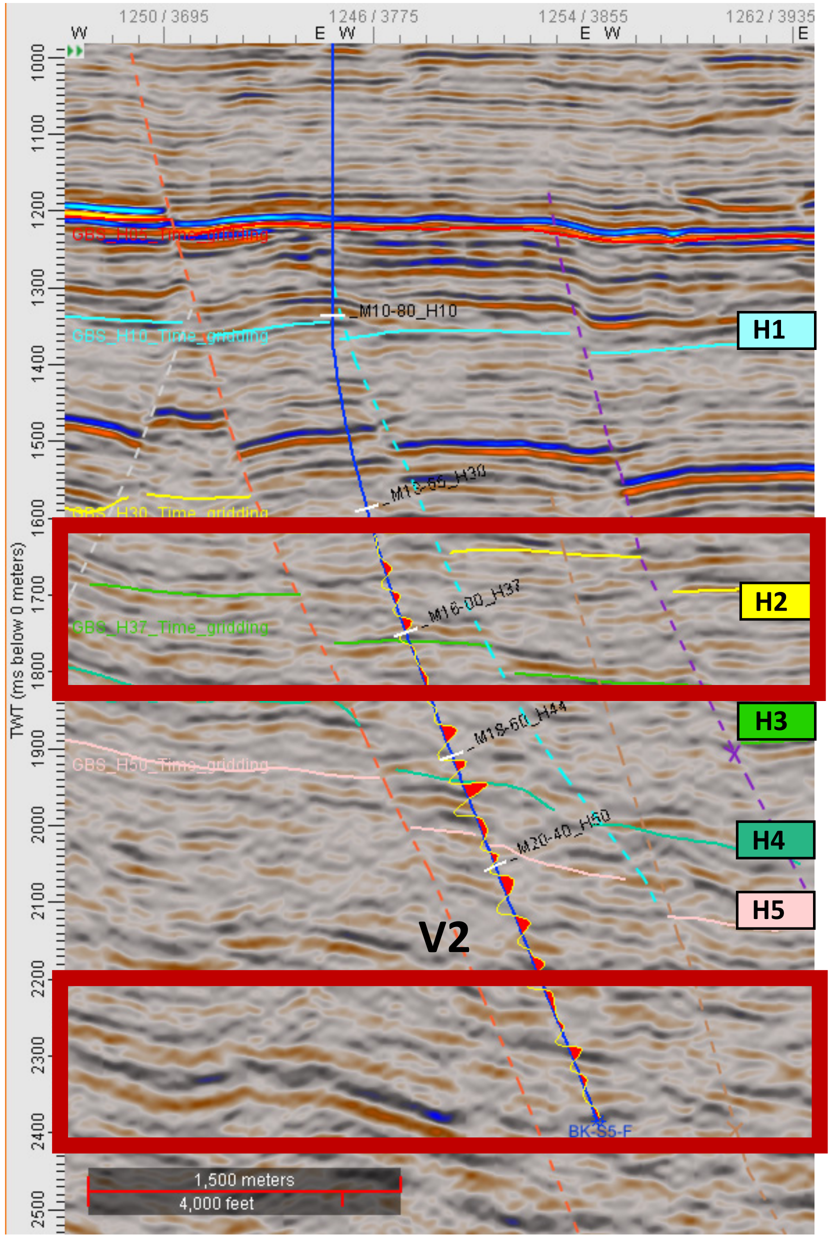


Relevant Logs
ML Predict Acoustic Transit Time (DT)
Generate Acoustic Impedance and Seismogram
Seismic Well Tie

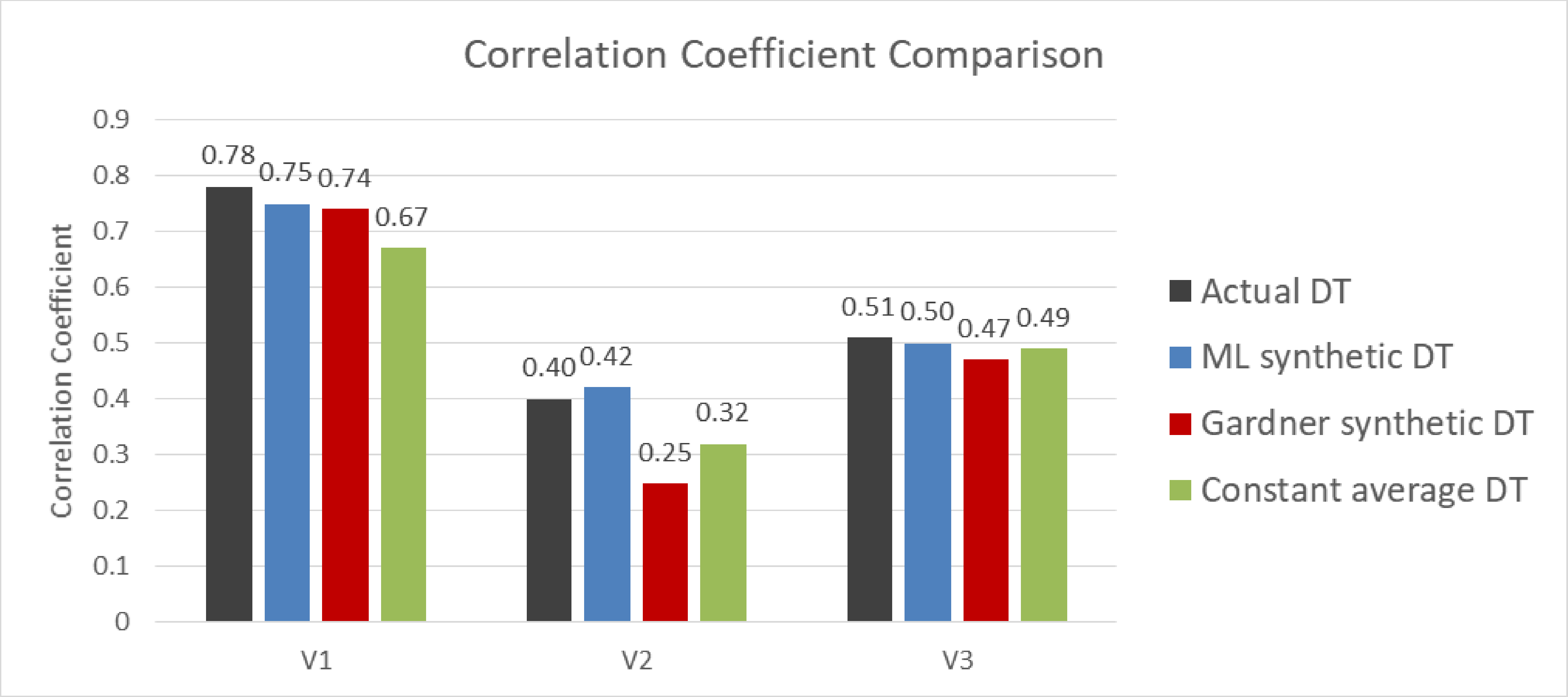
Constant DT

Constant DT = 300$\mu s/m$
Corr. Coefficient: 0.32
Time shift: -2.8 ms





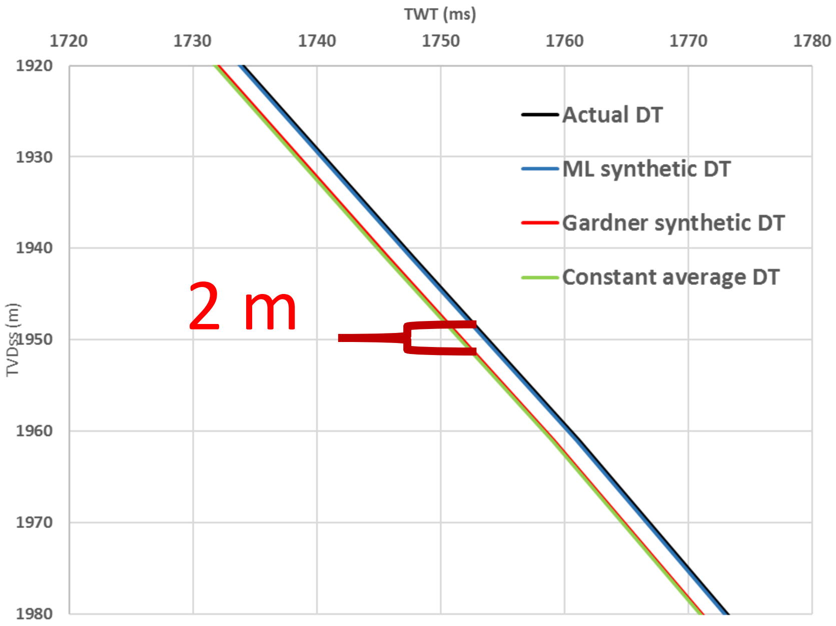
Well Tie Results



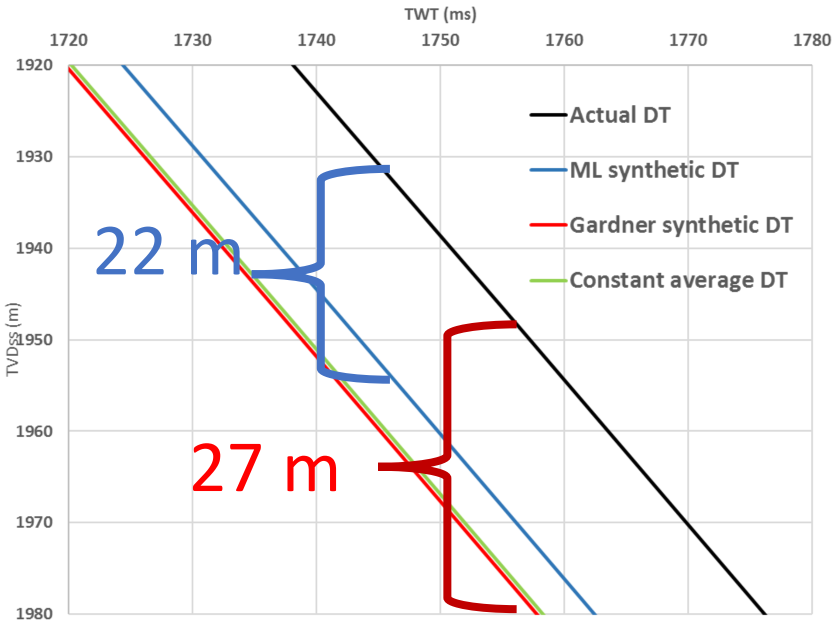
Relevant Logs → ML Predict Acoustic Transit Time (DT) → Generate Acoustic Impedance and Seismogram → Seismic Well Tie

Time Depth Comparison

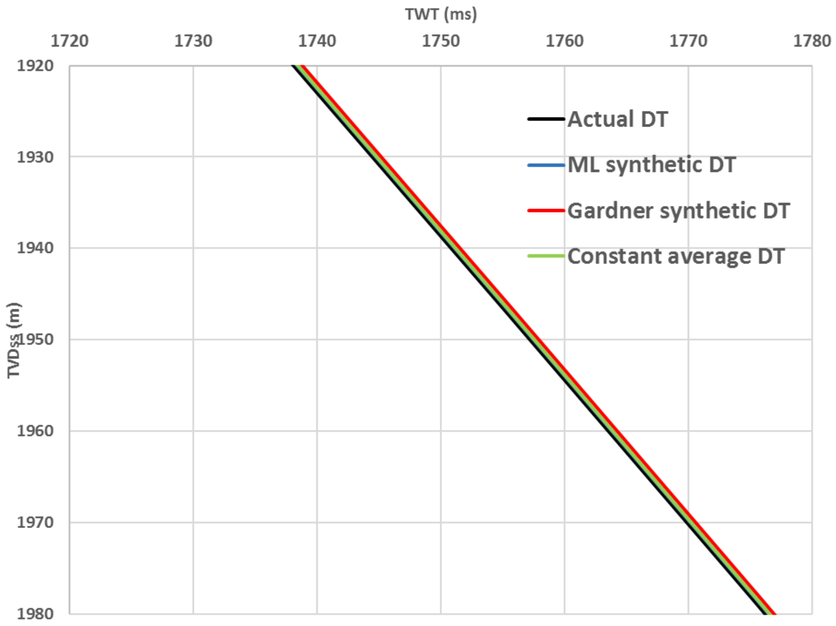
V1



V2



V3



Conclusion

- To DT synthetic using ML is more accurate than conventional methods.

- Seismic well tie using ML DT is resemble to actual DT.

Benefits

- Reduce number of sonic data acquisition.
  - Saving time.
  - Save cost 14$k/well.

- Reduce operation risks.