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Estimating Ultimate Recovery in Shale Wells Based on Facts

Faegheh Javadi

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Estimating Ultimate Recovery in Shale Wells Based on Facts

Faegheh Javadi

Thesis Submitted to the
Benjamin M. Statler College of Engineering and Mineral Resources
at West Virginia University

in partial fulfillment of the requirements for the degree of
Master of Science in
Petroleum and Natural Gas Engineering

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2014

Keywords: Decline Curves, Marcellus Shale, Estimated Ultimate Recovery,
Artificial Neural Networks.

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ABSTRACT

Estimating Ultimate Recovery for Shale Based on Facts

Faegheh Javadi

Natural gas, as one of the nation's major energy sources plays a vital role in the US energy mix. In recent years, the production from Shale has focused much attention on this source of hydrocarbon. As an essential step for the production planning, natural gas professionals estimate production and ultimate recovery (EUR) throughout the life of wells. The fluid production rate (q) usually varies as a function of rock properties, well, and completion design parameters. The variation associated with these parameters is a source of uncertainty in estimating the long term production for unconventional reservoirs.

A number of methodologies have been suggested to estimate the long term production of shale wells. Decline curve analysis is the most widely used methodology in the estimation of the future production profile (Arps, 1945). However, its results have been determined to be over optimistic (Fanchi et al. 2013 and Dinh et al. 2014).

Discrepancies between actual and estimated production values by Arps decline curves have been observed. This is dominant in low permeability reservoirs characterized by production over-estimation that is a consequence of large values of hyperbolic component (b -values higher than 1). A combination of Arps hyperbolic (in early time) and exponential decline (in later time) is employed to overcome this deficiency (production over estimation). This combination of Arps declines curves are referred to as Combined Decline Curves (CDC). The resulting estimation of EUR is quite conservative such that it provides lower EUR values than Power Law Exponential and the Stretched Exponential Decline Curve.

The major objective of this research is to condition the results of the CDC-EUR of shale wells to rock properties, well characteristics, and completion design parameters in a given shale asset. The first step of this study is CDC-EUR estimation using Arps combined decline curves. In order to have a more accurate (conservative) estimation, the hyperbolic curve will be switched to exponential decline during later time in the well's life. Then, artificial intelligence will be employed to condition the CDC-EUR to rock properties, well characteristics, and completion design parameters.

The major rock properties that will be studied in this research as input parameters include porosity, total organic carbon, net thickness, and water saturation. Moreover, the effect of several design parameters, such as well trajectories, completion, and hydraulic fracturing variables on CDC-EUR will be investigated. This model will help natural gas professionals to have a better understanding of the effect of rock properties and design parameters on future gas production of shale.

To my beloved husband Ali and my family

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Introduction

Natural gas, as one of the nation's major energy sources has a vital role in the US energy mix. In recent years, developments in well completion technologies made the unconventional shale gas production economically feasible. Therefore, the production from Shale has focused much attention on this source of hydrocarbon. As an essential step for the production planning, natural gas professionals estimate production and ultimate recovery (EUR) throughout the life of wells. The fluid production rate (q) may vary by rock properties, well, and completion design parameters. The variation associated with these parameters is a source of uncertainty in estimating the long term production for unconventional reservoirs.

In this thesis a data driven model has been generated in order to predict EUR for shale wells. Furthermore the effect of rock properties and design parameters has been studied. These analyses can provide valuable completion and stimulation strategies for operators.

Unconventional Reservoirs

Based on the reservoirs rock type and hydrocarbon properties hydrocarbon deposits are either conventional or unconventional reservoirs. Conventional reservoirs are known as the highly permeable oil and gas reservoirs which can produce at almost high rates relying on reservoirs own initial pressure. On the other hand, unconventional reservoirs such as tight gas sands, coal bed gas, shale gas, and tight oil refers to formations with the permeability on the micro-Darcy scale that makes it too complicated and difficult to produce despite their huge amount of reserves inside [Ilk, 2008]. Figure 2 shows different resources of natural gas.

The increases in U.S. natural gas production have come from unconventional development of energy resource plays, which have become more accessible and economic due to advancements in horizontal drilling and hydraulic fracturing. Since 1998 unconventional natural gas production has increased nearly 150%. This increase has resulted in unconventional production becoming an increasingly larger portion of total natural gas production, growing from 28 percent in 1998 to more than 70 percent of total natural gas production in 2012 Figure 2 shows U.S. natural gas production by different sources from 1990 to 2040 [U.S. EIA, 2014].

Shale gas reservoirs are the most important and fast-growing source of natural gas in U.S. It has the potential to significantly increase America's security of energy supply, reduce greenhouse gas

emissions, and lower prices for consumers. The U.S. Energy Information Administration (EIA) estimates shale gas currently contributes about 33 percent of U.S. natural gas production, an amount that is expected to grow significantly as this huge resource is developed [U.S. EIA, 2014].

Shale gas reservoirs are known as very fine grained, dark-gray or black organic-rich and are the most common sedimentary source rocks in the world. Shale gas is natural gas that is attached to, or adsorbed onto, organic matter or it is contained in thin, porous silt or sand beds interbedded in the shale [Alberta Energy, 2009]. For decades, shale was known that large gas resources are trapped in shale formations, the low permeability of this formation made gas production economically unfeasible. Nevertheless, several factors such as advanced horizontal drilling and hydraulic fracturing have come together in recent years to change this unfavorable economic assessment and make shale gas production economically viable. As it is shown in Figure 2 the shale gas share of total U.S. natural gas production increases from 40% in 2012 to 53% in 2040.

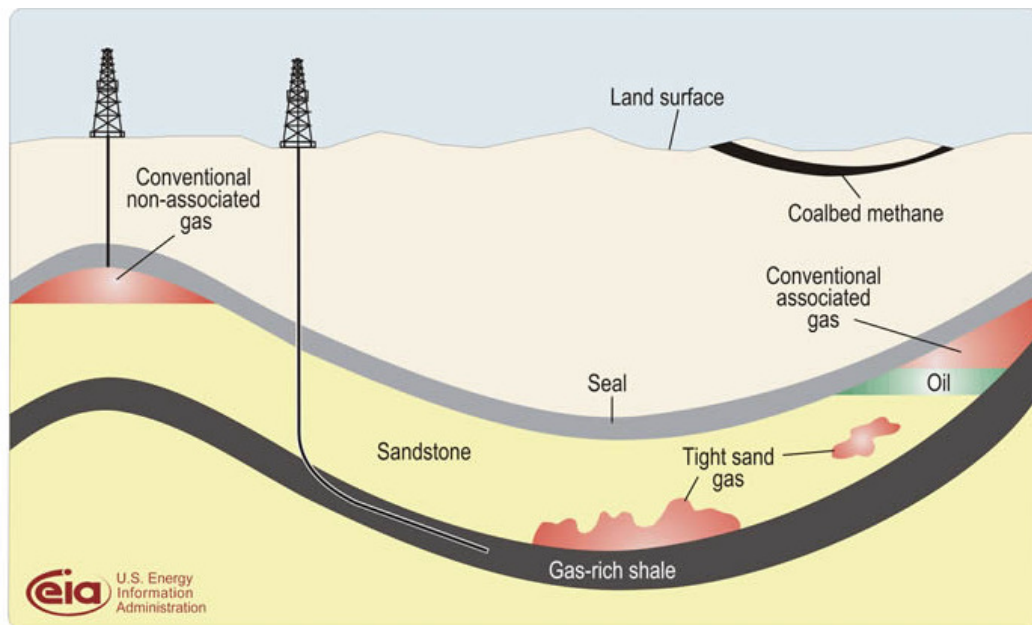


Figure 1. Schematic geology of natural gas resources (<http://www.eia.gov/todayinenergy/detail.cfm?id=110>)

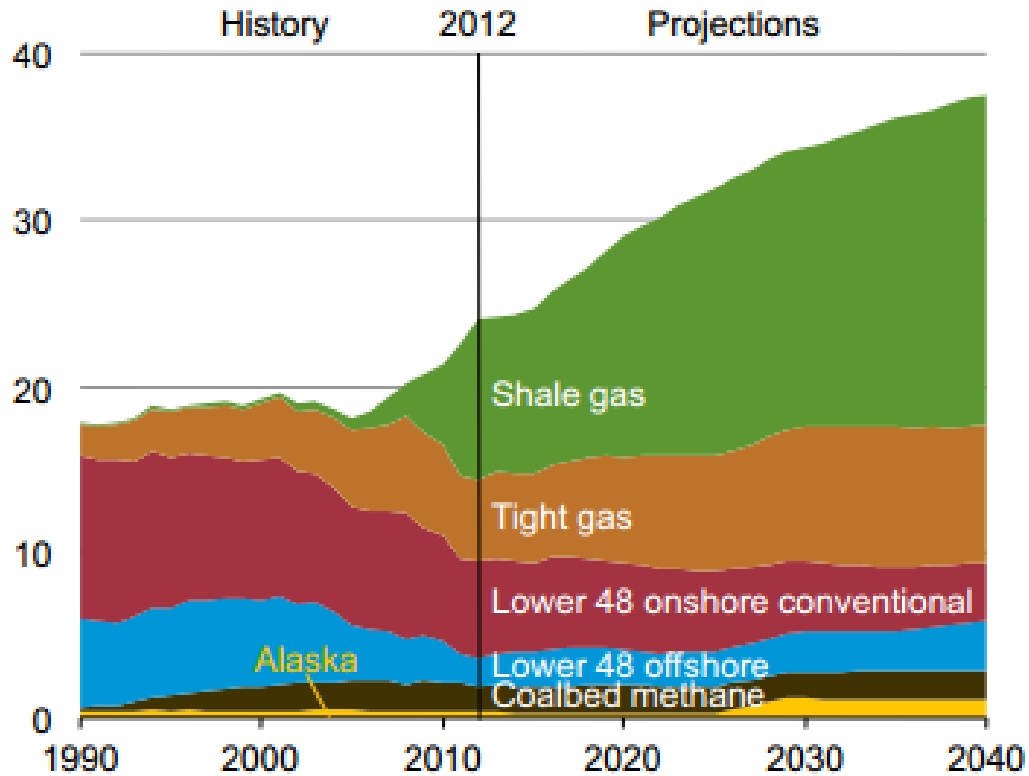


Figure 2. U.S. natural gas production by sources (1990-2040) [U.S. EIA, 2014]

The most important shale gas plays found in the US are Barnett Shale, Fayetteville Shale, Woodford Shale, Haynesville Shale, and Marcellus Shale. Each of these gas shale basins is different and each has a unique set of exploration criteria and operational challenges. Because of these differences, the development of shale gas resources in each of these areas faces potentially unique challenges. Figure 3 shows the wide distribution of highly organic shale plays in United States. The United States houses some of the largest shale gas reservoirs in the world which contribute majorly to the total domestic natural gas production in North America like the Barnett Shale of the Fort Worth Basin. Barnett Shale play in Texas produces about 6% of all natural gas produced in United States.

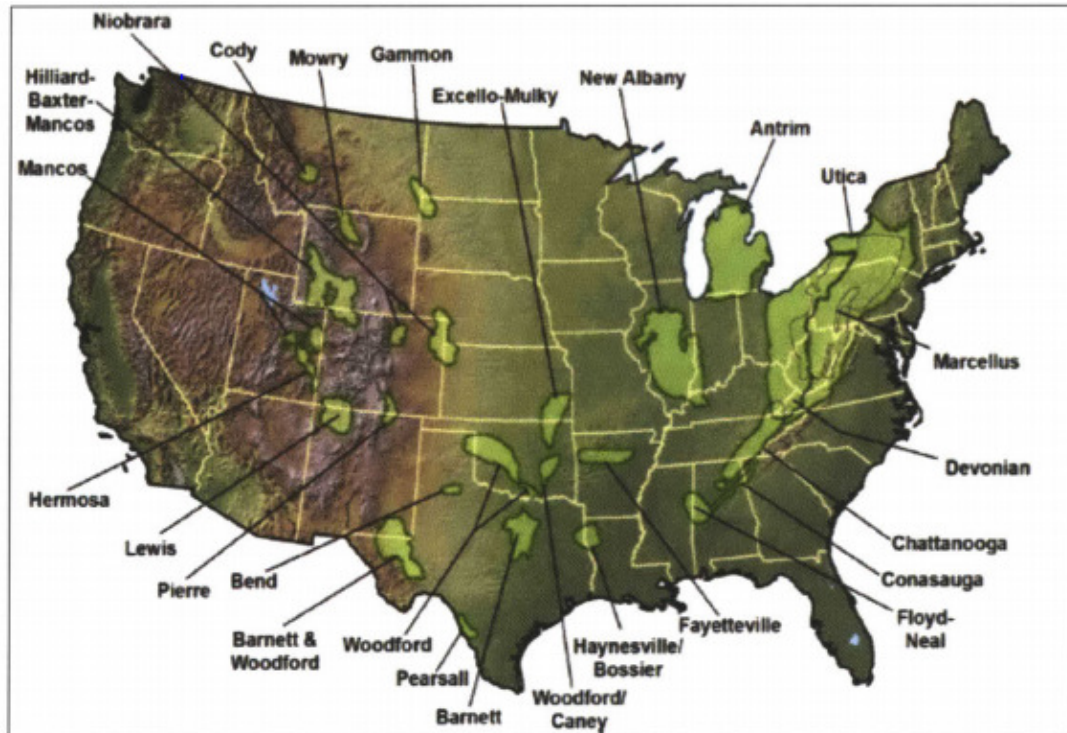


Figure 3. Shale plays distribution in United States [U.S. DOE, 2009]

The total recoverable gas resources in four new shale gas plays (the Haynesville, Fayetteville, Marcellus, and Woodford) may be over 550 TCF. Total annual production volumes of 3 to 4 TCF may be sustainable for decades. This potential for production in the known onshore shale basins, coupled with other unconventional gas plays, is predicted to contribute significantly to the U.S.'s domestic energy outlook [U.S. DOE, 2009]. Table 1 compares the geologic differences between major shale gas plays in the United States.

Table 1. Comparison of Unconventional Shale in the United States [U.S. DOE, 2009]

Gas Shale Basin	Barnett	Fayetteville	Haynesville	Marcellus	Woodford	Antrim	New Albany
Estimated Basin Area, square miles	5,000	9,000	9,000	95,000	11,000	12,000	43,500
Depth, ft	6,500 - 8,500 ⁸²	1,000 - 7,000 ⁸³	10,500 - 13,500 ⁸⁴	4,000 - 8,500 ⁸⁵	6,000 - 11,000 ⁸⁶	600 - 2,200 ⁸⁷	500 - 2,000 ⁸⁸
Net Thickness, ft	100 - 600 ⁸⁹	20 - 200 ⁹⁰	200 ⁹¹ - 300 ⁹²	50 - 200 ⁹³	120 - 220 ⁹⁴	70 - 120 ⁹⁵	50 - 100 ⁹⁶
Depth to Base of Treatable Water [#] , ft	~1200	~500 ⁹⁷	~400	~850	~400	~300	~400
Rock Column Thickness between Top of Pay and Bottom of Treatable Water, ft	5,300 - 7,300	500 - 6,500	10,100 - 13,100	2,125 - 7650	5,600 - 10,600	300 - 1,900	100 - 1,600
Total Organic Carbon, %	4.5 ⁹⁸	4.0 - 9.8 ⁹⁹	0.5 - 4.0 ¹⁰⁰	3 - 12 ¹⁰¹	1 - 14 ¹⁰²	1 - 20 ¹⁰³	1 - 25 ¹⁰⁴
Total Porosity, %	4 - 5 ¹⁰⁵	2 - 8 ¹⁰⁶	8 - 9 ¹⁰⁷	10 ¹⁰⁸	3 - 9 ¹⁰⁹	9 ¹¹⁰	10 - 14 ¹¹¹
Gas Content, scf/ton	300 - 350 ¹¹²	60 - 220 ¹¹³	100 - 330 ¹¹⁴	60 - 100 ¹¹⁵	200 - 300 ¹¹⁶	40 - 100 ¹¹⁷	40 - 80 ¹¹⁸
Water Production, Barrels water/day	N/A	N/A	N/A	N/A	N/A	5 - 500 ¹¹⁹	5 - 500 ¹²⁰
Well spacing, acres	60 - 160 ¹²¹	80 - 160	40 - 560 ¹²²	40 - 160 ¹²³	640 ¹²⁴	40 - 160 ¹²⁵	80 ¹²⁶
Original Gas-in-Place, tcf ¹²⁷	327	52	717	1,500	23	76	160
Technically Recoverable Resources, tcf ¹²⁸	44	41.6	251	262	11.4	20	19.2
<p>NOTE: Information presented in this table, such as Original Gas-in-Place and Technically Recoverable Resources, is presented for general comparative purposes only. The numbers provided are based on the sources shown and this research did not include a resource evaluation. Rather, publically available data was obtained from a variety of sources and is presented for general characterization and comparison. Resource estimates for any basin may vary greatly depending on individual company experience, data available at the time the estimate was performed, and other factors. Furthermore, these estimates are likely to change as production methods and technologies improve.</p> <p>Mcf = thousands of cubic feet of gas scf = standard cubic feet of gas tcf = trillions of cubic feet of gas # = For the Depth to base of treatable water data, the data was based on depth data from state oil and gas agencies and state geological survey data. N/A = Data not available</p>							

Marcellus Shale

The Marcellus Shale is the most expansive shale gas in the United States. The Marcellus Shale, also referred to as the Marcellus Formation, is a Middle Devonian-age black, low density, carbonaceous (organic rich) shale. This formation runs across the north-east south-west trend from west central of New York into Pennsylvania, eastern Ohio, through western Maryland, and throughout most of West Virginia extending across the state line into extreme western Virginia. Figure 4 shows the distribution of shale plays in the United States.

The Marcellus Shale covers an area of 95,000 square miles at an average thickness of 50 ft. to 200 ft. The depth of the formation is typically between 4000 to 85000 ft. While the Marcellus is lower in relative gas content at 60 scf/ton to 100 scf/ton, the much larger area of this play compared to other shale gas plays results in a higher original gas-in-place estimate of up to 1,500 TCF [U. S. DOE, 2009].

Measured total organic content of the Marcellus Formation ranges from less than 1% in eastern New York, to over 11% in the central part of the state and the shale may contain enough carbon to support combustion. The more organic-rich black shale can be bituminous, but are too old to contain 25 bituminous coal formed from land plants. In petroleum geology, this black shale are an important source rock that filled conventional petroleum reservoirs in overlying formations, are an unconventional shale gas reservoir, and are an impermeable seal that traps underlying conventional natural gas reservoirs. To the west, the formation may produce liquid petroleum; further east heating during deeper burial more than 240 million years ago cracked this oil into gas [Laughrey, et. al., 2004].

The Marcellus Shale filed under study in this thesis is a part of an asset which is located in Southern Pennsylvania and Northern West Virginia.

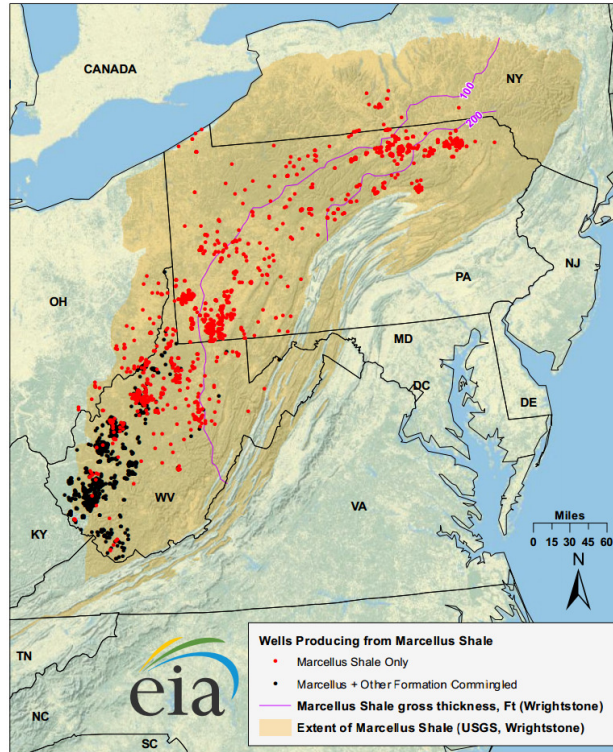


Figure 4. Marcellus shale play Distribution in [U.S. EIA, 2009]

Literature Review

For the most of gas and oil wells, the production analysis should be applied. The diffusivity equation which is a combination of continuity equation, flux equation (Darcy's Law) and an equation of state are the origin of all these analyses methods [Esmaili, 2013]. Production analysis for shale have been developed over the last 50 years based on models for gas production from coal beds and applied initially to low pressure fractured reservoirs [Walton, 2012]. With rapid demand for production from shale the need for development of a reliable, fast and cost efficient model is developing quickly.

Accordingly, different approaches have been discussed in the literature for production performance analysis and estimating the hydrocarbon reserves. Numerical reservoir simulation and modeling is one of these methods that are being used for this purpose [Freeman et al., 2009].

Numerical modeling of shale gas reservoir carries a very specific problem due to its distinct properties such as multiple gas-storage mechanisms, complex interaction between natural fractures and induced (hydraulic) fractures, and inherent heterogeneity associated with rock properties. Since most of the shale gas reservoirs are naturally fractured, the dual porosity models fit the best for modeling of fluid flow in this type of reservoir. Dual porosity approaches were introduced as dual porosity models in early 1960s by Warren and Root [1963]. Modeling the hydraulic fractures by using commercial reservoir simulators is usually done by generating the local grid refinement and inclusion of high conductivity to those fine grids to represent the hydraulic fractures. Several authors have used this technique [Kalantari et al. (2010), Li et al. (2011), Osholake et al. (2011)] to numerically model a shale reservoir.

In the workflow presented by Cipolla et al. [2009] discrete modeling of shale matrix and fracture network to that of dual porosity models are used to contract numerical reservoir simulation techniques. It is mentioned in the literature that numerical reservoir simulation is costly and difficult approach, especially for shale formations [Mohaghegh et al., 2011]. Alternatively, data-driven techniques are novel approaches for modeling shale reservoirs which take into account all aspect of the reservoirs from reservoir characteristics to completion etc [Esmaili et al., 2012].

Analytical and empirical approaches have been applied to large multi-variable data set from shale assets with different degrees of success. Different methods for analysis and forecasting the shale gas production in literature are related to various aspects of gas shale, including operational (e.g., drilling, completion, and production) and technological challenges.

Data-driven modeling has been developed with contributions from artificial intelligence, data mining, machine learning, and pattern recognition. These models can complement or replace the “knowledge-driven” models describing behavior of physical systems [Solomatine et al., 2008]. Top-Down modeling, which is an AI-based approach, is a novel reservoir modeling technique as an alternative to traditional reservoir simulation and modeling [Mohaghegh, 2009].

The other approach which is the most commonly used procedures is decline-curve analysis (DCA). Analysis of past production decline to predict future production performance is valuable to oil and gas industry operators and financial resource institutions. Prior to the development of DCA models, estimation of oil reserves was accomplished by calculating the contents of a reservoir based on saturation and percentage of recoverable oil over a certain known area [Valko, 2009]. This resulted in a very rough estimate of recoverable hydrocarbons [Valko, 2009].

Since the publication of Arps’ decline curve equations [Arps, 1945], estimation of ultimate recovery has been primarily performed using his methods. Traditional Arps’ Decline Analysis equation estimates a reliable ultimate recovery for conventional oil and gas wells; since they exhibit boundary dominated flow (BDF) to abandonment. This assumption does not apply to tight permeability shales, which are dominated by long transient flow regimes. Fetkovich’s works [1980, 1987] brought a better understanding and tried to add an analytical meaning to the problem. These approaches seemed to satisfy the industry until unconventional reservoir systems became a significant potential of reserves growth and future production. Unlike conventional reservoirs, analyzing shale production data using traditional decline curve methods is problematic because of the nature of the reservoir properties and flow behavior. Shale wells have a long transient flow due to the very low matrix permeability [Kanfar and Wattenbarger, 2012]. Therefore, application of Arps’ DCA to production data from the unconventional reservoirs results in significant overestimation of reserves [Okouma, 2012]. Power Law Exponential has been proposed by Ilk et al. [2008] to address the problems with EUR overestimation. This is an empirical method for unconventional (shale) gas production data by matching early transient flow without overestimation. Another method for extrapolating the future production for shale gas is Stretched Exponential Method [Valko, 2009]. This method is able to calculate the recovery potential using differential equations and can estimate the ultimate recovery for tight gas.

Future production performance predictions using hydrocarbon production analysis is very valuable for gas and oil industry operators and financial resource institutions. In 1945 Arps developed methods to generate decline trends in conventional reservoirs with great success.

Hydrocarbon recovery from unconventional shale reservoirs is increasingly crucial, especially in the US and Canada; it is important to analyze current production trends, predict future production performance and evaluate the productiveness of different hydraulic fracture stimulations and completion designs. The traditional Arps decline models have not successfully estimated recovery or future production in low permeability reservoirs [Duong, 2011].

Trend analysis for data has always been used to find the impact of different parameter on each other. As indicated earlier another objective of this thesis is conditioning EUR with rock properties, well, completion, and stimulation parameters for a large number of wells in Marcellus shale. Unconventional reservoirs have complex geological features and very low permeability of the matrix rock. These characteristics are different from conventional reservoirs and scientist try to better understand these complex behaviors in order to predict the future performance.

We know that technology improvements – hydraulic fracturing and horizontal drilling – enable natural gas to be economically produced from shale. However, making completion and stimulation decisions and analyzing well performance behavior based on available tools such as analytical and numerical techniques could be challenging [Mohaghegh, et al., 2013]. The problem of understanding shale gas production has been much involved due to the complicated and unpredicted response of these reservoirs to fluid and proppant injection [Esmaili, et al., 2013]. Furthermore, each of reservoir characteristics of shale such as TOC and thickness as well as geomechanical properties of rock are different within the same producing area of the reservoir. All these variations have impact on hydrocarbon production behavior in shale wells.

The limitations in our understanding of the complex phenomenon have eventuated in limitations in our ability to represent accurate modeling of the production from shale formations. Therefore several assumptions have been made to make the models work [Mohaghegh, 2013]. Making these assumptions as well as modifying different parameters in history matching process due to reservoir simulation model validation can result the non-unique sensitivity results in complex shale gas reservoirs.

Data Mining and pattern recognition technologies are one of the most reasonable alternatives for extracting useful information from large data sets and studying well performance behavior in shale [Gharehlo, 2012].

Data mining is a powerful new technology to process data and explore patterns or relationships between variables in the shale gas development process and it have proven to be capable of extracting useful information from large data sets and are extensively used in many industries. It

is widely used in different areas such as financial, medical, face and text recognition, and etc. Data mining techniques have a close relationship with artificial Intelligence, pattern recognition and machine learning and they enable to discover and present the information in a way which is understandable for humans.

Unlike conventional methods, data mining methods are able to detect and generate hidden patterns in the data [Mohaghegh, 2000]. In this research the advanced data mining technology being used is called Fuzzy Pattern Recognition.

Pattern Recognition is a branch of artificial intelligence focused on classification or description of observations. Pattern Recognition aims to classify data and extract useful information from the pattern. The patterns to be classified are usually groups of measurements or observations, defining points in an appropriate multidimensional space. In the other side fuzzy set theory is used to determine the appropriate multidimensional space that would provide optimum separation of overlapping classes, the result is known as Fuzzy Pattern Recognition [Mohaghegh, 2000]. When Fuzzy Pattern Recognition is applied to a limited number of classes of wells (Such as Poor, Average and Good wells) the process is called the Step Analysis or Well Quality Analysis (WQA). When a similar analysis is performed while every single well in the dataset is treated as a potential unique well quality the result is a continuous curve (rather than a discrete set of steps), called a Fuzzy Trend Analysis (FTA). The objective of these Fuzzy Pattern Recognition analyses is to discover hidden but important trends in the data set which cannot be discovered by statistical approaches [Esmaili et al., 2013].

Background

Decline Curve Analysis

Shale gas reservoirs have become an important source of natural gas supply in North America. Advancement of drilling and stimulation techniques has caused exploitation of these ultra-low permeability formations viable. Therefore well performance analysis for shale has become more significant. It is very essential for natural gas professionals to estimate the ultimate recovery for shale.

One of the common methods for calculating EUR is decline curve analysis. In this section two common decline curve methods, Arps' decline curves and Power Law Exponential, have been introduced.

Arps Decline Curve Analysis

Arps developed the mathematical relations for three types of graphical representation of production decline for conventional reservoirs [Arps, 1945]. These empirical equations define the historical exponential, hyperbolic, and harmonic decline types observed for different qualities of traditional reservoirs during boundary dominated flow of the wells. The basic concept of decline analysis involves fitting a trendline through a well's historical performance on a semi-log plot and extrapolating that line to estimate future production performance and ultimate recovery, assuming the past trend will not change under constant operational conditions. Arps models decline types using the concept of loss ratio (D) and its derivative (b) where D and b parameters are the decline parameter and decline exponent, respectively, expressed as follows:

$$\text{Loss-Ratio} \quad \frac{1}{D} = \frac{-q}{\left[\frac{dq}{dt}\right]} \quad (1)$$

$$\text{Derivative of Loss – Ratio} \quad b = \frac{d}{dt} \left[\frac{1}{D} \right] = - \frac{d}{dt} \left[\frac{q}{\left[\frac{dq}{dt}\right]} \right] \text{ where } 0 \leq b \leq 1. \quad (2)$$

When D is constant, equation 1 leads to an exponential decline which can be derived for the case of pseudo-steady state (or boundary dominated) flow in a closed reservoir containing a constant compressibility liquid and being produced at a constant wellbore flowing pressure (Ilk, 2008).

The three decline types have b values from 0 to 1. For the exponential case b value equals to 0. Values $0 < b < 1$ indicate hyperbolic decline, and a b value equal to 1 shows harmonic decline (Arps, 1945).

In 1980, Fetkovitch provided some more theoretical bases to the Arps decline equations by developing type curves for early transient flow [Fetkovitch, 1980].

In the Hyperbolic model, the production time declines with time. The empirical equation for Hyperbolic decline is

$$q = q_i * \frac{1}{(1 + bD_i t)^{\frac{1}{b}}} \quad (3)$$

Where, q is time-varying production rate, q_i is the initial production rate parameter, b is the hyperbolic decline exponent parameter ($0 < b < 1$), and D_i is the initial decline rate parameter. Integration of Eq. (3) leads to an expression for cumulative production, G_p

$$G_p = \frac{q_i^b}{D_i(b-1)} (q(t)^{1-b} - q_i^{1-b}) \quad (4)$$

Analysis of production decline from tight gas and shale gas wells using Eq. (3) typically results in a best-fit value of greater than unity for the decline exponent parameter, b [Lee and Sidle, 2010]. This leads to the physically unrealistic result that cumulative production becomes unbounded as time increases, as can be seen from the following:

$$\lim_{t \rightarrow \infty} G_p = \frac{q_i^b}{D_i(b-1)} \left(\frac{1}{q(t)^{b-1}} - \frac{q}{q_i^{b-1}} \right) \rightarrow \infty \quad (5)$$

Fetkovich et al. [1987] have argued that such anomalous behavior, i.e., values of $b > 1$ in Eq. (3) or Eq. (4), arises when data from the transient-flow period are used to fit a model that is only appropriate during boundary-dominated flow. Supporting this assertion is the observation that best-fit b values that start out being greater than one tend to decrease with time as more and more data become available [Blasingame et al., 2005]. However, the use of the hyperbolic model continues to remain popular for EUR estimation purposes. A heuristic approach to keeping the long-term reserve estimates finite, with best-fit b values greater than unity, involves switching to

an exponential decline with a prescribed minimum decline rate based on analogy or intuition [Harrell et al., 2004].

Power Law Exponential Decline Curve (PLE)

Arps' decline curve analysis results in overestimation of EUR for shale reservoirs. Therefore several alternative decline curve methods which are empirically formulated for shale have been used to calculate EUR. One of the recent methods is Power Law Exponential Decline Curve (PLE) which has been proposed by Ilk et al. [2008] to overcome the deficiencies of Arps' method. Power Law Exponential decline model is empirically developed for shale gas production data analysis by matching early transient data without overestimating reserves as compared to hyperbolic decline prediction with a high b-exponent.

Loss ratio during transient linear and bilinear flow has a power law relation with time. Therefore, the PLE loss ratio (D) can be calculated by the following equation:

$$D = D_{\infty} + D_1 t^{-(1-n)} \quad (6)$$

As the behavior of the proposed relation (Eq. 6) is a decaying power law formulation, this result is called the power law loss-ratio formulation. Forecasting D parameter is sensitive to D_{∞} values. It sets a limit on how the loss ratio can become and prevents the model from over-prediction [Seshdari and Mattar, 2010]. It should be noted that this model is able to model transient, transition and boundary dominated flow.

The following Power Law rate-time relation is resulted by substituting Eq. (6) into Eq. (3):

$$q = q_i \exp\left(-D_{\infty} t - \frac{D_1}{n} t^n\right) \quad (7)$$

Where q_i is the initial flow rate, D is decline constant at time one, D_{∞} is decline constant at infinite time, and n is the decline exponent.

Soft Computing

Soft computing is the collection of techniques that uses the human mind as model aiming to formalize human cognitive processes [Cabrera et al., 2009]. Soft computing methods can handle imprecision, uncertainty, partial truth, and approximation. The objective of the soft computing methods is to make low cost, analytic and complete solutions for complex systems in which traditional computational methods have not yielded such solutions [Zadeh, 1994]. Soft computing techniques are comprised of fuzzy logic, neuro-computing, evolutionary and genetic computing,

and probabilistic computing. Artificial neural networks are one of the main branches of soft computing. They have been applied to numerous applications such as signal processing, image processing, control, etc.

Artificial neural networks have been used in several aspects of reservoir engineering. The advantages of computer process and artificial neural networks in solving some fundamental petroleum engineering problems are discussed by Mohaghegh and Ameri [Mohaghegh and Ameri, 1995]. One of the neural networks applications in reservoir engineering is estimating ultimate recovery, which is an essential step for the production planning [Basinski, et al., 1997; Ouenes, et al., 1998]. Moreover, petrophysical properties estimation using artificial neural networks such as permeability estimation [Mohaghegh et al., 1995; Elshafei and Hamada, 2009a; Malki et al., 1996; Shokir et al., 2006], hydrocarbon saturation estimation [Morshed and Jagath, 1998; Elshafei and Hamada, 2009b], and relative permeability predictions [Guler et al., 2003; Silpngarmlers et al., 2002] have been widely studied for different scenarios.

Neural network applications in reservoir engineering also include PVT and fluid analysis [Elsharkawy, 1998; Hegeman et al., 2009], history matching [Esmaili, et al., 2012; Ramgulam, 2006; Sampaio et al., 2009; Mohaghegh, et al., 2011; Shahkarami, et al., 2014; Firoozjaee and Khamehchi, 2014], and field development strategies [Ayala et al., 2007; Doraisamy et al., 2000; Gorucu et al., 2005, Zargari, et al., 2011]. Since in this study artificial expert systems are used to perform to estimate ultimate recovery, in the upcoming sections artificial neural networks and reservoir characterization techniques are described in more details.

Artificial Neural Networks

Artificial neural networks (ANNs) now are computational methodologies that perform multifunctional analyses. They have become well established as viable, multipurpose, powerful computational methodologies with solid theoretic support and with strong potential to be effective in solving complex non-linear problems [Dayhoff and James, 2001]. This methodology is inspired by functionality of human brain and the ability of neuron networks to process information in parallel. The fundamental processing unit of human brain is called neuron. A neuron consists of a soma (cell body), axons (sends signals), and dendrites (receives signals). A schematic of a biological neuron is shown in Figure 5.

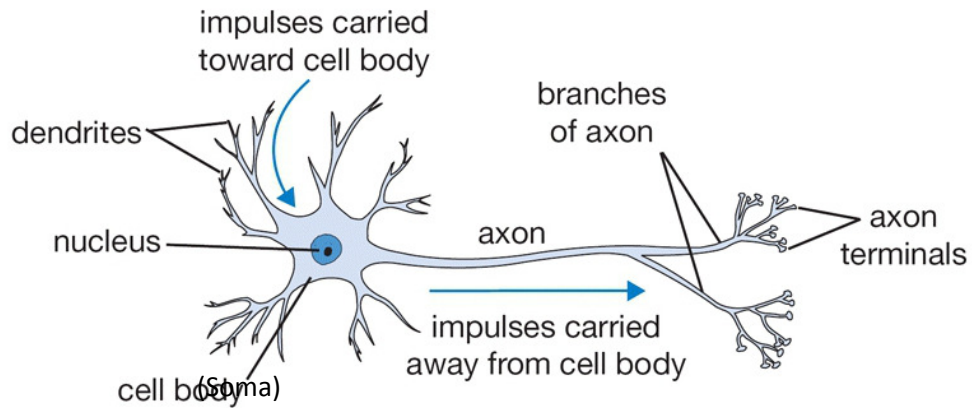


Figure 5. Structure of a neuron [source: <http://www.wpclipart.com/medical/anatomy/cells/neuron/neuron.png.html>]

ANNs are able to recognize patterns (pattern recognition is the study of how machine can observe the environment, learn to discover patterns of interest from their background and make good and reasonable decisions about categories of the patterns [Basu et al., 2010]), detect trends, classify, predict, and solve highly non-linear problems through deriving meaning from complicated or imprecise data [Esmaili, 2014]. A very important feature of these networks is their adaptive nature, where “learning by example” replaces “programming” in solving problems [Jha, 2004]. Therefore, data availability is the key factor in this method.

ANNs consist of simple computational unit called neurons, which are richly interconnected by weighted connection lines. Figure 6 shows the mathematical structure of a neuron. The input vector of the artificial neuron is a vector X which has n elements with connection to weight $w(n)$. Each of these inputs is multiplied by the connection weight. The neuron has also another input, $b(n)$, which is bias or threshold connections. This helps the learning of the data and ultimately improves representation of the data by neural network. Then, inputs are passed to activation or transfer function. Activation functions are the most important part of an ANN which transforms input signals to output signals. There are too many transfer functions available for different systems. The most popular activation functions are logistic or sigmoid. The typical ranges of these functions are between 0 and 1 or -1 and 1, depending on the function type. The mathematical equation of each neuron can be shown by the following equation:

$$y = f\left(\sum_{i=1}^n x_i \cdot w_i + b\right) \quad (8)$$

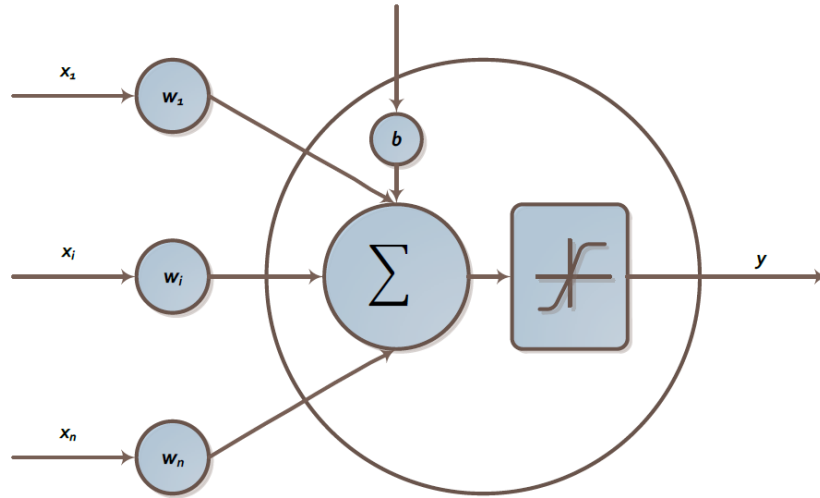


Figure 6. Mathematical structure of neuron. [Gharehlo, 2012]

The most common type of activation function is the sigmoid function. A S-shaped graph, which is non-linear, well behaved, differentiable, and strictly increasing function. A sigmoid function can be shown as the equation below:

$$f(y) = \frac{1}{1 + e^{-\alpha y}} \quad (9)$$

Where α is the slope parameter and is able to obtain different shapes of the function.

ANNs consist of several layers of neurons (nodes). The first or the lower layer is an input layer where external information is received. The middle layer is hidden layer and can be consist of one or more layers. The last or the highest layer is an output layer. Figure 7 shows the architecture of an ANN with one hidden layer. All the layers are fully connected by synaptic weights.

Data processing procedure in an ANN consists of three steps including training, testing (calibration), and verification. In training phase an input-output dataset is used to adjust the weights of the network. A set of data is used to test and estimate how good the model has been trained. In order to verify the model, a set of examples (not used in previous steps) are used to assess the performance or generalization of a trained model [Esmaili, 2012].

A popular method of learning, called supervised learning or associate learning, involves modifications of the synaptic weights of a neural network by providing input and matching output patterns. The training of the network is repeated for many examples in the set, until the network reaches a steady state. Once the network is trained, the connecting weights between neurons are established and it is said the network has “learned” or “trained”. When the training continues for

too long, the network is overlearned or overfitted. Overlearning or memorization means that the neural network extracts too much information from the individual cases and forgetting the relevant information of the general case [Mohaghegh 2000]. In order to avoid this problem, cross-validation methods can be used. In cross-validation, testing set (instead of training set) is used in order to compare the performance of the resulting network. Since the output of testing data is not provided for the network, the generalization capability can be evaluated by the predicted outputs of testing set. Once the network is trained the verification process can be started.

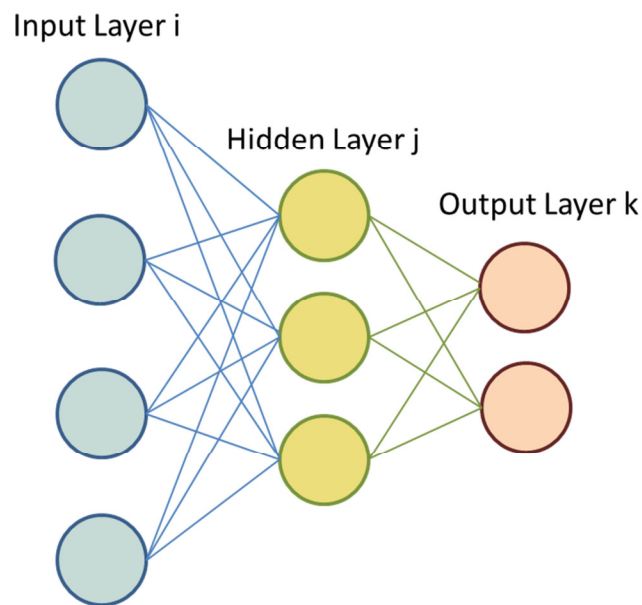


Figure 7. Artificial Neural Network architecture.

Feed-Forward Backpropagation Networks

One of the most commonly used supervised training algorithms is Backpropagation. The Feed Forward Backpropagation network is a network in which the artificial neurons are organized in layers, send their signals forward, and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layer. The Backpropagation algorithm uses supervised learning, which means that the inputs and outputs is provided into the network and then the error which is the difference between actual and expected results, is calculated. The idea of the Backpropagation algorithm is to reduce the error, until the

ANN learns the training data. The training usually begins with random weights, and the goal is to adjust them so that error will be minimal [Gershenson].

Consider a feed-forward network with n input and m output units. It can consist of any number of hidden units and can exhibit any desired feed-forward connection pattern. We are also given a training set $\{(x_1, t_1), \dots, (x_p, t_p)\}$ consisting of p ordered pairs of n - and m -dimensional vectors, which are called the input and output patterns. Let the primitive functions at each node of the network be continuous and differentiable. The weights of the edges are real numbers selected at random. When the input pattern x_i from the training set is presented to this network, it produces an output o_i different in general from the target t_i . What we want is to make o_i and t_i identical for $i = 1, \dots, p$, by using a learning algorithm. More precisely, we want to minimize the error function of the network, defined as

$$E = \frac{1}{2} \sum_{i=1}^p \|o_i - t_i\|^2 \quad (10)$$

For each input j , its output is defined as

$$o_j = f(z_j) = f\left(\sum_{k=1}^n w_{kj} x_k\right) \quad (11)$$

The variable w_{ij} denotes the weight between neurons i and j .

To look at how to reduce the error, we look at how the error changes as we change the weights. We start at the layer immediately before the output. Working out the effects of earlier layers will be more complex. First we can write total error as a sum of the errors at each node:

$$E = E_1 + E_2 + \dots + E_m \quad (12)$$

Calculating the partial differential of the total error with respect to a weight w_{ij} is defined as:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial z_i} \frac{\partial z_i}{\partial w_{ij}} = \frac{\partial E}{\partial z_i} x_i \quad (13)$$

$\frac{\partial E}{\partial z_i}$ can be represented by δ_i . Consider that $j \in \text{Outputs}$. Since the output of all units $k \neq j$ are independent of w_{ij} , the summation of error can be dropped and the contribution of E by j is considered:

$$\delta_i = \frac{\partial E}{\partial z_i} = \frac{\partial}{\partial z_i} \frac{1}{2} (t_i - o_i)^2 = -(t_i - o_i) \quad (14)$$

$$\begin{aligned}
& o_i) \frac{\partial o_i}{\partial z_i} \\
& = -(t_i - o_i) \frac{\partial}{\partial z_i} f(z_i) \\
& = -(t_i - o_i)(1 - f(z_i))f(z_i) \\
& = -(t_i - o_i) - (1 - o_i)o_i
\end{aligned}$$

The change in weight, which is added to the old weight, is equal to the product of the learning rate and the gradient, multiplied by -1

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = -\eta \delta_i x_i \quad (15)$$

Where, x_i is the output of the node in the feed-forward step and η is the learning rate ($0 \leq \eta \leq 1$). This coefficient affects networks teaching speed. When the error signal for each node is computed, the weights of each node are updated. The training process continues until the error is reached the minimum threshold.

Problem Statement

As an essential step for the production planning, natural gas professionals estimate production and ultimate recovery (EUR) throughout the life of wells. Decline curve analysis is the most widely used methodology in the estimation of the future production profile. However, its results have been determined to be over optimistic for unconventional reservoirs. Decline curve analysis is a graphical-mathematical method that does not include the effect of reservoir characteristics and completion design parameters on production behavior.

The major objective of this research is to condition EUR of shale wells extracted from decline curve analysis to rock properties, well, and completion design parameters. The first step of this study is EUR estimation using Arps decline curves. In order to have a more accurate estimation, the hyperbolic curve will be switched to exponential decline during later time in the well's life. In this study, artificial intelligence will be employed to condition production characteristics such as "EUR" to rock properties, well, and completion design parameters. The data-driven model is capable of finding the hidden patterns among reservoir properties, well, and completion parameters and the production of the wells. In this case statistical methods are not able to find a relationship between the EUR and rock properties, well and completion parameters. One of the reasons is that these parameters are not independent and each of them may have an impact on other parameters. Therefore the best tool to develop a model and condition EUR to these parameters is Artificial Neural Networks (ANN).

Methodology

As described earlier, this research aims estimating ultimate recovery and connecting reservoir characteristics, well properties, and completion design parameters to EUR for shale wells. The process is divided to three different key steps:

- 1) Data preparation
- 2) Artificial neural network training
- 3) Model validation

Figure 9 shows the general work flow of development AI-based shale reservoir model.

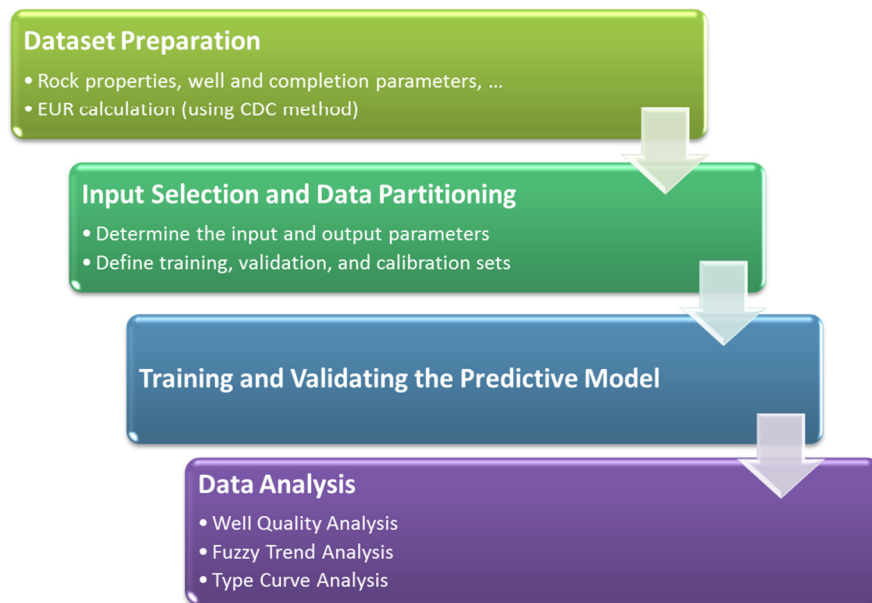


Figure 8. Work Flow of Development AI-Base Shale Reservoir Model

Data preparation

The first and most important step in development of data-driven model is preparing the dataset which is going to be used in training the model. This dataset consists of reservoir characteristics, geomechanical properties, completion and stimulation data and the amount of EUR associated with each well. An extensive data mining and analysis process should be conducted at this step to fully understand the data that is housed in this database. The data compilation, quality control and

preprocessing are the most important and time consuming steps in developing an AI-based reservoir Model.

This study focused on a part of Marcellus Shale including 164 wells with multiple pads, different landing targets, diverse reservoir properties and different completion and stimulation information. Marcellus shale in the area of Pennsylvania is consists of two layers as Upper Marcellus (UM) and Lower Marcellus). A thin bed limestone layer known as Purcell is separated Marcellus layers. Based on the well deviation and completion strategy, one or both layers may be exposed to the production. Reservoir characteristics of each layer including matrix porosity, matrix permeability, pay thickness, net to gross (NTG), initial water saturation and total organic content (TOC) of each well was given by the operator. In order to have consistent values for each well an average of reservoir properties based on well completion zone was calculated (Esmaili, 2013).

The interpreted geomechanical logs including shear modulus, minimum horizontal stress, young's modulus, and poisson's ratio for all wells in the area were provided.

The completion data of the wells include some information regarding the shot density, perforated/stimulated lateral length, number of stages and etc. which was imported into the database. The stimulation data, on the other hand, was provided in stage base by operator which comprises complete information about the amount of injected clean water, rate of injection, injection pressure, amount of injected slurry and etc. Since the production is available on a per well basis, the volumes of fluid and proppant for multiple hydraulic fracture stages performed on the same well were summed while the rates and pressures for these cases were averaged.

The production history of the wells contains the dry gas rate, condensate rate, water rate, casing pressure and tubing pressure in daily format. The maximum and minimum length of production history is about five years and one and half years respectively. Because of scattered condensate rates and also low condensate to gas ratio (maximum is about 16 STB/MMCF), this data was combined with the dry gas and the rate of rich gas was estimated for the wells.

$$GE_{Cond} = 133,800 \frac{\gamma_o}{M_o} \frac{SCF}{STB} \quad (14)$$

Where $\gamma_o = \frac{141.5}{Condensate\ API + 131.5}$ and $M_o = \frac{44.43\gamma_o}{1.008 - \gamma_o}$.

Estimated ultimate recovery should be calculated for all 164 wells. Analytical tools, used widely for unconventional reservoirs, appear to work quite well in tight gas reservoirs. Several analytical

¹ William D. McCain, Jr (1990), "The Properties of Petroleum Fluids", Page 195.

methods in the literature are used for calculating EUR. These techniques such as Power Law Exponential (PLE), Stretched Exponential Decline Curve (SEDC) have improved the results of Arps' hyperbolic decline curve for shale wells. In this study the combination of hyperbolic and exponential decline curves are used to determine the EUR which is called Combined Decline Curve (CDC). Arps' hyperbolic decline curves for shale result over estimation of EUR calculation. Therefore, in order to have more accurate (conservative) estimation, the hyperbolic curve will be switched to exponential decline during later time in the well's life. This tool is providing a good estimation of EUR using CDC. Figure 9 shows the result of gas production estimation in log-log plot using Power Law Exponential (PLE), Hyperbolic, Stretched Exponential Decline Curve (SEDC), and Combined Decline Curve (CDC) for a shale well. Result shows that Arps' hyperbolic decline and combination decline (exponential for tail) are the optimistic and conservative methods respectively. Therefore, the most conservative method is selected for EUR calculation to avoid over estimation. Figure 10 shows how CDC changes from hyperbolic to exponential.

After all above-mentioned calculations the data set includes six groups of data as well information, reservoir characteristics, geomechanical properties, completion data, stimulation data and production estimation.

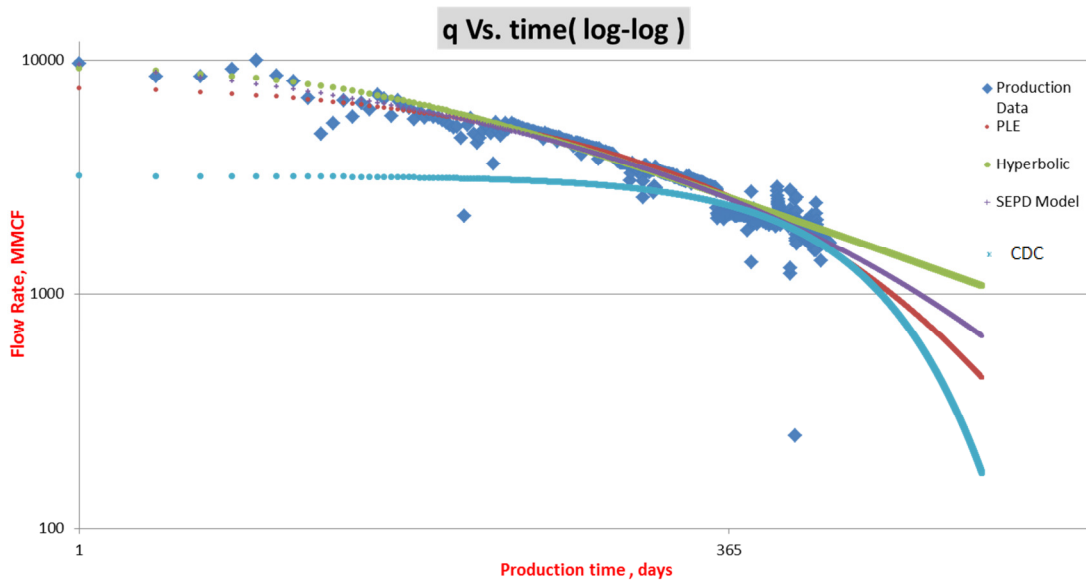


Figure 9. Comparing different decline curve methods for estimating gas production in a shale well

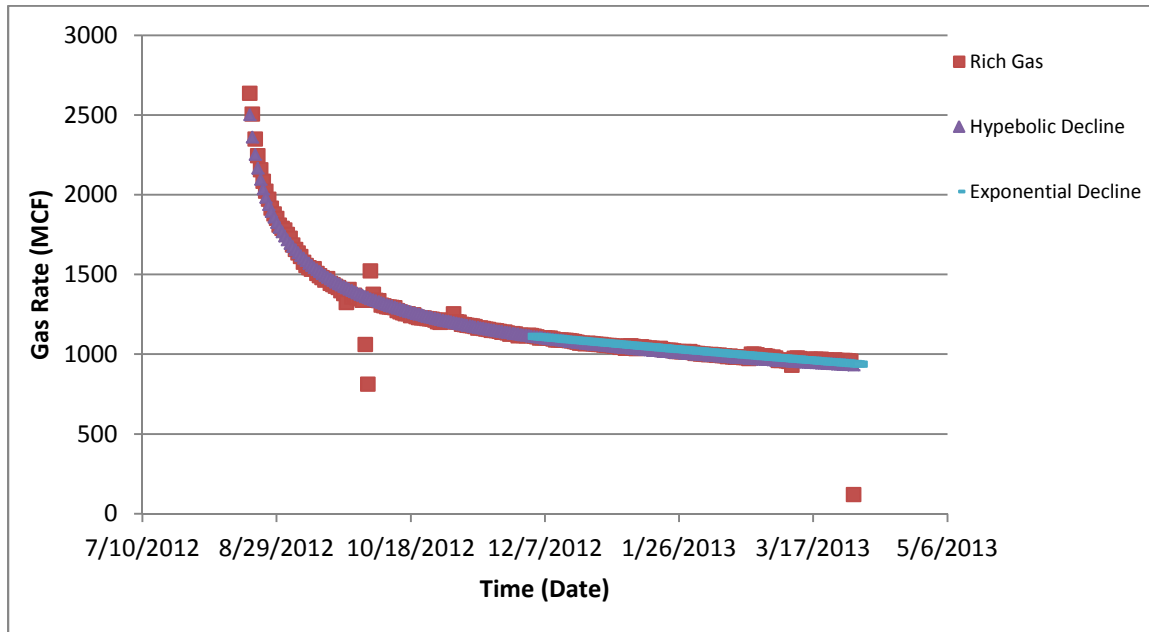


Figure 10. Combination of hyperbolic decline and exponential decline curve (CDC) for EUR calculation

Input Selection and Data Partitioning

Sampling is very important because it helps to reduce the complexities of the data and provide a unified data set for training and testing the networks. As mentioned before, for developing an ANN three sets of data are needed, training set, calibration set, and validation set. In this study the whole number of data points (wells) are 164. In order to prevent the network from over training, 10% of the data are selected as calibration set. For validating the model, 10% of data is set aside. In other words, the neural network does not see these data during the training process. Then the outcome of the network for validation set determines how the model results for blind cases.

After preparing the dataset, the next step is to determine the input and output parameters of the neural network. In this study we have 36 parameters for describing each well and one output parameter which is EUR. Table 2 shows all parameters including well information, reservoir characteristics, geochemical properties, completion data, stimulation data, and production estimation. Selecting all 36 parameters as input results a very complex model. Therefore it was tried to minimize the number of parameters as long as getting better results. In order to do this, key performance indicator (KPI) tool which is provided by IMproveTM software is used to identify the influence of each parameter on output (EUR). KPI is a useful tool to determine the

degree of contribution of each parameter on output. Figure 11 shows the list of parameters and their degree of influence on EUR.

Table 2. Six groups of Parameters in the dataset

Group 1- Well Information	Easting	Group 5- Stimulation Data	Avg. Inj. Pressure(psi)
	Northing		Avg. ISIP
	MD (ft)		Avg. Breakdown Pressure
	BTU Area*		Avg. Maximum Pressure
	Deviation Type		Avg. Injection Rate(bbl/min)
Group 2- Reservoir Characteristics	Matrix Porosity		Avg. Max Rate
	Matrix Permeability (mD)		Avg. Breakdown Rate
	Net Thickness (ft)		Fluid Vol.(bbl)
	Water Saturation (%)		Slurry Vol. per Stage(bbl)
	TOC (%)		Clean Water Vol. per Stage (bbl)
	Avg. Langmuir Vol. (scf/tom)		Max Proppant Concentration(lb/gal)
	Avg. Langmuir Pressure (psi)	Proppant per Stage(lb)	
Group 3- Geomechanical Properties	Bulk Modulus	Total Proppant Inj.(lb)	
	Shear Modulus	Avg. Fracture Gradient	
	Young's Modulus	Group 6- Production Estimation	Estimated Ultimate Recovery
	Poisson's Ratio		
	Min Horizontal Stress	* The area is divided into 4 BTU sections of Dry Low, Medium and Wet based on the condensate Cluster Spacing content of gas	
Group 4- Completion Data	Stimulated Lateral Length (ft)		
	Shot Density (shot/ft)		
	No. of Clusters per Stage		
	Total No. of Stages		
	Cluster Spacing		

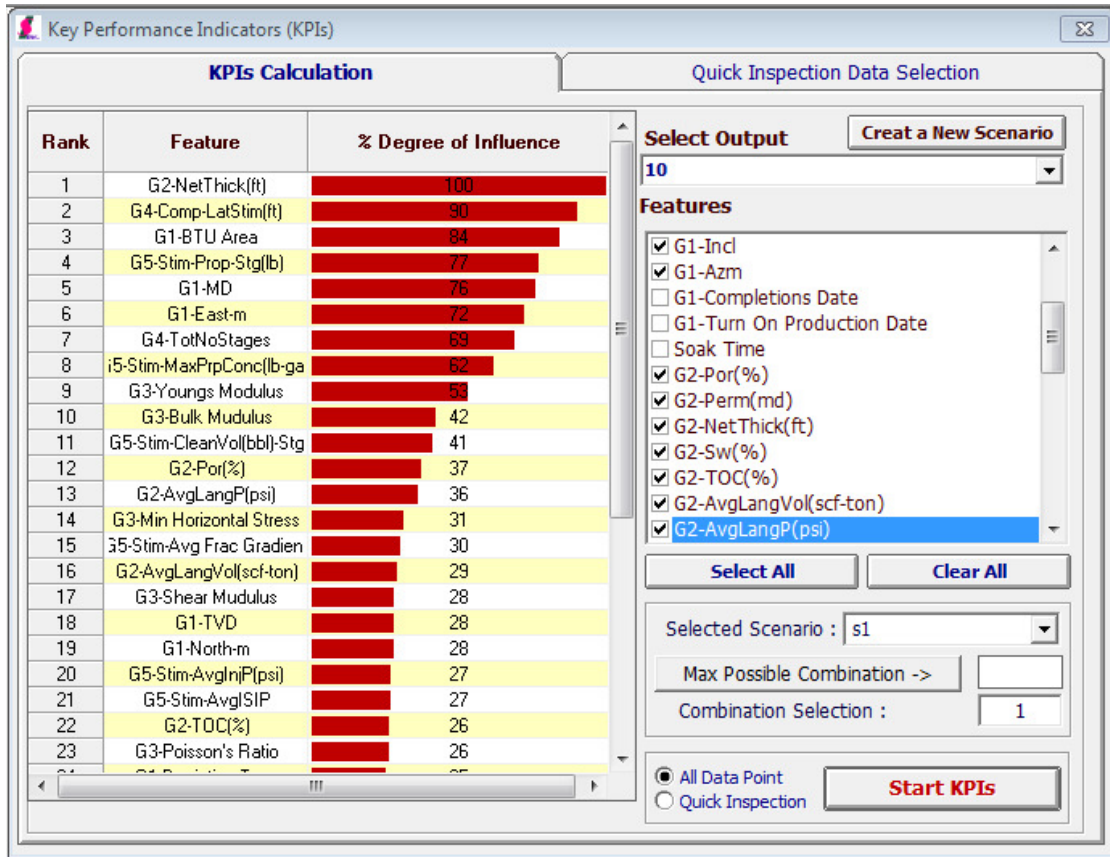


Figure 11. Key Performance Indicator Sorts All Parameters Based on Their Influence on EUR

Another technique which is used for input selection is fuzzy pattern recognition. This technique is also provided by IMprove™ software. One application of fuzzy pattern recognition is deducing understandable trends from complex behavior. Figure 12 shows an example of fuzzy pattern recognition on minimum horizontal stress and 10-year-EUR. Actual data shows no relation or trend between data. However fuzzy pattern recognition demonstrates that more minimum horizontal stress result more EUR.

Both KPI selection and fuzzy pattern recognition tools are performed to select the most effective parameters as an input for neural network. Table 3 illustrates 18 parameters as input for neural network.

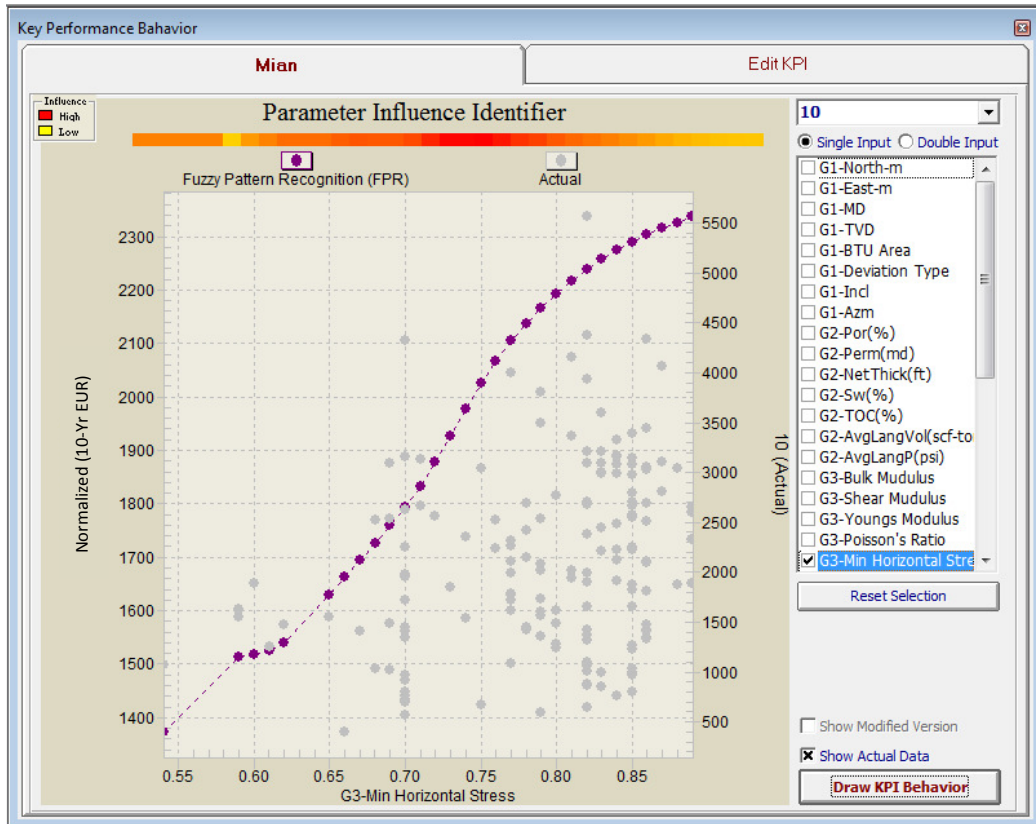


Figure 12. Fuzzy pattern recognition is able to find the trends between kpi parameters.

Table 3. Input parameters of neural network

Neural network Input Parameters	
Easting	Avg. Langmuir Vol. (scf/tom)
MD (ft)	Avg. Langmuir Pressure (psi)
BTU Area	Young's Modulus
Deviation Type	Min Horizontal Stress
Matrix Porosity	Stimulated Lateral Length (ft)
Net Thickness (ft)	Cluster Spacing
Water Saturation (%)	Avg. Injection Rate(bbl/min)
TOC (%)	Avg. Breakdown Rate
Proppant per Stage(lb)	Clean Water Vol.(bbl)

Artificial Neural Network Training

After preparing the data set and selecting the input parameters, artificial neural network can be trained. For this purpose IMprove™ software was used to train and validate the network. In this thesis different data-driven models have been developed using the IMprove™ software to estimate the ultimate recovery for shale wells and discover the impact of completion parameters on EUR. The networks have three layers (input, output, and single hidden layer) and using feed-forward backpropagation as training mechanism. Back propagation algorithm is one of the most widely used and popular techniques to optimize the feed forward neural network training. The number of nodes in hidden layer is determined by the total number of input parameters.

The parameters of feed-forward backpropagation which are responsible for the algorithm convergence are learning rate, momentum, and weight decay. Learning rate is a control parameter of training algorithm, which controls the step size when weights are iteratively adjusted. Momentum determines how much influence the previous iterations learning will have on the current iteration's. Finally, weight decay has the effect of controlling the growth of weights and results in the learning rule preferring smaller weights. These parameters remain constant during the learning process. The default values of these parameters in IMprove™ software are used to develop neural network models. Figure 13 shows the architecture of the neural network in this thesis.

IMprove™ provides different activation functions™ such as Logistic (Sigmoid), Gaussian and tangent Hyperbolic and Gaussian Complement but for the purpose of this thesis the activation or transfer function of Sigmoid or Logistic is used.

As explained before 80% of data was used for training the neural network and 20% for calibration and validation (blind set). A neural network is trained when R-squared is above 0.09 for all cases. Figure 14 illustrates the cross plot of a trained neural network for 10-year-EUR with R-squared of 0.96 for all cases. The network response was also studied for blind data and resulted R-squared of 0.85. Accurate achieved results are demonstrated the capability of Artificial Intelligence and Data mining tools in predicting highly nonlinear relationships between parameters.

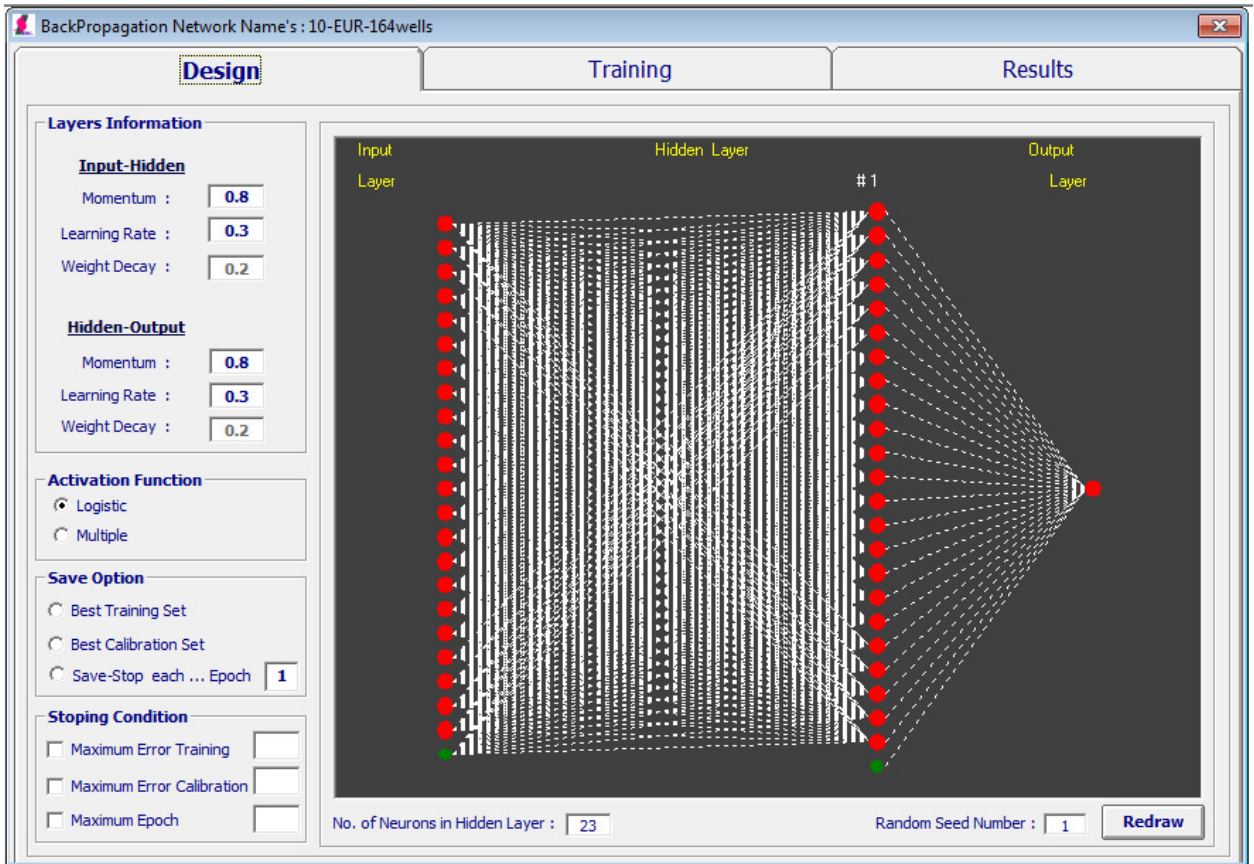


Figure 13. Neural Network Architecture in this thesis

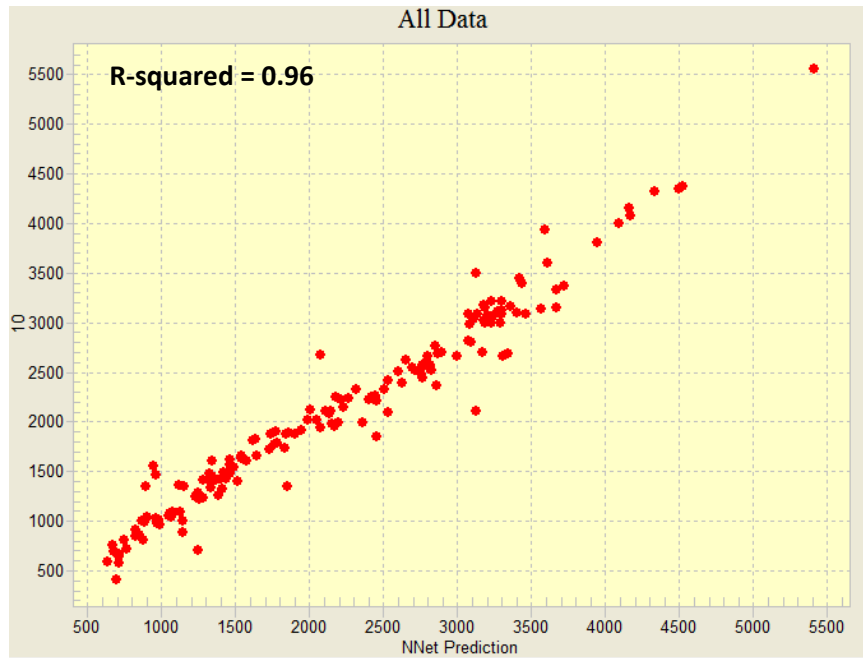


Figure 14. All Cases Cross Plot

Given all the facts about the complexity of the shale reservoirs, the physics of production from these reservoirs are not fully understood. Therefore, using conventional statistical approaches are not a good choice for decision making. Data mining technology is a powerful alternative for this purpose. These methods are able to extract the trend between data. One of the objectives of this study is providing meaningful analysis of reservoir, completion, and stimulation parameters of Marcellus shale on EUR. Therefore, the result of these analyses can be suggested as optimum completion and stimulation design for Marcellus shale.

In this study conventional statistical methods are applied to show its weakness. Then pattern recognition techniques as well as fuzzy set theory were used to do more accurate analysis. When fuzzy set theory is used to determine the appropriate multidimensional space that would provide optimum separation of overlapping classes, the result is known as “Fuzzy Pattern Recognition”. This analysis was also performed by using IMproveTM.

The main objective of this section is to provide insight into the operation practice of Marcellus Shale and to evaluate the role of each native and design parameters in EUR. The outcome of this analysis is used to identify the optimum completion and stimulation design to achieve maximum EUR which are the key factors in shale reservoir management.

Pattern recognition is tool to identify the relationship in raw data. This technique tries to classify data and extract the pattern between them. Well Quality Analysis (WQA) is a unique and proprietary process through which the data in the data set is averaged using the principles of Fuzzy Set Theory and plotted using bar charts in order to reveal hidden patterns in the data. During this process nothing is added or removed from the data. When a similar analysis is performed while every single well in the dataset is treated as a potential unique well quality the result is a continuous curve (rather than a discrete set of steps), called a “Fuzzy Trend Analysis (FTA)”. It is important to note that the result of “Fuzzy Trend Analysis” is usually a non-linear two-dimensional line. This analysis was also performed by using IMproveTM.

One of the methods for evaluating some reservoir properties is type curves. Different kinds of type curves such as Blasingame, Fetkovich, and Agarwal et al. curves are used for production analysis from shale. Because of the complexity of fluid flow in shale, the generated type curves are usually based on some assumptions such as elliptical shape of fractures, the limited outer and etc. Nevertheless for a quick look shale reservoir interpretation, having type curves will make the production analysis even more convenient for practical purposes. Data-driven methods are proposing a new type curve which can be used to assist operators for decision making. This type

curves are developed by plotting one of the model outputs (in this study 10 or 15 years EUR) against another parameter while selecting a third parameter for the type curves. By changing the value of the third parameter from minimum to maximum in several steps a set of type curves can be generated. During this operation one can hold the values of all other involved parameters at overall average or select the minimum or the maximum from the entire data set for all the parameters. In this thesis IMprove™ software was used in order to generate type curves for our data set.

Results and Discussion

In this chapter the results and discussion of the work is presented. As mentioned earlier the objective of this research is to estimate the amount of EUR in shale and investigate the relationship between well and completion design parameters with EUR. This study focused on part of Marcellus shale including 164 horizontal wells with different completion, stimulation characteristics, and reservoir properties. Two AI-based models are developed for this purpose using IMprove™ for predicting 10-year-EUR and 15-year-EUR.

The AI-based model for 10-year-EUR is trained and validated using 132 data points (80 percent) for training and 32 wells (20 percent) as blind set for validation and calibration. The result of this process is illustrated in Figure 15. This scatter plot shows all data (training and testing data) and their actual and predicted 10-year-EUR values (blue dots for models output and green triangles for the actual data). Figure 16 and Figure 17 show the cross plot for all cases and blind data set respectively. In these figures, the x-axis is the predicated 10-year-EUR by neural network while the y-axis is the actual data. R-squared for all cases and blind case is 0.96 and 0.86 correspondingly. These results represent high accuracy of the model. It should be noted that the blind dataset was never introduced to the network during the training process. In other words, it has not been used, in any shape or form, during the development of the model.

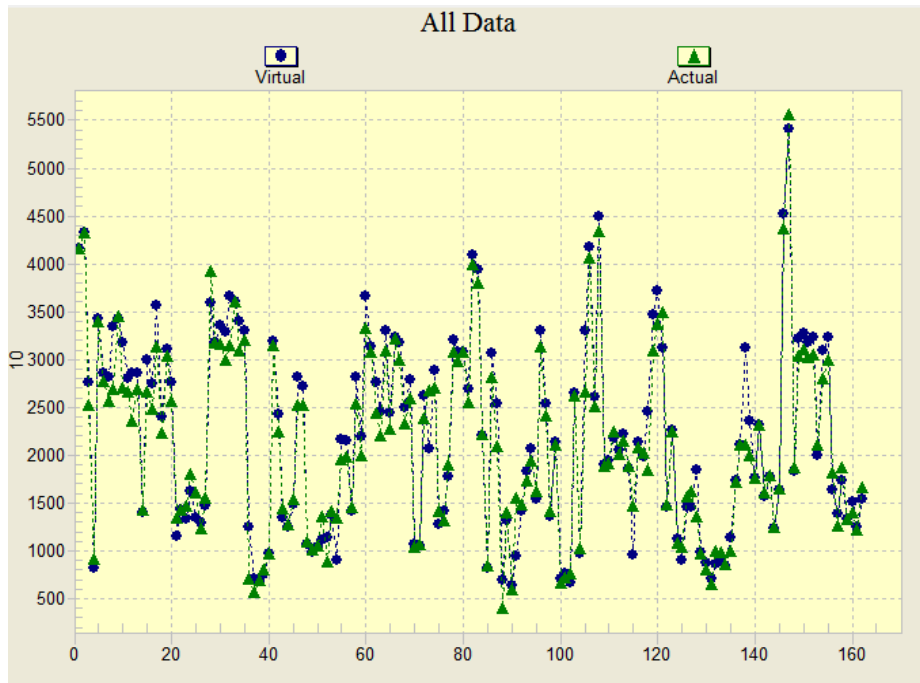


Figure 15. Trained AI-Based Model for 10-year-EUR ($R^2 = 0.96$)

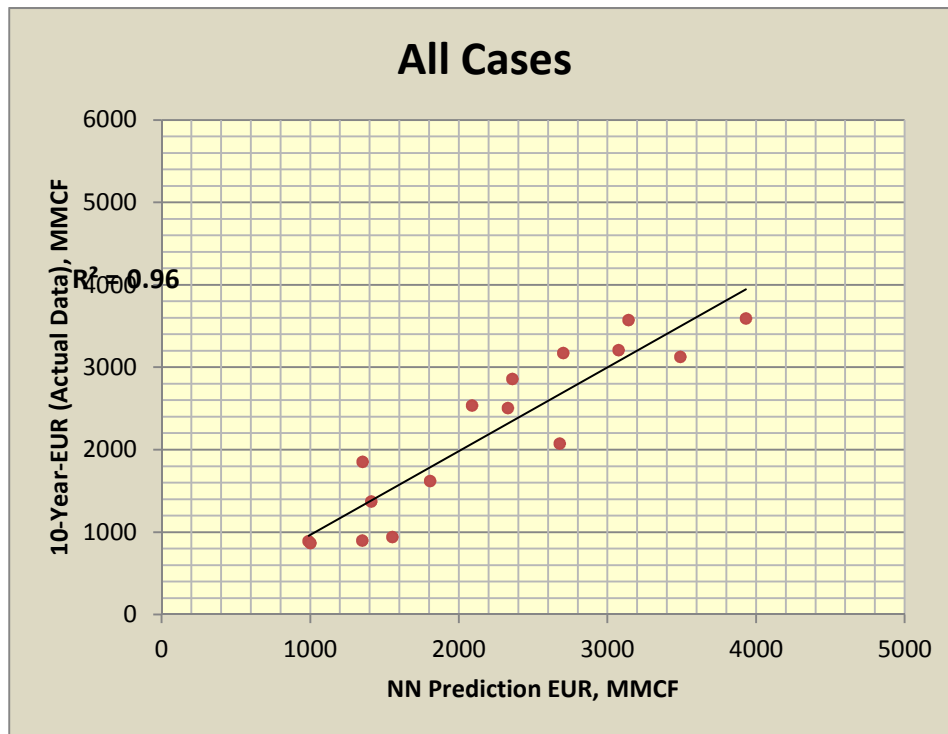


Figure 16. Neural Network Cross Plot for All Cases – 10-year-EUR ($R^2=0.96$)

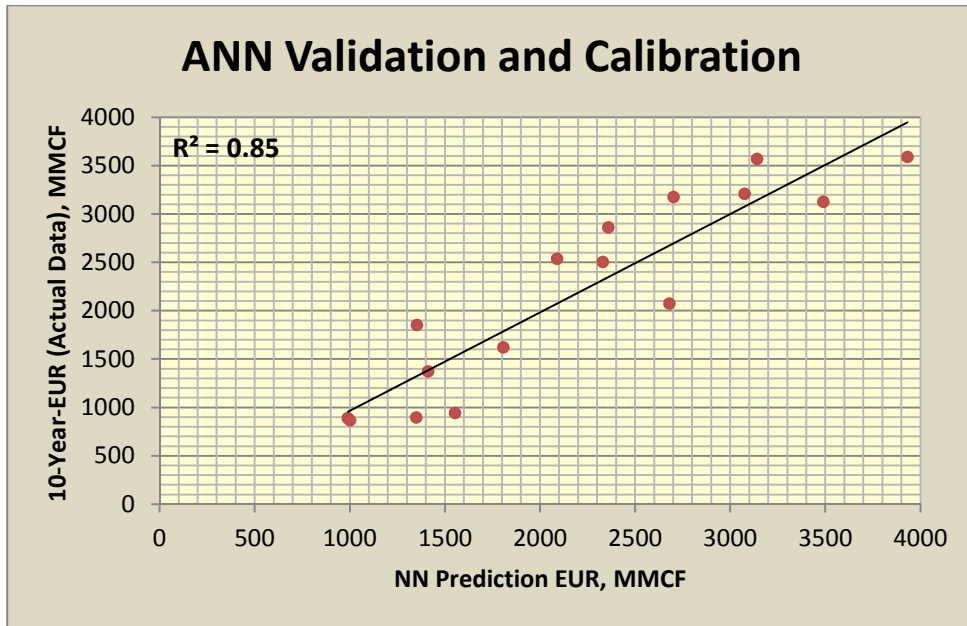


Figure 17. Neural Network Testing with Blind Set Cross Plot - 10-year-EUR ($R^2=0.85$)

The AI-based model for 15-year-EUR is developed using 113 (80 percent) training data and 28 wells (20 percent) as blind set for validation and calibration. The scatter plot of trained model for all cases is shown in Figure 17. This plot shows all training and testing data and their actual and virtual values for 15-year-EUR (blue dots shows the output of the model and green triangles shows the actual data). The cross plot for all cases and blind data set are illustrated in Figure 18 and Figure 19 respectively. R-squared for all cases is 0.92 and for blind case is 0.82. These plots show that the trained network works well for both training and blind data.

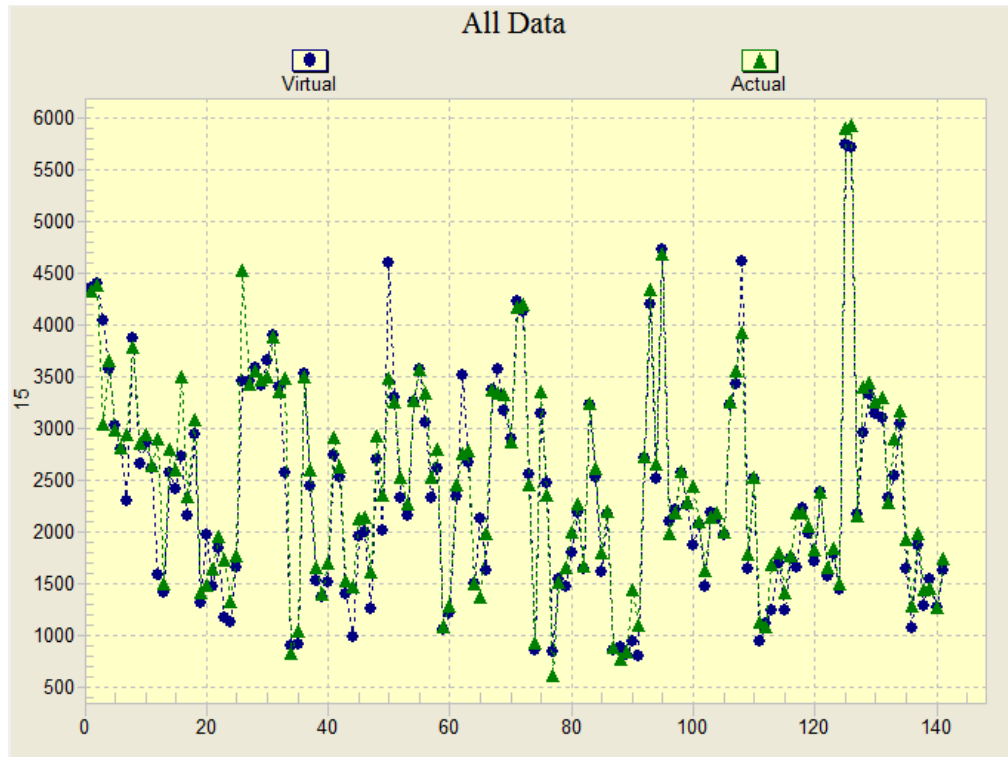
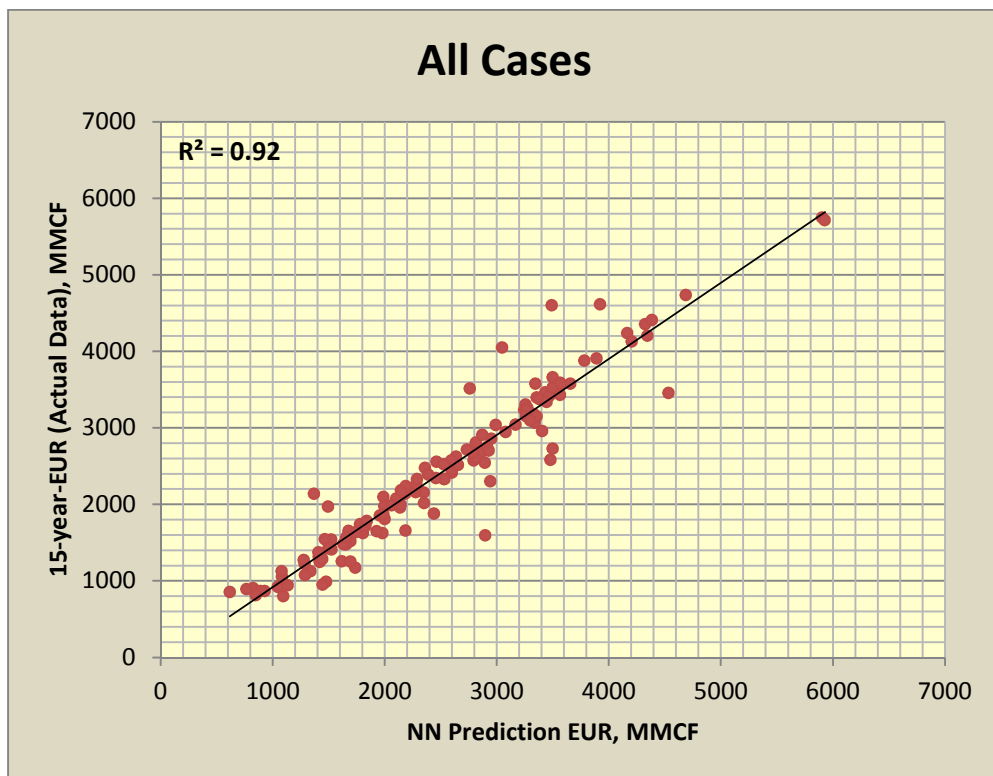


Figure 18. Trained AI-Based Model for 15-year-EUR ($R^2 = 0.92$)



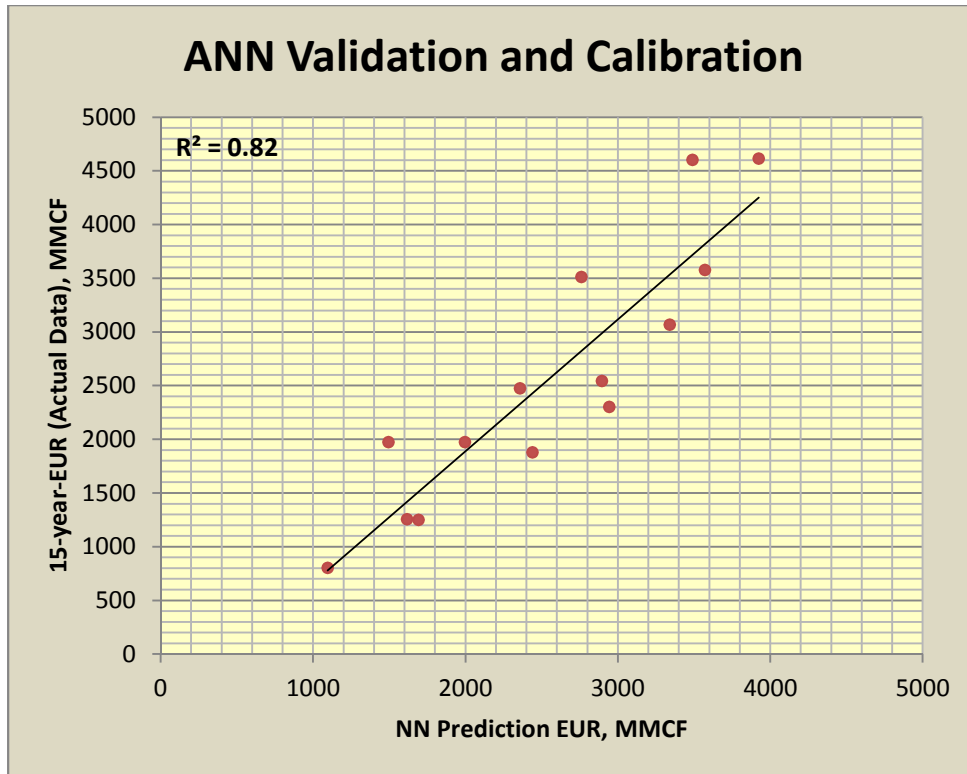
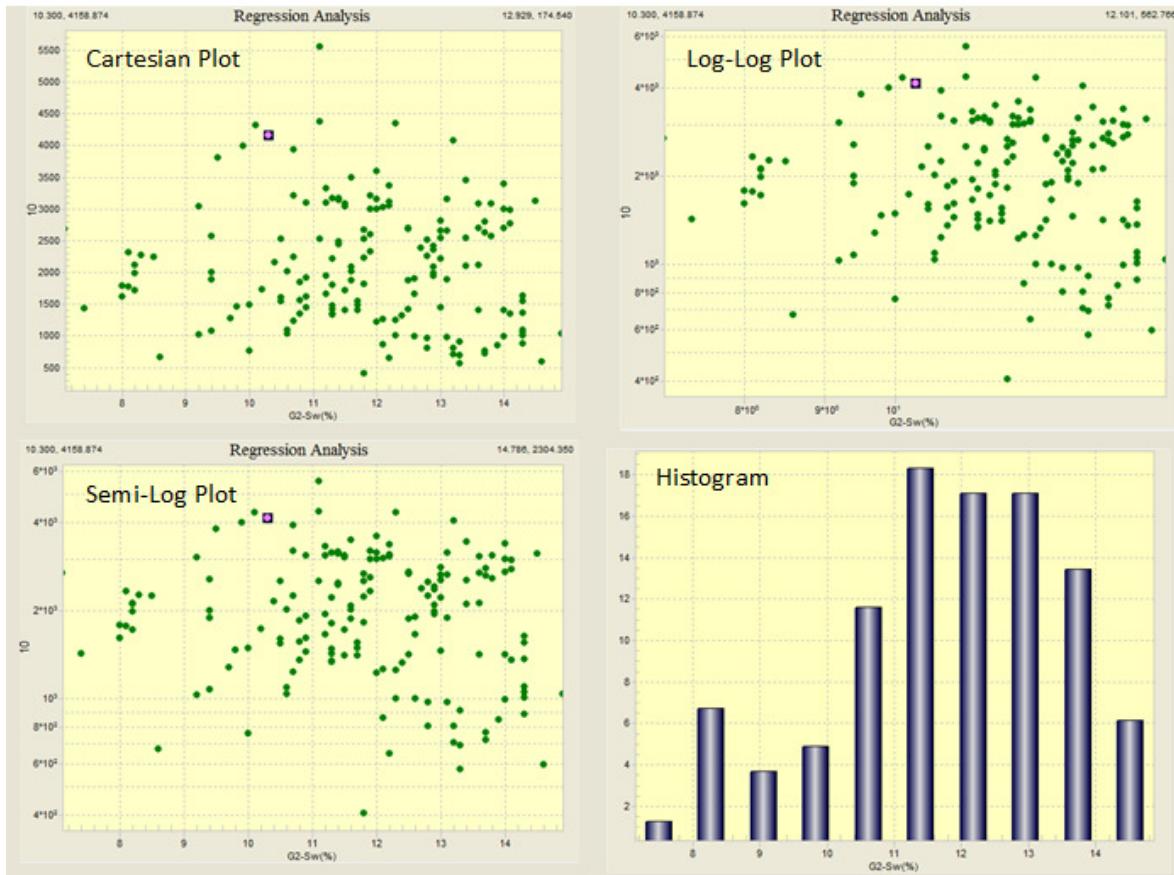


Figure 19. Neural Network Cross Plot for All Cases – 15-year-EUR ($R^2=0.82$)

The models trained in this research can be applied for predicting the EUR for the wells which have not produced for enough time. As mentioned before, one of the common ways to estimate the ultimate recovery is using decline curves. But it should be noted that this method needs enough production data in order to generate the curves and predict the EUR. Therefore this technique cannot employ on wells with short production profile. In this case our approach is very useful. The developed models in this study are able to predict the amount of EUR for young wells and also for the wells which have not produced or drilled yet.

The other objective of this study is discovering the trends and relationship between reservoir characteristics, completion, and stimulation properties and EUR in Marcellus shale. Due to the complexities of fluid flow in shale reservoirs analytical and numerical tools are not able to extract the patterns and relationships between parameters. Therefore suggesting development strategies and decision making based on these analyses could be challenging. Therefore, when it comes to shale assets AI-based methods may be a proper alternative.

In this section some conventional statistical methods are used to show their weakness in extracting the trends between data for shale reservoirs.



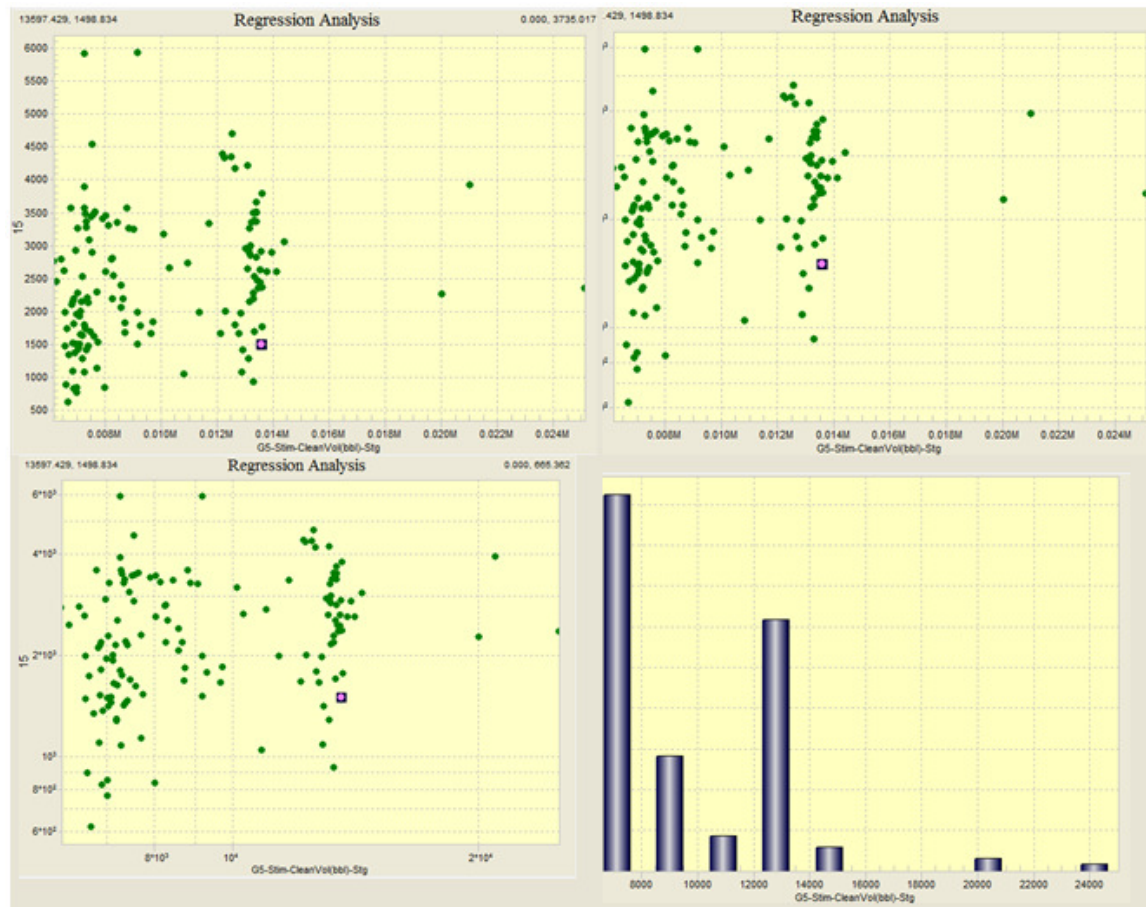


Figure 22 show statistical analysis for Water Saturation (S_w) and Stimulation Clean Volume versus 10-year-EUR. The data consist of 164 horizontal wells drilled in Marcellus shale. The figures show Cartesian, semi-log, log-log, and histogram of these parameters. That can be observed that these methods could not find any patterns in these plots. However it is obvious that higher water saturation results lower production and EUR. The same thing is correct about injected clean volume. We know that higher amount of injected clean volume can cause better production performance which cannot be found by conventional methods.

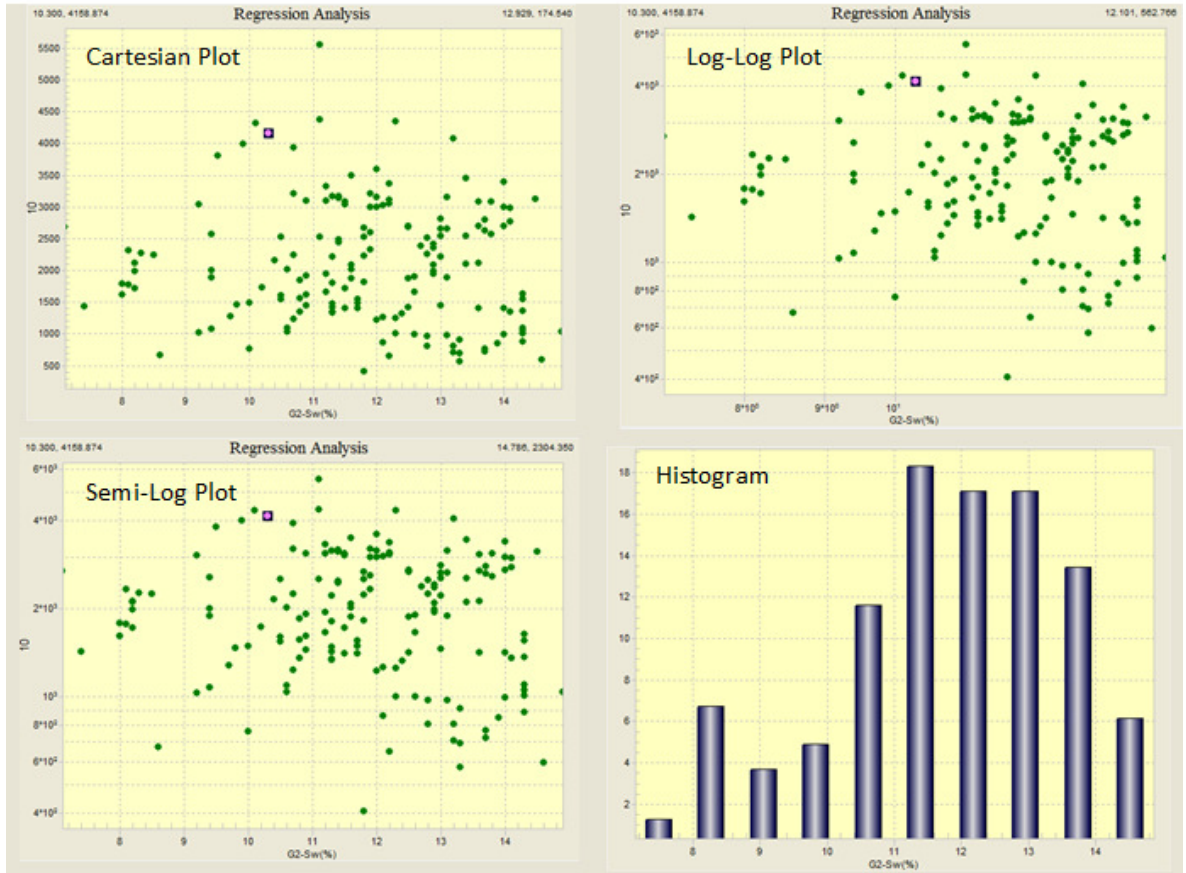


Figure 20. . Correlation between Water Saturation (%) with 10-year-EUR

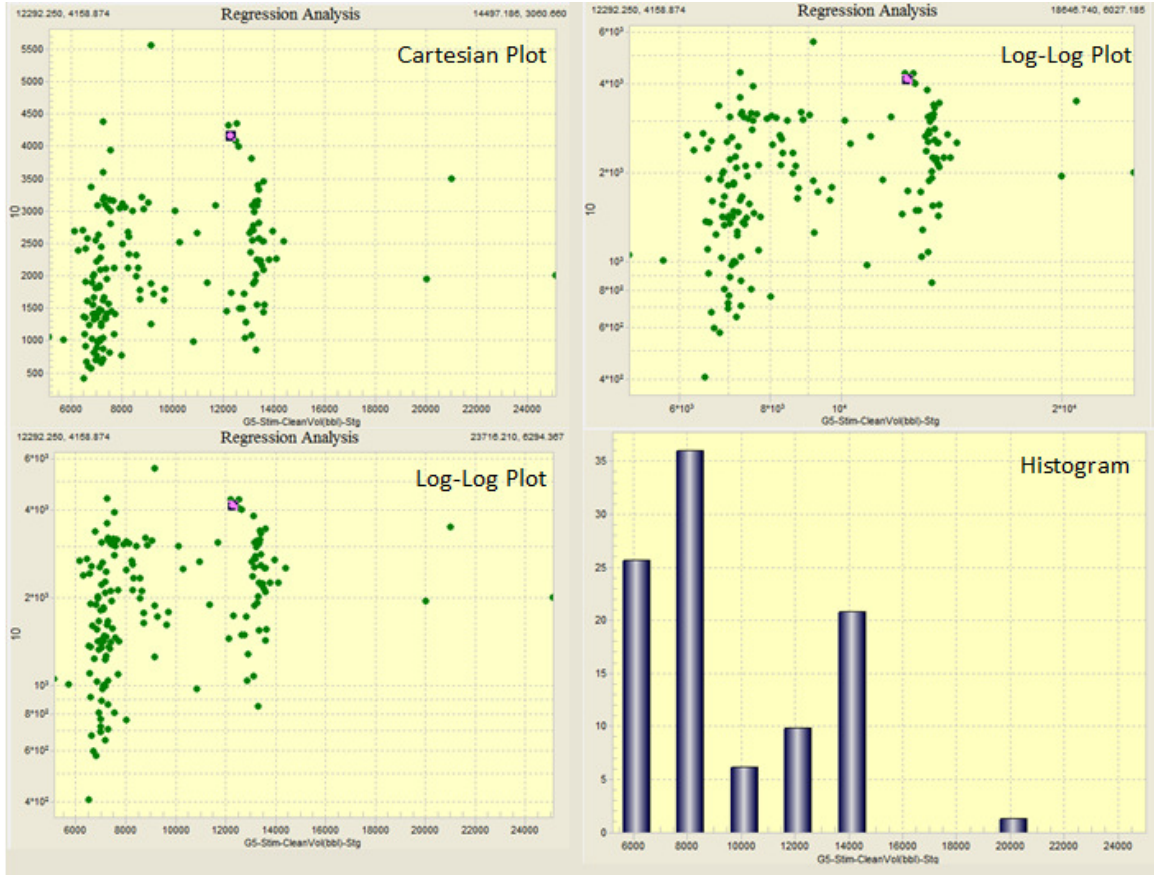
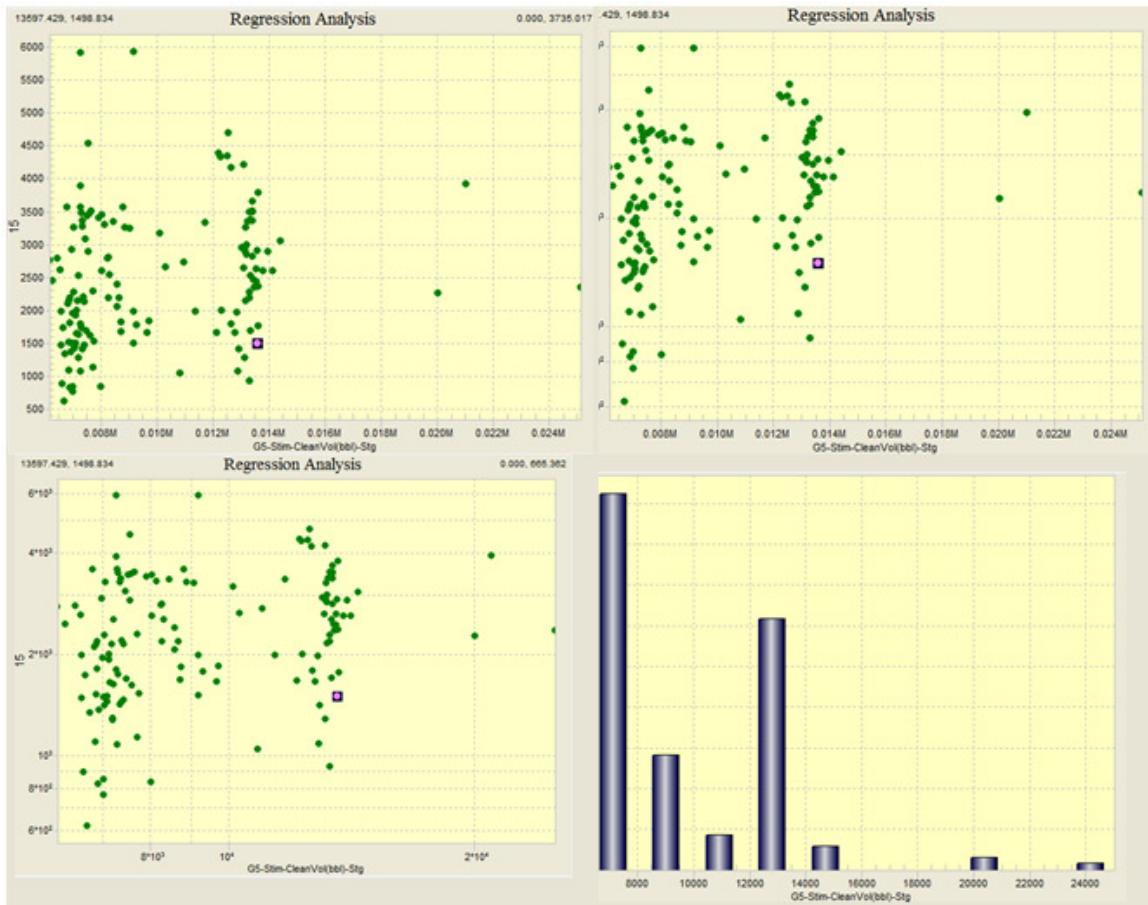


Figure 21. Correlation between Stimulation Clean Volume (bbbl) with 10-year-EUR

The same analysis was done for 15-year-EUR. The data set consists of 143 horizontal wells in Marcellus shale. The results show that conventional statistical analysis could not discover any trends between data (



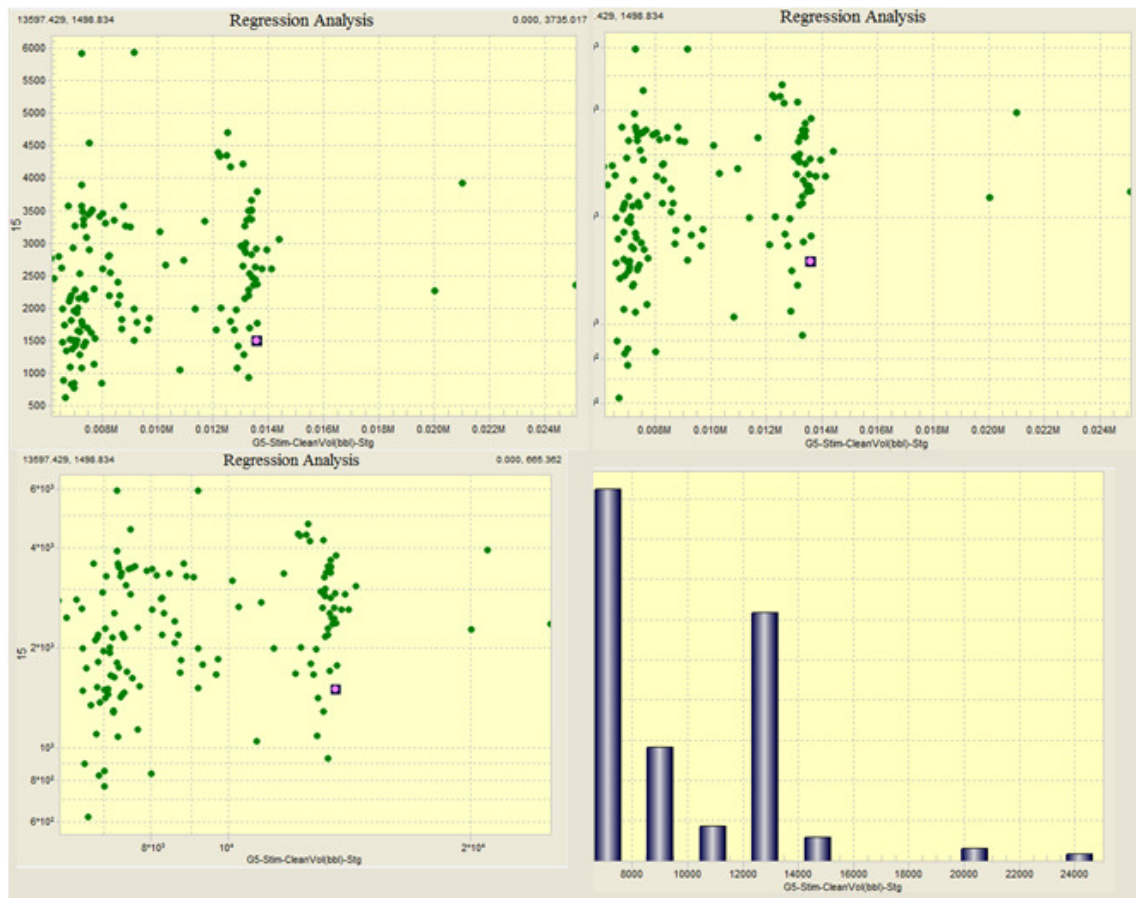


Figure 23).

Moreover, we tried to cluster data based on S_w and injected clean volume to find a pattern between variables. Figure 24 and Figure 25 represent 10-year-EUR values versus Measured Depth. These data are classified into three clusters based on water saturation and injected clean volume. Even though the data are clustered still we do not observe a clear trend for these parameters.

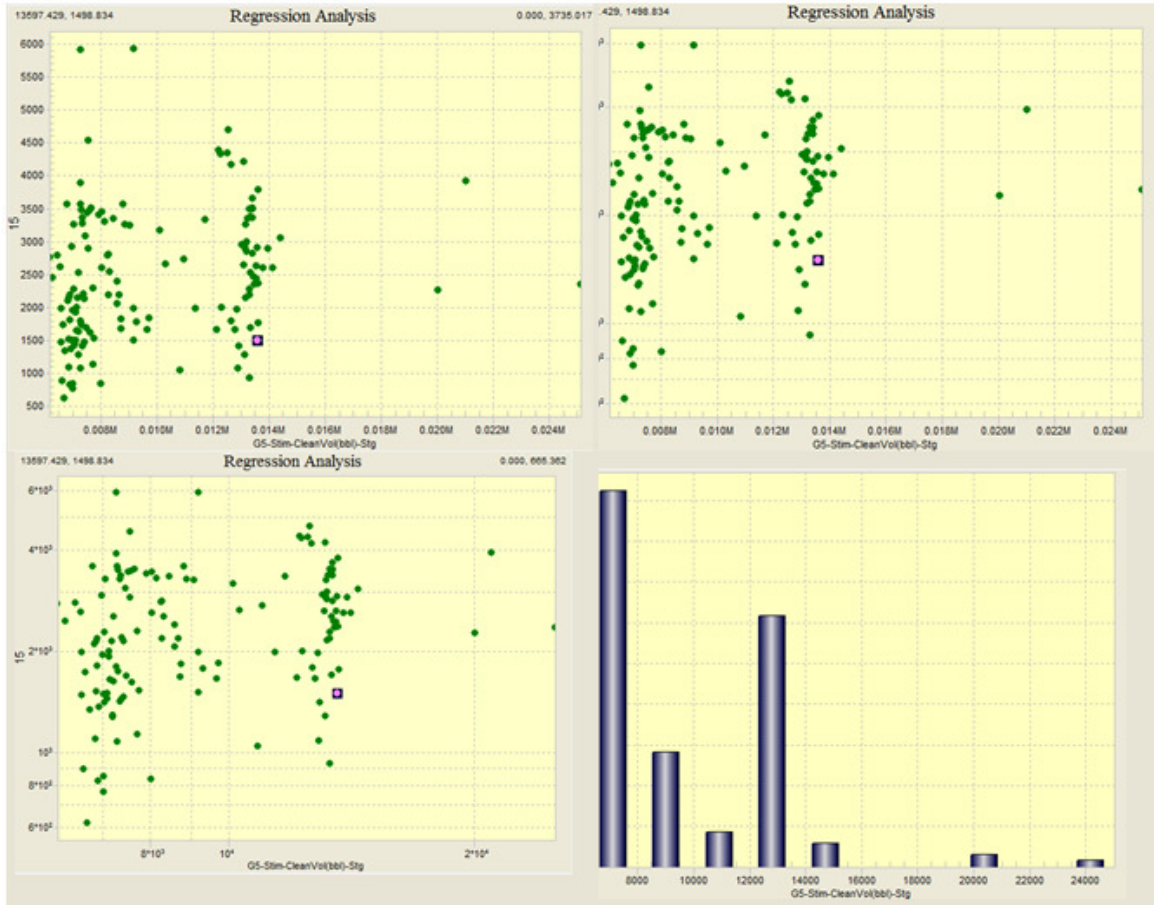


Figure 22. Correlation between Water Saturation (%) with 15-year-EUR

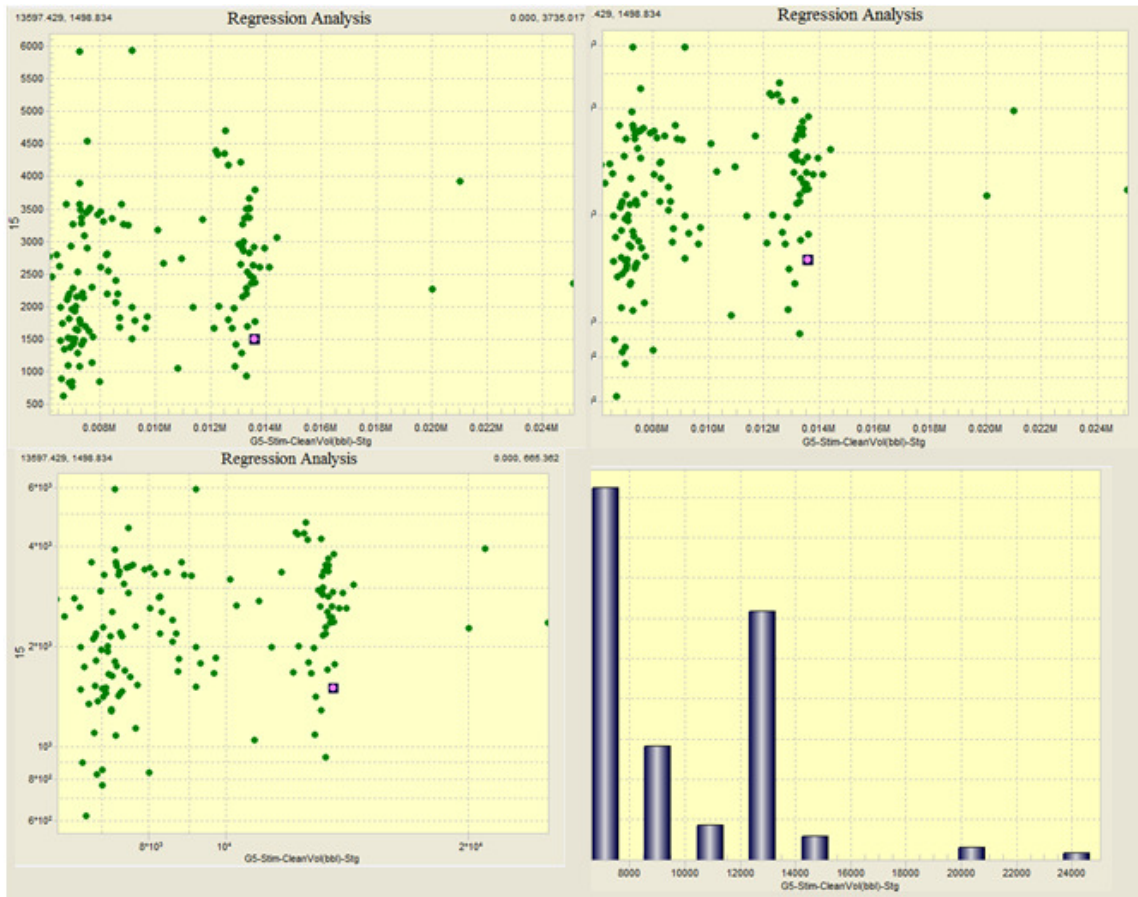


Figure 23. Correlation between Stimulation Clean Volume (bbl) with 15-year-EUR

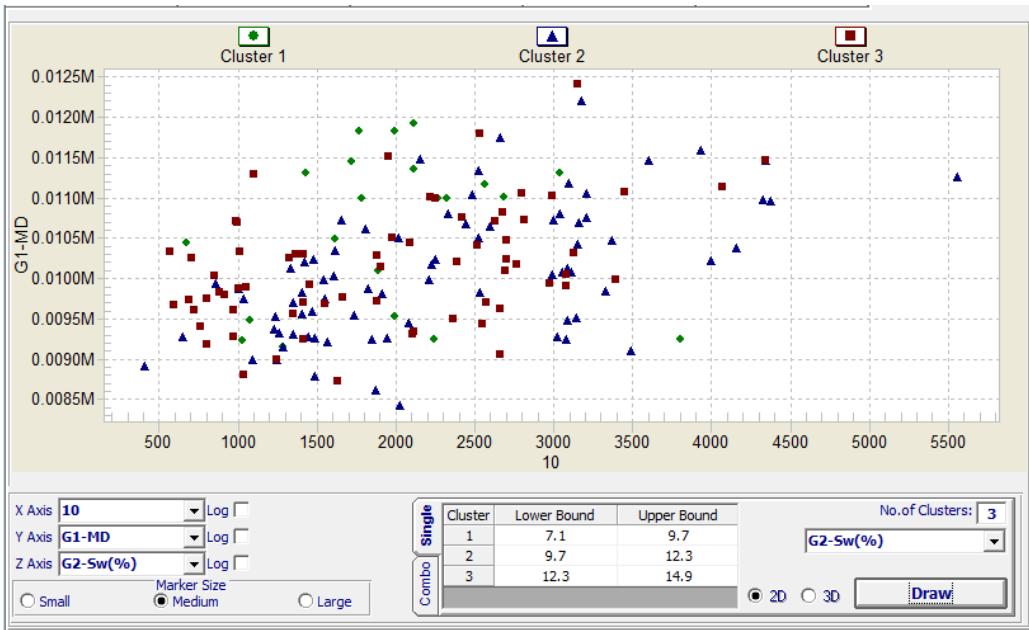


Figure 24. 10-year-EUR vs. Measured Depth Clustering based on Water Saturation

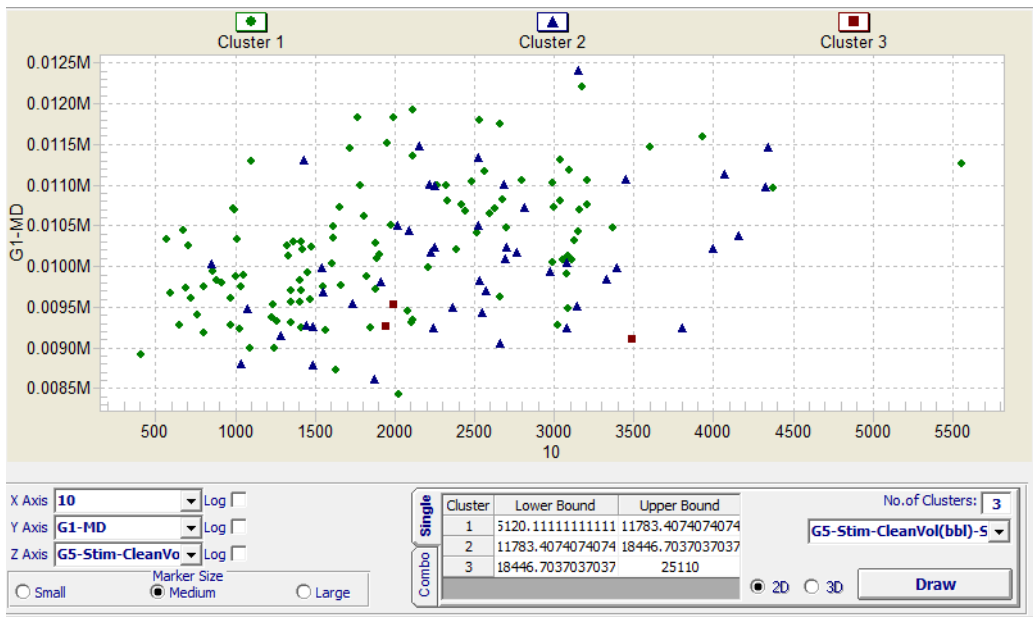


Figure 25. 10-year-EUR vs. Measured Depth Clustering based on Injected Clean Volume

Conventional analysis results illustrated the discrepancies of these methods for data analysis in shale reservoirs. To address these complexities advanced fuzzy pattern recognition technology is used in order to disclose any hidden pattern in dataset.

The main objective of this section is to provide insight into the operation practice of Marcellus Shale and to evaluate the role of each native and design parameters in EUR. The outcome of this analysis is used to identify the optimum completion and stimulation design to achieve maximum EUR which are the key factors in shale reservoir management.

Type curves

Upon successful development of the data-driven predictive model, type curves are generated to assist engineers during the decision-making process. These decisions could be location of the new well or completion and stimulation plans. In this type curves y-axis is one of the model outputs (in this study 10 or 15 years EUR) and x-axis is an input parameter while a third parameter is another input parameter which is represented by type curves. It should be noted that all other parameters was kept constant which is equal to the average of parameter for all wells.

In this section the impact of reservoir and completion characteristics is studied on both 10-year-EUR and 15-year-EUR using type curves. The results of this analysis are shown in figures below. Figure 27 shows two sets of type curves (10 years EUR) for measured depth (x-axis) and water saturation (curves) for all wells (entire field). In this analysis measured depth is changing as a continuous parameter. However for water saturation different discrete values are used. All other parameters were kept constant. The generated curves are the results of trained model. Unlike statistical methods, it is clearly illustrated that type curves are able to find the pattern of data. Here we see that decrease in the water saturation correlates with higher EUR for shale wells in this asset.

In Marcellus shale porosity plays a very important role in the production. In other words, higher porosity results higher EUR. It is observed from Figure 27 that more porosity results more EUR. Another application of this type curves is predicting the EUR for a new drilled well. In this case some stimulation and reservoir information should be available for that well. For example if the measured depth of the well is 11,000 feet and the porosity is 7.5% the estimated value for 15-year-EUR will be around 2500MMCF.

The thickness of Marcellus shale varies from a few feet to around 250 feet. The range of net thickness in the area of this study is 110 to 170 feet. Marcellus shale becomes thicker in east part of the reservoir. Higher thickness means better well performance which is clearly presented in Figure 28. The figure shows the type curves for net thickness of the reservoir as a function of stimulated lateral length for entire asset. It is observed that EUR is significantly impacted by the

reservoir thickness. This results show that the model was capable of learning the physics from data.

Marcellus shale has a complex physics and its behavior to stimulation process (injection proppant and slurry) is unpredictable. Proppant is a porous material such as sand used in hydraulic fracturing to ensure that the fracs remain open. It is mentioned in the literature that the performance of fractures is improved through the injection of proppant. The same theory is true in this study. Figure 29 demonstrates the effect of injected clean volume and injected proppant on 10-year-EUR. That means the model was successfully able to discover the relationship between injected proppant and clean volume and EUR. In other words, increase in EUR is linked to increase of both parameters. These curves show that the EUR is more sensitive to the amount of injected proppant.

Type curves can be generated to address sensitivity of EUR values to all involved parameters. Minimum horizontal stress and Young's modulus are analyzed as examples of rock mechanical properties. As mentioned before, in order to get more production from a horizontal well, the well should be drilled in the direction of minimum horizontal stress. This situation causes hydraulic fractures to grow easily with no overlapping. Like fuzzy pattern recognition the results of type curves have contrast with this theory (Figure 30). It is because of other parameters that have more effect on EUR than minimum horizontal stress.

We know that when Young's modulus is a large number producing width for the fracturing becomes more difficult. It is shown in Figure 31 that higher Young's modulus can reduce the amount of EUR. It should be noted that the effect of Young's modulus on EUR is insignificant which is more clear in 10-year-EUR type curves.

The effect of cluster spacing is also studied in Figure 32. Cluster spacing is plotted as a function of lateral length. The resulted type curves illustrate that decreasing the length of cluster spacing has improved the value of 10-year-EUR. It is also observed that increasing lateral length with specific cluster spacing has almost no positive effect on EUR. Therefore in order to increase EUR we should consider changing the combination of parameters.

It can be concluded that the data-driven model was successfully learned the physics of the reservoir and is able to provide useful information about the reservoir and the impact of different parameters on EUR.

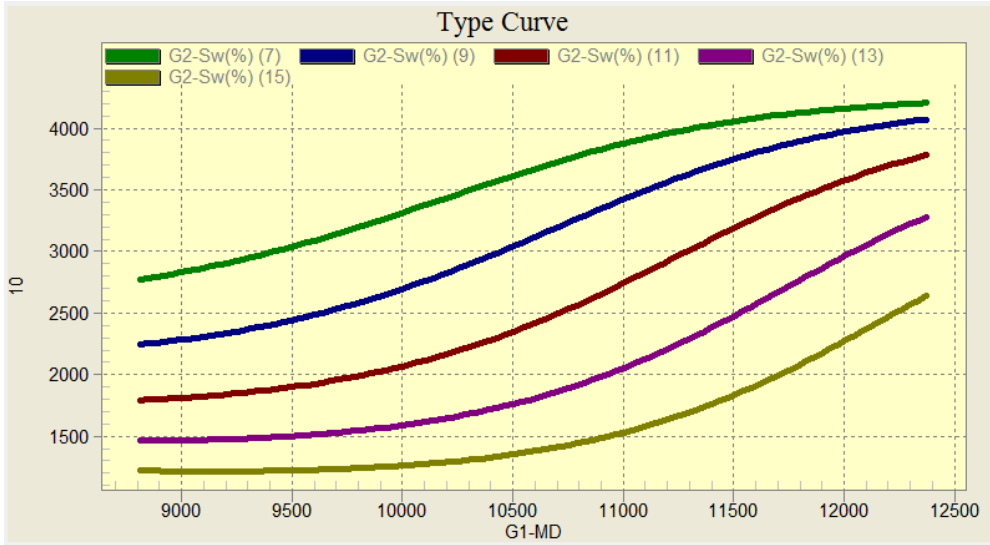


Figure 26. 10-year-EUR as A Function of Measured Depth and Different Water Saturation values.

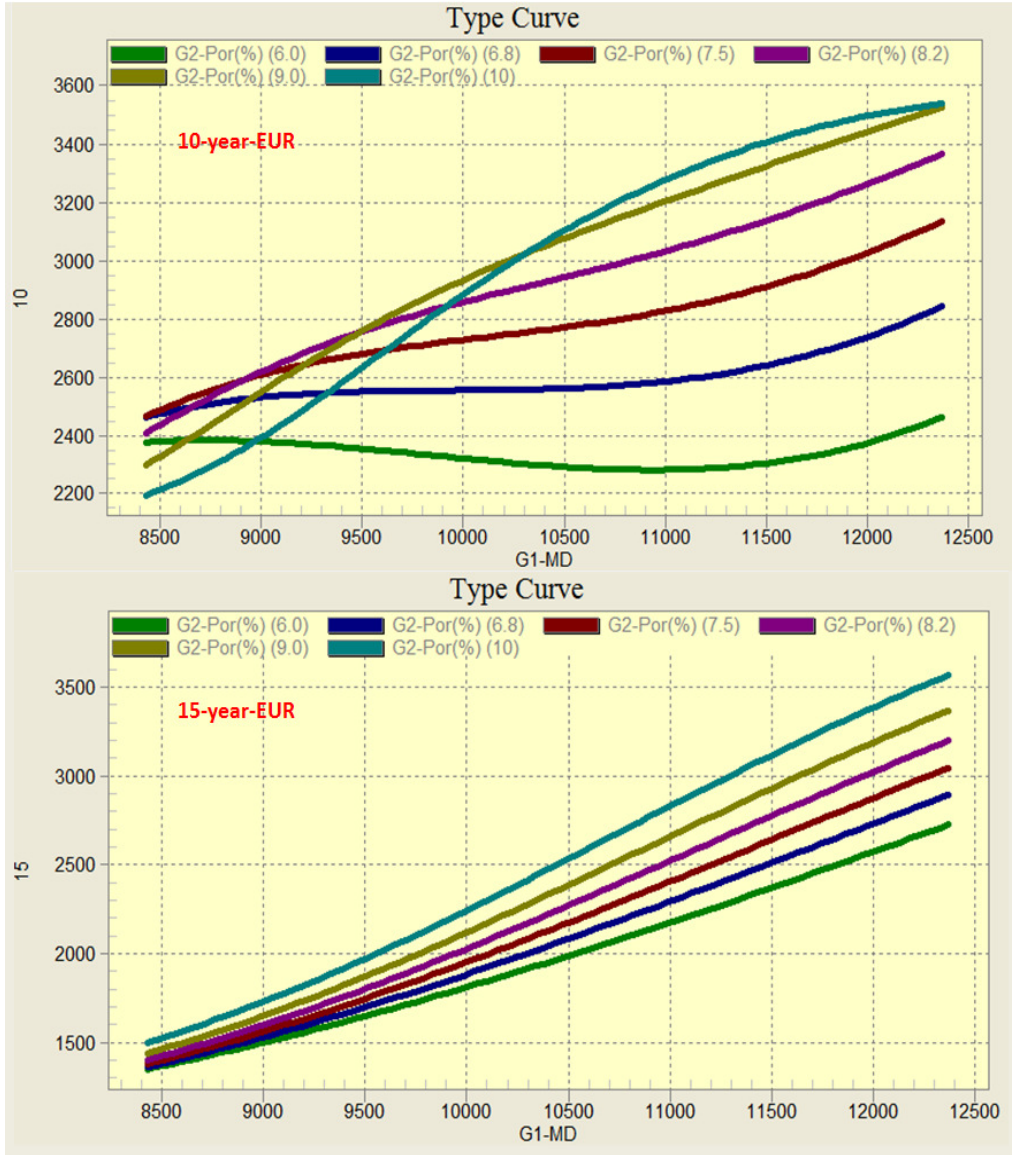


Figure 27. Type Curves for 10 and 15 years EUR. EUR as A Function of Measured Depth and Different Porosities.

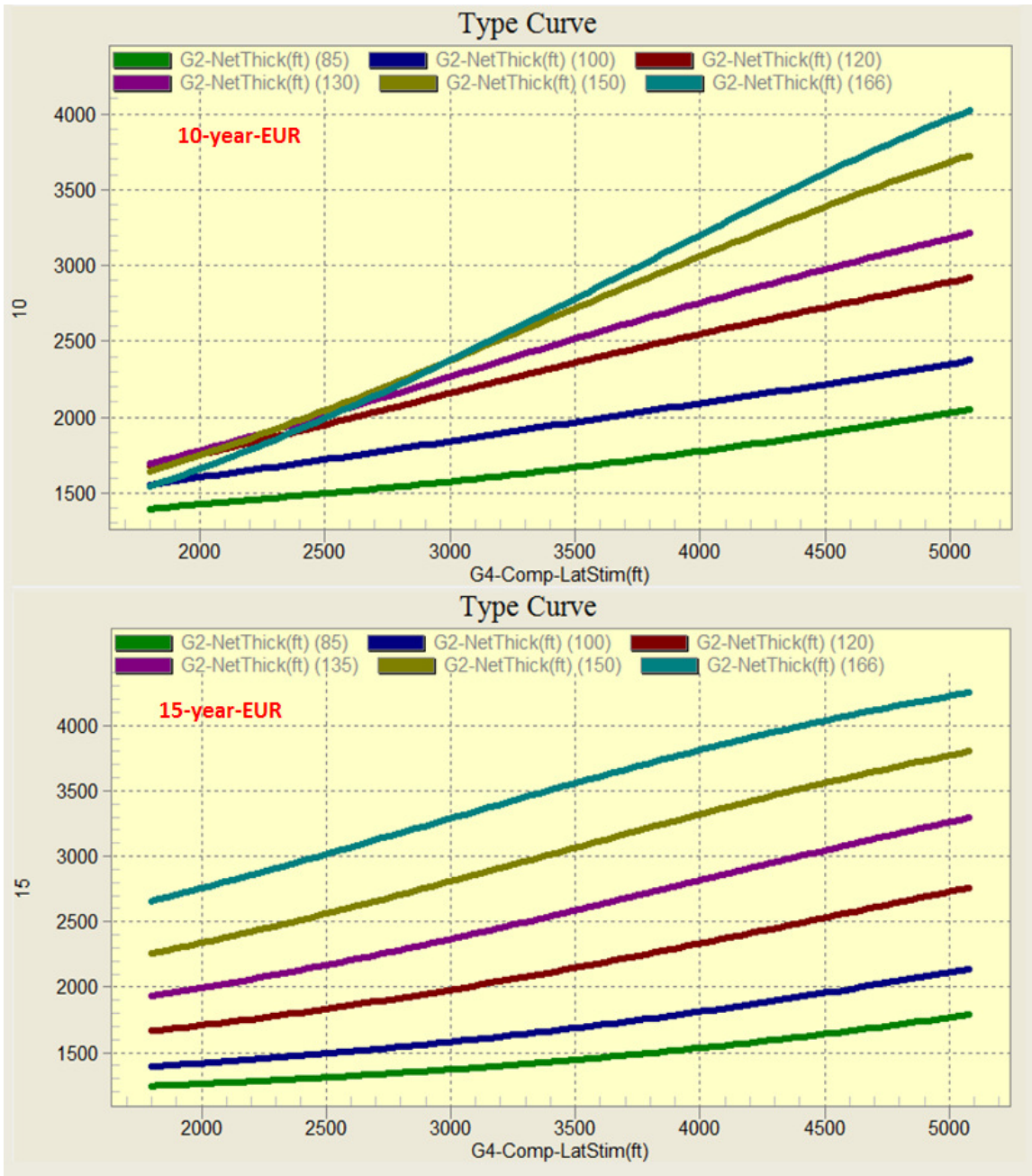


Figure 28. Type Curves for 10 and 15 years EUR. EUR as A Function of Stimulated Lateral Length and Different Net Thickness.

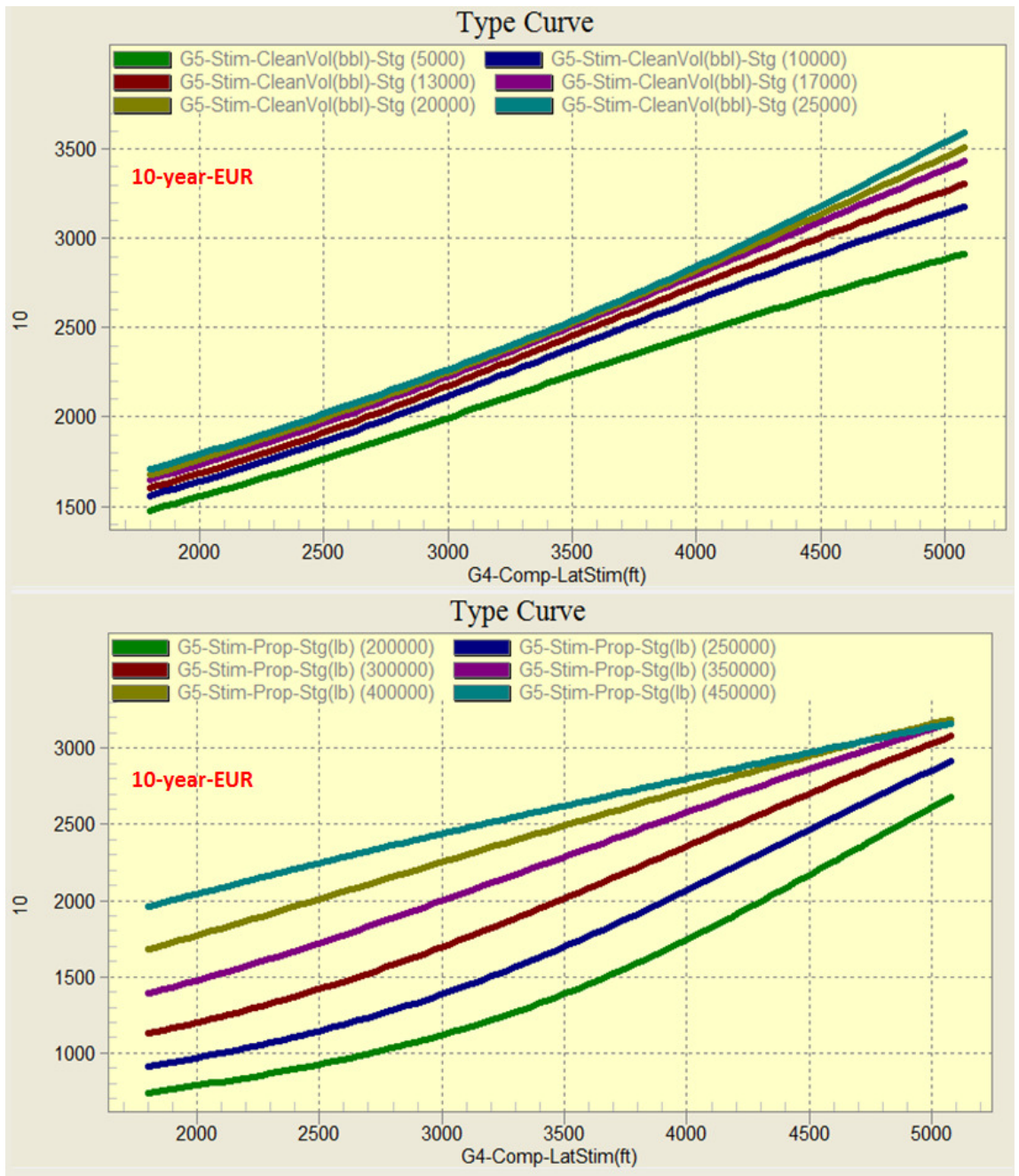


Figure 29. Type curves for 10-year EUR. Top: EUR as A Function of Stimulated Lateral Length and Injected Clean Volume. Bottom: EUR as A Function of Stimulated Lateral Length and Injected Proppant.

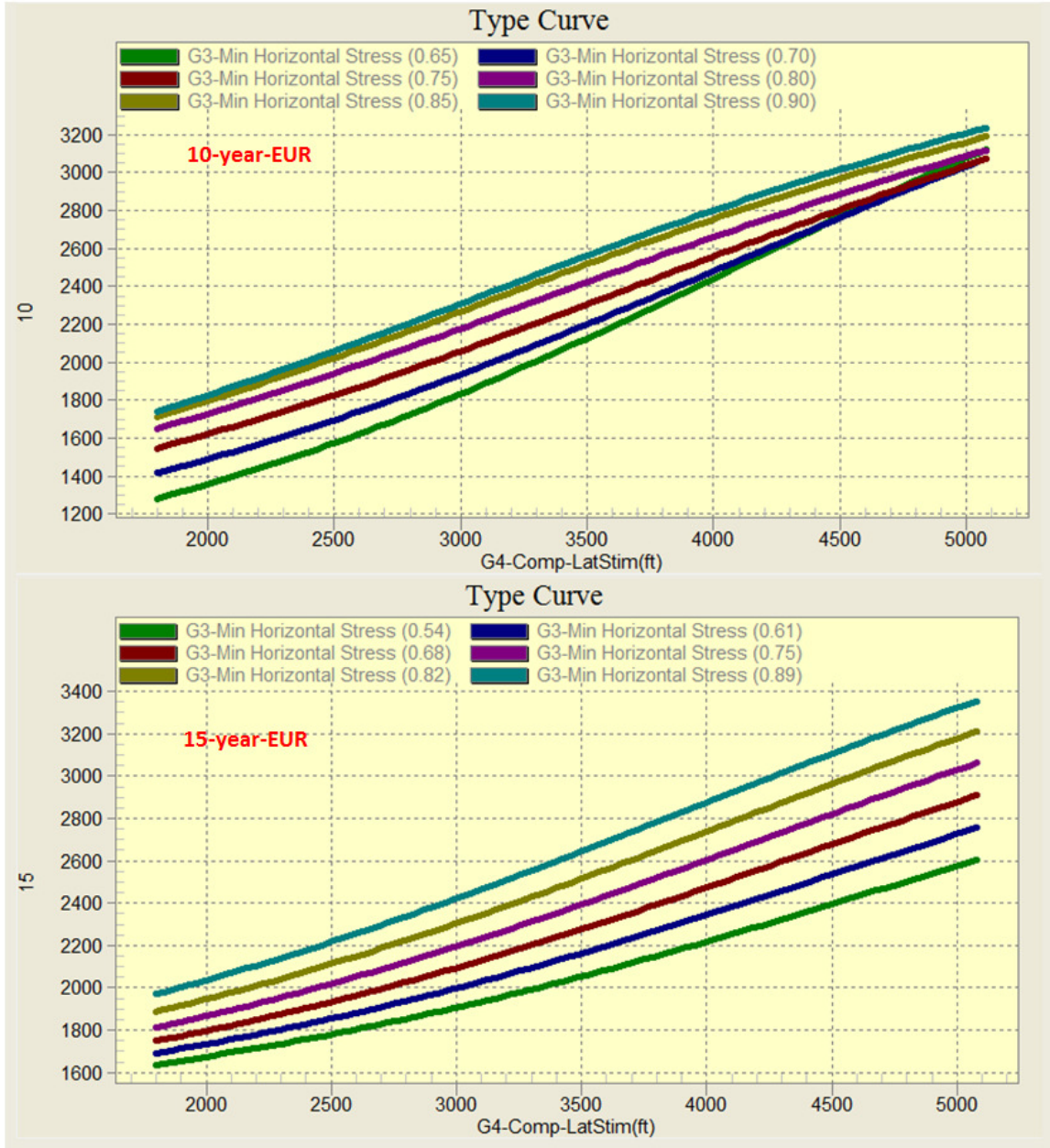


Figure 30. Type curves for 10-year EUR and 15-year-EUR. EUR as A Function of Stimulated Lateral Length and Minimum Horizontal Stress

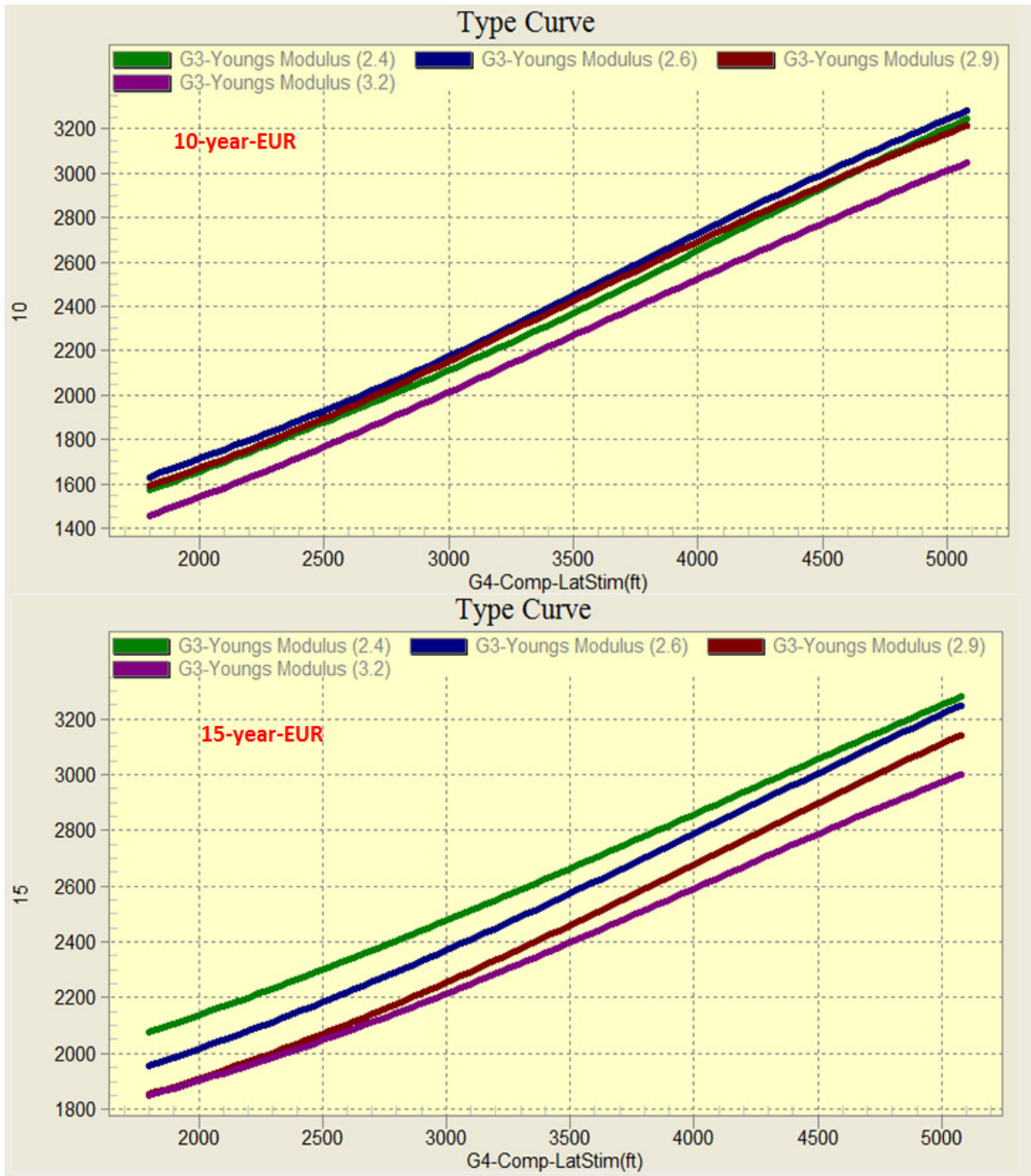


Figure 31. Type curves for 10-year EUR and 15-year-EUR. EUR as A Function of Stimulated Lateral Length and Young's Modulus

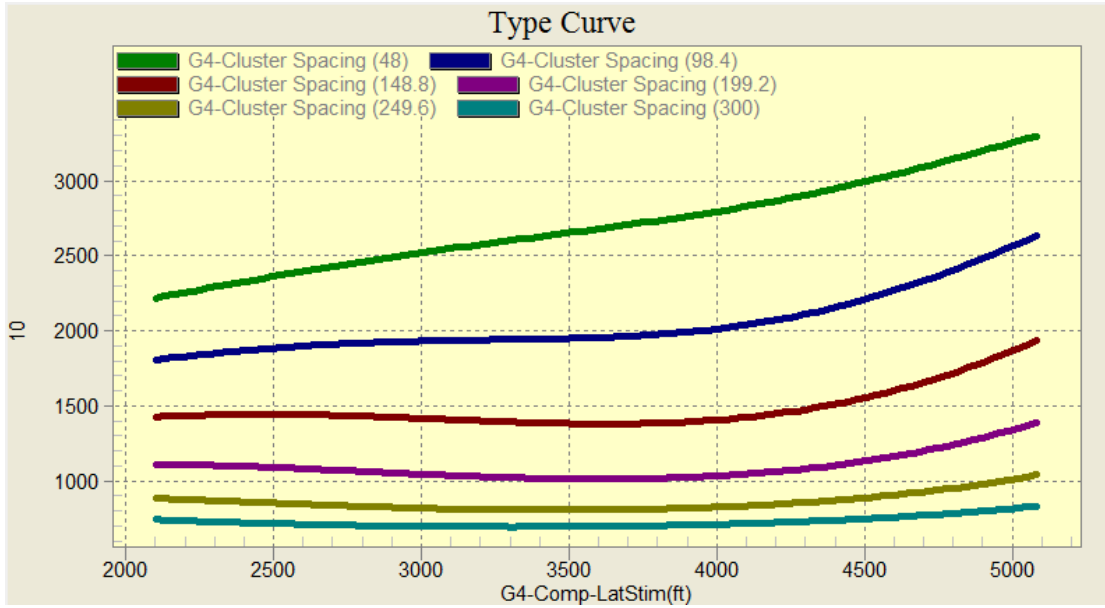


Figure 32. Type curves for 10-year EUR. EUR as A Function of Stimulated Lateral Length and Cluster Spacing

Conclusion

- Decline curve analysis was used in order to calculate 10-year-EUR and 15-year-EUR for shale wells. In this study Arps hyperbolic curve is used for the earlier time of the production and then it was switched to Arps exponential curve. The result of EUR using this method was more conservative than other decline curve techniques.
- Two data-driven models using AI tools and pattern recognition were developed in order to estimate the ultimate recovery (10 and 15 years EUR) for the wells with no production history in Marcellus shale. This technique could successfully learn the physics complex flow mechanism of shale from data.
- The trained model was validated with blind data set. This data was not introduced to the model and the EUR values were predicted by the model. The result shows the accuracy of almost 85 percent for 10-year-EUR and 82 percent for 15-year-EUR.
- Applications of fuzzy pattern recognition (WQA and FTA) were used in order to discover the relationship between input parameters and EUR. These analyses are applied on data and could discover the hidden patterns between EUR and those parameters. These patterns can be used as a tool for operators in order to exploit the optimum hydraulic fractures design parameters.

The results of this research show that higher EUR can be obtained in the east part of the reservoir. Also porosity and net thickness as well as minimum horizontal stress has positive impact on EUR. It is also observed that increasing Young's modulus reduces the amount of EUR. It can be observed that longer lateral length, more number of stages results more EUR. Moreover, Reducing cluster spacing increases the EUR. As it is discussed in the result section, proppant and clean injection improves the ultimate recovery of the shale wells.

- After training the model type curves are generated in order to identify the sensitivity of parameters and their impact on EUR. This method provides useful information for operators in order to make thoughtful decisions about well performance. The results show similar information to the result of pattern recognition method. This means the model is consistent and could learn all the information from raw data.

Recommendations for future works

- Different decline curve methods can be used and compared in order to calculate EUR for shale wells.
- The developed model in this thesis can be updated if a longer production history of Marcellus shale wells would be available.
- Trained predictive models and type curve analysis can be used in order to provide the optimum value for completion and stimulation parameters
- It is also recommended to investigate the effect of static and design parameters on other reservoirs and formations

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Appendix 1: Type Curves

Type Curves for 10-year- EUR:

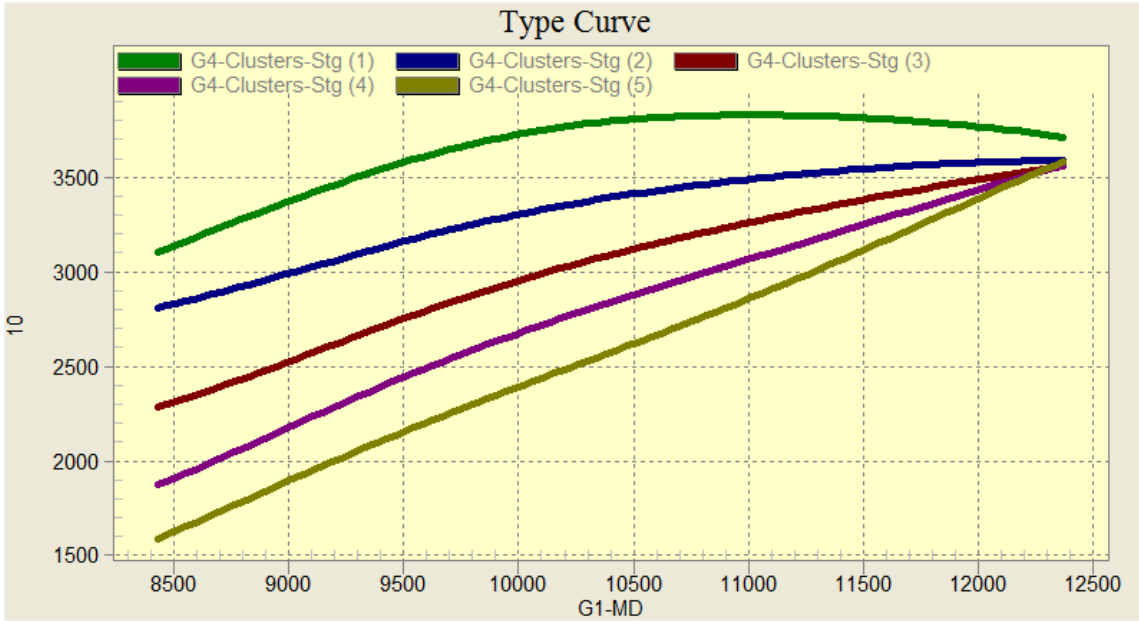


Figure A- 1. 10-year-EUR as A Function of Measured Depth and Number of Clusters per Stage

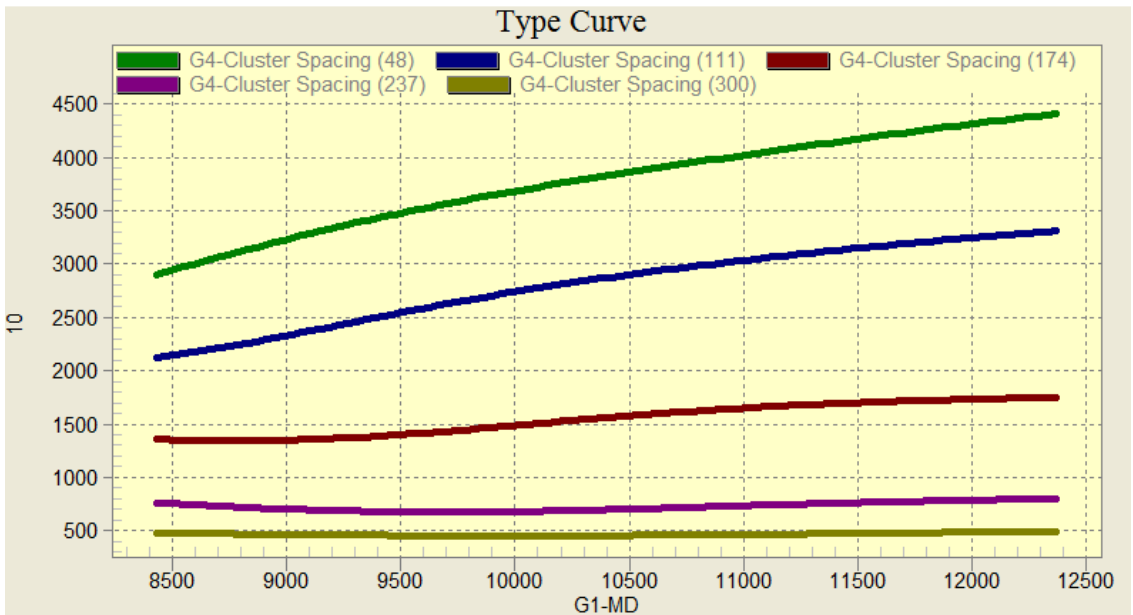


Figure A- 2. 10-year-EUR as A Function of Measured Depth and Cluster Spacing

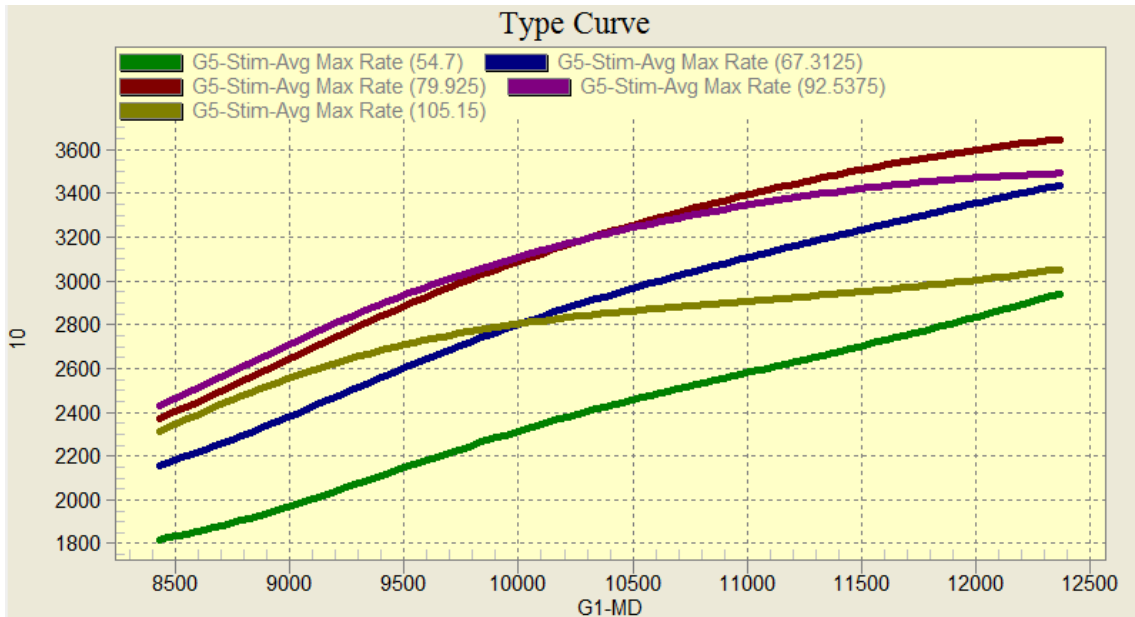


Figure A- 3. 10-year-EUR as A Function of Measured Depth and Average Maximum Rate

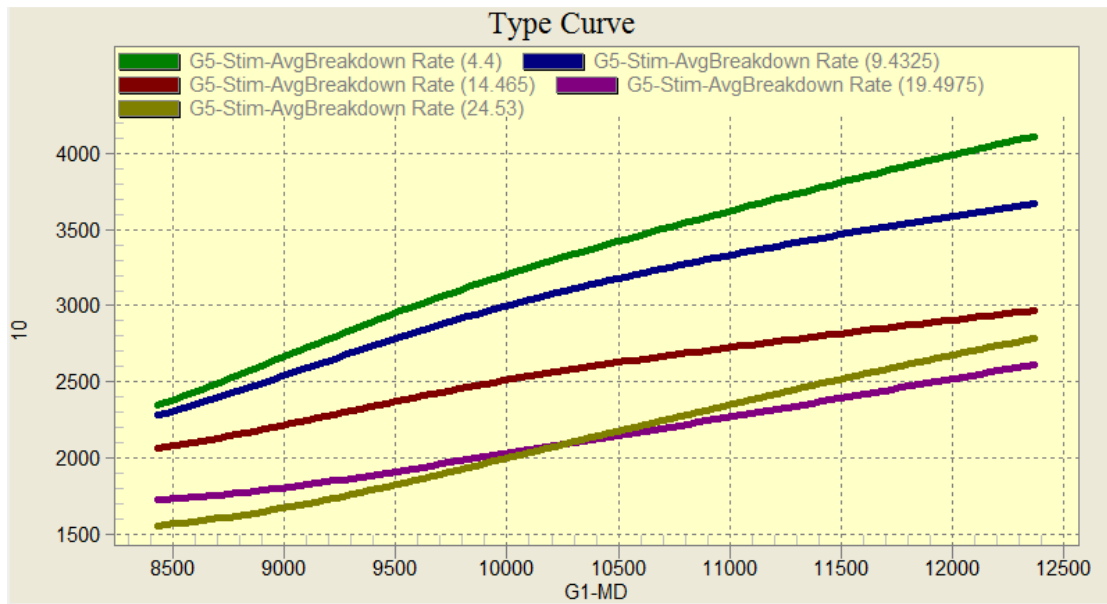


Figure A- 4. 10-year-EUR as A Function of Measured Depth and Average Breakdown Rate

Type Curves for 15-year- EUR:

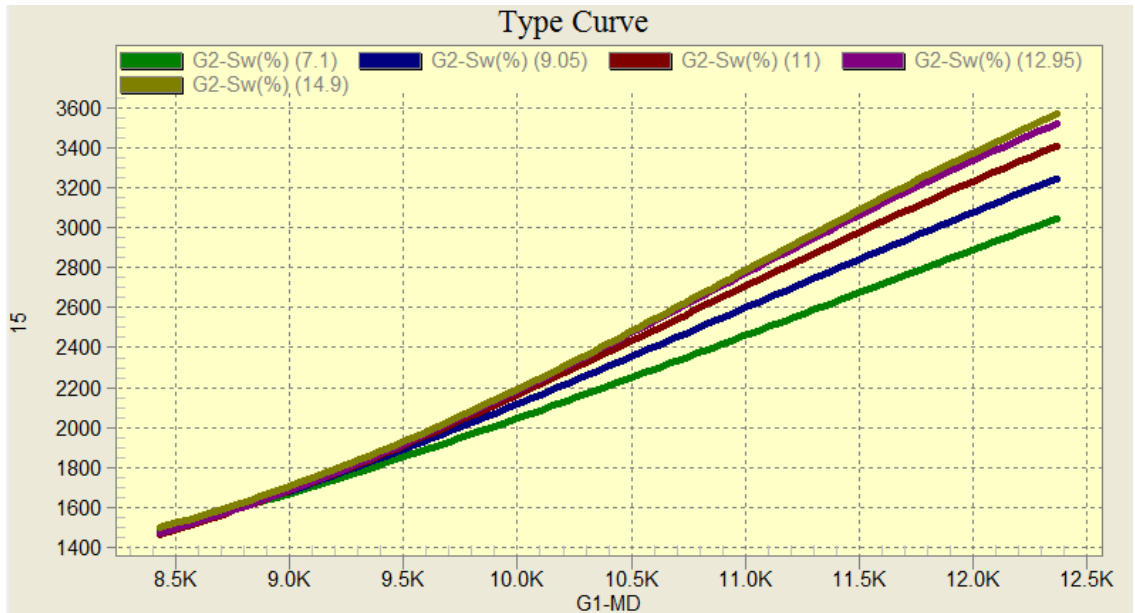


Figure A- 5. 15-year-EUR as A Function of Measured Depth and Water Saturation

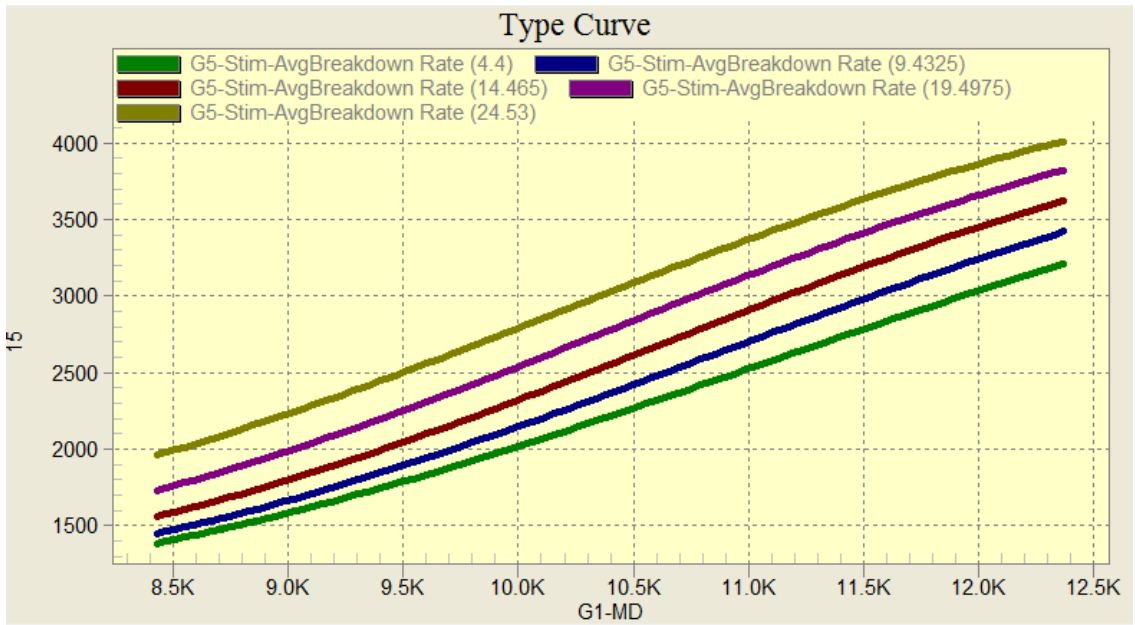


Figure A- 6. 15-year-EUR as A Function of Measured Depth and Average Breakdown Rate

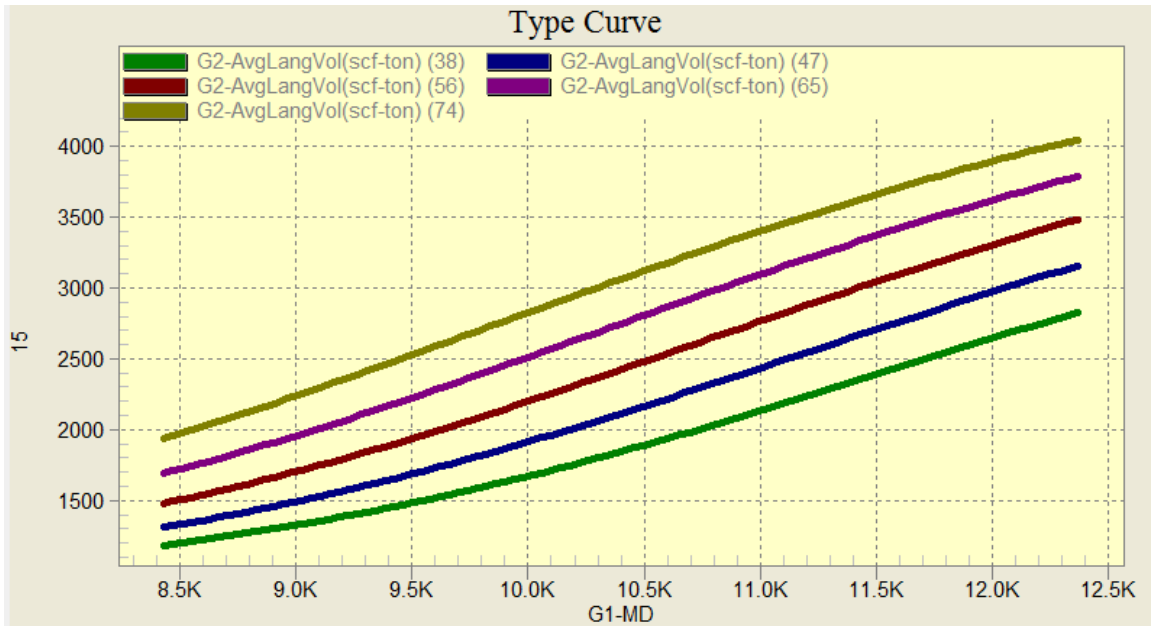


Figure A- 7. 15-year-EUR as A Function of Measured Depth and Average Langmuir volume

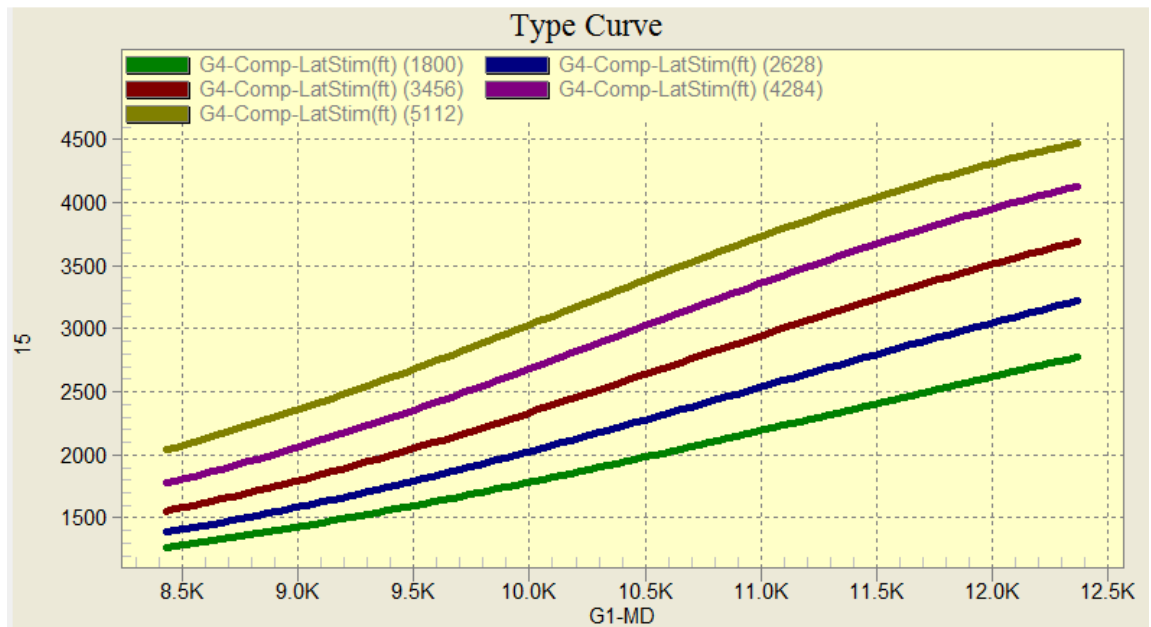


Figure A- 8. 15-year-EUR as A Function of Measured Depth and Lateral Length

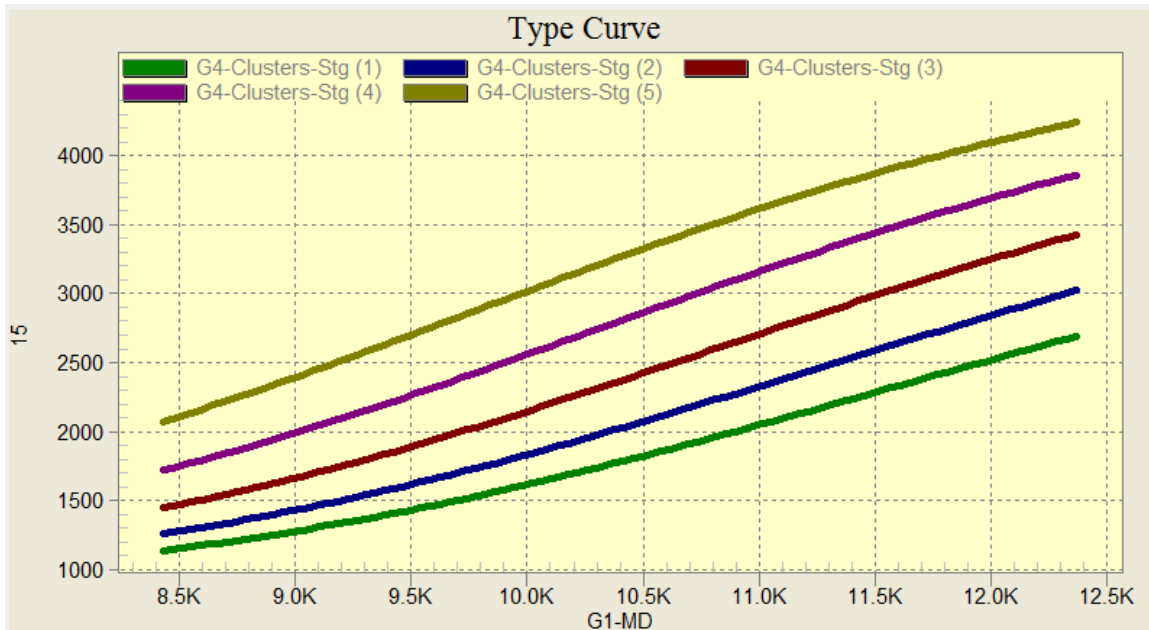


Figure A- 9. 15-year-EUR as A Function of Measured Depth and Number of Clusters per Stage

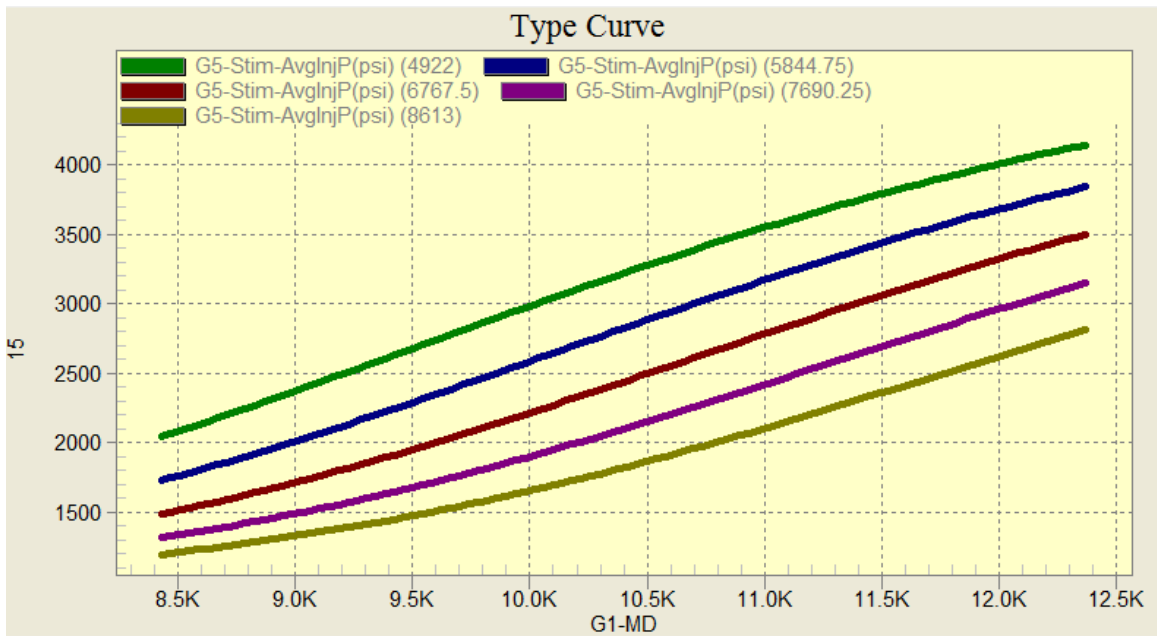


Figure A- 10. 15-year-EUR as A Function of Measured Depth and Average Injection Pressure

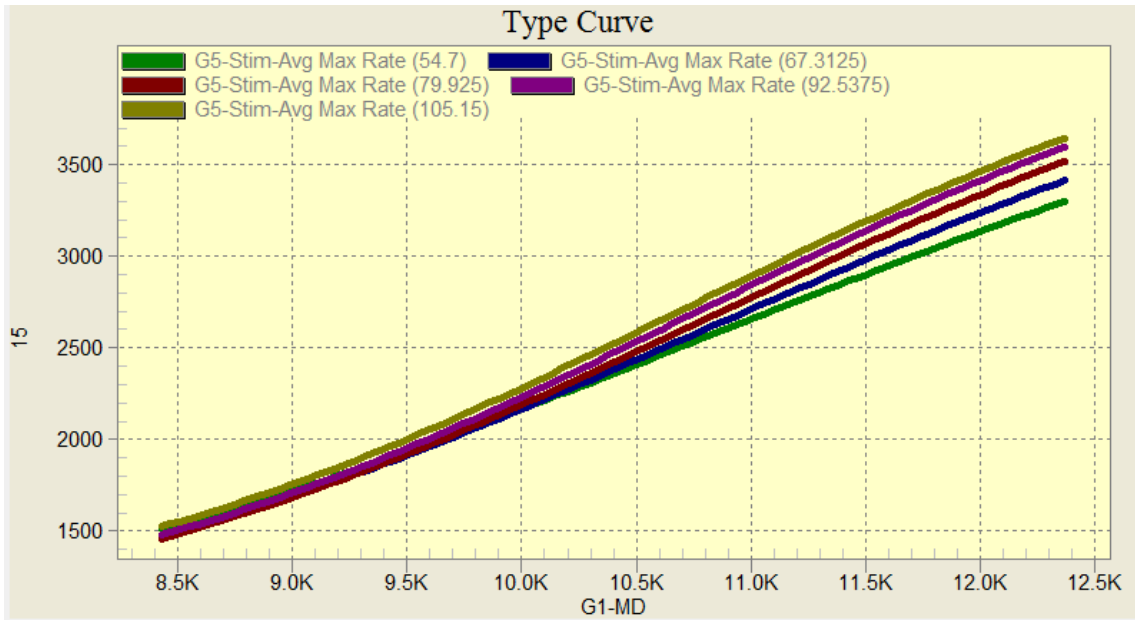


Figure A- 11. 15-year-EUR as A Function of Measured Depth and Average Maximum Injection Rate

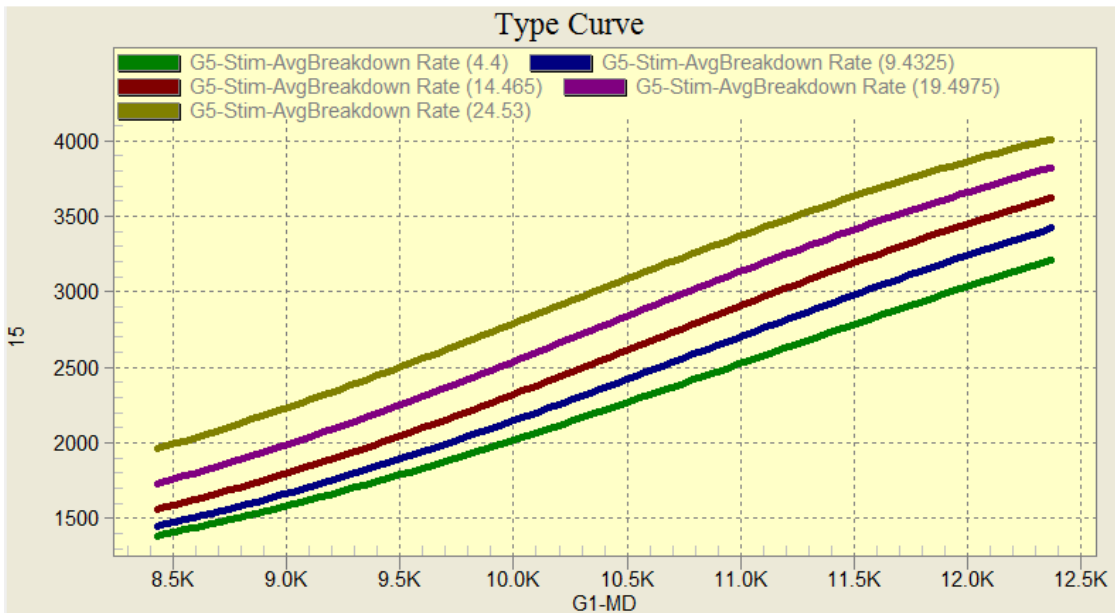


Figure A- 12. 15-year-EUR as A Function of Measured Depth and Average Breakdown Rate