Introduction
The objectives of this work are to identify heterogeneous thin sands via machine learning (artificial neural network) and evaluate the impact of tuning thickness on the recognition. The thin sands within the study interval mainly developed in a complex fluvial to shallow marine environment. Multiattribute classification using supervised Artificial Neural Networks (ANNs) is employed to predict the distribution of these thin sands within six subintervals and the role of tuning thickness in the prediction is discussed.

Geological Setting
The study interval within the Albian age, Cretaceous Formation, conformably overlies the Lower Cretaceous Formation and is overlain by one of Cenomanian age. The lower part of the study interval was deposited in a variety of interrelated sedimentary environments, principally within fluvial and fluvio-marine delta systems. These systems periodically prograded basinward to the east. The upper part of the study interval is a thick sequence of sandstone, siltstone and shale with thin intervals of limestone, coal and varying amounts of ironstone. It represents a shallow marine, prodelta and distributary mouth bars environment.

The depositional environment changed back and forth and interplayed between marine and fluvial in the early Cretaceous. This variety results in extremely heterogeneously-distributed thin sands. The study interval is divided into six subintervals, which are P1-P6 from bottom to top (Figure 1).

Figure 1 Sand bodies within the study interval developed in the Albian age, early Cretaceous and highlighted with the blue box. Modified after Sharland et al. (2001).

Data Analysis
In this study, we attempt to recognize the thinner sand bodies, but this recognition is restricted by seismic resolution. The effects of thin-bed tuning on seismic signature and the limits of seismic resolution have been discussed extensively by geoscientists (Widess, 1973; Kallweit and Wood, 1982). Practically, the tuning thickness, which is one-quarter wavelength (one-half period) can be calculated by the below equation:

$$\text{Tuning thickness} = \frac{V}{4f}$$  \hspace{1cm} (1)

where V is seismic velocity and f is the dominant frequency.

Figure 2 Left: Dominant frequency attribute within the seismic survey. Middle: average dominant frequency (red arrows) on the histogram. Right: velocity histogram based on the sonic logs of 123 wells within the study area.

To determine the tuning thickness, seismic and log data are investigated to obtain frequency and velocity information. The dominant frequency seismic attribute within the study interval shows the
dominant frequency is 33.5Hz. Velocities extracted from the sonic log of 123 wells within the study interval indicate the average velocity is 11000 feet/s (Figure 2). The resulting tuning thickness of the seismic volume within the study area is about 82 feet (Equation 1). Therefore, we can generally resolve 82 feet or thicker interval based on the available seismic data.

The feasibility that six subintervals can be resolved is evaluated. Thickness histograms generated from well logs show the thickness of the subintervals ranges from 0 to 320 feet, but most of them are greater than the tuning thickness which is marked by red arrows on the histograms (Figure 3). Therefore, all the subintervals should be possible to resolve using the seismic data, but thin sand identification could be affected for those units (P3, P4 and P6) that may be less than the tuning thickness.

Figure 3 Histograms show thickness distributions within six subintervals (P1-P6). Tuning thickness (82 feet) is marked by red arrows on the histograms.

Integrated Thin Sand Prediction

Multi-attribute analysis based on machine learning is widely applied to solve all kinds of challenges in hydrocarbon exploration. Due to distributed parallel structure and ability to learn and generalize, ANNs can solve complex geological problems even without knowledge of the intrinsic theory of the problem and the relationships among involved variables (Li, 2012). Supervised ANNs require prior information such as typical sedimentary facies at control wells to train the input data (seismic attributes). Once the network is trained to map from the prior information to the input seismic data, geological content between well controls can be identified by the trained network (Zhang et al., 2016).

Figure 4 An integrated workflow of multiattribute classification based on supervised ANNs to predict the thin sands.

An integrated workflow of multiattribute classification based on supervised ANNs was established to characterize the thin sands within six subintervals (Figure 4). Firstly, isopach and sand thickness maps of six subintervals are generated for log data. Isopach and sand thickness maps provide the general trend of thin sand distribution in these six subintervals and can be used to guide and validate the prediction using supervised multi-attribute classification.
The second step is seismic attribute generation and selection. In this workflow, the performance of supervised classification relies strongly on what kind of seismic attributes are used. One multi-level scheme of seismic attribute selection is adopted. The criteria for selecting seismic attributes are (1) Seismic control - Amplitude, Frequency and Phase (AFP). The main factors in defining seismic facies are variations in amplitude, frequency and phase. Therefore, the selected attributes for facies recognition must include ones related to amplitude, frequency and phase; (2) geological control including stratigraphic and structural. Attributes reflecting geological characteristics, especially stratigraphic and structural characteristics, are preferred to choose; (3) reservoir-quality (porosity) control. Reservoir quality (porosity) depends on depositional environment and affects the media properties and seismic response (Figure 5).

According to these criteria, ten seismic attributes representing AFP, geological control and reservoir quality are selected from the attribute library (Table 1). The attributes were practically categorized into complex, stratigraphic and structural attribute based on Petrel (Schlumberger, 2014).

We next apply supervised analysis for multi-attribute classification. Geological model based on log data is selected and is used to supervise ANN classification. To obtain the spatial distribution of the thin sands, the network was trained on the training dataset and then applied to the whole 3D seismic survey. Supervised classification can not only add significant details and enhanced lateral resolution, but also allow the interpreters to avoid manual labelling.

![Figure 5 Multi-Level scheme of seismic attribute selection](image)

![Table 1 Seismic attributes of three categories for classification](image)

The thin sands of six intervals predicted by the supervised multiattribute classification are verified qualitatively and quantitatively. The predicted sand thickness is compared to log-based thickness map and shows similar distribution of thin sands (Figure 6). The cross plots of the sand thickness between seismic predictions and log measurement at well locations quantitatively validate the seismic prediction with high correlation (Figure 7).

**Discussion**

The multi-attribute classification using ANNs is applied to six subintervals and identifies thin sands, but seismic prediction varies with the subintervals thickness and is quantified by the correlation of log
measurement and prediction at the well locations (crossplots in Figure 7). The curve of correlation coefficients on the crossplot shows the prediction variation versus subinterval of varying thickness. The thickness distribution of six subintervals is investigated through histograms and the average thickness curve on the histograms shows thickness variations of six subintervals (Figure 7). The positive correlation of the coefficients and the average thickness of the subintervals is observed by comparing these two curves and suggests that seismic prediction is still affected by tuning thickness though multiattribute classification based on supervised ANNs is used.

![Figure 7 Top: thickness crossplots of seismic prediction and log measurement at well locations and coefficient curve shows seismic prediction variation with subinterval thickness. Bottom: thickness histogram and average thickness curve of subintervals (P1-P6).](image)

**Conclusions**

A complex fluvial to shallow marine environment in the early Cretaceous resulted in heterogeneously-distributed thin sands. The study interval containing thin sands is divided into six subintervals (P1-P6). Supervised artificial neural networks are employed to classify multiple seismic attributes and predict the thin sands of six subintervals. Qualitative and quantitative validation by log data shows the thin sands are well characterized and tuning thickness still has an effect on seismic prediction.

**Acknowledgements**

We appreciate the constructive comments and support from Mahdi AbuAli, Arun Garg, Chuanyu Sun, Peter Crisi and Ali H. Rabaan.

**References**