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INTELLIGENT WHILE-DRILLING SYSTEMS

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Resumo

À medida que empresas de petróleo são requeridas a perfurar em áreas cada vez mais complexas, tecnologias que podem significantemente reduzir tempo não-produtivo e tornar a perfuração mais segura têm recentemente recebido grande atenção. De acordo com esta tendência, tecnologias que podem prematuramente detectar problemas de perfuração, cujas evidências (assinaturas ou padrões) estão embutidas nos dados obtidos em tempo real – por exemplo, vibração da broca, problemas de *dogleg*, influxos, estabilidade de poço, prisão de coluna, perda de circulação, falhas de brocas e BHA – têm se tornado uma importante área de pesquisa e desenvolvimento. Tais tecnologias possuem diferentes configurações. As configurações mais simples são usadas para alertar sobre a iminência de problemas de perfuração. Estes sistemas podem ser baseados em dados obtidos de sensores situados na sonda (dados de superfície) ou podem combinar estes dados com aqueles oriundos de sensores localizados no interior do poço. Uma tecnologia mais avançada inclui sistemas fechados (realimentados) que, ao detectarem certos problemas de perfuração, podem automaticamente corrigir ou minimizar tais problemas através da otimização de parâmetros operacionais em tempo real. Os usuários destes sistemas inteligentes podem estar localizados na sonda (sondador) ou podem ser especialistas trabalhando remotamente nos chamados Centros de Decisão em Tempo Real.

O presente artigo apresenta uma revisão de diversos sistemas inteligentes para a perfuração citados na literatura. Ele detalha as diferentes ferramentas e técnicas aplicadas no desenvolvimento de tais sistemas, incluindo as tecnologias de transferência de dados do poço, filtragem de dados e algoritmos usados no reconhecimento prematuro de padrões que caracterizam problemas tipicamente encontrados durante a perfuração. Uma vez que falsos alarmes representam um problema recorrente em tais sistemas, os mesmos serão discutidos em detalhes neste artigo.

Abstract

As oil companies are required to drill in areas with increased drilling complexity, technologies that can significantly reduce non-productive time (NPT) and make the drilling process safer have been gaining great acceptance. In keeping with this trend, technologies that can, in advance, detect drilling troubles whose signatures are embedded in the real-time data sets — for example, bit whirl, dogleg buildup, fluid kicks, well bore instability, stuck pipe, lost circulation, bit and bottom hole assembly failure — have become an important area for research and development. Such technologies may have different configurations. For instance, the simplest ones are used to alert operators about the onset of drilling troubles. They may be based on real-time surface information or may combine real-time surface and sub-surface information. More advanced technologies include closed-loop systems that are able to automatically optimize operational drilling parameters in real-time when the onset of drilling problems are detected. The users of intelligent while-drilling systems may be on the rig site (e.g., the driller) and/or may be drilling experts remotely (e.g., from Halliburton's Real Time Operations Center™).

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This paper presents a critical review of the several intelligent while-drilling systems published in the literature. It details the different tools and techniques applied in the development of such systems, including the technologies for down-hole data transfer and for data filtering, and algorithms for early identification of typical response patterns that characterize critical drilling events. Since false patterns recognition has been a serious problem related to these systems, it will be extensively addressed in this paper.

1. Introduction

The oil and geothermal industries have long recognized the need of advisory or intelligent-while-drilling-systems (IWDS), that is, automated systems to prematurely alert and avoid costly drilling problems. The development of such systems is based on the fact that certain signals show up in the drilling data. These signals are usually in the form of re-occurring patterns embedded in the real time data sets. They portend the onset of such problems as: fluid kicks, bit and BHA vibration, stuck pipe, well bore instability, lost circulation, washout in the drill string, plugging or loss/damage of bit nozzles, etc.

IWDS were thought initially to be used mainly to improve the real-time performance of the "driller on the brake". A good driller can make more footage and avoid problems, thus, creating added value for the contractor and operator. Conversely, a driller - who is not previously trained, lacked experience, or just is not a good candidate for real time operations - can adversely affect the overall well costs, sometimes significantly. Nowadays, the use of IWDS was expanded to benefit specialists working remotely, for example, from Halliburton's Real Time Operations Center™ (Pellerin et al., 2003). Although such specialists are chosen from the most experienced professionals in a company, there is no doubt that their performance would be greatly improved by using reliable IWDS. These systems could help the specialists to prematurely identify down-hole, hidden problems that otherwise would only be identified in a late stage, making the mitigation of the problem more difficult.

A typical strategy for developing IWDS is to decide on a set of the most critical events and take existing data sets from specific geologic provinces and search for re-occurring patterns. Once the patterns are successfully identified, algorithms can be developed to filter out false patterns and to assign probabilities for onset of an event. Neural network, fuzzy logic, Fast Fourier Analysis (FFT), recursive estimation, and CuSum are common tools and techniques used in the development of such systems (Ali, 1994; Siruvuri et al., 2006; Finger et al., 2003; Hargreaves et al., 2001).

IWDS are obviously more robust when both downhole and surface data are used. However, since down-hole data is usually more expensive and complex to acquire than surface data, there are many systems that try to understand down-hole events based solely on surface data. However, the use of only surface data must be done with extreme care to avoid erroneous results. For example, surface vibrations can be considerably different from down-hole vibrations. Indeed, sometimes what is measured on the surface is misleading. Occasionally the opposite also occurs; there is significant surface vibration with no significant down-hole dysfunction (Finger et al., 2003; Henneuse, 1992; Dubinsky, 1992; Macpherson et al., 2001).

Downhole annular pressure (PWD) is becoming a standard measurement and provides an accurate way to identify drilling problems. A critical situation where PWD can be used with great success is when there is a small difference between fracture and pore pressure gradients. PWD is a valuable tool to enhance the capabilities of an IWDS (Paes et al., 2005; Hutchinson and Cooper, 1998).

The development of enhanced means to transfer down-hole data to surface will favorably impact the development of improved IWDS. Faster data rate transfer than those provided by current mud pulse telemetry - which typically functions at 3 to 6 bits/sec, rising to 12 bits/sec under ideal conditions - is required by IWDS to adequately address in a timely manner dynamic drilling problems, such as bit vibration. This is due to the fact that vibration is better interpreted by examining signals that have been Fourier transformed to the frequency domain, where plots of transform amplitude vs. frequency show the spectral content of the signal. However, for a FFT to identify a resonance, the system must be sampled at twice or more the frequency of the resonance. For example, the minimum sample rate to diagnose a 40 Hz resonance is 80 Hz. An alternative is to compress down-hole measurements related to dynamic drilling events into diagnostic words suitable for MWD transmission. Data compression, however, requires sufficient down-hole computational power and the development of robust, autonomous down-hole algorithms. A still more innovative alternative is the use of intelligent drill strings capable of transmitting data at rates up to 2-megabits per second. Advantages of this technology are as follows: a) the capability to receive commands from surface when changes in down-hole tool functionality are required; b) distributed measurement along the drill-string, which is an important advantage compared to the current mud pulse telemetry that requires all sensors be in close proximity to the mud pulse tool; and c) ability to transmit data when circulation stops, which is very important during well-control situations.

In addition to the IWDS, there are alternatives to early detection of drilling problems. For example, during the planning phase of a well, estimations of torque and drag, and equivalent circulating density (ECD) are required. Thus, curves of the simulated variables can be plotted against real time measurements. An example of such approach is depicted in figure 1.

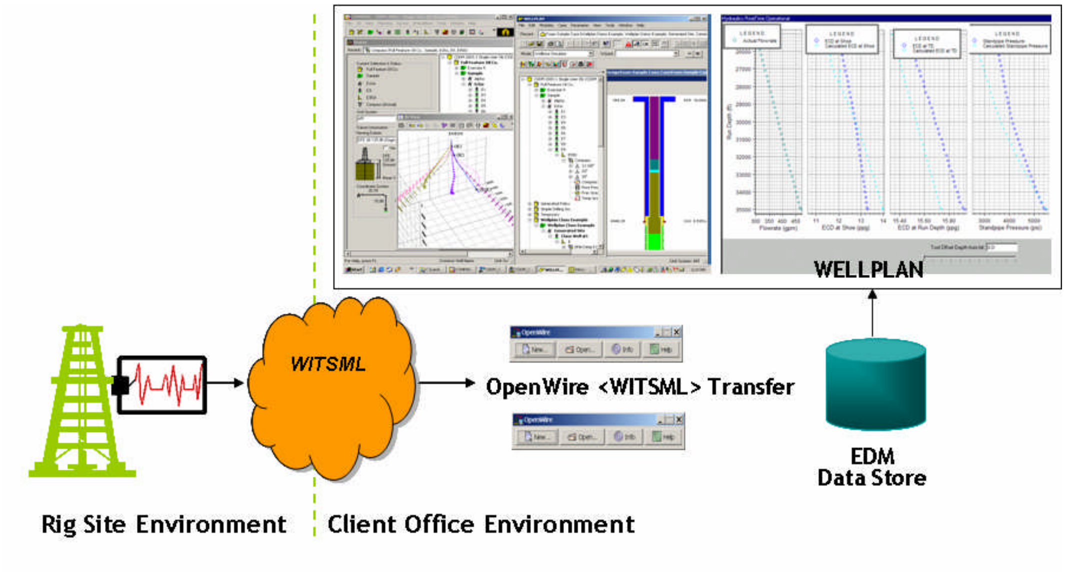

Figure 1. Real-time rig data are transmitted to the client office and automatically fed into Landmark's WELLPLAN software for torque/drag and ECD monitoring in real-time.

The next sections will further detail the scope and tactics involved in the development of an IWDS

2. Overview of an IWDS Implementation Based on Surface Data

As discussed in the Introduction, there are several different tasks involved in the successful implementation of a typical IWDS. A plan should focus on critical drilling events, take existing data sets from specific areas, and search for re-occurring patterns. Then, algorithms could be developed and validated against field data and, finally, be used to early detection of pertinent events in future drilling operations.

2.1. Data Browser and Search for Event Recognition Signatures

A great amount of good quality historical data containing signatures of drilling problems is required in the development of an IWDS. Data are used to search for the signatures of such events and to help in the development and calibration of the event-recognition algorithms. To properly handle the data, a browser, like the one shown in figure 2, is required.

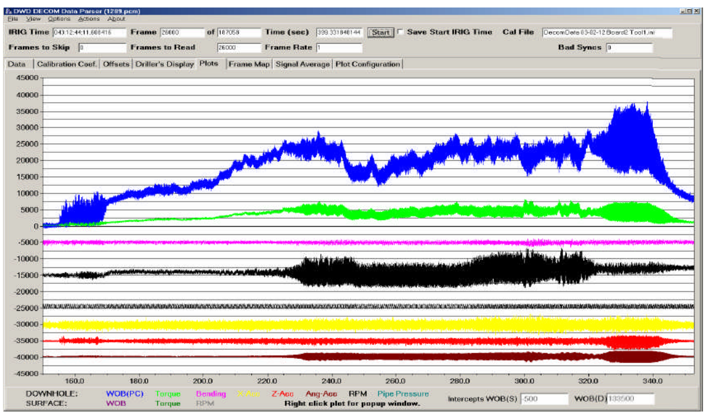

Figure 2. Example of a data browser showing down-hole and surface data (Mansure et al., 2003).

To explain the process of capturing an event signature, a gas kick example will be used. The importance of early gas kick detection relies on the fact that a gas kick becomes much more difficult to control as the volume of the gas influx is allowed to increase, and it may finally become impossible to circulate the gas to surface without losing circulation and thus initiating an underground blowout. Therefore, someone searching for gas kicks signatures should consider the following:

Warning signs of kicks:

- Primary indicators: Increased in return flow rate and pit level;
- Flowing well with pumps off;
- Hole takes less mud than normal when tripping.

Secondary Indicators:

- Pump pressure decrease and pump stroke increase;
- Increase in the bit penetration rate (caution since this can also be the indication of a formation change);
- String weight change;
- Cut mud weight.

It should be stressed that before the historical data can be browsed for the identification of event signatures, it should be validated to remove erroneous data (i.e., outliers). Outliers include bad data due to sensors malfunction or calibration. Time-delays between variables that are related have also to be corrected. The time-delay issue will be discussed in details in the next section.

The data validation should preserve, as much as possible, the raw data. Proper preservation means that smoothing filters not be used in this initial phase. Simple data validation also includes checks for maximum operational limits, that is, maximum values of mud tank volumes, WOB, torque, ROP, hook load, etc.

2.2. Time-Delay Estimation

The time-delay estimation problem occurs in IWDS applications. For example, when there is a change in the pump flow rate, there is - due to the compressibility of the drilling fluid - a delay before a corresponding change in stand pipe pressure or in flow-out-rate is observed. The lag between the pressure and flow may be computed based on physical parameters (McCann et al., 1990). An alternative is the use of a cross-correlation based method as seen in figure 3.

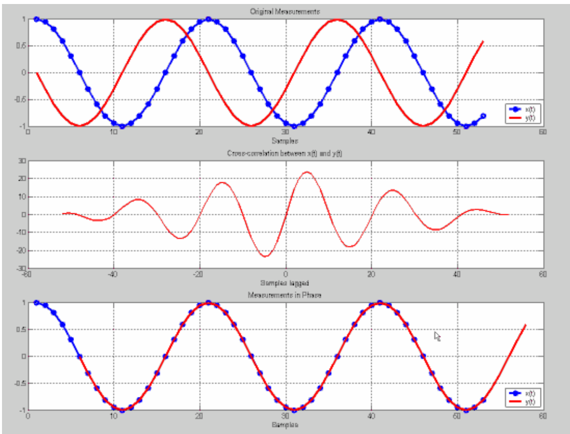

Figure 3. Example of the use of a cross-correlation based method to calculate the lag between two signals. The figure shows the delayed signals, the calculated cross-correlation, and the signals in phase.

The basic model is as follows: two sensors record delayed replicas of a signal, in the presence of noise:

$$x(t) = s(t) + w_x(t) \tag{1}$$
$$y(t) = A\, s(t - D) + w_y(t) \tag{2}$$

where D is the delay of the signal at the y-sensor relative to the signal at the x-sensor, A is the relative amplitude gain, and $wx(t)$ and $wy(t)$ are sensor noises. Given $x(t)$, $y(t)$, t=0 . . ., $N - 1$, we want to estimate the delay D. The basic idea is to shift the signal $y(t)$ and compare the shifted waveform with $x(t)$; the best match occurs when the shift equals the delay D. This notion is made clearer by using the cross-correlation between the two signals. We assume that $s(t)$ is a stationary process, and that the noises are zero mean.

The cross-correlation between the two signals $x(t)$ and $y(t)$ is calculated by,

$$R_{xy}(\tau) = A R_{ss}(\tau - D) + R_{w_x,w_y}(\tau) \tag{3}$$

where $R_{w_x,w_y}(\tau)$ is the cross correlation between the two noise processes, and $Rss(t)$ is the autocorrelation of the signal. If the noises are uncorrelated, $Rxy(t)$ will have a peak at t = D, the unknown delay. Actually, due to effects of finite length estimates and the presence of noise, the cross-correlation estimate may not show a sharp peak. (Note: the worst scenario is when sensors noise are correlated.) The data may be pre-filtered in order to sharpen the peak; equivalently, we can multiply the estimated cross-correlation by a window function (see Swami et al. 2003).

2.3. Automated Operation Detection

A very important feature of an IWDS is its ability to automatically detect drilling operations (drilling rotating/sliding, tripping in/out, reaming, washing, etc.). Based on the automated recognition of an operation taking place when the system is running, the right routine can be assigned to detect drilling problems. For example, if there is an increase in flow out during a tripping out operation, the system should be aware that, during such operation, the increase in flow out may be normal. In this case, the system should focus on other indictors to decide whether a fluid influx or a false alarm is taking place.

A rule-based system based on surface measurements of the mud logger may be applied to develop an automated operation system. Typical outputs of the system are operation name as well as time to initiate and end the operation.

Automated operation detection can also be used to generate automated well reports. Another important application is in benchmarking (Thonhauser et al. 2006; Mason and Chen, 2006).

2.4. Real-Time Recursive Parameter Estimation

IWDS needs to make decisions in real-time as in adaptive prediction. In this case, it is necessary to investigate possible time variation in the system's properties during the collection of data. An optimal algorithm that can provide such capabilities is the Kalman Filter. It combines all available measurements data, plus prior knowledge about the system and measuring devices, to produce an estimate of desired variables in such a way that the estimated *error* covariance is minimized when some presumed conditions are met. Thus, if we were to run a number of candidate filters many times for the same application, then the average results of the Kalman filter would be better than the average results of any other (Bishop, 2001).

A typical application of Kalman filter to a real-time well-control advisor can be found in Milner (1992) and is described as follows:

Consider a system that is represented by states θ_1, $\theta_2 \ldots \theta_n$. States for a real-time control advisor would be bottom-hole pressure, volume of gas, kick position, etc. A model of the dynamic behavior of states can be expressed by

$$Y(j+1) = S(j)\, Y(j)+\omega(j) \tag{4}$$

where, S(j) is an assumed deterministic state transition matrix describing the behavior of the states, $\omega(j)$ is random uncertainty in the state transition model, and j is an index for time. Let us consider the measurements of the form

$$Z(j) = H(j)\, X(j)+\varepsilon(j) \tag{5}$$

where, H(j) is an assumed deterministic measurement matrix describing the relationships between the states and the measurements, and $\varepsilon(j)$ is random uncertainty in the measurements. The minimum error estimated of X(j+1) may be computed at each observation of Z(j+1) by

$$\hat{Y}(j+1) = S(j)\, \hat{Y}(j) + G\, (j+1)[Z(j+1) - H(j+1)\, S\, (j+1)\, \hat{Y}(j)] \tag{6}$$

where, $\hat{Y}(j+1)$ is the estimate of Y(j+1) and G(j+1) is a set of weights calculated from the magnitudes of the uncertainties $\varepsilon(k)$ and $\omega(k)$, and the measurement and state transition equations (Maybeck, 1979).

2.5. Event Flagging

It can be shown that for certain general assumptions concerning the residual error samples (differences between the actual measurements and the predicted measurements), a minimum error test for a jump or trend is derived by computing the conventional CuSum chart, which can be defined as:

$$CuSum(n) = \sum_{j=1}^{n} res(j) \tag{7}$$

Conventional *CuSum* is usually used in IWDS to flag drilling problems. An important variation of the conventional *CuSum* is the self-starting *CuSum*. It was developed as a way of setting up a *CuSum* control without the demand for a large number of samples to estimate parameters. It can be started with as few as three observations because it does not require exact knowledge of the in-control mean and standard deviation. Writing $\bar{X}_j$ and s_j for the mean and standard deviation of the first *j* readings, the self-starting *CuSum* chart uses as summand

$$U_n = \Phi^{-1}\left[F_{n-2}\left(\sqrt{\frac{n-1}{n}}\,\frac{X_n - \bar{X}_{n-1}}{s_{n-1}}\right)\right] \tag{8}$$

where Φ is the standard normal cumulative distribution function, and F_{n-2} is the cumulative distribution function of a *t*-distribution with $n - 2$ degrees of freedom. The sequences U_n follow an exact standard normal distribution for all $n > 2$ and are statistically independent. Thus, they can be cumulatively summed using known-parameter settings. As the in-control history grows, the self-starting *CuSum* chart approaches a known-parameter *CuSum* chart of N(0,1) quantities (Hawkins and Olwell, 1998).

Figure 4 is an example of the application of a self-starting *CuSum* to flag an event based on a signal that is expected to have a constant mean under normal situation. Note that, in this particular case, it is possible to monitor the variation of the signal without the need of a recursive parameter estimator like the Kalman Filter. The figure shows the data signal, the result of the self-starting *CuSum* as well as the alarm or flag. Note that the *CuSum* was tuned to allow positive and negative mean shifts. Typical mean shifts used in process control are 0.5, 1, and 2 standard deviations.

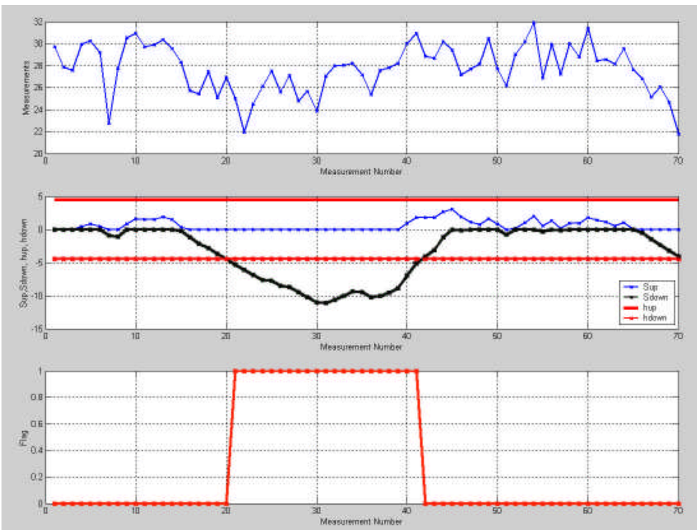

Figure 4. Application of a self-starting *CuSum* to monitor the variation of a signal (positive and negative mean shifts) (Hawkins and Olwell, 1998).

2.6. False Alarms

Many existing IWDS allege high sensitivities. For example, for gas kick advisory systems, high sensitivity should be able to detect gas kick of around a barrel. However, such high sensitivities should be analyzed considering false alarm rates. A system that generates excessive false alarms will not be trusted when a genuine alarm occurs. A natural consequence may be the operator simply ignores the alarms or sets the limits so wide that the alarms are never triggered.

False alarms essentialy happen due to data problems (noisy data, sensors problems, etc.) and inaccurate or inadequate algorithms, as discussed below (Hargreaves et al., 2001; McCann et al., 1993; Milner, 1992; Dudley et al., 2006):

- Poor measurement quality is an important source of false alarms. Accurate and reliable surface and down hole sensors should be installed and carefully maintained and calibrated. The very best sensors can also help to reduce data noise problems;
- False alarm rates tend to increase in the high noise conditions that are typically encountered during drilling a well. Therefore, the predictive system should be able to effectively provide noise compensation. Probabilistic methods like Bayesian approach may be applied for this purpose;

- Most systems still use a windowed threshold as the means of trend detection. However, windowed threshold trend detection is still poorly optimized for noise and does not take into account the shape of a trend;
- Flow measurements are key indicators of typical drilling problems, such as a kick. However, one problem with using flow data is the high level of noise in the measurements. Mud flow is often measured with crude sensors (pump strokes for flow in, and the flow paddle for flow out). These sensors are particularly noisy. Also, the presence of heave on deepwater rigs has caused problems with existing kick detection systems;
- One of the most difficult parts of the design of an IWDS is the selection of adequate models. No matter the type of models to be used, there is a need for a comprehensive model set to develop, test, and validate the final model. It is not only necessary to capture the event of interest but also a series of other events which, otherwise, could trigger false alarms because they look more like the event of interest than normal drilling;
- The alarm detection and pattern classification may be the weakest link in an IWDS. Interpretation of data patterns can be difficult, and experts do not always agree. Numerous additional test cases with known problems situations should be examined to finalize the design of these tools;
- The models of the flow path (including all surface mud systems) are complex and highly rig-dependent, and require accurate modeling and calibration to perform optimal and minimize false alarms;
- Outputs of a probability history may be helpful to minimize false alarms by assisting the operator in interpreting alarms. For example, if a false alarm occurs, the probability will generally fall quickly if further evidence fails to appear. However, when a kick is actually occurring, the probability that a kick is occurring will increase with time;
- During turbo drilling, with little or no pipe rotation, the main source of noise in the measurements is mud pressure surges from reciprocating mud pumps. As this noise is essentially deterministic, it lends itself to noise cancellation approaches. An approach has been utilized which subtracts the mud pressure signal from the vibration measurements, correcting the time delay effects with the use of a cross correlation function;
- When there is an abrupt movement of the drill-string, a pressure wave is transmitted through the circulation system. A kick detection routine should ignore this event to avoid triggering a false alarm;
- IWDS should provide the operator a sensitivity control to tune the alarm to his particular configuration. They should also contemplate the fact that the models used may have some sort of regional dependence.

3. Conclusions

- IWDS are key tools to help oil and geothermal companies to succeed in complex drilling situations by efficiently minimizing costly problems.
- Enhanced automated operation detection and predictive models, combined with probabilistic alarm detection features, have greatly benefited the accuracy of IWDS. However, false alarms still represent a major concern.
- Petrobras and the State University of Campinas (UNICAMP) have established an important partnership to develop IWDS. As a result of this partnership, UNICAMP has already developed an innovative real-time ROP predictor based on a dynamic neural network. The model estimation used is an Auto-Regressive with Extra Input Signals model or ARX model (Noorgard et al., 2000). The architecture used is a feed-forward network trained with the Levenberg-Marquardt algorithm (Marquardt, 1963). Mud-logging data from an offshore field in the Campos Basin, Brazil, were used to train and validate the ROP predictor. Other IWDS components are currently under development by UNICAMP.

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