PREDICTION OF RESERVOIR PROPERTIES FOR GEOMECHANICAL ANALYSIS USING 3-D SEISMIC DATA AND ROCK PHYSICS MODELING IN THE VACA MUERTA FORMATION, NEUQUÉN BASIN, ARGENTINA

by

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ABSTRACT

The Vaca Muerta Formation in the Neuquén Basin has recently received a lot of attention from oil companies interested in developing its shale resources. Early identification of potential zones with possible good production is extremely important to optimize the return on capital investment. Developing a work flow in shale plays that associates an effective hydraulic fracture response with the presence of hydrocarbons is crucial for economic success. The vertical and lateral heterogeneity of rock properties are critical factors that impact production. The integration of 3D seismic and well data is necessary for prediction of rock properties and identifies their distribution in the rock, which can also be integrated with geomechanical properties to model the rock response favorable to hydraulic stimulation.

This study includes a 3D seismic survey and six vertical wells with full log suites in each well. The well logs allowed for the computation of a pre-stack model-based inversion which uses seismic data to estimate rock property volumes. An inverse relationship between P-impedance and Total Organic Content (TOC) was observed and quantified. Likewise, a direct relationship between P-impedance and volume of carbonate was observed. The volume of kerogen, type of clay, type of carbonate and fluid pressure all control the geomechanical properties of the formation when subject to hydraulic fracturing.

Probabilistic Neural Networks were then used to predict the lateral and vertical heterogeneity of rock properties. TOC and volume of kerogen behaved as adequate indicators of possible zones with high presence of hydrocarbons. Meanwhile, the volume of carbonate was a valid indicator of brittle-ductile rock. The predicted density volume was used to estimate geomechanical properties (Young’s Modulus and Poisson’s Ratio) and to identify the zones that have a better response to hydraulic stimulation. During the analysis of geomechanical properties, Young’s Modulus was observed to have a direct relationship with volume of carbonate and an inverse relationship with TOC, enabling the identification of brittle and
ductile rocks zones. The analysis detected zones that had a good presence of hydrocarbons and brittle rock. The information was integrated with the analysis of geomechanical properties generating a model with the most possible zones of good production. This model will aid in the future exploration and development of the Vaca Muerta Formation.
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LIST OF ABBREVIATIONS

Constrained Sparse Spike Inversion ........................................... CSSI
Differential Horizontal Stress Ratio ........................................... DHSR
Feet ................................................................. ft
Hertz ................................................................. Hz
Kilometers ......................................................... Km
Low Frequency Model .................................................... LFM
Meters ................................................................. m
Mili Seconds ..................................................... ms
Multi-Attributes ..................................................... MA
Newton per square meter ................................................ N/m²
Percentage Weight ................................................ wt%
Poisson’s Ratio .................................................. v
Pounds per square inch over foot ...................................... psi/ft
Probabilistic Neural Network ........................................ PNN
Quality Control .................................................... QC
Reservoir Characterization Project ..................................... RCP
Square Kilometers ................................................ Km²
Square Miles .................................................. mi²
Total Organic Carbon ................................................ TOC
Young’s Modulus ................................................... E
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I would like to dedicate this Master’s thesis to my father, my mother and my wife.
There is no doubt in my mind that without their encouragement and support, I could not have accomplished this challenging venture.
CHAPTER 1
INTRODUCTION

The Neuquén Basin is located on the central-eastern side of the Andes in Argentina, bordering the eastern side of central Chile (Figure 1.1). It extends over a total area of 66,900 mi\(^2\) (EIA, 2015; Howell et al., 2005). The Vaca Muerta Formation is the richest source interval in the Neuquén Basin (Cruz, 2002; Kietzmann et al., 2014; Mitchum and Uliana, 1985). It is also the most important shale-oil and shale-gas reservoir in Argentina with a main focus on the central part of the Neuquén Basin, also known as Neuquén embayment (Figure 1.1) (EIA, 2015; Kietzmann et al., 2014; Legarreta and Villar, 2015).

Figure 1.1: Location map of the Neuquén Basin in the west-central side of Argentina. The embayment zone of the Neuquén Basin is located in the detailed map on the right. Modified from EIA (2015).

As a shale-oil and shale-gas play, the Vaca Muerta Formation has excellent characteristics with high total organic carbon (TOC) levels from 1.0 to 8.0 of weight percentage (wt%),

1
with spikes to 12 wt% or even higher. The depth ranges from 3,000 to 10,000 feet (ft) (915 to 3,050 meters), and overpressure conditions exist with ranges from 0.6 to 1.0 psi/ft. These characteristics make the Vaca Muerta a world-class play and a prime target for exploration (Boyer et al., 2011; EIA, 2015; Fantín et al., 2014; Fernández-Badessich et al., 2016; Garcia et al., 2013; Kietzmann et al., 2014).

According to the Energy Information Administration (EIA, 2015), in recent years the Vaca Muerta Formation has been the main target for exploration and production of unconventional resources in Argentina. The Vaca Muerta has gas and oil resources estimated at 1,202 trillion cubic feet of gas and 270 billion barrels of oil in place respectively, and its recoverable is estimated as 308 trillion cubic feet of gas and 16 billion barrels of oil and condensate (EIA, 2015). Currently, more than 75% of the hydrocarbon discovered in Argentina were generated in the Vaca Muerta (Kietzmann et al., 2014; Uliana et al., 1999), with a prevalence of oil over gas (Kietzmann et al., 2014; Legarreta et al., 2005). These statistics show the significance of Vaca Muerta Formation for the present and future of energy development in Argentina (Fernández-Concheso, 2015).

Previous work in the area of study were performed by the Reservoir Characterization Project in 2015. A post-stack and pre-stack seismic inversion were performed by Jorge Fernández-Concheso (2015) to characterize the distribution of rock properties within the Vaca Muerta Formation. Cluster analysis was used by Kyla Bishop (2015) to develop a mechanical stratigraphy model for the Vaca Muerta Formation with the purpose of identifying the variation in geomechanical properties. This study offers an update of the seismic inversion performed by Jorge Fernández-Concheso (2015). The drilling of two new wells in the area allows to have an improvement in well control that reduces the uncertainty for the seismic inversion results. Additionally, the geomechanical analysis has a different approach where the density used is obtained from rock properties prediction instead of the seismic inversion.
Characterization of the Vaca Muerta Formation continues as an essential task to understand the lateral and vertical heterogeneity within the rock and its effects on production. The emphasis of this study is to integrate pre-stack seismic and rock property data to improve the understanding between the distribution of rock properties into the formation and how this could impact hydraulic stimulation response within the Vaca Muerta. The study attempts to lead better planning support through the improvement of reservoir models and target identification, which reduces risk and costs.

This introductory chapter includes the geological background, the description of the area and data available, and the workflow used for this study. Chapter two explains the inversion theory, including the results of crossplots of elastic parameters and rock properties, and the results for the pre-stack seismic inversion performed using Jason\textsuperscript{TM} software. Chapter three explains the prediction of reservoir properties using neural networks. Chapter four explains predicted zones of good response to hydraulic stimulation. Chapter five integrates the reservoir properties prediction and geomechanical parameters. Chapter six contains conclusions and recommendations for this study.

1.1 Research Objectives

The objectives of this study are:

- To discriminate which zones could be associated with rich hydrocarbon presence.
- To define zones of the Vaca Muerta Formation that would have a better response to hydraulic stimulation based on geomechanical properties.
- To integrate rock properties prediction with geomechanical parameters to define potential zones to fracture hydraulically.

1.2 Geological Settings of Neuquén Basin

The Neuquén Basin was developed as a back-arc basin during Mesozoic time and was partially connected to the proto-Pacific Ocean. Several potential source rocks rich in organic
matter are part of the thick sediment sequence filling the basin (Kietzmann et al., 2014; Legarreta and Villar, 2015; Sagasti et al., 2014; Urien and Zambrano, 1994). A broadly triangular shape describes the Neuquén Basin, with two main regional divisions known as the Neuquén Andes to the West and the Neuquén Embayment to the East and South-East (Figure 1.2) (Howell et al., 2005).

![Figure 1.2: Structural domain and boundaries of Neuquén Basin. Modified from Bishop (2015); Sagasti et al. (2014).](image)

### 1.2.1 Geodynamic Evolution

According to Howell et al. (2005), the Neuquén Basin has a highly complex structural framework controlled by tectonics changes in the western margin of Gondwana. Three phases describe the evolution of the Neuquén Basin:

1. Syn-rift phase: Extensional strains during the Late Triassic-Early Jurassic, associated with Gondwana separation, were characterized by the presence of a number of isolated
depocenters. The geometry of the depocenters was controlled by transcurrent faults and the basin was filled largely by continental deposits of the Precuyo Group (Figure 1.3 (A)) (Kietzmann et al., 2014).

2. Post-rift phase: During the Early Jurassic and Early Cretaceous, volcanic activity was caused by the subduction of Nazca plate below the western margin of Gondwana (South American plate). This volcanic activity led to the development of a magmatic arc along the western margin of the basin. Subsidence in the back-arc controlled the flooding processes into the basin, which was occasionally connected to the proto-Pacific Ocean through breaches in the magmatic arc. Most of the basin fill was caused by an extensive period of thermal subsidence and regional back-arc extension controlled by variation in the sea level oscillation. The Vaca Muerta Formation was deposited during this phase (Figure 1.3 (B)) (Howell et al., 2005; Kietzmann et al., 2014).

3. Compression and foreland basin phase: Tectonic changes marked the beginning of this phase at the end of Early Cretaceous. Compressional regime was generated by significant reduction in the spreading rate of South Atlantic plate and also a decreasing of the subduction angle in the Pacific plate. As a consequence of the tectonic, inversion in previous extensional features converted the Neuquén into a foreland basin. Periodic compressional stress continued through the Cenozoic and Tertiary controlling the uplifting of the western portion of the basin (Figure 1.3 (C)) (Howell et al., 2005; Kietzmann et al., 2014).

Different transgressive-regressive cycles occurred from the Lower Jurassic to Lower Cretaceous (post-rift phase), where thick successions of siliciclastics, evaporites and carbonates deposits were accumulated in marine and continental settings (García et al., 2013; Mitchum and Ulina, 1985). Tectonism generated changes in the eustatic sea level that were considered the main cause of transgressive-regressive cycles (García et al., 2013; Sagasti et al., 2014). The Mendoza Group was deposited during a transgressive-regressive cycle occurring
Figure 1.3: Schematic representation of the three phases describing the Neuquén Basin evolution from Late Triassic to the Cenozoic including the (A) synrift phase, (B) postrift phase and (C) foreland phase (Howell et al., 2005).
from the Late Jurassic to Early Cretaceous. During this cycle were deposited the deep marine calcareous sediments of the Vaca Muerta Formation, the limestone of the Quintuco Formation, and the continental sandstones of Tordillo Formation (Figure 1.4) (Bishop, 2015; Garcia et al., 2013; Kietzmann et al., 2014; Mitchum and Uliana, 1985; Sagasti et al., 2014).

Figure 1.4: General stratigraphic column in the study area for the Vaca Muerta Formation in the Neuquén Basin. Modified from Leanza (2012); Sylwan (2014).

1.2.2 The Vaca Muerta Formation

The Vaca Muerta Formation consists of highly bituminous black and grey shales, marls and limestones deposited in an anoxic marine environment with low energy (Bishop, 2015; Garcia et al., 2013; Stinco and Barredo, 2014).

The Vaca Muerta Formation overlies the continental deposits of the Tordillo Formation representing the Late Jurassic marine transgression. In the area of study, the top of the Vaca Muerta Formation describes a transition to limestones and siltstones of the Quintuco and
Loma Montosa Formations (Garcia et al., 2013; Stinco and Barredo, 2014). The Vaca Muerta consists of alternating marls, organic-rich shales and limestones associated with distal ramp facies prograding from east to west, indicating that younger rock can be found in the west zone (Bishop, 2015; Stinco and Barredo, 2014).

The Vaca Muerta Formation is part of depositional system called Quintuco-Vaca Muerta that started in the Early Tithonian due to marine transgression from the Pacific Ocean. The Vaca Muerta Formation represents the distal and deep marine deposits and the Quintuco Formation consists of shallow marine deposits (Sagasti et al., 2014).

Facies differentiation within the Vaca Muerta Formation was identified according to the geographical location within the basin. Toward the South-Southwestern zone of the Neuquén Basin, the Vaca Muerta Formation consists in carbonates and marls deposited under tidal influence. Within the embayment area, the deposits change toward the East to the shoreface sediments of the Quintuco Formation. Volcanic episodes in the Western margin of the basin generated shallow-marine volcanic deposits that covered wide extensions. The Northern area of the Neuquén Basin, the basin to middle ramp deposits of the Vaca Muerta Formation are covered by middle to inner ramp oyster-deposits of the Chachao Formation (Figure 1.5) (Kietzmann et al., 2014; Stinco and Barredo, 2014).

The facies differentiation was used to create three subdivisions (Howell et al., 2005; Stinco and Barredo, 2014). The Lower Vaca Muerta corresponds to a low angle carbonate platform characterized by the presence of marls and limestones. The Middle Vaca Muerta corresponds to slope deposits with a predominant presence of siliciclastic sediments. The Upper Vaca Muerta also corresponds to a carbonate platform associated with an open shelf environment (Figure 1.6) (Garcia et al., 2013; Kietzmann et al., 2014; Stinco and Barredo, 2014). The thickness of the Vaca Muerta Formation in the study area is between 250 meters to 270 meters.

Figure 1.7 (A) illustrates a schematic section of the Lower Mendoza Group in the central sector of the Neuquén Basin, which shows lithostratigraphic relationships and sequence
Figure 1.5: Schematic representation of post-rift environment with facies distribution where the Vaca Muerta Formation was deposited. Modified from Stinco and Barredo (2014).

Figure 1.6: Illustrative rock properties related to the subdivision within the Vaca Muerta Formation. GR, TOC and Young’s modulus from well logs describes different behavior for the Upper, Middle and Lower Vaca Muerta. Modified from Barbosa (2017); Bishop (2015).
geometries (Kietzmann et al., 2014). Figure 1.7 (B) is an arbitrary seismic section with direction South-East to North-West in the study area, which shows similar depositional characteristics observed in figure 1.6 (A) in the central sector of Neuquén Basin. The section is flattered in the Quintuco Formation to allows the visualization of clinoforms in the Vaca Muerta Formation. The top of the Quintuco Formation and Tordillo Formation can be identified clearly in the seismic section. The top of the Vaca Muerta Formation is often less certain to be identified, as it slowly grades into the overlying carbonates of the Quintuco Formation.

![Figure 1.7: (A) Schematic cross-section of the central Neuquén sector showing sequence geometries with low-angle platform (2°) and prograding from SE to NW. Modified from Kietzmann et al. (2014). (B) Arbitrary section in the study area flattered on the Quintuco Formation, which shows the prograding sedimentation in the Vaca Muerta Formation from SE to NW.](image-url)
The Vaca Muerta Formation is considered an unconventional play because of its organic content, great thickness, thermal maturity, mineralogy, porosity and geomechanical properties (Fantín et al., 2014). The thermal maturity of the Vaca Muerta Formation, with vitrinite reflectance $R_o$ between 0.8% to 2%, shows an oil window in the eastern zone and a gas window in the central and western zone (Figure 1.8). Most of the embayment area is considered in the oil window with oil between 35-45° API (Garcia et al., 2013).

![Figure 1.8: Thermal maturity of the Vaca Muerta Formation and location of the study area. Modified from Lanusse et al. (2012); Stinco and Barredo (2014).](image)

The regional stress regime that affected the Neuquén Basin is the main factor in creating natural fractures in the Vaca Muerta Formation. Figure 1.9 shows three stress regimes zones during the Andean orogeny. A strike slip stress regime is observed in almost all of the basin, but it is highest in the west and shows a gradual decreasing toward the east, indicating a maximum horizontal stress is in the west-east direction. Zone four, within a larger strike
slip stress regime, has the highest horizontal stress applied in the basin compared with the other three zones. A transitional zone is recognized in zones one and two, where the strike slip stress starts a transitional change to normal stress. Finally, zone three is identified as a normal stress regime (Garcia et al., 2013).

Figure 1.9: Map with the main stress regime zones and the stress analysis. The study area is located in zone 3 (Fernández-Concheso, 2015; Garcia et al., 2013).

1.2.3 The Quintuco Formation

The Quintuco Formation is composed of different quantities of limestones, dolomite, anhydrite, and a mixture of quartz and volcanic sands that were deposited in a shallow marine environment associated with the proximal carbonate ramp and shelf (Hurley et al., 1995; Sagasti et al., 2014; Zeller et al., 2015a). In the study area, the Quintuco Formation
overlies the Vaca Muerta Formation and its main composition is related to the presence of
marls and limestones.

As part of the Quintuco-Vaca Muerta depositional system, the Quintuco Formation rep-
presents the top set of the system related to similar prograding sediments deposited in different
ages, which marks the contact with the top of the Vaca Muerta Formation. The Quintuco
is an overpressured formation which shows gradients up to 1.0 psi/ft (Garcia et al., 2013;
Sagasti et al., 2014).

Although the Quintuco Formation has been briefly described as a part of the depositional
system that includes the Vaca Muerta Formation, it is recognized for being a carbonate reser-
voir in the Neuquén basin (Bishop, 2015).

1.3 Study Area and Available Data

Data for this project were provided by Wintershall Holding GmbH, as part of an agree-
ment with the Reservoir Characterization Project (RCP). The study area is located in the
central-eastern sector of the Neuquén Basin inside the embayment zone. The P-wave seismic
data used in this study has an approximate area of 600 km$^2$. There are six vertical wells
inside the block. Three vertical wells (Well A, Well G and Well I) in the north-east area,
and another three vertical wells in the south-west area (Well B, Well C and Well H). All
of them have a complete suite of logs. Shear sonic data are available for all wells, allowing
for the calculation of elastic properties. Ultrasonic Borehole Imager (UBI) and Oil-Based
MicroImager (OBMI) data are the image logs available because of the drilling of these wells
with oil-based muds (Figure 1.10). Table 1.1 illustrates the data available for the wells
located in the study area.

Data from sidewall core and cuttings are available, such as X-Ray Di-fraction (XRD)
and Pyrolisis Rock-Eval, which allow for the calibration of mineralogy and TOC calculations
from logs. Some wells even have petrophysical measurements on core, such as porosity, grain
density, water, oil, and gas saturations, as well as Computarized Tomography (CT) Scans
Table 1.1: Data available in the study area for Well A, Well B, Well C, Well G, Well H and Well I.

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Figure 1.10: Study area corresponding to the pre-stack seismic data (orange polygon) used in the research and the current data available in the Vaca Muerta Project.
and core photos. There is a wealth of information from reports on mud log data, as well as drilling and completion reports. These can provide important information on drilling events related to formation pressure and wellbore stability, important for geomechanical understanding of the reservoir.

Surface microseismic was acquired during the hydraulic fracturing of Well G and Well I. The FracStar\textsuperscript{TM} array was composed of ten lines of around three kilometers length with stations of 12 geophones, placed every 14 meter and 2 ms of sample rate (Figure 1.11). Production data is also available from Well G and Well I, where four stages were tested in Well G and five stages were tested in Well I (Figure 1.12).

![Figure 1.11: Illustrates the microseismic acquisition geometry at Well G. The same geometry was used for the microseismic acquisition at Well I. The yellow star is the location of Well G. The receiver lines are in black and the blue dots are microseismic events.](image)

Wintershall also provided an updated set of horizons with a stratigraphic seismic interpretation. These horizons are used to define the vertical gate of the reservoir during the construction of the Low Frequency Model (LFM) and seismic inversion process. Besides,
Figure 1.12: Cartoon illustrates the approximate vertical distribution of the four stages tested at Well G, and the five stages tested at Well I.

these horizons are used to extract of horizon slices in the Lower, Middle and Upper Vaca Muerta. The horizons available for this study are:

- Quintuco
- Secuencia 8 (S8)
- Secuencia 7 (S7)
- Secuencia 6 (S6)
- Secuencia 4 (S4)
- Secuencia 3 (S3)
- Secuencia 1 (S1)
- Tordillo
As the Vaca Muerta Formation is the main focus of this study, the horizons used are: Secuencia 4, Secuencia 3, Secuencia 1 and Tordillo. Tordillo horizon corresponds to the top the Tordillo Formation, which is a strong reflector in the seismic that can be followed along the study area. Secuencia 1 (S1) horizon corresponds to the top of the Lower Vaca Muerta, which is also a strong reflector in the seismic in the study area. Secuencia 3 (S3) horizon corresponds to the middle section of the Middle Vaca Muerta. Despite the reflector in the seismic is not as strong as Secuencia 1 and Tordillo, this horizon can also be followed along the study area.

Although the top of the Vaca Muerta Formation is not often easy to identify in seismic, Secuencia 4 (S4) horizon coincides in some zones of the study area with the top of the Vaca Muerta Formation. The stratigraphic interpretation of Secuencia 4 indicates the possible top of the Vaca Muerta Formation in a small area of the Southern and Eastern zone, where the proximal zones of the Neuquén Basin is located. Toward the Northern and Western zone of the study area, Secuencia 4 horizon coincides more with the top of the Middle Vaca Muerta.

The interpretation of Secuencia 4 horizon follows a stratigraphic sequence which coincides with increasing the carbonate content in the rock toward the South and North-East, and increasing of total organic carbon (TOC) toward the North and West of the study area. For the purpose of simplifying the understanding in the extraction of slices in further chapters, Secuencia 4 will be taken into account as the top of the Middle and base of the Upper Vaca Muerta.

1.4 Methodology

The methodology of study encompasses several steps were the pre-stack seismic and well log data is used. The first step includes the identification of relationships between rock properties and elastic parameters. The second step involves seismic inversion to determine elastic properties. The third step includes the use of neural networks to predict rock properties. Figure 1.13 shows the general workflow for the first three steps. The fourth and final step integrates rock properties and geomechanical parameters (Figure 1.14).
Figure 1.13: General workflow methodology for the first three steps of this study.

Figure 1.14: General workflow for the step four of this study.
A seismic inversion was previously performed by Fernández-Concheso (2015) using the same seismic data set as part of his reservoir characterization study in RCP. This new study performs an update of the pre-stack seismic inversion with the addition of new well data. An important step before starting the seismic inversion is data-preconditioning, which was done in the previous seismic inversion by Fernández-Concheso (2015). A new log data-preconditioning was performed by Wintershall in 2016 to improve the corrections done previously and to normalize the log data.

Originally, the maximum angle of incidence of the seismic data used in the study was 42°, but Fernández-Concheso (2015) edited the data to a maximum angle of incidence of 36° during the data preconditioning. The seismic data quality was poor, from 37° to 42°, especially in the Vaca Muerta Formation. Four angle-stacks were created: the near-stack from 1° to 9°, the midnear-stack from 10° to 18°, the midfar-stack from 19° to 27° and the far-stack from 28° to 36°. The angle of incidence used for the inversion is not adequate to obtain a reliable result in the estimation of density.

This chapter has a brief section to explain the seismic inversion theory before showing the results obtained during the update of the seismic inversion.

2.1 Seismic Inversion Theory

This section describes the concepts of deconvolution, pre-stack seismic inversion and its workflow, the sparse spike method, the low frequency model and the wavelet.

2.1.1 Deconvolution and Pre-stack Seismic Inversion

Deconvolution is used in seismic to remove negative effects caused by the convolution. It is an effective process that helps reduce multiple energy (Veeken and Da Silva, 2004;
Yilmaz, 2001). The seismic signal is sent through the earth and this behaves as a filter for transmitted and reflected seismic signal. Deconvolution tries to remove the deformation effect in the seismic response that was generated by that filter (Veeken and Da Silva, 2004). The earth as a filter, also absorbs high frequencies of the wavelet as transmission occurs (Duenas, 2014; Russell, 1988).

At normal incidence, the reflection coefficient between two layers is represented by a single spike. The reflectivity formula describes this response (Russell, 1988; Veeken and Da Silva, 2004):

\[ R_{\text{P-wave}} = \frac{\rho_2 V_2 - \rho_1 V_1}{\rho_2 V_2 + \rho_1 V_1} \] (2.1)

Where \( V_1 \) and \( \rho_1 \) are the compressional velocity and density of the upper layer, and \( V_2 \) and \( \rho_2 \) are the compressional velocity and density of the lower layer.

Compressional wave (P-wave) and shear wave (S-wave) are generated when a seismic ray strikes the boundary between two layers beyond the normal incidence angle. In this case, the reflection coefficient can be described as a function of P-wave, S-wave and rock density using the Zoeppritz equations. The Aki-Richards equation offers a good approximation of Zoeppritz equations for reflection coefficient with a specific range of incidence angles (Aki and Richards, 2002; Fernández-Concheso, 2015; Russell, 1988):

\[ R_{\text{P-wave}}(\theta) = \frac{1}{2} \left[ 1 - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right] \frac{\Delta \rho}{\rho} + \frac{1}{2} \left[ 1 + \tan^2 \theta \right] \frac{\Delta V_p}{V_p} - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \frac{\Delta V_s}{V_s} \] (2.2)

Where \( V_p \) is the P-wave velocity, \( V_s \) is the S-wave velocity, \( \rho \) is the rock density, and \( \theta \) is the angle of incidence.

Pre-stack seismic inversion exploits AVO effects in the data set and uses angle stacks to estimate elastic subsurface parameters keeping the major geological characteristics from well log data (Buland and Henning, 2003; Russell, 1988; Veeken and Da Silva, 2004). With the Aki and Richards (2002) approximation, the main products obtained are acoustic impedance, shear impedance and density (Buland and Henning, 2003; Russell, 1988). From these prod-
ucts, other elastic parameters are obtained including Poisson’s ratio, Mu-rho, Lambda-rho and Vp/Vs. During this process, seismic inversion removes the wavelet from seismic traces to obtain an earth model from the seismic data (Figure 2.1) (Barclay et al., 2007).

![Figure 2.1: Example of a seismic data trace where the wavelet is removed to obtain an earth model. Modified from Barclay et al. (2007).](image)

There are two different approaches in the pre-stack seismic inversion process. A deterministic inversion estimates just a single result for each of the elastic parameters from many different acceptable inversion solutions. On the other hand, stochastic inversion uses variograms to prepare the input model before estimating all of the most realistic inversion results in each elastic parameter (Cooke and Cant, 2010). In stochastic inversion, the quantification of uncertainties from input model are retained in the final results (Veeken and Da Silva, 2004). The seismic inversion that is used in this study is the deterministic inversion.

Several methods to perform deterministic seismic inversion are known: Simple integration of seismic traces, sparse spike inversion, colored inversion and model-based inversion. This thesis will focus on Sparse Spike inversion with the Aki-Richards equation using Jason™ software and it assumes on isotropic subsurface model. Figure 2.2 shows the general workflow used in this study to perform pre-stack seismic inversion.
2.1.2 Constrained Sparse Spike Inversion (CSSI)

The Constrained Sparse Spike Inversion (CSSI) is a deterministic method that uses a simulated seismic trace obtained from reflectivity spikes to generate a real seismic response when convolved with a wavelet. The inversion algorithm works in a multi-trace approach that speeds up the process. A low frequency model from well log data is used in the constrained option to obtain better results and model convergence for trace to trace solutions (Figure 2.3). This multi-trace process offers better stability of the computed solution (Barclay et al., 2007; Russell, 1988; Veeken and Da Silva, 2004).

The use of the sparse spike inversion method has advantages, like the data are used in the calculation and the low frequency information are included mathematically in the solution.
Due to the statistical nature of the method, problems occur in data with low signal-to-noise ratio. When inverted, the output lacks detail, leaving only the blocky component as the result (Fernández-Concheso, 2015; Russell, 1988).

### 2.2 Low Frequency Model

Seismic data suffers from critical loss of information in the low frequency band. The low frequency band is needed to define the reservoir properties. The typical band of low frequencies is from 0 Hz to 8-10 Hz (Pendrel, 2015). The construction of a low frequency model (LFM) using well log data is necessary to correct for the missing frequencies. P-impedance, S-impedance and density from well log data were used to build the LFM for the pre-stack seismic inversion. However, lateral changes into the reservoir are not controlled and it is necessary to use analytical interpolation methods to define the connection between wells. This implies that an optimal well control is necessary to reduce interpolation error (Fernández-Concheso, 2015; Pendrel, 2015).

Even with the addition of two new wells, it is still considered a limited number of wells in the study area to avoid problems in the interpolation process. Although this could be a limitation, all the interpolation methods available in Jason\textsuperscript{TM} software were used to generate and test several low frequency models (LFM). The best LFM approach for this study was obtained using global kriging with 40,000 variograms. This geostatistical method of
interpolation uses a spatial correlation model that applies linear combination of weights to the well data. The horizon weights added to the interpolation process helped to reduce issues caused by lack of well control and generates an improved LFM. The LFM used in the study was built by Johnson (2017) at Wintershall’s office in Kassel, Germany.

The LFM was generated using the information from five of the six wells available. Well C was removed because the seismic data showed strong differences in frequencies caused by the merge of two seismic surveys around the well location. Inclusion of Well C would generate a negative impact in the seismic inversion result. The LFM for P-impedance, S-impedance and density was generated taking into account areal weights for the global kriging method previously mentioned to improve the result during the interpolation process. Figure 2.4, Figure 2.5 and Figure 2.6 show the LFM with high-cut frequency of 10 Hz for P-impedance, S-impedance and density models, respectively well log data for each parameter showed in the figures are also displayed with frequency filtered to the LFM.

![Figure 2.4: Arbitrary line of the low frequency model (LFM) for the P-impedance over Well A, Well G and Well I with cut-off frequency of 10 Hz.](image)
Horizon extraction from the LFM is a process used to visualize and to quality control (QC) of the interpolation method used. The main purpose to make sure there are no bull-
eyes around well locations. The Global kriging method showed the best results compared with the other interpolation methods available in Jason™ software (Figure 2.7) (Johnson, 2017). The high values of P-impedance could be related to the low angle platform in the proximal zone of the Neuquén Basin, which the study area is located.

![Figure 2.7: Horizon extracted from the low frequency model (LFM) volume of the P-impedance to QC the results of global kriging interpolation method. There are no bull-eyes observed as result of the interpolation with Global Kriging. This horizon was extracted 10 ms below the top of the Middle Vaca Muerta using the horizon Secuencia 4 (S4).](image)

### 2.3 Well-tie and wavelet estimation

The well-tie and wavelet estimation is a critical step that has a great impact in the seismic inversion. The wavelet is a transfer function that connects seismic data and the impedance log (Duenas, 2014). A successful well-tie requires an optimum wavelet estimation. Having a good wavelet in the well-tie process leads to a high correlation coefficient. However, it is also important to obtain the best match possible between the seismic data and the synthetic
instead of only relying on the correlation coefficient values.

The well-tie process in this study was done for the six wells available using density and P-wave data. A wavelet was estimated for each of the four angle-stacks used in this study where the vertical gate applied was from the top of Quintuco Formation to the Top of Tordillo Formation (base of Vaca Muerta Formation). The mid-near angle-stack was used to define the multi-well wavelet instead of the near angle-stack. The mid-near still has high frequencies but without the noise and artifacts that the near angle-stack has. Figure 2.8 shows the multi-wavelets estimated for each of the angle-stacks where the phase is around -90°. The wavelet estimation and well-ties obtained by Johnson (2017) at Wintershall’s office in Kassel, Germany.

Figure 2.8: Estimated wavelets for each of the four angle-stacks.
Figure 2.9 shows the well-tie for Well I, where a good match between the seismic data and synthetic is observed. There is a correlation coefficient of 87% in the near stack, 88% for the mid-near, 80% for the mid-far and 68% for the far. Well A, Well B, Well H and Well G show high values of correlation coefficient (>68%) for all the angle stacks. They also show a good match between seismic data and the synthetics. It is important to mention that the well-tie for Well C shows a low correlation coefficient, and a clear mismatch between the frequency of seismic data and the frequency of synthetics. As mentioned previously, the area around Well C has problems because of the merge between different seismic surveys (Figure 2.10). As a consequence of high differences in frequency between the seismic data and the synthetic, the well-tie of Well C is not reliable enough to be used in the seismic inversion process.

![Figure 2.9: Well-tie of Well I for each angle-stack.](image)

The mid-near angle-stack bandwidth in Figure 2.11 shows the frequencies used in the parametrization for the inversion process. A frequency of 10 Hz was selected as merge-cut based on the frequency analysis performed on the four angle stacks. Seismic frequencies below 10 Hz does not offer enough information to perform the inversion correctly. A LFM is
Figure 2.10: Near angle-stack around Well C shows low correlation that makes the well not reliable for seismic inversion.

generated to compensate for this problem (0-10 Hz) and provide the necessary information to complete the seismic inversion.

Figure 2.11: Bandwidth of mid-near angle-stack. The low frequency model uses a high-cut filter of 10 Hz in red color. The seismic bandpass is from 10 Hz to 70 Hz in cyan color.
2.4 Inversion Parameters

The process to obtain the best inversion parameters is described as a complex iterative test to define which values generate the most realistic elastic parameters selected. The rock physics constraints were useful to improve the inversion results. P-impedance and S-impedance were very stable and reliable. On the other hand, density is not reliable because of its lower offset angle. Table 2.1 illustrates the final parameters used in the pre-stack inversion.

Table 2.1: Pre-stack inversion parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time window</td>
<td>Quintuco Fm. - Tordillo Fm.</td>
</tr>
<tr>
<td>Seismic misfit signal to noise ratio nears (dB)</td>
<td>12</td>
</tr>
<tr>
<td>Seismic misfit signal to noise ratio mid-nears (dB)</td>
<td>18</td>
</tr>
<tr>
<td>Seismic misfit signal to noise ratio mid-fars (dB)</td>
<td>18</td>
</tr>
<tr>
<td>Seismic misfit signal to noise ratio fars (dB)</td>
<td>12</td>
</tr>
<tr>
<td>Wavelet scale factor nears</td>
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</tr>
<tr>
<td>Wavelet scale factor mid-nears</td>
<td>1</td>
</tr>
<tr>
<td>Wavelet scale factor mid-fars</td>
<td>2</td>
</tr>
<tr>
<td>Wavelet scale factor fars</td>
<td>2</td>
</tr>
<tr>
<td>Merge cut-off frequency (Hz)</td>
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</tr>
<tr>
<td>Contrast misfit P-impedance uncertainty (%)</td>
<td>0.05</td>
</tr>
<tr>
<td>Contrast misfit S-impedance uncertainty (%)</td>
<td>0.01</td>
</tr>
<tr>
<td>Contrast misfit Density uncertainty (%)</td>
<td>0.05</td>
</tr>
<tr>
<td>Gardner uncertainty</td>
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</tr>
<tr>
<td>Gardner slope (%)</td>
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</tr>
<tr>
<td>Mudrock uncertainty</td>
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</tr>
<tr>
<td>Mudrock slope (%)</td>
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</tr>
<tr>
<td>Rock physics equations cut-off frequency (Hz)</td>
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</tr>
<tr>
<td>Seismic misfit multiplier</td>
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</tr>
<tr>
<td>Contrast misfit power</td>
<td>3</td>
</tr>
<tr>
<td>Seismic misfit power</td>
<td>3</td>
</tr>
</tbody>
</table>
2.5 Quality Control of Inversion Results

The parametrization of the seismic inversion is part of the process to obtain reliable inversion results. The accuracy of those results need to be tested using several quality controls (QC).

- Blind well test.
- Crossplot pseudo-curves from inverted acoustic impedance and filtered original log data.
- Compare the contribution of LFM and inverted seismic bandpass with band limited analysis.
- Match inverted results with well log.

2.5.1 Blind Well Test and Comparison of Inversion Results with Filtered Well Log

These two quality controls (QCs) were performed to identify the reliability of the seismic inversion. The blind well test consists of removing each well at a time to analyze the prediction for each well location. The generation of pseudo curves from inversion results is done to compare with well data and observe how well the curves match each other. As part of the QC process, the filtered acoustic logs overlay the pseudo-curves obtained from inversion results. Additionally for this QC process, the LFM log curve with a frequency of 10 Hz overlays the selected well for the blind well test. The blind well test and the comparison shows similar results in each well and each elastic parameter tested. Only one blind well test with its respective comparison is displayed in this section to show the trend and results of the inversion for P-impedance, S-impedance and density.

Figure 2.12 shows the blind well QC performed for P-impedance curves in Well G and also the comparison of pseudo curves from the inversion and log. The P-impedance prediction for Well G is in blue and has a good match compared with the filtered log data in pink. As
observed, the LFM in pink shows the general trend and the pseudo-curve in blue from the inversion results is influenced by the seismic contribution. The comparison between pseudo curves and filtered well curves is observed in Well A, Well B and Well I with an excellent match.

Figure 2.12: Blind well test in Well G and comparison of pseudo curves with filtered log data for P-impedance. Blue represents the pseudo curves. Pink shows the filtered log data and the low frequency model (LFM) with frequency of 10 Hz.

Figure 2.13 shows the blind well QC performed for the S-impedance curves in Well G and also the comparison of pseudo curves from the inversion and log. The S-impedance prediction for Well G in blue has a good match compared with the filtered log data in pink and also shows the general trend with the LFM. The comparison between pseudo curves and filtered well curves is observed in Well A, Well B and Well I with a good match.

Figure 2.14 shows the blind well QC performed for the density curves in the same Well G and also the comparison of pseudo curves from the inversion and log. The LFM in blue shows the main trend and indicates the contribution below 10 Hz. The comparison between pseudo curves in blue and the filtered log data in pink for the other four wells has an acceptable match. Although the density shows a reasonable match in the trend, in detail it is difficult
Figure 2.13: Blind well test in Well G and comparison of pseudo curves with filtered log data for S-impedance. Blue represents the pseudo curves. Pink shows the filtered log data and the low frequency model (LFM) with frequency of 10 Hz.

obtain a reliable density result from the inversion.

2.5.2 Pseudo-curves from Inversion Results vs Filtered Well Log

Crossplots using the pseudo-curves from inversion results and the filtered well log are another QC that indicates the reliability of the inversion. The best results of inversion must be close to the relationship $X=Y$, which suggests a correlation of 100%. The reality is that inversion results never show 100% correlation, but it is considered an excellent result when the correlation yields a high value. Figure 2.15 shows the crossplot of P-impedance between log curves and the the pseudo curves obtained from inversion. The correlation is 98%, which indicates that the inversion process to obtain P-impedance was acceptable and the results are good. Figure 2.16 shows the crossplot with S-impedance curves and the the pseudo curves from inversion. Again, the correlation is high and shows 96%. This indicates that the inversion process to obtain S-impedance yielded reasonable results. Figure 2.17 shows the crossplot with density curves and the the pseudo curves from inversion. The correlation
Figure 2.14: Blind well test in Well G and comparison of pseudo curves with filtered log data for density. Blue represents the pseudo curves. Pink shows the filtered log data and the low frequency model (LFM) with frequency of 10 Hz.

is lower than those shown in P-impedance and S-impedance, even if 89% of correlation is not really low, the relationship indicates that the inversion process to derive density has problems and the results are not completely reliable. It is necessary to clarify the limitations and uncertainty inherent in it. This density result could be used for the calculation of geomechanical parameters, but it is necessary clarify the limitations and uncertainty inherent in it.

2.5.3 Band-limited Inversion Results

Full bandwidth inversion results contain the combined data from seismic and the LFM. A band limited analysis allows the identification the individual contribution from each of them. This separated analysis shows that the contribution made by seismic and the LFM is balanced and offers good and stable inversion results. Figure 2.18 (A) shows the P-impedance results with a low pass filter from 0 Hz to 10 Hz, which indicates the contribution made by the LFM to the P-impedance result in the seismic inversion. Figure 2.18 (B) shows the
bandpass results for P-impedance with a frequency band from 10 Hz to 70 Hz, which is the contribution made by the seismic data.

Figure 2.19 (A) shows the S-impedance results with a low pass filter from 0 Hz to 10 Hz, which indicates the contribution made by the LFM to the S-impedance result in the seismic inversion. Figure 2.19 (B) shows the bandpass results for S-impedance with a frequency
Figure 2.17: Crossplot of the pseudo curves from inversion vs filtered log data for density.

Figure 2.18: Band limited analysis for P-impedance inversion results. (A) shows contribution made by the low frequency model (LFM) from 0 Hz to 10 Hz. (B) shows the contribution from seismic with bandpass from 10 Hz to 70 Hz.
band from 10 Hz to 70 Hz, which is the contribution made by the seismic data.

Figure 2.19: Band limited analysis for S-impedance inversion results. (A) shows contribution made by the low frequency model (LFM) from 0 Hz to 10 Hz. (B) shows contribution from seismic with bandpass from 10 Hz to 70 Hz.

Figure 2.20 (A) shows the density results with a low pass filter from 0 Hz to 10 Hz, which indicates the contribution made by the LFM to the S-impedance result in the seismic inversion. Figure 2.20 (B) shows the bandpass results for density with a frequency band from 10 Hz to 70 Hz, which is the contribution made by the seismic data.

2.6 Inversion Results

The results obtained during the QC provided confidence in the parametrization process used to proceed with the seismic inversion of the complete volume. Figure 2.21 shows the final inversion results for P-impedance. Figure 2.22 shows the final inversion results for S-impedance. P-impedance and S-impedance shows a range of lower values in the acoustic
Figure 2.20: Band limited analysis for density inversion results. (A) shows contribution made by the low frequency model (LFM) from 0 Hz to 10 Hz. (B) shows contribution from seismic with bandpass from 10 Hz to 70 Hz.

response into the Vaca Muerta Formation. This is related to the lower values of density and also the presence of TOC into the shale play, to be explained in chapter 3. Despite the top of the Vaca Muerta Formation is not often easy to identify in seismic interpretation, the inversion results for P-impedance and S-impedance show to be useful in the identification of the top of the Vaca Muerta Formation, which slowly grades into overlying carbonates of the Quintuco Formation.

Figure 2.23 shows the inversion results for the density with lower values of density into the Vaca Muerta Formation compared with the Tordillo Formation and the Quintuco Formation. The variations in density is related to the lateral and vertical variation of the compositional mineralogy. The density increase toward zones with higher carbonate content, and decrease in zones with high values of TOC.
Figure 2.21: Inversion results for P-impedance. The top of the Vaca Muerta and Tordillo Formation can be followed easily in the P-impedance results.

Figure 2.22: Inversion results for S-impedance. The top of the Vaca Muerta and Tordillo Formation can be followed easily in the P-impedance results.
Figure 2.23: inversion results for density. Density results do not allow following easily the top of the Vaca Muerta and Tordillo Formation.

Figure 2.24 shows an example of a horizon that has been extracted from the P-impedance inversion results in the Middle Vaca Muerta. The horizon was extracted in the top of the Middle Vaca Muerta using a 10 ms window, which provides a better visualization of the lateral variation of P-impedance. The trend in the top of the Middle Vaca Muerta illustrates a decreasing in P-impedance values towards the west. This reduction of P-impedance coincides with the geological description that corresponds to the distal area of the platform, and also related to anoxic zones where high preservation of organic matter is expected. High values of P-impedance toward the east are related to the increasing of carbonate content in the rock that it is associated to the proximal area of the platform.

2.7 Summary

Pre-stack seismic inversion was performed focusing in the Vaca Muerta Formation and including the bottom section of Quintuco Formation. Two new wells were added to update the deterministic pre-stack inversion performed by Fernández-Concheso (2015). The new well data provided good and similar results for P-impedance and S-impedance compared
Figure 2.24: Horizon extracted from inversion results of P-impedance. The horizon was extracted using the horizon Secuencia 4 (S4) which coincides the top of Middle Vaca Muerta, with the previous pre-stack inversion performed by Fernández-Concheso (2015). The study has more well control that helps to reduce uncertainty in the area around the new wells and improve the inversion results. P-impedance and S-impedance were the main objectives of the seismic inversion in this section of the study. The inversion results of those elastic parameters were acceptable. Additionally, Mu-Rho, Lambda-Rho, Vp/Vs and density parameters were predicted. The inverted density shows reasonable results, but the restriction in the offset angle (lower than 45°) makes it not reliable. That is the main reason to avoid the use of the density inversion results for the calculation of geomechanical parameters, which is part of Chapter 4. The other inversion results are used as external attributes in the prediction of reservoir properties explained in Chapter 3.
The Vaca Muerta Formation shows low values of P-impedance and S-impedance. These elastic parameters have shown specific acoustic response associated with the vertical and lateral composition of the shale. High presence of TOC in the shale is related to low values of P-impedance and S-impedance. That relationship is explained in more detail in Chapter 3.
Neural network algorithms are inspired by a biological computing scheme emulating neurons to process data and create progressive learning. They can identify complex relationships between several variables existing in a network (Aminian and Ameri, 2005; Mohaghegh, 2000). Neural networks are recognized for having excellent abilities of pattern recognition in highly heterogeneous formations which make them better for predicting any possible rock properties from well log data rather than statistical methods. The prediction of the rock property will be reliable when the mathematical transforms applied to attributes include a physical and geological sense in the output (Aminian and Ameri, 2005; Vega, 2012). Neural network architecture has been proven to be excellent when interpolating relationships to predict rock properties, but they are not so good for extrapolation (Hampson et al., 2001). It is suggested to use neural networks with a sufficient number of well logs to minimize the impact of extrapolation.

Neural network and seismic inversion use seismic and log data as input for their processes. Neural network has advantages over seismic inversion such as 1) predicting log properties besides acoustic impedance, 2) using other seismic attributes besides the conventional stack, 3) not trusting in any particular forward model, 4) can obtain greatly enhanced resolution, 5) using crossvalidation to QC the success of the prediction, and 6) not requiring the knowledge of the wavelet (other than the wavelet that is used for well-tie in this project) (Hampson et al., 2001). Hampson & Russell Software offers a module called Emerge\textsuperscript{TM} which provides this type of analysis.
3.1 Seismic Attributes

The seismic attributes used in Emerge\textsuperscript{TM} to compute reservoir parameters are classified in basic types by Russell (2004):

- Instantaneous attributes: derived from a combination of seismic trace and the Hilbert transform of the trace.

- Windowed frequency attributes: The amplitude spectrum of seismic trace is computed over a running window.

- Recursive attributes: Derived by applying a recursive operator along the seismic trace.

- Bandpass attributes: Narrow-band filter slices of seismic traces

- Multi-trace attributes: They are found by applying an operator to a local collection of seismic traces in a 3D volume.

- AVO attributes: Derived from pre-stack seismic data.

- Model-based attributes: Include an a priori model as component of the final solution.

Other seismic attributes that could be applied are 1) sample-based attributes that are computed sample by sample over the seismic volume and 2) horizon-based attributes that are computed as the average over a time window around a seismic horizon on a 3D seismic volume (Russell, 2004). For Emerge\textsuperscript{TM}, all attributes must be sample-based.

3.2 Multi-Attribute Analysis and Convolutional Operator

According to Hampson et al. (2001), Multi-Attribute (MA) linear regression computes a linear arrangement of seismic attributes to identify their correlation with the desired rock property from well logs. A single weight is assumed for each attribute during the MA regression which would generate a conflict caused by differences between log and seismic frequencies. The frequency of the targeted well log is higher than the seismic frequency and
it would not be optimal to relate the log sample with seismic attributes. To correct this situation, the MA regression use a *convolutional operator* assuming that each sample of the target log is associated to a group of adjacent samples on the seismic attribute (Figure 3.1).

![Figure 3.1: Multi-Attribute analysis assuming 1 point as convolutional operator using 3 seismic attributes for a specific targeted log (Hampson & Russell, 2015).](image)

The targeted log is modeled by the following linear equation (Hampson et al., 2001):

\[ L = w_0 + w_1 * A_1 + w_2 * A_2 + w_3 * A_3 + ... + w_n * A_n \]  

(3.1)

Where the * represents the convolution, \( w_i \) are a convolutional operator of specific length.

The mean-squared prediction error is used to derive operator coefficients (Hampson et al., 2001):

\[ E^2 = \frac{1}{N} \sum_{i=1}^{N} (L_i - w_0 - w_1 * A_1 - w_2 * A_2 - w_3 * A_3 - ... - w_n * A_n)^2 \]  

(3.2)

The error validation \( E \) will identify which well is giving higher error in the MA regression.

The seismic attributes available in Emerge\textsuperscript{T,M} for Multi-Attribute analysis consist in 17 attributes derived from seismic traces and divided in instantaneous, combination of instantaneous, windowed frequency, derivatives, integrated and time. Also available for the analysis are external attribute from seismic inversion (Table 3.1).
Table 3.1: Attributes available for Multi-Attribute analysis. Modified from Hampson et al. (2001); Hampson & Russell (2015).

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amplitude envelope</td>
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<td>Instantaneous phase</td>
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<tr>
<td>Instantaneous frequency</td>
<td></td>
</tr>
<tr>
<td>Amplitude-weighted cosine phase</td>
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<tr>
<td>Amplitude-weighted frequency</td>
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<tr>
<td>Amplitude-weighted phase</td>
<td>Combination of Instantaneous</td>
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<td>Cosine instantaneous phase</td>
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<td>Apparent polarity</td>
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<tr>
<td>Average frequency</td>
<td>Windowed Frequency</td>
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<td>Dominant frequency</td>
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<td>Derivative instantaneous amplitude</td>
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<td>Integrate absolute amplitude</td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>Time</td>
</tr>
<tr>
<td>Seismic inversion</td>
<td>External attributes</td>
</tr>
</tbody>
</table>

3.2.1 Step-wise regression

There are many methods used to determine the attributes selected for analysis. One such procedure is known as Exhaustive Search, which is the most optimal but takes the most amount of time. This procedure uses all the possible combinations to find the best attributes that correlates the targeted log (Hampson et al., 2001).

Another procedure and the one that Emerge uses for this process is the Step-Wise Regression. This procedure may be less optimal but the computational time is much shorter than Exhaustive Search. Step-Wise Regression assumes that the best combination of attributes is already known, then the next best combination of attributes includes the previous one in the arrangement. Step-Wise Regression procedure would never use an attribute that was previously selected. This process avoids the concern about whether the complete list of attributes are linearly independent, but it does not guarantee that the best possible combination of

46
attributes would be found (Hampson et al., 2001).

The validation in the MA analysis is a round robin cross-validation approach. That means each well is removed from the calibration one well at a time and the calibration is done without that well contributing. The new (one well less) calibration function is then applied to that well and a blind prediction error is computed from the unused well. The first validation well is restored to the training set and a new well is removed. The process is repeated and its prediction error is added to the previous prediction error. The process continues for all wells used in the calibration. The validation well prediction errors are added up and divided by the amount of wells in the full calibration to get the average validation error. That error will always be greater than the training or all well calibration.

The MA regression analysis helps to identify how many attributes will give the best possible combination that has the lowest prediction error. The MA transform with N+1 attributes will always show a decreasing in the prediction error compared to the transform with N attributes. If more attributes are added, a reduction in the prediction error is constantly expected showing a better fit of the training data but not related to an optimal training result. The reduction in the prediction error will not necessarily give good results because the inclusion of more attributes could add more noise and wrong data generating something known as over-training (Hampson et al., 2001).

### 3.3 Probabilistic Neural Networks

Several neural network algorithms are used to predict properties in reservoir characterization, but this study only applies Probabilistic Neural Network (PNN) because of its mathematical simplicity and its satisfactory accuracy compared with the other types of neural networks (Sawant and Topannavar, 2015). PNN applies a generalized nonlinear approach using Gaussian weighting functions to fit the seismic attributes with the training sampling. The training process relies on the identification of the optimal weight for each seismic sample into the window analyzed from the sample of each well used (Hampson et al., 2001). Figure 3.2 illustrates the architecture of a PNN that consist in four layers: input layer, pattern
layer, summation layer and output layer.

![Architecture of PNN](image)

Figure 3.2: Architecture of PNN (Sawant and Topannavar, 2015; Shahsavari, 2012).

An example of the training of PNN consists of a series of single seismic samples for each attribute in the analysis window for each well (Hampson et al., 2001). The following series shows the example for three attributes:

\[
\begin{align*}
\{A_{11}, A_{21}, A_{31}, L_1\} \\
\{A_{12}, A_{22}, A_{32}, L_2\} \\
\{A_{13}, A_{23}, A_{33}, L_3\} \\
\vdots \\
\{A_{1n}, A_{2n}, A_{3n}, L_n\}
\end{align*}
\]

Where the \( n \) training examples and for the three attributes \( A \), and the parameter \( L_i \) are the target log for each example.
Using the obtained training data from the previous step, the PNN assumes that every single log value in the training data can have a new output of log value being written as a linear combination. Every single data sample with attributes can be estimated with the following equation (Hampson et al., 2001):

\[
L'(x) = \frac{\sum_{i=1}^{n} (L_i \exp(-D(x, x_i))}{\sum_{i=1}^{n} \exp(-D(x, x_i))}
\]

(3.3)

Where,

\[
D(x, x_i) = \sum_{j=1}^{3} \left( \frac{x_j - x_{ij}}{\sigma_j} \right)^2
\]

(3.4)

The value \(D(x, x_i)\) is the distance between the input point and its respective training point, and it is scaled by the parameter \(\sigma_j\) (Hampson et al., 2001). This determines the optimal set of smoothing parameters \(\sigma_j\) by training the network to have the lowest validation error for the output network. The total prediction error for the training data is calculated using the following equation (Hampson et al., 2001):

\[
E(\sigma_j) = \sum_{i=1}^{n} (L_i - L'_i)^2
\]

(3.5)

The resulting network has a reduction in the validation error depending on the choice of the parameter \(\sigma_j\) used in the previous equation. Now that the optimal combination of attributes has been found, the validation is applied to the complete seismic volume to compute the prediction of the targeted log in a volume (Hampson et al., 2001).

### 3.4 Prediction of Reservoir Properties

Identifying which rock properties make a shale an unconventional play is part of this study through the process of finding the relationship between those rock properties and geomechanical parameters. Three main rock characteristics will help to define a shale as an unconventional reservoir. Additionally, two more rock properties will be included in the prediction, 1) density for estimation of geomechecanical properties and 2) volume of kerogen for the identification of hydrocarbon distribution into the formation. The characteristics and
properties are:

- Total Organic Carbon (TOC): Defining the source rock
- Volume of carbonate and Quartz: Defining how brittle is the rock
- Volume of Clay: Defining how ductile is the rock
- Total porosity: Defining the storage of the hydrocarbon
- Density: Used to estimate geomechanical properties integrating seismic inversion results
- Volume of Kerogen: identify the occurrence and distribution of the type of hydrocarbon in the rock

This section of the study does not focus on the generation of prediction volumes for total porosity, volume of clay and volume of quartz. It focuses on developing the prediction volume for TOC and volume of carbonate with the inclusion of volume of kerogen, and the density for geomechanical parameter estimation.

During the conditioning of well data prior the Emerge™ procedure in Hampson & Russell™ software, well-ties were performed with the same wavelet used during the seismic inversion in Jason™ software. The well-ties show high values, higher than 80%, of correlation coefficient for each well (not in the case of Well C with lower correlation and differences in frequency in the seismic). Even with those high correlation values, the Well G and Well I show some small differences between the seismic and the synthetic, probably generating an impact during the prediction of rock properties.

There are two options for the seismic data to be used in the Emerge™ process. The first is to use the available post-stack seismic data and the second is to use the same pre-stack seismic used for the inversion. To select which one would be better for the rock property prediction, it was decided to run Emerge™ using both sets of seismic data to be evaluated.
in one single rock property. The first test is using the post-stack data that contains all the information of amplitude and frequency in one set, with the addition of the seismic inversion results as external attributes which provides the data from the angle stacks. The second test uses the pre-stack data which has four angle stacks, where the mid-near angle stack was selected as main seismic data volume because of its preservation of high frequencies and less noise. This test also has the same external attributes from seismic inversion results, plus the other three angles stacks (Near, Mid-Far and Far). The big difference is that the training process and MA analysis is applied, not only to the mid-near angle stack, but also to the other three angle stacks.

Having mentioned this process, the great risk with Emerge\textsuperscript{TM} is to add noise or irregular data to the prediction process, generating a negative impact in the outcome. The result of both processes is very similar with better results for the pre-stack data. The addition of the three angle stacks as external attributes, and posteriorly running the training and MA analysis on them, shows good results with low additional noise impact. According to the results obtained, the near-mid angle stack was selected as the main seismic data. The list of additional external attributes from seismic inversion plus the three angle stacks used in the prediction model are in the Table 3.2.

Five wells were selected from the six available. Well C is not used for the rock property prediction for the same reason that it was removed from the seismic inversion. The targeted rock properties share the same training process for each well. The window of the rock property prediction is focused in the Vaca Muerta Formation. It includes a small part of the top of Tordillo Formation (around 10 milliseconds) and part of the bottom of Quintuco Formation (around 25 milliseconds). The prediction using Neural Networks will be valid exclusively into the window created for the Vaca Muerta Formation.

The given frequency of the measured logs are higher than the seismic frequency, a high-cut filter of 80-90 Hz has been applied to each desired rock property and also the sampling was reduced from 2 ms to 1 ms. Several frequency tests were performed to evaluate probable
Table 3.2: External attributes used for rock property prediction.

<table>
<thead>
<tr>
<th>External Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-impedance</td>
</tr>
<tr>
<td>S-impedance</td>
</tr>
<tr>
<td>Vp/Vs</td>
</tr>
<tr>
<td>Mu-Rho</td>
</tr>
<tr>
<td>Lambda-Rho</td>
</tr>
<tr>
<td>Poisson’s Ratio</td>
</tr>
<tr>
<td>P-impedance bandpass</td>
</tr>
<tr>
<td>S-impedance bandpass</td>
</tr>
<tr>
<td>Vp/Vs bandpass</td>
</tr>
<tr>
<td>Near angle stack (Seismic)</td>
</tr>
<tr>
<td>Mid-far angle stack (Seismic)</td>
</tr>
<tr>
<td>Far angle stack (Seismic)</td>
</tr>
</tbody>
</table>

Improvement of the output resolution. The high-cut frequencies were tested for different ranges, including 70-80 Hz, and posteriorly for 80-90 Hz, 90-100 Hz, 100-120 Hz and 120-130 Hz. The results showed that 70-80 Hz and 80-90 Hz were optimal and stable, so 80-90 Hz was selected for the training process.

### 3.4.1 Elastic Parameters and Rock Properties Relationships

Identification of relationships between elastic parameters and rock properties is part of the reservoir characterization process. Crossplots of P-impedance, S-impedance and Vp/Vs are very useful to identify relationships with rock properties. TOC, volume of carbonate, volume of clay, volume of quartz, total porosity and density were tested to define their relationship with acoustic response that help in the prediction process.

Crossplots of P-impedance versus Vp/Vs are used to define lithology (shale, sandstone) and fluid (gas, oil) differentiation. The rock physics analysis is focused in the Vaca Muerta Formation. In this case where the reservoir is a shale play, a lithology differentiation is not needed. Nevertheless, it could be useful in discriminating the marls inside the shale play based on high values of density and P-impedance, and low values of total porosity (Dvorkin et al., 2001). The marl relationship is also associated to high values of volume of carbonate.
Additionally, it is expected that low values of P-impedance and Vp/Vs are related to the presence of gas in the reservoir (Chi and Han, 2009), but in the Vaca Muerta Formation, the differentiation of fluids is not clear with this type of crossplot analysis.

Crossplots of P-impedance versus S-impedance show a good visualization of relationships between rock properties and elastic parameters that helps in the rock property prediction. Figure 3.3 illustrates the mineralogy ternary plot that shows the characteristics of several shale plays, including the Vaca Muerta Formation (Sonnenberg, 2014). This study attempts to identify which mineralogy characteristics have an impact on the hydraulic stimulation of the reservoir and also on the recognition of good production zones. The following analysis illustrates the relationships between elastic parameters and rock properties.

![Figure 3.3: Comparison of predominant mineralogy of shales plays around the world in a ternary plot (Sonnenberg, 2014).](image)

**3.4.1.1 Relationship between TOC and Elastic Parameters**

Total organic carbon (TOC) is the weight percentage (wt%) that resides within the organic portion of the rock. TOC has been used in the oil industry to associate the carbon
in the kerogen fraction of the rock, but in practice, it also includes the portion of the carbon that resides within bitumen. (Gonzalez et al., 2013).

Organic shales are typically defined by the quantity of TOC present (Gonzalez et al., 2013), which in the case of the Vaca Muerta Formation is from 2 to 8 wt% (spikes to 12 wt%). The quantification of TOC is an important step to identify a potential shale reservoir, and define a relationship in the quality of the shale play. The kerogen in the TOC has similar petrophysical characteristics than pore fluids (low bulk density, high neutron porosity, low photoelectric factor), and it can be difficult to differentiate from pore volume (Gonzalez et al., 2013).

A organic-rich shale, like the Vaca Muerta Formation, were exposed to temperatures between 50° and 150° Celsius in order to generate hydrocarbons during the thermal cracking in the catagenesis (part of the thermal dissolution or pyrolysis) (Figure 3.4). Immature and mature terms are used to describe source rocks and also the current state of the kerogen contained in the rock (Crain, 2016).

Figure 3.5 illustrates the crossplot between P-impedance and S-impedance color coded by TOC. Low values of P-impedance and S-impedance are related with high values of TOC into the Vaca Muerta Formation. This characteristic also indicates that in zones with high TOC, the rock can have a ductile behavior with a poor response to hydraulic stimulation (Sierra et al., 2010; Slatt, 2013).

Figure 3.6 (A) shows the crossplot between P-impedance versus TOC color coded by Young’s Modulus. It can be observed the role that Young’s Modulus plays in the Vaca Muerta Formation. Lower values of TOC are related with high values of Young’s Modulus. This is an indication of brittle rock and its association with the TOC. Figure 3.6 (B) illustrates the crossplots between P-impedance versus TOC but color coded by Poisson’s Ratio. Poisson’s ratio does not show a relationship with TOC nor with P-impedance. The irregular distribution into the shale play makes it not reliable to define zones of brittle rock.
Figure 3.4: Generation of hydrocarbon related to pyrolysis and depth. It shows the range of temperature needed to generate hydrocarbons (Crain, 2016; Petrowiki, 2016).

Figure 3.5: Crossplot of P-impedance versus S-impedance calculated from well log data, and color coded by TOC. Low values of P and S impedance show high TOC. The analysis is focused in the Vaca Muerta Formation.
3.4.1.2 Relationship between Volume of Carbonate and Elastic Parameters

Carbonate rocks are made of particles of carbonate minerals embedded in a cement. They formed by the precipitation from solution at surface temperatures or by the accumulation and lithification of fragments of preexisting carbonate rocks, or bioclasts created by calcareous organisms. Carbonate rocks originate in areas favoring biological activity in shallow and warm seas (Rey and Mueller, 2016).
For the formation of sedimentary rocks a longer deposition time is needed, as the sediment has to be compacted and cemented into hard beds or strata. Carbonate rocks have characteristics of facies and texture. (1) Usually show banking as well as sedimentary structures, like bedding. (2) Each layer of a sedimentary rock reflects the conditions during deposition, with the source material as indicator (containing organisms, shells or ichnia). The most common carbonate rocks are limestone and dolomite (Petrowiki, 2016; Rey and Mueller, 2016; Strata, 2015).

Variation in carbonate depositional patterns and lithofacies are controlled by five major variables: (1) tectonic, (2) eustatic change, (3) volume of sediments, (4) climate, and (5) oceanography. Relative sea level variation is controlled by the combination of eustatic position and tectonic subsidence or uplift. Relative sea level fluctuations are a major control over carbonate production and the resultant lithofacies distribution (Strata, 2015).

Figure 3.7 illustrates the sequence with the main four cycles in the Neuquén Basin: inner shelf, shelf edge, slope and basin. These cycles are characterized by vertical transition of lithofacies which indicates changes in the depositional environments. Carbonate rocks are deposited in the inner shelf.

Figure 3.7: Schematic section with the main four cycles in the Neuquén Basin (Zeller et al., 2015b).
Figure 3.8 illustrates the crossplot between P-impedance and S-impedance color coded by volume of carbonate. Low values of P-impedance and S-impedance are related with low values of volume of carbonates in the Vaca Muerta Formation. This characteristic is the opposite of TOC behavior previously observed, and indicates that in zones with high volume of carbonate, the rock is brittle.

![Crossplot of P-impedance versus S-impedance calculated from well log data, and color coded by volume of carbonate. The points with high P and S impedance show high volume of carbonate. Low values of P and S impedance show high TOC. The analysis is focused in the Vaca Muerta Formation.](image)

Figure 3.8: Crossplot of P-impedance versus S-impedance calculated from well log data, and color coded by volume of carbonate. The points with high P and S impedance show high volume of carbonate. Low values of P and S impedance show high TOC. The analysis is focused in the Vaca Muerta Formation.

Figure 3.9 illustrates an inverse relationship between volume of carbonate and TOC. The presence of this specific relationship in the Vaca Muerta Formation helps identify and differentiate brittle zones better and probable areas of good presence of hydrocarbons. This relationship is unique in Vaca Muerta, but it does not mean that it could not be present in other shale plays around the world. The comparison should be done with shale plays of similar characteristics as the Vaca Muerta Formation (Figure 3.3). Additionally, other types of carbonates, like dolomite, have not been reported in the Vaca Muerta Formation. However, dolomite has been reported in the Agrio Formation, which is part of the middle and upper section of the Mendoza Group in the Lower Cretaceous (Figure 1.4) (Tunik et al., 58...
Figure 3.9: Crossplot of P-impedance versus TOC calculated from well log data, and color coded by volume of carbonate. The points with low TOC are related with the presence of high volume of carbonate. Low values of P and S impedance show high TOC. The analysis is focused in the Vaca Muerta Formation.

### 3.4.1.3 Relationship between Volume of Kerogen and Elastic Parameters

Kerogen is a part of the organic matter portion contained in sedimentary rocks like shales, and it is neither soluble in aqueous alkaline solvents nor in organic solvents. This definition applies for ancient sedimentary rocks where the early diagenesis is completed (Dow, 1977; Tissot and Welte, 1984). The term kerogen is applied for some author as solely the insoluble organic matter of oil shales that yield oil upon burning and heating, and is regarded as the main source for hydrocarbon generation (Tissot and Welte, 1984; ?). The origin of this used of the term kerogen is because was applied to the organic material found in Scottish shales (Tissot and Welte, 1984).

The term kerogen is used for some authors as the total organic matter in sedimentary rocks. However, it is understood that bitumen is the fraction that can be extracted using organic solvent, and the term kerogen does not include soluble bitumen (Figure 3.10).
Kerogen is 1,000 times more abundant than coal plus petroleum in reservoirs and 50 times more abundant than bitumen, which makes it the most important form of organic carbon on earth. In ancient nonreservoir rocks, like shales or limestones, kerogen usually represents a range from 80 to 90% of the organic matter within the rock and bitumen represents the rest (Tissot and Welte, 1984). Kerogen in sedimentary rocks is used to identify source rock in order to predict the type, maturation and distribution of hydrocarbon expected in a sedimentary basin (Dow, 1977).

The kerogen has four sources: marine, lacustrine, terrestrial and recycled. Most oil has been formed from marine and lacustrine kerogen, and coal is form by terrestrial kerogen. In petroleum studies, the kerogen is classified in three basic types based on the ratio between carbon (C), hydrogen (H) and oxygen (O): type I, type II and type III (Tissot and Welte, 1984), which can be classified according to the source of the material (Figure 3.11) (Crain, 2016). The types of kerogen identified in the area of study are Type I and II, which are
associated to the generation of oil (Garcia et al., 2013). For this study, the volume of kerogen is used to identify the distribution and zones with higher presence of hydrocarbon.

In addition, the purpose of predicting TOC and kerogen content in this study is to confirm the trend and distribution of the organic matter within the Vaca Muerta Formation. As a major fraction of the composition of TOC, kerogen content should offer a similar distribution of TOC but with lower values than TOC. However, TOC shows lower values than kerogen content in this study. TOC was estimated for the weight percentage (wt%) and kerogen content was estimated as part of the volume in percentage (%). That could explain the relatively high values of kerogen content compared with TOC. The petrophysical estimation of these two parameters was performed by Wintershall using empirical equations and posterior calibrations with core data. The range of error in the estimation of TOC and kerogen content could also be a factor that might impact the result and could generate that difference of values between TOC and kerogen.

Figure 3.11: Classification of kerogen based on the source of the material (Grigo, 2011).

Figure 3.12 shows the crossplot between P-impedance and S-impedance color coded by volume of kerogen, and illustrates the distribution of hydrocarbon in the Vaca Muerta Formation due its association with TOC. This rock property shows a good relationship with P and S impedance. It can be observed that low values of volume of kerogen is related with
high values of P and S impedance. Volume of kerogen has a similar behavior to TOC and as a portion of the organic matter, kerogen allows for the identification of the type of hydrocarbon generated based on the environmental nature of the organic matter. According to Garcia et al. (2013), the eastern side of the Neuquén Basin has the presence of kerogen type I and II (for oil generation) and kerogen type III and IV (for gas generation). The study area is located in the eastern zone and cover the oil window predominantly (Figure 1.8). Figure 3.13 shows a general relationship between the TOC and the kerogen quality. The ranges of TOC, from 0.7 wt% to 8.5 wt%, registered in the eastern zone of the Neuquén Basin illustrate a relationship of good quality of the kerogen in the Vaca Muerta Formation (Garcia et al., 2013).

Figure 3.12: Crossplot of P-impedance versus S-impedance calculated from well log data, and color coded by volume of kerogen. Low values of P and S impedance show high TOC. The analysis is focused in the Vaca Muerta Formation.

3.4.1.4 Relationship between Density and Elastic Parameters

The density is defined as the mass per volume of a substance or rock. It is important to mention the difference between mass, density and weight. Density is the physical property (it is mass (kilograms) per unit volume). Weight is the force experienced by that mass in
the presence of a gravitational field. The weight of an object on the Moon is 1/6th of its weight on Earth, but its mass (and density) is the same wherever this object is (Jones, 2007). Bulk Density is the parameters used for the estimation of the density of a rock. It is commonly used when referring to the mixture of the compositional mineralogy of a rock. This measurement includes the weight of the rock divided by the total volume of the grains, inter-grains void volume, and volume of the pore structure in the rock (Crain, 2016; Jones, 2007; Petrowiki, 2016).

The density of the commonest rock forming minerals are close related. The actual densities of geologic materials vary from 880 kg/m$^3$ for ice (and almost 0 kg/m$^3$ for air) to more than 8,000 kg/m$^3$ for some rare minerals. Rocks are generally between 1,600 kg/m$^3$ (sediments) and 3,500 kg/m$^3$ (gabbro - volcanic rock). Shales can have a density range between 1,950 kg/m$^3$ and 2,720 kg/m$^3$ (Figure 3.14) (Jones, 2007).

Figure 3.15 shows the crossplot between P-impedance and S-impedance color coded by density. As it was expected, the density shows a good relationship with P and S impedance. Figure 3.16 shows the crossplot of P-impedance versus TOC color coded by density. There is a relationship between TOC and density where high values of density are related with low values of TOC. In this case, it would be expected to have high values of density associated with high values of volume of carbonate, as well as a probable good response to hydraulic

<table>
<thead>
<tr>
<th>Total Organic Content, Weight %</th>
<th>Kerogen Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;0.5</td>
<td>Very poor</td>
</tr>
<tr>
<td>0.5 to 1</td>
<td>Poor</td>
</tr>
<tr>
<td>1 to 2</td>
<td>Fair</td>
</tr>
<tr>
<td>2 to 4</td>
<td>Good</td>
</tr>
<tr>
<td>4 to 12</td>
<td>Very good</td>
</tr>
<tr>
<td>&gt;12</td>
<td>Excellent</td>
</tr>
</tbody>
</table>

Figure 3.13: General relationship between the TOC and the kerogen quality (Schlumberger, 2017).
Figure 3.14: Bars illustrate the range of bulk sample densities of various kinds of rocks (Jones, 2007).

Figure 3.15: Crossplot of P-impedance versus S-impedance calculated from well log data, and color coded by density. Low values of P and S impedance show high TOC. The analysis is focused in the Vaca Muerta Formation.
3.4.2 Prediction of TOC

The TOC data in the Vaca Muerta was estimated using the empirical equation proposed by Schmoker and Hester (1983):\[ TOC = \left( \frac{A}{\rho_B} \right) - B \] (3.6)

Where $\rho_B$ is the bulk density and A and B are fitting parameters. Additionally, the TOC calculated was calibrated using core data and litho-scanner\textsuperscript{TM} tool from well logs.

The training of TOC was performed with the log curves from Well A, Well B, Well G, Well H and Well I. Well C was not used because of the problems in the seismic data around the well. Figure 3.17 shows an example of the training process of the TOC curve for Well G. During the training process, a high-cut filter of 80-90 Hz was applied to assure the well data was the same frequency as the seismic. It was also resampled to 1 ms in order to increase the resolution and reach the desired accuracy. The window selected is between the two red lines corresponding to the Vaca Muerta Formation and the external attributes used.
in the training are shown in the Table 3.2. The same process was performed for the training process of the other four wells used in the prediction.

Figure 3.17: Training of TOC curve from Well G with high-cut filter at 80-90 Hz.

3.4.2.1 Multi-Attribute Regression for TOC

During the MA analysis, Figure 3.18 was generated to illustrate the average error for the five wells used in the process. Well G and Well I show the higher average error, and as it was mentioned previously, which was produced by issues in the well-tie. This high error will cause a reduction in the prediction accuracy for the area of those two wells.

During the MA analysis, Figure 3.19 shows the validation error which indicates an operator length of five point as optimal for the prediction process. The red line is indicating the validation error and also marks the attributes that could be used for the prediction. It is expected that the error decrease, but when the error curve starts to increase, the point in which the curve changes is considered to be where the attributes will give the most probable combination for prediction. In this case, the validation error is showing five attributes, but the change in the slope from the fourth attribute to the fifth is small, giving minimum improvement. That fifth attribute could be discarded to avoid ”over-training”. Moreover, the
fifth attribute found in the MA regression was the $V_p/V_s$ bandpass from inversion results, which could add noise to the prediction. For this process, only four attributes were picked for an operator length of five points.

The list of the four most probable attributes used for the prediction of TOC are in the Table 3.3.
Table 3.3: Four most probable attributes obtained in multi-attribute analysis for prediction of TOC.

<table>
<thead>
<tr>
<th>Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/P-impedance</td>
</tr>
<tr>
<td>Amplitude Envelope (applied to Mid-far angle stack)</td>
</tr>
<tr>
<td>Integrate (applied to Near angle stack)</td>
</tr>
<tr>
<td>Lambda-Rho</td>
</tr>
</tbody>
</table>

3.4.2.2 Validation of Multi-Attribute Regression for TOC

The validation of the four attributes and operator length of five for the TOC data generated a modeled curve over and near each well (Figure 3.20). The validation was explained previously and consists in removing a different well at a time for every analysis performed.

Figure 3.20: Validation of the MA regression for TOC. The black line is the real TOC data and the red line is the modeled TOC for the prediction.

As it was expected, Well G and Well I show higher average error compared with the other wells, and those two wells have lower matches for the prediction process.

The crossplot for the actual TOC data and the predicted TOC is showing high correlation, around 92%, giving confidence in the process of the prediction analysis before using PNN (Figure 3.21).
Figure 3.21: Crossplot of the validation of MA regression for actual TOC vs. predicted TOC with correlation around 92%.

Figure 3.21 also shows high correlation between the actual and the predicted TOC, but the correlation in the ranges of TOC lower than 2 wt% seems to decrease showing a variation in the data behavior with a circular shape. This swirling behavior in the crossplot is generated because of the use of filtered log data that have a high-cut filter to put the log data in the seismic frequency.

### 3.4.2.3 Validation of Neural Networks for TOC

The Probabilistic Neural Network (PNN) was applied after the MA analysis, and its validation in Figure 3.22 shows a good correlation for each well with an average of 86%. The validation keeps the lower correlation for Well I and Well G, as it was expected for their higher error showed in Figure 3.18.

The crossplot of the PNN validation shows excellent correlation, around 96%, using all well data (Figure 3.23). It can be seen that the anomaly observed in the MA analysis (TOC values lower than 2%) disappears, which shows better distribution after the application of PNN.
Figure 3.22: Validation of the PNN for TOC. The black line is the real TOC data and the red line is the modeled TOC for the prediction.

Figure 3.23: Crossplot of the validation of PNN for actual TOC vs. predicted TOC, with correlation around 96%.

Additional QC was performed to test the prediction process without relying exclusively on the correlation of actual and predicted TOC. According to Schuelke (2017) (personal communication, February 20, 2017), the extraction of the predicted TOC log has been performed
to crossplot with the real data without filtering. The distribution of the TOC data showed similar correlation with the results obtained in Figure 3.23 and it does not show swirling behavior of the data displayed (Figure 3.24 (A)). A final test was performed where the real TOC well data is overlaid on the predicted TOC data to QC the match between both curves. This test showed the same trend and a good match between the predicted TOC and the log data (Figure 3.24 (B)). These two QC’s were applied for each rock property predicted that was performed in this study but only prediction of TOC is displayed. It is also important to mention, that the swirling anomaly observed in the crossplot of the MA analysis for TOC prediction disappears when the PNN is applied in the next step of the process.

Applying this validation to the complete seismic volume, the result of the TOC prediction is shown in Figure 3.25. An arbitrary line from the seismic volume over the results for Well A, Well G and Well I shows a good match with some minor mismatches caused by the higher error in Well G and Well I.

Figure 3.25 shows zones with lower TOC around Well I compared with higher TOC values around Well A and Well G. This vertical and lateral heterogeneity shown in the Upper and Middle Vaca Muerta could indicate part of the distribution of sediment in the...

Figure 3.24: (A) Crossplot of real TOC data without filtering versus extracted TOC log from predicted results. (B) Comparison of real TOC data and extracted TOC log. The blue line is the predicted TOC and the red line is the TOC log without filtering.

Applying this validation to the complete seismic volume, the result of the TOC prediction is shown in Figure 3.25. An arbitrary line from the seismic volume over the results for Well A, Well G and Well I shows a good match with some minor mismatches caused by the higher error in Well G and Well I.

Figure 3.25 shows zones with lower TOC around Well I compared with higher TOC values around Well A and Well G. This vertical and lateral heterogeneity shown in the Upper and Middle Vaca Muerta could indicate part of the distribution of sediment in the...
progradling zone from the proximal platform with lower TOC to the distal platform and slope
with more anoxic areas associated with higher presence of TOC. The Upper Vaca Muerta
shows lower TOC values compared with the Middle and Lower Vaca Muerta, but the TOC
is especially low around Well I (0.5 wt% to 1.5 wt%). The Middle Vaca Muerta around
Well I also has lower values of TOC compared with Well A and Well G zones. The Lower
Vaca Muerta shows a predominance of high values of TOC where it has been reported as a
zone of high ductility with an expected bad response to hydraulic stimulation (Garcia et al.,
2013).

Figure 3.25: Arbitrary section of the TOC prediction for the Vaca Muerta Formation crossing
Well A, Well G and Well I. Secuencia 4 (S4), Secuencia 3 (S3) and Secuencia 1 (S1) horizons
are observed to identify the Lower, Middle and Upper Vaca Muerta.

An important observation is the presence of a small zone between the Lower and Middle
Vaca Muerta showing high differentiation in TOC values. This small zone has lower values
of TOC, 3 wt% to 4.5 wt%, compared with the surrounded areas in the Lower and Middle
Vaca Muerta (Figure 3.25). The geological environment could be associated to fluctuations
in the transgressive period where the organic matter was not deposited and preserved in the
same rate than the Lower and the rest of the Middle Vaca Muerta.

Figure 3.26 and Figure 3.27 are horizon slices showing the horizontal distribution of TOC. The horizon slice of Figure 3.26 was extracted 30 ms below the top of the Lower Vaca Muerta where the predominance of TOC is higher toward the West and North-West. The slightly reduction of TOC in the East and South-East could be related to topographic high of the soft slope in the platform.

Figure 3.27 is an horizon slice extracted in the Middle Vaca Muerta. It has a 10 ms window and it is 40 ms below of the top of the Middle Vaca Muerta. The horizontal distribution continues to show the same trend, where higher values of TOC in the zone are located toward the West and North-West of the area. The highest value of TOC in the zone are in the range of 4.5 wt% to 5 wt% and the lowest in the South-East zone is about 1.5 wt%. This could be associated with the topographic high of the platform.

The areas of Well A, Well G and Well I show differences in TOC. This confirms the distribution of TOC previously described in Figure 3.25 the Well I area has lower TOC than Well A and Well G.

3.4.3 Prediction of Volume of Carbonate

The volume of carbonate data was estimated using the following equation:

\[ V_{carbonate} = 1 - (V_{quartz} + V_{clay}) \]  \hspace{1cm} (3.7)

The volume of quartz was estimated using the following equation:

\[ V_{quartz} = \left( \frac{GR_{log} + 102}{2.63} \right) \times x \] \hspace{1cm} (3.8)

where \( x \) is a calibration parameter used to fit the XRD data. The GR used was also corrected for uranium because it is considered that GR is influenced more by organic matter than by clay content.
The volume of clay was estimated using the following equation:

\[
V_{\text{clay}} = \left( \frac{I_{GR}}{3 - 2I_{GR}} \right)
\]  

(3.9)
where $I_{GR}$ is the normalization of the Gamma Ray and it is also corrected for Uranium.

Figure 3.28 shows an example of the training of volume of carbonate log data performed in all the wells available. A high-cut filter of 80-90 Hz was used with a sampling of 1 ms, and an analysis window focusing in the Vaca Muerta Formation.

Figure 3.28: Training of volume of carbonate log data for Well G with a high-cut filter at 80-90 Hz.

### 3.4.3.1 Multi-Attribute Regression for Volume of Carbonate

Figure 3.29 illustrates the error for each well in the MA analysis. Well A and Well I show the higher average error.

Figure 3.30 illustrates the validation error which indicates an operator length of five point for the prediction of volume of carbonate. For this process, only four attributes were selected as the best possible combination for the prediction of volume of carbonate.

The list of the four most probable combination of attributes used for the prediction are in the Table 3.4.

### 3.4.3.2 Validation of Multi-Attribute Regression for Volume of Carbonate

The validation process using four attributes and an operator number of five generated a modeled curve over and near around each well for the volume of carbonate data (Figure 3.31).
Figure 3.29: Average error for volume of carbonate in each well.

Figure 3.30: Validation error for an operator length of five points.

Table 3.4: Four most probable combination of attributes obtained in MA analysis for prediction of volume of carbonate.

<table>
<thead>
<tr>
<th>Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Square root of P-impedance</td>
</tr>
<tr>
<td>Integrate (applied to Mid-far angle stack)</td>
</tr>
<tr>
<td>Derivative (applied to Far angle stack)</td>
</tr>
<tr>
<td>Square of Mu-Rho</td>
</tr>
</tbody>
</table>
The correlation observed using each well separately is 79%.

Figure 3.31: Validation of the MA regression for volume of carbonate with correlation of 79%. The black line is the real volume of carbonate data and the red line is the modeled one for the prediction.

It can be observed that Well A and Well I show higher average error as it was mentioned in the Figure 3.29. This error generates a reduction in the match between real data and the modeled for the prediction.

The crossplot for the actual volume of carbonate data and the predicted one shows a high correlation of around 84%. The process shows a good correlation, which allows moving forward with prediction process using PNN (Figure 3.32).

3.4.3.3 Validation of Neural Networks for Volume of Carbonate

The Probabilistic Neural Network (PNN) was applied to the MA regression selected and its validation in Figure 3.33 shows a lower correlation compared with the MA regression, 72%. Higher error is observed in Well A and Well I. The crossplot of the PNN validation using all wells data shows a good correlation, around 85% (Figure 3.34).

The crossplot validation analysis using the information of all the wells show a slightly better correlation in the PNN than the MA regression. On the other hand, the correlation
Figure 3.32: Crossplot of the validation of MA regression for actual volume of carbonate vs. predicted volume of carbonate with correlation around 84%.

Figure 3.33: Validation of the PNN for volume of carbonate with correlation of 72%. The black line is the real data and the red line is the modeled data for the prediction.

in the validation analysis using each well separately shows that the MA regression approach has better correlation than the PNN. It was determined that the results obtained with the MA regression are good enough for the prediction and PNN would not improve those results.
Figure 3.34: Crossplot of the validation of PNN for actual data of volume of carbonate vs. predicted data, with correlation around 96%.

For the prediction of volume of carbonate, it was selected the MA regression analysis instead of PNN approach.

Figure 3.35 shows the lateral and vertical distribution of volume of carbonate around Well A, Well I and Well G. Higher presence of volume of carbonate are registered around Well I compared with the zone of the other two well in the left. That coincides with the lower presence of TOC in the same area around Well I. The Upper Vaca Muerta shows higher carbonate than the Middle and Lower Vaca Muerta, but the Middle Vaca Muerta shows higher content of carbonate around Well I that can be interpreted as the proximal zone of the platform. The decreasing of carbonate content is related with zones showing an increment of TOC, which also can be related to deeper and anoxic zones with better preservation of the organic matter.

Figure 3.36 shows an horizon slice that illustrates the horizontal distribution of volume of carbonate. The horizon slice was in the Upper Vaca Muerta using a 10 ms window. The predominance of high volume of carbonate is toward the South-East and North-East. This morphology is characteristic of the topographic high of a lower angle platform showing progradation toward the North-West. The reduction of carbonate content toward the West
Figure 3.35: Arbitrary section of the PNN prediction for volume of carbonate for the Vaca Muerta Formation crossing Well A, Well G and Well I. Secuencia 4 (S4), Secuencia 3 (S3) and Secuencia 1 (S1) horizons are observed to identify the Lower, Middle and Upper Vaca Muerta.

is part of the mineralogy factor that plays an important role in the control for stimulation response of the rock.

Figure 3.37 shows an horizon slice 40 ms below the top of the Middle Vaca Muerta, which illustrates the lateral distribution of carbonate content. The higher content of carbonate is observed toward the North-East and South-East of the study area. This coincides with the topographic high of the proximal zone of Neuquén Basin and a less anoxic area with less preservation of TOC. The Western part of the section has a lower volume of carbonate but is still high enough to consider that this mineralogy is part of the system that controls the stimulation response rock.
Figure 3.36: 10 ms window horizon slide of the Upper Vaca Muerta with the lateral distribution of volume of carbonate. Secuencia 4 (S4) horizon was used to extract this slice.

Figure 3.37: 10 ms window horizon slide extracted 40 ms below the top of the Middle Vaca Muerta with the lateral distribution of volume of carbonate. Secuencia 4 (S4) horizon was used to extract this slice.
3.4.4 Prediction of Volume of Kerogen

Figure 3.38 shows an example of the training of volume of kerogen for Well G with the same parameters used in previous predictions, the high-cut filter of 80-90 Hz, sampling of 1 ms and analysis windows focus in the Vaca Muerta Formation.

![Figure 3.38: Training of volume of kerogen log curve for Well G with high-cut filter at 80-90 Hz.](image)

3.4.4.1 Multi-Attribute Regression for Volume of Kerogen

The MA analysis shows an average error for each well used (Figure 3.39). Again, Well G and Well I show the higher average error per each well.

Figure 3.40 shows the validation error which indicates an operator length of three point for the prediction of volume of carbonate. Only four attributes were picked for this process.

The list of the four most probable combination of attributes used for the prediction of volume of kerogen are in Table 3.6.

3.4.4.2 Validation of Multi-Attribute Regression for Volume of Kerogen

The validation of the most probable attributes used in the prediction of volume of kerogen generated a modeled curve over and near each well (Figure 3.41). The validation also shows
Figure 3.39: Average error for volume of kerogen in each well.

Figure 3.40: Validation error for an operator length of five points.

Table 3.5: Four most probable combination of attributes obtained in MA analysis for prediction of volume of kerogen.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Square P-impedance</td>
<td></td>
</tr>
<tr>
<td>Amplitude Envelope (applied to Far angle stack)</td>
<td></td>
</tr>
<tr>
<td>Instantaneous Frequency (applied to Far angle stack)</td>
<td></td>
</tr>
<tr>
<td>1/Poisson’s Ratio</td>
<td></td>
</tr>
</tbody>
</table>
a average correlation of 86%.

Figure 3.41: Validation of the MA regression for volume of kerogen. The black line is the real data and the red line is the modeled data for the prediction with an average correlation of 86%.

Again, the wells that showed higher average error, Well G and Well I, have the lower match for the prediction.

Figure 3.42 illustrates the crossplot for the actual volume of kerogen data and the predicted data shows high correlation of 86%. It is an optimal correlation offering excellent chances to get an appropriate prediction using PNN.

3.4.4.3 Validation of Neural Networks for Volume of Kerogen

The Probabilistic Neural Network (PNN) was applied to the MA regression selected and its validation in Figure 3.43 showed good correlation for each well. The lower correlation for Well I and Well G was expected according to Figure 3.39.

The crossplot of the PNN validation shows excellent correlation, around 95%, using all well data (Figure 3.44).

Figure 3.45 shows the vertical and lateral distribution of volume of kerogen into the Vaca Muerta Formation. The higher content of TOC, related to the kerogen content, indicates
Figure 3.42: Crossplot of the validation of MA regression for actual volume of kerogen vs. predicted volume of carbonate with correlation around 89%.

Figure 3.43: Validation of the PNN for volume of kerogen. The black line is the real data and the red line is the modeled data for the prediction with 87% of correlation.

an optimal quality of kerogen for the generation of hydrocarbon. The volume of kerogen illustrates the presence of hydrocarbon, where high volume of kerogen is related to the
generation of and presence of high volume of oil in the study area. It can be observed that high occurrence of oil is registered around the zone of Well A and Well G compared with the zone around Well I that is richer in carbonate and lower in presence of TOC. The Lower Vaca Muerta is the zone with the highest occurrence of generation of oil and is associated to high presence of TOC.

Figure 3.46 shows a horizon slice illustrating the horizontal distribution of hydrocarbon presence. The horizon slice was extracted 40 ms below of the top of the Middle Vaca Muerta with a 10 ms window. The kerogen content in this section shows strong lateral changes which indicates the heterogeneity of distribution of hydrocarbon (oil) in the Middle Vaca Muerta. The occurrence of hydrocarbon toward the North-East zone is the lowest in the area. The center zone around Well G is the highest presence of oil in the study area. Around Well I is observed a high occurrence of oil, which indicates that such zone could be a good target for landing horizontal wells. The South and South-East zones have variations between moderately good and good occurrence of oil. High kerogen content associated with higher presence of carbonate around Well I and also toward the South-East indicates a good response to hydraulic stimulation with oil presence that can be targeted by horizontal
Figure 3.45: Arbitrary section of the PNN prediction for volume of kerogen for the Vaca Muerta Formation crossing Well A, Well G and Well I. Secuencia 4 (S4), Secuencia 3 (S3) and Secuencia 1 (S1) horizons are observed to identify the Lower, Middle and Upper Vaca Muerta.

wells. The West area shows low presence of kerogen which indicates a lower generation of hydrocarbon.

3.4.5 Prediction of Density

Figure 3.47 shows an example of the training of density for Well G with the same parameters used in previous predictions, a high-cut filter of 80-90 Hz, sampling of 1 millisecond and analysis windows on the Vaca Muerta Formation.

3.4.5.1 Multi-Attribute Regression for Density

The MA analysis shows an average error for each well used (Figure 3.48). Well A and Well I have the higher average error for the prediction of density.
Figure 3.46: 10 ms window horizon slide 40 ms below the top of the Middle Vaca Muerta with the lateral distribution of kerogen content. Secuencia 4 (S4) was used to extract this slice.

Figure 3.47: Training of density log curve for Well G with high-cut filter at 80-90 Hz.

Figure 3.49 illustrates the validation error, which indicates an operator length of five point for the prediction of density. Four attributes were picked as the most probable combination of attributes to obtain the density.
The list of the four most probable combination of attributes used for the prediction of density are in Table 3.6.

3.4.5.2 Validation of Multi-Attribute Regression for Density

The validation of the four attributes for the density log data produced a modeled log for each well with an average correlation of 95% (Figure 3.50).
Table 3.6: Four most probable combination of attributes obtained in MA analysis for prediction of volume of kerogen.

<table>
<thead>
<tr>
<th>Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/P-impedance</td>
</tr>
<tr>
<td>Integrate (applied to Near angle stack)</td>
</tr>
<tr>
<td>Amplitude Envelope (applied to Mid-far angle stack)</td>
</tr>
<tr>
<td>Filter 35/40/45/50 (applied to Near angle stack)</td>
</tr>
</tbody>
</table>

Figure 3.50: Validation of the MA regression for density. The black line is the real data and the red line is the modeled data for the prediction of density with a correlation of 95%.

Well A and Well I show higher average error and they have a discrete match between the real density log data and the predicted data.

The crossplot for the actual density log data and the predicted data shows a correlation of 96% (Figure 3.51). It is an excellent correlation in the MA analysis that offers a good chance to obtain an appropriate property prediction using PNN.

### 3.4.5.3 Validation of Neural Networks for Density

The Probabilistic Neural Network (PNN) was applied to the MA regression selected and its validation in the Figure 3.52 showed good correlation for each well. The lower correlation for Well I and Well G was expected.
Figure 3.51: Crossplot of the validation of MA regression for actual density versus the predicted density with correlation of 96%.

Figure 3.52: Validation of the PNN for density. The black line is the real data and the red line is the modeled data for the prediction with 95% of correlation.

The crossplot of the PNN validation shows excellent correlation, around 98%, using all well data (Figure 3.53).

Figure 3.54 shows the density prediction using the PNN and illustrates the lateral and vertical distribution of density in the Vaca Muerta Formation. The variation of density values
are associated to the composition of the rock. High occurrence of carbonates is related to higher density and high presence of TOC is related to lower values of density. The density volume obtained in this section will be used to estimate geomechanical parameters in Chapter 4.

Figure 3.55 shows a horizon slice illustrating the horizontal distribution of density in the Vaca Muerta Formation. The horizon slice was extracted in the Upper Vaca Muerta with a 10 ms window. It can be observed that high values of density related with high occurrence of carbonate are located in the South-East and North-East. The zones with a reduction in density values and also associated with an increasing of TOC are located in the Western part of the study area.

3.5 Interpretation and Analysis of Rock Property Results

The rock properties predicted in this section showed an interesting relationship to understand the depositional environment and the geomechanical response of the Vaca Muerta Formation. It is important to define a balance in TOC and volume of carbonate occurrence to discriminate those zones with best hydrocarbon presence and in a good condition to have
3.5.1 Interpretation and Analysis of TOC

The distribution of TOC into the Vaca Muerta Formation showed an inverse relationship with P and S impedance, as well with volume of carbonate. The horizontal distribution with low values of TOC was identified in the South-East and East of the study area. The vertical distribution of TOC values has a marked differentiation that allows seeing the three general zones of the Vaca Muerta Formation: the Lower, the Middle and the Upper Vaca Muerta (Figure 3.56).

The Lower Vaca Muerta showed the highest TOC values in the formation, associated to an anoxic zone with high preservation of organic matter. Well I showed lower values of
Figure 3.55: 10ms window horizon slide in the Upper Vaca Muerta for the prediction of density. Secuencia 4 (S4) horizon was used to extract this slice.

TOC compared with the zones around Well G and Well A and can be related to higher part of the low angle platform that was located toward the East part of Neuquén Basin (Proximal zone). Although the high values of TOC in the Lower Vaca Muerta could be related as a ”sweet spot” or zone with high presence of hydrocarbon, the ductile behavior can impact the hydraulic stimulation response of the rock and not to be optimal to produce the reservoir. Even if the rock has a good response to hydraulic stimulation, the high TOC in the Lower Vaca Muerta allows the rock to have an internal elastic behavior. This behavior is a deformation over the fracture face that occurs around the proppants that were injected during the hydraulic stimulation. It does not allow keeping the fracture open to produce the zone and in this case, a more rigid rock would be ideal for being considered a better ”sweet spot”.

The Middle Vaca Muerta showed to be an intermediate zone with moderate to moderately high values of TOC. The lateral and vertical variation in the preservation of TOC was affected by the fluctuation of the sea level caused by several transgression-regression cycles. The lower occurrence of TOC around Well I and a higher presence of TOC around Well A and Well
Figure 3.56: Arbitrary line over Well A, Well G and Well I showing the lateral and vertical distribution of TOC. Secuencia 4 (S4), Secuencia 3 (S3) and Secuencia 1 (S1) horizons are observed to identify the Lower, Middle and Upper Vaca Muerta.

G indicates a similar sedimentation environment observed in the Lower Vaca Muerta. It can be observed a zone of low angle platform toward the East with limited conditions for a good preservation of organic content, and deeper and more anoxic zone toward the West. Based on TOC, the hydrocarbon presence and hydraulic stimulation response will be different from Well I to the area of Well A and Well G. Well I would have better hydraulic response but less presence of TOC. Well A and Well G would have a hydraulic stimulation response but not as good as the Well I area, but the occurrence of hydrocarbon would be better.

According to Bishop (2015), the Middle Vaca Muerta is the zone with higher presence of natural fractures. As her study was done with well data exclusively, it would not guarantee that the lateral distribution of natural fracture would keep constant in the complete area of this study. The presence of natural fractures and veins of calcite (beefs) would comprise the
hydraulic stimulation response of the zone. During the hydraulic stimulation, the pressure would be released through previous weak zones which are the natural fractures and the "beefs". This problem needs to be take into account during the development planning of the field. It is important to mention that a small zone in the lower part of the Middle Vaca Muerta has lower values of TOC (3-4 wt%). This zone shows differences compared with higher values of TOC observed in the rest of the Middle Vaca Muerta (4-6.5 wt%) and also the Lower Vaca Muerta (7-10 wt%). This differentiation is related to a variation in the depositional environment associated to the fluctuation in the sea level. This section could be showing a cycle with a different depositional behavior trend that makes it unique in the Vaca Muerta Formation. This zone has a lateral extension that covers the complete area of study and also the TOC presence decrease toward the East. The thickness of this zones has a range between 23 to 25 meters. It could be an interesting zone to test for oil because of its moderated TOC values that would make the rock more brittle than the Lower Vaca Muerta and the rest of the Middle Vaca Muerta. This consideration also applies for the zone around Well I because of its lower TOC values toward the East. For the rest of the Middle Vaca Muerta, the TOC values are good enough to be considered an interesting zone to test for hydrocarbons.

The Upper Vaca Muerta is the section with lower TOC values registered in the prediction. The TOC values that generate hydrocarbons in the Vaca Muerta Formation are at least from 2 wt% (Sonnenberg, 2017). The TOC values are low but enough for the generation of hydrocarbon, especially toward the West zone of the study area. This zone would be particularly brittle to have good response to hydraulic stimulation. Although the natural fracture and "beefs" could play an independent role that impact the rock response to stimulation as in the Middle Vaca Muerta. Despite the low values of TOC, the lower section of the Upper Vaca Muerta could be considered a prospective zone with moderate to low presence of hydrocarbons.
3.5.2 Interpretation and Analysis of Volume of Carbonate

Volume of carbonate showed an inverse relationship with TOC and a direct relationship with P and S impedance. Due to the inverse relationship that the volume of carbonate has with TOC values, the analysis described in the TOC interpretation will be closely related to this analysis. The carbonate occurrence as well as the TOC in the Vaca Muerta Formation helps to identify the brittle zones into the rock (Figure 3.57).

![Figure 3.57: Arbitrary line over Well A, Well G and Well I showing the lateral and vertical distribution of volume of carbonate. Secuencia 4 (S4), Secuencia 3 (S3) and Secuencia 1 (S1) horizons are observed to identify the Lower, Middle and Upper Vaca Muerta.](image)

The Lower Vaca Muerta has the lowest occurrence of carbonate in its whole extension (9 to 19%), but this increases (to 25%) around the location of Well I where was previously described the low angle platform of the proximal zone of the Neuquén Basin in the East. Because of its lower content of carbonate and high TOC, the Lower Vaca Muerta has ductile behavior. It is a zone with high presence of hydrocarbons but with a limitation to be
produced caused by the ductility of the rock.

The Middle Vaca Muerta has higher content of carbonate (24 to 41%), but with some variations in zones with higher presence of TOC. Around the Well A location, the increasing occurrence of TOC shows the opposite response of volume of carbonate. The increasing carbonate content toward the East of the study area shows a zone with brittle rock around the Well I, but related to a decreasing of TOC content. The Middle Vaca Muerta shows zones around Well G where the occurrence of TOC and carbonate is relatively high for both and could be a ”sweet spot”. It is important to remark again that natural fractures in the Middle Vaca Muerta could negatively impact the hydraulic stimulation.

The Upper Vaca Muerta is the zone with higher content of carbonate in the Vaca Muerta Formation (26 to 56%). This zone has highly brittle rock with lower presence of TOC. Despite having low TOC, the brittle characteristics of the rock, based on its high carbonate content, could make the Upper Vaca Muerta a good prospective zone.

3.5.3 Interpretation and Analysis of Volume of Kerogen

High values of TOC are indicators of high values of kerogen. After the generation of hydrocarbon, the occurrence of kerogen would show the distribution of hydrocarbon into the shale play (Figure 3.58). According to Garcia et al. (2013), the type of kerogen registered in the zone of study is type I and II, which indicate the predominance of oil.

The Lower Vaca Muerta shows the higher presence of hydrocarbon as it was expected for its high occurrence of TOC. Based on TOC and volume of kerogen, this zone would be a good ”sweet spot” (9.5 to 13%), but its ductile behavior would not allows producing it appropriately. The Middle Vaca Muerta has lower occurrence of hydrocarbon compared with the Lower Vaca Muerta (6 to 9.5%). The lateral distribution of volume of kerogen shows that around the Well I zone, the presence of hydrocarbon decreases in the middle toward the top. The high volume of carbonate and the lower TOC in the area makes it not a good oil zone toward the East. But the areas where Well A and Well G are located show high occurrence of hydrocarbon and they could be considered a good ”sweet spot”. The zone
between the Lower and the Middle Vaca Muerta shows a good occurrence of hydrocarbon where the volume of kerogen is from 7% to 9%. This zone also has a moderately high volume of carbonate from 29% to 36% would make it a good ”sweet spot” based on rock properties.

The Upper Vaca Muerta does not show a high presence of hydrocarbon. The lower zone of the Upper Vaca Muerta shows moderated presence of hydrocarbon, but the middle and upper section of the Upper Vaca Muerta shows low to null presence of hydrocarbon based on kerogen content. The lower zone of this section can behave as an unconventional play, but the middle and upper zone of the Upper Vaca Muerta could not have generated hydrocarbon which make them a different type of reservoir. Both zones could behave as carbonate reservoirs with similar characteristics and same source rock than the Quintuco
Formation. Although the presence of hydrocarbon is reduced in the Upper Vaca Muerta, good brittle behavior of the rock could offer interesting results in production for future tests. It is found a decrease in hydrocarbon presence toward the East zone of the study area, which indicates sections with good brittle characteristics for their high carbonate content and associated with the carbonate platform in the proximal zone of the Neuquén Basin.

The differences in the values from kerogen content from well logs and the predicted volume are related to the range of error, which shows a variation about 10% between the log data and the predicted kerogen content.

3.5.4 Interpretation and Analysis of Density

The density volume predicted shows an interesting relationship with the rock properties analyzed previously. The high presence of carbonate is related with high density and the high presence of TOC is associated with low density. This is also related to the acoustic impedance response for specific mineralogy zones in the Vaca Muerta Formation. The estimation of this volume was performed exclusively for the geomechanical analysis of chapter 4.

3.6 Summary

Rock property prediction was performed using Emerge TM in Hampson & Russell TM software. The inversion results were used as external attributes for the prediction of reservoir properties. TOC, volume of carbonate, volume of kerogen and density were successfully predicted using PNN. TOC was used to identify the source rock in the Vaca Muerta Formation. The distribution of TOC into the rock showed an inverse relationship with P and S impedance, as well with volume of carbonate. The TOC prediction results had a good match with original filtered log data.

The volume of carbonate prediction showed a good match with original data. It allows the discrimination of zones where brittle rock could be found. The volume of kerogen offered the distribution of oil in the Vaca Muerta Formation. It is associated to TOC content in the rock and it is a good indicator of zones where hydrocarbon was generated. The density was
also predicted and it will be used for geomechanical parameter estimation.

Based on the use of TOC, volume of carbonate and also with help of volume of kerogen, the best zones with hydrocarbon would be in the Middle Vaca Muerta and the unique zone between the Lower and the Middle Vaca Muerta. Those zones have good presence of hydrocarbon and also good occurrence of carbonate, which leads to it likely responding well to hydraulic stimulation and having good production.
CHAPTER 4
GEOMECHANICAL CHARACTERIZATION

The study of changes in the stress, temperature and pressure that impact the mechanics and mineralogy of the rock is known as reservoir geomechanics (Grazulis, 2016). Rock deformation and strength behavior are components of geomechanics, which are controlled by the distribution of the stress and rock properties (Schön, 2015). Geomechanical properties are important parameters that reservoir engineers use to understand the rock and design drilling and completion plans (Bishop, 2015; Grazulis, 2016).

Stress and strain are fundamental geomechanical properties. Stress is the force acting on a given area in the subsurface which can have normal and shear components. Normal stress is the perpendicular force to a plane and the shear stress is the force along the face of a plane. The deformation or strain is the response to a stress that changes the length, volume, and shape of the rock (Bishop, 2015; Fox et al., 2013; Schön, 2015). The analysis offered by a geophysical approach using seismic data and rock physics would lead to the definition of trends in the geomechanical parameters in the Vaca Muerta Formation. Although the Vaca Muerta Formation has an anisotropic behavior (Barbosa, 2017), the workflow used in this study is based on a geomechanical isotropic model.

4.1 Geomechanical Properties in Unconventional Reservoirs

Unconventional reservoirs, like the Vaca Muerta Formation, have low permeability and it is necessary to stimulate the rock to induce fractures for the rock to produce. Geomechanical properties are used to predict the rock behavior under a given stress and also predict the stability of the wellbore (Grazulis, 2016). Geomechanics plays an important role in the production of unconventional reservoirs, particularly because of the need for conductivity pathways which are created by hydraulic stimulation (Bishop, 2015).
The mineralogy composition, pore pressure, fluids, and rock properties are critical factors that affect the geomechanical properties. Mudrock has specific depositional and diagenetic processes that generate natural layers, where clay minerals are aligned in a preferred orientation. With the presence of carbonate or quartz, the alignment orientation may not be kept during the sedimentation (Bishop, 2015; Grazulis, 2016).

4.1.1 Geomechanical Parameters Theory

Stress (usually referred as $S$ or $\sigma$) is a pressure or tension that is applied on every surface at a specific point (Figure 4.1). Strain is the deformation response when stress is applied on the material surface (Figure 4.2). The deformation is described as a relationship between stress and strain using parameters called moduli: shear modulus ($\mu$), bulk modulus ($k$), bulk compressibility ($1/k$ or $\beta$), Young’s modulus ($E$), lambda ($\lambda$), and Poisson’s ratio $v$ (Fox et al., 2013).

The deformation and failure of rock material is associated with elastic properties. Static moduli can be calculated using measurements from core samples and dynamic moduli can be estimated from sonic wave velocity and density (Fjaer et al., 2008; Fox et al., 2013). As
it was mentioned before, the deformation of the rock can be described by several types of
geomechanical properties or moduli, but the most common geomechanical properties are
Young’s modulus \((E)\) and Poisson’s ratio \((v)\) (Grazulis, 2016). Young’s modulus is defined
as the ratio of stress applied in one direction and the resulting strain in the same direction.
It is also known as rock stiffness where high \(E\) is associated to high applied stress (Fox et al.,
2013; Schön, 2015). Poisson’s ratio is defined as the relative variation of the radius divided
by the relative change of axial length in the stress direction (Schön, 2015).

These geomechanical properties have been estimated using Lamé parameters. (1) Lambda
\((\lambda)\) which relates stresses and strains in perpendicular directions and it is related to incompres-
sibility of the rock, and (2) Mu \((\mu)\) or shear modulus, related to rock resistance to simple
shear or rock rigidity (Fox et al., 2013; Ji et al., 2010). Lamé parameters were calculated
with the following equations (Close et al., 2012):

\[
\lambda = \left( \frac{Z_p^2 - 2Z_s^2}{\rho} \right)
\] (4.1)
\[ \mu = \left( \frac{Z_s^2}{\rho} \right) \]  
(4.2)

Where \( Z_p \) is P-impedance, \( Z_s \) is S-impedance, and \( \rho \) is density.

Young’s modulus \((E)\) and Poisson’s ratio \((v)\) were estimated with the following equations:

\[ E = \frac{\mu(3\lambda + 2\mu)}{\lambda + \mu} \]  
(4.3)

and

\[ v = \frac{\lambda}{2(\lambda + \mu)} \]  
(4.4)

Figure 4.3 illustrates the ideal situation for Young’s modulus and Poisson’s ratio, where brittle rock is associated with high values of \( E \) and low values of \( v \). For brittle rock, a rock would be easily fractured when a stress regime is kept fixed with no variations. When variations are present in the stress regime, temperature, fluid type and mineralogy are present, and the rock can turn from ductile to brittle (Grazulis, 2016). Young’s modulus and Poisson’s ratio are useful geomechanical parameters to evaluate zones of the rock that can have a good response to hydraulic stimulation.

There are three main stresses that are part of wellbore stability. Wellbore stability is related to two sets of stresses known as far-field and wellbore stresses. Far-field stresses consist in the vertical stress or overburden \( (S_V \text{ or } \sigma_1) \), the minimum horizontal stress \( (S_{hmin} \text{ or } \sigma_2) \) and the maximum horizontal stress \( (S_{Hmax} \text{ or } \sigma_3) \). The natural occurrence of far-field stresses can be altered when a well is drilled through the rock and drilling fluids are injected. The \( S \) notation makes reference to the orientations and requires the specification of relative magnitudes, whereas the \( \sigma \) notation simply describes relative magnitudes and not the stress orientation (Bishop, 2015; Grazulis, 2016). Figure 4.4 illustrates three types of stress states.
or faulting regimes based on the variation of the magnitude and orientation of the three principal stresses (Fox et al., 2013). The main stress regime acting on the Vaca Muerta Formation for the study area is the normal faulting with average pore pressure of 0.75 psi/ft, $S_{hmin}$ of 0.85 psi/ft, $S_{Hmax}$ of 0.92 psi/ft and $S_V$ of 1.06 psi/ft (Figure 1.9) (Garcia et al., 2013).

According to Fjaer et al. (2008), when the properties of material that compound the rock are directionally dependent, it can be said that the material is anisotropic with respect to the property of interest. There are several common forms of anisotropy in rocks: (1) the
vertical transverse isotropy (VTI), (2) the horizontal transverse isotropy (HTI), and (3) the orthotropic anisotropy. A transversely isotropic material shows the same properties in the plane of isotropy, but in the transverse plane exhibits different properties. An orthotropic material shows different properties in all directions (Figure 4.5) (Fjaer et al., 2008; Willis, 2013).

Figure 4.5: Isotropic material (left) $V_1 = V_2 = V_3$. Vertical transverse isotropic (VTI) material (middle) $V_1 = V_2 \neq V_3$. Orthotropic material (right) $V_1 \neq V_2 \neq V_3$ (Willis, 2013).

A vertical transverse anisotropy material can be a layered rock. A horizontal transverse anisotropy (HTI) can be found in a massive sandstone with vertically oriented planar fractures. An orthotropic material could be a combination of layered rock with vertically oriented fractures (Willis, 2013; Zoback, 2007). Bedding parallel microcracks caused by the generation of hydrocarbons, aligned platy minerals and kerogen, and pore geometry are considered other geologic causes of anisotropy in a rock (Willis, 2013). Shale rocks have specific depositional and diagenetic processes that cause layering (Figure 4.6) (Hart et al., 2013). This layering within the shale generates a significant impact in the concentration of the stress during hydraulic stimulation. In addition, the compositional mineralogy of the layers interacts to define where the rock will reach the failure point to create fractures throughout the hydraulic stimulation (Davey, 2012).
Figure 4.6: Schematic representation of anisotropy in shale rocks. (a) Layering shows a vertical axis of symmetry, making the rock vertically transverse isotropic (VTI) media. Vertical fracture orientation in a homogeneous rock illustrates a horizontal transverse isotropic (HTI) medium. (c) Usual combination of layering with several scale and orientation of fractures in shale rocks (Hart et al., 2013).

The incorporation of anisotropy analysis in the study is a difficult task due the narrow azimuth nature of the seismic data.

4.2 Analysis of Geomechanical Parameter Results and Interpretation

Geomechanical analysis using seismic data and rock properties allows understanding the distribution of brittle rock inside the reservoir. This study is designed to quantify the relationship between rock properties and geomechanical parameters. The creation of an isotropic geomechanical model allows for the identification of zones with better response to hydraulic stimulation. P-impedance, S-impedance and density are used for the estimation of geomechanical parameters.
4.2.1 Density Volume

The calculation of Young’s modulus ($E$) and Poisson’s ratio ($v$) uses the Lamé parameters Lambda ($\lambda$) and Mu ($\mu$). These two parameters are related to the density and the first approach in this study is to define which density volume should be used for that process. An analysis to compare the density from inversion and the density obtained using probabilistic neural network (PNN) was performed to decide which volume was the most reliable for the estimation of geomechanical properties.

Pre-stack seismic inversion provides the tools for the physical estimation of density, but the Aki-Richards approach using the Zoeppritz equation makes it very difficult to obtain a reliable density volume. As it requires far offsets with an incidence angle higher than 45°; but even with that specification, it is still difficult to obtain a reliable density volume. This study uses a pre-stack seismic data with a maximum incidence angle of 36°. Figure 4.7 (A) illustrates the inversion results for the density which shows some small anomalies, especially in the Lower Vaca Muerta. The match of Well A, Well G and Well I is good with small differences. The density inversion result seems to be stable, but taking into account the limitation previously mentioned, the density may not be reliable for being used in further calculation without clarifying its restrictions.

Probabilistic neural networks (PNN) are useful for the prediction of rock properties. The statistical approach provides a good prediction result when the data is interpolated, but could have some problems when extrapolating the data (Hampson et al., 2001). The training process uses linear or non-linear relationships to obtain results without the issues caused by extrapolated data. Figure 4.7 (B) shows the density prediction results obtained with PNN. The density from PNN looks more stable compared with the inversion results. The match of Well A, Well G and Well I is very good with small differences, but better than the match observed in the inversion result. The Lower Vaca Muerta has a stable lateral extension in the study area where the occurrence of high TOC is known and it is related to lower values of density. The density volume from PNN illustrates the continuity expected...
with the extension of low values of density within the Lower Vaca Muerta. The Middle Vaca Muerta shows geological features with some stratigraphic differentiation between beds where the variation in density is clear. High values of density are related to an increasing in the carbonate content and it is more clear toward the East zone of the basin (around Well I). The Upper Vaca Muerta shows high values of density that can be related to a high content of carbonate, especially towards the East.

According to the analysis performed in both volumes of density and also based on the limitation of each approach, the density volume obtained from PNN will be used for the estimation of Young’s modulus and Poisson’s Ratio.

4.2.2 Poisson’s Ratio

Poisson’s ratio usually provides a good measure for evaluating the reservoir quality in conventional plays, where low $\nu$ is generally an indicator of high quality sands and presence
of gas (Barclay et al., 2007; Sena et al., 2011). On the other hand, in unconventional plays like the Vaca Muerta Formation, low values of \( v \) are an indicator of brittle zones in the rock. Those brittle zones are related to lower values of clay (<30%) and TOC, and high values of carbonate and quartz separately (Sena et al., 2011). The Vaca Muerta Formation in the study area has an average clay content less than 30% and also low quartz content, which put the reservoir into the brittle zone respect to carbonate content (Bishop, 2015). The lateral and vertical variation of TOC and carbonate are factors that control the brittleness of the rock, where the response to hydraulic stimulation can vary from one zone to another.

Poisson’s ratio \( (v) \) was obtained from the seismic inversion with a physical and reliable approach. It was computed using a relationship between P-velocity \( (V_p) \) and S-velocity \( (V_s) \) to extract \( v \) directly from the pre-stack seismic data without using the density (Equation 4.5). The estimation of \( v \) using Lamé parameters could not be necessary and could be considered a duplicity of the work, but the introduction of density in the equation would be a QC to quantify how valid the prediction of the density is. Equation 4.4, established in the introduction of this chapter, uses Lamé parameters for the estimation of \( v \) that includes P-impedance and S-impedance from inversion results and introduces the density from the prediction process with PNN.

\[
v = \frac{V_p^2 - 2V_s^2}{2(V_p^2 - V_s^2)} \quad (4.5)
\]

Figure 4.8 (A) shows the results of Poisson’s ratio obtained from seismic inversion where the distribution of \( v \) can be observed around the wells. Figure 4.8 (B) shows the results of \( v \) obtained from Lamé parameters, combining inverison results and density from PNN. Both results are very similar with a good match between them. Small differences can be observed around Well C due to the poor well-tie, where \( v \) has lower values in the inversion results than the combined option. The match around Well A, Well G and Well I is very good
with minimum differences toward the Lower Vaca Muerta. This analysis indicates that the density volume predicted using PNN is reliable enough to be used in further calculations of geomechanical properties. As Poisson’s ratio from seismic inversion has a physical approach with the relationship of $V_p$ and $V_s$, the volume obtained in that process will be used in further analysis for the impact of $v$ in the Vaca Muerta Formation.

Figure 4.8: Arbitrary line crossing over the whole six wells available in the study area. (A) Poisson’s ratio from inversion results. (B) Poisson’s ratio from Lamé parameters.

According to Curia (2016) (personal communication, November 29, 2016), Wintershall uses values of Young’s modulus $E$ and Poisson’s ratio $v$ as the two conditions needed to fulfill the identification of brittle rock. For Poisson’s ratio $v$, the starting value to consider a brittle rock is lower than 0.275. Figure 4.8 (A) shows a profile section on an arbitrary line over the available wells in the area of study. The zones in study area with $v$ lower than 0.275 are in dark blue to red-orange. The zones in yellow (greater than 0.275) would show the zones with less brittle characteristics. In this analysis, the first inconsistency of $v$ to define brittle rock in the study area can be observed. The bottom of the Quintuco Formation is covered in the $v$ results and shows high values in yellow in the upper part of the section.
This formation is rich in carbonate and has a brittle response which does not correspond to the results illustrated. Additionally, the Lower Vaca Muerta shows high values of $v$ (above 0.3) that would indicate more ductile characteristics, but the values of $v$ around Well C decrease to 0.17, which is not expected in the Lower Vaca Muerta. Although those lower values indicate a sudden change to brittle behavior, it could be caused by the poor well-tie.

Figure 4.9 shows a 10 ms window horizon slice extracted in the zone between the Lower and the Middle Vaca Muerta that illustrates the lateral distribution of $v$ in the rock. The figure shows a predominance of $v$ values lower than 0.24 indicating brittle behavior which is expected in that zone. The North-Eastern part of the area around Well A, Well G and Well I shows a distribution of $v$ where lower values were expected, especially around Well A and Well G. The North and North-Western area around Well H shows higher values (>0.25) where low values were expected in that area. Values of $v$ are the lowest (<0.23) around Well B which indicates more brittle characteristics in those areas.

Figure 4.10 shows a 10 ms window horizon slice extracted from a section 40ms below the top of the Middle Vaca Muerta. This figure shows a predominance of $v$ values higher than 0.25 which indicates a less brittle behavior. In addition to that, the study areas show a more homogeneous and constant distribution of $v$, where the zones around Well A, Well G, Well I and Well H are identified with values of $v$ lower than 0.27 indicating that the area would have more brittle characteristics rather than a ductile behavior. The Southern area with Well B shows values of $v$ from 0.275 to 0.225 approximately, which indicates that the Vaca Muerta Formation would have brittle behavior in that area.

Figure 4.11 shows a 10 ms window horizon slice extracted from the top of the Upper Vaca Muerta. This figure shows a predominance of $v$ values lower than 0.23 which indicates a brittle behavior of the rock. The distribution of $v$ is more heterogeneous compared with the Middle Vaca Muerta slice (Figure 4.10), but the range of $v$ values are from 0.28 to 0.18 in some areas. This range of $v$ indicates that most of this section of Upper Vaca Muerta should have brittle characteristics. But even lower values of $v$ were expected due to the
higher content of carbonate.

### 4.2.3 Young’s Modulus

Young’s modulus ($E$) is an indicator of brittle behavior in shale rocks and the presence of high values of $E$ are related to brittle zones. However, the use of $E$ alone is insufficient to identify the zones with best response to hydraulic stimulation. It is also necessary to use the differential horizontal stress ratio (DHSR) to understand the stress field distribution, where low values of DHSR and high values of $E$ would indicate the best zone for hydraulic stimulation (Sena et al., 2011). Instead of using DHSR in this study, Chapter 5 will have an approach to identify good zones for hydraulic stimulation with good presence of hydrocarbons based on the integration of rock properties and geomechanical parameters.
After deciding which density volume to use, the estimation of Young’s modulus \( E \) is a straightforward process, starting with calculation of the Lamé parameters Lambda \( (\lambda) \) and Mu \( (\mu) \) described previously in equations 4.1 and 4.2. Applying \( (\lambda) \), Mu \( (\mu) \) and density \( (\rho) \) to the equation 4.3, was determined the \( E \) result for the area of study.

Figure 4.12 shows the results for \( E \) in a profile section on an arbitrary line crossing all six available wells in the study area. In personal communication from Curia (2016) (personal communication, November 29, 2016), it was stated the values for geomechanical parameters that are used by Wintershall in the identification of brittle zones in the Vaca Muerta Formation. For Young’s modulus \( (E) \), the starting value to consider a brittle rock is higher than \( 2.5e+10 \ \text{N/m}^2 \). The results show that a great part of the Vaca Muerta Formation would be in the brittle zone. Dark blue to light blue color would be considered in the zone.
of the rock with low brittle characteristics.

The Lower Vaca Muerta shows values of $E$ lower than $2e+10$ N/m$^2$ which indicates a rock with more ductile characteristics. The interval between the Lower and Middle Vaca Muerta shows values above $2.5e+10$ N/m$^2$ that make it an interesting zone. The Middle Vaca Muerta has a vertical heterogeneity that show zones of brittle behavior around Well $I$ and decreasing in brittleness around Well $G$ and Well $A$, but with inter-bedded zones with brittle and less brittle characteristics. The upper part of Middle Vaca Muerta around Well $B$ shows a high extension of brittle rock, but lower values of $E$ in the lower part of Middle Vaca Muerta show an inter-bedded zone of brittle and less brittle rock. Well $H$ and Well $C$ show inter-bedding of brittle and less brittle rock but with more presence of less brittle rock around Well $C$. The Upper Vaca Muerta has a predominance of $E$ values above $3e+10$ N/m$^2$ and brittle behavior in a zone of green color with transition to red-yellow color which
correspond to the base of the Quintuco Formation.

Figure 4.12: Arbitrary line of Young’s modulus results crossing over the six wells available in the study area. Young’s modulus was estimated using equation 4.3.

Young’s modulus ($E$) from well log differs for the ($E$) estimated from seismic data. Two factors can generate that difference in this study. (1) Although the density log data is used in the seismic inversion and the neural network prediction, the estimation of density from well logs using neural network showed to be more accurate than the density prediction with seismic data because of the limitations mentioned previously for both methods that generate deficiencies in the inversion and prediction processes. Besides, the well data acquisition obtains the measurements directly from the rock into the wellbore, which allows having good density and sonic results. That implies that the Young’s modulus ($E$) predicted with seismic data should be almost the same or at least very similar on the well location due the use of ($E$) estimated from well log data to constraint the results. (2) other factor which generates a difference between the ($E$) estimated from seismic inversion and well data is the scale and vertical resolution used in both calculations. Velocities of the compressional wave ($V_p$) and the shear wave ($V_s$) can have different scales from the sonic tool that acquired the log data into the wellbore compared with the seismic data acquired in the field. During their processing, the seismic data use a velocity model of the rock sequence that provides lower
resolution that the one obtained with sonic log data.

Figure 4.13 shows a 10 ms window horizon slice extracted in the Lower Vaca Muerta with the lateral distribution of Young’s modulus (E). The lateral distribution of E in the lower Vaca Muerta illustrates a trend with predominance of higher values of E toward the North-East and South-East compared with the zones in the North-West and South-West. In general, the study area shows a prevalence E values lower than 2.5e+10 N/m² which makes the Lower Vaca Muerta a zone with ductile characteristics. However, the values of E around Well A, Well I and Well B are close to 2.5e+10 N/m² which illustrates a rock with a moderate brittle behavior.

![Figure 4.13: Horizon slice of Young’s modulus extracted in the Lower Vaca Muerta with 10 ms window. Secuencia 1 (S1) was used to extract this slices.](image)

Figure 4.13 shows a horizon slice of E extracted 40 ms below the top of the Middle Vaca Muerta in a 10ms window. The Northern and Southern area show the highest values in the section. Around Well A and Well H, the values of E are low and indicates a zone of ductile
rock in the center of the section. Most of the area has values below $2.5 \times 10^{10}$ N/m$^2$ which indicates that this section is more ductile than brittle.

Figure 4.14: Horizon slice of Young’s modulus extracted 40 ms below the top of the Middle Vaca Muerta with 10 ms window. Secuencia 4 (S4) horizon was used to extract this slice.

Figure 4.15 shows a 10 ms window horizon slice extracted in the Upper Vaca Muerta with the lateral distribution of Young’s modulus $E$. This section of the Upper Vaca Muerta is characterized for having values of $E$ $2.5 \times 10^{10}$ N/m$^2$, which indicates brittle behavior. The Southern area with Well C and Well B show the highest values of $E$, and the central and Northern zone shows the lowest values in the area. The area around Well A and Well G are in the lower limit to be considered brittle, and Well I is in zone with rock more brittle.

4.2.4 Definition of Brittle Zones with Geomechanical Properties

Poisson’s ratio and Young’s modulus usually show an inverse relationship to differentiate brittle and ductile rock (Figure 4.3). Figure 4.16 illustrates a crossplot of Young’s modulus versus Poisson’s ratio for the Vaca Muerta Formation and color coded by P-impedance.
Figure 4.15: Horizon slice of Young’s modulus extracted in the Upper Vaca Muerta with 10 ms window. Secuencia 4 (S4) horizon was used to extract this slice.

Poisson’s ratio does not show significant variation and does not have an inverse relationship with Young’s Modulus that could define brittle rock. The relationship observed keeps a constant value of Poisson’s ratio whereas Young’s modulus increases. Poisson’s ratio does not offer a reliable indicator of brittle or ductile rock in the Vaca Muerta Formation.

Figure 4.16 also shows the values stated by Wintershall (Table 4.1), which illustrates the values of Young’s modulus $E$ and Poisson’s ratio $v$ used in the definition of brittle rock. Table 4.1 shows two scenarios, optimistic and less optimistic. This study uses the range of values in the optimistic scenario for geomechanical analysis. According to the values in Table 4.1, brittle and ductile rock can be separated in the Vaca Muerta Formation. The values greater than $2.5\times10^{10}$ N/m$^2$ in $E$ and lower than 0.275 in $v$ would be considered part of brittle rock (optimistic scenario).
Table 4.1: Geomechanical values used by Wintershall for the identification of brittle rock in the Vaca Muerta Formation. Personal communication, November 29, from Curia (2016).

<table>
<thead>
<tr>
<th>Young’s Modulus</th>
<th>Poisson’s Ratio</th>
<th>Characteristics</th>
<th>Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt; 3.0e+10 N/m²</td>
<td>&lt; 0.25</td>
<td>More Brittle</td>
<td>Less optimistic</td>
</tr>
<tr>
<td>&gt; 2.5e+10 N/m²</td>
<td>&lt; 0.275</td>
<td>Brittle</td>
<td>Optimistic</td>
</tr>
</tbody>
</table>

Figure 4.16: Crossplot of Young’s modulus versus Poisson’s ratio and color coded by P-impedance.

Young’s modulus and Poisson’s ratio exist simultaneously at each surface point of the rock. Figure 4.17 shows the individual contribution of each geomechanical moduli (Young’s modulus and Poisson’s ratio) to observe how they are related to each other with the range of values that this study uses to discriminate brittle and ductile rock. Figure 4.17 (A) shows the results and definition of brittle and ductile rock in the Vaca Muerta Formation based on Poisson’s ratio. These results show that a large part of the Vaca Muerta is defined as brittle and a small part in the Lower Vaca Muerta is ductile. The upper part in the circle belongs to Quintuco Formation and \( v \) indicates that the rock is ductile. The Quintuco is a carbonate rich formation which has brittle characteristics that confirm Poisson’s ratio does
not play a significant role to define brittle rock in the Vaca Muerta Formation.

Figure 4.17 (B) shows the results of the discrimination of brittle rock based on Young’s modulus in the Vaca Muerta Formation. $E$ shows a better distribution of brittle-ductile rock where the Lower Vaca Muerta and part of the Middle Vaca Muerta have more ductile behavior. Brittle characteristics were observed in a zone previously described in chapter 3 between the Lower and Middle Vaca Muerta. The Upper Vaca Muerta and its contact with the Quintuco Formation shows brittle behavior as it was expected.

![Figure 4.17: (A) arbitrary line showing the discrimination of brittle and ductile rock base in Poisson’s ration. (B) Discrimination of brittle and ductile rock based in Young’s modulus.](image)

Using Young’s modulus and knowing the limit defined by Wintershall about what rock is considered brittle and ductile, allows for the creation of interpretative subdivisions in the data range of $E$. The subdivision would help in the discrimination and visualization without modifying the brittle-ductile limit established by Wintershall. Table 4.2 shows the subdivision created using $E$ for the definition of brittle-ductile zones and keeping the limits.
Table 4.2: Subdivision to define brittle and ductile zones based in Young’s modulus.

<table>
<thead>
<tr>
<th>Young’ Modulus (N/m²)</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt; 3.0e+10</td>
<td>Brittle</td>
</tr>
<tr>
<td>2.75e+10 - 3.0e+10</td>
<td>Moderately Brittle</td>
</tr>
<tr>
<td>2.5e+10 - 2.75e+10</td>
<td>Less Brittle</td>
</tr>
<tr>
<td>2.25e+10 - 2.5e+10</td>
<td>Less Ductile</td>
</tr>
<tr>
<td>2.0e+10 - 2.25e+10</td>
<td>Moderately Ductile</td>
</tr>
<tr>
<td>&lt; 2.0e+10</td>
<td>Ductile</td>
</tr>
</tbody>
</table>

Figure 4.18 shows an arbitrary line with higher discrimination zones of brittle and ductile rock for the Vaca Muerta Formation. The brittle zone was subdivided into three sub-zones to visualize and differentiate the brittle behavior variation based on Young’s Modulus. The same subdivision, but decreasing $E$, was performed to ductile rock. Green, brown and red show the three subdivisions for brittle behavior in the Vaca Muerta. The Upper and the upper section of Middle Vaca Muerta illustrates the zones with higher presence of brittle rock. Green is present in the Upper Vaca Muerta and also the bottom part of Quintuco Formation which indicates the highest $E$ in the section. Brown is disseminated in the upper section of the Middle Vaca Muerta and also in the zone between the Lower and Middle Vaca Muerta. The red color in the brittle zone has a high presence in the upper section of the Middle Vaca Muerta, as well in a big part of the section between the Lower and Middle Vaca Muerta.

Figure 4.19 shows a 10 ms horizon slice in the zone between the Lower and Middle Vaca Muerta showing more brittle characteristics than the Lower and Middle. Brittle zones are identified toward the Eastern zones of the study area around Well I and Well B, less brittle zones are around Well A, Well G and C. The ductile areas are identified toward the Western zone around Well H. The proximal zone of the basin toward the East was expected to be more brittle due to a less preservation of TOC and higher carbonate content in the platform.

Ductile zones in the Vaca Muerta Formation would not be considered areas of interest. Chapter 5 will make an analysis of their mineralogy to define what ranges of TOC and
Figure 4.18: Arbitrary line showing the discrimination of brittle and ductile rock base on Young’s modulus.

Figure 4.19: Horizon slice extracted from the zone between the Lower and the Middle Vaca Muerta with a window of 10 ms.
carbonate content create an impact in the geomechanical properties of the rock.

4.3 Summary

Young’s modulus and Poisson’s ratio were estimated for geomechanical analysis to differentiate brittle and ductile rock in the Vaca Muerta Formation. Poisson’s ratio was estimated during the seismic inversion process using a relationship between P-velocity \((V_p)\) and S-velocity \((V_s)\). Young’s modulus was calculated using Lame parameters which utilized P-impedance and S-impedance from inversion and density from PNN.

Poisson’s ratio shows deficiencies to discriminate brittle and ductile rock in the Vaca Muerta Formation. Instead of showing decreasing of values when Young’s modulus increases, \(\nu\) keeps constant values and does not show a good discrimination for brittle and ductile rock. It illustrates brittle zones in the Lower Vaca Muerta and most of the Middle Vaca Muerta where it was not expected. Additionally, \(\nu\) shows ductile rocks in the Upper Vaca Muerta and the bottom part of Quintuco Formation where more brittle characteristics were expected for its carbonate content.

Young’s modulus was more efficient to identify brittle and ductile rock. Direct relationships of \(E\) with P-impedance, S-impedance and density indicate a sensitive response with the compositional variation of the rock. Being able to determine a response in any lithological change is critical to discriminate brittle and ductile rock. Lower Vaca Muerta has ductile behavior as the Upper Vaca Muerta is the opposite with brittle characteristics. The zone between the Lower and the Middle Vaca Muerta shows brittle behavior keeping the same trend of increasing values of P and S impedance and density in the zone. The Middle Vaca Muerta was more heterogeneous and shows brittle and ductile zones. The brittle zones are defined in the upper section of Middle Vaca Muerta. The ductile zones are concentrated toward the middle and lower sections of the Middle Vaca Muerta.

As Poisson’s ratio is not a good indicator to define appropriately brittle zones in the Vaca Muerta Formation, it was decided not to use it as geomechanical parameter for this task. \(E\) shows better results to discriminate brittle and ductile rock. Knowing the limits
of $E$ values used by Wintershall to define brittle zones, a new discrimination was created for brittle-ductile rock based on a subdivision of the current values. This subdivision shows three ranges for brittle rock and three ranges for ductile rock, with the main purpose of visualizing a more detailed variation in the ductility and brittleness in the Vaca Muerta Formation.
Unconventional reservoirs consist of a large variety of mineral compositions, depositional record and rock properties. Shale plays are not vertically or laterally homogeneous, nor consist solely of biogenic and terrigenous sediments from deep marine environments (Slatt and Abousleiman, 2011). These characteristics influence the geomechanical properties of the rock. As one of the factors that impact the geomechanical parameters, the mineralogical heterogeneity of shales needs to be discriminated to define brittle and ductile zones.

Brittle rocks in shale formations have a small to large region of elastic behavior under applied stress, but solely a small region of ductile behavior before it fractures. The opposite behavior indicates the elastic characteristics of ductile rocks (Slatt and Abousleiman, 2011). This concept implies that even ductile zones in the Vaca Muerta Formation can have a rock failure response during the hydraulic stimulation process. However, their elastic response would not allow for optimal fractures and could have a negative impact on production and economics.

5.1 Relationship Between Rock Properties and Geomechanical Parameters

Identifying a relationship between rock properties and geomechanical parameters will lead to the definition of mineralogy ranges that will help discriminate brittle and ductile rock based on rock properties. TOC and the volume of carbonate play an important role in the elastic behavior of Vaca Muerta Formation.

According to the subdivision done for Young’s modulus ($E$) in the previous chapter in Table 4.2, relationships of $E$ with TOC, carbonate and kerogen content allow the identification and differentiation of those rock properties within brittle and ductile zones. Although Table 4.2 illustrates six clusters defining brittle and ductile characteristics within the Vaca
Muerta Formation, the subdivision that integrates rock properties and Young’s modulus has seven clusters. The seventh cluster is added in the brittle zone were TOC values are lower than 2 wt% and generation of hydrocarbon is not expected. Table 5.1 shows the integration of the brittle-ductile subdivision of $E$ and its rock property relationship. Ranges of values for TOC, carbonate and kerogen content were defined for each interval selected in the Young’s modulus data range. That defines a unique facies association for each cluster, which four of them are in the brittle zones and three of them are in the ductile zone.

<table>
<thead>
<tr>
<th>$E$ (N/m$^2$)</th>
<th>TOC (wt%)</th>
<th>Carbonate (%)</th>
<th>Kerogen (%)</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>$&gt; 3.25e+10$</td>
<td>&lt; 2.0</td>
<td>&gt; 41</td>
<td>&lt; 4.5</td>
<td>Brittle</td>
</tr>
<tr>
<td>3.0e+10 - 3.25e+10</td>
<td>2.0 - 2.4</td>
<td>38 - 41</td>
<td>4.0 - 4.5</td>
<td>Brittle</td>
</tr>
<tr>
<td>2.75e+10 - 3.0e+10</td>
<td>2.4 - 3.0</td>
<td>35 - 38</td>
<td>4.5 - 5.2</td>
<td>Moderately Brittle</td>
</tr>
<tr>
<td>2.5e+10 - 2.75e+10</td>
<td>3.0 - 4.5</td>
<td>30 - 35</td>
<td>5.2 - 7.4</td>
<td>Less Brittle</td>
</tr>
<tr>
<td>2.25e+10 - 2.5e+10</td>
<td>4.5 - 5.5</td>
<td>26 - 30</td>
<td>7.4 - 8.8</td>
<td>Less Ductile</td>
</tr>
<tr>
<td>2.0e+10 - 2.25e+10</td>
<td>5.5 - 6.8</td>
<td>22 - 26</td>
<td>8.8 - 10</td>
<td>Moderately Ductile</td>
</tr>
<tr>
<td>$&lt; 2.0e+10$</td>
<td>&gt; 6.8</td>
<td>&lt; 22</td>
<td>&gt; 10</td>
<td>Ductile</td>
</tr>
</tbody>
</table>

Crossplots of Young’s modulus versus Poisson’s ratio were generated and color coded by the three rock properties used in this study. Ellipses were used to visually show the subdivision ranges that illustrate the values used to define clusters for each rock property and their relationship with Young’s modulus.

Figure 5.1 shows the crossplot of Young’s modulus ($E$) versus Poisson’s ratio ($v$) color coded by TOC and divided by the main brittle-ductile rock limit defined by Wintershall (Table 4.2). It can be observed and confirmed that Poisson’s ratio does not play a significant role as an indicator of brittle and ductile rock at the study location. Only a small range of $v$ values encompass the full range of TOC values, therefore $v$ does not discriminate the elastic behavior of the rock based on the compositional mineralogy. On the other hand, Young’s modulus has a good discriminative relationship with TOC values and it is an excellent indicator to define brittle and ductile rock in the Vaca Muerta Formation.
Figure 5.1: Crossplot of Young’s modulus versus Poisson’s ratio color coded by TOC and subdivided by the brittle-ductile rock ranges from Table 5.1.

Figure 5.2 and Figure 5.3 are crossplots of Young’s modulus $E$ versus Poisson’s ratio $v$ color coded by volume of carbonate and volume of kerogen respectively. As it was observed with TOC, the relationship between $v$ and volume of carbonate shows that $v$ does not play a significant role for discrimination between brittle-ductile rock. Using the same association process applied to TOC, the ranges of carbonate and kerogen content were defined for the subdivided zones based on $E$. Table 5.1 shows the integration of brittle-ductile rock defined by $E$ and the relationship with volume of carbonate and volume of kerogen in the Vaca Muerta Formation.

The crossplots show that brittleness in the Vaca Muerta Formation is associated with the increase in carbonate content and decrease of TOC. The ductility of the rock is related to higher TOC and lower carbonate content. A cluster analysis was done associating TOC and carbonate content facies, and also including the volume of kerogen, which indicates the presence of hydrocarbon and confirms TOC trends in the brittle zones that were defined using Young’s modulus.
Figure 5.2: Crossplot of Young’s modulus versus Poisson’s ratio color coded by volume of carbonate and subdivided by the brittle-ductile rock ranges from Table 5.1.

Figure 5.3: Crossplot of Young’s modulus versus Poisson’s ratio color coded by volume of kerogen and subdivided by the brittle-ductile rock ranges from Table 5.1.
5.2 Cluster Analysis and Definition of Brittle Zones with Presence of Hydrocarbon

In shale plays, the identification of zones with a high presence of hydrocarbons are associated with high TOC in the rock. However, high TOC in the Vaca Muerta Formation is related to ductile rock. The ductility of the rock as well as the presence of natural fractures, created by hydrocarbon generation or tectonics, could cause problems in the hydraulic stimulation response of the rock. Besides, the stress regime is a factor that may inhibit or help in the fracture propagation in the rock (Mabrey, 2016). On the other hand, the presence of quartz and carbonate are considered the compositional mineralogy that gives stiffness to the rock.

According to Bishop (2015), a higher presence of natural fractures in the Vaca Muerta Formation is located within the middle section, with a minor presence of natural fractures in the Lower and Upper Vaca Muerta. The facies association between TOC and volume of carbonate is an important factor that impacts the development of natural fractures within the Vaca Muerta Formation. Although the lateral distribution of natural fractures in the complete section of the Vaca Muerta cannot be evaluated by well data analysis, it illustrates the major fracture trends in the vertical section and it can be assumed that a lateral presence of natural fractures is related to compositional variation of the mineralogy. It is important to mention that these fractures behave as planes of weakness which release the pressure during hydraulic stimulation and cause a negative impact for microseismic. These natural fractures generate weak microseismic events that sometimes cannot be recorded by geophones on the surface.

The Vaca Muerta Formation in the study area has less than 30% clay content and a regular presence of carbonate that should place the reservoir in the brittle zone (Bishop, 2015). However, TOC plays a significant role in providing a ductile behavior in the formation. The previous cut-off for Young’s modulus $E$ described in Table 5.1 illustrates the cluster analysis used to progressively discriminate brittle-ductile zones with high hydrocarbon content and
to classify the reservoir in different geomechanical categories.

Limestones and marlstones have high carbonate content and low TOC in the Vaca Muerta Formation. This represents the highest Young’s modulus $E$ limit which indicates a high brittleness with low presence of hydrocarbon characterizing those zones with possible good response to hydraulic stimulation but with some limitations in hydrocarbon presence. Table 5.2 shows brittle and ductile zones related to colors and good completion targets. The productive zone (purple) is associated with the low presence of TOC but higher than 2 wt% in the Upper Vaca Muerta. The productive zone (light blue) is related to the zones with TOC lower than 2 wt% and high carbonate content in the Upper Vaca Muerta (Table 5.2). This light blue zone could have similar characteristics observed in the Quintuco Formation, which is a carbonate reservoir with the Vaca Muerta Formation as source rock.

The occurrence of natural fractures can be related to the high brittleness in the formation and the stress regime present in the area of study. Natural fractures are the pathways for hydrocarbon migration which was generated in the Vaca Muerta Formation. In addition to the natural fractures, other planes of weakness (beefs) can have a negative impact in the hydraulic stimulation (Bishop, 2015; Wang and Gale, 2009). Based on the association of brittle-ductile rock and hydrocarbon presence, this facies with high carbonate content and low TOC would have a good response to hydraulic stimulation and could produce hydrocarbons, even as conventional or unconventional reservoirs. These zones should be taken into account as a completion target.

The lowest limit of Young’s modulus $E$ is related to a facies association (blue) that needs to be avoided in completion plans because of its low carbonate content and high TOC (Table 5.2). The Lower Vaca Muerta could be considered a ”sweet spot” based exclusively on TOC and hydrocarbon presence, but the ductility of the rock indicates that it is a poor candidate for hydraulic fracture stimulation as a consequence of its reduced stiffness and plastic behavior. The failure point of the rock can be reached during the hydraulic stimulation process, but the fracture would not be opened permanently because of its plastic
deformation that may cover the injected proppant. Natural fractures and the presence of "beefs" can also play an important role in this zone, which would add even more negative impact during the hydraulic stimulation process and it would be the cause of weak events in microseismic (Fox et al., 2013).

According to the cut-off presented in Table 5.1, the other two ductile zones (yellow and green) with moderately high TOC and poor carbonate content are expected to have a similar plastic behavior (Table 5.2). The increasing trend of the carbonate content and progressive reduction of TOC would increase the stiffness of the rock, generating better response to hydraulic stimulation but still having plastic behavior. Natural fractures were generated as a response to the increasing brittleness with higher carbonate content. The moderate rich kerogen present in the rock also contributes to the creation of natural fractures due the hydrocarbon generation process which releases water that overpressures and breaks the rock.

The other two brittle zones with moderate carbonate content and relatively low TOC (brown and orange) could be good zones for completion targeting due to its brittle characteristics and hydrocarbon content. The pathways created by the hydraulic stimulation can stay open due to the stiffness of the rock and the proppant injected, but the presence of natural fracture can affect the stimulation and be a path to release the pressure applied during the stimulation process. Table 5.2 illustrates the brittle-ductile zones with presence of hydrocarbon that can be prospective ideal locations for landing and completion.

Table 5.2: shows the completion targets related to rock properties and brittle-ductile rock generated using Young’s modulus.

<table>
<thead>
<tr>
<th>Completion Target</th>
<th>TOC (wt%)</th>
<th>Carbonate (%)</th>
<th>Kerogen (%)</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good - light blue</td>
<td>&lt; 2.0</td>
<td>&gt; 41</td>
<td>&lt; 4.5</td>
<td>Highly Brittle</td>
</tr>
<tr>
<td>Good - purple</td>
<td>2.0 - 2.4</td>
<td>38 - 41</td>
<td>4.0 - 4.5</td>
<td>Brittle</td>
</tr>
<tr>
<td>Good - orange</td>
<td>2.4 - 3.0</td>
<td>35 - 38</td>
<td>4.5 - 5.2</td>
<td>Moderately Brittle</td>
</tr>
<tr>
<td>Good - brown</td>
<td>3.0 - 4.5</td>
<td>30 - 35</td>
<td>5.2 - 7.4</td>
<td>Less Brittle</td>
</tr>
<tr>
<td>Avoid - green</td>
<td>4.5 - 5.5</td>
<td>26 - 30</td>
<td>7.4 - 8.8</td>
<td>Less Ductile</td>
</tr>
<tr>
<td>Avoid - yellow</td>
<td>5.5 - 6.8</td>
<td>22 - 26</td>
<td>8.8 - 10</td>
<td>Moderately Ductile</td>
</tr>
<tr>
<td>Avoid - dark blue</td>
<td>&gt; 6.8</td>
<td>&lt; 22</td>
<td>&gt; 10</td>
<td>Ductile</td>
</tr>
</tbody>
</table>
Figure 5.4 shows an arbitrary line in the study area with the cluster analysis that illustrates the distribution of brittle-ductile zones related to TOC, volume of carbonate and volume of kerogen. The distribution of zones with presence of hydrocarbons and brittle rock are illustrated in brown, orange, purple and light blue, which would be the best zones for landing and completion. With TOC values lower than 2 wt% and no generation of hydrocarbon expected, the light blue zone might behave as a conventional reservoir like the Quintuco Formation. In this case, the light blue zone should have a different horizontal well design compared with the other three brittle zones (purple, orange and brown), which are identified as unconventional reservoirs. The ductile zones with high presence of hydrocarbon are shown in blue, yellow and green, which would be zones to avoid for completion plans.

The best zones with brittle rock and high occurrence of hydrocarbons are located around \textit{Well I}, \textit{Well G} and also \textit{Well B}. The Middle Vaca Muerta has the higher occurrence of these two characteristics selected as the most probable zones for a good response to hydraulic stimulation and has good presence of hydrocarbons. \textit{Well I} and \textit{Well B} are located in the proximal zone of a low angle carbonate platform corresponding to a zone with less anoxic conditions.
conditions for organic matter preservation and more occurrence of carbonate.

The zone in green, which corresponds to a less ductile zone with good presence of TOC, is widely distributed in the Middle Vaca Muerta. This zone should not be considered for landing and completion, but it is important to complement this study with the inclusion of quartz content in the zone. The volume of quartz associated to volume of carbonate would help to better discriminate the green zone and possibly obtain additional brittle rock with a good occurrence of TOC.

The yellow and blue colored zones are described as the zones with higher ductility due to their high TOC and the progressive reduction of carbonate content. The higher occurrence of the facies associated to the blue color is in the Lower Vaca Muerta, which corresponds to an anoxic zone with a high preservation of organic matter. The yellow zone surrounds the blue zone in the Lower Vaca Muerta, but it is also present in the Middle Vaca Muerta with a higher occurrence around Well A.

Figure 5.5 shows a 10 ms window horizon slice in the zone between the Lower and Middle Vaca Muerta. The North-Eastern and South-Eastern zones show the most interesting areas for landing and completion. The zone around Well I shows the best characteristics of brittleness and hydrocarbon occurrence for completion targets. Although Well A and Well B also show good zones, they are closely surrounded with ductile rock which could impact the hydraulic stimulation. Well H and Well C are located in zones of high TOC and ductile characteristics and therefore should be avoided.

Figure 5.6 shows a 10 ms window horizon slice in the top of the Middle Vaca Muerta. The Southern and North-Eastern zones illustrate the facies and the geomorphology associated with the proximal zone of the carbonate platform. The reduced presence of TOC is due to the low preservation of organic matter present in the low angle platform. The zone in light blue could be considered a productive zone, but taking into account that it might behave as a conventional reservoir. This zone would depend on their natural fracture network to storage the hydrocarbon. Zones around Well A, Well G, Well I and Well H also show
brittle behavior with occurrence of TOC. Purple, orange and brown zones illustrate the discrimination of brittle zones related to their TOC content as productive zones. These three zones would have a behavior as unconventional reservoirs. The most interesting productive zones would be associated with the orange and purple clusters.

The well planning for horizontal wells in the Vaca Muerta Formation needs to include the stress analysis in the zone of interest. Taking into account that the stress distribution in the study area is $S_V > S_{H\text{max}} > S_{H\text{min}}$, the optimum hydraulic fracture stimulation should be done in the direction of maximum horizontal stress ($S_{H\text{max}}$), where the propagation and growth of a complex induced fracture network would be more constant (Bredehoeft et al., 1976; Fox et al., 2013). This indicates that the design and drilling of the horizontal well should
be in the direction of the minimum horizontal stress \(S_{H_{\text{min}}}\). The stress analysis would complement the identification of zones with good brittleness and presence of hydrocarbon would help to define the areas where the landing of horizontal wells would be optimal for production.

For unconventional reservoir, the maximum horizontal stress \(S_{H_{\text{max}}}\) has an orientation West-East which indicates that the design of horizontal wells should be perpendicular to this stress orientation. The wells should be drilled with an direction South-North which is the orientation of minimum horizontal stress \(S_{H_{\text{min}}}\), and it is also necessary to include an analysis of the formation dip for the targeted zone. In the case of the light blue zone that has characteristics as a conventional reservoir with high brittleness and TOC lower than 2 wt%,
the horizontal well design should be different. The well should be drilled in the orientation of the maximum horizontal stress ($S_{Hmax}$), which is West-East. It is important to mention that this section of the Upper Vaca Muerta could have natural fracture which would act as the reservoir storage for hydrocarbons.

Figure 5.7 shows an arbitrary line crossing through Well G in the direction South-North. The formation has a general inclination to the South which suggests a horizontal well design with a well drilled in the South-North direction. According with the cluster analysis described previously, the zones in brown, orange and purple are the most interesting zones as unconventional reservoirs. More concentration of brittle rock with presence of hydrocarbons is observed in the Middle Vaca Muerta toward the North of the study area. Three horizontal wells are suggested and displayed in the section, where different zones are targeted in the Vaca Muerta Formation. The well $Hz-01X$ targets the zone between the Lower and Middle Vaca Muerta with a combination of the three cluster zones (brown, orange and purple). This section has a thickness between 22 to 25 meters and higher pressures that make it a highly prospective area. The well $Hz-02X$ targets the upper section of the Middle Vaca Muerta in a zone with high brittle rock which corresponds to the purple zone. The well $Hz-03X$ targets the brown and orange zones in the middle section of the Middle Vaca Muerta.

Figure 5.8 shows an arbitrary line crossing through Well G in the direction West-East. The lateral continuity of the cluster zones for brittle-ductile rock with hydrocarbon presence is observed having more brittle rock toward the East. The light blue zone shows the carbonate rich rock with TOC lower than 2 wt%. This zone might behave as a conventional reservoir and horizontal wells should be drilled in same direction of this section, which the orientation of the maximum horizontal stress ($S_{Hmax}$).

Figure 5.9 shows an arbitrary line crossing through Well I in the South-North direction. This section illustrates a higher occurrence of facies associated with brittle rock and presence of hydrocarbons. The Middle Vaca Muerta shows prospective zones toward the North of the study area. Several horizontal well are suggested to target the upper and middle section
Figure 5.7: Arbitrary South-North line through Well G that shows the brittle zones with occurrence of hydrocarbons in the study area. Prospective horizontal wells are suggested to target interesting zones to produce. $S_{H_{\text{min}}}$ shows the orientation of the minimum horizontal stress. The prospective zone between the Lower and Middle Vaca Muerta has a range of thickness between 22 meters to 25 meters.

of the Middle Vaca Muerta with well design in the South-North direction. An additional horizontal well ($H_{z-5X}$) is suggested to target the section between the Lower and Middle Vaca Muerta. This section shows a good combination of the three zones (brown, orange and purple) that could make it an interesting unconventional reservoir to produce. The Thickness of this sections is between 22 to 25 meters.

Figure 5.10 shows an arbitrary line crossing through Well I in the direction West-East. The distribution of facies associated with brittle and occurrence of hydrocarbons increases toward the East. However, it is important to mention that upper section of Middle Vaca Muerta and the Upper Vaca Muerta show a predominance of facies with brittle rock and presence of hydrocarbons. That section could be considered prospective along the study area. In addition to that, the section between the Lower and Middle Vaca Muerta also has a constant presence in the study area, but with small variation in thickness and composition.
Figure 5.8: Arbitrary West-East line through Well G that shows the brittle zones with occurrence of hydrocarbons in the study area. An example of a prospective horizontal well shows the drilling direction in conventional reservoirs, which is the same orientation of the maximum horizontal stress ($S_{H_{\text{max}}}$).

Again, the light blue zone might behave as a conventional reservoir for the lack of hydrocarbon generation because of the low values of TOC (2 wt%). Horizontal wells should be drilled in the same direction of the maximum horizontal stress ($S_{H_{\text{max}}}$).

Having a rock that might behave as a conventional reservoir in the Upper Vaca Muerta, it is important to take into account that supplementary analysis would be necessary to identify the best reservoir zones. The analysis should use data from the Upper Vaca Muerta and the bottom of the Quintuco Formation prior to define the target zone and design the horizontal well. Natural fracture analysis will be a critical task to produce this zone. In this study, it is not clear the identification of the contact between the top of the Upper Vaca Muerta and the base of the Quintuco Formation. It is possible that some zones that are considered Upper Vaca Muerta in the study area are part of the bottom section of the Quintuco Formation. The upgrading carbonate content from the Upper Vaca Muerta to the Quintuco Formation,

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which vary depending of the position in the stratigraphic sequence, makes it difficult to differentiate the Upper Vaca Muerta.

Additional petrophysical analysis could help to identify the bed and laminae differentiation in an upgrading resolution to relate mineralogy composition and geomechanical response of the rock.

### 5.3 Summary

The prediction of reservoir properties allowed the identification and discrimination of zones with presence of hydrocarbon. Additionally, the mineralogy association in the Vaca Muerta Formation helped in the definition of zones with a good response to hydraulic stimulation based on TOC and carbonate content.

The integration of geomechanical parameters (Young’s modulus) and rock properties in the Vaca Muerta Formation was done using cluster analysis to define relationships which
discriminate brittle and ductile rock associated to the presence of hydrocarbon.

The Upper Vaca Muerta showed a predominance of brittle zones with TOC lower than 2 wt% which indicates that the TOC in the rock is not enough to generate hydrocarbon. In this case and taking into account the presence of natural fracture in the section, the upper section of the Upper Vaca Muerta might be considered a conventional reservoir like the Quintuco Formation with the Vaca Muerta Formation as source rock. In a minor occurrence, the contact between the Middle and Upper Vaca Muerta showed a few sections with TOC higher than 2 wt%, but continuing in low values. This illustrated a brittle rock with presence of hydrocarbon that behaves as an unconventional reservoir.

The Middle Vaca Muerta and the section between the Middle and Upper Vaca Muerta showed good zones of brittle rock with occurrence of hydrocarbon. The North-Eastern and South-Eastern zone of the study area are more ideal for completion plans than the zones located toward the Western zone of the area.
The Lower Vaca Muerta showed high ductility with high TOC and low carbonate content. The Upper Vaca Muerta showed high brittleness with low TOC and high carbonate content. This opposite relationship indicated that their characteristics make them poor reservoirs and need to be avoided for landing and completion plans.

The design of horizontal well in the rock that was identified as an unconventional reservoir should have the same direction of the minimum horizontal stress ($S_{Hmin}$), which is South-North. This allows the hydraulic fracture stimulation of the rock in the orientation of the maximum horizontal stress ($S_{Hmax}$), which is West-East. The rock that might be considered a conventional reservoir in the Upper Vaca Muerta should have a different well design for the landing and completion. Horizontal wells should be drilled in the same direction of the maximum horizontal stress ($S_{Hmin}$).
The lateral and vertical composition of the Vaca Muerta Formation are critical factors which control the geomechanical behavior of the rock. The presence of high carbonate content is correlated to brittle rock and the occurrence of high TOC is associated with ductile behavior of the rock. Other factors that could impact the geomechanical response of the rock would be natural fractures, pore pressure and stress. Integration of those three factors to the analysis performed in this study will lead to better understanding and a more accurate reservoir characterization of the Vaca Muerta Formation.

The Lower Vaca Muerta shows the highest organic matter carbon (TOC) associated with high presence of hydrocarbons. The Middle Vaca Muerta shows lower TOC and an upward increasing of carbonate content. The lower zone of Middle Vaca Muerta has a higher TOC and lower carbonate content presence compare with the middle and Upper zone of the section. The Upper Vaca Muerta showed the highest carbonate content and the lowest TOC in the section. It is considered that hydrocarbon generation in the Vaca Muerta Formation started with 2 wt% TOC (Sonnenberg, 2017), and the Upper Vaca Muerta has a predominance of TOC values lower that 2 wt% with few zones reaching 2.4 wt%. This indicates that the generation of hydrocarbons in that section is poor. Toward the North-Eastern and South-Eastern zones is observed a lower presence of TOC and an increasing of carbonate content compared with the Western zone of the study area which has the higher TOC trend. This geomorphological distribution of the composition of the shale describes the proximal and the beginning of the distal zones of the low angle platform in the Neuquén Basin.

Facies with characteristics observed in the Middle and Upper Vaca Muerta are associated with deposits that have higher frequency of gravity influence like carbonate debris flow, storm waves, slumps and turbidites. A low angle carbonate platform shows those deposits with
higher proportion of siliciclastic material due to the change generated by the flows. In addition, the upper section of the Middle Vaca Muerta represents a transition toward the shoreface with a reduction of TOC and increase of carbonate content which is exposed to storm waves. Several fields around the world have similar characteristics than the Vaca Muerta Formation. Some possible analogous shale plays in United States and around the world are:

- Wolfcamp Shale - Delaware Basin in Texas, US
- Barnett shale - Bend Arch-Forth Worth Basin in Texas, US
- Eagle Ford - Maverick Basin-East Texas Basin in Texas, US
- Utica Shale and Marcellus Shale - Appalachian Basin of Eastern North America, US
- Moroccan Jurassic and Devonian deposits - Tadla and Tindouf Basins
- Whitehill Shale - Karoo Basin in South Africa
- Horn River Shale - Horn River Basin in British Columbia, Canada
- Devonian reef complex - Canning Basin of Western Australia
- Qusaiba Shale, Diyab Shale and Shilaif Shale - Rub’ Al-Khali Basin, United Arab Emirates

The cluster analysis defined the zones with presence of hydrocarbon and brittle rock, which could have probable good response to hydraulic stimulation. That analysis showed that the section between the Lower and Middle Vaca Muerta has an interesting hydrocarbon potential. This section has an approximately thickness in the range of 23 to 25 meters, and consist of moderately high carbonate content and low TOC. It is also important to mention
that this zones is the deepest prospective section in the study area, which indicates the presence of high pressure that could be a plus for production purposes.

Horizontal wells have been more productive in several shale plays around the world. That efficiency is related to the ability of fracturing a longer section in the zones with hydrocarbon. This design of several stimulation zones in a horizontal well is called multi-stages, which allows producing continuously in the good zones.

Poisson’s ratio ($v$) was estimated from seismic inversion and Young’s modulus ($E$) was obtained using a combination of seismic inversion results and the prediction of the density using a probabilistic neural network. The $v$ did not show good relationships with rock properties and inversion results, and it was not able to define brittle and ductile rock. However, Young’s modulus ($E$) has good relationship with rock properties and elastic parameters from inversion results and was useful in the identification of brittle and ductile rock. The Upper Vaca Muerta shows brittle characteristics which is the opposite case with the ductile behavior of the Lower Vaca Muerta. The Middle Vaca Muerta shows a different mechanical behavior depends on the section. The lower section is more ductile but the middle and upper sections of the Middle Vaca Muerta are more brittle.

The relationship between rock properties and geomechanical parameters show that a high presence of TOC is associated with a ductile behavior in the rock. High carbonate content is associated with brittle characteristics in the reservoir. According to this relationship, the best production zones would be associated with a balance in the occurrence of brittle rock and a moderated presence of hydrocarbon. These zones were located toward the North-Eastern and South-Eastern of the study area. The Middle Vaca Muerta and a relatively thin section between the Middle and the Lower Vaca Muerta showed the best characteristics that would have rock with a good response to hydraulic stimulation and good hydrocarbon content.
6.1 Recommendations for future studies

This study established a work flow for the development of an isotropic model for geomechanical parameters based on dynamic Young’s modulus and Poisson’s ratio. Evolving from an isotropic model to a calibrated (core data - static moduli) anisotropic model would generate a more accurate model to help in the fracture design and to enhance the production results. The calibration with static moduli is needed in order to normalize and have more realistic values of Young’s modulus and Poisson’s ratio which usually shows that the dynamic geomechanical moduli values are higher than static moduli.

A new wide azimuth 3-D seismic data set has been acquire by Wintershall that could be useful in the future to perform anisotropic azimuthal seismic inversion, where more accurate elastic parameters would be obtained for further geomechanical properties calculations. Integration with rock physics analysis would lead to enhance the model suggested in this study. In addition to this, the anisotropic seismic inversion could be integrated with the anisotropic well analysis previously done by Barbosa (2017), which would help to calibrate the new model.

A 3C Multicomponent seismic data set was acquire by Wintershall that could be useful for the determination of shear and compressional waves, and their direction of propagation. The shear wave (S-wave) is sensitive to the Shear modulus of the rock and they have a response to change in the stiffness and strength. The S-wave provides great assistance to differentiate fluid-saturation based on lithological changes within the formation. In addition, the S-wave also has ability to image rock fracture density and orientation. The knowledge of the direction and density of fractures can be very important to succeed in the reservoir characterization.

A closure pressure analysis would generate a better fracture design. This new study can be done using well log data and also a different approach using volumes obtained from seismic inversion and density prediction. It would help to identify the pressure in the fracture and to define the proppant design to keep the fracture open without collapsing.
The integration of microseismic and rock physics analysis would identify the heterogeneity of the mineral composition which impact the microseismic events. In addition to this integration, a natural fractures analysis can be done performing the identification of fracture networks using seismic attributes to visualize their patterns and distribution in the Vaca Muerta Formation.

An integration of seismic analysis and well data would lead to identify overpressure zones within the Vaca Muerta Formation. Overpressure zones can be the most productive zones in the section, they can generate a negative impact during drilling where blowout, stuck pipe and caving can be observed.
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