OPTIMIZATION OF DRILLING PARAMETERS USING SPECIFIC ENERGY IN REAL TIME

BY

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To

My

Family

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All praises and adorations are due to Allah, the lord of incomparable majesty. May Allah bestow peace on his Prophet Mohammed (peace and blessings of Allah be upon him), and his family.

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My family members owe special thanks for their continuous love and support showered on me all through the ages.

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NOMENCLATURE

Roman

Symbol		**Unit**
a_1	formation strength parameter	
a_2	exponent of normal compaction trend	
a_3	under-compaction exponent	
a_4	pressure differential exponent	
a_5	bit weight exponent	
a_6	rotary speed exponent	
a_7	tooth wear exponent	
a_8	hydraulic exponent	
A_B	borehole area	(in^2)
B	fractional bearing wear	
b	bearing constant	
Bc	bit cost	($)
C_b	bit cost	($)
C_1	proportionality constant in penetration rate equation	
C_f	cost per drilled interval	($/ft)
C_{fd}	formation drillability parameter	
Cr	daily rig rate	($)
D	depth of borehole	(ft)
d_b	diameter of the bit	(in)
d_n	equivalent bit nozzle diameter	(in)

Dia	bit diameter	(in)
E	rock hardness	(psi)
E_s	bit specific energy	(psi)
f_1	formation strength function	
f_2	formation normal compaction function	
f_3	formation compaction function	
f_4	pressure differential of bottom hole function	
f_5	bit diameter and weight function	
f_6	rotary speed function	
f_7	tooth wear function	
f_8	hydraulic function	
F	rate of penetration	(ft/hr)
F	distance drilled by bit	(ft)
h	bit tooth dullness, fractional tooth height worn away	
HP_b	bit hydraulic horse power	(psi)
H_1,H_2	constants for tooth geometry of bit types	
K	proportionality constant for rock strength effect	
N	rotary speed	(rpm)
Q, q	volumetric flow rate	(gpm)
R^2	regression coefficient	
R	rate of penetration	(ft/hr)
Tor	torque	(lbf-ft)
T	torque	(lbf-ft)
t	time (usually bit rotating time)	(hours)
t_b	bit drilling time	(hours)

t_c	drill pipe connection time	(hours)
t_t	round trip time	(hours)
W	weight on bit	(1000 lbf)
W_{vert}	vertical weight on bit component	(1000 lbf)
W/d	weight on bit per inch of bit diameter	(1000 lbf/in)
$(W/d)_{max}$	bit weight per diameter where teeth fails	(1000 lbf/in)
$(W/d)_t$	threshold bit weight at which the bit starts to drill	(1000 lbf/in)

Greek

Symbol		**Unit**
μ	bit specific coefficient of sliding friction	
Δp	differential pressure	(psi)
ρ	drilling fluid's density	(ppg)
ρ_c	equivalent circulation density	(ppg)
τ_H	formation abrasiveness constant	(hours)
τ_B	bearing constant	(hours)
τ_y	yield stress	(lbf/100ft^2)
λ	bit hydraulic factor	(dimensionless)

Subscripts

Symbol		**Unit**
B	bit or borehole	
f	function	
min	minimum	
max	maximum	
N	nozzle	

Abbreviations

Symbol		**Unit**
ANFIS	adaptive neuro fuzzy systems	
ANN	artificial neural networks	
BHA	bottom hole assembly	
BNN	bayesian belief networks	
CI	computational intelligence	
DEO	drilling efficiency optimization	
DSE	drilling specific energy	(psi)
DT	decision trees	
ECD	equivalent circulating density	(ppg)
FL	fuzzy logic	
FN	functional networks	
FS	fuzzy sets	
FTWD	formation testing while drilling	

KNN	k-nearest neighbor	
LWD	logging while drilling	
LR	logistic regression	
MLP	multilayer perceptrons	
MSE	mechanical specific energy	
MD	measured depth	(ft)
MW	mud weight (density)	(ppg)
MWD	measurements while drilling	
NB	naive bayes	
NN	neural network	
Opt	optimum	
PN	probabilistic networks	
PSO	particle swarm optimization	
PWD	pressure while drilling	
QA/QC	quality assurance/quality control	
RF	random forests	
ROP	rate of penetration	(ft/hr)
RPF	radial basis function	
RPM	revaluation per minute	(rpm)
RT	real time	
RTOC	real time operations center	
SPP	standpipe pressure	(psi)
SVM	support vector machines	
WOB	weight on bit	(1000 lbf)

ABSTRACT

Full Name : [Mohammed Ali Nasser Khamis]

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Drilling optimization has been used widely to maximize the drilling efficiency of oil and gas wells. Several soft and hard wares were used in the optimization process, such as, Measurements While Drilling (MWD), surface sensors, computer software, and experienced expert personnel. The disadvantage of using conventional drilling optimization processes is the independency of real time data which make the optimization process inefficient. Real time and rig-site data should be used to make the optimization more accurate and efficient. The main parameter that should be looked into in the optimization process is the drilling time that can be optimized by increasing the penetration rate.

In this research the rate of penetration (*ROP*) will be optimized using drilling specific energy (DSE) based on real time and rig-site data. The work will involve adequately defining the problems to be solved, formulating the objectives of drilling optimization tasks into mathematical equations and solving the formulated optimization problems. Introducing bit hydraulics will improve the ROP significantly. The first part of this work will involve the development of a correlation between rate of penetration (*ROP*) and the affecting parameters such as Weight on Bit (*WOB*), Revolution per Minute (*RPM*), Torque (T), drilling fluid circulation rate (Q_m), and bit hydraulics (HP_b). The proposed

optimization technique will be used to identify the optimum value or solution to all the involved parameters, for example increasing WOB may increase the ROP but it will shorten the bit life and it may cause bit failure, therefore, optimization is required.

The field data Quality Assurance/Quality Control (QA/QC) will be implemented and the Particle Swarm Optimization (PSO) technique will be used.

This work will have impact on the oil and gas technology area by improving the drilling operations efficiency. This improvement will be achieved by reducing the drilling cost through the development of an efficient drilling system that is based on real time good quality data.

ملخص الأطروحة

الاسم الكامل:محمد علي ناصر خميس

عنوان الرسالة:تحسين معاملات الحفر عن طريق إستخدام الطاقة النوعية في الزمن الفعلي

التخصص: هندسة البترول

تاريخ الدرجة العلمية:يوليو 2013

إن الحفرالأمثل للآبار النفطية يستخدم على نطاق واسع لتحقيق الكفاءة القصوى للحفر. لقد إستفادت تقنية الحفر من العديد من البرامجيات في عملية تحسين كفاءة الحفر مثل القياس أثناء الحفر، أجهزة الإستشعار السطحية، برامج الكمبيوتر، بالإضافة إلى الأشخاص ذوي الخبرة في هذا المجال. إن من سلبيات عمليات تحسين الحفر التقليدية هي عدم إستخدام البيانات في الوقت الفعلي والذي بدوره يؤدي إلى جعل عملية التحسين غير فعالة. إن البيانات في الوقت الفعلي وكذلك البيانات من موقع الحفر يجب أن تُستخدم لجعل عملية التحسين أكثر دقة وكفاءة. إن المعاملات الرئيسية التي ينبغي أن نأخذها بعين الإعتبار في عملية تحسين الحفر هي بيانات الحفر التي يمكن تحسينها بشكل أمثل من خلال زيادة سرعة الحفر.

في هذا البحث تم تحسين سرعة الحفر باستخدام طاقة الحفر النوعية على أساس الوقت الفعلي وبيانات الحفر. إن هذا البحث إشتمل على تعريف كافة المشاكل التي يتعين حلها وكذلك صياغة أهداف الحفر الأمثل في شكل معادلات رياضية ومن ثم حل هذا المعادلات. إن إدخال هيدروليكية مثقب الحفر (أداة الحفر) ساهمت في تحسين معدل سرعة الحفر بشكل كبير. إن الجزء الأول من هذا البحث إشتمل على تطوير علاقات رياضية بين سرعةالحفر والمعاملات المؤثرة على سرعة الحفر مثل (الوزن على مثقب الحفر، معدل دوران المثقب، عزم الدوران، معدل جريان سائل الحفر وكذلك هيدروليكية المثقب). إن تقنية تحسين الحفر المقترحة إستُخدمت لتحديد القيمة المثُلى أو الحل لكل المعاملات المؤثرة (على سبيل المثال فإن زيادة الوزن على المثقب ربما يكون سببا في زيادة سرعة الحفر ولكن سوف يؤثر سلبا على عمر المثقب ويقصر من عمره وقد يؤدي ذلك إلى إنهيار المثقب ومن ثم ضرورة إستبداله لذلك فإن عملية التحسين المثلى تكون مطلوبة).

إن التدقيق في جودة البيانات المستخدمة تم تنفيذه في هذا البحث عن طريق معايير خاصة وتم إستخدام تقنية التحسين بطريقة سرب الجزيئات Particle Swarm Optimization(PSO).

إن هذا البحث سوف يكون له تأثير على مجال تكنولوجيا النفط والغاز عن طريق تحسين كفاءة معاملات الحفر. هذا التحسين سوف يتحقق من خلال تقليل كلفة الحفر عن طريق تطوير نظام فعال للحفر والذي يستند إلى بيانات ذات نوعية جيدة في الوقت الفعلي وجعل عملية الحفر أكثر كفاءة وأقل كلفة.

CHAPTER 1

INTRODUCTION

Real-time data for drilling operations denotes information that is delivered immediately after collection. There is no delay in the timeliness of the information provided. Real-time data is often used for navigation or tracking. Some uses of this term confuse it with the term dynamic data. In reality, the presence of real-time data is irrelevant to whether it is dynamic or static. With the advent and evolution of the digital oilfield, an increased flow in real-time data is readily available to any operating company for drilling operations at any rigsite. In turn, the flow of data provides drilling engineers with an improved understanding of events occurring at the rig site in near real time and increases the data, originally only available from the daily paper, to continuous, real-time data.

Figure 1 gives the data transmission methodology of the process. Real time data in the drilling phase of a well is a basic operation premise. The value of real time data within the drilling knowledge base is the ability to relate what we are seeing in real time with patterns and events from the past. This comparison can help make decisions that could potentially cost or save millions of dollars. Real time data can also provide a robust collaboration tool where the office and rig simultaneously view all the past and current drilling data. Every operator has seen the benefit of using MWD, (Measurement While Drilling), technology for well placement, logging, optimization, etc. Real time optimization of drilling parameters during operations aims to optimize weight on bit, bit rotation speed to obtain maximum drilling rate as well as to minimize the drilling cost. In other words, the objective of optimizing drilling parameters in real-time is to arrive to methodology that considers past drilling data and predicts drilling trend advising optimum drilling parameters in order to save drilling costs and reduce the probability of encountering problems. Because of the importance of the real time data, several techniques were developed to increase the real time drilling efficiency and cut drilling cost. Continuous monitoring of real-time drilling parameters for quality and consistency is one of the techniques used.

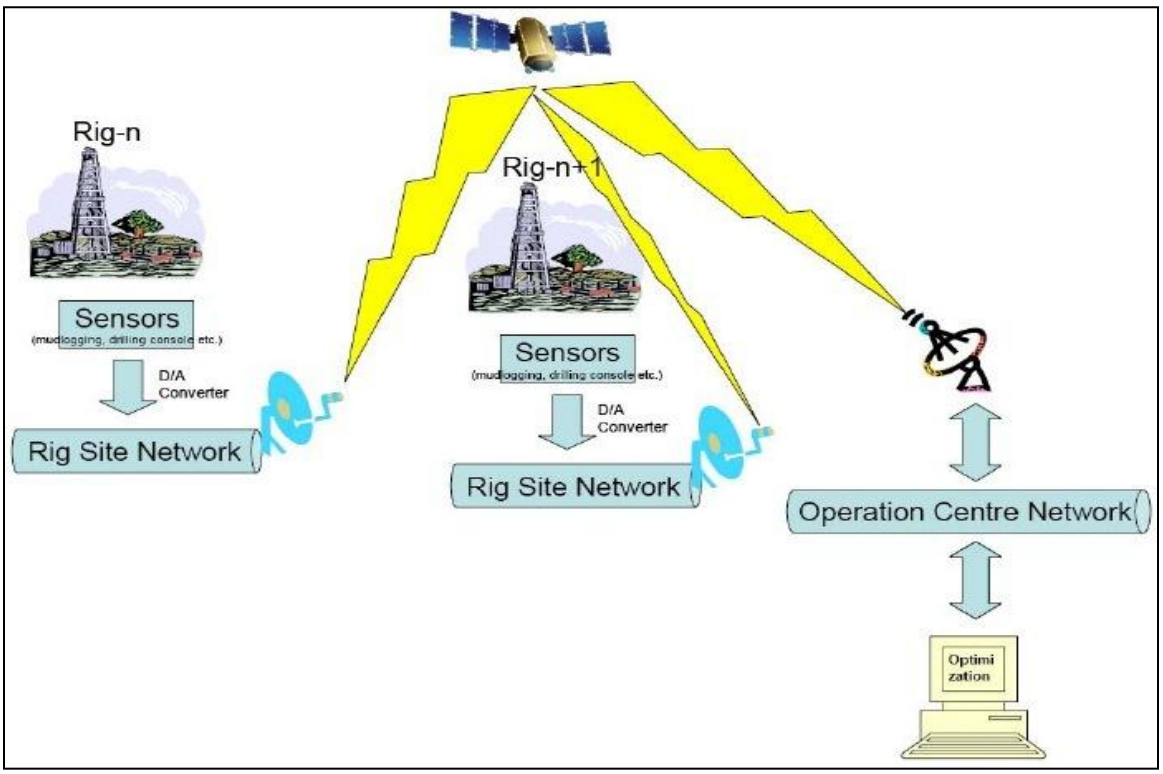


Figure 1: Drilling optimization data transmission process (Tuna and Evren 2010)

1.1 Optimization of Drilling Parameters

Drilling optimization is a process that employs downhole and surface sensors, computer software, Measurement While Drilling (MWD), and experienced expert personnel – all dedicated to reduce trouble time and increase drilling efficiency (D.C-K Chen, 2004).

The objective of optimizing drilling parameters in real time is to arrive to a methodology that considers past drilling data and predicts drilling trend advising optimum drilling parameters in order to save drilling cost and reduce the probability of encountering problems. Figure 2 provides the timeline of some important achievements in drilling optimization history. In 1950s the scientific period took place with expansion in drilling research. After 1970s rigs with full automation systems started to operate in oil and gas fields. Operator companies developed techniques of drilling optimization in the mid of 1980s. In 1990s different drilling planning approaches were brought to identify the best possible well construction performance. After 2000s real time operations support centers were built. In recent years drilling parameters are easily acquired, stored and transferred in real time.

The traditional optimization process consists of: (i) pre-run modeling, (ii) real-time data measurement and monitoring, and (iii) post-run analyses and knowledge management. At the center of this process are the personnel who are expert in these technologies and who can make recommendations to avoid trouble and improve drilling performance. Generally, a comprehensive drilling optimization should include solutions for: (1) drill string integrity, (2) hydraulics management, and (3) wellbore integrity. However, new drilling optimization technologies emphasize information management and real-time decision making. On the other hand the traditional three-step optimization process will not fit the real time process and has had to be changed. First pre-run modeling needs to be changed to "real-time modeling". This change is required because the input parameters for pre-run models have typically been out-dated and incorrect. Therefore, modeling results were often of little use for real-time decision making. Second, integrated real-time modeling and data are required to allow detailed diagnoses on the downhole environment.

Third, a rig-to-office integration is best so the optimization process can be monitored 24/7 by an asset team. These three new technologies have been summarized by (Chen 2004) as (1) real-time modeling, (2) integrated real-time modeling and data, and (3) a real time operation center (RTOC).

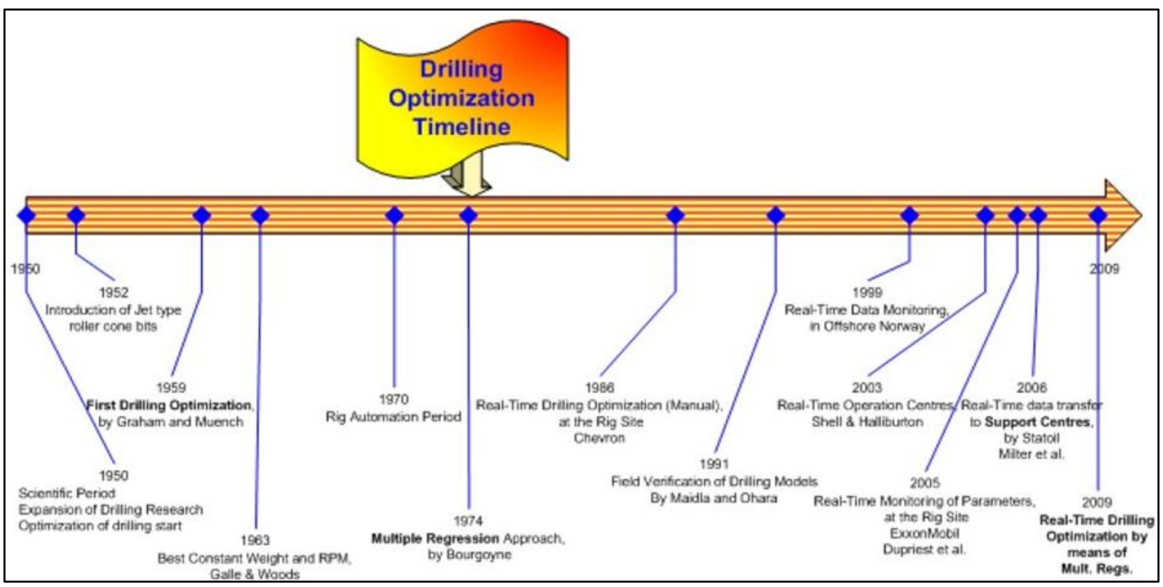


Figure 2: Time line for drilling optimization (Tuna and Evren 2010)

1.2 Real Time Modeling

Conventional modeling is usually run during well planning to avoid a set of predicted data. As drilling processes, the input parameters may change intentionally or unintentionally. As a result, conventional, stand-alone computer software requires constant manual updating to produce pertinent results. Such a procedure, however, has proven to be impractical.

In contrast, real-time modeling is automatically updated using "correct" input data, which is no doubt more accurate. In addition, real-time modeling is always "on" allowing continuous monitoring to prevent drilling accidents. Real time modeling also allows integration with real time data to enable real time decision making. To date, several real-time drilling optimization-related modeling programs have been or are being developed:

- BHA dynamics
- Torque and drag
- Pore pressure/fracture gradient prediction
- Hydraulics
- Hole cleaning
- Wellbore stability

1.3 Integrated Real Time Modeling and Data

Although real-time modeling produces better results than the conventional, stand-alone modeling, the delivery of useful information in a useful form and diagnosis of a problem requires an integration of modeling with downhole data. For example, the integration of the following models and data is always beneficial.

- Bottom Hole Assembly (BHA) dynamics model with downhole vibration data
- Pore pressure model with Pressure While Drilling (PWD) and Formation Testing While Drilling (FTWD) data
- Hydraulic model with PWD data
- Hole cleaning model with PWD and solids in mud
- Wellbore stability model with Logging While Drilling (LWD) imaging data

1.4 RTOC

The first Real-Time Operation Center (RTOC) was set-up by Shell E&P in New Orleans in early 2002. Since then, several other RTOCs for different operators have been developed particularly for offshore rigs.

There are many reasons to setup RTOCs. First, wells drilled offshore are very expensive. They clearly require full attention by the best staff available. Second, critical decisions are always multidisciplinary; and multidisciplinary decision making with expert staff is impractical to arrange at a rig. Third, a permanent, common ground needs to be identified for office and offshore staff throughout planning and execution; and RTOCs readily satisfy this element. Lastly, full time (24/7) real-time drilling optimization monitoring and information management is required to avoid hazards; and 24/7 monitoring available to key personnel is best done an RTOC.

Drilling rate of penetration model should be defined in order to conduct the real-time data analysis for drilling rate of penetration optimization. The model described below aims to optimize WOB and RPM where multiple linear regression technique will be used as an optimization methodology. Multiple regressions are used to find the parameters of an equation which make that equation to be best representation of the data (Mitchell 1995). A code will be designed to find the coefficients of the model; mathematically correlating rate of penetration with the controllable drilling and uncontrollable parameters. The mission is to obtain drilling data at a rig site network, pipe the collected data to the operation center, and run the analysis and send feed back to the rigsite as shown in Fig. 2. The data process technique is performed to the drilling data set to achieve general equation to predict drilling rate of penetration as a function of input drilling parameters. The multiple regression technique is based on regression model that contains more than one regressor variable (Montogomery and Runger 2003). Multivariable data analysis is characterization of an observation unit by several variables (Davis 2002). Multivariable analysis method get affected for the changes in magnitude if several properties simultaneously. Multiple regressions consider all possible interactions within combination of variable as well as the variables themselves. Mathematical model for the penetration rate might be written as a function of drilling parameters as illustrated in Fig. 4. The optimized WOB and RPM should lie within the operation window of their respective applicable range.

$$\frac{dF}{dt} = f\left(\frac{W_{vert}}{d_b}, N, h\right) \quad (1)$$

Drilling cost per foot equation (Eq. 2) is defined to account for daily rig rate, bit cost, and timings required in the course of bit runs.

$$C_f = \frac{C_b + C_r(t_t + t_c + t_b)}{\Delta F} \quad (2)$$

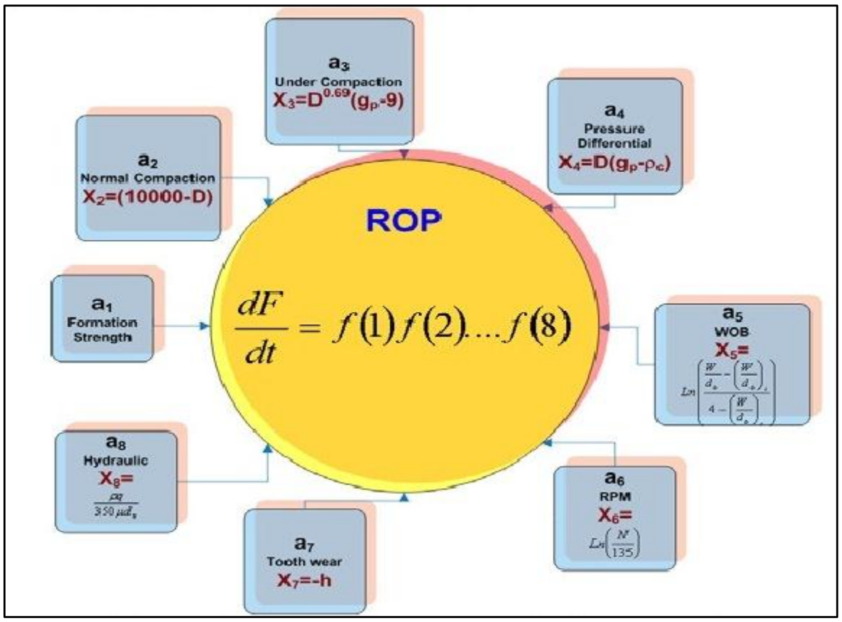


Figure 3: General rate of penetration equation (Tuna and Evrin 2010)

After the necessary calculus the optimized equation for the vertical weight component for each diameter of bit size is as set in Eq. 3 after (Bourgone et al. 1986).

$$\left[\frac{W_{vert}}{d_b}\right]_{opt} = \frac{a_5 H_1 \left(\frac{w}{d_b}\right)_{max} + a_6 \left(\frac{W}{d_b}\right)_t}{a_5 H_1 + a_6} \quad (3)$$

In a parallel routine the optimum bit speed (N) can be expressed as illustrated in Eq. 4 after (Bourgone et al. 1986).

$$[N]_{Opt} = 60\left[\frac{\tau_H}{t_b}\frac{\left(\frac{W}{d_b}\right)_{max}-\left(\frac{W_{vert}}{d_b}\right)_{Opt}}{\left(\frac{W}{d_b}\right)_{max}-4}\right] \quad (4)$$

1.5 Mechanical Specific Energy

The concept of mechanical specific energy (MSE) has been used effectively in lab environments to evaluate the drilling efficiency of bits. MSE analysis has also been used in a limited manner to investigate specific inefficiencies in fields operations (Dupriest et. al. 2005). In early 2004, an operator initiated a pilot to determine whether the concept might be used more broadly by rig-site personnel as a real-time tool to maximize the rate of penetration (ROP). The results have exceeded expectations. The average ROP on the six rigs selected for the three-month pilot was increased by 133% and new field records were established on 10 of 11 wells.

The MSE surveillance process provides the ability to detect changes in the efficiency of the drilling systems, more or less continuously.

Real time MSE surveillance is used to find the flounder or founder point for the current system and in some cases the cause of founder. MSE is a ratio. It quantifies the relationship between input energy and (ROP). This ratio should be constant for a given rock, which is to say that a given volume of rock requires a given amount of energy to destroy. The relationship between energy and ROP derived by Teal is:

$$MSE = \frac{Input\ Energy}{Output\ ROP} (5)$$

$$MSE = \frac{480xTorxRPM}{Dia^2xROP} + \frac{4xWOB}{Dia^2x\pi} (6)$$

It is useful to relate MSE to the drill off curve (Fig. 5). In region II, the linear slope means that the ratio of input energy WOB to ROP is constant. Since MSE equals to this ratio, it must also be a constant value, but only if the bit is operating within the linear portion of the curve. When the bit is in region I or III, a disproportionate amount of energy is being used for the given ROP. This provides a useful diagnostic. If MSE is constant the bit is efficient and operating in region II. If MSE rises, the system is foundering. By plotting MSE continuously at the rig site, the driller can see whether it moves in or out of founder as various parameters are tested.

The energy required to destroy a given volume of rock is determined by its compressive strength. Teal derived the specific energy equation by calculating the torsional and axial work performed by the bit and dividing this by the volume of rock drilled (Dupriest 2005). Although there is clearly a connection between rock strength and energy required for destroying it, Teal was surprised when lab drilling data showed the MSE value to be numerically equal to rock compressive strength in psi. This is useful from an operations standpoint because it provides a reference point for efficiency. If the observed MSE is closed to the known confined rock strength, the bit is efficient. If not, energy is being lost. The value should change as the lithology changes. However, field experience has shown that the energy losses that occur when the bit founder are usually so large that they cannot be confused with the small changes that occur with rock compressive strength.

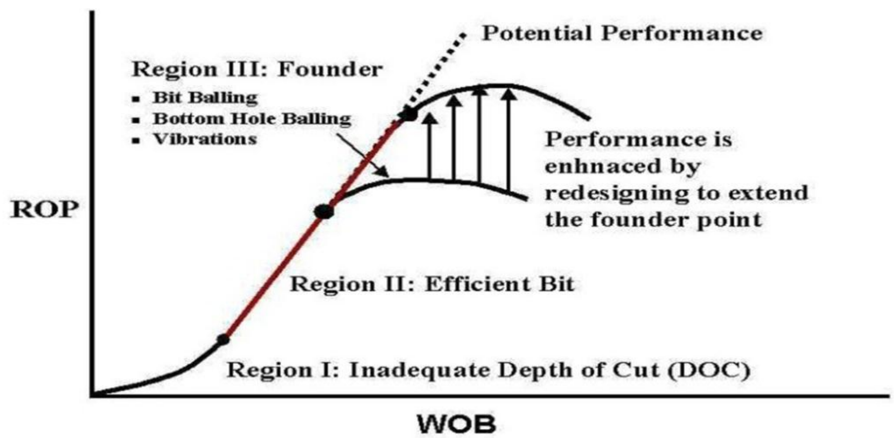


Figure 4: Relationship between ROP and WOB (Dupriest 2005)

1.6 Drilling Specific Energy

The concept of mechanical specific energy (MSE) – the original equation developed by Tealhas been modified by Miguel Armenta (Miguel 2008) to include a bit hydraulic-related term on the (MSE) correlation. DSE can be calculated as shown in Eq. 7.

$$DSE = \frac{WOB}{A_B} + \frac{120\pi * RPM * T}{A_B * ROP} - \frac{1{,}980{,}000 * \lambda * HP_B}{A_B * ROP} \qquad (7)$$

The first two terms on the right hand side of Eq. 7 are similar to those on Teal's original equation. However, the third term represents the bit hydraulic related term. The number 1,898,000 is a unit conversion factor. The parameter Lambda (λ) is a dimensionless bit hydraulic factor depending on the bit diameter (Fig. 8). The ratio of bit hydraulic power HP_B and bit area (HP_B/A_B) is the bit Hydraulic power per square inch HSI (hp/in^2). The

(DSE) concept was evaluated by applying Eq. 7 and the relationship of DSE and ROP was investigated for different drilling parameters (WOB, and HSI). DSE vs. ROP for different WOB values for all the experiments shows grouping of curves according to the WOB (Fig. 6). A good agreement between the experimental data and the DSE model was observed. All the curves have similar pattern showing three main regions: (1) High DSE and low ROP indicating inefficient drilling; (2) low DSE and high ROP which indicate efficient drilling; (3) A transition zone from region 1 to region 2 in between these two regions. (Miguel 2008).

Field data was used to calculate DSE using Eq. 7 to identify inefficient drilling condition. The DSE and ROP both were plotted first against depth to identify any particular pattern. After that, the drilling parameters WOB, RPM, Torque and HIS were also plotted vs. depth in order to explain the observed pattern (Fig. 6).

In order to show the effect of the hydraulic term or the HSI, again DSE was plotted vs. ROP but this time the data is grouped according to the HSI. The WOB curves are kept on the plot to make a connection with Fig. 5. It was shown in Fig. 7 that all the data with HSI between 0.5 hp/in^2 and 1.7 hp/in^2 are located on the inefficient drilling region (Region 1: high DSE and low ROP) for their particular WOB. On the other hand all the data with HSI between 5.8 hp/in^2 and 7.9 hp/in^2 are on the efficient drilling region (Region 2: low DSE and high ROP). It is revealed from Fig. 7 that the bit hydraulic is the driver to move from inefficient drilling when the WOB is constant. When increasing HSI not only are the cutting removed faster underneath the bit, but also the bit cutting structure is kept clean to break new rock more effectively.

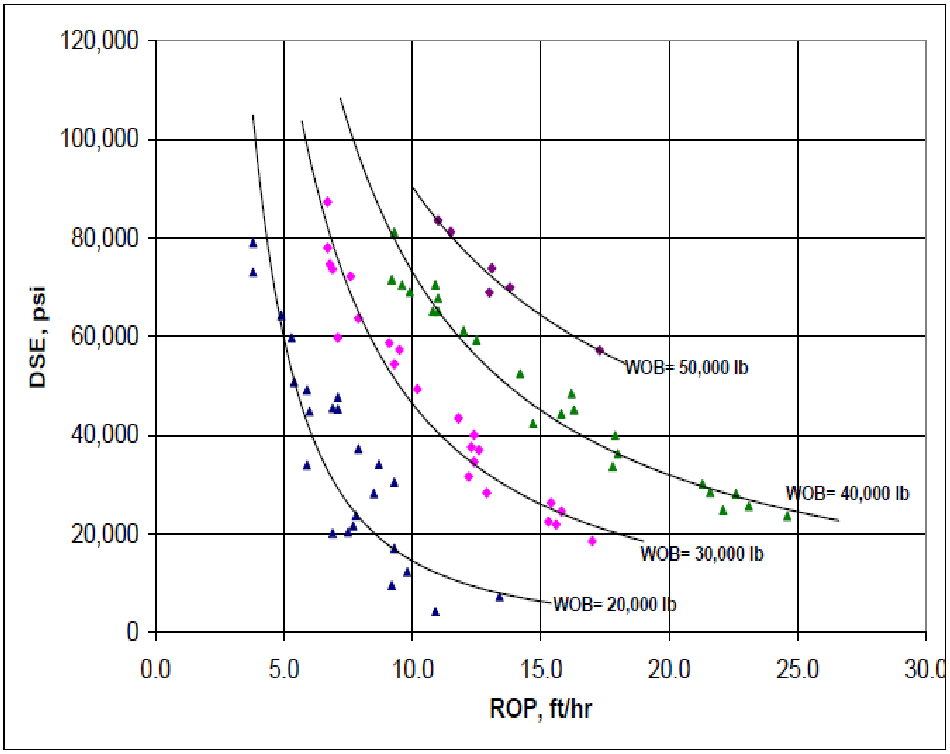


Figure 5: DSE vs. ROP with experimental data grouped according to the WOB(Miguel Armenta 2008)

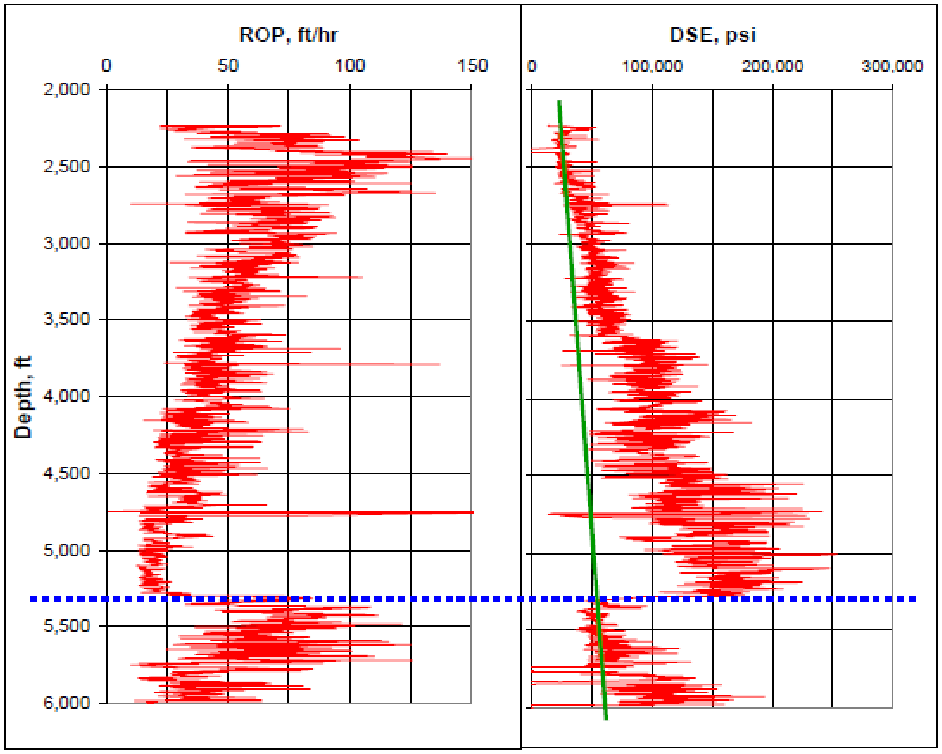


Figure 6 : ROP and DSE vs. depth for field data(Miguel Armenta 2008)

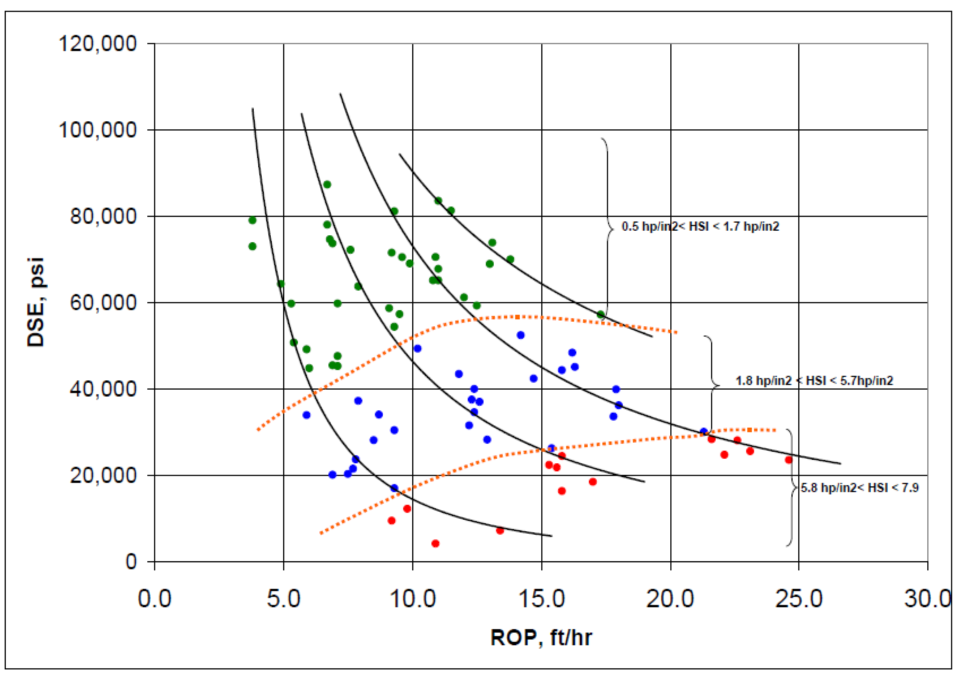


Figure 7: DSE vs. ROP with experimental data grouped according to the HIS (Miguel Armenta 2008)

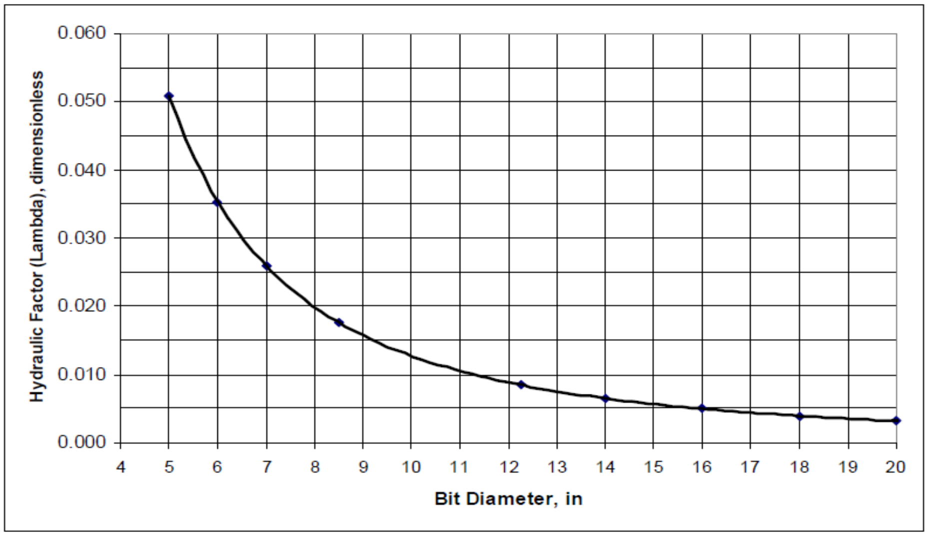


Figure 8: Hydraulic Factor (λ) (Miguel Armenta 2008)

1.7 Particle Swarm Optimization

In computer science, particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position and is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

PSO is originally attributed to Kennedy, Eberhart and Shi, (Kennedy, 1995) and (Shi, 1998), and was first intended for simulating social behavior, (Kennedy, 2001), as a stylized representation of the movement of organisms in a bird flock or fish school. The algorithm was simplified and it was observed to be performing optimization. The book by Kennedy and Eberhart, (Kennedy, 1997), describes many philosophical aspects of PSO and swarm intelligence. An extensive survey of PSO applications is made by Poli, (Poli, 2007) and (Poli, 2008).

PSO is a metaheuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics such as PSO do not guarantee an optimal solution is ever found. More specifically, PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time, etc.

1.7.1 Basic Particle Swarm Optimization Algorithm

In the basic particle swarm optimization algorithm, particle swarm consists of "*n*" particles, and the position of each particle stands for the potential solution in D-dimensional space. The particles change its condition according to the following three principles:

(1) to keep its inertia (2) to change the condition according to its most optimist position (3) to change the condition according to the swarm's most optimist position.

The position of each particle in the swarm is affected both by the most optimist position during its movement (individual experience) and the position of the most optimist particle in its surrounding (near experience). When the whole particle swarm is surrounding the particle, the most optimist position of the surrounding is equal to the one of the whole most optimist particle; this algorithm is called the whole PSO. If the narrow surrounding is used in the algorithm, this algorithm is called the partial PSO.

Each particle can be shown by its current speed and position, the most optimist position of each individual and the most optimist position of the surrounding. In the partial PSO, the speed and position of each particle change according the following equality (Shi, 1998):

$$v_{id}{}^{k+1} = v_{id}{}^{k} + c_1 r_1{}^{k}\left(pbest_{id}{}^{k} - x_{id}{}^{k}\right) + c_2 r_2{}^{k}\left(gbest_{d}{}^{k} - x_{id}{}^{k}\right)$$

$$x_{id}{}^{k+1} = x_{id}{}^{k} + v_{id}{}^{k+1}$$

In this equality, $v_{id}{}^{k}$ and $x_{id}{}^{k}$ stand for separately the speed of the particle "i" at its "k" times and the d-dimension quantity of its position; $pbest_{id}{}^{k}$represents the d-dimension quantity of the individual "i" at its most optimist position at its "k" times. $gbest_{id}{}^{k}$is the d-dimension quantity of the swarm at its most optimist position. In order to avoid particle being far away from the searching space, the speed of the particle created at its each direction is confined between $-v_{dmax}$, and v_{dmax}. If the number of v_{dmax} is too big, the solution is far from the best, if the number of v_{dmax} is too small, the solution will be the local optimism; c_1 and c_2 represent the speeding figure, regulating the length when flying to the most particle of the whole swarm and to the most optimist individual particle. If the figure is too small, the particle is probably far away from the target field, if the figure is too big, the particle will maybe fly to the target field suddenly or fly beyond the target field. The proper figures for c_1 and c_2 can control the speed of the particle's flying and the solution will not be the partial optimism. Usually, c_1 is equal to c_2 and they are equal to 2; r_1 and r_2 represent random fiction, and 0-1 is a random number.

CHAPTER 2

LITERATURE REVIEW

Many researches have been performed for drilling real-time data. Most of these researches focused on application of the real-time data in the optimization of the drilling parameters. Several softwares were built in order to be able to handle the tremendous amount of data so it can be easily visualized and analyzed.

Onoe et al. (1991) described the concept, design and capabilities of an advanced real-time information system for drilling. The objectives of this system are to provide significant increases in drilling efficiency and engineering accuracy while at the same time to enhance operational safety and optimize the data management associated with drilling operations. Three important attributes distinguish this system from other "real-time" systems either existing or under development. First, the system provides "real-time" engineering models for decision support augmented by a "real time" expert system. Second, the system can be interfaced with any data acquisition hardware. Third, it addresses a wider range of data analysis and engineering functionality. Additionally, scenarios for its utilization in the field to optimize drilling operations are provided. It was also recognized that this system would need to grow and adapt to accommodate new technology and changing requirements during the 1990's and beyond.

Wolfgang and Gerhard (2007) addressed the problem related to the real-time data and developed essential steps criteria to measure and evaluate data quality. Quality control and improvement, data quality benchmarking, and accessibility of controlled data are management strategy proposed in their paper and therefore significant time saving was achieved compared to a manual quality control. A visual concept has been introduced, which allows the surfing of time and depth based data with unique navigation concept.

Gerhard (2004) investigated the use of process related data measured in real time for performance analysis while and after drilling. This process showed that it is possible to automatically derive activities and events from real-time data, just as it is possible to accomplish an understanding of various events, which results in non-optimal performance or trouble time through visual inspection of data plots. Quality problems with existing real-time data, revealed during post analysis were discussed as well as their origin in the historically developed pattern of geology-driven, depth-based view of all the drilling process. High resolution operation analysis can be performed with existing data which showed a very high potential for automated process optimization and early problem recognition.

Zoellner et al. (2011) studied several cases to monitor drilling hydraulics by analyzing fluid flow in relation to pump pressure and other relevant sensor channels. He tried to early recognize the on-set of the hydraulics related problems to take preventive action. The concept is based on recognition variations in expected behavior of rig sensor responses using hybrid algorithms, which link analytic, static and knowledge bases concepts. The outlined concept to display previous start-up sequences and corresponding parameters to provide a reference for the driller should result in a minimization of start-up time and pressure surge of the current sequence in the sense of an on-going optimization process within one BHA run and therefore lost and hidden lost time can be avoided.

William and Jeff (2005) showed how Mechanical Specific Energy (MSE) was implemented in a drilling information system in real time on the rig and at remote monitoring locations. The study showed that the use of MSE in real time is a useful tool for both drillers and drilling engineers. Conducting MSE tests in real time is an effective way to develop an understanding of MSE behavior and contributes to acceptance by rig personnel. The general practice of adjusting drilling parameters to minimize the value of MSE is a good rule of thumb.

Miguel Armenta (2008) presented a novel correlation to identify inefficient drilling conditions using experimental and field data. Results showed that Drilling Specific Energy (DSE) can be used to identify inefficient drilling conditions. Experimental results illuminated the importance of including bit hydraulics into Specific Energy analysis for drilling optimization. The new hydraulic term included on the specific energy correlation is the key to correctly matching the amount of energy used to drill and the rock compressive strength. Also, this term illuminates how much hydraulic energy is needed to drill faster and efficiently when the mechanical energy (axial and torsional) is increased.

Mohan et al. (2009) presented a new correlation to identify inefficient drilling conditions using MSE. Hydro Mechanical Specific Energy (HMSE) was introduced encompasses hydraulic as well as mechanical energy. The HMSE equation will be of value during both planning and operational phases of selecting drilling parameters and also optimize them.

Hermann et al. (2011) presented a technology which explains how automatic operations detection was carried out to address the proposed challenges and the necessary reporting and user interaction needed. The theory and one case history on this was presented and covered the startup phase of such initiative, and all of its push backs, and lead the readers through the implementation and final results that were successfully archived. Performance target selection should aim at consistent operation around a best practice rather than operational time only. Based on the definition of a target value it is possible to calculate the difference in performance for crews, rigs, or complete rig fleets as a savings potential. This process can be highly automated and translated to instant performance reports e.g. to be used on the rig as well as trend monitoring on a management level, for example by means of a management score board. Continues monitoring of performance trends will lead to continuous improvement with higher operational consistency and safety

Steve and Jamal (2010) presented to inform operators and other drilling organizations in the cost-effectiveness and importance of real time data management techniques and information transfer complimenting technology in drilling operation at certain scenarios. This technique can save the oil and gas industry operator money in the current drilling operations and even in future operations. Also fill some of the knowledge gap in the industry and also save money in the environmental and safety sector of this industry which can be very expensive when incidents occur. Following the Real Time data management and information transfer technique will allow for safe and efficiency drilling with maximum ROI and reduced risks.

Catheryn and Paul (2010) illustrated techniques for improving collaboration and analysis of real-time and historical drilling data, increasing the cost of effectiveness of drilling efforts, and presents a case study highlighting the achievable benefits. A drilling knowledge base makes it possible to unlock the value of all the drilling data a company has paid to collect but rarely uses due to its disparate nature. Earth model software makes it possible to perform multi-well analysis and implement the collaborative workflows to facilitate the type of drilling analysis and planning that the industry has known for years can reduce NPT, increase drilling efficiency, and ultimately reduce costs. These workflows can be used for completely green exploration wells, where you have no data and can create a drilling knowledge base during drilling; for fields where some offset data is available; and for established fields where many wells have already been drilled. Each well added to the knowledge base effectively decreases drilling uncertainty.

Thomas and Serkan (2011) presented a description and features of the Micro-Flux Control (MFC) system, benefits of standard application, and case studies with real field data. MFC technology is virtually applicable on any conventional well without compromising existing rig components in order to authorize and optimize data analysis during drilling operations. The overview of the different regions has shown that appropriate real time micro-flux analysis of naturally occurring or intentionally induced events combined with Dynamic Mud Weight Management (DMWM) has provided a significant advantage in Non-Productive Time (NPT) reduction and an obvious advantage in overall safety.

Tuna and Evren (2010) developed a model to optimize drilling parameters during drilling operations such as weight on bit, bit rotation speed in order to obtain maximum drilling rate and hence minimize the cost per foot and the overall drilling cost. The model developed used actual field data collected through modern well monitoring and data recording systems, which will be used in predicting the rate of drilling penetration as a function of available parameters. The study demonstrated that drilling rate of penetration could be predicted at relatively accurate levels, based on past drilling trend. The optimum weight on bit and bit rotation speed could be determined in order to achieve minimum cost drilling. It is believed that by means of effective communication infrastructures and thorough team efforts having efficient real-time drilling optimizations based on statistical syntheses are not too distant.

Alum and Egbon (2011) developed semi-analytical model for Rate of Penetration (ROP) based on the original Bourgoyne and Young Model using real time bit records obtained from wells drilled in Niger Delta reservoirs. Simple regression analysis was applied on the equation on the parameter that contains differential pressure to obtain regression constants which were then used to generate mathematical relationship between ROP and drilling fluid properties.

Yashodhan et al. (2011) developed Artificial Neural Network (ANN) based software system to replace the human factor of applying operating parameters such as Weight on Bit (WOB) and RPM. By following the real-time ANN recommendations, changes can be implemented to increase overall penetration rate (ROP) while maximizing bit life by managing the dull condition. As a result of applying the model developed here the operator completed the 8-1/2'' hole section almost three days ahead of plan even with the unplanned trip to retrieve the lost cone. The reduction in drilling days saved the operator approximately $150,000.

Eric et al. (2011) discussed the job of the optimization center at Shell Upstream Americas. The team of that center is highly effective improvement team capable to help drive performance optimization and the delivery of top quartile performance on its wells in North America and beyond. Using the optimization approaches taken, it has been possible to help accelerate well delivery times and associated learning curves by as much as factor of three, often in a minimum amount of time. A main conclusion is therefore that this approach is a highly effective way to bring performance optimization focus to field operations. The workflow and organizational structure was applied to well delivery optimization with projects ranging from shale gas drilling in the Continental US and Canada as well as hard rock drilling in the Middle East.

Koederitz and Johnson (2011) described the development and field testing of an autonomous drilling system. This system software uses a test process to evaluate and quantify the drilling performance for a given set of target setpoints. The research method is used to identify these setpoints; its development was based on early work in the application of real-time Mechanical Specific Energy (MSE) display. Overall, the field testing results were favorable, displaying that the potential for autonomous drilling optimization without drilling knowledge is practical, flexible, and economical, exhibiting promise in a range of cost-effective applications.

Bataee and Mohseni (2011) predicted the proper penetration rate, optimizing the drilling parameters, estimating the drilling time of a well and therefore reducing the drilling cost for future wells using Artificial Neural Networks (ANNs). Based on their model they got some valuable observations. Increasing Weight on Bit (WOB) or rotary speed does not always increases Rate of Penetration (ROP). This study shows in some parts which the driller exerts high WOB and rotary speed (N), the ROP value decreases due to cleaning problem and bit floundering. This is the ability of ANN analysis whether no equation can find the actual amounts of parameters which maximize penetration rate. As results show always less mud weight used leads in higher ROP value which is a correct concept. Great range for N and WOB is used and observed that best one was neither the maximum nor the minimum value. An appropriate ROP was selected based on the previous ROP to be achieved by using the modeled function and applying the corresponding drilling bit parameters.

Voss (2010) described the drilling of a sidetrack from a well that was originally drilled on 2005 and makes comparisons between two projects proposed with respect to equipment used and planning techniques implemented. The original 2005 wellbore was drilled directionally through approximately 5000 ft of salt. This caused several drilling related issues, including severe vibration and downhole tool failures. With the objective of improving drilling performance on the sidetrack well while avoiding disastrous failure, the operator and Service Company jointly used a structure engineering optimization process. As a result of the total system optimization program the target well compared to the offset well, ROP was doubled from 15.5 to 30.6 ft/hr, saved the operator $2.1 Million in this hole section, resulted in 76% reduction in drilling removable time (DRT), exhibited minimum vibration throughout the entire run. Total System Approach and proper pre-well planning were shown to be the key to success, including: Service company teams and operator communicating all risks and contingencies, efficient planning and field execution, improved bit selection proper bit and reamer synchronization, well-trained service company rig and office engineering services.

Rashidi et al. (2010) conducted study to demonstrate the effects of changing the drilling parameters bit wear and bit designs on ROP for both approaches. Optimum bit types and designs with corresponding drilling parameters can be globally recommended for entire bit runs using ROP model. The Mechanical Specific Energy (MSE) model can be used to adjust the operating parameters to reach a maximum ROP value "locally", or in real-time with no effect of bit design or bit wear integrated. The flexibility of using an ROP model as opposed to the MSE equation transformed into an ROP equation is also investigated. MSE model is easier to use in terms of finding the inefficiencies and reaching the instantaneous optimization level. The MSE model has its limitation in planning and post analysis of the drilling phases. MSE is useful as a tool to detect possible drilling problems while drilling without addressing the exact causes. The ROP model is more comprehensive compared to the MSE model. It includes bit wear, bit hydraulics and bit design, which gives the user the capability to optimize bit runs and hole sections for lowest $/ft. The ROP models can be used in all phases of the drilling cycle including pre-planning, real-time drilling and post analysis. The big advantage of ROP models over the MSE model is that it can recommend drilling parameters that maximize the ROP over the entire bit run and not just instantaneously, meaning that ROP models can be used as a global optimization tool while MSE models are only local.

Tagir et al. (2010) proposed an expert system which offers an efficient way of combining some basic measurements provided by the surface sensors for early diagnosis and prevention of possible damage of downhole drilling equipment, primarily the drill bit itself. The fundamental theory behind the proposed approach is based on certain elements of fractal analysis as well as artificial neural networks. Some real filed data examples used for training the model and assessing the current drill bit conditions by using the proposed methodology. For extending this experience to a real field application, one should apply the results of the studies obtained in the experimental borehole (i.e. a determined optimal combination of the diagnostic criteria and the sampling frequency) to subsequent boreholes drilled in the same general area, so that the input-output data will be somewhat clustered to reduce uncertainties in problematic scenarios. Authors believe that this methodology opens new opportunities for real-time drilling optimization that can be efficiently implemented within the scope of the existing drilling practice. It should be noted that neural networks-based expert systems usually perform satisfactory interpolation, while it may generate erroneous results in case of extrapolation. Because of this, the more representative and diverse database from the previous experience that is available, the higher the probability of accurate diagnosis that can be potentially achieved.

Nitin et al. (2010) included six case histories where the use of downhole drilling data increases drilling efficiency. These cases described four different applications where a downhole optimization sub's (DHOS) real-time data was used to improve drilling operations. The case studies are proof that having optimization sensors that provide information like bending moments, DWOB, etc. are essential to answer such questions and are key tools in the benchmarking process. Armed with these tools, even the most difficult of wells will have an engineered solution.

Rashidi et al. (2008) presented a new method to combine Mechanical Specific Energy (MSE) and Rate of penetration (ROP) models to calculate real time bit wear which takes into consideration the fundamental differences between MSE and ROP models and that the latter only takes into account the effect of bit wear. Encouraging results have been obtained which shows a linear relationship between MSE (Rock Energy) and rock drillability (Drilling Strength) equations with the use of K_1 as a constant of proportionality. Change in mud weight and bit wear are the two most dominant factors which cause an irregularity in normal decreasing trend of the inverse of coefficient K_1 versus depth. The developed model is correlative using different sliding coefficient of friction to account for variations in bit parameters like bit diameter, number of cutters, cutter diameter, back rake and side rake, etc. which are not accounted for in the ROP equation presented and the MSE calculation. This approach has been verified with a small dataset, and by analyzing more bit runs the authors believe this can become a valuable tool in real time analysis of bit wear.

Sawaryn et al. (2010) discussed how data quality influences workflows and decision-making in drilling and completions and examines the use of semi-automated processes for quality assurance. With poor data, additional steps are required and workflows must be repeated. In even relatively simple situations, controlled tests suggest that small changes or omissions may have a significant influence on the work efficiency or outcome. In earlier work, the quality of any data stream has been described in terms of identity, presence, measurement frequency, accuracy, continuity, units and associated metadata. For some of these a degree of self-checking is possible, applying simple algorithms to the data stream to detect presence and bounds, with alarms to alert the operator if these are transgressed. In other cases, such as the change in drag and torque with depth, the stream must be checked against a trend, called a pseudo-log determined from the physics. These calculations are performed by "smart agents" directly in real time on the WITSML data feed from the rig. The paper describes the early work developing smart agents to address data quality and structure of the associated toolkit that can be used to construct more complex agents from a wider selection of data sources, including system generated ones. The computational resources required are also discussed. The increase in digital data and skills shortage makes manual assurance of all the data streams neither practical nor cost effective. Since current applications are not tolerant of errors and omissions, a step change in data quality is needed if more automated workflows are to be achieved. Greater assurance of the data at source and an improved understanding of the workflows will help.

Mostofi et al. (2010) developed rock strength log of Asmary formation from backward simulation of drilling operation. This log is critical for analysis such as drilling optimization, sand production evaluation and wellbore stability. According to the bit constants estimated from the field and other bit constants that have been previously calculated from laboratory tests, the drilling operation is simulated and the drilling optimization to minimize the cost per foot value is carried out. Based on cost equation, the best bit runs are introduced which can reduce the drilling operation up to 38%. Drilling simulation can improve the drilling schedule estimation. On the other hand, drilling project can be analyzed more accurately from economical view before drilling operation starts.

Rashidi et al. (2010) described the real-time application of a developed model for bit wear analysis. The model was developed based on the difference between rock energy model, Mechanical Specific Energy (MSE), and rock drillability from rate of penetration model. It has been modified and implemented as an engineering module in the newly developed software, Intelligent Drilling Advisory system (IDA's), and used to estimate real-time bit wear for both roller cone and PDC bits. The drilling data is retrieved by the software from a remote server for the analysis. The data is subsequently quality controlled before calculating instantaneous bit wear while the bit is in the hole. In this research, bit runs for two offset wells in Alberta, Canada, will be analyzed in detail using the software module. Similarities between the recorded bit wear outs reported in the field and the simulation results indicate that the procedure can be used for bit wear estimation with good accuracy. Depth for normalization of constant K 1 and multiplication factor are set manually for each bit run section to get a smother bit wear trend. The automatic calibration and setting of these factors will be integrated into the future development of the software. Calculated final bit wear out values show good matches compared to the field data. This engineering software module could be used to identify unnecessary tripping which will result in time and cost reduction as well as an additional tool to aid in estimation bit wear status while drilling.

Eric and William (2010) addressed the measuring techniques that involved data quality control (QC) and automatic drilling operations detections of routine drilling operations that are available today in modern drilling programs, and goes through examples of how implementation was carried out in the onshore area that drilled a series of similar wells. Measurement accuracy, training, and the development of new work processes were successfully implemented that led to major Key Performance Indicator (KPI) time savings between 31% and 43%. You cannot improve what you don't measure. And in this case you cannot measure without a proper data quality control procedure in place. The automatic operations detection technology, preceded by a rigorous data QC process was a means to help prepare meaningful reports to flag opportunities to improve safety and performance.

Mark et al. (2011) focused on the technical challenges faced when drilling the Haynesville shale play in North Louisiana. One of the most daunting is penetrating the hard, abrasive Hosston sandstone-shale sequence and hard Knowles limestone in the intermediate section of the overburden. The operator applied a systematic drilling efficiency optimization (DEO) approach encompassing well planning, well execution and post-well analysis to drive performance improvement through these formations. Optimization efforts focused on polycrystalline diamond compact (PDC) bit design, bit hydraulic, positive displacement motor (ODM) selection, soft torque rotary system (STRS) utilization, bottom hole assembly (BHA) design and active management of drilling parameters. Combined, these efforts reduced cost per foot and days per thousand feet by over 50% while drilling approximately 70 well over a two year period. Significant technical lessons were as follows: (1) PDC cutter selection, cutter placement, blade layout and nozzle placement and orientation can be refined to yield longer, faster bit runs in the Hosston and Knowles formations. (2) Higher hydraulic horsepower contributed to improved bit performance in both hard and soft formations. (3) Low speed, high torque downhole motors helped protect PDC bits from damage caused by torsional stick-slip. (4) STRS allowed wider ranges of WOB and RPM to be used without stick-slip and improved bit performance on both rotary and motor assemblies. (5) The number and placement of stabilizers in BHAs could be adjusted to make them less prone to buckling and lateral vibration over desired range of WOB and RPM. (6) Active monitoring of drilling parameters, Stick-Slip Alarm (SSA) and MSE by rig site and remote personnel improved recognition and mitigation of drilling dysfunctions and improved average ROP and run length.

CHAPTER 3

STATEMENT OF THE PROBLEM, OBJECTIVES AND METHODOLOGY

2.1 Statement of the Problem

The oil and gas industry spends millions of dollars each year collecting vast amounts of drilling data, yet has not made effective use of this data to improve drilling performance. Drilling analysis is necessary for improving the return on investment of drilling operations, but comprehensive drilling analysis has not been a regular part of well planning and operations. So why it is that comprehensive drilling analysis is not a consistent part of drilling best practices? Millheim et al. (1998) suggest that 95% of drilling activities are operationally focused; placing emphasis on doing, rather than planning or analyzing and many people in drilling operations thrive on operating by “gut instincts” and succeeding through heroic efforts.

Mechanical specific energy in real time was first used in the US in 2005.Drilling specific energy was introduced by Miguel in 2008 by introducing the hydraulic term into the MSE correlation.

Drilling analysis implementations often tend to be focused on just one form of the real time wide knowledge base, and are not oriented towards automatically maintaining this data through real time updates. Furthermore, many organizations have not yet adopted technologies with these real time capabilities (Veeningan et al., 2008)

Most of the early studies performed in the literature have forecasted static drilling optimization processes. The drilling parameters were required to be investigated off-site due to lack of the opportunity for transferring data in real time. Tuna and Evren, 2010 observed that no work have been done for drilling optimization utilizing statistical correlations in real time environment. However real time data is not used efficiently in drilling optimization and no comprehensive quality control check is performed in real time. In addition, one of the challenges that faces the fast pace development of oil and gas fields is the need to make critical decision with incomplete data, or to have extensive geological data but not properly analyzed or checked for quality.

The data that are readily available through MWD contains valuable information that could be utilized by proper analysis in real time to support decision making. The methodology developed in this research can bridge that gap.

3.2 Objectives

Optimization of drilling penetration rate will have direct effects on the total cost reduction together with elimination of problems and increase in bit life. It has been reported that drilling optimization should be based on the accumulated and statistically processed empirical data rather than working with implicit relations.

The main objective of this research work is to develop a technique to optimize the drilling parameters in real time to achieve the maximum rate of penetration based on the drilling specific energy (DSE). The ultimate objective will be achieved by developing a six step approach (six tasks)

1. Data verification (QC/QA) to check the real-time drilling data.
2. Pre modeling analysis
3. Model development: develop a correlation between *ROP* and *WOB*,*RPM*, and Q_m for historical and real time data.
4. Model validation
5. Optimization
6. Real time application

3.3 Methodology

The following steps summarize the scope of the work in order to achieve the objectives of this study.

1. Collect data and select a clean and uniform lithology for each individual well.
2. Check the quality of the collected data using (Wolfgang and Gerhard 2007)criteria.

2.1 Data Standardization

2.2 Unit conversion

2.3 Null values

2.4 Depth reference

2.5 Data Quality Control

2.5.1 Range Check

2.5.2 Gap Filling

2.5.2.1 Bigger than the defined gap depth

2.5.2.2 Smaller than the defined gap depth

2.6 Outlier Removal

2.6.1 Mean filter

2.6.2 Median filter

2.7 Logical Checks

2.7.1 Hole depth check

2.7.2 Physical trend

2.8 Data Access and Visualization

3. Analyze the collected data
4. Use the collected data after quality check to develop a mathematical model between rate of penetration (ROP) and the affected parameters; weight on bit (WOB), rotary speed (RPM), torque (T), and mud flow rate (Q_m).
5. Develop a mathematical model between weight on bit (WOB) and torque (T) based on Pessier and Fear equation.
6. Develop a mathematical expression between the dimensionless bit hydraulic factor lambda (λ) and the bit diameter and then simplify the drilling specific energy equation (DSE) accordingly.
7. Use artificial intelligence (AI) techniques to predict the rate of penetration based on (WOB, RPM, T, and Q_m) to validate the developed model. The following methods have been used:

7.1.Artificial Neural Network (ANN)

7.2. Fuzzy Logic (FL)

7.3. Support Vector Machines (SVM)

7.4. Functional Networks (FN)

7.5. Genetic Algorithm (GA) as an optimization tool

8. Optimization of the drilling parameters (WOB, RPM, and Q_m) to maximize the rate of penetration by minimizing the drilling specific energy using particle swarm optimization (PSO).

CHAPTER 4

DATA ACQUISITION

The drilling data used in this study was collected from Middle East region. Data from three vertical wells located in different sites in the Middle East oil fields were received. The data is of two classes: (1) lithology of different drilled sections with some information of the average drilling parameters such as like; WOB, RPM, information of drilling bits such as bits' diameters, number and sizes of nozzles, bits' setting depths and the drilling fluid rheology; and properties such as: mud density, viscosity and mud flow rates;(2) digital data of the measured drilling parameters as a function of depth. These parameters include: WOB, Torque, RPM, Mud flow rate, and mud equivalent circulation density. Other data such as temperature, standpipe pressure hook load and gas chromatography analysis were recorded. Clean and uniform lithology sections were selected for each individual well. It was found that the best section with good thickness for all the three wells was the limestone sections. Limestone was found in Well 1 in two zones, Section 1 (4480ft – 7213ft) of 2733 ft thickness while Section 2 (10022ft – 14380ft) of 4358 thickness. Limestone was found in Well 2 in one section (8043ft – 8530ft) with thickness of 487 ft and it was found in Well 3 in one section also (7804ft – 9746ft) with thickness of 1942 ft.

Table 1 presents general information for Section 1 of Well 1 like bit number, manufacturer, type and diameter. Information also includes the number of nozzles in the bit and their sizes, the depth that the bit was set in and out and finally the drilling equivalent circulation density (ECD).Table 2 summarizes some statistics of the measured drilling parameters such as weight on bit (WOB), revolution per minute (RPM), torque

(T), drilling mud flow rate and the rate of penetration (ROP).Tables 3 and 4 summarize the information for Section 2 of well 1.

Table 1: General information for Section 1 of Well 1(4480ft – 7213ft)

Bit No.	18
Manufacturer	Smith
Type	MS616
Diameter	12.25
Nozzles	6x16
Depth Set in	4475
Depth out	7318
Mud ECD	10.5

Table 2: Drilling parameters statistics for Section 1 of Well 1

	WOB (klbf)	RPM (rpm)	T (kft.lbf)	Mud Flow (galUS/min)	ROP (ft/h)
Minimum	1.026	62	6.360	379.86	28.34
Maximum	39.753	142	20.883	779.16	84.76
Range	38.727	81	14.522	399.30	56.42
Average	19.028	114	15.769	756.42	54.90
SD	7.113	13	2.589	34.51	8.97

Table 3: General information for Section 2 of Well 1(10022ft – 14380ft)

Bit No.	22
Manufacturer	Smith
Type	MS616
Diameter	8.5
Nozzles	6x14
Depth Set in	10011
Depth out	xxxx
Mud ECD	10.5

Table 4: Drilling parameters statistics for Section 2 of Well 1

	WOB (klbf)	RPM (rpm)	T (kft.lbf)	Mud Flow (galUS/min)	ROP (ft/h)
Minimum	1.630	103	4.965	263.94	15.48
Maximum	24.911	162	10.026	693.27	57.92
Range	23.281	59	5.061	429.32	42.44
Average	13.841	147	7.816	530.09	39.29
SD	4.657	8	0.928	26.27	7.96

Sample of the lithology for Section 2 of Well 1 for the upper part is shown in Fig. 9. The complete lithology for Section 1 and Section 2 of Well 1 and the complete data of well 2 and well 3 are shown in Appendix A.

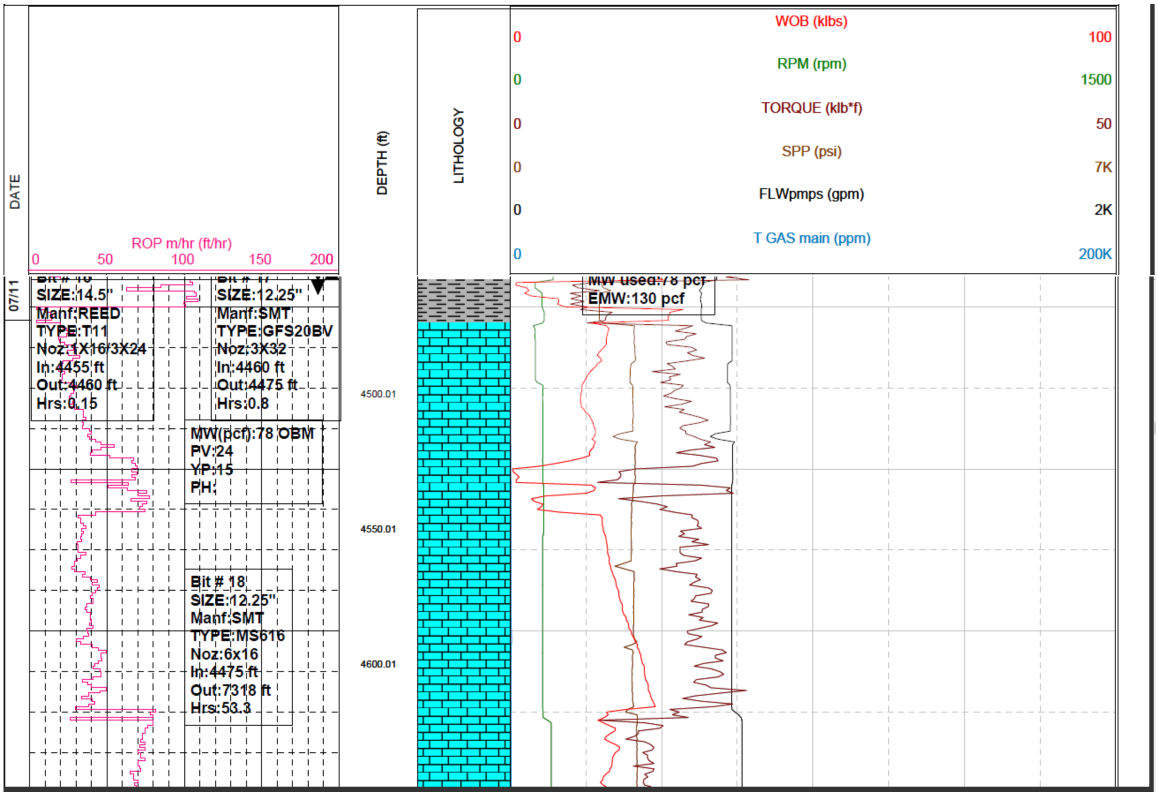


Figure 9: Lithology of Section 1 Well1 – upper part

CHAPTER 5
MODEL DEVELOPMENT

In this chapter the development of the models that have been used in this research is explained. The drilling specific energy (*DSE*) that was modified by Miguel Armenta (Miguel 2008) to include a bit hydraulic-related term on the (MSE) correlation will be simplified further to facilitate the calculations.

5.1 Drilling Specific Energy model

TheDrilling specific energy (*DSE*) equation is a modification of Teal's MSE equation, where the first two terms on the right side of the equation are the same terms included on Teal's original equation. The third term on the right side is the bit hydraulic-related term. The number 1,980,000 is a unit conversion factor. Lambda (λ) is a dimensionless bit-hydraulic factor depending on the bit diameters Fig. 8.

$$DSE = \frac{WOB}{A_B} + \frac{120\pi * RPM * T}{A_B * ROP} - \frac{1{,}980{,}000 * \lambda * HP_B}{A_B * ROP} \quad (7)$$

The digital data was extracted from that figure using digitizer software in order to obtain a model representing the hydraulic factor (λ) as a function of bit diameter.

Table5shows the digital form of the data of Fig. 8.

Table 5 : Digital data of bit diameter vs. hydraulic factor λ

Bit diameter, in	Hydraulic Factor, (λ)
4.99	0.0506
5.21	0.0465
5.48	0.0421
5.72	0.0388
6.01	0.0351
6.28	0.0323
6.59	0.0290
6.91	0.0265
7.29	0.0240
7.68	0.0216
8.04	0.0194
8.47	0.0177
9.01	0.0156
9.58	0.0139
10.14	0.0123
10.74	0.0111
11.32	0.0098
11.85	0.0089
12.26	0.0083
12.72	0.0078
13.23	0.0073
13.85	0.0067
14.53	0.0062
15.20	0.0055
16.00	0.0050
16.84	0.0044
17.54	0.0044
18.02	0.0039
18.60	0.0038
19.06	0.0038
19.47	0.0036
20.00	0.0030

The best model selected to correlate the hydraulic factor (λ) with the bit diameter was

$$\lambda = a\, {D_B}^{b}. \qquad (8)$$

The coefficients a and b were estimated according to the data in Table 5 using non-linear regression and the final model is

$$\lambda = 1.21439\, {D_B}^{-1.99018}. \qquad (9)$$

In order to make this form simpler and to get the bit diameter of power 2, the coefficient a, was re-estimated using non-liner regression again. Eq.(10) represents the final form of the model.

$$\lambda = 1.2651\, {D_B}^{-2} = \frac{1.2651}{{D_B}^{2}} \qquad (10)$$

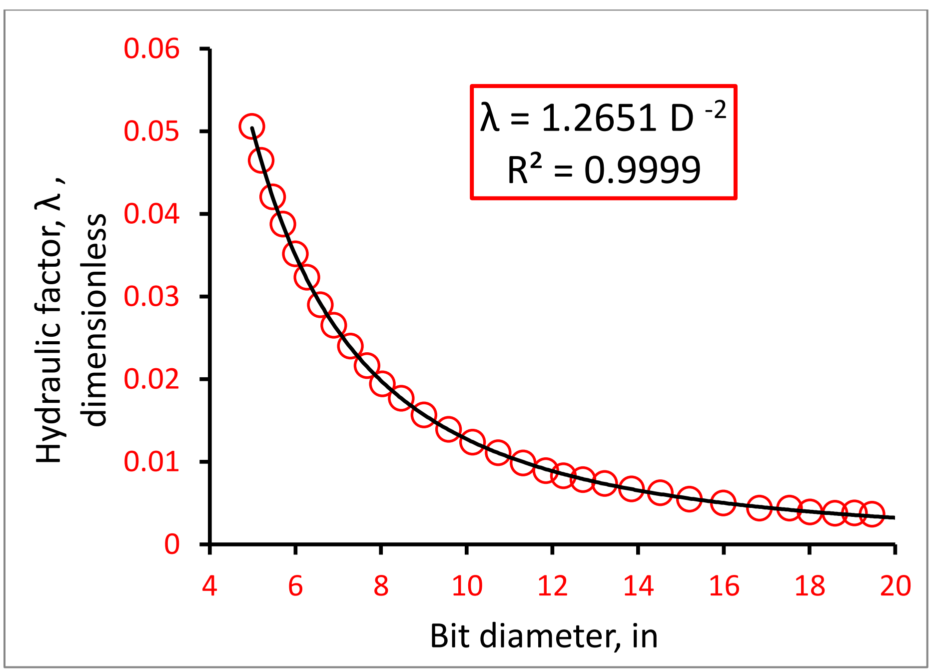


Figure 10 : Hydraulic factor vs. bit diameter (modeling)

The DSE equation now can be simplified according to the Lambda equation (Eq. 10) as follows;

$$DSE = \frac{WOB}{A_B} + \frac{120\pi * RPM * T}{A_B * ROP} - \frac{1{,}980{,}000 * \lambda * HP_B}{A_B * ROP}\ , \qquad (7)$$

since;

$$A_B = \frac{\pi}{4} D_B{}^2 \qquad (11)$$

and;

$$\lambda = \frac{1.2651}{D_B{}^2} \qquad (10)$$

By substituting the area of the bit formula and lambda formula into the DSE equation we can get the modified DSE equations.

$$DSE = \frac{4 * WOB}{\pi * D_B{}^2} + \frac{480 * RPM * T}{D_B{}^2 * ROP} - \frac{3{,}189{,}335 * HP_B}{D_B{}^4 * ROP} \qquad (12)$$

5.2 Rate of Penetration Model

This research aims to optimize the drilling parameters in order to maximize the rate of penetration (*ROP*). The objective function is used for optimization is the DSE. This equation includes the drilling parameters that will be optimized (*WOB*, *RPM*, HP_B). The optimization was achieved by minimizing the DSE. The DSE equation also includes the *ROP* that would be maximized which is a function of the drilling parameters (*WOB*, *RPM*, *T*, HP_B). Because of that, it is necessary to develop a model to correlate the ROP with the drilling parameters.

The *ROP* is a function of many drilling parameters some of which are controllable while others are uncontrollable. In this research only controllable parameters will be considered when developing the *ROP* model.

ROP is a function of WOB, RPM, Torque and Q_m.*ROP* model also can be represented as

$$ROP = f_1 + f_2 + f_3 + f_4, \tag{13}$$

where the functions f_1, f_2, f_3, f_4, for typical and complete set of data, are

$$f_1 = C_1(WOB)^{C2} + C_3 \tag{14}$$

$$f_2 = C_4(RPM)^{C5} + C_6 \tag{15}$$

$$f_3 = C_7(T)^{C8} + C_9 \tag{16}$$

$$f_4 = C_{10}(Q_m)^{C11} + C_{12} \tag{17}$$

$$ROP = C_1(WOB)^{C2} + C_3 + C_4(RPM)^{C5} + C_6 + C_7(T)^{C8} + C_9 + C_{10}(Q_m)^{C11} + C_{12}. \tag{18}$$

The coefficients C_3, C_6, C_9 and C_{12} can be lumped into one coefficient, C'_9.

$$ROP = C_1(WOB)^{C2} + C_3(RPM)^{C4} + C_5(T)^{C6} + C_7(Q_m)^{C8} + C'_9. \tag{19}$$

However, the data given in this research did not represent a typical data set and therefore the best model representation of the data was found to be of the form

$$ROP = C_1(WOB)^{C2}(RPM)^{C3}(T)^{C4}(Q_m)^{C5} \tag{20}$$

The coefficients (C_1, C_2, C_3, C_4, C_5) were estimated using non-linear regression.

Eq.(21) represents the *ROP* model for the data of Well 1with correlation coefficient of 0.956. Fig.11 shows the cross plot of the *ROP* measured vs. calculated.

$$ROP = 0.00095(WOB)^{0.12729}(RPM)^{1.2758}(T)^{1.3747}(Q_m)^{0.1746} \quad (21)$$

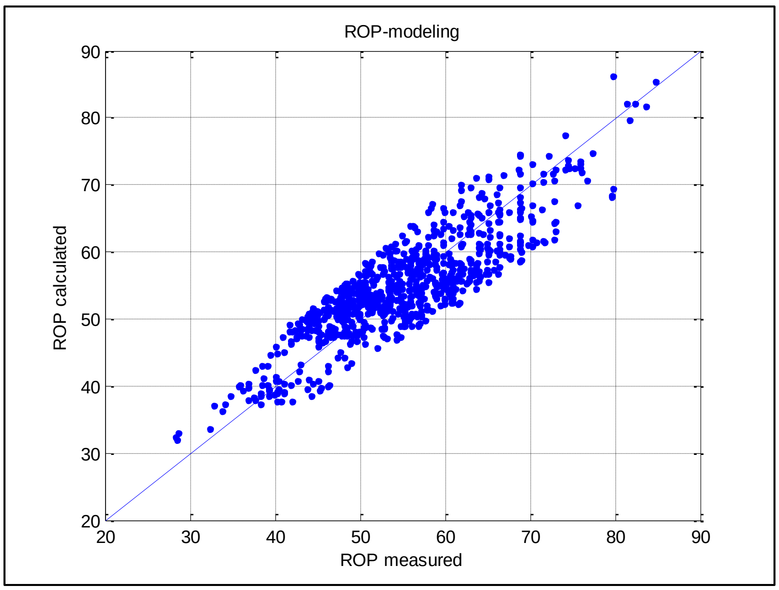


Figure 11: Measured ROP vs. calculated cross plot

5.3 Weight on Bit and Torque modeling

Since the torque is a function of WOB, it is better to have a model that represents this correlation. Pessier and Fear (Pessier and Fear 1992) introduced a bit specific coefficient of sliding friction to express torque as a function of WOB on the MSE equation as shown in Eq. (22).

$$\mu = 36\frac{T}{D_B \times WOB} \qquad (22)$$

Eq.(22) can be rearranged as

$$T = \frac{1}{36}\mu \times D_B \times WOB \qquad (23)$$

The coefficient of friction, (μ) was calculated according to each set of data of weight on bit (WOB), bit diameter (D_B) and Torque (T). This coefficient was plotted against WOB to find a correlation between them. The best model found was;

$$\mu = a_1(WOB)^{a_2} \qquad (24)$$

In order to estimate the coefficients a_1 and a_2 non-linear regression was used. The correlation obtained between coefficient of friction (μ) and WOB is

$$\mu = 20.016(WOB)^{-0.78} (25)$$

Figure12 shows the relation between coefficient of friction (μ) and WOB for the data of Well 1.Figure 12 shows that the coefficient of friction (μ) is a strong function of WOB. The model developed for the coefficient of friction shows good correlation as shown in Fig. 12. Figure 13represents the cross plot of the calculated and the actual values of coefficient of friction indicating the accuracy of the model with absolute error less than 3.5 % (Fig. 14).

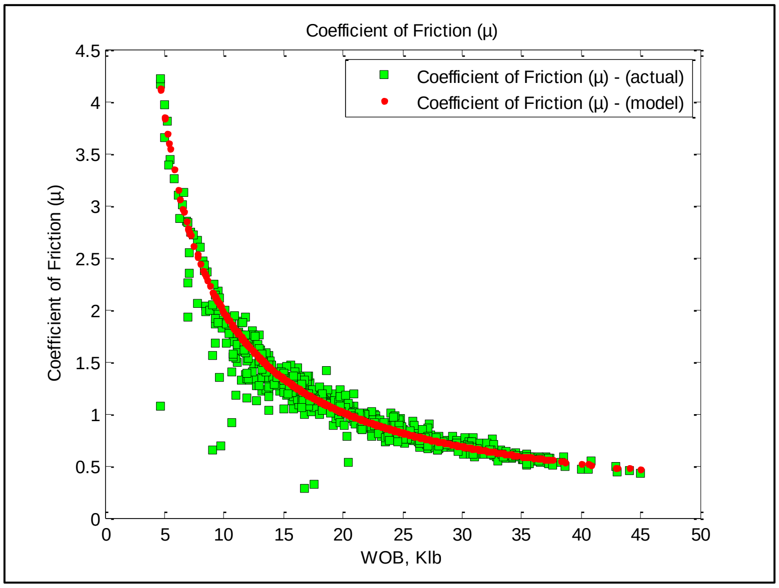


Figure 12 : coefficient of friction vs. WOB

The torque equation (Eq. 23) can be modified to include the coefficient of friction model (Eq. 25) as shown inEq. 26.

$$T = \frac{a_1 D_B (WOB)^{1+a_2}}{36} \qquad (26)$$

By substitutingEq. 25 into Eq.23 the formula of torque can be obtained.

$$T = \frac{20.016 D_B (WOB)^{0.22}}{36} \qquad (27)$$

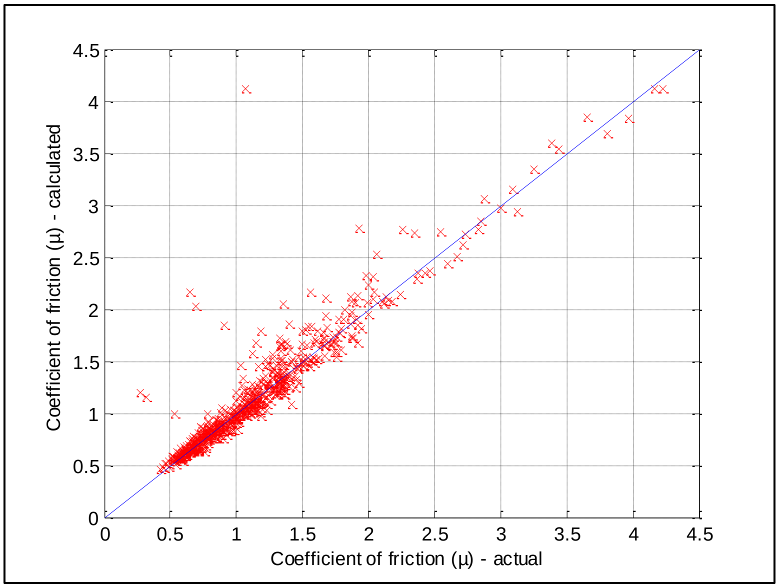


Figure 13 : Coefficient of friction cross plot

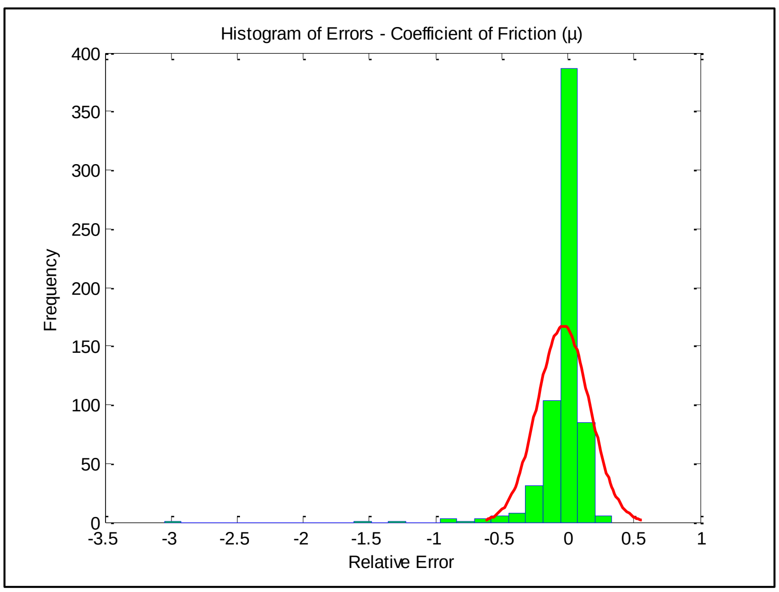


Figure 14: Histogram error for Coefficient of friction model

CHAPTER 6
ARTIFICIAL INTELLIGENCE APPLICATION

6.1 Introduction

For the last two decades, Artificial Intelligence has been used extensively in several applications in oil industry. A good number of research has been carried out on the use of various computational intelligence (CI) schemes to predict the rate of penetration using such schemes as logistic regression (LR), k-nearest neighbor (KNN), multilayer perceptron (MLP), radial basis function (RBF), bayesian belief networks (BBN), naïve bayes (NB), random forests (RF), functional networks (FunNets), support vector machines (SVM), artificial neural networks (ANN), probabilistic networks (PN), adaptive-neuro fuzzy systems (ANFIS) and decision trees (DT).

CI covers all branches of science and engineering that are concerned with understanding and solving problems for which effective computational algorithms do not exist. Thus it overlaps with some areas of artificial intelligence, and a good part of pattern recognition, image analysis and operations research. It is based on the assumption that thinking is nothing but symbol manipulation. Thus, it holds out the hope that computers will not merely simulate intelligence, but actually achieve it. CI relies on heuristic algorithms such asfuzzy systems, neural networks, support vector machines and evolutionary computation. In addition, CI also embraces techniques that use swarm intelligence, fractals and chaos theory, artificial immune systems, wavelets, etc.

Fuzzy sets (FS) have been around for nearly 40 years. These fuzzy sets, are in fact Type-1 FS and Type-2 FS (fuzzy fuzzy). Type-2 FS was introduced by Zadeh (1975) as an extension of the concept of Type-1 fuzzy. Type-2 FS have grades of membership that are themselves fuzzy. For each value of primary variable, the membership is a function (not just a point value) - the secondary MF-, whose domain - the primary membership - is in the interval {0,1}, and whose range - secondary grades - may also be in {0,1}. Hence, the MF of a Type-2 FS is three dimensional, and it is the new third dimension that provides new design degrees of freedom for handling uncertainties. Such sets are useful in circumstances where it is difficult to determine the exact MF for a FS, as in modeling a word by a FS.

6.2 Support Vector Machines

Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. They belong to a family of generalized linear classifiers. They can also be considered as a special case of Tikhonov regularization. SVMs map input vectors to a higher dimensional space where a maximal separating hyperplane is constructed. Two parallel hyperplanes are constructed on each side of the hyperplane that separates the data. An assumption is made that the larger the margin or distance between these parallel hyperplanes, the better the generalization error of the classifier will be.

SVMs have been used extensively in many engineering areas including defect prediction in software engineering, surface tension prediction in chemistry, geotechnical engineering and oil and gas with very promising results.

6.3 Functional Networks

Functional networks (FunNets) are an extension of neural networks which consist of different layers of neurons connected by links. Each computing unit or neuron performs a simple calculation: a scalar typically monotone function *f* of a weighted sum of inputs. The function *f*, associated with the neurons, is fixed and the weights are learned from data using some well-known algorithms.

The main idea of functional networks consists of allowing the *f* functions to be learned while suppressing the weights. In addition, the *f* functions are allowed to be multidimensional, though, they can be equivalently replaced by functions of single variables. When there are several links, say *m* links, going from the last layer of neurons to a given output unit, we can write the value of this output unit in several different forms (one per different link). This leads to a system of $m-1$ functional equations, which can be directly written from the topology of the neural network. Solving this system leads to a great simplification of the initial functions *f* associated with the neurons.

Castillo et al. (2001) gave a comprehensive demonstration of the application of FunNets in statistics and engineering. It was however observed in literature that not much has been done on the field of oil industry.

CHAPTER 7

RESULTS AND DISCUSSION

7.1 Data Verification

The quality of the collected data was checked according to established quality check criteria as mentioned in Section 3.3. According to the literature and practices the quality control or quality assurance QC/QA of any data, is of high importance. This was proven in this study where the analysis of the data after the QC/QA check gives good results in terms of modeling and prediction.

The first objective of this research was to perform quality control check of the drilling data which will help to accomplish the second objective which is developing a correlation between rate of penetration and the following drilling parameters; WOB, RPM, torque and mud flow rate.

7.2 Pre-Modeling Analysis

In order to develop models for real data it is very important to check the relation between the input parameters and the objective output parameter. This step is important since it gives an idea about how the input parameters correlate with the output parameter and also the final form of the model under development. Therefore, some techniques were used to achieve this objective. The next section shows the definitions of some terminology

Correlation is a statistical technique that can show whether and how strongly pairs of variables are related.

Covariance is a measure of how much two random variables change together. If the greater values of one variable mainly correspond with the greater values of the other variable, and the same holds for the smaller values, i.e., the variables tend to show similar behavior, the covariance is positive

Variance is a measure of how far a set of numbers is spread out.

Correlation Coefficient between two series, say x and y, equals

$$Correlation\ Coefficient = \frac{Covariance(x,y)}{[Variance(x)]^2 \times [Variance(y)]^2},(21)$$

where;

Covariance(*x,y*) is the sample covariance between *x* and *y*.

$$Covariance(x,y) = \frac{1}{n-1} \times \sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})(22)$$

Variance(*x*) is the sample variance of x:

$$Variance(x) = \frac{1}{n-1} \times \sum_{i=1}^{n}(x_i - \overline{x})^2(23)$$

Variance(*y*) is the sample variance of y:

$$Variance(y) = \frac{1}{n-1} \times \sum_{i=1}^{n}(y - \overline{y})^2(24)$$

For the data of Section 1 of Well 1, Table6 shows the correlation between the input parameters (*RPM*, *T*, *WOB*, Q_m) and the output parameter (*ROP*). The correlation indicates how the input parameters are related to the output. It is clear from this table that the effect of the *RPM* is the most significant with a weight of about 0.55 and *WOB* is the second parameter in importance but it negatively affects the *ROP* (-0.42). The table indicates also that the mud flow rate has the least effect.

On the other hand, Table 7 shows the correlation for Section 2 of Well 1 indicating different effect of the input parameters compared with Section 1 of Well 1. The *RPM* has the highest effect in that section with a weight of 0.15 while its effect in Section 1 for the same well was 0.55. This indicates that effect of the input parameters on*ROP* will vary for different sections in the same well. It was observed that the effect of Torque in Section 1 was positive (as the Torque increases the *ROP* increases) while the Torque effect was negative in Section 2. The same conclusion was observed for the effect of *WOB* and mud flow rate. In conclusion, in order to increase the *ROP* for Section 1 it is better to increase *RPM* and decrease the *WOB* while it is better to increase the *RPM* for Section 2 and keep the other parameters unchanged.

For the data of Well 2Table 8 shows the correlation between these input parameters and the *ROP*. In this case it was noticed that the most important parameter that affect significantly the *ROP* was the torque of a weight of 0.92 and the second important parameter is the *WOB* of a weight of 0.3. Such analysis can help in developing the model of the *ROP* according to the weight of the input parameters.

Table 6: Correlation coefficient for the drilling parameters for Section 1 Well 1

	RPM (rpm)	T(kft.lbf)	WOB (klbf)	Mud Flow (galUS/min)	ROP (ft/h)
ROP (ft/h)	0.545602598	0.110688188	-0.42254669	0.045620743	1

Table 7: Correlation coefficient for the drilling parameters for Section 2 Well 1

	RPM (rpm)	T(kft.lbf)	WOB (klbf)	Mud Flow (galUS/min)	ROP (ft/h)
ROP (ft/h)	0.146521983	-0.048588375	0.041726013	-0.002711915	1

Table 8: Correlation coefficient for the drilling parameters for Well 2

	RPM (rpm)	T(kft.lbf)	WOB (klbf)	Mud Flow (galUS/min)	ROP (ft/h)
ROP (ft/h)	0.132982355	0.924444172	0.290867694	0.068729166	1

Table 9: Correlation coefficient for the drilling parameters for Well 3

	RPM (rpm)	T(kft.lbf)	WOB (klbf)	Mud Flow (galUS/min)	ROP (ft/h)
ROP (ft/h)	0.142931849	0.426967947	-0.572030731	-0.241666696	1

7.3 Modeling

Developing the models of rate of penetration, drilling specific energy and torque was discussed in Chapter 5. In this chapter the results of these models for different cases will be studied. The model for each well and for a certain section of clean lithology is shown in model development chapter. Nonlinear regression technique was used to develop these models. The final form of the model is

$$ROP = c_1(WOB)^{c_2}(RPM)^{c_3}(T)^{c_4}(Q_m)^{c_5} (8)$$

In order to estimate the coefficients C_1toC_5, nonlinear regression Matlab codes were developed. Table 5 displays the coefficients obtained for the first section of Well1. The model gives good results of predicting the *ROP* based on the drilling parameters with correlation coefficient of 0.864.

Table 10: ROP model coefficients of Well 1

C_1	0.177564
C_2	-0.24455
C_3	0.89470
C_4	0.43401
C_5	0.1500
R	0.864

According to the model coefficients it is clear that for this section the *WOB* has a negative effect on the *ROP* where the *ROP* increases as *WOB* decreases. This gives us an idea about the bit floundering effect. This useful conclusion can help to avoid crossing the bit floundering region which will result in bit damage. Avoiding the bit floundering will increase the bit life by minimizing the *WOB* and will definitely shorten the total trip time needed to change the bit. On the other hand, the other drilling parameters like; *RPM*, *T*, and mud flow rate have positive effect for this section where the ROP increases with the increase of these parameters. Figure 15 shows the correlation between the measured and the predicted *ROP* based on this model for Well 1. Figure 16 illustrates the model histogram error and it shows normally distributed error with maximum absolute error of less than 10%. The results of the ROP model developed shows good agreement between the actual and the calculated ROP. Figure 17 represents the actual ROP and the calculated ROP vs. depth. The results of the *ROP* modeling for the other cases of Wells 2 and 3 are shown in Figs. 18 to 23. Results obtained for the ROP modeling for Wells 2 and 3 show good estimation of the ROP with absolute error less than 15%.

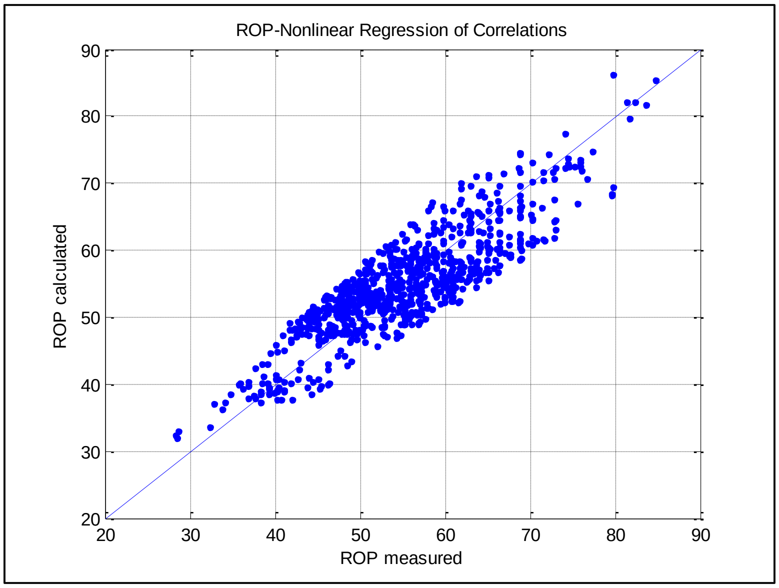


Figure 15: *ROP* measured vs. predicted for drilling data from Well 1

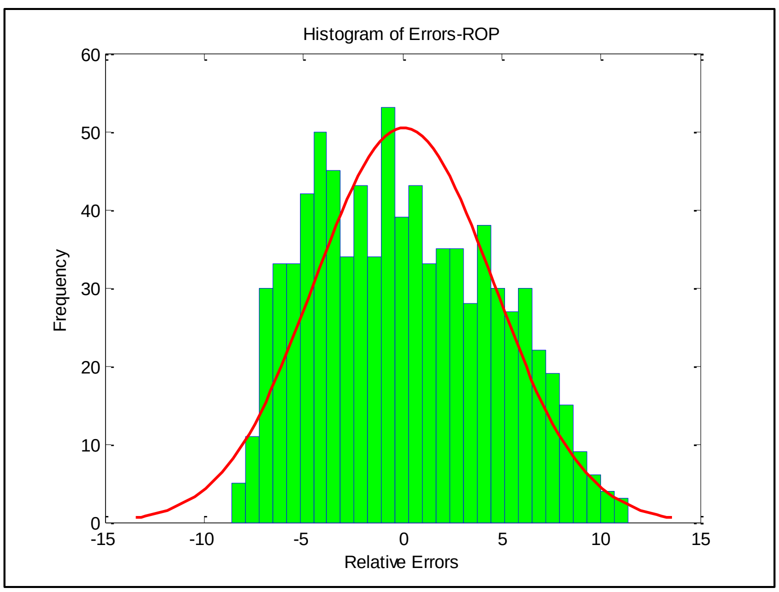


Figure 16: Histogram error for ROP model of data from Well 1

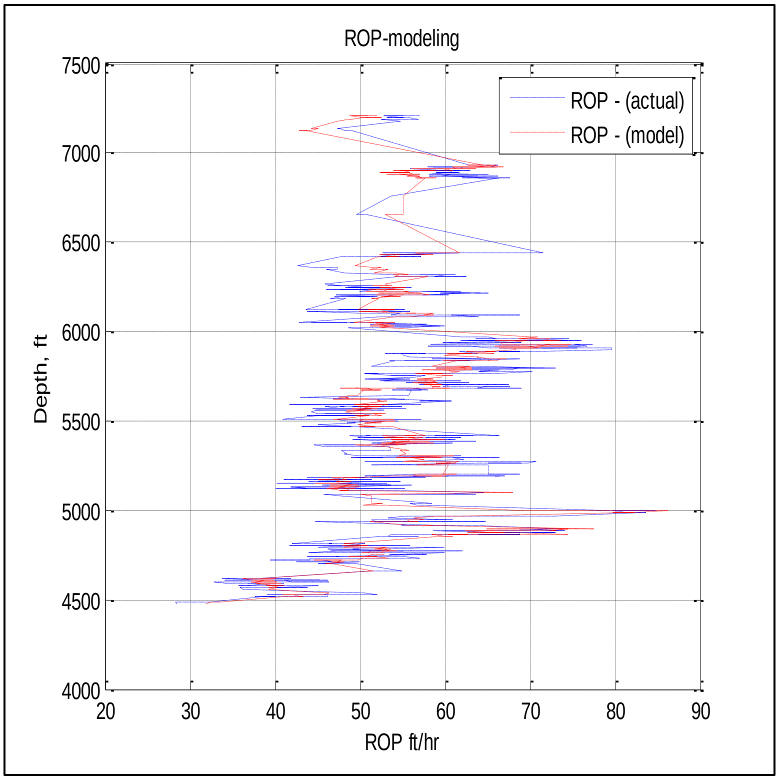


Figure 17: calculated *ROP* vs. actual *ROP* as function of depth of Well 1

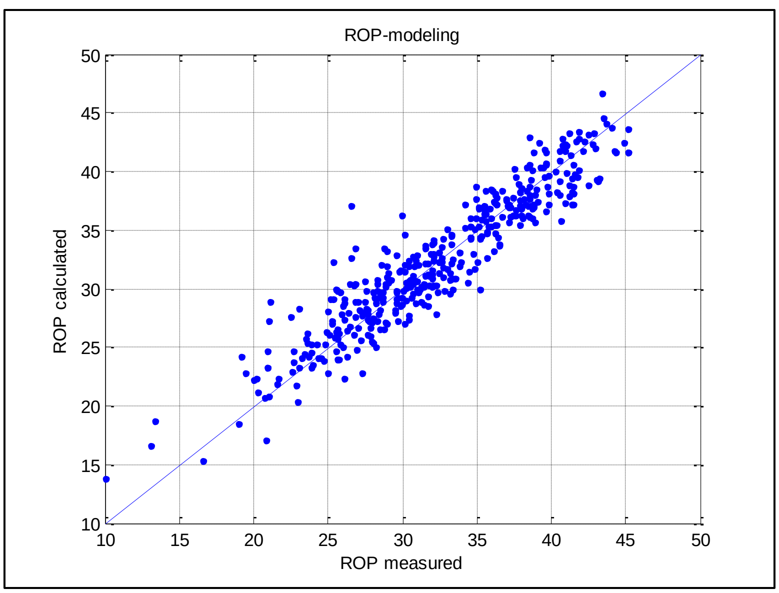


Figure 18 : *ROP* measured vs. predicted for drilling data from Well 2

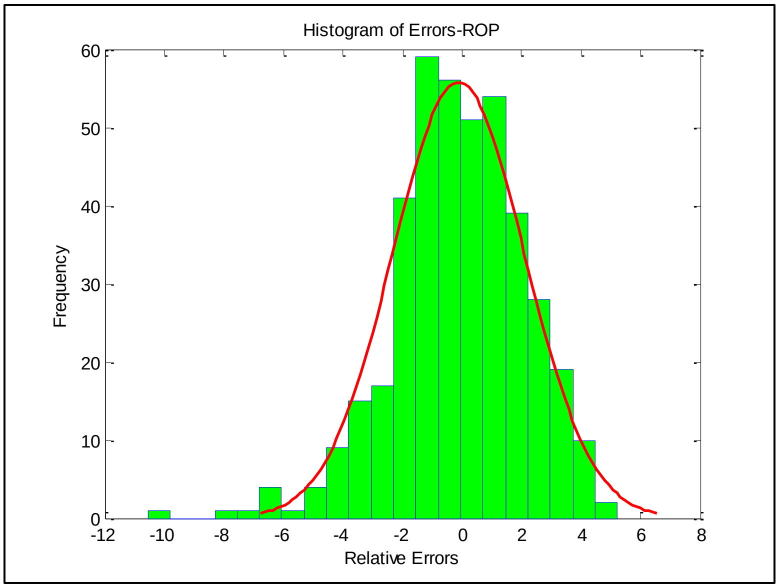


Figure 19 : Histogram error for ROP model of data from Well 2

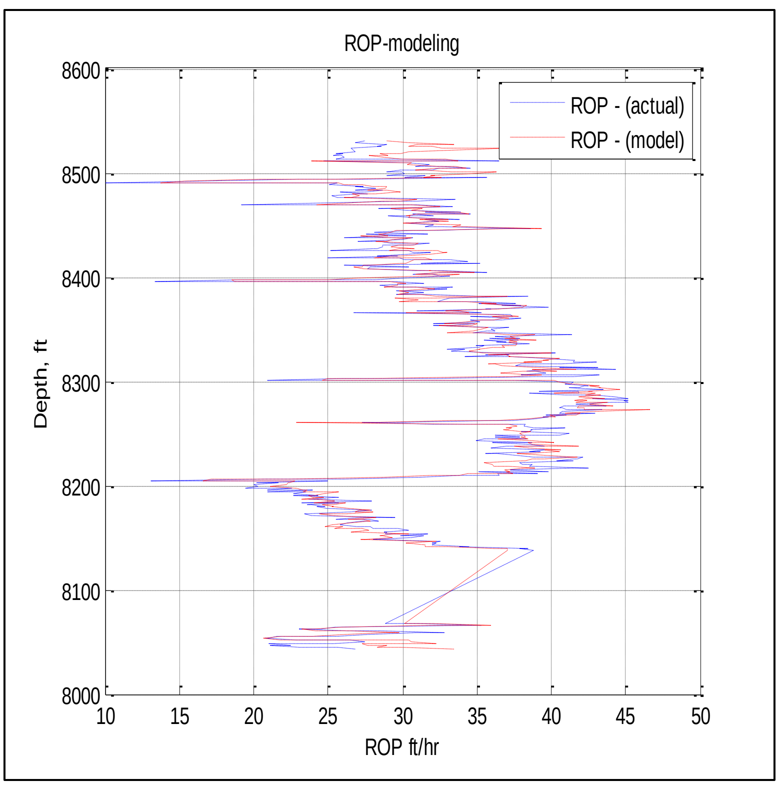


Figure 20 : calculated *ROP* vs. actual *ROP* as function of depth of Well 2

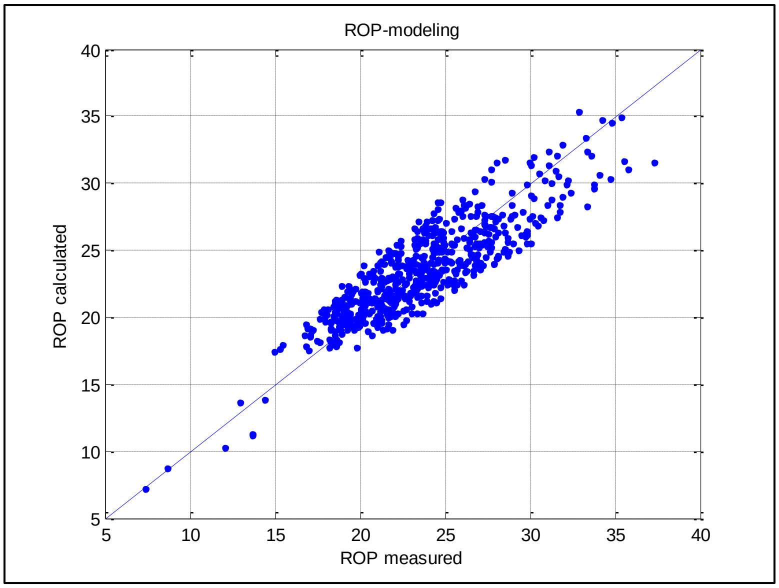


Figure 21: *ROP* measured vs. predicted for drilling data from Well 3

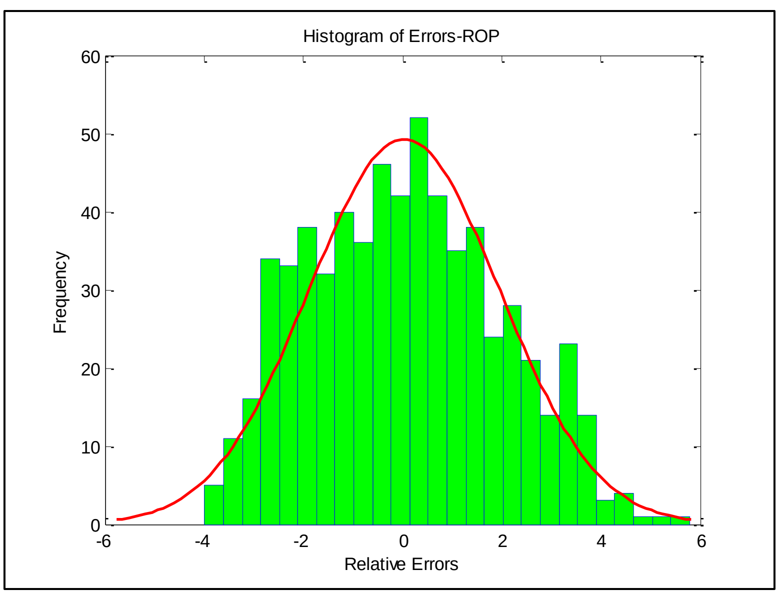


Figure 22 : Histogram error for ROP model of data from Well 3

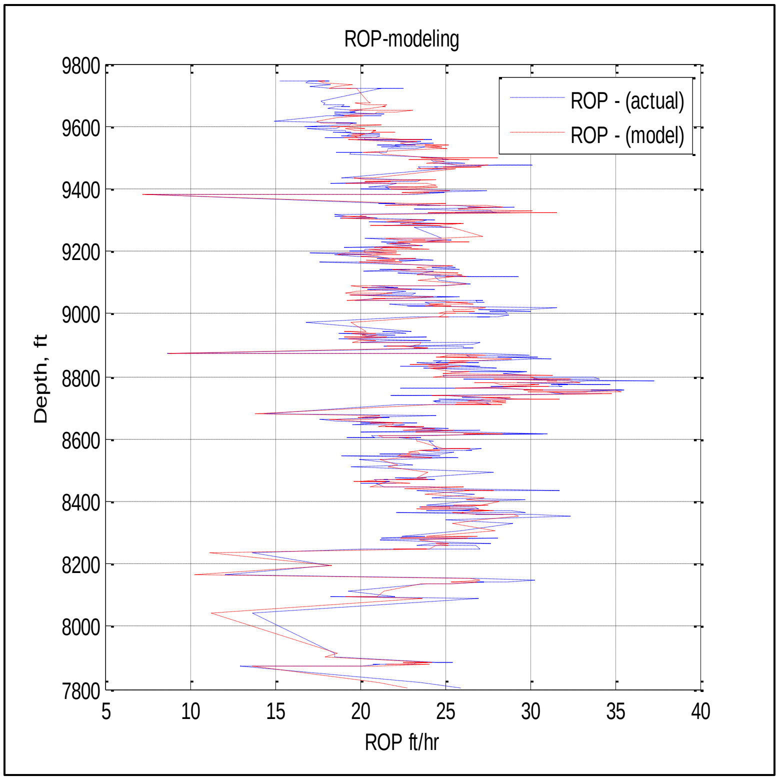


Figure 23: calculated *ROP* vs. actual *ROP* as function of depth of Well 3

The main objective of this research is to optimize the drilling parameters based on the drilling specific energy in Eq. 7.In that equation, the *WOB*, *RPM*, *T*, area of the bit, dimensionless bit hydraulic factor, bit horse power and *ROP* are the input parameters. The torque is a function of WOB, bit diameter, and the dimensionless bit specific coefficient of sliding friction,μ, according to Pessier and Fear correlation, (Eq. 9).

$$T = \frac{\mu(D_B)(WOB)}{36} (25)$$

$$\mu = 36 \frac{T}{(D_B)(WOB)} (26)$$

The dimensionless bit specific coefficient of sliding friction, μ, in Eq. 26 was calculated according to each set of data for each section in each well, (weight on bit weight on bit, bit diameter and torque). This coefficient was plotted against *WOB* to find a correlation between them. The best model found was of the form shown in Eq. 29.

$$\mu = a_1(WOB)^{a_2} (29)$$

In order to estimate the coefficients a_1 and a_2, nonlinear regression was used and it results in the form in Eq. 30.

$$\mu = 26.142(WOB)^{-0.805} (30)$$

By substitutingEq. 30 into Eq. 25 the formula of torque can be obtained as shown in Eq. 31.

$$T = \frac{26.142 D_B (WOB)^{0.195}}{36} (31)$$

Figure 24 shows the measured and the calculated bit specific coefficient of sliding friction, μ, as function of *WOB*. The correlation obtained was of good accuracy with correlation coefficient of 0.90. The cross plot of the actual values of coefficient of sliding friction, μ, vs. the estimated values is illustrated in Fig. 25. The results of molding this coefficient for Well 1 shows good prediction with error less than 8% as shown in Fig. 26 and the error was normally distributed. The results of the other cases of Wells 2 and 3are presented in the Figs. 27 to 32.

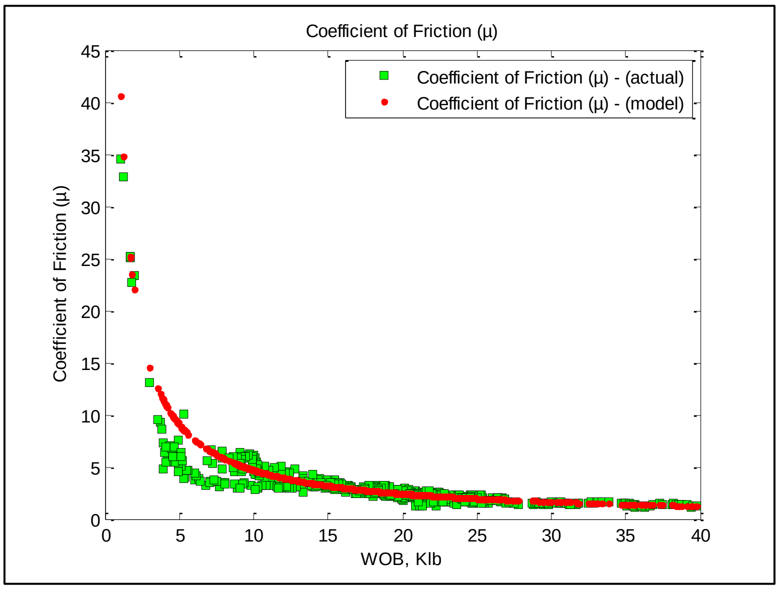


Figure 24: bit specific coefficient of sliding friction vs. WOB for Well 1

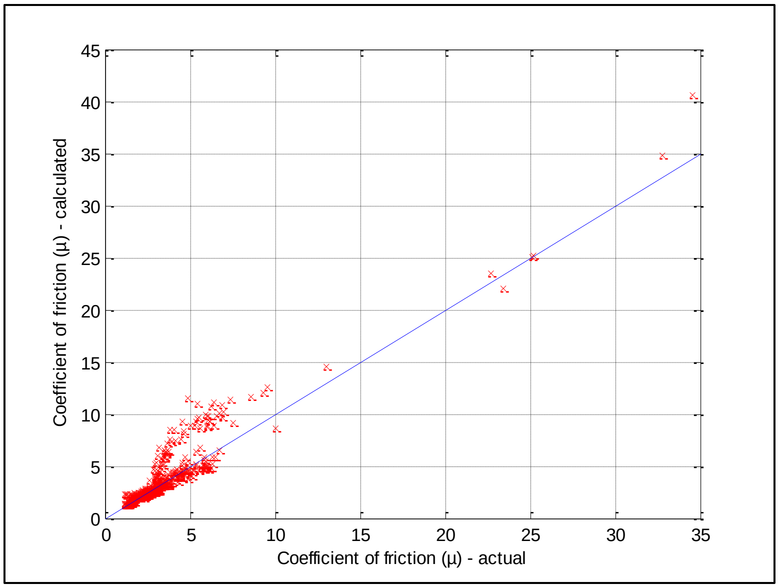


Figure 25 : Coefficient of friction cross plot of Well 1

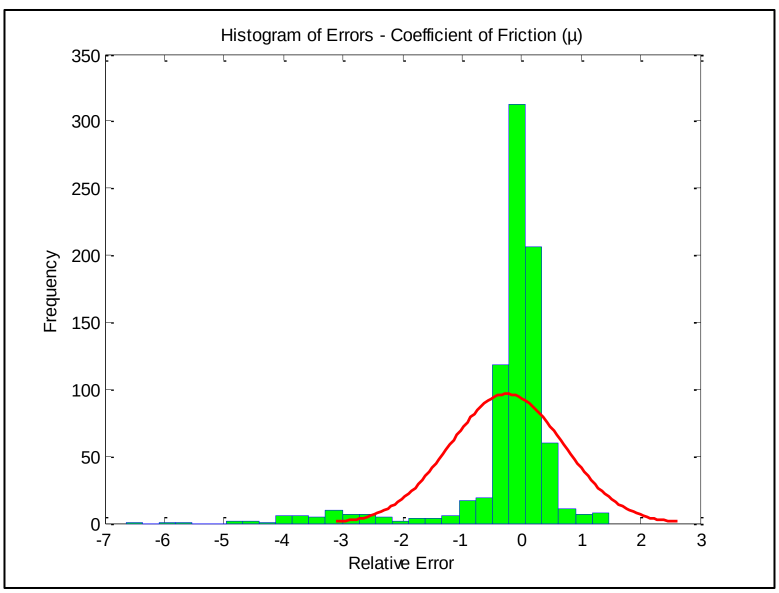


Figure 26 : Histogram error for Coefficient of friction model of Well 1

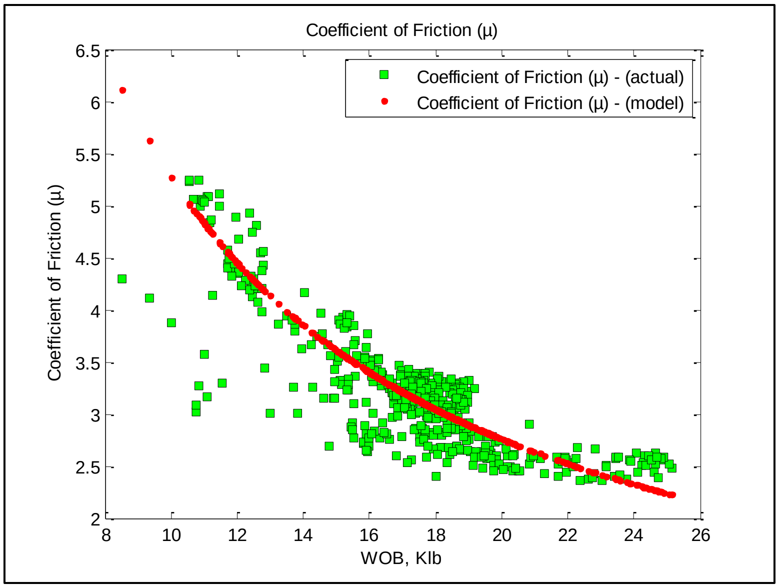


Figure 27 : bit specific coefficient of sliding friction vs. WOB for Well 2

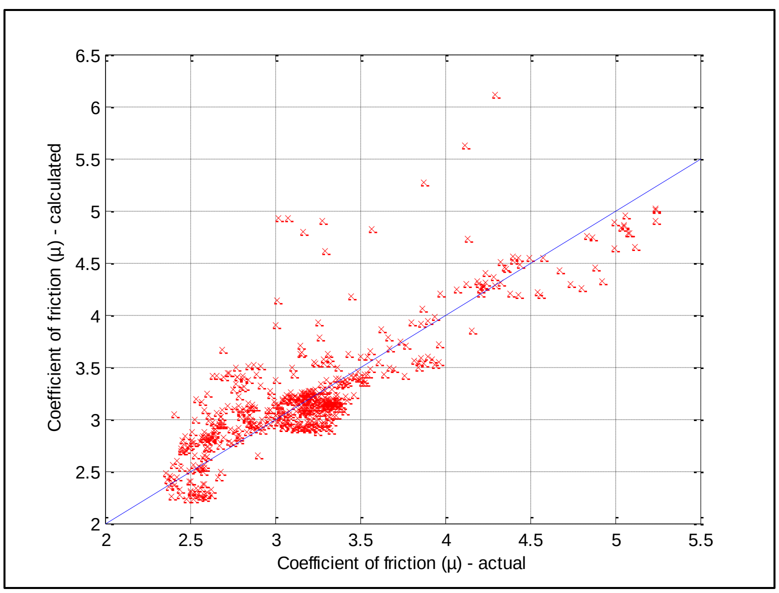


Figure 28 : Coefficient of friction cross plot of Well 2

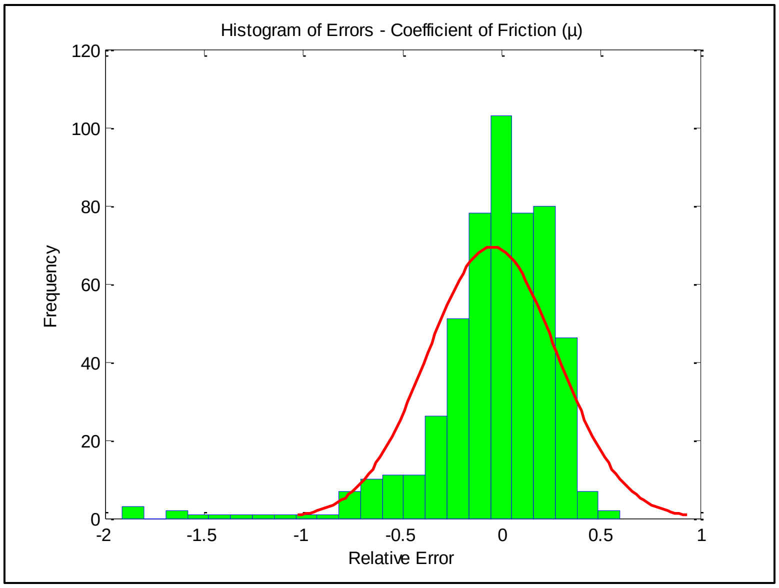


Figure 29 Histogram error for Coefficient of friction model of Well 2

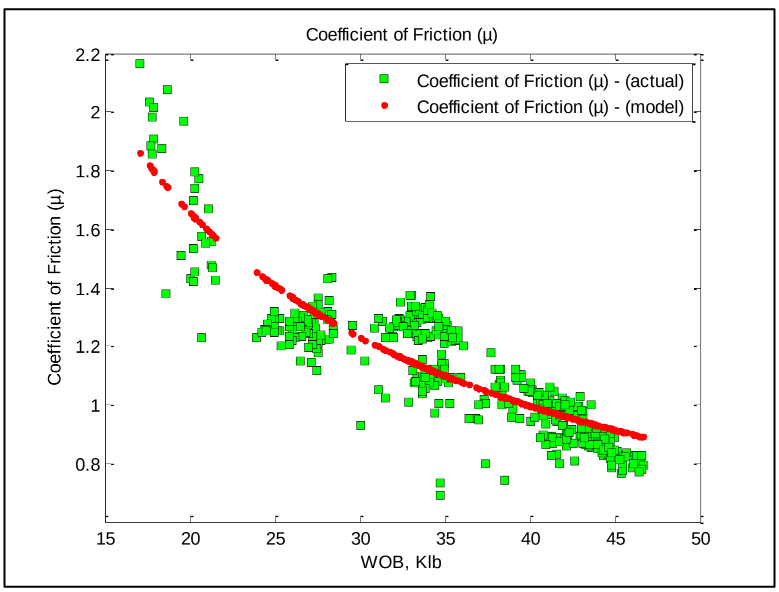


Figure 30: bit specific coefficient of sliding friction vs. WOB for Well 3

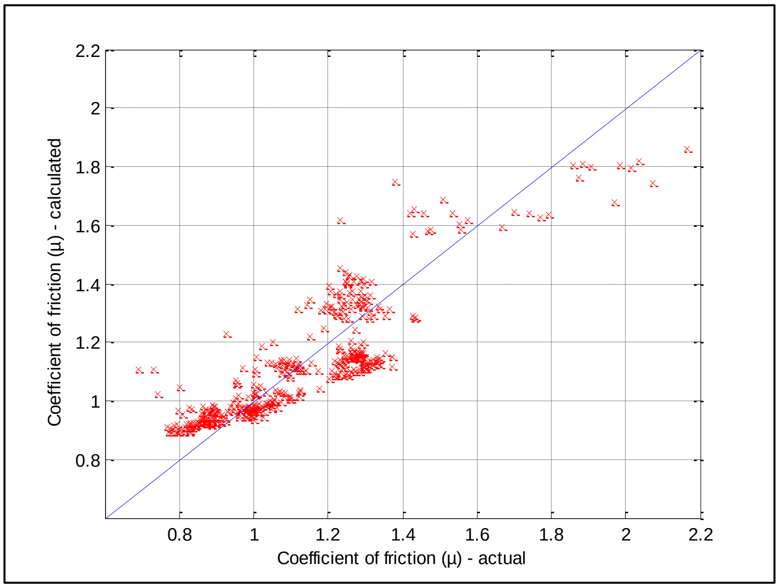


Figure 31: Coefficient of friction cross plot of Well 3

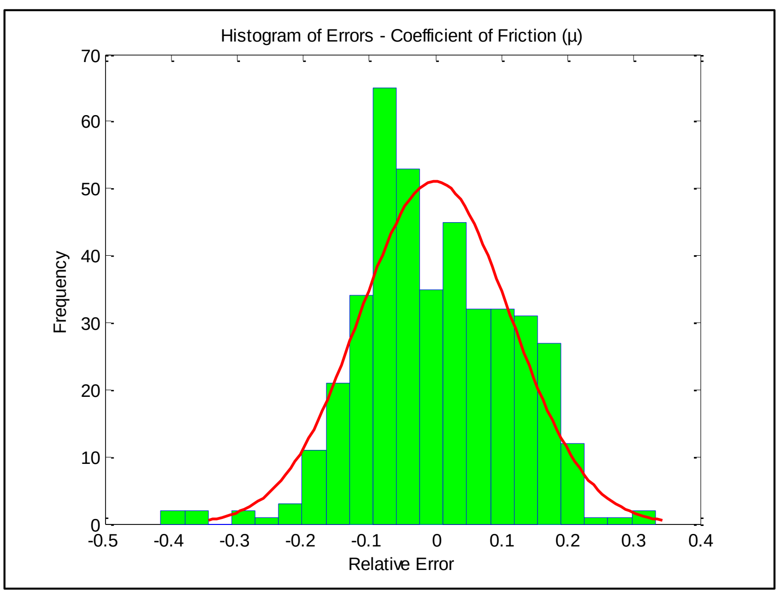


Figure 32: Histogram error for Coefficient of friction model of Well 3

Finally, the input parameters of the drilling specific energy equation (*DSE*), now can be used to estimate the *DSE* and therefore the drilling parameters can be optimized in order to maximize the *ROP* by minimizing the *DSE*.

7.4 Model Validation

In order to validate the new developed model, artificial intelligence(AI) was used to check how well the model results. The following AI techniques were used

1. Neural networks (NN)
2. Fuzzy logic (FL)
3. Support vector machines (SVM)
4. Functional networks (FN)
5. Genetic Algorithm (GA) as optimization tool

7.4.1 Neural Networks (NN)

The model architecture in terms of number of neurons, layers and the type of connection function were determined based on trial and error process because it was the most successful criteria in developing the model. Different transfer functions were tested. The best function was log sigmoid. However, the best learning algorithm for training the NN was the cascade-forward. Several problems were faced during training the network. The model was trapped at some point and caused the training to be stopped. This problem was related to the local minimum. To overcome this problem, the maximum number of validation failure was increased to 300. In order to train the network 70% of the data was used while 15% was used for validation and the other 15% for testing. The NN can be classified based on the interconnection between the neurons and layers into two types; feed-forward Type1 and cascade-forward Type2. For feed-forward, the input sweeps directly to the output layer and does not allow internal feedback of information. On the other hand, cascade-forward allow internal feedback of information, which is better for dynamic models. Both of the two types of the NN were used but the later was recommended. Figure 33 illustrates the structure of the cascade-forward NN.

Different transfer functions were applied to both the input and output data like log-sigmoid and purelin (linear transfer function).It was found that the optimum number of layers is three layers with different number of neurons (5, 10, 5) for cascade-forward NN type. Figure 34 shows the NN results for the data of Well 1 with overall correlation coefficient of 0.895 which is close to the results obtained from the developed model 0.87. Similarly, results obtained from the NN for Well 2,Fig. 35shows that NN can model the ROP with correlation coefficient of 0.892 compared to the ROP model developed with correlation coefficient of 0.88.

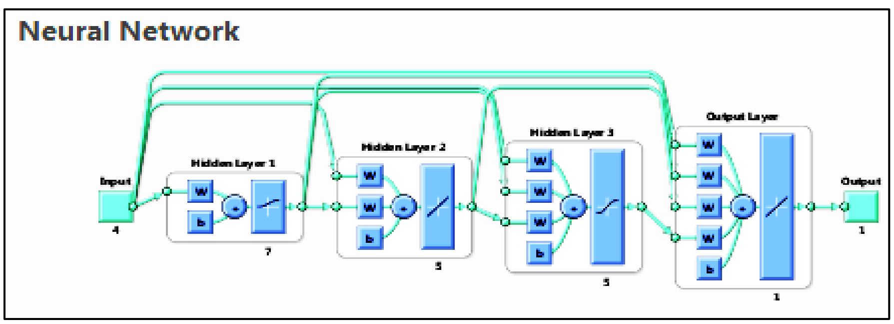


Figure 33: ANN structure

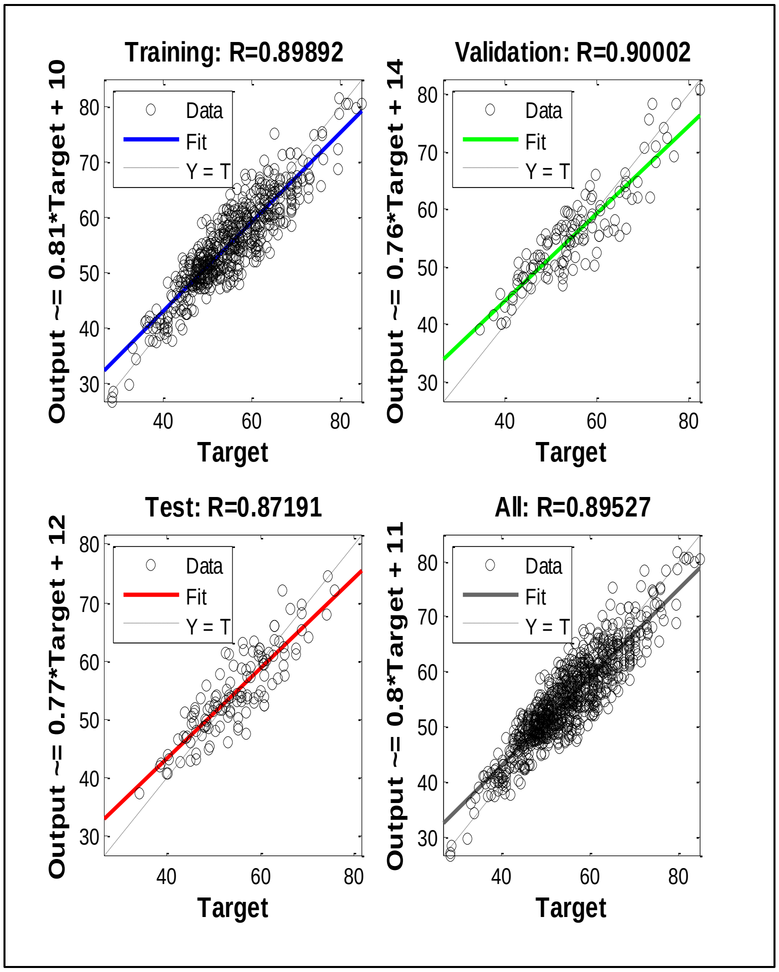


Figure 34: Correlation Coefficient of the ANN model for the data of Well 1

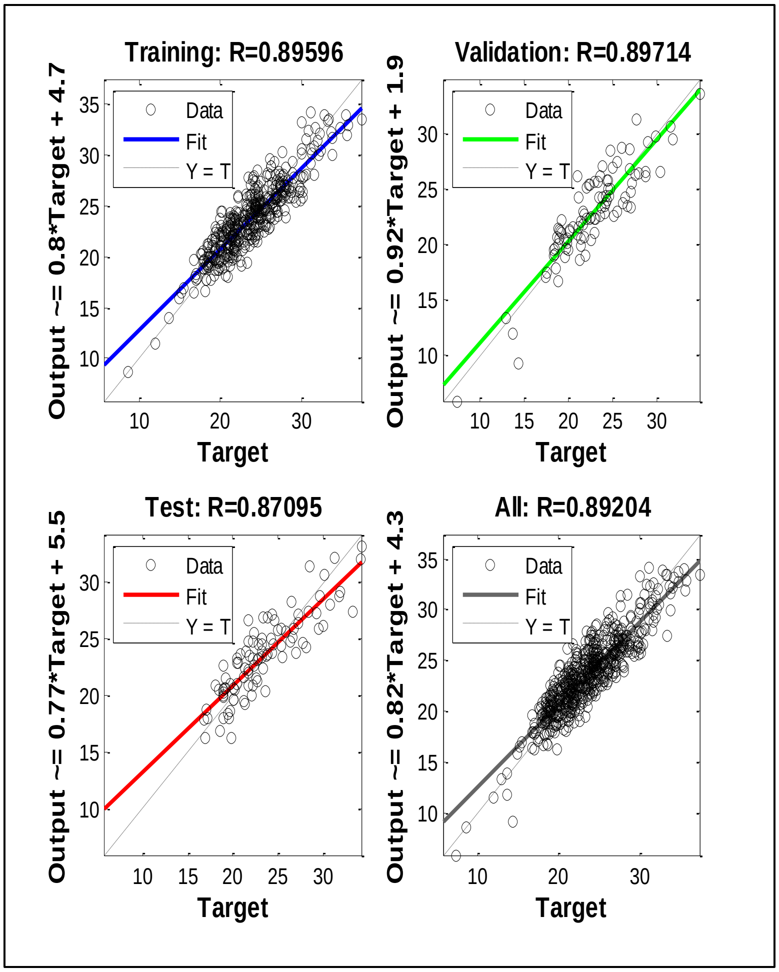


Figure 35: Correlation Coefficient of the ANN model for the data of Well 2

7.4.2 Fuzzy Logic (FL)

Fuzzy logic is the second tool used in this study. It is of two types; grid partition, and sub clustering. The grid partition needs many MMfs to get better prediction but it requires much time and more powerful systems to achieve such a task. Because of this the sub clustering was used. The only parameter was changed is the radii (range of influence) to have better results. Radius was range from 0.01 up to 0.2and it was noted that better prediction for training data will achieved as the radii decreased. For testing data, the effect of the radius is the same to some point after that the error was increased although the radius was decreased. For this reason the value of this parameter should be optimized. Optimization can be accomplished using trial and error technique or by using genetic algorithm (GA). In this study genetic algorithm was used in order to find the optimum value of the radius. The optimum value was found to be 0.145 in terms of the mean square error (MSE) but in terms of correlation coefficient the optimum radius was 0.01. The correlation coefficient for the whole data was 0.7 indicating that the results obtained from the both the developed model and NN is better than FL results. Figure 36 shows the results obtained using FL for the data of Well 1.FL is not as good as NN for this type of data with correlation coefficient of 0.7. Results achieved using FL for Well 2 give a correlation coefficient of 0.65 which is not good compared with the NN results as shown in Fig. 37. Similarly, FL did not show good results for the other cases.

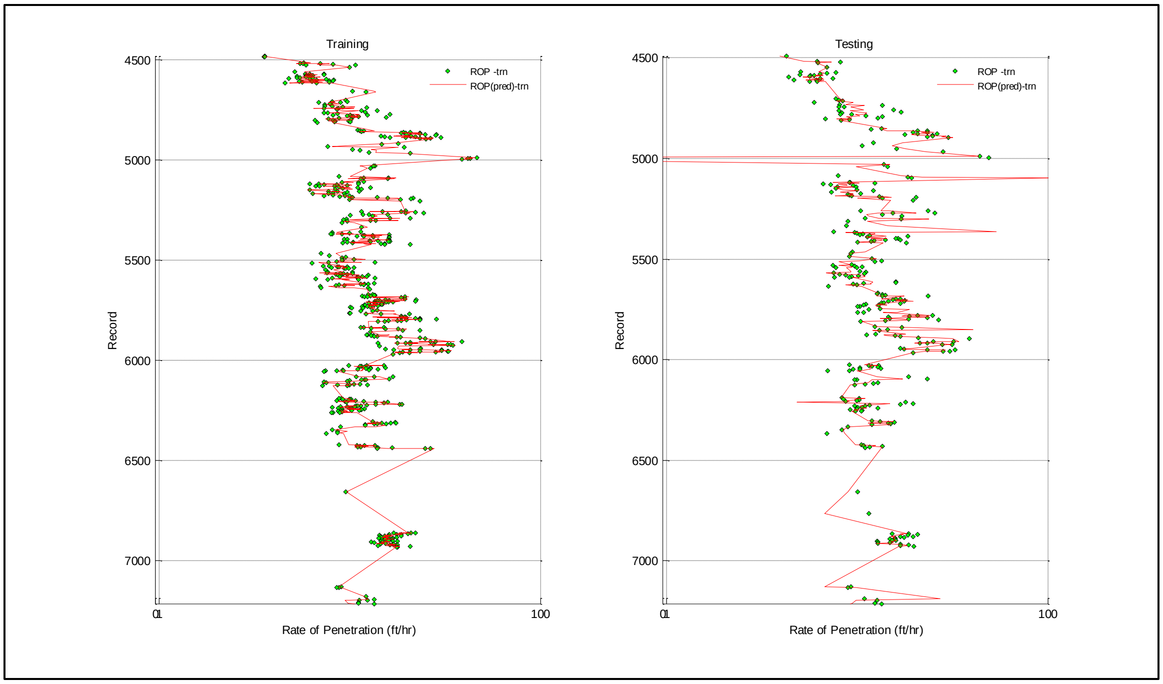


Figure 36: The predicted *ROP*vs. the actual *ROP*for both training and testing data for Well 1

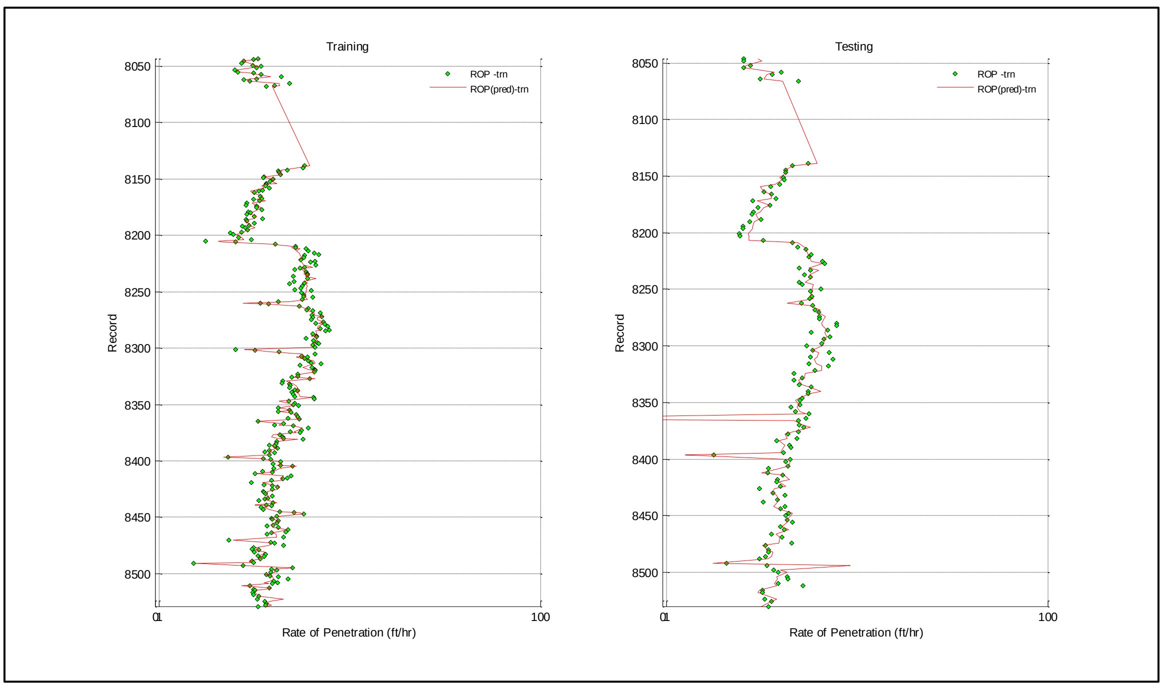


Figure 37:The predicted *ROP* vs. the actual *ROP* for both training and testing data for Well 2

7.4.3 Support Vector Machines

Support Vector Machines (SVM)with different kernel functions was used. The kernel functions that were used are; gaussian, poly, polyhomog, heavy tailed radial basis function (htrbf), radial basis function (rbf). Both the gaussian and the poly kernel functions work for this type of problem while the other function did not work. In order to model the data, 70% of the data was used to train the model while 30% was used to test the model.

The parameters: c, lamda, espilon, kerneloption were varied toget the optimum combination of these values that give the best results.The optimum values of these parameters are given below which give the best results in modeling the ROP with correlation coefficient of 0.88 for training and 0.86 for testing.

The best parameters used for SVM model are the following;

C = 100;

Lambda = 1e-6;

Epsilon = 0.04;

Kerneloption = 0.30;

Figure 38 shows the results of SVM for the training data with (R= 0.88) and Fig. 39 shows the results for the testing data (R=0.86).Results for Well 2 are shown in Figs. 40 and 41 with almost the same correlation coefficient attained from the data of Well 1.

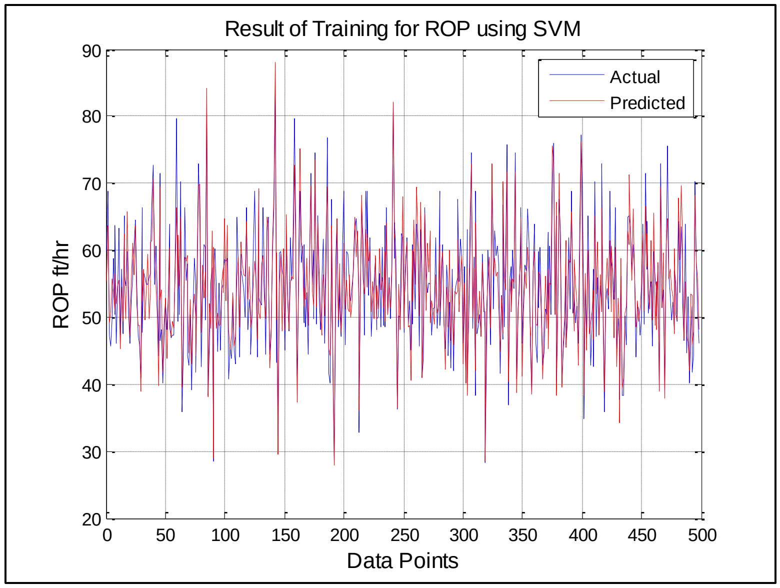


Figure 38: Predicted vs. actual *ROP* for the training data of Well 1

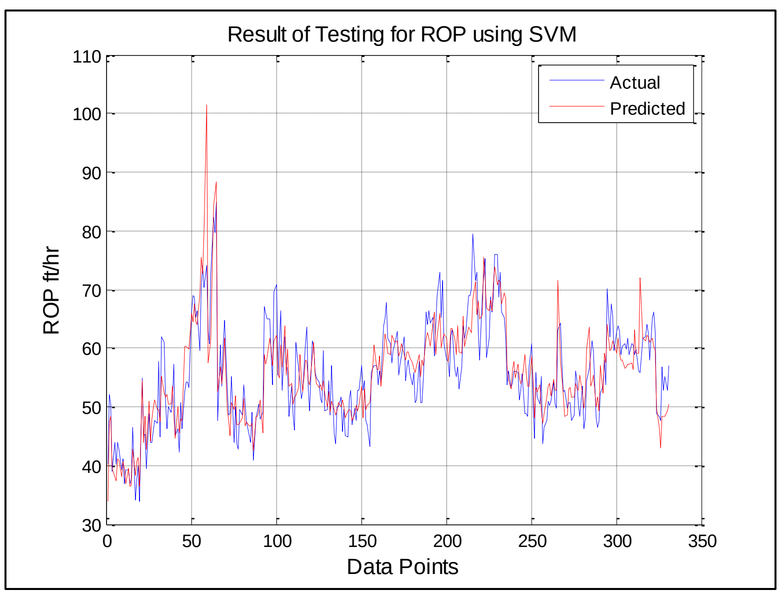


Figure 39: Predicted vs. actual ROP for the testing data of Well 1

Figure 40: Predicted vs. actual *ROP* for the training data of Well 2

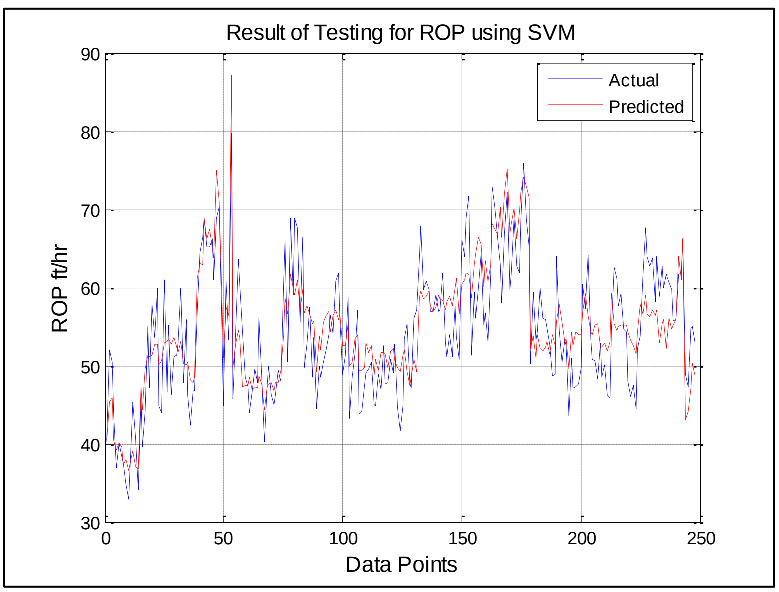


Figure 41: Predicted vs. actual ROP for the testing data of well 2

7.4.4 Functional Network

Functional Network (FN) was applied using 70% of the data for training and 30% for testing. This tool gives the same correlation coefficient achieved using SVM for both training and testing 0.88 and 0.86 respectively. Figs. 42 and 43 shows the results obtained using FN for both the training data and the testing data for Well 1 while Figs. 44and 45show the results for Well 2 with correlation coefficient of 0.86 for training and 0.85 for testing.

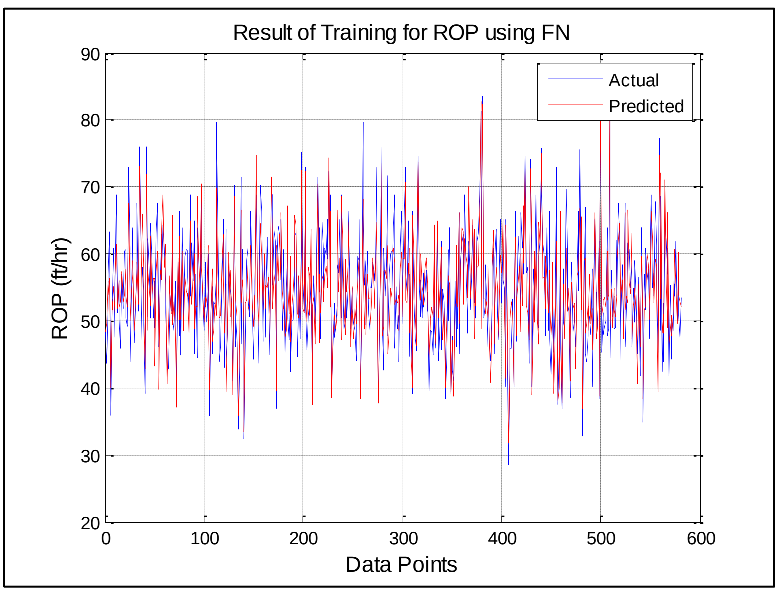


Figure 42: Predicted vs. actual *ROP* for the training data of Well 1

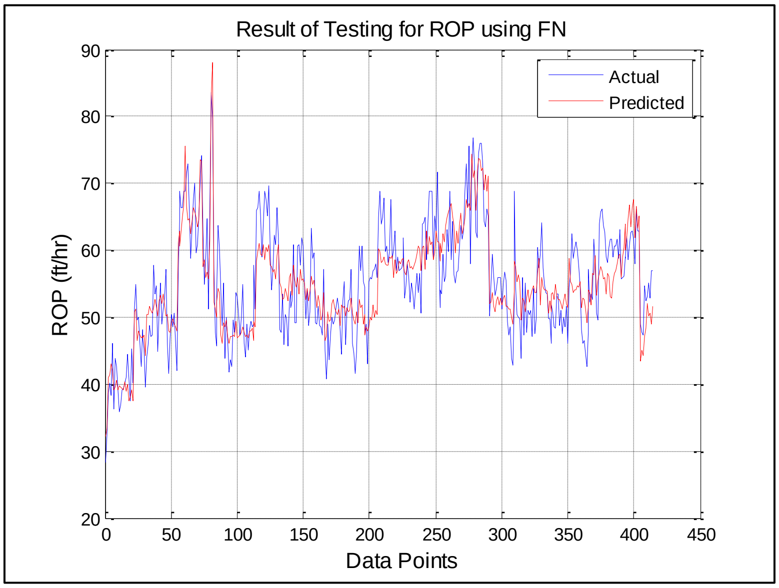


Figure 43: Predicted vs. actual *ROP* for the testing data of Well 1

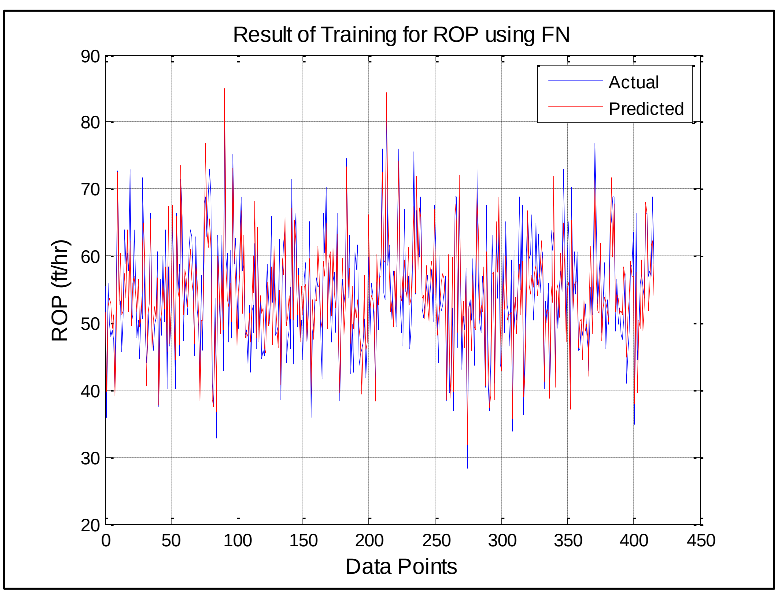


Figure 44: Predicted vs. actual *ROP* for the training data of Well 2

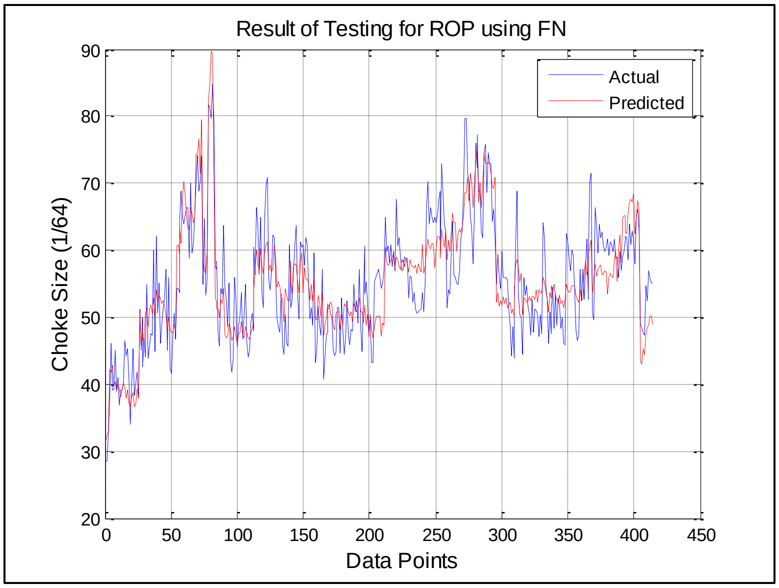


Figure 45: Predicted vs. actual *ROP* for the testing data of Well 2

In conclusion, the results obtained from the developed model and the different artificial intelligence techniques are in good agreement and this indicates the accuracy of the models developed. Among the different artificial intelligence techniques, fuzzy logic was not good in prediction the ROP compared with the other techniques.

7.5 Optimization

The main goal of this research work is to maximize the rate of penetration (*ROP*) by optimization the drilling parameters (*RPM, WOB,* Q_m). The objective function is the drilling specific energy equation (DSE). In order to optimize these parameters the DSE equation will be minimized which yields maximization of the *ROP*. Particle swarm optimization technique (PSO) was used to minimize the objective function. Matlab codes were developed to achieve the optimization. Three codes were developed: the main code, the PSO code and the objective function code. Based on the results the optimum parameters that minimize the DSE were determined. Figure 46 shows the flow chart demonstrating the process of the optimization.

The flow chart in Fig. 46 illustrated the optimization process in a simple way to be understood. The process consists of three segments, the main code, the PSO code, and the DSE code. In the main code the data will be read checked for quality and analyzed. The constants and weights will be set and the lower and upper limits for the parameters would be set also. The mail code will call the PSO code to start the optimization. Through the PSO code, the PSO parameters will be assigned and then the objective function will be called for optimization. In this code the drilling parameters values are changed randomly until the minimum value of the DSE isbeing achieved and the optimum drilling parameters are reported. The DSE code includes the objectives function where the ROP model and the DSE parameters and coefficients will be read and then the DSE values for each set of data will be calculated and fedback to the PSO code. The ultimate goals of optimization are (1) reduction of the drilling time and (2) saving money. Reduction of the drilling time can be achieved by maximizing the rate of penetration through drilling with the optimum parameters. Putting more weight on bit to increase the ROP will shorten the bit life since the floundering point will be reach and this will dull the bit faster as shown in Fig 4 region III. Drilling with the optimum weight on bit will not only maximize the rate of penetration but also it will save the bit life for longer time which will definitely reduce the total cost of drilling operation and reduce the tripping time needed to replace the bit. The same conclusion can be said for the RPM. We searched within the bounds shown on Table 11. The PSO results show that the optimum parameters are on the boundaries of the search domain. For example, the optimum parameters obtained for Section 1 of Well 1 are RPM = 75.5, WOB = $4.6x10^3$lb, and Q_m = 940gpm. These values are expected because the correlations developed from the field data indicate that ROP follows a particular trend with each of these parameters. For instance, in Section 1 of Well 1 where the ROP is negatively correlated with WOB, then it is expected that the minimum possible WOB will give the highest ROP for this section. That is the reason why, the optimum WOB is the lower bound set for the WOB in the search algorithm. The same arguments hold for other parameters. In situations where the correlations do not follow any specific trends, then we may expect that the optimum parameters will lie within the search domain instead of the boundary.

Table 11: Original drilling parameters for Well 1

	RPM	*WOB* (1000 lb)	Q_m (gpm)
Min	15	4.6	850
Max	75.5	45	940

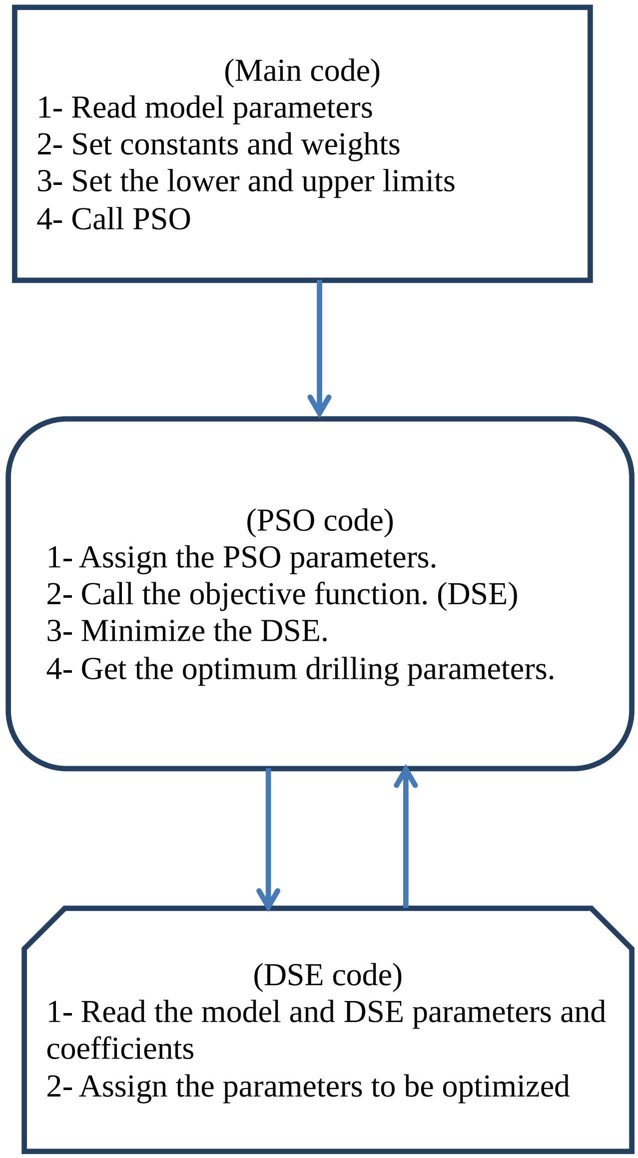


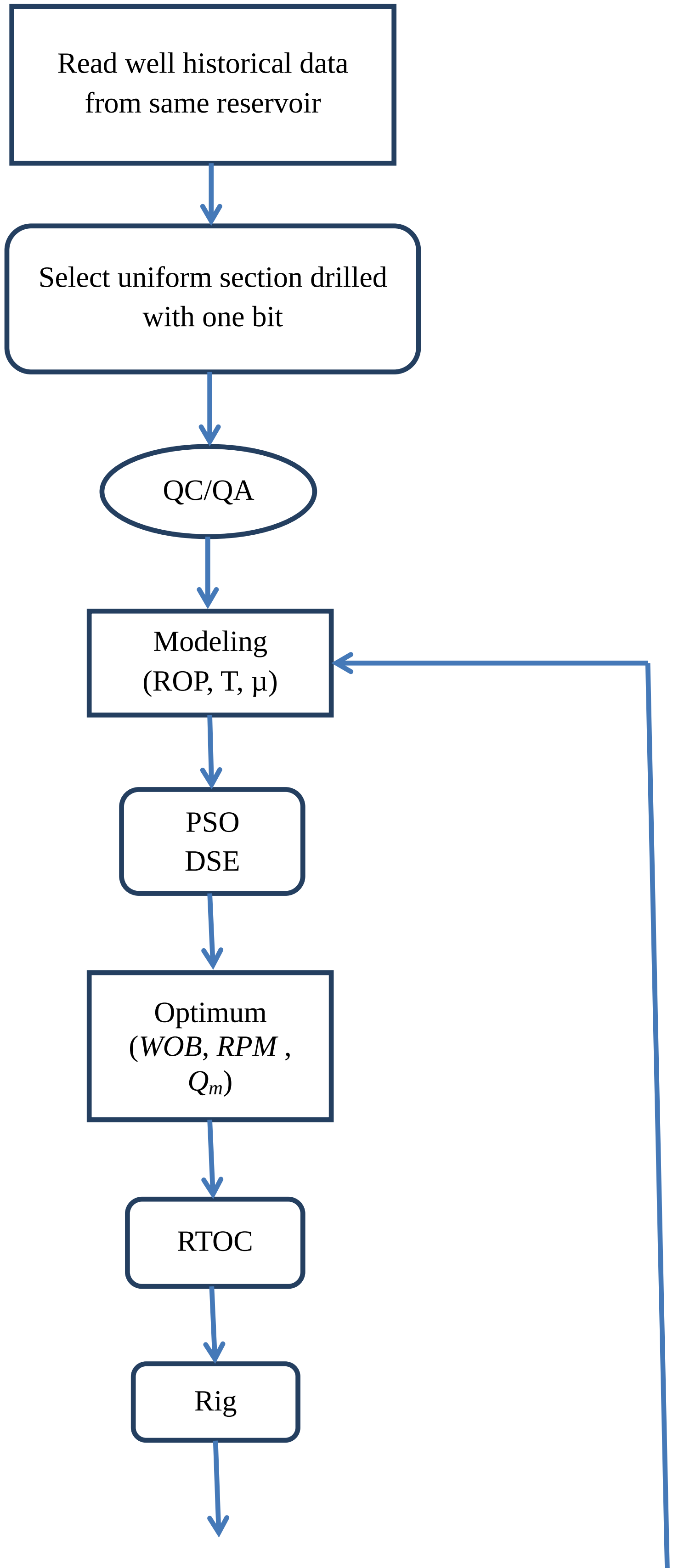
Figure 46: Optimization flow chart

7.6 Real Time Application

The objective of optimizing drilling parameters in real time is to make recommendations in real time to the drilling rig to use the new updated optimum drilling parameters simultaneously. The methodology developed here consider past drilling data and predicts the optimum drilling trend by optimizing the drilling parameters so that drilling and problem occurrence can be reduced.

Because of the importance of the real time data, several techniques were developed to increase the real time drilling efficiency and cut drilling cost. Continuous monitoring of real time drilling parameters for quality and consistency is one of the techniques used. The objective function that was used in the optimization process was the DSE equation. The following section shows the calculations of this function for the cases considered in this study.

In order to apply the optimization process in real time a methodology was developed as shown in the flow chart in Fig. 47. First of all the historical data from an old well in the same reservoir should be read, then a uniform and clean lithology would be selected. After that the data should be checked for accuracy by applying the QA/QC criteria. The next step is to model the rate of penetration, the torque and coefficient of friction according to the historical data. Then the PSO technique should be applied to determine the optimum drilling parameters (*WOB*, *RPM*, and Q_m) to start drilling the same lithology for the new well using these recommended optimum parameters. While drilling, new data from the new well is received and the same data should be processed according to the same procedure above. In other words, quality of the real time data collected while drilling should be checked and then modeled. If the models generated based on the historical data are valid for the new data then it is recommended to continue with the same optimum parameters otherwise the new data should be modeled and the optimization procedure should be applied again in order to get the optimum parameters for that section. This procedure will be repeated continuously in real time.


Read well historical data from same reservoir
Select uniform section drilled with one bit
QC/QA
Modeling (ROP, T, μ)
PSO
DSE
Optimum (WOB, RPM , Q_m)
RTOC
Rig

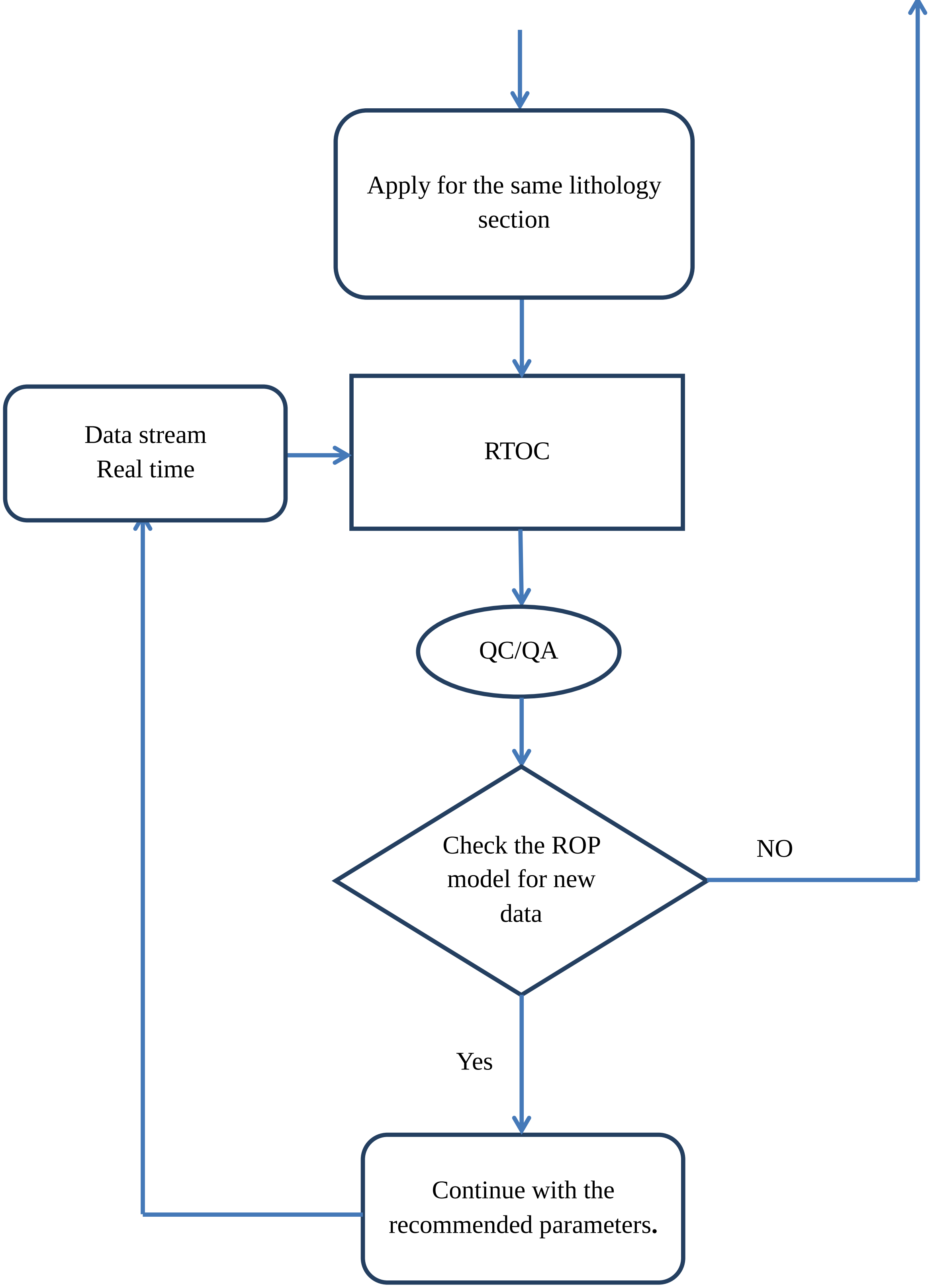


Figure 47: Real time application of optimization

CONCLUSION

A technique to optimize the drilling parameters in real time to achieve the maximum rate of penetration based on the drilling specific energy equation (DSE) has been developed. It succeeded in reducing the drilling time in the cases studied by over 30%.

1. The technique enhances the reliability in the optimization process by incorporating QA/QC criteria to check the correctness of the data in real time.

2. Pre- modeling analysis has been utilized to obtain insight into the influence of the input parameters on the output.

3. A new modeling approach has been developed

    a) Rate of penetration models were developed using historical data

    b) Relationship between weight on bit and torque was achieved and correlation between coefficient of friction (μ) and weight on bit was established

    c) A correlation between bit hydraulic factor (λ) and bit diameter was developed.

    d) The drilling specific energy equation was simplified to incorporate the bit hydraulic factor and the bit diameter.

4. The rate of penetration models were successfully validated using the artificial intelligence techniques (NN, FL, SVM and FN). Generally results obtained from

the rate of penetration model and the different artificial intelligence techniques are in good agreement.

5. Particle swarm optimization was successfully used for the first time to minimize the drilling specific energy in order to determine the maximum rate of penetration corresponding to the optimum drilling parameters.

6. A new methodology is proposed to optimize the drilling parameters in real time in order to maximize the rate of penetration.

RECOMMENDATIONS

It is recommended to use this work methodology and apply it for horizontal wells and to extend the technique to model heterogonous formation.

Appendix A (Data)

This Appendix contains the data used in this research for three vertical wells. The data includes general information for each section and some statistics of the measured drilling parameters as presented in the tables below. The data includes also the lithology of each section as shown in the figures below.

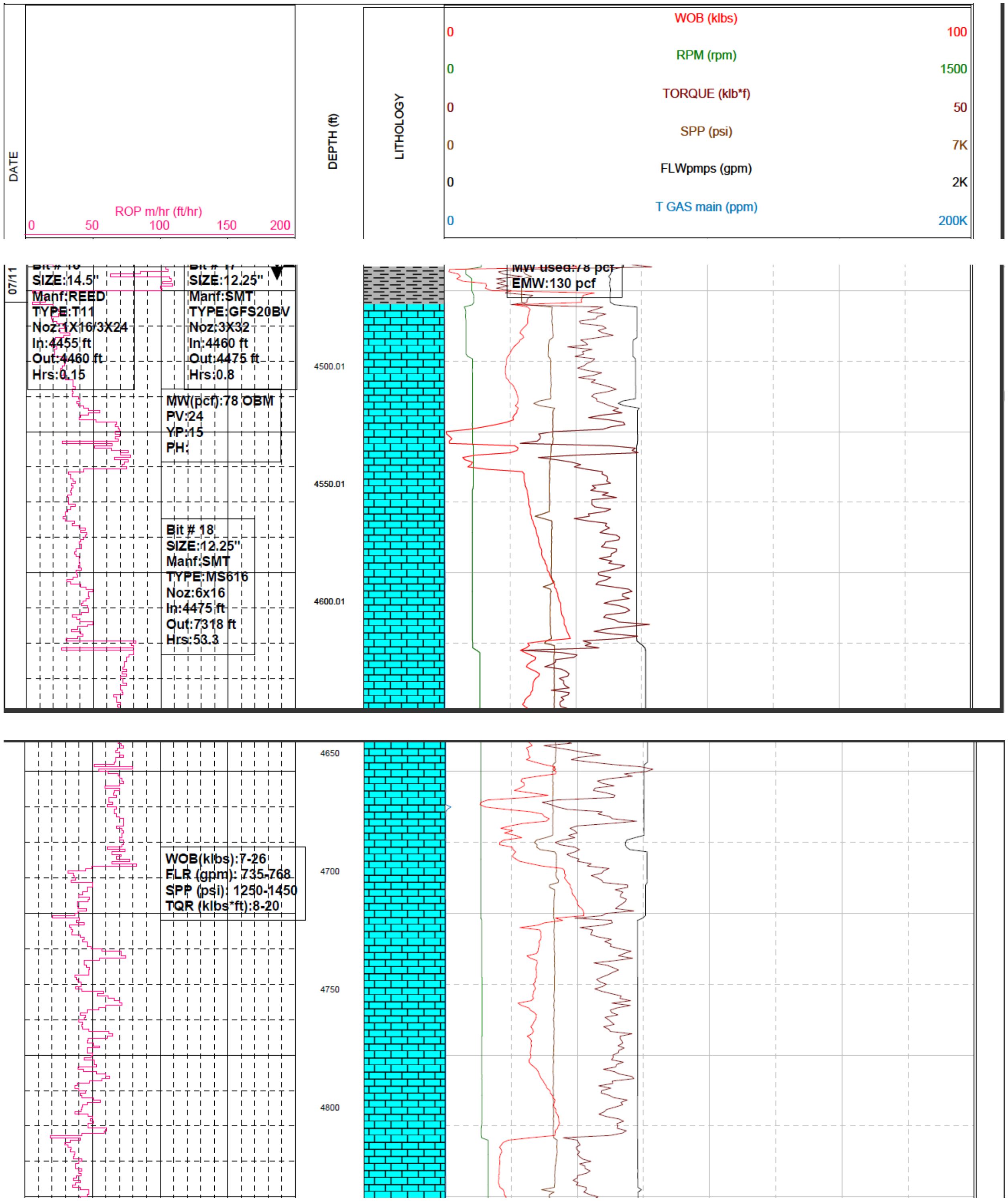
Table 12: General information for Section 1 Well 1 (4480ft-7213ft)

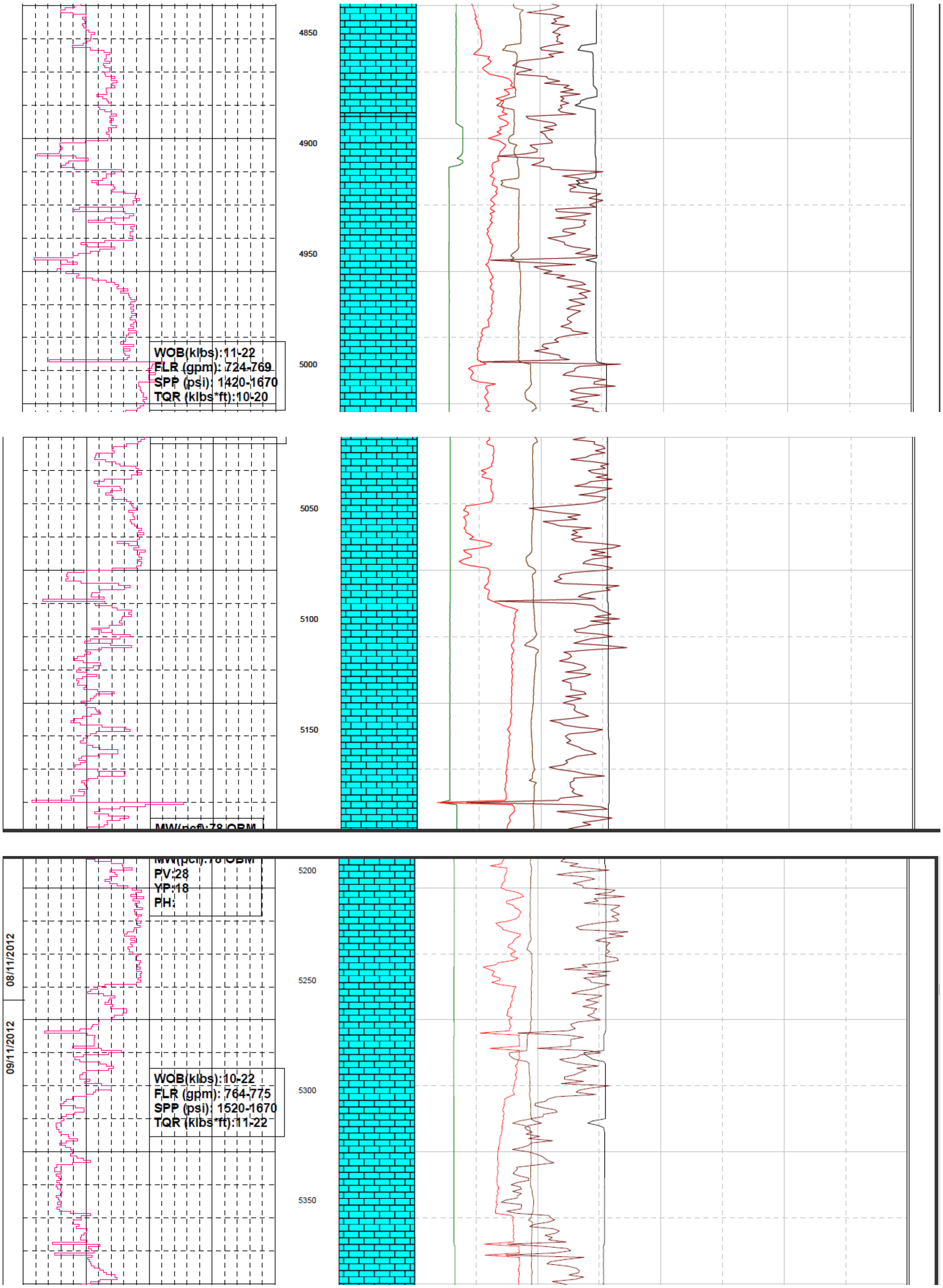
Bit No.	18
Manufacturer	Smith
Type	MS616
Diameter	12.25
Nozzles	6x16
Depth Set in	4475
Depth out	7318

Table 13: Measured drilling parameters statisticsfor Section 1 Well 1

	WOB (klbf)	RPM (rpm)	T (kft.lbf)	Mud Flow (galUS/min)	ROP (ft/h)
min	1.026	62	6.360	379.86	28.34
max	39.753	142	20.883	779.16	84.76
range	38.727	81	14.522	399.30	56.42
average	19.028	114	15.769	756.42	54.90
SD	7.113	13	2.589	34.51	8.97

Mud ECD= 10.5 ppg


DATE
ROP m/hr (ft/hr)
0 50 100 150 200
DEPTH (ft)
LITHOLOGY
WOB (klbs) 0 100
RPM (rpm) 0 1500
TORQUE (klb*f) 0 50
SPP (psi) 0 7K
FLWpmps (gpm) 0 2K
T GAS main (ppm) 0 200K
07/11
SIZE:14.5"
Manf:REED
TYPE:T11
Noz:1X16/3X24
In:4455 ft
Out:4460 ft
Hrs:0.15
SIZE:12.25"
Manf:SMT
TYPE:GFS20BV
Noz:3X32
In:4460 ft
Out:4475 ft
Hrs:0.8
MW(pcf):78 OBM
PV:24
YP:15
PH:
Bit # 18
SIZE:12.25"
Manf:SMT
TYPE:MS616
Noz:6x16
In:4475 ft
Out:7318 ft
Hrs:53.3
EMW:130 pcf
4500.01
4550.01
4600.01
4650
4700
4750
4800
WOB(klbs):7-26
FLR (gpm): 735-768
SPP (psi): 1250-1450
TQR (klbs*ft):8-20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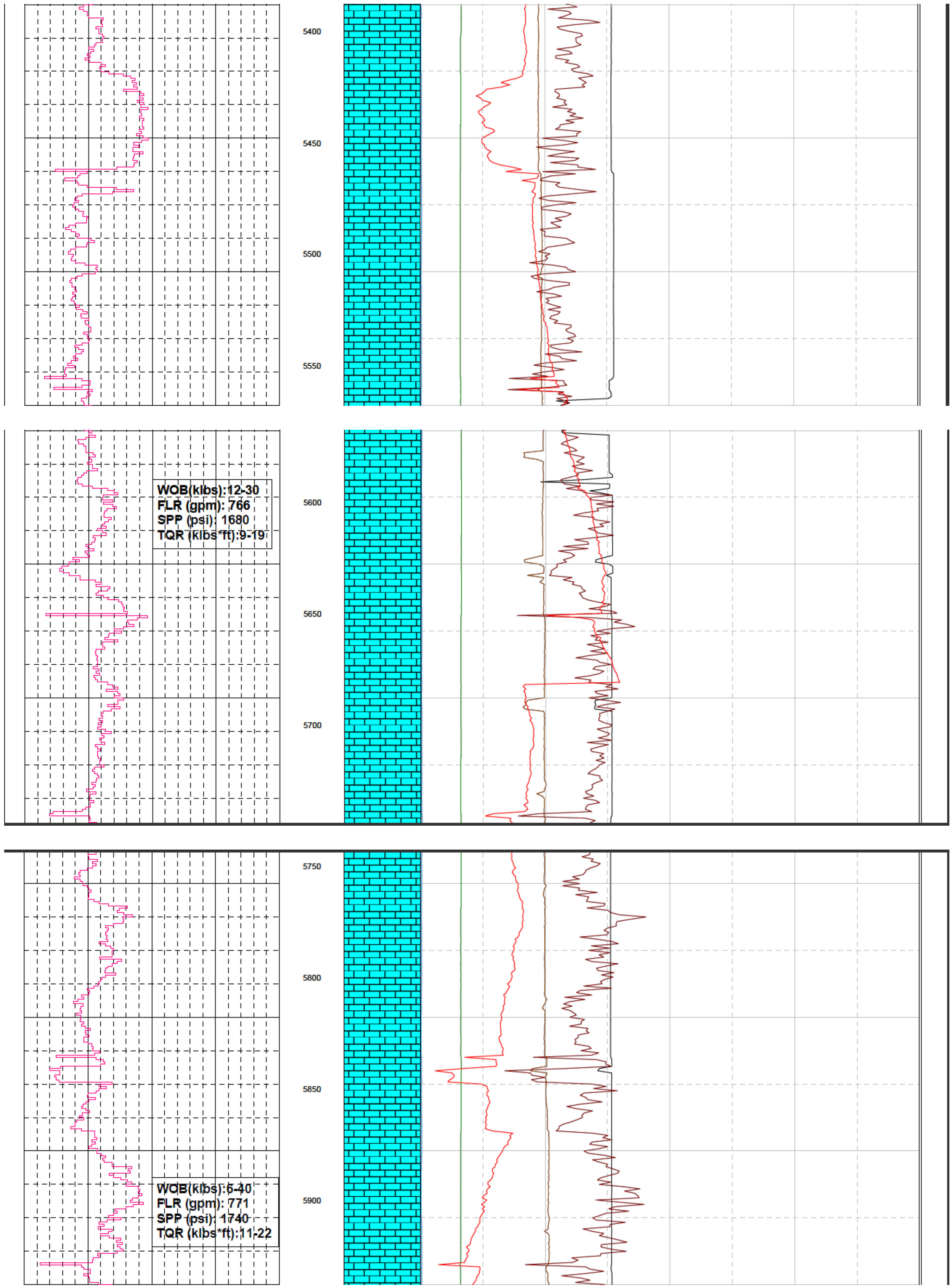
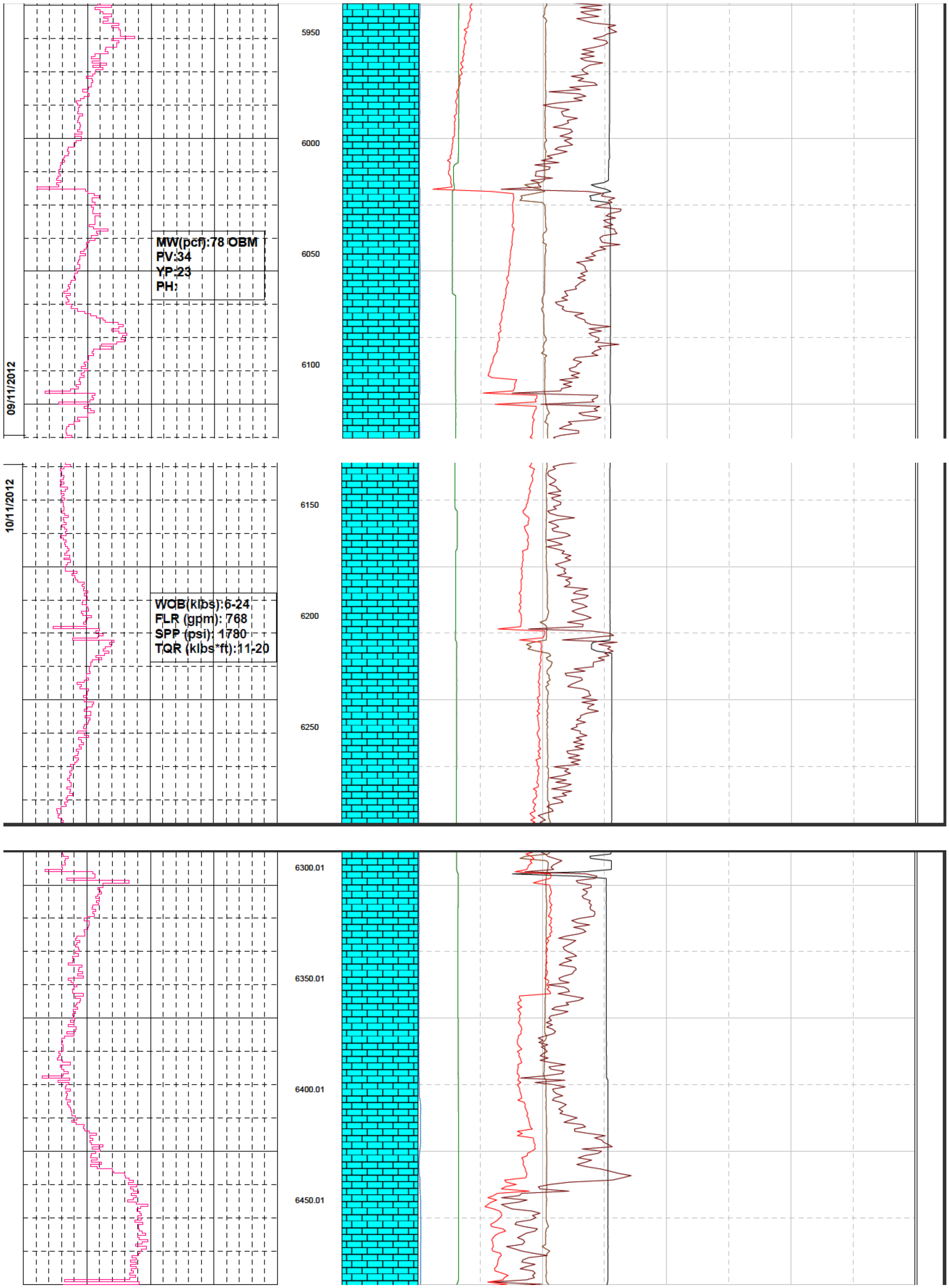
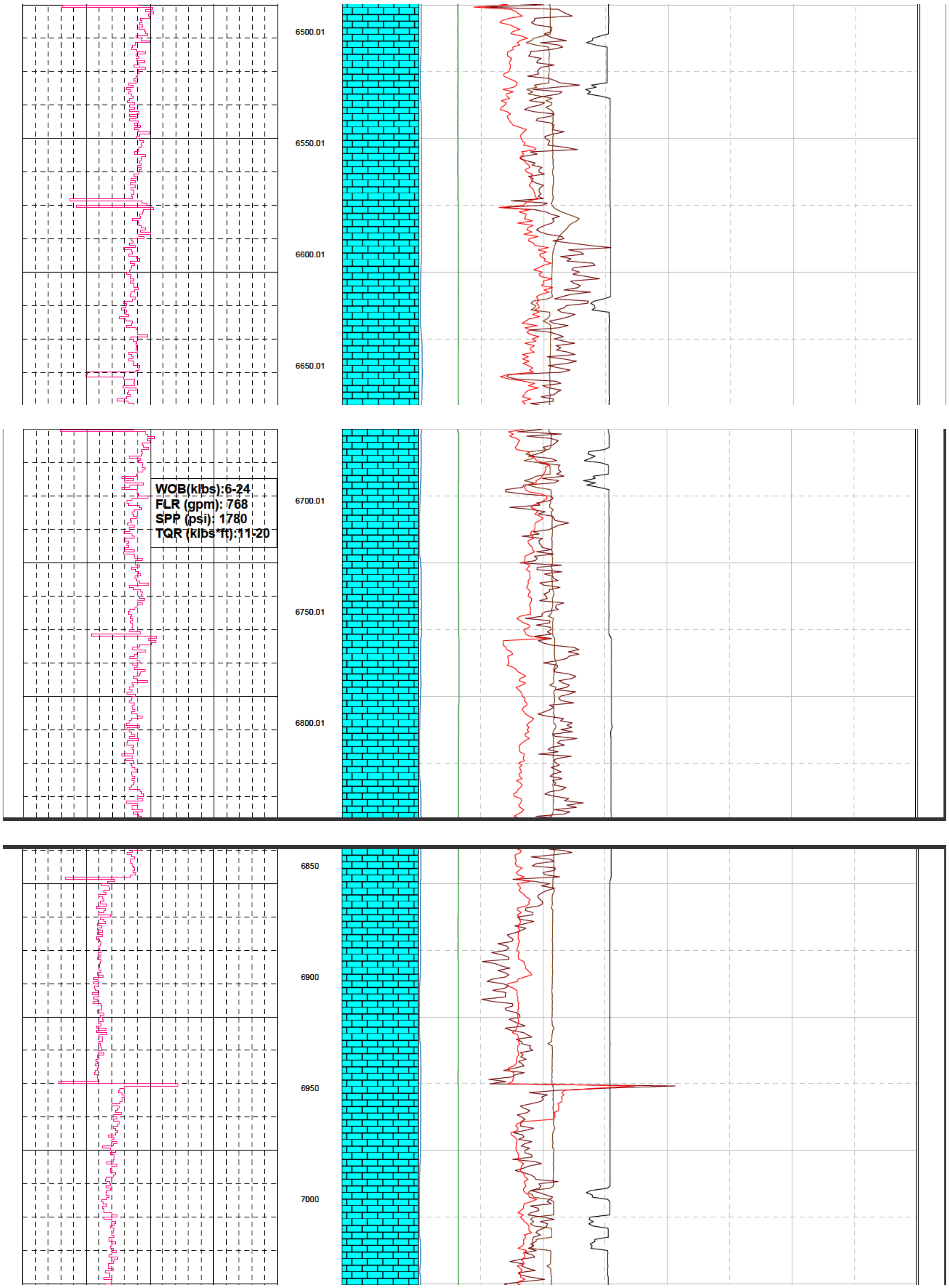
4900
4950
5000
WOB(klbs):11-22
FLR (gpm): 724-769
SPP (psi): 1420-1670
TQR (klbs*ft):10-20
5050
5100
5150
MW(pcf):78 OBM
PV:28
YP:18
PH:
5200
5250
08/11/2012
09/11/2012
5300
WOB(klbs):10-22
FLR (gpm): 764-775
SPP (psi): 1520-1670
TQR (klbs*ft):11-22
5350


5400
5450
5500
5550
WOB(klbs):12-30
FLR (gpm): 766
SPP (psi): 1680
TQR (klbs*ft):9-19
5600
5650
5700
5750
5800
5850
5900
WOB(klbs):6-40
FLR (gpm): 771
SPP (psi): 1740
TQR (klbs*ft):11-22



09/11/2012
10/11/2012
MW(pcf):78 OBM
PV:34
YP:23
PH:
WOB(klbs):6-24
FLR (gpm): 768
SPP (psi): 1780
TQR (klbs*ft):11-20
5950
6000
6050
6100
6150
6200
6250
6300.01
6350.01
6400.01
6450.01


6500.01
6550.01
6600.01
6650.01
WOB(klbs):6-24
FLR (gpm): 768
SPP (psi): 1780
TQR (klbs*ft):11-20
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6850
6900
6950
7000

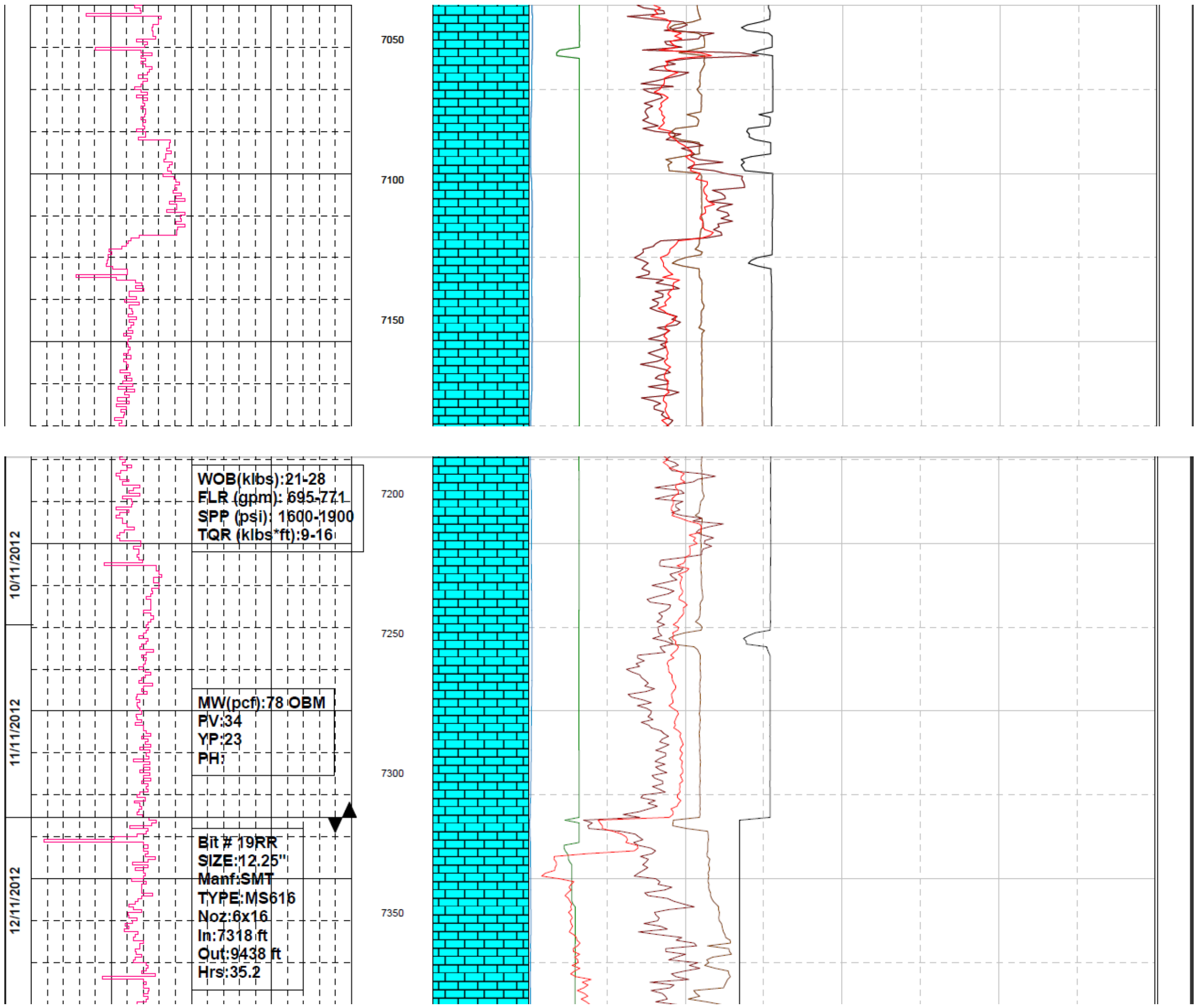


Figure 48: Lithology of Section 1 Well 1 (4480ft – 7213ft)

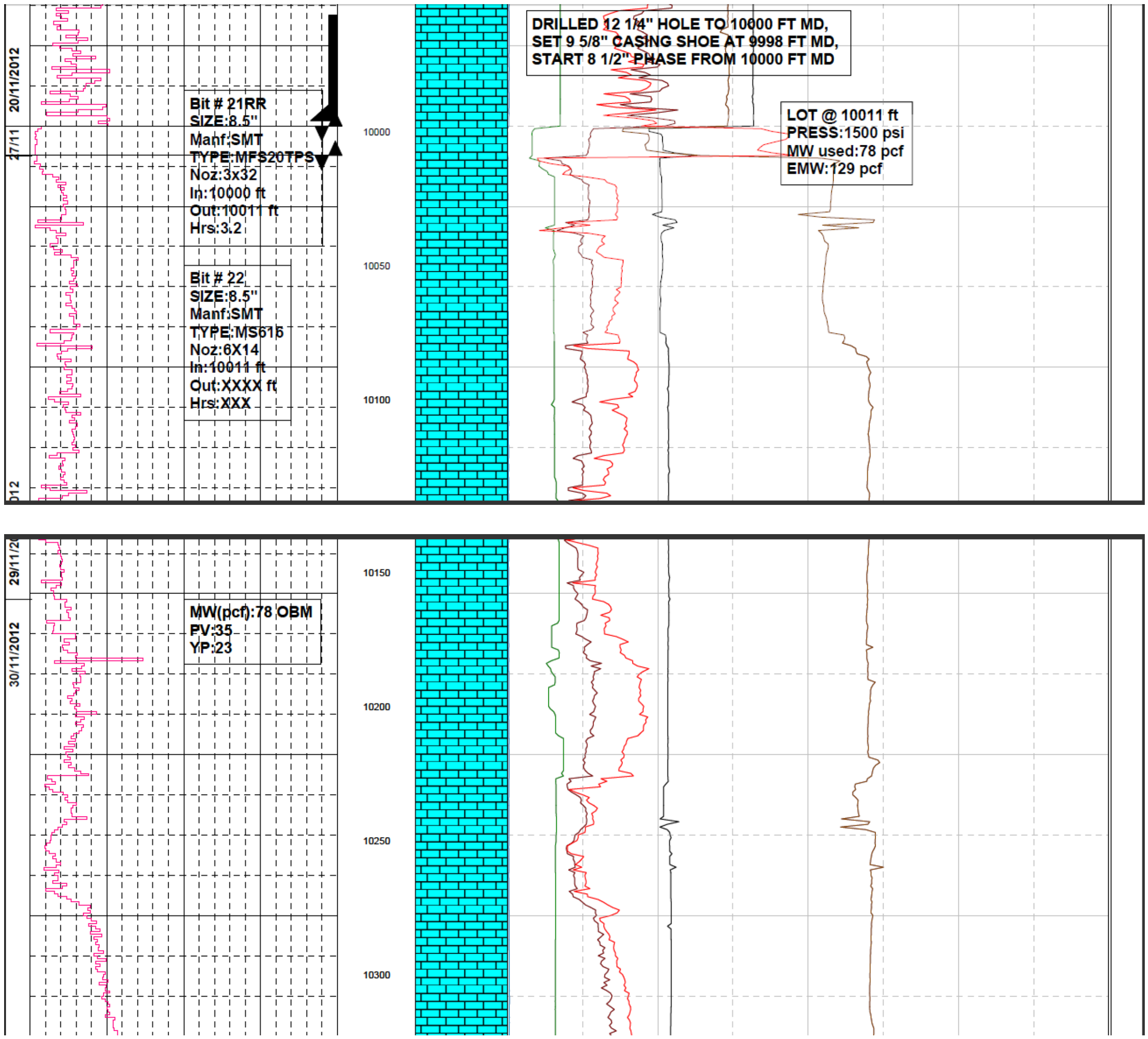
Table 14: General information for Section 2 Well 1 (10022ft-14380ft)

Bit No.	22
Manufacturer	Smith
Type	MS616
Diameter	8.5
Nozzles	6x14
Depth Set in	10011
Depth out	xxxx

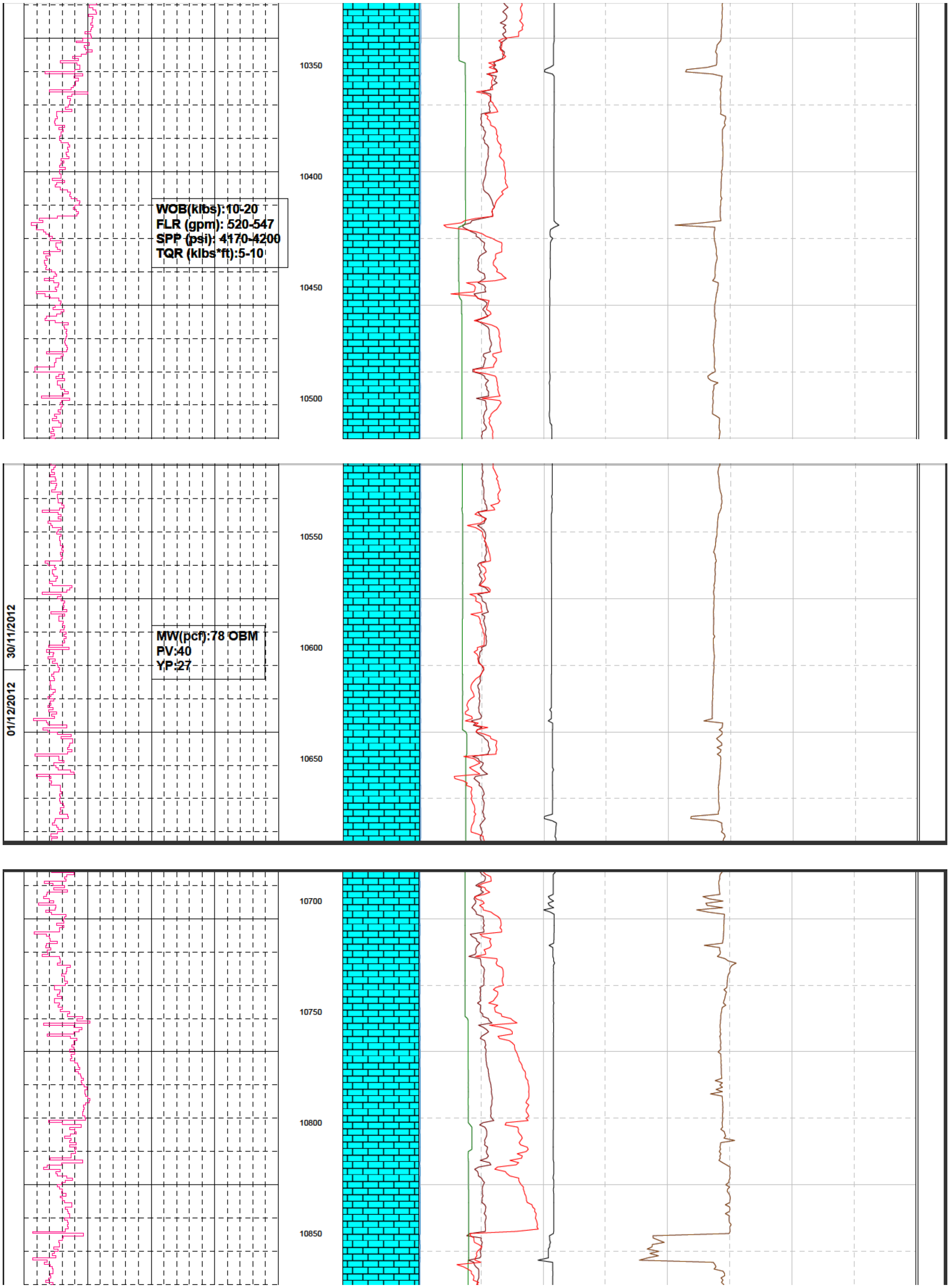
Table 15: Measured drilling parameters statistics for Section 2 Well 1

	WOB (klbf)	RPM (rpm)	T (kft.lbf)	Mud Flow (galUS/min)	ROP (ft/h)
min	1.630	103	4.965	263.94	15.48
max	24.911	162	10.026	693.27	57.92
range	23.281	59	5.061	429.32	42.44
average	13.841	147	7.816	530.09	39.29
SD	4.657	8	0.928	26.27	7.96

Mud ECD= 10.5 ppg



20/11/2012
27/11
29/11/20
30/11/2012
Bit # 21RR
SIZE:8.5"
Manf:SMT
TYPE:MFS20TPS
Noz:3x32
In:10000 ft
Out:10011 ft
Hrs:3.2
Bit # 22
SIZE:8.5"
Manf:SMT
TYPE:MS616
Noz:6X14
In:10011 ft
Out:XXXX ft
Hrs:XXX
MW(pcf):78 OBM
PV:35
YP:23
10000
10050
10100
10150
10200
10250
10300
DRILLED 12 1/4" HOLE TO 10000 FT MD,
SET 9 5/8" CASING SHOE AT 9998 FT MD,
START 8 1/2" PHASE FROM 10000 FT MD
LOT @ 10011 ft
PRESS:1500 psi
MW used:78 pcf
EMW:129 pcf


10350
10400
WOB(klbs):10-20
FLR (gpm): 520-547
SPP (psi): 4170-4200
TQR (klbs*ft):5-10
10450
10500
10550
30/11/2012
01/12/2012
MW(pcf):78 OBM
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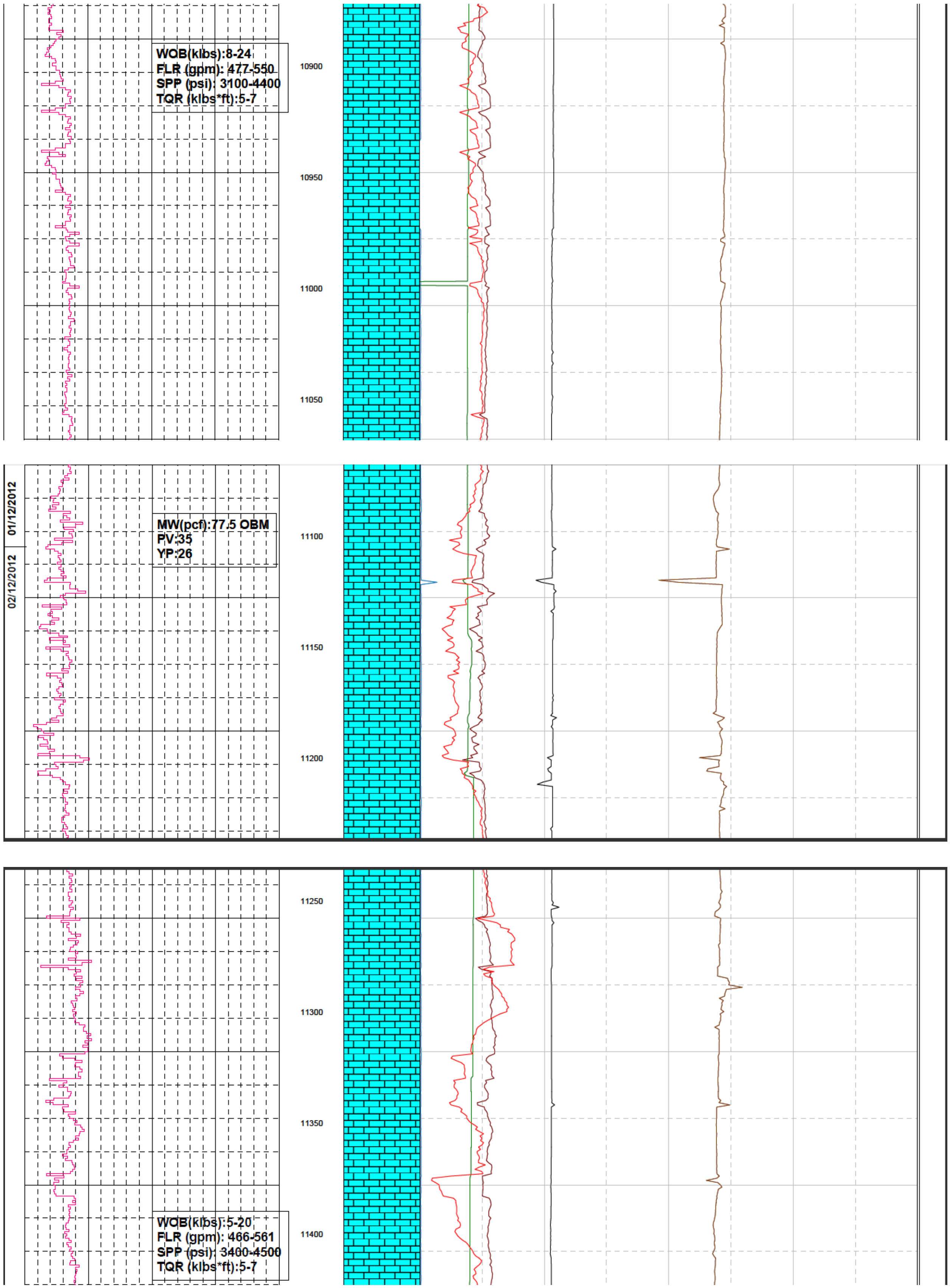
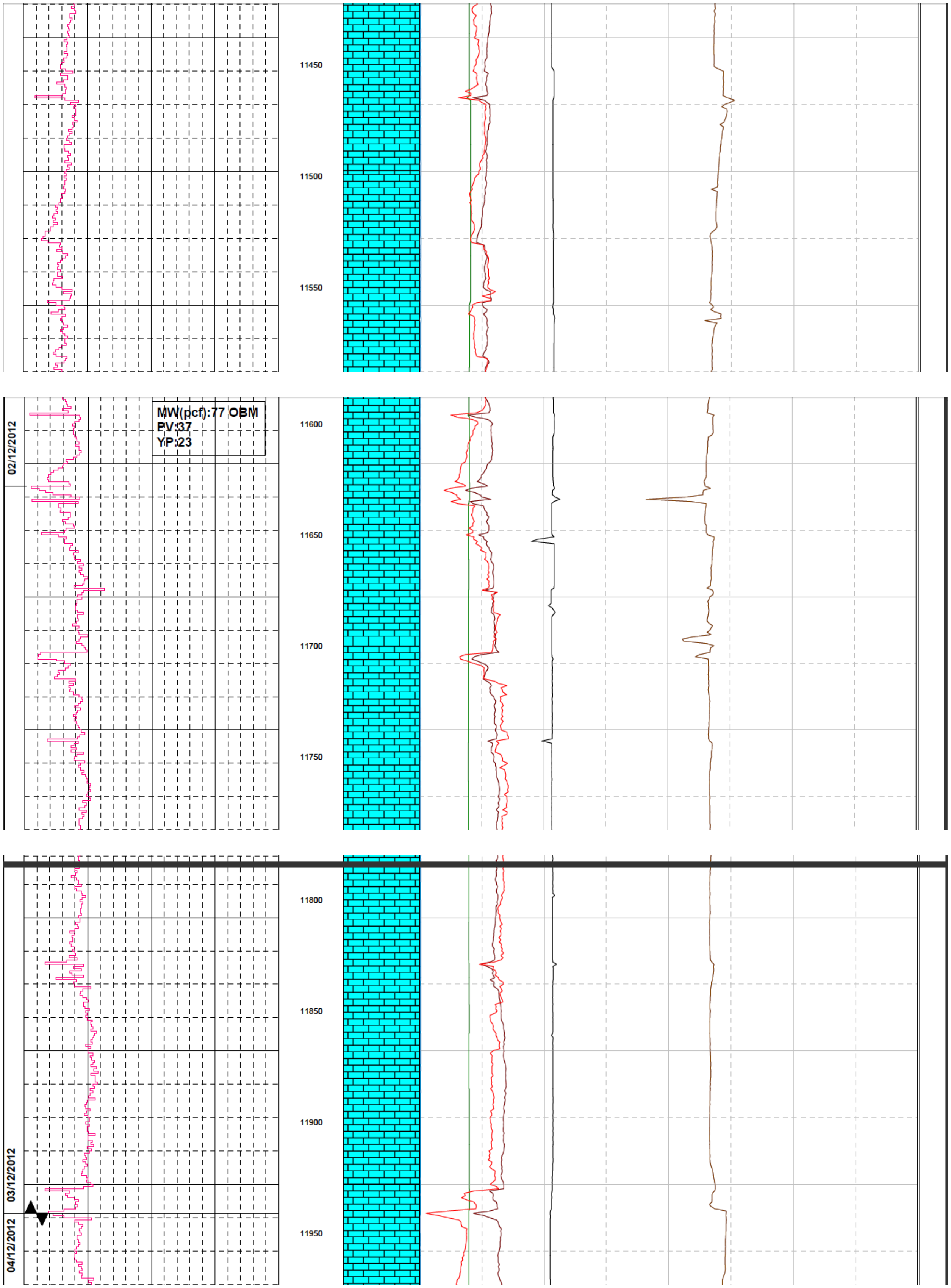
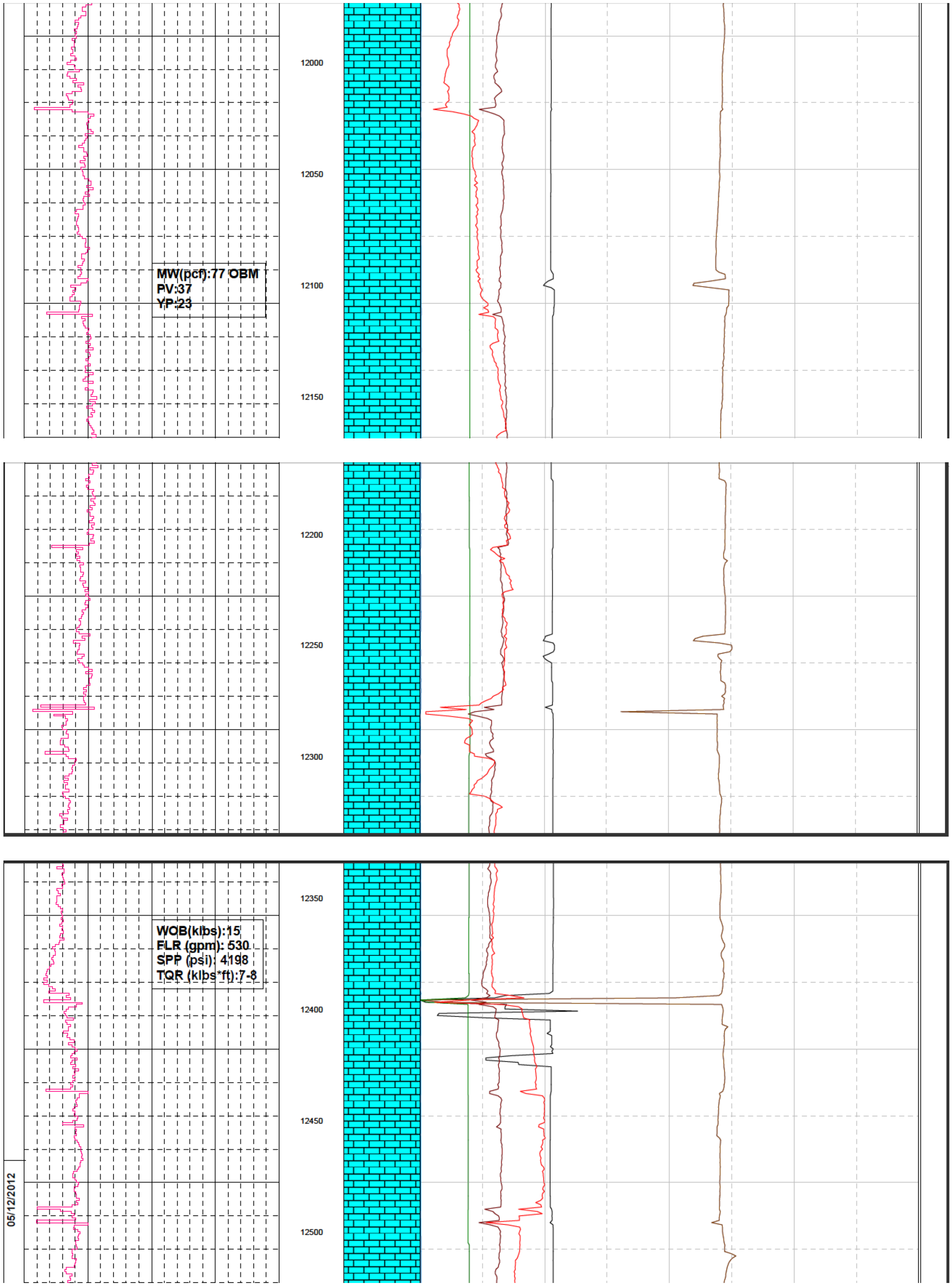
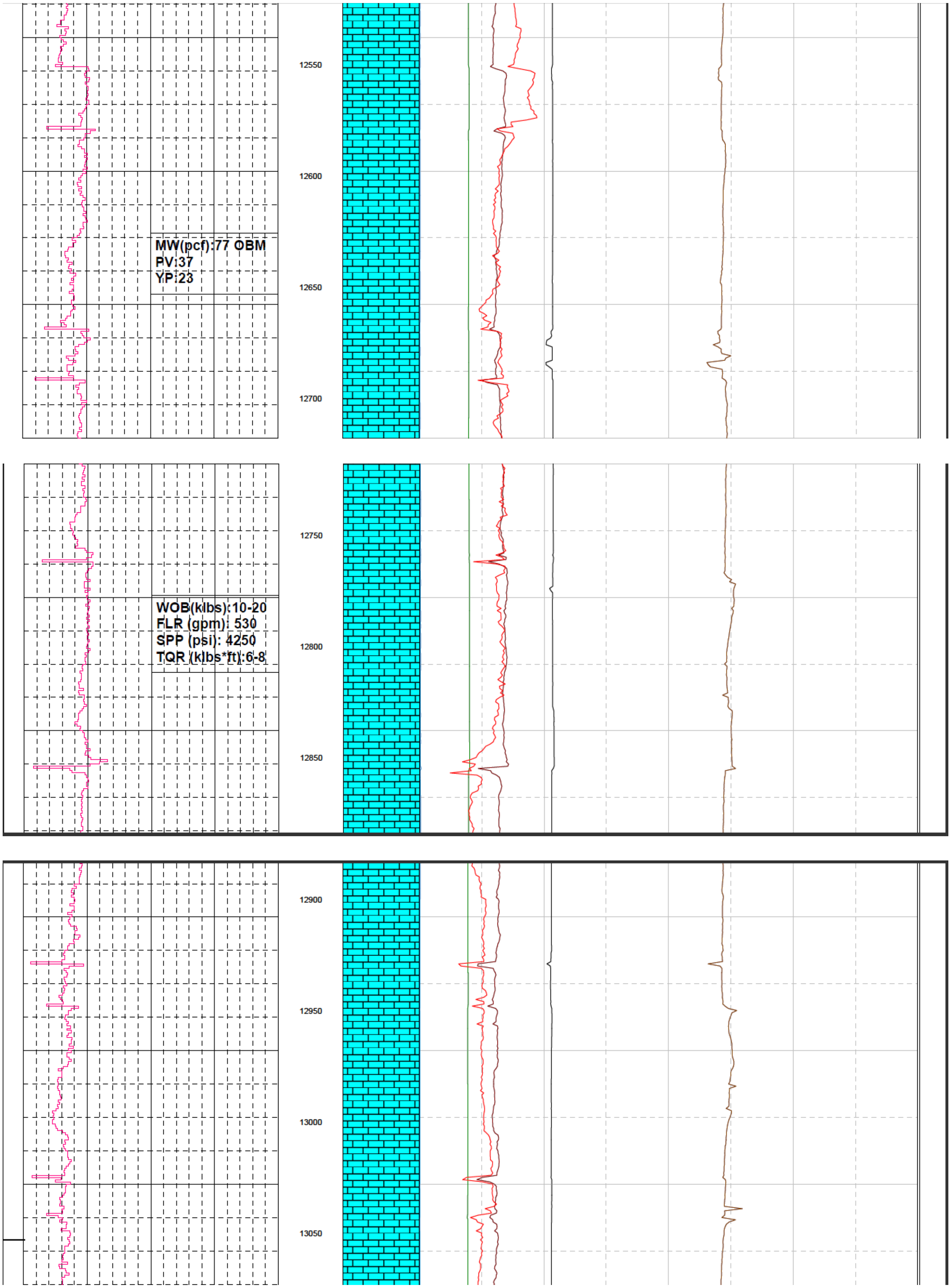
YP:27
10600
10650
10700
10750
10800
10850

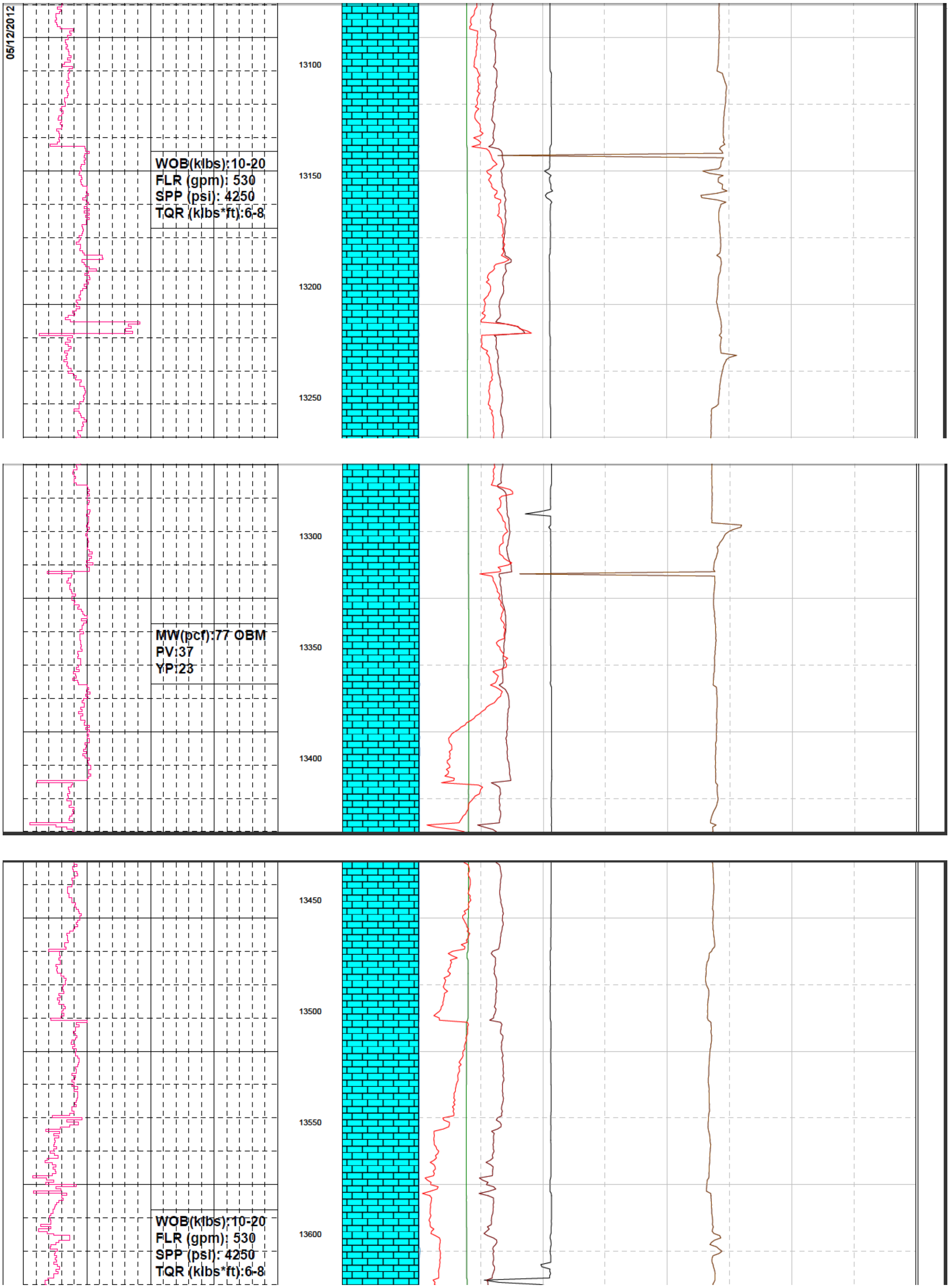

WOB(klbs):8-24
FLR (gpm): 477-550
SPP (psi): 3100-4400
TQR (klbs*ft):5-7
10900
10950
11000
11050
01/12/2012
02/12/2012
MW(pcf):77.5 OBM
PV:35
YP:26
11100
11150
11200
11250
11300
11350
11400
WOB(klbs):5-20
FLR (gpm): 466-561
SPP (psi): 3400-4500
TQR (klbs*ft):5-7

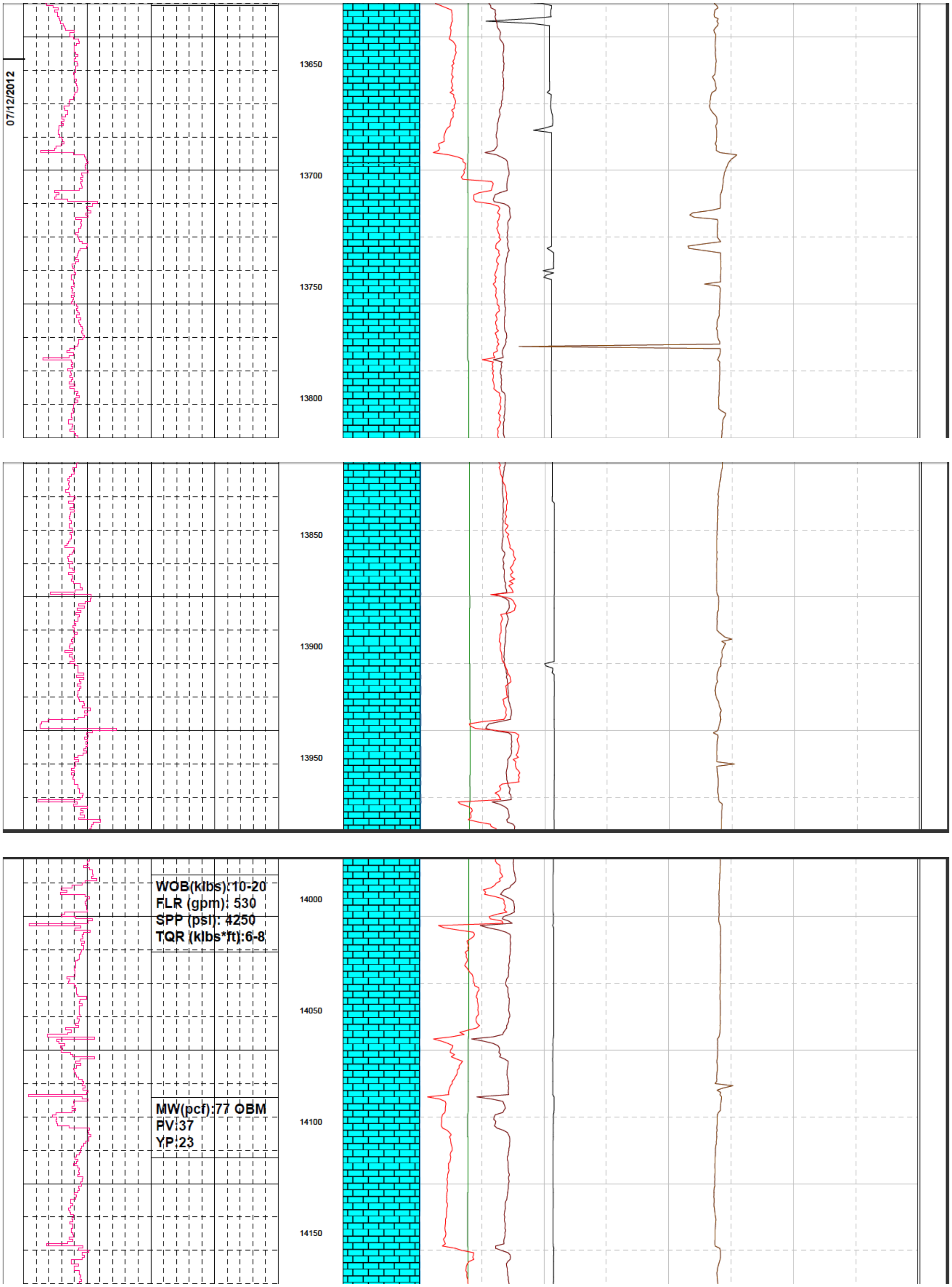

11450
11500
11550
02/12/2012
MW(pcf):77 OBM
PV:37
YP:23
11600
11650
11700
11750
11800
11850
11900
03/12/2012
04/12/2012
11950


12000
12050
12100
12150
MW(pcf):77 OBM
PV:37
YP:23
12200
12250
12300
12350
12400
12450
12500
WOB(klbs):15
FLR (gpm): 530
SPP (psi): 4198
TQR (klbs*ft):7-8
05/12/2012



12550
12600
MW(pcf):77 OBM
PV:37
YP:23
12650
12700
12750
WOB(klbs):10-20
FLR (gpm): 530
SPP (psi): 4250
TQR (klbs*ft):6-8
12800
12850
12900
12950
13000
13050


05/12/2012
WOB(klbs):10-20
FLR (gpm): 530
SPP (psi): 4250
TQR (klbs*ft):6-8
13100
13150
13200
13250
13300
MW(pcf):77 OBM
PV:37
YP:23
13350
13400
13450
13500
13550
13600
WOB(klbs):10-20
FLR (gpm): 530
SPP (psi): 4250
TQR (klbs*ft):6-8


07/12/2012
13650
13700
13750
13800
13850
13900
13950
14000
WOB(klbs):10-20
FLR (gpm): 530
SPP (psi): 4250
TQR (klbs*ft):6-8
14050
14100
MW(pcf):77 OBM
PV:37
YP:23
14150

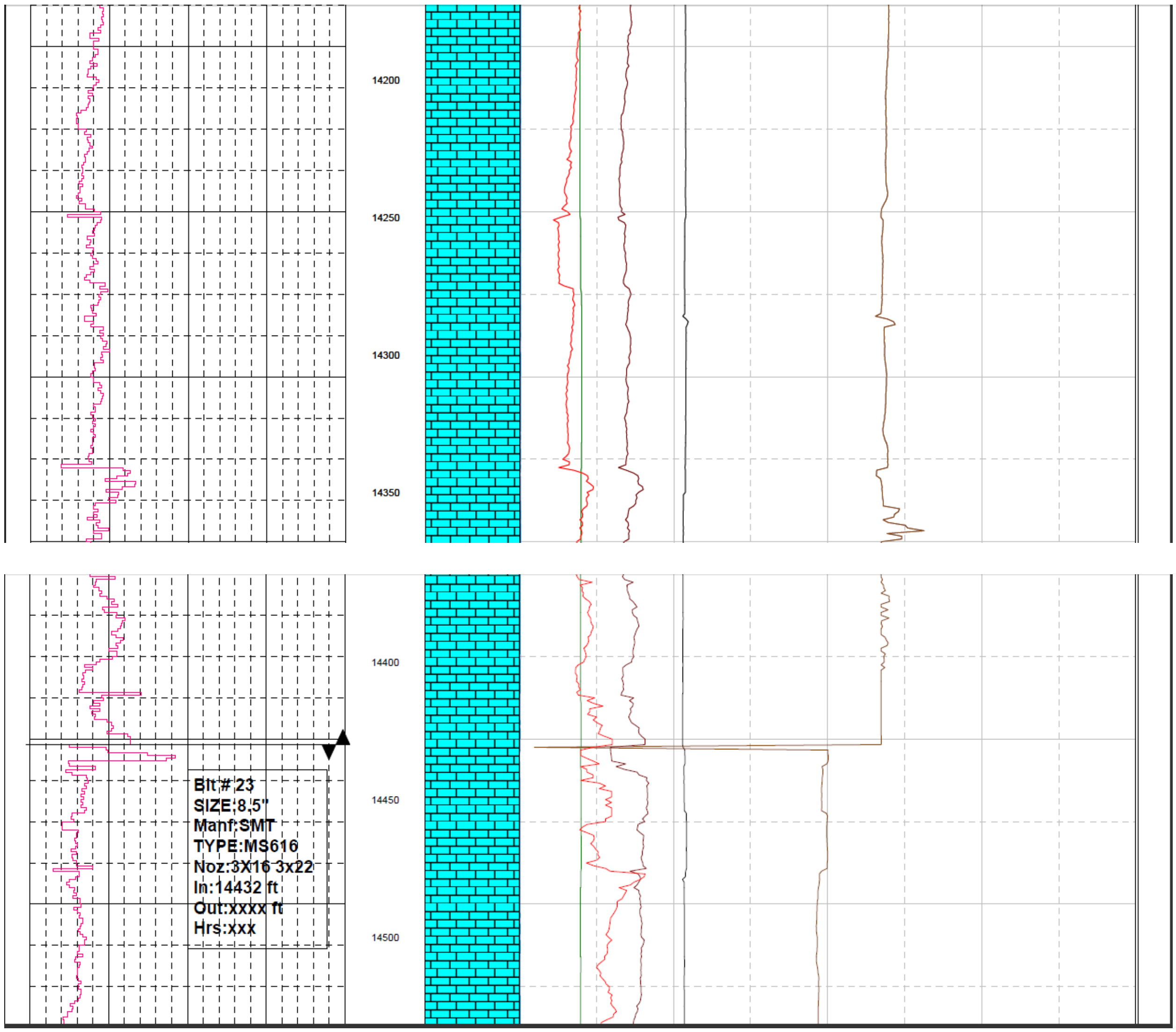


Figure 49: Lithology of Section 2 Well 1(10022ft-14380ft)

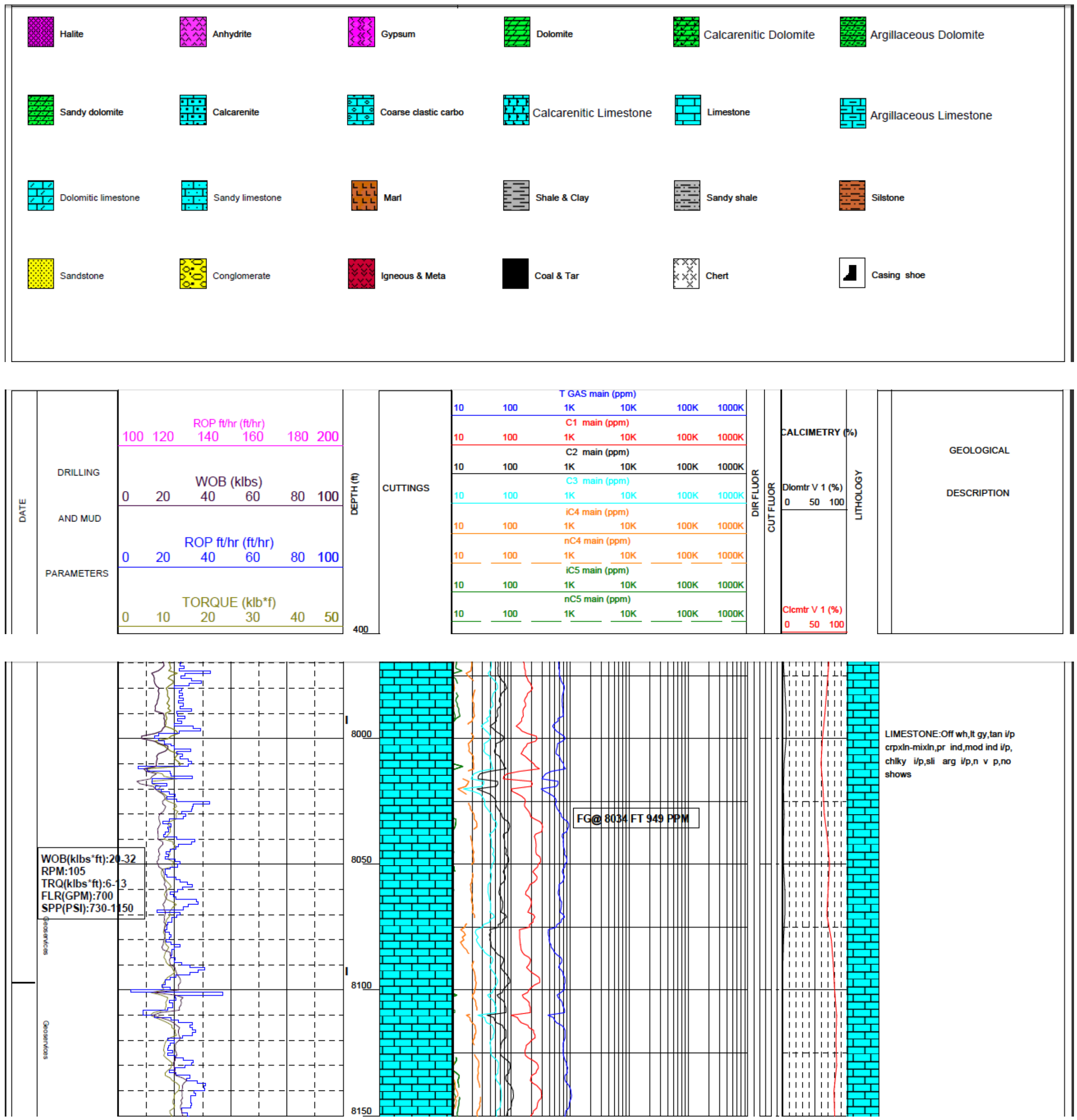
Table 16: General information for Section 1 Well 2 (8043ft-8530ft)

Bit No.	7
Manufacturer	VAREL
Type	MKS78W
Diameter	12
Nozzles	8X18
Depth Set in	7557
Depth out	xxxx

Table 17: Measured drilling parameters statistics for Section 1Well 2

	WOB (klbf)	RPM (rpm)	T (kft.lbf)	Mud Flow (galUS/min)	ROP (ft/h)
min	17.053	104	7.9955	664.71	10.07
max	46.671	105	15.6210	789.66	45.16
range	29.619	1	7.6255	124.95	35.09
avrg	35.205	105	12.7653	698.09	32.36
SD	7.323	0	1.3864	5.64	6.34

Mud ECD= 11.18 ppg


Halite
Anhydrite
Gypsum
Dolomite
Calcarenitic Dolomite
Argillaceous Dolomite
Sandy dolomite
Calcarenite
Coarse clastic carbo
Calcarenitic Limestone
Limestone
Argillaceous Limestone
Dolomitic limestone
Sandy limestone
Marl
Shale & Clay
Sandy shale
Silstone
Sandstone
Conglomerate
Igneous & Meta
Coal & Tar
Chert
Casing shoe
DATE
DRILLING
AND MUD
PARAMETERS
ROP ft/hr (ft/hr)
100 120 140 160 180 200
WOB (klbs)
0 20 40 60 80 100
ROP ft/hr (ft/hr)
0 20 40 60 80 100
TORQUE (klb*f)
0 10 20 30 40 50
DEPTH (ft)
CUTTINGS
T GAS main (ppm)
C1 main (ppm)
C2 main (ppm)
C3 main (ppm)
iC4 main (ppm)
nC4 main (ppm)
iC5 main (ppm)
nC5 main (ppm)
10 100 1K 10K 100K 1000K
DIR FLUOR
CUT FLUOR
CALCIMETRY (%)
Dlomtr V 1 (%)
0 50 100
Clcmtr V 1 (%)
0 50 100
LITHOLOGY
GEOLOGICAL
DESCRIPTION
400
8000
8050
8100
8150
WOB(klbs*ft):20-32
RPM:105
TRQ(klbs*ft):6-13
FLR(GPM):700
SPP(PSI):730-1150
FG@ 8034 FT 949 PPM
LIMESTONE:Off wh,lt gy,tan i/p
crpxln-mixln,pr ind,mod ind i/p,
chlky i/p,sli arg i/p,n v p,no
shows

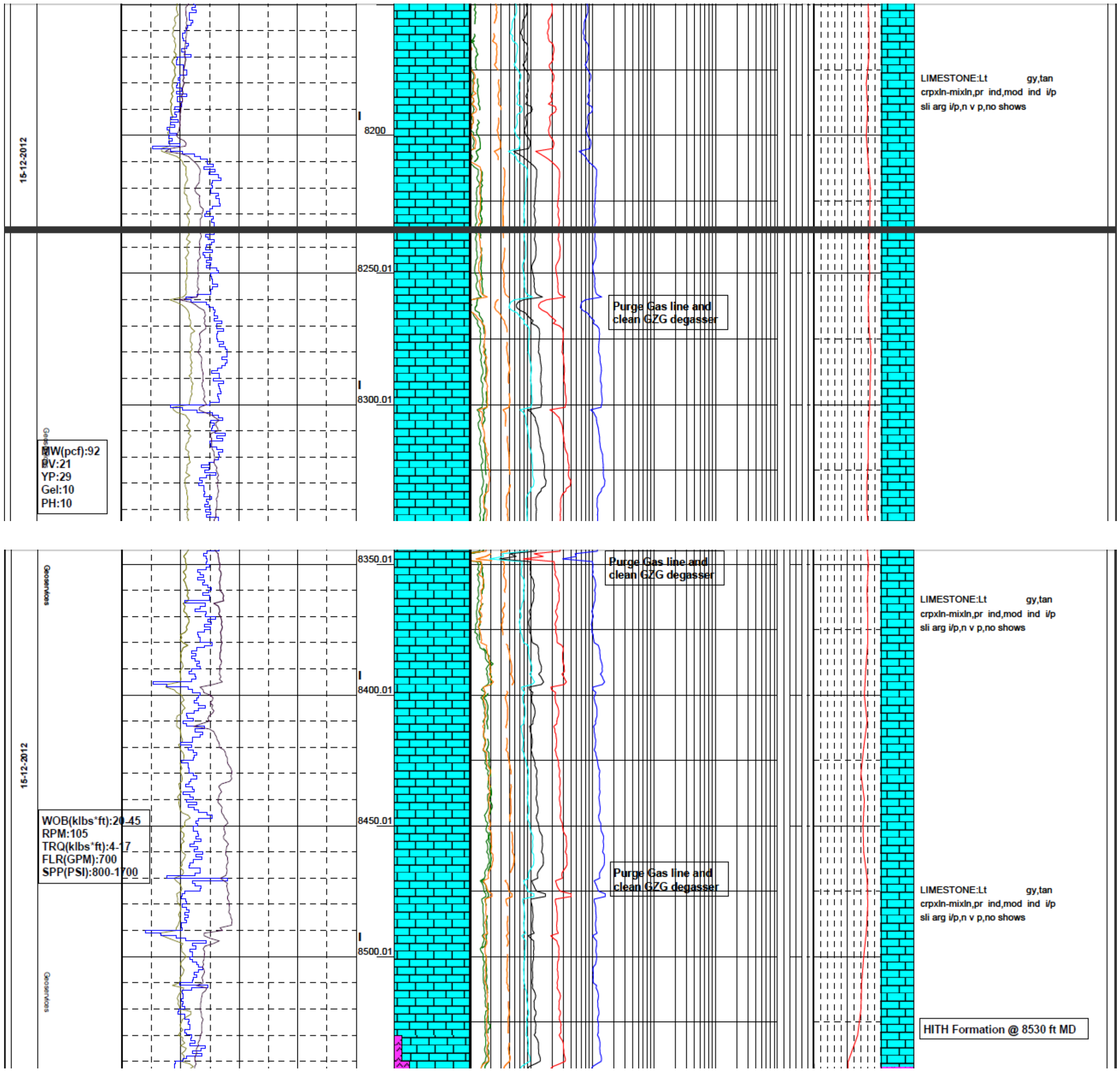


Figure 50: Lithology of Section 1 Well 2(8043ft-8530ft)

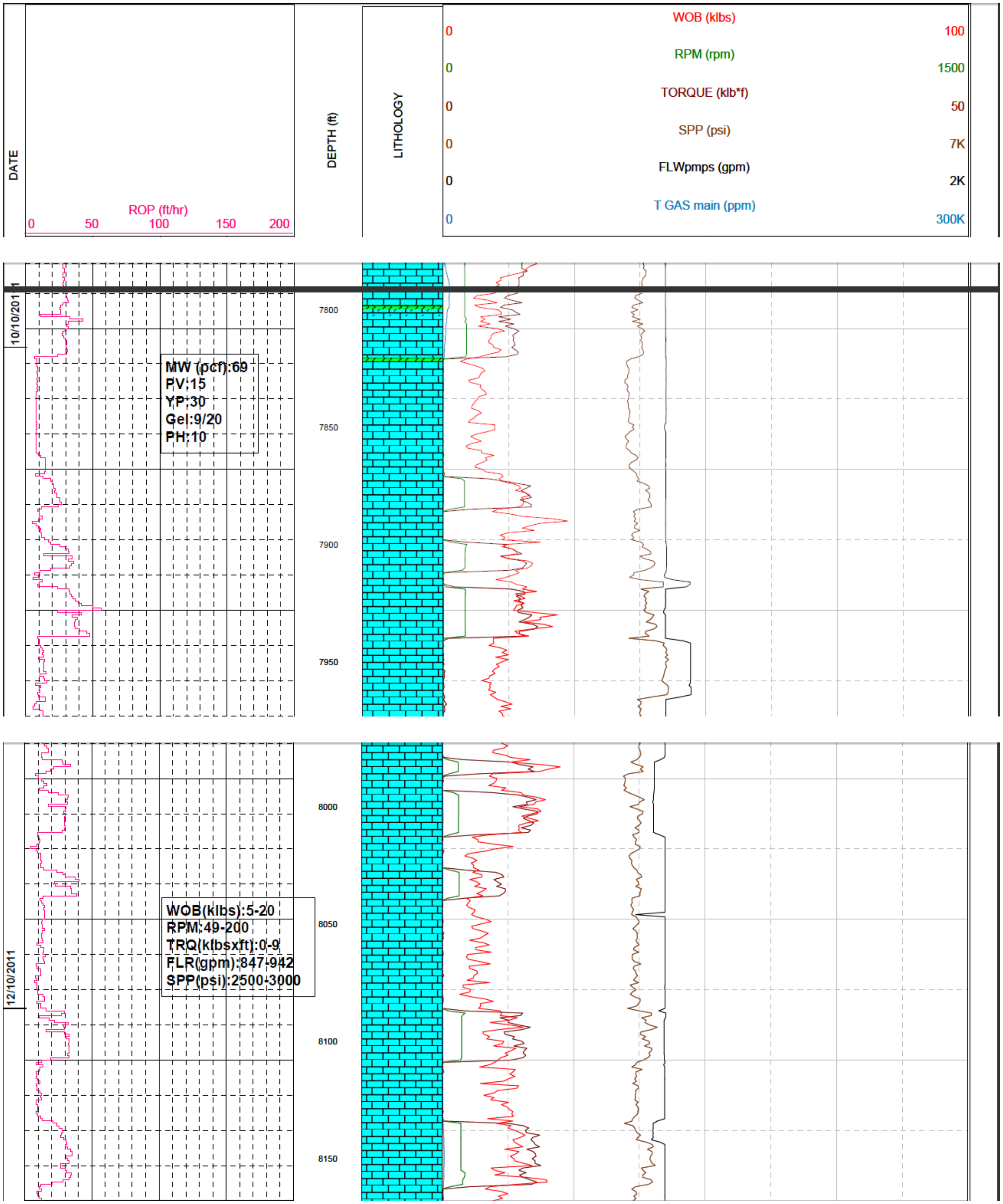
Table 18: General information for Section 1 Well 3 (7804ft-9746ft)

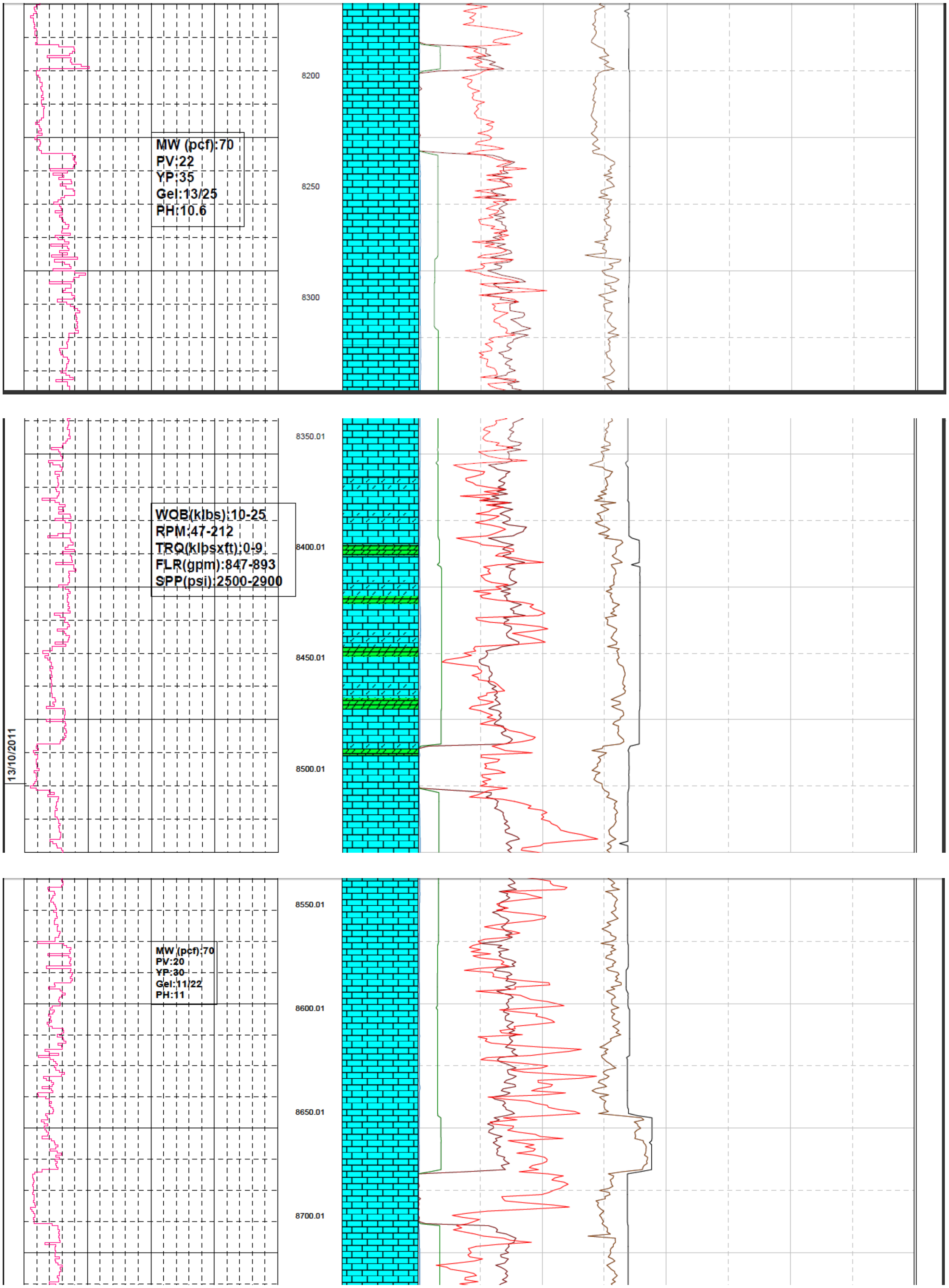
Bit No.	9
Manufacturer	SEC
Type	FMH39632
Diameter	16
Nozzles	12X12
Depth Set in	7700
Depth out	10025

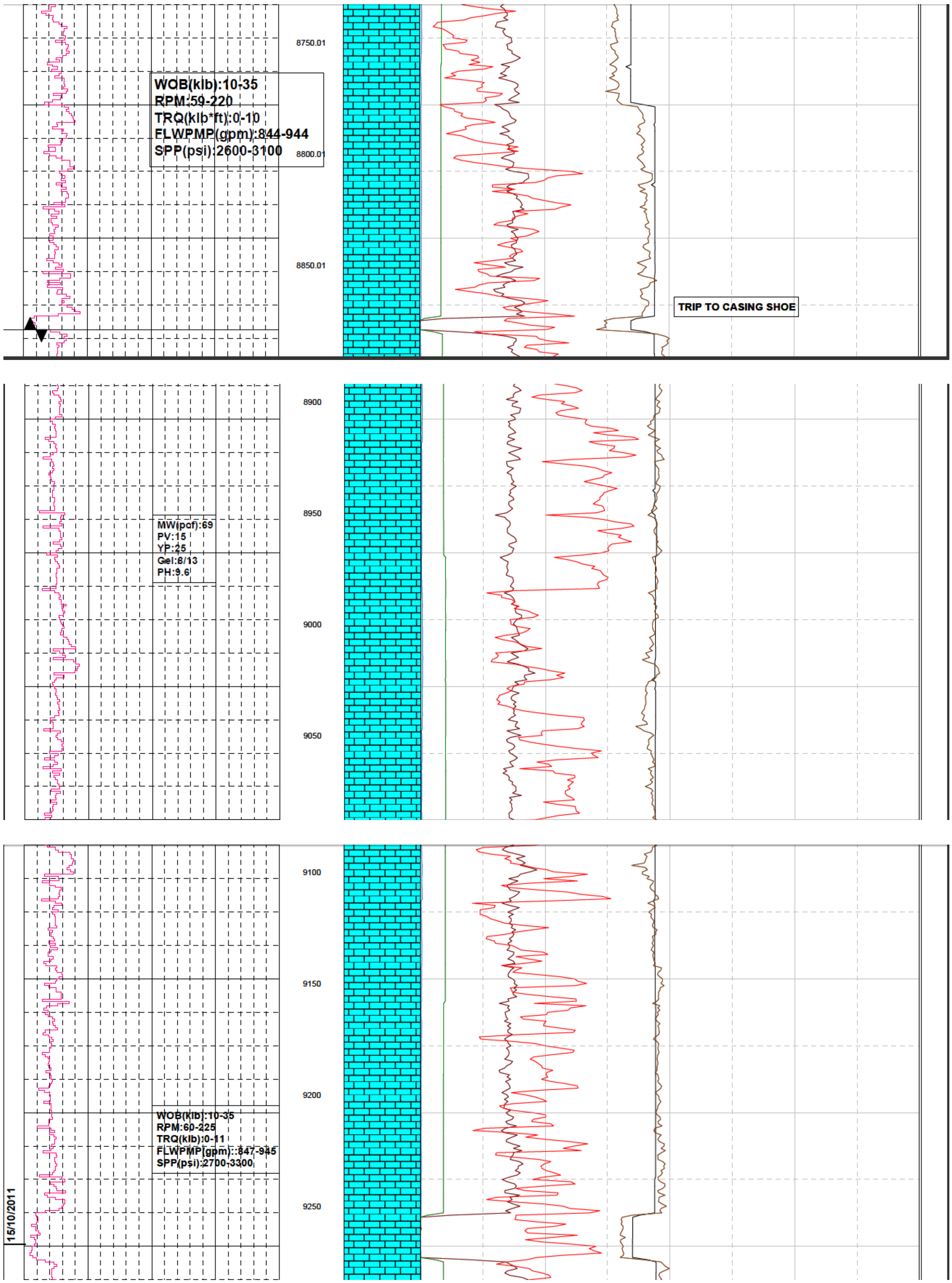
Table 19: Measured drilling parameters statistics for Section 1 Well 3

	WOB (klbf)	*RPM* (rpm)	*T* (kft.lbf)	Mud Flow (galUS/min)	*ROP* (ft/h)
Min.	4.641	47	5.775	850	14.93
Max.	45.000	75	11.749	940	37.32
Range	40.359	28	5.974	90	22.39
Average	20.952	66	8.906	913.59	23.66
SD	8.251	5	0.780	40.35	3.85

Mud ECD= 9.26 ppg


DATE
ROP (ft/hr)
0
50
100
150
200
DEPTH (ft)
LITHOLOGY
WOB (klbs)
0
100
RPM (rpm)
0
1500
TORQUE (klb*f)
0
50
SPP (psi)
0
7K
FLWpmps (gpm)
0
2K
T GAS main (ppm)
0
300K
10/10/2011
7800
7850
7900
7950
MW (pcf):69
PV:15
YP:30
Gel:9/20
PH:10
8000
8050
8100
8150
12/10/2011
WOB(klbs):5-20
RPM:49-200
TRQ(klbsxft):0-9
FLR(gpm):847-942
SPP(psi):2500-3000


8200
MW (pcf):70
PV:22
YP:35
Gel:13/25
PH:10.6
8250
8300
8350.01
WOB(klbs):10-25
RPM:47-212
TRQ(klbsxft):0-9
FLR(gpm):847-893
SPP(psi):2500-2900
8400.01
8450.01
13/10/2011
8500.01
8550.01
MW (pcf):70
PV:20
YP:30
Gel:11/22
PH:11
8600.01
8650.01
8700.01



8750.01
WOB(klb):10-35
RPM:59-220
TRQ(klb*ft):0-10
FLWPMP(gpm):844-944
SPP(psi):2600-3100
8800.01
8850.01
TRIP TO CASING SHOE
8900
8950
MW(pcf):69
PV:15
YP:25
Gel:8/13
PH:9.6
9000
9050
9100
9150
9200
WOB(klb):10-35
RPM:60-225
TRQ(klb):0-11
FLWPMP(gpm)::847-945
SPP(psi):2700-3300
9250
15/10/2011

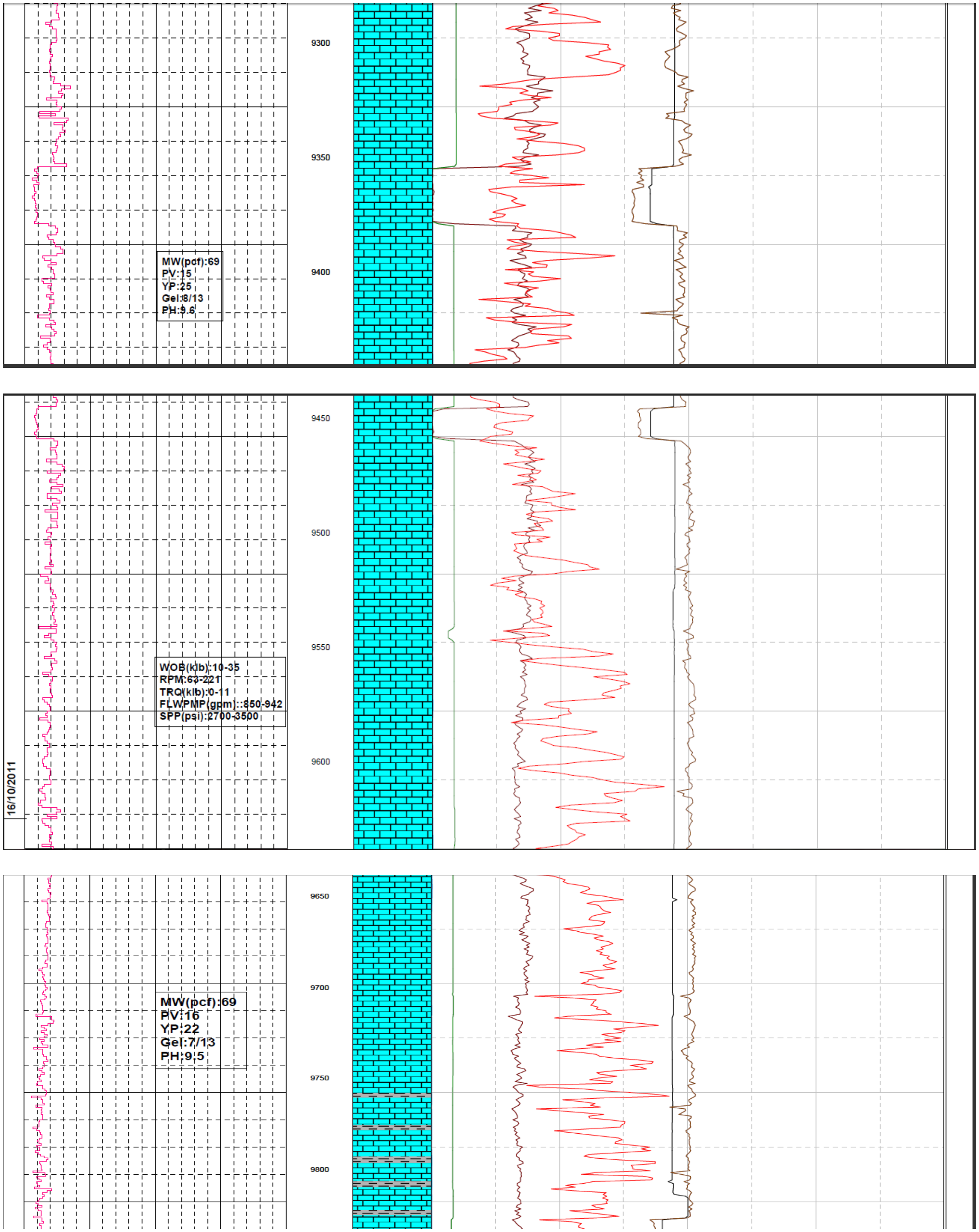


Figure 51: Lithology of Section 1 Well 3(7804ft-9746ft)

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