RESERVOIR CHARACTERIZATION IN TERMS OF PERMEABILITY FROM WELL LOGS USING NON PARAMETRIC TECHNIQUES (ANN, ACE) FOR IMPROVED RECOVERY FROM OFFSHORE FIELDS

A Project Report
submitted by,

BINU ELDHO KURIAN (R770214028)

GEEVARGHESE RAJU(R770214008)

In partial fulfilment of the requirements

for the award of the degree of

MASTERS OF TECHNOLOGY

in

PETROLEUM EXPLORATION

Under the Guidance of

Dr. Pushpa Sharma
Professor
UPES, Dehradun

DEPARTMENT OF PETROLEUM ENGINEERING & EARTH SCIENCE

COLLEGE OF ENGINEERING STUDIES

UNIVERSITY OF PETROLEUM & ENERGY STUDIES

Bidholi Campus, Energy Acres,

Dehradun-248007

April-2016

DECLARATION BY THE SCHOLAR

I hereby declare that this submission is my own and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other Degree or Diploma of the University or other Institute of Higher learning, except where due acknowledgement has been made in the text.

BINU ELDHO KURIAN (R770214028)

GEEVARGHESE RAJU (R770214008)

CERTIFICATE

This is to certify that the thesis titled **RESERVOIR CHARACTERIZATION IN TERMS OF PERMEABILITY FROM WELL LOGS USING NON PARAMETRIC TECHNIQUES (ANN, ACE) FOR IMPROVED RECOVERY FROM OFFSHORE FIELDS**

submitted by *BINU ELDHO KURIAN (R770214028) and*

GEEVARGHESE RAJU (R770214008)

to the University of Petroleum & Energy Studies, for the award of the degree of MASTER OF TECHNOLOGY in Petroleum Exploration is a bonafide record of project work carried out by him under our supervision and guidance. The content of the thesis, in full or parts have not been submitted to any other Institute or University for the award of any other degree or diploma.

Internal Mentor:

Dr. Pushpa Sharma
Professor
Dept. of Petroleum & Earth
Sciences, UPES, Dehradun.

ACKNOWLEDGEMENTS

This project involved the collection and analysis of information from a wide variety of sources and the efforts of many people beyond me.

We would like to express my sincere gratitude to Dr. Pushpa Sharma (Professor, Dept. of Petroleum and Earth Sciences, College of Engineering Studies –University of Petroleum & Energy Studies, Dehradun) for guiding me throughout the completion of the project and for explaining many important basics from the scratch and for his constant help when we needed it..

Finally we express thanks and appreciation to Dr. Mandira Agarwal (Professor, Dept. of Petroleum and Earth Sciences, College of Engineering Studies –University of Petroleum & Energy Studies, Dehradun) our parents and our friends for their consistent guidance and help without which this work would not have been possible. We would also like to thank all those who are knowingly or unknowingly involved in completion of my project.

ABSTRACT

Conventional multiple regression for permeability estimation from well logs requires a functional relationship to be presumed. Due to the inexact nature of the relationship between petrophysical variables, it is not always possible to identify the underlying functional form between dependent and independent variables in advance. An accurate reservoir description is very important in reservoir evaluation, and permeability prediction is the key for a successful characterization. Permeability is one among the most important parameters affecting the productivity of hydrocarbon bearing reservoir. Thus understanding the heterogeneity of reservoir and characterizing it with consistent input of permeability is very crucial. Formation permeability is measured directly from the core sample studies performed in laboratory. However it is very costly and is not feasible for the whole reservoir. Also, permeability cannot be inferred directly from any well log measurements. Earlier, various methods have been used for the permeability prediction using empirical relationship, statistical regression, etc. These methods are not applicable for all reservoirs, since permeability varies largely due to different depositional environments. When large variations in pertrological characters are exhibited, parametric regression often fails or leads to unstable or erroneous results, So a nonparametric approach for estimating optimal transformations of petrophysical data to obtain the maximum correlation between observed variables has been introduced which are Artificial neural network (ANN) and Alternating conditional expectation (ACE).. These methods prove to be more robust as they require no priori assumption regarding functional form.

TABLE OF CONTENTS

1. INTRODUCTION

1.1. GENERAL

Due to heterogeneity of the rock properties the oil reservoirs in the world are not exactly same. Investigating about the characteristics of these hydrocarbon bearing reservoirs; studying the reservoir rock types and most significantly the vertical and horizontal heterogeneities is an important part of a reservoir characterization procedure. Reservoir characterization has played important role in advanced reservoir management. It maximizes convergence and integrates multi-disciplinary data to improve the reliability of the reservoir anticipations. It is known that precise reservoir management and simulation demands a measurement of the special distribution of reservoir properties and a better understanding of the nature of reservoir heterogeneity at different formations. Reservoir rock type determination has presented a challenge for cases whenever no direct measurements of reservoir rock types are available. The direct identification of reservoir rock type and permeability can be carried out using core analysis whereas indirect measurements can be done through log analysis. An efficient and reliable management strategy can be put into effect only after getting the details of rock properties of the reservoir. Permeability is the most important parameter amongst these rock properties.

1.2. PERMEABILITY

Permeability is one of the most important characteristics of hydrocarbon bearing formations. An accurate knowledge of permeability provides petroleum engineers with a tool for efficiently managing the production process of a field. In the oil and gas industry the permeability is used to determine whether a well should be completed and brought on line. Permeability is also essential in overall reservoir management and development (e.g., for choosing the optimal drainage points and production rate, optimizing drainage points and production rate, optimizing completion and perforation design, and devising EOR patterns and injection conditions). [Ref 1]

1.2.1. Permeability Measurement Techniques:

The three major permeability measurement techniques are wireline log analysis (including the RFT method), laboratory testing of core samples, and well testing.

1.2.1.1. **Wireline log measurements**: Five methods are established for obtaining permeability from wireline tool measurements.(1)Empirical correlation of permeability with porosity (ϕ) and intergranular surface area; (2)Measurement of producible formation fluid with nuclear magnetism log (NML); (3)Estimate of mineral concentrations by geochemical logging tool (GLT); (4)Correlation of permeability with Stoneley Wave velocity by acoustic logging tools; (5)Pressure/time measurement of formation fluids with the RFT tool.

1.2.1.2. **Core permeability:** Core analysis allows direct measurement of permeability under controlled laboratory conditions. For this reason, core derived permeability is often considered to be the standard. Core permeability is an accurate representation of a particular core sample under specific laboratory conditions. As long as the measurements are consistent over a particular interval, the core permeability can be very useful in completion design, specifically in choosing the phasing and vertical spacing of perforation.

1.2.1.3. **Permeability from well testing**: The many procedures that fall under well testing can be classified into 3 categories. (1)Short term tests involving DST, IMPULSE testing, and transient rate and pressure testing (TRAP) where the radius of investigation is typically limited; (2) Conventional tests-classic pressure drawdown or injection test and pressure buildup involving single or step rate; (3) Advance tests involving methods beyond the traditional single layer horizontal permeability evaluation, including layered reservoir testing, vertical interference testing and multiwall interference testing. Although each technique has a different application, all involve making an abrupt change in flow-starting, stopping, or abridging flow, injecting fluid, or changing the flow from one value to another. Reservoir properties are deduced from the well's response to these changes, measured by BHP gauges and BHP transient rates in TRAP and Layered reservoir testing. [Ref 2]

2. LITERATURE REVIEW:

2.1. Wireline Logging: The oil and gas industry uses wireline logging to obtain a continuous record of a formation's rock properties. Wireline logging can be defined as being "The acquisition and analysis of geophysical data performed as a function of well bore depth, together with the provision of related services." The measurements are made referenced to "TAH" - True Along Hole depth: these and the associated analysis can then be used to infer further properties, such as hydrocarbon saturation and formation pressure, and to make further drilling and production decisions. Wireline logging is performed by lowering a 'logging tool' - or a string of one or more instruments - on the end of a wireline into an oil well (or borehole) and recording petrophysical properties using a variety of sensors. Logging tools developed over the years measure the natural gamma ray, electrical, acoustic, stimulated radioactive responses, electromagnetic, nuclear magnetic resonance, pressure and other properties of the rocks and their contained fluids.

The data itself is recorded either at surface (real-time mode), or in the hole (memory mode) to an electronic data format and then either a printed record or electronic presentation called a "well log" is provided to the client, along with an electronic copy of the raw data. Well logging operations can either be performed during the drilling process, to provide real-time information about the formations being penetrated by the borehole, or once the well has reached Total Depth and the whole depth of the borehole can be logged.

Real-time data is recorded directly against measured cable depth. Memory data is recorded against time, and then depth data is simultaneously measured against time. The two data sets are then merged using the common time base to create an instrument response versus depth log. Memory recorded depth can also be corrected in exactly the same way as real-time corrections are made, so there should be no difference in the attainable TAH accuracy.

The measured cable depth can be derived from a number of different measurements, but is usually either recorded based on a calibrated wheel counter, or (more accurately) using magnetic marks which provide calibrated increments of cable length. The measurements made must then be corrected for elastic stretch and temperature.

There are many types of wireline logs and they can be categorized either by their function or by the technology that they use. "Open hole logs" are run before the oil or gas well is lined with pipe or cased. "Cased hole logs" are run after the well is lined with casing or production pipe.

Wireline logs can be divided into broad categories based on the physical properties measured.

2.1.1. Gamma Ray Logging: A method of measuring naturally occurring gamma radiation to characterize the rock or sediment in a borehole or drill hole. It is a wireline logging method used in mining, mineral exploration, water-well drilling, for formation evaluation in oil and gas well drilling and for other related purposes.

Different types of rock emit different amounts and different spectra of natural gamma radiation. In particular, shales usually emit more gamma rays than other sedimentary rocks, such as sandstone, gypsum, salt, coal, dolomite, or limestone because radioactive potassium is a common component in their clay content, and because the cation exchange capacity of clay causes them to absorb uranium and thorium. This difference in radioactivity between shales and sandstones/carbonate rocks allows the gamma tool to distinguish between shales and non-shales.

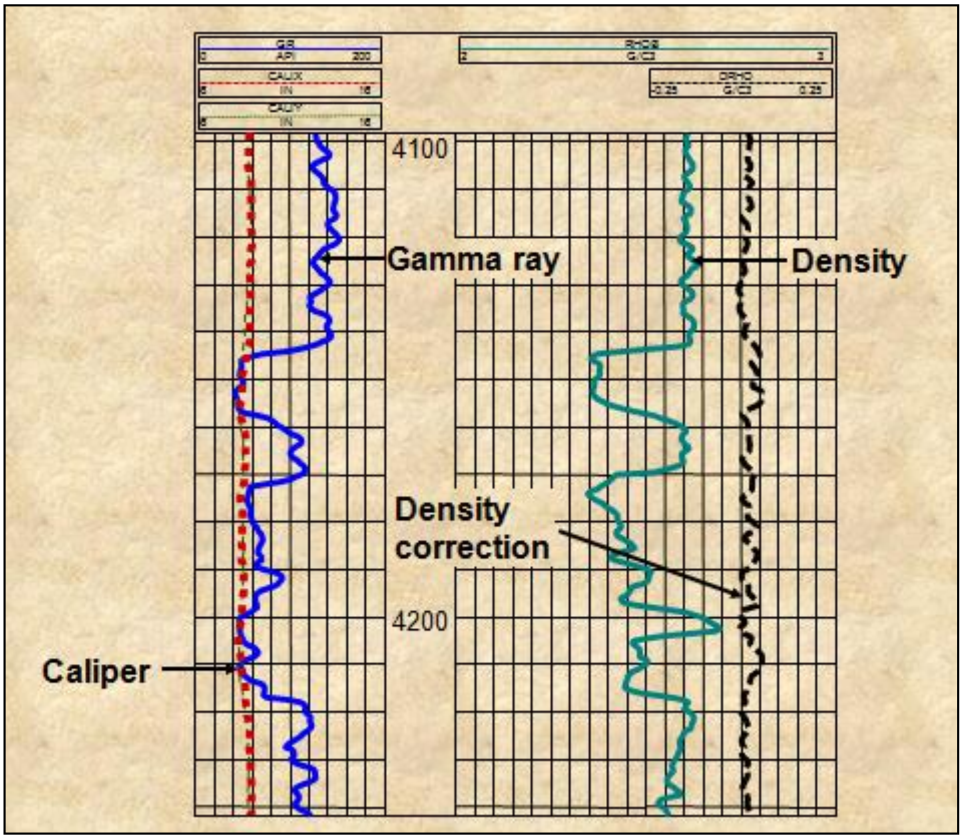


Fig1. Gamma log

The gamma ray log, like other types of well logging, is done by lowering an instrument down the drill hole and recording gamma radiation variation with depth. Gamma radiation is usually recorded in API units, a measurement originated by the petroleum industry. Gamma logs are attenuated by diameter of the borehole because of the properties of the fluid filling the borehole, but because gamma logs are most often used in a qualitative way, corrections are usually not necessary. Three elements and their decay chains are responsible for the radiation emitted by rock: potassium, thorium and uranium. Shales often contain potassium as part of their clay content, and

tend to absorb uranium and thorium as well. A common gamma-ray log records the total radiation and cannot distinguish between the radioactive elements, while a spectral gamma ray log (see below) can. For standard GR logs, the value measured is calculated from thorium in ppm, Uranium in ppm and potassium in percent. GR API = 8 × Uranium concentration in ppm + 4 × thorium concentration in ppm + 15 × potassium concentration in percent. Due to the weight of uranium concentration in the calculation anomalous concentrations of uranium can cause clean sand reservoirs to appear shaley.
An advantage of the gamma log over some other types of well logs is that it works through the steel and cement walls of cased boreholes. Although concrete and steel absorb some of the gamma radiation, enough travels through the steel and cement to allow qualitative determinations.

2.1.2. Resistivity Logging: A method of well logging that works by characterizing the rock or sediment in a borehole by measuring its electrical resistivity. Resistivity is a fundamental material property which represents how strongly a material opposes the flow of electric current. In these logs, resistivity is measured using 4 electrical probes to eliminate the resistance of the contact leads. The log must run in holes containing electrically conductive mud or water.
Resistivity logging is most commonly used for formation evaluation in oil- and gas-well drilling. Most rock materials are essentially insulators, while their enclosed fluids are conductors. Hydrocarbon fluids are an exception, because they are almost infinitely resistive. When a formation is porous and contains salty water, the overall resistivity will be low. When the formation contains hydrocarbon, or contains very low porosity, its resistivity will be high. High resistivity values may indicate a hydrocarbon bearing formation.

Usually while drilling, drilling fluids invade the formation, changes in the resistivity are measured by the tool in the invaded zone. For this reason, several resistivity tools with different investigation lengths are used to measure the formation resistivity. If water based mud is used and oil is displaced, "deeper" resistivity logs will show lower conductivity than the invaded zone. If oil based mud is used and water is displaced, deeper logs will show higher conductivity than the invaded zone. This provides not only an indication of the fluids present, but also, at least qualitatively, whether the formation is permeable or not.

2.1.3. Density Logging: A well logging tool that can provide a continuous record of a formation's bulk density along the length of a borehole. In geology, bulk density is a function of the density of the minerals forming a rock (i.e.matrix) and the fluid enclosed in the pore spaces. This is one of three well logging tools that are commonly used to calculate porosity

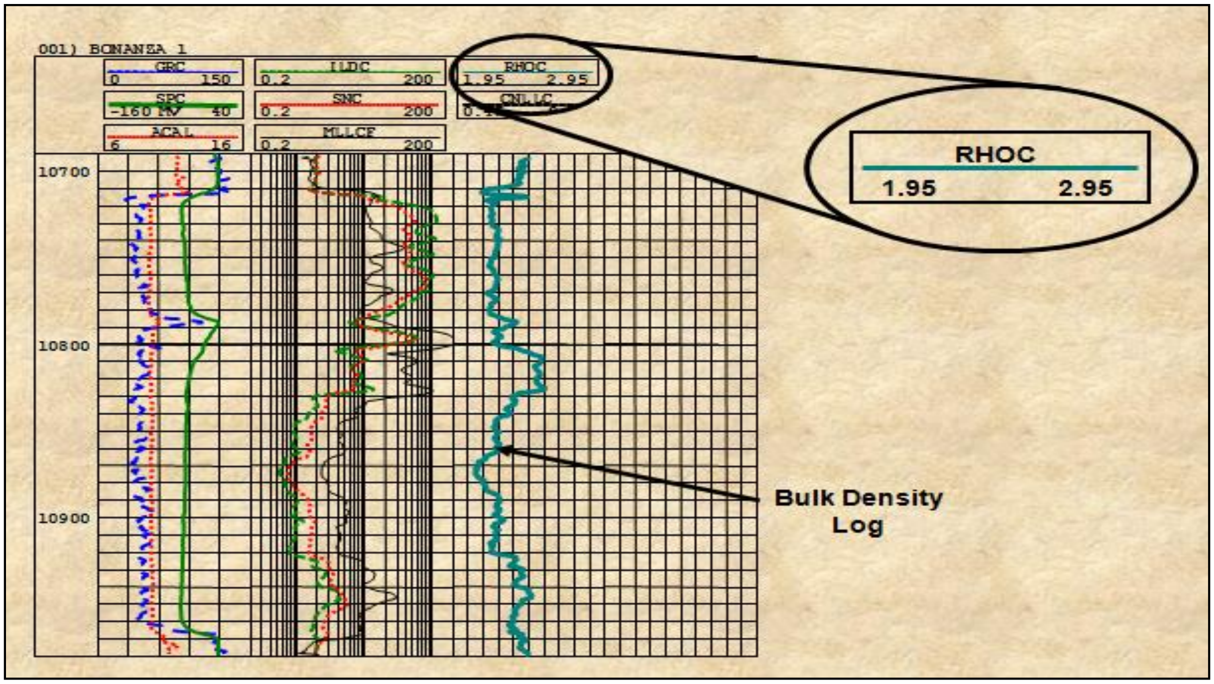


Fig 2.Density Logging

A type of active nuclear tool, a radioactive source and detector are lowered down the borehole and the source emits medium-energy gamma rays into the formation. These gamma rays interact with electrons in the formation and are scattered in an interaction known as Compton scattering. The number of scattered gamma rays that reach the detector, placed at a set distance from the emitter, is related to the formation's electron density, which itself is related to the formation's bulk density.

Electron density is a measure of bulk density.Radioactive source is used to generate gamma rays, gamma ray collides with electrons in formation, losing energy and the detector measures intensity of back-scattered gamma rays, which is related to electron density of the formation.Bulk density, ρ_b, is dependent upon: lithology, porosity, density and saturation of fluids in pores

Bulk density varies with lithology: Sandstone 2.65 g/cc, Limestone 2.71 g/cc and Dolomite 2.87 g/cc.

$$\rho_b = \phi\, S_{xo}\, \rho_{mf} + \phi\,(1 - S_{xo})\,\rho_{hc} + V_{sh}\,\rho_{sh} + (1 - \phi - V_{sh})\,\rho_{ma}$$

ρ_b = Recorded parameter (bulk volume)

$\phi\, S_{xo}\, \rho_{mf}$ = Mud filtrate component

$\phi\,(1 - S_{xo})\,\rho_{hc}$ =Hydrocarbon component

$V_{sh}\,\rho_{sh}$=Shale component

$1 - \phi - V_{sh}$=Matrix component

2.1.4. Neutron Porosity: Its measurement employs a neutron source to measure the hydrogen index in a reservoir, which is directly related to porosity. The Hydrogen Index (HI) of a material is defined as the ratio of the concentration of hydrogen atoms per cm^3 in the material, to that of pure water at 75 °F. As hydrogen atoms are present in both water and oil filled reservoirs, measurement of the amount allows estimation of the amount of liquid-filled porosity.

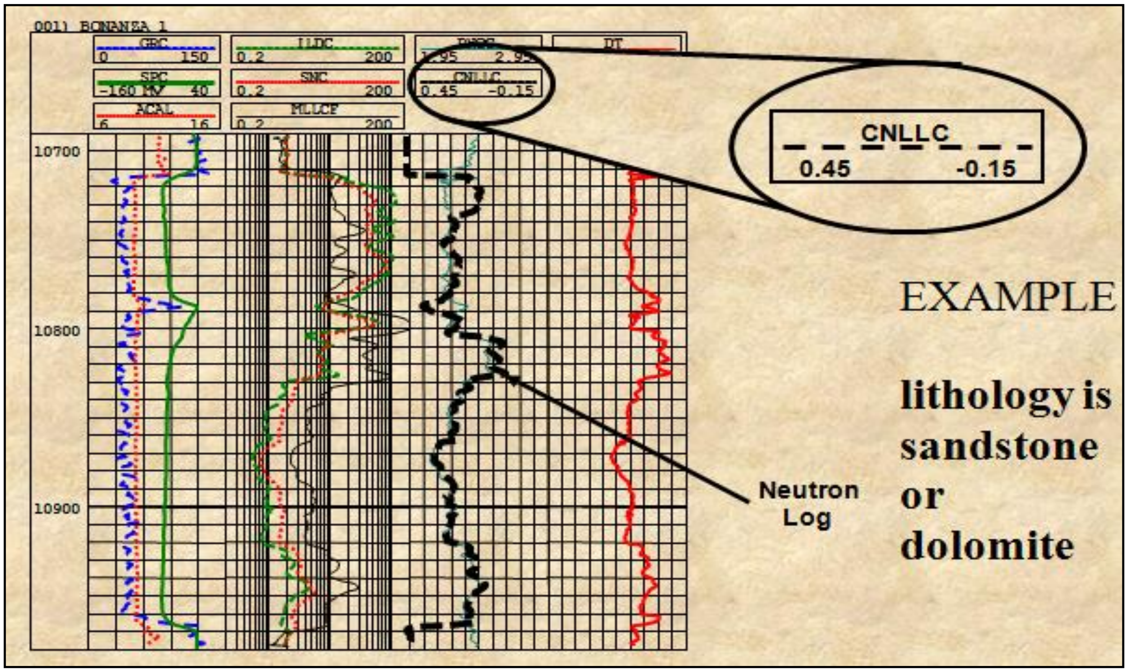


Fig 3. Neutron Porosity log

Subject to various assumptions and corrections, values of apparent porosity can be derived from any neutron log. One can not underestimate the slowdown of neutrons by other elements even if they are less effective. Certain effects, such as lithology, clay content, and amount and type of hydrocarbons, can be

recognized and corrected for only if additional porosity information is available, for example from sonic and/or density log. Any interpretation of a neutron log alone should be undertaken with a realization of the uncertainties involved.
The quantitative response of neutron tool to gas or light hydrocarbon depends primarily on hydrogen index and "excavation effect". The hydrogen index can be estimated from the composition and density of the hydrocarbons.
Given a fixed volume, gas has considerably lower hydrogen concentration. When pore spaces in the rock are excavated and replaced with gas, the formation has smaller neutron-slowing characteristic, hence the terms "Excavation Effect". If this effect is ignored, a neutron log will show a low porosity value. This characteristic allows a neutron porosity log to be used with other porosity logs (such as a density log) to detect gas zones and identify gas-liquid contacts. [Ref 4]

3. OBJECTIVE:

The main aim of the project is to identify the underlying functional form between dependent and independent variables and thereby predict permeability from the limited core data and interrelate it with the log data sheets, making it possible to expand the prediction to uncored wells. The well data or core data are not recoverable in every well in a field as it is a highly expensive and time consuming. We have the log data of four wells (Well A, B, D &E) and core permeability data of two wells (Well D, E). We have to propose a model to calculate permeability of porous media, which is the main objective of this study. The purpose of this study is to develop a methodology for the permeability prediction of an oil field using conventional logs. Artificial Neural Networks (ANN) is applied for permeability prediction using 'backpropagation' algorithm for training the feed forward network. One hidden layer and one output layer is used in the network architecture. Hit and trial method is used for determining the number neurons present in the hidden layer. Similarly Alternating conditional expectation (ACE) algorithm is also used to predict the permeability of well A, B. And the best method having more reliable data values is found out.

4. MULTIPLE REGRESSION

Conventional multiple regression for permeability estimation from well logs requires a functional relationship to be presumed. Due to the inexact nature of the relationship between petrophysical variables, it is not always possible to identify the underlying functional form between dependent and independent variables in advance. An accurate reservoir description is very important in reservoir evaluation, and permeability prediction is the key for a successful characterization. Permeability is one among the most important parameters affecting the productivity of hydrocarbon bearing reservoir. Thus understanding the heterogeneity of reservoir and characterizing it with consistent input of permeability is very crucial. Formation permeability is measured directly from the core sample studies performed in laboratory. However it is very costly and is not feasible for the whole reservoir. Also, permeability cannot be inferred directly from any well log measurements. Earlier, various methods have been used for the permeability prediction using empirical relationship, statistical regression, etc. These methods are not applicable for all reservoirs, since permeability varies largely due to different depositional environments. When large variations in pertrological characters are exhibited, parametric regression often fails or leads to unstable or erroneous results, So a nonparametric approach for estimating optimal transformations of petrophysical data to obtain the maximum correlation between observed variables has been introduced which are Artificial neural network (ANN) and Alternating conditional expectation (ACE). These methods prove to be more robust as they require no priori assumption regarding functional form. [Ref 3]

In this study, an artificial neural network has been designed that is able to predict the permeability of the formations using the data provided by geophysical well logs with good accuracy. Artificial neural network, a biologically inspired computing method which has an ability to learn, self-adjust, and be trained, provides a powerful tool in solving pattern recognition problems.

The next step is to develop correlations between permeability and well log responses using the ACE algorithm to examine our data by GRACE software. We use this non-parametric regression techniques to model the data. Thus, it provides a powerful tool for exploratory data analysis and correlation. After using both the techniques we define the more reliable one and that is used for predicting the permeabilities for further cluster wells.

4.1. Introduction to MATLAB

MATLAB is a programming language developed by MathWorks. MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation.

Programming and developing algorithms is faster with MATLAB than with traditional languages because MATLAB supports interactive development without the need to perform low-level administrative tasks, such as declaring variables and allocating memory. Thousands of engineering and mathematical functions are available, eliminating the need to code and test them yourself. At the same time, MATLAB provides all the features of a traditional programming language, including arithmetic operators, flow control, data structures, data types, object-oriented programming, and debugging features.

MATLAB helps you better understand and apply concepts in a wide range of engineering, science, and mathematics applications, including signal processing and communications, control system design, machine learning, computational finance and computational biology. Add-on toolboxes, which are collections of task- and application-specific MATLAB functions, add to the MATLAB environment to solve particular classes of problems in these application areas. [Ref 2]

4.1.1. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial Neural Networks (ANNs) are relatively crude electronic models based on the neural structure of the brain. The brain learns from experience. Artificial neural networks try to mimic the functioning of brain. Even simple animal brains are capable of functions that are currently impossible for computers. Computers do the things well, but they have trouble recognizing even simple patterns. The brain stores information as patterns. Some of these patterns are very complicated and allow us the ability to recognize individual faces from many different angles. This process of storing information as patterns, utilizing those patterns, and then solving the problems encompasses a new field in computing, which does not utilize traditional programming but involves the creation of massively parallel networks and the training of those networks to solve specific problems. The exact workings of the human brain are still a mystery, yet some aspects are known. The most basic element of the human brain is a specific type of cell, called 'neuron'. These neurons provide the abilities to remember, think, and apply previous experiences to our every action. They are about 100 billion in number and each of these neurons connects itself with about 200,000 other neurons, although 1,000 to 10,000 is typical. The power of the human mind comes from the sheer numbers of these basic components and the multiple connections between them. It also comes from genetic programming and learning. The individual neurons are complicated. They have a myriad of parts, subsystems and control mechanisms. They convey information via a host of 75 electrochemical pathways. Together, these neurons and their connections form a process, which is not binary, not stable, and not synchronous.

4.1.1.1. TYPES OF ARTIFICIAL NEURAL NETWORKS

a) SINGLE LAYER FEED FORWARD NETWORK

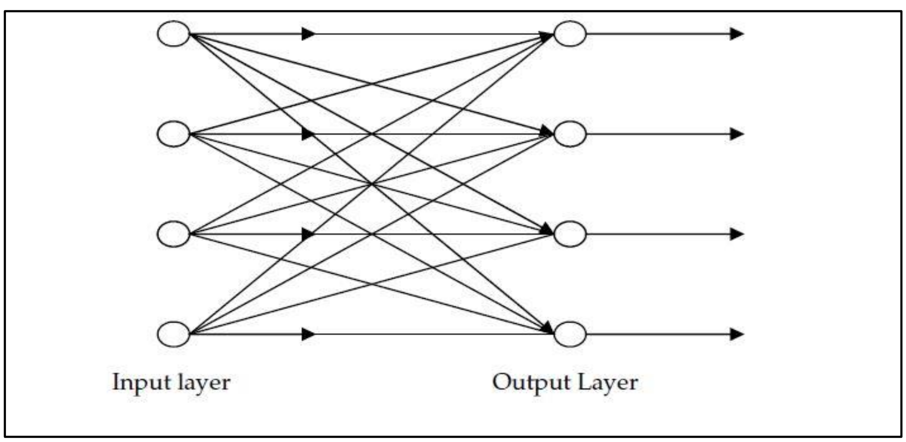


Fig 4. Single layer feed forward network

A neural network in which the input layer of source nodes projects into an output layer of neurons but not vice-versa is known as single feed-forward or acyclic network. In single layer network, 'single layer' refers to the output layer of computation nodes as shown in the above figure.

b) MULTILAYER FEED FORWARD NETWORK

This type of network consists of one or more hidden layers, whose computation nodes are called hidden neurons or hidden units. The function of hidden neurons is to interact between external input and network output in some useful manner and to extract higher order statistics. The source nodes in input layer of network, supply the input signals to neurons in the second layer (1st hidden layer. The output signals of 2nd layer are used as inputs to the third layer and so on. The set of output signals of the neurons in the output layer of network constitutes the overall response of network to the activation pattern supplied by source nodes in the input first layer

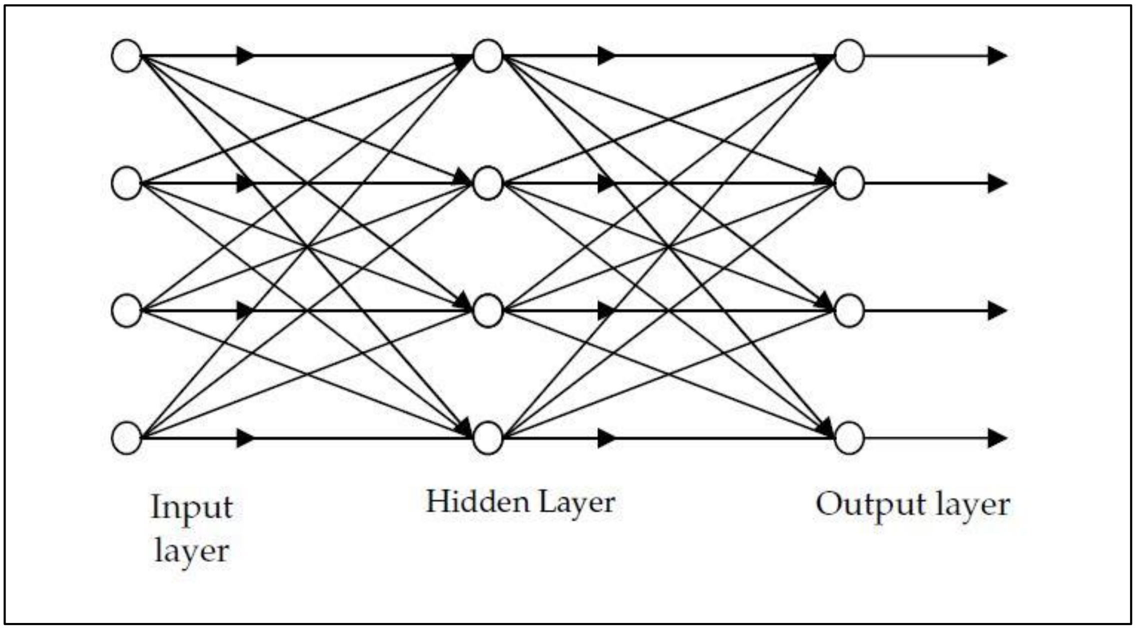


Fig 5: A multilayer feed forward network

4.2. ALTERNATING CONDITIONAL EXPECTATIONS (ACE)

The ACE algorithm, originally proposed by Breiman and Friedman, provides a method for estimating optimal transformations for multiple regressions that result in a maximum correlation between a dependent (response) random variable and multiple independent (predictor) random variables. In the present work, we utilize the ACE technique to examine our data by GRACE software for permeability prediction from different well log data.

4.2.1. **The ACE Algorithm:** The GRACE program has been used which generates an optimal correlation between a dependent variable (say y) and multiple independent variables (say, x1, x2, x3, upto x30).This is accomplished through non-parametric transformations of the dependent and independent variables. Non-parametric implies that no functional form is assumed between the dependent and independent variables and the transformations are derived solely based on the dataset. The final correlation is given by plotting the transform dependent variable against the sum ofthe transformed independent variables.

The correlation thus obtained can be showed to be optimal. A model predicting the value of y from the values of x1, x2… xn is written in the generic form

$y = f^{-1}(z)$

Where $z = \Sigma z_i$ and $z_i = f_i(x_i)$

The procedure for this approach is given by

1) Calculate the data transform:

$z_i = f_i(x_i)$, $i = 1,2, \ldots, n$

2) Calculate the transform sum:

$z = \Sigma z_i$, $i = 1, 2, \ldots, n$

3) Calculate the inverse transform:

$y = f^{-1}(z)$

Given n observation points, we wish to find the best transformation functions f1(x1), f2(x2), ………… , fn(xn) , but not as algebraic expressions, rather as a relationships defined point wise. The method of ACE constructs and modifies the individual transformations to achieve maximum correlation in the transformed space. Graphically this means that the plot of $z = \Sigma z_i$ against z' = f (y measured) should be as near to the 45o straight line as possible. The resulting individual transformation are given in the form of a point by point and/or table, thus in any subsequent application (graphical or algebraic) interpolation is needed to obtain the transformed variables and to apply the inverse transform to predict y. Naturally, the smoother the transformation the more justified and straightforward the interpolation is, therefore, some kind of restriction on smoothness is built into the ACE algorithm. In other words, based on the concept of conditional expectation, the correlation in transformed space is maximized by iteratively adjusting the individual transformations subject to a smoothness condition.

5. WORKFLOW

- We apply optimal transformation by using GRACE software for ACE
- Further, we train and build a feed forward neural network for permeability prediction using ANN in MATLAB.
- Comparison of Regression values are done to find the more reliable method
- Then we compare and match the predicted permeability curve and actual permeability curve with respect to depth range from both ANN and ACE method.
- Lastly, permeability is predicted for the non-cored wells, i.e., Well A & Well B using the most reliable technique.

5.1. Permeability Prediction using ACE algorithm in GRACE:

1. The log data of well D & well E was taken into consideration for this project. The log data consisted of 4 log suite comprising of gamma ray, bulk density, neutron porosity & deep resistivity

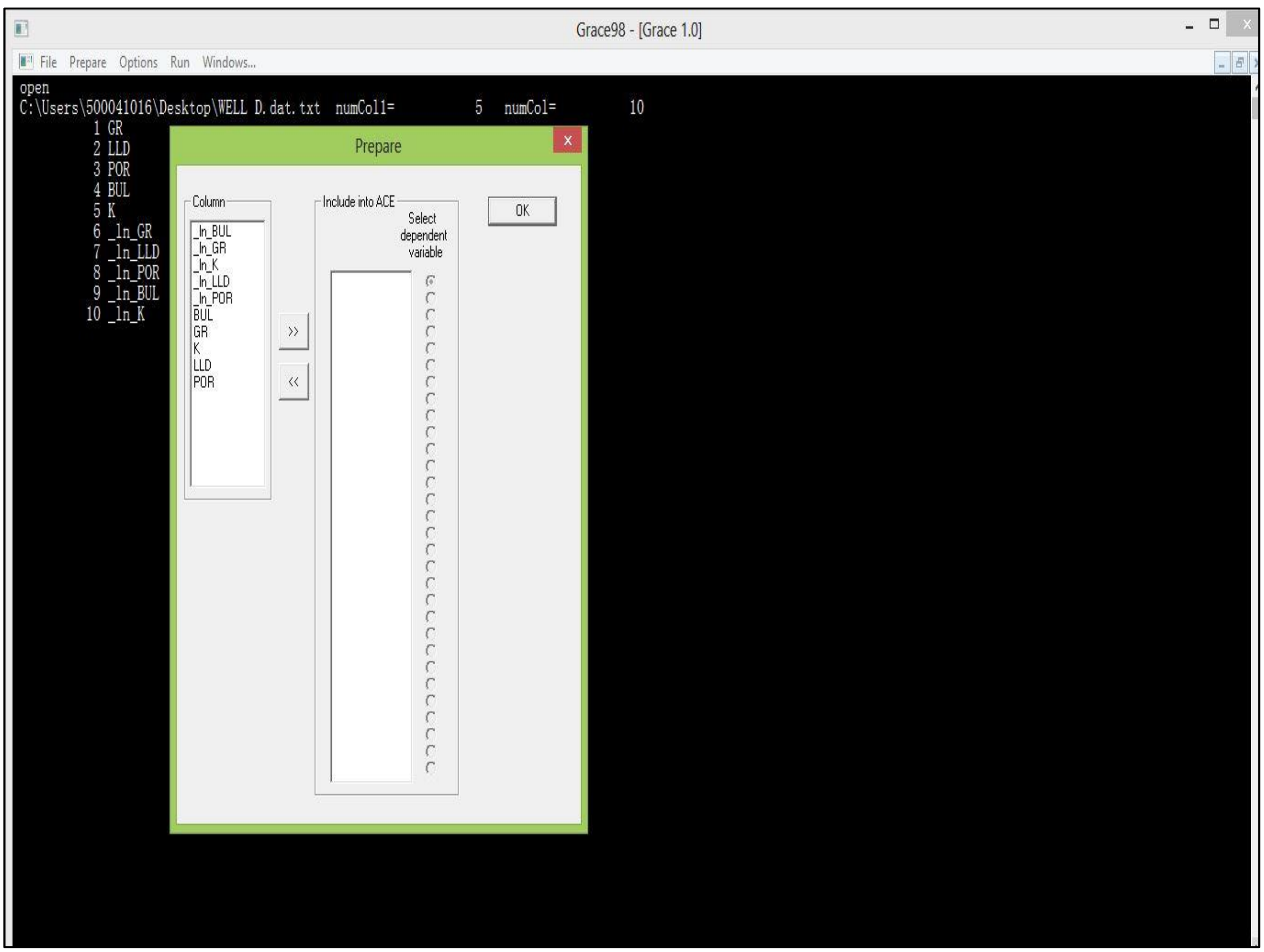
well name	depth(m)	GR(GAPI)	LLD(ohm-m)	NPHI(v/V)	RHOB(g/cc)	known permeability k(mD)
D	1493.06	16.287	4.215	0.2232	2.422	0.822
D	1494.59	24.767	2.161	0.2883	2.447	21.252
D	1501.29	26.409	2.325	0.2858	2.402	38.919
D	1504.04	35.969	2.83	0.1705	2.473	1.757
D	1505.56	34.654	2.473	0.2223	2.373	1.447
D	1508	34.843	2.578	0.28	2.393	36.599
D	1509.06	34.948	2.172	0.2848	2.383	154.297
D	1509.22	40.488	2.148	0.279	2.357	244.271
D	1509.52	36.34	2.031	0.2767	2.363	132.276
D	1510.28	24.508	3.141	0.2249	2.4	0.833
D	1515.62	54.554	4.048	0.2476	2.311	10.539
D	1520.34	33.272	4.99	0.1384	2.553	49.576
D	1525.07	57.8	1.835	0.2897	2.512	181.371
D	1530.86	28.392	4.49	0.1338	2.582	368.857
D	1535.13	36.911	2.643	0.2064	2.547	1.287
D	1543.51	24.196	5.232	0.1297	2.523	42.461
D	1543.66	27.486	6.175	0.1205	2.516	17.942
D	1545.03	25.093	6.874	0.1349	2.473	3.174
D	1550.06	21.565	11.644	0.0708	2.586	2.501
D	1554.94	64.015	1.975	0.2629	2.424	241.427
D	1560.27	24.724	5.361	0.1481	2.523	23.034
D	1564.84	14.773	5.974	0.1528	2.504	16.309
D	1570.03	25.123	6.24	0.1246	2.586	367.512
D	1579.63	18.902	9.858	0.0914	2.615	2.523

D	1585.27	36.525	3.845	0.1534	2.566	28.884
D	1590.14	42.519	5.933	0.0918	2.607	384.298
D	1595.93	63.515	4.025	0.1483	2.568	3.894
D	1602.33	31.584	2.107	0.2937	2.38	423.45
D	1605.08	42.266	2.233	0.2377	2.367	5.495
D	1610.11	31.962	2.176	0.2728	2.328	67.391
D	1615.14	42.187	2.337	0.2519	2.52	1.222
D	1620.32	53.632	2.377	0.1887	2.555	1.027
D	1625.35	30.041	3.832	0.2002	2.582	11.275
D	1630.99	43.71	1.739	0.3056	2.512	328.041
D	1635.1	42.858	1.422	0.2506	2.345	85.375
D	1644.85	31.307	1.909	0.2941	2.408	346.218
D	1649.12	44.433	2.217	0.2543	2.402	12.385
D	1652.63	39.675	3.397	0.2559	2.434	2.182
D	1661.62	41.96	1.525	0.2698	2.573	1.939
D	1679.45	26.796	2.698	0.297	2.375	143.841
D	1681.73	46.311	2.921	0.2442	1.986	1.048
D	1708.1	25.05	4.971	0.1767	2.559	2.135
D	1708.25	19.873	5.477	0.152	2.57	199.397
D	1708.4	21.22	6.454	0.1489	2.576	110.254
D	1708.56	21.896	7.702	0.1588	2.582	14.217
D	1708.71	22.94	5.308	0.1882	2.584	49.833
D	1709.32	27.792	4.389	0.2061	2.631	111.444
D	1709.47	28.049	4.666	0.1882	2.619	201.746
D	1709.62	30.786	4.572	0.2019	2.609	37.694

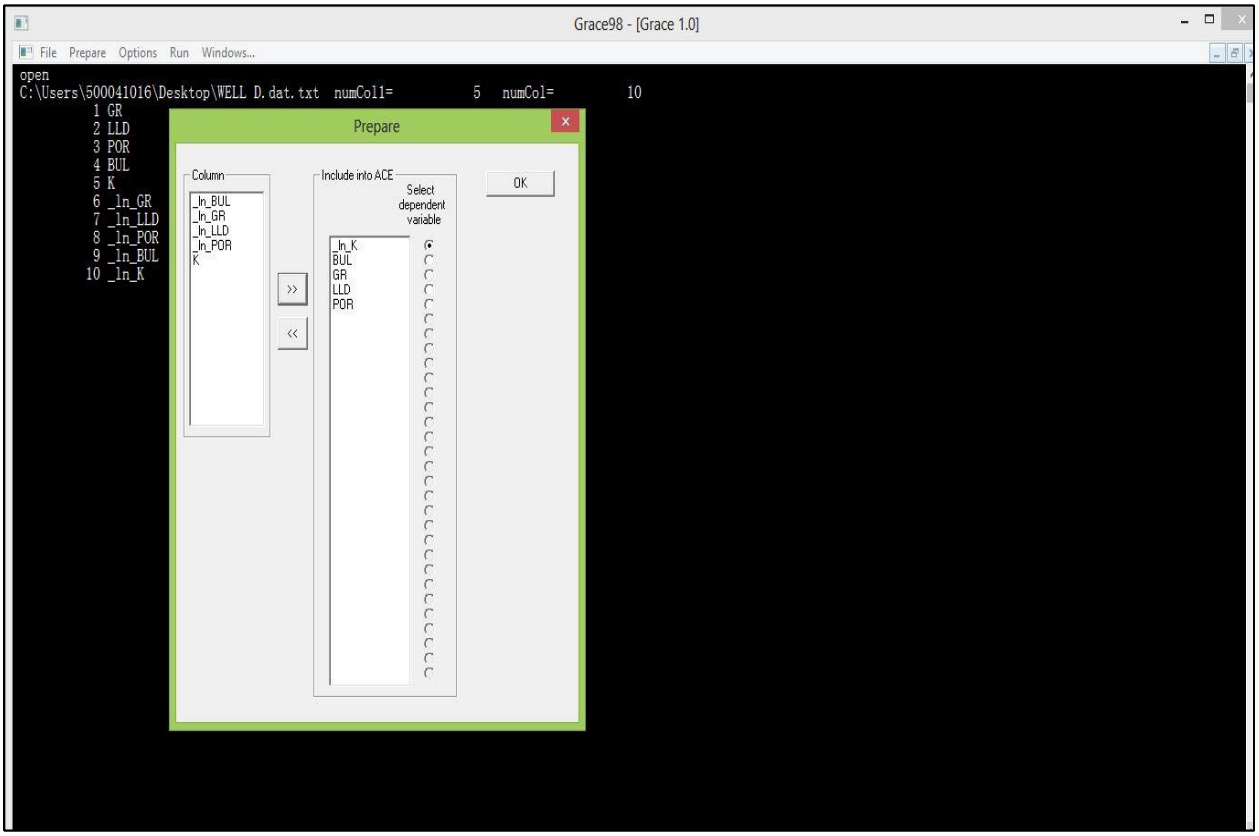
well name	depth(m)	GR(GAPI)	LLD(ohm-m)	NPHI(v/V)	RHOB(g/cc)	known permeability k(mD)
E	1520.19	28.4375	1.4306	0.2856	2.4785	36.73
E	1525.07	24.9844	2.1316	0.2212	2.418	0.969
E	1530.1	33.5313	2.4299	0.2632	2.4063	7.298
E	1535.13	31.1875	5.1205	0.1553	2.4961	5.84
E	1540	40.8125	2.0435	0.1499	2.5703	4.525
E	1545.03	43.4688	4.3803	0.1113	2.584	126.646
E	1550.06	27.875	3.7231	0.1157	2.5273	36.171
E	1560.12	16.7188	3.3475	0.1714	2.3848	1.249
E	1565.15	57.25	1.3784	0.2515	2.5508	3.619
E	1570.02	28.0781	3.3284	0.1841	2.5586	9.072
E	1575.05	37.4688	4.184	0.1611	2.5137	4.731
E	1580.24	66.0625	1.233	0.1597	2.0996	3.808
E	1584.5	47.4688	1.2729	0.2808	2.4727	281.928
E	1590.14	32.2813	3.6448	0.1733	2.4336	1.196
E	1593.65	42.8438	1.4375	0.2686	2.4356	80.578
E	1601.57	43.1875	3.2558	0.1392	2.5684	17.353
E	1605.38	37.5	1.6205	0.2451	2.3184	26.886
E	1610.11	38.0313	2.3521	0.21	2.4023	1.065
E	1616.51	34.8438	1.1169	0.2568	2.4648	12.567
E	1620.01	18.0625	1.9063	0.2354	2.3203	2.609
E	1625.19	67	2.423	0.2642	2.4219	182.578
E	1630.07	50.4375	1.427	0.2822	2.4727	327.046
E	1636.93	46.9063	1.3412	0.2852	2.502	128.894
E	1639.98	36.7188	3.4244	0.1567	2.5606	15.455

E	1645.31	44.375	2.7838	0.2339	2.5273	0.785
E	1650.03	29	5.2421	0.1753	2.4434	1.618
E	1655.06	27.8125	2.5238	0.1626	2.5566	9.019
E	1661.77	40.75	1.528	0.2627	2.4902	7.889
E	1670.46	30.0781	3.0182	0.1704	2.6094	86.731
E	1677.92	36.875	1.1522	0.3061	2.541	209.754

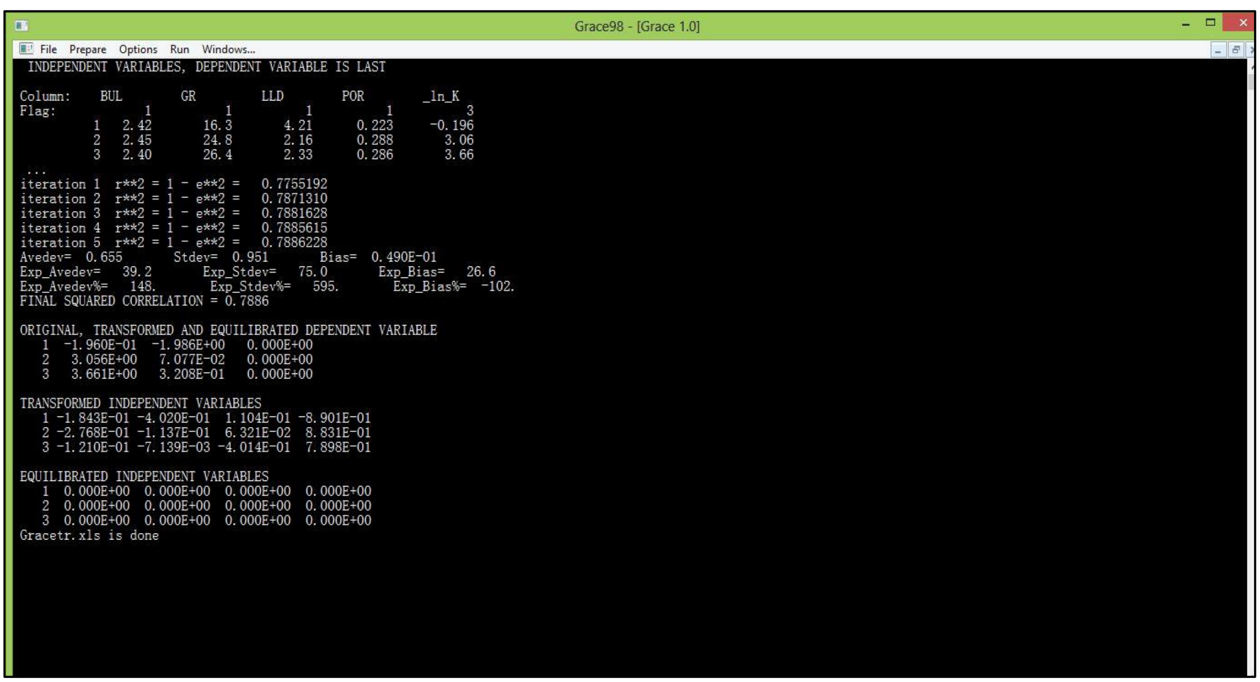
2. Create a data file arranging your data in columns. The first line should contain the names of the columns.
3. The log & core data of well D was used in the ACE algorithm for creating a linear relationship and the data of well E was used to predict and verify permeability.
4. The GRACE application was then launched, the training data was imported into GRACE workspace.



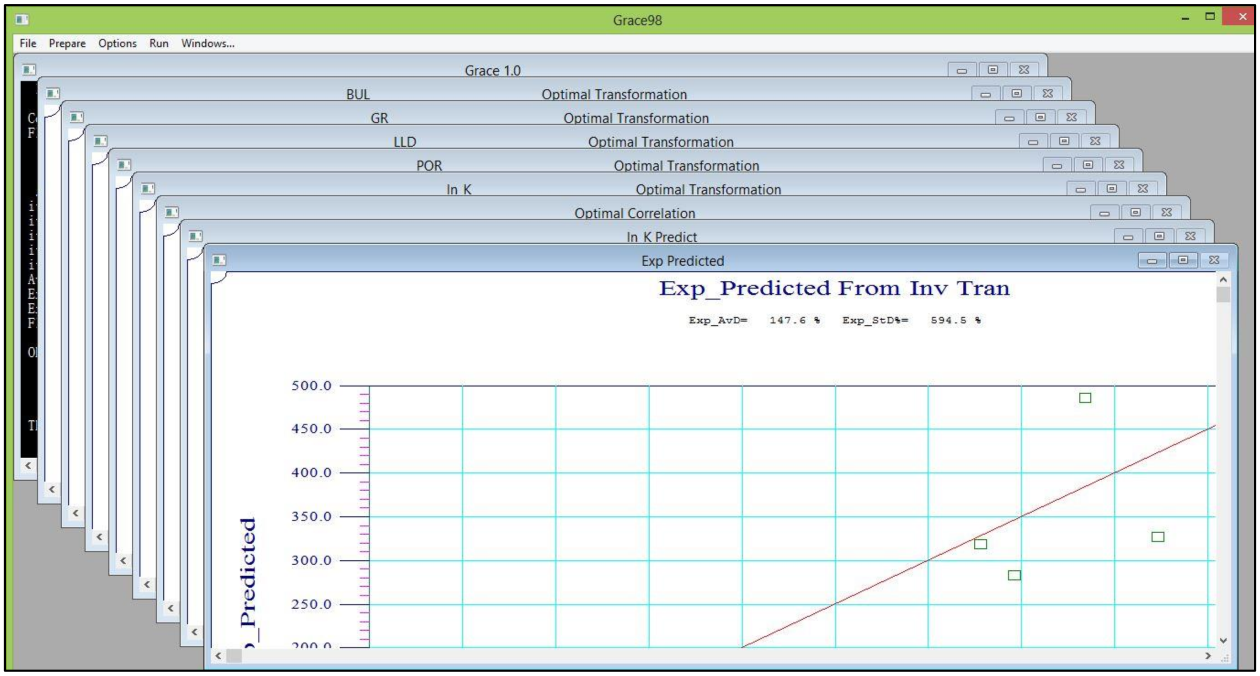
5. We consider independent variables bulk density, gamma ray log, laterolog deep, and porosity for neutron porosity hydrogen index and the dependent variable is natural log of permeability.



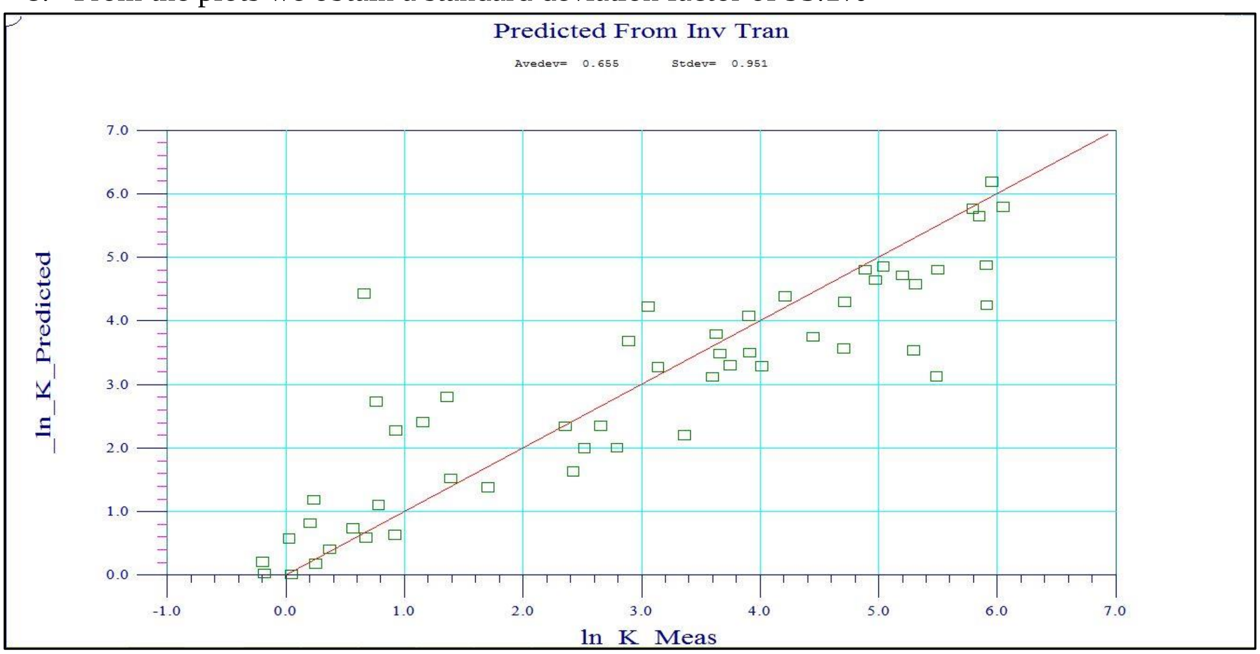
6. Execute calculations using Run menu item



7. The results are cascaded in windows to view the optimal transformations of the dependent and independent variables, optimal correlations, the predicted permeability regression is also obtained.

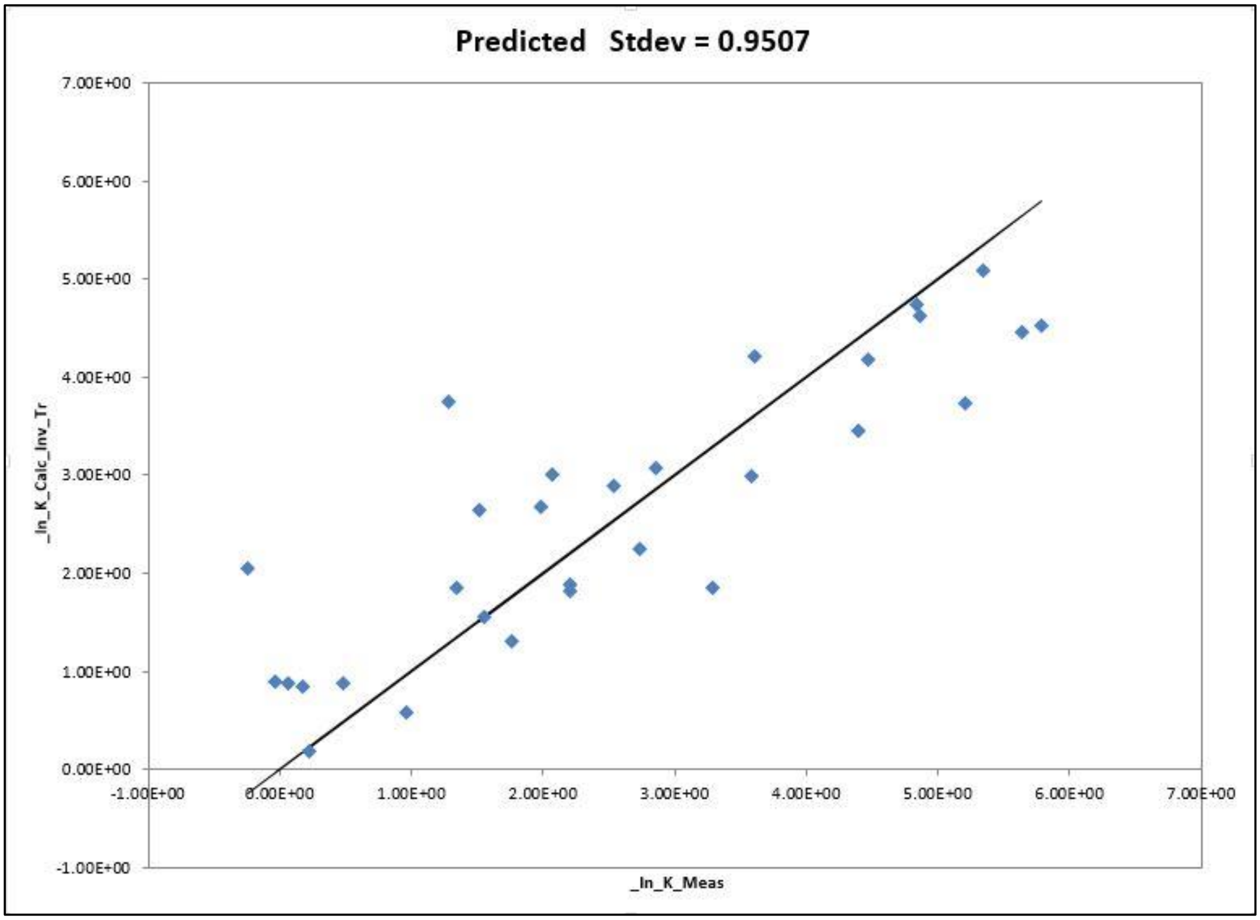


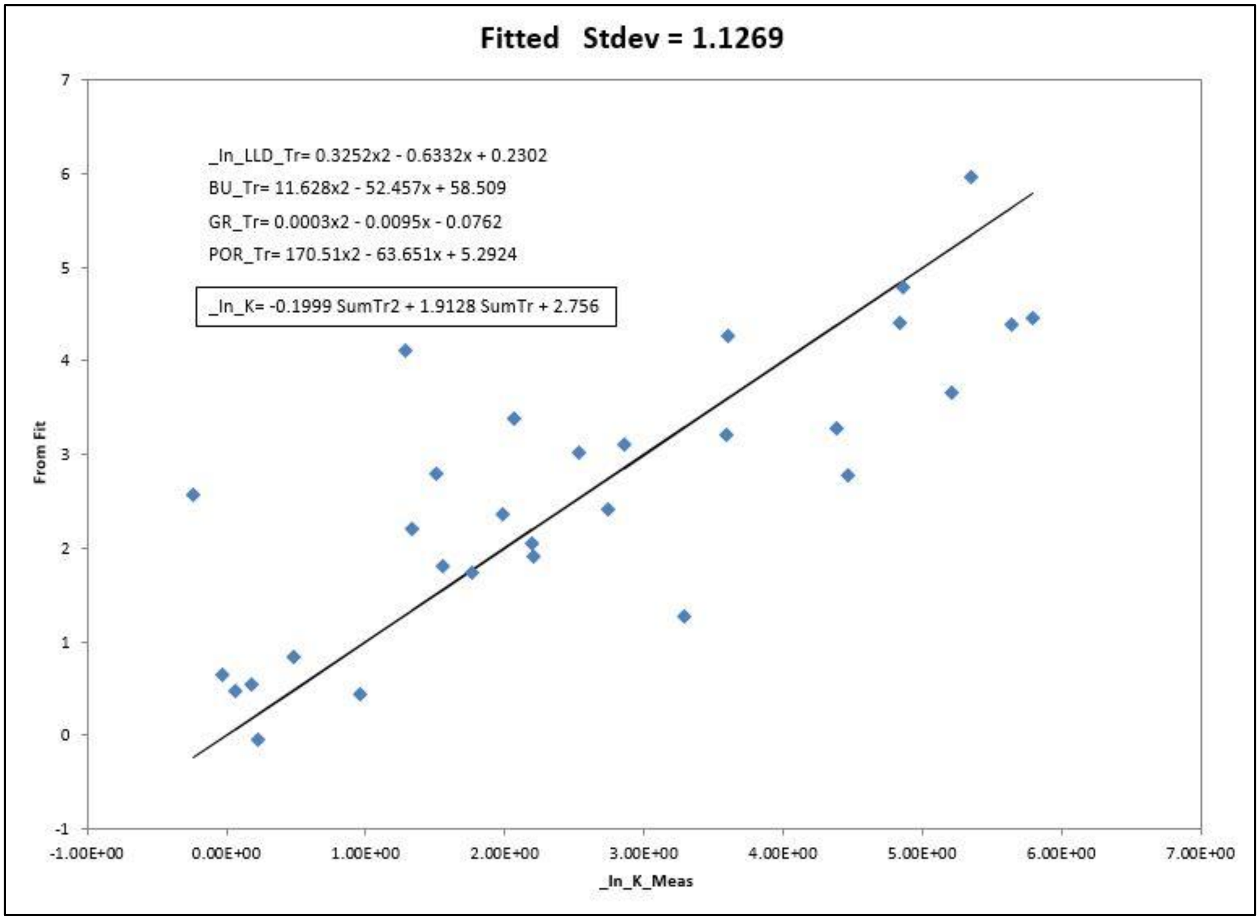
8. From the plots we obtain a standard deviation factor of 95.1%



9. Finally, the GRACE program generates an EXCEL file that summarizes the results, we get a regression of 0.9507 and a plot generating functional forms,

   The functional forms used for predicting the remaining cluster wells are:-





ln_LLD_Tr= 0.3252x2 - 0.6332x + 0.2302

BU_Tr= 11.628x2 - 52.457x + 58.509

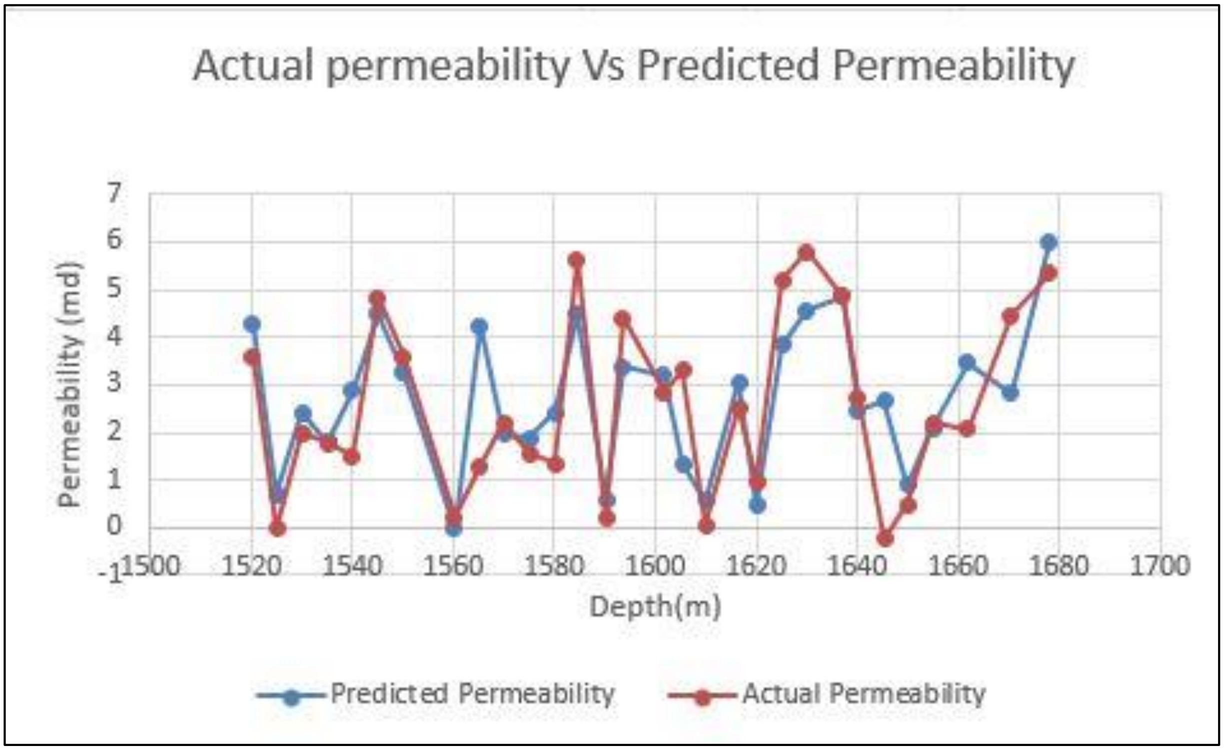
GR_Tr= 0.0003x2 - 0.0095x - 0.0762

POR_Tr= 170.51x2 - 63.651x + 5.2924

ln_K= -0.1999 SumTr2 + 1.9128 SumTr + 2.756

10. Those functional forms are used for predicting the permeability of well E and is verified with the actual known values and graph plotted in EXCEL.

Depth(m)	Predicted Permeability
1520.19	4.29665978
1525.07	0.690379113
1530.1	2.423895856
1535.13	1.796228536
1540	2.871004483
1545.03	4.473936796
1550.06	3.25373397
1560.12	-0.015790737
1565.15	4.242478556
1570.02	1.959635475
1575.05	1.884368269
1580.24	2.412346278
1584.5	4.47476521
1590.14	0.603878567
1593.65	3.368638104
1601.57	3.184767179
1605.38	1.35727011
1610.11	0.562999794
1616.51	3.072379732
1620.01	0.455067896
1625.19	3.839724367
1630.07	4.555949161
1636.93	4.86530689
1639.98	2.477792672
1645.31	2.667558153
1650.03	0.885303488
1655.06	2.09397799
1661.77	3.454641528
1670.46	2.8258196
1677.92	6.004512656



Actual permeability Vs Predicted Permeability
Permeability (md)
7
6
5
4
3
2
1
0
-1
1500
1520
1540
1560
1580
1600
1620
1640
1660
1680
1700
Depth(m)
Predicted Permeability
Actual Permeability

11. Predicted permeability of Well A

Depth(m)	Predicted Permeability
1440.58	3.437707602
1445.45	1.512453111
1450.02	-1081.064035
1455.05	0.419831985
1460.24	1.634372186
1465.42	4.050635157
1470.14	1.619668651
1474.71	3.441039152
1480.05	0.803711335
1484.16	0.697137567
1490.87	1.25581832
1494.07	0.524184082
1500.62	-9.422083036
1504.43	1.877042638
1510.07	1.3337709
1515.25	3.065199259
1520.13	7.315426875
1525.46	1.025449549
1530.03	1.009912
1535.52	2.437732546
1540.09	2.28889239
1543.75	3.087710712
1545.58	-3.934417535
1550.76	3.901089597
1555.03	1.559729267
1560.06	2.508358105
1563.87	2.886365537

1570.12	1.020240376
1574.99	1.13396261
1580.02	0.382710672
1584.44	1.741965413
1590.08	1.749490184
1596.18	1.36618134
1600.14	0.876615555
1606.08	1.683252118
1610.04	-28.7420087
1614.46	1.914245544
1617.06	0.740716851
1620.1	1.916593845
1625.89	1.879432061
1630.01	0.881816967
1636.56	0.095004214
1640.07	1.876908764
1645.55	4.231523008
1650.13	1.675269319
1655.92	2.621682788
1660.03	1.625804674
1662.32	1.176118486
1665.06	5.868840572

Similarly of well B

Depth(m)	Predicted Permeability
1440.58	7.312949476
1445.45	1.34462599
1450.02	1.449125355
1455.05	3.172145687
1460.24	2.392130343
1465.42	4.677192089
1470.14	0.60091647
1474.71	4.817567222
1480.05	5.677464581
1484.16	4.346503955
1490.87	3.789016319
1494.07	3.171388802
1500.62	2.756864764
1504.43	1.965862404
1510.07	1.870211587
1515.25	1.921415247
1520.13	4.691093326
1525.46	3.524249287
1530.03	1.529266179
1535.52	7.268653415
1540.09	0.982047139
1543.75	2.019844638
1545.58	1.152240886
1550.76	3.851088461

5.2. Permeability Prediction using ANN toolbox in MATLAB:

1. The log data of well D & well E was taken into consideration for this project. The log data consisted of 4 log suite comprising of gamma ray, bulk density, neutron porosity & deep resistivity.

well name	depth(m)	GR(GAPI)	LLD(ohm-m)	NPHI(v/V)	RHOB(g/cc)	known permeability k(mD)
D	1493.06	16.287	4.215	0.2232	2.422	0.822
D	1494.59	24.767	2.161	0.2883	2.447	21.252
D	1501.29	26.409	2.325	0.2858	2.402	38.919
D	1504.04	35.969	2.83	0.1705	2.473	1.757
D	1505.56	34.654	2.473	0.2223	2.373	1.447
D	1508	34.843	2.578	0.28	2.393	36.599
D	1509.06	34.948	2.172	0.2848	2.383	154.297
D	1509.22	40.488	2.148	0.279	2.357	244.271
D	1509.52	36.34	2.031	0.2767	2.363	132.276
D	1510.28	24.508	3.141	0.2249	2.4	0.833
D	1515.62	54.554	4.048	0.2476	2.311	10.539
D	1520.34	33.272	4.99	0.1384	2.553	49.576
D	1525.07	57.8	1.835	0.2897	2.512	181.371
D	1530.86	28.392	4.49	0.1338	2.582	368.857
D	1535.13	36.911	2.643	0.2064	2.547	1.287
D	1543.51	24.196	5.232	0.1297	2.523	42.461
D	1543.66	27.486	6.175	0.1205	2.516	17.942
D	1545.03	25.093	6.874	0.1349	2.473	3.174
D	1550.06	21.565	11.644	0.0708	2.586	2.501
D	1554.94	64.015	1.975	0.2629	2.424	241.427
D	1560.27	24.724	5.361	0.1481	2.523	23.034
D	1564.84	14.773	5.974	0.1528	2.504	16.309
D	1570.03	25.123	6.24	0.1246	2.586	367.512
D	1579.63	18.902	9.858	0.0914	2.615	2.523

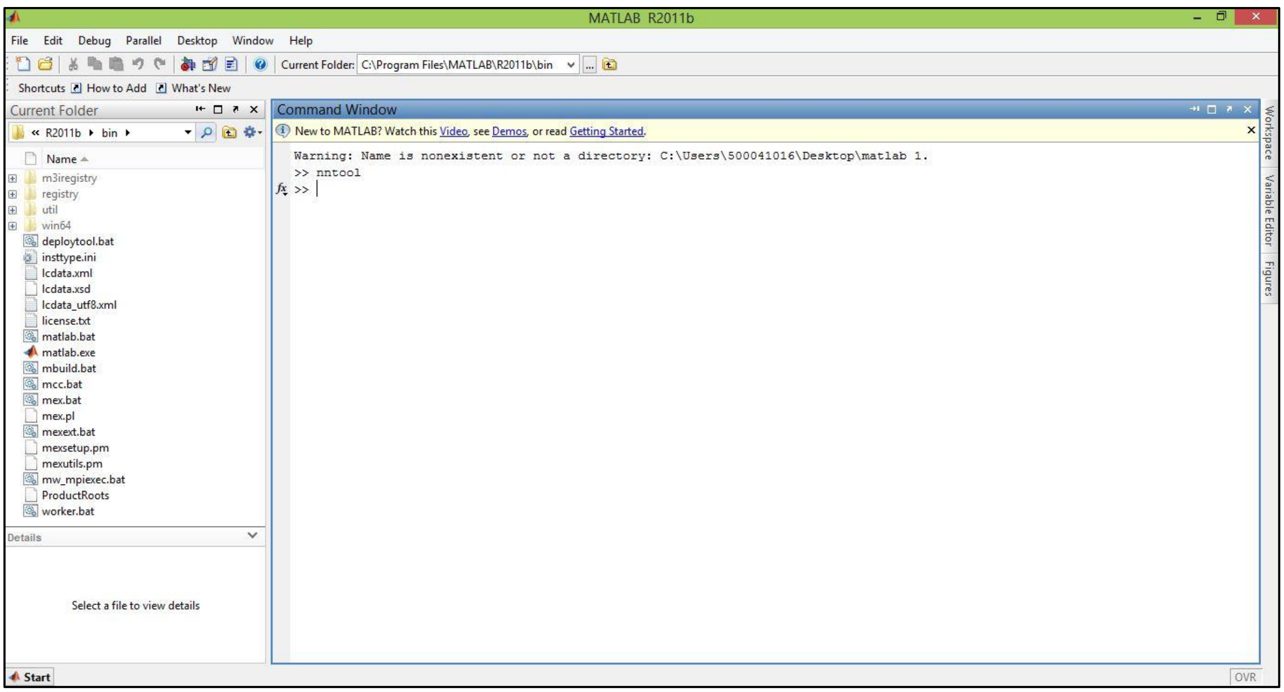
D	1585.27	36.525	3.845	0.1534	2.566	28.884
D	1590.14	42.519	5.933	0.0918	2.607	384.298
D	1595.93	63.515	4.025	0.1483	2.568	3.894
D	1602.33	31.584	2.107	0.2937	2.38	423.45
D	1605.08	42.266	2.233	0.2377	2.367	5.495
D	1610.11	31.962	2.176	0.2728	2.328	67.391
D	1615.14	42.187	2.337	0.2519	2.52	1.222
D	1620.32	53.632	2.377	0.1887	2.555	1.027
D	1625.35	30.041	3.832	0.2002	2.582	11.275
D	1630.99	43.71	1.739	0.3056	2.512	328.041
D	1635.1	42.858	1.422	0.2506	2.345	85.375
D	1644.85	31.307	1.909	0.2941	2.408	346.218
D	1649.12	44.433	2.217	0.2543	2.402	12.385
D	1652.63	39.675	3.397	0.2559	2.434	2.182
D	1661.62	41.96	1.525	0.2698	2.573	1.939
D	1679.45	26.796	2.698	0.297	2.375	143.841
D	1681.73	46.311	2.921	0.2442	1.986	1.048
D	1708.1	25.05	4.971	0.1767	2.559	2.135
D	1708.25	19.873	5.477	0.152	2.57	199.397
D	1708.4	21.22	6.454	0.1489	2.576	110.254
D	1708.56	21.896	7.702	0.1588	2.582	14.217
D	1708.71	22.94	5.308	0.1882	2.584	49.833
D	1709.32	27.792	4.389	0.2061	2.631	111.444
D	1709.47	28.049	4.666	0.1882	2.619	201.746
D	1709.62	30.786	4.572	0.2019	2.609	37.694
D	1709.78	31.706	3.806	0.2223	2.588	4.012
D	1709.93	30.773	3.331	0.2433	2.58	1.266
D	1710.08	28.773	3.385	0.2312	2.576	1.962
D	1711.45	37.3	2.086	0.2601	2.275	55.376

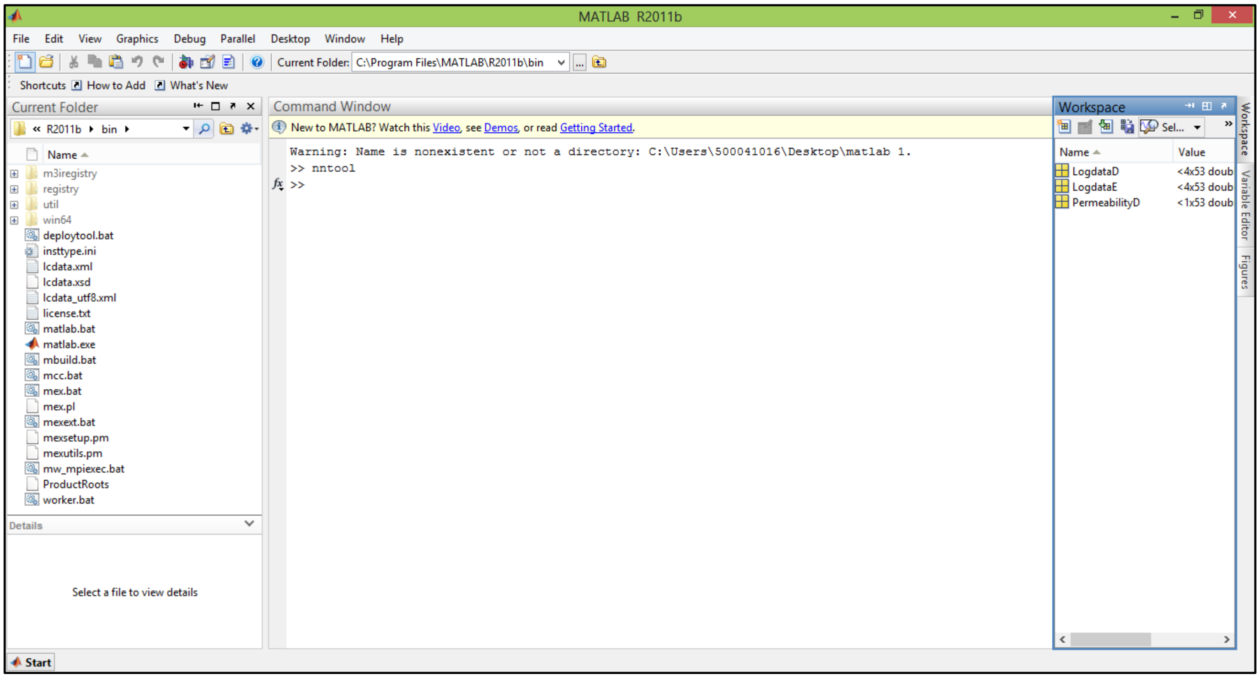
well name	depth(m)	GR(GAPI)	LLD(ohm-m)	NPHI(v/V)	RHOB(g/cc)	known permeability k(mD)
E	1520.19	28.4375	1.4306	0.2856	2.4785	36.73
E	1525.07	24.9844	2.1316	0.2212	2.418	0.969
E	1530.1	33.5313	2.4299	0.2632	2.4063	7.298
E	1535.13	31.1875	5.1205	0.1553	2.4961	5.84
E	1540	40.8125	2.0435	0.1499	2.5703	4.525
E	1545.03	43.4688	4.3803	0.1113	2.584	126.646
E	1550.06	27.875	3.7231	0.1157	2.5273	36.171
E	1560.12	16.7188	3.3475	0.1714	2.3848	1.249
E	1565.15	57.25	1.3784	0.2515	2.5508	3.619
E	1570.02	28.0781	3.3284	0.1841	2.5586	9.072
E	1575.05	37.4688	4.184	0.1611	2.5137	4.731
E	1580.24	66.0625	1.233	0.1597	2.0996	3.808
E	1584.5	47.4688	1.2729	0.2808	2.4727	281.928
E	1590.14	32.2813	3.6448	0.1733	2.4336	1.196
E	1593.65	42.8438	1.4375	0.2686	2.4356	80.578
E	1601.57	43.1875	3.2558	0.1392	2.5684	17.353
E	1605.38	37.5	1.6205	0.2451	2.3184	26.886
E	1610.11	38.0313	2.3521	0.21	2.4023	1.065
E	1616.51	34.8438	1.1169	0.2568	2.4648	12.567
E	1620.01	18.0625	1.9063	0.2354	2.3203	2.609
E	1625.19	67	2.423	0.2642	2.4219	182.578
E	1630.07	50.4375	1.427	0.2822	2.4727	327.046
E	1636.93	46.9063	1.3412	0.2852	2.502	128.894
E	1639.98	36.7188	3.4244	0.1567	2.5606	15.455

E	1645.31	44.375	2.7838	0.2339	2.5273	0.785
E	1650.03	29	5.2421	0.1753	2.4434	1.618
E	1655.06	27.8125	2.5238	0.1626	2.5566	9.019
E	1661.77	40.75	1.528	0.2627	2.4902	7.889
E	1670.46	30.0781	3.0182	0.1704	2.6094	86.731
E	1677.92	36.875	1.1522	0.3061	2.541	209.754

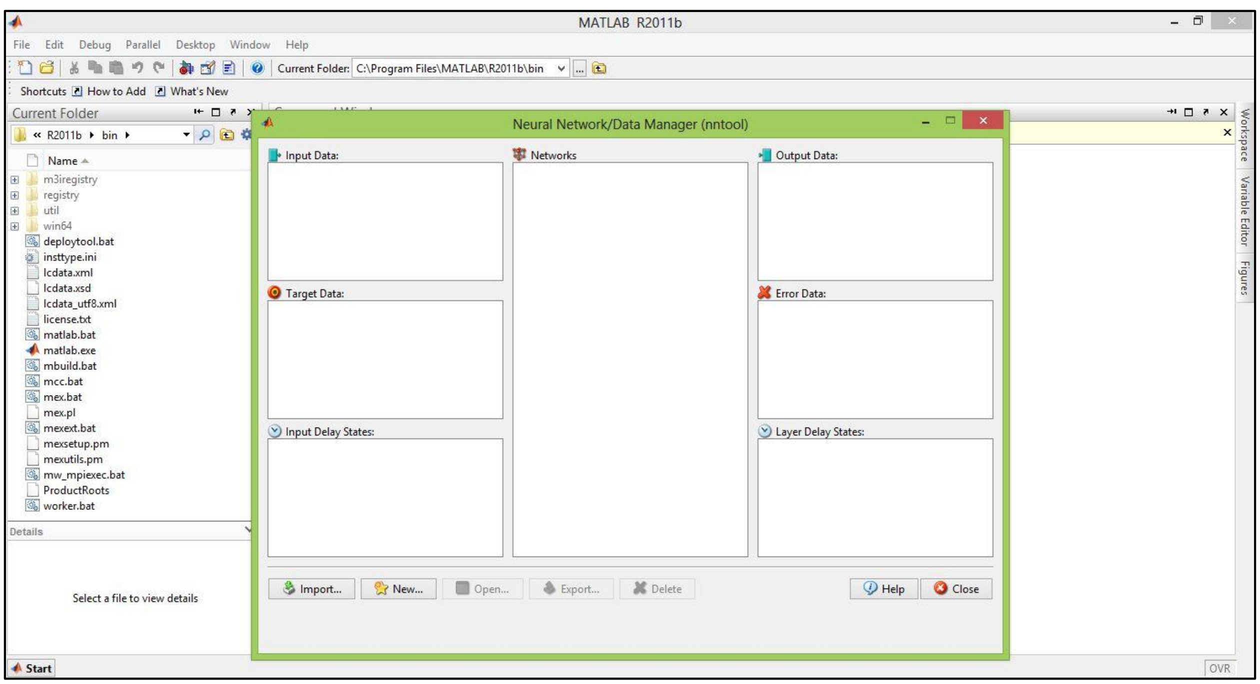
2. The log & core data of well D was used for training the neural network and for validation purpose while the data of well E was used to predict and verify permeability.

3. The MATLAB application was then launched, the training data was imported into MATLAB workspace.

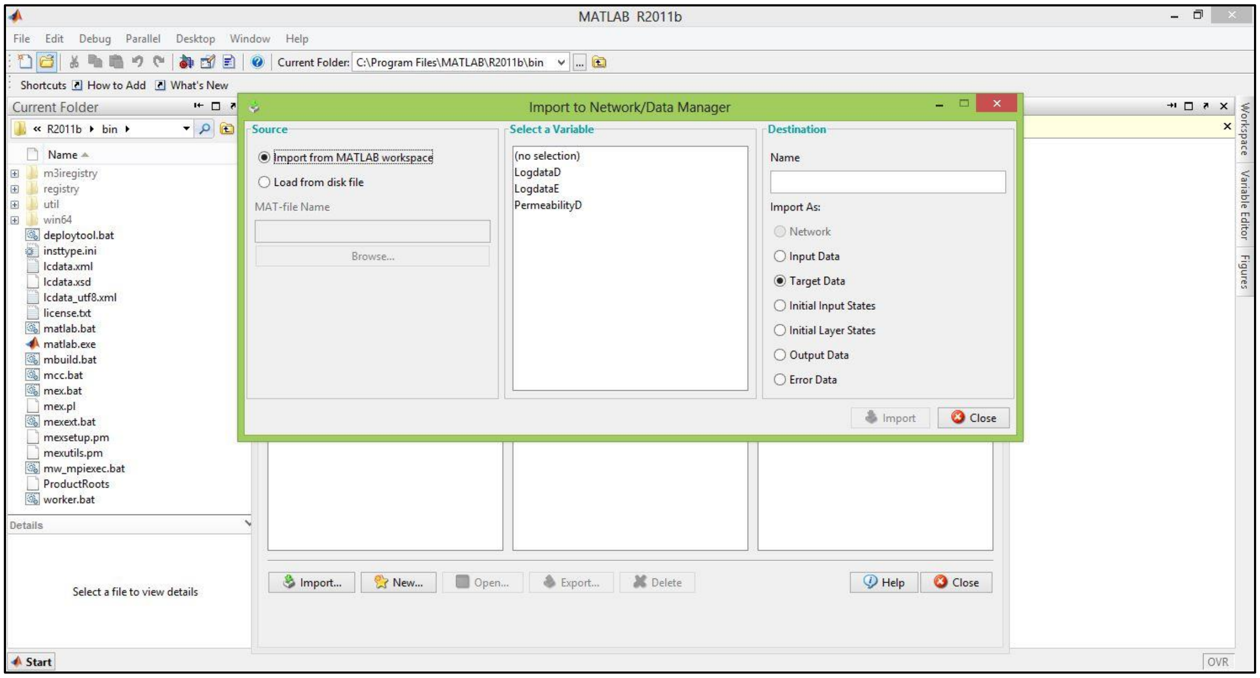




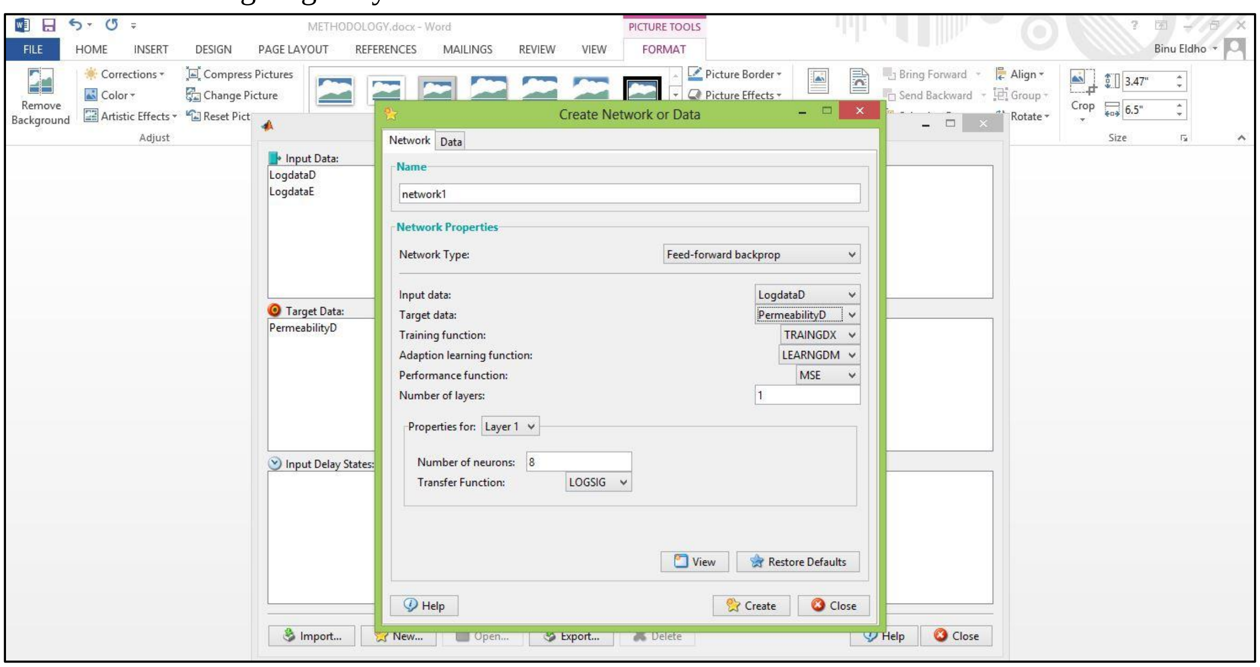
4. After the data is imported and variables are defined, the neural network tool (nntool) was launched



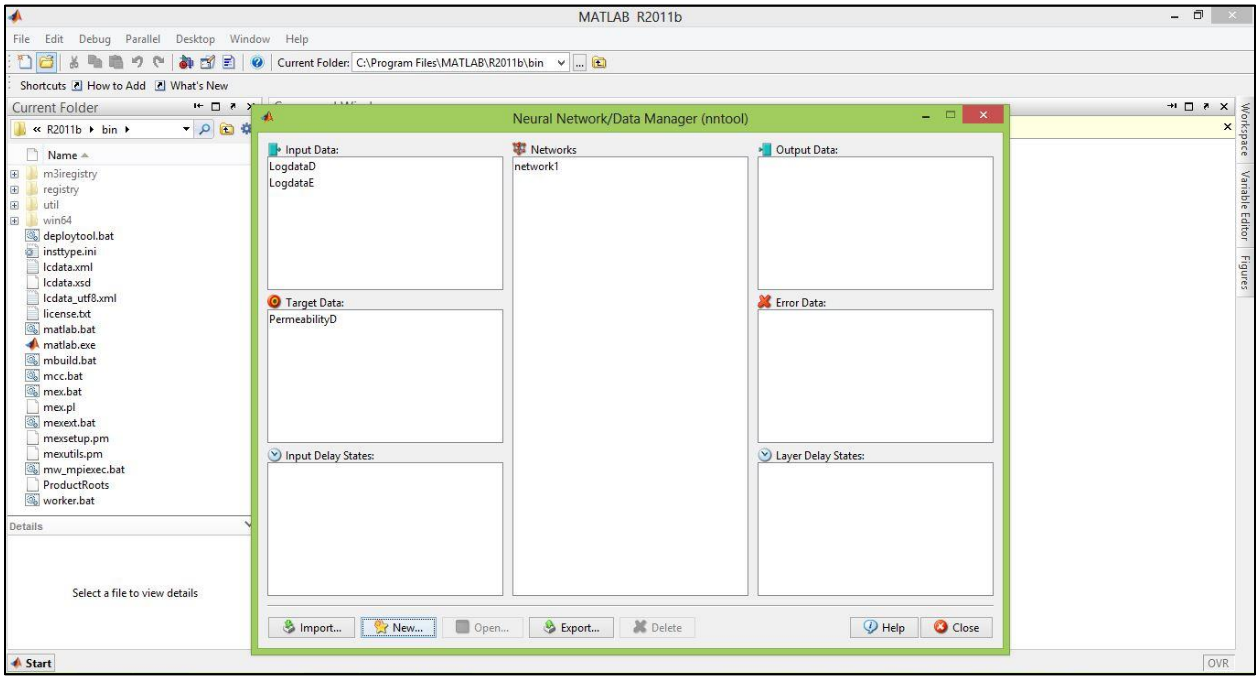
5. Next the data is imported to data manager



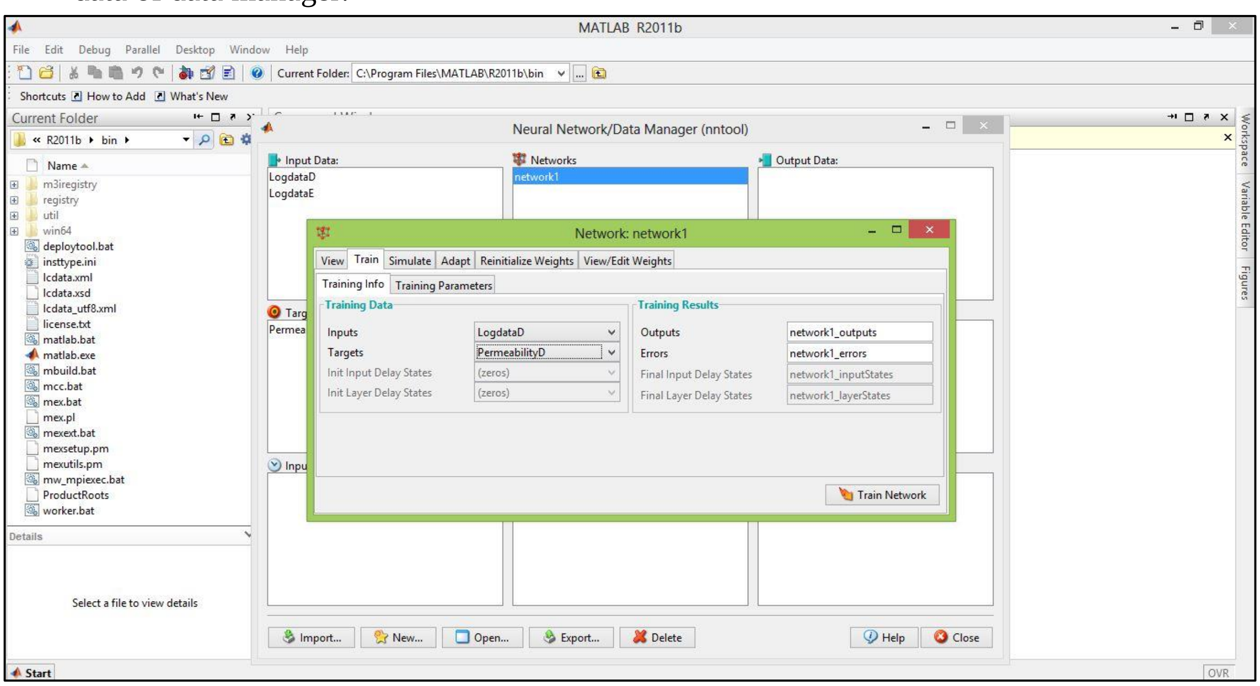
6. Using well D log data as input and core permeability as target, a neural network is created using single layer and 8 neurons.

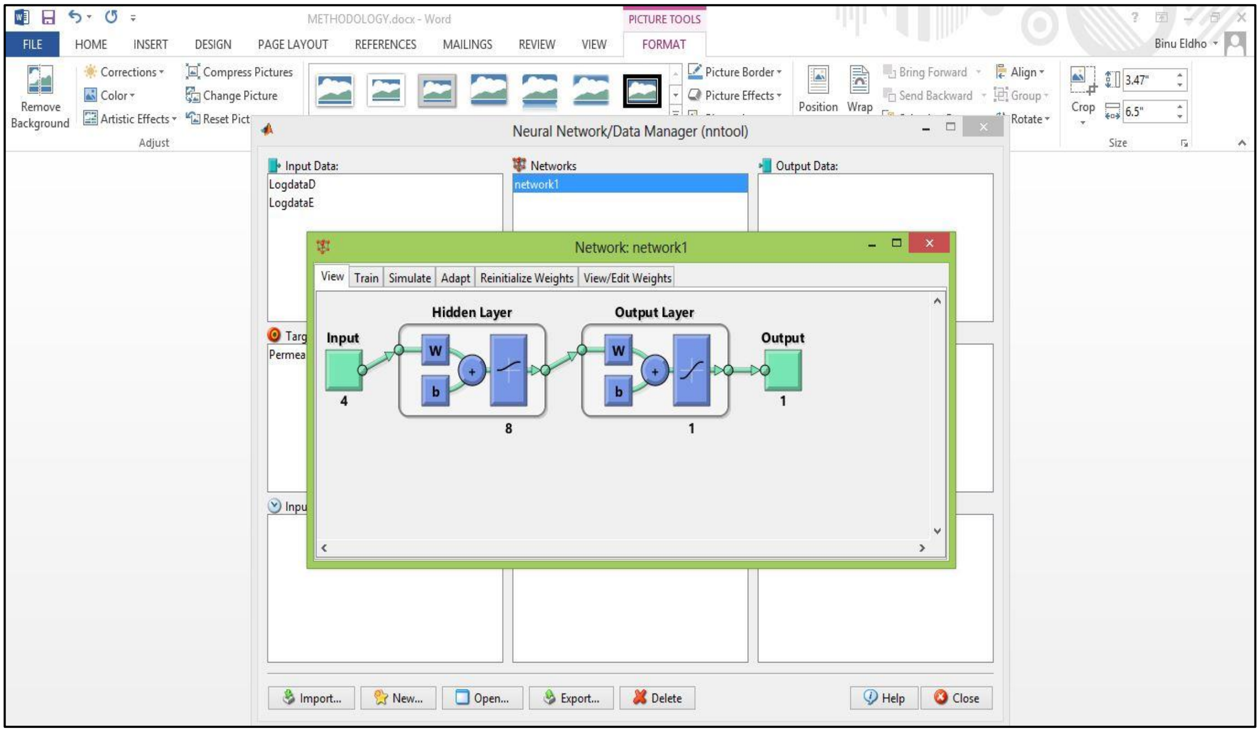


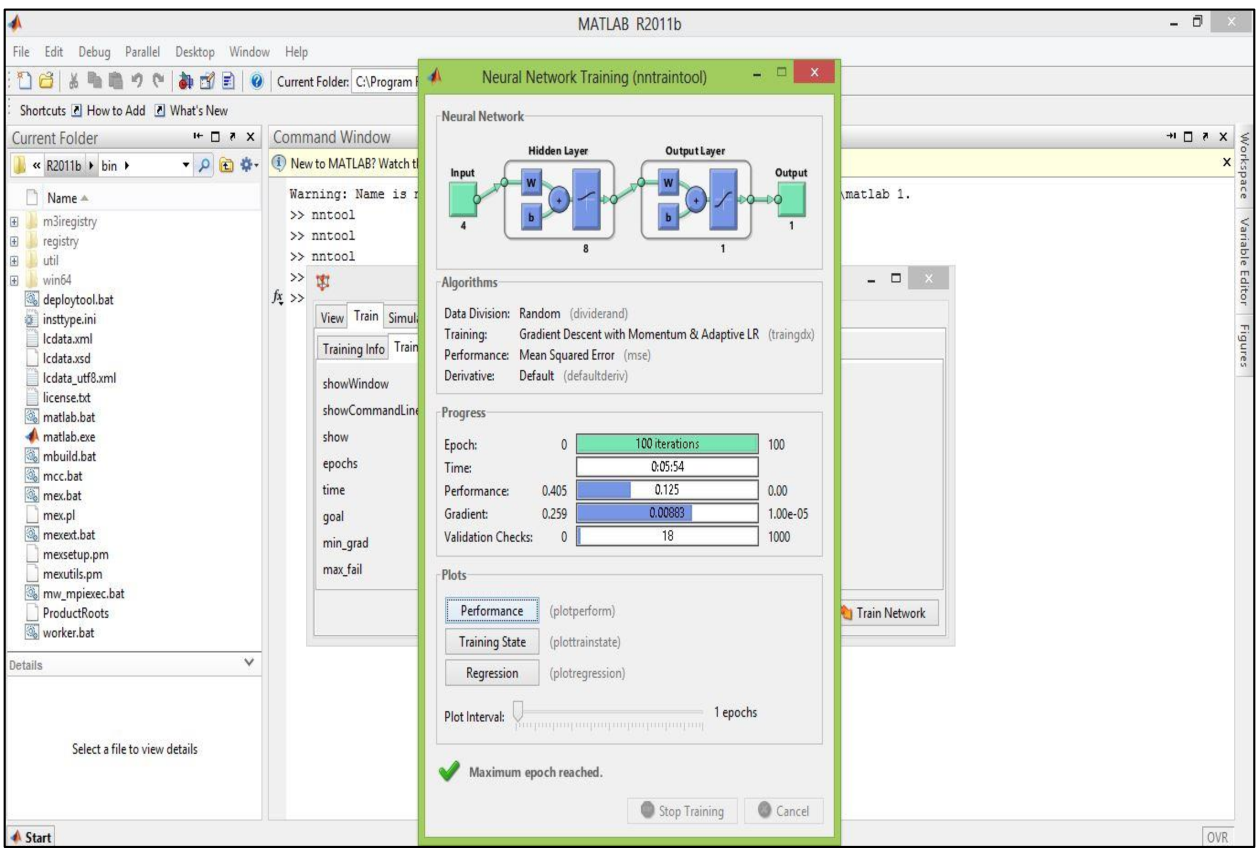
7. The network is created in networks of data manager.



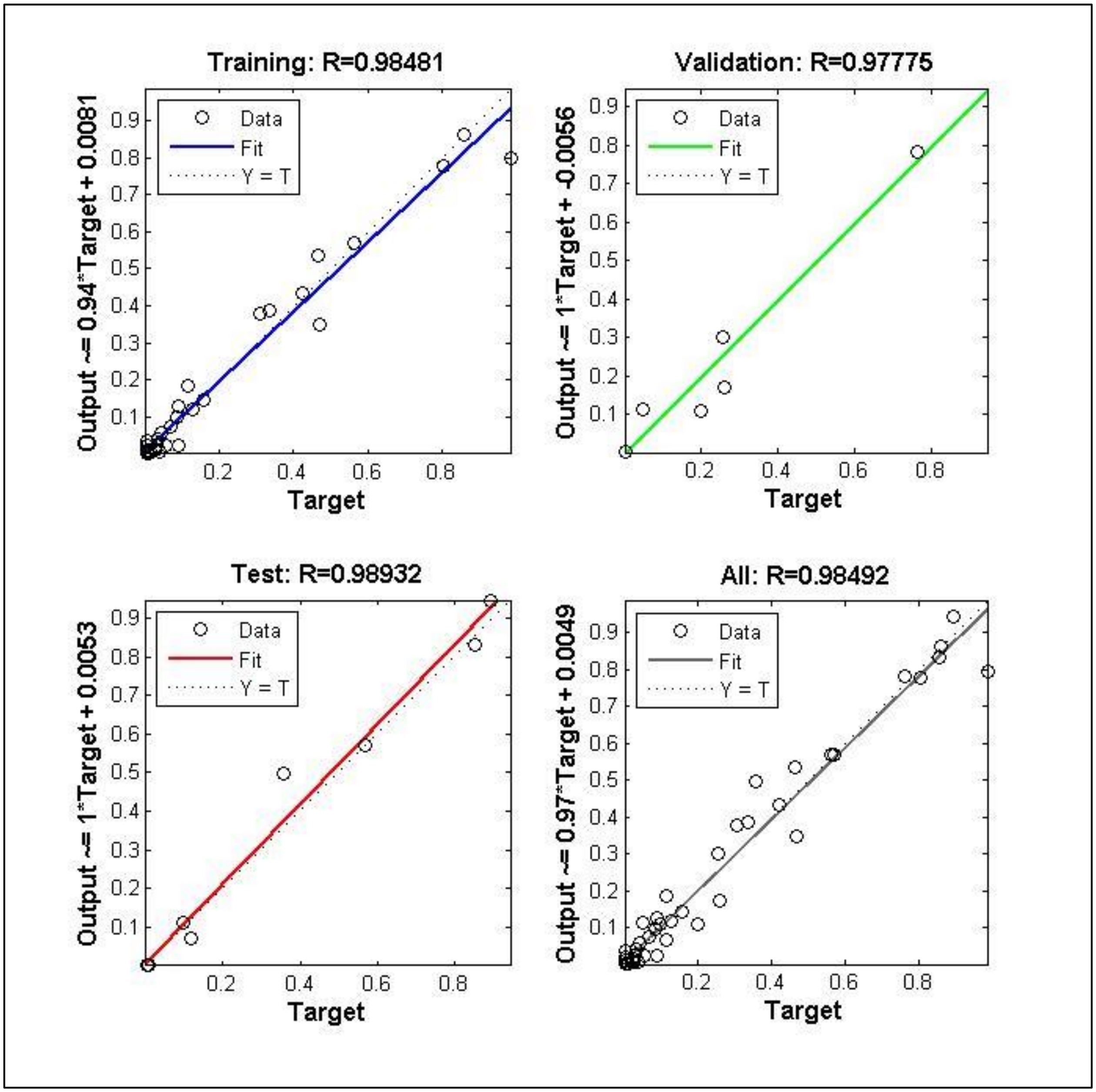
8. Now we train the network using data of well D and store the trained network in output data of data manager.



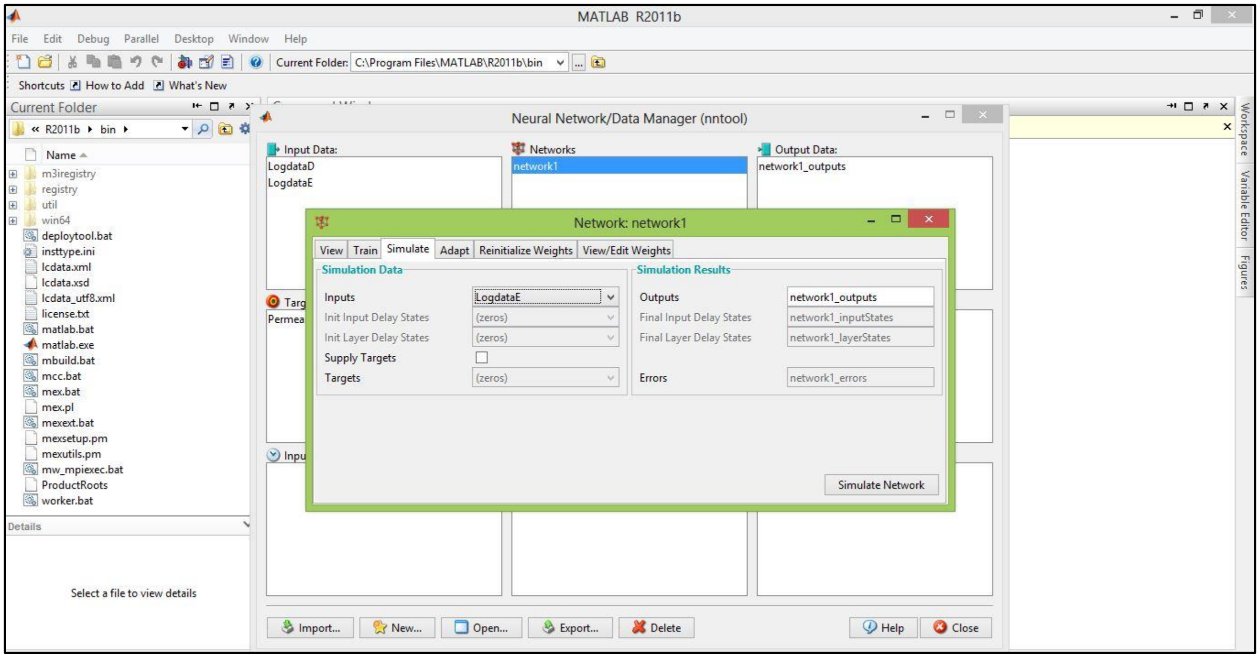

Neural Network/Data Manager (nntool)
Input Data:
LogdataD
LogdataE
Networks
network1
Output Data:
Network: network1
View
Train
Simulate
Adapt
Reinitialize Weights
View/Edit Weights
Hidden Layer
Output Layer
Input
Output
W
b
4
8
1
1
Import...
New...
Open...
Export...
Delete
Help
Close


MATLAB R2011b
Neural Network Training (nntraintool)
Neural Network
Hidden Layer
Output Layer
Input
Output
Algorithms
Data Division: Random (dividerand)
Training: Gradient Descent with Momentum & Adaptive LR (traingdx)
Performance: Mean Squared Error (mse)
Derivative: Default (defaultderiv)
Progress
Epoch: 0 100 iterations 100
Time: 0:05:54
Performance: 0.405 0.125 0.00
Gradient: 0.259 0.00883 1.00e-05
Validation Checks: 0 18 1000
Plots
Performance (plotperform)
Training State (plottrainstate)
Regression (plotregression)
Plot Interval: 1 epochs
Maximum epoch reached.
Stop Training
Cancel
Command Window
>> nntool
>> nntool
>> nntool
Current Folder
Select a file to view details
Train Network

9. The regression is obtained with an overall regression of 0.984



10. This trained network is simulated to predict the permeability of well E.



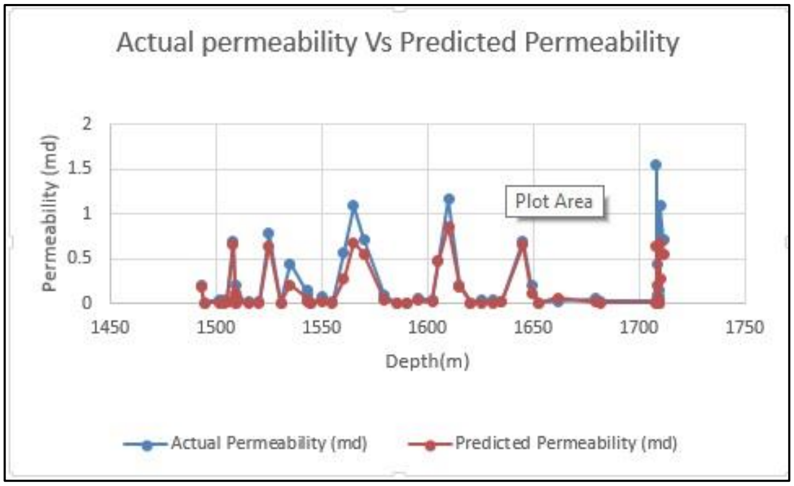
11. The predicted permeability from the neural network is saved in an Excel data sheet and is compared with the actual permeabilities for verification and a graph is plotted.

1	Depth	Predicted Permeability
2	1493.06	0.19108
3	1494.59	0.0020677
4	1501.59	0.0076188
5	1504.29	0.0025692
6	1505.56	0.019898
7	1508	0.65165
8	1509.06	0.11041
9	1509.22	0.0019171
10	1509.52	0.055366
11	1510.28	0.016766
12	1515.62	0.003317
13	1520.34	0.0074425
14	1525.07	0.64404
15	1530.86	0.0020099
16	1535.13	0.20356
17	1543.51	0.04213
18	1543.66	0.012097
19	1545.03	0.0022561
20	1550.06	0.010615
21	1554.94	0.0019906
22	1560.27	0.26532
23	1564.84	0.67923
24	1570.03	0.5527
25	1579.63	0.029155
26	1585.27	0.0022157
27	1590.14	0.0019215
28	1595.93	0.03433
29	1602.33	0.017196

30	1605.08	0.4678
31	1610.11	0.86493
32	1615.14	0.19108
33	1620.32	0.0020677
34	1625.35	0.0076188
35	1630.99	0.0025692
36	1635.1	0.019898
37	1644.85	0.65165
38	1649.12	0.11041
39	1652.63	0.0019171
40	1661.62	0.055366
41	1679.45	0.016766
42	1681.73	0.003317
43	1708.1	0.0074425
44	1708.25	0.64404
45	1708.4	0.0020099
46	1708.56	0.20356
47	1708.71	0.04213
48	1709.32	0.012097
49	1709.47	0.0022561
50	1709.62	0.010615
51	1709.78	0.0019906
52	1709.93	0.26532
53	1710.08	0.67923
54	1711.45	0.5527

12. The predicted values are compared with the actual core data values for verification. the actual permeability values that were measured in the laboratory in comparison with network's estimation. Although the permeability value covers a wide range, the network is able to follow the trend closely. After plotting core measurements versus network predictions, one can see the divergence of the

predictions from a perfect match, which is the unit slope line On plotting the measured permeability with estimated permeability from the network, we have got R = 0.9848, 0.9777, 0.9893 and 0.9849 for training, validation, blind testing and over all correlation respectively.



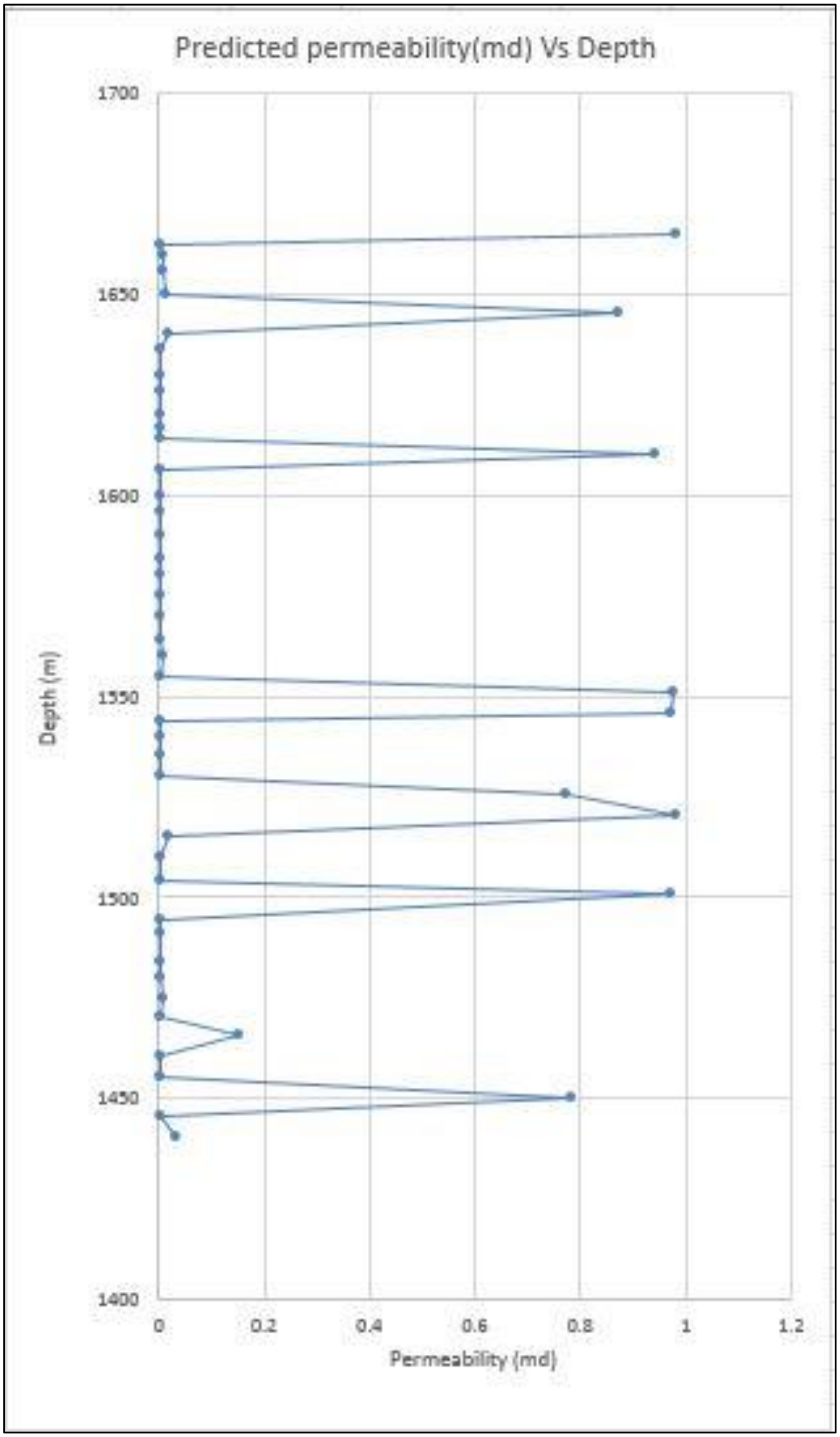
6. RESULT & DISCUSSIONS

Scatter plot of measured permeability from core data of Well D versus estimated permeability generated through ACE method shows regression of 0.951 . Whereas, the correlation for the same through ANN method comes out to be 0.984. Hence, for estimating the permeability of Well A and Well B Artificial Neural Network model was employed. The network for the same was trained by core data values of permeability from Well D and now this network was simulated to predict the permeability values for rest of the wells. The permeabilities of well A and well B are predicted using the neural network created.

Well A

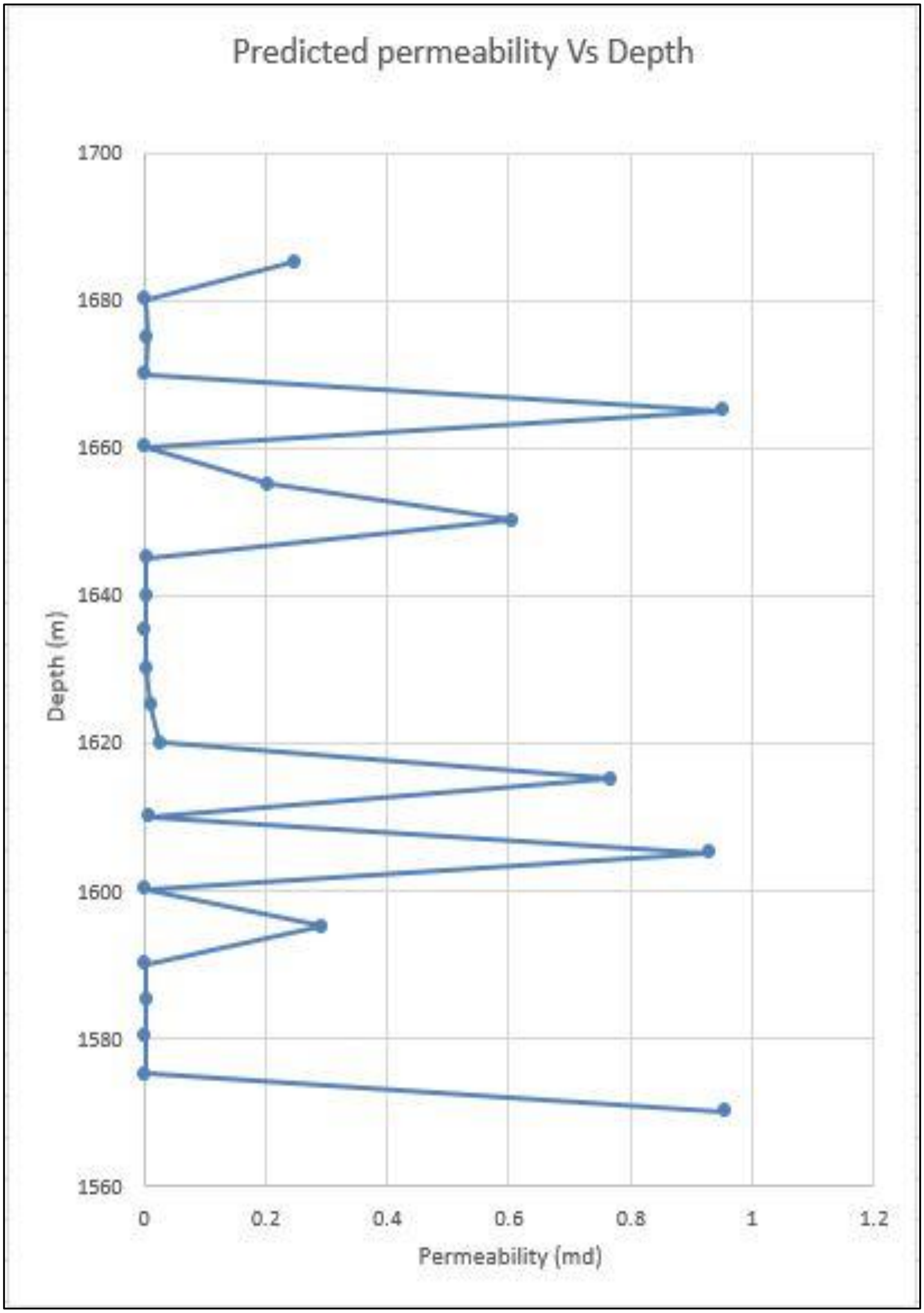
Depth(m)	Predicted permeability(md)
1440.58	0.035866
1445.45	0.0019266
1450.02	0.78554
1455.05	0.0019133
1460.24	0.0032127
1465.42	0.15238
1470.14	0.0028321
1474.71	0.0074752
1480.05	0.0020611
1484.16	0.001921
1490.87	0.002297
1494.07	0.0019834
1500.62	0.9708
1504.43	0.0031208
1510.07	0.003964
1515.25	0.016959
1520.13	0.98426
1525.46	0.77322
1530.03	0.0019423
1535.52	0.0035477
1540.09	0.0038931
1543.75	0.0021655
1545.58	0.97402
1550.76	0.97668
1555.03	0.0019176
1560.06	0.0083621

1563.87	0.0039793
1570.12	0.0022299
1574.99	0.0021682
1580.02	0.0019278
1584.44	0.0021268
1590.08	0.002839
1596.18	0.0023354
1600.14	0.0021972
1606.08	0.0029625
1610.04	0.9419
1614.46	0.0019949
1617.06	0.0020166
1620.1	0.0025554
1625.89	0.0031762
1630.01	0.0019211
1636.56	0.001929
1640.07	0.017389
1645.55	0.87093
1650.13	0.011516
1655.92	0.010294
1660.03	0.0078724
1662.32	0.0025174
1665.06	0.98061


Predicted permeability(md) Vs Depth
1700
1650
1600
1550
1500
1450
1400
Depth (m)
0
0.2
0.4
0.6
0.8
1
1.2
Permeability (md)

Well B

Depth(m)	Predicted permeability(md)
1570.07	0.9568
1575.1	0.0028613
1580.13	0.0022139
1585.01	0.0048802
1590.03	0.0025525
1595.06	0.29396
1600.09	0.0019827
1605.12	0.92959
1610	0.0070668
1615.03	0.76822
1620.06	0.026998
1625.09	0.011939
1630.12	0.0044166
1635.14	0.0025357
1640.02	0.0037195
1645.05	0.0037133
1650.08	0.60616
1655.11	0.20457
1660.14	0.002424
1665.02	0.95274
1670.04	0.0028058
1675.07	0.005089
1680.1	0.0022808
1685.13	0.24983


Predicted permeability Vs Depth
1700
1680
1660
1640
1620
1600
1580
1560
Depth (m)
0
0.2
0.4
0.6
0.8
1
1.2
Permeability (md)

7.CONCLUSION

We identify an underlying functional form between the dependent and independent variables and thereby predict the permeability from the limited core data and interrelate it with the log data sheets, thus making it possible to expand the prediction to uncored wells in a cluster formation. We study both the ANN toolbox in MATLAB and ACE algorithm in GRACE and find the one with higher grade of accuracy thereby increasing the reliability of reservoir characterization. ANN toolbox in MATLAB serves as a better option for permeability prediction with an overall efficiency of 98.1%.

8. REFERENCES

1. SPE/DOE 35412 Optimal Transformations for Multiple Regression: Application to Permeability Estimation from Well Logs Guoping Xue, Akhil Datta-Gupta, Peter Valko, and Tom Blasingame, Texas A&M University.

2. Wilkipedia

3. A case study on permeability modeling and reservoir performance in the absence of core data in niger delta, Nigeria, I.Aigbedion

4. Well logging and formation evaluation, Toby Darling

5. GeoConvention 2012: Vision 1 Porosity and PermeabilityEstimation using Neural Network Approach from Well Log Data Akhilesh K. Vermaa, b*, akverma@gg.iitkgp.ernet.in

6. Mahanti, S., Selvaraj, P., Upadhyay, H., (2008): Depositional Processes and Reservoir Characterization of Kamalapuram Formation, Nagapattinam Sub Basin, Cauvery Basin, India, AAPG, GEO India Expo XXI, Noida.