



Real-Time Drilling Optimization Based on MWD Dynamic Measurements – Field Test Results

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Abstract

Real-time drilling optimization that relies solely on surface data has proven ineffective because it does not take into account the behavior of the BHA downhole. Surface weight-on-bit and rotary speed optimized for maximum penetration rate is of little use if it induces severe downhole vibration that results in costly damage to the BHA. An MWD drilling dynamics measurement tool is, therefore, a required component of a closed loop drilling control system (DCS).

This paper presents the initial field-test results of a control system that uses a neural network for predictive control in drilling optimization. The system was tested on-line during a controlled field experiment at the Baker Hughes Experimental Test Area in Mounds, Oklahoma. Essentially, the system acquires surface and downhole data and generates quantitative advice (best weight-on-bit and rotary speed, etc.) for the Driller.

Key aspects of the field test were evaluating the performance of the DCS, and characterization of the formation being drilled by the downhole drilling dynamics measurements. During the test there was no real-time telemetry link between the MWD sub and the surface, and data from an offset well was used successfully to describe the formation. The relationship between these formation parameters and the dynamic measurements was investigated off-line, once the dynamics information was retrieved at the surface. Such a scenario may be likely, at least in the short term, due to the time-delay in getting MWD information to surface.

This successful field-test is an encouraging additional step towards real-time drilling optimization using a closed loop drilling control system.

Introduction

During the past 20 years the high-profile technology developments within the energy industry have focused primarily on production, this being driven by the move to deepwater and other challenging environments. Development of downhole and surface drilling technology has, to a great degree, been left to the service companies and drilling contractors. The high spread-costs of deepwater exploration has resulted in the drive for improved drilling performance in harsh and expensive environments, coupled with a demand for greater reliability from increasingly more complex

downhole Measurement While Drilling tools.

These goals are not exclusive, but rather are interdependent, as it is unacceptable to optimize one to the detriment of the other. Hence the need for a system that takes a combination of surface and downhole data inputs, and recommends drilling parameters selected so as to optimize rate-of-penetration (ROP) while at the same time allowing the BHA to behave within acceptable limits.

The project discussed in this paper will be developed in two phases:

Phase I: The development of an "Advisor" system that utilizes downhole dynamics data and surface drilling parameters, to produce drilling models used to provide the Driller with recommended drilling parameters for optimized performance.

Phase II: This phase will link the output of an "Advisor" system directly with rig instrumentation systems so as to produce an automatic Driller that optimizes drilling while taking into account the downhole dynamics behavior. In other words, the industries first closed loop automated drilling control system.

Phase I is required for proof of concept. We will need to verify that the system is capable of generating meaningful advice with a high degree of consistency. Advice which, when followed by the Driller, results in improved drilling performance.

Before we can move from the Advisor phase to the true closed loop drilling control system, we will need to develop capabilities that require close interaction with a drilling contractor and a rig instrumentation provider; namely the development of a "man safe" system with well understood failure behavioral modes. There will also need to be links to hole cleaning and annular pressure calculations so as to ensure the annulus is not overloaded with cuttings. Final control of such a system would ultimately remain with the Driller. He should accept a DCS as just another tool to help him optimize the performance of his rig.

The benefits of such a closed loop Drilling Control System are many, and touch several aspects of the drilling and evaluation process.

Benefits Relating to Performance Drilling

- Improved ROP
 - Longer bit runs
 - More sections drilled in a single run
 - In gauge hole (Less formation drilled)
- Reduced downhole vibration
 - Less wasted energy downhole
 - Less trips due to MWD failure
 - Reduced BHA failure
- Steady state drilling
 - Consistent start up after connections

Benefits Relating to Formation Evaluation Measurements

- Improved quality of measurement
 - In gauge hole
 - Reduced time between drilling and measurement
 - Less vibration effects on measurements
- Improved MWD data transmission
 - Less noise due to vibration

What is envisioned is a Drilling Control System where you dial in acceptable vibration levels and request the system keep control parameters within an optimal range that falls within user defined end points. Specifically we would define minimum and maximum acceptable values for WOB, RPM and Torque, and for various types of vibration (lateral, axial and torsional). Tolerance of highly undesirable occurrences, such as whirl, bit bounce, stick-slip and, to some degree, torsional oscillation, would be set at a number approaching zero.

Brett, Warren and Wait [1] have published a paper dealing with their experiences with computer controlled drilling, in which they express their reservations about a computer controlled rig based on many issues such as the reliability of sensors, the maintenance of these same sensors, personnel requirements, and so on. This current project, however, rather than address the automation of an entire rig, aims only at obtaining the optimum drilling parameters (for example WOB and RPM) to produce the optimum rate-of-penetration while drilling. The optimum rate-of-penetration may be less than the maximum rate-of-penetration when damaging vibrations occur, or constraints are set (MWD logging speed, for example). In other words, a smart addition to existing WOB and RPM control systems.

Previous Attempts to Build a Drilling Control System

Over the past 50 years technological developments within surface systems has lagged the downhole arena. For evidence of this we need only compare the divergence in evolution of the aircraft and drill floor instrumentation panels of the 1950's through to the 1980's. Rig floor instrumentation had effectively stagnated. Early "Automatic Drillers" did little more than

maintain a constant WOB, and those that did attempt some form of ROP optimization did so without taking in to account the effects their parameter selection had on downhole dynamics.

In the late 1960's and early 70's attempts to develop various forms of drilling control systems [2, 3, 4] were taking place. At the same time the first meaningful papers were being presented on the identification and cause of damaging downhole dynamics [5]. Unfortunately there was a disconnect between the two efforts and early control systems either ignored the downhole dynamics component or recommended very broad actions, such as the practice of avoiding predefined bands of rotary speed. In one case a system was developed that had the potential to aggravate dynamics problems through the practice of maintaining constant RPM at the surface regardless of variations in torque [6]. These early attempts at automated control were further hindered by the state of existent rig instrumentation and control systems, and the available computing power. Several early systems included some form of expert-system, typically a rule based system overlaying a knowledge base. The disadvantage of such systems was their inability to cover all potential scenarios, and they quickly lost the confidence of the end-user.

In 1990 Brett, Warren and Wait [1] documented the most serious effort up to that point in time at "Computer-Controlled Drilling". In it, an important question was asked; in the dozen or so previous attempts at drilling control systems the conclusions and reports were always positive. Why then did not one of those efforts result in a commercial system being developed? The paper suggested that computer based drilling control systems were possible and capable of achieving meaningful results. However they stated that achieving an economically viable system was not a simple task primarily due to the cost of the improved rig instrumentation and control infrastructure required. It was postulated that this was the main issue underlying the failed emergence of a commercial system.

This is probably a valid assumption, but it should also be pointed out that even in the early 90's the efforts to develop DCS systems still paid little attention to the downhole dynamics component of the control equation, and would hence be limited in their capabilities.

The early 1990's saw the introduction of improvements to rig instrumentation systems that represented a step change in the drilling control process. Rig instrumentation networks, the majority running on some form of Profibus System, now had high-speed access to upwards of 2,500 rig sensors. The replacement of the old style band brake drawworks with new hydraulic based systems allowed for dynamic control of WOB both positively and negatively. New smarter "Automated Drillers" were introduced. Systems which could maintain steady drilling conditions by

referencing parameters such as WOB, RPM, Delta Standpipe Pressure and Torque. These systems were capable of swapping between the primary controlling parameter as conditions varied. However, they still lacked the important link to definitive downhole dynamic measurements.

The early 1990's also saw the introduction of the first reliable downhole dynamics measurements [7, 8]. Earlier work carried out on surface based measurement systems had proven the need for definitive downhole measurements. The cause and effect of dysfunctional dynamics was now understood. One of the last remaining hurdles to a viable drilling control system was the low telemetry rate between the downhole dynamics tools and the surface systems, which currently are typically 2-10 bps. Early attempts at using surface simulators to extrapolate anticipated downhole dynamics behavior [9] in order to provide advice on drilling parameter selection, were somewhat successful, but highlighted the complexity and non linear nature of the dynamics problem.

To overcome this problem the use of more complex and capable modeling tools, such as artificial neural networks (ANN) would be explored. Early tests, carried out in several areas of the energy industry [10, 11], show great promise.

Prior Work on Drilling Models

For the last couple of decades many varieties of mathematical models, usually termed drilling models, have been developed to describe the relationship between applied forces and motions (for example, weight-on-bit and rotary speed), and the obtained rate-of-penetration. Both analytical and numerical approaches were suggested to describe the very complex three-dimensional movement of the BHA.

In many of these empirical models the relationship was in terms of a "bulk" formation related parameter, such as the formation constants of Bingham's early work [12]. One of these constants was later related to formation pore pressure by Jordan and Shirley [13], and the use of drilling models as pore pressure "predictors" was initiated. There followed many models, such as Wardlaw's analytic model [14], Belloti and Gacia's sigma-factor [15], Warren's drilling models [16,17], Jogi's drillability equation [18], to name a few, all attempting to describe the relationship between control parameters and observed rate-of-penetration with varying degrees of complexity.

Once a model has described the relationship between the system input and output sufficiently well, then it should be possible to use that model to answer certain inverse questions, such as: "What is the weight-on-bit and rotary speed to obtain the optimum rate-of-penetration?" In other words, these models may be used in a drilling control system whose goal is to optimize the rate-of-penetration. However, cursory inspection reveals

that a more complete question is: "Given a certain size and type of bit, on the end of a certain drillstring, at a certain depth, drilling with certain mud properties and flow rates in a certain lithology, what is the weight-on-bit and rotary speed to obtain the optimum rate-of-penetration?" Unfortunately this question is so complex, involving the interaction of so many different components (only a few of which are listed), that it is difficult to utilize the developed drilling models to obtain an answer. In addition, the developed drilling models are linear while the drilling process contains non-linearities (the intersection of a bed boundary by the drill bit is an example), and the achievement of an optimized rate-of-penetration may result in destruction of the BHA, because most models do not deal with drillstring dynamics.

Any model that is to be used in a control system must deal with the dynamics of the drillstring. Applying a certain set of control parameters results not only in a certain rate-of-penetration, but also in certain motions and forces in the BHA, which must be measured downhole while drilling.

In some instances the results derived by the mathematical models are not in agreement with the field data. Common problems associated with the development of an analytical or numerical mathematical model of drillstring dynamics include:

- the desired complexity and universality of the model for detailed description of drilling phenomena is often compromised by practical limitations on the model's complexity (computation time, stability of the model);
- many parameters affecting the model are either unknown or insufficiently studied for proper modeling;
- the existence of an inaccurate description of the surface and downhole boundary conditions;
- the assumption of many factors, and the reduction in the number of key parameters taken into account by the model, decreases the overall accuracy of the model and in many cases the model becomes inadequate.

Drilling Process as Dynamic System

As shown above, there are many possible options for a mathematical description of the drilling process as a complex system with many influencing parameters. We have chosen to consider the drilling process as a dynamic system.

Dynamic systems can be viewed two ways: the internal view or the external view. The internal view - which attempts to describe the internal workings of the system, originates from classical mechanics. The prototype problem was the problem to describe the motion of the planets. For this problem it was natural to give a complete characterization of the motion of all planets. The other view on dynamic systems originated in electrical engineering. The prototype problem was to

describe electronic amplifiers. It was natural to view an amplifier as a device that transforms input voltages to output voltages and disregard the internal detail of the amplifier. This resulted in the input-output view of systems. Such models are often referred to as input-output models or “black box” models.

Due to the lack of real-time information about the internal state of the whole system, a “black box” approach is, in our opinion, better suited for modeling of the drilling process.

In our simplified approach, the drilling process is affected by the following inputs, which we divided into three main categories (Figure 1):

- Controls comprising Hook Load, Rotary Speed, and Mud Flow Rate;
- Environment, including, for example, lithology and mechanical properties of the formation, etc.;
- Hardware, which consists of BHA (Bottom Hole Assembly), drill bit, wellbore geometry, etc.

Controls and Environment change continuously while drilling; Hardware changes from run to run, but it is known and considered as a set of constants for a particular bit run. Environment is usually unknown or known approximately and partially from offset wells. Under the influence of these inputs (C, E, H) the drilling process generates responses, i.e. outputs of the “black box”. Some of them can be measured at the surface (surface responses – R_S), e.g. ROP, Surface Torque, oscillations of Hook Load and drill string RPM, etc., while others should be measured downhole (downhole responses – R_D), e.g. actual WOB, bit RPM variations, torque at the bit, other parameters characterizing drill bit dynamics. Responses measured downhole are preprocessed and decimated by a multi-channel MWD drilling dynamics tool to reduce the amount of data to be transmitted to the surface via a telemetry channel. If an MWD telemetry system is used then the downhole data are significantly delayed and further decimated.

Our approach implies that the Drilling Control System uses all available data to generate advice for the Driller or to deliver a command directly to the drilling control equipment, if this is an available option. In the first case it acts as a “Drillers’s Advisor”, in the second - as a “Closed Loop Drilling Control System”. In both cases, the DCS operates as a discrete system, on a time step-by-step basis. This time step, Δt (modeling time step), is bounded by a minimum value: $T_D \leq \Delta t$. This lower boundary (T_D) is determined by the availability of the “fastest” data and the speed we can process data at each time-step. With the data available so far, T_D is equal to five seconds.

Numerous experiments show that in general it takes in the order of two to three minutes for the Drilling Process to stabilize. This stabilization time (T_S) introduces a sort of “watershed” in the way we simulate

the drilling process. If T_D is significantly smaller than T_S and Δt can be chosen small, then the control system can trace the dynamics of the drilling process. In this case we speak of dynamic models – they trace how the responses change from one time step to the next one.

Otherwise, it is more practical to consider drilling as a sequence of “drilling steps”. Each step is a transition from one stable state to another stable state. The duration of each step is not fixed, but is determined by the events when changes in controls or in formation occur. In this case, we refer to static drilling models.

Models of the Drilling Process

Static Case

As experiments and experience show, the response of the system remains stable when controls and environment do not change. Changes in controls (C) and/or environment (E) disturb the system, but when the controls and environment stabilize, the system response stabilizes as well. Experiments show that the stabilization time is about two minutes, so if $\Delta t \geq T_S$ (modeling time step is greater than the stabilization time) then it is impossible to trace the dynamic behavior of the system. Instead, we consider drilling to be composed of a set of “drilling steps” (Figure 2). Each step is a transition from one stable state (C_n, E_n, R_n) to another stable state ($C_{n+1}, E_{n+1}, R_{n+1}$). Of course, the duration of each of these steps might be different.

We assume that there are only two reasons why transitions may occur: change in the values of the controls and/or environment. In this case R_{n+1} (the new values of the responses) can only depend on:

- new values of controls (C_{n+1}) and environment (E_{n+1});
- previous stable state (C_n, E_n, R_n);
- transition path (stage BD).

The last point is an especially difficult one to formalize. For example, as was observed during the field tests, even the same Driller may have different ways of changing the control values. It is thought that this factor need not be taken into account because the preliminary field tests show that when formation does not change (i.e. $E_n = \text{const}$) the system response (R_n) in the stable state depends only on the control values (C_n).

So, the following assumption was made as a working hypothesis: considering H being a constant, only controls C_{n+1} and environment E_{n+1} define R_{n+1} :

$$R_{n+1} = F(C_{n+1}, E_{n+1}) \quad (1)$$

Dynamic Case

As previously mentioned, the dynamic model of the drilling process applies when the modeling time step is much less than the system stabilization time.

A dynamic-systems approach to “black box” modeling based on the Takens Embedding Theorem was first

suggested by Casdagli [19]. The use of delay variables in the structure of these dynamical models is similar to that originally studied by Leontaritis and Billings [20], and is common in linear time-series analysis and system identification [21].

The key idea of this approach to nonlinear system identification is to embed the measured input-output variables in a higher dimensional space built not just with current values of controls and responses ($C(t)$, $R(t)$), but also transforms of C , R (for example their numerical derivatives). Practically, the behavior of the drilling process is described by embedding both the inputs and outputs in the form:

$$R_{n+1} = F_R(C_{n+1}, \{C_n, R_n\}, \dots, \{C_{n-N}, R_{n-N}\}) \quad (2)$$

where N is the number of time delays. Figure 3 illustrates this approach.

For example, a simple model (with just one delay) may use the current control values of $WOB(t_0)$ and $RPM(t_0)$, the current surface response of $TORQUE(t_0)$, the current response of $ROP(t_0)$, and the future controls of $WOB(t_0+\Delta t)$, and $RPM(t_0+\Delta t)$ to produce an estimate for the future $ROP(t_0+\Delta t)$ and $TORQUE(t_0+\Delta t)$ responses. More sophisticated models will use more delays, large sets of controls and responses as well as environmental data as inputs.

Due to a theorem of Takens these embedded models can be faithful to the dynamics of the original system. In particular, deterministic prediction is possible from an embedded model with a sufficient number of delays. Thus, embedding opens the way towards a general solution for extracting “black box” models of the observable dynamics of nonlinear systems directly from input-output time-series data. It can solve the fundamental existence problem for a class of nonlinear system-identification problems.

Utilization of NN for modeling.

In both approaches to simulate the drilling process we end up with the necessity to estimate some nonlinear function using the examples of input-output relations produced by the drilling process.

It was chosen to utilize neural networks for this task due to their “universal approximation” property [22]. Neural networks with at least a single hidden layer have been shown to be able to approximate any arbitrary function (with a finite number of discontinuities) if there are a sufficient number of basis functions (hidden neurons). By changing the structure of the neural network one may vary its capacity and generalization properties.

Structure of the DCS

A model created on the basis of “historical” data is applicable only in situations similar to those observed in the data used for the construction of the model. Since we want to optimize drilling performance over the entire

range of operational parameters, it is necessary to use models created with data from more than one well. This, as well as other requirements, led to the following strategy in implementing and using the Advisor (Figure 4):

- Data collected from different wells are merged and stored on a data server;
- After a new well has been planned and information about the BHA, drill bit, etc. is available, a request is made for the relevant data model;
- Using this information, models are created or extracted from the pool of available models;
- These models are used on the new well for optimization.

Advisor Structure

To make the system more robust, generic and easily extendable to future MWD tools, a modular structure of the Advisor was chosen (Figure 5). Each module is associated with some system response and the Advisor uses sets of selected modules to generate recommendations.

Modules have to comply with a predefined external interface, but no constraints are imposed on module implementation. In the current project, modules are based on Neural Network models, but other types of mathematical models may be considered.

Each module takes control parameters as inputs and produces a “cost” associated with the predicted value of the future response. “Costs” produced by different modules are normalized. This allows comparison of various responses, even if they are quite different in their nature (e.g. whirl vs. bit bounce). The set of responses considered for optimization, and the corresponding cost functions associated with them, define the optimization strategy.

During the real-time operation of the Advisor, models can be adapted using recent real-time drilling data when found necessary (Figure 6). This improves accuracy of the local prediction, both time- and state-wise, and increases stability of the control procedure.

Field Tests

It is impossible to have historical data for all combinations of parameters affecting drilling, and models based on input-output data will always do some interpolation and extrapolation.

A controlled field experiment was performed to test the developed software and to estimate the accuracy of the underlying neural network models. This test was carried out at the BETA (Baker Hughes Experimental Test Area) facility located near Tulsa, Oklahoma in June 2002.

A battery powered MWD drilling dynamics tool was used for downhole measurements. That multi-sensor tool acquires and processes a number of dynamic

measurements downhole, and calculates diagnostic parameters which quantify the severity of the drilling vibrations. These diagnostics are then immediately transmitted to the surface via MWD telemetry and/or stored into the tool memory.

During the field test the detailed data stored in the tool memory during drilling were dumped to the surface computer on a periodic basis. Information about the formation at BETA facility was also available from offset wells. A PDC bit used in the test is presented in Figure 7.

A serious constraint for the test selection was the time. As downhole data became available only at the end of each day, we had only limited time (until the next morning) to process the data and to create models. Although training of the NN model (when data are prepared and structure of NN is defined) does not require human interaction, it is nevertheless a rather time consuming process, especially for big data sets.

It was decided to use static models, which have fewer inputs and hence can be trained much faster. It allowed us to test the majority of the Advisor software package and to see some "action" in real-time during the test. Further data processing, as well as a comprehensive analysis of the dynamic models, was carried out in the office after the field test.

One of the required conditions for this test was to drill with various WOB and RPM and through different formations, in order to collect a diverse data set. This diverse data set was then used for the following offline study. Mud properties, flow rate and BHA/bit were kept constant through the entire testing to minimize the number of factors affecting the drilling process.

Tests of static models

During the test, the real-time computed True Vertical Depth (TVD) was used as a reference to determine formation properties at the corresponding depth from offset well data. Then these values together with surface WOB, surface RPM (all averaged on one-minute intervals) were used as inputs to the NN models to estimate ROP and downhole diagnostics. Computed values of ROP were compared to those actually observed. As Figure 8 illustrates they are in good agreement.

With all the needed data on hand, it was interesting to see if we can evaluate the properties of the formation at the bit using available dynamic data. For this purpose neural networks were created; they used the current values of WOB, RPM, ROP and downhole diagnostics as inputs. As Figure 9 illustrates, such straightforward attempts to estimate formation properties did not yield very good results.

Estimation of the formation at the bit may be very useful not only for the DCS but for other applications as well. During the course of this project there was no in-depth investigation of this problem, as it requires a quite

different approach to the design of NN predictors.

Dynamic Models

Testing of dynamic models was performed offline using data collected during the field test. Various parameters that affect the creation of NN model and influence its performance (i.e., how well it simulates the dynamic system) were evaluated in these tests. The testing included an assessment of the particular inputs used for NN training, the number of neurons utilized in NN, duration of the modeling step, and so on.

Test Description

For each test, 60% of the available data were used for building a model. Each model was trained to predict certain responses one time-step ahead. Trained models were then tested on the remaining 40% of the data. A set of models was used to simulate the future responses several time-steps ahead. Controls that were actually observed during the field test were used as future controls (Figure 10).

To evaluate the accuracy of such multi-step prediction, the computed values of the responses are compared to the actual responses measured the same number of steps ahead, and a percentage full scale (%FS) error is computed. It was found that errors computed during each test have a distribution which is best of all approximated by the following function:

$$f_e(x) = \frac{1}{2\beta_e} \exp\left(-\left|\frac{x}{\beta_e}\right|\right) \quad (3)$$

Value of β_e is computed in each test to produce the best fit of function (3) to the test error distribution. This "effective" prediction error (β_e) allows a consistent comparison of the accuracy of different models investigated in different tests and is used to determine optimal values of parameters that affect the creation of the NN model and influence its performance.

Parameters evaluation

One parameter that was evaluated is the amount of delays at the neural network input. Although feed-forward neural networks are essentially static, their usage may be extended to solve dynamic problems by utilizing delay lines. In other words by using data from a number of previous time steps. Figure 11 shows how the accuracy of models that use the same inputs depends on the number of delays. Duration of the time step in these tests is five seconds.

Prediction error grows with an increase in the prediction horizon, but as Figure 11 illustrates a larger number of time delays improves accuracy. The same behavior was observed for models that use different sets of inputs and for different durations of the modeling step. More time delays means more inputs into the NN, which

results in a larger problem to be solved to train the model. This in turn increases time to train the NN model.

Another example of a parameter that influences the performance of the dynamic neural network models is the duration of the time step. The minimum duration of the time step possible with the data acquired during the field test is five seconds. For longer intervals the value of each mnemonic is computed by averaging the available data over the time step. Figure 12 shows accuracy of prediction for modeling steps of different durations.

It is interesting to note that although the models operating on shorter time steps would require more steps to estimate value of responses for the same time horizon, they produce better results.

Based on optimal values of these and other parameters, NN models simulating the drilling process were created. Figure 13 shows actual ROP against predicted ROP.

During the simulation (prediction three minutes ahead in this example) only actual controls measured during the field test are used as future inputs. Actual responses are used only to initialize simulation of drilling dynamics. No actually measured responses are used when simulation has started. Off course dynamic model, tested in such a way, can't accommodate for formation changes, which will happen within three minutes of simulation. But, nevertheless, the model shows good results when formation does not change by too much.

If information about the formation to be drilled through is available, then it may be used to great benefit in dynamic models as well. Another model of the drilling process which utilizes look-ahead formation information to make predictions was created using data from an offset-well. Figure 14 shows the measured and simulated ROP for the part of the test that drilled through a section with fast formation changes. Clearly models using formation data as inputs perform better in this complex situation.

Conclusions

The structure of the drilling process has been studied in order to create a conceptual design of a "Drilling Advisor" that could provide recommendations on which drilling controls to adjust, and when. Models, along with an optimization strategy, were then designed to fit this concept and implemented in a software module that was tested at BETA.

For the model development a pseudo-statistical approach was employed as an alternative to traditional analytical and numerical approaches. This approach is based on long-term accumulation of practical field knowledge and utilization of this knowledge for overall improvement of the model and implementation of self-learning and self-adjusting capabilities during drilling.

Tests were performed to determine the optimal parameters of the neural network models. A measure of

the model accuracy was designed that allows proper comparison of the various test results.

It is shown that neural network models can predict development of the drilling process accurately enough when used on wells drilled through similar lithology with the same BHA and bit. Even better accuracy may be achieved, especially for long term prediction, if information about the formation along the well path is available (for example, from offset wells).

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Nomenclature

BHA = bottomhole assembly
C_n = control parameters at *n*-th time step
DCS = drilling control system
E_n = environment properties at *n*-th time step
MWD = measurement while drilling
NN = neural network
ROP = drilling rate of penetration
RPM = rotations per minute
R_n = responses at *n*-th time step
R_S = surface measured responses
R_D = downhole measured responses
TVD = true vertical depth
WOB = weight on bit
%FS = percent of full scale error

References

1. Brett, J.F., Warren, T.M., Wait, D.E., "Field Experiences with Computer Controlled Drilling". Paper SPE 20107, 1990
2. Young, F.S., "Computerized Drilling Control". Paper SPE 2241, 1969
3. Bromell, R.J., "Automation in Drilling". Paper SPE 1842, 1967
4. Zamora, M., Merchant, M.A., "Optimized PC-Based Expert Systems". Paper SPE 16488, 1987
5. Cunningham, R.A., "Analysis of Downhole Measurements of Drill String Forces". ASME May 1968
6. Young, F.S., Sampson, T.J., "An Analysis of Automatic Closed-Loop Control of Rotary Drive Engines". Paper SPE 3231, 1971
7. Close, D.A., Owens, S.C. and Macpherson J.D., "Measurement of BHA Vibration Using MWD", SPE/IADC 17273, 1988
8. Heisig, G., Sancho, J., and Macpherson J.D., "Downhole Diagnosis of Drilling Dynamics Provides New Level Drilling Process Control to Driller", SPE 49206, 1998
9. Dubinsky, V.S., Baecker, D.R., "An Interactive Drilling Dynamics Simulator for Drilling Optimization and Training". Paper SPE 49205, 1998

10. Dashevskiy, D., Dubinsky, V., Macpherson, J.D., "Application of Neural Networks for Predictive Control in Drilling Dynamics". Paper SPE 56442, 1999
11. Saputelli, L. Malki, H., Canelon, J. Nikolaou, M. "A Critical Overview of Artificial Neural Networks Applications in the Context of Continuous Oil Field Optimization". Paper SPE 77703, 2002
12. Bingham, M.G., "A New Approach to Interpreting Rock Drillability", Petroleum Publishing Company, 1965.
13. Jordan, J.R and O.J. Shirley, 1966, "Application of Drilling Performance Data to Overpressure Detection" JPT, No 11.
14. Wardlaw, H.W.R., 1972, "Optimization of Rotary Drilling Parameters," PhD Thesis, University of Texas.
15. Bellotti P., and Giacca D. "AGIP Deep Drilling Technology - 2", OGJ, vol 76, No. 35, pp 148
16. Warren T.M., 1981, "Drilling Model for Soft-Formation Bits", JPT, vol 33, no. 6, pp 963.
17. Warren T.M., and Oniya E.C., 1987, "Roller Bit Model with Rock Ductility and Cone Offset", SPE 16696
18. Jogi P.N., and Zoeller W.A., 1992, "The Application of a New Drilling Model for Evaluating Formation and Downhole Drilling Conditions", SPE 24452
19. Casdagli M., "A dynamical systems approach to modeling input-output systems," in Nonlinear Modeling and Forecasting, SFI Studies in the Sciences of Complexity, Proc. M. Casdagli and S. Eubank, Eds. Reading, MA: Addison-Wesley, 1992, vol. XII.
20. Leontaritis I. J., Billings S. A., "Input-Output parametric models for nonlinear systems part I: Deterministic nonlinear systems," *Int. J. Control*, vol. 41, no. 2, pp. 303–328, 1985.
21. Gershenfeld N. A., "The Nature of Mathematical Modeling." Cambridge, U.K: Cambridge Univ. Press, 1999.
22. Liu G.P., "Nonlinear identification and control: a neural network approach", Springer-Verlag, 2001

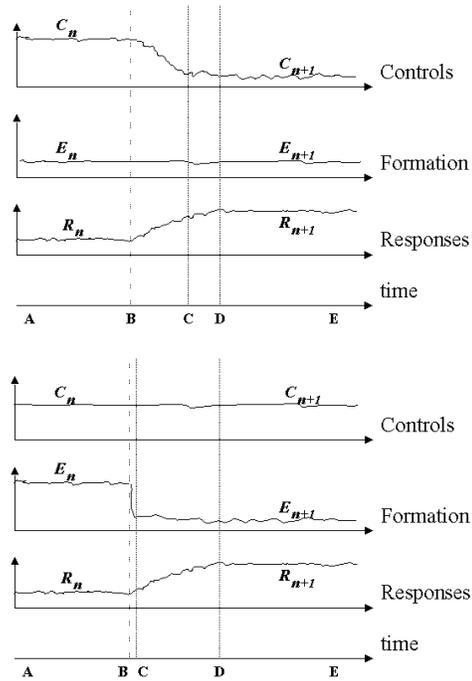


Figure 2. Drilling step:
 AB – stable state;
 BC – controls (environment) change to new value; responses start changing;
 CD – responses stabilize;
 DE – new stable state.

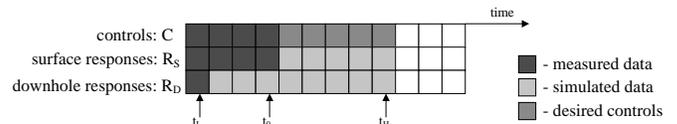


Figure 3. NN model uses available data to predict system responses.

Figures

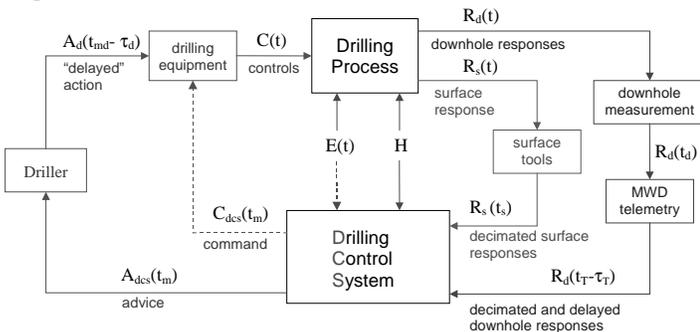


Figure 1. Data flow diagram.

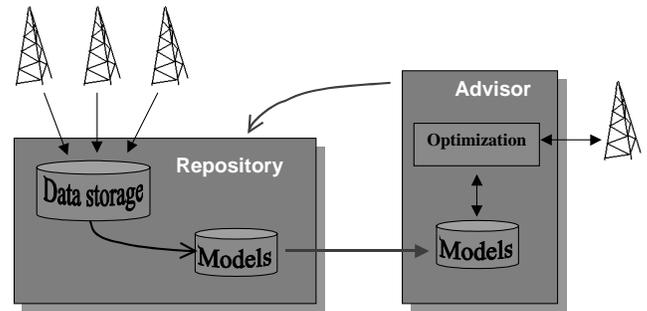


Figure 4. Block diagram of the drilling control system.

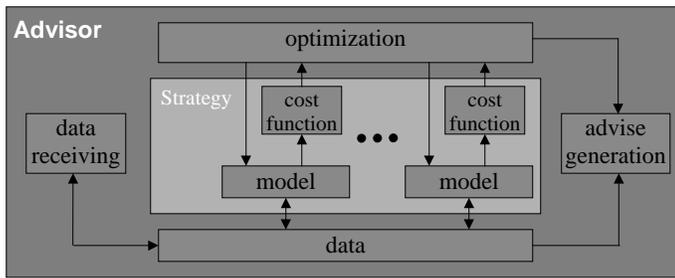


Figure 5. Block diagram of the Advisor.

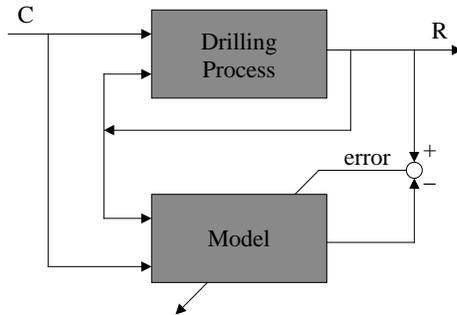


Figure 6. Neural network models can be adapted to current conditions while drilling.



Figure 7. PDC bit used in the field test.

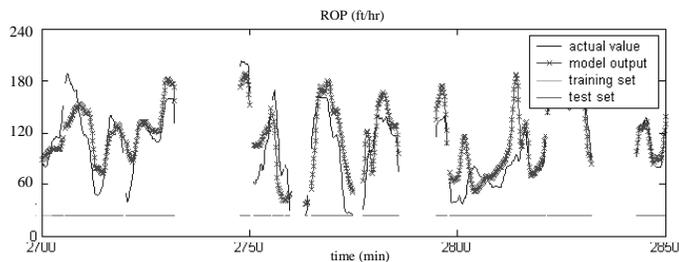


Figure 8. Measured ROP and ROP predicted by static model. Model uses surface WOB, surface RPM and set of parameters describing formation near the bit as inputs.

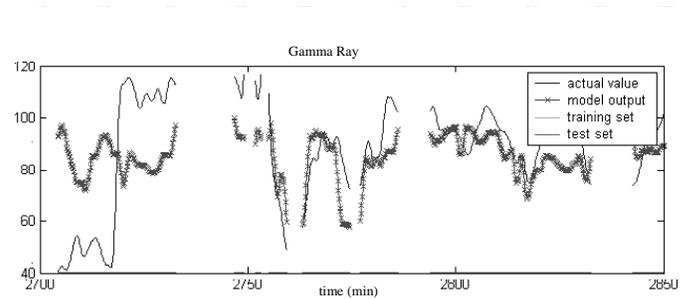


Figure 9. GR estimated using surface and downhole measured data.

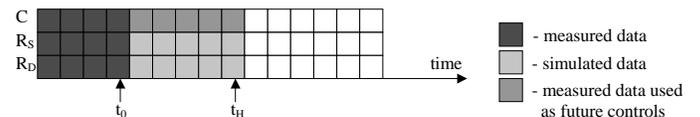


Figure 10. Test of the dynamic models. Controls that were actually observed during the field test were used as future controls.

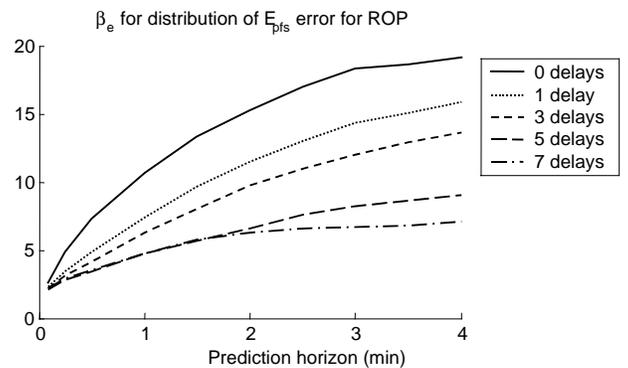


Figure 11. Data from more previous steps increase accuracy of prediction.

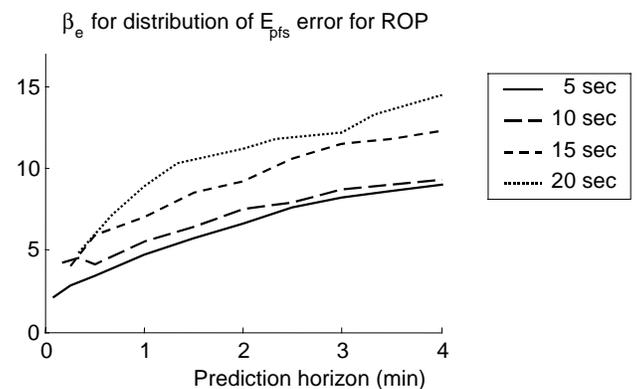


Figure 12. Accuracy of prediction for shorter modeling step is higher.

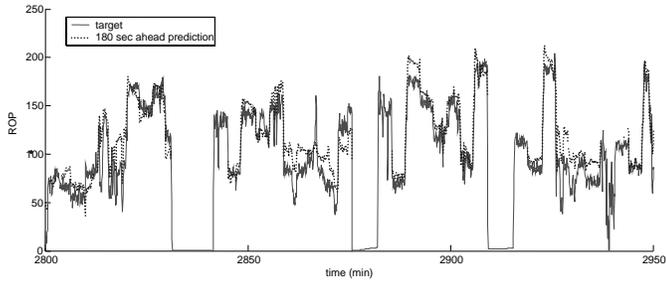


Figure 13. 36 steps ahead prediction of the ROP done by the model operating on 5 seconds intervals.

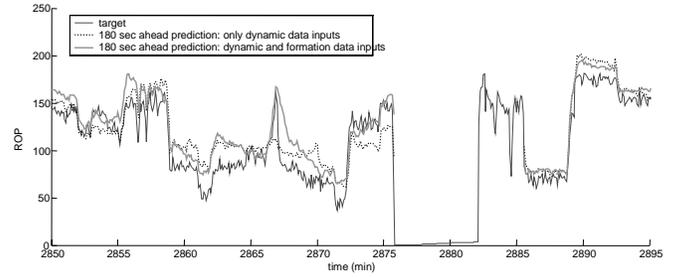


Figure 14. Close-up of the section with formation changes (2860min – 2875min). Prediction accuracy is increased when look-ahead formation information is used.