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# A MACHINE LEARNING APPROACH FOR CALIBRATING SEISMIC INTERVAL VELOCITY IN 3D VELOCITY MODEL

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## Summary

Velocity model technique is routinely used to convert data from the time-to-depth domain to support prospect evaluation, reservoir modelling, well engineering, and further drilling operation. In Vietnam, the conventional velocity model building workflow oversimplifies the interval velocities as only well interval velocities are populated into 2D grids for depth conversion or oversimplified calibration interval velocities by applying a single scaling factor function. This study explores the 3D velocity model workflow to obtain accurate and high-resolution interval velocities using a machine learning approach for both fields A and B in Cuu Long basin, offshore Vietnam.

To design an effective approach to depth conversion, the anisotropy factor analysis was performed to understand the differences between the seismic and well interval velocities in geological layer in the 3D structural model. The seismic interval velocity was multiplied by the anisotropy factor to achieve the scaling seismic interval velocity. The scaling seismic interval velocity, elastic attributes, geometric attributes, structural and stratigraphic attributes were used as training features (variables) for predicting interval velocity using the supervised learning algorithm in the machine learning model. Supervised learning offers an opportunity to develop an expert-knowledge-based automated system, which incorporates both domain knowledge and quantitative data mining [1]. The random forest regression algorithms were selected for predicting interval velocity after evaluating several machine learning algorithms. To provide insight into the uncertainty of final interval velocity, a depth uncertainty analysis was conducted using a blind well test for 24 wells and 7 horizons.

The comprehensive 3D velocity model using machine learning approach was built for the first time in Cuu Long basin, offshore Vietnam. The result showed the machine learning algorithm can address the disadvantages of conventional velocity calibration to create highly accurate depth representations of the subsurface including a measure of the uncertainty.

**Key words:** Velocity model, seismic attribute, depth uncertainty analysis, machine learning, Cuu Long basin.

## 1. Introduction

The velocity profile of the field can be simple or complex depending on the data quality and the complexity of geological data, the calibration interval velocity played a significant role in providing accurate time-depth conversion results. The conventional approach of calibrating internal velocity is a linear relationship between seismic interval velocity with well interval velocity. The high uncertainty associated with time-to-depth conversion can lead to unreliable reservoir depth models, ambiguous reservoir volumetric calculations and potential drilling hazards.

Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. Encouraged by the rapid growth of machine learning techniques and by their huge success in other industries, the geoscience community has embarked upon initiatives to integrate machine learning capabilities into geophysical data analysis [2].

In this study, the supervised learning algorithms (multiple linear regression, multiple polynomial regression, gradient boosting regression, random forest

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regression) were used for predicting interval velocity. The machine learning model was trained on selected input data (the scaling seismic interval velocity, geometric attributes, structural and stratigraphic attributes) and supervised with well interval velocity. As a result, the best supervised learning algorithms were selected for being capable of predicting further outcomes (interval velocity) for a 3D velocity model.

This paper showed an innovative methodology for calibrating interval velocity by predicting interval velocity from the machine learning approach. The final calibrating interval velocity was evaluated numerically, visually, and for geological consistency, while the depth uncertainty could be estimated from a depth error analysis in a blind well test method.

## 2. Methodology

### *2.1. 3D Structural model*

In this case study, the 3D structural model was created by using seven horizons in the time domain with reasonable horizontal and vertical velocity resolution (Figure 1). This is because seismic velocities in general can provide a reliable regional velocity trend and the velocity field varies smoothly with depth. Therefore, the small horizontal and vertical resolution is not necessary for the velocity model process. The vertical resolution can be measured via standard variogram analysis, and it is recommended not to be greater than half of the vertical range [3].

### *2.2. Velocity data preparation and analysis*

There are several areas we need to focus on during the review of velocity data to ensure the good quality input data for velocity model building. Poorly positioned wells, miscorrelated horizons, and inconsistent formation tops can introduce distortions in the implied velocity field and result in false structuring.

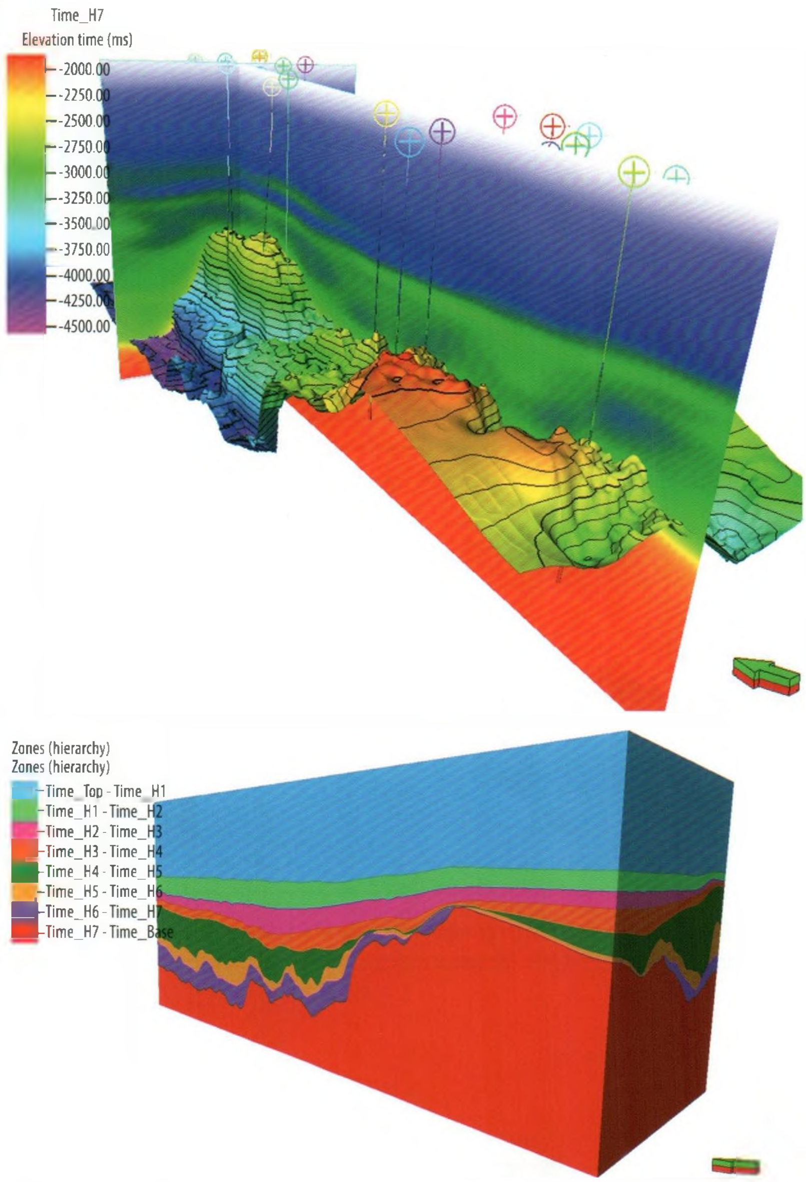


***Figure 1.*** *3D structural model creation.*

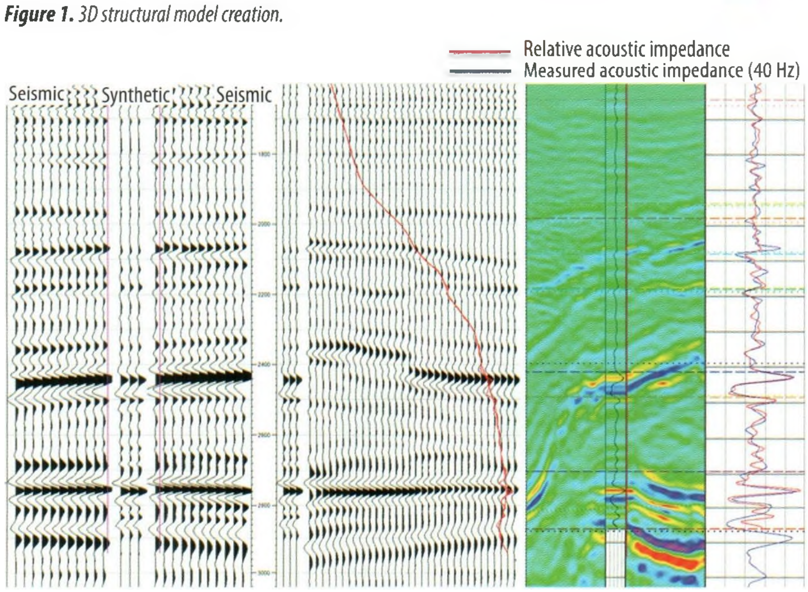


***Figure 2.*** *The seismic well-tie QC step.*

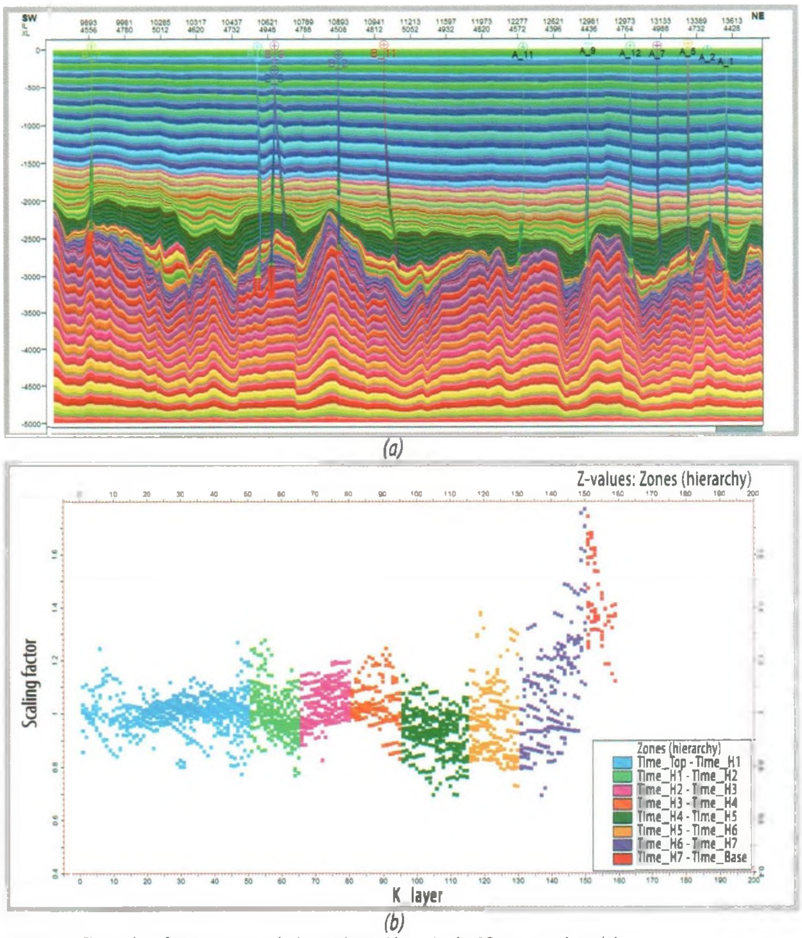


*Figure 3. The scaling factor varies with the geological layer in the 3D structural model.*

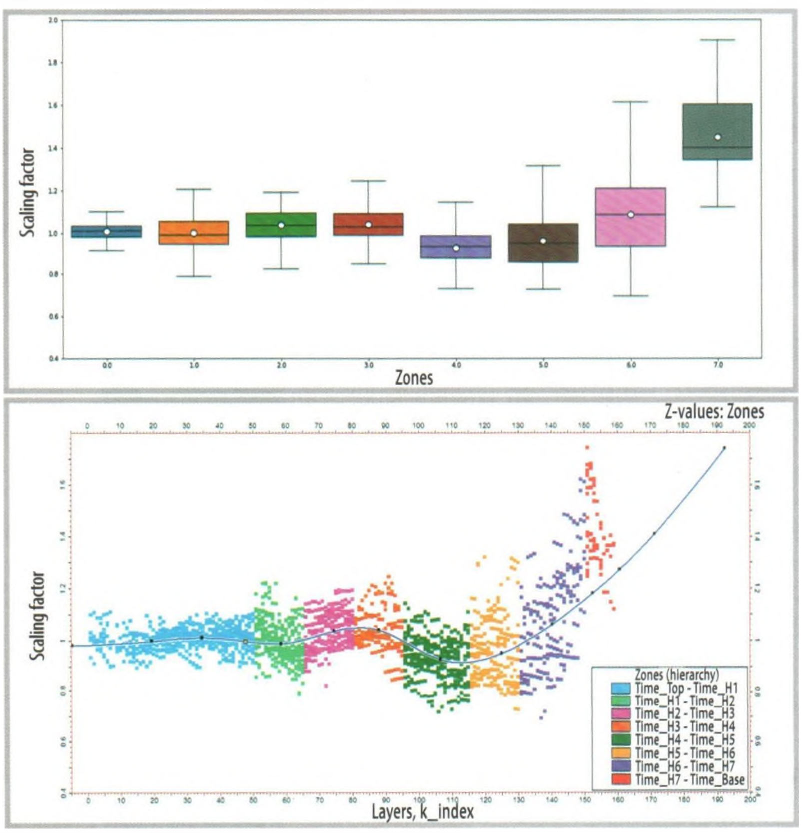


*Figure 4. The best-fit curve for scaling seismic interval velocity.*

The seismic well-tied is one of the key components of the velocity modelling workflow. It is the bridge between geological information (well data in depth) and geophysical information (seismic in time). The seismic well-tie was done for 24 wells in this study. The generated synthetic was compared with seismic data to determine the amount of time shift/stretching required on the time-depth relationship (TDR) to improve the matching between well logs and seismic data. The relative acoustic impedance (generated using preliminary inversion parameters) was also compared with the measured acoustic impedance log at well location with the well-tied TDR.

The scaling factor is the quotient of well interval velocity and seismic interval velocity and is a function of geological layer in the 3D structural model. The objective of the scaling factor process was to scale the seismic interval velocity to the well interval velocity by understanding how the velocity varies vertically and horizontally.

The intersection in Figure 3a shows the geological layer in the study area and the cross-plot in Figure 3b shows how the scaling factor varies with the geological layer in the 3D structural model. The X-axis shows the geological layers (K_layer) while the Y-axis displays the scaling factor which is the quotient of well interval velocity and seismic interval velocity. The scaling factor value equals to 1 means the well interval velocity has the same value as the seismic interval velocity. The scaling factor value is greater than 1 means the well interval velocity is faster than the seismic interval velocity. The well interval velocity is slower than the seismic interval velocity when the scaling factor value is less than 1.

The scaling factor can be displayed as boxplot and removed interval velocity outlier of each zone before digitising a best-fit curve for scaling seismic interval velocity (Figure 4). The scaling factor points above the best-fit curve (blue curve) has positive error while the scaling factor points below the best-fit curve has negative error.

The scaling interval velocity quality was examined by the residual scaling factor (the quotient of the wells interval velocity and the scaling seismic interval velocity) and the correlation between scaling seismic interval velocity with well interval velocity. The scaling factor value was reduced and improved the correlation between seismic interval velocity with well interval velocity after applying the scaling factor (Figures 5 and 6). However, the high variation of residual scaling factor was presented below the H4 zone since the complex structural geology of these zones. Often, the degree of geological complexity causes significant variation of the residual scaling factor when seismic interval velocity is calibrated with well interval velocity using the single scaling function.

### ***2.3. Machine learning approach for interval velocity prediction***

Machine learning can support interpretation through the identification and characterisation of underlying patterns in seismic and log data that are beyond human comprehension or obscured through traditional means of visualising and interacting with the data [1]. The elastic attributes (acoustic impedance, density and the compressional to shear-wave velocity ratio), structural and stratigraphic attributes (3D curvature, chaos, ISO-frequency) were generated and resampled into a 3D structural model. Then, these attributes and scaling seismic interval velocity were exported with geometric attributes information (IJK grid cell indices, XYZ grid cell coordinates) from proprietary E&P software platform to a web-based interactive computing platform to build the machine learning model.

To train the machine learning model, the collection features were divided into two parts, training data and test data. The training data was implemented to build up a machine learning model, while the test data was to validate it. K-fold cross-validation (K = 5) was

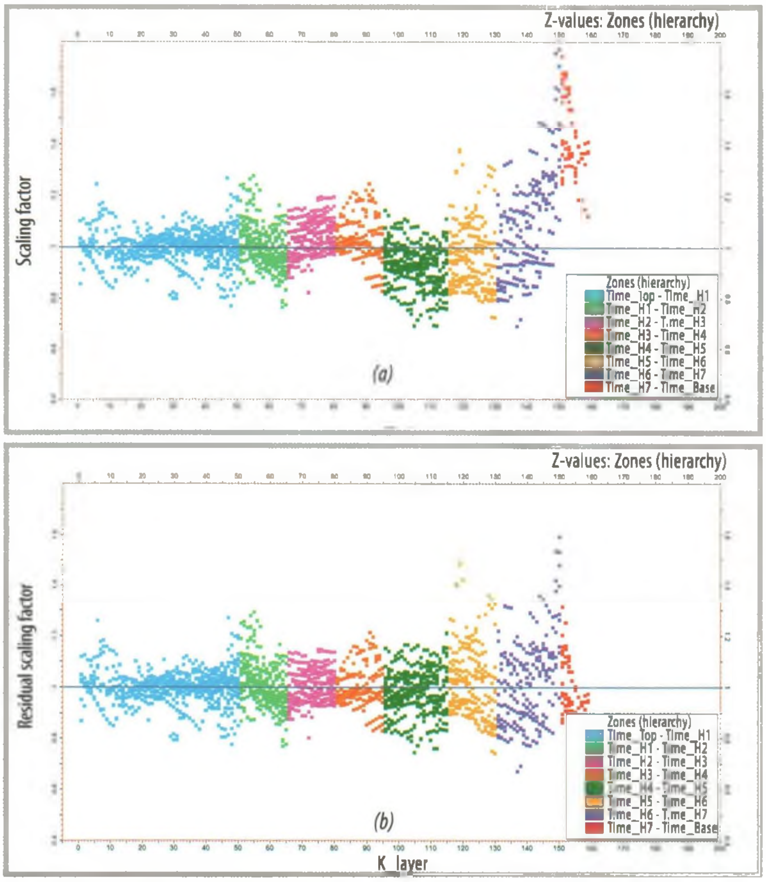


***Figure 5.*** *The scaling factor (a) and the residual scaling factor (b).*

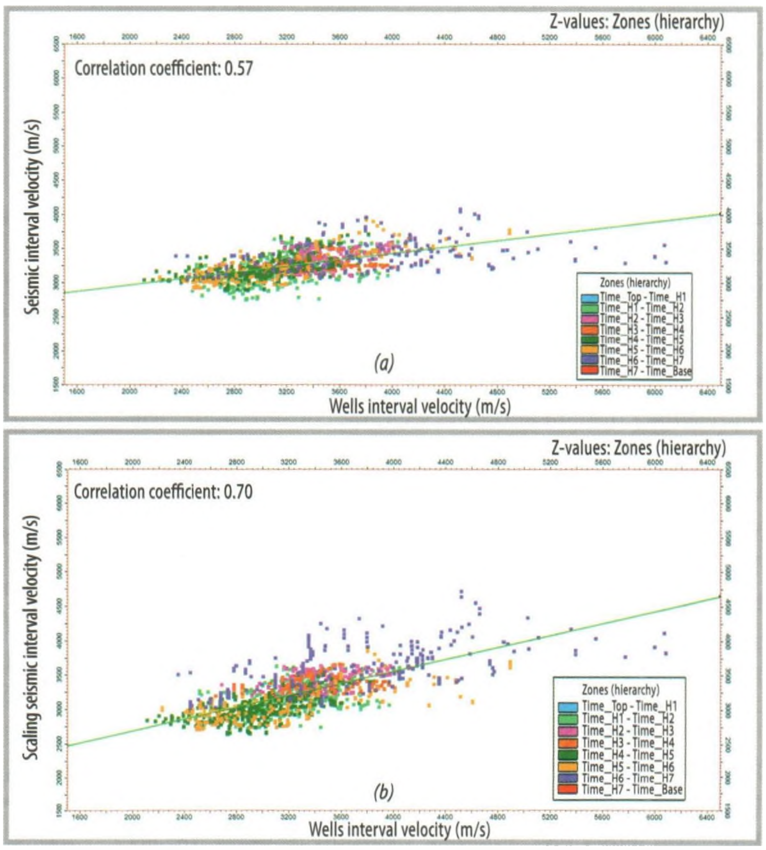


***Figure 6.*** *The correlation between seismic interval velocity and well interval velocity (a), and the correlation between scaling seismic interval velocity and well interval velocity (b).*

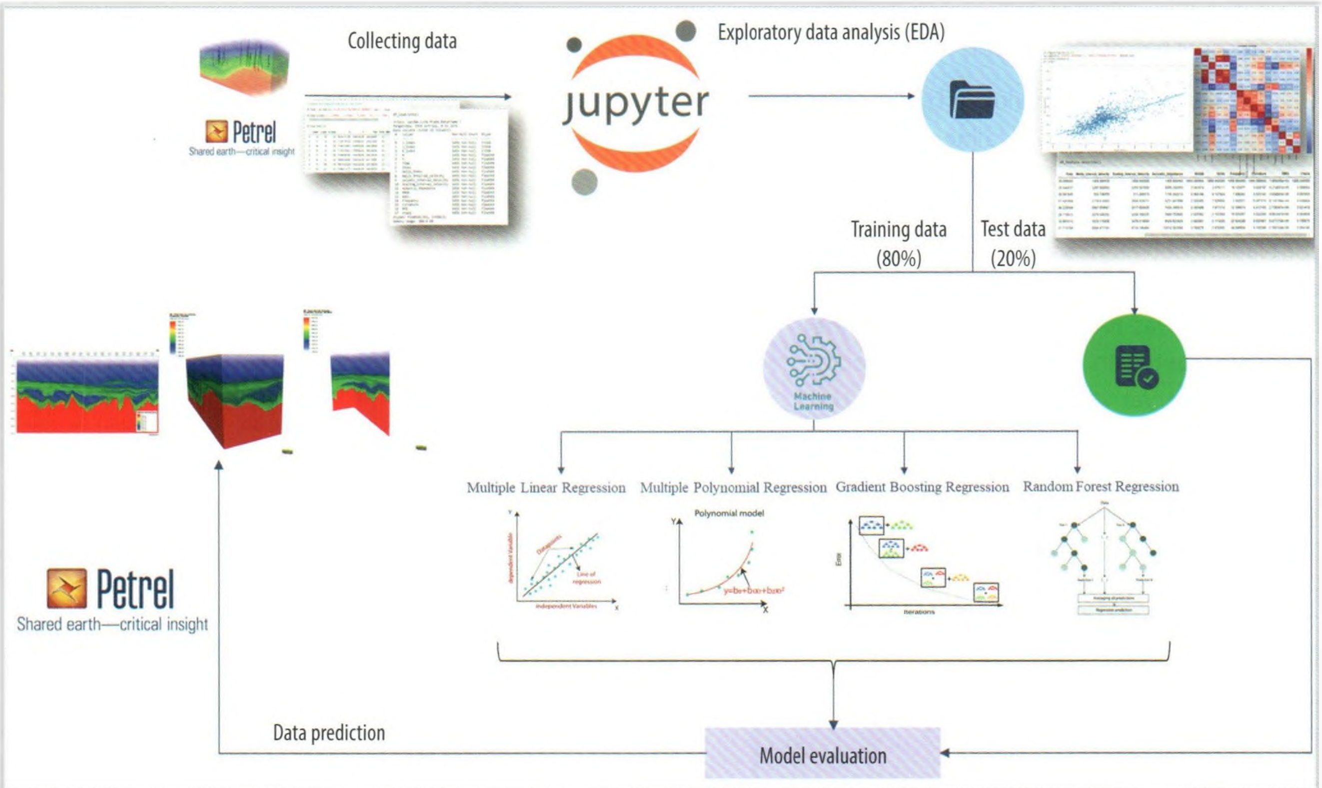


***Figure 7.*** *The general workflow for predicting interval velocity using machine learning approach.*

***Table 1.*** *The evaluation metrics for model evaluation*

| Machine learning algorithm | R-squared (%) | Mean squared error | Mean absolute error |
|---|---|---|---|
| Random forest regression | 80.5 | 55484.61 | 156.04 |
| Gradient boosting regression | 77.90 | 61728.01 | 180.55 |
| Multiple polynomial regression | 63.80 | 78214.99 | 202.47 |
| Multiple linear regression | 59.70 | 103826.06 | 236.28 |

also implemented to estimate the skill or performance of the machine learning model and avoid overfitting during the training process.

Model evaluation is an integral part of the model development process. It helps to find the best model that represents our data and how well the chosen model will work for predicting new datasets. Three evaluation metrics were used in this study, mean absolute error (MAE), mean squared error (MSE) and coefficient of determination (R2). The random forest regression algorithm [4] showed the best algorithm (the highest R-squared, the lowest mean squared error and mean absolute error) for predicting interval velocity in this study (Table 1).

The random forest regression model was used for predicting interval velocity for target zones from H1 to H7, the result of interval velocity prediction was re-imported to a proprietary E&P software platform to build the 3D velocity model for domain conversion.

### *2.4. Depth uncertainty analysis*

The depth uncertainty analysis was performed for all 24 wells and 7 horizons in this study to estimate the depth uncertainty of the velocity model for both methods (scaling factor function and machine learning algorithm). The depth comparison between the actual horizons and the calculated horizons of each well (using adjusted velocities by excluding one well) was performed to understand the variation of depth error (depth residual).

For example, the new (partial) velocity model was rebuilt using calibrated seismic interval velocities of all wells (from well 1 to well 23, except well 24) to convert all the horizons of well 24 from time to depth. The actual horizons of well 24 were used to correlate with the calculated depth of horizons to estimate the depth residual of all horizons at well 24. The process was repeated for the rest of other wells (well 1 to well 23) to

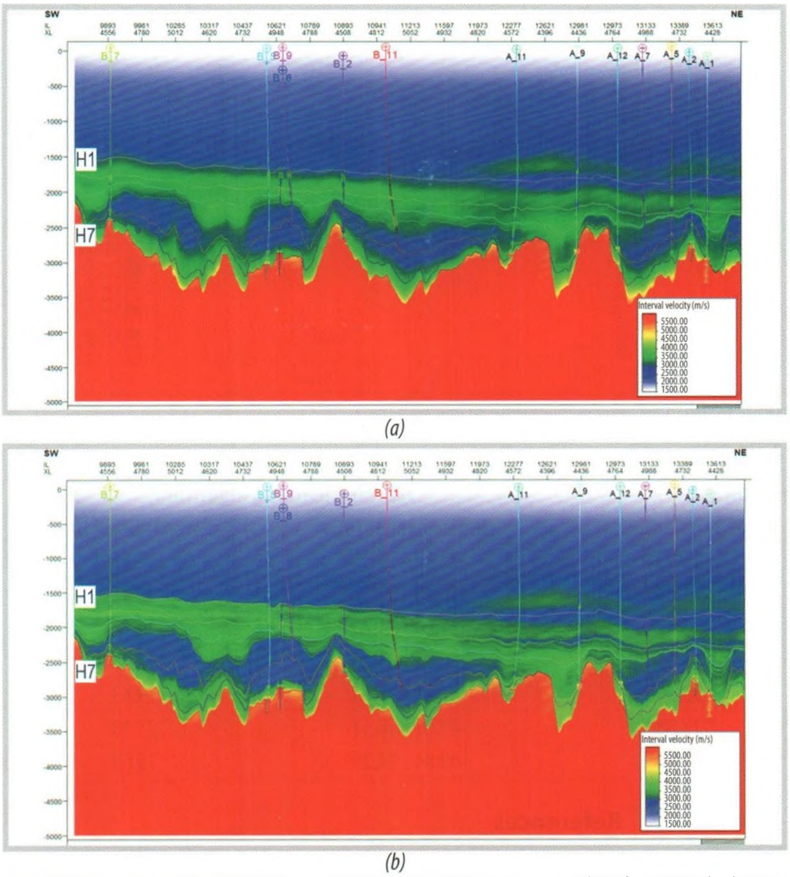


***Figure 8.** The scaling seismic interval velocity using scaling factor function (a) and the final interval velocity using machine learning approach (b).*

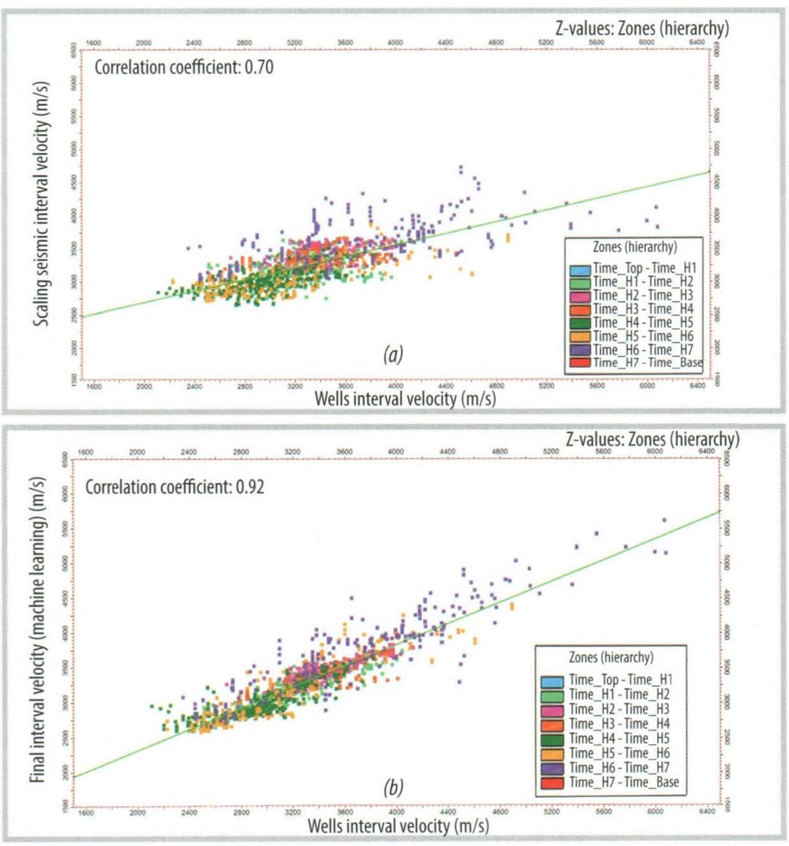


***Figure 9.** The correlation between scaling seismic interval velocity and well interval velocity (a), and the correlation between final interval velocity (machine learning approach) and well interval velocity (b).*

obtain the depth residual range of horizons for all wells in this field.

### 3. Results and discussion

The final interval velocity using machine learning approach preserved high resolution velocity from the zone H1 to H7, reduced residual scale factor and improved significant correlation between final interval velocity with well interval velocity (Figures 8 and 9).

The residual scaling factor value is around 1 in the cross-plot, which indicates that the calibrated seismic interval velocity is approximate to the well interval velocity (Figure 10b). The range residual scaling factor of the machine learning approach was minimised compared to the single calibrating function approach below the zone H4.

The depth uncertainty results performed by 2 different approaches of the scaling factor function (traditional method) and machine learning algorithm (a new approach) (Table 2). The result proved that the machine learning algorithm can address the disadvantages of the conventional velocity calibration to preserve lateral and vertical velocity resolution while reducing the uncertainty of time-to-depth conversion. The depth uncertainty analysis shows the mean uncertainty prognosis is 15.56 m at the top horizon H1 (approximately 0.76% depth uncertainty vs. target depth) and the mean uncertainty prognosis is 19.64 m at the base horizon H7 (approximately 0.56% depth uncertainty vs. target depth).

Due to the complexity of the geological structure the residual range is increased at deeper parts (H5 to H7). However, by using machine learning algorithms, the mean uncertainty prognosis was reduced up to 37.33% compared to the conventional scaling factor function approach below the H4 because the range residual scaling factor was minimised in these zones.

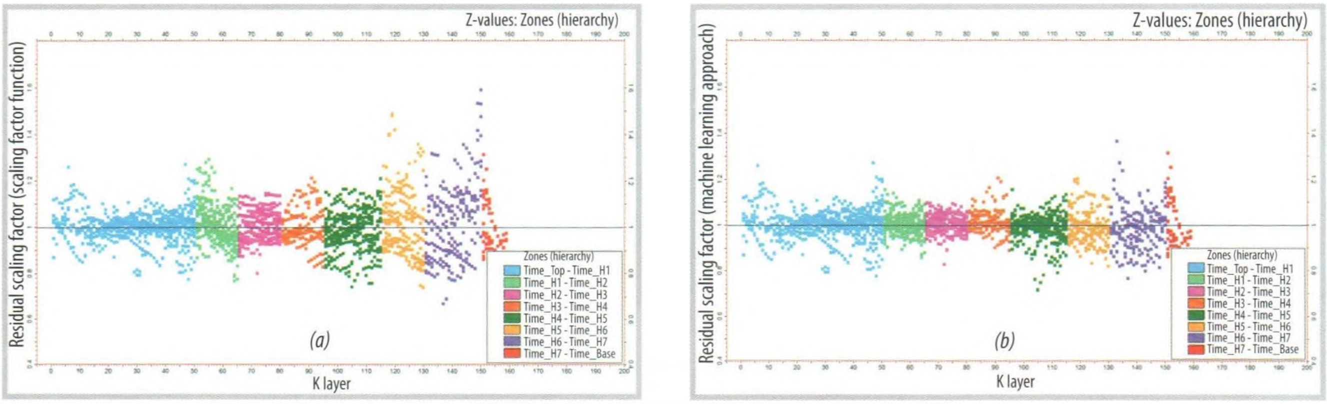


***Figure 10.*** *The residual scaling factor using scaling factor function (a) and residual scaling factor using machine learning approach (b).*

***Table 2.*** *The depth uncertainty analysis result*

| Zone | Scaling factor function | | Machine learning algorithm | |
|---|---|---|---|---|
| | Residual range (m) | Mean residual (m) | Residual range (m) | Mean residual (m) |
| H1 | -25.58 - 32.21 | 15.43 | -27.34 - 33.31 | 15.56 |
| H2 | -55.81 - 33.30 | 15.67 | -56.29 - 29.67 | 13.91 |
| H3 | -30.99 - 35.84 | 16.42 | -31.64 - 34.78 | 14.77 |
| H4 | -42.62 - 35.58 | 14.03 | -26.96 - 33.66 | 12.47 |
| H5 | -34.64 - 54.29 | 22.55 | -34.11 - 31.18 | 19.43 |
| H6 | -80.15 - 36.48 | 27.88 | -41.01 - 18.51 | 21.10 |
| H7 | -89.75 - 24.40 | 31.34 | -49.84 - 34.29 | 19.64 |

## 4. Conclusion

The study demonstrated the machine learning algorithm predicted accurate interval velocity including a measurement of the uncertainty. An accurate 3D velocity model is important not only for the converted depth surfaces but also the depth conversion of the seismic inversion results such as acoustic impedance, density, compressional and shear velocity cubes. The final calibrated interval velocity cube could be applied for 1D/3D pore pressure analysis and 1D/3D mechanical earth model (geomechanics) study, as well as basin modelling processes, etc.

In order to combine classic geo-statistics with quantile random forests algorithm in machine learning model, the embedded model estimator (EMBER) algorithm can be applied for predicting interval velocity with embedded estimations based on neighbouring well data using random forest algorithm in this field in the future. The used algorithm is a modified decision forest so that it trains the predictive ability of the spatial estimator as well as the standard data variables (embedding). Realisations with realistic geological texture can be performed by sampling from the envelope with an appropriate stationary random function allowing for additional hard conditioning at the data sample locations if required [5].

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## References

[1] Laura Bandura, Adam D. Halpert, and Zhao Zhang, "Machine learning in the interpreter's toolbox: Unsupervised, supervised, and deep-learning applications", *SEG International Exposition and Annual Meeting, USA, 14 - 19 October 2018*. DOI: 10.1190/segam2018-2997015.1.

[2] Zhao Zhang, Adam D. Halpert, Laura Bandura, and Anne Dutranois Coumont, "Machine learning based technique for lithology and fluid content prediction – Case study from offshore West Africa", *SEG International Exposition and Annual Meeting, USA, 14 - 19 October 2018*. DOI: 10.1190/segam2018-2996428.1.

[3] Eduardo Lugo Flores, Marcos Victoria, and Guillermo Sanchez Roa, "Depth conversion: Application of an innovative methodology: Added value to a fractured carbonate reservoir interspersed with tertiary and Mesozoic salt bodies within a very complex structural setting", *EUROPEC/EAGE Conference and Exhibition, UK, 11 - 14 June 2007*. DOI: 10.2118/106650-MS.

[4] Leo Breiman, "Random forests", *Machine Learning*, Vol. 45, pp. 5 - 32, 2001. DOI: 10.1023/A:1010933404324.

[5] Colin Daly, "An application of an embedded model estimator to a synthetic nonstationary reservoir model with multiple secondary variables", *Frontiers in Artificial Intelligence*, Vol. 4, 2021. DOI: 10.3389/frai.2021.624697.