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Data Processing and Interpretation While Drilling

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Abstract
Processing techniques applied in military systems research and development focusing on detection, classification, localization systems for sonar and radar, as well as data fusion, situation assessment, and data mining have important applications to processing drilling data. In both situations, an important goal is to extract maximum information and interpret data as quickly as possible as it is acquired. Existing systems, developed by BAE SYSTEMS that demonstrate the conversion of these techniques to drilling data including,

a. Kick Sentinel - Automated data interpretation while controlling kicks,
b. Intelligent Drilling Monitor – Kick detection, Loss circulation, and other problem detection, and
c. Rate of Penetration Optimization – Continuous optimization of WOB and RPM calculated by processing data during drilling

are described and the underlying technologies including optimum estimation of states through recursive state space tracking (e.g. Kalman filtering), optimum trend and jump detection processing, tools for reasoning under uncertainty such as Bayesian nets, and classification processing such as neural nets are described.

Introduction
Maximizing production of a well, minimizing cost to drill a well, and minimizing risk of errors or accidents are the three critical concerns in drilling. The success in achieving each of these has one overriding common element, successful monitoring and interpretation of data while drilling.

Traditionally this process has been approached by the drilling community through development of "best" models to plan the well and predict the expected or normal measurements. Data collected during drilling is compared with plan and, by engineering analysis, problems are identified and corrective actions are taken. For many complex physical processes encountered during drilling this is the only possible approach. However, we believe in some key applications, dramatic improvements in response time and interpretation accuracy are possible through a much stronger computer coupling of the models and the data processing. This improvement in response time and accuracy, in turn, will have a direct impact on the three goals or concerns. Wells will produce more, wells can be drilled at lower cost, and the number of accidents costing lives and environmental damage will be less.

The coupling techniques and processing are very similar to those developed by the military to achieve data interpretation and response formulation in real time for weapon systems, and more recently combat situation assessment and response.

Maximizing or minimizing, sometimes conflicting, objective functions (e.g. maximum probability of remaining undetected vs. minimum time to egress for a submarine; or minimizing formation damage vs. minimizing probability of a kick for drilling) is usually dependent on the following factors: (1) a clear and concise definition of objective functions and the associated expected or normal data; (2) early detection of anomalous data or events with credible signals (i.e. low false alarm rate) that are proof positive that something is unusual; (3) correct interpretation of data resulting in correct situation diagnosis; (4) rapid calculation of appropriate responses and control to correct the situation, (5) careful monitoring of data during the corrective actions to determine that the desired responses are achieved, and (6) immediate situation reassessment and plan revision to return to factor (1).

The systems described in this paper apply advanced methods of coupling engineering models with data processing to successfully implement the six steps outlined above.

Kick Sentinel
The Kick Sentinel is a real-time extension of the Well

Site Advisor (WSA), a system developed previously by Tracor Applied Sciences (now BAE SYSTEMS) under DEA-49. Participants in DEA-49 were Chevron, Mobil, Shell, Baker Hughes INTEQ, British HSE, AGIP, JNOC, Amoco, Exxon, Schlumberger Sedco Forex, and Elf Aquitaine. An expert panel consisting of Dub Goins, Jim Langston, and Bill Rehm provided technical direction for DEA-49. The purpose of the Kick Sentinel is to assist rig personnel during well control events by providing real-time estimates of kick parameters, accurate predictions of future pressures and volumes based on those parameter estimates, and automatic detection of problems such as lost circulation or additional influx. The Kick Sentinel can work with both the driller's and weight and wait kill methods. In addition, the system provides a unique set of diagnostic worksheets to assist in diagnosing problems once their symptoms have been detected.

Figure 1 contains a functional diagram of the Kick Sentinel. The dotted rectangle in the upper left represents the third party data sources that supply data to the system. These sources include rig data acquisition systems such as Petron's DRIL DATA or Epoch's RigWatch system, a WITS Level 0 data stream, manual input, and file input. All data are acquired using the Kick Sentinel DataServer.

The KICK Sentinel can process data asynchronously at speeds up to one data point per second. A data point consists of five values: a time tag, a pump rate, a casing pressure measurement, a standpipe pressure measurement, and a pit level measurement. Time tag, pump rate, and at least one of the remaining three measurements are required on each update. Although optimal parameter estimation will occur when all three measurements are present on each update, the ability of the KICK Sentinel to provide kick parameter estimates with any measurement subset allows it to function during periods of incomplete or inconsistent data. In general, processing proceeds according to the following steps:

- Data are acquired from the DataServer and smoothed,
- Kick circulation and pump operation are dynamically modeled using Kalman filters.
- Kalman filter outputs are continuously monitored for problems using Cumulative Sum (CuSum) sequential statistical tests.
- Data are analyzed by a Bayesian confidence analysis to interpret and diagnose the situation.

The following will briefly outline each of these steps.

Smoothing. Data are smoothed, using a time-weighted smoother with a five-minute window, to reduce measurement noise while still preserving underlying jumps or trends. The weight assigned to each point in the window is inversely proportional to the time interval between it and the current point. Figure 2 contains an example of the smoother applied to the field kick data discussed in [1]. These data are from a gas kick in oil base mud and were collected at approximately 20-second intervals from the time the well was shut-in until the kick was circulated out of the well. Note how smoothing preserves underlying trends and movements in the data while significantly reducing the noise in the data.

Real-time modeling. Recursive processing techniques known as Kalman filtering [2] are the core technology applied to achieve the desired real time capabilities. These techniques allow the design engineer to use sophisticated techniques that measurements taken during the control process and engineering models in a strongly coupled complimentary way which minimizes estimation and prediction errors.

Kalman filters are widely used to model dynamic systems in a number of application areas including navigation, tracking, process control, and signal processing. In a Kalman filter, the system being modeled is described in terms of states and their uncertainties. States are those parameters that can be used to characterize the current condition of the system and to predict its future condition. The filter has two components: (1) a system model that is used to predict the state of the system at time t+1 given its state at time t, (2) a measurement model that relates the system's state values to measurements on the system. In general, at time t+1 the system model is used to predict the state of the system based on its state at time t and then the predicted state is corrected using measurements made at time t+1. This is illustrated in figure 3. Kalman filter processing provides several advantages when used to model kick circulation:

- It is adaptive. Kalman filters can model changing conditions is a way that traditional simulations or mathematical models cannot. For example, if the pumping rate during circulation needs to be changed the Kalman filter will automatically adjust to account for this. In contrast, traditional simulations based on static shut-in conditions cannot easily handle such unplanned operational changes.

- It uses simple models. The system model needs only to be accurate enough to predict from time t to t+1. Properly combining predictions at t+1 with measurements at t+1 is the key to accurate state estimation. This allows Kalman filters to be used in situations where the underlying physical processes are not well understood but where good measurement models and good approximate system models are available.

- It provides a measure of information quality. A Kalman filter is said to be observable if the n states of the filter can be estimated from n noise free measurements. This property insures that the system and measurement models are properly coupled and ensures that the filter can accurately estimate all of its states. This is in distinct contrast to many simulations that have parameters or employ models that can not be directly verified through observation.
- It provides multiple ways to measure process dynamics. Kalman filters provide many parameter sets that can be used to monitor the system being modeled including the state estimates themselves, differences between the observed measurements and projected measurements, and the state covariance matrix. Each parameter set provides different insights into the operation of the system and possible problems.

In the Kick Sentinel, the kick is modeled as a uniform mixture of gas and drilling mud that has a bottom and a migration velocity that are independent of pumping rate. This model is implemented as a seven state Kalman filter whose states are: bottomhole pressure, volume of gas, distance of kick from the bottom of the well, kick velocity, ratio of mud volume to gas volume, gas mass, and liquid volume as discussed in [1].

Problem Detection. The CuSum test [3] is a well-known statistical test used in quality control to detect processes that are “out of control”, i.e. behaving differently from what is expected. Consider a process that generates time ordered observations x_1, x_2, x_3, … and suppose the observations have an expected or target value of q. For n observations, the CuSum is defined by:

$$CS(n) = \sum_{j=1}^{n} (x_j - q)$$

If the process is in control, *CS*(n) will be near zero since the x_j's will tend to wander randomly about q and the sum of these deviations will tend to zero. Figure 4 illustrates CuSum processing. A mask is constructed based on a truncated V shape. A line passing through the center of the mask represents the target value q. The CuSum, *CS*(n), is accumulated backward from the present and at each n its value is compared to the mask. The slope of the mask's V determines the maximum mean shift to accept in the process. The difference between the target and the mask at the bottom or truncated portion of the V determines the amount of variance about the target value we are willing to accept in the process. This may also be thought of as the outlier tolerance of the system.

Interpretation. The Kick Sentinel provides a set of situation interpretation worksheets to aid in analyzing the causes for both shut-in and circulation problems. Upon selection, each worksheet (shut-in or circulation) is initialized to reflect the current status of the well, e.g. kick location, casing pressure status (high, near expected, low), etc. The worksheets are based on the expert systems developed for DEA-49 [1] that were built using input from both the expert panel and industry participants. However, their operation offers significantly more insight than usually obtained through traditional expert system interfaces. After the worksheet has been initialized, the user is able to select additional information buttons to include knowledge that is unavailable to the Kick Sentinel. Whenever an information button is selected, the worksheet enables or disables all remaining buttons depending on their ability to affect the diagnostic outcome.

User Interface. The KICK Sentinel uses a traffic light analogy for alarm notification. If no problems are present, a green light is displayed on the main window. If the system has begun to detect a problem, a yellow light is displayed, and, if the system is certain a problem has occurred, a red light is displayed. Windowed CuSums are used to determine if Kalman filter estimates of casing pressure, standpipe pressure, and pit gain are equal to the actual measurements of these quantities. The underlying hypothesis during kick circulation is that there are no problems occurring. If one of the monitored CuSums detects a problem then the hypothesis that the kick is proceeding normally is cast in doubt and an alarm light is turned on. The color of the light depends on the severity of the problem. In addition to the CuSum detectors, the KICK Sentinel monitors casing pressure and shoe pressure and turns an alarm light on if these quantities move outside of a user configurable target range associated with them. Again, the color of the trouble light is related to how far from the target range the estimates are.

Figures 5 and 6 contain screen shots for the main KICK Sentinel window and the Graphs/Predictions window. The main window is divided into two parts. The upper part of the window displays the current error status as a red, yellow, or green light. It is large and can be seen from a significant distance. The lower part of the window contains a log displaying the error status for each time update processed and a short text message explaining why the alert occurred.

Intelligent Drilling Monitor

The Intelligent Drilling Monitor (IDM) was developed to provide an early warning to drilling crews of possible circulation problems so that they may take timely corrective actions. The effort was supported by the Gas Research Institute.

The IDM system consists of an interface to the rig data acquisition system, a processing engine to examine incoming sensor data for indications of circulation problems, and a user interface implemented from a commercially available SCADA system. The processing engine and data interface algorithms were developed in C++ and can currently accept data from a variety of sources and formats. . IDM runs on a PC under the Windows NT operating system.

The diagnostic capability of IDM is provided by unique algorithms, similar in approach to the Kick Sentinel discussed previously, employing a Kalman filter, a statistical detection procedure, and a Bayesian network. The Kalman filter produces a dynamic model of the well (updated with each measurement). The Cumulative Sum statistical procedure identifies significant deviations of the raw data or the Kalman filter output from values expected during normal operations. A reasoning process is then required to decide among several possible causes of a deviation. IDM makes decisions using a Bayesian Network, which is a probabilistic reasoning tool that emulates some aspects of human causal reasoning. The inputs to the algorithm are measurements of inflow, outflow, stand-pipe pressure, pump speed and pit volume. The main outputs are the probabilities of circulation loss, pump efficiency loss, kick, sensor error, plugged bit, and washout.

The IDM system has been field tested on a geothermal wells and has been laboratory tested with recorded data. While no kicks occurred during these tests, the system was able to indicate circulation loss & pump efficiency loss with a low false alarm rate and to distinguish between actual circulation problems & apparent problems caused by sensor errors.
The system has been tested further with additional recorded drilling data. A series of controlled tests at the LSU Training Well Facility demonstrates IDM's ability to detect kicks as well as loss of circulation.

Figure 7 shows the top-level data flows for the IDM field system. The OPC data interface provides a uniform data connection for the rest of the field system, whatever rig data-acquisition system is used. It writes the rig data to the process database. The processing engine reads rig data from the process database and writes fault probabilities & alerts to the process database. The user interface reads both rig data and outputs from the processing engine for display.

Figure 8 shows the data flows for the IDM processing engine. Normal drilling operations are modeled using a seven-state Kalman filter [2]. Evidence is extracted from the raw data and the output of the Kalman filter using the CuSum sequential statistical process [3]. A Bayesian belief network [4] is used to estimate problem/fault probabilities based on incoming evidence.

The key data are stroke count, flow measurements and pressure measurement. Pit levels are used only to confirm kick or loss of circulation because they are changed by surface activities, such as mixing mud. In fact, the system can often detect problems (by examining flow readings) before the pit level changes noticeably. Without inflow measurements the system can still detect circulation problems, but cannot distinguish between loss of circulation and loss of pump efficiency. Pressure measurements enhance kick detection and are needed for detection of bit plug & washout. The system is designed to use outflow measurements because otherwise the main kick & loss detection is little more than a threshold test on pit level.

The Kalman filter smoothes measurements of outflow, inflow and pit level. It also estimates pump efficiencies and parameters which relate circulation pressure to flow. (The pump efficiencies and circulation pressure parameters cannot be measured directly.) At any time, the values of these quantities define the state of the well. State estimates are an optimal (minimum mean squared error) combination of projections from the state model of the well and measurements of well parameters. The measurements used are flow meter readings, the pump-stroke counter reading, pit level, and the stand-pipe pressure. When a state estimate is desired, the state model is used to project ahead from the last estimate. A set of measurements is taken and combined (using an optimally generated Kalman gains matrix) with the projected state to form a new state estimate at the current time. One step in the combination is to predict the measurements from the projected state. The differences between the actual measurements and the predicted measurements are called innovations.

Innovations indicate changes in the well circulation and are used to adjust state estimates. For example, if flow drops the Kalman filter predicts that pressure will drop: if the pressure drop matches the prediction then the pressure innovation is near zero and there is little change to the pressure parameter estimates.

The CuSum test uses cumulative sums of deviations to detect both large deviations from an expected value and smaller systematic deviations from an expected value. The deviations considered in IDM are flow differentials, stand-pipe pressure innovations, and the difference between estimated pump efficiency and a perfect efficiency of one.

The Bayesian network uses evidence generated by the CuSum test to estimate the probabilities of faults. (A symptom detected by the CuSum test does not necessarily indicate a specific fault. For example, an apparent excess of outflow over inflow could be caused by a sensor error or a well kick.) The faults detected by IDM are loss of circulation, well kick, loss of pump efficiency, bit plug, washout, and sensor errors. The processing engine translates the probabilities into alert levels for display.

Figure 9 shows the Bayesian network for IDM. An arrow from one node to another indicates that the former influences the latter. For example, a kick would cause pit level to rise. If these influences are represented correctly then the network software will automatically make the correct inferences about unknown nodes from whatever is known.

The system does not burden the operator by requiring maintenance of rig activity codes, but does display activity indicators. Any difference between these indicators and actual rig activity suggests a fault or sensor error. For example, suppose the display indicates that mud is being added to the pits. The system has no direct way to observe such activity, and reaches this conclusion because pit levels are rising while flows appear to be in balance. If mud is not being added then there is a sensor problem and the well is probably taking a kick.

The IDM GUI is shown in Figure 10. The upper left side of the GUI contains a plot where the operator selects which data are to be displayed. The right side of the GUI contains warning lights for the various faults diagnosed by IDM. The lights change from green to yellow and then to red as the probability of the fault approaches one. There are also large numerical readouts of the various inflow and outflow measurements. The bottom left of the GUI contains a display of system comments which are stored in an Access database. Comments are generated automatically when IDM is started or when faults are diagnosed or cleared. Comments may also be manually entered by the operator.

Rate of Penetration Optimization

Although rate of penetration (ROP) optimization has been studied since the 60s [5], it is believed the combination of current computer capabilities, improvements in measurements and data quality, and the advanced processing described in this paper afford an opportunity to achieve, for the first time, near minimum cost drilling. The savings from such a system has been shown to be on the order of 20% or more per well in drilling ahead costs, which for off shore wells drilled today results in savings of $1,000,000 or more.

In pursuit of the advanced drilling ROP optimization, BAE SYSTEMS under contract to Mobil, BP, Texaco and Chevron, developed a real time ROP optimization system termed ROPO21 for rate of penetration optimization for the 21st century. Figure 11 is a functional diagram of the ROPO21 real time system.

Prior to initiation of processing of real time data, information used to enhance the predictive components of ROPO21 may be input, including data from off-set wells or pseudo well log data derived from seismic data. These data are used to calculate initial coefficient values in the ROP models and thus begin the processing for each bit run with predictions based on the prior wells or pseudo logs. Input of these data is indicated at the top left of figure 11.

The real time inputs to ROPO21 during drilling are shown at the far left center of figure 11 and include: rate of penetration (ROP), weight on bit (WOB), RPM, Depth, equivalent circulation density (ECD) or mud weight, Flow, Torque, Bit Parameters (cost, nozzle area, IADC code, and dull grade at end of each bit run) and cost parameters associated with rig rate.

<u>Data Smoothing</u> - The data as collected by the field instrumentation can be erratic and contain numerous invalid data points (e.g. negative values of ROP, WOP and null values of RPM or Torque as well as spurious jumps to unreasonable values). Data smoothing and outlier rejection is required prior to processing by the remainder of the system.

<u>Data Sorting Based on Lithology Estimates-</u> It is clear that estimation of the ROP model coefficients requires that data only from common rock strength or drillability strata should be processed and that separate ROP coefficients are required for each rock type. Consider the case of drilling in a soft formation with a transition to a hard layer. The data will show that WOB increased but that ROP decreased. Equivalently, a negative coefficient would be calculated for the WOB effect on ROP. Clearly, this is an earth transition effect and does not reflect the characteristics of drilling in a fixed lithology. In order to continuously estimate "optimum" WOB and RPM, the processed data must be applicable to common rock drillability. This is a key problem addressed by ROPO21.

Functional processing performed by the lithology sorting includes the collection of noncontiguous segments of data from comparable lithology regions and sending these data, corresponding to lithology types, forward for processing.

a) **Bit Wear Analysis-** In order to predict and optimize drilling performance, models of bit performance and bit wear or efficiency for the expected lithology are required. Prior methods rely on data from previous bit runs and dull gradings for different lithologies and drilling scenarios to obtain these models. The ROPO21 system continuously estimates bit efficiency during drilling and uses this to predict future performance.

ROP Analysis -ROP processing is designed to estimate parameters or coefficients in the Bourgoyne and Young model [6] that describes the observed rate of penetration dependence on drilling control variables (e.g. WOB, RPM, Flow, etc.), the current bit condition h, and lithology distribution.

As shown in figure 11, there are three Kalman filters that process data for each of three lithology types. Separate coefficients are maintained in a database for each bit type and each lithology type. When an optimum solution is calculated for the remainder of the well (multiple bit runs), at any point during processing, the ROP model coefficients used for each future lithology type and bit type are obtained from the current database of coefficients. Thus, the values used are always the current best estimates.

The final ROP model selected for the ROPO21 prototype was an assumed exponential model for ROP as proposed by in reference [6]. The original approach of reference [6] was to obtain empirical coefficients for each of the variables from data obtained during drilling of prior wells in similar areas and to model bit wear based on assumed bit wear models and parameters calculated from prior dull gradings for similar bits. This approach was modified for the ROPO21 system to allow input of continuous updates for each coefficient based on performance during drilling and to use the bit wear estimates as estimates of bit wear to replace the modeled values based on historical dull gradings. An eight state Kalman filter is implemented with states defined as the eight coefficients in the reference [6] regression model.

Lithology Prediction - Estimates of optimum WOB and rpm applicable to future drilling operations must be based on an expected future lithology. Since the system must retrieve a set of default coefficients for each lithology type, future lithology prediction must be quantified with a distribution function identical to the lithology filter parameter set in the ROPO21 system,. The lithology filter processes drilling data so that the data are segmented into three lithology bands and therefore the lithology predictor must predict these three values (SORT = Hard, Medium, or Soft in ROPO21). A predicted future distribution over these three bands (based on prior wells or seismic data) must be obtained in order to simulate the ROP for future bit runs.

Several approaches have been investigated to provide conversion of well log or seismic pseudo log data to values of the predicted drillability or SORT variable. Several types of neural nets including radial basis functions and perceptron topologies have been investigated. The current ROPO21 prototype uses a linear prediction model to predict SORT. Bit runs were processed and the values of the calculated SORT variable were stored for each bit run at each measured depth. The SORT data were defined to be the dependent variable and the log values (density, deltaT, Gamma, UCS, etc) were defined as the independent variables in a regression analysis. A final global predictor of the SORT values was developed.

Optimzation - The most accurate calculations of optimum WOB and RPM are obtained by a search over all reasonable values of WOB and RPM with each pair of values used to simulate the drilling of the remaining bit run to a point of minimum cost per foot. These simulated bit runs begin with the bit at the currently estimated wear level and terminate when the bit is worn to a value of 1. The history of the bit run is then searched to find the point corresponding to the minimum cost per foot. The pair of WOB/RPM values that yield the lowest minimum cost per foot are reported as the optimum solution. This search technique eliminates the assumptions necessary for analytical solutions as defined in reference [6] and execution times are a few seconds with the directed search method used in ROPO21 based on the Nelder and Mead algorithms [8].

Processing Results – The ROPO21 processing has been compared to data collected for a large number of actual wells. Extensive statistical comparisons have been made between actual dull grades for bits and ROPO21 wear estimates. Figure 12 is an example scatter plot for wear estimate versus dull grade. The ROPO21 estimates are clearly highly correlated with actual wear and the scatter observed is considered consistent with the human dull grade procedure and expected variance.

The primary outputs of ROPO21 are the recommendations for minimum cost WOB and RPM and the expected cost savings resulting from the recommendations. Figure 13 is a sequence of output plots from ROPO21 showing contours of cost/ft along with the current operating point and the recommended minimum cost point. Figure 14 is an example output plot from ROPO21 comparing the current cumulative cost to depth and the expected cost to depth using the recommended "optimum"" values for WOB and RPM. The expected savings are indicated as approximately $200,000 at a depth of 10000 feet.

Conclusions

The systems described in this paper have common underlying principals of operation. Each incorporates models of the drilling process of interest and combines these models with real time measurements to obtain estimates and predictions of future behavior that are maintained current and reflect the current drilling situations. This processing approach is similar to the tracking and situation assessment processing applied in military weapons systems and is considered an optimum approach for controlling or understanding dynamic systems. These approaches, if applied at the well site, have the potential to significantly improve the drilling process in many areas. The three principal concerns in drilling; maximum production, minimum cost, and minimum risk can be significantly improved by their application.

References

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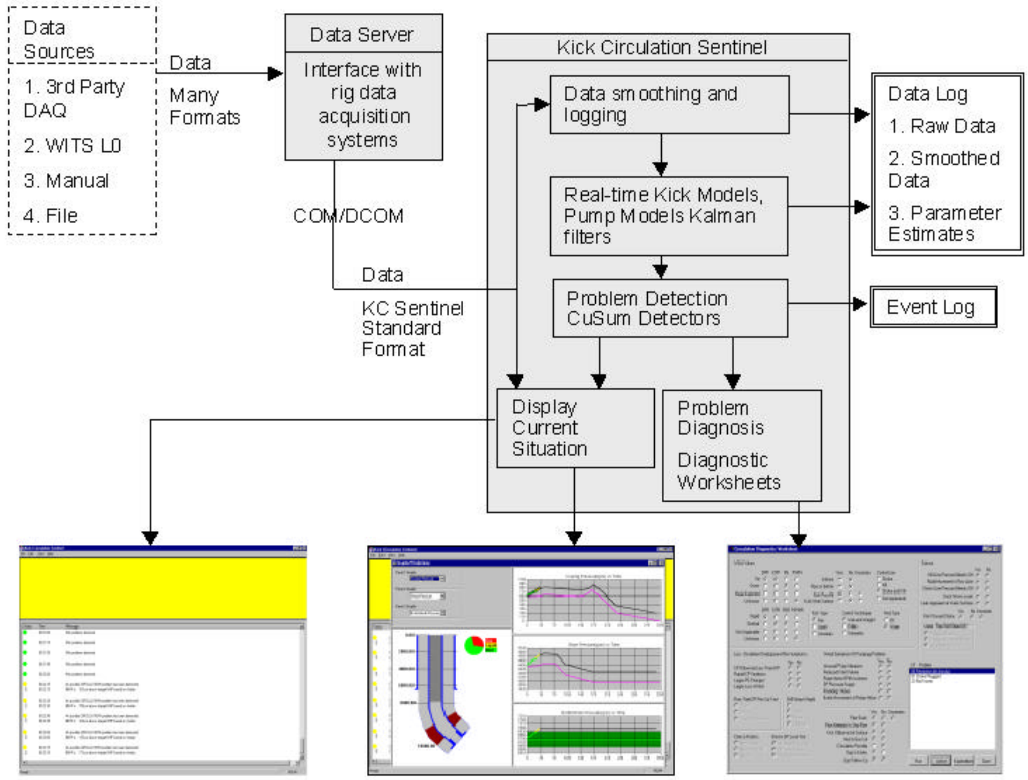

Figure 1 - KC Sentinel Functional Diagram

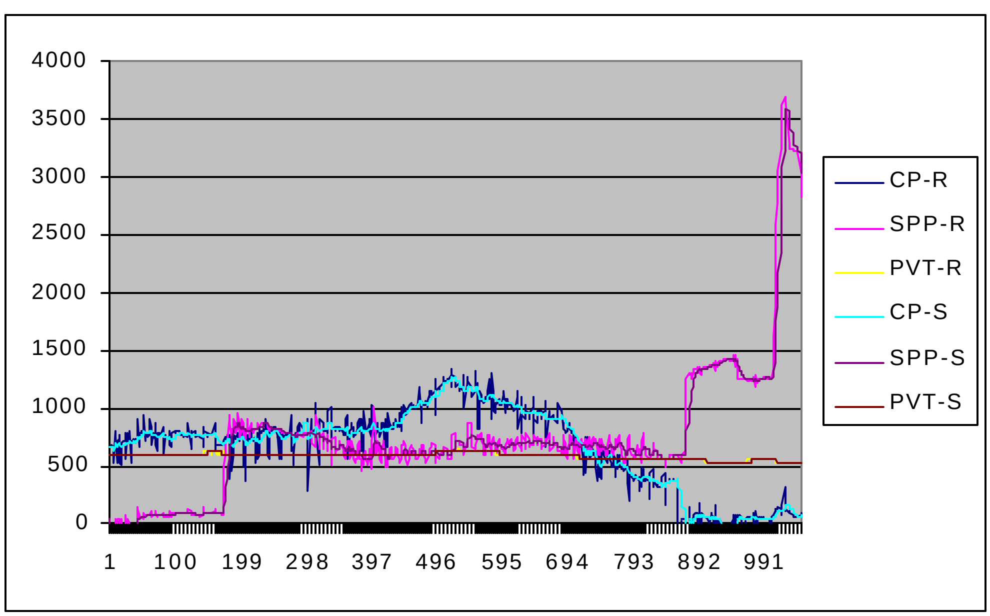

Figure 2 - Smoothing Reduces Measurement Noise

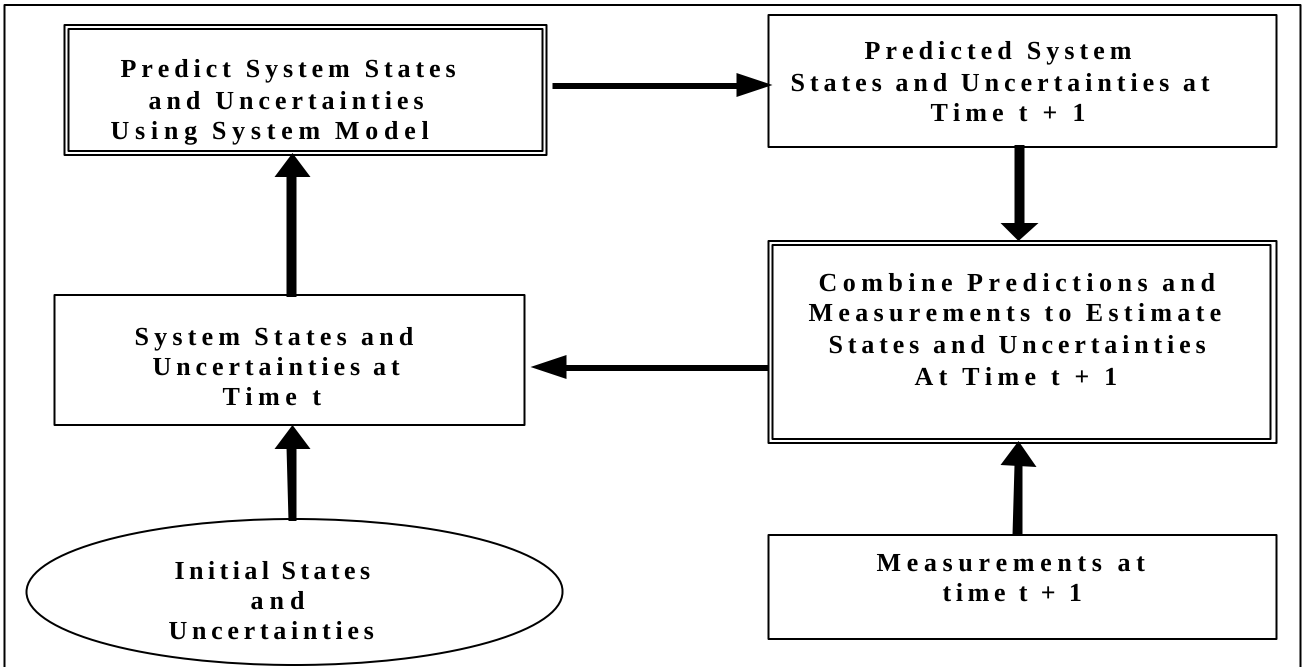

Figure 3 – Kalman Filter Processing Diagram

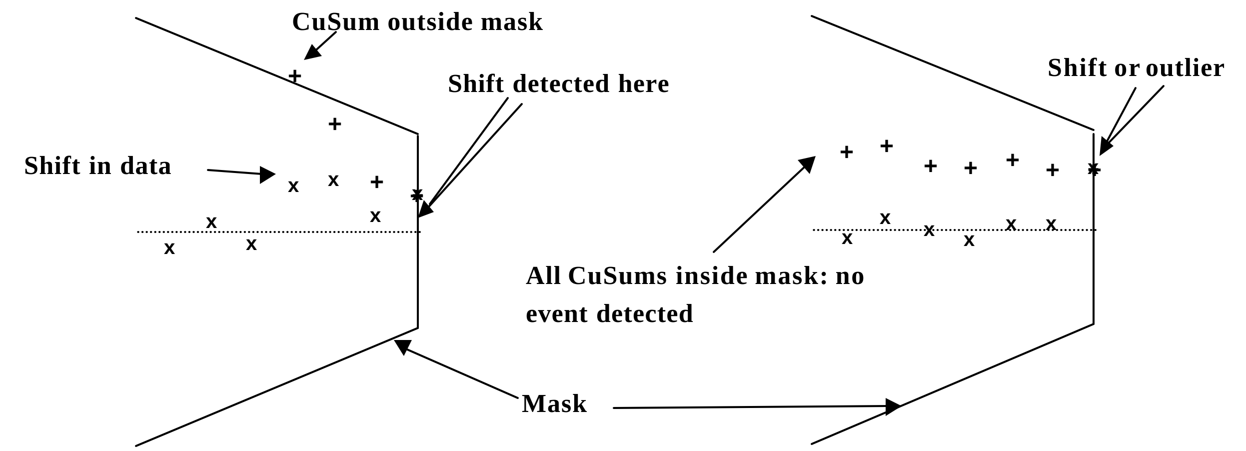

Figure 4 – CuSum Processing
x = Data Point, + = CuSum

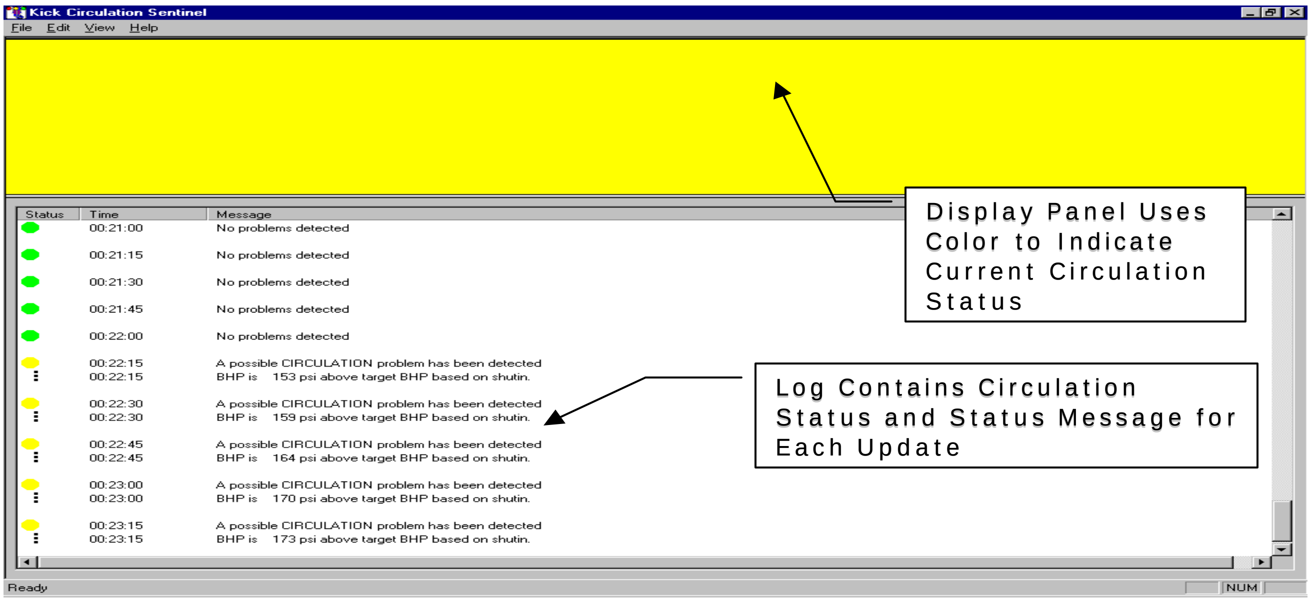

Fig 5 – Main KC Sentinel Window

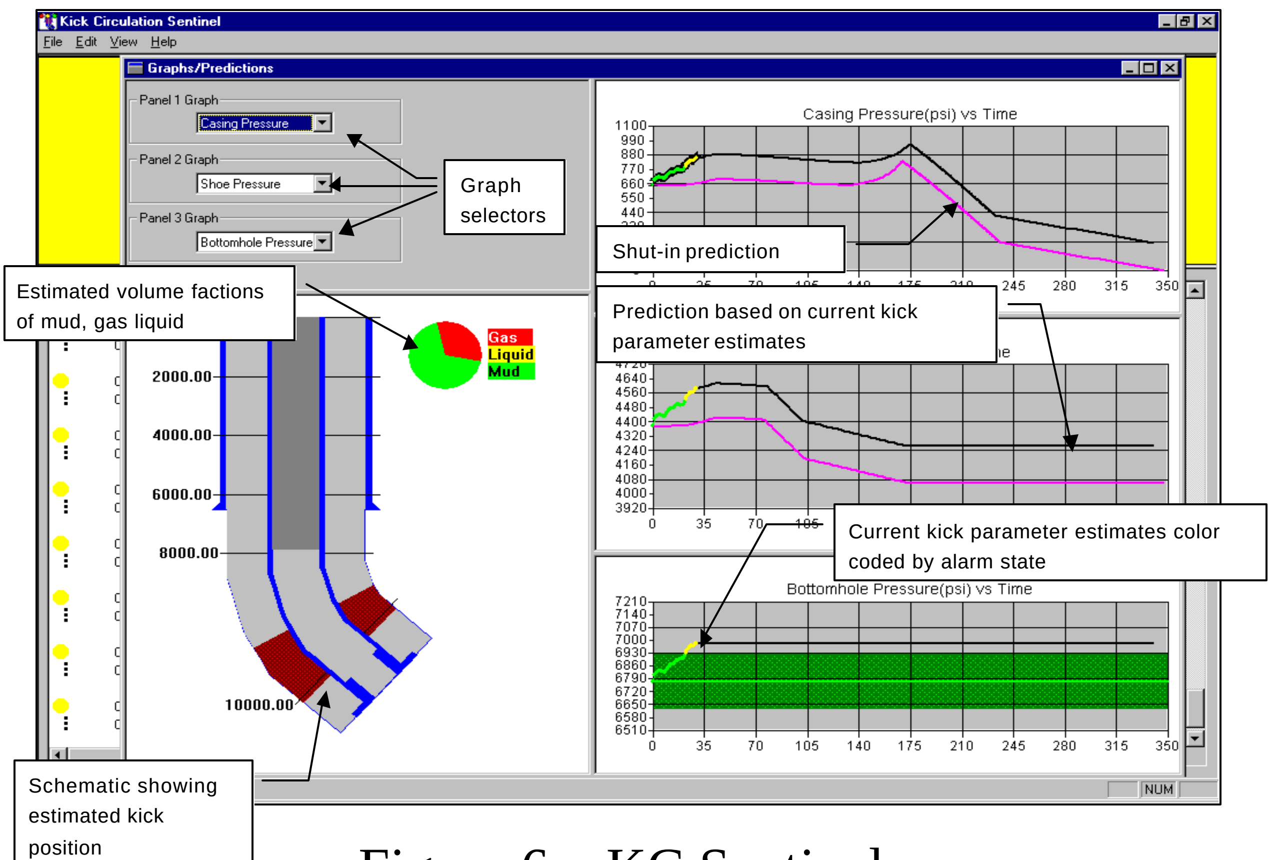

Figure 6 – KC Sentinel Graphs/Predictions Window

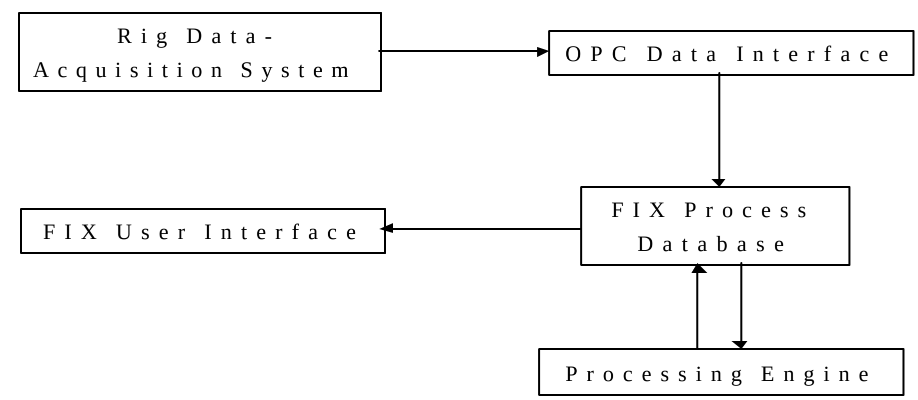

Figure 7 – IDM Field System

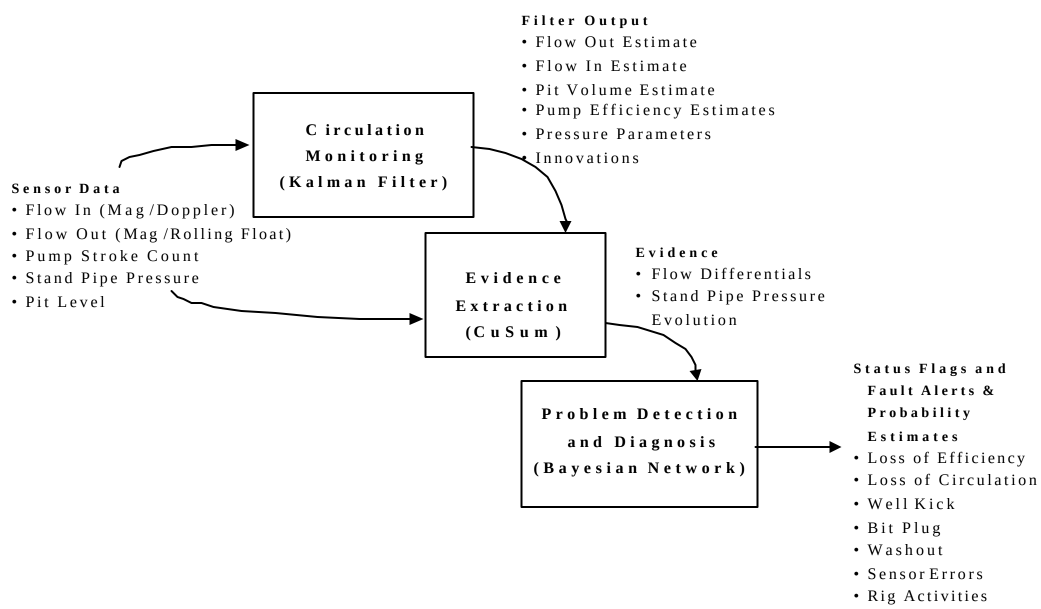

Figure 8 – IDM Processing Engine

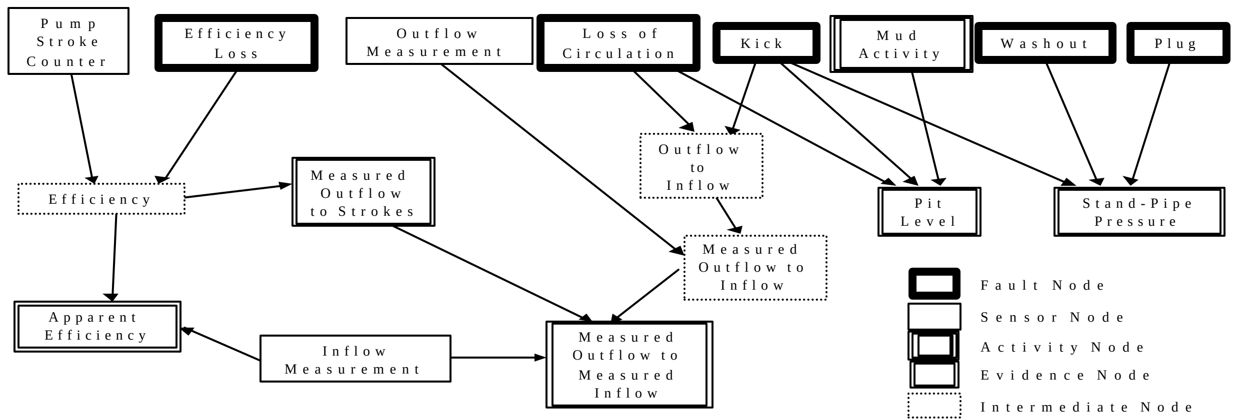

Figure 9 – IDM Bayesian Network

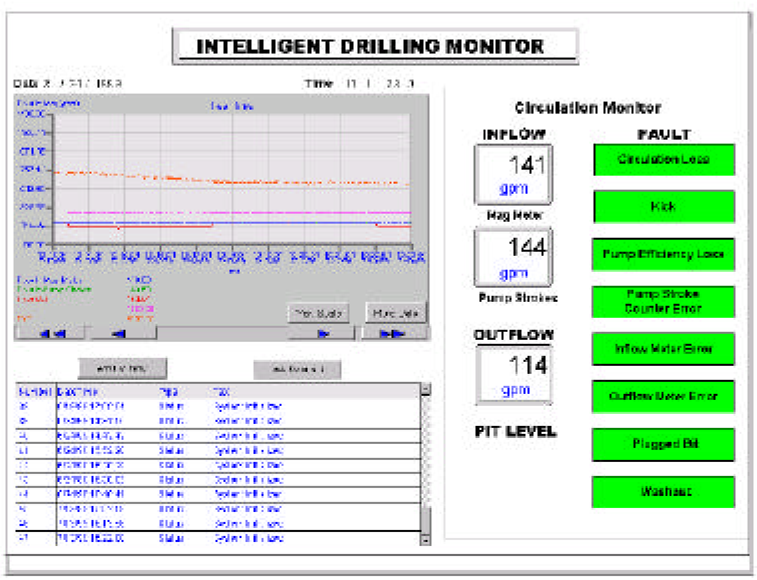

Figure 10 – IDM Graphical User Interface

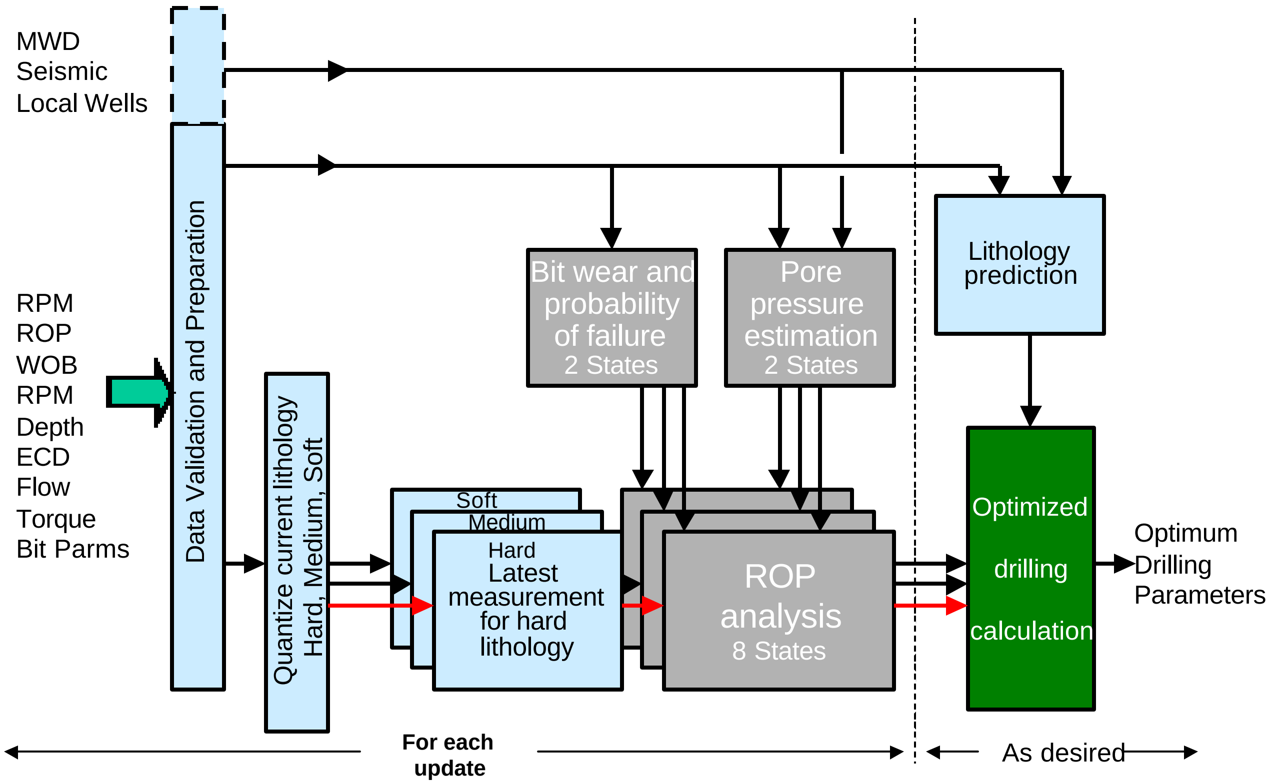

Figure 11 Functional Diagram for Rate of Penetration Optimization

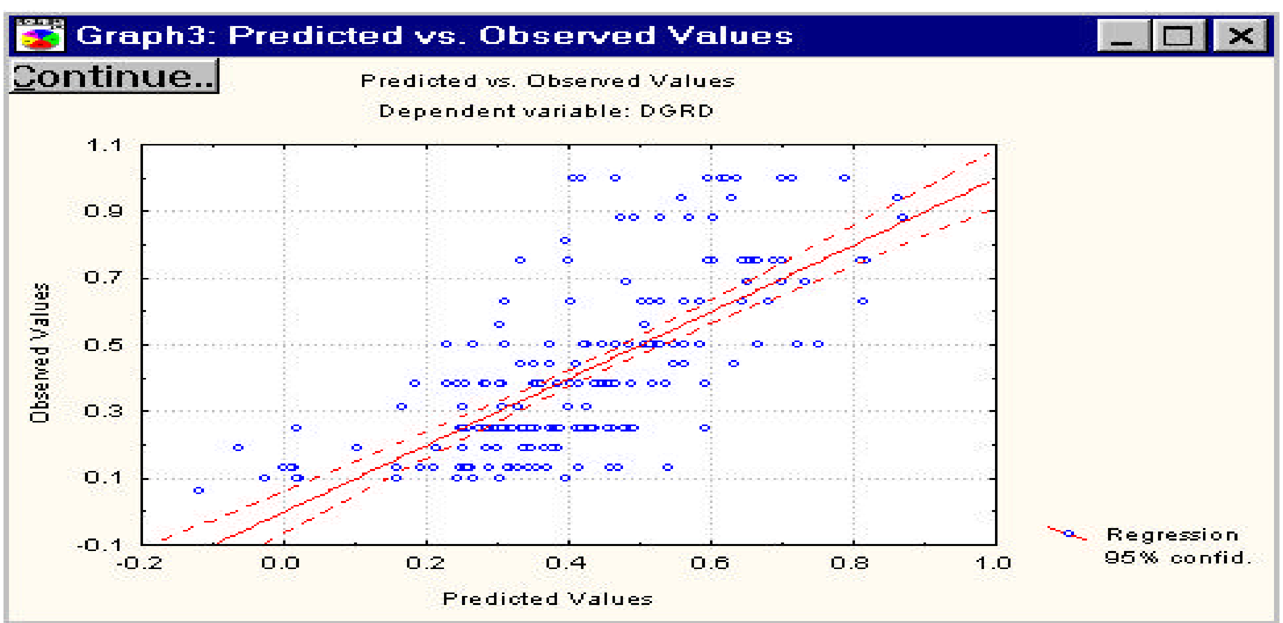

Figure 12 Converted dull grade wear estimate(observed) versus ROPO21 wear estimate (predicted) (207 bit runs)

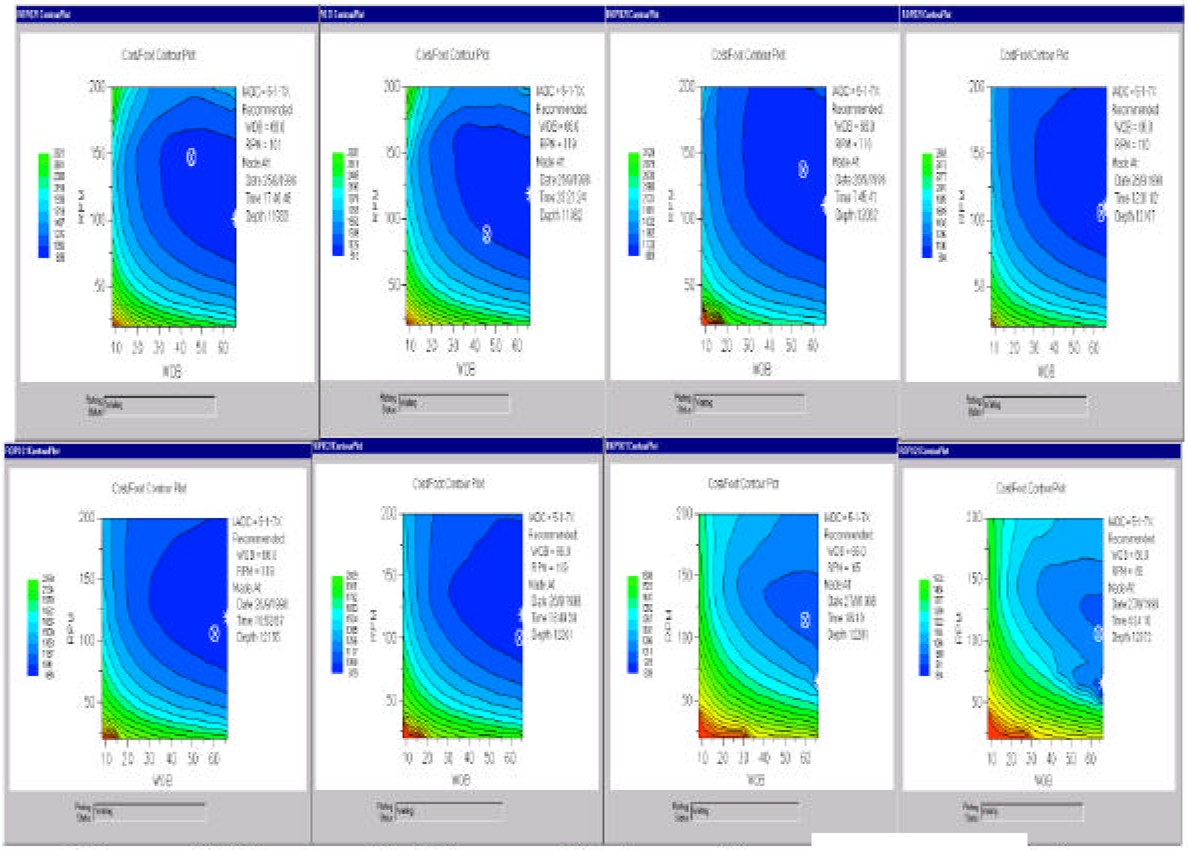

Figure 13 Sequential Screen Captures for a **Selected** bit run

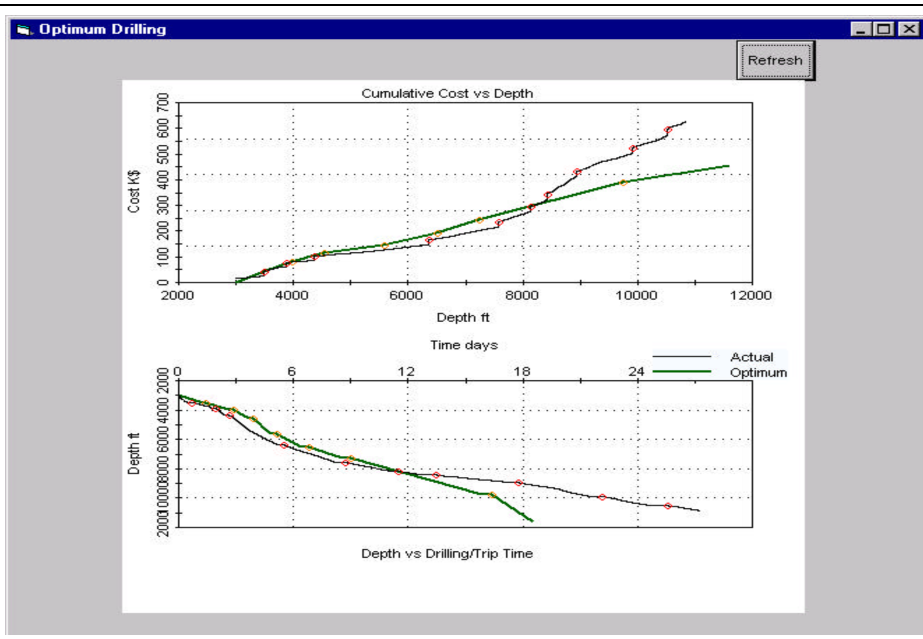

Figure 14
Actual Cost and Depth versus ROPO21 Optimum Prediction