

**EVALUATION OF STRUCTURAL DRIVEN
GEOTHERMAL SYSTEMS: A COMPREHENSIVE
GEOPHYSICAL ANALYSIS IN THAR PLATFORM,
SOUTHERN INDUS BASIN, PAKISTAN**



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DEDICATION

To my Loving Parents, Spouse and Muhammad Zohan

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ABSTRACT

Geothermal energy resources are a renewable energy source that is an emerging field worldwide. These resources are economically viable and environmentally sustainable. Geothermal energy potential exists in Pakistan; however, these resources have not yet been fully tapped due to a lack of research interest and proper methodology. The current study aims to determine the potential of geothermal energy in the subsurface by utilizing 2D and 3D seismic and well data to explore the geothermal potential of the sandstone reservoir in the Southern Indus Basin of Pakistan. The study area, Sanghar Block, lies in the Thar Platform. The major subsurface structures present in this area are horst and graben, which are considered perfect structure for the trapping of geothermal energy. The detailed studies are performed on the Lower Goru Formation, which is considered as major reservoir in the study area. Effective evaluation of geothermal reservoir characteristics from well and seismic data plays a fundamental role in harnessing subsurface geothermal resources. Facies identification was achieved using borehole data through artificial intelligence techniques, indicating that the key facies present in the Lower Goru Formation are shale and sandstone. As the shale containing naturally radioactive lithology have a radioactive element like U, Th and K, which are also considered a source of heat. It has been considered based on present studies that the existence of radioactive elements such as U, K, and Th in these facies is a dynamic source of heat in the subsurface. Geothermal reservoir properties such as average porosity, the volume of shale, heat production, radiogenic heat production, and permeability were computed from well logs and seismic data. A DFFNN was utilized to demonstrate the variation of geothermal reservoir characteristics along the seismic transect. In the DFFNN data is split into 70 % for training and 30% for testing purposes. The models are optimizing by using multiple hidden layers which control the over and underfitting of geothermal and petrophysical model parameters. The major function of DFFNN is to boost the incorporation of well and seismic data for geothermal reservoir characterization by estimating rock characteristics gained from model based seismic inversion. DFFNN technique achieved excellent correlation values from 85-98% for geothermal and petrophysics properties by utilizing multiple attributes while in traditional techniques which often suffer from poor resolution and high ambiguities when estimating these properties. The current research is innovative because of its amalgamation of machine learning and statistical methods, which permits the evaluation of geothermal properties (average porosity, the volume of shale, heat production, radiogenic heat production, and permeability) on seismic sections that are typically insights in the studied interval. The results of subsurface geothermal reservoir characteristics average values derived from logs curve data: average porosity (15.90%), volume of shale (33.80%), heat production ($0.933 \mu\text{W}/\text{m}^3$), radiogenic heat production ($1.20 \mu\text{W}/\text{m}^3$), and permeability (16.37 mD) are relatively promising which signifies that the present study zone is promising for geothermal potential. The quality control of seismic to well ties is confirmed by generating the relationship between synthetic seismogram, real seismic and time to depth chart, while the validation of facies prediction is confirmed by using well reports. The geothermal analysis is compared with published and international values for the validation of results Based on the current results, it has been determined that the innovative methods have enhanced prediction accuracy and minimized the ambiguity in geothermal characteristics, and this study has a positive impact on Pakistan renewable policy as it provides an alternate source of fossil fuel and coal and promote renewable energy target.

Key words: Geothermal Energy, Heat Production, Radiogenic Heat Production, Permeability, Machine Learning, Deep Feed Forward Neural Network.

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LIST OF ABBREVIATIONS

2D	-	Two-dimensional
3D	-	Three-dimensional
AI	-	Artificial intelligence
ANNs	-	Artificial Neural Networks
CDP	-	Common Depth Point
DFFNN	-	Deep Feed Forward Neural Network
DL	-	Deep Learning
DT	-	Sonic log
FT	-	Formation Temperature
GG	-	Geothermal Gradient
GHPL	-	Government Holdings Private Limited
GR	-	Gamma ray log
HP	-	Heat Production
IGR	-	Gamma Ray Index
K	-	Permeability
LFM	-	Low Frequency Model
LGF	-	Lower Goru Formation
LLD	-	Resistivity log
LOF	-	Local Outlier Factor
MAA	-	Multiattribute analysis
MALR	-	Multiattribute linear regression
MBSI	-	Model-based seismic inversion
ML	-	Machine Learning
MLFN	-	Multi-Layer Feed-forward Network
NPHI		Neutron Porosity
PHIA	-	Average Porosity
PNN	-	Probabilistic Neural Network
RHOB	-	Density log
RHP	-	Radiogenic Heat Production
SIB	-	Southern Indus Basin
SVM	-	One-Class Support Vector Machine
V _{shl}	-	Volume of Shale

LIST OF SYMBOLS

a	-	Lithological Constant
C_k	-	Concentration of Potassium
C_{Th}	-	Concentration of Thorium
C_u	-	Concentration of Uranium
F	-	Formation Factor
H	-	Integration Operator
M	-	Cementation Exponent
R	-	Reflectivity Series Data
S	-	Seismic Traces
T	-	Two-way Travel Time
V	-	Velocity
W	-	Wavelet extracted from seismic
Δt	-	Sonic Log
Δt_{fld}	-	Fluid Travel Time
Δt_{ma}	-	Matrix Travel Time
ρ	-	Density
ρ_b	-	Bulk Density
ρ_f	-	Fluid Density
ρ_m	-	Matrix Density
ϕ	-	Porosity

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Geothermal energy is a renewable resource that is independent of weather or sunlight. It is crucial in the global energy landscape. Its baseload production capability, near-continuous operation, and minimal carbon dioxide (CO₂) emissions make it a compelling choice for the present and future (Kolawole & Evenick, 2023; Norden et al., 2023). Factors such as growing energy demand, depleting hydrocarbon resources, and transitioning towards a clean energy future require utilizing and developing geothermal energy (Faulds et al., 2024; Kolawole & Evenick, 2023; Zimik et al., 2023). Three essential geological conditions that facilitate the development of geothermal resources within accessible depths are shallow crust heat, permeable reservoir rock, and circulating fluids. This combination is most common near seismically active tectonic settings, where dynamic processes generate heat and permeability (Arafa-Hamed et al., 2023; Mitjanas Coll, 2023; Norden et al., 2023).

However, high-temperature areas near volcanoes are traditionally favored for geothermal electricity generation, and other geological contexts offer diverse applications. Since ancient times, geothermal energy has been used for bathing and washing. This approach extends to various usages, involving cooling and heating functions, industrialization procedures, greenhouses, fish farming, and tourism. Different from electricity generation, these applications can utilize geothermal resources of various temperatures, making them far more widespread globally (Chen et al., 2023; Ngobidi, 2022; Soltani et al., 2019). Furthermore, direct usage can reduce support on external energy sources such as fossil fuels and provide a consistent energy supply independent of external factors (Dellerman, 2021; Hamza et al., 2022).

A geothermal reserve is basically defined as resources located beneath the earth where heat can be obtained cost-effectively at a minimal price compared to other energy resources like hydrocarbon. It is used for generating electricity and for various other agricultural, industrial, or domestic applications in the near future (Mirzaa et al., 2024; Soltani et al., 2022). The geothermal resources capture the heat energy in rocks and fluids that fill the pore spaces and fractures within the rock. Geological and geophysical datasets are most commonly used for the assessment of geothermal resources, such as

characteristics of rock within the formation, heat production (HP), average porosity (PHIA), temperature, and permeability (K) of the formation, thickness and depth of the formation to determine the geothermal area within the subsurface, and geochemistry of the geothermal reservoir. There is a difference between the geothermal reserves and resources, such as resources that are extracted economically based on the current price, while reserves are verified with the help of detailed reservoir analysis, like deeper drilling in the interested geothermal resource (Dellerman, 2021; Lund et al., 2011). Consequently, the major circumstances in assessing reserves are the price of drilling and the quality of the subsurface formation and its lithology (Anyia et al., 2025).

Radioactive elements such as Uranium (U), Potassium (K), and Thorium (Th) are considered the main source of generation of heat generation within the subsurface. The estimated heat within the Earth is approximately 1.3×10^{30} J. Heat is wasted from the subsurface with a mean rate of $8.5 \mu\text{W}/\text{m}^3$ (Anees et al., 2023; Dar et al., 2023). In most regions, this heat comes to the surface, so it is considered less economical to manipulate this huge heat reserve. The main concept of the heat movement in the subsurface is due to conduction and convection within the lithosphere. Rocks are comparatively bad conductors of heat (Clesi & Deguen, 2023). The geothermal thermal gradient is an increase in temperature within the Earth at a rate of $30 \text{ }^\circ\text{C}/\text{km}$ (Khan & Raza, 1986; Kolawole & Evenick, 2023). The temperatures several kilometers below the Earth's surface are only around $100 \text{ }^\circ\text{C}$ higher than the surface. Furthermore, power generators that operate at such low temperature differences have extremely low efficiency. Recent advances in binary-cycle geothermal plant technologies have enabled them to take advantage of moderate temperature resources at shallow depths for low to moderate power production (Dellerman, 2021; Mariita, 2009; Soltani et al., 2022). With recent advancements in drilling technology, it might already be cost-effective to drill deeper than 5 km and reach the required elevated temperature of 200 to $300 \text{ }^\circ\text{C}$. However, it is not enough to simply reach the hot rock. It is necessary to have sufficient pore space and fractures for the fluids to permeate and circulate in order to extract heat. Unfortunately, the K of the rock reduces due to an increase in depth and overburden. This causes a lot of regions to have hot rocks at depth, but the regions suffer from unsuitable geological conditions, and the current technological barriers make it economically unfeasible to extract geothermal energy (Singh et al., 2020).

There are some geological conditions where plate boundaries and the well on them such as inactive volcanoes associated with hotspot temperature, may be locally

shifted several kilometers into the subsurface due to convection by molten rocks. These rocks have temperatures in the vicinity of 1,000 °C and act together with the surrounding rocks, initiating surficial appearances of geothermal phenomena, for example, geysers and hot springs (Dellerman, 2021; Kazaz & Abu-Nada, 2025; Singh et al., 2020). There are some other geological conditions that capture heat, creating a heat resource. In such zones, temperatures lie between 200 to 300 °C when drilling is made up to several meters, and these areas are considered appropriate for utilizing geothermal energy. The most important geothermal fields of the Earth exploit such conditions (Korucan et al., 2024).

In the current study, log curves and seismic data were utilized for geothermal assessment. Petrophysical analysis involves the examination of the physical and chemical properties of rocks and sediments, particularly their ability to store and transport fluids. This analysis plays a crucial role in the exploration and production of geothermal reservoirs. It involves utilizing various types of data, such as well logs (including resistivity, porosity, and sonic logs), core data, seismic data, and other relevant information to comprehend the physical properties of rocks and the distribution of fluids within them (Ali et al., 2021). The petrophysical analysis aims to assess the geothermal potential and fluid flow properties of subsurface rocks (Ali et al., 2019; Amigun et al., 2012). Petrophysical analysis can be broadly classified into two types including: conventional and unconventional methods. Conventional petrophysical analysis is a traditional approach that evaluates the physical and chemical properties of subsurface rocks to assess their ability to store heat and transmit fluids, particularly in geothermal reservoirs. On the other hand, machine learning (ML) based petrophysical analysis is used to evaluate the physical and chemical properties of subsurface facies (Naseer et al., 2025a; Naseer et al., 2025b). ML-based petrophysical and facies analysis is typically applied to lithology that encounters shale and tight sand (Muther et al., 2022; Naseer et al., 2025c).

In geothermal resources, seismic interpretation techniques provided more detailed subsurface descriptions with better resolution. Prior geothermal analysis is built on seismic data, which holds various examples of stratigraphic and structural mapping of geothermal fields (Priezzhev et al., 2019). Additionally, attribute analysis based on seismic data provides information on the recognition and description of extreme K fractured zones. Conventional seismic interpretation techniques were developed decades ago for exploration plays to describe the reservoir (Abbasi et al., 2015). Nowadays, the oil industry is focused on exploring renewable energy resources and developing more

progress toward geothermal reservoirs. The traditional seismic characterization techniques show limitations in such scenarios; hence, advanced research and development methods are considered for better geothermal reservoir understanding (Qureshi et al., 2021)

However, seismic inversion analysis has become an essential tool, still employed in seismic reflectivity inversion and interpretation. The multiplication of density and acoustic velocity is commonly referred to as acoustic impedance, and it is closely related to various rock parameters (Sams & Carter, 2017). Unlike seismic reflectivity, which occurs at the intersections of different strata, acoustic impedance takes on consistent values within rock layers, providing a simple and clear link with geology and stratigraphy, but has a temporal limit, whereas the corresponding wells in the vicinity allow for the injection of higher resolution data with limited spatial coverage (Pendrel, 2006; Russell & Hampson, 1991). Therefore, integrating seismic and well data is crucial for establishing an elastic relationship to enhance geothermal reservoir characterization. The density, P-wave velocity (V_p), and S-wave velocity (V_s) of the Earth's subsurface, which determine its elastic characteristics, are often modeled using an inversion approach (Moncayo et al., 2012; Morozov & Ma, 2009). However, this simple technique requires extensive computational power and time to resolve heat capture within complex geological settings. The use of advanced ML techniques can assist in addressing the difficulties required in characterizing geothermal reservoirs. Hence, in the present era, industries are rapidly adopting ML-based solutions to help characterize (Maurya et al., 2020; Reading et al., 2015).

The types of ML systems are classified based on the amount of supervision with which they are trained, including supervised, unsupervised, and semi-supervised learning. In supervised learning, the algorithm is trained on a set of labelled data to generate a function that can map inputs to target variables. Examples of algorithms in this category include linear regression, K-nearest neighbors, and random forest (RF) (Farsi et al., 2021; Géron, 2022). In unsupervised learning, the training data is completely unlabeled, and the goal is to identify natural groupings within the dataset, such as those achieved through K-means or hierarchical clustering. (Alloghani et al., 2020). Semi-supervised learning deals with partially labelled data, where the amount of unlabeled data is significantly greater than the amount of labelled data (Erofeev et al., 2019). Clustering strategies are typically employed with limited guidance, and some techniques, such as deep belief networks, combine supervised and unsupervised algorithms (Liu, 2017).

However, this simple technique requires extensive computational power and time to resolve reservoirs deposited within complex geological settings. Advanced ML algorithms have emerged as an efficient means of addressing these complexities. As a result, the oil and gas industry has increasingly turned to ML based solutions to characterize complex reservoirs (Huang et al., 2017).

Deep Learning (DL) is a branch of Artificial Intelligence (AI) that employs Deep Feedforward Neural Network (DFFNN) and Probabilistic Neural Network (PNN), featuring multiple layers to discover intricate patterns and correlations within datasets. It works on nonlinear regression techniques, which performs excellent in complicated geological data than the linear regression approach. It allows multiple attribute analysis which provides a better result for properties and facies prediction. DFFNN used high-dimensional input data and provided excellent convergence with minimum error. This model beat the conventional algorithms because of its high accuracy of prediction with minimum uncertainty, specifically with inadequate and noisy data. In geophysics, DL is useful in a variety of applications, particularly in seismic and well data analysis (Wang et al., 2023). Seismic data, which is collected through the study of seismic waves, can be used to create subsurface images of geological structures and is a crucial tool for the exploration and production of fluids. Applications of DL algorithms include improving the resolution of seismic images and enhancing their interpretation. In well data analysis, DL is used to analyze logs, core data, and other well measurements to better understand the subsurface geology and make more informed decisions about drilling and production (Zhang & Zhan, 2017).

1.2 Research Area

This study focuses on the Thar Platform, which is a sub-basin within the Southern Indus Basin (SIB). The Indian Shield geologically delineates the SIB on the eastern side and the Indian plate on its western margin. The southern extent of this is limited to the offshore Murray Ridge/Owen Fracture zone (Uddin et al., 2021). The Thar Platform exhibits a gentle monocline slope analogous to the Punjab Platform. The underlying basement topography primarily controls this slope. Notably, the thin sedimentary wedge progressively near the Indian Shield, whose outward appearance manifests as Nagar Parkar High (Shah et al., 2021; Younas et al., 2016). A key distinction between the Thar Platform and the Punjab Platform lies in the presence of buried structures resulting from

extensional tectonics, as shown in Figure 1.1. These structures are credited to the counterclockwise movement of the Indian Shield. In the west, the platform eventually merges with the Kirthar and Karachi Trough and is surrounded by the Mari-Bugti Inner Folded Zone in the north. It is noteworthy that the Thar Platform displays a remarkable development of early-to-middle Cretaceous reservoirs, making it a geologically significant area for further exploration and potential resource development (Rasool et al., 2018).

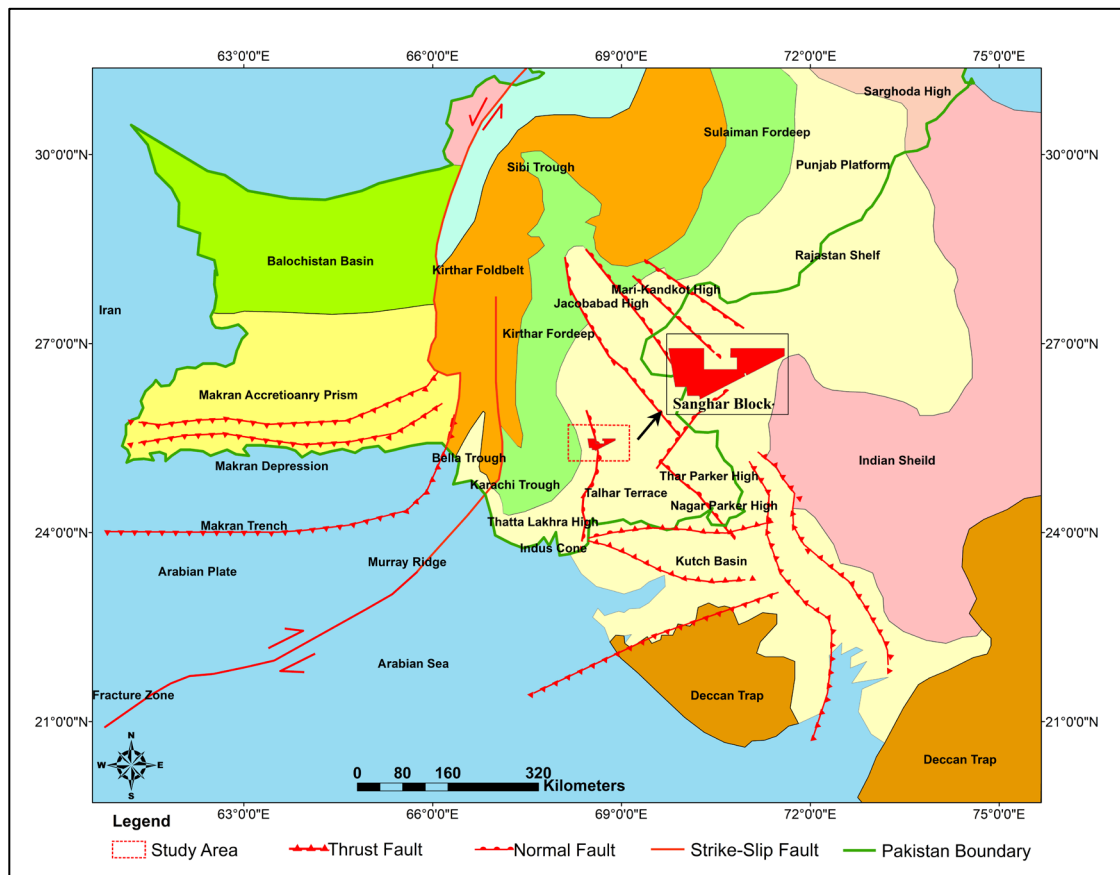


Figure 1.1 Location map of the study area with highlighted Sanghar Block and its surrounding region. Red represents the area of interest, and the three blocks of interest, 3D Nim Tay Block, Sanghar Block-1, and Sanghar Block-2, are present in this region (Ahmed & Khan 2011).

1.3 Significance of Study

Evaluating the Thar Platform's SIB geothermal potential is crucial for Pakistan's environmental sustainability, energy security, and regional development. Adding variety to the energy mix of Pakistan is susceptible to price swings and energy instability due to its significant dependence on imported fossil fuels. Geothermal energy encourages sustainability and diversity by providing a sustainable, local, and renewable alternative.

By 2030, Pakistan's energy consumption is expected to double. The Thar Platform geothermal resources easily meet the sustainability and economic development of foster. Geothermal energy production can assist national efforts to prevent climate change by reducing reliance on fossil fuels and associated greenhouse gas emissions. South Asia's energy independence can be increased using the region's geothermal assets, such as the Thar Platform. This will lessen the region's reliance on imports of petroleum fuels and foster global energy integration.

Clean, sustainable energy resources with no harmful effects of geothermal energy on the environment. Compared with hydrocarbon created power production, its use may lessen the consequences of climate change, reduce water pollution, and enhance air quality. By examining the geothermal capabilities of the Thar Platform, scientific knowledge and research techniques can be advanced, and the geological background and geothermal procedures occurring in the area can be better understood. Pakistan has the potential to lead the way in geothermal studies and advancement in the region and impart its knowledge and skills to other nations dealing with comparable energy related issues (Jarwar et al., 2023).

The Cretaceous reservoir has potential for geothermal resources and is not considered a primary energy source within the Thar Platform. The major focus of geophysicists in our country is on hydrocarbon exploration. Therefore, this study is mandatory to explore geothermal energy sources across the region. In past studies, data acquisition, exploration, and development within the Thar Platform have focused on the primary reservoir of interest in hydrocarbons. Some localized studies within a block segment have been carried out individually by companies. However, efforts to evaluate regional geothermal reservoirs are missing, and this study needs to address this lag. Not only is this beneficial to the energy sector, but it will also have a direct impact on national interest and the economy.

Whereas, based on the advancements in the field of AL and ML in relation to geothermal exploration, the focus of this research shall be to address and resolve the problem with the help of available ML advanced algorithms, based on the quality of the results obtained. This will save time and increase the quality and efficiency of the work. This has not been done in Pakistan for geothermal potential exploration at any given level. Moreover, once this study has been successfully accomplished and delivered, the same concept and approach can be implemented in other geological basins in Pakistan with geothermal potential. This study will help exploit untapped regions and exponentially

increase the capacity of renewable energy resources for regions using the most advanced sustainable solutions.

1.4 Research Rational

In the present era, ML has become popular for estimation of geothermal reservoir properties because it is efficient, less time consuming and less expensive. Big datasets of wells and seismic data could be utilized to train ML procedures to uncover patterns and relationships that would be challenging or difficult to identify using conventional techniques. ML makes better precision and clarity by minimizing ambiguity even when the input datasets are imperfect or noisy. The conventional approach is lengthier and takes a lot of time; it is mostly enjoyed on pre stack seismic data to finish the technique, whereas post stack seismic data has done the same work thoroughly. Similarly, this simple and comprehensive methodology can be useful for geothermal reservoirs, which face similar challenges worldwide.

The current research differs from previous geothermal studies in Pakistan, which focused on an abandoned well study and a theoretical framework. In comparison, this research integrates seismic and well data with ML algorithms like DFFNN to evaluate geothermal potential. The innovative techniques include estimating geothermal and petrophysics properties, conducting model-based inversion analysis and predicting facies on LGF for identify of geothermal spots. Moreover, this is a novel application of neural networks models for geothermal estimation on the Thar platform, making the workflow more accurate, predictive, and robotic than traditional method.

1.5 Problem Statement

In the contemporary era, sustainable alternative energy sources have become widely adopted globally. However, in Pakistan, geothermal energy remains an untapped and underexplored resource. Structural features within the Cretaceous strata of the SIB, Pakistan, significantly influence the potential for a commercially viable structurally controlled geothermal reservoir. The Cretaceous strata exhibit distinctive rock formations and sedimentary layers, which may provide valuable insights into the geothermal activity as witnessed in the literature survey of the region. Examining structurally controlled geothermal systems entails investigating how geological features, including faults, fractures, and folds, impact the development and distribution of geothermal reservoirs.

1.6 Research Question

The primary energy supply of Pakistan majorly relies on conventional energy resources, and the renewable energy resources are extremely limited. The need of the hour is to increase renewable energy resources in order to meet energy requirements, as well as go green and reduce CO₂ and greenhouse gas emissions. The previous geothermal studies have focused on abandoned well analysis or theoretical review of geothermal resources. The present study is based on geophysical data for the assessment of geothermal potential. This study presents a thorough understanding of different reservoir parameters such as PHIA, K, bottom hole temperature, formation pressure, and predicts missing data sets through state-of-the-art ML approaches in Thar Platform, SIB, Pakistan.

1.7 Data Used

The data utilized in the research work consisted of well logs and seismic data obtained from the Directorate General of Petroleum Concession (DGPC). The 3D seismic data of Nim Tay Block, (15 km²) and 2D data of Sanghar blocks that is divided in two sub block Sanghar Block-1 which include Sono-2 and Sono-5 wells and four seismic dip line and one strike line and Sanghar Block-2 comprise of 20 seismic line from which six are strike line and remaining fourteen are dip line is integrated with eight wells lying within this seismic data for structural mapping and stratigraphic distribution of properties. The three wells are located on the Nim Tay Block, and five wells are located in the Sanghar Block. There are three types of wells that are present in the study area: six wells out of ten are exploratory, two wells are appraisal, and the remaining two are development wells. While in seismic data, the orientation of 2D seismic dip line is west to east, while the strike line is north to south. Tables 1.1 & 1.2 show the seismic data and names of wells used in studies.

Table 1.1: Details of well data utilized for the study.

Well Name	Longitude	Latitude	Well Type
Tando Allah Yar-1	68.74356111° E	25.42441944° N	Exploratory
Tando Allah Yar-2	68.74710833° E	25.41579166° N	Appraisal
Tando Allah Yar-3	68.74196666° E	25.43404722° N	Appraisal

Bukerani-1	68.71006400° E	25.37916400° N	Exploratory
Jarwar-1	68.80984893° E	25.39830959° N	Exploratory
Babar-1	68.45965672° E	25.39393376° N	Exploratory
Allah Dino-1	68.49918550° E	25.54944841° N	Exploratory
Jumman Shah-1	68.73079444° E	25.47576388° N	Exploratory
Sono-2	68.55249166° E	25.26001944° N	Development
Sono-5	68.55519166° E	25.24252222° N	Development

Table 1.2: Details of seismic data that are utilized to fulfill geothermal potential evaluation.

3D Seismic Data		
3D post-stack seismic data of Nim Tay covering the area of 15 km ²		
2D Seismic Data		
Sanghar Block-1		
Line Name	Orientation	Line type
G862-SGR-140	West to East	Dip Line
G862-SGR-161	West to East	Dip Line
G862-SGR-162	West to East	Dip Line
G862-SGR-163	West to East	Dip Line
GO-872-SGR-510	North to South	Strike Line
Sanghar Block-2		
G862-SGR-102Ext	West to East	Dip Line
G862-SGR-103Ext	West to East	Dip Line
G862-SGR-142	West to East	Dip Line
G862-SGR-142Ext	West to East	Dip Line
G862-SGR-143	West to East	Dip Line
G862-SGR-145	West to East	Dip Line
GO-832-SGR-26	West to East	Dip Line
GO-832-SGR-29	West to East	Dip Line
G0-872-SGR-170	West to East	Dip Line
G0-872-SGR-170A	West to East	Dip Line
G0-872-SGR-171	West to East	Dip Line

G0-872-SGR-171A	West to East	Dip Line
G0-872-SGR-197	West to East	Dip Line
G0-872-SGR-518	West to East	Dip Line
G947-SGR-168S	North to South	Strike Line
G862-SGR-153	North to South	Strike Line
G862-SGR-154	North to South	Strike Line
G862-SGR-157	North to South	Strike Line
G862-SGR-176	North to South	Strike Line
GO-832-SGR-27	North to South	Strike Line

1.8 Research Objectives

Based on the research question to study the geothermal prospect of the Thar Platform, the following objectives are formulated:

1. To characterize subsurface structural compartments and surface geological features in a seismic area for geothermal anomaly detection.
2. To evaluate the geothermal potential of Cretaceous-age strata for a better understanding of geothermal systems.
3. To perform an in-depth facies analysis of potential geothermal formations through conventional reservoir modeling enhanced by advanced machine learning techniques, aiming to accurately delineate favorable geothermal hotspots.

1.9 Research Outline

Chapter one serves as an introduction with a primary focus on assessing geothermal energy in the Sanghar Block located on the Thar Platform of LIB. The chapter highlights the growing demand for renewable and sustainable energy sources, with geothermal energy considered an untapped alternative. It describes the favorable subsurface structures, such as normal faults with horst and graben geometry, which have the potential to trap geothermal energy. The chapter also outlines research objectives aimed at assessing geothermal resources by utilizing seismic and well data combined with ML techniques to identify promising geothermal sites. Additionally, it emphasizes the importance of advanced methods like DFFNN and ML and discusses their advantages over traditional techniques.

The second chapter provides a detailed review of existing research on geothermal resource techniques both regionally and globally. It begins with an explanation of core

geothermal concepts such as HP, GG, heat generation phenomena, and the differences between geothermal reserves and resources. This chapter also includes a literature review related to geology, tectonics, and sedimentary basins, which helps identify gaps in current studies, particularly in the Thar platform. Additionally, it covers interesting formations like LGF. The chapter concludes by emphasizing the need for diverse techniques, such as combining well logs, seismic data, and machine learning approaches, to enhance geothermal potential subsurface analysis. The methodology is detailed in Chapter 3, discussing seismic 2D and 3D data, as well as log sources used in the studies. It involves the structural interpretation of the subsurface using seismic and well data, followed by the estimation of geothermal and petrophysical properties. The next section describes model-based seismic inversion for identifying impedance in the study area. The chapter also covers the application of DFFNN after inversion results. Finally, it explains the methodology of machine learning-based facies prediction in detail, along with corresponding graphical abstracts.

Chapter 4 shows the result of the objective that is achieved during analysis. The primary objective of the study is to determine the accurate subsurface structure. The structure interpretation is performed on the three seismic blocks, in which one is 3D seismic Nim Tay Block, the other is Sanghar Block-1 and 2. Thar Platform is mostly affected by extension forces, due to which normal faults are present in the subsurface, and these faults are an ideal trapping geometry for a geothermal reservoir. The second objective of the research is to identify the geothermal properties for the LGF. Ten wells are utilized for this purpose, and the major properties vital for geothermal characterization are K, PHIA, HP, formation temperature (FT), geothermal gradient (GG), radiogenic heat production (RHP), and shale volume (Vshl). Furthermore, model based seismic inversion was initially performed to generate the impedance section by removing the effect of the wavelet. Calibrated geothermal properties curves from well data are utilized to train the seismic attributes for pressure prediction using geostatistical and Artificial Neural Network (ANN) analysis. These impedance sections, along with the original seismic trace and the calculated geothermal properties curve from well, are used to train the seismic attributes using the Multattribute Analysis (MAA) approach. After achieving maximum correlation, predicted properties through DFFNN are then applied to the whole seismic dataset to generate sections. Chapter 5 provides comprehensive discussion of the results and compares the findings with worldwide geothermal assessment.

CHAPTER 2

LITERATURE REVIEW

Approximately 4.56 billion years ago, the Earth was formed, attributed to the accretion of hot gas and cloud dust. This initial heat and gravitational differentiation yielded a molten core and a near-solidus mantle. The subsequent core separation by gravitational settling emits significant heat, driving a continuous dissipation process through the Earth's surface (Clesi & Deguen, 2023; Wilczyński et al., 2023). While primordial heat contributes to this ongoing heat loss, radiogenic sources comprise 83 % of ground heat flow within the mantle and crust. Notably, across the radioactive decay of U, Th, and K, the crust produces around 40 % of the observed flow (Clesi & Deguen, 2023). Heat transfer within the Earth occurs primarily through mantle convection, crustal conduction, and advection. Nevertheless, this surface flow is not constant, with heat loss through the oceans typically being higher than that through the continental shields. At depth, accurate temperature measurements prove challenging without extrapolation to the surface (Prater, 2023). Establishing the upper crust's thermal gradient requires estimating mean ground temperature, which varies considerably from sub-zero polar regions to tropical areas exceeding 30 °C. Notably, the inner core's temperature reaches around 7,000 °C, contrasting with the average surface temperature of 15 °C. The geothermal gradient is the primary measurement used in the geothermal investigation (Kolawole & Evenick, 2023).

The Earth's thermal regime, characterized by a total surface heat flow of 47 ± 2 TW, underpins the viability of geothermal energy (Lucazeau, 2019). At the surface, this translates to an average heat flow density of 0.092 W/m² and a corresponding geothermal gradient of 35 °C/km (Davies et al., 2019). This internal heat is primarily generated by radiogenic decay within rocks, notably through the isotopes of thorium (²³²Th), potassium (⁴⁰K) and uranium (²³⁸U). The energy released in the decay process is absorbed by surrounding rocks, contributing to the Earth's thermal budget. The rate of this heat generation depends on the abundance and decay characteristics of these radioactive isotopes (Coşkun & Çetin, 2016).

Thermal transport within the Earth primarily occurs through mantle convection, while conduction dominates heat transmission across the crust. Consequently, resulting geothermal gradients and heat flow exhibit remarkable spatial variations. Higher heat

flow values are observed in regions with significant RHP or thinner crusts, such as the basin and mid-oceanic ridges in the western United States (Pussak, 2014). Its correlation with geologic age and tectonic activity suggests that younger, more active regions tend to be hotter. Notably, exceptionally high heat flow values cannot be solely attributed to crustal HP, implying hotter-than-normal mantle conditions beneath such regions (Zarrouk & Moon, 2014). In general, the thermal state of the lithosphere mirrors that of the underlying asthenosphere, exhibiting thermal coherence (Mariita, 2009). Thus, continental crust regions showcase mean ground heat flow values of approximately $5.9 \mu\text{W}/\text{m}^2$ (Norden et al., 2023), subject to variations arising from localized factors like radioactivity, crustal thickness, and water advection (Clesi & Deguen, 2023).

This dynamic heat flow serves as the driving force behind geothermal energy, enabling continuous power generation from the Earth's internal heat. On average, the temperature of the earth rises at approximately $30 \text{ }^\circ\text{C}/\text{km}$. This implies that, supposing an average surface temperature and a conductive thermal gradient, the interior of Earth reaches well over $300 \text{ }^\circ\text{C}$ at a level of just 10 km (Lund et al., 2011). This significant temperature rise with depth underscores the vast thermal potential for geothermal energy utilization. Geothermal resource development and exploration can reveal their potential for clean and efficient energy production, direct heat application across diverse industries, and the deployment of environmentally friendly heating and cooling systems. This focuses on the advantages of using geothermal energy from an economic and environmental standpoint.

2.1 Geothermal Power Production

For electricity generation, geothermal energy utilization necessitates high-temperature resources exceeding $150 \text{ }^\circ\text{C}$ (Alhamid et al., 2016). It is possible to transform this thermal energy into mechanical energy. Driving turbines and generating electricity through established steam power plant technologies. Direct steam, flash, binary plant, and enhanced geothermal systems are the categories for power generation.

a) Direct Steam: This method utilizes high-temperature steam directly from production wells for maximum efficiency but is the rarest due to its dependence on exceptionally hot geothermal resources. The steam is processed to remove impurities and then drives turbines for electricity production (Rajaković-Ognjanović et al., 2011).

- b) **Flash Steam:** More prevalent than direct steam, this method utilizes pressurized hot water transported from production wells. As pressure decreases during transport, a portion of the water explosively boils (flashes) into steam, driving turbines for electricity generation. The remaining water is reinjected to maintain reservoir pressure and productivity (Mariita, 2009).
- c) **Binary Cycle:** With the help of a heat exchanger, hot water is pumped through a secondary working fluid with a lower boiling point than water to transfer heat. This backup liquid evaporates and propels turbines for electricity generation before condensing into a liquid and returning to the heat exchanger for the cycle to repeat (Clesi & Deguen, 2023).
- d) **Enhanced Geothermal Systems:** This method aims to obtain heat from resources with insufficient natural K by creating subsurface fracture systems through water injections. EGS improves the rock's K, allowing injected water to be heated and, through production wells, returned to the surface, which is related to naturally occurring hydrothermal systems. EGS technology offers potential for resource development in areas with limited natural K or water availability (Schulte, 2022).
- e) **Ground-Source Heat Pumps:** Ground-source heat pumps represent a highly versatile application of geothermal energy, utilizing ambient ground temperatures (typically 40 to 80 °C) to achieve both heating and cooling in buildings (Ngobidi, 2022). These electric heat pumps operate on a simple principle:
 - i. **Heating:** During winter, by transferring heat from the comparatively warmer ground to the inner air of the building, GHPs successfully maintain acceptable temperatures.
 - ii. **Cooling:** In summer, the process reverses, transferring heat from the indoor air to the cooler ground, providing efficient and sustainable air conditioning.

Based on the current research, the major focus of geothermal resources is on the ground source heat pump and enhanced geothermal system.

2.2 Geothermal Potential of Pakistan

Pakistan's economic development requires a consistently reliable energy supply, as the country is viewing a surge in industrialization, urbanization, and population growth that is driving up energy demand. Unfortunately, developing nations such as Pakistan are encountering significant obstacles in meeting their enormous energy demand (Ali et al.,

2016) and have to bear the expense of importing energy to meet the demand (Fridleifsson, 2001; Guo et al., 2011). Pakistan is facing challenges in managing supply and demand in the power sector due to the aforementioned causes (Asif, 2009; Mirza et al., 2008). The exorbitant cost of traditional fuel sources has compelled policymakers to shift towards renewable sources. Among numerous categories of renewable resources, such as solar power and wind energy, utilizing geothermal resources remains a significant challenge for Pakistan. In the past few decades, there has been a lack of focus on conducting feasibility studies, generating reports, and analyzing data related to geothermal power plants (Ahmad, 2014).

Pakistan's economic progress correlates with the reported per capita energy consumption. The world's top ten countries that consume energy per capita are mentioned in Table 2.1, and countries in Southeast Asian are shown in Table 2.2. It has been forecasted that the energy demand will continue to rise. However, conventional energy sources are depleting gradually, increasing their prices, and becoming a major contributor to environmental emissions (Raza et al., 2015). Conventional energy sources release harmful emissions into the environment, such as CO₂, SO_x, and NO_x where x is a number represented as 2, 3 and 4. Hydrocarbon and coal reserves are depleted, so renewable sources are considered the most promising resolution for power generation of the upcoming era. Due to their low emissions and environmental friendliness, alternative energy sources, including biogas, wind, geothermal, and solar, are good substitutes for fossil fuels in the face of rising energy consumption. Energy demand is expected to rise by 2% per year, but the potential of green energy production is growing at a pace of 5.2% per year, which is more than double the consumption rate. Thus, maintaining energy supply and demand is best achieved through renewable resources (Younas et al., 2016).

Pakistan possesses a diverse and abundant portfolio of renewable energy resources, nurtured by its unique geographical and climatic characteristics. These resources, including sunlight, water, wind, ocean tides, and biomass, offer sustainable and replenishable alternatives to conventional fossil fuels (Jarwar et al., 2023). Sindh boasts a 1,000 km coastline, which is responsible for the constant ocean tides. In contrast, Punjab represents considerably high solar irradiance, and the Khyber Pakhtunkhwa (KP) has a high potential for wind power (Sheikh et al., 2013). In addition, the country experiences a mean wind speed of 5 to 7 m/s, which portrays the guaranteed capability accorded by wind power (Kazmi & Sheikh, 2019). Even though there are many options for sustainable resources, geothermal energy presents an extremely positive outlook for

Pakistan. While currently comprising only 2% of the national renewable energy generation, geothermal surveys indicate a staggering potential of 240 GW of electrical energy production (Pazheri, 2015; Zarrouk & Moon, 2014). This untapped potential surpasses all other renewable resources in the country and warrants further exploration and development.

Interestingly, despite this immense potential, geothermal energy research in Pakistan remains considerably limited, accounting for only 4% of all research on alternative energy sources like renewable energy (Shah & Solangi, 2019). This highlights the need for amplified study and progress efforts to unlock the immense potential of geothermal energy in Pakistan's renewable energy mix. Ahmad (2018) asserted that wind and solar energy possess alternating characteristics and are relatively costly, requiring intricate control schemes for effective integration into the grid, in contrast to geothermal energy. Geologists affirm through structural studies that Pakistan is situated at the intersection of tectonic plates, thereby possessing abundant geothermal reservoirs spanning low, medium, and feverish temperatures, which could significantly bolster the country's energy sector.

Globally, there is an increasing emphasis on harnessing geothermal energy, as evidenced by the installed capacity worldwide in 2015 (Soltani et al., 2019). Regrettably, Pakistan lacks operational geothermal power plants (Younas et al., 2016). As such, of all the renewable energy sources mentioned above, geothermal energy is still the least used in Pakistan to produce power. The warm waters and the solid rock framework inside the small pore spaces of a geothermal region or reservoir serve as heat sinks (Singh et al., 2020). These reservoirs are usually found in tectonically active zones or areas with strong geothermal gradients (Tiwari et al., 2022).

There are three essential parts that comprise of a typical geothermal area include heat chamber, a reservoir and a fluid matrix that moves heat from geothermal sources into the earth's outermost layer. The liquid geochemistry of each geothermal source displays distinct features (Tiwari et al., 2022). These chemical discharge fluid rate and temperature determine the possibility of using geothermal energy. The amount of heat of the liquid, which serves as a conductor of heat from the deeply heated bedrock to the surface, is used to classify geothermal deposits. The temperature describes the heat concentration of a liquid and is intricately linked to temperature. In general, there are three types of geothermal resources named as high-enthalpy, greater than 225 °C,

medium-enthalpy between 80 to 225 °C, and low- enthalpy less than 80 °C (Alhamid et al., 2016).

Utilizing the natural heat of the Earth, geothermal energy offers a convincing substitute for fossil fuels. It provides dependable capacity and ecologically friendly electricity generation as its primary advantages. Geothermal projects minimize their negative environmental effects and reduce reliance on imported fuels by using a locally available and renewable resource, in contrast with traditional power plants. In addition, regardless of the weather, hydrothermal power plants have high capacity factors and can consistently produce electricity (Alhamid et al., 2016). It is imperative to recognize the possible obstacles linked to geothermal energy generation. The possible discharge of geogenic gases naturally found deep under the earth, some of which can be hazardous if treated improperly, is one cause for concern. Adopting appropriate mitigation techniques to address these emissions is essential for geothermal energy's secure and accountable growth (Dellerman, 2021). Geothermal energy offers much more than traditional power sources when used with the right technology and laws. Its clean, dependable, and renewable qualities make it an invaluable tool for shifting to environmentally friendly power. However, ethical and efficient use of this resource still requires careful assessment of any potential environmental risks.

Table 2.1: Energy consumption of the world's top ten countries (Sharmin et al., 2023).

Country	Oil	Natural Gas	Coal	Nuclear Energy	Hydroelectricity	Renewables
	Measured in Terawatt-hour					
Canada	1055.4	4.29	0.48	0.83	3.59	0.58
US	922.4	29.76	10.57	7.40	2.43	7.48
France	2.91	1.55	0.23	3.43	0.55	0.74
Germany	443.8	3.26	2.12	0.62	0.18	2028
China	139.9	13.63	86.17	3.68	12.25	11.32
Russia	383.6	4080.45	887.35	223.41	197.41	538.561
Japan	484.4	1004.98	1365.52	51.77	74.88	620.23
Saudia Arabia	1514.8	1203.57	1.279	5.31	18.29	34.60
South Korea	778.4	619.28	798.562	168.58	3.55	152.30
Singapore	3642.0	130.59	4.81	2.147	2.22	6.57
Brazil	4.46	1.46	0.71	0.13	3.42	2.39

Table 2.2: The energy mix of the South Asian countries (unit Terawatt-hour) (Sharmin et al., 2023).

Country	Oil	Natural Gas	Coal	Nuclear Energy	Hydroelectricity	Renewables
	Measured in Terawatt-hour					
Afghanistan	3.242	15	112.5	0.7	0.62	17.448
Bangladesh	152.8	291.98	49.94	8.188	0.97	3.761
Bhutan	1.92	0.523	0.16	2.5	9	5.49
Maldives	0.01	0.34	0.39	0.01	0.43	2.4
India	2791	581.83	5581	46.19	174.92	1053.02
Pakistan	275.1	383.85	177.1	22.43	36.41	108.67
Nepal	0.71	2.223	0.7	0.16	6	0.347
Sri Lanka	55.15	0.738	16.95	1.46	7.125	22.812

Pakistan began exploring geothermal energy in 1975. During the early 1980s and 1990s, the Geological Survey of Pakistan (GSP) conducted extensive surveys, leading to the discovery of numerous thermal springs, documented by Ahmad (2014). Bakht (2000) presented a comprehensive overview of Pakistan's geothermal resources at the World Geothermal Congress. Despite these promising findings, Pakistan's national energy plan for 2009 to 2022 lacked clarity regarding the possibilities of geothermal sources. Zaigham et al. (2009) later emphasized the geological potential for developing Hot Dry Rock (HDR) geothermal energy, particularly near urban and industrial centers lacking surface thermal manifestations like hot springs. They emphasized the probability of HDR geothermal for delivering sustainable, CO₂-free energy. This was followed by Shah and Solangi (2019) investigation of the Himalayan, Karakorum, and Hindukush geology. Notably, analysis of the biological features of geothermal fluid in Pakistan's northern region revealed promising reservoir temperatures exceeding 150 °C, prompting further exploration for potential electricity generation. While an appearance of interest for a geothermal potential source at the Parliament House was issued in 2009, concrete action in this area remains limited (Salam et al., 2020).

2.3 Geothermal Energy Zone of Pakistan

The classification of Pakistan's geothermal energy resources is determined by their occurrence in distinct tectonic zones. It is based on thermometry and modes of occurrence, including the distribution in sedimentary basins (Gondal et al., 2017). The geothermal energy resources in Pakistan can be categorized into three zones firstly, the Himalayan Karakoram Hindu Kush area, secondly, the sedimentary basins of Pakistan, and at last the Chagai Volcanic Arc of Baluchistan as shown in Figure 2.1. The details studies of Geothermal energy that has been done in past is discussed in Table 2.3 along with the techniques and work done by different scientist.

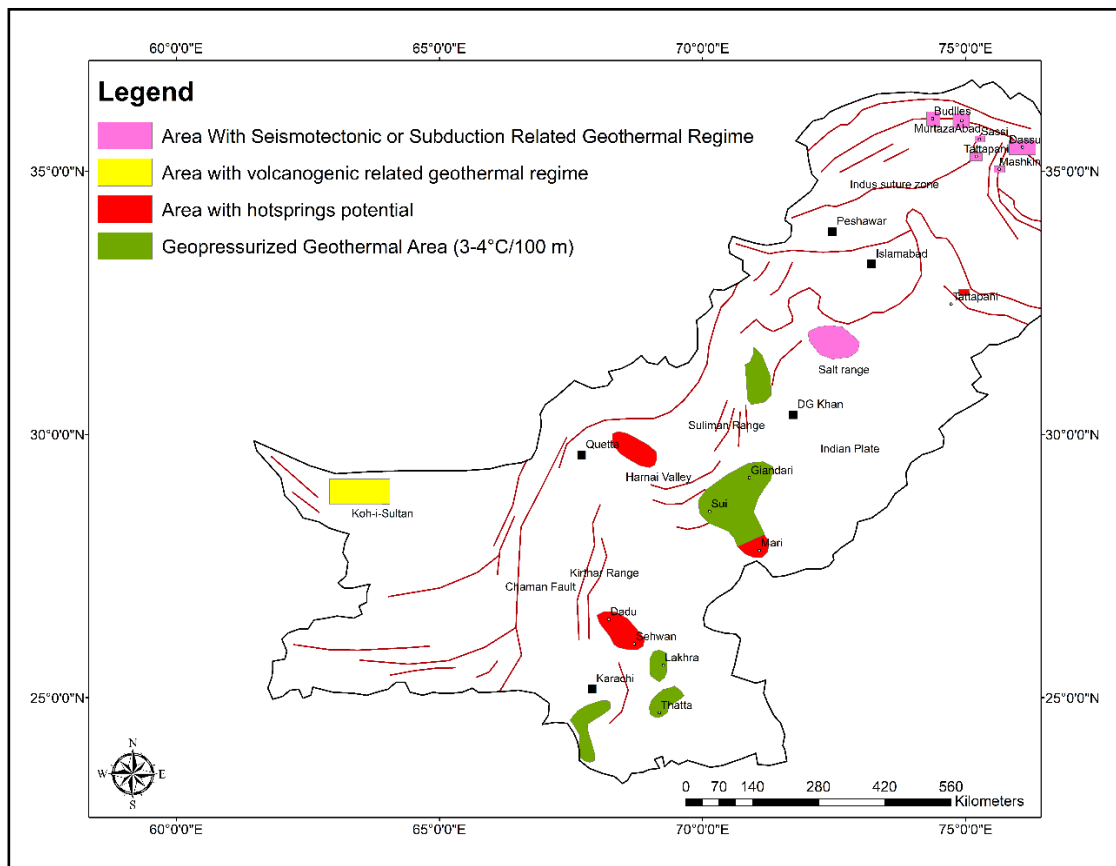


Figure 2.1 Geothermal gradient map of Pakistan showing the category of geothermal zone. The interested study area lies in the geopressurized geothermal area shown in the green block (Mehmood et al., 2019).

Table 2.3: Literature review of geothermal techniques and work that is done in Pakistan in past.

Topic	Author	Objective	Conclusion
Utilization of Abandoned Oil and Gas Wells for Geothermal Energy Production in Pakistan	Mahmood., et al., 2019	Research focuses on the reuse of dry oil and gas wells in Pakistan, which could be utilized for the extraction of geothermal energy from HDR resources on an everlasting basis. An extensive temperature range (393–643 K) exists in different areas of Pakistan, subject to the geological setting of rocks.	The deep seated dry rocks are approached for HDR geothermal energy. These hot dry rocks get thermal energy from the earth's internal heat. The current study concludes that HDR geothermal energy can provide an alternate solution to defeat the energy crisis of Pakistan.
Potential for heat production by retrofitting abandoned gas wells into geothermal wells	Mahmood., et al., 2019	Study is to evaluate heat production from abandoned gas wells in the Indus Basin, Pakistan, with the goal of extracting geothermal energy for power generation. A mathematical model of thermal and hydraulic coupling processes is used to generate an accurate 3D numerical model for the representation of an abandoned gas reservoir, which provides suitable conditions of a geothermal reservoir.. An abandoned well located in the Chiltan Formation is used to obtain key geological parameters.	The heat transfer and flow regime of an injection-production well pair is modeled by first studying the geology of the Indus Basin at a location where oil and gas production has occurred. An abandoned gas reservoir is used to provide the geological parameters that are needed to construct a geothermal reservoir model.
Geothermal Energy Potential of Pakistan on the Basis of Abandoned Oil and Gas wells	Asif et al., 2017	Describes the background of the “Hot Dry Rocks” as the exploitable renewable geothermal energy source, the relevant technology, the hot dry rock in Pakistan and possible employment of the data of the exploratory Oil and Gas wells to discover the potential targets for the comprehensive study to be required for designing the electric power generation options.	There is need to study the HDR resources to overcome the energy crises and for the commercial development of Pakistan. As discussed above the HDR resources are much deeper than the hydrothermal resources. Initially in the introductory phase of this technology development cost of well is high because of its depth. In case of Pakistan, subsurface information of exploratory Oil and Gas wells can be used, and such cost can be saved.

Pakistan geothermal renewable energy potential for electric power generation: A survey Pakistan geothermal renewable energy potential for electric power generation: A survey.	Umair et al., 2016	High cost of conventional fuel forced policy makers to renewable energy generation. In various categories of renewable generation, such as wind and solar energy, Geothermal energy is still an open challenge for Pakistan. This energy generation plant, feasibility study and reports, and data analysis are never touched in past decades.	Geo-tectonics suggests that Pakistan lie on the junction of tectonic plates. Therefore, the country is abundant in geothermal energy resources. Various hot springs are located along MKT, MMT, and MBT in Pakistan. Furthermore, Makran region along coastal belt several mud volcanoes are identified. Moreover, indications of Quaternary Volcanism in Chagai Volcanic Arc.
Review of geothermal energy development efforts in Pakistan and way forward	Irfan et al., 2016	The study discusses the efforts made so far in the development of Geothermal resources for power generation and recommends measures for future planning.	Pakistan has the potential for tapping considerable amounts of energy from its very rich geothermal resources dispersed all over the country. The vastly distributed resources have the ability to generate power through a variety of developed technologies. Apart from the cost intensive Power plants, geothermal energy can be very beneficial as direct use in the domestic and commercial sectors.
Greener energy: Issues and challenges for Pakistan-geothermal energy prospective	Tauqeer et al., 2014	Geothermal energy produces zero carbon emissions, potentially making it one of the cleanest sources of energy at our disposal. In addition, it can create a constant 24 h base-load power where other renewable energies are unable whereas solar energy can only be produced during daylight hours, and is diminished with cloud cover and wind turbines are dependent on wind speed which is inherently variable	Pakistan is an energy-deficient country, indigenous energy sources of Pakistan are strategically important. Although proven benefits on social aspects and macro level are associated with local geothermal energy production, the future supply of geothermal energy depends on energy prices and technical progress, both of which are driven by energy policy priorities. With efficient use of geothermal energy resources

An overview Of Geothermal Resources of Pakistan	Malik Sikander Bakht, 2000	Studies deals with geologic and tectonic features associated with the surface manifestation of geothermal activity in Pakistan. Major tectonic elements during the Cenozoic and Mesozoic have shaped the Geological structures observed in Pakistan today. These structural elements are indicators for delineating and developing the potential geothermal resources of the country.	Number of thermal springs exist in Pakistan. Studies of these springs are far from complete. It is suggested that detailed geochemical and radiometric studies should be carried out. After the data is collected and the therapeutic value of these springs is ascertained some of them can be developed as spa as USA and Iceland. Exploration may be undertaken in order to ascertain the underground source of energy.
Geothermal resources of Pakistan and methods for early-stage exploration	Muhammad Naseer Mughal, 1998	Energy is produced by various means in Pakistan, including hydroelectric dams, coal, nuclear and gas fired power stations. One additional alternative is geothermal energy, which is the subject of the present study, but its contribution today is negligible. Geothermal areas have been identified in three areas of Pakistan, the Himalayan collision zone, the Chaghi volcanic arc, and the Indus basin margin	The advantage of geothermal power in a country like Pakistan, where coal and oil resources are limited, is obvious. The geothermal resources can provide a clean source of energy, especially in selected areas of the northern collision zone of Pakistan and in the Chaghi area in Baluchistan. Direct utilization for bathing and heating and possibly electrical production may satisfy local needs in villages and small towns
Geothermal Energy Resources of Pakistan	Nayyer Alam Zaigham, 2005	The prospects for the geothermal energy sources of Pakistan with the view of the geological set up of the country	In Pakistan, these manifestations of geothermal energy are found within three geotectonic or geothermal environments, i.e. the geo-pressurized systems related to basin subsidence, the seismo-tectonic or suture-related systems, and the systems related to Neogene-Quaternary volcanism

2.3.1 Sedimentary Basins of Pakistan and their Geothermal Potential

The extensive sedimentary basin in Pakistan arises from plate collisions involving Eurasian, Indian, and Arabian tectonic plates. The noteworthy transform zone (Bela-Chaman), exceeding 800 km in length, separates the Indus region from the eastern side and Baluchistan in the western margin. Pakistan encompasses a sedimentary surface of approximately 300,000 km² and a sedimentary volume of 1,000,000 m³, indicating the potential for substantial hydrocarbon yields. Diverse petroleum plays are evident in Pakistan, spanning the Miocene, Eocene, Paleocene, Cretaceous, Jurassic, Permian and Cambrian age (Mehmood et al., 2017; Zaigham, 2009; Zaigham et al., 2009). The primary sedimentary basin of Pakistan is the Indus Basin. Hydrocarbons linked to thermal

sedimentary aquifers, resulting from secondary faults within the Indus Basin, have given rise to numerous hydrocarbons-associated geothermal springs. The Upper, Middle, and Southern Indus basins constitute additional divisions within the broader framework of the Indus Basin.

2.3.1.1 Upper Indus Basin

The complete north side of Punjab region, along with the Banu and Kohat regions in KP, falls within the purview of Upper Indus Basin (UIB), also called the Northern Indus Basin. This sub-basin is characterized by extensive (up to 7,000 m deep) Pre-Cambrian to Pleistocene marine and continental fluvial deposits. Since the initial discovery of industrial oil at the Khaur location in 1915, the UIB has stood as the primary oil-producing region. A segment of Pakistan's UIB, recognized for its warm water bodies, is the Potwar-Kohat Basin (Ahmad, 2014; Anees et al., 2023).

The Potwar Basin, Pakistan's most prominent geothermal basin, houses numerous hydrocarbon-generating sources and numerous wells that concurrently yield geothermal hot fluids, varying temperatures between 80 to 140 °C as shown in Table 2.4. Because of elevated temperature and extreme pressure within the Basin, which present potential geothermal reservoirs for electricity production, numerous unproductive wells lacking hydrocarbon discoveries have been securely sealed.

Table 2.4: The temperature data in oil and gas drill holes from the UIB, covering the Punjab and KP region in Pakistan, as well as the Potwar Basin, has been sourced from petroleum companies operating in the region (Ahmad, 2014).

S.NO	Depth (m)	Temperature (C ⁰)
1	1747.64	160
2	1779.95	139
3	1523.93	116
4	1407.49	106
5	1493.45	144
6	1621.15	143
7	1444.38	130
8	1376.71	111
9	1635.78	144

10	1203.90	101
11	1577.26	125
12	1460.53	130
13	1560.19	142
14	1615.36	140
15	1203.90	100
16	1447.12	114
17	1402.32	114
18	1131.06	99
19	1505.64	136
20	1467.23	143
21	1287.10	132

2.3.1.2 Middle Indus Basin

There are three primary features of the middle Indus basin which includes eastern side platform area, a depression in the center, and the Thrust and Fold Belt in the western part. This basin has proven profitable for hydrocarbon plays from the Jurassic, Cretaceous, Paleocene, and Eocene eras. The depression, characterized by widespread sedimentary rock, serves as a hydrocarbon source. The Fold Belt is marked with reliable anticlines, while the Thar Platform manifests as a monocline dipping westward, featuring structural and stratigraphic traps, paleo-topographic anatomy, traps induced by salt, and intermittent compression folds (Gondal et al., 2017; Kazmi & Sheikh, 2019).

The Middle Indus Basin is home to numerous warm fluid sedimentary water bodies and geothermal lakes at numerous sites. This area, encompassing small portions of Sindh and Baluchistan Provinces and the southern segment of Punjab Province, consists of sedimentary rocks spanning from the Precambrian to the Quaternary period. The central depression exhibits the maximum thickness within the sedimentary section. Hydrocarbon discoveries have been recurrent in the basin since 1954, and these resources are presently under production. Coproduced and geopressed geothermal hot waters have been reported at various locations, as shown in Table 2.5 (Gondal et al., 2017).

Table 2.5: The temperature data in oil and gas drill holes from the MIB (Ahmad, 2014).

S. No	Depth (m)	Temperature (C°)
1	678.45	105
2	1097.53	116
3	1342.88	125
4	1396.22	125
5	1358.13	93
6	615.67	83
7	323.68	65
8	640.05	60
9	501.68	74
10	501.37	79
11	475.46	167

2.3.1.3 Southern Indus Basin

Southern Indus Basin (SIB) is a renowned basin recognized for discovering numerous hydrocarbon fields in Pakistan. This north-elongated zone encompasses most of Sind Province and certain areas of Baluchistan Province. The basin has sedimentary units fluctuating from Mesozoic to recent ages, with a thickness ranging from 5,000 to 100,00 m. It has a platform area on the east side, several peaks and valleys, a sizable bowl shape, and a Folded Zone in its western part, much like the MIB. This sub-basin has seen significant oil and gas finds, especially in the Early Jurassic, Paleocene, and Eocene plays as shown in Table 2.6 (Jarwar et al., 2023; Kazmi & Sheikh, 2019).

Hydrocarbon production is strongly associated with the coproduction of geopressured hot waters. Daily thousands of warm water barrels are discharged into streams or reinjected into boreholes. The Sanghar-Badin Rift Basin is a substantial source of hot water exceeding 110 °C, coupled with hydrocarbons as shown in Table 2.7. Referred to as the northern side of Sindh with respect to the sedimentary basin, the hydrocarbon reservoirs situated in the higher sector of the LIB produce heated fluids with temperatures surpassing 150 °C (Mehmood et al., 2019; Mehmood et al., 2017).

Table 2.6: The temperature information from oil and gas drill holes in the LIB, located in Sindh Province, Pakistan, and the Badin Sanghar Rift Basin, has been obtained from petroleum companies operating in the region (Ahmad, 2014).

S.NO	Depth (m)	Temperature (°C)
1	1001.83	128
2	938.13	97
3	947.57	95
4	1162.45	108
5	716.25	90
6	607.13	98
7	919.54	96
8	957.33	116
9	945.15	121
10	789.39	106
11	998.461	121
12	954.59	98
13	801.89	107
14	783.29	104
15	699.18	102
16	721.95	101
17	650.26	98
18	685.77	104
19	1376.71	150

Table 2.7: The temperature data from oil and gas drill holes in the LIB, situated in Sindh Province, Pakistan, specifically in the Upper Sindh, has been sourced from petroleum companies operating in the region (Ahmad, 2014).

S.NO	Depth (m)	Temperature (°C)
1	511.73	160
2	588.24	139
3	448.03	116
4	339.23	51
5	557.76	86
6	482.78	76

7	492.23	130
8	626.94	92
9	355.99	12
10	365.13	55
11	362.39	54
12	366.96	59
13	298.69	54
14	617.19	74
15	277.66	53
16	636.39	82
17	521.79	75
18	1249.62	160
19	900.94	105
20	868.03	109
21	1066.75	126
22	836.03	107
23	92.96	115

2.4 Geology of Southern Indus Basin

The basin exhibits an inactive-ridge duplex structure, featuring an inactive back-thrust laterally the Kirthar Fold Belt, a frontal culmination wall along the fold belt margin, and intra-molasse detachments within the Kirthar depression and out-of-syncline sequences. Within the Karachi depressions and Kirthar, numerous significant domes and anticlines are present, with nearly housing minor gas fields such as Kothar, Hundi, Sari, and Manzarani. On the east side of the basin, including the Thar Platform, faulted and slanting blocks of Mesozoic strata form structural traps that host minor hydrocarbon fields. Deccan Trap and sedimentary rocks superimpose these fault chunks in unconformity of tertiary age, Incidental deep-seated fossil failed rift of the SIB and associated tectonic features, along with the overlays of surface geology and recorded earthquake epicenters as shown in Figure 2.2 (Rasool et al., 2018; Rauf et al., 2019).

The vast anticlinal structures of the Sukkur rift zone, home to gas resources like Khandkot and the enormous Mari field, which has reserves of 6.3 TCF, are found on the northern side of the SIB. LGF sandstone from the Cretaceous period is the main reservoir

rock in the Sindh monocline. Extraction comes from the Paleocene Ranikot limestone and sandstone in the Karachi depression and the Eocene Sui Main/Habib Rahi limestone in the Kirthar depression and Sukkur Rift zone. Strong geothermal gradients, varying from 2 to 4 °C/100 m, are characteristic of the SIB; the Damiri-01 well records its greatest gradient, shown in Figure 2.3 (Shah et al., 2021; Uddin et al., 2021). Planned representation of tectonic models describes the various stages of evolution of the SIB. Primarily, in the late Paleozoic, the Gondwanaland is breakdown. Secondly, continues extension of crust which creates a normal tilted fault. Thirdly, subsidence of the stretched crust due to subsequent sedimentation of the Mesozoic and Tertiary sediments on the tectonic basis. Last but not least, models demonstrate the amending tectonic environments and present-day geological setting in the SIB. The position of the cross section is shown in Figure 2.2.

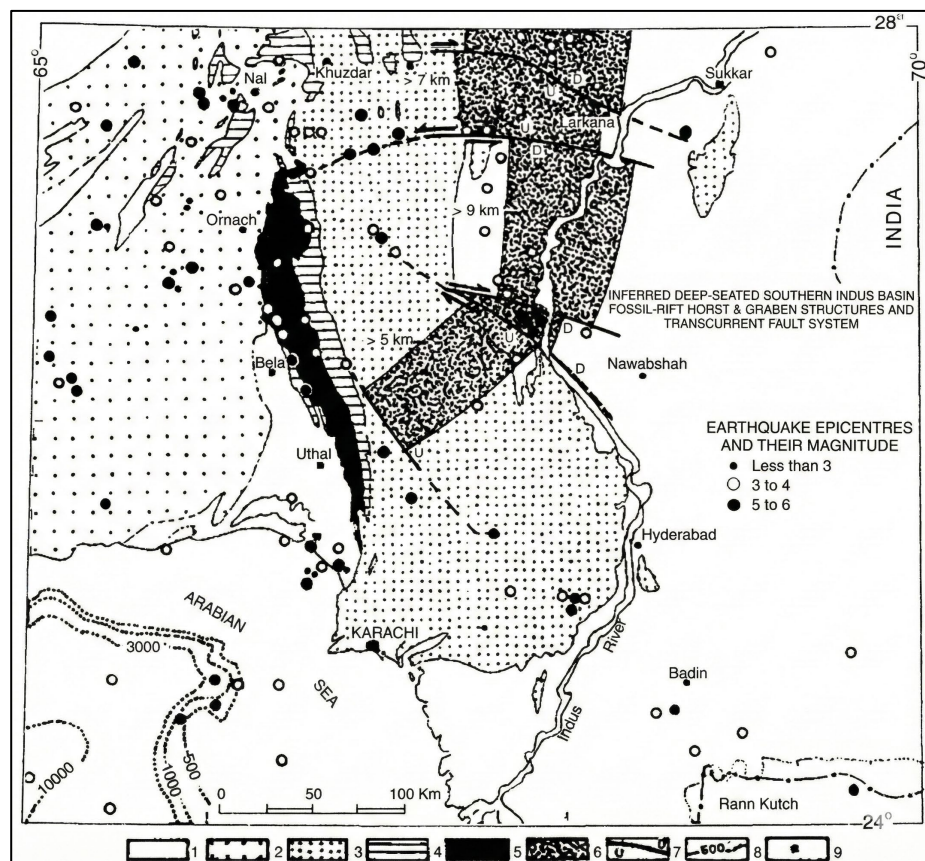


Figure 2.2 Inferred deep-seated fossil failed rift of the SIB and associated tectonic features, along with the overlays of surface geology and recorded earthquake epicenters (from 1905 to 1981). Geological legend: (1) Quaternary sediments, (2) Neogene sediments, (3) Paleogene and Cretaceous sediments, (4) Jurassic sediments, (5) Ophiolites and melanges, (6) Oceanic crust inferred as a deep-seated fossil failed rift, (7) Deep-seated transcurrent faults associated with the fossil rift, (8) Water depth contours in the Arabian Sea, and (9) City location.

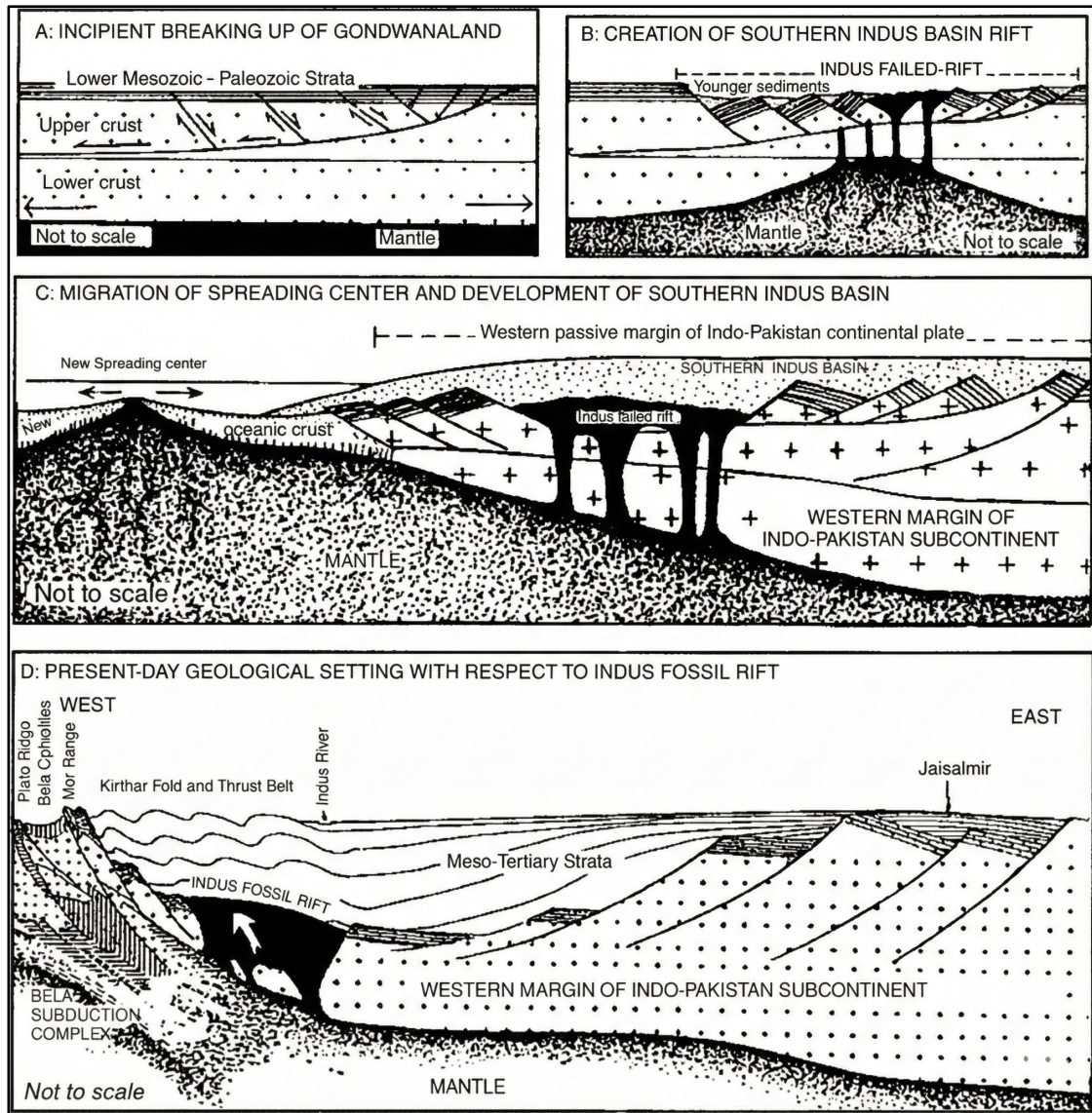


Figure 2.3 Proposed schematic tectonic models illustrating stages of evolution of the SIB. (A) Incipient breakup of Gondwanaland during the Late Paleozoic as phenomena of thinning of the overlying lithosphere resulting from plastic flow in the lower part and extension faulting in the upper part. (B) Continued stretching of the upper crust caused thinning, tilted block faulting, and upwelling of magma that appears to stop just before the end of the Paleozoic, giving birth to the Indus failed rift. (C) Subsidence of the stretched crust due to subsequent sedimentation of the Mesozoic and Tertiary sediments in the tectonic basin. A new and complete spreading center developed sometime in the Cretaceous. (D) Model illustrates the modifying tectonic environments and present-day geological setting in the SIB (Shah et al., 2021). The location of the cross section is shown in Figure 2.2.

2.5 Geothermal Potential of Southern Indus Basin

The SIB is bounded by the Sukkar Rift to the north and the Murray Ridge in the marginal zone of the Arabian Sea to the south. Within this basin are the Thar Platform, Kirthar Foredeep, Kirthar Fold Belt, Karachi Trough, and Offshore Indus (Quadri &

Shuaib, 1986). Geothermal gradients of 2.5 °C/100 m have been observed in Khairpur and Jacobabad wells, but their impractical drilling depth of 2100 m limits their utility for power production. The Jhatpat well shows a reduced geothermal gradient of 1.7 °C/100 m as shown in Figure 2.4. In contrast, the Lakhra field, specifically Lakhra-01 drilled to 3200 m, proves suitable for geothermal energy extraction with a geothermal gradient of 3.3 °C/100 m (Khan et al., 2013). The well's endpoint estimates an FT of around 130 °C. The southwest Sunbak and Sari Singh wells in the Lakhra field present geothermal gradients of 2.7 °C/100 m and 3 °C/100 m, respectively. Khan and Raza (1986) identified two geothermal regimes in the Badin Block, the eastern and western regimes, with the latter displaying higher geothermal gradients.

Except for Patar well, wells in the eastern regime, including Nabisar, Digh, Badin, and Patar exhibit geothermal gradients ranging from 2.1 °C/100 m to 2.3 °C/100 m. Abandonment characterizes all eastern regime wells except for Patar. Conversely, the western regime shows geothermal gradients ranging from 2.65 °C/100 m to 3.1 °C/100 m in Talhar, Tarai, and Khaskeli well, 4 °C/100 m in Damiri well, and 2.9 °C/100 m in Mirpur-Batoro well (Munawar et al., 2022). The western geothermal regime in the Badin Block attributes higher geothermal temperatures to Cretaceous-Paleocene basaltic lava-flows, with Damiri well-being the hottest spot as shown in Figure 2.5. In the Offshore Indus Basin, 14 wells with a maximum depth of 5 km exhibit geothermal gradients of 2.43 °C/100 m, 2.6 °C/100 m, and 2.27 °C/100 m for Marine A1, B1, and C1, respectively. Coastal areas of Kirthar Basin host five wells including Karachi-1, Karachi-2, Korangi Creek, Dabbo Creek, and Paitiani Creek. Karachi-1 and Karachi-2 display geothermal gradients of 2.3 °C/100 m and 3 °C/100 m, respectively. Dabbo well demonstrates an extraordinary geothermal gradient of 3.7 °C/100 m, yielding a stratum temperature of 163 °C at the well's bottom. Paitani and Korangi Creek also exhibit similar geothermal gradients, rendering them conducive to geothermal energy extraction. Thank you for the suggestion that the relation should be established as described below;

The geological setting is essential for the determination of geothermal heat present in the subsurface. The Thar Platform of SIB recorded a high GG of 4°C/100 m in Damiri well. This higher GG is associated with subsurface structure like host and graben geometry; rift zones and faults lines and these geological features are the source of heat transfer from deep crust via convection and conduction. However, the interesting formation LGF has an interbed of shale and sandstone, the shale unit is enriched with radiogenic elements like U, Th and K which is considered as a primary source of heat

production. The GG of this area is also high due to the presence of Deccan Trap with is volcanic rock and plays a vital role in the elevation of subsurface temperature. Therefore, features like lithology, sediment thickness, structural traps, tectonic activity and facies directly define the potential of geothermal energy.

In the SIB, major reservoirs include the Early Paleocene Ranikot Group, Late Cretaceous Pab Sandstone, and Early to Middle Cretaceous LGF. Depths at which these formations are encountered in wells are 2254 m for Pab Sandstone, 2359 m for LGF, 3542 m for Sembar, and 3578 m for Chiltan Formation (Ehsan et al., 2018; Beswetherick & Bokhari, 2000). LGF, being deeper among other formations in the Middle and Southern Indus basins, is of prime importance, constituting about 65% of the accumulation of oil and gas wells with an average PHIA of 16 to 30% and K ranging from 1 to 2,000 mD (Wandrey et al., 2004). It serves as a quality reservoir in hydrocarbon wells including Khaskeli, Matli, Tando Adam, Turk, Duphri, Lashari, Kato, and Bhatti drilled in Badin, Hyderabad, Mirpurkhas, and Sanghar areas. This characteristic of the LGF holds promise for CO₂ sequestration, enhancing heat storage capacity and mitigating CO₂ concentration in the atmosphere (Dar et al., 2023). However, In the Middle and Southern Indus Basin Upper Goru Formation is lying on top of LGF that is acts as a regional seal/cap rock (Raza et al., 1990).

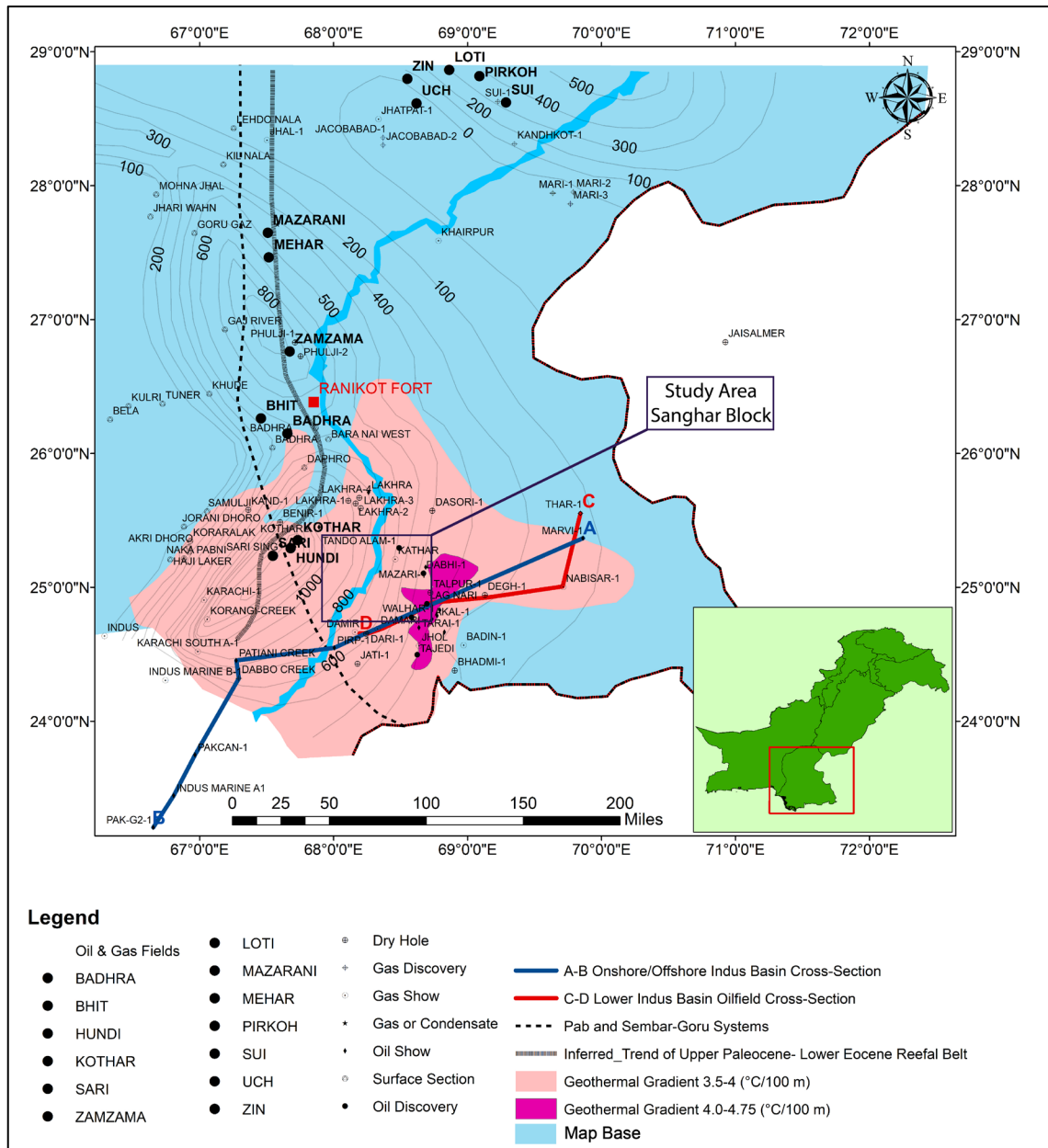


Figure 2.4 Isopach map indicates the stratigraphic thickness of the Ranikot Formation with highlighted major oil and gas fields in this region. The cross-section lines AB and CD were developed to understand the subsurface structure trends of the study region. The primary petroleum-producing systems are the Pab Sandstone and Sembar-Goru, which extend into the SIB and have been marked on the map (adopted from Ehsan et al., 2025).

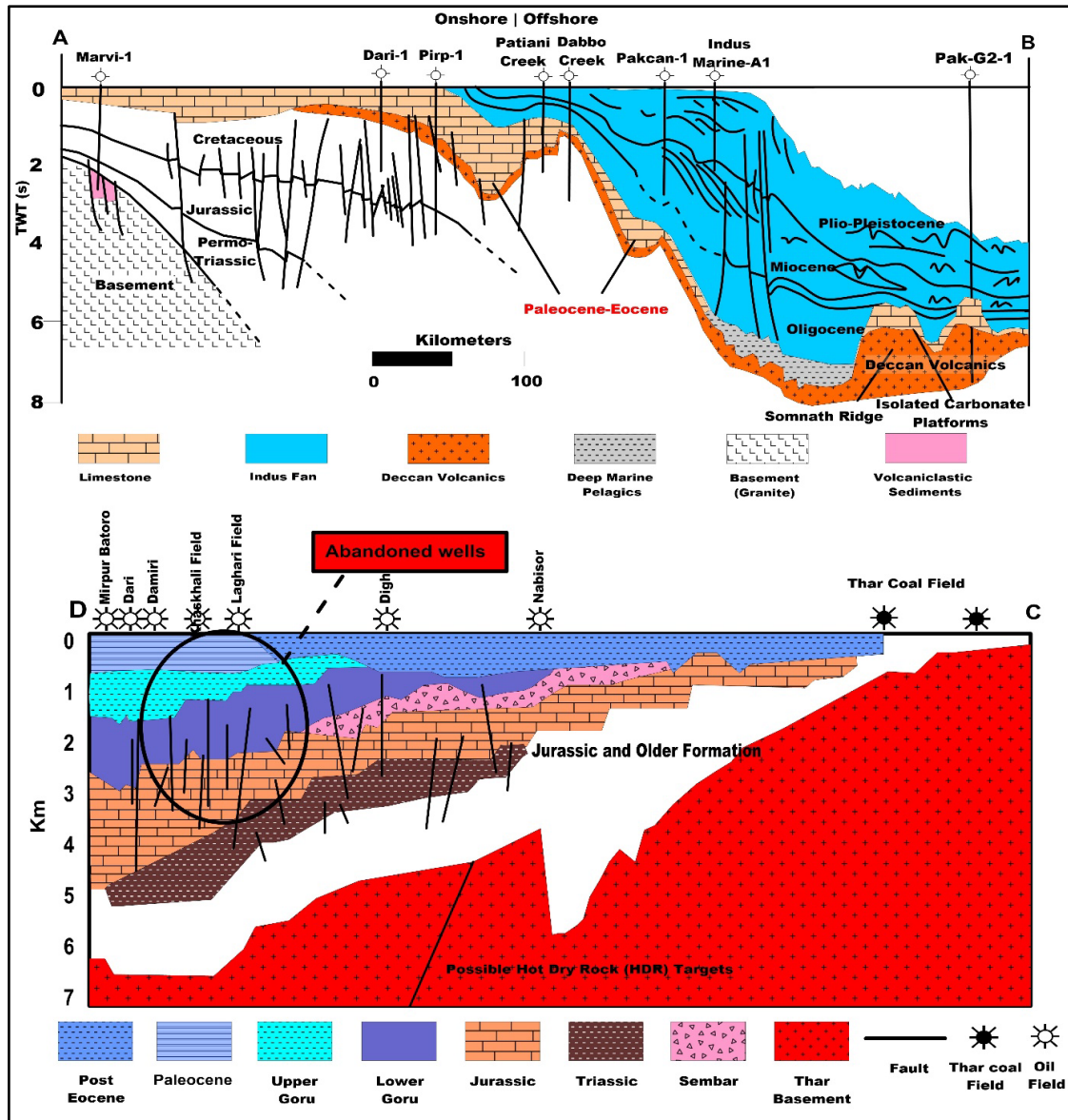


Figure 2.5 The geological cross-section lines; Lines AB indicate Pakistan's Onshore and Offshore Indus basins with major structural elements. Line CD of the Thar-Rift in the southern part of the Indus Basin of Pakistan with major structural elements for the location of wells (Ehsan et al., 2025).

2.5.1 Cretaceous Age Geothermal Potential in Southern Indus Basin

Interbedded shale, limestone, and siltstone define the LGF. The lowest part of a shale mixture is thin to irregularly bedded, calcareous, hard, splintery grey to olive-green shale combined with light-colored limestone. The higher portion transitions into the Parh limestone in a thin-bedded, light-colored porcelaneous limestone with subordinate shale. At the particular location in Gum town, the width of the Formation is 536 m. In the Quetta region, the thickness decreases to about 70 m in the north, and in the south, some

boreholes have found Gum deposits between 1,200 to 2,700 m thick. Foraminifera and belemnites abound in the LGF (Malkani et al., 2017).

2.5.2 Paleocene Age Geothermal Potential in SIB

The Khadro Formation, named after Khadro Nala (type section Bara Nai) encompasses the *Cardita beaumonti* beds, *Venericardia* shales and the basal portions of the Karkh, Gidar Dhor, and Jakker groups, as well as the Bad Kachu and Thar formations. Comprising sandstone, shale, limestone, and Early Paleocene-age volcanic rocks, the Khadro Formation also includes igneous formations like the Deccan Trap basalts. These igneous rocks have been found in underground boreholes in the Kirthar monocline and are part of the Early Paleocene Khadro/Ranikot Formation in the Kirthar basin. They are also exposed in the Kirthar Fold Belt (Malkani et al., 2017).

The primary seal that is acting in the Ranikot Formation is a marine shale (Qureshi et al., 2021). As demonstrated in Figure 2.6, the shales of Sembar, LGF, and Kirthar formations also work as shale beds consider as effective seals in numerous wells, containing those in the Mehar, Zamzama and Bhit fields. In other regions, the Ranikot/Khadro member loses its seal properties because of sand. Although, the shales of Ranikot mainly act as a primary seal (Asim et al., 2014; Manzoor et al., 2023).

2.5.3 Deccan Trap

The Deccan Traps potentially covered an expansive area exceeding 150,000 km² in Peninsular India and adjacent areas. The western most extension of the traps is acknowledged to extend outside the current sequence of the Indus River in the south of Pakistan. Sindh's trap occurrences have limited available information compared to comprehensive studies conducted by numerous scientists in India (Agheem et al., 2011; Zhuang et al., 2015). Almost 12 m thick basalt flow interstratified with Upper Cretaceous sandstone at Bor Hill. Another basalt bed, 12 to 27 m thick, was reported from Ranikot to Jakhmari, overlying Danian to Maestrichtian beds of *Cardita beaumonti* and underlying freshwater beds of Lower Ranikot, with one flow traceable for 35 km (Nasir et al., 2013). In Sindh, adjacent Kutch and Kathiawar, the predominant view is that the trap is subaerial.

Burmah Oil Company boreholes in Lakhra revealed basalt zones (14, 76, and 27 m thick) interbedded with sediments at the base of the Ranikot Formation. Near Thatta,

at least eleven basalt flows with thicknesses ranging from 1 to 34 m and interbedded with tuff and clay were encountered. The presence of 130 m of volcanic rocks in boreholes 80 km apart suggests a widespread coverage of the Deccan Trap in southern Sindh, potentially extending under the younger cover (Shahzad et al., 2022). Basaltic flows in the lower part of the Ranikot Formation have been reported in offshore drill cores, and the Porali volcanic in the Mor Range are considered part of the Deccan magmatism. The age of the trap in Sindh, Late Cretaceous, aligns with global findings. The Deccan magmatism dates from 67 to 62.5 Ma, suggesting a broader period from about 100 to 30 Ma (Malkani & Mahmood, 2017). Deccan magmatism as part of global-scale events necessitates meticulous study and synthesis. Phenomenon related to crust-mantle imbalance during the Mesozoic, is manifest in high heat flow, eruptive activity, land, and sea redistribution, Gondwana supercontinent breakup, mantle rise along crustal fractures, biota changes, and potentially the first record of true morphogenic. The manifestations of this extensive vulcanicity remain incompletely understood (Agheem et al., 2011; Malkani et al., 2017). Table 2.8 demonstrates detailed information of formation with geothermal prospect present in the Thar platform of SIB.

Table 2.8: Detailed of the formation with geothermal potential in the SIB (Qureshi et al., 2021)

Formations	Lithology	Geothermal Significance
Ranikot Formation	Limestone, Sandstone, Shale and Volcanic flow	Deccan Traps basalts are acting as a host which enhances GG via magmatic heat
Deccan Traps	Basaltic lava flow	Act as heat sources; trap heat and influence geothermal gradient in the Khadro and Ranikot
Lower Goru Formation	Interbed of shale and sandstone	High PHIA and K along with U rich shale as a heat source.

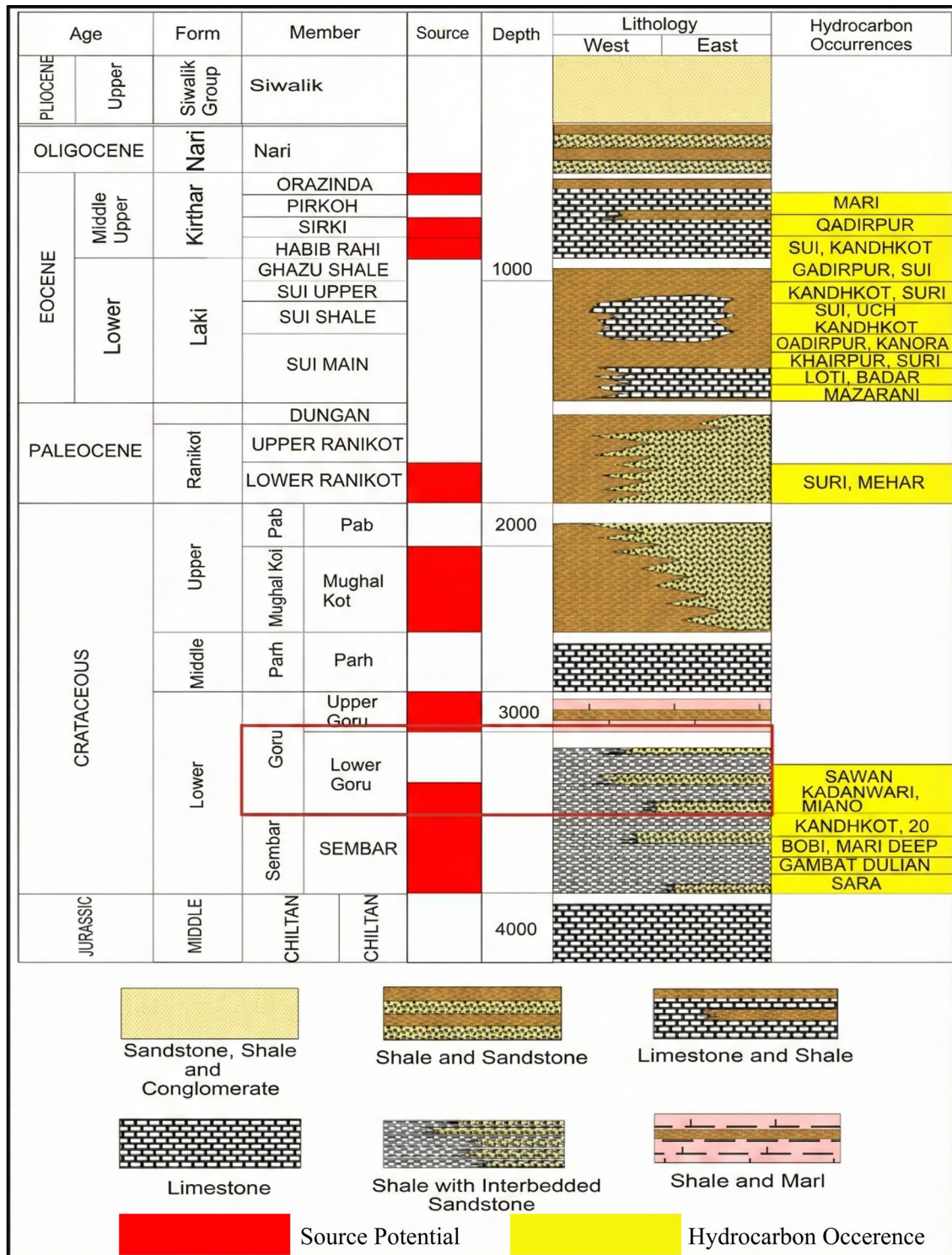


Figure 2.6 Stratigraphy of Thar Platform SIB showing the complete stratigraphy with sequence along with marked interested formation LGF with red color (modified after Ehsan et al., 2024; Shakir et al., 2022).

2.6 Initial Assessments of Geothermal Sources

Pakistan's geothermal energy perspective has been tentatively evaluated and is shown in Table 2.9. There are six major sources of geothermal energy, and the proposed development of these resources is demonstrated up to 2050 along with an amount of energy produced in Mwe unit.

Table 2.9: Initial assessments of geothermal energy reserves in Pakistan (Ahmad, 2014).

Geothermal Resources	Planned Resources			
	Resource Estimation	2030	2040	2050
	Measured in Mwe			
Geo Pressured and Co-Produced	40,000	15,000	10,000	1,000
Hydro-thermal Resources	30,000	30,000	50,000	10,000
Deepest Geothermal Resources	30,000	30,000	50,000	10,000
Thermal Benefits	MWt			
Shallow Geothermal	600,00	400,00	10,000	1,000
Immediate Use	30,000	5,000	5,000	5,000

2.6.1 Co-produced and Geo-Pressured Geothermal Reservoirs

The majority of Pakistan's hydrocarbon reservoirs are associated with abundant hot waters, commonly known as co-produced and geopressured geothermal fluids. Tables 2.3, 2.4, 2.5, and 2.6 illustrate the documented temperature range of hot water, spanning from 80 °C to above 150 °C. Initial appraisals derived from numerous depleted, producing, and abandoned oil and gas wells within the Indus Basin suggest that these co-produced and geopressured geothermal energies have the potential to deliver an extra 40,000 MW of warmth and power at a lower rate related to hydrocarbon resources of the region (Anees et al., 2023; Kazmi & Sheikh, 2019).

Based on initial investigations, the Sanghar area in the Sindh area may have substantial potential for co-produced and geo-pressured geothermal energy resources. In Pakistan, 841 boreholes for exploration have been sunk since 1866 and more than 500 of these wells have proved to be dry or have produced no commercial discoveries. After analyzing temperature data, the researcher found that 300 wells in Pakistan might provide geothermal energy higher than 105 °C, which might be used to generate electricity. Furthermore, 1164 wells have been sunk for development and production from which

many were originally intended to be hydrocarbon assessment wells, but they are now dry or diminished, providing a viable supply of geothermal energy for the production of electricity (Rasool et al., 2018). Nevertheless, thorough investigations are necessary to evaluate each well's possibility of producing electricity.

2.6.2 Resources of Geothermal Reservoir

Geothermal energy resources are abundant in many parts of Pakistan and can be observed as continuously streaming warm water, eruptions, and springs. These geothermal potential sources are most famously associated with the northern part of Pakistan, which includes Kashmir, Chitral, and Gilgit Baltistan. The temperatures there range from 80 °C to above 180 °C. In these regions, the geothermal potential exceeds 30,000 MW, contributing to both electricity generation and heating in Gilgit Baltistan, Chitral, and Azad Kashmir. Additionally, Punjab, KP, Baluchistan, and Sind Provinces host numerous hot water springs serving as sources of geothermal energy (Jarwar et al., 2023).

2.6.3 Enhanced Geothermal Systems

The geological and tectonic characteristics, seismically active zones, and presence of abandoned deep, dry oil and gas wells exhibiting elevated temperatures indicate the availability of deep geothermal resources in numerous parts of the state. These resources, potentially exceeding 30,000 MW of electricity, could be harnessed and developed through enhanced geothermal system (Mehmood et al., 2019).

2.6.4 Shallow Geothermal Energy Reservoirs

SGER serves as a shallow geothermal energy resource and remains accessible within depths ranging between 10 to 500 ft. These resources are utilized to warm and chill buildings and provide hot water. Given the widespread sunshine across Pakistan, the shallow geothermal energy resources are conservatively estimated to exceed 60,000 MW, encompassing power and heat sources available throughout all provinces (Abbas et al., 2014).

2.6.5 Geothermal Energy Reservoirs for Direct Utilization.

The northern side of Pakistan, containing Baltistan, AJK, Gilgit, and KP, remains distinguished, aimed by its lower temperature, warm water bodies. Furthermore, Baluchistan, Sindh and Punjab provinces also feature less-grade temperature springs and water aquifers. These groundwater reserves and streams have low temperatures. Water all shows promise for immediate usage (Mehmood et al., 2017).

2.6.6 Assessment of the Geothermal Energy Potential for Electricity Generation

Pakistan presently produces more than 80% of its power using petroleum sources, including gasoline, natural gas, and diesel. Approximately 15% of the power is sourced from wind, hydropower, and nuclear power sources. The nation's economic dependence on imported fossil fuels is substantial, with an average annual import bill surpassing 15,000,0000 USD. Geothermal potential is accessible in all provinces of Pakistan and presents opportunities for power generation, heating and cooling of buildings, hot water supply, and various direct-use applications. Harnessing these resources can significantly diminish reliance on imported fossil fuels (Rasool et al., 2018; Zaigham, 2009).

2.7 Geothermal Play Type

A narrowed subsurface segment capable of yielding its inherent limited thermal energy is denoted as a geothermal reservoir. Historically, geothermal systems were categorized by Alam (2021), Sharmin et al. (2023), and Dashti and Gholami Korzani (2021) into three conventional type : (1) maximum temperature, (2) modest temperature, and (3) minimum temperature geothermal reservoirs, distinguished by variations in heat content and heat dynamics. The beneficial, viable harnessing of renewable energy in a particular area necessitates the consideration of geological factors beyond enthalpy (Williams, 2011). Many scholars argue that relying solely on temperature and heat content is insufficient to classify geothermal reservoirs (Lee, 2001). Modern categorization of geothermal reservoirs involves classifying them according to various geological characteristics. This includes their geological setting, hydrogeological and thermal regime, approach to heat transfer, compressional regime, fluid understanding, fractures, lithology, stratigraphic sequence, and diagenesis. These geological attributes influence PHIA, K, temperature distribution (both laterally and vertically), fluid flow,

and the overall behavior of the reservoir (Moeck, 2014). Figure 2.7 illustrates this classification framework.

The two main categories of active and passive geothermal systems are convection-controlled geothermal reservoirs (CV) and conduction-controlled geothermal reservoirs (CD), depending on the heat transfer regime. Further differentiation within these groups is established on geological controls, with geological characteristics influencing heat transfer mechanisms, reservoir systems, and K structures. As a result, this system of categorization creates several kinds of geothermal reservoirs (Moeck, 2014). A description of these kinds is given in brief in Figure 2.7.

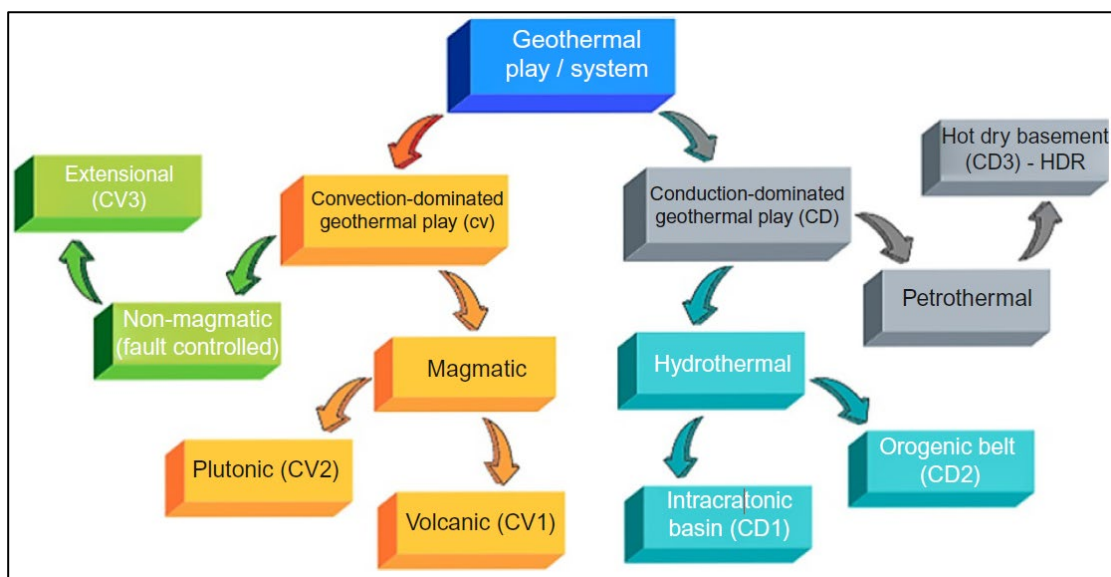


Figure 2.7 Categorization of Geothermal Play, there are two types of geothermal play, one is conduction dominant geothermal (CD) play and other is convention dominated geothermal play (CV). The major focus of current studies is toward the HDR (CD3) which is a part of conduction-dominated geothermal play (Moeck, 2014).

2.7.1 Convection Controlled Geothermal Play.

According to Kolawole and Evenick (2023), geologically dynamic geothermal reservoirs frequently include high enthalpy resources produced by the continuous movement of liquid in the lithosphere and asthenosphere. These reservoirs usually originate in active plate borders characterized by volcanic activity (Deon et al., 2012) and tectonic activity (Nukman & Moeck, 2013). Examples of these places include magmatic arcs, rifting zones, and mid-ocean ridges (MORs) situated beyond subduction zones.

Additionally, convention-dominated geothermal reservoirs are established through hotspots resulting from intraplate magmatism.

2.7.2 Conduction Controlled Geothermal Play

Conduction-dominated (CD) geothermal reservoirs, often termed passive geothermal reservoirs, lack involvement in active tectonism or volcanism. They can be categorized as both lithology and facies classification, specifically fault-controlled and hydrothermal, known as Petro-thermal. Applying EGS skills is common for enhancing reservoir circumstances, including saturation and K, in conduction-controlled geothermal phenomena. CD geothermal reservoirs, characterized by low heat flow, are primarily influenced by lithology, and facies exhibit a limited impact from fault systems. Without deep-water resources, these plays are warmed by natural geothermal incline. These various kinds of reservoirs typically form in intra-cratonic basins. When heat is retained in an inactive continental crust's deep aquifer, it is referred to as a "hydrothermal—intra-cratonic-type (CD1) geothermal reservoir." In these kinds of reservoirs, the focus is on identifying elevated temperature depths with feasible reservoir properties, and various reservoir stimulation techniques may be implemented if needed (Zimmermann, 2008).

Petro-thermal of HDR reservoirs are controlled by fault geothermal reservoirs in stable tectonic hot dry basements (Moeck, 2014). CD Petro-thermal reservoirs earn their designation due to their minimal natural fluid involvement, with heat generation measured by faults and fractures through which fluid extracts heat. This is due to igneous basement rocks such as granite, diorite, and more, which have their own insignificant reservoir characteristics (PHIA/K). Therefore, EGS expertise enhances reservoir circumstances in the hard rock basement (Genter et al., 2000). A minimum requirement of one production well, one injector hole, and an exchanger for heat are needed for CD3 reservoirs and that is the major focus of this research. Heat exchangers can be created from crystalline basements or hot dry rock (HDR) using improved fracturing techniques. The heating rate of these reservoirs is higher than that of geothermal reservoirs. Radioactive substances in the igneous basement and transmission from the Moho are the main sources of heat for Petro-thermal infrastructure.

2.8 Geothermal Assessment Techniques

The assessment of geothermal potential relies on integrating geophysical, geological, and geochemical methods to estimate the presence of underground heat sources. Geophysical techniques provide detailed subsurface analysis of structure and fluid pathways. Methods like seismic, gravity, magnetic, and resistivity are commonly used to evaluate geothermal potential (Spichak & Manzella, 2009). In seismic studies, two types of methods are employed: seismic reflection and refraction. These help identify lithology and fault boundaries in the subsurface, while magnetic methods are used to locate conductive zones associated with thermal fluids and cap rocks. Each method has limitations such as cost, sensitivity, and resolution, so combining approaches enhances the accuracy of results. Geochemical techniques involve analyzing gases and hydrothermal fluids to estimate subsurface temperatures using geothermometers like Na-K-Ca and Na-K (Zhang, 2024). These methods are cost-effective but require chemical equilibrium, which may not always be present in active systems.

Geological approaches include identifying geothermal hotspots, conducting surface mapping, and studying tectonics to locate geothermal systems (Alam, 2021). Geology and tectonic information support the initial characteristics and analysis background of ML and seismic inversion. Having knowledge of sequence stratigraphy, facies, structure, and thermal zones helps in selecting meaningful attributes to train ML models like DFFNN for estimating geothermal and petrophysical properties and predicting facies. For example, the LGF is considered a geothermal reservoir because of its porosity and permeability, which allows these regions to be highlighted through model training. Moreover, the selection of seismic attributes, generation of synthetic seismograms, and integration of well data with seismic tie-ins are guided by geological controls. This field expertise provides excellent interpretation, which helps minimize overfitting and enhances the accuracy of prediction estimates when applying ML and inversion techniques to geothermal assessment.

However, these techniques are mainly qualitative and do not help determine reservoir parameters such as depth and temperature. Nonetheless, geological studies are primarily used in early stages of geothermal assessment to gather initial subsurface information. The estimation of the direct drilling temperature gradient and mathematical modeling are crucial for assessing geothermal potential. Wells with depth-temperature profiles provide clues about thermal gradients and heat flow in the subsurface (Jolie et

al., 2021). However, this method is costly, but its results offer the most reliable data. In the current research, combining these conventional methods with ML models like DFFNN enhances resolution and precision for subsurface geothermal and petrophysical properties. These integrated techniques offer a strong assessment of geothermal potential in the Thar Platform.

2.9 ML Approach for Facies Analysis.

Identification of the facies' using ML is a different approach, which was used to investigate a geothermal reservoir from the well data. The goal of facies analysis is either to predict a value (regression problem) or classify the facies (classification problem) to delineate the potential geothermal reservoir bearing unit (Martin et al., 2021; Naseer et al., 2025b). These methods can be categorized by two main paradigms such as knowledge-driven and ML (data-driven). All these methods are common in the main procedure, where they take in attributes (models, well logs, seismic attributes) and predict the final output based on the rules and relations between them. The key difference is in the way the method has “learned” those rules and relations (Halotel et al., 2020). In knowledge-driven methods, those rules and relations are observed and dictated by the analyst. On the other hand, in ML the algorithm extracts the relations and rules during the training phase from the presented attributes (Hussain et al., 2022). Figure 2.8 given below demonstrates the ML types.

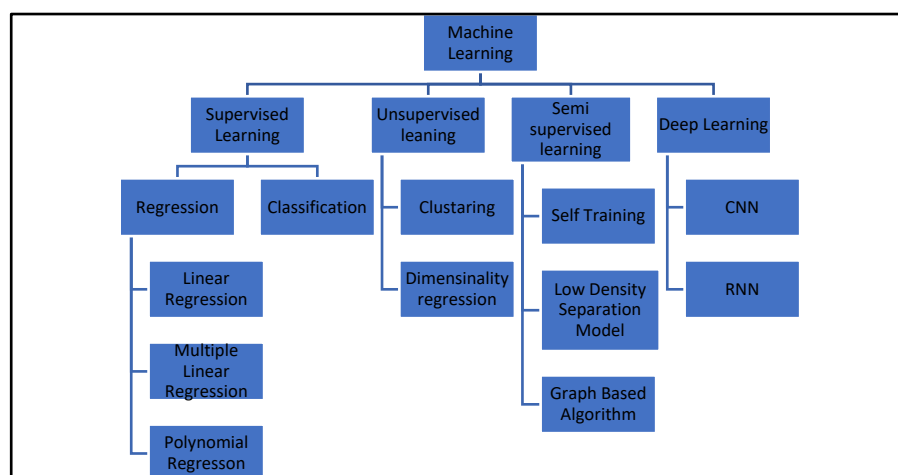


Figure 2.8 ML types that are mainly used for the prediction and classification of the algorithms (Ayodele, 2010). There are four different types of machine learning, and the major interest of the study is toward supervised learning, which is further divided into classification and regression methods. In present studies major aim is to identify the facies at well position, so the classification algorithm is used for this purpose.

2.9.1 Supervised Learning

This type of ML is based on using labeled data to train the learning algorithm. The data was described as labeled since it consists of pairs, an input that can be represented by a vector and its corresponding desired output, which can be described as a supervisory signal (Nafea et al., 2024). The learning mechanism was described as supervised since the correct output was known and the learning algorithm attempts to iteratively predict this output and was corrected to reduce the variation gap between its predicted and the actual output (Rathje et al., 2024). Analyzing the training data allows the supervised learning algorithm to produce a function that was called a classifier function if the output was discrete, and a regression function if the output was continuous (Doyoro et al., 2025). The learning algorithm generalizes detected patterns and features from the training data to a new input data in a reasonable way, and thus the produced function predicts the output corresponding to any provided input.

The various stages of the supervised ML method. Regression algorithms (continuous output) and classification algorithms (discrete output) are considered as the main categories of supervised learning. Regression algorithms attempt to uncover the best function that fits points in the training dataset. Regression algorithms include linear regression, multiple linear regression, and polynomial regression (Schuster et al., 2024). Classification algorithms, on the other hand, aim to uncover the best fit class for the input data through assigning each input to its correct class (Yang et al., 2024). In this case, the output of the predictive function is in discrete form, and its value is one of the different classes available, as shown in Figure 2.9.



Figure 2.9 Different stages of supervised learning, initiated by training data to learning algorithms and in the end outcomes of trained data (Tiwari et al., 2024).

2.9.2 Unsupervised Learning

Unlike supervised learning, this method uses an input dataset without any labeled outputs to train the learning algorithm. There is no right or wrong output to each input object and no human intervention to correct or adjust as in supervised learning. Thus, unsupervised learning is more subjective than supervised (Tyagi et al., 2022). The main goal of unsupervised learning is to learn more about the data through identifying the fundamental structure or distribution patterns that are found in the data itself. Learning by itself, the algorithm attempts to represent a particular identified input pattern while reflecting it on the overall structure of input patterns. Thus, the different inputs are clustered into groups based on the features that were extracted from each input object (Yu & Ma, 2021; Morales et al., 2022). Figure 2.10 represents the distinct stages of unsupervised ML methods.

Even though the algorithm will not assign names to the resulted clusters, it can still produce and differentiate among them and use some of them to assign new examples into other clusters. This approach is driven by input data and can work well when there is adequate data available for use. An example of that is social information filtering algorithms, like those used by Amazon.com to recommend books to users. These algorithms are based on finding similar groups of people, then adding new members to these groups (Bhattacharya, 2022; Whiteley et al., 2021). Algorithms included in unsupervised learning can be divided into three main categories include clustering, dimensionality reduction and anomaly detection (Caza-Szoka, 2015).

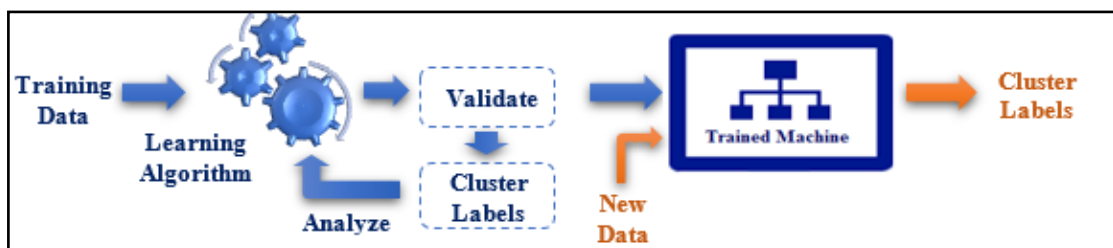


Figure 2.10 Various stages of unsupervised learning. Starting from the training data and after applying different learning algorithms, the end result is cluster labels (Tiwari et al., 2024).

2.9.3 Semi Supervised Learning

This method falls between the supervised and unsupervised learning methods where a large amount of data, some of which are labeled, and the rest are not. Many real-

life learning problems fall under this area of ML. The reason for that is that semi-supervised requires less human intervention since it utilizes ridiculously insignificant amounts of labeled data and a large amount of unlabeled data. Utilizing less labeled datasets is more appealing since such datasets are extremely hard to collect as well as expensive and may require access to domain experts as demonstrated in Figure 2.11. Unlabeled datasets on the other hand are cheaper and easier to get access to (Fan et al., 2022).

Both supervised and unsupervised learning techniques can be utilized to train the learning algorithm in semi-supervised learning. Unsupervised learning techniques can be used to unfold hidden structures and patterns in the input dataset. Whereas supervised learning techniques can be utilized to make guess predictions on the unlabeled data, feed the data back to the learning algorithm as training data and use gained knowledge to make predictions on new sets of data. Thus, the unlabeled data is used to modify or reprioritize predictions or hypothesis obtained from labeled data (Lan et al., 2021). Figure 2.11 illustrates the distinct stages of a semi-supervised ML method.

To make use of the unlabeled training data, all semi-supervised learning algorithms do at least one of the following assumptions (Su et al., 2022) smoothness assumption, cluster assumption and manifold assumption.

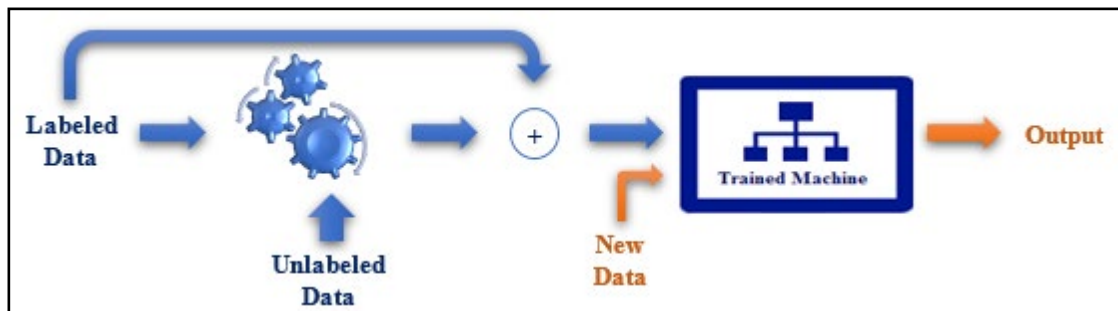


Figure 2.11 Different stages of semi supervised learning initiated from labeled and unlabeled data shown in blue color to the final output, orange arrow (Tiwari et al., 2024)

CHAPTER 3

RESEARCH METHODOLOGY

In the present era, due to the innovation of technology and advancement in the analysis era. The present research introduces novel algorithms to solve a challenging real-world problem that was previously unsolvable. Mathematical and computational techniques have made it possible to study beneath the Earth surface in a way that allows one to approximate the appropriate geothermal reservoir analysis that is not predictable by utilizing conventional techniques. The integration of complex and big data over numerical methods through DL allowed it to minimize the ambiguities in high chances of realizing their real capability. The workflow that is utilized in present research is different from the traditional geothermal assessment techniques in literature. The traditional methodology is based on physical seismic interpretation, modeling, and experimental methods of heat flow calculations by utilizing gradient and borehole data. These methods are often poor resolution and are unable to perform integration of multiple data sets. On the other hand, the existing study used an amalgam technique which included model based seismic inversion, geothermal and petrophysical properties estimation and DFFNN for the prediction of key geothermal parameters like PHIA, K, HP, FT, RHP and Vshl across the seismic transect. The integration of this research enhanced both accuracy of prediction and spatial resolution. Moreover, the incorporation of ML approach for the classification of reservoir characteristics calculation has not been utilized in previous geothermal investigation in the SIB specifically in Thar platform, assembling these techniques novel and innovative for future exploration of geothermal resources.

3.1 Research Approach

The aim of the research was to evaluate the geothermal potential that was present in the Thar Platform. Three blocks were identified to perform the details analysis, 2D seismic data of Sanghar Block-1, 2 and 3D seismic cube of the Nim Tay Block. To evaluate geothermal potential, the first step was to understand the subsurface geometry and structure of the area, which was done with the help of seismic data interpretation. Initially, the base map of the study area was made to determine the orientation of study

block and then with the help of seismic and well data, the synthetic seismogram was made to estimate the exact time of LGF in the seismic section. Secondly, fault and horizon were marked in the seismic section to interpretate the exact geometry of the subsurface. In last by using the horizon data time contour map of the LGF was developed by using velocity the depth contour map was made to understand the exact depth and structure of geothermal anomaly. The next step after the interpretation was to estimate the geothermal properties like HP, RHP, PHIA, K, and Vshl. The details of each calculation along with their parameters and formulas are discussed in the below sections.

In the next step, the model based seismic inversion was performed by using interpreted seismic and well data, first of all statistical wavelet was generated by using seismic data after that well to seismic to tie was established to know the exact position of the LGF. After that, a low frequency model (LFM) was generated for the LGF. The reason for making LFM was to extract the lower frequency from the seismic data that was not attenuated in the original seismic data. In the next step the model-based inversion analysis was performed to know the exact correlation and error present in inversion analysis. In last the variation of inverted Z_p was shown in the seismic section along with their well location.

After the model-based inversion analysis was applied, the DFFNN on the geothermal properties and shows their variation on the seismic section specifically on the control lines where the well is present. It works on nonlinear regression techniques, which performs excellent in complicated geological data than the linear regression approach. It allows multiple attribute analysis which provides a better result for properties and facies prediction. DFFNN used high-dimensional input data and provided excellent convergence with minimum error. This model beat the conventional algorithms because of its high accuracy of prediction with minimum uncertainty, specifically with inadequate and noisy data. For DFFNN the first step is single attribute analysis and its relations with seismic, impedance and geothermal properties and that MAA by using 20 attributes was applied on the seismic section which provide the validation and application result, and, in the end, cross plot is generated between actual vs predicted geothermal properties. Finally, DFFNN is applied to the geothermal properties by using a best attribute that provides a maximum correlation between actual vs predicted properties. After achieving a maximum correlation, the final part of DFFNN was to display these properties on the seismic section as shown in Figure 3.1.

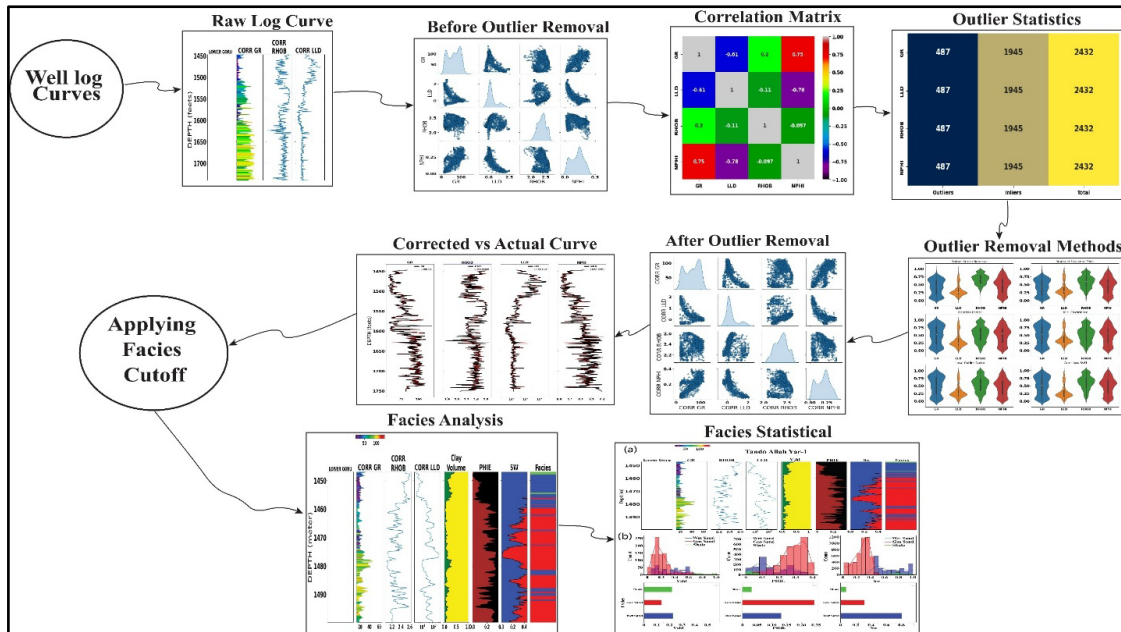


Figure 3.2 Complete workflow for facies analysis. Initiated by cleaning of log curve data by removing outlier, five different methods are used to remove the outlier and, in the end, actual and predicted log curve are displayed. In the second phase the corrected log curve is used to predict the facies on each well that are encountered in the study area.

3.1.1 Seismic Interpretation

Seismic data interpretation is important in the field of geophysics and geology because it allows us to gain insight into the subsurface of the earth. Seismic data is collected by sending sound waves (or seismic waves) into the ground and measuring the response of these waves as they bounce off different layers of rock and sediment. It involves analyzing these measurements to create images of the subsurface structure of the earth. This can help geoscientists to understand the location and characteristics of different rock formations, faults, and other geological features that may be important for a variety of applications, including exploration for oil and gas and mineral exploration. The seismic surveying approach is undoubtedly the most employed geophysical hydrocarbon exploration technique. This is primarily because it can detect subsurface structure that range in size from small to large (Björk et al., 2010). The basic aim of seismic interpretation is the consistent characterization of geology, and all aspects of interpretation work towards this objective. Refraction seismic data interpretation must be correct for oil and gas exploration to be effective (Herron, 2011). The details of seismic data interpretation workflow were discussed in Figure 3.3.

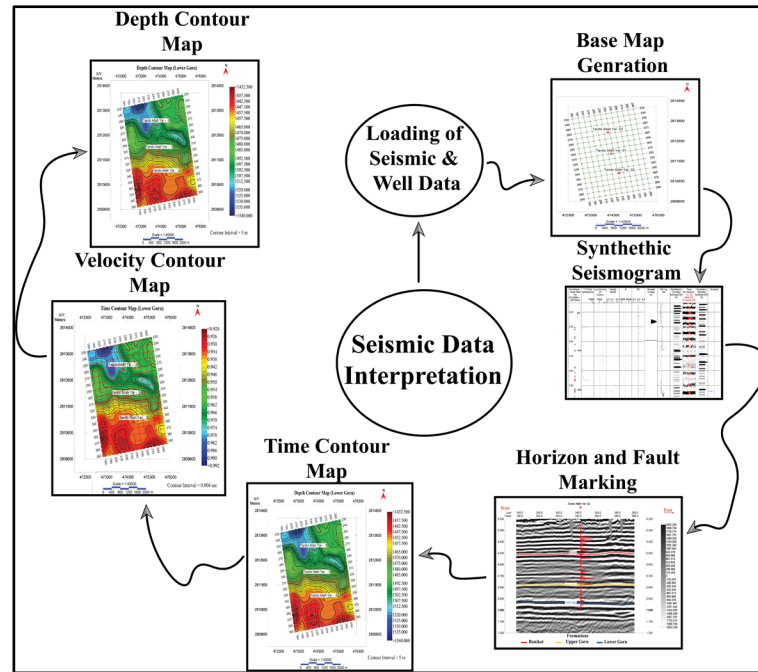


Figure 3.3 Detailed methodology of seismic interpretation adopted for structure analysis.

3.1.2 Loading of Seismic and Well Data

A 3D seismic cube (Nim Tay Block) and 2D seismic lines, consisting of dip and strike lines in SEG Y format for the Sanghar Block was utilized in the present study. The data is loaded into SMT Kingdom Suits 2017 using SEG Y headers for seismic line loading. For present study, a 15 km² 3D seismic cube of the Nim Tay and 2D seismic data consist of six strike line and fourteen dip line were provided with its ten wells, i.e., Allah Dino-1, Babar-1, Bukerani-1, Jarwar-1, Jumman Shah-1, Sono-2 Sono-5, Tando Allah Yar-1, Tando Allah Yar-2, Tando Allah Yar-3. The integrated workflow comprises all the available data sets utilized for the identification of litho-stratigraphic units as well as seismic tie correlations.

3.1.3 Generation of Base Map

Once seismic and well data loading was complete, a base map displaying the seismic data and wells was generated. The base map shows the orientation of the overall grid. In the 3D cube of Nim Tay Block consist of three well Tando Allah Yar-1,2 and 3 along, with two kinds of seismic lines inline, and the cross line. The crosslines start from 176 to 297, and the inline ranges between 230 and 392 shown in Figure 3.4. The orientation of inline is from east to west, and for a cross line, the orientation is from north to south. The location of well on the grid was demonstrated in Table 3.1.

The second seismic area named Sanghar Block-1, consists of five 2D seismic lines and two wells. Out of five 2D seismic lines, four were dip lines and one is striking line. The orientation of the dip line from west to east and strike line was north to south. The Sono-2 and 5 were present on strike line GO-872-SGR-510 with SP 220 and 265 respectively as shown in Figure 3.5. The third seismic area was named Sanghar Block-2, which consists of twenty seismic lines, out of which six were strike lines and the remaining fourteen are dip lines. The orientation of strike lines was north to south, and the orientation of dip lines was east to west as shown in Figure 3.6. The well Bukerani-1 and Jarwar-1 were present at the dip line G862-SGR-102Ext and G862-SGR-103Ext respectively while remaining wells were present on strike lines like Allah Dino-1 was present in strike line G862-SGR-153, Babar-1 was lies in strike line G862-SGR-176 while Jumman Shah-1, Tando Allah Yar-1,2 and 3 were present on the strike line G947-SGR-168S as shown in Figure 3.6.

Table 3.1: Location of the Well on the seismic described based on 2D and 3D seismic line numbers.

Well Name	Inline	Cross line
Tando Allah Yar-1	310	235
Tando Allah Yar-2	350	242
Tando Allah Yar-3	267	237
	2D seismic Line	
Allah Dino-1	G862-SGR-153	
Babar-1	G862-SGR-176	
Bukerani-1	G862-SGR-102Ext	
Jarwar-1	G862-SGR-103Ext	
Jumman Shah-1	G947-SGR-168S	
Sono-2	GO-872-SGR-510	
Sono-5	GO-872-SGR-510	

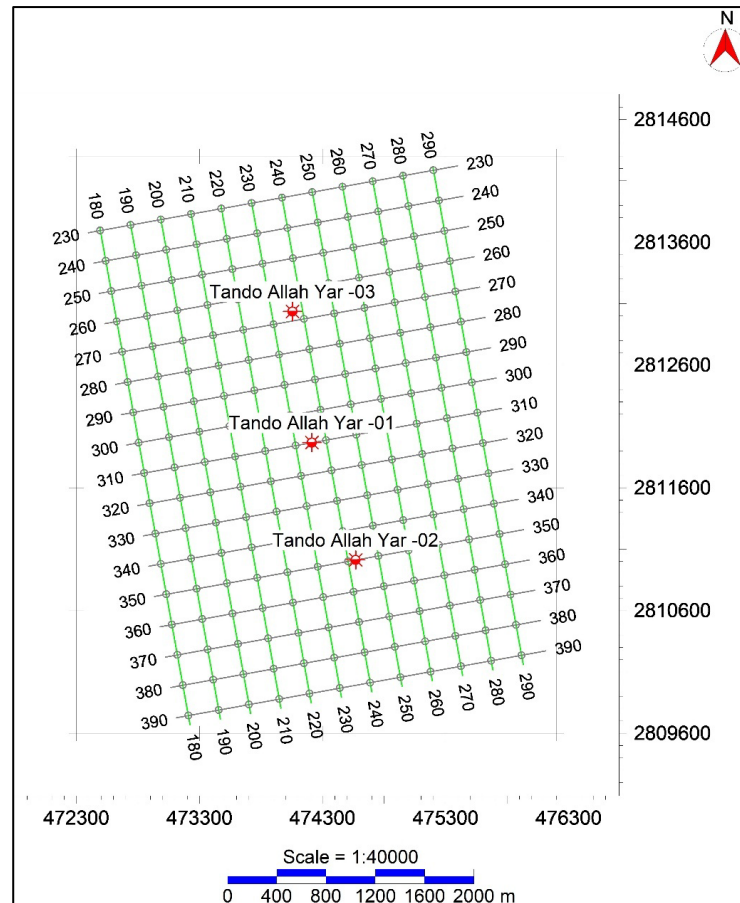


Figure 3.4 Base map of 3D seismic cube of Nim Tay Block along with three wells locations of Tando Allah Yar-1, 2 and 3. The inline is starting from 230 to 392 while crossline is 176 to 297.

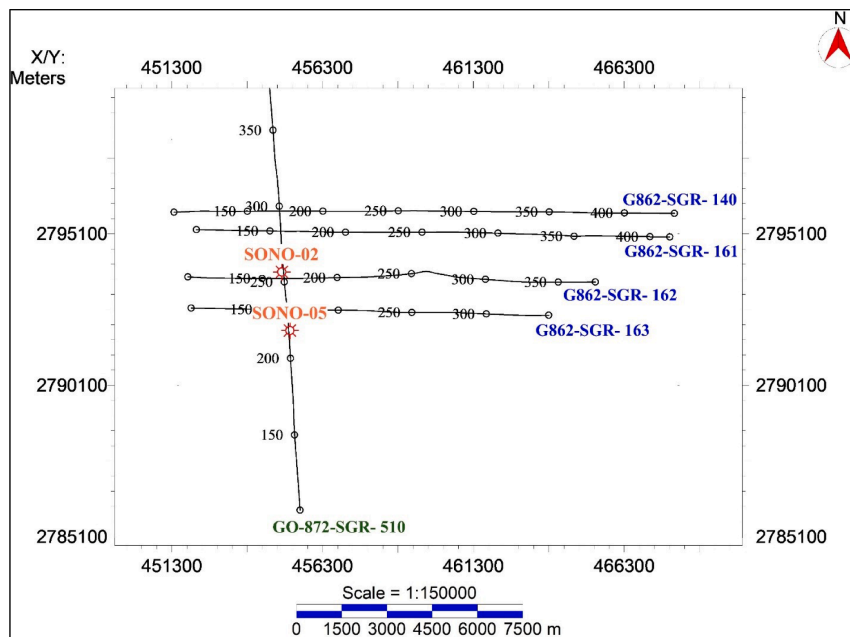


Figure 3.5 Base map of Sanghar Block-1 consists of four seismic dip lines and a strike line. Sono-2 and Sono-5 are located at the seismic strike line G0-872-SGR-510 at the SP 220 and 265 respectively, the orientation of dip lines is west to east and strike line is north to south.

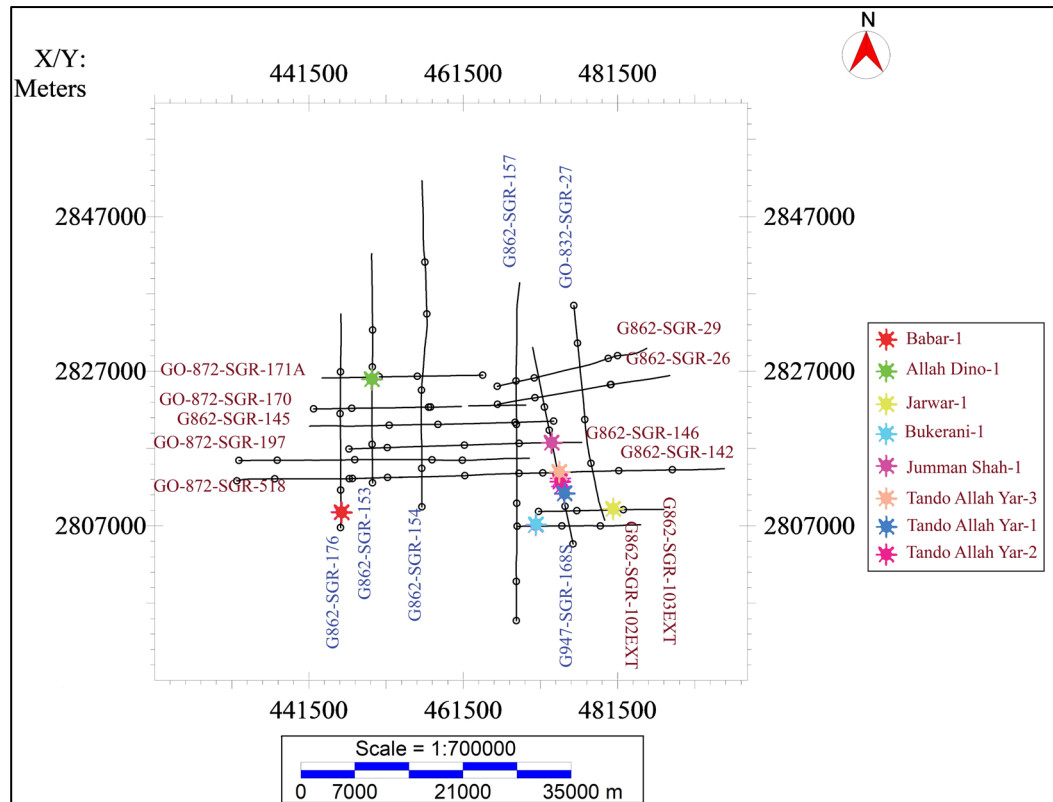


Figure 3.6 Base map of Sanghar Block-2 shows the orientation of 2D seismic lines and the names of wells along with their location. The dip line direction is from west to east while the strike line is north to east, there is strike line name as G947-SGR-168S which is tilted, and its direction is northwest to southeast.

3.1.4 Synthetic Seismogram

A synthetic seismogram is a 1-D forward model of acoustic energy that travels through the earth's horizons and has an acoustic impedance contrast. The synthetic, using Sanghar Block wells, was created by the merging of earth reflectivity series that were obtained from the logs such as sonic and density. The wavelet required for synthetic generation was extracted using 3D seismic cube of Nim Tay Block and 2D seismic line of Sanghar Block. The degree of correspondence between a seismic section and a synthetic seismogram was dependent on the quality of well log data sonic (DT) and density (RHOB) logs are required to produce a synthetic seismogram. Before marking the horizons, a synthetic seismogram of the given wells was generated (Hampson et al., 2001).

For a well to seismic tie, a seismogram is required. Therefore, DT and RHOB from all wells, along with their GR log as references, are employed in well to seismic correlation. The seismic data traces surrounding the wellbore were used to form a wavelet, which was then convolved with the impedance log generated from the well's DT

and RHOB to produce a final synthetic seismogram. After that, the synthetic was compared to the seismic data, and changes were performed using shift and stretch. The well-to-seismic relation was completed once the nature of synthetic and seismic data was matched, and work moved on to the next phase, which was the selection of horizons using the time depth chart correlation produced during the tie. The synthetic seismograms based on Tando Allah Yar- 3, Sono-2, and Jarwar-1 are displayed in Figure 3.7, Figure 3.8, and Figure 3.9, respectively.

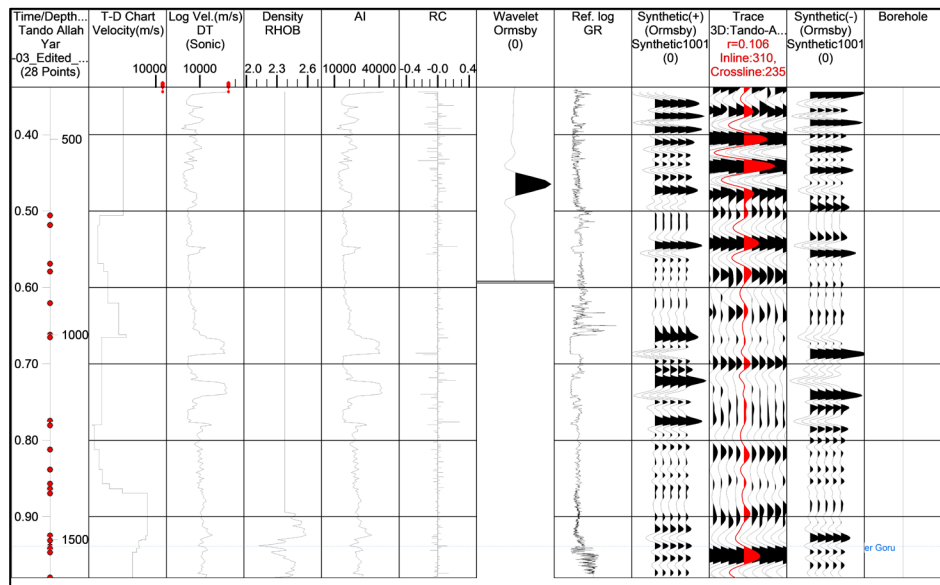


Figure 3.7 Synthetic seismogram of Tando Allah Yar-3 well showing the LGF at the time of 0.93 sec. Ormsby wavelet is used to convolution of RC and AI.

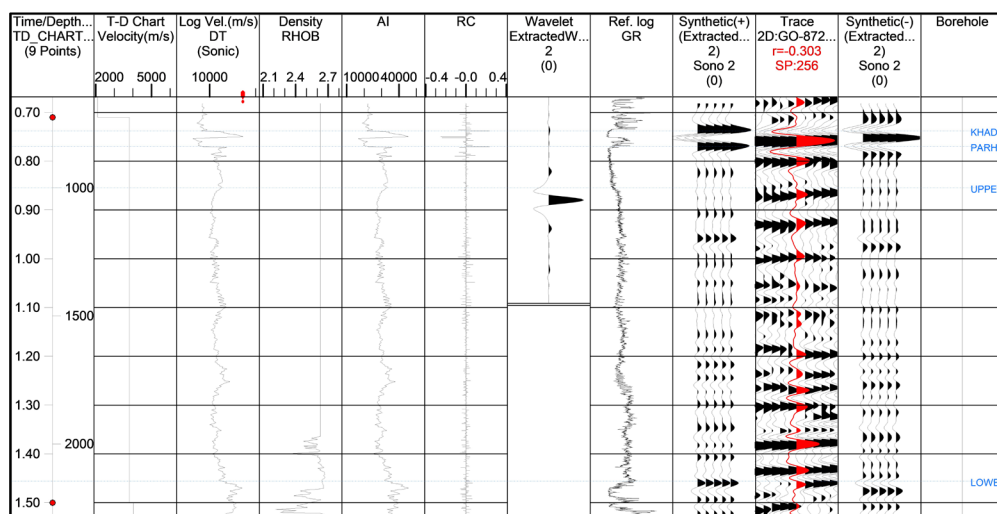


Figure 3.8 Synthetic seismogram of Sono-2 well showing the LGF at the time of 1.45 sec. The extracted wavelet from the seismic section is utilized from convolution between RC and AI and GR log is used as a reference.

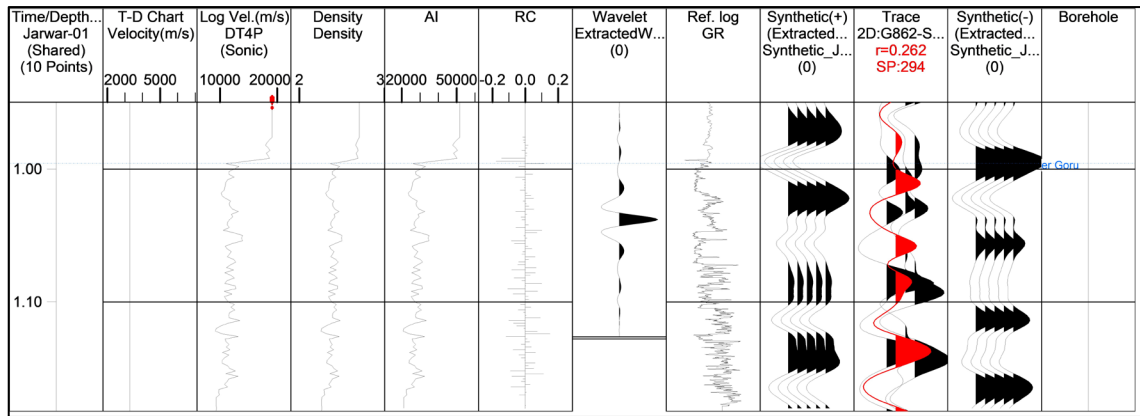


Figure 3.9 Synthetic seismogram of Jarwar-1 well showing the LGF at the time of 1.02 sec. Extracted wavelet from the seismic data is used for the convolution of RC and AI.

3.1.5 Seismic to Well Tie

The synthetic seismogram creation and execution of seismic to well tie is due to the reason for marking the exact reflector of horizons on the seismic section. Figures 3.7, 3.8 and 3.9 show the exact location of formations after the accomplishment of well to seismic ties, along with extracted wavelets, their amplitude, and the correlation coefficient. Therefore, the targeted formations, i.e., LGF, are marked at their corresponding times throughout the seismic data of the research area. Table 3.2 shows the well to seismic tie of each well that is present in the study area.

Table 3.2: LGF time on the well location along with their velocity information.

Sr. No	Well Name	Time (sec)	Velocity(m/s)
1	Allah Dino-1	1.423	3281.79
2	Babar-1	1.394	3091.82
3	Bukerani-1	1.323	2515.49
4	Jarwar-1	0.99	2361.61
5	Jumman Shah-1	1.152	2663.19
6	Sono-2	0.71	3302.40
7	Sono-5	0.73	3264
8	Tando Allah Yar-1	1.198	2777.96
9	Tando Allah Yar-2	1.059	2900.84
10	Tando Allah Yar-3	1.070	2721.49

3.1.6 Marking of Horizon and Faults

Following the ties, the marking of the concern reflector is initiated, which is in correspondence with the tops present in the wells. The Time-Depth graph created through the seismic to well tie will then be used by software to show these formations top (depth domain data) on the seismic (time) accurately. The primary target of structure interpretation is to mark the LGF. The reflectors on the seismic data are highly visible and can easily be identified and recognized, thus aiding in data matching, particularly during seismic to well tie (Khan et al., 2021).

After the approval of reflectors at the concerned formation tops, horizons and faults have been marked at specific intervals in the seismic data. For consistency of interpretation, often every line both inline, crossline (3D seismic cube), dip line and strike line (2D seismic line) were interpreted. As every line was interpreted, a hunting tool was used to interpolate the data across the entire seismic, allowing the software to automatically select the appropriate horizons based on marked interpretation and similar reflector characteristics. Similarly, faults were interpreted along with the interpretation of horizons throughout the entire seismic and then fault surfaces for the entire seismic data were created.

3.1.7 Time Contour Map

After the marking of structure on the seismic data the next step was to create the time contour map of the LGF. The time contour map confirms the overall variation of the time in the LGF. With the help of time contour maps, the possible prospects and leads were identified for the further drilling process. In most cases, the trapping geometry was performed between the fault closing structure.

3.1.8 Velocity Contour Map

In the current study, velocity mapping was also a part of the research. Velocity maps are made by utilizing roots mean square velocity of the LGF. Generally, lower velocity demonstrates highly saturated and porous formations, which are tremendous condition for geothermal reservoirs because of the heat storage and transmit capacities. In contrast, the extreme velocity indicates the compacted lithological along with less K due to which movement of fluid is resistance. Abrupt change in velocity distinctions

noted with structural features like faults might boost K, fluid migration as well as heat transfer.

3.1.9 Depth Contour Map

After making the time and velocity contour map the next step is to know the exact depth of formation. The depth of the formation is simply calculated by the formula shown in equation 3.1.

$$S = \frac{V \times T}{2} \quad (3.1)$$

where V is the velocity taken by the velocity map and T is a two-way travel time of formation. As the time that is used is two-way travel time as the interested time is one way travel, so the given equation is divided by 2 to know the exact depth of interested formation.

3.2 Geothermal Properties Evaluation

The main aim of this study was to evaluate geothermal properties based on log curve data sets. The major reason for analyzing geothermal characteristics more reliably is to make informed decisions regarding drilling operations, completion, and testing based on the gathered data. These properties require the mandatory constraints that enable more realistic models of geothermal reservoirs, i.e., a static model. Overall, Petrophysicists have a significant role in the achievement of wells and connections in various fields such as production geology, technology, reservoir engineering, and exploration seismology. The chemical and physical characteristics of rocks are evaluated during petrophysics along with the fluids within the rock empty spaces. The geothermal properties are assessed by employing the well logs, while they can also be estimated in the laboratory by the core data. The geothermal reservoir properties evaluation regains both qualitative and qualitative characteristics that are quite noteworthy. The volumetrics, such as fluids, Vshl, the recognition of source rock, and the aquifer capacities, can be attained by the relationships between the properties achieved from calculation. These properties are keen interest for petroleum engineers, geologists, geophysicists, and core analysts.

Most of the time, conventional seismic data analysis can demonstrate numerous questions in geophysics regarding zone of interest. Geothermal properties evaluation is a

study that utilizes variation of dataset including well logs, cores, and production data to attain more realistic physical properties by combining all the available data sets. The techniques are mostly associated with hard limitation data of bore holes at various positions consequently having not much reliance on seismic. The key geothermal reservoir characteristics included S_w , K , PHIA, HP, RHP, GG, Vshl, and the connectivity among fluids. Nowadays, comprehensive assessment of geothermal reservoirs is needed by carefully selecting the wireline suits for interpretation that optimize the accuracy in saturations, PHIA, lithologies, and K , etc.

3.2.1 Heat Production

In the laboratory, GR spectrometry is widely employed to evaluate HP (Alqahtani et al., 2023). A variety of investigators have employed diverse techniques to assess HP, such as the GR approach for airborne spectrometry and the GR logging method (El Gendy et al., 2024). When determining the relationship between depth and HP as shown in equation 3.2.

$$HP = 0.0158 \times (GR - 0.8) \quad (3.2)$$

Whereas HP is heat production measured in microwatt per meter cube, GR is a gamma ray log, and its values are in API.

3.2.2 Radiogenic Heat Production

RHP is calculated in a unit of $\mu\text{W}/\text{m}^3$ using equation 3.3 (Čermák et al., 1991).

$$RHP = (9.52C_u + 2.56C_{Th} + 3.48C_k) \times \rho \times 10^{-5} \quad (3.3)$$

Where C_U is concentration of uranium (ppm), C_{Th} is concentrations of thorium (ppm), and C_K is concentrations of potassium (wt. %), and ρ is the rock's density expressed in kg/m^3 . For U, Th, and K, the corresponding production of heat constants are 9.52, 2.56, and 3.48 W/kg. They show how each radioactive element contributes to the generation of radiogenic heat, with U, Th and K having the largest contribution.

3.2.3 Formation Temperature

The thermal heat budget of sedimentary basins is dictated by heat transfer at the lithosphere-asthenosphere boundary and lithospheric heat sources. Tectonic evolution influences heat flow and average geothermal gradients in the sedimentary basins

(Kolawole and Evenick, 2023). The FT is a key factor that affects the wellbore fluid temperature and is used to compute geothermal gradients by utilizing bottom hole and surface temperatures (Al Saedi et al., 2019). In order to explore a geothermal reservoir, the subsurface temperature is considered a key parameter. Therefore, borehole temperature records obtained from drilled well data contribute substantially to the current knowledge about the thermal regime, and target geological formation is relevant for geothermal energy (Agemar, 2022). Equation 3.4 was used to compute formation temperature (FT).

$$FT = \text{Surface Temperature} + (\text{Geothermal Gradient} \times \text{Depth}) \quad (3.4)$$

3.2.4 Geothermal Gradient

Geothermal gradients serve as valuable indicators of subsurface temperature distribution and are among the most frequently utilized parameters in logging geophysics (Kutasov and Eppelbaum, 2014). They play a crucial role in understanding regional and subregional tectonics and are instrumental in evaluating the geothermal resource potential of an area (Nwankwo and Ekine, 2010). The equation used for the geothermal gradient is shown in equation 3.5,

$$GG = \frac{FT - St}{\text{Depth}} \quad (3.5)$$

Whereas GG is geothermal gradient, FT is the formation temperature, St is the surface temperature.

3.2.5 Calculation of Gamma Ray Index

The Gamma Ray Index (IGR) is computed from GR log data. The amount of natural radioactivity in the formation influences the GR log value. Because shale contains many radioactive materials, it has a high value of GR log. Shale volume can be estimated by using the method (equation 3.6) (Rider, 1986)

$$IGR = \frac{Gr_{\log} - Gr_{c\ln}}{Gr_{shl} - Gr_{c\ln}} \quad (3.6)$$

Where,

IGR = Index Gamma Ray.

Gr_{log} = Value of GR at interested depth.

Gr_{cln} = Minimum GR value (An average lowest value GR log).

Gr_{shl} = Maximum GR Value (An average highest value of GR log).

3.2.5.1 Calculation of Volume of Shale by Stieber Model

The volume of shale was estimated by the Stieber model, which was considered as a nonlinear technique. It is utilized for approximating the volume of shale information in which the shale acts as a bound between the sandstones. It is an updated version of the index gamma ray log for the variation of shale, specifically in thin shale bed within thick sandstone bed (Azeem et al., 2017). Equation 3.7 demonstrates the Stieber model.

$$V_{shl}_{Stieber} = \frac{0.5 \times IGR}{1.5 \times IGR} \quad (3.7)$$

Whereas IGR is an index gamma ray log. This model is performed well when there are interbedded sand and shale in the formation. Through this model the calculation of PHIA and K is also enhanced because of its accuracy.

3.2.5.2 Calculation of Volume Shale by Clavier Model

It is an empirical model that enhanced volume of shale calculation in lithology where shale is in scattered and structured forms. This model is affected when the gamma ray log curve shows high reading such as above 200 API due to that reason clavier model is utilized for the correction of nonlinear trend of gamma ray log (Adepehin et al., 2022). The equation 3.8 demonstrates the clavier model.

$$V_{shl}_{clavier} = 1.7 - (3.38 - (IGR + 0.7)^2)^{\frac{1}{2}} \quad (3.8)$$

This equation is worth full where GR ranges are high in shale content, confirmation, and additional real approximation of reservoir characteristics. It utilizes information where there is interbedded shale to improve reservoir properties for better estimation of the fluid present in the sub surface.

3.2.6 Volume of Clean

The formula in equation 3.9 is used for calculation of clean volume (Rider, 1986).

$$V_{cln} = 1 - V_{shl} \quad (3.9)$$

3.2.7 Permeability

The capability of a rock to transmit fluids is known as permeability. It is calculated by the diameter of the interconnecting channels (pore throats or capillaries) among pores. It is a crucial factor in characterizing any hydrocarbon resources. It is expressed in millidarcies or darcies. The K of LGF was determined using the Tixier (1949), Timur (1968), and Coates and Dumanoir (1973) equations.

3.2.7.1 Determination of Irreducible Water Saturation

The water that capillary force keeps in the pore spaces is known as irreducible water saturation (S_{wirr}). The pressure within the grains prevents the water saturation in the uninvaded zone (S_w) from migrating when a zone reaches irreducible water saturation (Olutoki et al., 2024; Meng et al., 2023). Irreducible water saturation for the majority of the rocks used for reservoirs in the field varies from below 10% to greater than 50% (Adepehin et al., 2022). Equation 3.10 was used to estimate the S_{wirr} :

$$S_{wirr} = \sqrt{\frac{F}{2000}} \quad (3.10)$$

Whereas F is a formation factor, and F was calculated by Archie's equation 3.11.

$$F = \frac{a}{\phi^m} \quad (3.11)$$

Where ϕ is a PHIA, a is a lithologic constant and m is a cementation exponent.

3.2.7.2 Permeability Estimation by Tixier Method

According to Tixier's 1949 proposal, the K of a reservoir is determined directly by its cubic PHIA and indirectly by its irreducible water saturation. The following mathematical proof exists for Tixier's equation (equation 3.12):

$$K_{Tixier} = 250 \frac{\phi^3}{S_{wirr}} \quad (3.12)$$

Whereas K_{Tixier} is a Tixier Permeability, ϕ^3 is Porosity, S_{wirr} is an Irreducible water saturation.

3.2.7.3 Permeability Estimation by Timur Method

It was calculated by the diameter of the interconnecting channels (pore throats or capillaries) among pores. It is expressed in millidarcies or darcies (Riyadi et al., 2024). The K of the LGF was determined using the Timur (1968) equation 3.13. Timur (1968) presented a different K equation that was applied in this comparative analysis. Timur's K was calculated across the 0.5-foot depth of the wellbore using the previously computed irreducible water saturation; the mean values were then gathered for every reservoir.

$$K_{Timar} = 250 \frac{\phi^{4.4}}{S_{wirr}^2} \quad (3.13)$$

Whereas K_{Timar} is a Timur permeability.

3.2.7.4 Permeability Estimation by Coates and Dumanoir Method

The Coates and Dumanoir (K_{cd}), an improved empirical K technique with the support of core and log studies, have been more successful for studying heterogeneous formations (Mohaghegh et al., 1997). This approach was used to PHIA and irreducible water saturation (S_{wirr}) as input parameters to compute K. This approach yields K values in good agreement with core data (Chen et al., 2008; Adepehin et al., 2022). So, the Kcd approach adopted to estimate K in the Lower Gour Formation as shown in equation 3.14.

$$K_{cd} = \left[100 \times \frac{PHIA^2 (1 - S_{wirr})}{S_{wirr}} \right]^2 \quad (3.14)$$

3.2.7.5 Permeability Estimation by Absolute Method

Absolute permeability is an estimation of single fluid flowing from the reservoir rock, whereas the permeability is the transmit of fluid from porous medium. It is a fundamental characteristics of reservoirs, such as solid fluid and fluid interactions that is dependent of the type of fluid like oil, gas and water offered the fluid dominates 100% of the empty spaces (Yan et al., 2021; Wood, 2020). Absolute permeability is calculated with the help of effective porosity as shown in eq 3.15.

$$K_{abs} = -2.04 + (30.15 \times PHIE) - (34.16 \times PHIE^2) \quad (3.15)$$

3.2.8 Porosity Calculation

Porosity is number of pores present in the rock and that pores are fluid filled. There is different method for the calculation of porosity and the detailed of these methods are described below.

3.2.8.1 Estimation of Density Porosity

Porosity with the help of density can be calculated with the help of RHOB. Following formulation (equation 3.16) is used to evaluate porosity (Schmoker & Halley, 1982).

$$PHID = \frac{\rho_m - \rho_b}{\rho_m - \rho_f} \quad (3.16)$$

Where,

ρ_m = Density of matrix (2.35 to 2.65 g/cm³ for LGF)

ρ_b = Formation bulk density.

ρ_f = Fluid Density.

PHID = Density Porosity.

3.2.8.2 Estimation of Neutron Porosity

The NPHI value is brought straight from the neutron log, which goes corresponding to the RHOB.

3.2.8.3 Estimation of Average Porosity

The total number of pores present in a rock is referred to as its porosity. These pores are a critical component of the reservoir for hydrocarbon buildup. The PHIA is calculated using RHOB and NPHI log values. The PHIA of a reservoir is computed by applying the formula given below (equation 3.17) (Rider, 1986).

$$PHIA = \frac{PHID + PHIN}{2} \quad (3.17)$$

3.2.8.4 Estimation of Sonic Porosity

Sonic log is used for calculation of porosity. The need for PHIS can be used when the condition of bore holes is too bad. So, the sonic log is only log that helps to know about correct porosity. The formula in equation 3.18 of calculation of PHIS (Rider, 1986).

$$PHIS = \frac{\Delta t - \Delta t_{ma}}{\Delta t_{fld} - \Delta t_{ma}} \quad (3.18)$$

Where,

Δt = sonic log values ($\mu s/ft$).

Δt_{ma} = matrix travel time ($\mu s/ft$).

Δt_{fld} = fluid travel time ($\mu s/ft$).

3.2.8.5 Estimation of Effective Porosity

The fraction of connected pore spaces in relation to the bulk volume is known as PHIE. PHIE is a parameter utilized in computations as it characterizes the interconnected pore spaces that comprise recoverable hydrocarbon fluids. PHIE is computed using equation 3.19 (Kamel and Mohamed, 2006).

If the condition of the boreholes is good

$$PHIE = PHIA \times (1 - V_{shl}) \quad (3.19)$$

Use equation 3.19 if the condition of the borehole is bad (Caving) than PHIE is calculated by using equation 3.20,

$$PHIE = PHIS \times (1 - V_{shl}) \quad (3.20)$$

As our zones of interest have undergone caving, PHIE is calculated using sonic log porosity.

3.2.9 Resistivity of Water Calculation

Resistivity of water (R_w) is calculated with the help of Pickett plot method. Pickett plot method represents deep resistivity on x-axis and PHIA log on y-axis. The plot is based on the logarithmic of Archie equation (Kebing et al., 2019). Water Saturation points (S_w) will be plotted on a straight line with a negative slope of value m . Water zones define the lower most line on the plot. The R_w may be estimated from a location on the line because $S_w = 1$. Other parallel lines with different S_w can be drawn once the water

line is formed, assuming a constant n (usually 2). Then, in terms of S_w , other data can be plotted and evaluated. The Pickett plot is used to estimate the resistivity of water LGF.

3.2.10 Saturation of Water

S_w refers to the amount of water in a formation that is not equal to the amount of hydrocarbon present. S_w denotes the saturation of water. It's computed by adding 1 by a S_w . In our case Archie equation 3.21 is used for the calculation of S_w .

$$S_w = \sqrt[n]{\frac{a \times R_w}{R_t \times (PHIA)^m}} \quad (3.21)$$

S_w = Saturation of Water.

a = Tortuosity factor.

m = Cementation factor.

n = Saturation exponent.

R_w = Resistivity of formation and water.

$PHIA$ = Average porosity

3.3 Machine Learning Techniques for Facies Classification

Multiple well logs, including GR, LLD, and RHOB, were obtained from LAS and CSV files. The data was organized in depth, and certain logs, such as resistivity, were converted to a logarithmic scale to improve interpretability. Improvements were made to guarantee the accuracy of data, such as correcting resistivity logs with base-10 transformations. The collection of data was then processed for further investigation by calculating critical petrophysical parameters. For example, V_{shl} was calculated utilizing the linear interpolation approach based on corrected gamma-ray measurements. $PHIA$, another key characteristic for facies classification, was extracted from the RHOB using the standard equation for density porosity, which requires a matrix density of 2.65 g/cm³ and fluid density of 1.0 g/cm³ (typically representing sandstone).

Using formation tops data, the well was separated into several geological formations, and every region was investigated separately. The LGF was of particular interest. This zoning enabled the identification of facies based on established criteria in the petrophysical characteristics Table 3.3, which indicates the cutoff used for predicting facies. Criteria for V_{shl} were defined using geological knowledge and empirical evaluation, which permits the distinction between shale and clean sand facies, as well as various lithological variables. Facies were then classified into depth ranges according to

these thresholds, with each interval distinguished by their dominant lithology and petrophysical characteristics (Qassamipour et al., 2020).

Table 3.3: Cutoffs for lithology prediction in LGF (Qassamipour et al., 2020).

Lithology	Cutoff
Shale	$V_{shl} > 0.3$
Wet Sand	$V_{shl} \leq 0.3 \ \& \ S_w > 0.45$
Gas Sand	$V_{shl} \leq 0.3 \ \& \ S_w \leq 0.45$

Unsupervised ML algorithms were used to discover and remove outliers from the facies classification, ensuring their accuracy. Several algorithms were used, including the Isolation Forest, Elliptic Envelope, Local Outlier Factor (LOF), and One-Class Support Vector Machine (SVM). The algorithms involved were selected for their capacity to identify variations in multivariate data, with each offering a unique approach to spotting outliers. Isolation Forest was utilized to locate and isolate aberrant data points, while the Elliptic Envelope technique used a Gaussian distribution to detect deviations. The LOF method detected local density-based outliers, while the One-Class SVM collected portions of the data where typical cases are clustered. Data points identified as outliers by these techniques were either discarded or marked for further research.

Visualization techniques, including cross plots and histograms, were used to show the range of facies across formations and to contrast the data set prior to and following outlier removal. The graphical representations also served to validate the effectiveness of outlier detection, revealing that removing aberrant data increased the overall accuracy of the facies categorization as shown in Figure 3.2. The combined use of petrophysical research and ML-based outlier elimination verified that the final facies categorization was accurate and representative of the underlying subsurface lithology.

The present research is totally different from conventional facies estimation techniques like K- means clustering, Bayesian Classification and Principle component analysis because these techniques are categorized as unsupervised ML and linear regression approach with encounter the geological point of view, while on the other hand, DFFNN is a nonlinear regression and supervised learning approach with integration multiple geophysical data simultaneously which is not possible by traditional methods. The novelty of these advanced techniques improves the prediction model with highly

confidence and make a better alignment with geological formations for effective geothermal assessment.

3.4 Seismic Inversion Analysis

Seismic inversion is a subsurface geological modelling approach that employs seismic data as an input and a well log as a control (Richa et al., 2022). This is performed by converting the amplitude data into acoustic impedance. Forward modelling and inverse modelling are the two basic types of geophysical modelling. Inverse modelling predicts an earth model from a geophysical respond, whereas forward modelling predicts geophysical respond from the earth model (Akpan et al., 2020). The use of the seismic inversion method aids in the conversion of information about the earth's reflectivity over time into impedance data. Seismic records are taken by sending the signal from the earth surface to subsurface. These signals reflect back from the subsurface and relieve the composition of layer as shown in Figure 3.10. Multiple interactive surveys based on 3D are now retrieved from various seismic reversals and are regarded as a significant tool for processing (Narayan et al., 2024). Seismic inversion deals with two types of seismic data, pre-stack, and post-stack seismic data. Post-stack seismic data produces only P-impedance, whereas pre-stack seismic data produces both P and S acoustic impedance and its derivatives such as V_p/V_s , Λ -rho, μ -rho to estimate fluid and lithology parameters from the subsurface. Seismic inversion is a 1-D convolution model, in which seismic traces are a convolution of earth reflectivity and wavelet with noise (Zhang et al., 2021). However, only post-stack inversion is discussed in this research. Seismic inversion's main goal is to change seismic reflection information into a quantifiable property of rock that illustrates the reservoir. Inversion outcomes illustrate higher resolution and more accurate interpretations than dealing with seismic amplitudes. Due to which reservoir parameters like PHIA and net pay can be better estimated. Another advantage is that interpretation efficiency is increased, which more than compensates for the time wasted in the inversion process (Smith et al., 2022).

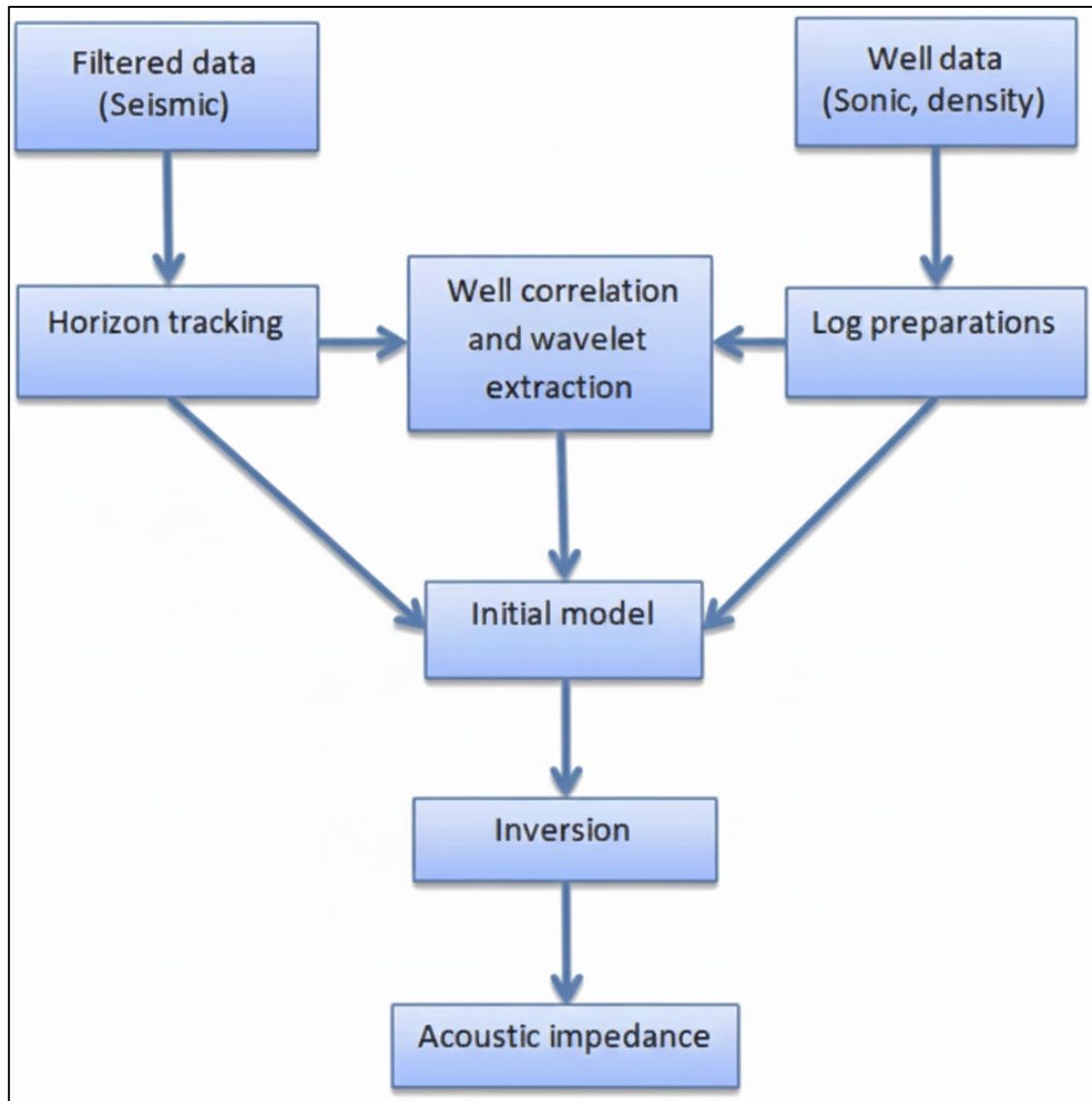


Figure 3.10 Generalized workflow of seismic inversion (Veeken, and Silva, 2004).

3.4.1 Post-Stack Seismic Inversion

Stacked seismic data is given as input for post stack inversion. Stacking reduces the noise effect from the signal by keeping true amplitude preserved (Narayan et al., 2024). Traces from common-mid-point (CMP) are picked and stacked at zero incidence angle. Resulting seismogram represents reflectivity at normal incidence. So, inversions performed on such seismic data are called post-stack seismic inversions. Seismic post stack inversion is a robust technique with its simpler assumptions as shown in Figure 3.11. It has two approaches between band limited and broad band inversion methods respectively (Ali et al., 2023).

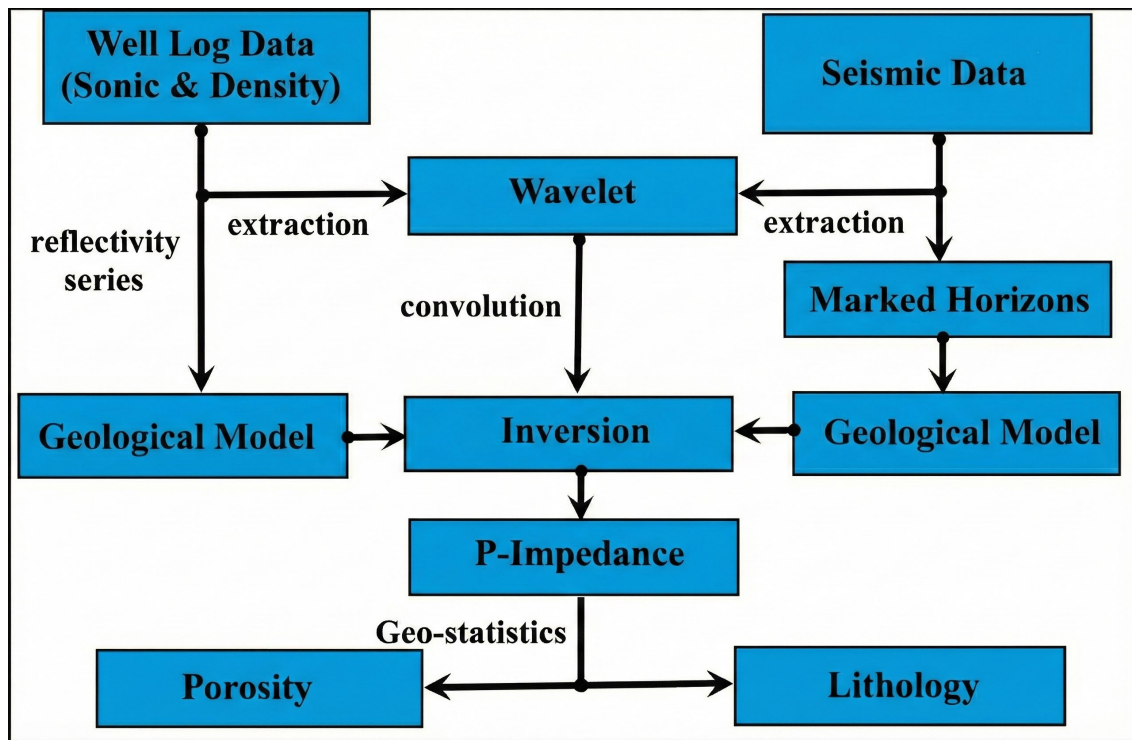


Figure 3.11 Generalized post stack inversion process (Mallick, 1995).

3.4.2 Low Frequency Model

The computation of low frequency model (LFM) is the next step of the inversion. It was created by incorporating low frequencies from well interpolated data within stratigraphic framework following marked horizons (Meng et al., 2021). Thus, the low frequency component (0-15 Hz) is incorporated to obtain the absolute acoustic impedance in the inversion algorithm (Russell and Hampson, 1991). The model based seismic inversion technique uses an initial model (LFM) based on impedances information (using combination of DT, and RHOB), structural information (horizon data) and the interpolation of properties between wells following the structural and stratigraphic patterns. The initial model contributes to the structural delineation and overall compaction trend without incorporating the seismic data (Zhang et al., 2021). The initial model is established by using all wells of Sanghar Blocks along with the developed stratigraphic model using low frequencies up to 15 Hz.

3.4.3 Model Based Seismic Inversion

The foundation of model-based inversion is convolution theory. The convolution theory states that normal incidence seismic trace can be modeled as convolution of source wavelet with earth reflectivity plus the addition of noise (Akpan et al., 2020). Model based inversion starts with initial geological model and perturbs this model until a good correlation between synthetic seismogram and seismic trace is obtained. Model based inversion is appealing because it cannot directly invert seismic data (Zhang et al., 2021). Model based inversion is effective for thin reservoirs because seismic data is band limited; the resolution and accuracy of direct inversion methods cannot fulfill the requirement of exploration industry (Russell, 1988). Model based inversion contains both high frequency and low frequency components so detailed information about stratigraphic and physical properties is obtained as shown in equation 3.22.

$$J = weight_a \times (S - W * R) + weight_b \times (M - H * R) \quad (3.22)$$

In the equation mentioned, seismic trace mentioned by S, W for wavelet extracted from seismic data, reflectivity series by R data, initial created model denoted by M and H integration operator. As it is obvious that the initial part of equation is modeled with seismic trace and other part modeled the initial model estimated (Russell, 1988). In the above equation the first part modeled the seismic trace, and the second part modeled the initially estimated impedance.

3.5 Neural Networks

One of the primary difficulties in reservoir characterization of sandstone and shale formations is finding zones with good PHIA and K (Amjad et al., 2023). The innovative techniques include the extraction of features from seismic data which is then correlated with reservoir behavior and mixing them to gather subsurface characteristics. DFFNN is a contemporary tool for this purpose (Wang et al., 2019). Firstly, the relationship between the input parameters like geothermal properties or petrophysics and seismic data is established and later their properties are expanded on the whole seismic section by utilizing different attributes like inverted impedance. This procedure assists in forecasting of primary reservoir characteristics, for example, fluid, lithology, and the extent of the productive region. This procedure combines data from boreholes, inversion, and seismic data, manipulating ML systems to enhance prediction (Colwell & Kjøsnes, 2018). Mostly geothermal properties like PHIA, Vshl, K, HP, RHP, FT, and GG are modeled and

applied to improve reservoir mapping. Amongst neural networks, one of the most common utilizations is the MLF model, which is trained by backpropagation as shown in Figure 3.12. Two basic types of neural networks are applied to seismic data: one is known as Classification, and the other is sample-based prediction. The classification approach is used to predict the characteristics that are present in the zone of the seismic section. This approach is used by defining aim categories like fluid or facies types and model is trained to distinct between these properties (Moa et al., 2022; Naseer et al., 2025c). Log curved data is used for this purpose, which is restricted to one dimension of data that provides highly efficient resolution, and this data is utilized for training and neural network assist to apply these features all over the seismic transects. The classification model is more authentic because it can deliver assurance for predictions, backup additional conversant decision-making in subsurface assessment (Din et al., 2023). On the other hand, in sample estimation, the model is trained by using borehole location with the help of inversion data (like P-Impedance) and seismic data attributes (such as root means square attribute, chao attributes, similarity and instantaneous phase and frequency attributes). However, sometimes there are a variety of attributes that may mislead the data due to which the model goes to overfit, so to avoid this error, the cross validation is used to identify the most important inputs. By focusing on up to 20 attributes the model performance is marginally improved. While the training procedure includes the iterative technique by adjusting the weight, 70 % of the data is used for training and 30% for predicting this error in the data is minimized. However, the neural network is working based on maximum accuracy as compared to linear regression model which is more sensitive to overfitting that makes validation crucial for reliable outcomes (Amjad et al., 2023).

The complete procedure of DFFNN is to produce a nonlinear approach that estimates log curve values like geothermal properties by using seismic attribute from neighbor regions. Input data consists of seismic transect or 3D seismic data and borehole log with calibrated log curves. Two types of attributes are using in DFFNN one is external attribute that is estimated by inverted impedance and internal attribute extracted by using seismic data as shown in Figure 3.13. Features mining and preconditioning are used to minimize the data range and make training of the model more efficient (Moa et al., 2022). The DFFNN model utilized these characteristics to estimate required standards as a sum of known examples.

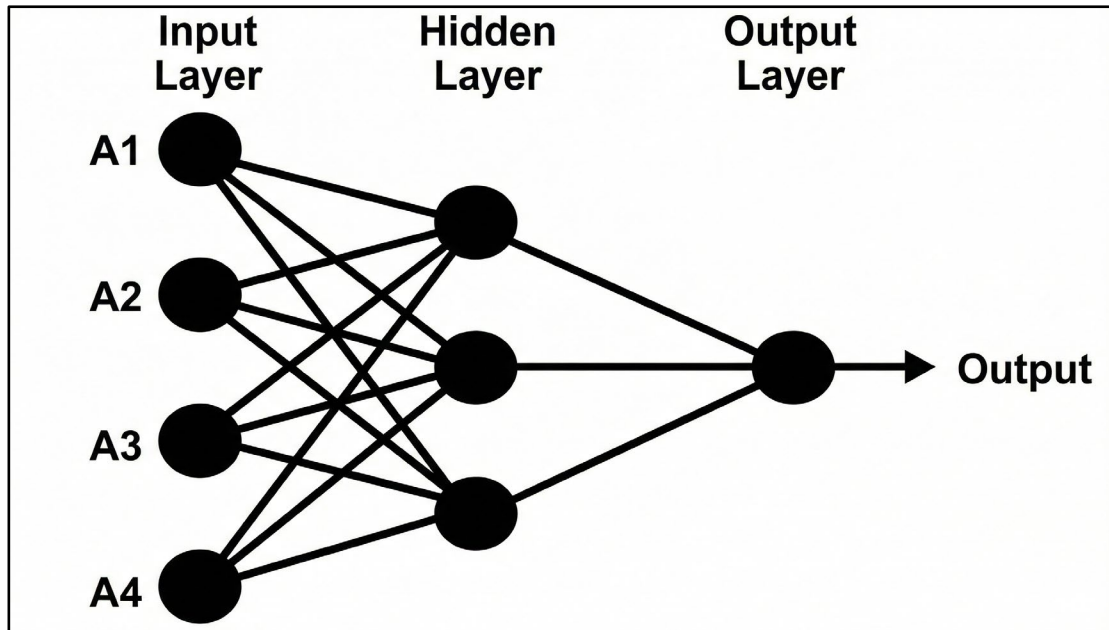


Figure 3.12 Schematic of a multi-layer feed-forward artificial neural network (Moseley & Krischer, 2020).

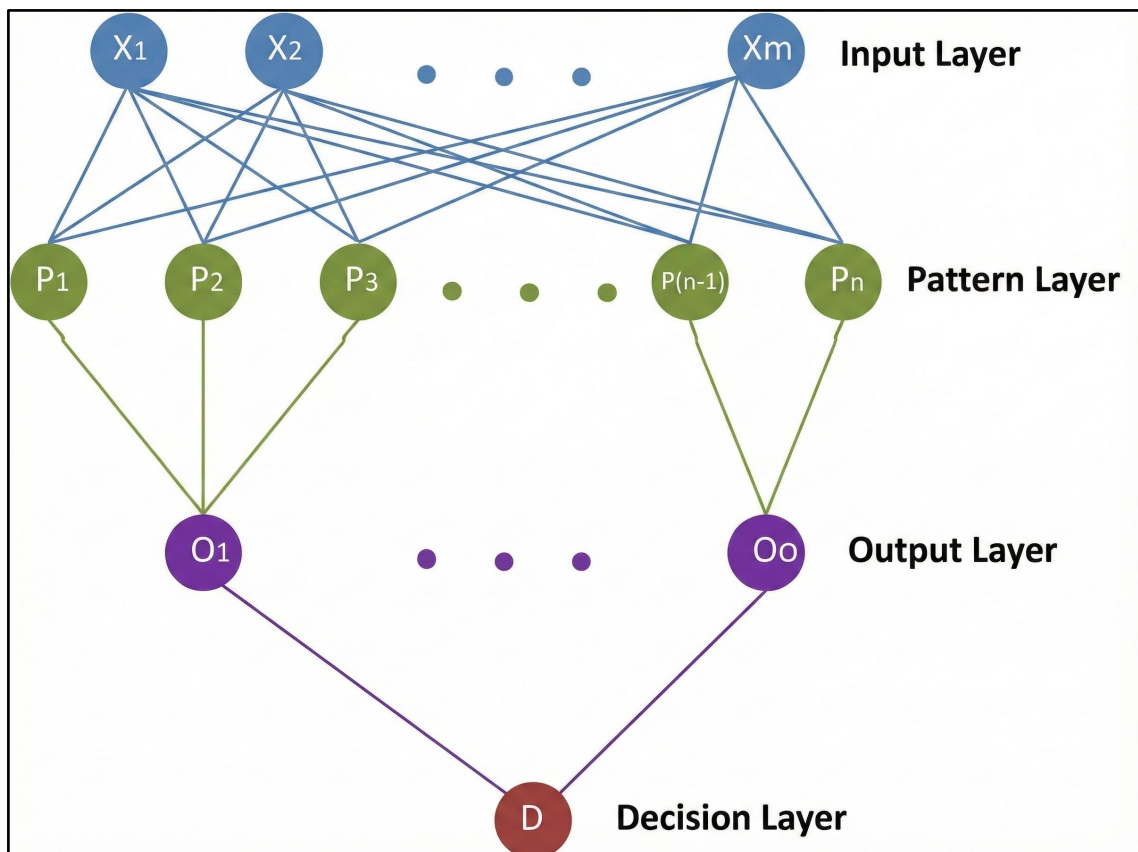


Figure 3.13 Basic design of a DFFNN showing the four major steps for performing the function (Subrahmanyam and Roo, 2008).

3.5.1 Geothermal Properties Prediction by Neural Network

The geothermal properties prediction by neural Network is done with the help of Hampson-Russell in the module of Emerge. Different steps are followed in emerging to run the DFFNN. The details of these steps are shown in Figure 3.14.

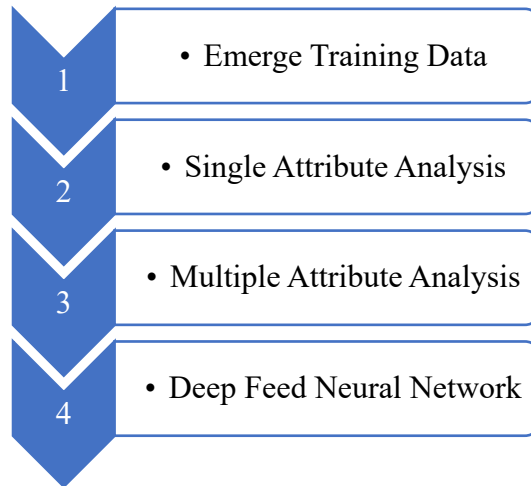


Figure 3.14: The workflow of a DFFNN is a systematic step that is applied to each geothermal property to show the variation in the seismic section.

3.5.1.1 Emerge Training Data

The goal of the emerge procedure is to combine well log and seismic data. The overall goal is to estimate a well log property using seismic data features. That characteristic might be any measured geothermal parameters, such as Vshl, K, PHIA, HP, RHP, and GG, or a determined lithologic attribute, like Vshl. The loading of seismic, impedance, and well data is done in emerge training.

3.5.1.2 Single Attribute Regression

After loading data, the next step is to examine the single attribute transform, for which the single attribute list is reviewed. The test of non-linear transformation is performed and applied to both the target (Vshl, K, PHIA, HP, RHP, and FT) and external attributes (inversion result). In single attribute analysis, the target Vshl, K, PHIA, HP, RHP, and FT), correlation and error should be observed; the maximum correlation should be higher at its maximum values than is known as good correlation.

3.5.1.3 Multi Attribute Regression

In multiple attribute regression (MAA) different numbers of attributes are run. MAA shows the validation error as well as the training error. The correlation of MAA depends on the number of different attributes that are run. The higher the correlation less will be error. The total number of attributes in the is selected based on log curve statistics and chooses those attributes that performed a good result in that specific property.

3.5.1.4 Deep Feed forward Neural Network

To increase target prediction, neural network capabilities were used. The Neural Network's non-linear properties will boost both the predictive power and the resolution of the derived target volume because of this. Under the heading of Neural Network, emerge contains various algorithms, the Discriminant analysis algorithm is not strictly a Neural Network, but included it in this group because of its classification capabilities (Amjad et al., 2023). In the above given algorithms, our interest is in DFFNN. For DFFNN multiattribute selection process has determined which attributes are best for predicting the target log. By selecting a different number of attributes (called integrated absolute amplitude), they are constructing a neural network with precisely the same attributes as those used in that transformation (Colwell & Kjøsnes, 2018). In DFFNN the training window is defined based on interested formation. Current studies are focused on LGF so the zone is defined by marked LGF horizon in the seismic section and logs data for training of model. By defining the window, the prediction is only limited to the interested zone and the prediction outside of this range may be overfit or underfit due to less coverage of data. Due to this reason the calibration and selection of training windows is crucial for the reliability of model output. DFFNN correlation values of (85 to 98%) are estimated by utilizing DFFNN. The data that is used for training consists of geothermal and petrophysics properties (PHIA, Vshl, HP, RHP, K and FT) that are correlated with twenty seismic attributes that are extracted by well data. The data was split into a ratio of 30% for validation and 70% for training with defined sampling interval and iteration. The model is run on LGF and model based seismic inversion output reflects the lithology divergences. These conventions permitted strong training and precise prediction of properties across the seismic transect.

The correlation is significantly higher than with multiattribute regression. Because of the non-linear structure of the operator, this is frequently the case with neural

networks. Note also that the neural network has been utilized only within the training windows. This was done for two reasons. The first reason is if the neural network were applied to the entire window, the application time could be quite significant. Second, the reason is about extrapolating beyond the limits of the training data was difficult for the neural network. As a result, it is likely to be less accurate outside of the training windows than multi-linear regression (Wang et al., 2019; Moa et al., 2022).

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Seismic Data Interpretation

The subsurface structural interpretation is performed to understand the complex geometry exist in the subsurface. The major concern of present studies is based on geothermal potential evaluation, so the structure of the subsurface plays a vital role. The current study is based on 2D and 3D seismic data of the Sanghar Block. The 3D block is named Nim Tay Block which covers an area of 1 km², and 2D block consists of twenty-five dip and strike lines as mentioned in tables 1.1, 1.2 in chapter 1.

4.1.1 3D Seismic Interpretation of Nim Tay Block

The time depth information of the Tando Allah Yar -1 and 2 well for marking three horizons, including Ranikot, Upper Goru, and Lower Goru formations, is used to establish the well-to-seismic tie. The Ranikot Formation occurred 0.51 sec ago at the Tando Allah Yar-2 well site. The LGF reflector is designated at 0.95 3, whereas the Upper Goru Formation is marked at 0.78 sec. Since the data primarily covers the flat portion of the building, there are no noticeable defects in the study region. The LGF depth structure map is produced by utilizing velocity data and the time structure map to identify the LGF horizon structural relief below the surface.

The details of the LGF along with their time, depth, and velocity are shown in Table 4.1. The time is measured in seconds; depth is in meters and velocity is meter per second. The specifics of all the wells that are used in Sanghar Block are demonstrated which represent that the deeper time is present on the Sono-2 and Sono-5 well which is 1.43 sec and 1.51 sec, respectively. while the shallow time is observed in Tando Allah Yar-1 and Bukerani-1 that is 0.92 sec and 0.94 sec, respectively.

Table 4.1: Detailed of time, velocity and depth information of wells that are encounter in Sanghar block.

Sr. No	Well Name	Time (sec)	Velocity (m/s)	Depth (m)
1.	Tando Allah Yar-1	0.92	3101.05	1447
2.	Tando Allah Yar-2	0.95	3158.26	1536
3.	Tando Allah Yar-3	0.99	3068.34	1456
4.	Sono-2	1.43	2949.94	2166
5.	Sono-5	1.51	2987.65	2238
6	Allah Dino-1	1.20	3591	2335
7	Babar-1	1.08	3990.7	2155
8	Bukerani-1	0.94	3540.42	1664
9	Jarwar-1	0.99	2361.61	1169
10	Jumman Shah-1	1.02	3007.84	1534

The structural analysis has been carried out in Nim Tay Block to know better understanding of the subsurface structure. Due to limitation of data set the proper structure has not been identified on the seismic section. Three horizons are marked on the seismic section, Ranikot, Upper Goru and Lower Goru formations. Figure 4.1 demonstrates three marked horizons on the seismic arbitrary line along with the well to seismic tie (red wiggle) based on Tando Allah Yar-1, 2 and 3 wells. The Ranikot Formation is marked with the red color, yellow color Upper Goru Formation and blue color show the LGF. The LGF is marked on the crust of the seismic wiggle. The present seismic cube portion lies on the western side of the block where the structure is absent, and all the reflectors are dipping toward the easter portion of the block. Figure 4.2 represents the seismic inline 315 where the Tando Allah Yar-1 well is present in the inline 315 and crossline 338. The orientation of the line is from east to west and three horizons LGF, Upper Goru Formation, and Ranikot Formation are also marked on the inline 315. Figure 4.3 represents the seismic inline 345 where the Tando Allah Yar-2 well is in inline 345 and crossline 242. The orientation of the line is from east to west and three horizons LGF, Upper Goru Formation, and Ranikot Formation are also marked on the inline 345. Figure 4.4 represents the seismic inline 270, where the position of Tando Allah Yar-3 well is in inline 270 and crossline 238. The orientation of the line is from east to west and three horizons, LGF, Upper Goru Formation and Ranikot Formation is also marked on the inline 270.

Figure 4.5 shows the time contour map of the LGF, time contour map is directly made by the marked horizon. The time contour map shows the linear trend from north to south. There is a gradual increase in the time values, and the range of the time varies from 0.92 to 0.99 sec. The red color of the time contour of the map shows the shallow time region and blue color demonstrates the deeper time that is encounter in the LGF. The time at the well location of Tando Allah Yar-2 is shallow but as moving toward Tando Allah Yar-1 & 3 the time is increasing. The interval of the time contour map is 0.004 sec. Figure 4.6 shows the velocity contour map of the LGF. The velocity map is generated by analysis of the velocity window from the seismic section. The velocity contour map shows the linear trend from north to south. There is a gradual increase in the value of velocity varies between 3050 m/s to 3118 m/s. The low velocity zone that is present in the map, which is shown by yellow color is a potential zone for geothermal fluid. Figure 4.7 shows the depth contour map of the LGF, depth map is made with the help of velocity and time data. The depth contour map shows the linear trend from north to south. There is a gradual increase in the depth values, and the range of depth varies between 1432 to 1540 m. The green color shows a shallow depth and as moved toward the red color the deeper depth is shown in the contour map.

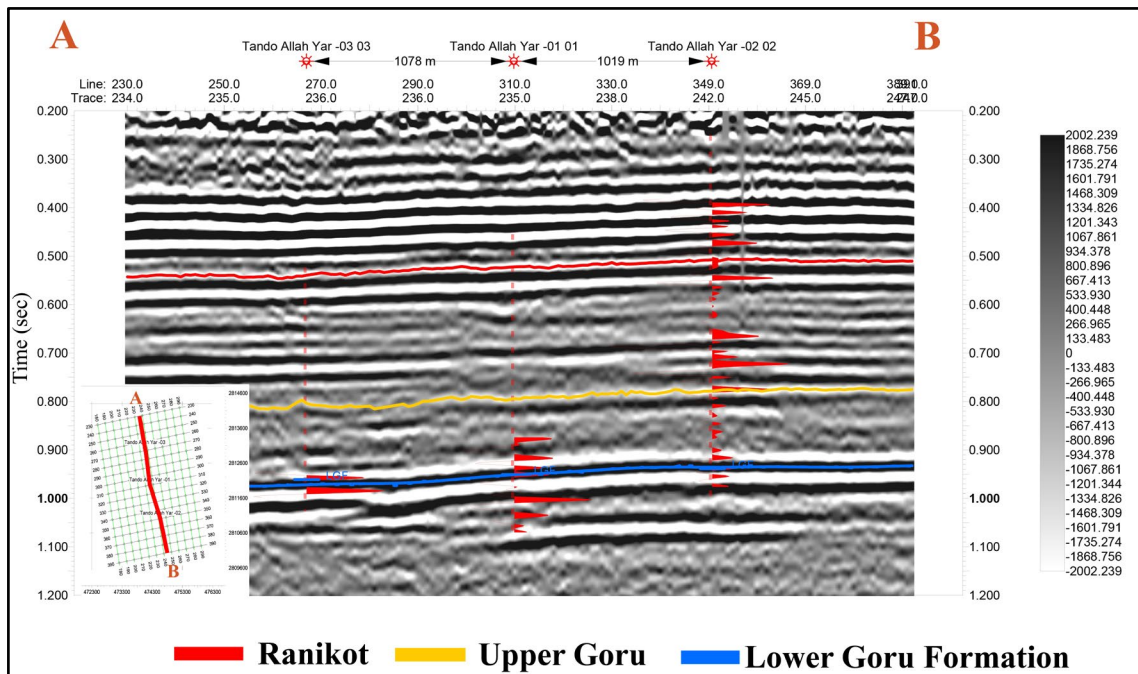


Figure 4.1 Interpreted arbitrary seismic inline shows the well to seismic tie to Tando Allah Yar-1, 2 and 3 along with three marked horizons on the seismic section. The blue color shows the interest in the LGF for study that is dipping towards the east side, and the LGF is marked at the time of 0.92 sec at Tando Allah yar-2 wells as moved toward Tando Allah Yar-3 the time is around 0.99 sec.

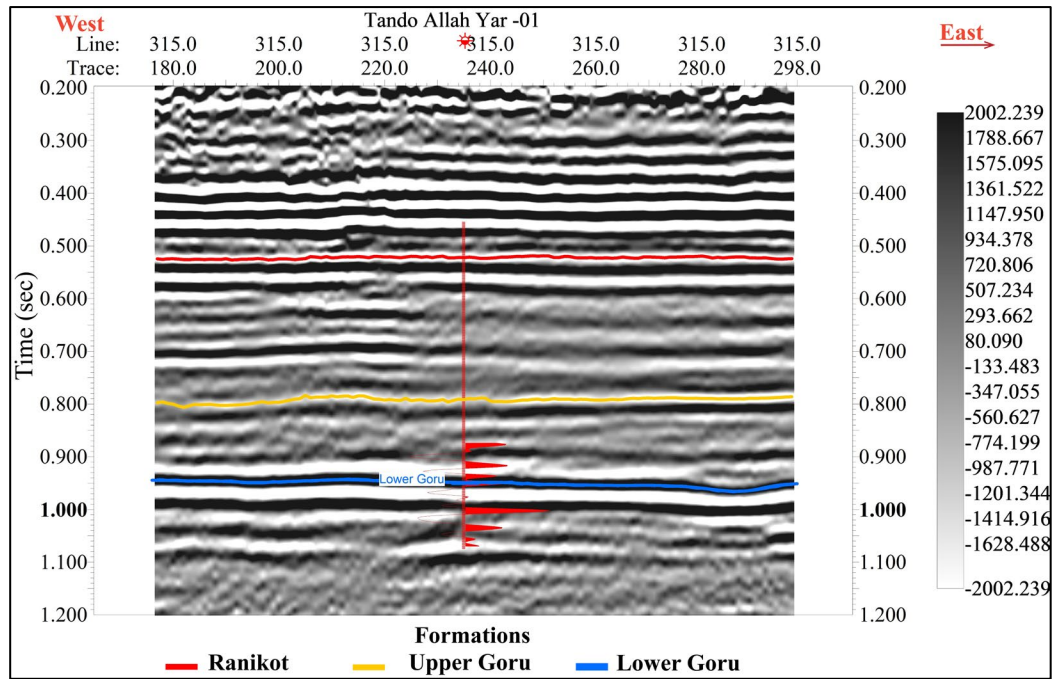


Figure 4.2 Interpreted seismic inline 315 showing the synthetic curve of Tando Allah Yar-1 along with three marked horizons on the seismic section. The blue color showed the interesting LGF that is used for study. The orientation of the inline is west to east and the color bar present on the right side of seismic section represents the amplitude. The black color shows a positive amplitude while white illustrates the negative amplitude. LGF is marked on a positive amplitude.

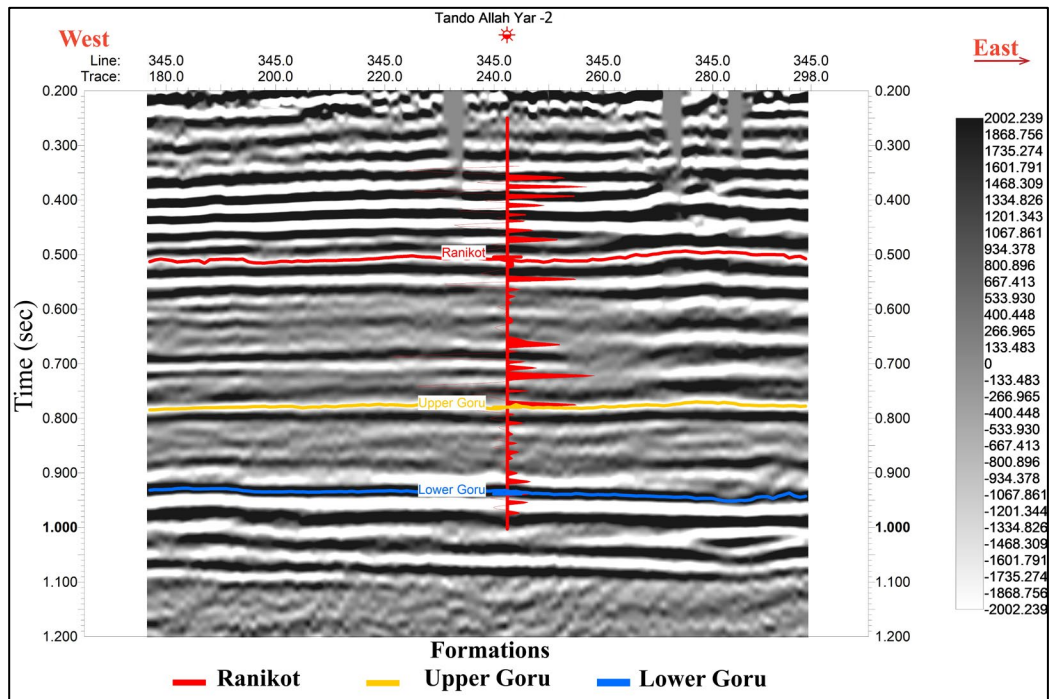


Figure 4.3 Interpreted seismic inline 345 of the 3D Nim Tay Block shows the red curve of synthetic seismogram of Tando Allah Yar-2 well along with three marked horizons on the seismic section. The blue color showed the interested LGF that is part on the positive amplitude.

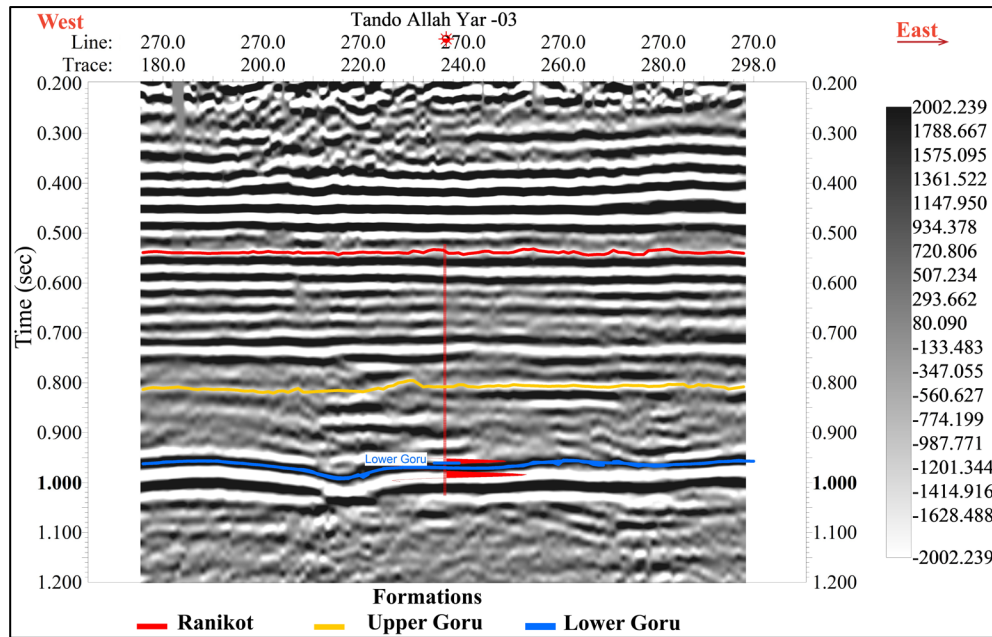


Figure 4.4 Interpreted seismic inline 270 shows the well to seismic tie to Tando Allah Yar-3 along with three marked horizons on the seismic section. The orientation of the line is west to east and blue color shows the LGF.

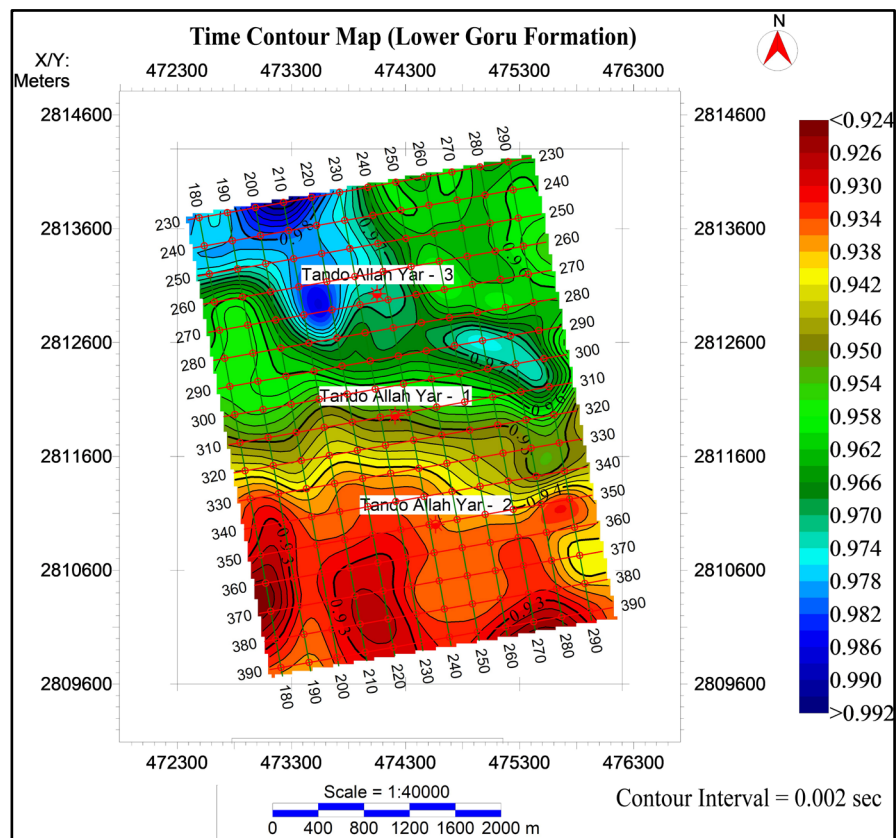


Figure 4.5 Time contour map of the LGF has been generated on the contour of 0.002 sec, which demonstrates that the time is going deeper from Tando Allah Yar-1 well to Tando Allah Yar-3 well. The deepest time is observed on the north part of map with blue color.

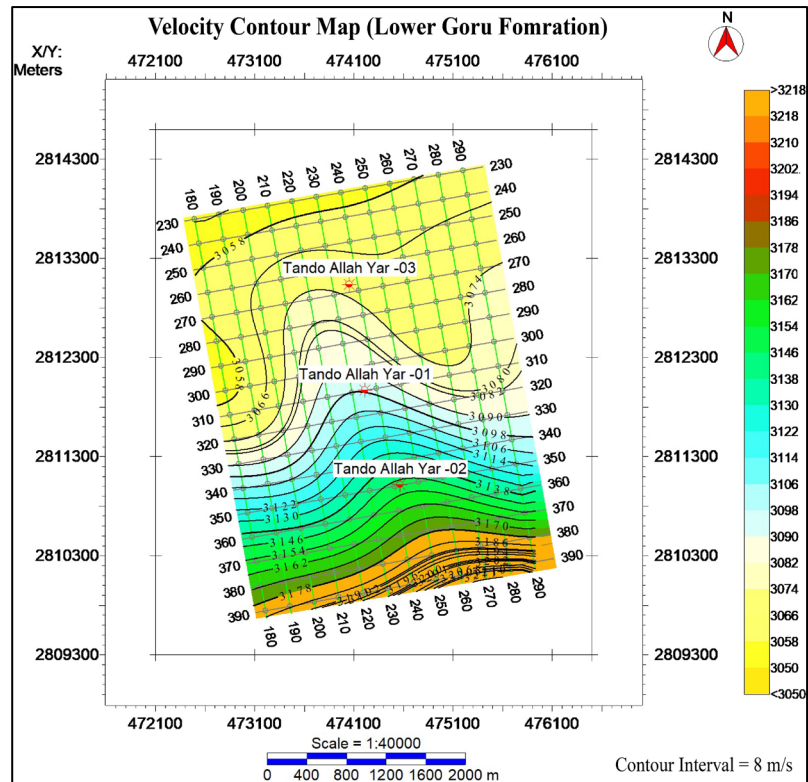


Figure 4.6 Velocity contour map of the LGF has been generated on the contour interval of 8 m/s, which demonstrates that the velocity is higher toward the south showing with yellow color.

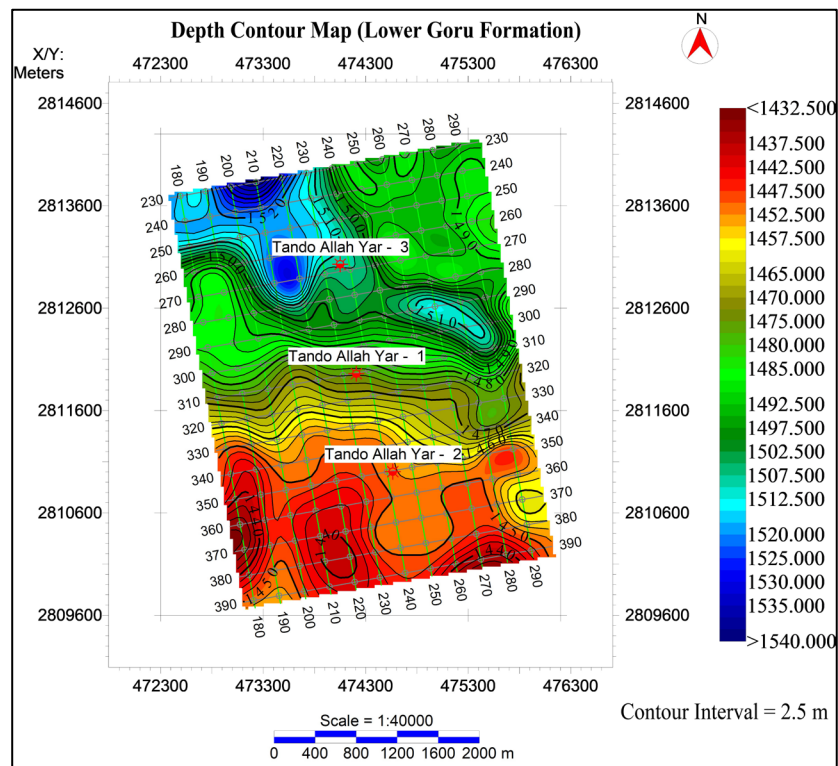


Figure 4.7 Depth contour map of the LGF has been generated on the contour interval of 2.5 m, which demonstrates that the depth and time are going deeper from Tando Allah Yar-1 well to Tando Allah Yar-3 well.

4.1.2 2D Seismic Interpretation of Sanghar Block-1

The structural analysis has been carried out in 2D seismic line (dips and strike line) to know the better understanding of the subsurface structure. The Sanghar Block-1 consists of six lines, two strikes, and four dip lines. The orientation of dip line is from east to west and for strike line direction is from north to south direction. Sono-2 and Sono-5 are located on strike line 872-SGR-510, at the shot point of 256 and 217, respectively. The proper structure compartment has been identified on the dip line G862-SGR-162 showing the presence of normal faulting horst and graben structure, which demonstrate the area is present in an extension regime. 862-SGR-162 is an east-west dip line, with Sono-2 located at shoot point 162 of the line. The data quality is acceptable. Following synthetic seismogram linkage of horizons on dip line employing Sono-2, the recognized horizons have associations over the complete seismic data set. The three horizons indicated in this section can readily be correlated/continued along the line, namely the Parh, Upper Goru, and Lower Goru formations. Figure 4.8 shows the interpreted seismic section 862-SGR-162. The thickness fluctuation across the interpreted horizons is minor. Horst and graben faults are visible on the line. Three faults are marked on the seismic section named as F1 (golden), F2 (red) and F3 (pink). The orientation of the line is west to east, and shot point on the seismic section is also increasing toward east. Figure 4.9 demonstrates the dip line 872-SGR-510 is oriented from the south to the north. 872-SGR-510 interacts with all other dip lines. This line contains high-quality data. This region marks the Parh, Upper Goru, and Lower Goru formations reflectors and correlates them with overlapping sections at tie locations. The base map is attached along the seismic section which shows the exact location and position of the seismic line. The time of LGF is marked at 1.43 sec at Sono-2 well. The details of time and depth of LGF at well location are discussed in Table 4.1.

Figure 4.10 shows the time contour map of the LGF, and the marked horizon directly makes the time contour map. The time contour map shows the linear trend from north to south. There is a gradual increase in the time values, and the range of time varies from 1.41 to 1.65 seconds. The blue color shows the deeper time and as moving toward the yellow or red color, the time is less. Three faults, marked on the seismic section, are visible in the contour map, which forms a closure geometry. The contour interval of the time map is 0.04 sec. Figure 4.11 demonstrates the average velocity contour map on Sanghar Block-1. Velocity contour maps are made with the help of a velocity window at

the LGF. The range of velocity lies between 2946 to 2988 m/s. The velocity around Sono-2 is less than Sono-5. In general trends, the lower velocity is an indication of a geothermal anomaly in the subsurface because the velocity of seismic waves is lower because of higher pressure and partial melting and specific geological formation (Sewell, 2022). Figure 4.12 represents the depth contour map of the LGF. The depth map is simply generated by a distance formula. The depth contour map represents a similar structure to the time contour map shows. The depth contour map is generated at the contour interval of 25 m. The depth variation in the overall contour map is shallow. The range of depth is between 2113 to 2388 m.

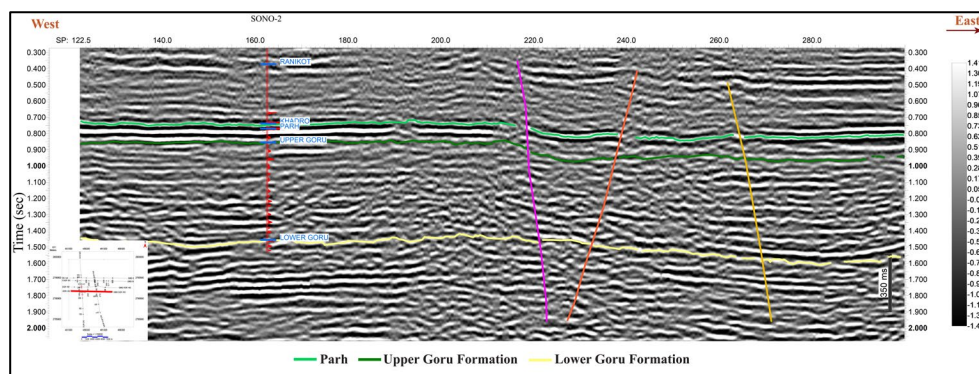


Figure 4.8 Structural interpretation on seismic dip line G862-SGR-162 shows the normal faulting along with horst and graben structure. The orientation of the line is west to east, and Sono-2 is drilled at SP 162. The red color in the legend represents the positive amplitude and blue color shows the negative amplitude and LGF is parked on the positive amplitude. The base map is showing in the seismic section with a highlighted dip line in red color.

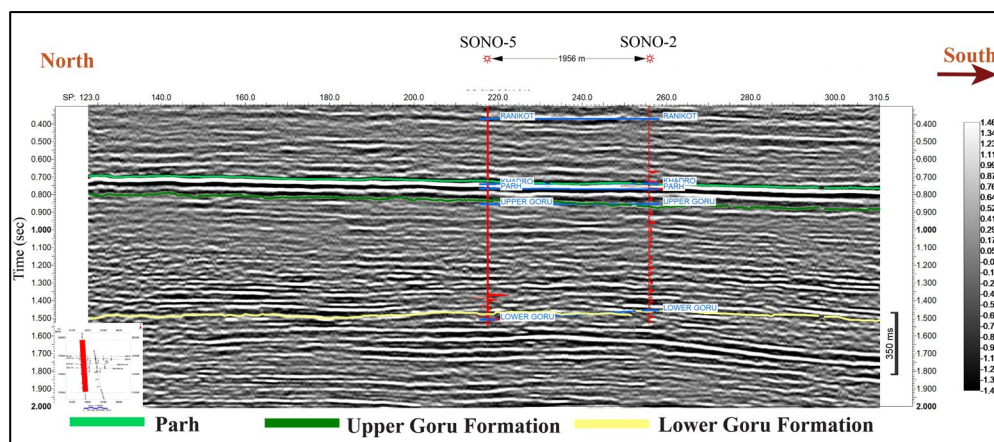


Figure 4.9 Structural interpretation on seismic strike line G872-SGR-510. The base map on the seismic section represents the line orientation, which is north to south. The LGF is shown here with sky blue color. The Sono-2 and Sono-5 wells are present in this seismic section. The distance between these two wells is 1956 m. In this seismic section, Sono-2 is drilled in 258 SP and Sono-5 is drilled in SP 218.

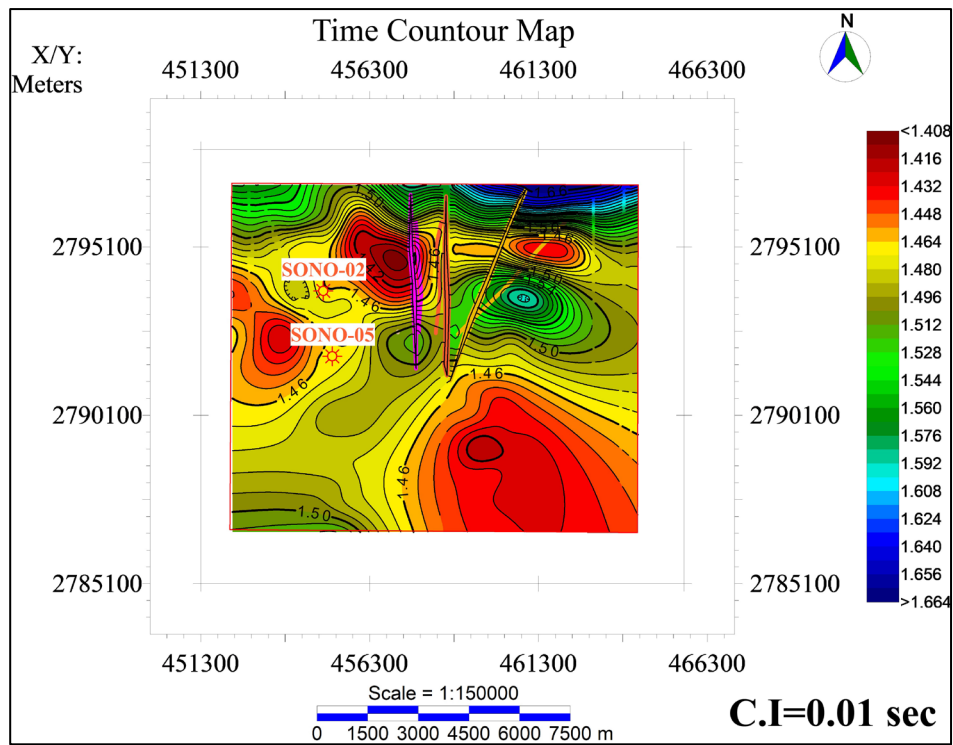


Figure 4.10 Two-way travel time map of LGF generated at the contour interval of 0.04 sec. The time around Sono-2 and 5 is shown in yellow color, which is between 1.46 to 1.48 seconds. Three faults that are marked on the seismic section are also present in the contour map, which represents the higher time from the surroundings.

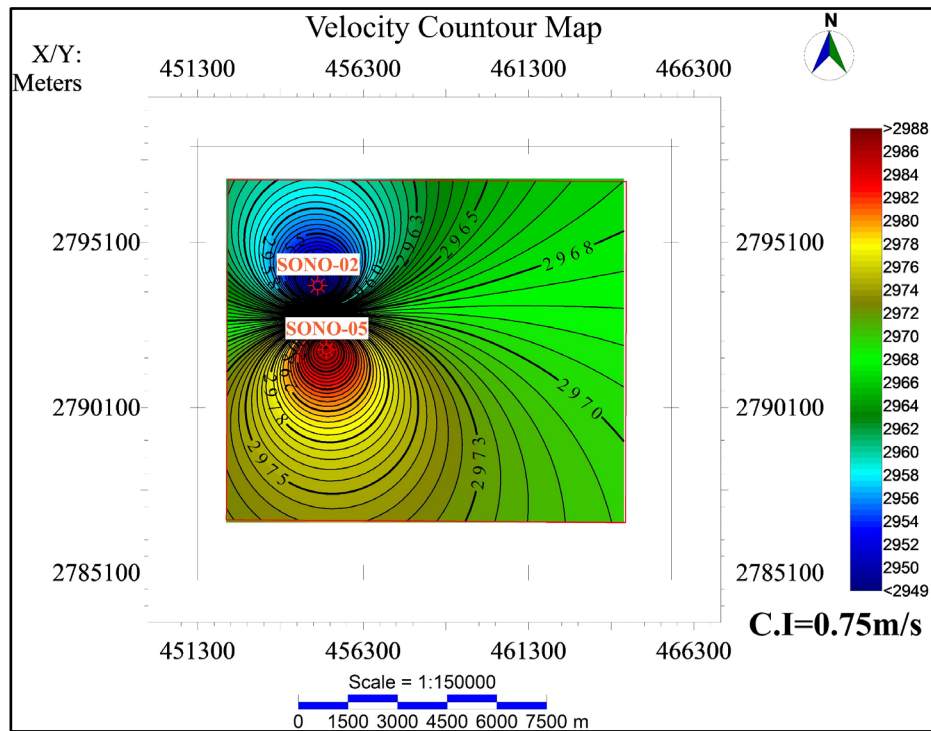


Figure 4.11 Average velocity contour map of the LGF. The velocity map is generated at the contour interval of 0.75 m/s. The velocity around Sono-2 (blue color) well is lesser than Sono-5 well (red color).

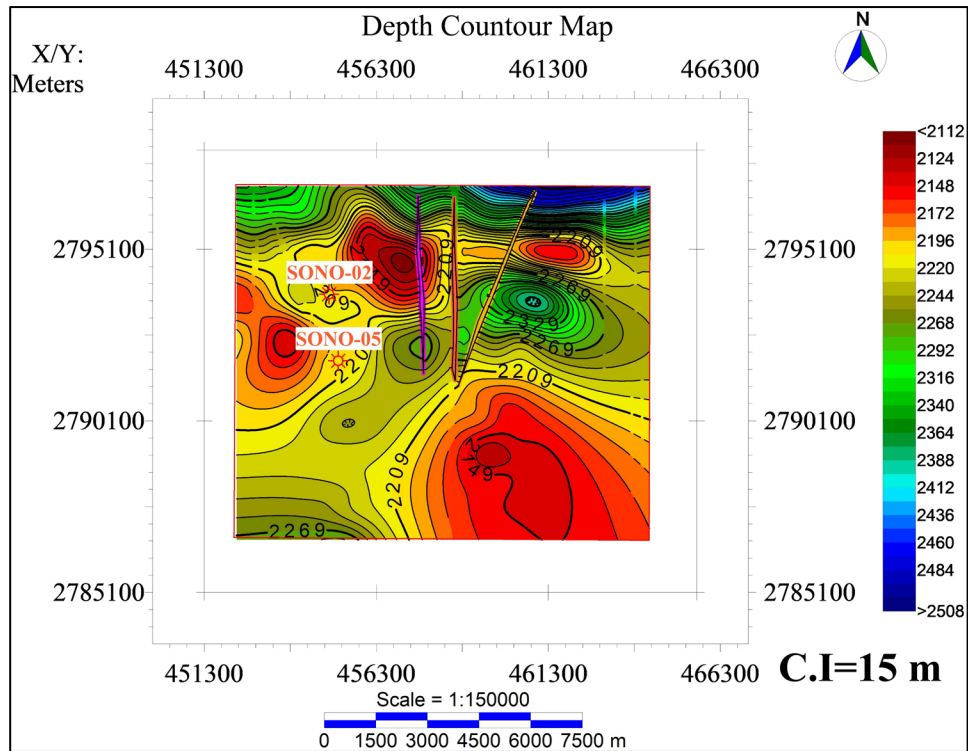


Figure 4.12 Depth contour map of the LGF. Sono-2 and 5 are present in the shallow depth, showing in yellow color. The contour interval is 25 m for the depth contour map. The deeper depth is encountered around the fault, which is an indication of graben geometry.

4.1.3 2D Seismic Interpretation of the Sanghar Block-2

The 2D seismic interpretation was performed on twenty seismic lines. The structural interpretation reveals that the Sanghar area lies in the extension regime. As there are formal faults that are encountered in the study area. There are eight wells present in this area. The six wells are present on the strike line, whose orientation is north to south, and two wells are in dip line with orientation east to west. The LGF horizons are marked with green color, and it is present on each seismic section. The seismic interpretation of G862-SGR-102Ext shows an intricate undersurface structure along with several normal faults, which permit considerable consequences for the geothermal reservoir compartment. The well Bukerani-1 is present at the shot point 735 as shown in Figure 4.13. The marked normal faults, in which some represent the listric features, indicate an extensional geological province that may assist deeper fluid passage. The presence of fault-bound compartments can enhance geothermal potential by creating natural pathways for hydrothermal fluid movement, thereby affecting reservoir K. Mapped seismic reflectors corresponding to the LGF suggest a few structural undulations that could be interpreted as differential compaction, rock type variations, or localized

traps for geothermal fluid accumulation. Therefore, the faulting and deformation could, in a relative sense, increase the fracture K, an important aspect of geothermal reservoirs and hence promote heat transport fluid movement. Further, stratigraphic terminations in the vicinity of faulted zones could indicate the mechanism for possible trapping by hydrothermal seals with geothermal fluids. It is pertinent to augment seismic interpretation with thermal gradient data and geophysical surveys to evaluate the potential of geothermal resources around study.

Figure 4.14 represents the seismic section GO-872-SGR-103Ext, which also represents the normal fault geometry. Four normal faults are marked on this seismic section, which demonstrates the horst and graben structure. The orientation of the line is west to east, and the horizon is slightly dipping towards the western portion. The Jarwar-1 is present on SP 294 and approximately 0.95 sec. The base map on the seismic section represents the dip line position and orientation. Figure 4.15 demonstrates the seismic strike line G862-SGR-153 with the well Allah Dino-1 is located on SP 366. As this is a strike, the fault is not dominantly visible in the seismic section. The orientation of the seismic line is north to south, and the SP is increasing toward south. The horizon LGF is also dipping toward the southern side of the seismic section. Only one fault is visible in this seismic section which is marked with red color. The seismic strike line G862-SGR-176 is shown in Figure 4.16. The orientation of the line is north to south, and the Babar-1 well is drilled at SP 148. LGF is marked on this seismic section too with green color. Two normal faults that are visible in this seismic section are marked with orange and golden color. In the last, the regional strike line G947-SGR-168S is displayed in which four well Tando Allah Yar-1, 2 & 3 and Jumman Shah-1 is present as shown in Figure 4.17. The Tando Allah Yar well is also present in 3D seismic Nim Tay Block. The LGF is also marking this seismic section with green color and data is dipping towards south. Two faults that are dominant and visible in the seismic section are marked on this seismic section. The base map is attached to the seismic section, which is located the location of the seismic line.

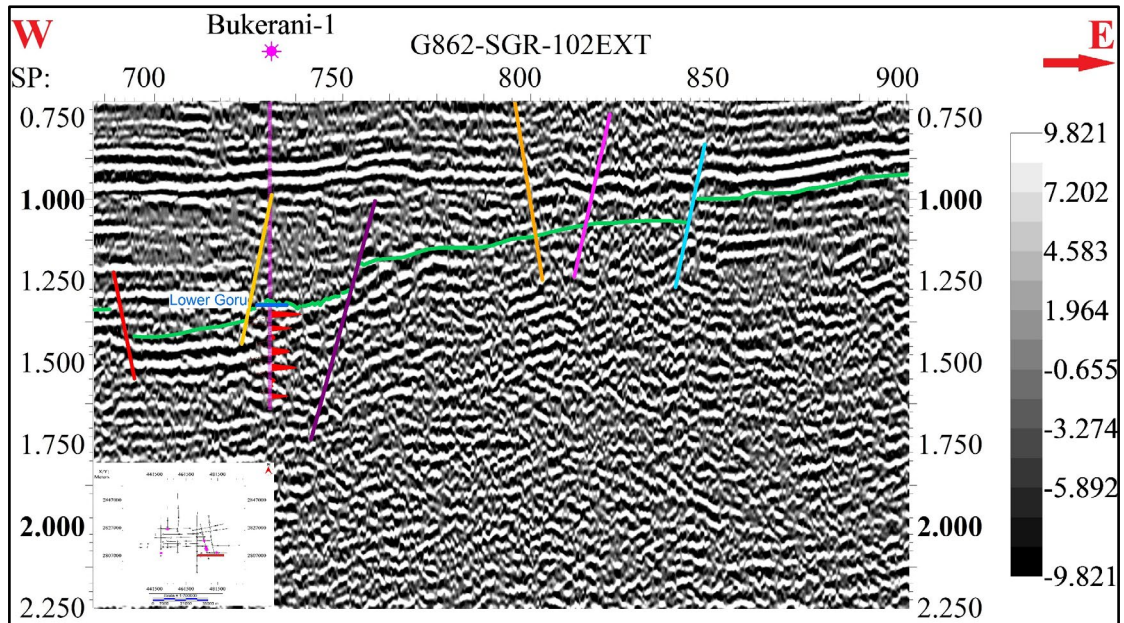


Figure 4.13 Interpreted dip seismic line G862-SGR-102Ext showing the location of Bukerani-1 well location at the shot point of 739. Normal faults are present in this seismic section which are making a horst and graben geometry. Different colors are used for fault marking and all the faults that are marked on the seismic section are major faults. The LGF is deeper toward the western side and shallow in the east ward direction. The base map that is present on the down left corner of the map shows the line location (red color).

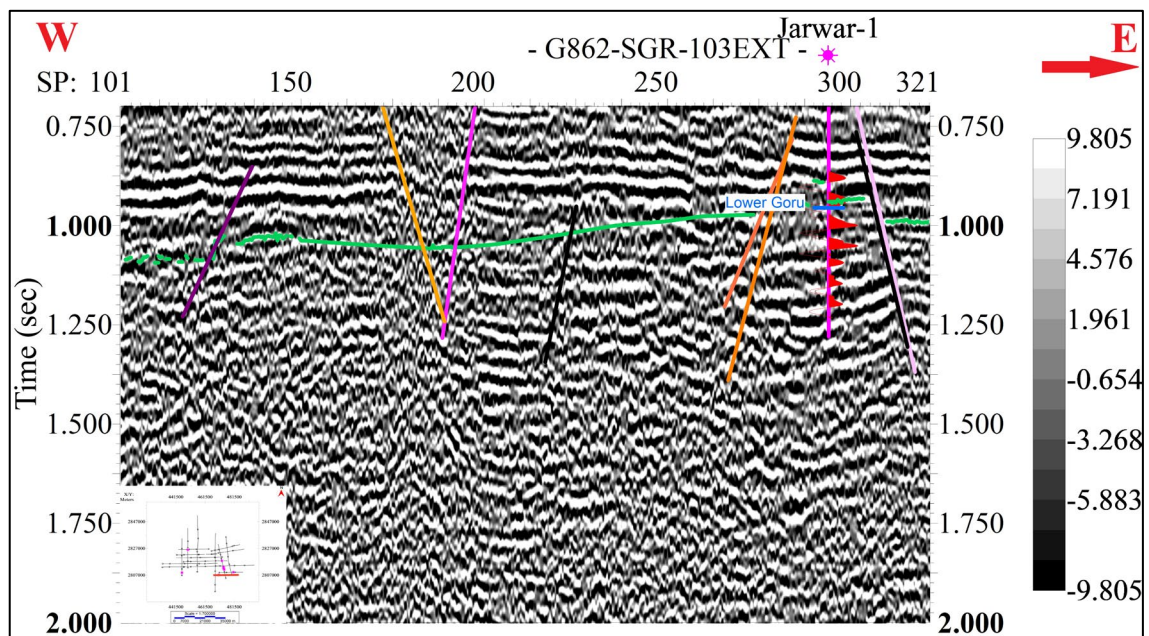


Figure 4.14 Interpreted dip seismic line G862-SGR-103Ext showing the location of Jarwar-1 well location at the shot point of 294. Normal faults are present in this seismic section which are making a horst and graben geometry. The LGF is deeper toward the western side and shallow in the east ward direction.

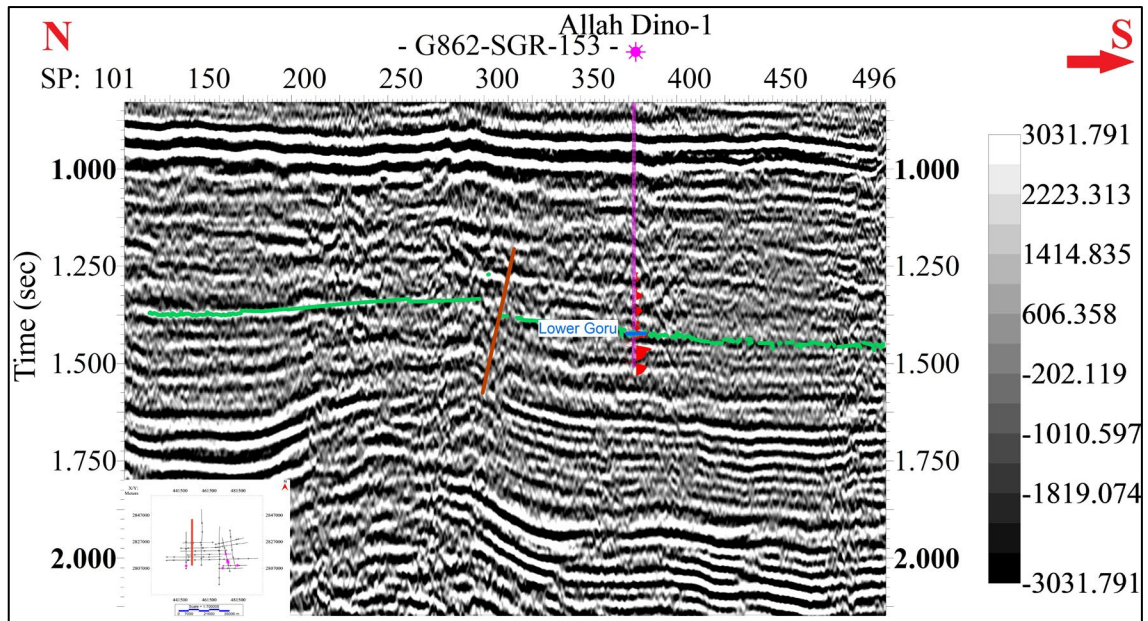


Figure 4.15 Illustration of interpreted strike seismic line G862-SGR-153 showing the position of Allah Dino-1 location at the shot point of 375. There is only one fault that is present in this strike line showing in red color. As the strike line is along the structure, the structure is not prominent on it. The orientation of the strike line is north to south, and it is present on the western side of the base map.

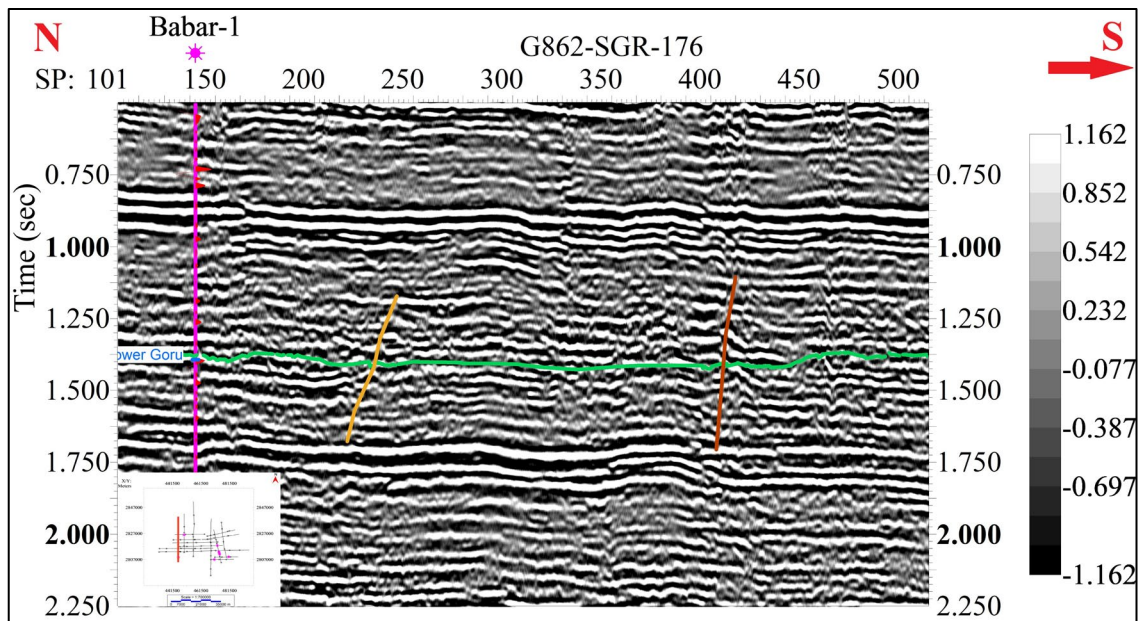


Figure 4.16 Interpreted 2D seismic strike seismic line G862-SGR-176 depicts the location of Babar-1 location at the shot point of 148 along with marked LGF horizon (Green color). Two normal faults are present in this seismic section as it is strike line so the major structure is not prominent in this seismic section. The strike line is oriented north to south. Strike line G862-SGR-176 is present on the left side of strike line G862-SGR-153.

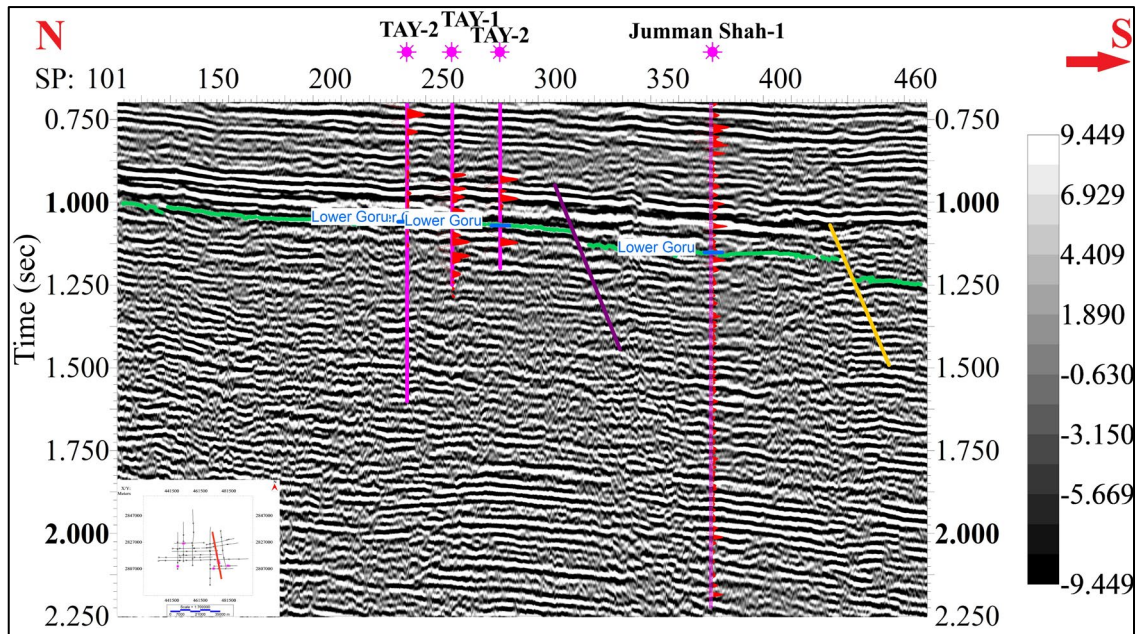


Figure 4.17 Interpreted strike line G947-SGR-168S. The orientation of the line is north to south with a marked LGF in green color. The synthetic curve of four wells is shown in this seismic section name as Tando Allah Yar-1, Tando Allah Yar-2, Tando Allah Yar-3 and Jumman Shah-1. The horizon of LGF is dipping toward the south as time is increasing toward south.

The time contour maps of LGF are shown in Figure 4.18 which demonstrates that the contour is made at the interval of 0.015 sec. The time of the LGF is increasing toward the west shown with green and blue color and lesser time is observed on east side with yellow and red color. The velocity map of the LGF, as shown in Figure 4.19, demonstrates vital information on the geothermal potential of the Sanghar area by exposing the subsurface lithology, porosity, and fluid dynamics. The remarked lowest velocity area, specifically in the green to blue color, demonstrates highly saturated and porous formations, which are a tremendous condition for geothermal reservoirs because of the heat storage and transmit capacities. In contrast, the region, which represents the extreme velocity area like red and yellow color indicates the compacted lithology along with less K due to which movement of fluid is resistant. Abrupt change in velocity distinctions noted with structural features like faults might boost K, fluid migration as well as heat transfer. It makes it compulsory to integrate velocity data with thermal and petrophysics properties to achieve a comprehensive geothermal evaluation. In the end, velocity data is utilized to make a depth map. The depth map is shown in Figure 4.20 which represents that the depth in LGF is increasing towards west side because of deeper depth of formation and shallow depth is encounter is eastern portion. The contour interval of depth map is 20 m. All the contour maps are generated on the same scale of 1:50000.

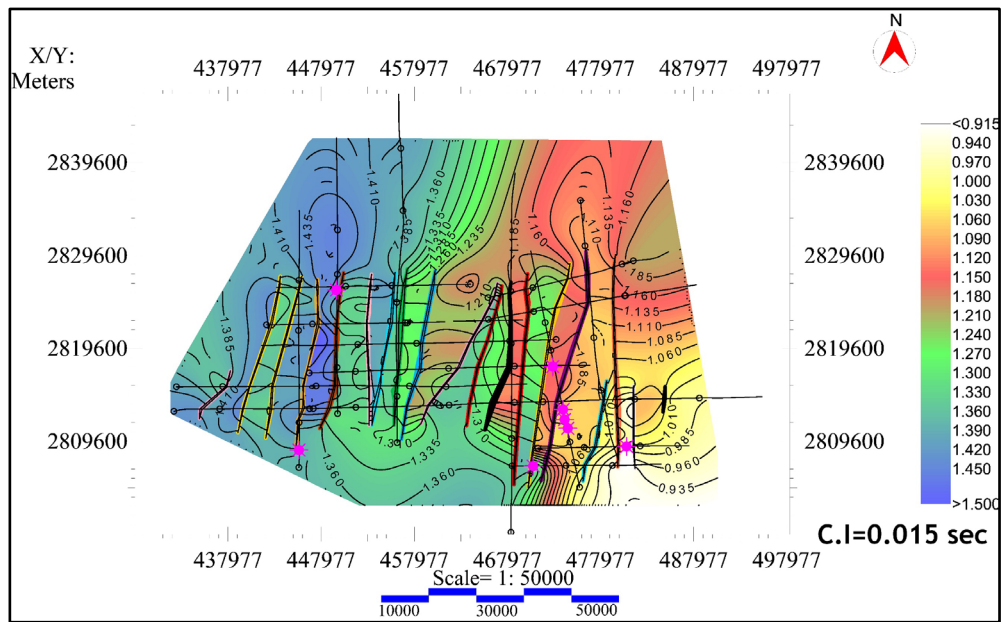


Figure 4.18 Two-way travel time map of the LGF. The map is generated at the contour interval of 0.015 sec. The shallow time (yellow and orange color) is observed on the eastern portion of the map and on the western side deeper time is observed (green and blue color.). The faults that are present on the map also demonstrate the horst and graben structure.

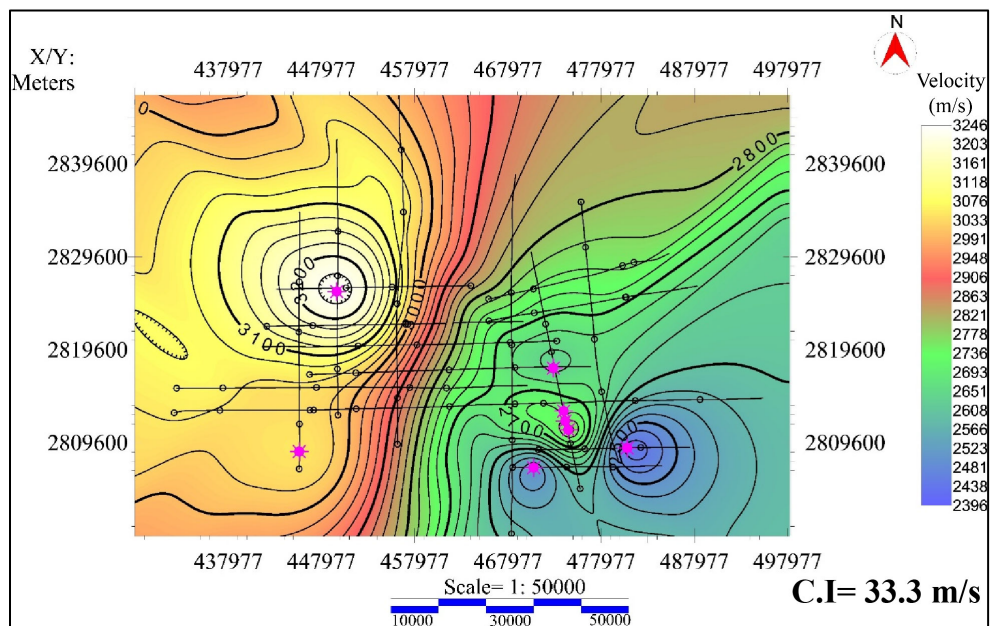


Figure 4.19 Velocity contour map of the LGF. The map is generated based on average velocity of LGF. The range of velocity is 2396 m/s² to 3246 m/s². The higher velocity is encountered in those zones where there is deeper time (yellow to orange color). The wells where the LGF is present in shallow depth show the velocity range in blue and green color.

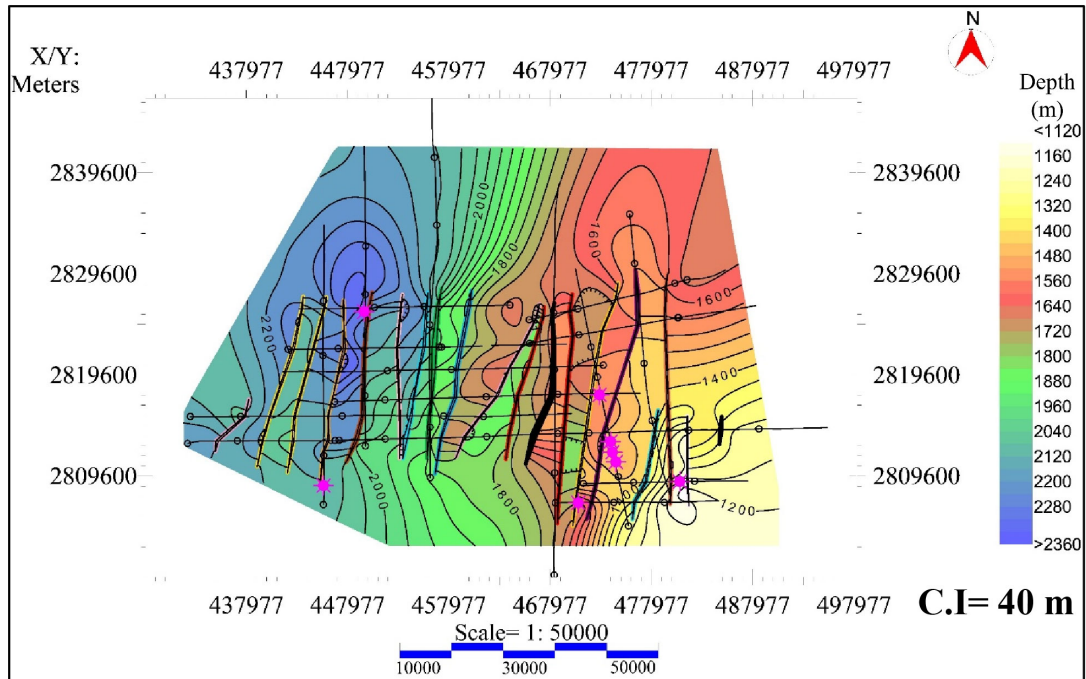


Figure 4.20 The figure depicts the depth contour map of LGF that is generated at the depth interval of 20 m. The depth of the LGF is increasing toward the western side. The major faults that are present in the seismic section at the LGF level are also present in the seismic section. The normal faulting present in the Sanghar area is also present in the depth contour map.

4.2 Geothermal Properties Estimation

The geothermal properties estimation is done on all ten wells that are available for the studies. The properties that are calculated based on log curves are Vshl, PHIA, K, FT, HP, and RHP (on those wells where spectral gamma rays are available). All the calculations are carried out for the LGF. The detailed results are shown below according to well. A standardized well log template is followed for each well, ensuring that the log curve colors remain the same across all wells.

4.2.1 Geothermal Properties Estimation on Tando Allah Yar-1

The comprehensive geothermal properties calculation is carried out on Tando Allah Yar-1 well at the LGF. The LGF starts at the depth of 1447 m and ends at the depth of 1750 m. In geothermal properties estimation, the properties like HP, RHP, K, average and PHIE, FT are calculated. In Figure 4.21 the log curves along with their results are displayed. Based on a log trend, where the gamma ray value is higher it means that shale content is increasing so the Vshl is higher at that specific depth interval like depth below 1600 meters. When there is higher shale content, the PHIE is low at that specific depth.

Due to an increase in shale content, the HP and RHP are also increased because of shales as it contains a radioactive element which increases the heat in subsurface. The K of the shale interval is relatively higher than that of the sand interval. Due to quite good results of HP, RHP, and K it is possible that the LGF has a potential with respect to geothermal prospect. The PHIA of Tando Allah Yar-1 is 19.12%, which is considered as the good PHIA. The absolute K equation is used for the calculation of K. The K is 18.65 mD for the LGF. The result of HP for Tando Allah Yar-1 is $1.0064 \mu\text{W}/\text{m}^3$, and RHP is $0.942 \mu\text{W}/\text{m}^3$, which are also in favor of geothermal potential evaluation. Detailed statistical results are shown in Table 4.2.

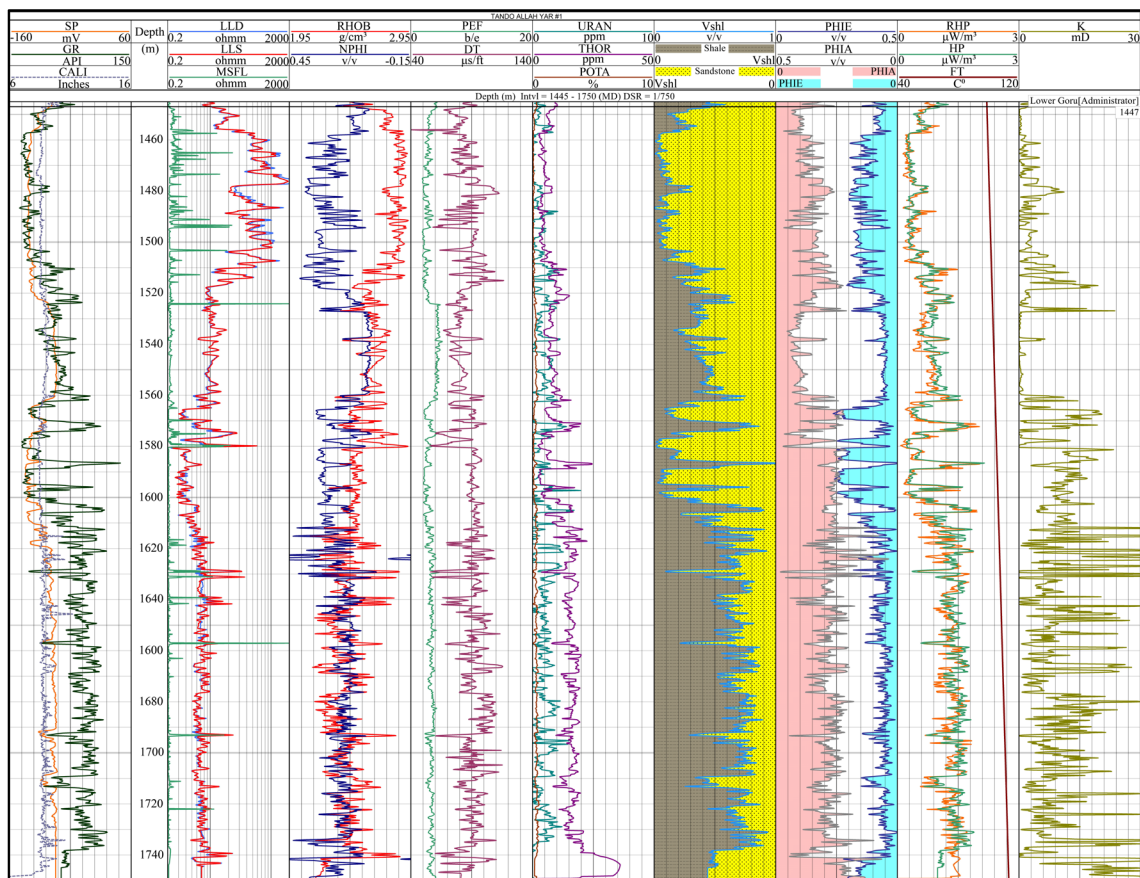


Figure 4.21 Geothermal properties estimation of LGF in Tando Allah Yar-1 well showing the results of Vshl, PHIA and PHIE, FT, HP, RHP and K. The Vshl log tract represents the bed of shale and sandstone according to the trend of GR behavior.

4.2.2 Geothermal Properties Estimation on Tando Allah Yar-2

The detailed analysis of geothermal properties is carried out on Tando Allah Yar-2. In geothermal evaluation, properties like HP, RHP, K, porosities and Vshl are calculated on the LGF. The detailed results of the log curves are shown in Figure 4.22,

whereas detailed results of all the well are shown in Table 4.2, due to quite good result of HP, RHP and K, it is possible that the LGF have a potential with respect to geothermal prospect. The PHIA of Tando Allah Yar-2 is 20.35%, which is considered good porosity. The absolute K method is used for the calculation of the K, which gives excellent permeability results. The K is 15.51 mD for Tando Allah Yar-2. The result of HP for Tando Allah Yar-2 is $1.2675 \mu\text{W}/\text{m}^3$, which is also in the favor of geothermal potential evaluation.

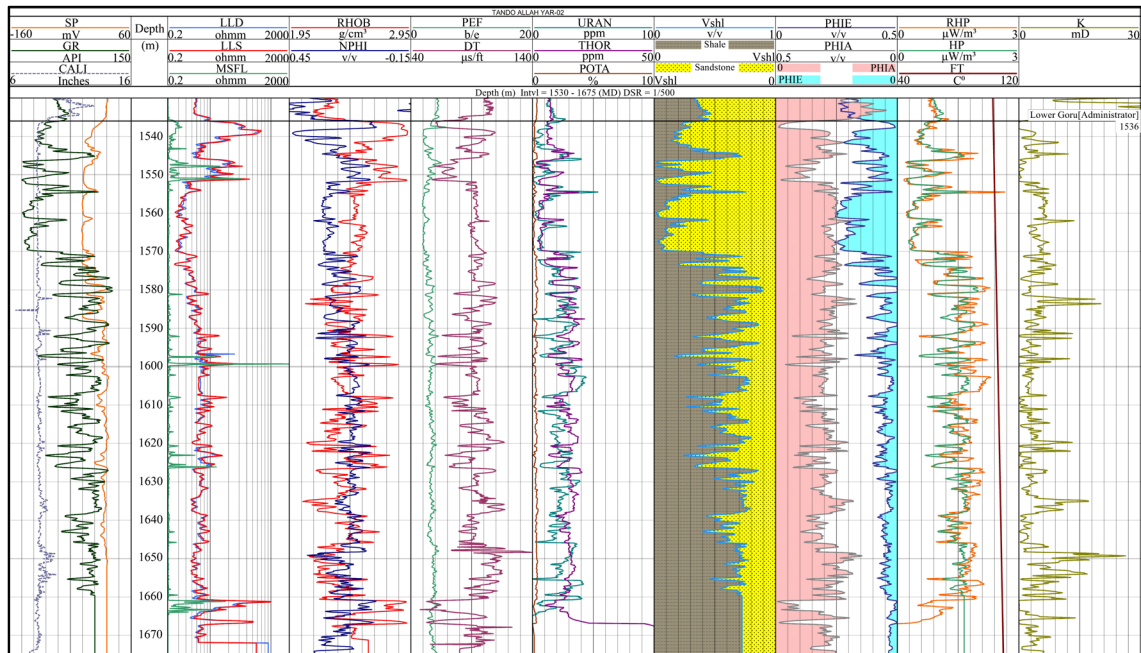


Figure 4.22 Geothermal properties estimation of LGF in Tando Allah Yar-2 well, showing the curve results. The yellow shaded color with dots represents sand lithology and brown color with dashes demonstrates the presence of shale.

4.2.3 Geothermal Properties Estimation on Tando Allah Yar-3

Geothermal properties calculation is also carried out for the LGF at Tando Allah Yar-3 well. The thickness of the LGF is 144 m. In geothermal properties, estimation the properties are estimated by utilizing log curve and result of interest are like HP, RHP, K, PHIA, PHIE, Vshl and FT are calculated. In Figure 4.23 the log curves along with their results are displayed. On the basis of a gamma ray log trend the gamma ray value is lower from the depth between 1470 to 1520 m and higher gamma ray is encountered in depth of 1560 to 1590 m which represents high shale content. When there is higher shale content the PHIE is relatively low and vice versa. Due to the increase in shale content the HP and RHP are also increased because of shales, as it contains a radioactive element which

increases the heat in the subsurface. The K of the shale interval is relatively higher than the sand interval. Due to quite good result of HP, RHP, FT, PHIA, PHIE, Vshl, and K, it is possible that the LGF have a potential with respect of geothermal prospect. The PHIA of Tando Allah Yar-3 is 15%, and PHIE is 12%, which is quite good porosities. The K is 19.05 mD for the LGF. The result of HP for Tando Allah Yar-3 is $0.6872 \mu\text{W}/\text{m}^3$, and RHP is $0.53 \mu\text{W}/\text{m}^3$ with FT 75.474°C . Detailed statistical results are shown in Table 4.2.

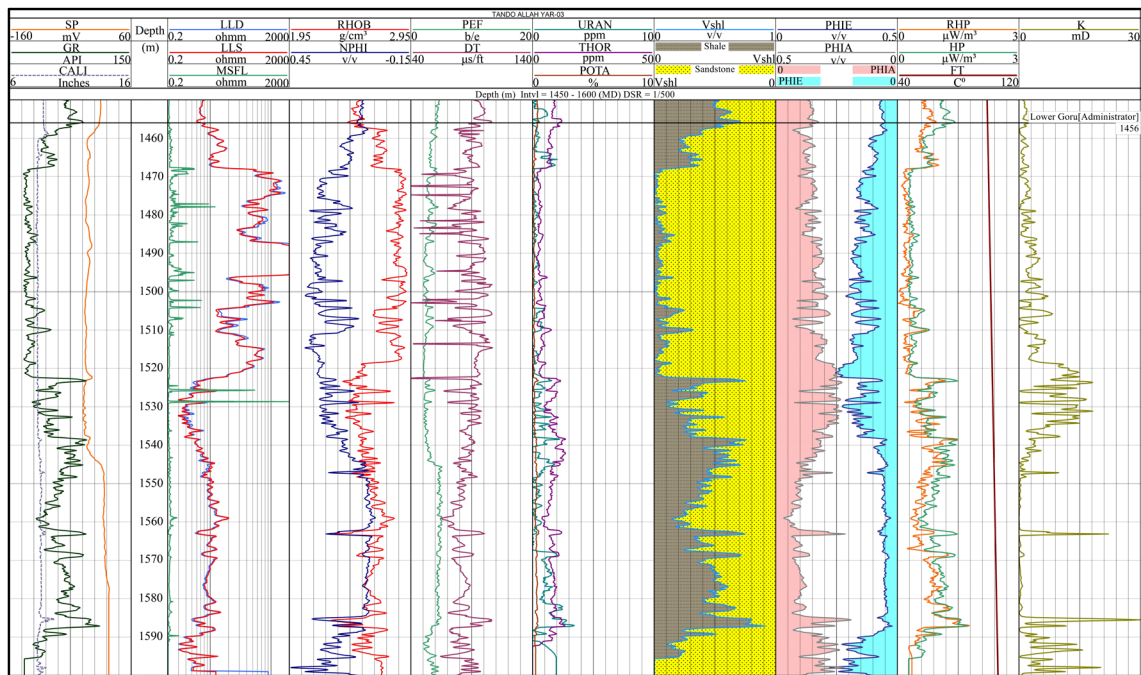


Figure 4.23 Geothermal properties estimation of LGF in Tando Allah Yar-3 well, showing the curves results of geothermal properties HP, RHP, and FT, and petrophysical properties Vshl, PHIA, PHIE and K. The trend of the GR is increasing from the depth 1540 to 1590m due to which shale content and geothermal properties is higher which is indication of geothermal anomaly.

4.2.4 Geothermal Properties Estimation on Jumman Shah-1

Jumman Shah-1 Well lies on the northern side of the Nim Tay Block. The distance between the Tando Allah Yar-3 and Juman Shah is 4754 m. In 2D seismic strike line G 947-SGR-168S the four well Jumman Shah-1 and Tando Allah Yar-1, 2 and 3 are present. The total thickness of the LGF in Jumman Shah-1 is 82 m. In the whole LGF the GR log shows a low value as the value is not greater than 40 API as shown in Figure 4.24. Due to low GR indicates that the Vshl content is 8% in Formation. The sandstone is dominant formation due to which it shows a good porosity, so the PHIA and PHIE are higher in the formation with estimated values of 21% and 19%, respectively. The average HP

encounter in the formation is $0.59 \mu\text{W}/\text{m}^3$ with FT of 62°C , with K of 19.05 mD. The statistical results of Jumman Shah-1 are also presented in Table 4.2.

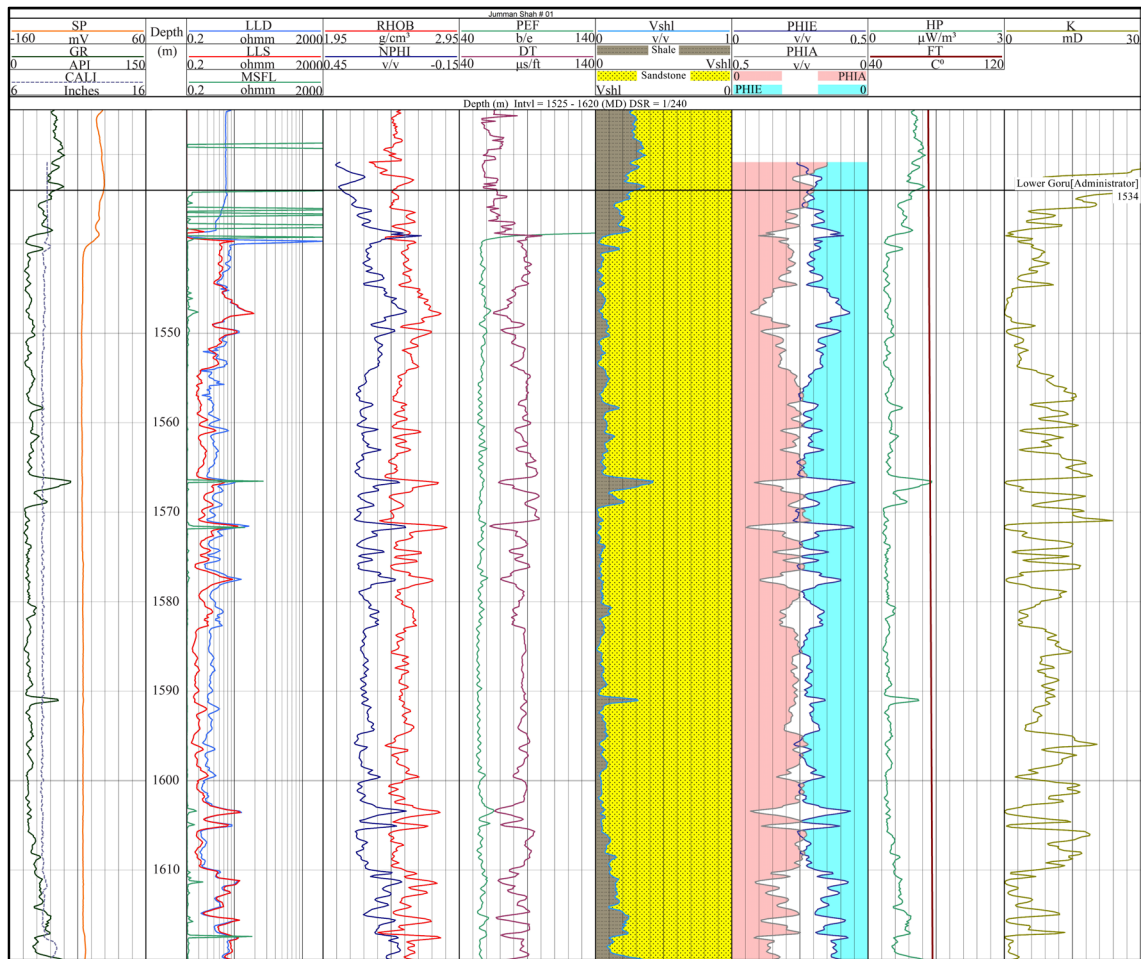


Figure 4.24 Result of LGF of Jumman Shah-1 well for geothermal reservoir properties estimation. The yellow shaded color with dots represents sand lithology and brown color with dashes demonstrates the presence of shale. The shale content is less because of the presence of low GR.

4.2.5 Geothermal Properties Estimation on Jarwar-1

The Jarwar-1 is present on the seismic dip line G862-SGR-103Ext at the shot point of 293. The Jarwar-1 well is drilled at a shallower depth of 1473 meters with the thickness of the LGF is only 40 m started from the depth of 1169 m and ending at 1209 m. The Jarwar -1 well is an exploratory well and drill in 2014. Figure 4.25 demonstrates the log curve result of Jarwar-1. The first track represents the SP and GR log. The value of GR is low in the formation, and mostly lower values indicate the sandstone lithology, and this indication is confirmed by calculation of Vshl, which is 14% which means that the clean volume is 86%. The PHIA and PHIE are 20% and 17%, respectively. The HP

is $0.56 \mu\text{W}/\text{m}^3$, whereas the RHP is not calculated on this well because of the absence of a spectral gamma ray log curve. The FT is 66.70°C encountered in the LGF. The detailed statistical results are discussed in Table 4.2.

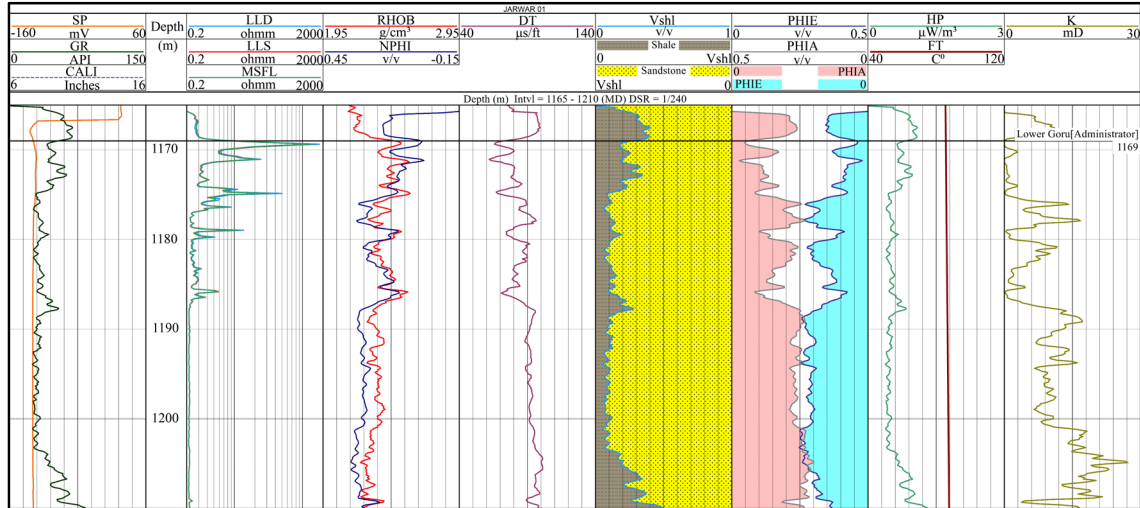


Figure 4.25 Geothermal properties estimation of LGF in Jarwar-1. The yellow shaded color with dots represents sand lithology and brown color with dashes demonstrates the presence of shale. The shale content is less because of the presence of low GR.

4.2.6 Geothermal Properties Estimation on Bukerani -1

The detailed results of the log curves are shown in Figure 4.26 of Bukerani-1 well, whereas detailed results of all the wells are shown in Table 4.2. Due to the excellent outcomes of HP, FT, PHIA, PHIE, Vshl and K it is possible that the LGF have quite good potential for geothermal prospect. The PHIE of Bukerani-1 is 11%, with PHIA is 19% which is consider as the quite good porosity. The K calculated by the absolute method provides an excellent K result in the LGF. The K calculated is 12 mD for Bukerani-1 well. The result of HP for Bukerani-1 is $1.53 \mu\text{W}/\text{m}^3$, and the FT in the LGF also encounters a higher temperature of 89.667°C , which is in favor of the geothermal potential reservoir. The Vshl is comparatively higher in the Bukerani-1 well, which is approximately 61%. The Bukerani-1 well is present in the seismic dip line G862-SGR-102Ext at shot point 730.

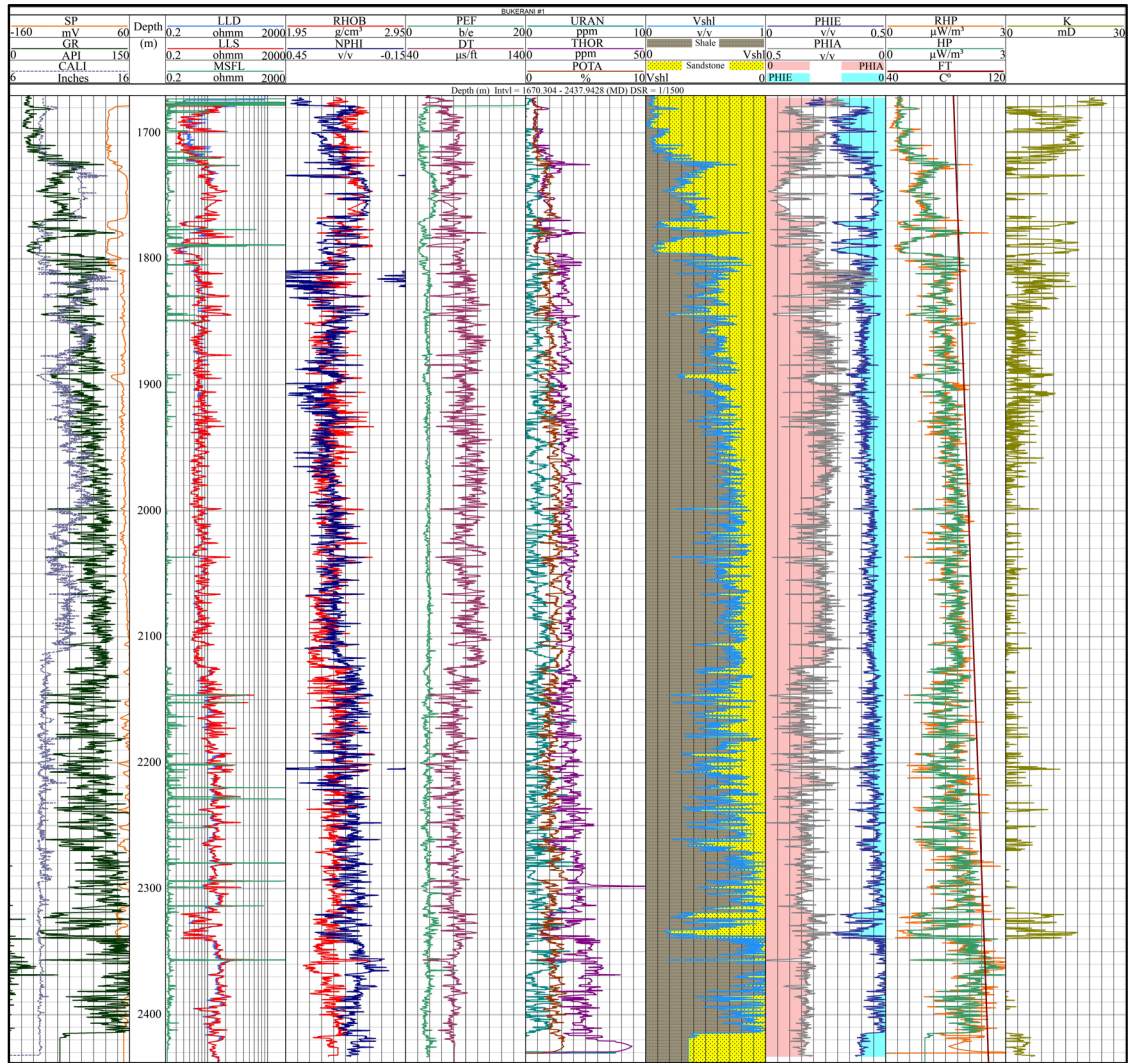


Figure 4.26 Geothermal properties estimation of LGF in Bukerani-1 well showing the results of Vshl, PHIA and PHIE, FT, HP, RHP, and K. The higher GR is encounter in the formation due to which the geothermal properties show the elevated result in the whole interval of LGF.

4.2.7 Geothermal Properties Estimation on Babar-1

In Figure 4.27 the log curves along with their results are displayed. On the basis of a log trend, where the gamma ray value is higher it means that shale content is increasing so the Vshl is higher at that specific depth. In the LGF the different intervals of sand and shale lithology are observed. When there is higher shale content, the PHIE is relatively low, and vice versa. Due to an increase in shale content, the HP and RHP are also increased because of shales they contain a radioactive element, which increases the heat in the subsurface. The K of the shale interval is relatively higher than that of the sand interval. Due to quite good result of HP, RHP and K, it is possible that the LGF have a potential with respect of geothermal prospect. The PHIA of LGF is 20% which is

consider as the good porosity. The absolute K equation is used for the calculation of K. The K is 15 mD for the LGF. The result of HP for Babar-1 well for the LGF is $1.399 \mu\text{W}/\text{m}^3$, and RHP is $2.242 \mu\text{W}/\text{m}^3$ with FT of 113.74°C , which is much higher than other well that are present in the study block. These characteristics are in favor of geothermal potential evaluation. Detailed statistical results are shown in Table 4.2.

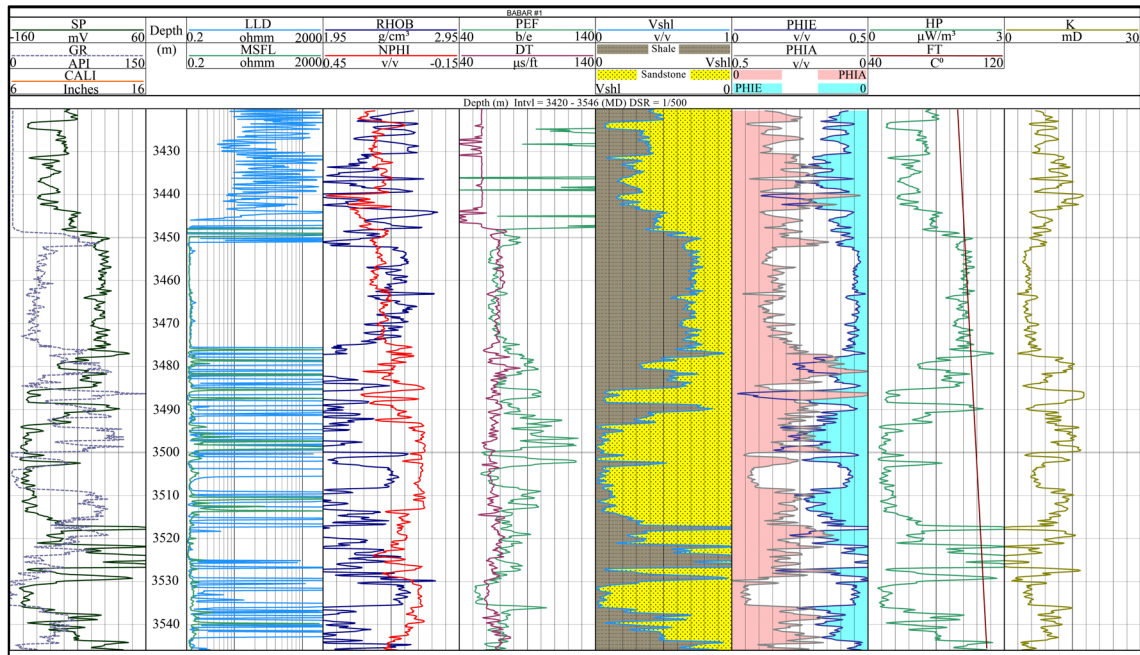


Figure 4.27 Geothermal properties estimation of LGF in Babar-1 well with log curve results showing the curves results of geothermal properties HP, RHP, and FT, and petrophysical properties Vshl, PHIA, PHIE and K. The trend of the GR is increasing from the depth 3450 to 3490m and 3520 to 3530 m due to which shale content and geothermal properties are higher which is indication of geothermal anomaly.

4.2.8 Geothermal Properties Estimation on Allah Dino-1

As the caliper log is unstable, the resistivity logs, RHOB, and NPHI show fluctuation so the reading and data quality in that specific zone is not reliable. The GR also shows the higher values at that specific zone, due to which Vshl is greater in this depth zone. The average Vshl is 38%, with clean volume is 62%, the result of PHIA and PHIE is 20% and 11%, respectively. The HP is $0.88 \mu\text{W}/\text{m}^3$ and RHP is $0.89 \mu\text{W}/\text{m}^3$. In the end, the K of the LGF is 18 mD as shown in Figure 4.28. The detailed result is also discussed in Table 4.2.

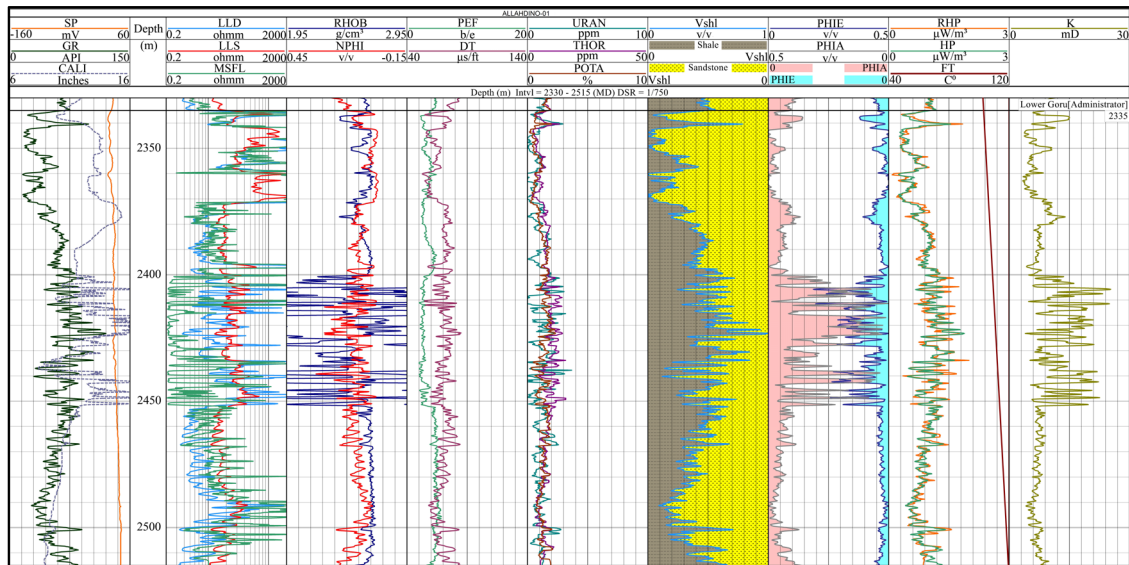


Figure 4.28 Geothermal properties estimation of LGF in Allah Dino-1 well showing the results of Vshl, PHIA and PHIE, FT, HP, RHP, and K. The higher GR is encounter in the formation due to which the geothermal properties show the elevated result in the whole interval of LGF.

4.2.9 Geothermal Properties Estimation on Sono-2

The detailed results of the log curves are shown in Figure 4.29. whereas detailed results of the wells are shown in Table 4.2. Due to excellent outcomes of HP, GG, PHIA and K it is possible that the LGF have quite good potential for geothermal prospect. The PHIA of Sono-2 is 9%, which is consider as the good porosity. The K calculated by absolute methods give an excellent permeability result in LGF. The K are 12 mD and for Sono-2. The result of HP for Sono-2 is $0.66 \mu\text{W}/\text{m}^3$ and the FT in the LGF is also encounters higher temperature of 112°C , which is favorable for the geothermal potential reservoir.

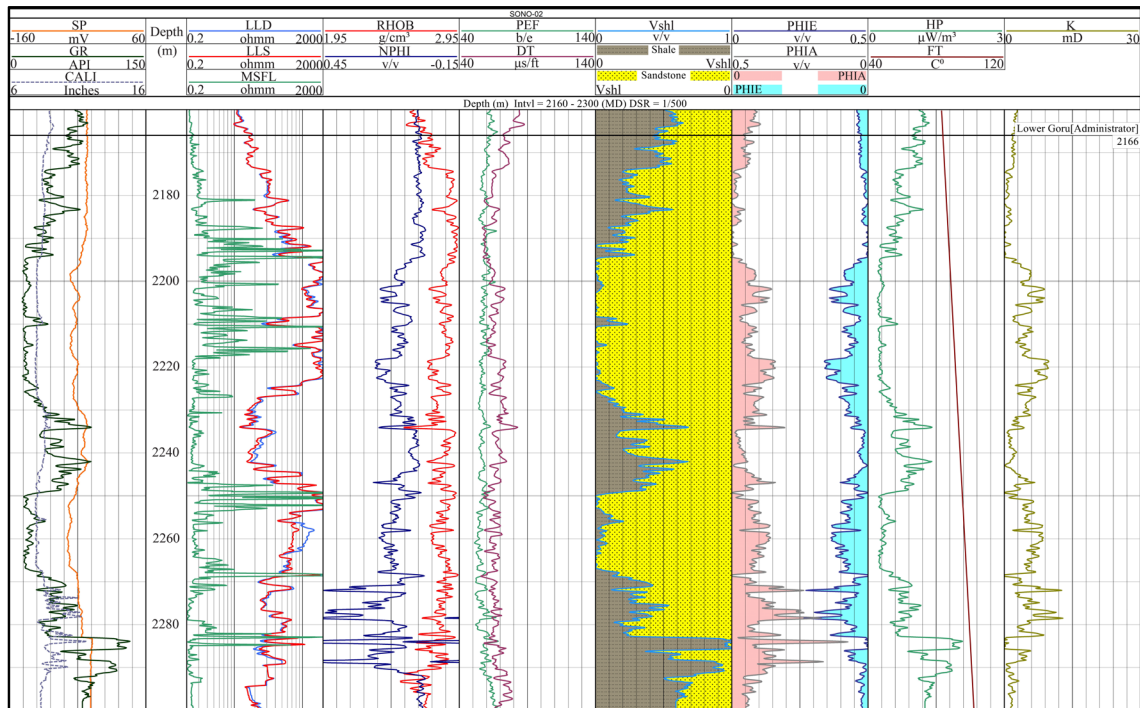


Figure 4.29 Geothermal properties estimation of LGF in Sono-2 well showing the result of geothermal parameters along with input log curve. The result shows a favorable geothermal zone starting from the depth of 2270 to log end because of highly shale content.

4.2.10 Geothermal Properties Estimation on Sono-5

The detailed results of the log curves are shown in Figure 4.30, whereas detailed results of all the wells are shown in Table 4.2. Due to quite good outcomes of HP, GG, PHIA and K, it is possible that the LGF has quite good potential for geothermal prospect. The PHIA of Sono-5 is 9-12%, which is considered as good porosity. The K calculated give an excellent permeability result in the LGF. The permeability is 13.5 mD for Sono-5, respectively. The result of HP for Sono-5 is $0.84 \mu\text{W}/\text{m}^3$ respectively and the geothermal gradient in the LGF is also encounters a higher temperature of 112°C , which is in the favor of geothermal potential reservoir.

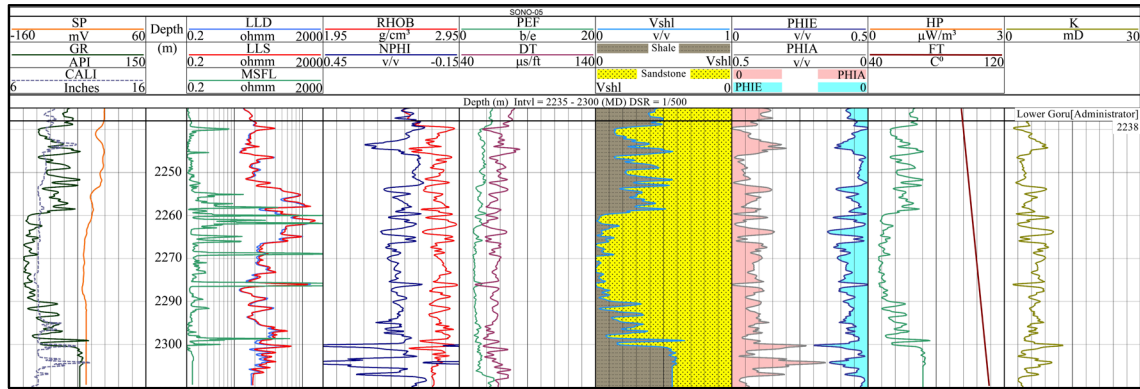


Figure 4.30 Geothermal properties estimation of LGF in Sono-5 well showing the results of Vshl, PHIA and PHIE, FT, HP, RHP, and K. The sandstone is dominant in well with good PHIA, PHIE and K

Table 4.2: Detailed geothermal and petrophysics properties estimation results of all the ten wells that is used in the research along with there facies that is estimated by the ML algorithm.

Well Name	Thickness (m)	Vshl (%)	PHIA (%)	PHIE (%)	K (mD)	HP ($\mu\text{W}/\text{m}^3$)	RHP ($\mu\text{W}/\text{m}^3$)	FT (C°)	Facies
Tando Allah Yar-1	303	44	19	14	18.65	1.0064	0.94	77.627	Major shale with an interbed of gas and wet sand
Tando Allah Yar-2	139	53	20	10	15.51	1.2675	1.07	77.814	Major shale with a thick bed of wet sand and thin bed of gas shale
Tando Allah Yar-3	1456	26	15	12	19.05	0.6872	0.53	75.747	Major shale with a thick bed of wet sand and thin bed of gas shale
Jumman Shah-1	144	8	21	19	19	0.51	N/A	77.001	Shale with thin bed of gas and wet sand
Jarwar-1	40	14	20	7	21	0.56	N/A	66.707	Interbed of shale and wet shale
Bukerani-1	789	61	19	11	12	1.54	1.545	89.667	Interbed of shale, wet sand, and gas sand
Babar-1	1391	43	20	5	15	1.399	2.242	113.746	Interbed of shale, wet sand, and gas sand
Allah Dino-1	183	38	10	5	18	0.88	0.896	99.705	Interbed of shale and wet shale
Sono-2	139	26	7	6	12	0.66	N/A	65.34	Interbed of shale and wet shale
Sono-5	62	25	8	5	13.5	0.84	N/A	68.23	Major shale and gas sand with thin bed of wet sand

4.3 Facies Analysis by ML Technique

Facies analysis is performed on the provided well data to know about the facies or lithology that is present on the LGF. On the present studies eight wells are utilized to facies identification such as Tand Allah Yar-1, 2 and 3, Jumman Shah-1, Babar-1, Allah Dino-1, Jarwar-1 and Bukerani-1 wells. These facies are identified based on ML

approach and two different python codes are utilized to perform this analysis. In the first part, the basic data QC along with cleaning of data is performed to removal the outliers and inlier from the data this is done with the help of unsupervised ML techniques and in the second part the cutoff is applied on the well data to identify the lithology aside by basic petrophysical parameter estimation like, PHIA, saturation and Vshl calculation. The detailed facies analysis results of each well are discussed independently.

4.3.1 Facies Identification of Tando Allah Yar Well

After loading the well log curve in the LAS format and well tops in the CSV format of Tando Allah Yar-1 well. The next step is QC of the data. As the interesting log curves are GR, RHOB, LLD and NPHI so the initial QC is performed on these log curves, for the quality check the pair plot is made among these log curves to know the quality of the data the Figure 4.31 represents the pair plot and relation between four log curves that is discussed previously. The peaks that are shown in the plot demonstrate the most frequent values on each log curve. While the scatter curves with red circles represent the data that is an outlier because these values are deviated from the normal log trend values. To remove these values, different algorithms or techniques are applied on the well curve. After making a pair plot, the next step is making a heat map based on these curves. Figure 4.32 shows the heat map along with their correlation coefficient among log curves. The legend of the heat map shows the correlation coefficient strength from the scale of 0 to 100%. The maximum correlation is present between the GR and NPHI log, which is 75 % that is shown in red color. This red color also represents shale lithology because of the higher gamma ray log curve corresponding to higher neutron log curve. In some log curves, the correlation coefficient drops to zero like correlation between NPHI and LLD, which is 78% this type of correlation represents that with an increase in LLD the NPHI is decreased, which is a clue to the presence of geothermal reservoir zone.

Figure 4.33 shows the box plot made between the four log curves. The main function of the box plot on this study is to know the comparative analysis of the different outlier removal techniques. Figure 4.33 (a) represents the box plot before the removal of the outlier, and Figure 4.33 (b, c, d, e, & f) represents the methods that are used for the outlier removal of the log curve of Tando Allah Yar-1 well. The x-axis represents the name of the log curve, and the y-axis shows the outlier result on the scale of 0 to 1. Figure 4.33 (b) illustrates the elimination of outliers using a standard deviation filter with a score

range of 0.25-0.75. The filter works by cutting off data that is away from a given standard deviation from the mean, making it a simple univariate approach. Mid-scores mean that it is good at capturing gross outliers but not particularly good at detecting subtle anomalies or, in some cases, multivariate relationships. For instance, while GR and LLD perform a little better than RHOB and NPHI, it could be that, being less skewed, GR and LLD, with a more symmetric distribution, helped in the detection process. This filter works efficiently for a rapid data secreting session; however, its shortcomings become manifest in the existence of simultaneous. Figure 4.33 (c) explicitly shows the Isolation Forest, which is considered as a sensible outlier recognition act among all four-log curves with scores clustering between 0.50 and 0.75. This shows that this method is moderately successful but not optimal for this dataset. Because it randomizes partitioning of the data to isolate outliers, Isolation Forest is fast in high-dimensional data but is less sensitive to local anomalies or subtle deviations. The consistent scores imply a similar performance across the different log types, whereas none could be singled out for particularly good detection. This approach may suffice for preliminary screening but will overlook complex patterns associated with outliers in well-logging data. Figure 4.33 (d) shows the minimum curvature that achieves maximum scores almost short of 1.00 for GR and LLD and still holds value for RHOB and NPHI at (greater than 0.75). Such a technique is best suited to multivariate Gaussian distribution modeling while ignoring outliers, hence its appropriateness in correlated well-logging data. This higher success rate reflects the capture of complex relationships (e.g., density-porosity) that univariate methods fail to capture. The slightly lower scores for RHOB/NPHI might arise from non-Gaussian distribution or noise, but by all means, Min. Covariance is proven to be the most robust method here. This is of utmost importance when the variables are interdependent, and the outliers are defined in context.

According to Figure 4.33 (e), a few curvature minimums realized the maximum scores, coming quite close to about 1.00 for GR and LLD and still pretty much holding up with RHOB and NPHI (greater than 0.75). This statistical method models multivariate Gaussian distributions without attention to outliers, thus being most appropriate for correlated well-logging data. The superior performance indicates that it can better represent complex correlations (density-porosity) that univariate approaches miss altogether. The slightly lower values for RHOB/NPHI might be due to non-Gaussian distributions or noise, but overall, Min. Covariance is the strongest method here. It applies distinctly when measurements have dependence among each other and when thrown off

measurement types are defined in the context. Figure 4.33 (f) LOF gives results that are significantly better than Isolation Forest, especially in GR and LLD, where they approach 0.75-1.00. This density method is designed to compare the density between a data point and between points neighboring that data point to flag it as an anomaly thus, it can pick up context-specific anomaly detection. The increased score of GR and LLD indicates such conditions that they have distinctly different outliers with reference to local identities from RHOB and NPHI, which have minor density variation. LOF does perform best when being able to account for outliers that are different from their immediate neighbors but may suffer a disadvantage in globally sparse cases where the density of data goes low. Its variable-specific results indicate the meaning of considering the data structure while choosing the methods to use when performing outlier detection. One-Class SVM However exhibits variable performance across the four variables in well logging, with scores in the range of about 0.25-0.75. Learning of a decision boundary would surround normal data points to classify outliers, and therefore the method performs best for the variables GR and LLD, with scores higher up in the range. This would suggest that One-Class SVM is a more robust dimensionality reduction tool for anomaly detection in these variables probably due to the fact that their distributions are more in concordance with the entered parameters set by the One-Class SVM for a meaningful definition of coherent dense normal region. For RHOB and NPHI, conversely, the scores are very much lower, meaning that the method has less value there. This inference can arise because of non-Gaussian distributions, noise therein, or perhaps due to the multimodal characteristics of these variables that hinder the One-Class-SVM attempts to efficiently delineate a clear boundary around "normal" data. Tuning to parameters and kernel selection inherent to the method may also lead to varied scores since inappropriate parameter settings would enclose either normal or highly nonnormal samples.

Figure 4.34. demonstrate the pair plot after the removal of the outlier from the log curve, the total number of outliers in the data set is 4874 and after the removal the outlier the scatter plot is more efficient and shows the reliable result which is now best for the future processing and analysis. Figure 4.35 illustrates the log curve track; there are four tracks that are shown the track 1 show the original GR with black color and corrected GR with red dotted color. The scale for the gamma ray is in API with a range 0 to 150 API. Track 2 represents the RHOB log with original and corrected curve the scale of the RHOB is lies between 1.7 g/cm^3 to 2.7 g/cm^3 . Track 3 shows the corrected and original LLD log curve and the scale of the LLD is 0 to 10^3 ohm-m and the last track 4 illustrated NPHI

log curve both original and corrected NPHI with a scale of 0 to 0.4 v/v. These four tracks are plot with respect to their depth on y-axis, the depth is ranged from 1430 to 1775 m, which is increasing from top to bottom. After the correction of log curves, the next step is to perform a petrophysical parameter for the facies analysis as shown in Figure 4.36. In petrophysical analysis Vshl, PHIE, S_w , and PHIA are estimated. The volume of cleaning is 28%, with Vshl 72%, the PHIA is 22%, PHIE is 15%, and S_w and hydrocarbons are 26% and 64% respectively, as shown in Figure 4.36 (a). The result of petrophysical analysis is also shown in the log curve tracks. Track 5 shows the log curve result for Vshl, track 6 represents the result of PHIE, track 7 illustrates the S_w result, and track 8 shows the facies analysis track. Three types of facies have been determined based on a log curve i.e., wet sand, gas sand and shale. The upper portion of the log track shows the gas sand facies, and then there is an interbed of shale and sand encountered. The dominant lithology that is encountered in LGF is shale, which is represented in green color. Figure 4.36 (b), which represents the cross plot between the total number of facies and Vshl, saturation water and PHIE. Shale facies are excellently predicted with help of Vshl and S_w while the gas sand is predicted best with PHIE, as shown in Figure 4.36 (b). To conclude, the major facies in LGF are an interbed of shale and sand, with more dominant shale in the Tando Allah Yar-1 well.

The detailed result of the facies analysis of Tando Allah-2 is discussed in Figure 4.37. The thickness of the LGF in Tando Allah Yar-2 well is 140 m. The major lithology encountered in the Tando Allah Yar-2 is shale (green color) with interbedding of wet sand (blue color) along with small thin beds of gas sand. Figure 4.37 (b) represents the bar plot that is made between the total number of counts on y-axis and the log curve Vshl, PHIE, S_w on x-axis. The color code of the bar represents the total count of facies based on the output log curve. The bar plot Vshl vs count shows the shale with higher values (green color) than gas sand (red color) and wet sand. The bar plot between the PHIE vs count predicted the higher values for the wet sand and lower values for the shale, and in the end, S_w vs count also represents the higher values for the shale. To conclude, the shale is dominant in the LGF with interbeds of wet sand and gas sand. Figure 4.37 (c) shows the petrophysical results in statistical foams, which represents that the average PHIA and PHIE in LGF are 17 % and 12%, respectively. The average Vshl is 37%, with the average volume of clean is 63% and S_w is 35%.

The facies analysis is also predicted on the Tando Allah Yar-3 well for the LGF. The LGF is started at the depth of 1456 m and ends at 1600 m with a total thickness of

144 m. The GR in the formation is lower in value so that it is plotted between 0 to 100 API as shown in Figure 4.38 (a). The extreme lower GR is encountered at the depth between 1475 to 1520 which is less than 20 API, and the higher values are only above 80 API, which is shown in the red color spectrum. At the same specific depth where GR shows the less values, the RHOB values also decreased, and LLD shows the higher values at that specific depth. Track 5 shows the result of the Vshl, which represents that the lower GR value demonstrates the dominance of sandstone and higher GR represents that the shale is dominant at that specific depth. The track 6 shows the PHIE result, which also justified the Vshl in such a way that the formation with sandstone shows high PHIE and formation with the shale represents lower PHIE. Saturation is also higher where the PHIE is higher, and sandstone lithology is dominant. Track 8 represents the facies prediction, which shows that the shale is dominant below the 1520 m and above the 1520 m of depth the wet sand is major lithology with interbedding of shale and gas sand.

Figure 4.38 (b) demonstrates the bar plot that is plotted between the facies and the output log curve. The three plots predicted the same facies with different counting numbers. The shale is best predicted with the help of Vshl, the gas sand and wet sand are fairly estimated by the PHIE, and the shale and wet sand are predicted via S_w bar plot. The green bar represents shale lithology, red shows the sand and blue represents the wet sand. The x-axis of bar plot shows the range of output log curve (Vshl, PHIE and S_w) that varies according to facies estimation. The detailed petrophysical analysis result is shown Figure 4.38 (c), the PHIE is good in LGF, which is 23 % with PHIA of 19 %. The Vshl is 25% and S_w is also 25%. Three facies that are found are shale, gas sand and wet sand is directly associated with geothermal potential in such a way that where there is gas and wet sand the PHIA and K is higher which is ideal for the heat storage and flow of fluid, However, presence of shale act as a seal for the thermal anomaly for geothermal reservoir. Facies are identify on the LGF and the petrophysics result that are present in the end represent the overall result of LGF as these results are similar to the petrophysical result that is calculated using traditional method. The reason to put the result in the end of image is to show the validation and comparison of conventional and unconventional techniques. This ML based prediction of facies beats the traditional approach both in geological and resolution reliability. Conventional methods are restricted to diverse data sources, limited amalgamation and poor resolution and prediction. While the advanced model systemizes the process of classification by preserving uniformity in geology, well logs and seismic attributes data.

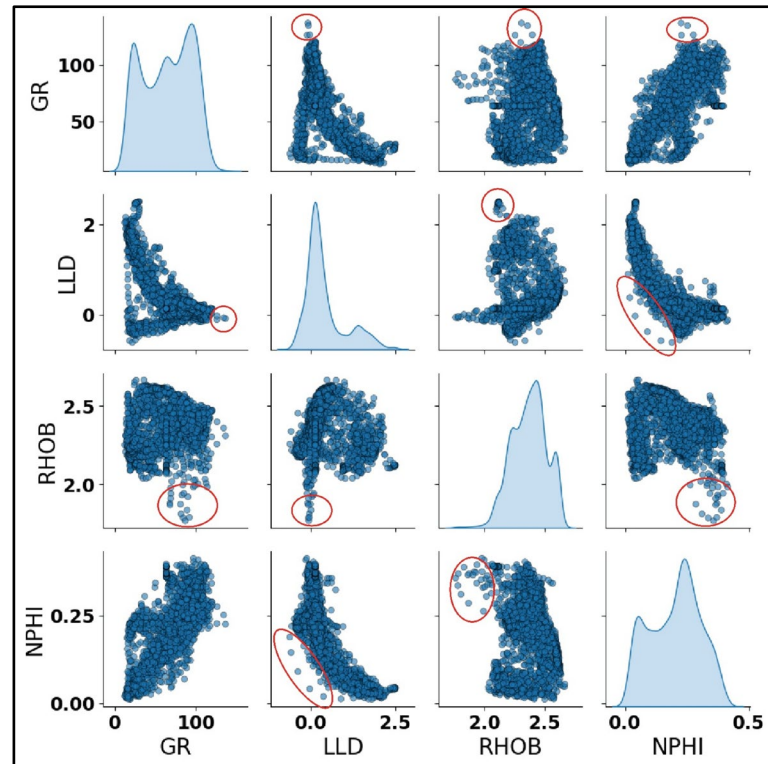


Figure 4.31 Pair plot before the removal of the outlier for Tando Allah Yar-1. The red circle present in the scatter plot demonstrates the outlier data in the log curve, and the peak plot shows the maximum number of values present in the plot.

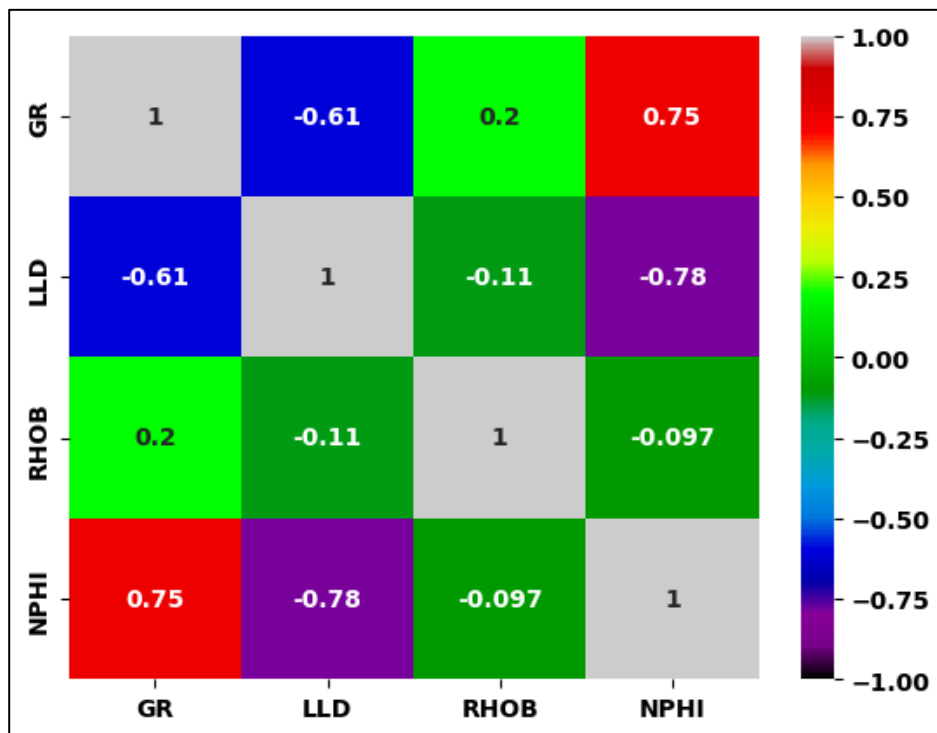


Figure 4.32 Heat map that is made among log curves to know there correlation coefficient strength. The red color shows the high strength in correlation and purple represents the lesser correlation coefficient.

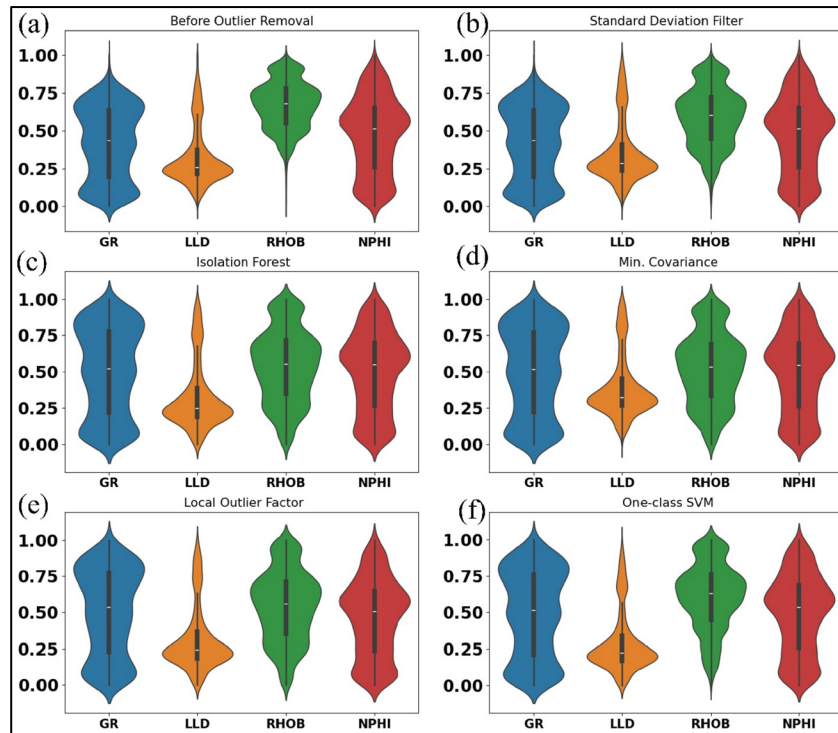


Figure 4.33 Outlier removal methods for Tand Allah Yar-1 well based on GR, LLD, RHOB, and NPHI log curve.

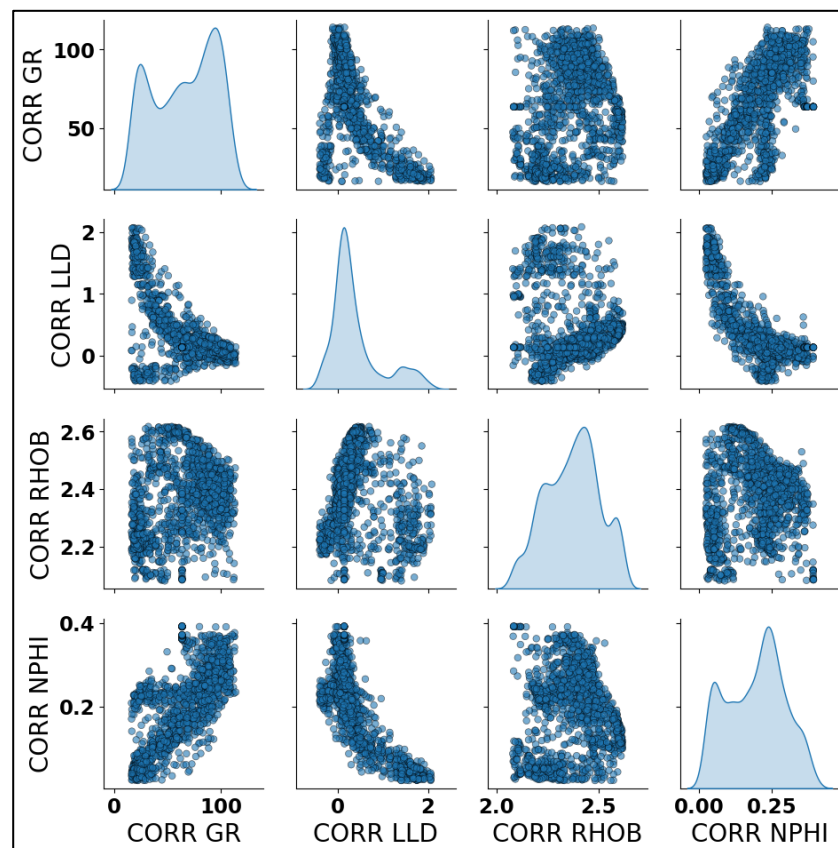


Figure 4.34 Pair plot after the removal of the outlier for Tando Allah Yar-1. The scatter plot demonstrates the clean data in the log curve and the peak plot shows the maximum number of values present in the plot.

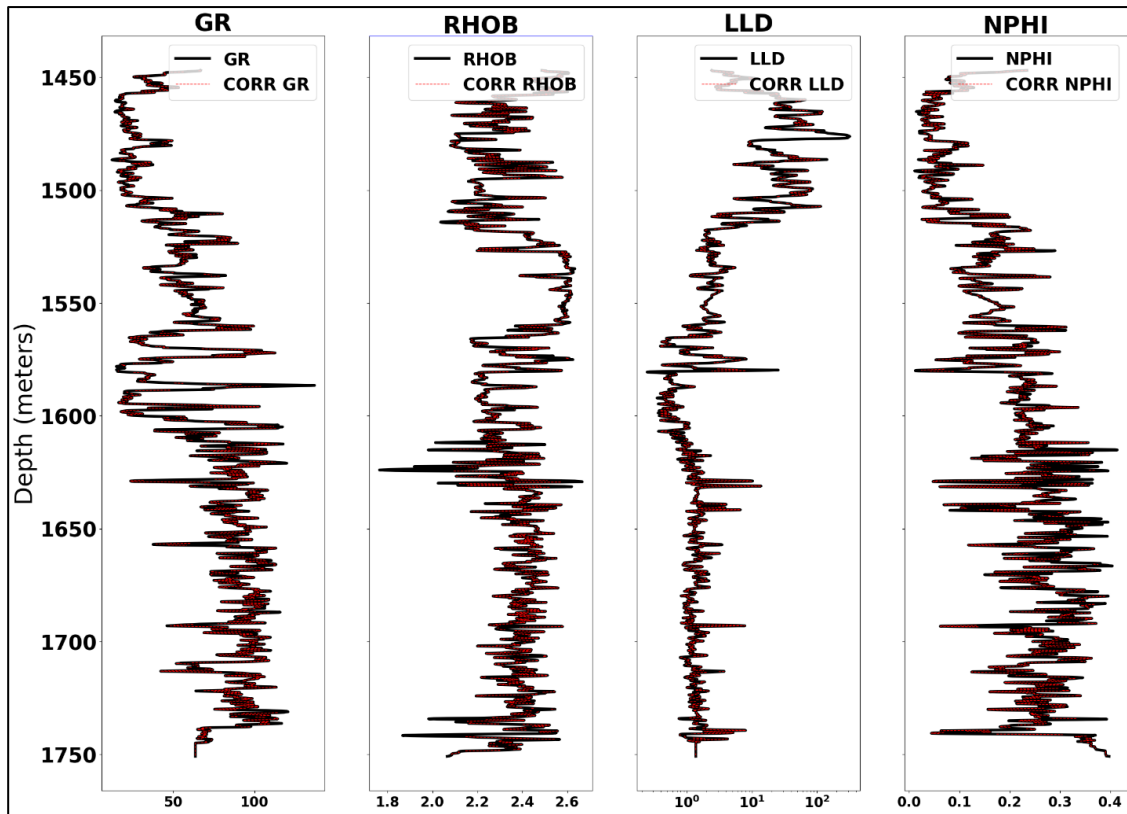


Figure 4.35 Graphical representation of GR, RHOB, LLD and NPHI log curves with the original versus corrected curve after the outlier. The black color represents the original curve, and the red color shows the corrected curve after the removal of the outlier.

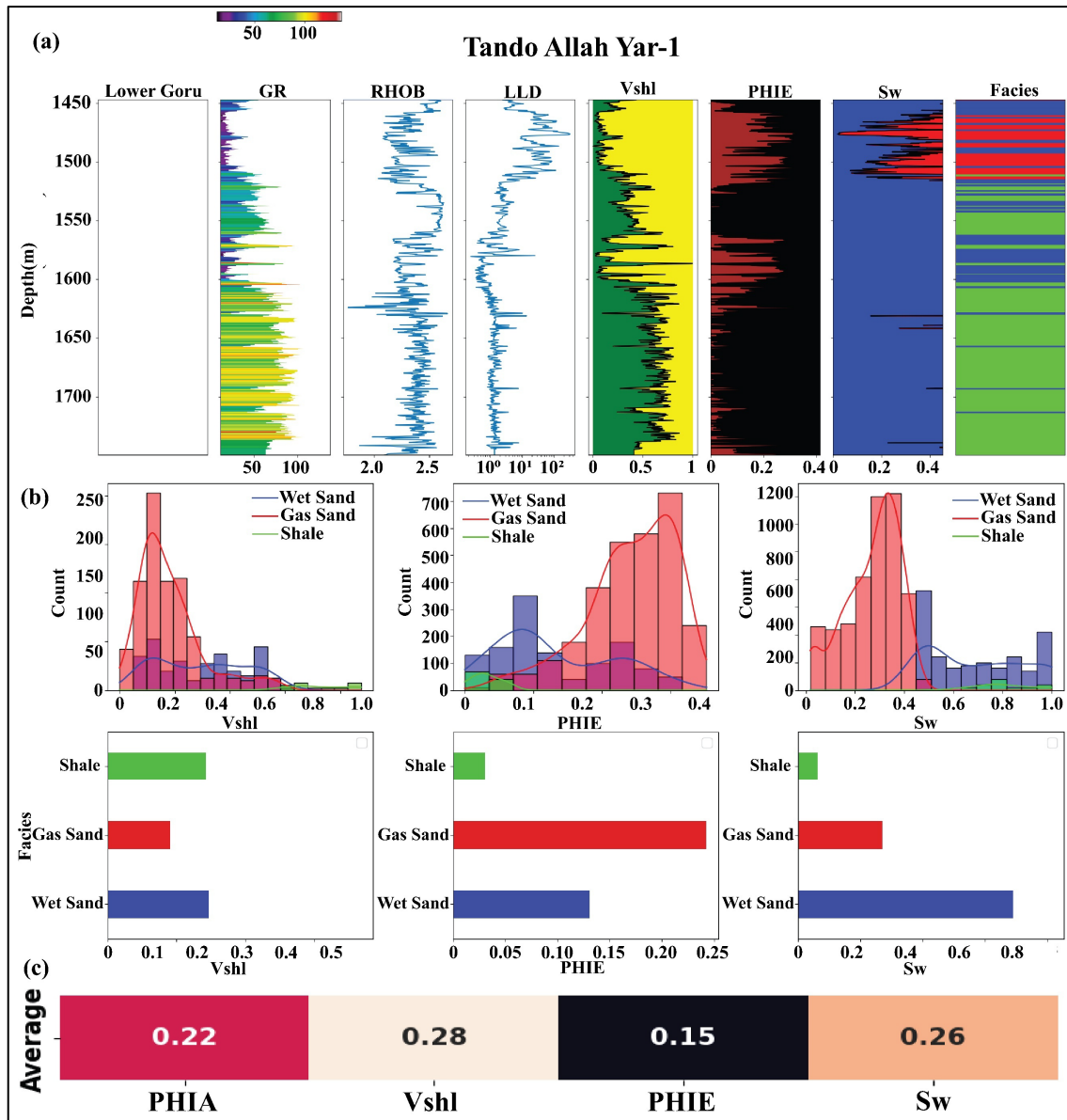


Figure 4.36 ML technique for the facies prediction based on the Tando Allah Yar-1 well. (a) illustrated the petrophysics result along with facies at track 8. (b) shows the result of facies that is present on the LGF for Tando Allah Yar-1 well, three facies are identified, named as wet sand in blue color, gas sand in red color, and shale in green color.

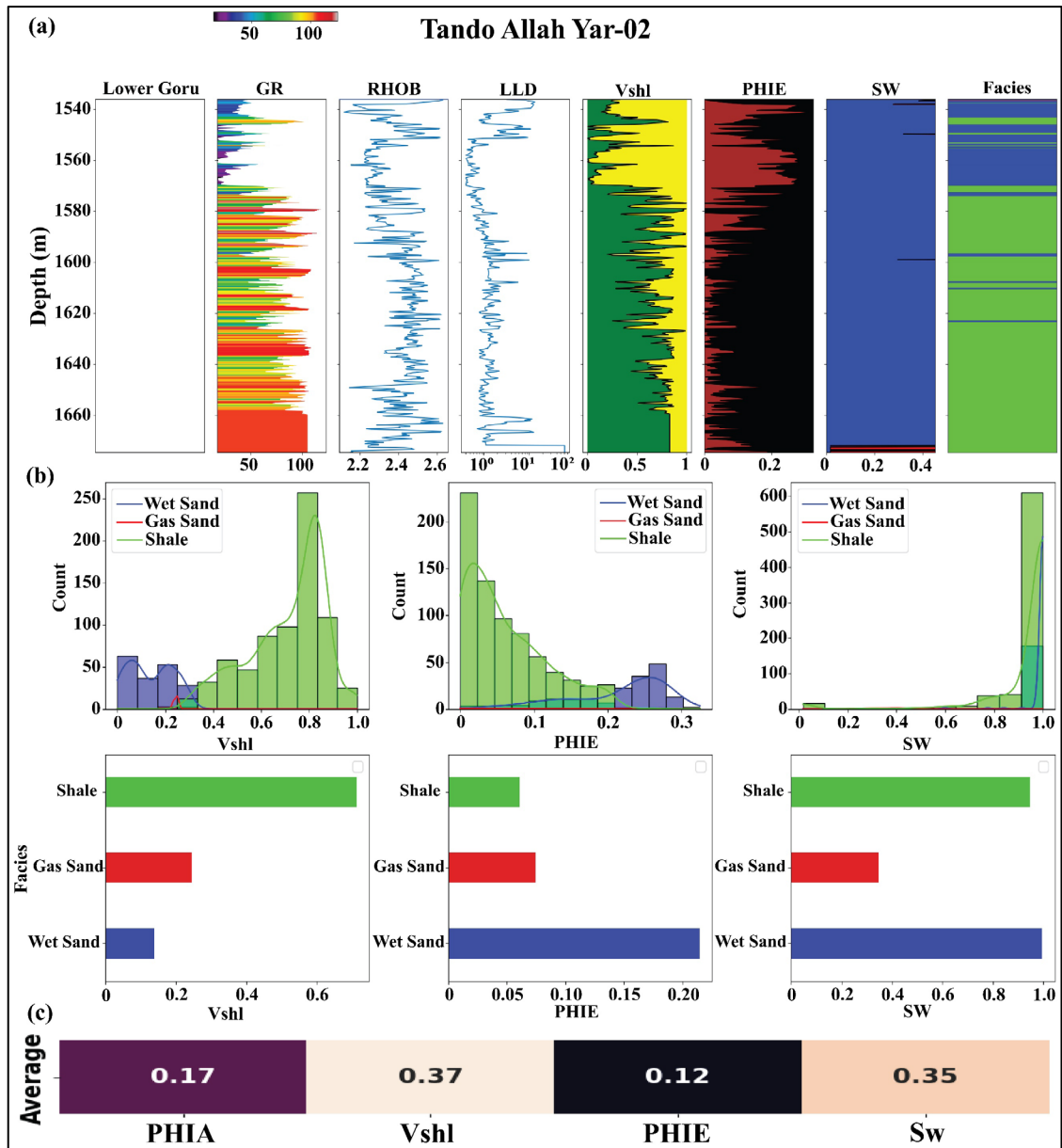


Figure 4.37 Facies prediction based on the Tando Allah Yar-2 well for LGF. (a) illustrate the log curves tracks along with the result of Vshl, PHIE and S_w and track 8 with facies prediction. (b) shows the bar plot for result of facies that is present on the LGF for Tando Allah Yar-2 well, three facies are identified named as wet sand in blue color, gas sand in red color, and shale in green color. (c) shows the petrophysics result of PHIE, PHIA, Vshl and S_w .

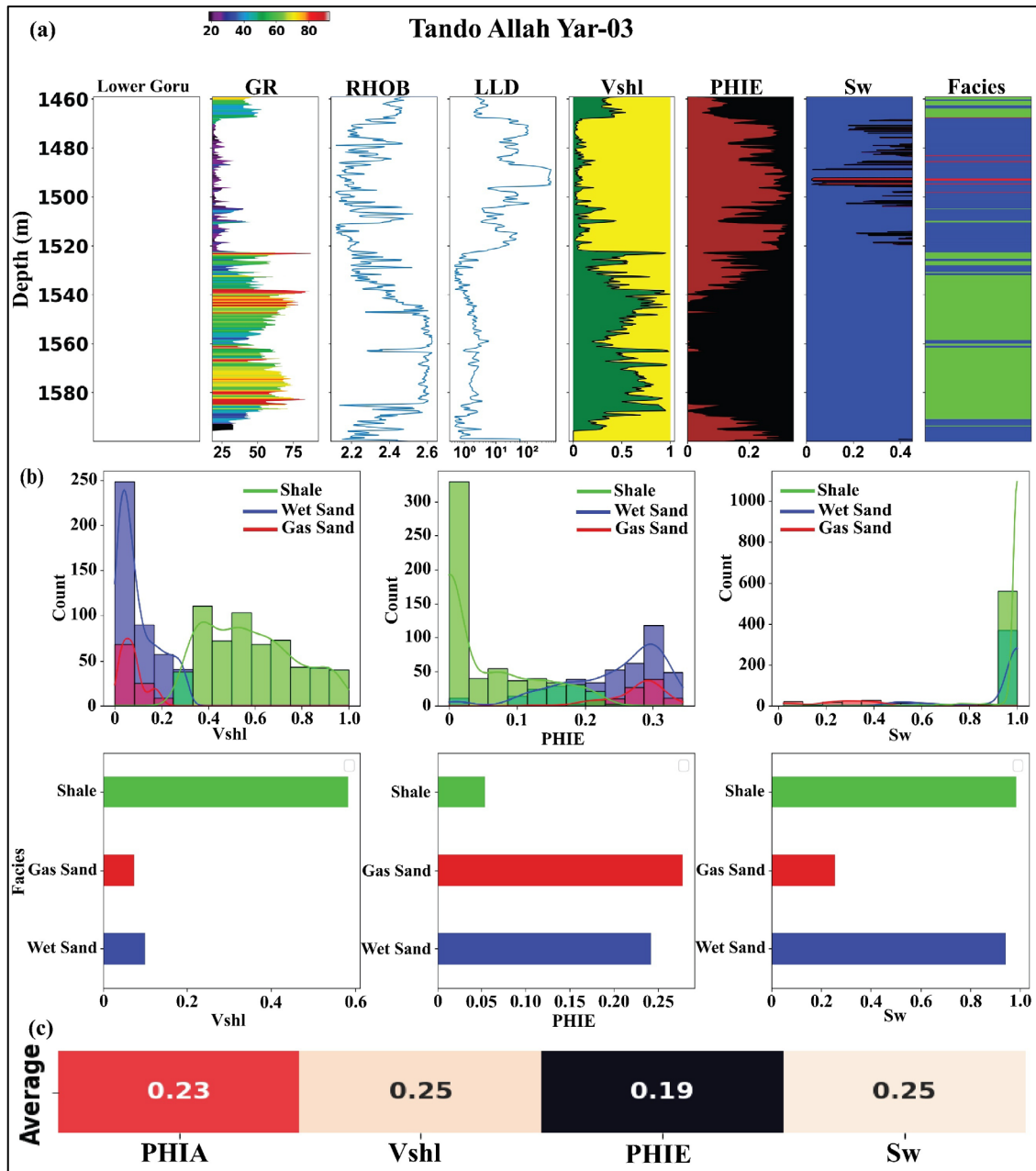


Figure 4.38 Petrophysics results of Tando Allah Yar-3 well with ML technique for the facies estimation. (a) Demonstration of the log curves results in track 5 to 7 along with facies represents in track 8. (b) Shows the result of facies that is present on the LGF for Tando Allah Yar-3 well, three facies are identified named as wet sand in blue color, gas sand in red color, and shale in green color. (c) Numerical petrophysical results of the LGF.

4.3.2 Facies Identification of Babar-1 Well

After the adjustment of log curves, the next step is to perform a petrophysical analysis for the facies analysis. In petrophysical analysis, Vshl, PHIE, Sw, and PHIA are estimated. The Vshl is 29%, the PHIA is 22%, the PHIE is 15% and Sw and hydrocarbon are 3% and 97%, respectively. The result of petrophysical analysis is also shown in the

log curve tracks. Track 5 shows the log curve result for V_{shl} , which is shaded in yellow and green colors. The yellow color represents sandstone lithology, and the green color represents the shale facies. track 6 represents the result of PHIE, which lies on the scale of 0 to 0.5, track 7 illustrates the S_w result the black color represents the hydrocarbon saturation, and the blue color shows the amount of water and track 8 shows the facies analysis track. Three types of facies have been identified based on a log curve: wet sand, gas sand, and shale. The upper portion of the LGF shows the interbed of wet sand and gas sand facies followed by interbed of shale and sand encountered. The dominant lithology that is encountered in LGF is shale and wet sand, represented in green color as shown in Figure 4.39 (a).

Figure 4.39 (b) represents the bar plot between the total number of facies and V_{shl} , S_w and PHIE. Shale facies and Gas Sand are excellently predicted with the help of V_{shl} and PHIE, while the wet sand is predicted best with V_{shl} and S_w . To conclude, the major facies in LGF is an interbed of shale and wet sand with a thin bed of gas sand in the Babar-1 well. Figure 4.39 (c) represents the statistical output of the petrophysical estimations.

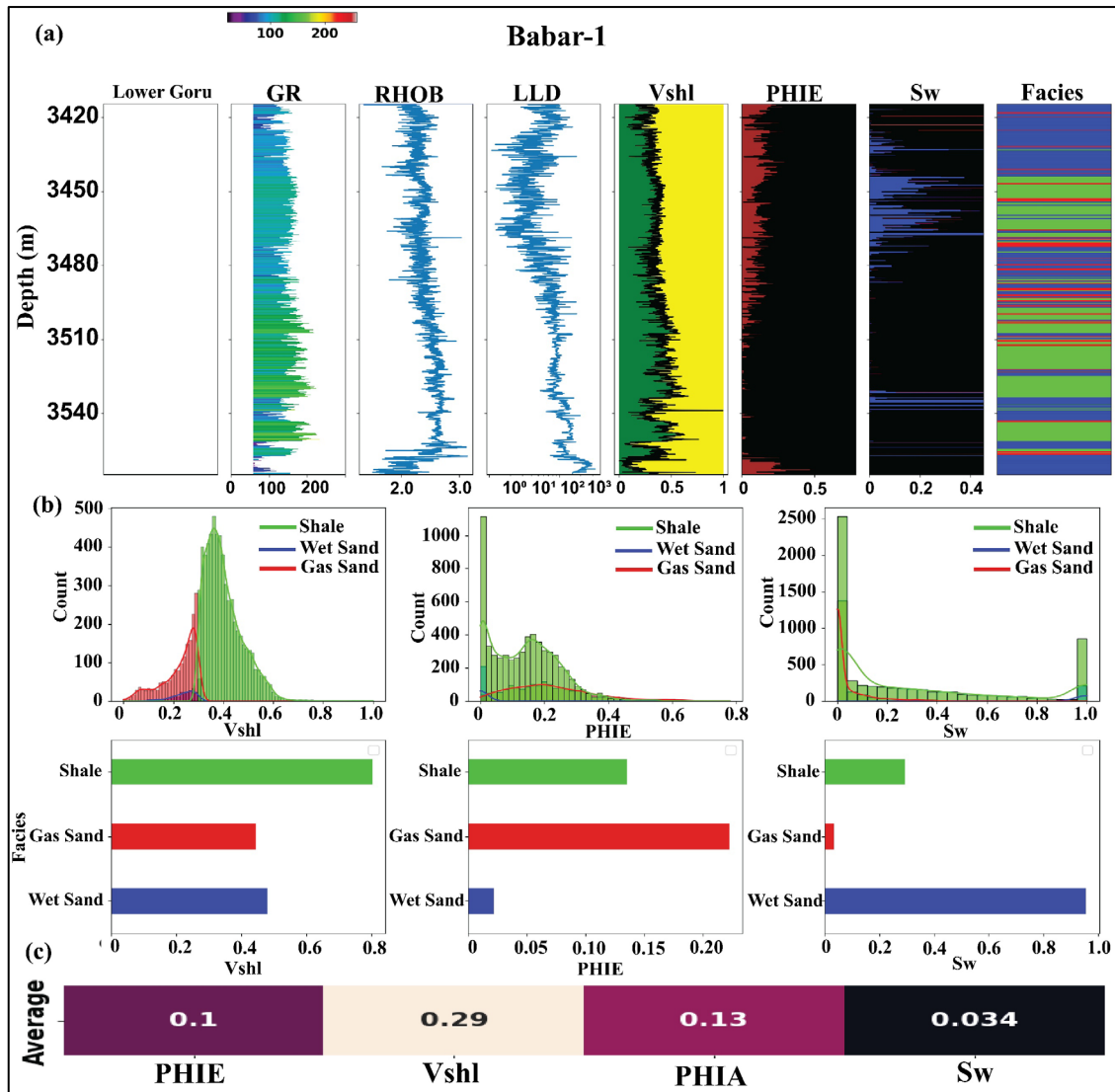


Figure 4.39 Facies prediction based on the Babar-1 well by ML approach. (a) Result of petrophysics and prediction of facies are shown from tracks 5 to 8. (b) Shows the result of facies that are present on the LGF for Babar-1 well, three facies are identified, named as wet sand in blue color, gas sand in red color, and shale in green color. (c) Estimated petrophysics result of the Babar-1 well at the LGF level.

4.3.3 Facies Identification of Bukerani-1 Well

The complete output of petrophysical analysis along with facies prediction of Bukerani-1 is shown in Figure 4.40 (a), where the sand encountered in the formation represents the PHIE is increased and where shale is present, the PHIE shows less value. The seventh track is for the S_w that is calculated by the Simandoux saturation water equation. The scale of S_w is plotted between 0 to 0.4 v/v, and the last track demonstrates the facies analysis that is identified based on log curve. The major lithology encountered in the Bukerani-1 is shale (green color) with interbedding of wet sand (blue color) along with thin beds of gas sand shown in red color.

Figure 4.40 (b) represents the bar plot that is made between the total number of counts on y-axis and the log curve Vshl, PHIE, S_w on x-axis. The color code of the bar represents the total count of facies based on the output log curve. The bar plot Vshl vs count shows the shale with higher values (green color) than gas sand (red color) and wet sand. The bar plot between the PHIE vs count predicted the higher values for the wet sand and less values for the shale and in the end S_w vs count also represents the higher values for the shale. To conclude the shale is dominant in the LGF with interbeds of wet sand and gas sand. Figure 4.40 (c) shows the petrophysical results in the statistical form, which represents that the average PHIA and PHIE in LGF are 13 % and 9%, respectively. The average Vshl is 29%, and S_w is 12%.

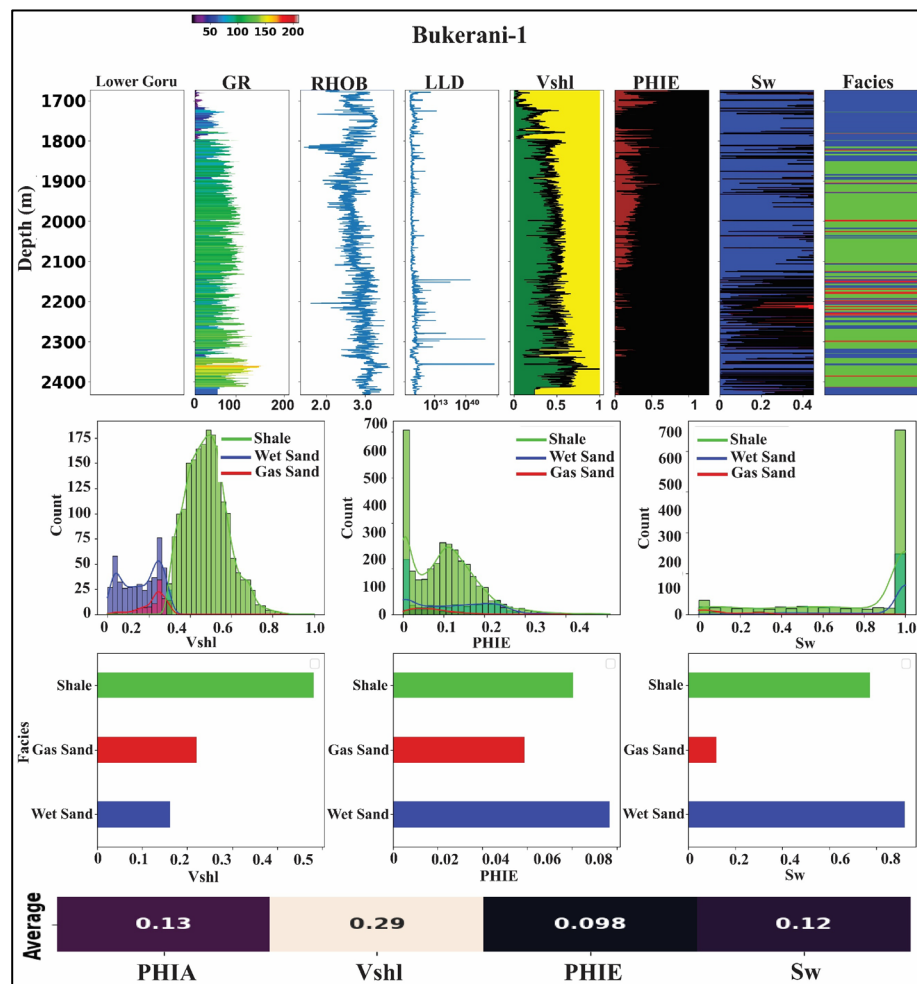


Figure 4.40 Detailed results of Petrophysics properties and facies analysis for LGF at Bukerani-1 well (a) demonstration of result in the log curve format with input log curve tract track 1 to 4 then output track shows from track 5 to 8. (b) Indicates the result of facies that is present on the LGF for Babr-1 well in the bar plot representation, three facies are identified as wet sand in blue color, gas sand in red color, and shale in green color. (c) Average results of PHIA, Vshl, PHIE and S_w in LGF for Bukerani-1 well.

4.3.4 Facies Identification of Allah Dino-1 Well

The facies analysis is also predicted on the Allah Dino-1 well for the LGF as mentioned in Figure 4.41 (a). The LGF is started at the depth of 2335 m and ends at 2510 m, which is approximately 135 m in thickness. The GR in the formation is lower so that it is plotted between 0 to 100 API. The overall GR curves fluctuate from a lower value (less than 30) to higher value (from 60 to 100 API). Figure 4.41 (b) demonstrates the bar and line plot that is plotted between the facies and output log curve. The two facies are estimated to be named shale and wet sand in the Allah Dino-1 well at LGF. These facies are exceptionally good predicted with the help of Vshl, PHIE and S_w . The thickness of facies varies in formation because of GR and S_w . The detailed petrophysical analysis result is shown Figure 4.41 (c), the PHIE in LGF that is 4 % with PHIA of 9 %. The Vshl is 41%, and S_w is also 100%.

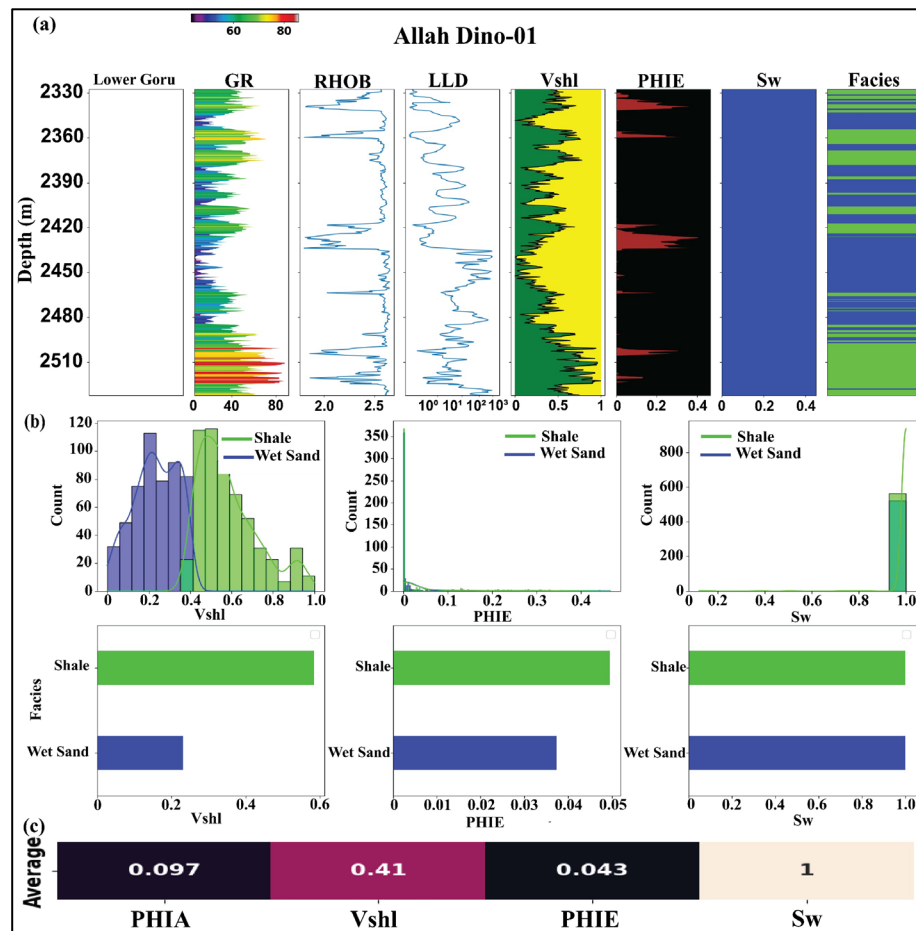


Figure 4.41 ML technique for the facies prediction based on the Allah Dino-1 well. (a) illustrated the log curves result along with facies at track 8. (b) shows the result of facies that are present on the LGF for Allah Dino-1 well, three facies are identified as wet sand in blue color, gas sand in red color, and shale in green color.

4.3.5 Facies Identification of Jumman Shah-1 Well

Figure 4.42 (a) depicts the facies prediction on the Jumman Shah-1 well for the interested LGF. The LGF lies at depths of 1534 to 2525 m, but the log curve data is only available for the depth 1535 to 1620 m with a thickness of 85 m. Figure 4.42 (b) demonstrates the bar plot that is plotted between the facies, output log curve and total number of counts for facies. The three plots predicted the same factors with different counts. The shale is best predicted with the help of S_w , the gas sand is fairly estimated by using PHIE, and the wet sand is predicted accurately via S_w and PHIE bar plot. The green bar represents shale lithology, red shows the sand, and blue represents the wet sand. The x-axis of bar plot shows the range of output log curve (V_{shl} , PHIE and S_w) that varies according to facies estimation. The statistical petrophysical analysis result is shown Figure 4.42 (c), the PHIE and PHIA in LGF are 16 % and 19 %. The V_{shl} is 22% and S_w is also 19%.

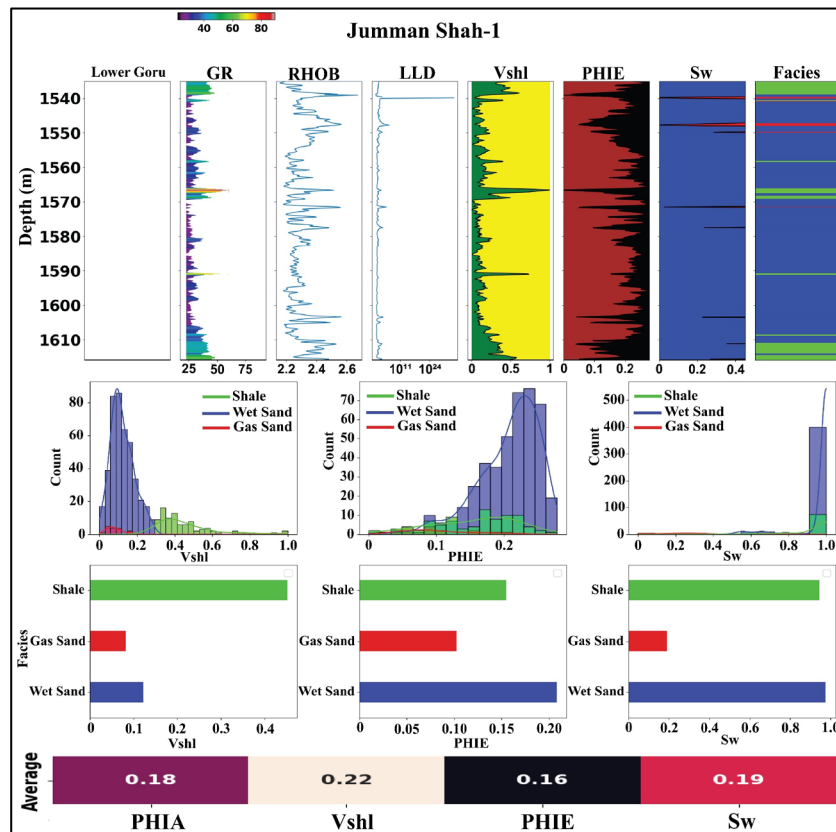


Figure 4.42 ML technique for the facies predication based on the Jumman Shah-1 well. (a) Three facies are predicted named shale, gas sand and wet sand on the LGF along with petrophysics curves result of V_{shl} , PHIE, and S_w . (b) shows the result in the form of bar plot for facies that are present on the LGF for Jumman Shah-1 well. (c) represent the numerical outcomes of petrophysics.

4.3.6 Facies Identification of Jarwar-1 Well

The facies analysis is also estimated on Jarwar-1 well. The LGF is an interesting formation, and it started at the depth of 1169 m and ends at 1473 m, but the availability of data is only available from the depth of 1170 to 1220 m which is approximately 50 m in thickness as shown in Figure 4.43 (a). The GR is incredibly low in formation and the maximum value of GR is going up to 60 API as shown in track 2, while track 3 represents the RHOB which shows the higher values on the upper portion as the depth is increasing the RHOB is decreased. LLD, which is present in track 4 also follows the same trend as values are increasing on upper portion of log from the depth of 1170 to 1185 m and below this depth the lower LLD is encounter. Track 5 depicts the result of Vshl which shows that where there is an increase in GR the Shale (green color) is dominant and where GR is low sandstone is dominant (yellow color). Track 6 represents the result of PHIE curve with is plotted in decimal from 0 to 0.3. PHIE is increase where the sandstone is dominant and decrease where the shale is present. Track 7 shows the result of S_w and track 8 represents the facies in the LGF. Two facies are estimated to be the Jarwar-1 well named as wet sandstone and shale, with dominant sandstone. Figure 4.43 (b) represents the facies' result in the form of bar plot where x-axis shows the petrophysics parameters Vshl, PHE and S_w while y-axis represents the total count of facies. Two facies, shale and sandstone, are present in LGF. The count of wet sand is higher, so the major facies is wet sand.

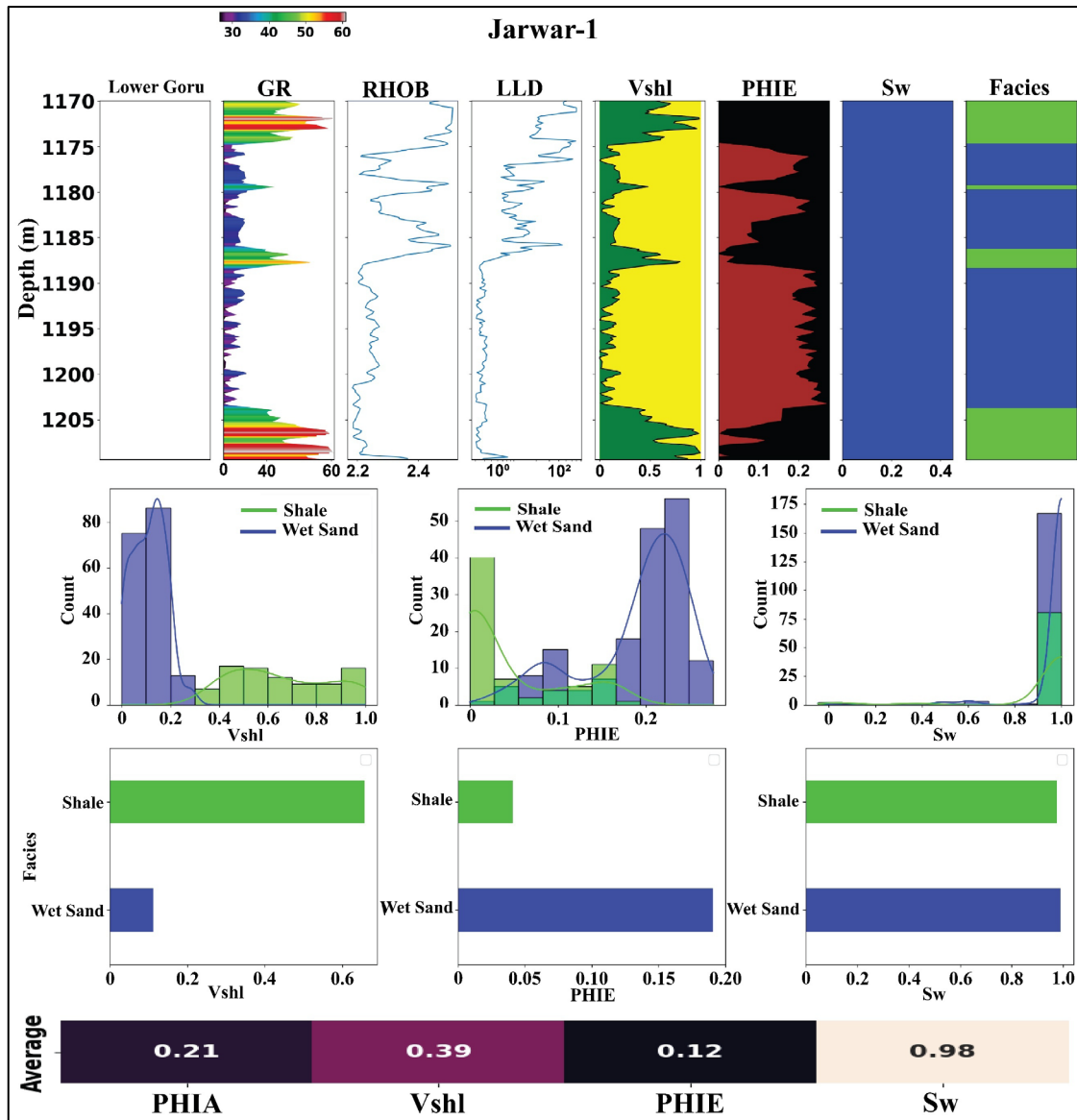


Figure 4.43 ML technique for the facies predication based on the Jarwar-1 well. (a) illustrated the log curves result along with facies result shown in track 8. (b) shows the result of facies that are present on the LGF for Jarwar-1 well, three facies are identified as wet sand in blue color, gas sand in red color, and shale in green color.

4.3.7 Facies Identification of Sono-2 Well

Figure 4.44 demonstrates the comprehensive results of facies analysis along with petrophysics results. The facies analysis is performed in LGF that is started at the depth of 2166 m and end at the depth of 2300 m. LGF is the last formation that is encounter in Sono-2 well. There are eight tracks shown in Figure 4.44 (a), which represent the input log curve and results of petrophysics. The first four tracks represent the input log curve of formation name, GR, RHOB and LLD. The y-axis represents the depth of the

formation and x-axis demonstrates the scale of the log curve. The GR log, which is represented in Track 2, shows a low value in overall formation. Tracks 5,6 and 7 illustrate the petrophysics result of V_{shl} , PHIE and S_w . In the trend of V_{shl} where there is lower V_{shl} the PHIE is higher and vice versa. Truck 8 shows the result of facies that are predicted based on log curves two facies are predicted on the LGF, the Sandstone and shale. There are interbed of shale and sand in the LGF. Where there is higher V_{shl} the lithology is shale and where the lower V_{shl} is encountering the lithology is wet sand. Shale lithology is shown in a green color, and sandstone is represented with blue color.

Figure 4.44 (b) represents the two distinct types of bar plots. The first-row bar plot demonstrates the total number of counts on y-axis and petrophysics log curve for V_{shl} , PHIE and S_w on the x-axis. The x-axis represents the result of the petrophysics range. The number of counts for V_{shl} and S_w shows that the major concentration is sandstone, while PHIE predicted shale lithology based on the lower PHIE values. The second series of cross plots is made between the predicted facies and the petrophysics log curve which also shows that the major lithology in the LGF is wet sandstone with interbed of shale. In the end the detailed statistical result of V_{shl} , PHIE, PHIA and S_w is shown in Figure 4.44 (c)

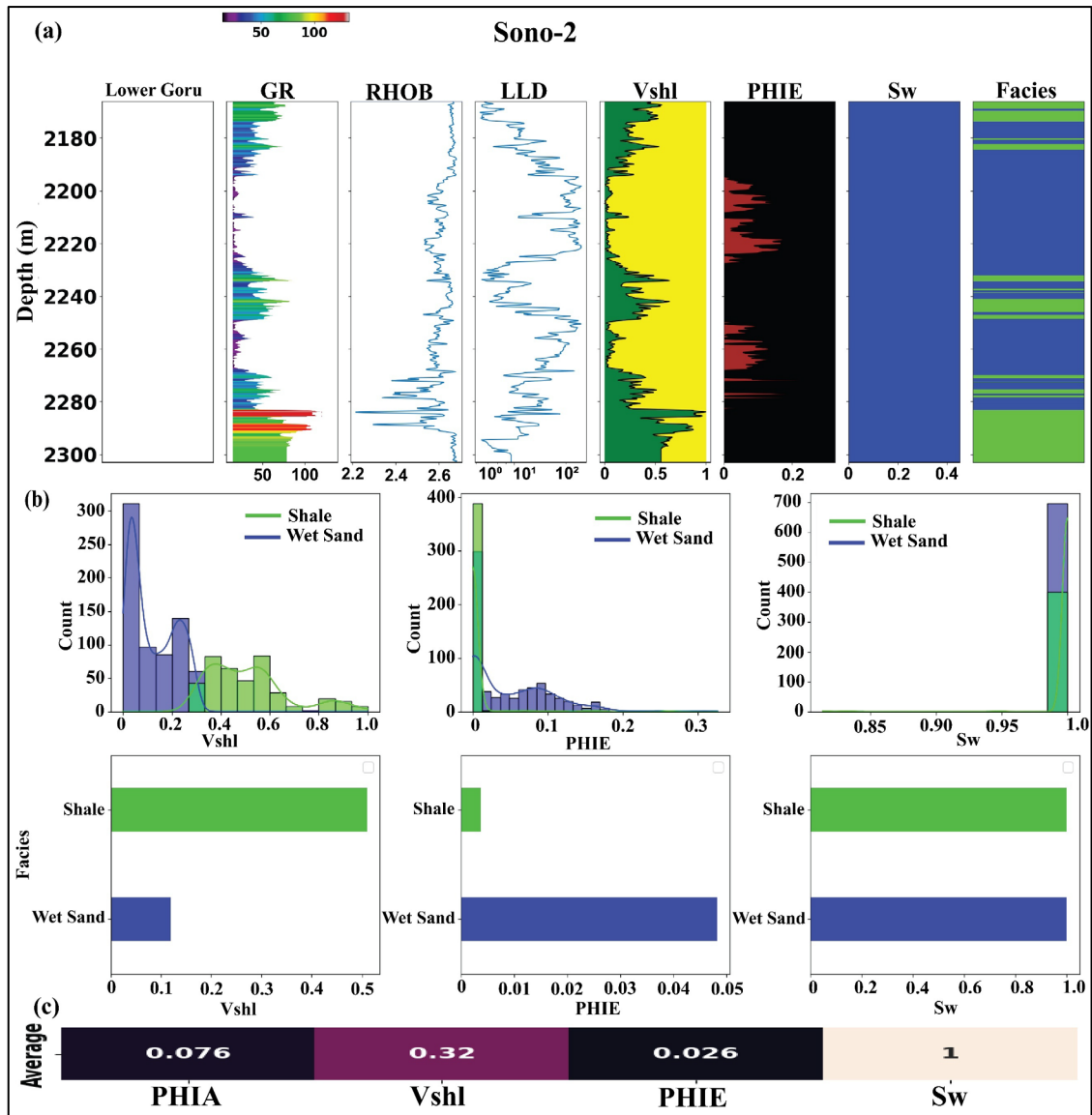


Figure 4.44 Demonstration of the facies analysis along with basic petrophysics result of Sono-2 well. (a) shows the log curves outputs along with the facies analysis result on track 8 as there are two facies that are estimated on the well shale and wet sand. (b) represent the cross plot with represent the facies prediction based on the concentration of Vshl, PHIE, and S_w . (c) illustrate the result of the petrophysics parameters.

4.3.8 Facies Identification of Sono-5 Well

Figure 4.45 demonstrates the comprehensive results of facies analysis along with petrophysics results. The facies analysis is conducted in LGF, which starts at a depth of 2238 m and ends at 2300 m. LGF is the last formation encountered in Sono-2 well. There are eight tracks shown in Figure 4.45 (a), representing the input log curve and petrophysics results. The first four tracks represent the input log curve of formation name, GR, RHOB and LLD. The y-axis represents the depth of the formation and x-axis demonstrates the scale of the log curve. The GR log, which is represented in Track 2,

shows a low value in overall formation. Tracks 5, 6 and 7 illustrate the petrophysics result of V_{shl} , $PHIE$ and S_w . In the trend of V_{shl} where there is lower V_{shl} the $PHIE$ is higher and vice versa. Track 8 shows the result of facies that is predicted on the basis of log curve three facies are predicted on the LGF the wet sand, gas sand and shale. There are interbed of shale and sand in the LGF. Where there is higher V_{shl} the lithology is shale and where the lower V_{shl} is encountering the lithology is wet sand. Shale lithology is shown with green color, and wet sand is represented with blue color and gas sand is shown in red color.

Figure 4.45 (b) represents the two distinct types of bar plots. The first-row bar plot demonstrates the total number of counts on y-axis and petrophysics log curve for V_{shl} , $PHIE$ and S_w on the x-axis. The x-axis represents the result of petrophysics range. The number of counts for V_{shl} and S_w shows that the major concentration is sandstone while $PHIE$ predicted shale lithology based on the lower $PHIE$ values. The second series of cross plots are made between the predicted facies and the petrophysics log curve which also shows that the major lithology in the LGF is gas sand with interbed of wet sand and shale. In the end the detailed statistical result of V_{shl} , $PHIE$, $PHIA$ and S_w is shown in Figure 4.45 (c)

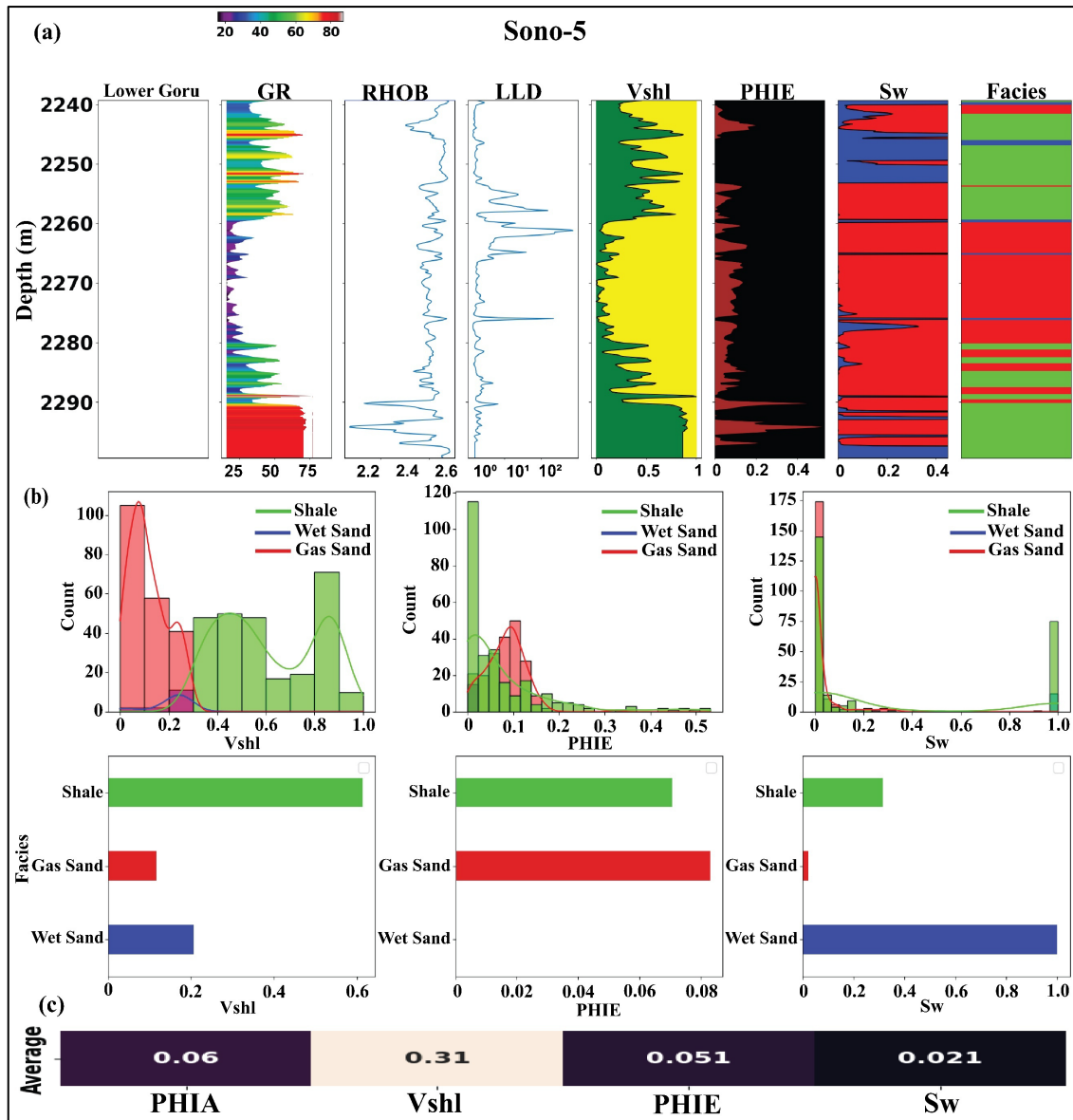


Figure 4.45 Demonstration of the facies analysis along with basic petrophysics result of Sono-5 well. (a) shows the log curves outputs along with the facies analysis result on track 8. (b) represent the cross plot with representing the facies prediction based on the concentration of Vshl, PHIE, and S_w . (c) illustrate the result of the petrophysics parameters.

4.4 Inversion Analysis and DFFNN on 3D Nim Tay Block

The next step of the research is to know the impedance variation in the study area for better understanding of the geothermal properties. The model-based inversion is utilized for the study after the PNN is applied on the well to know the variation of geothermal properties on the seismic section and map. The geothermal properties that are predicted in the well are K, Vshl, HP, RHP, PHIA and PHIE. The complete methodology

of model-based inversion is discussed in Chapter 3, and comprehensive results are shown below step by step.

4.4.1 Model Based Seismic Inversion

Initially, the 3D seismic block of the Nim-TAY Block is used to extract the statistical wavelet, which is convolved along the reflectance coefficient to generate the synthetic track on the borehole position. The temporal window bordered by the horizon, spanning from the top of LGF to the complete depth, is used to extract the wavelet. In order to obtain a good correlation, a seismic to well tie connection was constructed utilizing the seismic extracted wavelet. Finally, for further improvement in the coefficient of correlation, the log curve-based wavelet of 100 ms wavelength is chosen. Wavelets from the well data are extracted using the Tando Allah Yar-2 well. Which represents all of the seismic frequency ranges, wavelet frequency spectrum of 25 Hz is utilized. As seen in Figure 4.46, the wavelet extraction from well data has a standard phase of 10° and a dominating frequency of 20 Hz. For the establishment of an initial well tie and a time-depth relationship, synthetic traces are related to seismic traces. The time window of connection cross plot is nominated to encompass whole study period using accessible log data to compare artificial and actual traces. To view both synthetic and actual traces, the time window for the correlation plot is selected to cover the entire duration for which log data is currently available as shown in Figures 4.47, 4.48 and 4.49. The Figure 4.47, 4.48 and 4.49 depicts the correlation window of Tando Allah Yar-1, Tando Allah Yar-2 and Tando Allah Yar-3 for the whole thickness of the LGF. Track 1 indicates the DT log curve, whereas track 2 displays the RHOB curve with red color and P-Impedance trans with blue color. This is followed by the next to correlation track, which depicts both the red seismic trace and the blue synthetic trace. The last track shows the original seismic segment with LGF horizons. The over correlation between the original and synthetic wiggles is based on the correlation between these two wiggles. Figures 4.47, 4.48 and 4.49 illustrates the plot among the built and original seismic wiggle of Tando Allah Yar-1, 2 and 3, which revealed and 67%, 64% and 66% correlation, respectively.

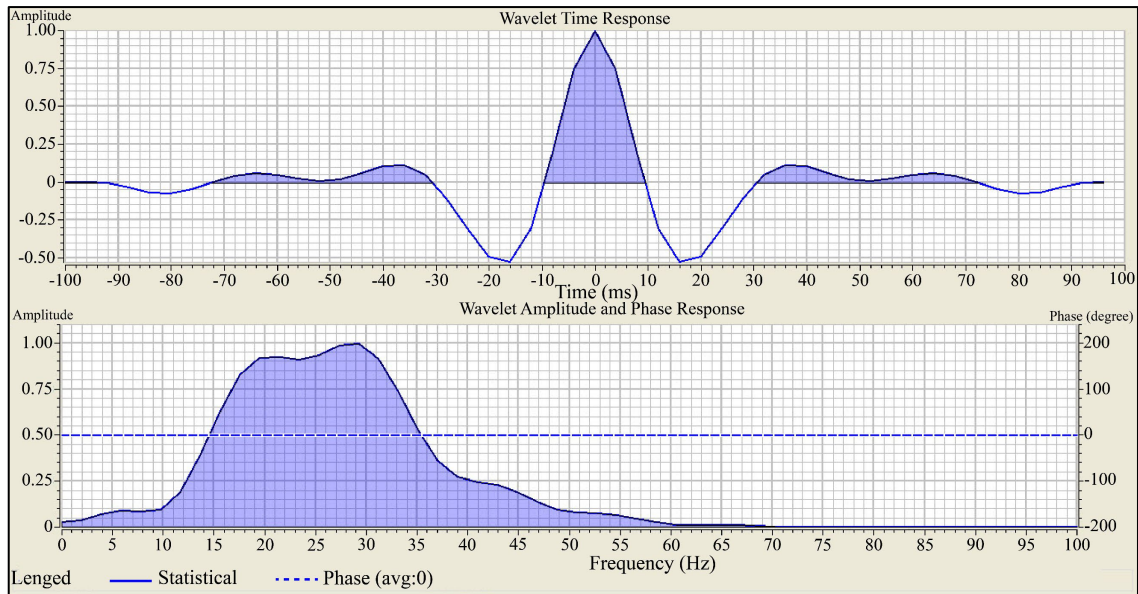


Figure 4.46 The statistical wavelet produced from the Tando Allah Yar-2 well is shown with a wavelength of 100 ms. The data is used to generate the wavelet, which includes spectrum and amplitude properties.

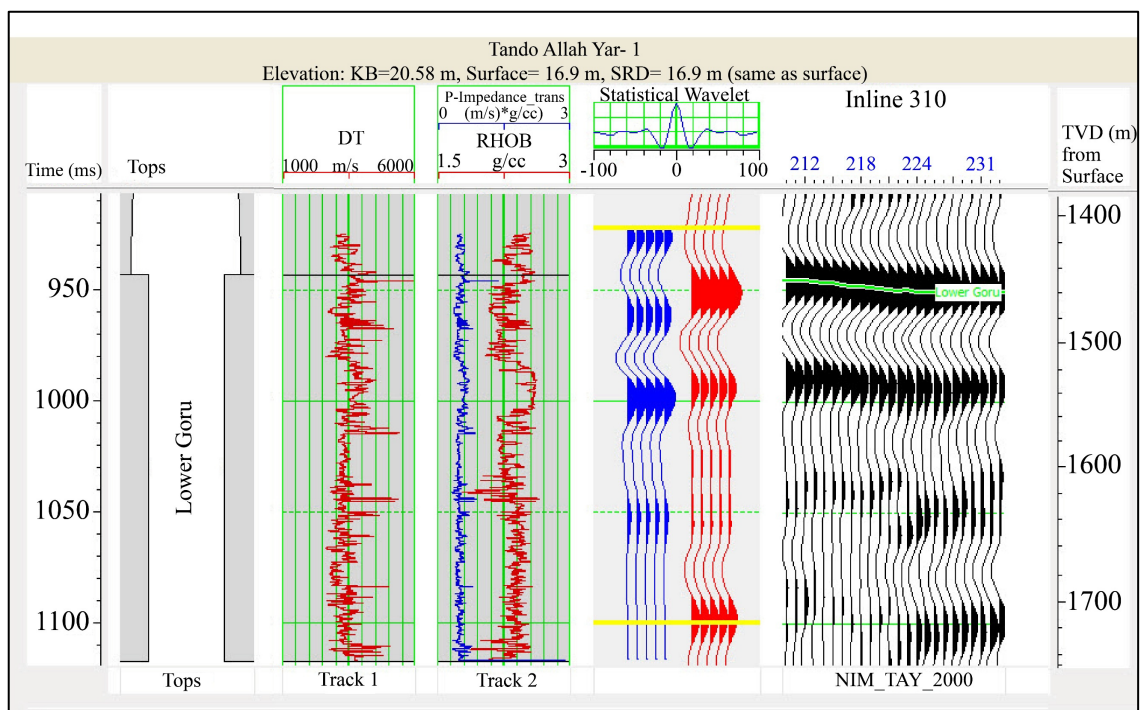


Figure 4.47 Well to seismic tie of Tando Allah Yar-1 well demonstrated that the correlation between synthetic and original seismic. The three log curve DT, RHOB and P-Impedance are used for the correlation along with statistical wavelet. The seismic section of inline 310 is shown in well to seismic tie.

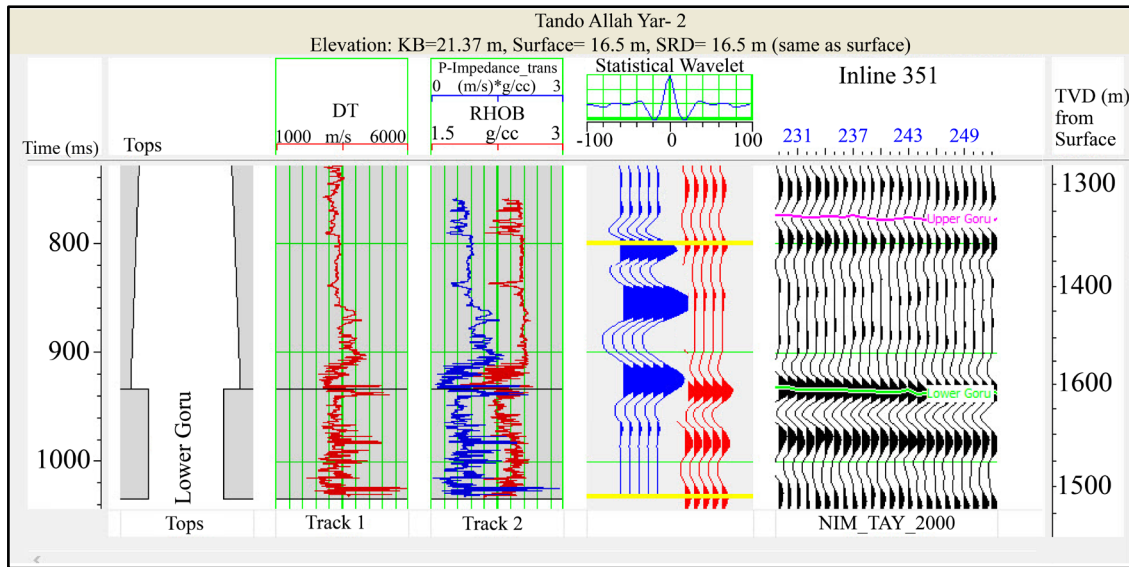


Figure 4.48 Well to seismic tie of Tando Allah Yar-2 well demonstrates that the correlation between synthetic and original seismic traces shown in blue and red color. The three input log curve DT, RHOB and P-Impedance are used for reference and correlation. The inline 351 seismic section of 3D Nim Tay block is shown along with marked LGF.

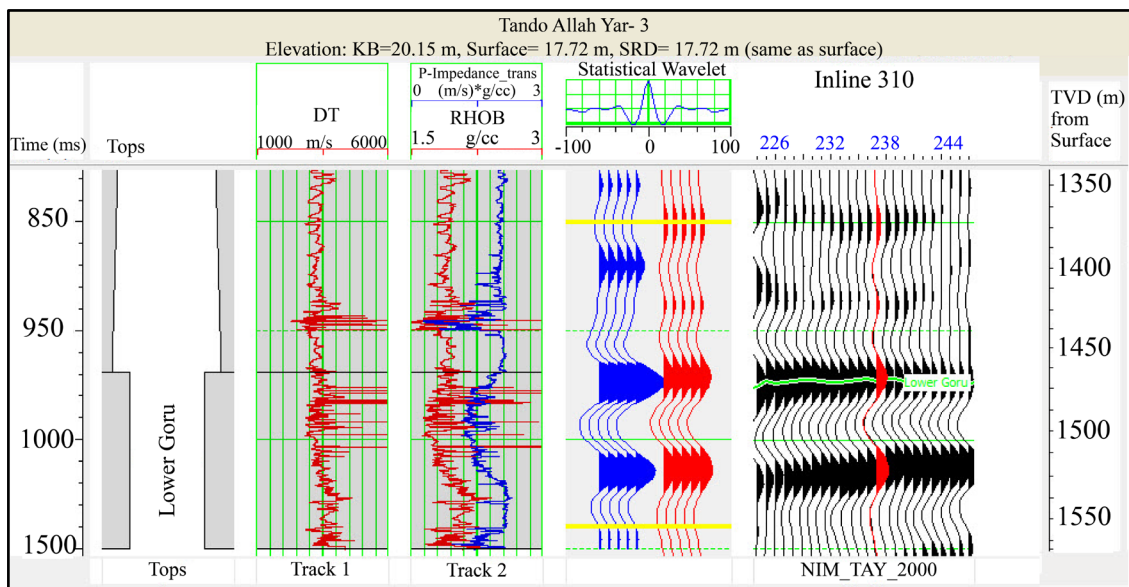


Figure 4.49 Well to seismic tie of Tando Allah Yar-3 well showing the inline 310 seismic section of Nim Tay Block along with original seismic (red color) and synthetic (blue color). Three log curve DT, RHOB and P-Impedance along with statistical wavelet is utilized to perform a tie.

The original seismic cube and the well-based wavelet of all three wells are used to construct the LFM for the seismic cube depicted in Figure 4.50. The model illustrates the impedance fluctuation in the LGF both vertically and laterally. Color codes are used to illustrate impedance differences; red denotes high impedance values while magenta

denotes low impedance. The total impedance calculated for the entire seismic cube. The P wave model that was chosen has a range of 6645 to 7003 $((\text{m/s}) * (\text{g/cc}))$. The formation's lower portion exhibits high Z_p values, whereas the higher section exhibits low impedance because of its high porosities that are filled with water. The well position has the maximum impedance at roughly 980 ms time. The Tando Allah Yar -1, 2 and 3 wells have also appeared on the arbitrary seismic line, and the estimated impedance at the well position has a strong connection with the developed acoustic impedance model.

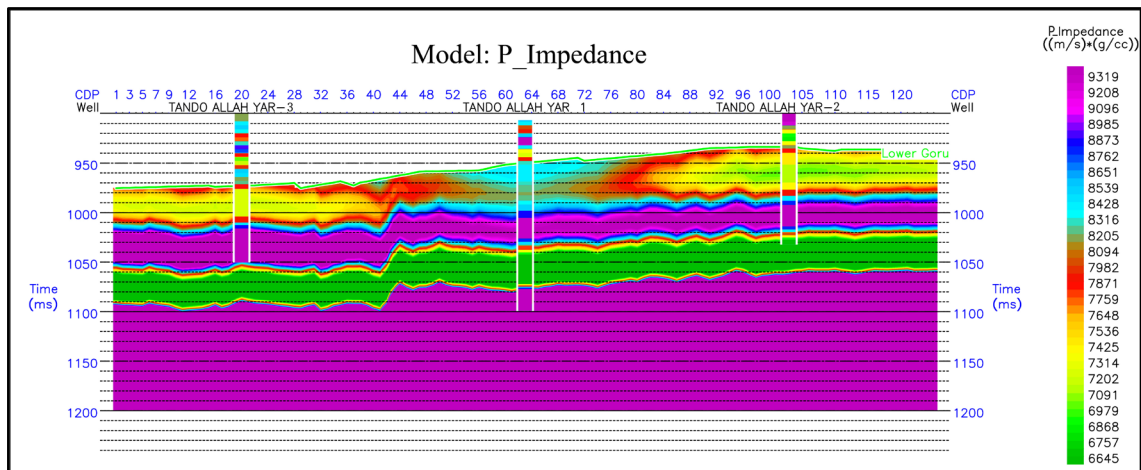


Figure 4.50 Low frequency model shown in arbitrary line of 3D Nim Tay Block with three well location of Tando Allah Yar-1,2 and 3, illustrate the P- Impedance. At the well locations, the impedance range is 6645 to 7648 $(\text{m/s}) * (\text{g/cc})$.

The inversion study of the seismic cube is carried out within the complete thickness of LGF. Inversion study of the Tando Allah Yar -1, 2 and 3 well are shows the initial inverted impedance track along with three different types of curves which are the initial model curve illustrated by black color, the inverted impedance Z_p is shown in red color, and an initial impedance curve created by the borehole log curve present in blue color curve. Impedance values range from Tando Allah Yar-1 well is from 47.2844 to 67682.2 $(\text{m/s}) * (\text{g/cc})$, for Tando Allay Yar-2 it ranged from -14.3328 to 71141 $(\text{m/s}) * (\text{g/cc})$ and for Tando Allah Yar-3 it is 35.1081 to 71.976 $(\text{m/s}) * (\text{g/cc})$ as stated in the Z_p track description, with an error around for Tando Allah Yar-1, 2 and 3 are 8599, 8395 and 8682 respectively as shown in Figure 4.51,4.52 &4.53. The wavelet extracted from the wells data is employed to create the impedance represented in blue shade beneath the wavelet track. The relationship between the created and original seismic traces is illustrated in Figures 4.50, 4.51 and 4.53, which are restricted by the correlation windows

represented by pale lines. Finally, the trace of error is displayed, that is the distinction among the previous results, suggesting minimal values. The last track shows the indicated horizons of LGF (green). The results reveal a good correlation of 96% for Tando Allah Yar-1, 98% for Tando Allah Yar-2 and 96% for Tando Allah Yar-4 wells across the artificial and actual traces. Inversion analysis is performed on all the three wells and curve results are shown in Figures 4.50, 4.51 and 4.52 for Tando Allah Yar-1,2 and 3, respectively. The details about well correlation and error are mentioned in Table 4.3.

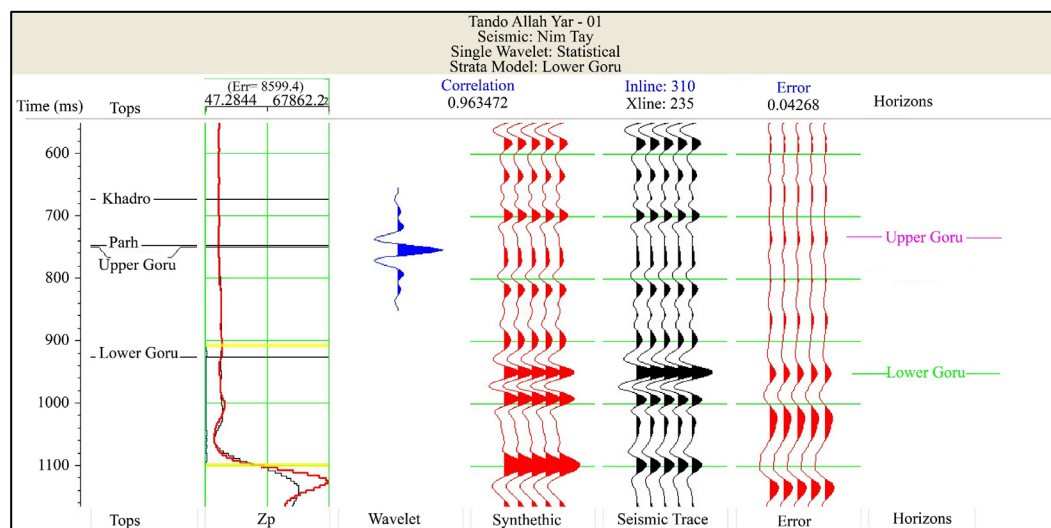


Figure 4.51 Inversion analysis of Tando Allah Yar-1 well showing the correlation of 96% and with minimum error of 4% showing in red color wiggles and the last track demonstrates the horizon location that is perfectly match with the well tops.

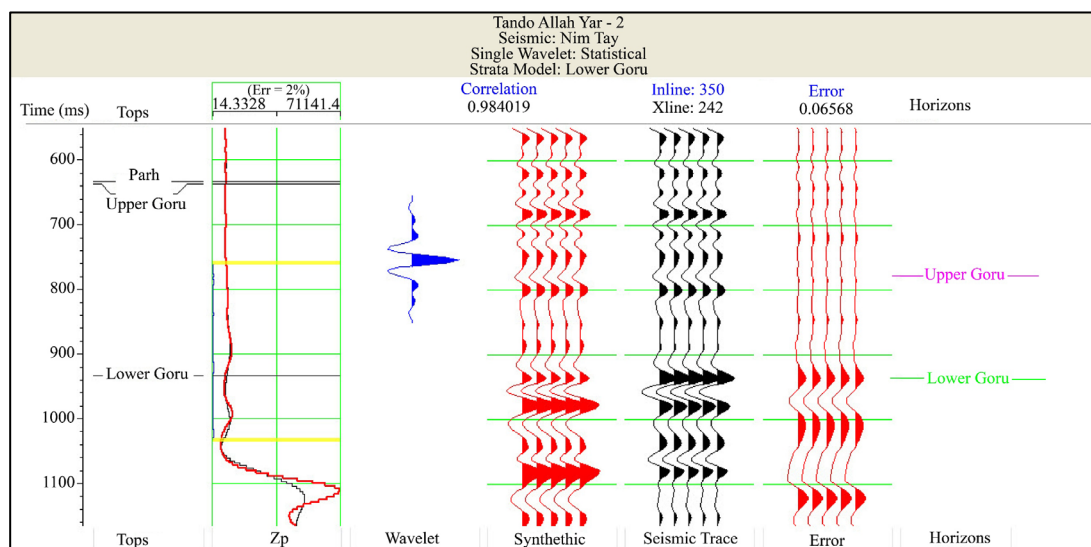


Figure 4.52 Inversion analysis of Tando Allah Yar-2 showing the correlation of 94% and with minimum error of 6% showing in red color wiggles and the last track demonstrates the horizon location that is perfectly match with the well tops. The seismic trace of inline 350 is shown in black color.

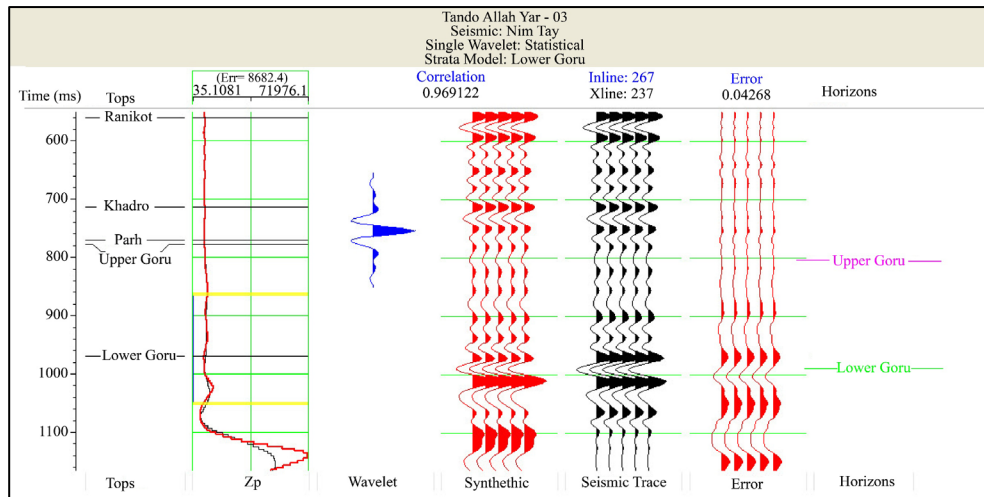


Figure 4.53 Inversion analysis of Tando Allah Yar-3 well showing the correlation of 96% and with minimum error of 4% showing in red color wiggles, seismic inline 267 is shown in black color and the last track demonstrates the horizon location that perfectly match with the well tops.

In Figure 4.54, the specific impedance section ranges from 6645 (m/s) * (g/cc) to 9319 (m/s) * (g/cc), covering a span from 1 to 120 CDP, with a time window of 900 to 1250 ms. Tando Allah Yar-2, drilled at 103 CDP, is plotted to show the correlation between inverted and well impedance. The other two wells, Tando Allah Yar-1 and 3, are located at 20 and 63 CDP, respectively. The CDP impedance variations are indicated by color fill, with purple representing higher values and green indicating lower impedance. LGF shows impedance variations, with higher values near Tando Allah Yar-1 and lower impedance (green color) toward the east and west portions of the seismic section. Figure 4.55 show the slice of Zp.

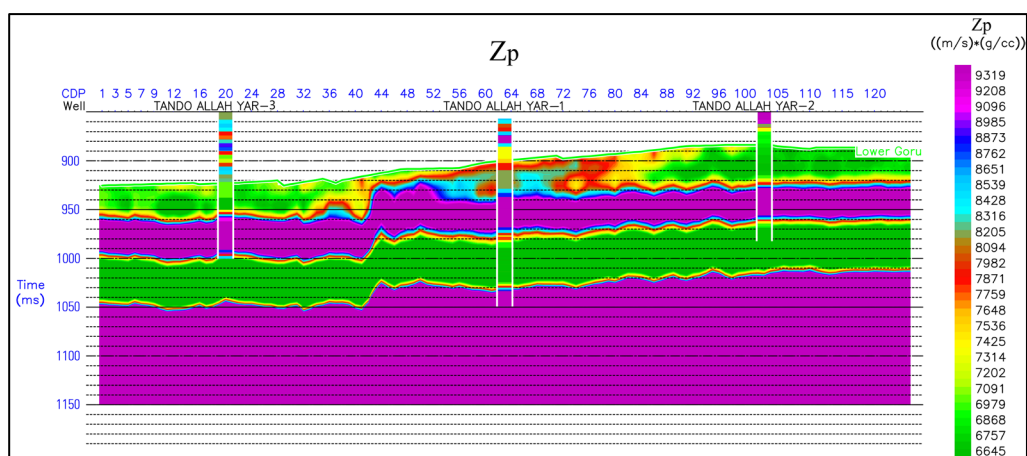


Figure 4.54 Arbitrary line illustrates the inverted Zp at the Tando Allah Yar well location. The range of impedance is higher in Tando Allah Yar-1 well as compared to Tando Allah Yar-2 and 3. The impedance of Tando Allah Yar-1 is 8205 to 8985 ((m/s) * (g/cc)).

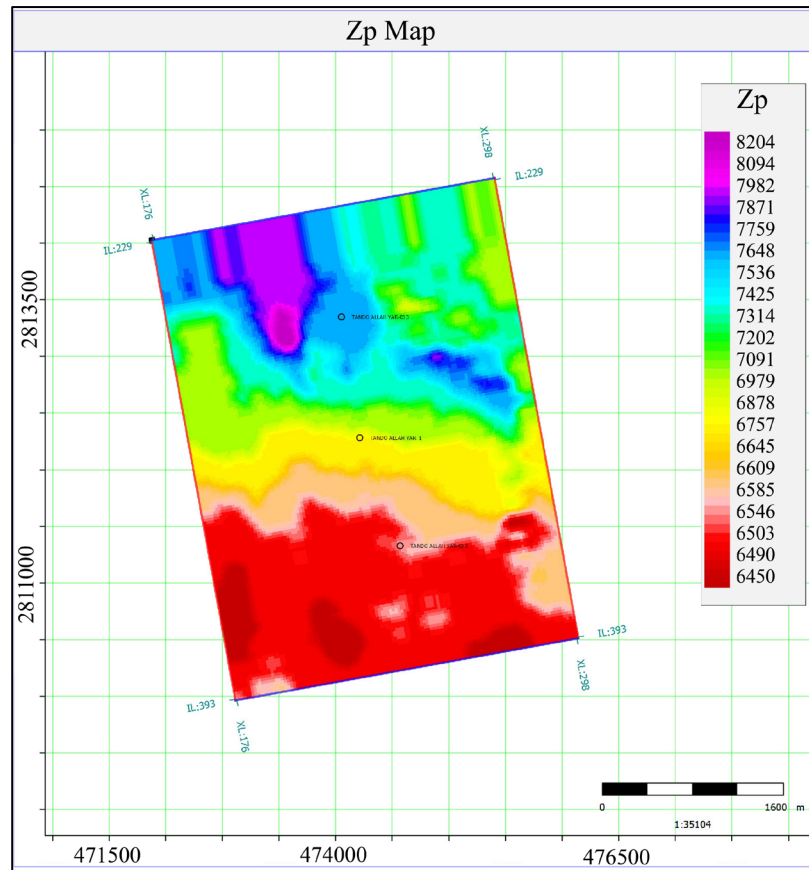


Figure 4.55 Slice of inverted Z_p map showing the variation of impedance in the 3D Nim Tay Block. The impedance is higher toward the northern portion of the map showing with sky blue shade.

4.4.2 Multiattribute Analysis (Linear Relation)

Calibrated HP, RHP, and K curves from Tando Allah Yar-1, 2, and 3 were employed to train seismic attributes at wells position using geo-statistical evaluation. MAA was performed on a most favorable set of 15 seismic attributes, yielding satisfactory results for predicting geothermal properties. Figure 4.56 (a) shows the overlap of the estimated (red) and calibrated HP (black) curves from well, drawn within a range of 0 to 3 $\mu\text{W}/\text{m}^3$. The estimated curve has an average error of 18%, equivalent to 0.209 $\mu\text{W}/\text{m}^3$. The time window covers the LGF interval from 900 to 1100 ms. A cross plot, indicating the relationship among well-based and predicted HP in Tando Allah Yar-1, 2, and 3, includes a linear regression line. HP values in the cross plot range from 0 to 3 $\mu\text{W}/\text{m}^3$, with actual HP on the x-axis and predicted HP on the y-axis as shown in Figure 4.56 (b). While the data shows an excellent correlation between the two HP curves, some intervals exhibit scatter, resulting in an error of over 18% in the Tando Allah Yar wells. The MAA is also run on the RHP, PHIA, K and V_{shl} and the results of correlations are shown in Table 4.3, while the detailed results of curves are shown in Figures 4.57, 4.58,

4.59 and 4.60. Figure 4.57 represents the curves and cross plot results of RHP. Figure 4.57 (a) demonstrates the actual verse predicted curve of the RHP in which the actual curve is shown in black color and predicted is shown in red color, total 20 attributes are applied on the RHP in which the validation of MAA gives the result of 36% and application of MAA gives the result of 79% correlation. While Figure 4.57 (b) illustrated the cross plot of actual vs predicted RHP for the Tando Allah Yar-1, 2 and 3 at LGF. The red square represents the Tando Allah Yar-1, green square shows the Tando Allah Yar-2 and purple represents the Tando Allah Yar well. The range of RHP is 0 to 2 $\mu\text{W}/\text{m}^3$ for both actual and predicted RHP, with a correlation of 79%.

Figure 4.58 demonstrates the multiattribute log curve and cross plot result of PHIA, which shows the overlap of the estimated (red) and calibrated PHIA (black) curves from well, drawn within a range of 0 to 0.38 v/v. The estimated curve has an average error of 18%, equivalent to 0.209 %. The time window covers the LGF interval from 900 to 1100 ms. A cross plot, indicating the relationship among well-based and predicted porosity in Tando Allah Yar-1, 2, and 3, includes a linear regression line. PHIA values in the cross plot range from 0.04 to 0.39 v/v, with actual PHIA on the x-axis and predicted PHIA on the y-axis. While the data shows an excellent correlation among the two PHIA curves, some intervals exhibit scatter, resulting in an error of over 3% in the Tando Allah Yar wells. Figure 4.59 (a) demonstrates the actual verse predicted curve of the K in which the actual curve is shown in black color and predicted is shown in red color, a total of 20 attributes are applied on the K in which the validation of MAA gives the result of 13% and application of MAA gives the result of 74% correlation. While Figure 4.57 (b) illustrated the cross plot of actual vs predicted K for the Tando Allah Yar-1, 2 and 3 at LGF. The red square represents the Tando Allah Yar-1, green square shows the Tando Allah Yar-2 and purple represents the Tando Allah Yar-3 well. The range of RHP is 0 to 30 mD for both actual and predicted K with the correlation of 79%. Figure 4.60 represents the multiattribute regression analysis of shale value, Figure 4.60 (a) demonstrates the validation and application of MAA by using 20 attributes for Vshl in LGF. The validation of Vshl represents the correlation of 16 % with an error of 77% while the application of the multiattribute represents the correlation of 84% with error of 9 %. The actual curve is shown with black line while predicted is with red line, the scale for Vshl is from 0 to 1 v/v. Figure 4.60 (b) illustrates the cross plot between predicted Vshl plotted on y-axis and actual Vshl plotted on x-axis. The legend shows the three well named as Tando Allah

Yar-1, 2 & 3. There is a linear line that is passed through all the scatter points shows the correlation of 84%, which is considered as quite a good correlation.

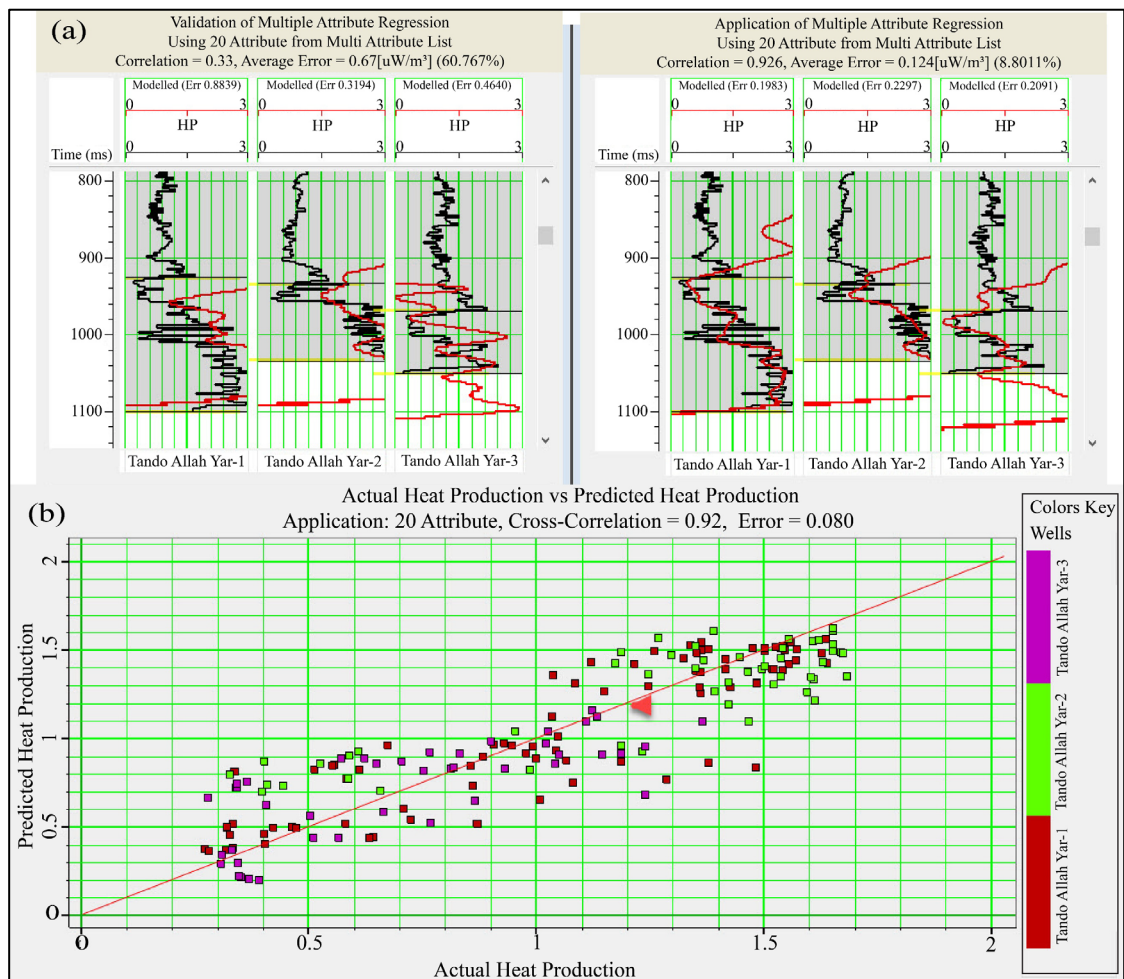


Figure 4.56 (a) Demonstration of MAA curve and (b) cross plot showing the validation and application correlation of HP at the well location for the Tando Allah Yar-1, 2 and 3.

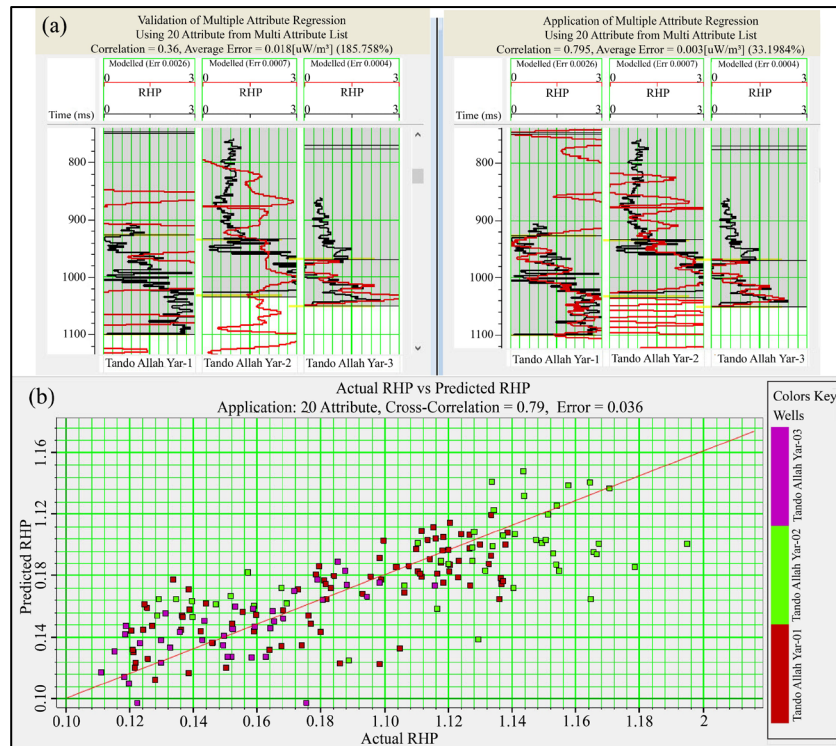


Figure 4.57 (a) Demonstration of MAA curve and (b) cross plot showing the validation and application correlation of RHP at the well position.

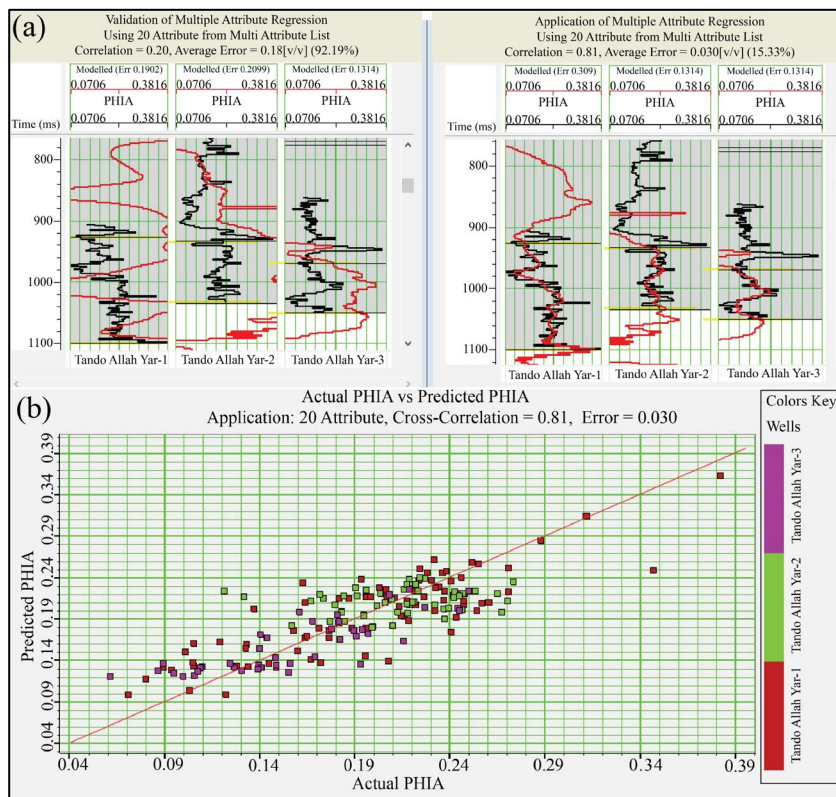


Figure 4.58 (a) Demonstration of MAA curve and (b) Cross plot showing the validation and application correlation of PHIA at the well position.

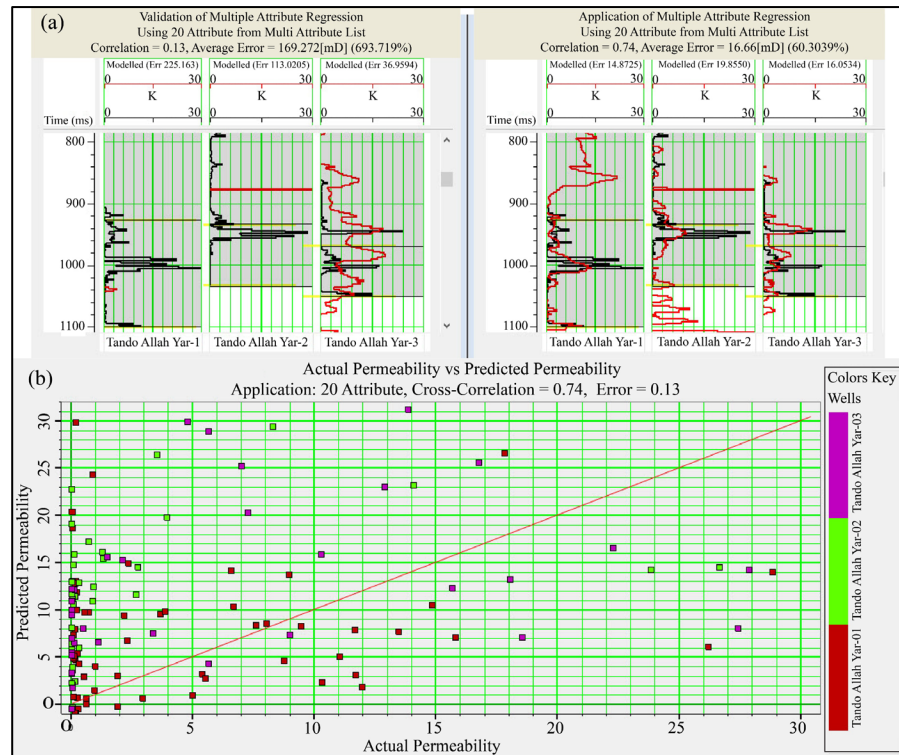


Figure 4.59 (a) Demonstration of MAA (b) Cross plot showing the validation and application correlation of K at the well location for the Tando Allah Yar-1, 2, and 3.

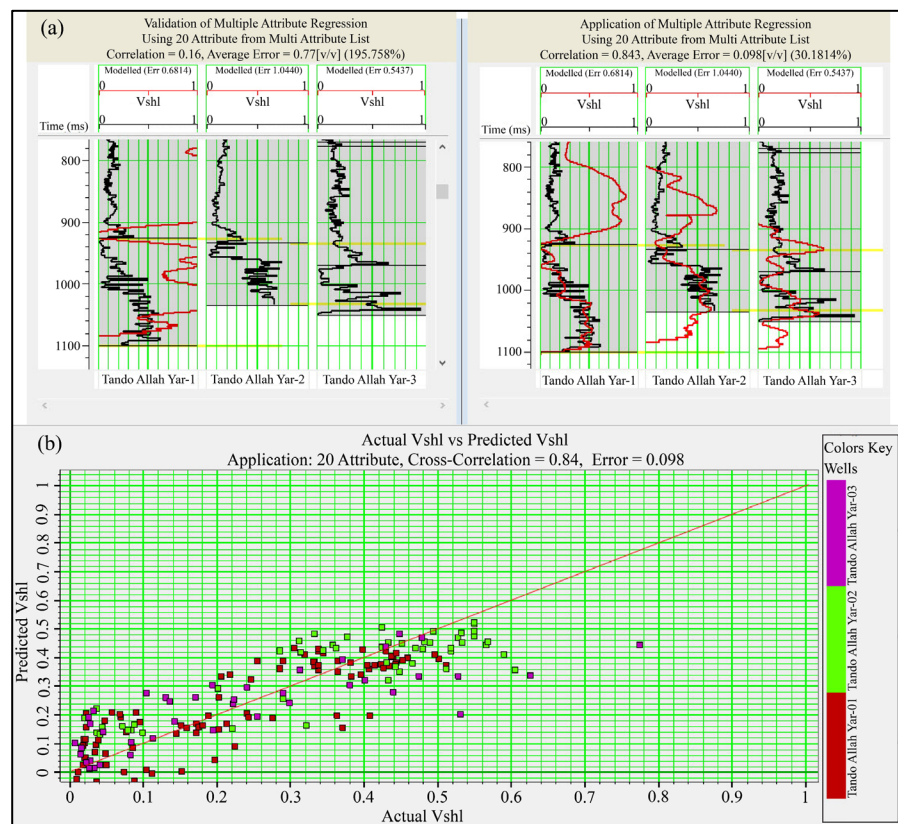


Figure 4.60 (a) Demonstration of MAA (b) Cross plot showing the validation and application correlation of Vshl at the well location for the Tando Allah Yar-1, 2, and 3.

4.4.3 Deep Feedforward Neural Networks

Applying DFFNN evaluation to HP, RHP, PHIA, K and Vshl on the Tando Allah Yar well location to improve correlation among the modeled and corrected well based parameters. Attributes from seismic and the modeled log curve trained by MAA were more refined using nonlinear DFFNN evaluation, which reduced data point scatter as demonstrated in Figure 4.61. The choice of obscure layers reduced mean error of 16.1% among predicted and well calculated HP curves, resulting in an extreme coefficient of correlation of about 93.4%, established on DFFNN results. The input in the DFFNN cross plot, Figure 4.61 (b), shows less scatter than the best-fit line compared to the MAA cross plot. The non-linear neural network approach and the various hidden layers employed in the DFFNN analysis are responsible for the strong correlation that exists between expected and accurately identified actual HP ranges. Because there were fewer layers that were concealed in the DFFNN investigation than in PNN or FNN, the exactness and reliability of the heat generation predictions were higher. Figure 4.62 showing the result of DFFNN applied to the RHP. Figure 4.62 (a) demonstrates the log curve outputs of DFFNN. There are two curves that are shown in the plot diagram, one shows the original curve of RHP, and the other shows the predicted curve of RHP in red color. The correlation between these two curves is quite good as on this stage of neural network both the log curve actual vs predicted are mirror images of one another with the correlation of 93% and error of 7 %. While Figure 4.62 (b) shows the actual verse predicted cross plot of the RHP after the implementation of DFFNN which shows the high linear correlation of 93%. The correlation cross plot is made by utilizing the three well Tando Allah Yar-1, 2 and 3 at the LGF. Figure 4.63 shows the result of DFFNN applied on PHIA. Figure 4.63 (a) demonstrates the log curve outputs of DFFNN. There are two curves that are shown in the plot diagram, one shows the original curve of PHIA, and the other shows the predicted curve of PHIA in red color. The correlation between these two curves is quite good as on this stage of neural network both the log curve actual verses predicted are mirror image of one another with the correlation of 88% and error of 13 %. While Figure 4.62 (b) shows the actual verse predicted cross plot of the PHIA after the implementation of DFFNN, which shows the high linear correlation of 88%. The correlation cross plot is made by utilizing the three well Tando Allah Yar-1, 2 and 3 at the LGF.

Figure 4.64 illustrates the DFFNN result of K that is applied on the three wells of Tando Allah 1, 2 and 3 at LGF. Figure 4.64 (a) shows the results of K with actual curves, which are shown with black color and the predicted curve with red curve. The overall correlation between these two curves is 86%. This correlation is cumulative correlation of all three well logs curve. Figure 6.64 (b) shows the cross-plot result of DFFNN on K. The linear trend line is passed between the actual vs predicted curve which represents the correlation of 86%. The legend shows the color code for the Tando Allah Yar-1, 2 and 3. Figure 4.65 showing the result of DFFNN applied on PHIA. Figure 4.65 (a) demonstrates the log curve outputs of DFFNN. There are two curves that are shown in the plot diagram, one shows the original curve of Vshl, and the other shows predicted curve of Vshl in red color. The correlation between these two curves is quite good as on this stage of neural network both the log curve actual vs predicted is mirror image of one another with the correlation of 91% and error of 9 %. While Figure 4.65 (b) shows the actual verse predicted cross plot of the Vshl after the implementation of DFFNN which shows the high linear correlation of 91%. The correlation cross plot is made by utilizing the three wells Tando Allah Yar-1,2 and 3 at the LGF.

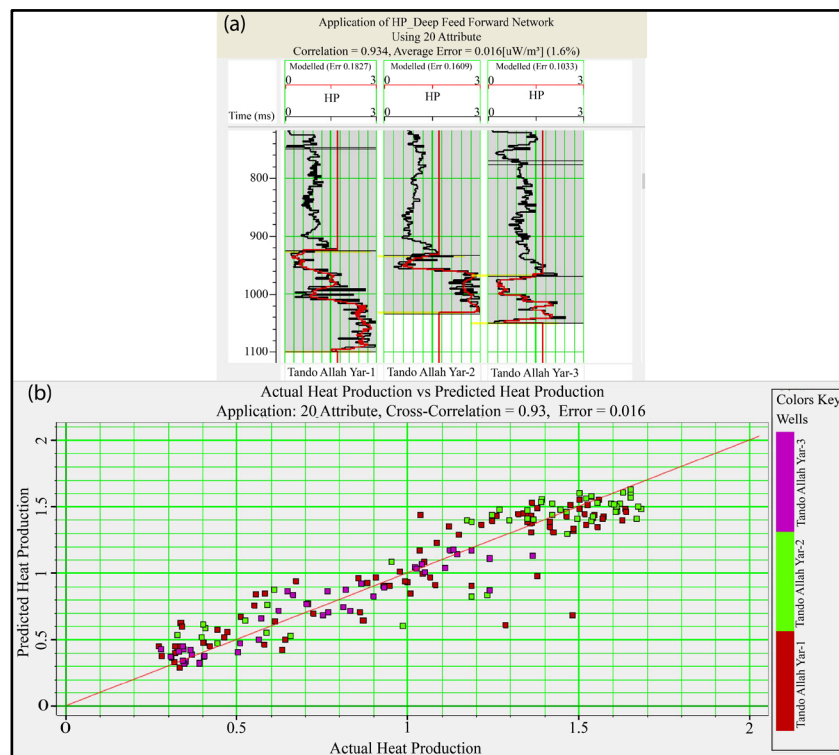


Figure 4.61 (a) Log curve DFFNN result of HP, (b) Cross plot showing the application of DFFNN correlation of HP at the Tando Allah Yar-1, 2 and 3 wells.

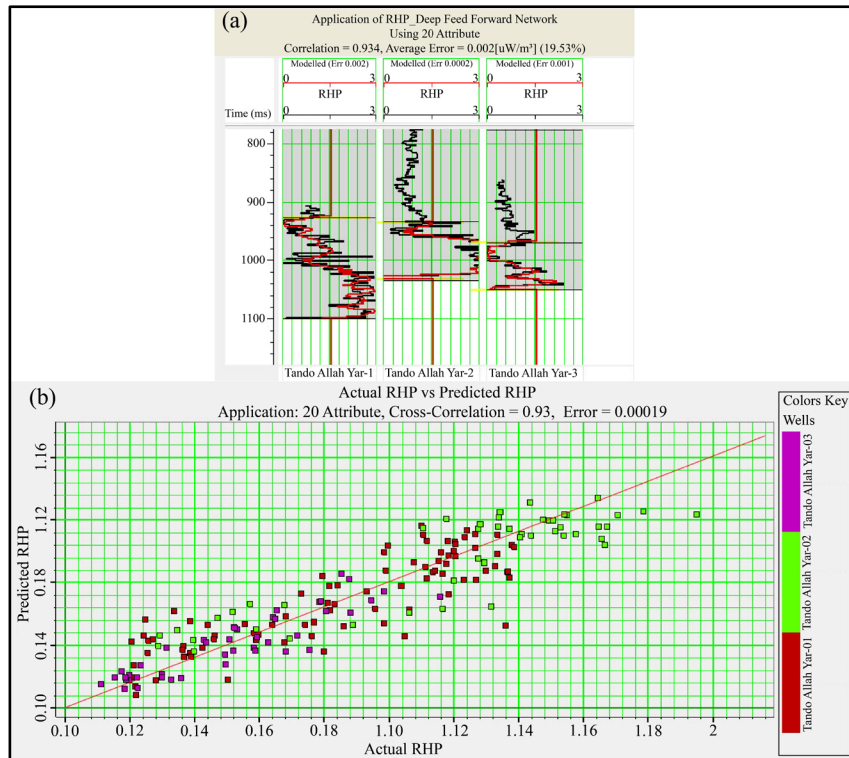


Figure 4.62 (a) Log curve DFFNN result of RHP, (b) Cross plot showing the application of DFFNN correlation of RHP at the Tando Allah Yar-1, 2 and 3 wells.

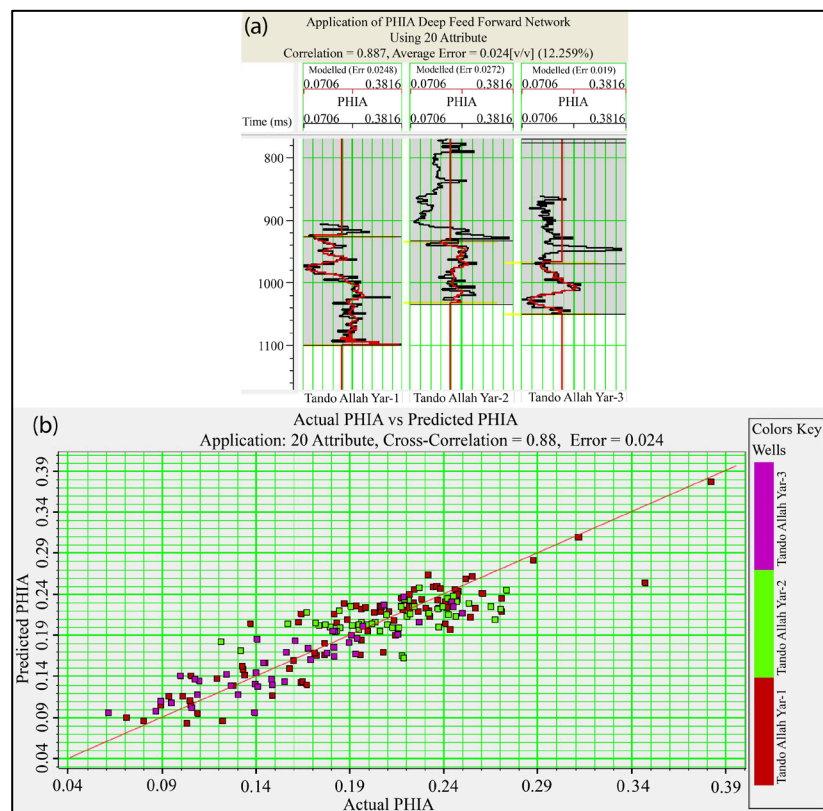


Figure 4.63 (a) Demonstration of DFFNN curve for PHIA and (b) Cross plot showing the application of DFFNN correlation of PHIA at the well location.

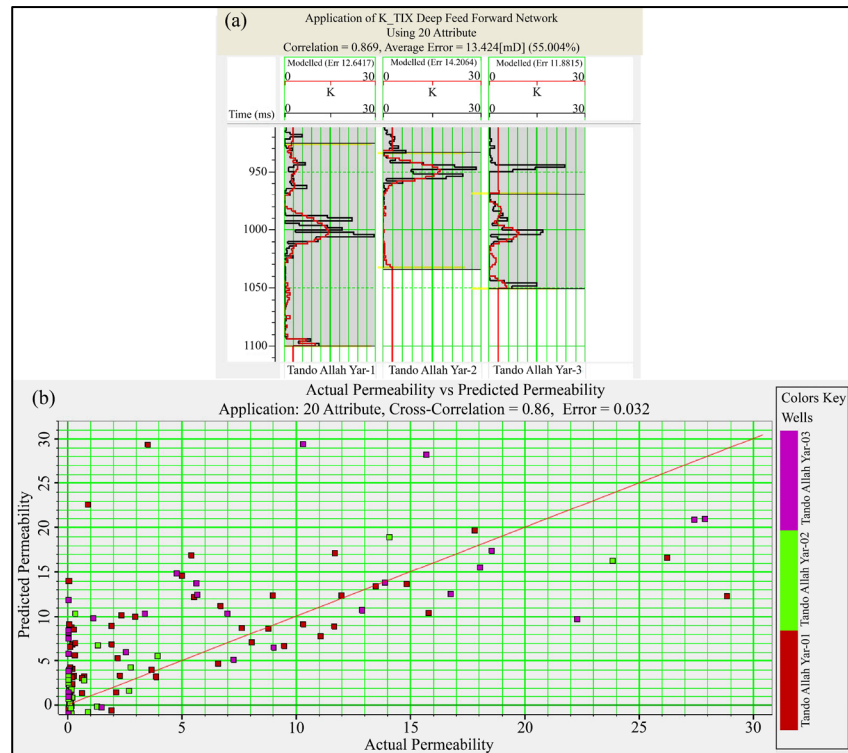


Figure 4.64 (a) Demonstration of DFFNN curve for K and (b) Cross plot showing the application of DFFNN correlation of K at the well position.

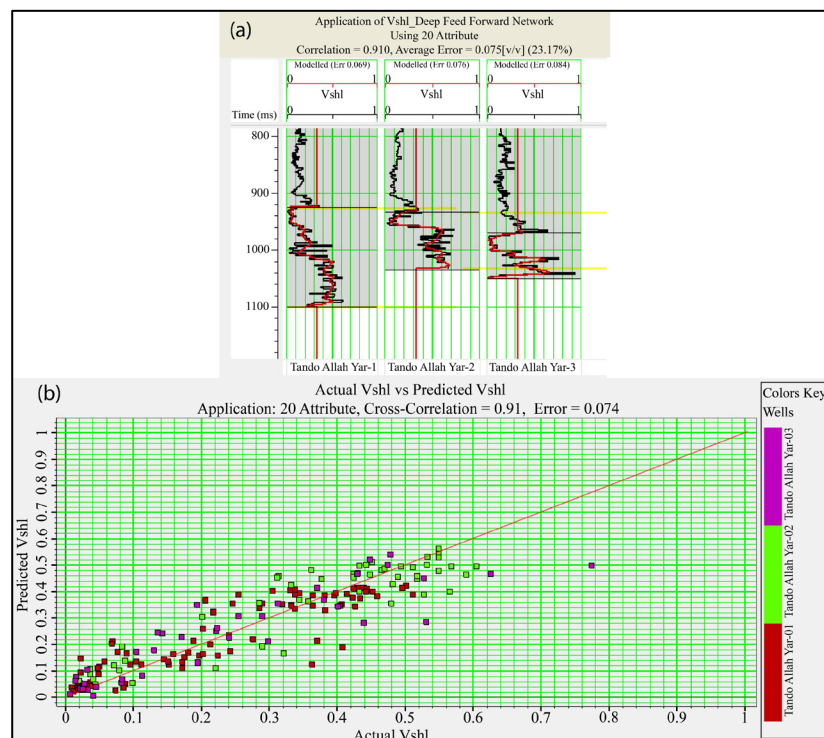


Figure 4.65 (a) Log curve DFFNN result of Vshl, (b) Cross plot showing the application of DFFNN correlation of Vshl at the Tando Allah Yar-1, 2 and 3 wells. The straight linear regression line is showing with red color.

Predicted HP curves, utilizing regression methods, are computed in all three well positions across the interesting region. Correlation was established among the initial curves, and it is argued that the DFFNN approach, which is employed as an innovative technique, is the optimum approach for getting accurate geothermal fluctuations within the extension basin, which is regarded as an ideal basin for geothermal exploration.

Data is applied across the entire seismic section to generate three-dimensional seismic variations in the subsurface of the LGF. The optimal results are captured in these HP sections. The HP section for an arbitrary seismic line, generated using Tando Allah Yar-1, 2 and 3, is shown in Figure 4.66. The same lateral and vertical extent is used in the LFM and impedance section of an arbitrary line. Color shading depicts HP variation within the LGF, with values between 0.27 to 1.74 $\mu\text{W}/\text{m}^3$. Higher HP intervals are indicated in green, while yellow signifies lower HP areas. The Tando Allah Yar wells are also depicted on the arbitrary seismic line to illustrate the relationship among seismic and borehole data in the LGF. There is a best match observed between the well color data and seismic data for the HP. The arbitrary line RHP is shown in Figure 4.67, which shows the moderate to high RHP because of the high concentration of radioactive element present in the subsurface. The range of RHP is 1.31 to 1.74 $\mu\text{W}/\text{m}^3$. On the arbitrary seismic section, the highest RHP is observed in Tando Allah Yar-3 well, the green line on the top of the RHP section represents the LGF. Figure 4.68 shows the arbitrary line with encounters three well Tando Allah Yar-1, 2 and 3, which shows the PHIA range between 10 to 25 %. The PHIA range varies from well to well. The range of PHIA is higher toward the Tando Allah Yar-3 well and less PHIA is encountered in Tando Allah Yar-1 and 2. Figure 4.69 demonstrates the K distribution on the arbitrary seismic section that is passed from Tando Allah Yar-1, 2 and 3 wells. The K is ranged for the scale of 0 to 20 mD. The range of K that is observed on all the tree wells is around 15 to 19 mD and Figure 4.70 shows the result of Vshl on all the wells as a seismic arbitrary section.

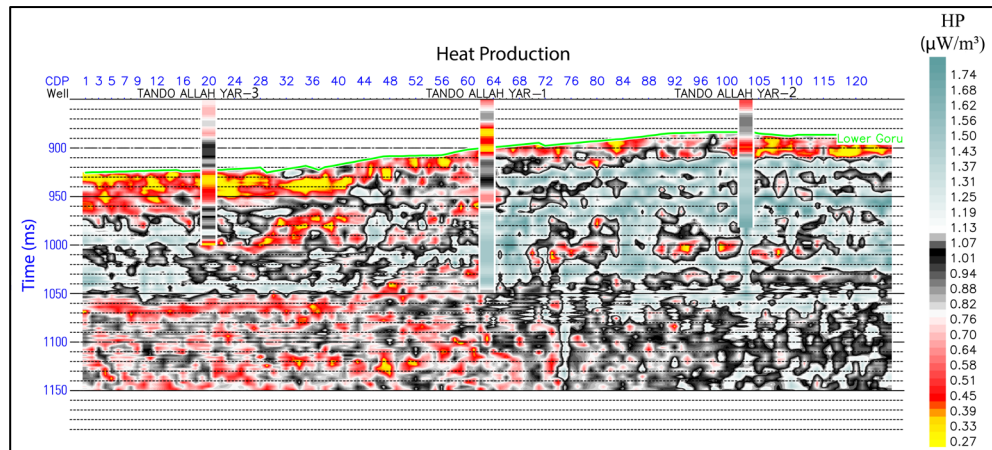


Figure 4.66 Arbitrary line of 3D Nim Tay Block passing through all three well demonstrates the HP on the seismic section. Higher HP is encountered Tando Allah Yar-2 and 1 well. The trend of the HP is to decrease toward the west side of the seismic section.

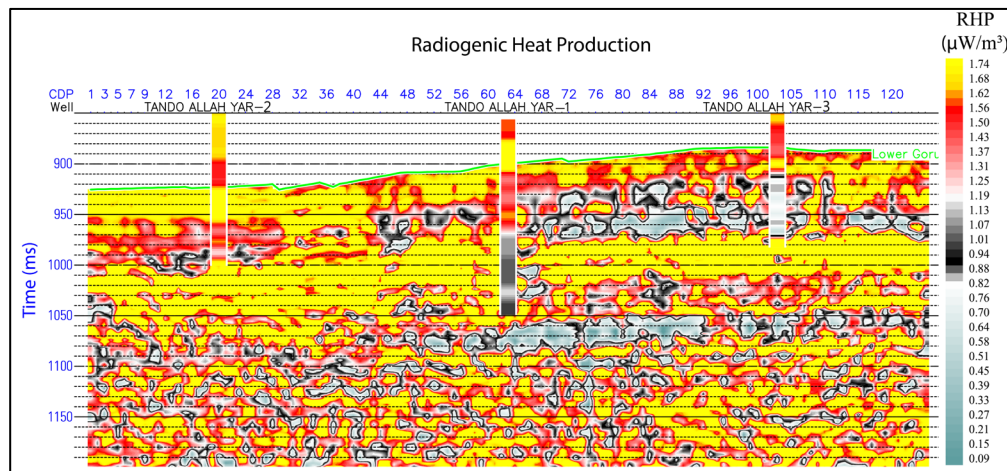


Figure 4.67 Arbitrary line passing through all three well of Nim Tay Block depicts the RHP on the seismic section. The trend of the RHP is higher at all well locations because of radioactive element concentration.

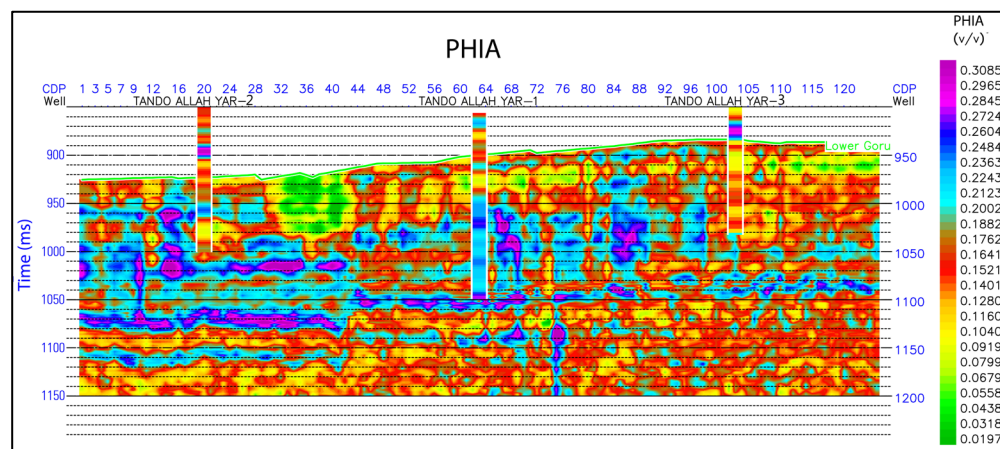


Figure 4.68 Arbitrary seismic line showing the result for the variation of PHIA on Tando Allah wells. The range of the porosity is lies between 10 to 25%.

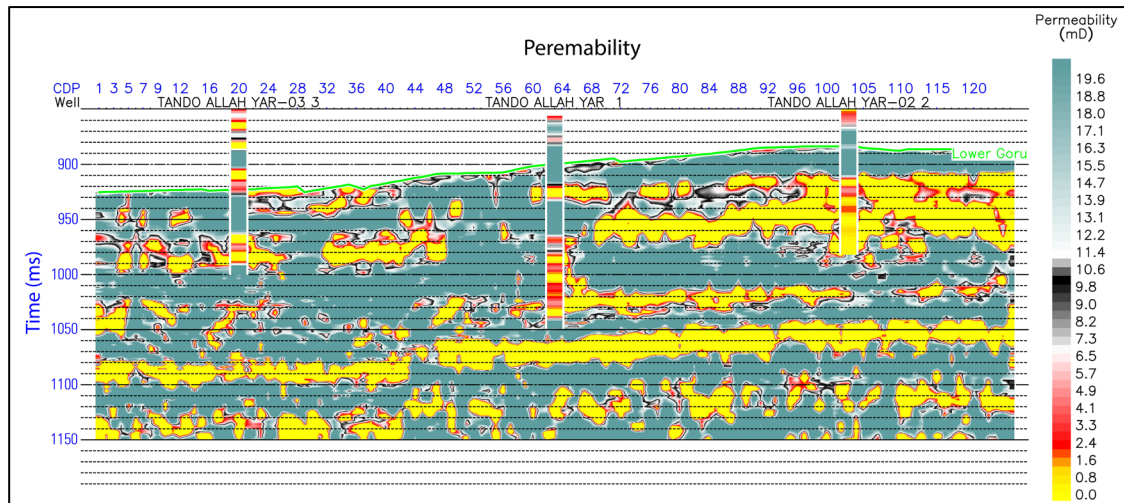


Figure 4.69 Arbitrary line of 3D Nim Tay Block demonstrates the variation of K on the seismic section. The best match is observed between the K log curve and seismic section which shows the significance of DFFNN on K.

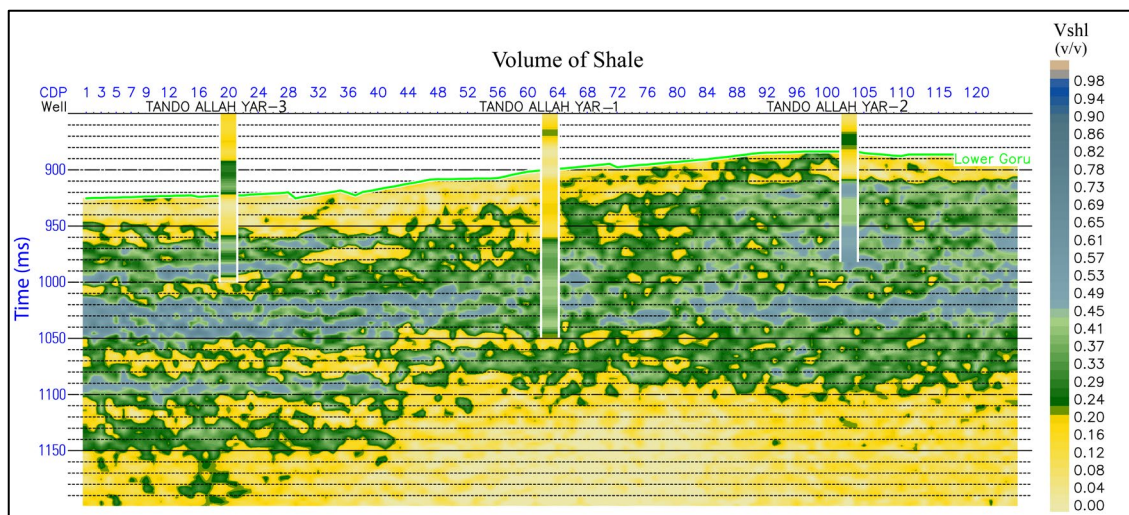


Figure 4.70 Vshl results on the arbitrary seismic line of Nim Tay Block with Tando Allah Yar 1, 2 and 3. There is a variation in the Vshl as it is increasing towards easter part of the seismic section.

4.4.4 Slices

After showing the result of DFFNN on the seismic section, the last step is to create slices of HP, RHP, PHIA, K, and Vshl. The purpose of mapping these slices is to illustrate the overall changes in geothermal parameters. The slices are made on the LGF by examining the Tando Allah Yar-1, 2, and 3 wells, as well as seismic data. These parameters are then extended to the entire Nim Tay Block. Figure 4.71 shows the variation of HP in the 3D Nim Tay Block, with higher HP values found in the eastern part of the map and lower values in the western part, while Tando Allah Yar-2 well

displays the highest HP values. Figure 4.72 shows the RHP map of LGF. The variation of RHP is increasing from south to north, and the highest values are encountered on the northern portion of map. Figure 4.73 represents the PHIA of LGF, the PHIA that is encountered on the wells is approximately in the range of 10 to 15%. Figure 4.74 shows the slice of K generated based on well and seismic data for LGF. In the last, the Vshl slice is generated to know the variation and shale and clean in the LGF shown in Figure 4.75.

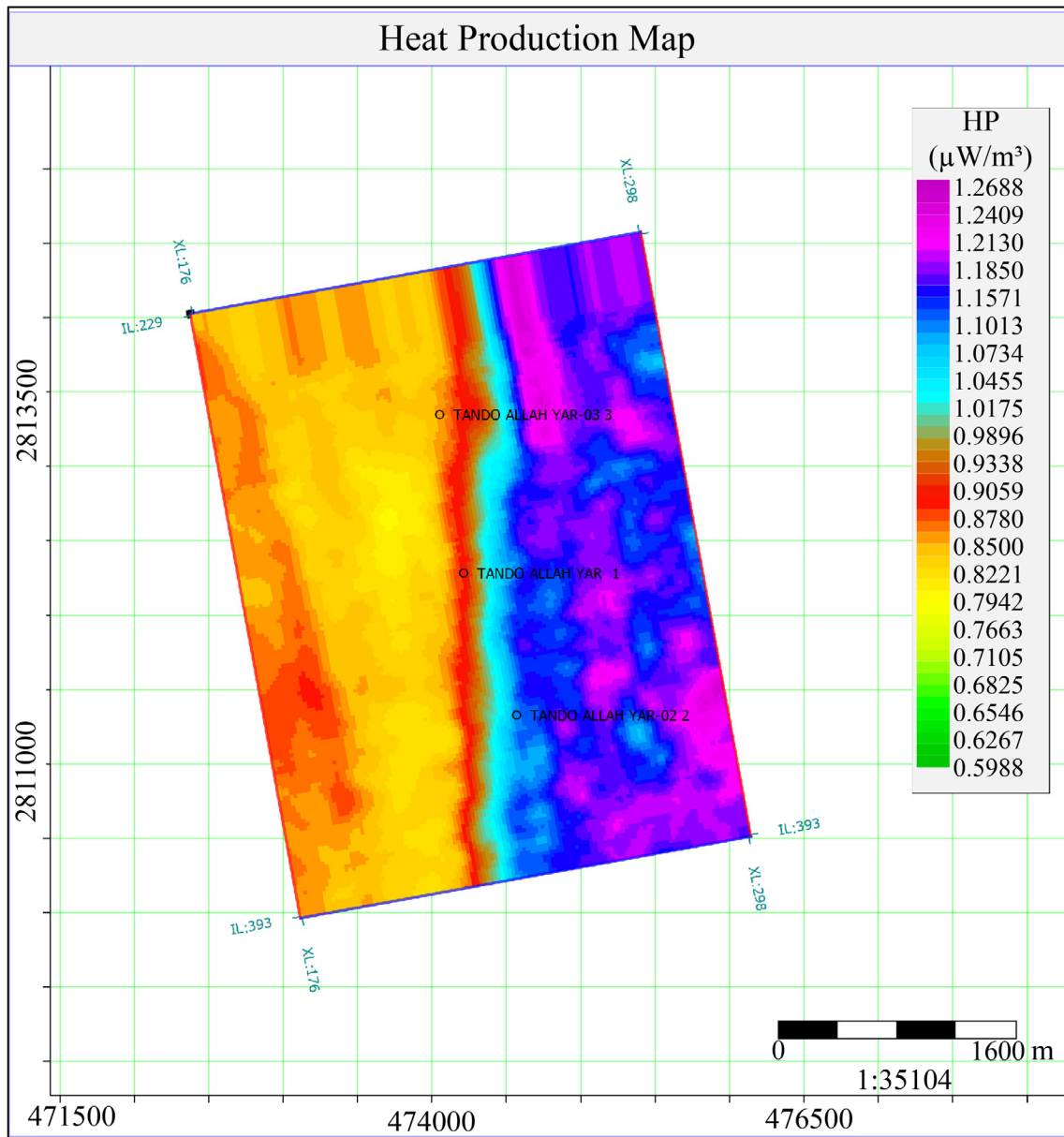


Figure 4.71 Slice represents the variation of HP in the LGF by using Tando Allah wells and 3D seismic cube. The variation in HP is observed on the eastern side of the map, and the highest value of HP is observed around the Tando Allah Yar-2 well.

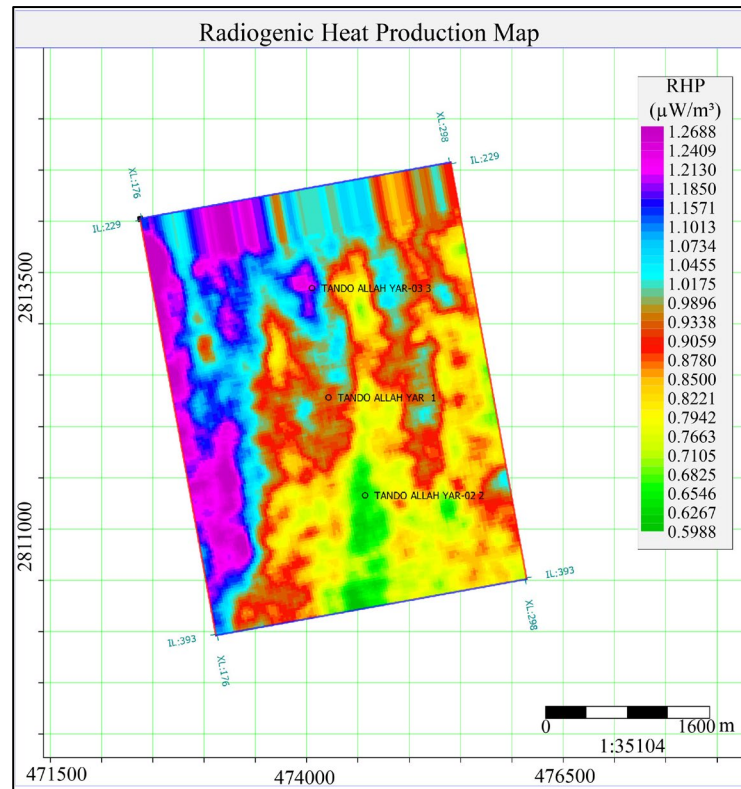


Figure 4.72 Map illustrates the variation of RHP in 3D Nim Tay Block. The highest value of RHP is observed around Tando Allah Yar-3 well which represent the abundance of radioactive elements.

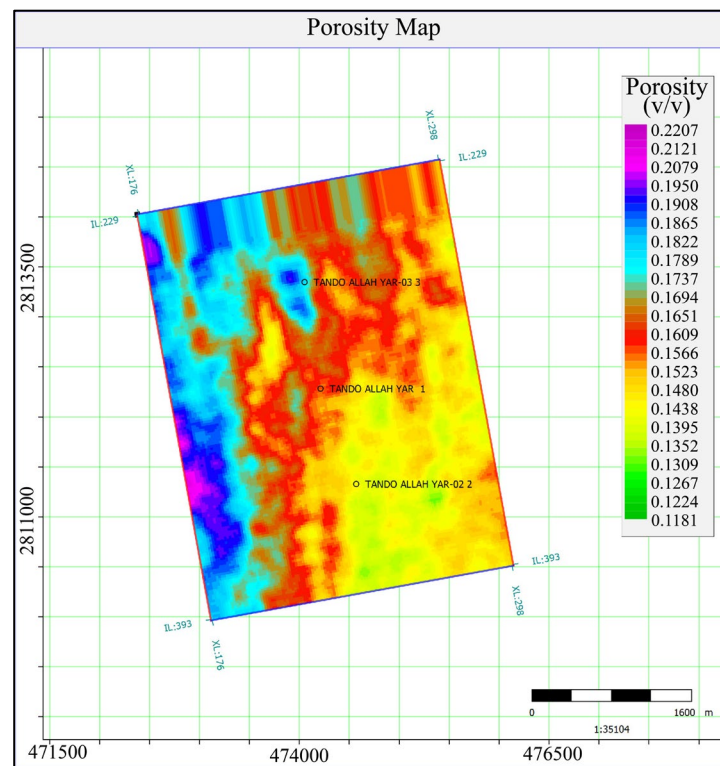


Figure 4.73 PHIA slice of LGF shows the change in the PHIA range from well to well. The highest PHIA is observed in the northwest part of slice.

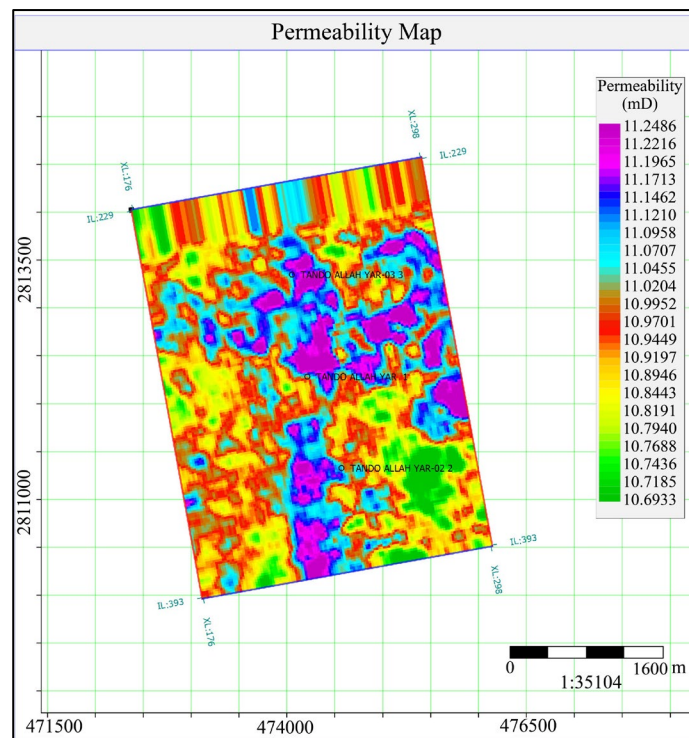


Figure 4.74 K slice of LGF for 3D Nim Tay Block represents the variation of K across the Tando Allah Yar- wells, while the range of K lies between 10 to 11 mD.

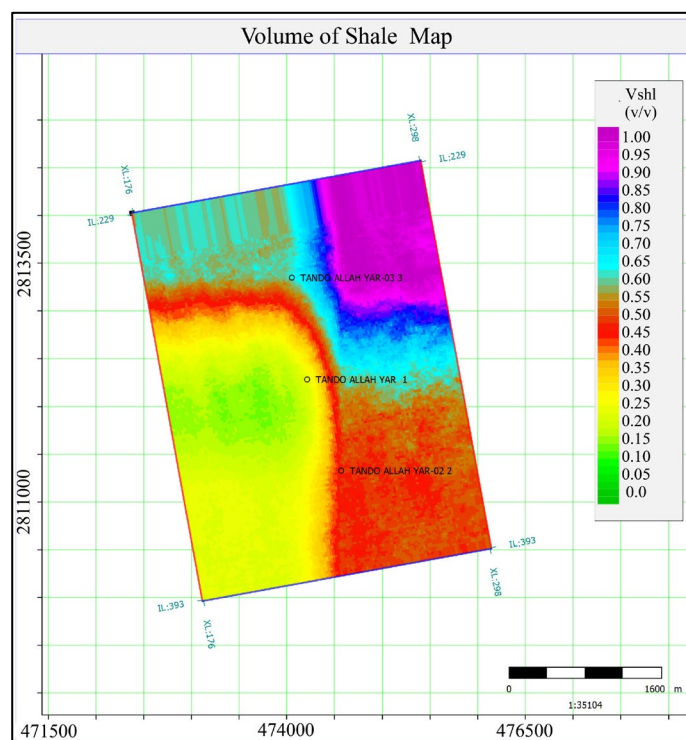


Figure 4.75 Slice represents the variation of Vshl on LGF for Nim Tay Block showing the overall variation of Vshl from Tando Allah Yar wells. Lower Vshl is encountered on the southwest portion of map while higher Vshl is present on the northeast side.

4.5 Inversion Analysis and DFFNN on Sanghar Block-1

Inversion analysis is performed on Sanghar Block-1 by using Sono-2 and 5 well. Firstly, model-based inversion analysis is performed on the control line G872-SGR-510 to know the variation of impedance in the seismic section after that DFFNN is applied on the geothermal properties to determine their exact range and deviation on the well.

4.5.1 Model Based Seismic Inversion

Initially, the 2-D strike line G872-SGR-510 is used to extract the statistical wavelet which is convolved along the reflectance coefficient to generate the synthetic track on the borehole position. A temporary window bordered by the horizon, spanning from the top of LGF to the complete depth, is used to extract the wavelet. In order to obtain a good correlation, a seismic to well tie connection was constructed utilizing the seismic extracted wavelet. Finally, to further improve the coefficient of correlation, the log curve-based wavelet of 100 ms wavelength is chosen. Wavelets from the well data are extracted using Sono-2 well. Which represent all of the seismic frequency ranges, wavelet frequency spectrum of 18 Hz is utilized. As seen in Figure 4.76, the wavelet extraction from well data has a standard phase of 15° and a dominating frequency of 18 Hz. For establishment of an initial well tie and a time-depth relationship, synthetic traces related to seismic traces. The time window of connection cross plot is nominated to encompass whole study period using accessible log data to compare artificial and actual traces. To view both synthetic and actual traces, the time window for the correlation plot is selected to cover the entire duration for which log data is currently available. Figure 4.77 depicts the correlation window of Sono-2 for the whole thickness of the LGF. Track 1 indicates the P-Impedance curve, track 2 shows the GR, whereas track 3 represents the DT curve. This is followed by the next to correlation track, which depicts both the red seismic trace and the blue synthetic trace. The last track shows the original seismic segment, as well as the LGF horizons. Figure 4.77 illustrates the plot among the built and original seismic wiggle of Sono-2, which revealed a 91% correlation. Figure 4.78 demonstrates the seismic to well tie of Sono-5 well for the LGF as the well is present on the same strike line G872-SGR-510 so same types of outputs are extracted.

The seismic strike line G872-SGR-510 and the well-based wavelet of all two wells are used to construct the LFM for the seismic strike line depicted in Figure 4.79. The model illustrates the impedance fluctuation in the LGF both vertically and laterally.

Color codes are used to illustrate impedance differences; red denotes high impedance values while purple denotes low impedance. The total impedance calculated for the entire seismic cube. The P wave model that was chosen has a range of 11294 to 11517 ((m/s) * (g/cc)). The formation lower portion exhibits high P-Impedance values, whereas the higher section exhibits low impedance because of its high porosities that are filled with water. The well position has the maximum impedance at roughly 980 ms time. The Sono-2 and Sono-5 well also appears on the seismic section, and the estimated impedance at the well position has strong connection with the developed acoustic impedance model.

The inversion study of the 2-D seismic is carried out within the complete thickness of LGF, as illustrated in the upper track of Figures 4.80 and 4.81. Inversion analysis study of Sono-2 and 5 well shows the Initial inverted impedance. Impedance values range from 325.474 to 64019.5 (m/s) * (g/cc) as stated in the Zp track description, with an error around 17654.4. The wavelet extracted by the well data is employed to create the impedance represented in blue shade beneath the wavelet track. The relationship between the created and original seismic traces is illustrated in Figure, which is restricted by the correlation windows represented by pale lines. Finally, the trace of error is displayed, that is the distinction among the previous results, suggesting minimal values. The last track shows the indicated horizons of LGF (green). The results reveal a good correlation of 98% across the artificial and actual traces for Sono-2 and for Sono-5 the correlation is 97%. Inversion analysis is performed on both well but the well and results of wells are given below and remaining well correlation and error is mentioned in Table 4.3.

The inversion (Zp) is then employed to the strike line G872-SGR-510 using the inverted impedance curve that was created at the well location. Variations in the facies and fluid characteristics in the LGF are indicated by horizontal and vertically shifts in the impedance values. Less impedance range indicate small-compressed region with excellent porosities, but high impedance values grow with higher sediment compaction. Additionally, the impedance values are decreased by fluid absorption within the rocks. The formation pressure and impedance have an inverse relationship; therefore, a geothermal potential zone may have incredibly low impedance values because of high fluid saturation. The strike line inverted section result shows the LGF estimated p-impedance values.

In Figure 4.82 the impedance ranges lie between 11353 ((m/s) * (g/cc)) to 17566 ((m/s) * (g/cc)), covering a range from 0 to 373 CDP with a time range of 800 to 900 ms.

Sono-2, drilled at 285 CDP, is plotted to show the correlation among inverted and well impedance. While Sono-5 is located at 190 CDP. The CDP Impedance variations are indicated by color fill, with purple representing higher values and green indicating low impedance. LGF shows slightly variation in impedance from Sono-2 to Sono-5 well.

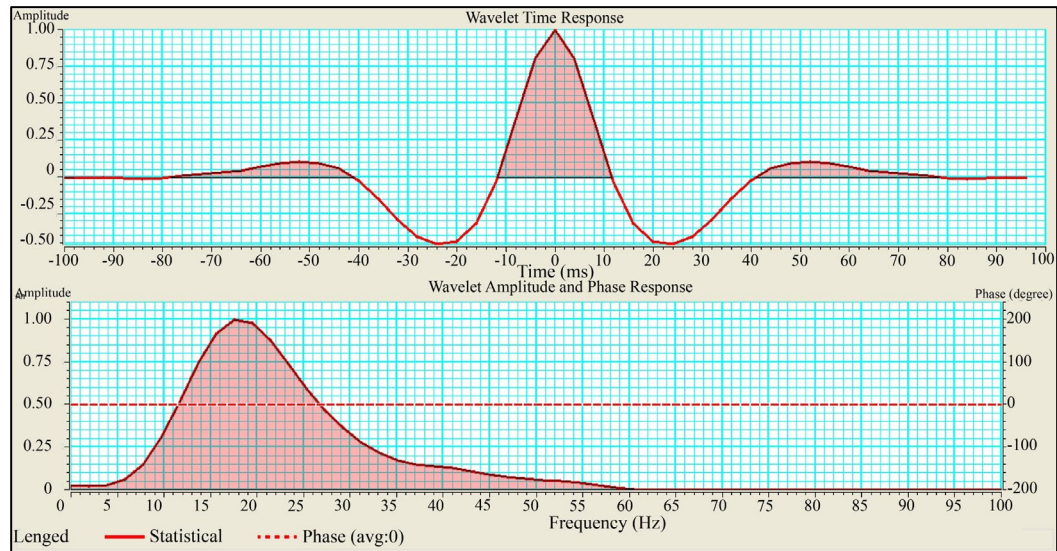


Figure 4.76 The statistical wavelet produced from the Sono-2 well is shown with a wavelength of 100 ms. The log curves are used to generate the wavelet, which includes spectrum, amplitude, and phase properties.

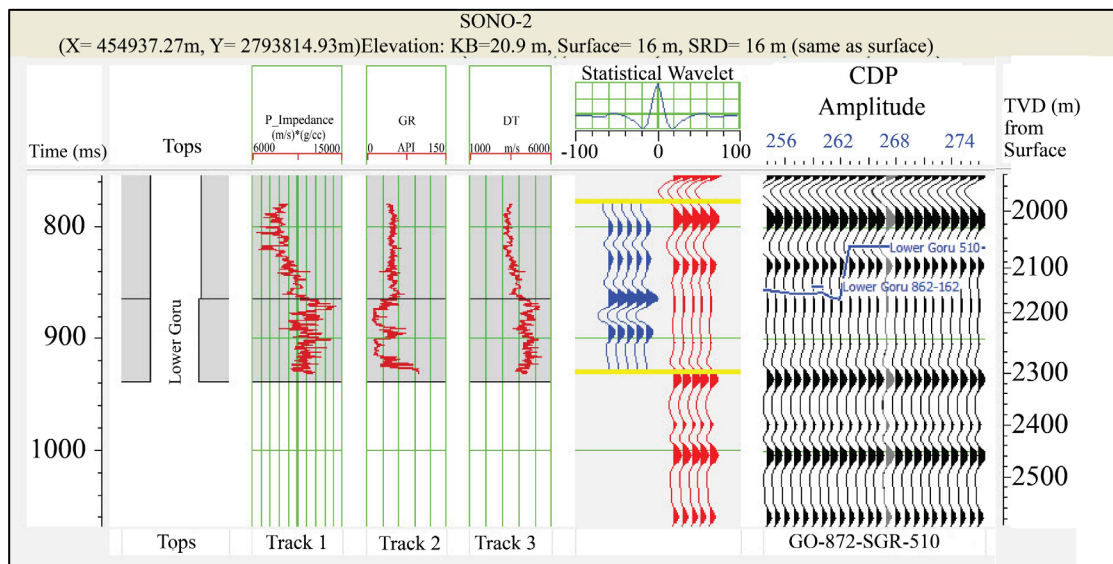


Figure 4.77 Seismic to well tie generated based on Sono-2 well show the correlation between the actual and synthetic seismic. The tracks 1,2 and 3 show the GR, DT and Impedance curve and blue color show the synthetic trace and red color represent the real seismic trace.

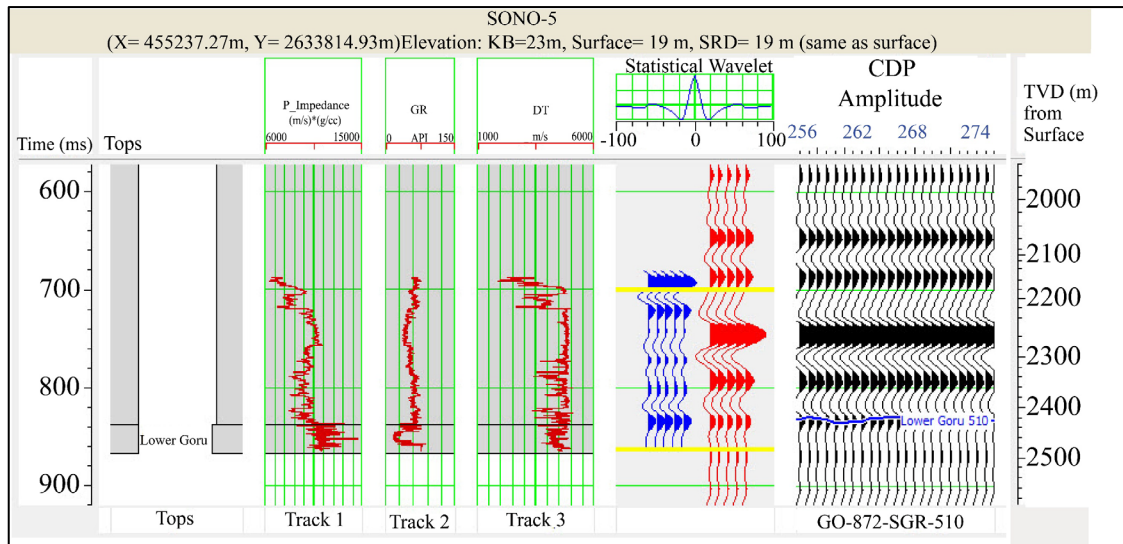


Figure 4.78 Seismic to well tie made on the basis of Sono-5 well, which shows the correlation among the actual and synthetic seismic. The tracks 1,2 and 3 show the GR, DT and Impedance curve and blue color show the synthetic trace and red represents the real seismic trace.

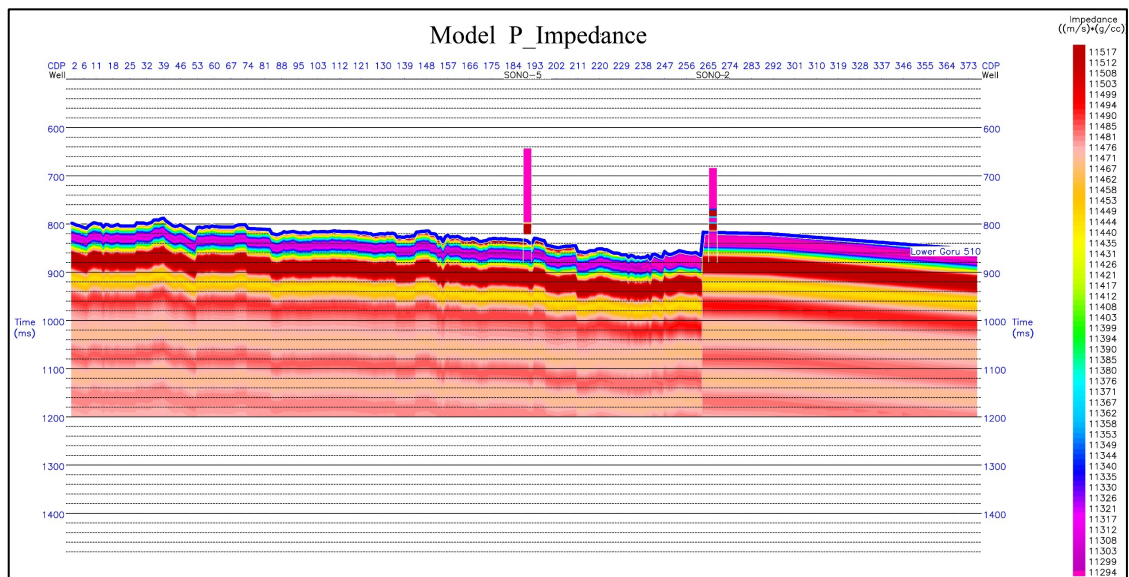


Figure 4.79 Low frequency model shown on strike line GO-872-SGR-510 with two well Sono-2 and 5 are located, demonstrate the P- Impedance. At the borehole position the impedance range is 11294 to 11453 ((m/s) *(g/cc)).

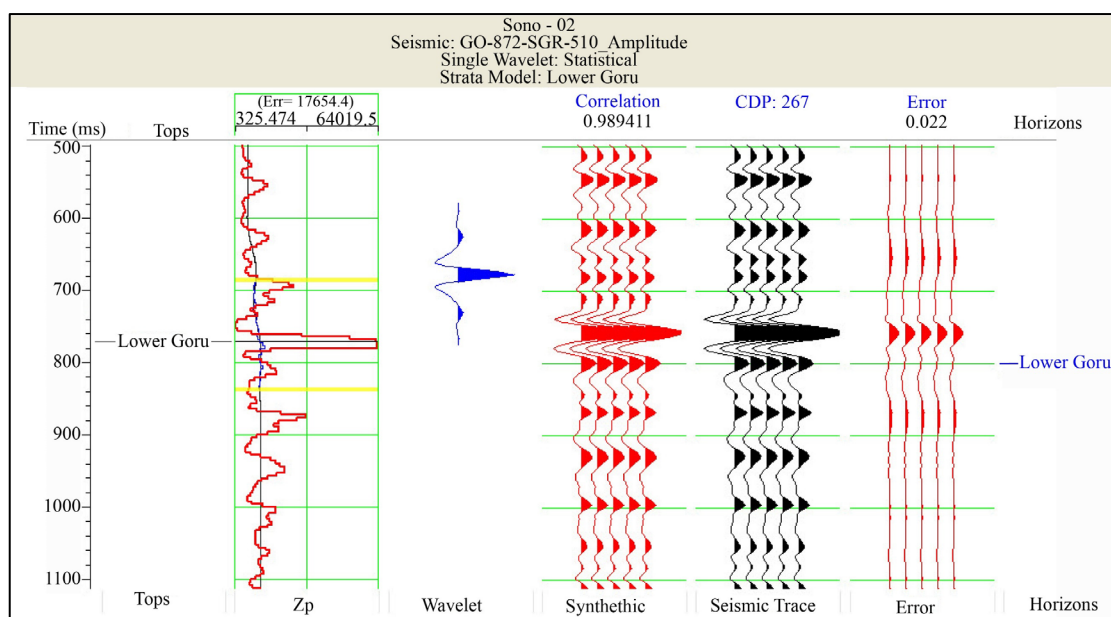


Figure 4.80 Model based seismic inversion analysis result showing the correlation of the 98% with minimum error of 2 %. The red wiggle represents the correlation and error section, while black color represents the actual seismic traces.

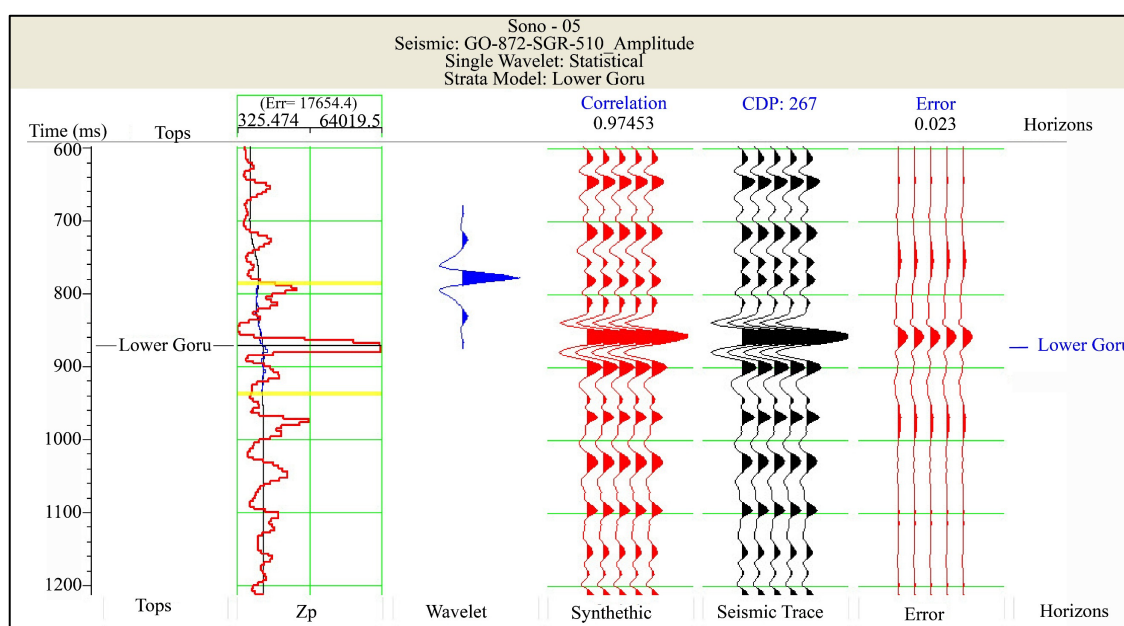


Figure 4.81 Model based seismic inversion analysis showing the correlation of the 98% with a minimum error of 2 %. The red wiggle represents the correlation and error section while black color represents the actual seismic traces.

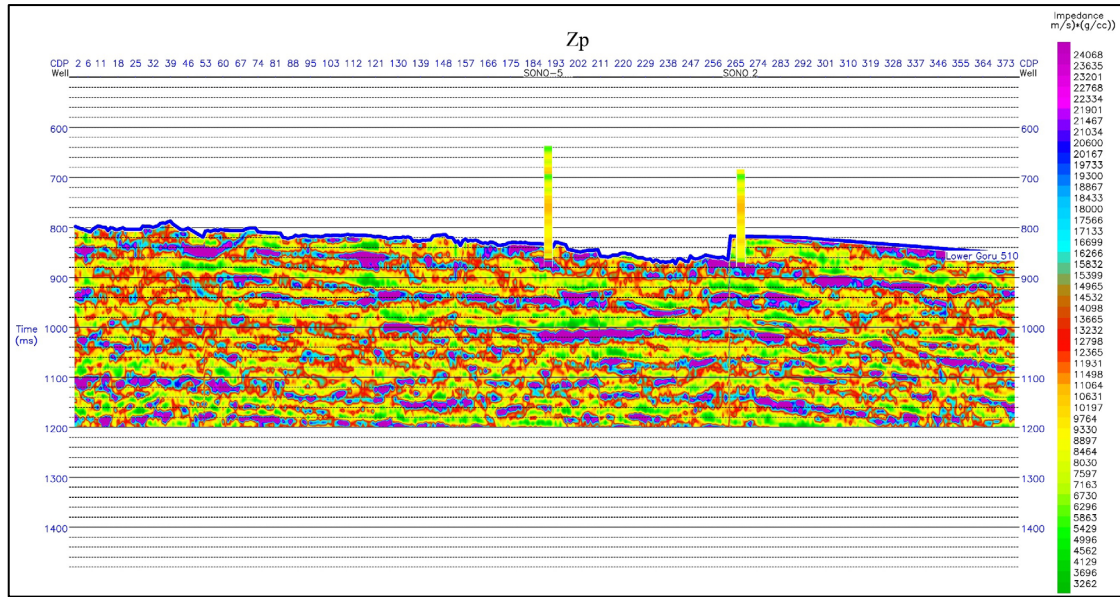


Figure 4.82 Strike line GO-872-SGR-510 illustrates the inverted Z_p at the Sono-2 and 5 well position. The range of impedance lies between 113696 to 14965 ((m/s) *(g/cc)).

4.5.2 Multiattribute Analysis (Linear Relation)

Calibrated HP, FT, K, PHIA, and Vshl curves from Sono-2 and 5 were employed to train seismic attributes at wells position using geo-statistical evaluation. MAA was performed on a most favorable set of 20 seismic attributes, yielding reliable results for predicting geothermal properties. Figure 4.83 represents the MAA result of HP that is generated by utilizing Sono-2 and 5 wells as seismic data as internal attributes and inverted Z_p as an external attribute. Figure 4.83 (a) represents the curve result of validation and application for HP, the black curve shows the actual log curve and red curve is predicted curve by using 20 attributes the validation correlation is 59% and application correlation of MAA is 60% this correlation is a commutative of correlation of Sono-2 and 5. Figure 4.83 (b) shows the cross plot that is generated among the predicted and actual curves of HP. This cross plot shows the linear relation among the actual and predicted parameters, and it is generated on the basis of application of MAA. Figure 4.84 (a) shows the multiattribute curve result analysis of PHIA, which shows the correlation of cumulative correlation of 57% and 58% for both validation and application of MAA respectively performed on the LGF. Figure 4.85 (b) is a cross plot for actual vs predicted PHIA with a linear correlation of 58%. Figure 4.85 (a) shows the overlap of the estimated (red) and calibrated K (black) curves from well, drawn within a range of 0 to 30 mD. The validation and application curve has an average error of 60% and 8 %,

equivalent to 0.57 and 0.12 mD. The time window covers the LGF interval from 900 to 1100 ms. A cross plot, indicating the relationship among well-based and predicted K in Sono-2 and 5, includes a linear regression line. K values in the cross plot range from 0 to 20 mD, with actual K on the x-axis and predicted K on y-axis. While the data shows an excellent correlation among the two K curves, some intervals exhibit scatter, resulting in an error of over 12% in the Sono-2 and 5 wells. Last but not least, the same methodology is performed on the Vshl, which gives the validation correlation of the MAA is also run on the HP, PHIA, K and Vshl and the results of correlations 48 for validation of Vshl and 84% for application of Vshl by applying 20 attributes on LGF as shown in Figure 4.86

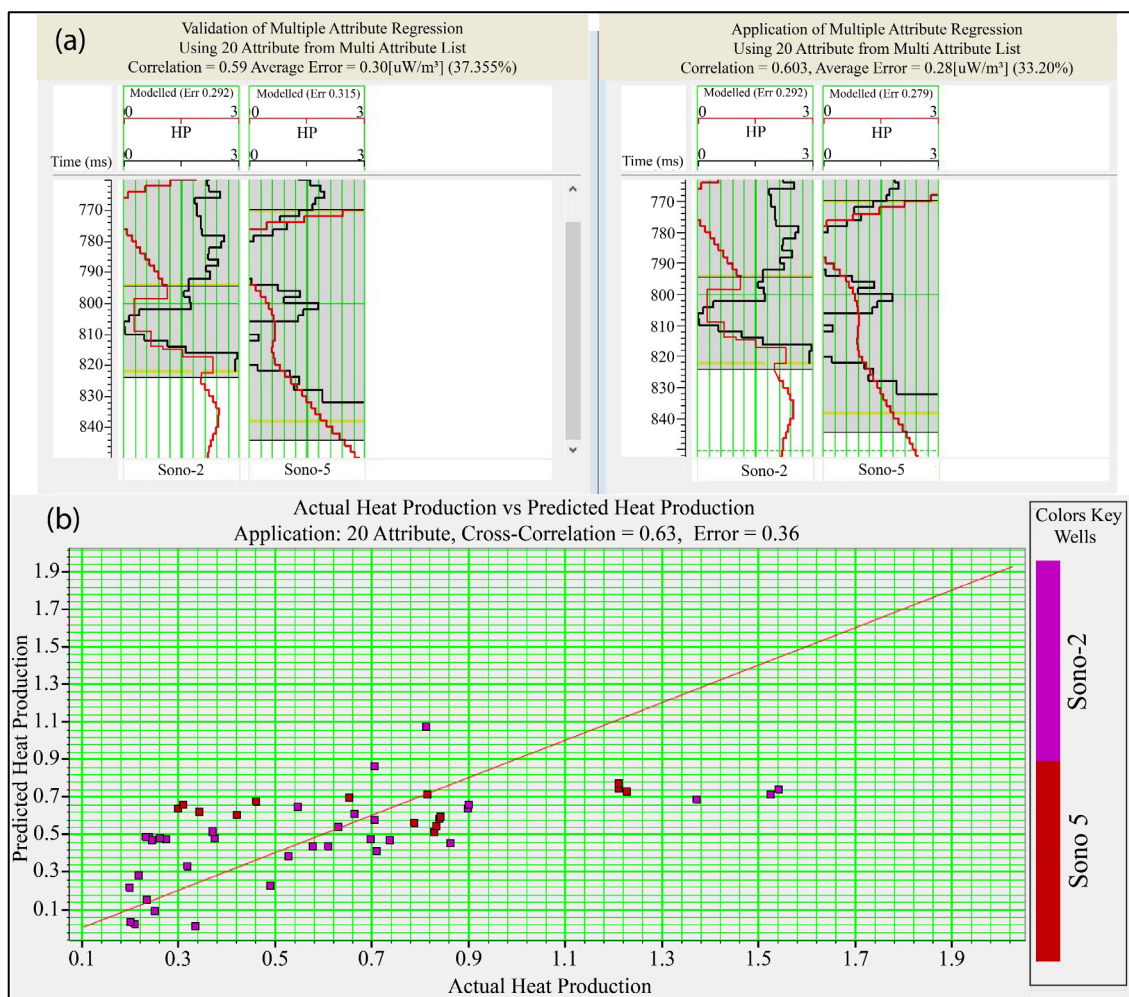


Figure 4.83 (a) Log curve representation of MAA showing the result of validation and application of MAA on LGF for HP. (b) cross plot of actual vs predicted HP generated based on Sono-2 and 5 for interested LGF.

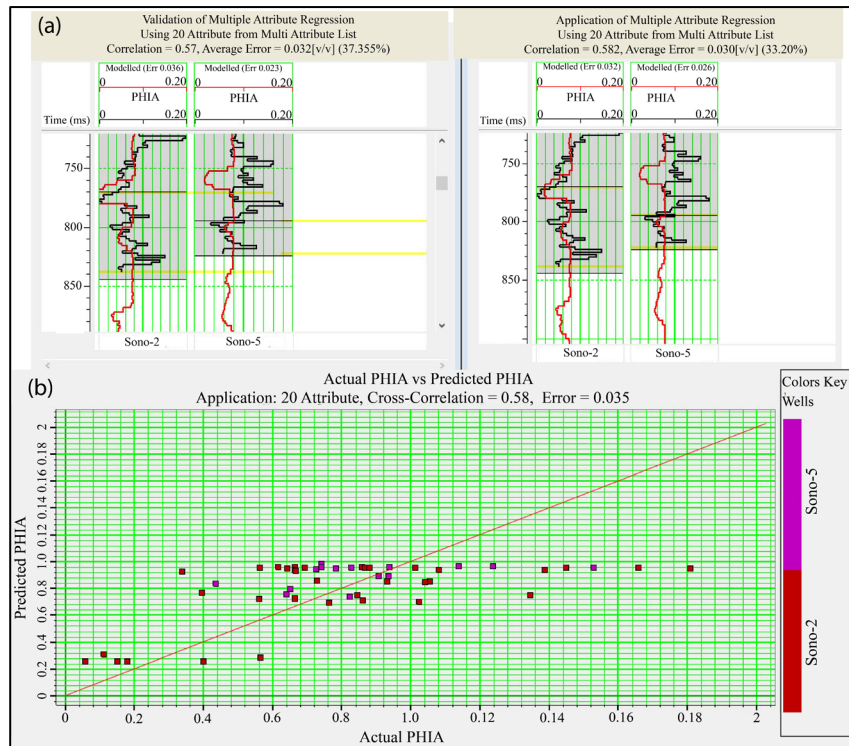


Figure 4.84 (a) Log Curve representation of MAA showing the result of validation and application of MAA on LGF for PHIA. (b) cross plot of actual vs predicted PHIA generated based on Sono-2 and 5 for interested LGF.

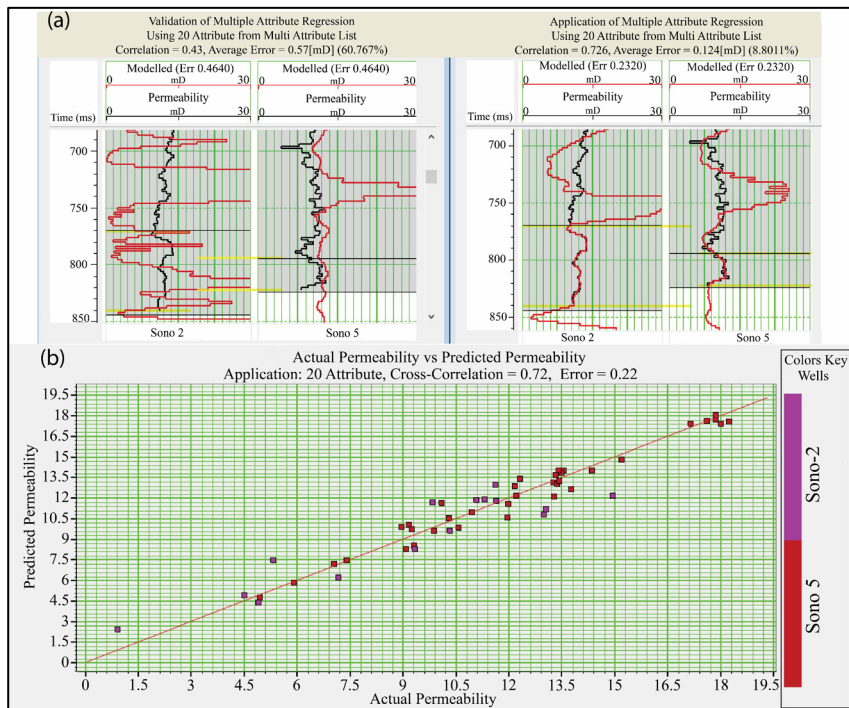


Figure 4.85 (a) Demonstration of MAA curve and (b) cross plot showing the validation and application correlation of K at the well position.

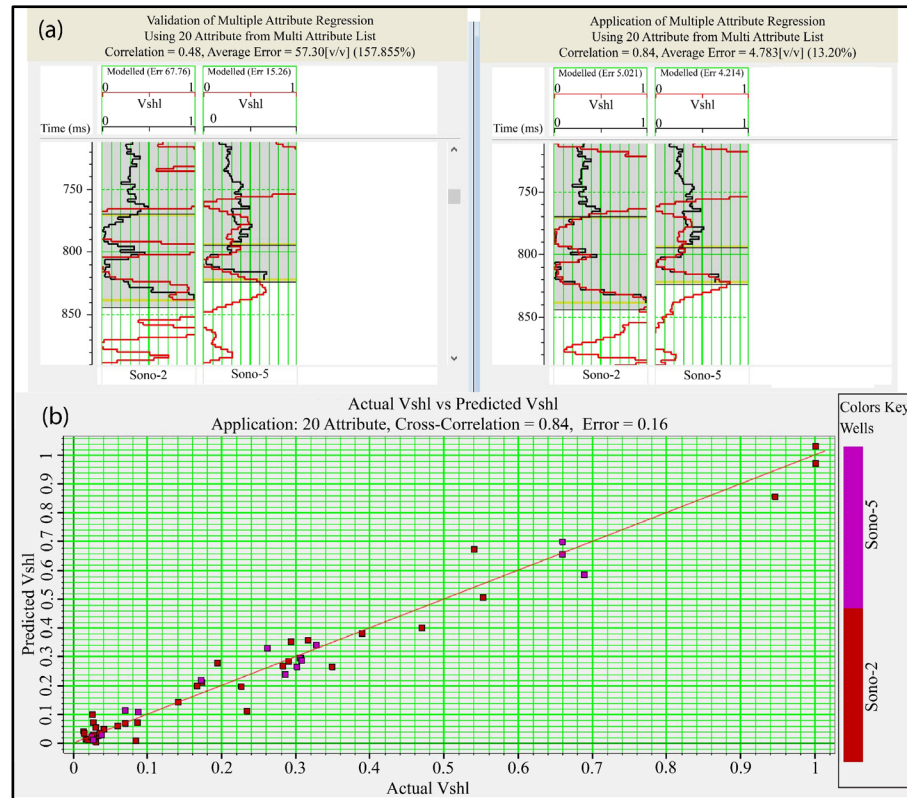


Figure 4.86 (a) Log curve representation of MAA showing the result of validation and application of MAA on LGF for Vshl. (b) cross plot of actual vs predicted HP generated based on Sono-2 and 5 for interested LGF.

4.5.3 Deep Feed Forward Neural Network

Applying DFFNN evaluation to HP, PHIA, K, and Vshl on the Sono-2 and 5 well position improved correlation among the modeled and corrected well based geothermal parameters. Attributes from seismic and the modeled log curve trained by MAA were more refined using nonlinear DFFNN evaluation, which reduced data point scatter. Figure 4.87 shows the result of HP that is run on the LGF by considering Sono-2 and 5 well. After applying DFFNN, the correlation reaches 99%, and the cross plot shown in Figure 4.87 (b) confirms the same correlation, indicating a particularly good prediction of HP on LGF. The results of applying DFFNN to PHIA are shown in Figures 4.87 (a) and (b). Figure 4.88 (a) displays the DFFNN curve for PHIA, where the black curve is the actual data, and the red curve is the predicted data. Both curves are mirror images, demonstrating an excellent match achieved with DFFNN. The correlation for DFFNN is 96%. Figure 4.88(b) shows a cross plot comparing the actual and predicted curves for PHIA, yielding the same result as the DFFNN curve. In Figure 4.89 (a), the selection of obscure layers reduced the mean error by 23.17% between predicted and well-calculated

K curves, resulting in an extremely high correlation coefficient of about 91%, based on DFFNN results. The input in the DFFNN cross plot in Figure 4.89 (b) shows less scatter than the best-fit line compared to the MAA cross plot. The nonlinear neural network approach and the use of various hidden layers in DFFNN contribute to the strong correlation observed between predicted and actual K values. Because fewer hidden layers were used in the DFFNN analysis compared to DFFNN, the accuracy and reliability of K predictions were higher. Lastly, applying DFFNN to Vshl resulted in a correlation of 98% shown in Figure 4.90.

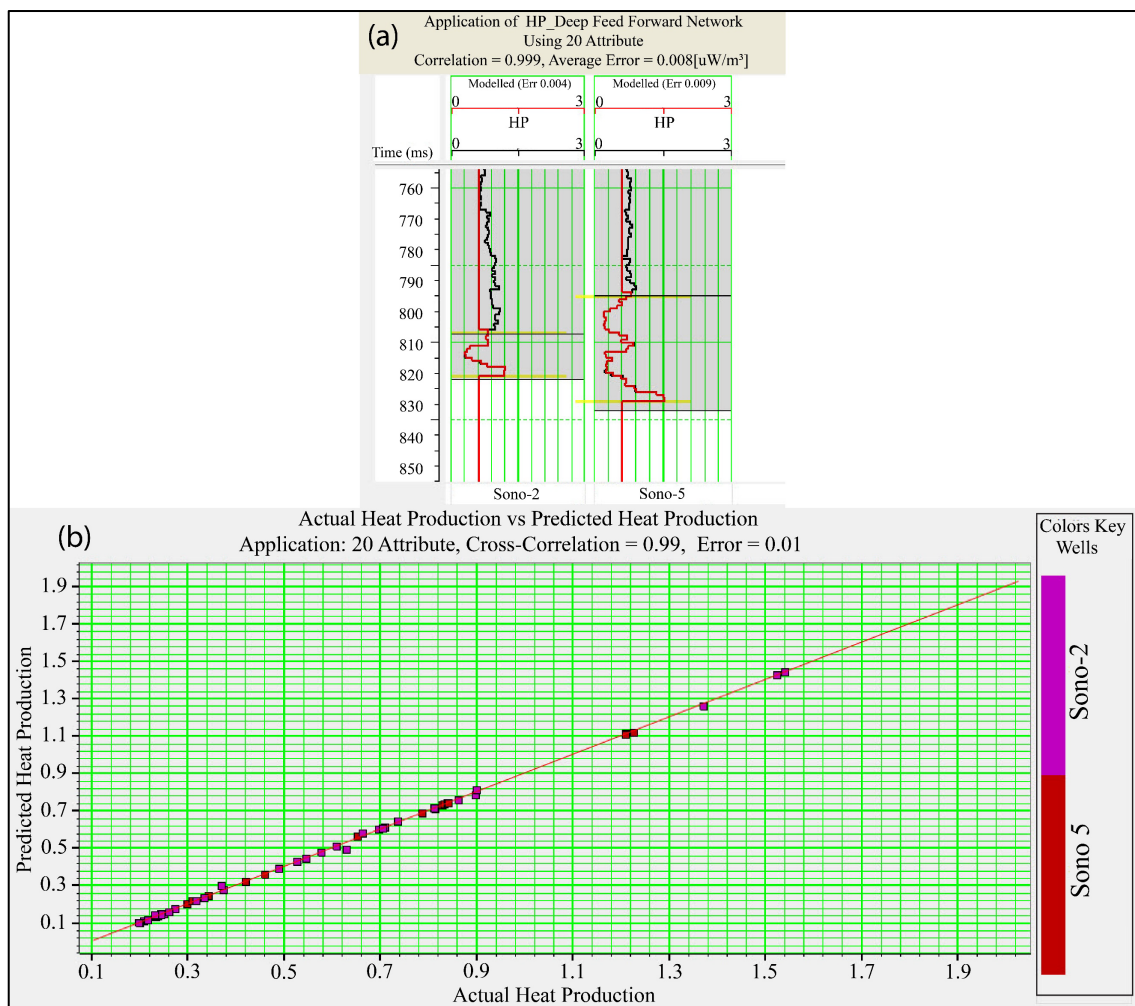


Figure 4.87 Result of HP after applying DFFNN on the LGF. (a) Log curve result of HP with the correlation of 99% (b) Actual vs predicted HP Cross plot generated for Sono-2 and Sono-5 wells for LGF the linear trend shows the best matched between actual and predicted value of HP.

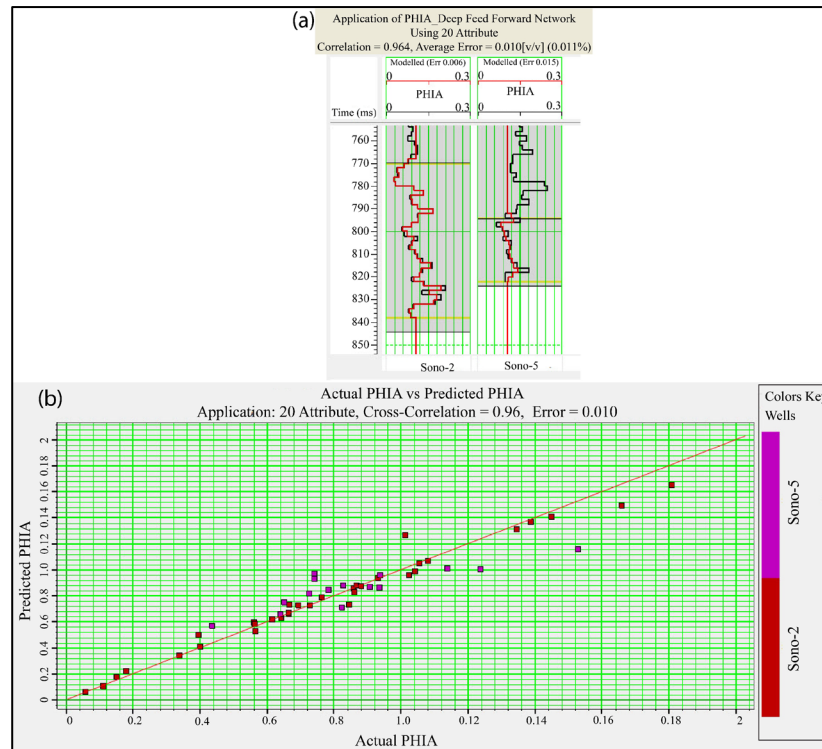


Figure 4.88 Result of PHIA after applying DFFNN on the LGF. (a) Log curve result of PHIA with the correlation of 96% (b) Actual vs predicted PHIA Cross plot generated for Sono-2 and Sono-5 wells for LGF the linear trend shows the best matched between actual and predicted value of PHIA.

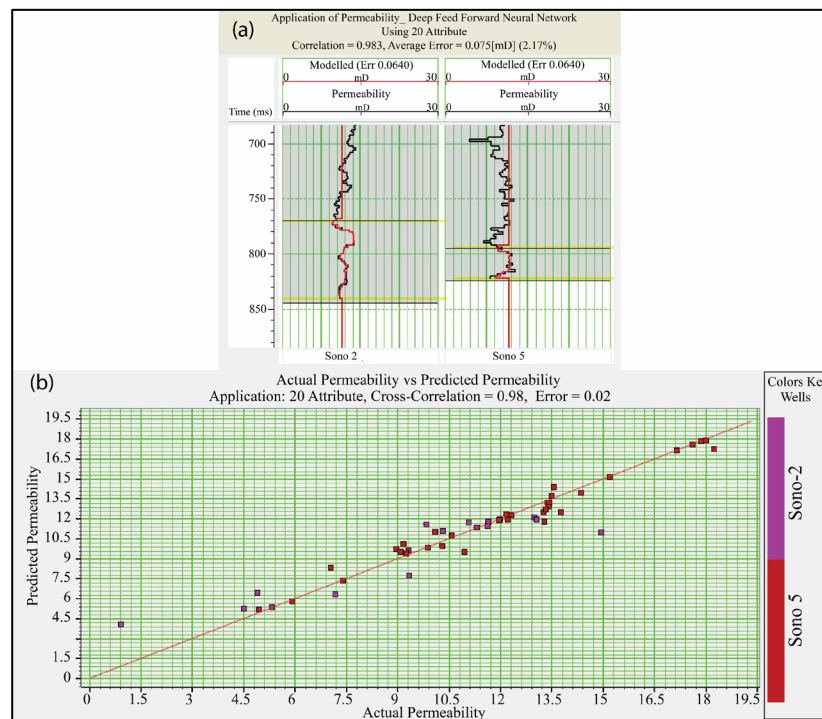


Figure 4.89 Result of K after applying DFFNN on the LGF. (a) Log curve result of K with the correlation of 96% (b) Actual vs predicted K cross plot generated for Sono-2 and Sono-5 wells for LGF the linear trend shows the best match between actual and predicted value of K.

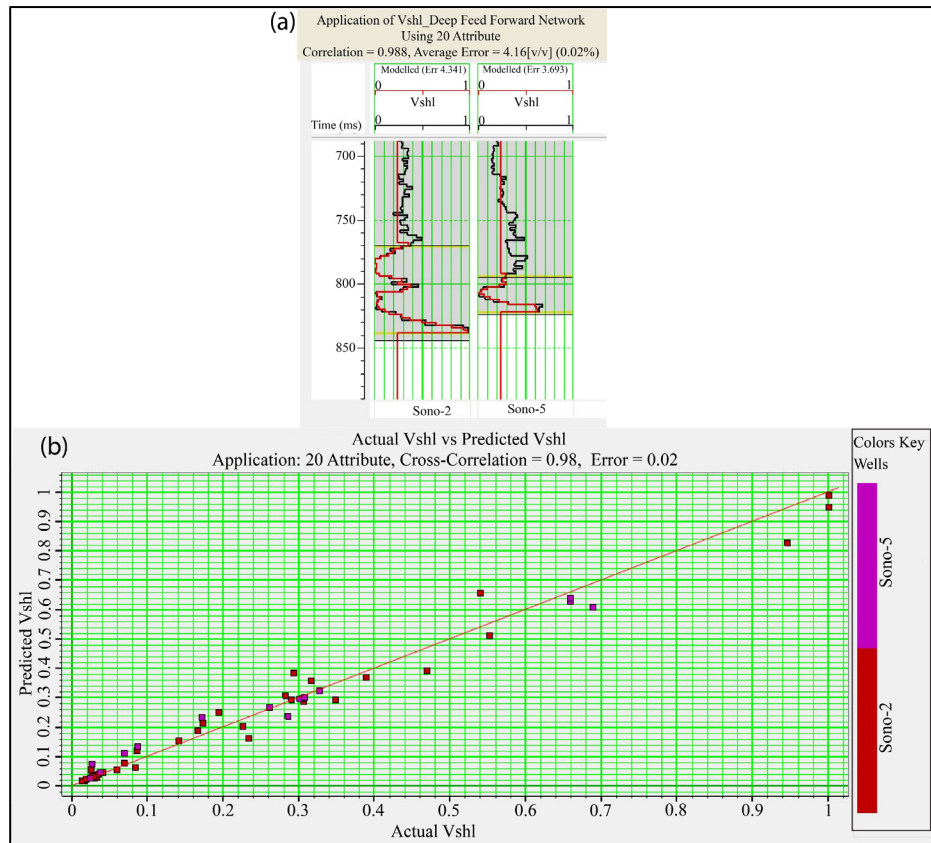


Figure 4.90 Result of Vshl after applying DFFNN on the LGF. (a) Log curve result of Vshl with the correlation of 96% (b) Actual vs predicted Vshl cross plot generated for Sono-2 and Sono-5 well for LGF the linear trend shows the best matched between actual and predicted value of Vshl.

4.5.4 Geothermal Variation on Seismic Section

Predicted geothermal properties curves, utilizing regression methods, are computed in two well positions across the interesting region. Correlation was established among the initial curves, and it is argued that the DFFNN approach, which is employed as an innovative technique, is the optimum approach for getting accurate geothermal fluctuations within the extension basin, which is regarded as an ideal basin for geothermal exploration. Data is then applied across the entire 2D seismic section to generate seismic variations in the subsurface of the LGF. The optimal results are captured in the seismic strike line. The HP seismic section for strike line GO-872-SGR-510 is generated by using Sono-2 and Sono-5 well. The best match is observed among the log curve and seismic data, consistency between the values of HP is observed in the seismic section the range of HP is between 0.56 to 0.88 $\mu\text{W}/\text{m}^3$ as shown in Figure 4.91. In Figure 4.92 the seismic variation of PHIA is shown on the strike line by using DFFNN at the LGF. The maximum PHIA is observed at the well location that is up to 12%. The K seismic section for strike

line is generated using two Sono wells, is shown in Figure 4.93. The same lateral and vertical extent is used in the LFM and impedance section of a strike line. Color shading depicts K variation within the LGF, with values between 0 to 20 mD. Higher K intervals are indicated in purple color, while green signifies lower K areas. The Sono wells are also depicted on the strike seismic line to illustrate the relationship between seismic and borehole data in the LGF. Figure 4.94 represents the FT result from the two wells that were used in research along with their geothermal gradient. The highest temperature is encountered on the Sono-2 and Sono-5 well, which is in the range of 111.950 °C. The seismic section shown the quite a good match with the well log curve. Figure 4.95 demonstrates the Vshl distribution on the seismic strike section. A higher Vshl is observed on the eastern side of the seismic section. The highest Vshl is observed on the Sono-2 well as compared to the Sono-5 well.

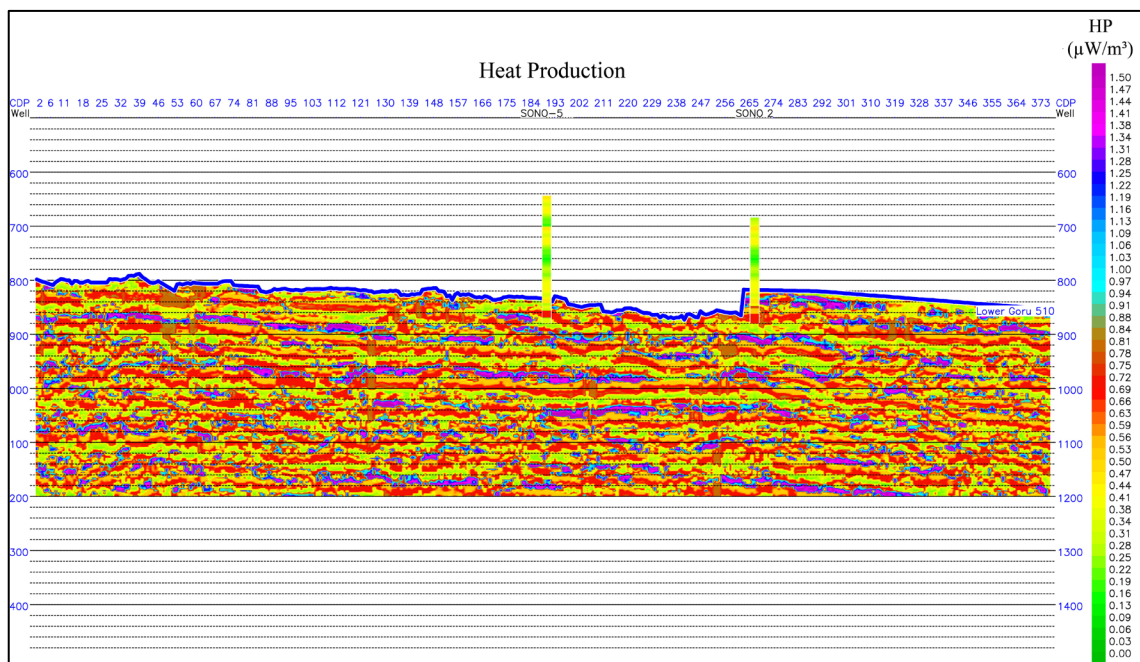


Figure 4.91 2D strike line GO-872-SGR-510 demonstrates the HP on the seismic section for the LGF shown in blue horizon. Higher HP is encountered Sono-2 well while the trend of the HP is to decrease toward the west side of the seismic section.

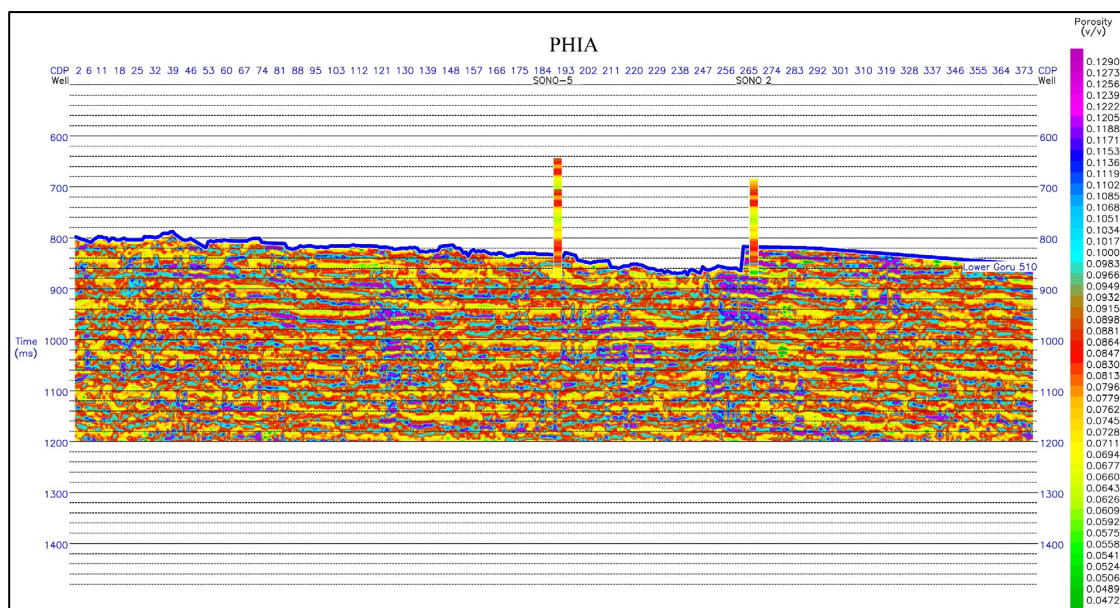


Figure 4.92 PHIA variation on the 2D seismic strike line GO-872-SGR-510 at LGF marked with blue color. Sono-2 and 5 indicate best match with seismic transect.

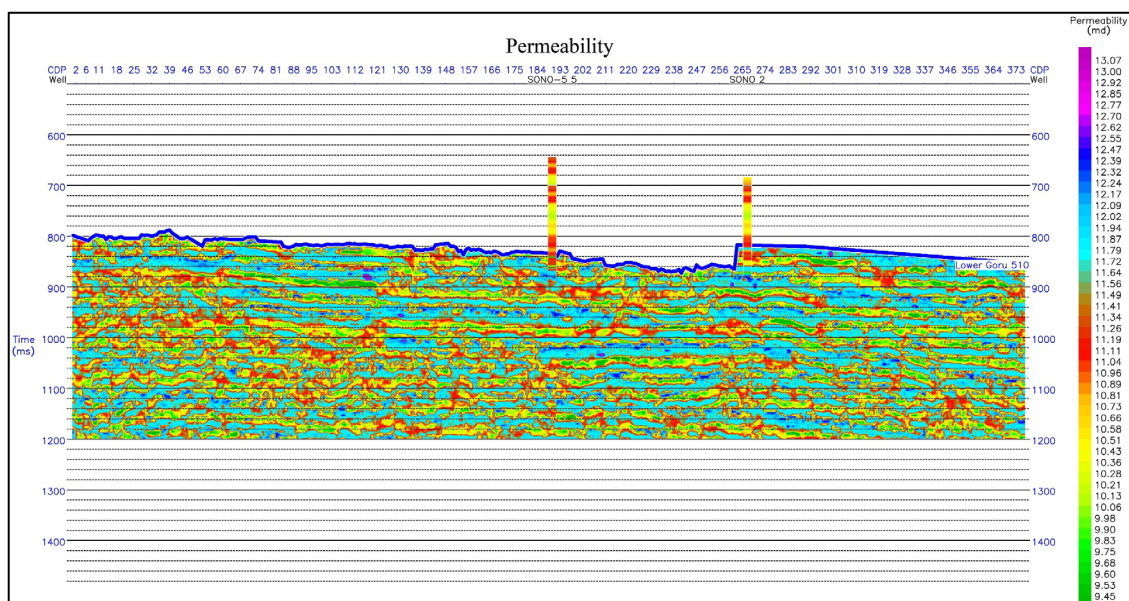


Figure 4.93 2D strike line GO-872-SGR-510 demonstrates the K on the seismic section. Higher K is encountered by Sono-2 well. The trend of the K is to decrease toward the west side of the seismic section.

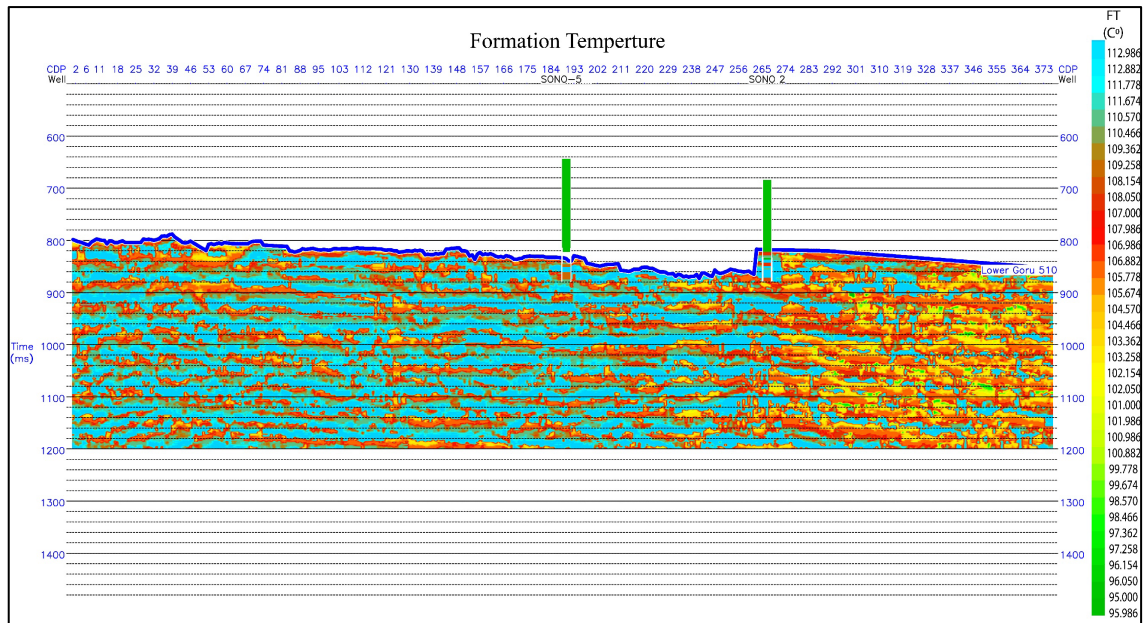


Figure 4.94 2Dstrike line GO-872-SGR-510 demonstrates the FT on the seismic section. The trend of the FT is to increase toward the east side of the seismic section.

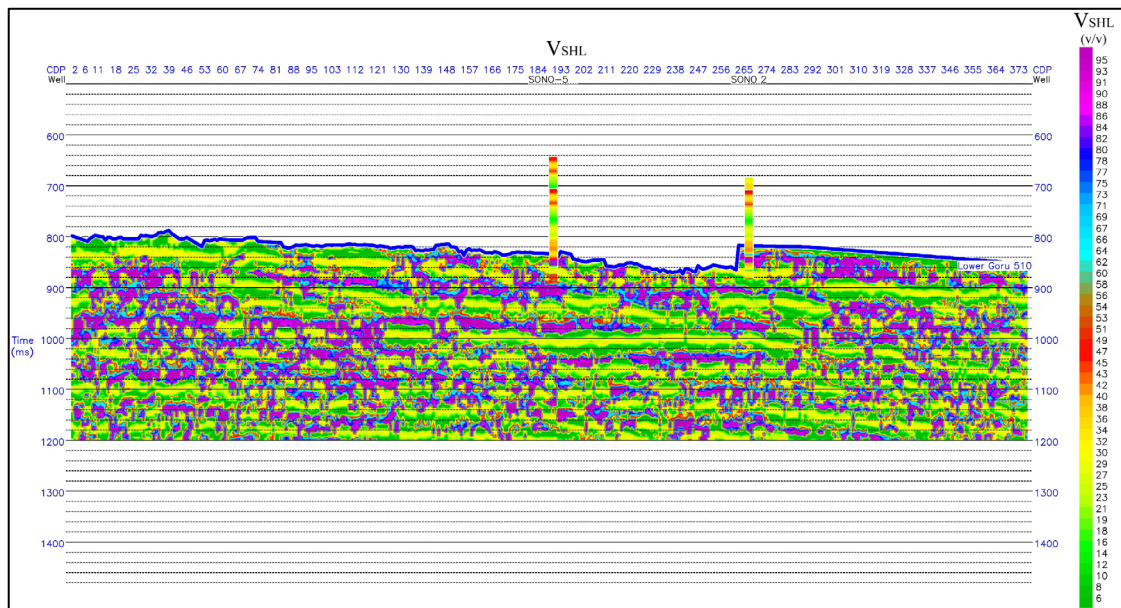


Figure 4.95 2Dstrike line GO-872-SGR-510 demonstrates the Vshl on the seismic section. Higher Vshl is encountered in well whereas the trend of Vshl is to increase toward the east side of the seismic section.

4.6 Inversion Analysis and DFFNN on Sanghar Block-2

. Firstly, model-based inversion analysis is performed on the control lines named G862-SGR-176, G862-SGR-153, G947-SGR-168S, G862-SGR-102Ext and G862-SGR-103Ext to know the change in impedance along the seismic section after that DFFNN is

firstly applied on well data to know the geothermal properties after that these properties are interpolate on the seismic section specifically on seismic control lines.

4.6.1 Model Based Seismic Inversion

Temporal window bordered by the horizon, spanning from the top of LGF to the complete depth, is used to extract the wavelet. In order to obtain a good correlation, a seismic to well tie connection was constructed utilizing the seismic extracted wavelet. Finally, to further improve the coefficient of correlation, the log curve-based wavelet of 100 ms wavelength is chosen. Wavelets from the well data are extracted using all the well that are present on the seismic section. Which represents all of the seismic frequency ranges, wavelet frequency spectrum of 35 Hz is utilized. As seen in Figure 4.96, the wavelet extraction from well data has a standard phase of 15° and a dominating frequency of 35 Hz. For the establishment of an initial well tie and a time-depth relationship, synthetic traces related to seismic traces. The time window of the connection cross plot is nominated to encompass the whole study period using accessible log data to compare artificial and actual traces. To view both synthetic and actual traces, the time window for the correlation plot is selected to cover the entire duration for which log data is currently available. The Figures 4.97, 4.98, 4.99, and 4.100 depict the correlation window of Allah Dino-1, Bukerani-1, Jarwar-1 and Jumman Shah-1 for the whole thickness of the LGF. The first three tracks represent the input log curve, which is followed by the next correlation track, which depicts both the red seismic trace and the blue synthetic trace. The last track shows the original seismic segment, as well as the LGF horizons. Figure 4.97 illustrates the plot among the built and original seismic wiggle of Allah Dino-1, which revealed a 90% correlation along with seismic strike line G862-SGR-153. Figure 4.98 demonstrates the seismic to well tie of Bukerani-1 well for the LGF as the well is present on the seismic dip line G862-SGR-102Ext. The well Jarwar-1 is present in G862-SGR-103Ext and the well to seismic tie of the line is demonstrated in Figure 4.99. At last, Figure 4.100 shows well to seismic tie of Jumman Shah-1 well with the seismic correlation of G947-SGR-168S.

The original seismic dip and strike lines and the well-based wavelet of all available wells are used to construct the LFM for the seismic line depicted in Figure 4.101, 4.102, 4.103 and 4.104. The model illustrates the impedance fluctuation in the LGF both vertically and laterally. Color legends are used to illustrate impedance differences

with red denotes high impedance values while purple denotes lower impedance. The total impedance calculated for all seismic dip and strike line. The P wave model that was chosen has a different range that varies from well to well and seismic lines. The formation lower portion exhibits high P-Impedance values, whereas the higher section exhibits low impedance because of its high porosities that are filled with water. The higher impedance range is observed in Allah Dino-1 and Jarwar-1 wells while lower impedance range are observed in Bukerani-1, Jumman Shah-1 wells.

The inversion analysis study of the 2-D seismic is carried out within the complete thickness of LGF, as illustrated in the upper track of Figures 4.105, 4.106, 4.107 and 4.108. Inversion analysis study of Allah Dino-1, Bukerani-1, Jarwar-1, and Jumman Shah-1 wells shows the initial inverted impedance track along with three diverse types of curves. An initial impedance curve created by the borehole log curve present in blue color curve. Impedance values range for Allah Dino-1 is 5773.71 to 9772.71 (m/s) * (g/cc), Bukerani-1 is 2175.4 to 11894.4 (m/s) * (g/cc), Jarwar-1 is 3773.71 to 6773.71 (m/s) * (g/cc) and for Jumman Shah-1 the range of impedance is varies from 3991 to 12161 (m/s) * (g/cc) as stated in the Zp track description. The wavelet extracted by the well data is employed to create the impedance represented in blue shade beneath the wavelet track. The relationship between the created and original seismic traces is restricted by the correlation windows represented by pale lines. Finally, the trace of error is displayed, which is the distinction among the previous results, suggesting minimal values. The last track shows the indicated horizons of LGF (green). The results reveal a good correlation of 96% across the artificial and actual traces for Allah Dino-1, Bukerani-1 shows the correlation is 98%, Jarwar-1 has a maximum correlation of 99% and Jumman Shah-1 shows the correlation of 96%. Inversion analysis is performed on both wells, but the well and results of wells are given below and remaining well correlation and error is mentioned in Table 4.3.

The inversion (Zp) is then employed to the dip seismic lines G862-SGR-102Ext and G862-SGR-103Ext and G862-SGR-153 and G947-SGR-168S using the inverted impedance curve that was created at the well location. Variations in the facies and fluid characteristics in the LGF are indicated by horizontal and vertically shifts in the impedance values. Less impedance range indicate small-compressed region with excellent porosities, but high impedance values grow with higher sediment compaction. Additionally, the impedance values are decreased by fluid absorption within the rocks. The formation pressure and impedance have an inverse relationship therefore a

geothermal potential zone may have exceptionally low impedance values because of high fluid saturation. The strike line inverted section result shows the LGF estimated p-impedance values.

In Figure 4.109 the impedance section G862-SGR-153 with well location Allah Dino-1 ranges between 11217 $((\text{m/s}) * (\text{g/cc}))$ to 20692 $((\text{m/s}) * (\text{g/cc}))$, covering a range from 5 to 777 CDP with a time range of 1380 to 1500 ms. Allah Dino-1, drilled at 530 CDP, is plotted to show the correlation among inverted and well impedance. The CDP Impedance variations are indicated by color fill, with purple representing higher values and red represent indicating low impedance. LGF shows slightly variation in impedance. As the seismic section is extended up to several kilometers, the control of Z_p on the western side is weak because of the presence of only one well in the seismic section.

In Figure 4.110 the impedance section G862-SGR-102Ext with well location Bukerani-1 ranges between 6099 $((\text{m/s}) * (\text{g/cc}))$ to 12016 $((\text{m/s}) * (\text{g/cc}))$, covering a range from 0 to 420 CDP with a time range of 900 to 1350 ms. Bukerani-1, drilled at 90 CDP, is plotted to show the correlation among inverted and well impedance. The CDP Impedance variations are indicated by color fill, with purple representing higher values and green represents indicating low impedance. LGF shows slightly variation in impedance. In Figure 4.112 the impedance section G862-SGR-102Ext with well location of Tando Allah Yar-1, Tando Allah Yar-2, Tando Allah Yar-3 and Jumman Shah-1 well ranges between 7496 $((\text{m/s}) * (\text{g/cc}))$ to 13173 $((\text{m/s}) * (\text{g/cc}))$, covering a range from 0 to 720 CDP with a time range of 1,000 to 1350 ms. Tando Allah Yar-1 is drilled at 295 CDP, Tando Allah Yar-2 is drilled at 258 CDP, Tando Allah Yar-3 is drilled at 335 CDP and Jumman Shah-1 is drilled at 525 CDP, is plotted to show the correlation among inverted and well impedance. The CDP Impedance variations are indicated by color fill, with purple representing lower values and red representing higher impedance. LGF shows slightly variation in impedance. In Figure 4.111 the impedance section G862-SGR-103Ext with well location Jarwar-1 ranges between 4361 $((\text{m/s}) * (\text{g/cc}))$ to 14765 $((\text{m/s}) * (\text{g/cc}))$, covering a range from 0 to 435 CDP with a time range of 900 to 1150 ms. Jarwar-1, drilled at 385 CDP, is plotted to show the correlation among inverted and well impedance. The CDP Impedance variations are indicated by color fill, with purple representing lower values and red representing higher impedance as shown in Figure 4.112.

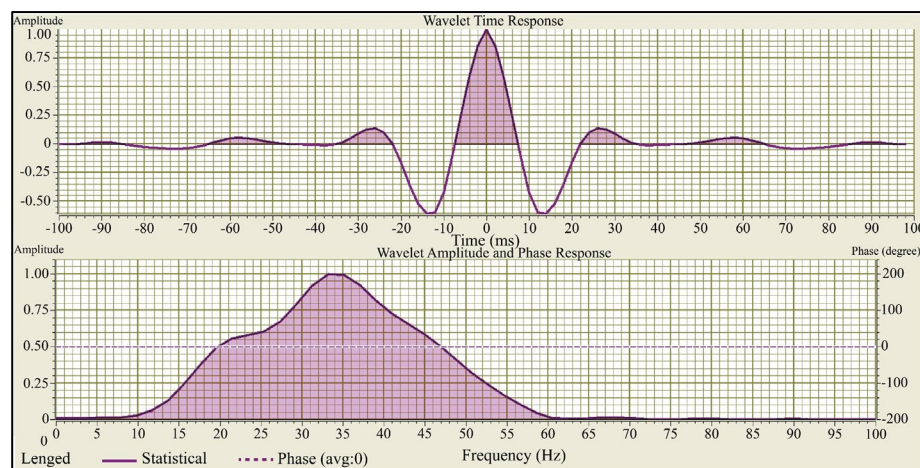


Figure 4.96 The statistical wavelet produced from the present on the Sanghar Block-2 is shown with a wavelength of 100 ms. The log curves are used to generate the wavelet, which includes spectrum, amplitude, and phase properties.

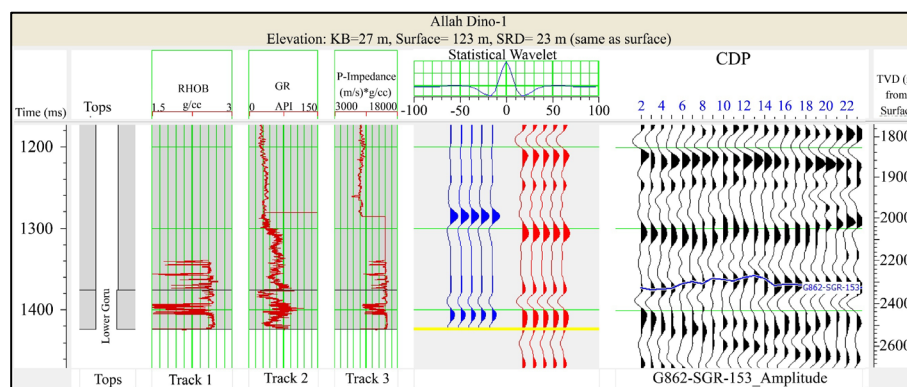


Figure 4.97 Seismic to well generated based on Allah Dino-1 well shows the correlation between the actual and synthetic seismic. Track 1 represents the RHOB, track 2 shows the GR and track 3 illustrates the P-Impedance curve and blue color shows the synthetic trace and red color represents the real seismic trace.

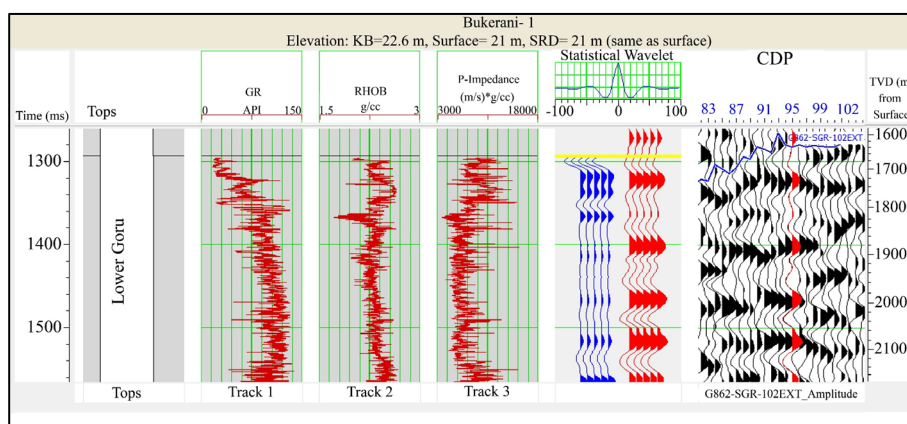


Figure 4.98 Seismic to well tie based on Bukerani-1 well which show the correlation among the synthetic and actual seismic of dip line G862-SGR-102Ext. The three log curves, GR, RHOB, and P-Impedance are used to develop correlations along with statistical wavelet.

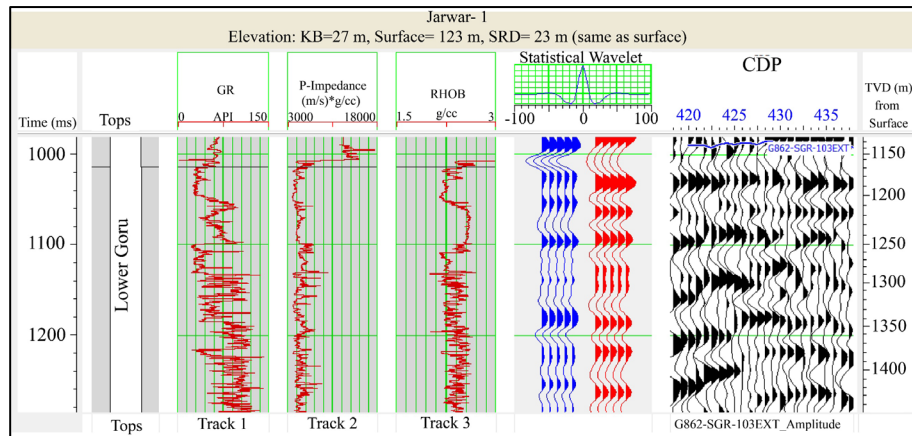


Figure 4.99 Seismic to well tie based on Jarwar-1 well which shows the correlation among the actual and synthetic seismic. The actual curve is shown with red and synthetic with blue whereas three log curve GR, RHO, P-Impedance and statistical wavelet is used for correlation.

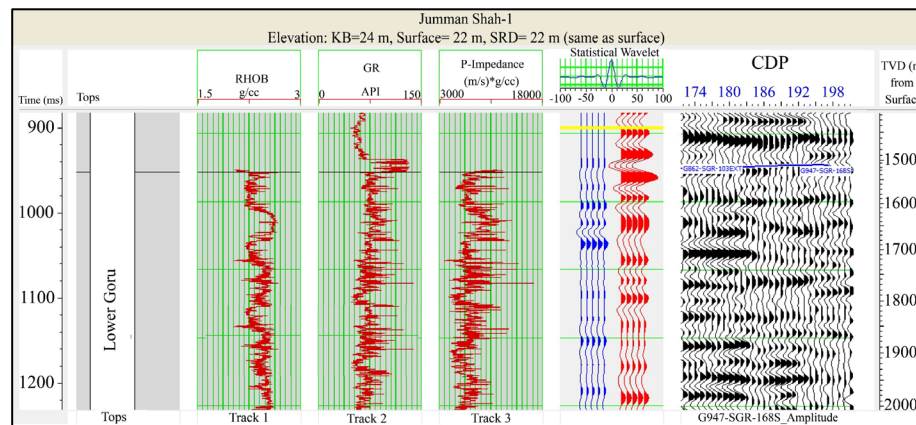


Figure 4.100 Seismic to well tie based on Jumman Shah-1 well which shows the correlation among the actual and synthetic seismic. The actual curve is shown with red and synthetic with blue whereas three log curve GR, RHO, P-Impedance and statistical wavelet is used for correlation.

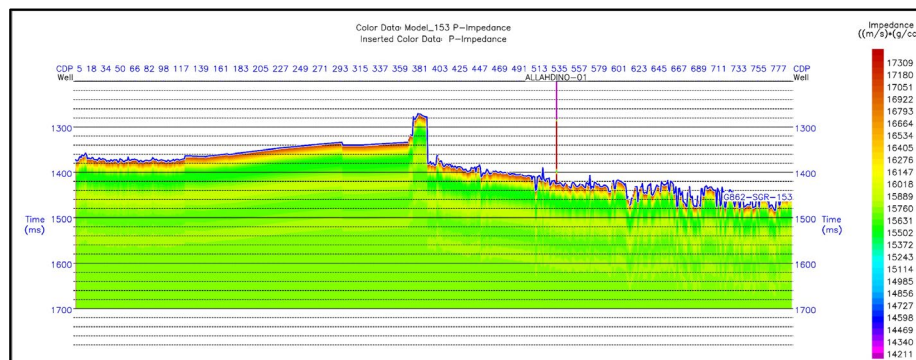


Figure 4.101 Low frequency model shown on strike line G862-SGR-153 with well Allah Dino-1 are located, demonstrate the P- Impedance. At the borehole position the impedance range is 14211 to 17309 (m/s) * (g/cc).

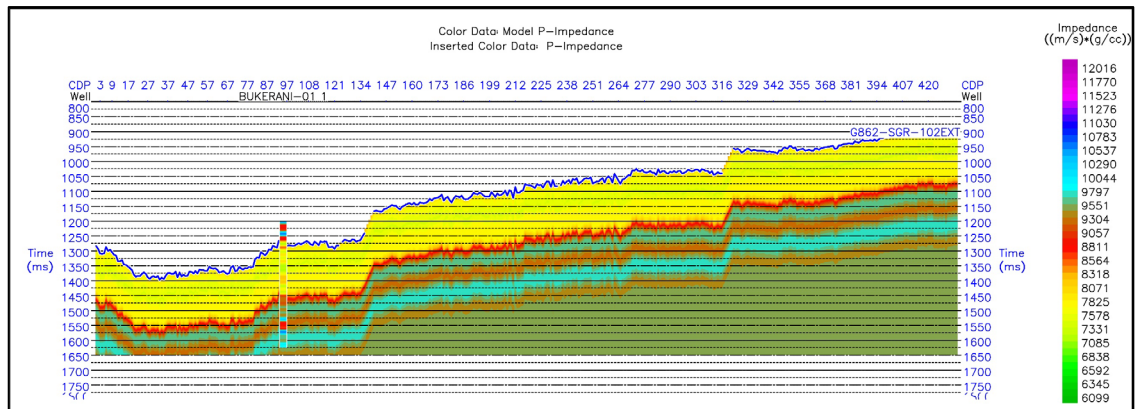


Figure 4.102 Low frequency model shown on strike line G862-SGR-102Ext with well Bukerani-1 is located, demonstrate the P- Impedance. At the borehole position the impedance range is 6099 to 12016 (m/s) * (g/cc).

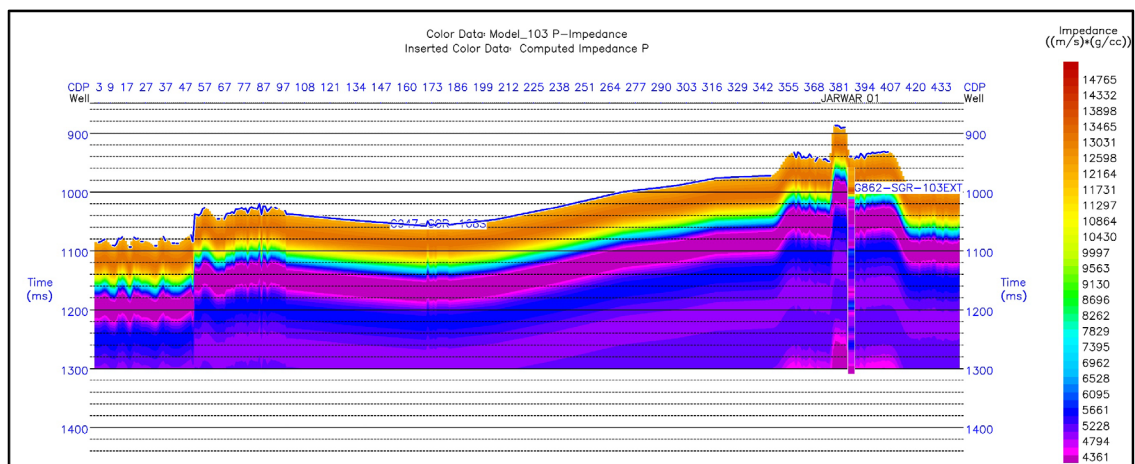


Figure 4.103 Low frequency model shown on strike line G862-SGR-102Ext with well Jarwar-1 is located, demonstrate the P- Impedance. At the borehole position the impedance range is 4361 to 14765 (m/s) * (g/cc).

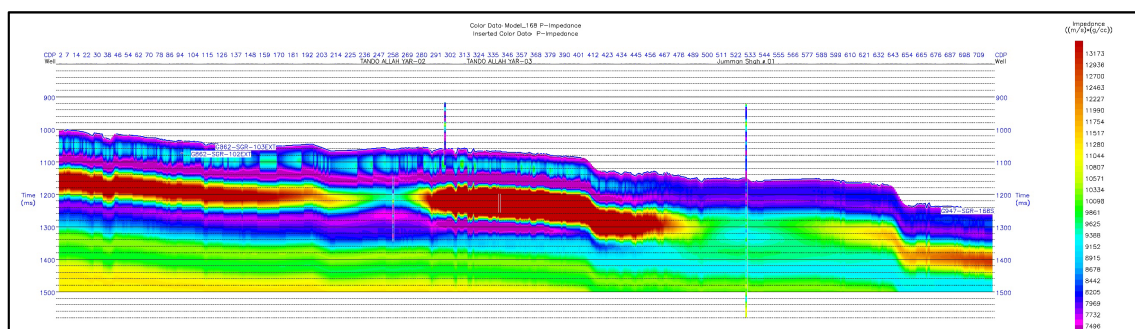


Figure 4.104 Low frequency model shown on strike line G947-SGR-168S with wells Tando Allah Yar-1, 2 and 3 and Jumman Shah-1 are located, demonstrating the P- Impedance. At the borehole position, the impedance range is 7496 to 13173 (m/s) * (g/cc).

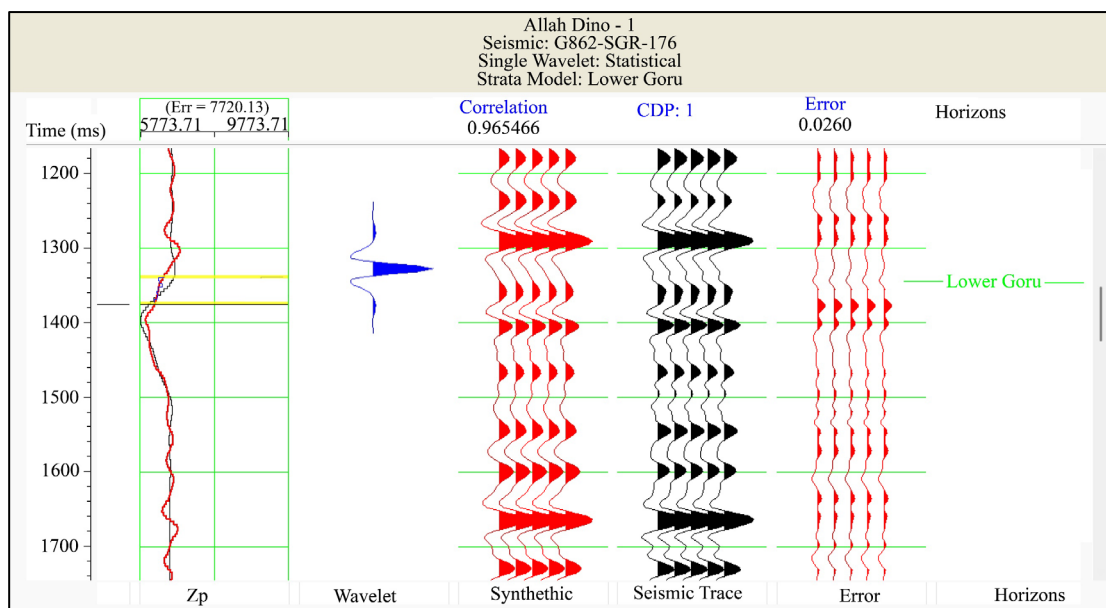


Figure 4.105 Model based seismic inversion analysis result of Allah Dino-1 showing the correlation of the 96% with minimum error of 2 %. The red wiggle represents the correlation and error section while black color represents the actual seismic traces.

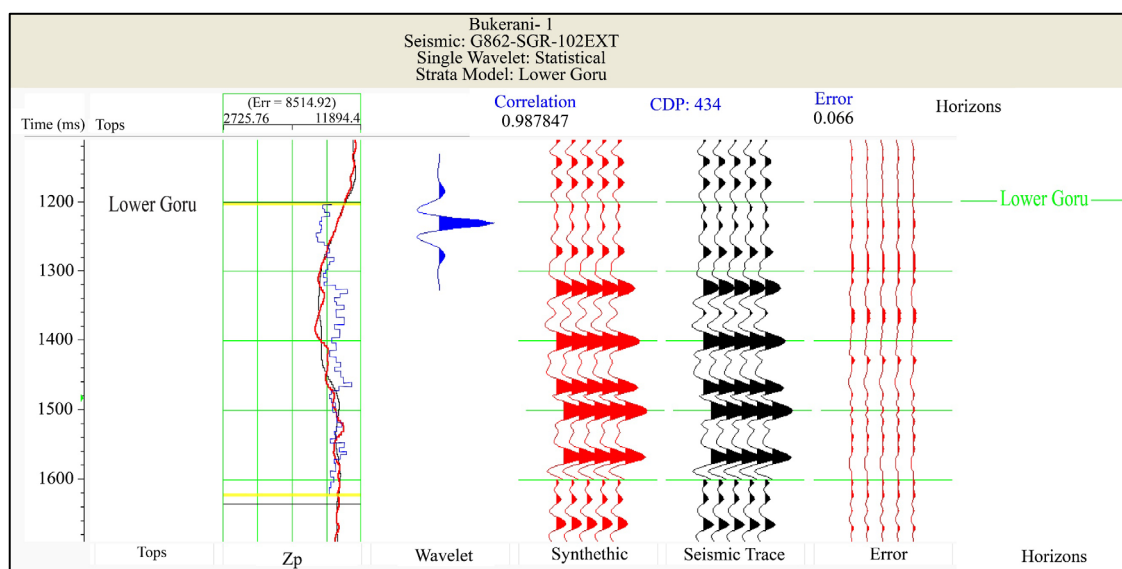


Figure 4.106 Model based seismic inversion analysis result of Bukerani-1 illustrate the correlation of the 98% with minimum error of 6 %. The red wiggle represents the correlation and error section while black color represents the actual seismic traces.

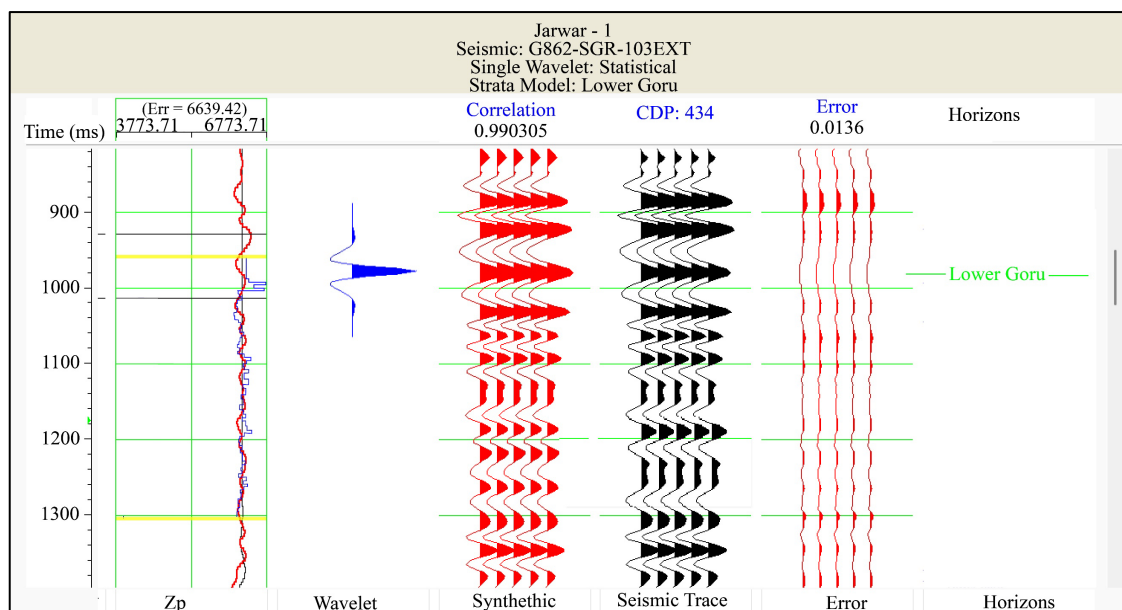


Figure 4.107 Model based seismic inversion analysis result of Jarwar-1 showing the correlation of the 99% with minimum error of 1 %. The red wiggle represents the correlation and error section while black represents the actual seismic traces.

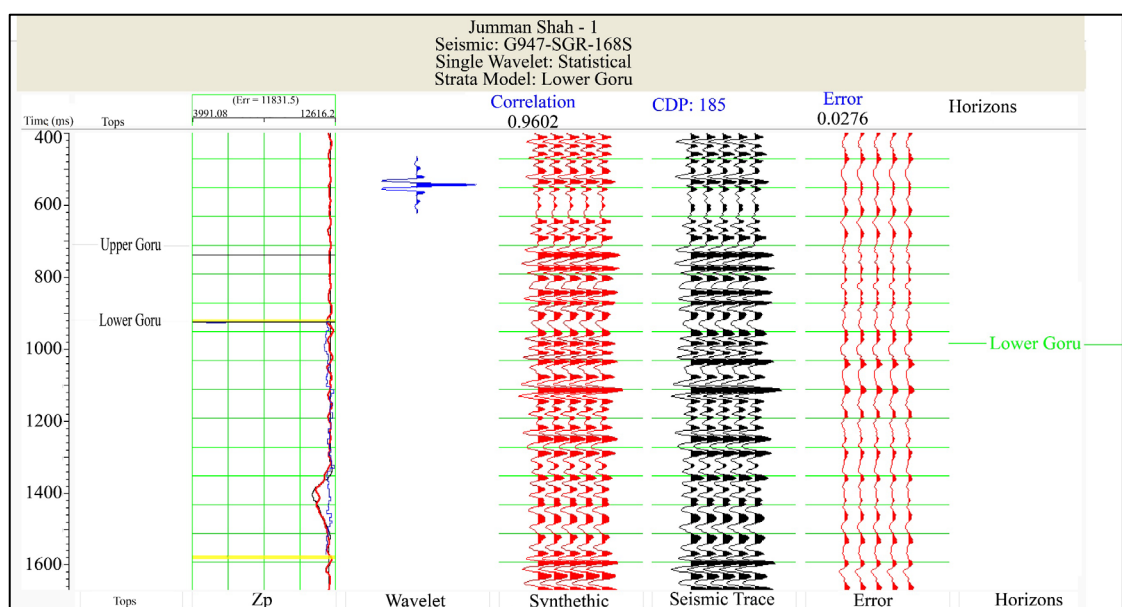


Figure 4.108 Model based seismic inversion analysis result of Jumman Shah-1 showing the correlation of the 96% with minimum error of 2 %. The red wiggle represents the correlation and error section while black color represents the actual seismic traces.

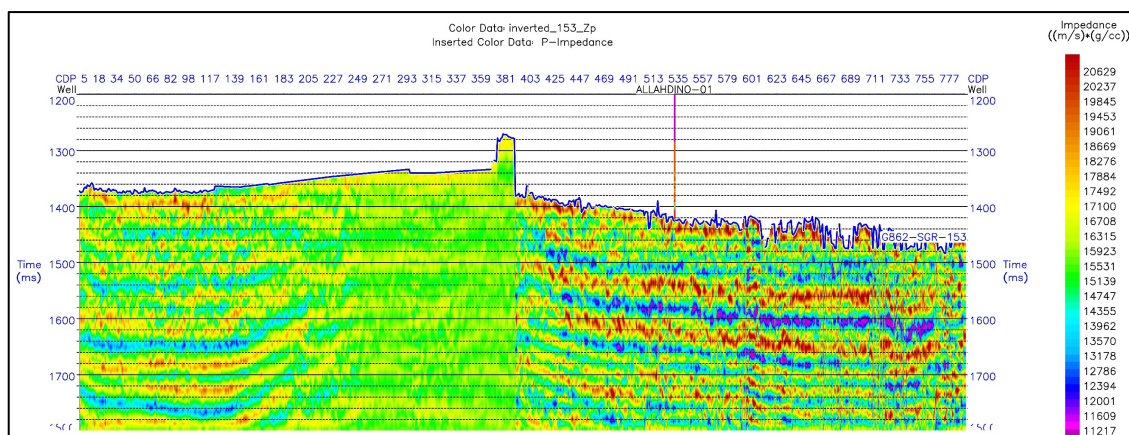


Figure 4.109 Strike line G862-SGR-153 illustrates the inverted Z_p at the Allah Dino-1 well position. The range of impedance lies between 11217 to 20629 ((m/s) *(g/cc)).

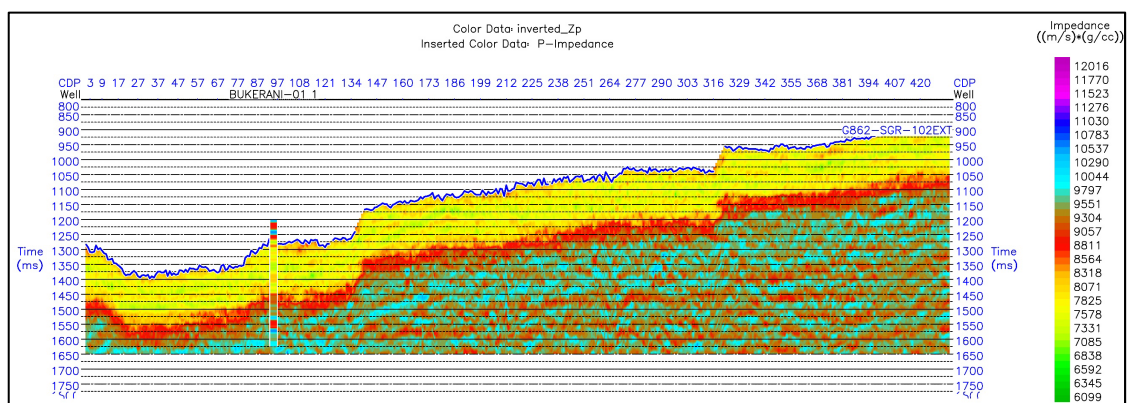


Figure 4.110 Strike line GO-862-SGR-102Ext illustrates the inverted Z_p at the Bukerani-1 well position. The range of impedance lies between 6099 to 12016 ((m/s) *(g/cc)).

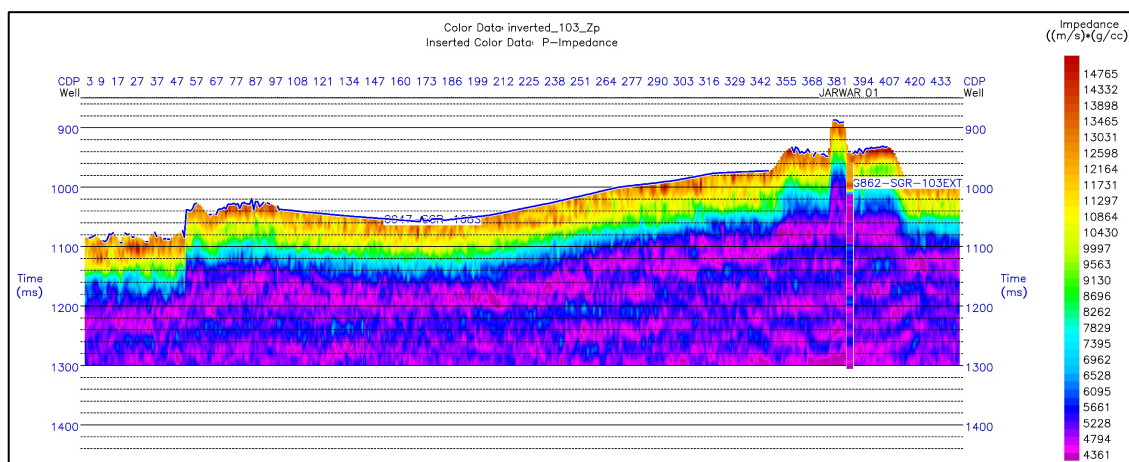


Figure 4.111 Strike line G862-SGR-103Ext illustrates the inverted Z_p at the Jarwar-1 well position. The range of impedance lies between 4361 to 14765 ((m/s) *(g/cc)).

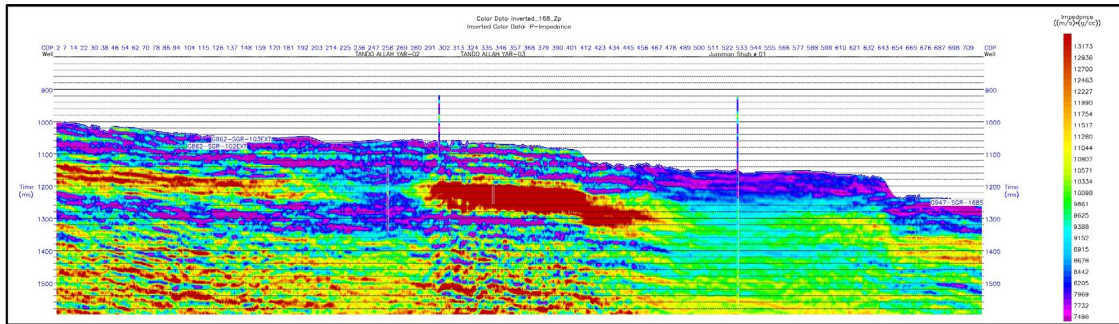


Figure 4.112 Strike line GO-947-SGR-168S illustrates the inverted Z_p at the Tando Allah Yar-1,2 and 3 and Jumman Shah-1 well positions. The range of impedance lies between 7496 to 13173 ((m/s) * (g/cc)).

Table 4.3: Inversion analysis results of well shows the correlation and error that is encountered in Sanghar Block.

Well Name	Correlation (%)	Error (%)
Allah Dino-1	96	4
Babar-1	93	7
Bukerani-1	98	2
Jarwar-1	99	1
Jumman Shah-1	96	4
Tando Allah Yar-1	96	4
Tando Allah Yar-2	98	2
Tando Allah Yar-3	96	4
Sono-2	98	2
Sono-5	92	8

4.6.2 Multiattribute Analysis (Linear Relation)

Figure 4.113 shows the MAA result of HP, generated using eight wells as seismic data as internal attributes and inverted Z_p as an external attribute. Figure 4.113 (a) displays the curve produced by applying HP. The black curve represents the actual log, while the red curve shows the predicted log using 20 attributes. The application correlation of the MAA is 73%, which reflects the correlation among the eight wells. Figure 4.113 (b) presents the cross plot of the predicted versus actual HP curves. This cross plot indicates a linear relationship between the actual and predicted parameters, based on the application of MAA. The actual HP curve is plotted on the x-axis, and the predicted HP is on the y-axis, with a scale range of 0 to 3 $\mu\text{W}/\text{m}^3$. The data of all eight well are present in the cross plot that is differentiate on the basis of their color code, red

color demonstrate the Allah Dino-1, orange color for Babar-1, golden color for Bukerani-1, yellow color for Jarwar-1, green color for Jumman Shah-1, blue color for Tando Allah Yar-1, magenta color Tando Allah Yar-2 and purple for Tando Allah Yar-3. The overall correlation is 73%. Figure 4.114 (a) shows the multiattribute application curve result analysis of RHP which shows the correlation of cumulative correlation of 82% for application of MAA performed on LGF. As the RHP is calculated by spectral gamma ray log (U, K and Th log) which is absent in Jarwar-1 and Jumman Shah-1. So, the RHP is not calculated on these two well. Figure 4.114 (b) is a cross plot for actual vs predicted RHP with a linear correlation of 82% and the scale of RHP is 0 to 3 $\mu\text{W}/\text{m}^3$. Figure 4.115 (a) represents the curve result of application for PHIA. The black curve shows the actual log curve and red curve is predicted curve by using 20 attributes application correlation of MAA is 82% this correlation is a commutative of correlation of eight well. Figure 4.115 (b) shows the cross plot that is generated among the predicted and actual curve of PHIA. This cross plot shows the linear relation among the actual and predicted parameter, and it is generated based on application of MAA. The actual curve of PHIA is plotted on the x-axis and predicted PHIA is plotted on y-axis with the scale range of 0 to 0.5 v/v. The data of all eight wells are present in the cross plot that is differentiated on the basis of their color code with correlation of 82%. Figure 4.116 (a) shows the overlap of the estimated (red) and calibrated K (black) curves from well, drawn within a range of 0 to 30 mD. The application curve has an average error of 61% equivalent to 0.26 mD. The time window covers the LGF interval from 700 to 1500 ms. A cross plot, indicating the relationship among well-based and predicted K in eight wells, includes a linear regression line. K values in the cross plot range from 0 to 50 mD, with actual K on the x-axis and predicted K on y-axis. While the data shows an excellent correlation between the two K curves, some intervals exhibit scatter, resulting in an error of over 61% in the eight wells as shown in Figure 4.116 (b). Last but not least same methodology is preformatted on the Vshl which give the application correlation of the MAA is 48% by using 20 seismic attributes as shown in Figure 4.117.

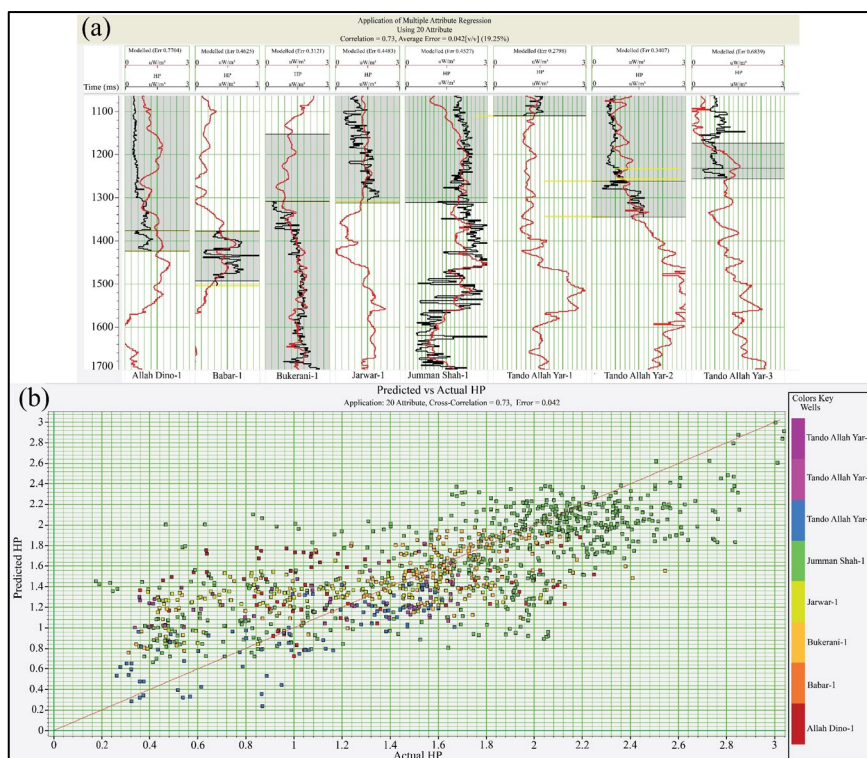


Figure 4.113 (a) Log curve representation of MAA showing the result of application of MAA on LGF for HP. (b) Cross plot of actual vs predicted HP generated based on eight well for interested LGF along with correlation of 73%.

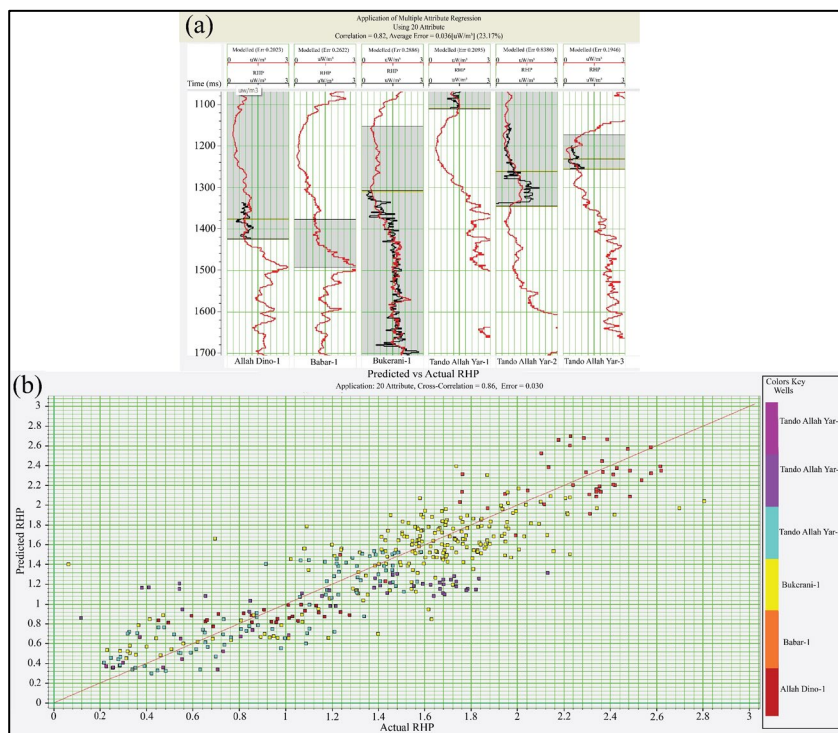


Figure 4.114 (a) Log curve representation of MAA showing the result of validation and application of MAA on LGF for RHP. (b) Cross plot of actual vs predicted RHP generated based on six wells for interested LGF.

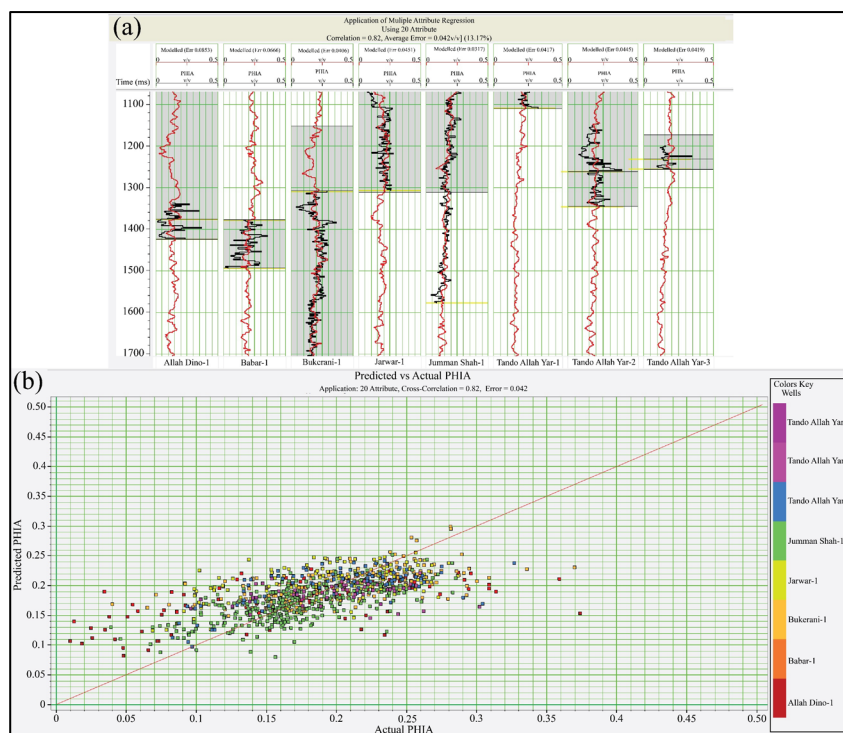


Figure 4.115 (a) Log curve representation of MAA showing the result of application of MAA on LGF for PHIA. (b) Cross plot of actual vs predicted PHIA generated based on eight for interested LGF.

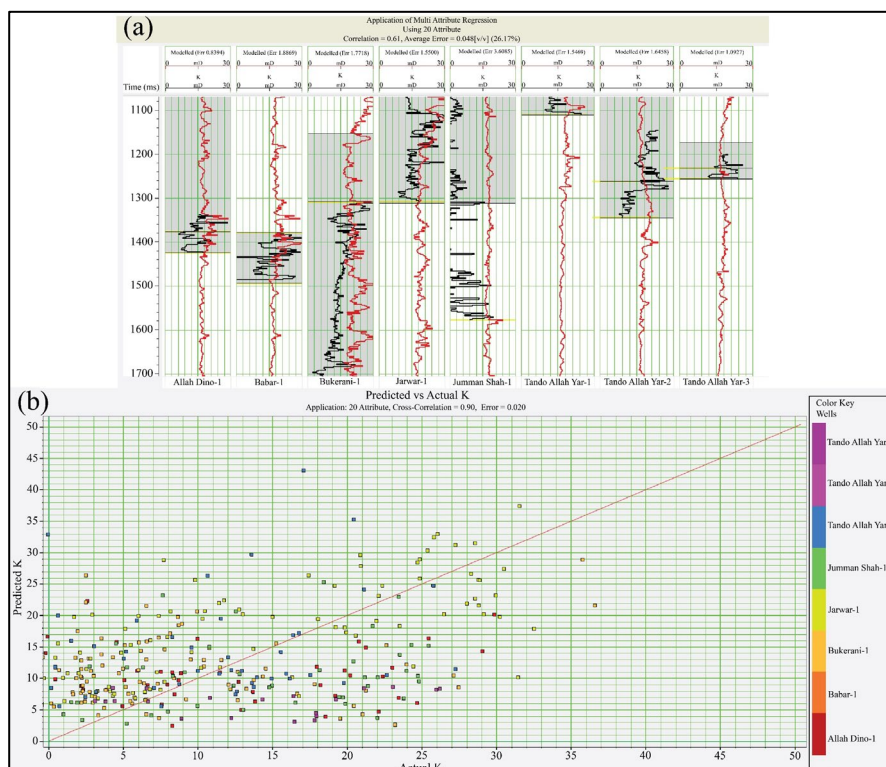


Figure 4.116 (a) Demonstration of MAA curve of K and (b) Cross plot showing the application correlation of K at the well position.

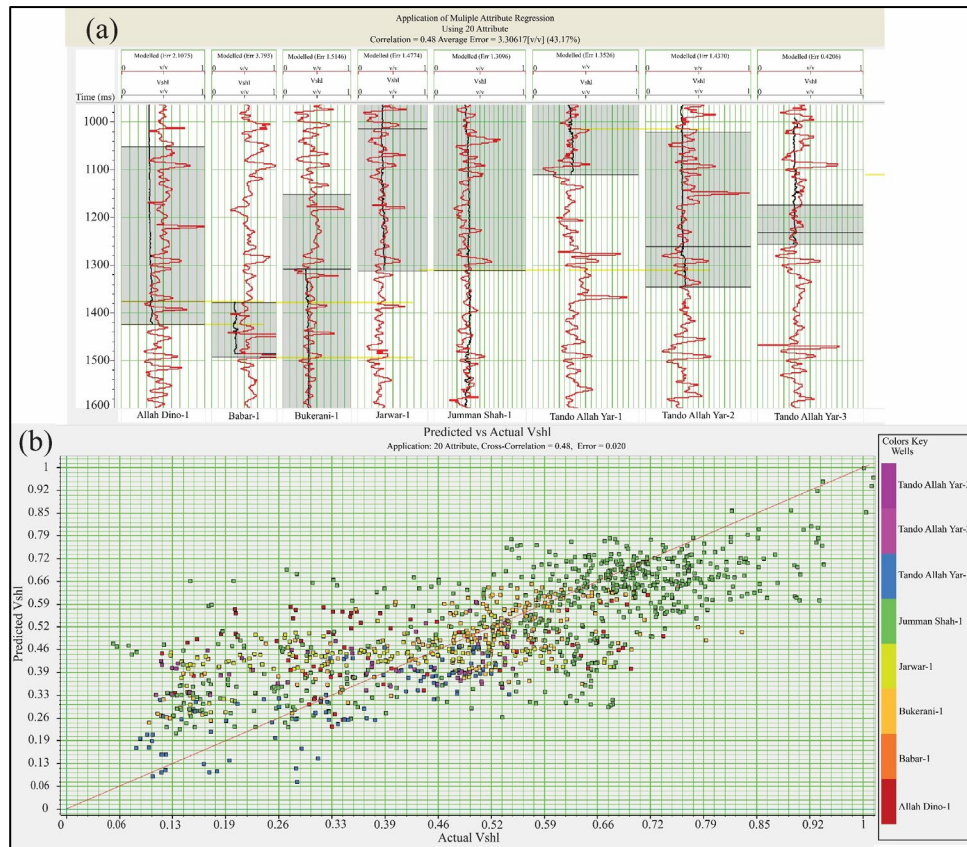


Figure 4.117 (a) Log curve representation of MAA showing the result of validation and application of MAA on LGF for Vshl. (b) Cross plot of actual vs predicted Vshl generated based on eight wells.

4.6.3 Deep Feed Forward Neural Network

Figure 4.118 (a) displays the results of HP applied to the LGF, considering all eight wells. After using DFFNN, the correlation is 86%, and the cross plot of actual vs. predicted HP in Figure 4.118 (b) shows the same correlation, indicating a quite good prediction of HP on LGF. Figure 4.119 (a) shows the DFFNN curve result of RHP based on six wells. The outcomes of DFFNN applied to RHP are shown in Figure 4.119 (a & b). Figure 4.120 (a) represents the DFFNN curve result of PHIA, where the black curve is the actual curve and the red is the predicted one. Both curves give a mirror image of each other, showing the best match of the curve by using a DFFNN. The correlation of DFFNN is 90%. Figure 4.120 (b) shows the cross plot of actual vs. predicted curves of PHIA, which provides the same result as the DFFNN curve. In Figure 4.121(a), the selection of ambiguous layers led to a reduced mean error of 8.17% between the predicted and well-derived K curves, achieving a high correlation coefficient of approximately 92% based on the DFFNN results. The input cross plot for the DFFNN in Figure 4.121(b) displays less scatter around the best-fit line compared to the corresponding MAA cross

plot. The non-linear neural network approach and the various hidden layers employed in the DFFNN analysis are responsible for the strong correlation that exists between expected and accurately identified actual K ranges. Figure 4.122 demonstrates the DFFNN curve and cross plot analysis of the Vshl, which shows the correlation of 93% and 7 % error.

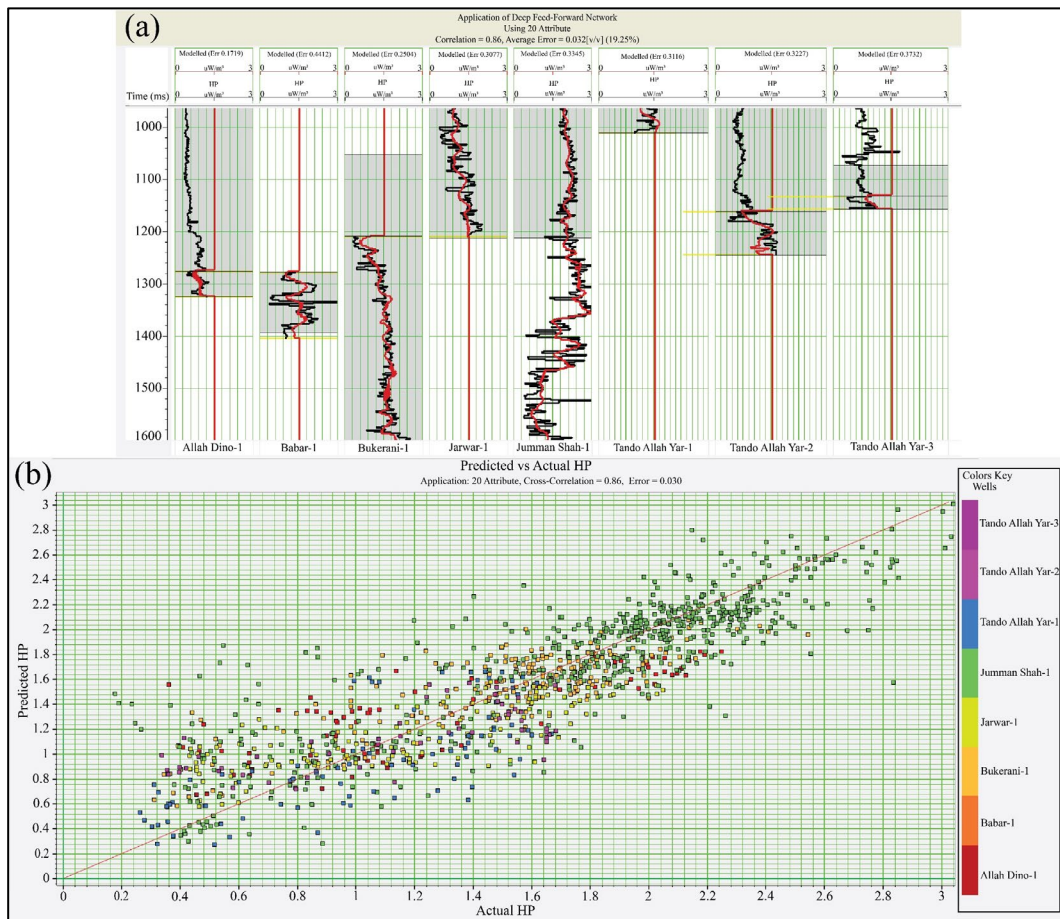


Figure 4.118 Result of HP after applying DFFNN on the LGF. (a) Log curve result of HP shows the correlation of 86% (b) Actual vs predicted HP cross plot generated by utilizing eight wells for LGF the linear trend shows the best match between actual and predicted value of HP.

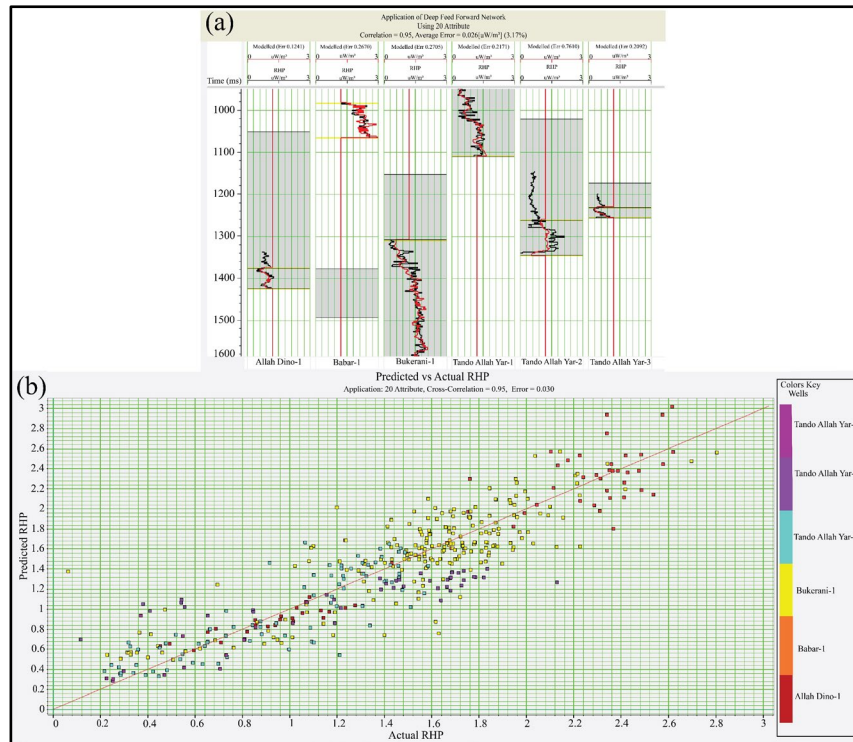


Figure 4.119 Result of RHP after applying DFFNN on the LGF. (a) Log curve result of RHP show the correlation of 95% (b) Actual vs predicted RHP cross plot generated by using six wells for LGF the linear trend shows the best match between actual and predicted value of RHP.

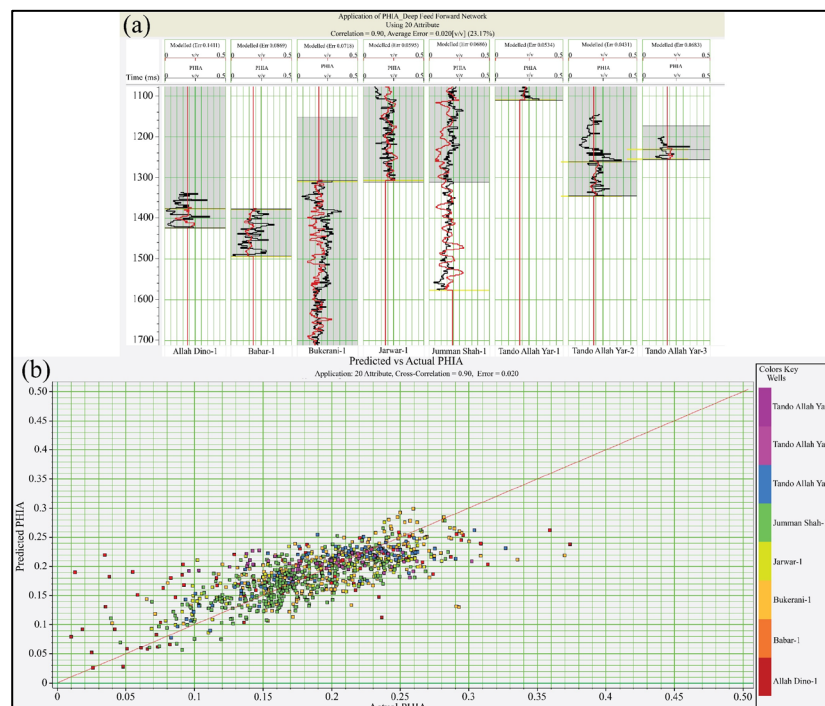


Figure 4.120 Result of PHIA after applying DFFNN on the LGF. (a) Log curve result of PHIA shows the correlation of 90% (b) Actual vs predicted PHIA cross plot generated for all the wells that are present in Sanghar Block-2 for the LGF the linear trend shows the best match between actual and predicted value of PHIA.

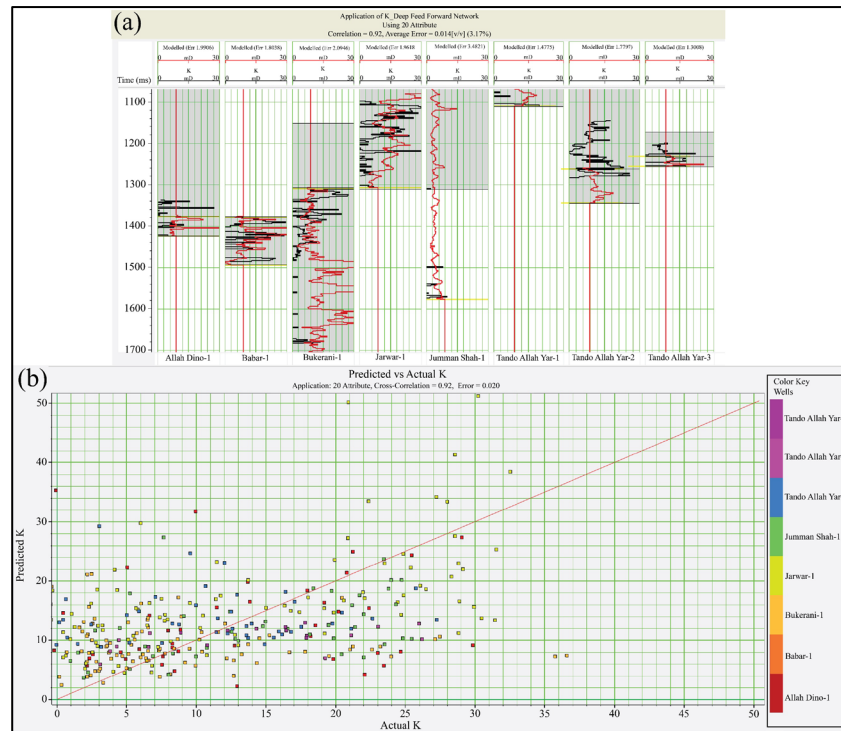


Figure 4.121 Result of K after applying DFFNN on the LGF. (a) Log curve results of K show the correlation of 92% (b) Actual vs Predicted K Cross plot generated for LGF by using eight wells the linear trend shows the best matched between actual and predicted value of K.

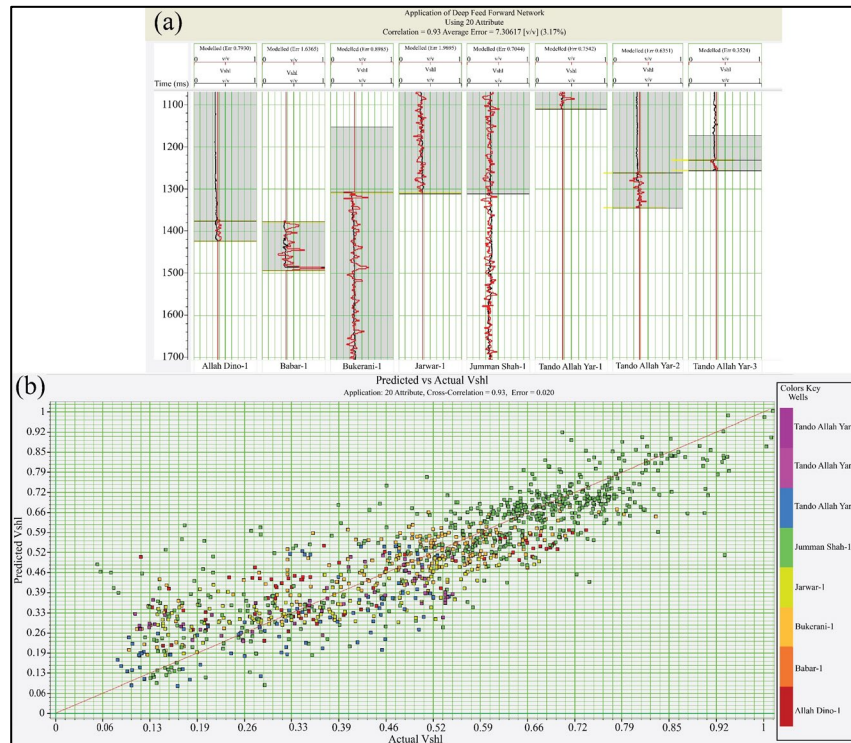


Figure 4.122 Result of Vshl after applying DFFNN on the LGF. (a) Log curve result of Vshl give the correlation of 93% (b) Actual vs Predicted Vshl cross plot generated for LGF the linear trend shows the best matched between actual and predicted value of Vshl.

4.6.4 Geothermal Variation on Seismic Section

After the application of DFFNN on the well data the last step is to show the variation of geothermal properties on the seismic section five seismic line are chosen for the variation of properties because the wells are present on that line. Two Dip line name as G862-SGR-102Ext and G862-SGR-103Ext with the presence of Bukerani-1 and Jarwar-1 well and three strike line named as G862-SGR-176 with well Babar-1, G862-SGR-153 with well Allah Dino-1 and regional seismic strike line G947-SGR-168S with presence of well Tando Allah Yar-1, Tando Allah Yar-2, Tando Allah Yar-3 and Jumman Shah-1 are used for demonstration of geothermal characteristics. Each Seismic line is discussed individually on the basis of these properties.

Estimation of geothermal characteristics curves, by using regression techniques, are calculated in Allah Dino-1 well positions across the LGF level. Correlation was established among the initial curves, and it is argued that the DFFNN approach, which is employed as an innovative technique, is the optimum approach for getting accurate geothermal fluctuations within the extension basin, which is regarded as an ideal basin for geothermal exploration. Data is then applied across the entire 2D seismic section to generate seismic variations in the subsurface of the LGF. The optimal results are captured in seismic strike line. The HP seismic section for strike line G862-SGR-153 is generated by using Allah Dino-1. The best match is observed among the log curve and seismic data, consistency between the values of HP is observed in the seismic section the range of HP lies between 0.75 to $1.75 \mu\text{W}/\text{m}^3$ as shown in Figure 4.123. In the surroundings of well position, the value of HP is reliable because of the good control of the well, but moved away from the well position, fluctuations in HP values are observed. In Figure 4.124 the seismic variation of RHP is shown on the strike line by using DFFNN at LGF. The variation of RHP is observed at a well location that is up to $1.25 \mu\text{W}/\text{m}^3$. The PHIA seismic strike line section is generated using Allah Dino-1 well, is shown in Figure 4.125. The same lateral and vertical extent is used in the LFM and impedance section of a strike line. Color shading depicts PHIA variation within the LGF, with values between 25 to 30%. Higher PHIA intervals are indicated in blue color, while green signifies lower PHIA zone. Figure 4.126 represents the K result for Allah Dino-1 well that was used with seismic section. The highest K is encountered in places where the PHIA is higher, which is a clue to a geothermal anomaly present in the subsurface. The seismic section shown the quite a good match with the well log curve. Figure 4.127 demonstrates the Vshl

distribution on the seismic strike section. A higher V_{shl} is observed on the surrounding portion of the well position.

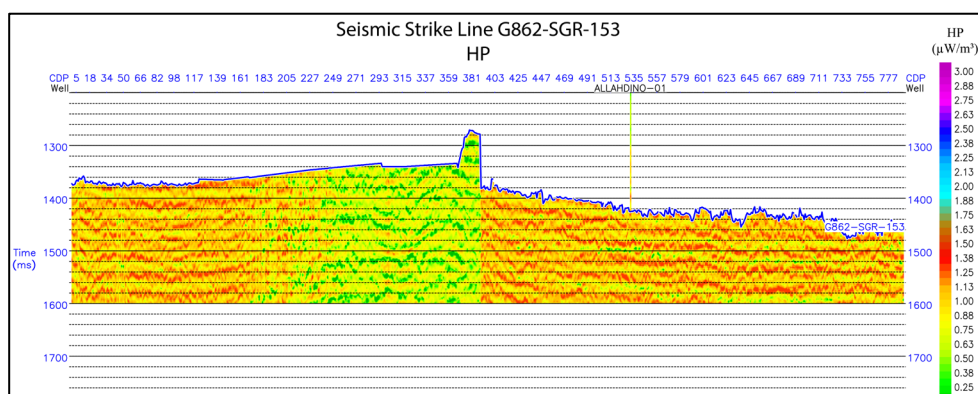


Figure 4.123 2D strike line G862-SGR-153 demonstrates the HP on the seismic section. Higher HP is encountered in the surrounding of the Allah Dino-1 well. The trend of the HP is to decrease around the CDP 230 to 390.

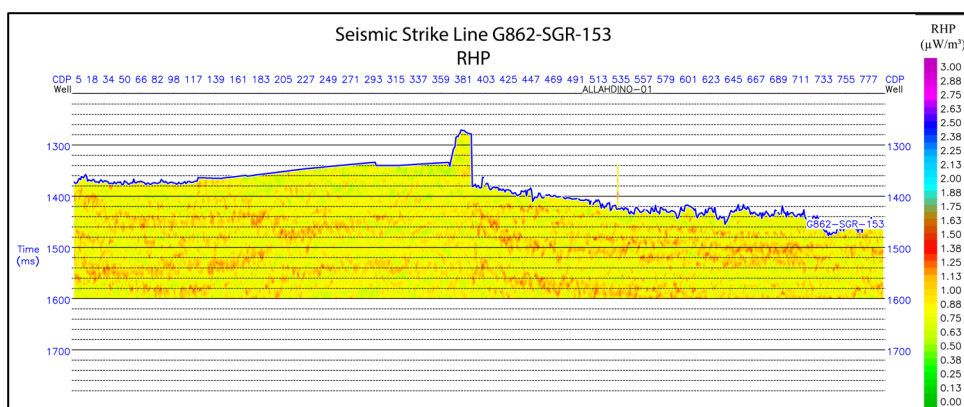


Figure 4.124 2D strike line G862-SGR-153 demonstrates the RHP on the seismic section. Consistence value in the seismic section is observed with the range of 0.63 to 1.25 $\mu\text{W}/\text{m}^3$.

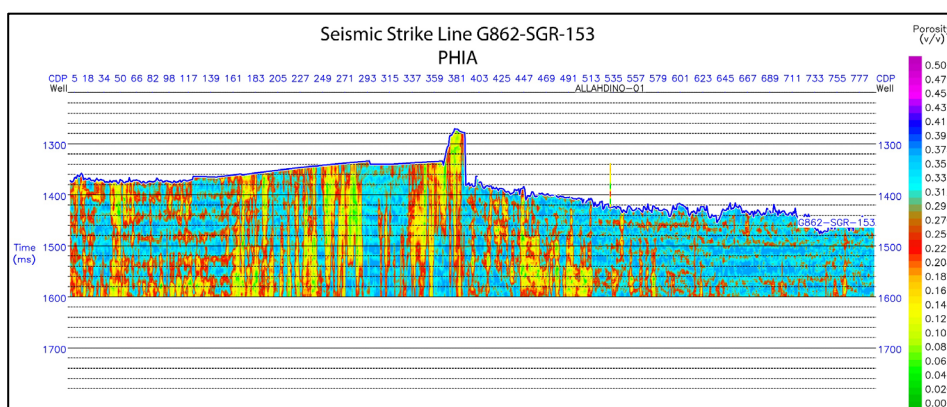


Figure 4.125 2D strike line G862-SGR-153 demonstrates the PHIA on the seismic section. The range of PHIA varies between 25 to 30%. The highest value of PHIA is encountered around the well position.

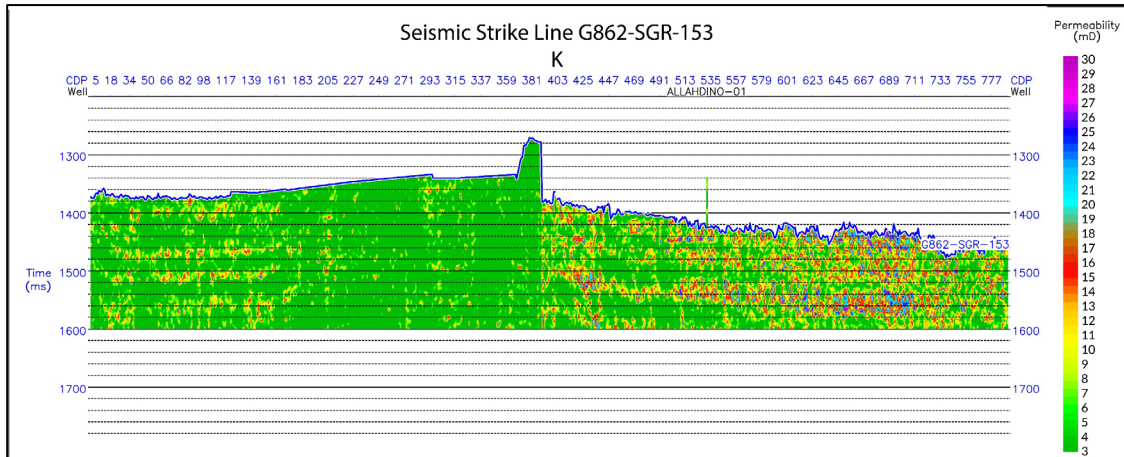


Figure 4.126 2D strike line G862-SGR-153 demonstrates the K on the seismic section. Higher K is encountered in the well position. The trend of K is to decrease toward the western side of the seismic section.

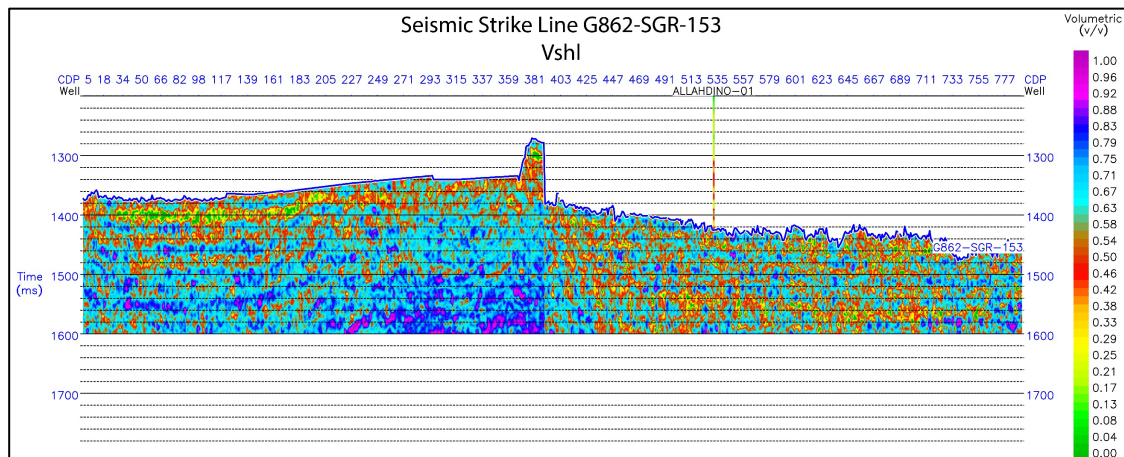


Figure 4.127 2D strike line G862-SGR-153 demonstrates the Vshl on the seismic section. Higher Vshl is encountered across the seismic section for LGF.

The dip line G862-SGR-102Ext is present on the southern portion of the base map, with the presence of Bukerani-1 at the 90 CDP. Geothermal characteristics are estimated on Bukerani-1 well and in the end, the whole variation of properties is shown in the seismic dip line, by using regression techniques, across the LGF. The correlation developed among the curves, and it is argued that the DFFNN approach, which is employed as an innovative approach, is the optimum technique for getting accurate geothermal variation in the extension regime, which is regarded as an ideal geometry for geothermal prospecting. Data is then applied across the entire 2D seismic section to generate seismic variations in the subsurface of the LGF. The optimal results are captured in seismic dip line. The HP seismic section for dip line G862-SGR-102Ext is generated by using Bukerani-1. The time of LGF in the dip line is decreasing toward the eastern

side of map. The durable relationship is established among the log curve and seismic data specifically for the HP. Figure 4.128 depicts the seismic section with the variation of HP that lies in the range of 0 to 3 $\mu\text{W}/\text{m}^3$ showing the quite fair uniformity. There is an excellent control of HP is observed in surrounding of the borehole position as the location between well and seismic is increase the change of HP values is observed. However, Figure 4.129 demonstrates the fluctuation of the RHP on the seismic section which represents the same trend as HP is followed. Moving toward the next seismic section which shows the distribution of PHIA in LGF which lies between 12 to 25% as shown in Figure 4.130. The trend of PHIA and K shows the direct relation between one another. In the seismic section where the PHIA is increasing the K also shows the highest values and vice versa shown in Figure 4.131. Finally, the Vshl variation is shown in Figure 4.132.

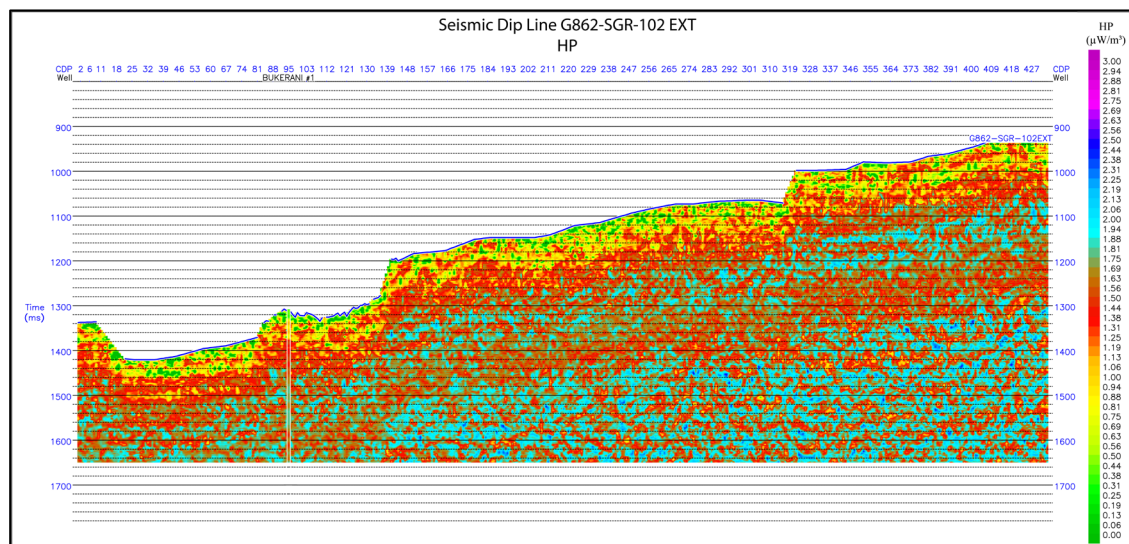


Figure 4.128 2D strike line G862-SGR-102Ext demonstrates the HP on the seismic section. Higher HP is encountered in surrounding of Bukerani-1 well. The trend of the HP fluctuated between the 0.13 to 1.55 $\mu\text{W}/\text{m}^3$.

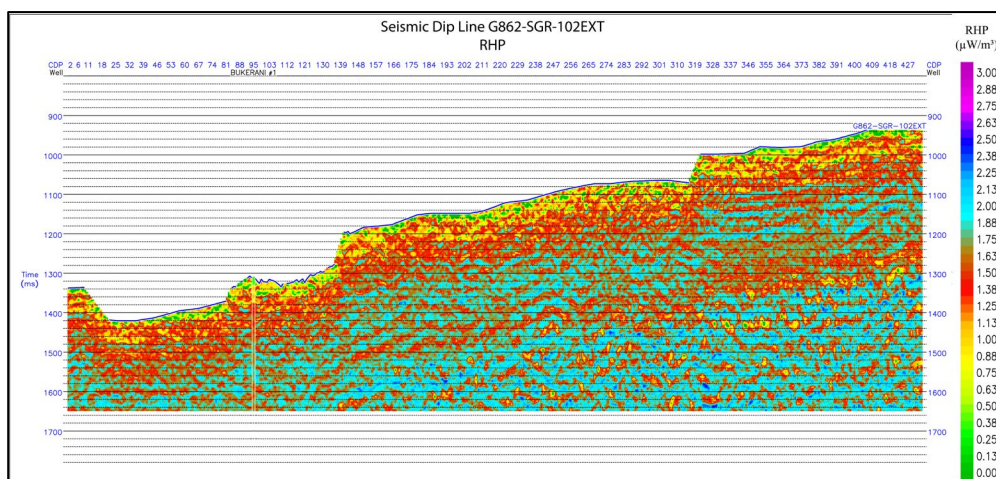


Figure 4.129 2D strike line G862-SGR-102Ext demonstrates the RHP on the seismic section along with well location of Bukerani-1. Overall LGF is deeper toward west and shows toward eastern side. However, the consistency value in the seismic section is observed with the range of 0.50 to 1.53 $\mu\text{W}/\text{m}^3$.

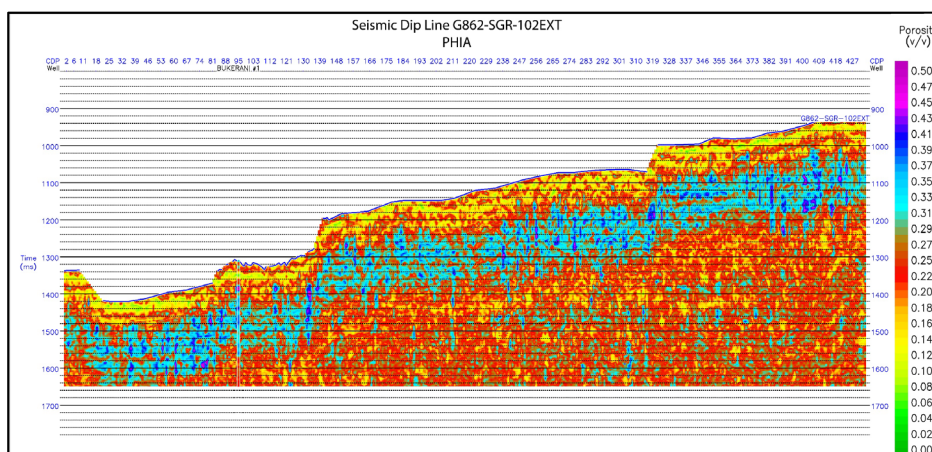


Figure 4.130 2D strike line G862-SGR-102Ext demonstrates the PHIA on the seismic section. The range of PHIA varies between 10 to 25%.

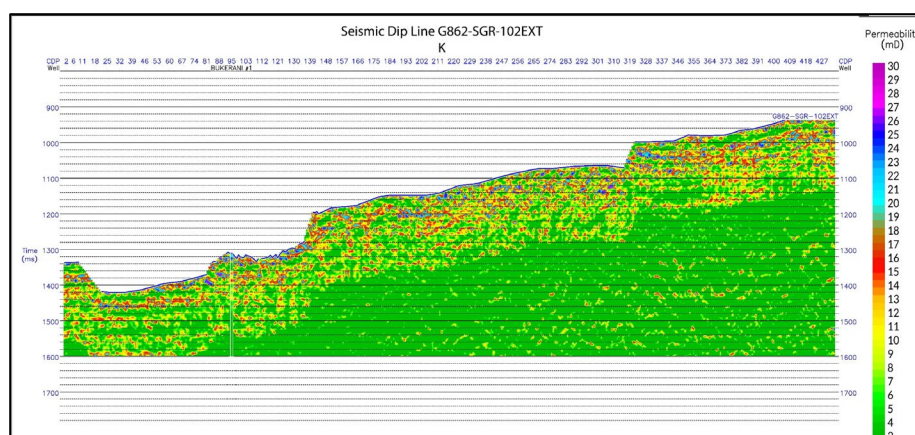


Figure 4.131 2D strike line G862-SGR-102Ext demonstrates the K on the seismic section. Higher K is encountered in the well position. The hold of well is weak as the distance between well and seismic is increased.

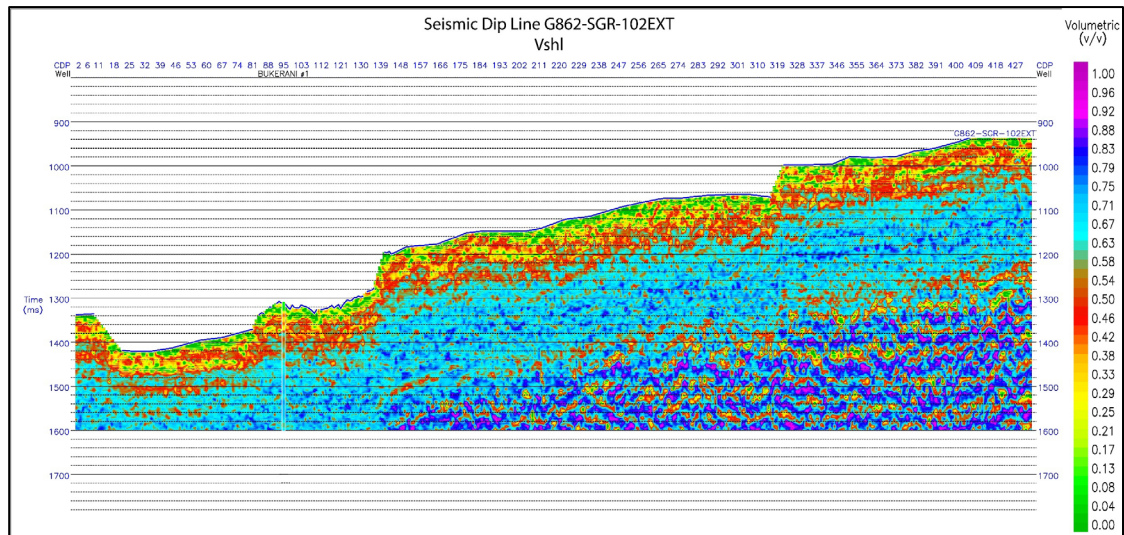


Figure 4.132 2D strike line G862-SGR-102Ext demonstrates the Vshl on the seismic section. On the upper portion of LGF lower Vshl is encountered but as it moved deeper the Vshl is increased.

Estimation of geothermal characteristics, by using regression techniques, are estimated in Jarwar-1 well location across the LGF. The HP seismic section for dip line G862-SGR-103Ext is generated by using Jarwar-1. The best match is observed among the log curve and seismic data, consistency between the values of HP is observed in the seismic section, the range of HP lies between 0.75 to 1.75 $\mu\text{W}/\text{m}^3$ as shown in Figure 4.133. The value of HP is observed high near the Jarwar-1 position but as the distance between the well and CDP is increasing the control of HP on the well location is minimum. Seismic transect of strike line G863-SGR-103Ext is also generated for PHIA by using Jarwar-1 well which is demonstrated on Figure 4.134. The PHIA of Jarwar-1 lies between the 25 to 30% as shown is color legend of seismic section. While Figure 4.135 illustrated the seismic section with K variation, the range of K lies at the range of 0 to 20 mD around the Jarwar-1 well position. Figure 4.136 demonstrates the Vshl distribution on the seismic strike section. A higher Vshl is observed on the surrounding portion of the well position.

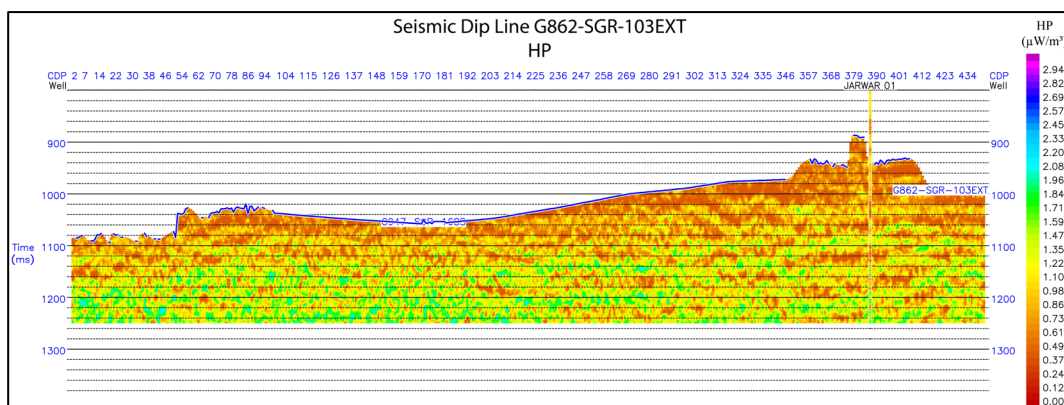


Figure 4.133 2D strike line G862-SGR-103Ext demonstrates the variation of HP on the seismic section. The range of HP is lies between the 0.75 to 1.75 $\mu\text{W}/\text{m}^3$.

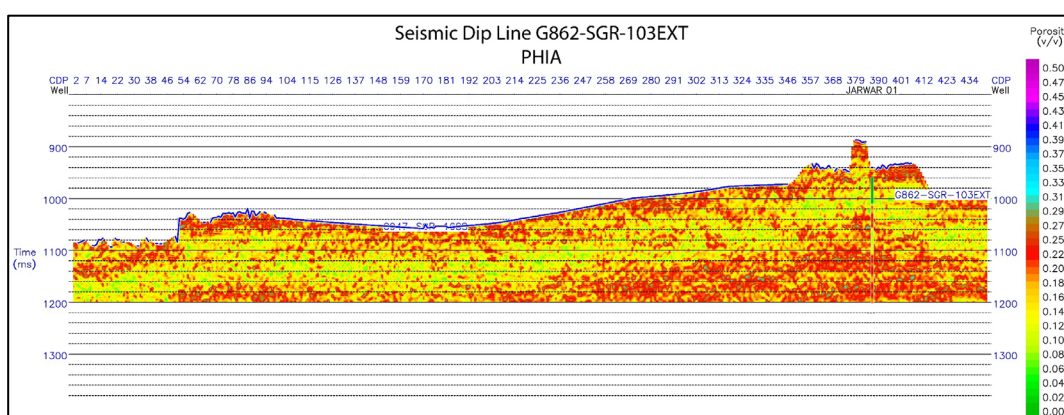


Figure 4.134 2D strike line G862-SGR-103Ext demonstrates the PHIA on the seismic section. The range of PHIA varies between 17 to 25% for LGF.

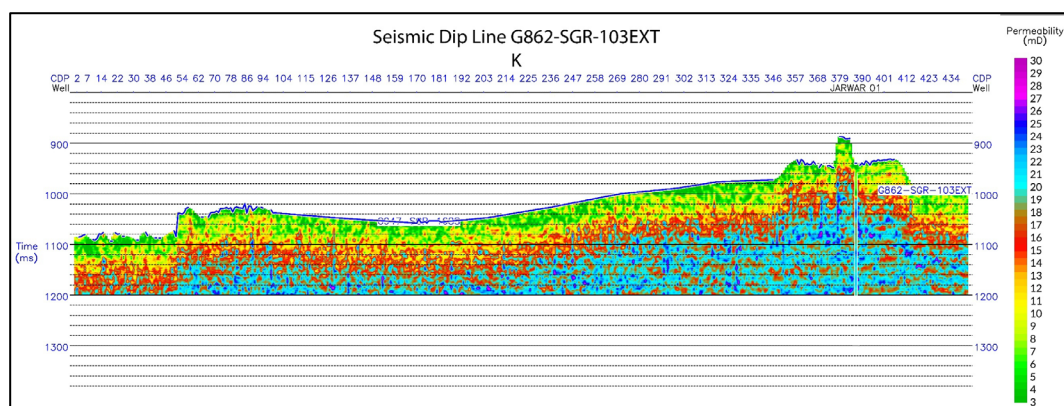


Figure 4.135 2D strike line G862-SGR-103Ext demonstrates the K on the seismic section. Higher K is encountered at the well position. The trend of K is to decrease toward the western side of the seismic section.

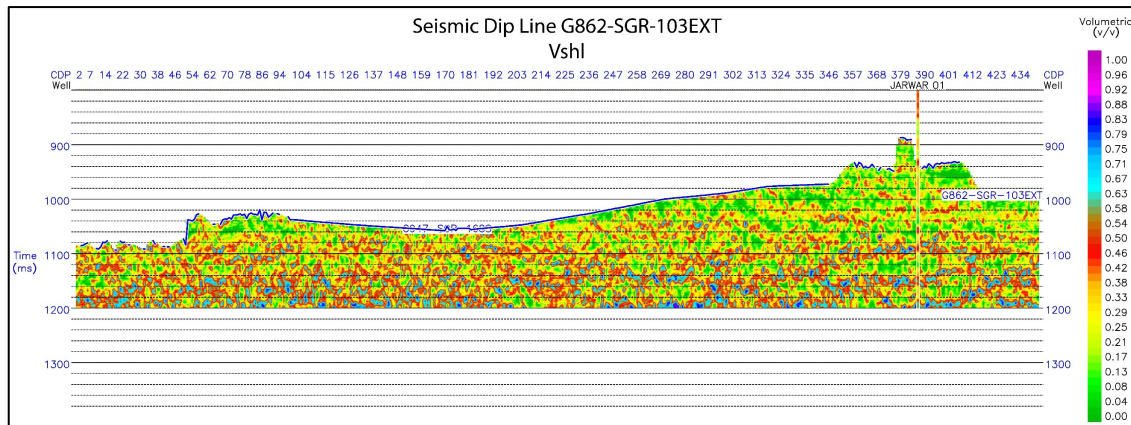


Figure 4.136 2D strike line G862-SGR-103Ext demonstrates the Vshl on the seismic section. The higher and lower Vshl is encountered in overall seismic section which demonstrates the presence of interbed of clean and shaly lithology.

Correlation is established between the geothermal properties curves, and it is argued that the DFFNN technique, which is employed as an innovative approach, is the optimum approach for getting accurate geothermal fluctuations within the extension basin, which is regarded as an ideal basin for geothermal exploration. Data is then applied across the entire 2D seismic section to generate seismic variations in the subsurface of the LGF. The optimal results are captured in seismic strike line. The HP seismic section for strike line G947-SGR-168S is generated by using four wells as discussed above. The seismic section of HP indicates that Tando Allah Yar-1,2 and 3 wells demonstrate the lower HP as compared to Jumman Shah-1 well the HP is higher on the eastern side where the high values are encountered which is between 0 to 3 $\mu\text{W}/\text{m}^3$ as depicts in Figure 4.137. In Figure 4.138 the seismic variation of RHP is shown on the strike line by using DFFNN at LGF. The variation of RHP is observed at a well location that is up to 1.25 $\mu\text{W}/\text{m}^3$. In the case RHP the spectral gamma ray is absent in Jumman Shah-1 well, so the RHP is calculated on the basis of remaining three well. The variation of PHIA is consistent in all over the seismic section, the range of PHIA is lies between the 20 to 30% which is consider as a good PHIA, the lateral change in the PHIA is less as compared to vertical change because as the depth is increasing the log curve is ended and the hold on PHIA will become week as shown in Figure 4.139. Figure 4.140 depicts the K outcomes by utilizing four wells on seismic strike line G947-SGR-168S. The highest K is encountered in the zone surrounding by Tando Allah Yar Well which demonstrates that on the western portion K is higher as compared to eastern side where Jumman Shah-1 well is present. The seismic section shown the quite a good match with the well log curve.

Figure 4.141 demonstrates the V_{shl} distribution on the seismic strike section. A higher V_{shl} is observed near the Jumman Shah-1 well. The trend of V_{shl} is increasing toward the eastern side.

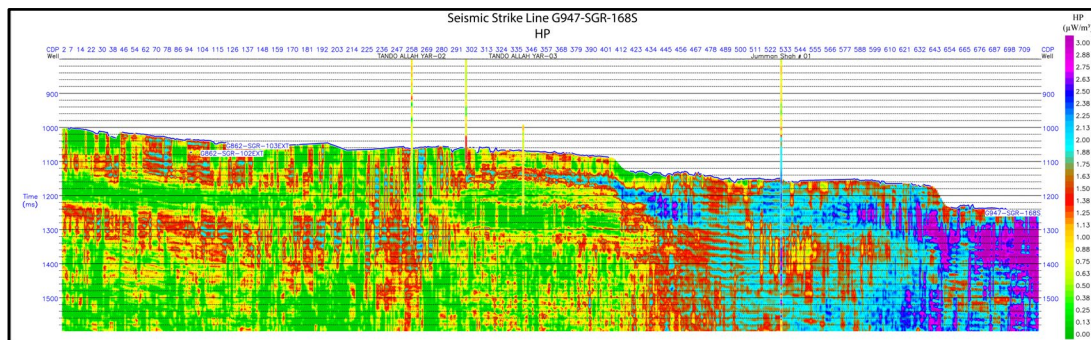


Figure 4.137 2D strike line G947-SGR-168S demonstrates the HP of LGF horizons on the seismic section. The trend of HP is increasing toward east side around the Jumman Shah-1 with the range of HP is greater than $2 \mu\text{W}/\text{m}^3$.

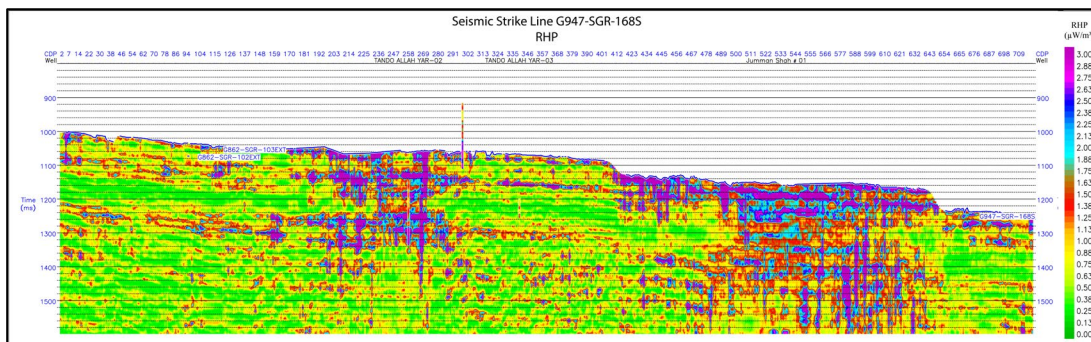


Figure 4.138 2D strike line G947-SGR-168S demonstrates the HP on the seismic section. The RHP is estimated by utilizing three well Tando Allah Yar-1,2 and 3 whereas in Jumman Shah-1 the spectral gamma ray is missing so on the basis of three well RHP is interpolated on the whole seismic section by using DFFNN algorithm.

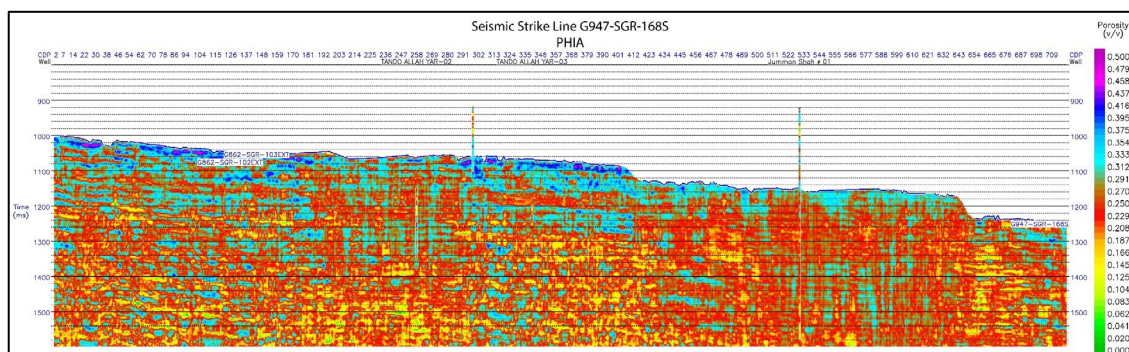


Figure 4.139 2D strike line G947-SGR-168S demonstrates the PHIA on the seismic section. The range of PHIA varies between 25 to 30%, the higher PHIA is observed around the Tando Allah Yar wells position.

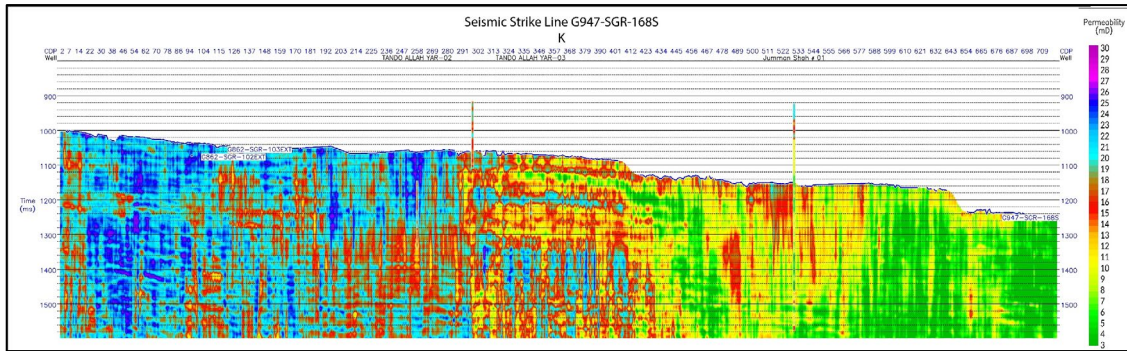


Figure 4.140 2D strike line G947-SGR-168S demonstrates K on the seismic section. Higher K is encountered in the well position. The trend of K is to decrease toward the eastern side of the seismic section.

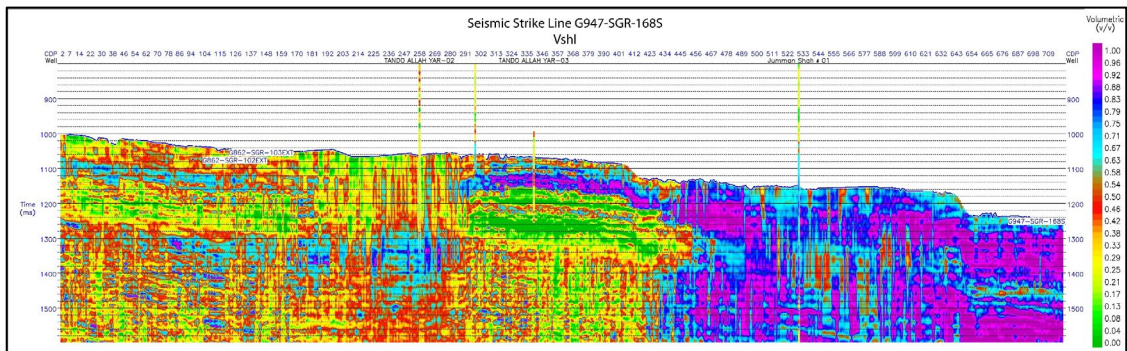


Figure 4.141 2D strike line G947-SGR-168S demonstrates the Vshl on the seismic section. The Vshl is increasing on the western portion of the map around the Jumman Shah-1 well because the LGF is dipping toward the eastern size where the time of LGF is increasing.

4.7 Geothermal Properties Mapping

The current study is based on the detailed analysis for geothermal exploration by estimating thermal and petrophysical properties along with their regional scale mapping. The analysis is performed on the basis of geothermal properties contour mapping which is color coded with rainbow template where the high values are illustrated by red to orange color and lower values are shown with blue to purple shade. Figure 4.142 (a & b) demonstrates the contour map of the HP and RHP where HP is range in 0.68 to 1.66 $\mu\text{W}/\text{m}^3$ and the RHP is lies between the 0.51 to 1.4 $\mu\text{W}/\text{m}^3$. The K, PHIA and PHIE also play a vital role in the geothermal reservoir because the reservoir is not only hot but also has an ability to capture and transmit fluids. Figure 4.142 (c & d) shows the PHIA and PHIE maps. The most promising zone with respect to geothermal point is that region in the map where there is high porosity greater than 15 % present in northeast side of map along the Jumman Shah-1 well, while a local zone is also present on middle and southern portion of map. In contrast K where it shows higher values greater than 20 mD

establishing a prominent zone geothermal prospect. Permeability is a crucial parameter because it is defined as the rate in which heat flows in the reservoir as shown in figure 4.142 (e). Figure 4.142 (f) indicates the FT map which provides the direct indication of geothermal anomaly. The map discloses a diverse thermal anomaly situated in the southeastern part of the map, where temperatures are elevated above 77°C. This area is centered around the Tando Allah Yar-1 and Tando Allah Yar-2 wells, representing the thermal essential of the potential prospect. The temperature gradient seems to decline near the northern western region, signifying the heat resource is most significant in the south to east. This regional highest temperature area is the main source of geothermal energy. Although the total variation of PHIA, PHIE and K do not perfectly intersection, there is a vital region of high to moderate permeability and porosity that interconnects with the temperature anomaly, signifying a feasible geothermal body. The thickness map of LGF reveals an immense reservoir anomaly, with thickness more than 1400 m, positioned in the northern part of the region, related with the Tando Allah Yar-3 well as shown in figure 4.142(h). Whereas the core temperature anomaly lies slightly to the south to east of this thickest section, the intersection of noteworthy thickness (>300m) with the high-temperature zone near Tando Allah Yar-1 is highly encouraging for economic viability. Figure 4.142 (f) The Vshl map is crucial for identifying both the reservoir quality and the effectiveness of the seal. The lowest shale content (less than 10-15%), indicative of the cleanest and most permeable reservoir rock, is found in the northeastern and southeastern corners.

Conversely, the map's center and western areas are distinguished by a large volume of shale, which is thought to function as a successful vertical seal (cap rock). Since they prevent vertical fluid and heat transfer while permitting buildup within underlying permeable strata, these shale-rich periods are probably going to serve as efficient vertical seals or cap rocks. Since they prevent vertical fluid and heat transfer while permitting buildup within underlying permeable strata, these shale-rich periods are probably going to serve as efficient vertical seals or cap rocks. The highest formation temperatures, a key factor in the potential for geothermal energy, are found in this target zone. Additionally, it exhibits a favorable mix of moderate to high effective porosity and high permeability, indicating the reservoir's potential to effectively store and transfer geothermal fluids. The zone's low shale content, which indicates good reservoir quality, and higher shale volume areas, which probably act as confining units and provide the required sealing integrity, define it. Additionally, the reservoir in this designated area is

quite thick, making it economically feasible to build. In particular, the region that includes the Tando Allah Yar-1, Tando Allah Yar-2, and Jarwar-1 wells is the most promising area for further investigation. All of the essential conditions—high temperature, high permeability, suitable porosity, and substantial reservoir thickness—are only found in this specific area. The discovered geological characteristics clearly point to the existence of a high-enthalpy, permeable reservoir that is successfully sealed by an overlying cap rock, meeting all of the requirements for a geothermal field that may be made profitable.

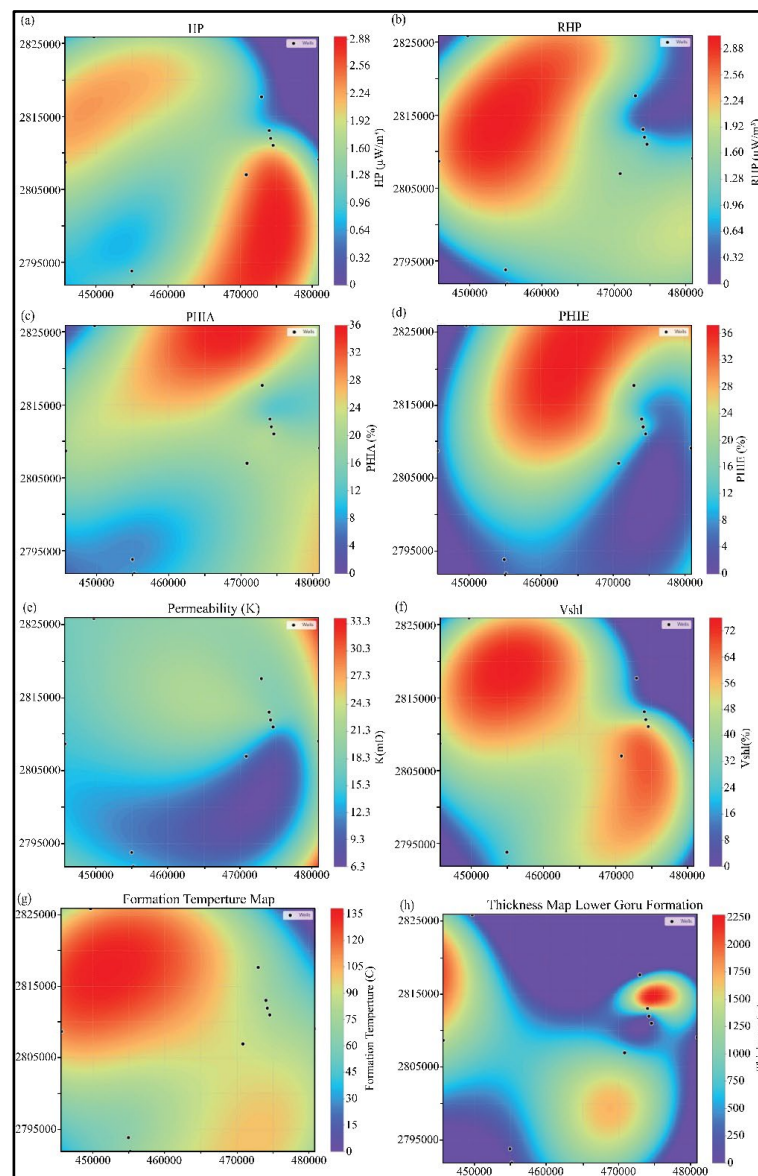


Figure 4.142: Petrophysics and thermal mapping of LGF generated using the well data of Sanghar block. (a) represent the slice map of Heat production (b) illustrate the Radiogenic heat production of the LGF (c&d) shows the porosities slice of LGF (e) shows the permeability slice (f) demonstrate the Vshl maps. In the last (g) represents the formation temperature and (f) demonstrate the thickness slice of LGF.

4.8 Discussions

The current study area is Sanghar Block, which is situated in Thar Platform, and it is considered the third largest district of Sindh. It is a sub-basin that is on the edge of SIB. The Thar Platform reveals a gentle monocline slope, which is similar to the Punjab Platform. The underneath basement topography mainly controls this slope. Particularly, the thin sedimentary section gradually increases adjacent to the Indian Shield, whose superficial presence shows as Nagar Parkar High (Shah et al., 2021; Younas et al., 2016). A major distinct feature among Punjab Platform and Thar Platform is the presence of extension geometry that is present in the subsurface. The presence of horst and graben structure provides a suitable trap for the placement of fluid in the hanging wall. It is noteworthy that the Thar Platform displays a remarkable development of early-to-middle Cretaceous reservoirs, making it a geologically significant area for further exploration and potential resource development (Rasool et al., 2018). A comprehensive petroleum as well as geothermal system in the Thar Platform consists of LGF as a primary reservoir while Sembar acts as a source and Ranikot as a seal in the region (Abbasi et al., 2016).

The reservoir of the Cretaceous (LGF) has potential for geothermal resources and is not considered a primary energy source within the Thar Platform. The major focus of geophysicists in our country is on hydrocarbon exploration. Therefore, this study is mandatory to explore geothermal energy sources across the region. In past studies, data acquisition, exploration, and development within the Thar Platform have focused on the primary reservoir interested in hydrocarbons. Some localized studies within a block segment have been carried out individually by companies. However, efforts to evaluate regional geothermal reservoirs are missing, and this study needs to address this lag. Not only is this beneficial to the energy department, but it also will directly impact on national interest and the economy. Hydrocarbon production is strongly associated with the coproduction of geopressured hot waters. Daily, thousands of warm water barrels are discharged into streams or reinjected into boreholes. The Sanghar-Badin Rift Basin is a substantial source of hot water exceeding 110 °C, coupled with hydrocarbons referred to as the upper portion of Sindh with respect to the sedimentary Basin, the hydrocarbon reservoirs situated in the higher sector of the LIB produce heated fluids with temperatures surpassing 150 °C (Mehmood et al., 2019; Mehmood et al., 2017). LGF sandstone from the Cretaceous period is the main reservoir rock in the Sindh monocline. Extraction originates from the Paleocene Ranikot limestone and sandstone in the Karachi depression

and the Eocene Sui Main/Habib Rahi limestone in the Kirthar depression and Sukkur Rift zone. Strong geothermal gradients, varying from 2 to 4 °C/100 m, are characteristic of the SIB.

The utilization of well and seismic data integration into conventional and unconventional techniques assist to estimate the geothermal variation. The seismic method assists in exploring the subsurface complex geological structure, stratigraphy and structural traps, and deep-seated geological features (Yasin et al., 2023). Geoscientists study various attributes from the horizons and apply them to analyses the subsurface geological stratigraphy, structures such as fractures and faults, and pore fluid characteristics (Schmelzbach et al., 2016). Seismic inversion is used to extract the physical properties of rocks and fluids from the seismic and well data. These characteristics may also be inferred from the seismic inversion in the presence of borehole data (Verma et al., 2024). In the exploration industry, seismic inversion is mostly used to locate fluid in the subsurface reservoir. The seismic inversion is based on physical parameters like density, inverted impedance, P and S wave velocity, which are sensitive to the rock saturation (Moon et al., 2024). These properties are derived from the inverted impedance, and petrophysical properties like PHIA, K, saturation, HP, and Vshl are approximated with the help of the inverted section (Li et al., 2023). The post-stack seismic inversion is based on model building from seismic, log curve, and geological data (Maurya et al., 2020). In the last few years, DFFNN has shown outstanding accuracy in predicting geothermal reservoir parameters (Aydin et al., 2020; Chen et al., 2024).

There are three seismic blocks, and the LGF is marked on all three blocks. The Nim Tay Block and Sanghar Block-2 are located in the same area, which is why the three wells Tando Allah Yar-1, 2, and 3 of the 3D Nim Tay Block are present on the 2D seismic line 947-SGR-156S along with Jumman Shah-1 well. The structure is marked on all the seismic sections for better understanding of subsurface geometry. Nisar et al. (2016) suggested that the Sanghar area is an extensional tectonic regime with normal faults forming a horst and graben structure, as indicated by the contour map, which further signifies closure structures toward the centers. Akhter et al. (2015) revealed that the structural interpretation of the Sanghar area shows normal local faults trending northwest to southeast and northeast to southwest at the Lower Goru sands (Cretaceous) and Chiltan limestone (Jurassic) formations, which are responsible for the horst and graben structures. The study confirms that the Sanghar Block lies within an extensional regime, with various normal faults observed at the LGF. Additionally, the contour map of the LGF shows that

the western portion exhibits deeper time and depth values, while the eastern portion shows shallower measurements, indicating that the LGF dips toward the west. On a regional scale, normal faults are present that create horst and graben geometry, which is considered an ideal structure from a geothermal perspective. The faults on the contour map confirm that the time/depth between faults varies, further supporting the horst and graben structure.

The detailed analysis of geothermal properties is carried out on ten wells of Sanghar Block well. In geothermal evaluation properties like HP, RHP, K, PHIA, Vshl and FT were calculated on the LGF. These properties assist to provide a clue about geothermal potential such as HP has a significance that it helps to find out the underground thermal region and potential geothermal zone as stated by (Limberger et al., 2018). RHP is used to estimate the decay of radioactive elements like U, Th, and K. These elements are considered a key source of subsurface heat for geothermal potential, specifically in a sedimentary basin (Jaupart & Mareschal, 2021). Vshl plays a vital role in the exploration of geothermal resources, if the Vshl is greater in the formation than it acts as a barrier for the flow of fluid, which diminishes its capability of heat extraction from the subsurface (Mao & Zhang, 2018). K is also very important for the evaluation of geothermal resources, if the connection between the rock matrix is good and there is ease for the flowing of fluid than it is considered as a good geothermal reservoir, typically in the sandstone the range of permeability lies between 0 to 100 mD (Azkia & Daud, 2021). Finally, PHIA is also a vital component in such a way that the pore space has the ability to hold a maximum amount of hot fluid considering as an excellent reservoir for geothermal potential (Weydt et al., 2022).

There are three different methods for calculating Vshl in the current studies; two methods, the Stieber and Clever equation methods, are used for the calculation of Vshl. According to Ehsan et al, (2023) and Ardebili et al, (2024), Stieber equations provide efficient results for Vshl in LGF, where sandstone and shale act as major lithologies. The average Vshl observed in the study area is 33%, which is considered low Vshl. This low Vshl is viewed as good potential for the geothermal reservoir because it has the capacity to store and transmit heat within the reservoir. The average PHIA encountered in the well is 15.9%, which constitutes good porosity; higher porosity enhances the rock's ability to store heat. When these rocks are interconnected, creating pathways for fluid flow within the reservoir, it results in good permeability. In the study area, the average K for the LGF is 16.371 mD, which is considered quite good permeability for the sandstone reservoir.

The average results of HP for wells are $0.930 \mu\text{W}/\text{m}^3$, and RHP is $1.02 \mu\text{W}/\text{m}^3$. According to the studies by Zhang et al, (2020), the average HP and RHP of sandstone in the Gonghe basin range from 0.92 to $2.81 \mu\text{W}/\text{m}^3$, indicating geothermal potential. In the current studies, RHP and HP vary from well to well, but wells Babar-1, Bukerani-1, Tando Allah Yar-1, and 2 show significant potential for geothermal exploration. Facies analysis was performed on ten wells using Python coding, with cutoffs applied to well log curves for GR, RHOB, and Vshl. Based on these three parameters, the facies are classified as gas sand, wet sand, and shale. The major facies identified are sandstone with interbedded shales. In the study area, three wells show an interbed of shale and wet sand, while the remaining seven wells contain gas sand, wet sand, and shale.

The estimated geothermal properties and predicted facies have been critically evaluated to estimate the geothermal assessment of the LGF within the Thar platform. The facies estimated is carried out via ML algorithms through which three facies have been identified named shale, gas sand and wet sand. These facies play a vital role in the behavior of reservoirs. Sand facies (wet and gas sand) is predicted by high PHIE and low GR values, signify zones with highest storage of fluid and K, assemble them promising for extraction of geothermal energy. While intervals with shale rich is identified by higher GR values act as little K barriers, dropping fluid moment but also act as heating insulator that assist as a heat trapping within the reservoir.

The geothermal characteristics investigation emphasizes that the PHIA is roughly 15.9% across the well that is in the limit of heat storage medium in LGF. Likewise, average K values is approximately 15.37 mD which shows that the pore of the sedimentary rock are interconnected with providing a path for the flowing of fluid. The essential element of geothermal energy indicators is HP and RHP and their values are $0.930 \mu\text{W}/\text{m}^3$ and $1.02 \mu\text{W}/\text{m}^3$ respectively in all the well present in the study area. The results of these properties demonstrate the moderate geothermal behavior in the sand facies where the PHIA and K overlap with raised generation of heat. Moreover, model based seismic inversion and DFNN elevated the spatial consideration of these geothermal characteristics across the seismic transect. Low inverted Z_p along with elevated PHIA interval and zone of fluid saturated emphasized the geothermal potential in those regions. The structure interpretation approves that the LGF, mostly in structure with favorable area like hosts and graben, holds the petrophysics and geothermal properties required for feasible geothermal resource development.

Seismic inversion is a technique that is used for known the impedance variation within the well and seismic section. The impedance plays a significant role in evaluating geothermal properties like PHIA. There is an inverse relationship between the porosity and impedance, which provides a clue for the porous material present in the subsurface. The statistical wavelet was generated for the initiation of model based seismic inversion for the LGF. A temporal window bordered by the horizon, spanning from the top of the LGF to the complete depth, was used to extract the wavelet. To obtain a good correlation, a seismic-to-well tie connection was constructed utilizing the seismic extracted wavelet. Finally, to further improve the coefficient of correlation, the log curve-based wavelet of 100 ms wavelength is chosen. Wavelets from the well data are extracted using the Sanghar well. Which represents all of the seismic frequency ranges, and a wavelet frequency spectrum of 25 Hz is utilized. Their frequency is recorded based on maximum amplitude. The higher dominant frequency is encountered in well. Higher frequency mostly provides detailed information about the subsurface due to which they are beneficial for detection of the shallow reservoir features. Synthetic traces are related to seismic traces for the establishment of an initial well tie and a time-depth relationship. The time window of the connection cross plot is nominated to encompass the whole study period using accessible log data to compare artificial and actual traces. To view both synthetic and actual traces, the time window for the correlation plot is selected to cover the entire duration for which log data is currently available.

The original seismic cube and the well-based wavelet of all three wells are used to construct the LFM for the seismic transects. The model illustrates the impedance fluctuation in the LGF both vertically and laterally. Color codes are used to illustrate impedance variations. The total impedance was calculated for the studies area is lies. Between the range of 6645 to 7003 ((m/s)*(g/cc)). The formation's lower portion exhibits high Z_p values, whereas the top section exhibits low impedance because of its high porosities that are filled with water. The well position has the maximum impedance with best match color code between seismic and well data.

The inversion study of the seismic data was carried out within the complete thickness of the LGF. The inversion study of the wells shows the initial inverted impedance track along with three distinct types of curves. The initial model curve is illustrated in black color, the inverted impedance Z_p is shown in red color, and an initial impedance curve created by the borehole log curve present in blue color curve. Impedance values range are varying from well to well as stated in the Z_p track description,

with a minimum error encounter in it. If this error is converted into percentage, it is less than 10 % that is acceptable in the seismic inversion analysis. The range of this error is dependent on the resolution of seismic data. The wavelet extracted by the well data is employed to create the impedance represented in blue shade beneath the wavelet track. The relationship between the created and original seismic traces is restricted by the correlation windows represented by pale lines. Finally, the trace of error is displayed, that is, the distinction among the previous results, suggesting minimal values. The results reveal a good correlation of 98% across the artificial and actual traces. Inversion analysis was performed on all wells correlations and errors are mentioned.

The inversion is then employed to the whole seismic data using the inverted impedance curve that was created at the well location. Variations in the facies and fluid characteristics in the LGF are indicated by horizontal and vertical shifts in the impedance values. The lower impedance range indicates a small, compressed region with excellent porosities, but high impedance values grow with higher sediment compaction. Additionally, the impedance values are decreased by fluid absorption within the rocks. The formation pressure and impedance have an inverse relationship therefore a geothermal potential zone may have exceptionally low impedance values because of high fluid saturation. The seismic inverted section, along with the arbitrary line result, shows the LGF estimated P-impedance values.

Calibrated HP, RHP, and K curves from well were employed to train seismic attributes at well position using geo-statistical evaluation. MAA was performed and constructed on a most favorable set of 15 seismic attributes, yielding satisfactory results for predicting geothermal properties. The overlap of the estimated (red) and calibrated HP (black) curves from the well, drawn within a range of 0 to 3 $\mu\text{W}/\text{m}^3$. The estimated curve has an average error of 8%, equivalent to 0.209 $\mu\text{W}/\text{m}^3$. The time window covers the LGF interval from 900 to 1300 ms. A cross plot, indicating the relationship between well-based and predicted HP in well-based, includes a linear regression line. HP values in the cross-plot range from 0 to 3 $\mu\text{W}/\text{m}^3$. The actual HP is plotted on the x-axis, and the predicted HP is on y-axis. While the data shows an excellent correlation between the two HP curves, some intervals exhibit scatter, resulting in an error of less than 8% in the well. The MAA is also run on RHP, Vshl, FT, and K, and the results of correlations.

The PHIA was calculated using well log data calculated with the help of RHOB and NPHI log. DFFNN was applied to predict the PHIA in the overall seismic section. The cross plot shows the result of actual vs predicted PHIA on all wells. The overall

correlation is 88%, with an error encounter of 2.40% by applying the different attribute. The average Vshl was calculated using well-log data calculated with the help of a gamma ray log. IGR was calculated and after that Stieber correction was applied to the IGR to get the accurate Vshl in the well position and the end the DFFNN was applied to show the overall variation of the Vshl on the arbitrary line seismic section. The cross plot shows the result of actual vs predicted Vshl on all wells.

DFFNN is a form of ANN that does not comprise assemblies that construct a loop among its layers. It begins with the input layer and receives its approach to the yield layer when appearing during any hidden layers (Khan et al., 2020; Li et al., 2022). DFFNN is a multi-layer back propagation neural network having three major nodes and input hidden and output nodes. Every node has a consequence linked to the closest nodes, and unseen layers aim to suitable the data for training reliability with the connected over-fitting. In comparison, certain of the hidden layers distribute concealed outcomes. Thus, the greater the number of layers, the smaller the training error and the greater the confirmation error. The training uses conjugate solution descent to investigate the greatest powers of the networks among layers, which forecast estimations as strongly as feasible to the truth one. Hence, DFFNN has excellent regulation of training factors at a greater speed than PNN (Sotelo et al., 2024).

Applying DFFNN evaluation to HP on the wells position improved the correlation among the modeled and corrected well-based HP curves. Attributes from seismic and the modeled HP log trained by MAA were more refined using nonlinear DFFNN evaluation, which reduced data point scatter. The choice of obscure layers reduced the mean error of 1.6% among predicted and well-calculated HP curves, resulting in an extreme coefficient of correlation of about 93.4%, established on DFFNN results. The input in the DFFNN cross plot shows less scatter than the best-fit line compared to the MAA cross plot. The non-linear neural network approach and the various hidden layers employed in the DFFNN analysis are responsible for the strong correlation that exists between expected and accurately identified actual HP ranges. Because there were multiple layers that were concealed in the DFFNN investigation than in PNN or FNN, the exactness and reliability of the heat generation predictions were higher. Additionally, the RHP and K are subjected to the DFFNN analysis. Predicted HP curves, utilizing regression methods, are computed in all three well positions across the interesting region. A correlation was established among the initial curves, and it is argued that the DFFNN approach, which is employed as an innovative technique, is the optimum approach for getting accurate geothermal

fluctuations within the extension basin, which is regarded as an ideal basin for geothermal exploration.

To summarize the geothermal properties of LGF both internationally and regionally, they have been compared with recorded data from geothermal systems worldwide. For example, the range of RHP and HP in this research falls between 0.66 and 1.54 $\mu\text{W}/\text{m}^3$, which can be compared to those in the Gonghe Basin of China, where RHP and HP range from 0.92 to 2.80 $\mu\text{W}/\text{m}^3$, clearly indicating geothermal production potential (Zhang et al., 2020). In comparison, international validation by Jaupart & Mareschal (2021) highlights that in sedimentary basins where RHP exceeds 1 $\mu\text{W}/\text{m}^3$ and HP increases by 0.80 $\mu\text{W}/\text{m}^3$, there is a strong indication of geothermal prospects, which aligns with the results obtained in LGF at Thar Platform. Furthermore, the average K and PHIA values calculated in this research are similar to those in geothermal reservoirs within the Paris and Western Canada Sedimentary Basins, where PHIA ranges from 12 to 20%, and K ranges from 10 to 50 mD, which are ideal for geothermal potential (Weydt et al., 2022; Azkia & Daud, 2021). These global standards support the conclusion that the geothermal reservoir properties in LGF fall within the ideal range for medium to high enthalpy geothermal systems.

In the Thar Platform, the dominant structure is horst and graben due to an extensional tectonic regime. These structure geometries are similar to those of the East African Rift present in the Basin and Range Province of the USA. Normal faulting has elevated the geothermal reservoir connectivity, facilitating fluid flow. These assessments support the interpretation results of LIB, where normal faulting is present and fluid flow is possible, thus enhancing geothermal evaluation of thermal fluid circulation. To summarize, the geothermal potential of LGF in the Thar Platform aligns well with global case studies of geothermal reservoirs. These characteristics position the Thar Platform as a significant future resource for geothermal exploration and development in Pakistan's renewable energy agenda.

The present studies provide a detailed analysis of LGF with respect to geothermal exploration using well and seismic data. There are certain limitations of the study that should also be acknowledged. The study was limited to the availability of only ten wells, which do not fully describe the regional trend of the Thar Platform. Moreover, due to the absence of rock core data and the unavailability of temperature data, an indirect approach was used for estimation, such as HP and RHP, which were based on well log parameters. However, novel approaches like Model-Based Inversion analysis and DFFNN help

increase the accuracy of prediction and resolution, but there is still a chance of uncertainty due to limited well control points. Additionally, other geophysical data (gravity and magnetic) are also required for the validation of the results.

Pakistan required advanced techniques for effective implementation of geothermal energy. First and Foremost, a dynamic governing framework and strategy are essential. This requires developing a vibrant administrative organization accountable for development of geothermal, rationalization approving processes, and contribution of attractive packages for both industrial and private stakeholders. Pakistan's dependence on imported fossil fuels highlights the urgent need to shift to renewable energy sources such as geothermal, to improve energy security and support economic stability.

Second, developing and adopting suitable geothermal skills is vigorous. For modest temperature resource in Pakistan binary cycle power plants are predominantly well location. Capitalizing in unconventional heat mining approaches will back hidden geothermal integration and sustainable production. It is also important to evaluate the economic viability of these projects, considering factors like local energy market conditions, government incentives, and financing options. Though geothermal projects may involve higher initial costs, their low operating expenses and capacity to generate inexpensive, baseload electricity offer significant long-term benefits by reducing reliance on costly fossil fuel imports.

Third, conducting a comprehensive resource assessment and exploration program is crucial. Although Pakistan shows known geothermal signs, especially along its seismic belt and northern areas, significant efforts are required to fully identify and harness these resources for power generation. This involves targeted geological and geophysical surveys, such as gravity measurements and exploratory drilling, to accurately locate suitable reservoirs and obtain essential data on temperature and permeability.

Finally, effective implementation depends on strong stakeholder collaboration and ongoing capacity building. This means forming partnerships among private investors, government bodies, and local communities, with the government facilitating permits and creating a supportive regulatory framework. Additionally, developing a skilled workforce through specialized training and capacity-building programs is essential for the sector's sustained growth. Geothermal energy's ability to deliver reliable, baseload power makes it a valuable complement to intermittent renewables like wind and solar, helping create a more stable and diverse national energy mix.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATION

5.1 Conclusion

Current studies demonstrate geothermal properties assessment using conventional and ML techniques on the LGF. The major results of geothermal properties by applying ML approaches are described as follows:

1. The delineation of subsurface structures through seismic data interpretation has confirmed the presence of an extensional tectonic regime beneath the surface. Because of this extension regime, normal faults are observed along horst and graben structures underground. These horst and graben formations create separate compartments that can trap reservoirs. The main structure is shown in the regional 2D seismic lines of Sanghar Block-1 and 2, where a series of normal faults are evident. Mapping indicates that, from east to west, the LGF dips increasingly with depth and time.
2. Geothermal properties estimation is carried out on all the wells at the LGF. The result of geothermal properties exhibits that the HP of four wells is greater than $1 \mu\text{W}/\text{m}^3$ which is considered as a good HP named as Tando Allah Yar-1 ($1.0064 \mu\text{W}/\text{m}^3$), Tando Allah Yar-2 ($1.2674 \mu\text{W}/\text{m}^3$), Babar-1 ($1.399 \mu\text{W}/\text{m}^3$) and Bukerani-1 ($1.54 \mu\text{W}/\text{m}^3$) while the RHP of these well is $0.94 \mu\text{W}/\text{m}^3$, $1.07 \mu\text{W}/\text{m}^3$, $1.545 \mu\text{W}/\text{m}^3$, $2.242 \mu\text{W}/\text{m}^3$ for Tando Allah Yar-1, 2, Babar-1 and Bekerani-1 respectively. The FT of the wells that are encountered in the study area at the LGF is in the range of 65 to 113 °C, which is also in favor of geothermal potential. However, the average PHIA is 15.5%, which is considered fair to good PHIA, along with the average K of 16.37 mD, and the Vshl is 33%.
3. Facies analysis of the LGF was estimated on all ten wells that lie in the study area. The facies evaluation confirmed that the major lithology of the LGF is sandstone with interbeds of shale.
4. The predicted geothermal reservoir properties are PHIA, HP, RHP, Vshl, and K, indicating the presence of a geothermal reservoir in the subsurface. It is argued that the DFFNN approach, which is employed as an innovative technique, is the optimum approach for getting accurate geothermal fluctuations within the extension basin, which is regarded as an ideal basin for geothermal exploration, with correlation values from 85 to 97.80% of all derived geothermal reservoir properties. PHIA and K values are high in the study area, which makes it more attractive for geothermal prospects.

5.2 Recommendations

1. The current approach for geothermal energy evaluation is highly innovative but to make the result more efficient, more geophysical methods should be included like gravity and magnetic methods which help to map the variation of hot fluid in the subsurface.
2. Based on the well log curve the temperature log curve of the well must be recorded to evaluate the exact temperatures of the formation with respect to geothermal properties evaluation.

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APPENDICES-PUBLICATIONS

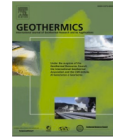
APPENDICES-A

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Geothermal investigation of sandstone reservoirs using a probabilistic neural network with 2D seismic and borehole data: insights into structural and reservoir characteristics

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ABSTRACT

One form of renewable energy that is gaining attention globally is geothermal energy resources. Geothermal energy potential exists in Pakistan; however, these resources have not yet been fully tapped because of a lack of research. The present study aims to utilize 2D seismic and well data to explore the geothermal potential of the Lower Indus Basin, specifically in the Sanghar Block, and the target was the Lower Goru Formation sandstone reservoir. The 2D seismic structural interpretation confirms that the area has normal faulting with the horst and graben structure, indicating extension tectonics. A seismic attributes analysis was performed on 2D seismic data, such as spectral decomposition, similarity variance, trace envelop, and instantaneous frequency. It also confirms the presence of geothermal anomalies, such as high frequency and reflectance, at the Lower Goru Formation. Two wells, Sono-2 and Sono-5, were utilised for studies in which heat production, formation temperature, average porosity, shale volume, and permeability were computed. Seismic inversion was performed to assess the impedance in the overall study block. Model-based seismic inversion analysis results indicated that 98 % and 92 % correlation were achieved at the Sono-2 and Sono-5 wells, respectively. Probabilistic Neural Network (PNN) techniques were employed for geothermal reservoir properties and interpolated in the seismic section to assess geothermal potential. The outcomes obtained from geothermal properties via PNN indicated excellent correlation values of 94.50–98.80 % around the well location. The findings of the study suggested the presence of geothermal resources in the study region.

1. Introduction

Renewable energy is eco-friendly, possibly sustainable, and produces very low carbon emissions. Geothermal energy resources are believed to be vital renewable energy resources around the globe, as they are abundant, stable, and reliable. Usually, geothermal energy is obtained from heating water and then released and converted on the ground (Zhao et al., 2024). This is not only an effective method for maintaining the pressure of the reservoir but also an effective method for subsurface water disposal (Gan et al., 2022). The sandstone reservoirs (porous and permeable), which are distributed in many sedimentary basins around the globe, are considered a prime geothermal reservoir target for the exploration of medium to deep geothermal resources (Xia et al., 2023). Sandstone reservoirs have specific structures (faults and fractures) are of

special interest due to high enthalpy geothermal targets in sedimentary basins (Haffen et al., 2017). The utilization of geothermal energy from a sandstone reservoir is exploited in major basins around the globe (Gan et al., 2022).

Preferably, core data is used to evaluate the reservoir properties and is also used to calculate the porosity and permeability, which are key parameters for geothermal reservoir evaluation. However, core samples are expensive, limited, and normally unavailable in deep reservoirs. To cope with this issue, seismic and well logs are used to obtain reservoir properties. The petrophysical parameters (porosity and permeability) are derived from well log data. Seismic reflection is the preferred method to obtain high-resolution subsurface imaging for deep geothermal reservoirs to understand the structure pattern (Ashraf et al., 2024a, 2024b; Abraham-A et al., 2022; Bredesen et al., 2021).

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APPENDICES-B

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Results in Engineering

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Lithofacies and sandstone reservoir characterization for geothermal assessment through artificial intelligence

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Deep Feed Forward Neural Networks
Seismic inversion
Facies analysis

ABSTRACT

Pakistan has potential for geothermal energy within the subsurface, but these resources are still unexplored due to limited research. The present study prime aims to utilize seismic and well data to explore the geothermal potential of the sandstone reservoir. Facies analysis was performed based on well data through machine learning, demonstrating that the major facies present are sandstone and shale in the target Formation. It has been inferred in the current assessment that the presence of radioactive elements in these lithologies is an active source of heat in the subsurface. Deep Feed Forward Neural Network (DFFNN) techniques were employed to populate geothermal reservoir parameters into the seismic section. DFFNN can enhance the integration of seismic and well data for reservoir characterization by estimating rock properties obtained from seismic inversion methods. DFFNN approach achieved correlation values from 88.60–93 % for geothermal properties at the well position. This study is novel due to its combination of statistical methods and an artificial intelligence approach that enables the identification of geothermal perspective maps (heat production and radiogenic heat production) on seismic sections that are typically not studied before. The outcomes of subsurface geothermal reservoir parameters average values derived from well logs data: average porosity (18 %), volume of shale (22.67 %), heat production (0.988 $\mu\text{W}/\text{m}^3$), radiogenic heat production (0.847 $\mu\text{W}/\text{m}^3$), and permeability (17.74 mD) are quite promising which indicates that the current study region is favorable for geothermal resources. It has been concluded that the current study approaches have improved the prediction accuracy of geothermal reservoir properties.

1. Introduction

The world is expanding and the demand for energy increases. To meet these energy demands, new energy sources are being explored. Investigations and development are underway to identify reliable and renewable energy sources, minimize carbon footprints, and create a greener environment for future generations. Many renewable energies

have emerged as the outcome of research and development, among which geothermal energy is one [1]. The energy from geothermal sources comes beneath the Earth's crust as a result of the planet's emergence and radioactive decay of minerals. The geothermal gradient, or the temperature variation across the center of the Earth and its outermost layer, causes the continual conduction of thermal energy in the form of radiant heat from the core of the Earth because of the

Abbreviations: ML, Machine Learning; DFFNN, Deep Feed Forward Neural Network; ANNs, Artificial Neural Networks; MALR, multi-attribute linear regression; PNN, Probabilistic Neural Network; MLFN, Multi-Layer Feed-forward Network; DL, Deep Learning; AI, artificial intelligence; PIIIA, Average Porosity; V_{sh} , Volume of Shale; K, Permeability; HP, Heat Productivity; RHP, Radiogenic Heat Production; LJB, Lower Indus Basin; GHPL, Government Holdings Private Limited; OGDCL, Oil and Gas Development Company Limited; 3D, Three-dimensional; DT, sonic log; LLD, resistivity log; GR, gamma ray log; RHOB, density log; LOF, Local Outlier Factor; SVM, One-Class Support Vector Machine; MBSI, Model-based seismic inversion; MAA, Multi-attribute analysis; LFM, Low Frequency Model; CDP, Common Depth Point; IGR, Gamma Ray Index; S_{wirr} , Irreducible water saturation; ρ , Density; C_U , Concentration of uranium; C_{Th} , Concentration of thorium; C_K , Concentration of potassium; F, Formation Factor; ϕ , Porosity; a, lithologic constant; m, Cementation Exponent; K_{Timur} , Timur permeability.

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EVALUATION OF STRUCTURAL DRIVEN GEOTHERMAL SYSTEMS: A COMPREHENSIVE GEOPHYSICAL ANALYSIS IN THAR PLATFORM, SOUTHERN INDUS BASIN, PAKISTAN

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