AES/TG/11-40 Analysis of Natural Fractures in the Basal Zechstein Carbonates in the Dutch Offshore Area Using Wireline Log Data

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Abstract
The primary gas reservoirs in the Southern Dutch offshore are in decline. Discoveries of new gas reservoirs are getting smaller and smaller reservoirs receive more attention. The three major carbonate beds in the Basal Zechstein (Z1C, Z2C and Z3C) are considered potential secondary gas reservoirs. To be able to develop the gas from these carbonates depends strongly on the presence of fractures. The fracture pattern of the Zechstein carbonates in the Dutch offshore is however not well known. Currently the most reliable methods to investigate fractures in the boreholes are borehole-wall imaging techniques. These imaging techniques are expensive and time-consuming and most of the time not included in the logging suite. Therefore, an alternative method of predicting fractures using basic wireline logs (Gamma ray, sonic, density, photoelectrics, resistivity and caliper) would be very valuable. In this study an artificial neural network (ANN) is developed in order to make fracture predictions based on wireline log data. Additional the ability of indicating fractures with a decision tree is explored for wells that have too few logs available for an ANN approach. Both the ANN and decision tree (DCT) are trained with supervised learning. The models are calibrated using core data (rotary sidewall core and slabbed core data) of fractured and non-fractured Zechstein carbonate intervals. The ANN is trained with success, where the degree of success is directly related to the amount of fractures identified in the core. The DCT approach resulted in a moderate fracture prediction performance and is best used in combination with an ANN. With this combination a fracture prediction has been made on several wells that were excluded from training with these two methods. The resulting fracture predictions have been compared with indications of mud losses and productivity data, showing a good match.
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<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>Artificial neural network</td>
</tr>
<tr>
<td>AT</td>
<td>Induction</td>
</tr>
<tr>
<td>Ca</td>
<td>Caliper</td>
</tr>
<tr>
<td>DCT</td>
<td>Decision tree</td>
</tr>
<tr>
<td>DROH</td>
<td>Density correction</td>
</tr>
<tr>
<td>Gr</td>
<td>Gamma Ray</td>
</tr>
<tr>
<td>DT</td>
<td>Sonic Tool</td>
</tr>
<tr>
<td>LLD</td>
<td>Laterolog deep</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean square error</td>
</tr>
<tr>
<td>MSFL</td>
<td>Micro resistivity</td>
</tr>
<tr>
<td>OBM</td>
<td>Oil based mud</td>
</tr>
<tr>
<td>Pef</td>
<td>Photoelectric factor</td>
</tr>
<tr>
<td>PLT</td>
<td>Production logging tool</td>
</tr>
<tr>
<td>RHOD</td>
<td>Density tool</td>
</tr>
<tr>
<td>SBM</td>
<td>Salt based mud</td>
</tr>
<tr>
<td>Z1C</td>
<td>Zechsteinkalk</td>
</tr>
<tr>
<td>Z2C</td>
<td>Hauptdolomite</td>
</tr>
<tr>
<td>Z3C</td>
<td>Plattendolomite</td>
</tr>
</tbody>
</table>
1 Introduction

The primary gas reservoirs in the Southern Dutch offshore are in decline. Discoveries of new gas reservoirs are getting smaller and secondary reservoirs are getting more attention. The three major carbonate stringers in the basal Zechstein (Z1C, Z2C and Z3C) are considered potential secondary gas reservoirs. The potential of the Zechstein carbonates offshore is not well known. Onshore the carbonates are deposited on the slope and are prolific reservoirs. Offshore the carbonates are deposited in the basin where the thickness of the carbonates is significantly reduced compared with the carbonates onshore. However, gas shows are observed in several wells that indicate sufficient amounts of gas in the basin carbonates. In the UK offshore sector, gas has already been developed with success from these carbonates in the Hewett field. The carbonates have a low permeability and are therefore considered a tight reservoir. The possibility of developing gas from the carbonates depends strongly on the presence of open fractures. The understanding of the fracture pattern is poor and a challenging task with the limited data available. Previously, methods have been developed that indicate fractures in the Zechstein carbonates with the use of cores, the dual laterolog, formation microscanner (FMS), gamma ray spectrometry and spinner wireline tools (Cooke-Yarborough, 1994). Unfortunately, the majority of the boreholes (operated by Total E&P in the Dutch offshore) do not contain FMS, and core data are limited. Running a FMS or extracting core data are expensive and time-consuming operations. An alternative method of prediction fractures using basic wireline logs (Gamma ray, sonic, density, photoelectrics, resistivity and caliper) would be applicable for the majority of the boreholes and therefore very valuable. Wireline logs are designed to respond to different formation properties (Schlumberger, 1989). A fractured zone can be detected based on the anomalier it may show on its response. It is therefore possible to combine several wireline log responses to identify and locate possible fractures in the formations.

This study investigates the possibility of applying an artificial neural network and decision tree to identify fractures in carbonates from basic wireline log data. Although the case study is done for the Zechstein carbonates in the Dutch offshore, a similar approach could be followed in other carbonate and possibly sandstones reservoirs, around the world.
Objectives of the Study

The objective of this study is to develop a model that can indicate fractures from wireline log data in the basal Zechstein formation, in the Dutch offshore K4, 5 blocks. The models investigated are an artificial neural network and a decision tree. Both models are based and trained on ground truth data with corresponding wireline logs. Artificial neural networks are designed for pattern recognition, where the decision tree responds on the basis of a threshold value with a corresponding weight. The study was performed during an internship at Total E&P (the Netherlands) in 2011, as part of the Master thesis in Petroleum Engineering at the Delft University of Technology, under supervision of R. Rieu (Total EPNL), Prof. S. Luthi (TUD) and Prof. G. Bertotti (TUD and VU Amsterdam).
2 Geological Setting

This study is focussed on the basal Zechstein located in the Dutch offshore in the K4, 5 blocks, near the border of the UK (fig. 2-1). The data used for this study consist of 10 boreholes, where 9 are located in K4,5 blocks (operated by Total E&P NL) and 1 borehole onshore (operated by NAM).

![Diagram](image)

Figure 2-1: Overview map indicating the location of the area of interest: blocks K4, 5. The figure also contains the different facies of the basal Zechstein formation, adopted from the study of Geluk (2000).

The basal Zechstein is overlying the continental Slochtern and the shaly Silverpit formation of the Rotliegendes group (fig. 2-2). It was deposited during the Permian in an interior basin that was formed through the regional subsidence of the Rotliegendes. Offshore the formation lies around a depth of 3300-4700 m that forms a lateral extensive deposit onshore and offshore. After regional subsidence desert conditions changed when the aeolian lower Permian sediments were transgressed by the Zechstein Sea. The base of the Zechstein formation is marked by the Kupferschiefer shale and is overlain by four main sedimentary evaporate cycles of the Zechstein (Z1-Z4). Each evaporite cycle is the result of a marine transgression that is succeed by a regression and reflects the effect of the increasing salinity (Cooke-Yarborough, 1994). The focus of this study lies in the Z1C and Z2C carbonates which are the most significant reservoir rocks of the Zechstein cycles (Cooke-Yarborough, 1994). The initial Zechstein transgression starts with the Zechsteinkalk (Z1C), which is a carbonate shelf deposit formed near the margins of the sea. This evaporite consists of brown limestone and organic rich dolomites (Geluk, 2000). The haupdtolomite (Z2C)
reflects the second transgression and is also a carbonate shelf deposit formed seawards of a coastal sabkha. The Z2C consists of dark coloured, bituminous, finely laminated carbonates (Geluk, 2000). The thicknesses of the evaporite cycles are variable over the area of interest and lie in the range of 15 to 20 m.

![Stratigraphic diagram of the Zechstein Group (Late Permian)](image)

**Figure 2-2:** Schematic stratigraphic diagram of the Zechstein Group (Late Permian). The carbonates discussed in this study are Z1, Z2: Coustery Total.

### 2.1 Basal Zechstein reservoir

Onshore the Zechstein formation is a good commercial reservoir. Going from the platform to the basin part it is strongly reduced in thickness (fig. 2-3). Despite the reduced thickness significant gas shows are recorded in the K4,5 blocks that indicate that the carbonates contain sufficient amount of gas. The presence of the gas is probably the result of diffusion or gas leaking from the Slochteren reservoir. The gas migrated from the reservoir across the Silverpit formation where it is trapped under the anhydrite evaporates of the basal Zechstein. The carbonates have an average porosity of 3% and low permeability, and they are considered a tight reservoir. Although the development of gas from tight reservoirs is challenging, the latest discoveries in K4-A2 and K1-A3 produced with success gas from these carbonates. This success was the result of a fracture network that created a permeable pathway through the tight reservoir. The presence of those fractures is considered essential for commercial production.
Figure 2-3: Schematic picture that indicates the area of interest (K4,5) and the reduced thickness of the cycles Z1C, Z2C depending on the facies; platform, slope and basin. Schematic is adopted from Geluk (2000).

Core data, mud losses and production data indicate that the basal Zechstein contains open natural fractures. However, the majority of the fractures in the carbonates are cemented with anhydrite and the open fractures are not consistent over the formation which compartmentalize the reservoir. More insight in the fracture properties in the carbonates of the basal Zechstein is therefore essential.

3 Methodology
The objective of this study is to develop a method to analyze fractures in the basal Zechstein carbonates from wireline log data. The wireline logs are designed to respond to different characteristics of the formation (Schlumberger, 1989). A fractured zone can be detected based on the anomaly it may show on its response. Taken several wireline log responses together it is possible to identify and locate possible fractures in the formations.

In this study the capability to indicate fractures from basic wireline log data with an ANN and DCT are investigated.

3.1 ANN
An ANN simulates the cognitive process of the human brain and is well suited for solving non-linear and complex problems (Haykin, 1994). The network has the ability to recognize patterns and develop their own generalization about given data (FitzGerald et al, 1999). This method has already been applied with success for converting wireline logs to common reservoir properties such as porosity and permeability (e.g. Huang et all., 1996; Huang and Williamson, 1997). Based on this success, in this study the ability to use wireline logs to identify fractures is therefore explored.
Figure 3-1: Schematic architecture of an ANN, consisting of an input, hidden and output layer.

The architecture used of an ANN consists of three successive layers: input layer, hidden layer and output layer (fig. 3-1). The input layer consists of wireline log data. The hidden layer consists of multiple neurons that are connected with each input data. This interconnection makes it a complex system, where the hidden neurons take into account the values of all input data to create a result that is finally sent to the output.

A neuron in the hidden layer computes the weighted sum of its input and passes the sum through its activation function. This function then transmits the neurons in a manner that depends on the Levenberg-Marquardt Backpropagation algorithm (Haykin, 1999).

The number of hidden neurons in the hidden layer has an influence on the generalisation of the network. Too many hidden neurons create overfitting, which causes the network to memorise results instead of generalising (Al-Anazi & Babadagli, 2010). Working with too few neurons will result in a network that is not able to learn the correct input and output algorithm (Bhatt, 2002). An optimum number of hidden neurons is therefore essential and can be determined with a sensitivity plot.

The Backpropagation learning process sends the input values forward through the network and computes the difference between the calculated output and the corresponding desired target (Neyamadpour et al., 2009). Based on this difference the weights between the neurons are updated, stopping when the computed output values best approximate the desired target values (Bhatt & Helle, 2002). The learning rate stands for how quickly the network converges. In this study the Levenberg-Marquardt is used because it can operate very fast (Bishop, 1995).

During the training process the available data was divided into three sets: learning (70%), validation (15%) and test (15%). The difference in required output is measured with the validation set, which is used to validate whether the learning of the network can be finished. The testing set is used to see if the network also works on data that were not used in the training or validation process.
3.2 DCT
The DCT is a tool that helps to make choices and includes the possible consequences and chances of the events. The tool can be seen as a simplified version of an ANN without the interconnection between the input data. The ability of indicating fractures with a decision tree is explored for wells that have too few logs available for an ANN approach. The decision is based on a threshold value with a corresponding weight. When a wireline log surpasses a certain threshold value a weight is coupled to the wireline log and is send to the output of the DCT (fig. 3-2). Each wireline log is treated independently, which make this tool capable to work with incomplete wireline log datasets.

![Decision Tree Diagram](image)

Figure 3-2: Schematic sketch of a decision tree.

4 Fracture Identification and Data
The principle data types used to identify fractures in this study are:

- Wireline log data (Gamma ray, sonic, density, photoelectric factor, resistivity and caliper)
- “Ground truth” data (slabbed core and rotary sidewall core data)
- Drilling data (mud losses and production logging tool)

The ANN and DCT are developed in order to make a fracture prediction in the basal Zechstein. The wireline logs and “ground truth” data are integrated to develop a model with supervised learning. This means that we provide the ANN and DCT with examples of the inputs (wireline logs) and targets (identified fractures in “ground truth data”) we want the models to compute. The drilling data is used to make a validation of the predicted fractures.

4.1 Wireline log data
The input data for the models to predict the fracture pattern consist of wireline logs. The logs used in this study are basic wireline logs that can have a response on possible fractures in the formation. Table 4-1 shows the wireline logs that contribute to this study and their characteristics and possible responses in a fractured zone:
<table>
<thead>
<tr>
<th>Tool</th>
<th>Gamma Ray (GR)</th>
<th>Caliper (Ca)</th>
<th>Density correction (DROH)</th>
<th>Density (RHOD)</th>
<th>Photo electrics (Pef)</th>
<th>Resistivity (LLD)</th>
<th>Resistivity (AT)</th>
<th>Resistivity (MSFL)</th>
<th>Sonic (DT)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Measure</strong></td>
<td>Natural radioactivity</td>
<td>Diameter and shape</td>
<td>Correction of the bulk density</td>
<td>Density</td>
<td>Photoelectric absorption factor</td>
<td>Resistivity</td>
<td>Resistivity</td>
<td>Resistivity</td>
<td>Soundwave</td>
</tr>
<tr>
<td><strong>Response to a possible fracture</strong></td>
<td>Spike, if fracture is filled with radioactive minerals</td>
<td>Spike, if edged are chipped away in a fractured zone or lost circulation material get stuck in a fracture</td>
<td>Spike, if the density tool crosses a fracture zone where the tool get out of balance</td>
<td>Spike, if the tool crosses a fracture that is filled with mud</td>
<td>Spike, if fracture is filled with minerals that have a high atomic number</td>
<td>Spike. if fracture is filled with mud</td>
<td>Spike. if fracture is filled with mud</td>
<td>Spike. if fracture is filled with mud</td>
<td>Spike, if a fracture is filled with mud</td>
</tr>
<tr>
<td><strong>Additional comments</strong></td>
<td>Important that the mud contains radioactive material</td>
<td>Variation in borehole size SHAPE can be caused by many factors</td>
<td>Sees only a small part of the borehole</td>
<td>Formations where fractures occur will produce low count rates on the detectors</td>
<td>Only is a valuable detector if the mud contains barite</td>
<td>Can be used only with salt based mud</td>
<td>Respond on oil filled fractures</td>
<td>Can be used only with oil based mud</td>
<td>Fracture plugs with mud solids are often not detected</td>
</tr>
</tbody>
</table>

Table 4-1: List of wireline logs used in this fracture analysis and their characteristics/response on possible fractures in the formation.
The following figure shows an overview of the boreholes that are excluded from the training of the ANN and contribute in this study to make a fracture prediction.

![Diagram of borehole locations](image)

**Figure 4-1:** Location of the wells and the available wireline logs used as input data for the ANN and DCT.

### 4.1.1 Limitations

The wireline logs available over the Zechstein interval are limited. The reason is that the targets of the majority of the wells were reservoirs of the Rotliegendes and Westphalian that are below the Zechstein formation. The result is that the wireline log data over the Zechstein interval is limited.

### 4.2 “Ground truth“ data

Fracture identification on “ground truth” data is used as target data for the supervised learning method. In this study two different type of ground truth data are used: rotary sidewall cores (well K4-A5) and slabbled core data (well EMM-08). The rotary sidewall cores (rSWC) of borehole K4-A5 intersect both carbonates Z1C and Z2C (fig. 3-1a). On the rSWC a fracture analysis was done by Total E&P NL. (*Schroeder & Cappelli, 2007*).

The slabbled core, from borehole EMM-08, covers only the evaporite cycle Z2C. The location of this borehole is ± 250 km from the area of interest and intersects the slope instead of the basin facies of the basal Zechstein (fig. 3-1b). Regardless of the distance from the K4, 5 blocks, EMM-08 is included in the dataset because of a lack of other possible ground truth data in the basal Zechstein formation.
The boreholes offshore that include core data over the basal Zechstein are K6-6 and K17-8. The boreholes do not contribute to this study because the cores do not intersect Z1C or Z2C but only Z3C, which is a carbonate with different formation characteristics.

![Facies map](image)

**Figure 4-2**: Facies map of the Zechsteinkalk (Z1C) and Hauptdolomit (Z2C). K4A5 consist of side well cores that cover Z1C and Z2C. Borehole EMM-8 contains core data only over the Z2C interval. Facies map is adopted from Geluk, (2000).

### 4.3 Drilling data

The boreholes K4-A2 and K4-12 contain drilling data that can be used as validation of the fracture prediction of the ANN and DCT. The drilling data used in this study are:

- Mud losses
- Production logging tool (PLT)

#### 4.3.1 Mud losses

In K4-A2 and K4-12 mud losses have been observed during drilling in the basal Zechstein carbonates. The cause of the losses in a carbonate formation can be due to natural fractures or induced fractures which occur when the equivalent circulation density exceeds the fracture gradient (Beda et al, 2001).

When the losses are due to natural fractures the losses can be considered a good indicator of possible connective fractures in the formation. The type of fracture responsible for the losses can be partly recognized by the amount of losses. Large amount of losses are generally only due to natural fractures, because it needs a connective network to cause these losses. The type of fracture responsible for small losses is more difficult to identify and can be due to natural fractures or induced fractures.

Observation of large amount of losses can be cross-checked with the fractures identify over that interval. Unfortunately, the boreholes where no losses have been observed cannot be used for this.
Figure 4-3: Overview of the amount of mud losses that are observed, which are used as input data for the ANN and DCT.

4.3.2 Production logging tool

The production logging tools is used to determine the location of the producing intervals in a reservoir. The borehole K4-A2 has a PLT available that intersects Z2C. The PLT consists of with several spinner flow meters, a pressure gauge, a temperature gauge and a fluid density. The spinner and temperature log are used to indicate the location of open fractures in K4-A2 for validation of the fracture prediction results of the ANN and DCT.

The spinner measures the rotations per minute in the borehole as a function of depth. When the spinner crosses a fracture that produces gas, a sudden increase in the spinner can occur that is visible on the log.

The temperature log can show a decrease when it crosses a fractured zone. The mud has a relative lower temperature and when it infiltrates the formation it can result in a decrease in the log measurements.

5 Model Types

The models are based on ground truth data and the corresponding wireline logs. The logs are designed to respond on formation characteristics. Two different carbonate intervals are investigated and therefore for each carbonate a different model is developed. Besides the formation characteristics the mud type used during drilling can also have an effect on certain logs. The boreholes investigated were drilled with two different mud: oil based mud (OBM) and salt-based mud (SBM). Thus, for each model four target data should be available. However, because of insufficient ground truth data, for the combination of carbonate Z1C
drilled with salt based mud, there was no ANN and DCT created for the model Z1C SBM (fig. 5-1)

As indicated in section 3.2 the ANN is not able to work with all incomplete wireline log dataset. The majority of the investigated boreholes are drilled with OBM and consists of different type of wireline log data sets. To make the ANN more applicable for different sets, three different network types are developed: OBM1, OBM2 and OBM3. The three networks differ in the type of wireline logs they need as input data. An overview of all developed model types is shown in table 5-1.

<table>
<thead>
<tr>
<th></th>
<th>Gr</th>
<th>Ca</th>
<th>DROH</th>
<th>RHOD</th>
<th>Pef</th>
<th>LLD</th>
<th>AT</th>
<th>MSFL</th>
<th>DT</th>
<th>Ground truth data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z1C</td>
<td>OBM1</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>K4-A5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OBM2</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>K4-A5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OBM3</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>K4-A5</td>
<td></td>
</tr>
<tr>
<td>Z2C</td>
<td>OBM1</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>K4-A5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OBM2</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>K4-A5</td>
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</tr>
<tr>
<td></td>
<td>OBM3</td>
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<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>K4-A5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SBM</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>EMM-08</td>
<td></td>
</tr>
</tbody>
</table>

Table 5-1: List of the seven developed ANN models. In each model the carbonate zone is indicated, the wireline logs used needed as input data, and the ground truth data used for the network.

Figure 5-1: The 10 models that are created. There is no ANN and DCT created for Z1C SBM because of insufficient ground truth data to train and base the models on.
6 Fracture Identification with an ANN

An ANN model should be designed and trained. The input data used for training are wireline logs. The target data consists of fractures identified on cores. The target data for training of the Z1C OBM* and Z2C OBM* models are fractures identified on rSWC from the K4-A5 well. The target data of the SBM models is based on a fracture analysis done on slabbend core data of the well EMM-08.

OBM*: collective name for the models; OBM1, OBM2 and OBM3 (table 4-1)

6.1 Target K4-A5 well

In the fracture study of K4-A5 (Schroeder & Cappelli, 2007), the fractures in the rSWC have been assessed in terms of their frequency (rare, common) and in terms of the percentage of the fractures that are open. These observations are non-numeric and relative. The quantification rare/common was quantified by the weights two and four and multiplied with the percentage of open fractures to create a numerical target. The target data were interpolated over depth to create a continuous file used to compare to the input logs. Fig. 6-1 shows the fracture analysis on the rSWC and the created target.

![Fracture analysis](image)

Figure 6-1: Fracture analysis in Z1C (a) and Z2C (b) on rSWC, well K4-A5. The figure indicates the fracture frequency, the percentage of open fractures and the target data.
<table>
<thead>
<tr>
<th>Bin</th>
<th>Frequency</th>
<th>Cumulative %</th>
<th>Bin</th>
<th>Frequency</th>
<th>Cumulative %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>53</td>
<td>86.9%</td>
<td>0</td>
<td>86</td>
<td>83.5%</td>
</tr>
<tr>
<td>0.2</td>
<td>0</td>
<td>86.9%</td>
<td>0.2</td>
<td>3</td>
<td>86.4%</td>
</tr>
<tr>
<td>0.4</td>
<td>3</td>
<td>91.8%</td>
<td>0.4</td>
<td>14</td>
<td>100.0%</td>
</tr>
<tr>
<td>0.6</td>
<td>2</td>
<td>95.1%</td>
<td>0.6</td>
<td>0</td>
<td>100.0%</td>
</tr>
<tr>
<td>0.8</td>
<td>2</td>
<td>98.4%</td>
<td>0.8</td>
<td>0</td>
<td>100.0%</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>100.0%</td>
<td>1</td>
<td>0</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Table 6-1: List of the distribution of the data points in the target data with a bin of 0.2, of data set K4-A5 Z1C and K4-A5 Z2C. Distribution of the data set is uneven because the majority of the interval does not contain any fractures.

6.2 Target EMM-08 well

The ground truth of well EMM-08 consists of slabbed core data. Here, the target output is based on fracture apertures on the slabbed core. The identification of the aperture of open fractures has been done on intervals of 0.5 ft. This distance corresponds to the wireline log-sampling rate.

In the slabbed core four kinds of discontinuities are observed: natural fractures, cemented fractures, pressure release fractures and stylolites (fig. 6-2, fig. 6-3).

Figure 6-2: a) Basal Zechstein slabbed core shows an example of an open fracture, well EMM-08 at 3934.16 m depth, b) Basal Zechstein slabbed core shows an example of an cemented fracture with anhydrite, well EMM-08 at 3894.23 m depth.

Figure 6-3: a) Basal Zechstein slabbed core shows an example of a pressure release fracture, well EMM-08 at 3950.53 m depth, b) Basal Zechstein slabbed core shows an example of a stylolite, well EMM-08 at 3877.27 m depth.
The natural fractures and pressure-released fractures are both open in contrast to the stylolites and cemented fractures. In this study we are only interested in pre-cored existing fracture (natural fractures) and not fractures that are created by the coring. The pressure release fractures and natural fractures each have their own characteristics in core data (table 6-2). Based on that difference the pressure release fractures are excluded from the target data. Finally the aperture of the natural fractures was determined with the programme Qwin, software for image analysis, and scaled to create the target output (fig. 6-4).

Fracture characteristics

<table>
<thead>
<tr>
<th>Pressure release fracture</th>
<th>Natural fracture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fracture origin at the core boundary or within the core itself</td>
<td>Fractures are in general extending across the core</td>
</tr>
<tr>
<td>Meet the core boundary orthogonally</td>
<td>Partly mineralized or coated crystallized fractures</td>
</tr>
</tbody>
</table>

Table 6-2: List of characteristics of natural fractures and pressure release fractures.

Core Fracture analysis

Figure 6-4: a) Fracture aperture analysed with Qwin of the slabbed core, well EMM-08 of the interval 3880 – 4010 m depth. b) Normalized fracture aperture of the slabbed core, well EMM-08 interval 3880 – 4010 m depth.
<table>
<thead>
<tr>
<th>Bin</th>
<th>Frequency</th>
<th>Cumulative %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>248</td>
<td>96.9%</td>
</tr>
<tr>
<td>0.2</td>
<td>1</td>
<td>97.3%</td>
</tr>
<tr>
<td>0.4</td>
<td>4</td>
<td>98.8%</td>
</tr>
<tr>
<td>0.6</td>
<td>0</td>
<td>98.8%</td>
</tr>
<tr>
<td>0.8</td>
<td>3</td>
<td>100.0%</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Table 6.3: List of the distribution of the data points with a bin of 0.2, data set SBM Z2C. The distribution of the data set is uneven because the majority of the interval does not contain any fractures.

6.3 Preprocessing of data

Before using data for training some pre-processing was performed. The input data for training consists of four to six wireline logs. The target data consists of the results of the analysed fractures in the slabbled core and the fracture analysis done on the rSWC. To get the correct wireline log data (input) of a certain core interval (target) a depth shift has been done between wireline logs and core data on the hand of the density log (appendix A). The resistivity logs were transformed to log10 and each wireline log was than scaled between 0 and 1.

6.4 Training of the ANN

The training of the ANN model was done in Matlab. The quality of the network performance depends on the number of input neurons, hidden neurons, type of algorithm and momentum learning method (Bhatt & Helle, 2002). The number of input neurons in the models varies between four to six wireline logs. The optimum number of hidden neurons for each model was determined with a sensitivity plot (fig. 6-5) and the network was trained with a backpropagation algorithm (Rumelhart et al, 1986) and Levenberg-Marquandt learning method (Hagan et al, 1996).

Figure 6-5: Sensitivity analyses that indicate the best validation performance based on the numbers of neurons. The minimum validation for Z1C OB1 and Z2C OB1 is with 4 neurons and 11 for Z2C SBM. Sensitivity plots of the other models are in appendix C.
The optimum number of neurons is determined on the minimum value of the best validation performance (BVP). Fig. 6-5 indicates that the BVP for Z1C OBM1 and Z2C OBM1 is with 4 neurons and Z2C SBM has a BVP with 11 neurons.

The training data are divided into three sets: training, validation and testing set. During training the development of the network error was observed over 100,000 epochs. An epoch stands for one iteration through the process of providing the network with an input and updating the network’s weights. To make the training results more reliable a random resampling of the data has been done to create different subset examples. The best networks found during the three sampling processes were used and the network with the lowest validation error was selected (AL-Anazi & Babadagli, 2010). The success of the training was assessed with the characteristics and results of the performance and the regression plot.

6.4.1 Performance and regression analysis

The performance plot shows three curves: a training, validation and test curve. As training progresses the training error naturally drops same as the validation and testing error. When the validation error stops dropping and start to increase, while the training error is steadily decreasing, then a situation of overfitting may have occurred. The stopping criterion of the training is before overfitting starts and is the moment where the error of the validation curve reaches its minimum error. The training of a network can be considered reasonable when the plots indicate the following characteristics:
- The mean-square error is small
- The test set error and validation set error have similar characteristics
- No significant overfitting has occurred

With the regression plot the prediction performance of the ANN model is assessed. The plot contains the training, validation, test and all curves. The dashed line indicates the perfect result where the output is similar with the target. The solid line represents the best possible fit of the data between the output and target. The Mean square error (MSE) gives an indication of the linear relationship between the output and target where R=1 indicates that there is an exact relationship and R=0 that there is no linear relationship between output and target.

Figures 6-6 to fig. 6-11 show the performance and regression results of the Z1C OBM1, Z2C OBM2 and Z2C SBM. The results of the other developed models are shown in appendix B.
Figure 6-6: Performance plot of the model Z1C OBM1. The green circle indicates the best fit during training and is the moment that the model stopped training.

The performance curve of the Z1C OBM1 model (fig. 6-6) shows on first sight a reasonable result: (1) MSE is small, (2) the validation and test curve have similar characteristics and (3) the model has stopped before overfitting occurred. However, a more common behaviour is when the validation and test error are larger than the training error. This plot indicates that the network is able to predict a target data that is not used for training, with a smaller error than the data set which the network is trained on. The regression plot in fig. 6-7 clarifies this behaviour.

Figure 6-7: Regression plot of ANN model Z1C OBM1.

The fig. 6-7 illustrates that the good fit and related low error of the validation and test curve is established on a minimal number of data points. Although the validation and training set should consist over each 10 points, the dataset seems to be uneven with only 13.1% data points that are higher than 0 (table 6-1). Apparently the few predicted points the fits are based on consist of a smaller
error than the fit of the training curve. This smaller error is also the reason for
the smaller error in the training and test curve in the performance plot (fig. 6-6).
Although the resample networks (appendix B) show similar results, the linear
regressions are still based on a minimal number of points. The good result can be
the result of a hit on a lucky network that happens to perform well on the
validation and test set. The minimum number of points the fits are based on
makes this regression result questionable.

![Performance plot of the model Z2C OBM1. The green circle indicates the best
fit during training and is the moment that the models stopped training.](image)

The performance curve of the Z2C OBM1 (fig. 6-8) model shows a better result
than Z1C OBM1. The MSE is small and unlike by the Z1C OBM1 model the test
and validation errors are larger than the training errors.

![Regression plot of ANN model Z2C OBM1.](image)

Fig. 6-9 shows the regression plot of Z2C OBM1. The model is based on a larger
data set than Z1C OBM1 (table 6-1). The fit of the test and validation curve of the
regression plot is still based on a minimal number of data points. The plot shows
a low MSE but the quality of this result is still unsure and can be again the result of a network that happens to perform well on the test and validation set.

![Best Validation Performance is 0.0019176 at epoch 19](image)

**Figure 6-10:** Performance plot of the model Z2C SBM. The green circle indicates the best fit during training and is the moment that the model stopped training.

The training performance of fig. 6-10 of the Z2C SBM network shows a relative high MSE. The characteristics of the test and validation are more or less similar but have a very large scatter. The figure also indicates that the validation error starts to increase before it reaches the minimum error while the training error is steadily decreasing; this could indicate overfitting.

![Training: R=0.79127, Validation: R=0.8287, Test: R=0.30514, All: R=0.64605](image)

**Figure 6-11:** Regression plot of ANN model SBM Z2C.

The fig. 6-11 shows the regression plot of Z2C SBM. The results of the regression plot indicate that the model hardly found a relation between input and target. Although the dataset is much larger, which would stimulate the performance of the training, the set is also in a higher degree uneven (table 6-3). This plot
indicates that the model, according to the regression plot, is insufficient to be used as prediction model.

6.5 Results of the ANN
As a result of the training, the error was reduced by adjusting the weights of the ANN. Figure 6-12 shows the ANN output of the supervised training. The ANN output consists of 70% training data, 15% validation data and 15% test data, which are compared to the target data.

![Diagram of ANN output comparison]

Figure 6-12: ANN output of the trained network compared with the target of the models Z1C OBM1 (a), Z2C OBM1 (b) and Z2C SBM (c).

In fig. 6-12a it can be seen that, despite the first target point at a depth of 4766 m, there is a good match between the output of the ANN and the target data. This indicates that the network is able to simulate the target data with success. In fig. 6-12b the match between target and ANN output is even better. The network can almost simulate the training data exactly, which is coherent with the good training results (fig. 6-8, fig. 6-9). The fig. 6-12c shows a poorer result in simulating the target data. The network is not able to simulate the target data precisely but the figure also indicates that the network responds to the presence of fractures (target data). Network Z2C SBM seems to be able to identify fractures but with a lesser degree of accuracy compared to the Z1C OBM1 and Z2C OBM1 models.
6.6 Sensitivity analysis

The networks Z1C OBM1 and Z2C OBM2 perform much better in the training than Z2C SBM. The primary difference in the training was the target data. The training data used in this study consists of two types of target data: rSWC and slabbled core data. The analyzed fractures in the two core data are based on different fracture characteristics and correspond different set of wireline logs. Unfortunately, these characteristics in the training data investigated with the limited data available. A property of the training data that is investigated is the percentage of fractures in the data set. The target data Z1C K4-A5 and Z2C K4-A5 consists of ± 14.5% fractures while Z2C EMM-0 has 3.1% fractures. The impact is investigated by reducing the percentage fractures in Z2C K4-A5 to 3.1%. This new generated target data is used to train a new model (Z2C OBM1a). Figure 6-13 shows the performance plot of the models Z2C OBM1 and Z2C OBM1a.

![Figure 6-13: a) Performance plot of Z2C OBM1. Training data consists of 16.5% fractures. b) Performance plot of Z2C OBM1a. Training data consists of 3.1% fractures.](image)

The figure makes clear that the MSE increased significantly, from 0.000489 to 0.010123, when the percentage of fractures is reduced to 3.1%. This indicates that the percentage fractures in the dataset have a large impact on the ANN performance.
7 Fracture Identification with DCT
The decision tree that is created is based on a threshold value and gives to each wireline log a certain weight. The threshold and weights are determined on the same input (wireline logs, table 4.1) and known target data (rSWC K4-A5, fig. 6.1, slabbed core EMM-08, fig. 6.4) as the ANN. The table 6-3 shows an example of the determined threshold values and weights for the models Z1C DCT OBM and Z2C DCT OBM.

<table>
<thead>
<tr>
<th>Wireline log</th>
<th>Threshold</th>
<th>Weight</th>
<th>Threshold</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sonic</td>
<td>52,00</td>
<td>10%</td>
<td>53,00</td>
<td>20%</td>
</tr>
<tr>
<td>Pef</td>
<td>5,20</td>
<td>3%</td>
<td>5,00</td>
<td>3%</td>
</tr>
<tr>
<td>Gamma ray</td>
<td>58,00</td>
<td>29%</td>
<td>29,00</td>
<td>9%</td>
</tr>
<tr>
<td>Density correction</td>
<td>0,04</td>
<td>21%</td>
<td>0,075</td>
<td>23%</td>
</tr>
<tr>
<td>Resistivity</td>
<td>500,00</td>
<td>37%</td>
<td>1550</td>
<td>45%</td>
</tr>
</tbody>
</table>

Table 7-1: List of the threshold values and the weights of the wireline logs of the DCT, based on well K4-A5.

The threshold is set to a value where the log response is optimal with the fractures in the target data. Fig. 7-1 shows an example of the method used to determine the threshold value and weight of the resistivity log in well K4-A5.

Figure 7-1: Method how the thresholds of the wireline log and the weights are determined for the DCT. The threshold was set to 0.5 and the weight was computed on 37%.

The weights are based on: (1) the percentage that the Fracture indication intervals matches the fractures in the target data; (2) percentage that the no fracture indication intervals matches the target data zero; (3) the percentage of the total fracture indication that correspond to the target data. The results (1), (2) and (3) are multiplied and scaled.
The weights and thresholds are used in the DCT to make a fracture prediction on the training data (fig. 7-2).

Figure 7-2: DCT output compared with the target in the models Z1C DCT OBM (a), Z2C DCT OBM (b) and Z2C DCT SBM (c).

In fig 6-14a it can be seen that there is a reasonable match between output of the DCT and the target data. The DCT response on the target but with a high error in the fracture prediction. Figure 6-14b indicates a moderate response. This figure makes clear that the DCT follow some target points but also indicates fractures that are not present in the target. In fig. 6-14c the DCT indicates almost on each depth a fracture, which does not match with the target. It seems that the DCT is responding to fractures but also to wireline log responses that are not related to fractures. Although, the model response on the presence of fractures the prediction error seems to be too large to be able to use this model for fracture prediction.
8 Merging Fracture Predictions of ANN and DCT

The ANN and DCT are both trained and based on the same data in order to make a fracture prediction from wireline logs. The fracture prediction of the ANN is based on pattern recognition and the fracture prediction of DCT depends on a threshold value with a corresponding weight. Figure 8-1 illustrates the difference in prediction performance between the ANN and DCT.

![Fracture prediction graphs]

Figure 8-1: ANN and DCT output compared with the target data of the models Z1C OBM (a), Z2C OBM (b). DCT output compared with the target data of the model Z2C SBM (c). ANN output compared with the target data of the model Z2C SBM (d).

In each figure the ANN is capable to learn and predict the target data with a significantly smaller error in comparison with the DCT output.
The ANN and DCT are based and trained on the same data and therefore related to each other. However the methods use each their own methodology to make a fracture prediction based on wireline log data. The ANN and DCT results are compared with each other and in the following figures the intervals are indicated where the two models correspond in their prediction of fracture occurrence, non-occurrence and where the prediction of the models do not match.

<table>
<thead>
<tr>
<th>Color</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green</td>
<td>ANN and DCT predict the presence of an open fracture</td>
</tr>
<tr>
<td>Red</td>
<td>ANN and DCT predict that there is no open fracture</td>
</tr>
<tr>
<td>Gray</td>
<td>ANN and DCT prediction do not match</td>
</tr>
</tbody>
</table>

![Fracture prediction graphs](image)

**Figure 8-2**: Fracture prediction of the ANN and DCT in the Z2C evaporite cycles of the wells, K4-A2, K5-A3 and K5-D3.
Figure 8-3: Fracture prediction of the ANN and DCT in the Z2C evaporite cycles of the wells, K5-CU1, K5-EC3, K5-EC1, K4-12, K5-A1 and in the prediction of K4-A2 in the evaporite cycle Z1C.
Figure 8-4: Fracture prediction of the ANN and DCT in the Z1C evaporite cycles of the wells, K5-A3, K5-D3, K5-CU1 and K5-EC3.
In 23% of the investigated boreholes the predicted fractures of the ANN and DCT indicates a reasonable match (well: K4-A2 Z2C, K5-D3 Z2C and K5-EC3 Z1C). Both methods indicate on the same locations possible fractures, with a similar fracture prediction.

The majority, (54%) indicates a moderate match (well: K5-A3 Z2C, K5-CU1 Z2C, K5-EC1 Z2C, K4-12 Z2C, K5-A1 Z2C K4-12 Z1C and K5-CU1 Z1C). The DCT predict a much higher degree of fractures compared to the ANN. The methods show only some coherent responses that are visible in small peaks in the DCT that match with the more resolute signature of the ANN.

In the other 23% of the boreholes there was no match between the fracture prediction of the ANN and DCT (well: K5-EC3 Z2C, K5-D3 Z1C, and K5-A3 Z1C). In these boreholes the ANN predicts no fractures in contrary with the DCT.

Figures 8-2, 8-3 and 8-4 illustrate that the DCT predicts to a much higher degree the occurrence of fractures. Each plot contains a column where the ANN and DCT are compared. The intervals where the ANN predicts possible fractures are confirmed by the prediction of the DCT. Locations where the fracture predictions of the DCT not correspond with the ANN are indicated as a mismatch. In this comparison the intervals that indicate fractures are dominant determined by the fracture prediction results of the ANN. In fig. 8-1 can be seen that the ANN is able to learn to predict the target data with a much smaller error than the DCT. This comparison between the ANN and DCT seems therefore to be coherent with the degree of accuracy the models are able to learn and predict their target data.
8.1 Validation with drilling data

Two kinds of drilling data (mud losses, PLT) are used to make a validation of the predicted fractures of the boreholes that were excluded from training. Figure 8-5 shows for each carbonate (Z1C and Z2C) a map that indicates for each well the amount of mud losses (relative) and amount of corresponding predicted fractures of the ANN and DCT (in terms of -,-,++,).

![Structural map of Rotliegendes; mud losses and fractures in Z1C](image1)

![Structural map of Rotliegendes; mud losses and fractures in Z2C](image2)

Figure 8-5: Overview of the structural map of the Rotliegendes on Z1C and Z2C. The map indicates the observed mud losses and amount of fractures indicated by the ANN and DCT.

The ANN and DCT indicate a high amount of fractures in K4-A2 Z1C (fig. 8-5). This figure also makes clear that in this well large mud losses are observed during drilling. Mud losses are an indication that the interval consists of fractures, which is coherent with the fracture prediction of the model in well K4-A2.

In the carbonate Z2C in fig. 8-5 large amount of losses are observed in K4-A2 and K4-12. The prediction models indicate also large amount of fractures in these intervals and the mud losses validate this prediction. The boreholes without losses are unfortunately not suitable as verification material in relation with
intervals where no fractures are predicted. This has to do with lost circulation material that is mostly used during drilling and prevent the occurrence of mud losses.

When we look to the locations of the boreholes with predicted fractures it seems that they are located close to inverted faults. These faults are the result of compressional forces and it is possible that these faults have a positive effect on the amount of fractures compared with extensional forces (normal faults).

Other drilling data that is used as verification is a PLT. This log is available over well K4-A2, and only intersects Z2C. Fig. 8-6 shows the fracture prediction of the ANN, DCT and the corresponding PLT of well K4-A2 Z2C:

![Fracture prediction of the ANN and DCT of the well K4-A2 Z2C and the PLT of K4-A2 Z2C.](image)

**Figure 8-6:** Fracture prediction of the ANN and DCT of the well K4-A2 Z2C and the PLT of K4-A2 Z2C.

The figure indicates with two circles (A1 and B1) the predicted fractures of the ANN and DCT. The predicted fractures in A1 correspond to a similar depth with A2 where the temperature of the PLT shows a decrease and the spinner indicates (A3) a change that can be due to a possible fracture. When we look at B1 the temperature doesn’t show a clear decrease but the spinner indicates in B2 a sudden chance that can again indicate a possible fractures.

The fig. 8-5 and fig. 8-6 indicates that the predicted fractures of well K4-A2, K4-12 corresponds with the observed mud losses and the possible fractures indicated by the PLT.
9 Discussion

The objective of this study was to develop a model that can indicate fractures from wireline log data in the basal Zechstein formation. Two methods are developed (ANN and DCT). The ANN was developed to make fracture predictions for wells that contain complete wireline line log data sets. Three ANN submodels were created for different mud types and reservoir layers. The DCT was developed for making fracture predictions for wells that have few logs to be suited for the neural network approach.

The good training results of the ANN, as shown by the low error in the regression and performance plots, indicate that the network is able to make a clear correlation between the input data (wireline logs) and target (core data). Moreover, the prediction results from untrained wells with other fracture indicators (mud losses and PLT data) suggest that the models are valid. Nevertheless, some caution is needed with respect to the reliability of the ANN and DCT. First, only few validation data (mud losses and PLT) were available. Only for 15% of the investigated wells were mud losses observed, and only for one layer in a single well a PLT was available. Second, the reliability of the models depends also on the quality of the training data (input and target). It is therefore important to keep in mind how representative the target data (core) is compared to the input data (wireline logs).

Slabbed core data
When identifying the fractures in slabbed cores the analysed fractures are inside the borehole. The wireline logs measure properties on the borehole wall, which means that the measurement of the logs does not exactly correspond to the analysed fractures. The analysed fractures can give a good indication for the presence of fractures in the formation around that depth, but is not an absolute certainty. It is possible that fractures are identified in the slabbed core but are not present in the formation that the wireline logs cover. This means that the developed models will learn a response of log characteristics that do not represent the occurrence of fractures in the formation. For fractures that are not present in the slabbed core but in the formation, this will have the opposite effect for the fracture prediction.

Rotary Sidewall Core Data
The rSWC are small discontinuous samples taken from the borehole wall. The samples cover only a fraction (4%) of the formation interval it has to represent and even much less when including the penetration of the formation that a log covers. Wireline logs penetrate much deeper in the formation than the samples of the rSWC. The samples give an indication of small parts in the formation that are used in this study to base on the fracture appearance of two intervals Z1C and Z2C in well K4-A5. The information the rSWC represents is a fraction compared with the wireline logs. A chance that a fracture presents in the formation is not covered by the rSWC analysis is quite high. This means that the developed models will not learn to recognize all the wireline characteristics that
are the result of fractures. It is therefore questionable if the rSWC can represent the fracture occurrence of the borehole environment that the wireline logs cover.

However, given all these unrepresentative target data, the ANN still seems to produce meaningful results. It could be that the fractures are present in networks that cover intervals of the borehole environment instead that a fracture occur alone in the formation. If these intervals are large enough it could be that the rSWC were able to get an indication of the location of these networks. The created target data on the rSWC would then give a rough but representative indication of the fractures that occur in the borehole wall. In order to assume this, more study has to be done of the fracture pattern in well K4-A5.

Other uncertainties that may impact the results of this study and the prediction performance of the models include: (1) depth mismatch of the wireline logs with core data; it was attempted to reduce these by depth shifting; (2) incorrect interpretation of a fracture in the core; (3) variable resolution of different logging tools. However, there is again no direct indication that these factors have significantly influenced our results.

Differences
The large difference in prediction error during the training of the ANN and DCT can be related to the method the models use to predict a fracture. The prediction of the DCT is less accurate and based on a threshold value whether a fracture is present or not. The ANN is a method that is able to recognize a pattern and does not directly dependent on a certain value of wireline logs. A possible fracture can result in a change in a wireline measurement and is visible on the log response but is not strictly coupled to a certain value. This difference in approach can be the reason for the large difference in the prediction accuracy between an ANN and DCT.
10 Conclusions and Recommendation

10.1 Conclusions
From this study it can be concluded that:

- The training results of the ANN, based on rSWC, indicate that the network is able to learn with success the target data based on the wireline log input.

- The training results based on the slabbed core data indicate that the network is able to learn the target data, but with a larger error than the rSWC.

- The percentage of fractures in the dataset has a large impact on the ability of an ANN to learn the training data.

- The DCT approach resulted in a moderate performance in the ability to predict the target data based on wireline log input.

- The DCT is best used in combination with the ANN.

- Comparison between fracture prediction and indication of fracture presence by mud losses and production logs showed a good match.

10.2 Recommendation for further research
In this study the possibility of predicting natural fractures with an ANN and DCT based on wireline logs is investigated. During this study more insights of the performance and predication capabilities of these models have surfaced.

The performance of the methods looks promising as they were capable to correlate wireline logs and possible fractures in the target data. The reliability is still unsure because of the data the ANN is based on, in combination with the limited data available for verification. Further research of the prediction capabilities of an ANN and DCT with more core data, FMI and PLTs is recommended.

It is important that the data the models are based and trained on consist of representative data. This means that the fractures used for supervised training represent with a certain degree of certainty the fractures around the borehole environment. Furthermore, the models should be used on untrained wells with the same available verification data to be able to investigate the reliability of the predicted fractures.

The identification of fractures at the wellbore is only a first step in the optimum development of a reservoir. It is vital but difficult to establish which fractures contribute most to gas production. A PLT can give information of the production quality of possible fractures. Therefore, an integration of analyzed fractures in core data with wireline log responses and PLT could give the models more dimension in order to give a quality to the predicted fractures. The possibility of integration these data would be valuable to investigate.
11 References

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12 Appendices
Appendix A

Depth shift of well EMM-08 based on the density log:
Appendix B

Sensitivity analysis to determine the number of neurons in the hidden layer of the developed ANN:
Appendix C
The training results of the ANN's with the resample data, resample dataset 2 model OBM Z1C:

Best Validation Performance is 0.00061189 at epoch 9

15 Epochs

Training: R=0.85963
Validation: R=0.99773
Test: R=0.87169
All: R=0.88797
Data set 2 OBM Z2C:

Best Validation Performance is 0.00038219 at epoch 21

27 Epochs
Dataset 3 OBM Z1C:

Best Validation Performance is 0.0090552 at epoch 14

![Graph showing mean squared error (mse) over 20 epochs]

Training: $R=0.90983$

Validation: $R=0.99981$

Test: $R=0.99922$

All: $R=0.92659$
Dataset 3 OBM Z2C:

Best Validation Performance is 0.00073795 at epoch 18

Mean Squared Error (msec)

24 Epochs

Training: R=0.99346

Validation: R=0.99769

Test: R=0.97694

All: R=0.98762
OBM Z2C with instead of 16.5% only 3.1% fractures in the training data that correspond with the number of fractures in dataset SBM Z2C.
Performance plots;
Regression plot

OBM Z1C

Training: $R=0.89681$

Validation: $R=0.99741$

Test: $R=0.99824$

All: $R=0.91285$

OBM2 Z2C

Training: $R=0.99982$

Validation: $R=0.99666$

Test: $R=0.99844$

All: $R=0.99108$
OBM3 Z1C

OBM3 Z2C
Following figure shows the target compared with the output of the ANN:
Following figure shows the predicted fracture pattern with the ANN of each boreholes in Z1C and Z2C:

Figure 5.14: Fracture prediction in the Z2C evaporite cycle of the wells, K4-A2, K5-A3, K5-D3, K5-CU1, K5-EC3, K5-EC1, K5-A1 and K4-12.
Figure 5.15:Fracture prediction in the Z1C evaporite cycle of the wells, K4-A2, K5-A3, K5-D3, K5-CU1, K5-EC3, K5-EC1, K5-A1 and K4-12.
### Appendix D

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Table 12-1: Lists of the weights and thresholds of Z2C EMM-08.

Following figures shows the predicted fracture pattern with the DCT of each borehole in Z1C and Z2C:
Figure 5.18: Fracture prediction in the Z1C evaporite cycle of the wells, K4-A2, K5-A3, K5-D3, K5-CU1, K5-EC3, K5-EC1, K5-A1 and K4-12
Appendix E
Well K4A2 Z1C: Basic wireline log with the fracture prediction of the ANN.
Well K4A2 Z2C: Basic wireline log with the fracture prediction of the ANN.
Well K5A3 Z1C: Basic wireline log with the fracture prediction of the ANN.

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Well K5A3 Z2C: Basic wireline log with the fracture prediction of the ANN.
Well K5D3 Z1C: Basic wireline log with the fracture prediction of the ANN.
Well K5D3 Z2C: Basic wireline log with the fracture prediction of the ANN.
Well K5CU1 Z1C: Basic wireline log with the fracture prediction of the ANN.
Well K5CU1 Z2C: Basic wireline log with the fracture prediction of the ANN.
Well K5CU1 Z1C: Basic wireline log with the fracture prediction of the ANN.
Well K5EC3 ~Z1C: Basic wireline log with the fracture prediction of the ANN.

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Well K5EC3-Z2C: Basic wireline log with the fracture prediction of the ANN.
Well K5EC1 Z2C: Basic wireline log with the fracture prediction of the ANN.
Well K5A1 Z2C: Basic wireline log with the fracture prediction of the ANN.
Well K412 Z2C: Basic wireline log with the fracture prediction of the ANN.