Non-Productive Time Reduction Using Heuristic Wellbore Hydraulics Modelling

Master Thesis

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With sincere love, I dedicate this thesis to my parents, my wife Magdalena and our daughter Lora for their unfailing support during my years of study.

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EIDESSTATTLICHE ERKLÄRUNG

Ich erkläre an Eides statt, dass ich die vorliegende Arbeit selbständig und ohne fremde Hilfe verfasst, andere als die angegebenen Quellen und Hilfsmittel nicht benutzt und mich auch sonst keiner unerlaubten Hilfsmittel bedient habe.

AFFIDAVIT

I declare in lieu of oath, that I wrote this thesis and performed the associated research myself, using only literature citied in this volume.

Leoben, May 2017

(Date)	**Dimitar Todorov**

“Measure what is measurable, and make measurable what is not so.”

- **Galileo Galilei**

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Abstract

The precise knowledge of the hydraulic pressure losses while drilling is one of the crucial factors for the success of the entire drilling process. The pump must operate providing the desired flow rate necessary for e.g. hole cleaning requirements and should do that within a predictable and accurate pressure range. The operating pressure is thereby concurrently limited by pipe and equipment constraints. Pore pressure, formation fracture gradients and resulting maximum allowable equivalent circulating density introduce additional complexity to the hydraulic system. However, taking the complete drilling system under consideration, severe challenges arise in representing the reality for pump pressure prediction due to the restricted knowledge of several relevant parameters at any given point in time.

This work demonstrates a method for simulating drilling hydraulics, applicable in real-time, as well as during the planning phase. The proposed method combines deterministic with non-linear heuristic approaches.

The deterministic approaches are based on classical rheological models incorporating fluid properties, borehole geometry, casing and drill string configuration as well as detailed information regarding the well path. Although the deterministic approaches work well when all input parameters of the model are well defined and known, in real-world applications a lack of accuracy is caused by several uncertainties: mud properties change with temperature and pressure along the flow path thru the wellbore; the relative roughness of the borehole wall, as well as the borehole diameter in open holes is typically not known as some examples.

To tackle those un-knowns and their non-linear impact on results, the classical models have been extended by data driven models, namely neural networks. Based on real-time sensor measurements, those extended models were trained for simulating the standpipe pressure on both, single and multi-well scenarios.

Furthermore, the concept has been extended by the addition of automated operation recognition results, allowing the variety of different operational states to influence the creating of individual state driven models for hydraulic analysis.

Finally, in order to meet the current requirements for a drilling hydraulics simulator, the results are presented in a clear and understandable interface, ensuring a detailed real-time wellbore hydraulic overview, including equipment and formation pressure limitations as well hole cleaning requirements.

Kurzfassung

Die genaue Kenntnis der hydraulischen Druckverluste beim Bohren ist einer der entscheidenden Faktoren für den Erfolg des gesamten Bohrprozesses. Die Pumpe muss mit der erforderlichen Durchflussrate arbeiten, um beispielsweise Loch-Reinigungsanforderungen zu erfüllen, und sollte dies in einem in einem exakt definierten Druckbereich tun. Der Betriebsdruck wird dabei gleichzeitig durch Rohr- und Gerätebeschränkungen begrenzt. Der Porendruck, die Formationsbruchgradienten und die daraus resultierende maximal zulässige äquivalente Zirkulationsdichte führen zu einer zusätzlichen Komplexität des Hydrauliksystems. Betrachtet man das gesamte Bohrsystem, ergeben sich bei der Darstellung der Pumpendruckvorhersage aufgrund der eingeschränkten Kenntnis von mehreren relevanten Parametern schwerwiegende Herausforderungen. Diese Arbeit veranschaulicht eine Methode zur Simulation von Bohrhydraulik, die sowohl in Echtzeit während des Bohrbetriebs als auch in der Planungsphase anwendbar ist. Die vorgeschlagene Methode kombiniert deterministische mit nichtlinearen heuristischen Ansätzen.

Die deterministischen Ansätze basieren auf klassischen rheologischen Modellen, die Fluideigenschaften, Bohrlochgeometrie, Verrohrung- und Bohrgestänge-Konfiguration, sowie detaillierte Informationen über den Bohrungspfad beinhalten.

Die deterministischen Ansätze zeigen bei bekannten und gut definierten Eingangsparameter für das Modell bei der praktischen Anwendung Ungenauigkeiten durch mehrere Faktoren: Eigenschaften der Bohrspülung sind Temperatur und Druck abhängig und ändern sich hierdurch entlang des Strömungsweges im Bohrloch; die relative Rauigkeit der Bohrlochwand sowie der Bohrlochdurchmesser in offenen Bohrloch sind in der Regel nicht genau bekannt.

Um diese Unbekannten und ihre nichtlinearen Auswirkungen auf die Ergebnisse zu bekämpfen, werden die klassischen Modelle um datengestützte Modelle erweitert, nämlich die sogenannten neuronalen Netze. Basierend auf Echtzeit-Sensor-Messungen wurden diese erweiterten Modelle für die Simulation des Standrohrdrucks auf sowohl Einzel- als auch Multi-Bohrungs-Szenarien trainiert. Darüber hinaus wurde das Konzept mit einer automatisierten Erkennung der Drilling Operation States erweitert, sodass die Vielfalt unterschiedlicher Betriebszustände und die damit verbundene Erstellung einzelner „State“-angetriebener Modelle für die hydraulische Analyse berücksichtig werden kann.

Um die aktuellen Anforderungen an einen Bohrhydraulik-Simulator zu erfüllen, werden die Ergebnisse in einer klaren und verständlichen Schnittstelle präsentiert, sodass eine detaillierte Echtzeit-Bohrloch-Hydraulik-Übersicht, inklusive Ausrüstungs- und Formationsdruckbegrenzungen sowie Lochreinigungsanforderungen, gewährleistet ist.

1 Introduction

Every business venture is driven by economic profitability and efficiency. The investors are constantly thinking about possibilities to reduce the capital and operational expenditures. The petroleum industry, amongst others, could be ranked as one of the riskiest and most expensive ventures known today. The largest portion of up to 60% of the funds invested in field developments can be allocated to the drilling process itself.

Oil well drilling is a complex process, involving many different operational stages, various technical expertise and a number of operational functions of the personnel involved.

Modern sensor and real-time data streaming technologies, offer the possibility for a continuous observation of the drilling process. Using real time rig sensor data, the industry can monitor and perform a variety of different analysis thus recognizing unexpected events at an early stage and performing all necessary counteractions to assure no harm is done to the involved personnel or the nature.

A drilling hydraulics monitor could be regarded as an indispensable part of any drilling rig. It is important to realize safe and efficient drilling. Furthermore, it is required to successfully detect and predict abnormal events while drilling, ideally with early problem-recognition prior to the problem occurring.

In the times of modern rotary drilling, a fluid needs to be circulated down the drill string, through the bit and up the annulus back to the surface. The circulation is required in order to remove the formation cuttings produced and to cool down the bit. Initially water was used for this task, however with the increased complexity of the drilling operations, the composition of the drilling fluids became more sophisticated in pursuance of a specific design which will limit the formation damage, improve cuttings transport, prevent shale swelling and generally boost the drilling performance.

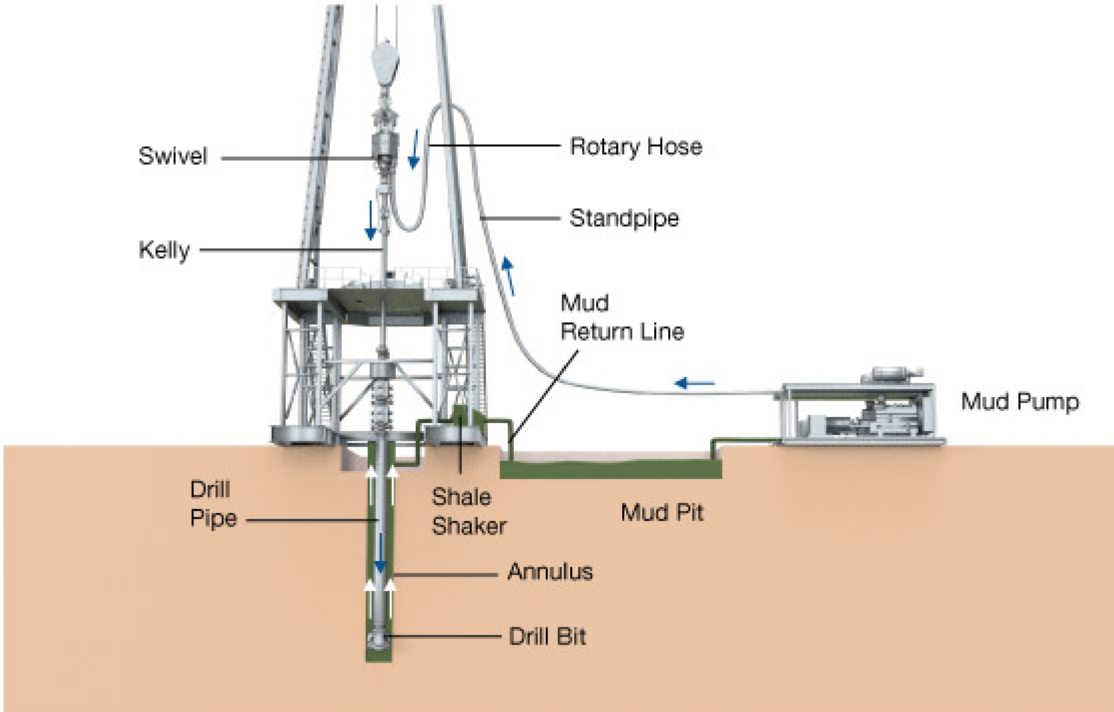

Figure 1 Drilling Rig Circulation System

The hydraulic power that is required to provide the circulation of the drilling fluid is provided by the mud pumps. Although several pumps may be used simultaneously, there are still maximum operating limits, which need to be taken into account.

Besides considering the pumps limitations, the pressure along the wellbore annulus should be additionally maintained within a safe pore pressure and fracture pressure window.

Thus, the task of a drilling engineer is to plan the operations in a way that the pressure is kept within a safe range by managing the various parameters and tubular design. This makes hydraulics monitoring all that more important.

1.1 Problem Statement and Objectives

This thesis will give insight to a novel approach, combining numerical methods with real-time operation recognition algorithms, for an optimal hydraulics' feedback while drilling with a reduced set of parameters and a simplified data input technique.

The presented hydraulic simulator, operates with mud logging sensor data, which are commonly available during drilling operations and thus the dependency on complex metadata, e.g. drill string configuration, is eliminated. It provides real-time evaluation of the wellbore status concerning hydraulics as well as capabilities for assistance in well planning procedures.

The simulated results are then presented in a graphical user interface, which aids the driller with decision making by clearly indicating the actual downhole conditions.

The first part of the work will describe the current industry standards regarding drilling hydraulics. A typical deterministic model will be briefly investigated and analyzed. The advantages and disadvantages of such an approach will be evaluated.

In the second part of the thesis, the general deterministic model will be replaced by the introduction of advanced numerical methods, namely by the usage of neural networks and automatic operation recognition algorithms.

In the final part, the described simulator is utilized to analyze several test scenarios, showing the impact of the drilling parameters on the stand pipe pressure, ECD's and the possibility for abnormal event recognition.

2 Conventional Industry Practices

2.1 Overview

Drilling hydraulics has been thoroughly discussed before; therefore, a detailed description and literature review is way beyond of the scope of this work. Relevant information is provided via an extensive list of reference to cover this aspect (Bourgoyne, Millheim, Chenevert, & Young Jr., 1986), (Zoellner, Thonhauser, Lueftenegger, & Spoerker, 2011), (De Sa & Martins, 1994). However, the following brief revision has the intention to give a basic overview of the drilling hydraulics practices used in the industry today.

2.2 Pressure Losses

The pressure change during pumping is a function of the fluid flow. The total pressure loss can be represented as:

$$\Delta P = \Delta P_{HydroSt.} + \Delta P_{Drill\ Pipe} + \Delta P_{BHA} + \Delta P_{Bit} + \Delta P_{Annulus} + \Delta P_{Surf.\ Tools} \quad \text{Eq.(2-1)}$$

2.2.1 Hydrostatic Pressure

Hydrostatic pressure results from the pressure exerted by a fluid column. It is a function of the fluid density and the vertical length of the fluid column.

$$\Delta P_{HydroSt.} = \rho_f . g . h \quad \text{Eq.(2-2)}$$

In oil well drilling, a common practice is to refer to hydrostatic pressures in terms of a pressure gradient. This will give the increase in pressure per unit of vertical depth.

2.2.2 Drill Pipe Pressure Losses

The drill pipes provide the connection between the bottom hole assembly and the surface equipment. Their function is to transmit torsional and axial forces and provide a conduit for the fluid circulation required for cooling the bit and cleaning the hole.

The losses in the pipes depend on their size, the mud rheological properties and the type of flow regime

2.2.3 Bottom Hole Assembly (BHA) Pressure Losses

The bottom hole assembly (BHA) is the part of the drill string which is located just above the bit and below the last drill pipe joint. Modern bottom hole assemblies may include a variety of components, each having different and rather small inner diameter. Thus, the frictional pressure losses across the bottom hole assembly may contribute significantly to the overall pressure loss.

2.2.4 Bit Pressure Losses

The drilling bit usually incorporates nozzles which have the purpose to improve the cleaning action of the drilling mud at the bottom of the hole. Years back, before jet nozzles were introduced, the bit performance was significantly reduced, since the rock particles were not entirely removed, and much of the action was consumed in regrinding these fragments.

- Bit nozzle velocity:

$$V_n = \frac{Q}{38{,}71.A} \quad Eq.(2\text{-}3)$$

Since the nozzles represent a short section of greatly reduced diameter, the pressure losses through this part of the drill string are significant.

- Pressure drop trough the nozzles:

$$\Delta P_{Bit} = \frac{d.Q^2}{2959{,}41.(0.95)^2.A^2} \qquad \text{Eq.(2-4)}$$

2.2.5 Annular Pressure Drop

The annular pressure drop is critical in order to ensure safe drilling operations and not fracture the formation. Furthermore, the annular velocity should be sustained within certain limits in order to establish effective cuttings transport while avoiding any hole erosion.

The prediction of the annular pressure losses however is not straightforward. Annulus eccentricity, drill string motion, mud rheology and tool joints add to the complexity of the pressure loss calculations.

- Annular Velocity [field units]:

$$v_a = \frac{Q}{A} = \frac{1270 * Q}{({d_{Hole,Csg}}^2 - {d_{OD}}^2)} \qquad \text{Eq.(2-5)}$$

Typically, an additional measure called equivalent circulation density (ECD) is used for evaluating the circulating conditions in the hole. The ECD shows the pressure losses in the annulus, expressed as a unit of density.

$$ECD = \frac{\Delta P_{Ann}}{TVD.g} + \rho_f \qquad \text{Eq.(2-6)}$$

2.2.6 Surface Pressure Drop

As the simulator can calculate the pressure drop at every point in the drill string and the annulus, for the surface losses which occur due to the flow through various surface components, such as goose necks, swivels, top drive or kelly, an overall surface component pressure loss is added, which is calculated according the latest API guidelines.

Basically, depending on the specific rig setup, these pressure losses can be classified into five standard types (American Petroleum Institute, 2009).

Case	Standpipe	Hose	Swivel	Kelly	C_{SC}
1	40 ft. x 3.0-in ID	45 ft. x 2.0-in ID	4 ft. x 2.0-in ID	40 ft. x 2.25-in ID	1,00
2	40 ft. x 3.5-in ID	55 ft. x 2.5-in ID	5 ft. x 2.5-in ID	40 ft. x 3.25-in ID	0,36
3	45 ft. x 4.0-in ID	55 ft. x 3.0-in ID	5 ft. x 2.5-in ID	40 ft. x 3.25-in ID	0,22
4	45 ft. x 4.0-in ID	55 ft. x 3.0-in ID	6 ft. x 3.0-in ID	40 ft. x 4.00-in ID	0,15
5	100 ft. x 5.0-in ID	85 ft. x 3.5-in ID	22 ft. x 3.5-in ID		0,15

Table 1 Surface Component Coefficients

The coefficient C_{SC} can then be used as follows [field units]:

$$\Delta P_{Surf.\ Tools} = C_{SC} . \rho_{surface} . \left(\frac{Q_{surface}}{100}\right)^2 \qquad Eq.(2\text{-}7)$$

2.3 Deterministic Approach

When the drilling mud leaves the discharge pump, it travels through the surface lines, top-drive or kelly, passes downward through the complete drill string and jetted through the bit nozzles it makes its way through the annulus back to the surface.

A common approach to handle the hydraulics throughout this cycle is to monitor the losses at each point in the system. One way of dealing with this challenge is to use a deterministic approach.

By definition, a deterministic system is a model where everything that happens and occurs in the system is well known and understood. The outcome is entirely based on physical effects and reactions. These events are then added up and can theoretically show the status of the system at any point in time (Weiss, 2013).

In terms of the drilling process, in order to approach the hydraulics deterministically one would require a precise knowledge of all necessary parameters. Amongst others, this includes a detailed description of the drill string, exact mud rheology, the wellbore construction elements, temperature, pore and fracture pressure gradients as well as the surface component specifications.

Once these parameters are obtained, a proper rheological model should be chosen. Rheological models are mathematical models, used to predict fluid behavior across a wide range of shear rates and provide a shear rate – shear stress relation, resulting in a viscosity to, in practical means, calculate the surface pumping pressure for a given fluid flow rate in the system.

No matter which rheological model is used, the frictional pressure drop calculations depend on whether the flow regime is turbulent or laminar. In this sense, a determination of an adequate critical flow regime criterion is of absolute importance for the success of the simulation.

2.3.1 Rheology of the Drilling Muds

The drilling fluid is one of the most important elements in the drilling process. It has a number of functions the most important of which are subsurface pressure control, cuttings removal and transport, suspension of the solid particles and bit cooling and lubrication. Beside these tasks, a proper selection of the mud will help in preventing formation damage; it may seal permeable formations or even control corrosion.

While circulating, the drilling fluid lifts the cuttings from the bottom of the hole to the surface. Efficient hole cleaning requires adequate circulating rates in order to prevail on the force of gravity acting upon the rock particles. Further factors for establishing a proper hole cleaning program include the drilling fluid density and rheology, annular velocity, hole angle and cutting slip velocity.

When speaking about drilling muds, one must differentiate between Newtonian and non-Newtonian fluid behavior.

Newtonian fluids represent the majority of the common fluids such as water, oils, various gases, etc. From a rheological point of view, they express the simplest model that accounts for viscosity. A fluid is categorized as Newtonian if it exhibits a constant viscosity at a given temperature and pressure. In other words, we can define a fluid as Newtonian if its shear stress is directly proportional to its shear rate with a constant of proportionality known as the viscosity.

- Newtonian Fluid Model:

$$\tau = \mu . \gamma \qquad Eq.(2\text{-}8)$$

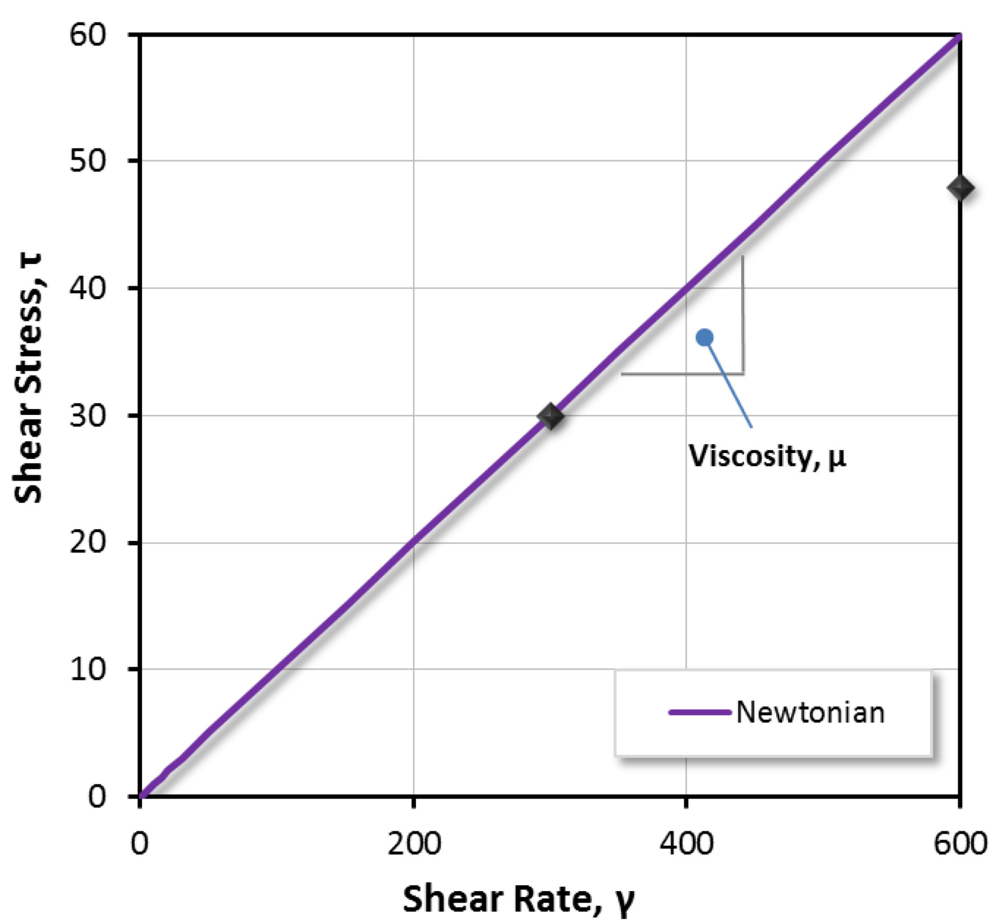

Figure 2 Shear Stress vs. Shear Rate Relationship for Newtonian Fluids

In case of a Newtonian fluid a high shear rate (i.e. a fast movement of the fluid), will result in a linear increase in shear stress. Generally, this has a positive effect on the cuttings transport efficiency since high shear stress on the cuttings moves them better as turbulence is created. However, when observing the situation in the annulus, it is clear that the velocity is not high enough. This leads to lower shear rates and shear stress on the cuttings which are not desired. Another important argument against the Newtonian fluids is the fact that high velocities in the drill pipe will result in enormous frictional pressure losses due to the pipe's smaller diameter.

When looking at the current drilling mud standards, we immediately realize that the non-compressive Newtonian rheological models are far away from fulfilling the real-life conditions. The drilling fluid properties must differ significantly from those of the Newtonian fluids.

To tackle these challenges the mud should meet certain criteria. Usually, what is desired is a fluid which exhibits a non-linear relationship between the shear stress and shear rate.

Such fluids are classified as non – Newtonian. We can also speak of thixotropic fluids where the viscosity decreases with time after a shear rate is applied or rheopectic fluids – the viscosity increases with time after the shear rate is applied.

There are various models where viscosity decreases with increasing shear rate:

- Bingham – Plastic Model

$$\tau = \tau_0 + \mu_p . \gamma \qquad \text{Eq.(2-9)}$$

The Bingham plastic fluids represent the simplest non – Newtonian fluids, which differ from the Newtonian fluids only in that their linear relationship between shear stress and shear rate does not go through the origin (see Figure 2). A Bingham plastic fluid flow curve is a straight line with a yield stress τ_0 which must be exceeded to initiate flow (Korobeinikov, 2000). The slope of the line defines the plastic viscosity.

- Power – Law Model

$$\tau = K.\gamma^n \qquad \textit{Eq.(2-10)}$$

The Power – Law model is more sophisticated than the Bingham Plastic model. It overcomes the weaknesses of the Bingham model at low shear rates. A Power – Law model does not assume a linear relationship between shear stress and shear rate. For this model, just as in the case of the Newtonian fluids, the plot begins from the origin (see Figure 2).

The Power Law index n indicates the degree of non – Newtonian behavior over a given shear rate range. If n=1 the behavior of the fluid is considered Newtonian. As n decreases in value the fluid becomes more non – Newtonian.

The consistency index K is a measure of the thickness of the fluid. An increase in K indicates an increase in the overall hole cleaning effectiveness of the fluid.

- Herschel – Bulkley (Yield Power – Law) Model

$$\tau = \tau_0 + k.\gamma^n \qquad \textit{Eq.(2-11)}$$

The Herschel – Bulkley model is the most accurate Non-Newtonian model but also the most complex among all and thus more difficult to implement.

The model reduces to the Bingham Plastic model when n=1 and it reduces to Power Law when τ_0=0 (see Figure 2).

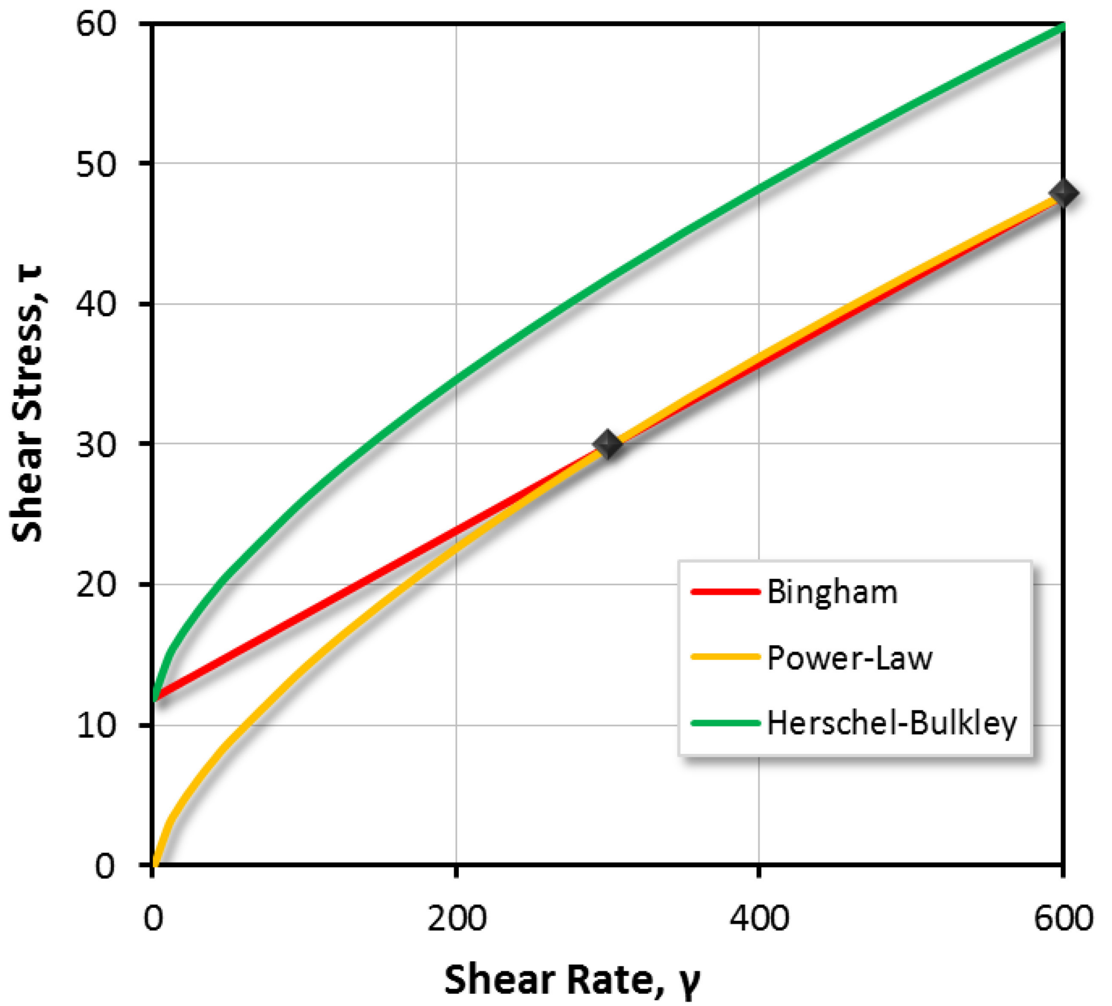

Figure 3 Shear Stress vs. Shear Rate Relationship for non - Newtonian Fluids

2.3.2 Pressure Drop Calculations

Once a rheological model has been chosen, one should predict whether the fluid is in laminar or a turbulent flow regime. For a fluid flow in laminar regime, analytical pressure drop solutions are available, whereas in the case of a turbulent flow, an empirical model must be applied.

The classical approach for defining the flow regime is through the usage of the Reynolds number. The Reynolds number is defined as the ratio of inertial forces to viscous forces.

$$N_{Re} = \frac{\rho . v . d}{\mu} \qquad \text{Eq.(2-12)}$$

In case of a Newtonian fluid a Reynolds number of 2100 is used as the boundary between laminar and turbulent flow. Theoretically there is a transition range between these two flow regimes. However, this zone is ignored as a separate flow regime since no analytical solution exists and the empirical solutions are weaker than those for fully turbulent flow. If case of a non – Newtonian fluid, a critical Reynolds number must be calculated, which will determine whether the flow is laminar or turbulent.

The following equations are used for the pressure drop calculations though the pipe and annulus for a Power – Law fluid:

- Pipe Flow [field units]

$$n = 3{,}32 \log \frac{\Theta_{600}}{\Theta_{300}} \qquad \text{Eq.(2-13)}$$

$$K = \frac{\Theta_{300}}{511^{n}} \qquad \text{Eq.(2-14)}$$

$$V_p = \frac{25{,}4 . Q}{{d_{In,Pipe}}^{2}} \qquad \text{Eq.(2-15)}$$

$$V_c = \left[\frac{5{,}82 . (10^{4}) . K}{\rho}\right]^{\left(\frac{1}{2-n}\right)} . \left[\frac{1{,}6}{d_{In,Pipe}} . \frac{3 . n + 1}{4 . n}\right]^{\left(\frac{n}{1-n}\right)} \qquad \text{Eq.(2-16)}$$

If $V_p > V_c$ the flow is turbulent and the following pressure drop equation should be used:

$$\Delta P_{Pipe,t} = \frac{8{,}91 . 10^{-5} . \rho^{0{,}8} . Q^{1{,}8} . \left(\mu_p\right)^{0.2} . L}{{d_{In,Pipe}}^{4{,}8}} \qquad \text{Eq.(2-17)}$$

If $V_p < V_c$ the flow is laminar and the following pressure drop equation should be used:

$$\Delta P_{Pipe,l} = \frac{K.L}{300.\,d_{In,Pipe}} . \left[\frac{16.\,V_a}{d_{In,Pipe}} . \frac{(3.\,n+1)}{4.\,n}\right]^n \qquad \text{Eq.(2-18)}$$

- Annular Flow [field units]

$$V_a = \frac{24{,}5.\,Q}{{d_h}^2 - {d_{Out,Pipe}}^2} \qquad \text{Eq.(2-19)}$$

$$V_c = \left[\frac{3{,}878.\,(10^4).\,K}{\rho}\right]^{\left(\frac{1}{2-n}\right)} . \left[\frac{2{,}4}{\left(d_h - d_{Out,Pipe}\right)} . \frac{2.\,n+1}{3.\,n}\right]^{\left(\frac{n}{1-n}\right)} \qquad \text{Eq.(2-20)}$$

If $V_a > V_c$ the flow is turbulent and the following pressure drop equation should be used:

$$\Delta P_{Annulus,t} = \frac{8{,}91.\,10^{-5}.\,\rho^{0{,}8}.\,Q^{1{,}8}.\,\left(\mu_p\right)^{0.2}.\,L}{\left(d_h - d_{Out,Pipe}\right)^{4{,}8}} \qquad \text{Eq.(2-21)}$$

If $V_a < V_c$ the flow is laminar and the following pressure drop equation should be used:

$$\Delta P_{Annulus,l} = \frac{K.L}{300.\,\left(d_h - d_{Out,Pipe}\right)} . \left[\frac{2{,}4.\,V_a}{\left(d_h - d_{Out,Pipe}\right)} . \frac{(2.\,n+1)}{3.\,n}\right]^n \qquad \text{Eq.(2-22)}$$

2.3.3 Temperature Effects and Density Behavior

Temperature is another important parameter that has an impact on the rheological and density properties of the drilling fluids. While the surface temperature of the mud can be easily measured and monitored, the actual temperature distribution down hole varies significantly from the one measured at surface conditions.

An easy and frequently used technique to represent the temperature distribution down hole is to create a linear fit between the surface temperature and the static bottom hole temperature. This method is suggested by the current API standards, with a correction factor accounting for the fact that the mud is in circulation and therefore unlikely to reach the geothermal temperature levels. This approach is simple and gives a brief approximation about the down hole temperature distribution. However, it fails in representing the true values along the complete well path.

During the years, the challenge of the wellbore temperature prediction has been thoroughly studied. Several mathematical models have been developed, based on thermodynamical energy balance equations (Holmes & Swift, 1970). These consider different effects such as conduction and convection. The results of these efforts are ordinary differential equations which’s solutions lead to a temperature gradient as a function of the depth. As in the case of the less complex API approach, these analytical models have also a number of shortcomings. One of the biggest limitations arises from the fact that these models assume an increase in the geothermal gradient with the increase in measured depth. This limits their application to vertical wells. An expression of the true vertical depth as a function of the measured depth will solve this issue, however the resulting equations are strongly non-linear and extremely complex to solve.

To add to the complexity of the thermal calculations, one should also acknowledge a number of other heat sources such as the fluid heating due to friction and the thermal effects due to the pressure drop.

The density of the drilling fluids is another parameter which varies throughout the wellbore length. In case of water based muds, these variations may be ignored due to the fact that such fluids are relatively uncompressible at the expected real-life conditions. This statement is however inaccurate when we consider oil based muds which possess a higher compressibility than the water based muds.

Regarding the solids content, typically laboratory models are generated using material balance equations. These can then be applied in real life environments.

2.3.4 Time Based Behavior of the Drilling Mud

The simulation of the pump start-up sequences after the drilling mud has had a period of static conditions, e.g. during slip to slip connections, is a major element of any drilling hydraulics simulator (Zoellner, Thonhauser, Lueftenegger, & Spoerker, 2011).

The drilling mud has the property to build a gel strength when left static. This is essential to keep the drilled cuttings and mud weighting additives suspended. Once the mud gets “gelled”, an additional amount of energy would be necessary to break the mud and gain normal circulation back again (Bjørkevoll , Rommetveit, Aas, Gjeraldstvei, & Merlo, 2003). A pressure peak will be observed on the stand pipe pressure log.

In narrow operating windows this pressure peak might be sufficient enough to cause issues such as formation fracturing, lost circulation or even lead to a collapse of the wellbore.

Pump start-up sequences provide an additional barrier for a deterministic approach, since these events are hard to model. However, they must be an essential part of every real-time hydraulics simulator since the impact of these pressure surges might be catastrophic.

2.3.5 Dynamic Surge und Swab Pressure Predictions

Pressure surges are known to cause well control issues. Pressure surges from pipe swabbing may cause a formation fluid influx which in term, in extreme cases, may lead to a blowout. At the same time, measured positive pressure surges cause formations fracturing, lost circulation problems, etc. and are also considered as a serious danger for the wellbore.

Usually, the magnitude of these surges is not critical for most of the wellbores, since proper casing designs and mud programs leave large enough margins between fracture pressures and formation fluid pressures.

However, there is still a portion of wells which do not have these safe margins. In these cases, the pressure must be held in narrow windows to assure intact operations. Additionally, there are examples where the margins may be large enough but pressure surges might still be a problem during specific operations, e.g. running of low clearance liners in deep wells (Mitchell, 1988).

The demand on the pressure surge predictions lead to several fluid-flow models. Burkhardt (Burkhardt, 1961), Fontenot and Clark (Fontenot & Clark, 1974) and Schuh (Schuh, 1964) provided the most complete steady-state pressure surge models. The models consider the complexities of the non-Newtonian behavior of the drilling mud. However, these models lack on the ability to predict dynamic pressure surges, particularly negative pressure surges resulting from fluid backflow when the pipe is brought into rest.

The first dynamic model was presented by Lubinski (Lubinski, Hsu, & Nolte, 1977).

Comparing all these models, a conclusion has been made that some effects cannot be predicted with a steady-flow-surge model (Mitchell, 1988). Moreover, the steady-state flow models tend to overpredict the peak surges with the error increasing with depth. A dynamic pressure surge model deals with these disadvantages but still lot more analysis and MWD data are needed to evaluate the quality of the predictions.

No matter the type of model used, analytical surge and swab pressure predictions are a major challenge for every drilling hydraulics simulator.

2.3.6 Downhole tools

A modern BHA is made up of various downhole components. Drill collars, heavy weight-drill pipe, downhole motors, rotary steerable systems, logging and surveying tools, subs, jars, just to name a few. The actual pressure drop through these components would be quite different compared to the pressure drop when modelling them simply as drill collars. These pressure differentials should not be ignored in accurate hydraulic simulation.

Usually two methods for downhole tool related pressure drop are used in the practice. One can either used a fixed pressure drop or a pressure drop coefficient. The fixed pressure drop is directly added to the pressure change across the grid point where the tool is placed.

Diverter subs and rotary steerable systems tend to be modelled better by using a fixed pressure drop.

The coefficient method is used to calculated the pressure drop as a function of the flow rate. Measurement and logging tools are usually modelled using the coefficient approach.

Downhole motors are a special case as their pressure drop is a function of the torque they produce which in turn is a function of the operating parameters. Each rotor-stator configuration for a given motor size can have a different, nonlinear relationship between the flow rate and the pressure drop. To include this additional pressure drop, the user must calculate the motor's pressure drop as a function of the flow and weight on bit as per manufacturer's manuals and enter the number into the simulation (Leonard, 2006).

From everything said so far, it is obvious that the simulation of the pressure drop across the BHA with its complex flow paths and geometries is challenging and can't be easily handled by an analytical model.

2.4 Disadvantages of the Deterministic Approach

As described so far, the prediction of the pressure losses throughout the drilling phase of a wellbore involves a series of complex models, approximations and calculation algorithms.

Good estimations of the downhole conditions are highly dependent on an accurate hydraulic model. Additionally, a continuous observation of the data and evaluation of possible deviations are obligatory. The influence of special equipment and components must not be neglected. Therefore, the calculated model should be periodically calibrated and calculated values should be corrected in respect to values measured downhole (PWD). With recent developments, the effects of fluid and pipe movements are also handled in a satisfactory level. For such a system to work a complete set of information is required including description of the drill string, wellbore construction elements (risers, casing strings, cement etc.), survey readings (MD, TVD, inclination), mud rheology, rheological models, turbulence criteria, pump specifications and architecture. Density and temperature readings are as well critical factors which contribute to the accuracy of the calculations.

Reliable sensor instrumentations are crucial for the success of the monitoring system. Another important factor is the calculation time. Since all calculations are done in real time an acceptable delay should be ensured.

Most of the available commercial wellbore hydraulic tools follow a similar data input procedure. The input can be divided into two main streams. The first one involves a manual data input routine. The user should load the data related to the drill pipe and BHA components such as IDs and ODs and lengths. Pressure differentials across specific tools like the mud motor or MWD equipment must be also included. Furthermore, the mud rheological parameters including the density, fan readings, temperature must also be precisely defined. Even a small error in these values may result in a big difference between the modelled and the real pressure drop (e.g. 0,01 SG means 1 bar deviation over 1000m TVD). Rock properties, bit design details, pump specification curves etc. must be also specified.

The second part of the input involves a real-time data input which is transmitted e.g. via WITS or WITSML data streams and loaded automatically in the simulator. In most cases, this part only includes the bit measured depth and the flow rate. Some of the more sophisticated tools however, may also include the torque or other specific data channels.

The real-time part is pretty much straightforward and isn't considered as a drawback for the deterministic concept. With current standards of the rig data transmission, the necessary data input is provided with a sufficient reliability and accuracy. Therefore, regarding the disadvantages, the focus is entirely set on the manual data input section.

It may be considered pretty easy to collect all these data parameters. However, experience so far shows that gathering this data actually represents an enormous challenge at present days. It is almost impossible to get all these parameters at a decent quality and on time. In most of the cases, we rely on morning reports to find out the necessary information, but these are quite subjective and very incomplete. Mud weight for instance is generally reported only once or twice a day, which is not good enough for a wellbore hydraulic model. Solids control equipment efficiency, changing the mud weight from flow out to flow in is crucial to know. Presumed that the data required is provided on time, one will still struggle with the amounts of data input required. The level of detail and the amount of input fields required makes such data loading procedures relatively complex and user unfriendly not to mention the increased possibility of human input errors. These difficulties are especially valid when we consider large real-time operating centers where the capability of multiple well handling and analysis is a basic requirement. Under such circumstances, one will need an increased amount of professional workforce and trained drilling engineers to configure and run the system.

Therefore, after experimenting with and analysis of this conventional approach in terms of monitoring wellbore hydraulics, a conclusion was made that the monitoring concept needs to be generally improved and simplified to fit into the current requirements to avoid all previously mentioned issues.

3 Concept Overview

3.1 Objective and Requirements

An analytical representation of the drilling hydraulics, as shown in the previous chapters, typically suffers from the lack of data throughout the simulation. Acknowledging this fact, the specifications and requirements for a novel, less demanding hydraulic simulator which overcomes the shortcomings of the standard deterministic approach were defined.

The main objective is to avoid the long data loading routines. Since detailed BHA data can be pretty much inconsistent, the program should be able to perform the simulations without the necessity of a drill string description. Another important point arises from the fact that mud rheology is also something, which is difficult to track on a real-time base. Therefore, mud information is also excluded from the input parameters. For this work, survey data was not used as an input parameter, since some research done previously, showed that it also has inconsistent quality.

A decision has been made to ignore the data described previously and try to simulate the standpipe pressure by using rig sensor data. Usually, rig sensor data is available. The data might still have problems, but if used accurately especially when sufficient quality control routines are applied, it can provide the necessary input for a good hydraulic simulator.

When performing any kind of simulations based on heuristic methods, one should be careful with the type and quality of the input data in respect to the simulated data range. Numerical methods can lead to uncertainties and errors if handled wrong. The user should ensure that the training and simulation are both done on identical wellbore phases, equipment and lithological characteristics. This is one slight disadvantage of such systems which might come into account if not considered for.

Summarizing, the specifications for the novel hydraulics monitoring concept can be defined as follows:

- No detailed data loading routines required
- No BHA information required
- No rheology needed
- No survey data
- Sensor data input
- Improve the simulation through external data driven drilling modeling packages – namely automatic operation recognition algorithms

3.2 Workflow

One of the main objectives of this thesis is to introduce a real-time hydraulics monitor. Usually, the products available regarding hydraulics calculations focus mainly on well planning tasks. These are used to simulate performance prior to real operations in order to get an overview about the specific equipment and material requirements as well as the operational parameters (Cayeux, Daireaux, Dvergsnes, & Saelevik, 2012).

The model described here aims at a different application – more precisely – the real-time monitoring of the drilling hydraulics.

For such a tool, to work accurately, some conditions should be met. A constant rig sensor data stream between the well site and the software client must be provided. The received data should be automatically checked for data uncertainties and errors. After the primary quality check is performed, the required data channels are fed into the model, which on hand, performs the necessary calculations. Finally, the output should be provided to user (e.g. the driller) in an understandable and user-friendly form. And last but not least, the entire process must be performed in an exactly defined time frame in order to ensure real-time capabilities.

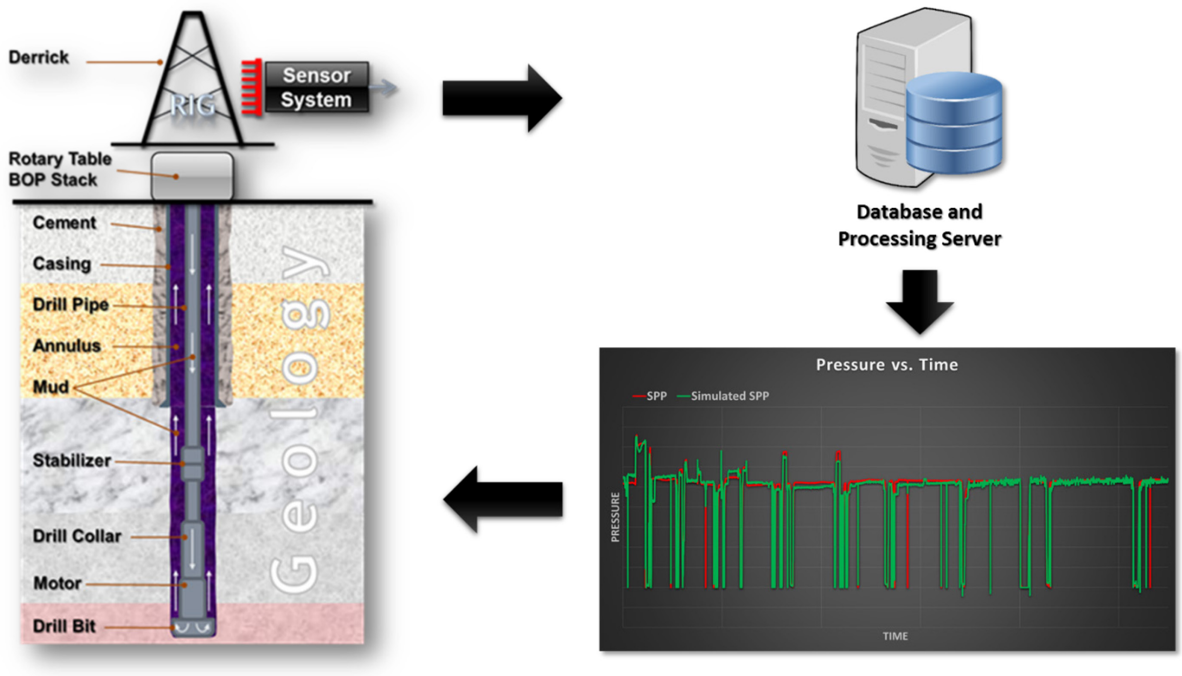

Figure 4 Model workflow

The program has been written in MATLAB ver. 2011b and makes use of built-in toolboxes, which allowed the author to concentrate primarily on the model itself. The graphical representations of the results are given using the proNova Plot software package and are loaded directly from a MySQL database.

3.3 Artificial Neural Networks

Once the specifications and workflow of the simulator are well defined, a mathematical model for simulating the stand pipe pressure only by the usage of real time sensor data should be chosen.

From a variety of curve fitting methods, a decision was made to use artificial neural networks.

Neural nets are widely used in pattern recognition because of their ability to generalize and to respond to unexpected inputs and patterns. Such methods are successfully being used in medicine, in financing, in oceans salinity prediction etc. They are useful when no concrete rules are available and thus a numerical approach will be less demanding than a model based approach. Because of these properties, the artificial neural networks gained extensive popularity in recent years.

The artificial neural networks mimic the basic behavior of the human brain. In general, they simulate essential functions of the human nervous system and thus are considered as a mathematical model of a biological neural system (Razi, Arzandeh, Naderi, Razi, & Ghayyem, 2013).

For a system to be classified as a neural network, it must have a labelled directed graph structure of artificial neurons (nodes) and connections. In turn, the nodes perform simple computations and each connection transmits a signal from one node to another called "connection strength" or "weight" giving the magnitude to which a signal has been amplified or diminished.

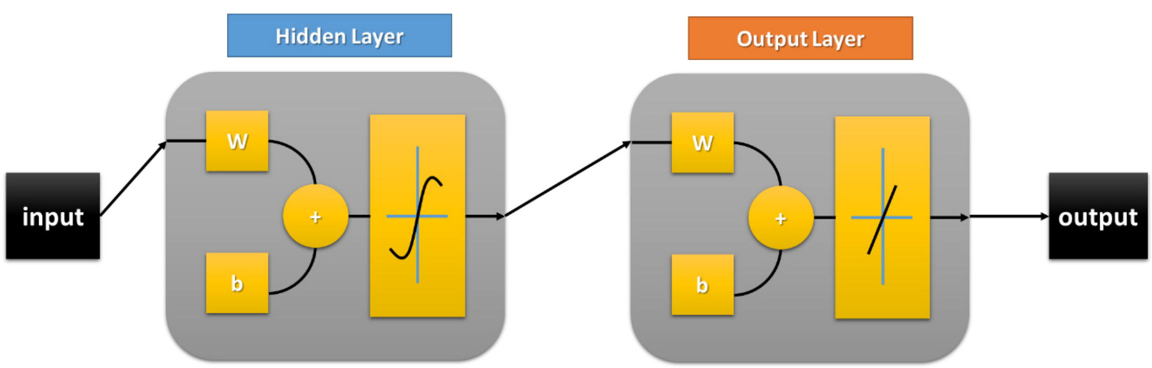

Figure 5 Two-layer feed-forward neural network

3.3.1 Neural Network Architectures

Single nodes are often insufficient for complex problems, and therefore more intricate networks must be used. The way the network is configured plays a key role in the performance and therefore should be carefully designed by the neural network developer.

The following subsections will give a general overview of the typical neural network architectures.

- Fully connected neural networks

An artificial neural network where the nodes in each layer are connected to all nodes in the following layer. The connections between the nodes may be either excitatory (positive weights), inhibitory (negative weights), or irrelevant (almost zero weights). This architecture is rarely used since it requires a large set of parameters.

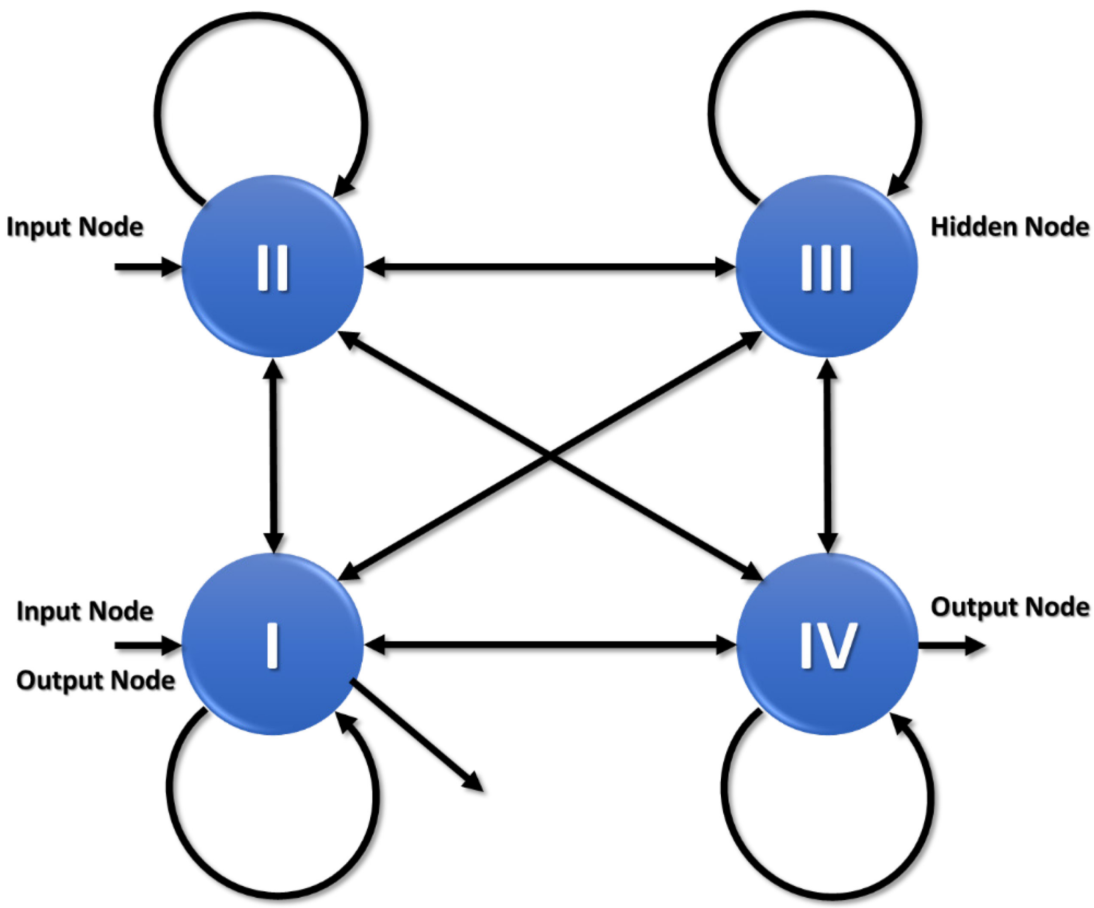

Figure 6 Symmetric fully connected network. Note that node I is an input as well as an output node

- Layered neural networks

These are networks in which the nodes are distributed within layers with no connection from layer j to layer k if j>k.

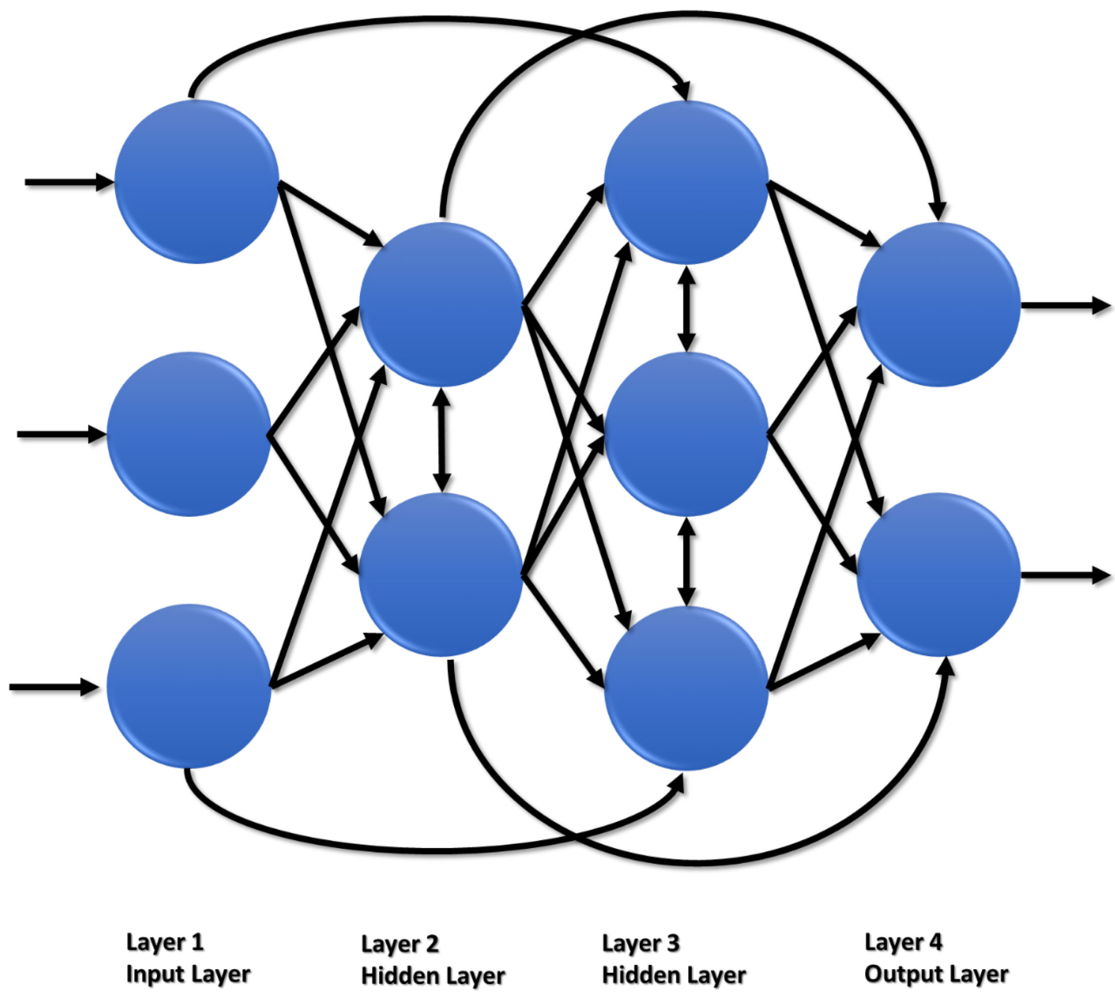

Figure 7 Layered network

- Acyclic neural networks

Acyclic networks represent a subclass of the layered neural networks with a specific configuration where connections are allowed between any layers i and j if i<j, but no connections are allowed in the case when i=j. This architecture requires less computational resources than the long and complex cyclic configurations. These types of networks are also known as recurrent networks.

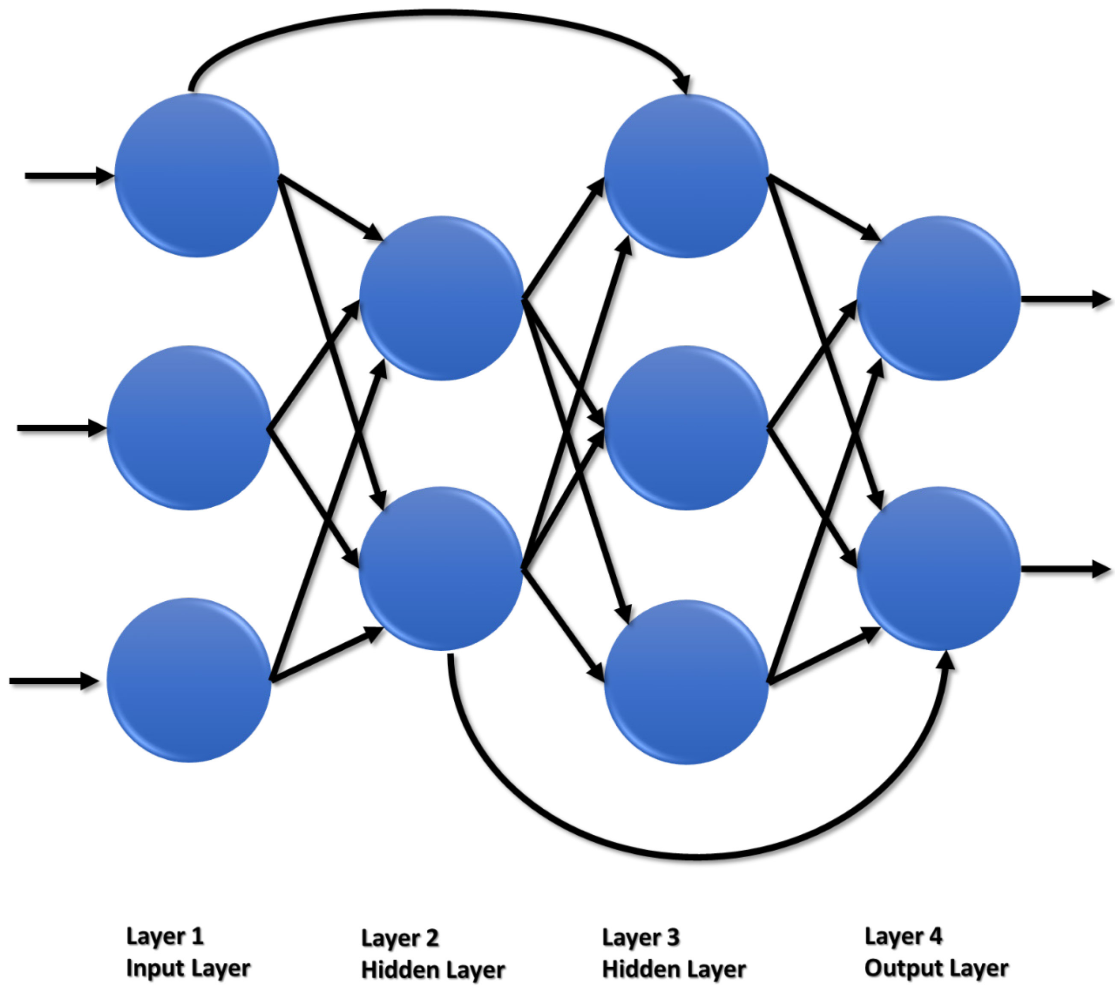

Figure 8 Acyclic network

- Feedforward neural networks

Feedforward networks represent a subclass of the acyclic networks where connections are only allowed from layer i to layer i+1. These networks are among the most common neural network setups. Their popularity is so high that neural networks are often thought to mean only feedforward networks.

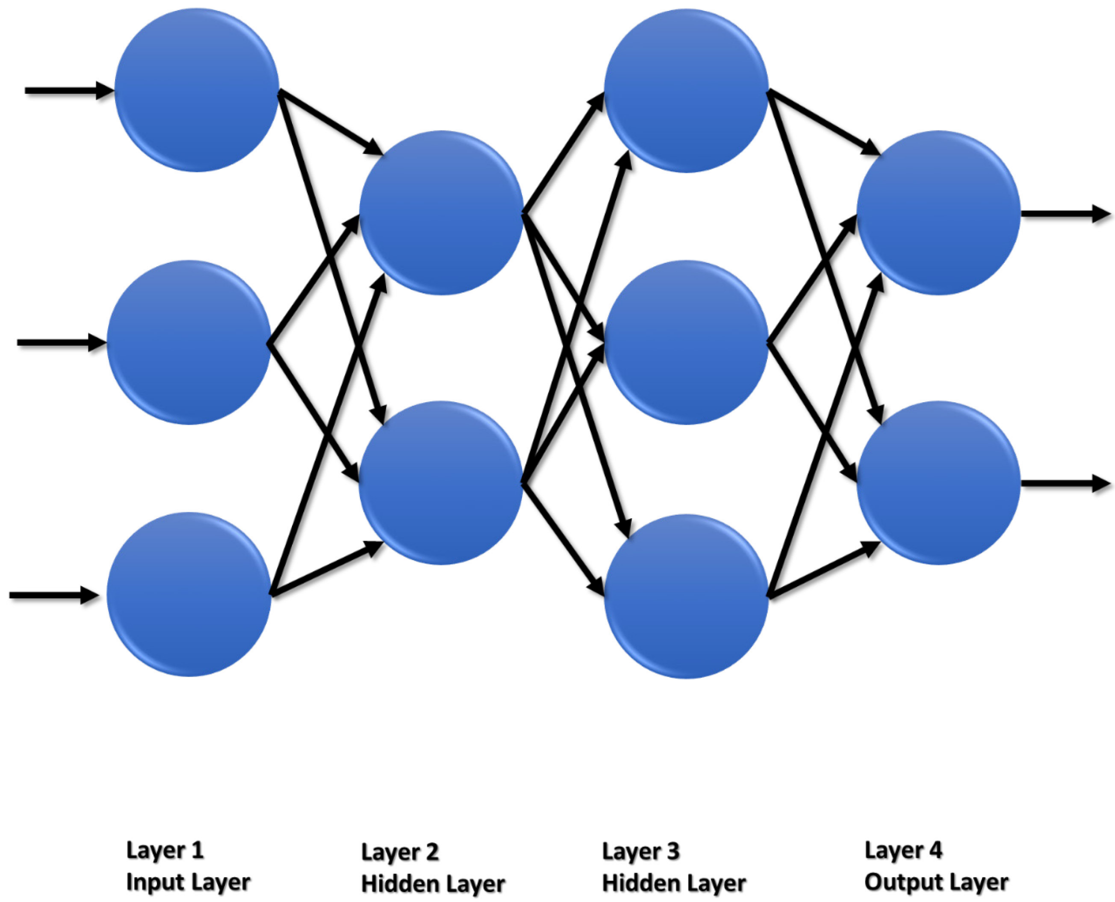

Figure 9 Feedforward 3-2-3-2 network

- Modular neural networks

Many problems are solved best by using the so called modular networks. This architecture consists of separate modules with interconnections within them. Such, certain tasks can be solved in independent small networks and then combine the results in an appropriate manner.

3.3.2 Training Multilayer Neural Networks

The objective of training a neural network consists in finding a set of weights that will cause the output values from the network to match the already known target values as precise as possible. Several configuration parameters should be considered when designing the network. First, one should determine how many hidden layers must be used in the network.

In the practice, the size of the neural network is commonly selected on a trial and error approach. A lot has been written covering the topic, but a general solution is still not clearly defined. A simple network with fewer nodes may not be sufficient for solving complex training tasks. On the contrary, a huge network may require lots of computation time. Furthermore, oversizing the network may lead to "memorization" of the training samples. Such networks are said to be over fitted. This phenomenon leads to bad results on new data sets, or in other words – the network has a poor generalization. The network is considered successful only if it performs well on new data samples.

Another challenge when training neural networks is to find the optimum set of weights that will give us an accurate output. The amount of these weights is often in the range of hundreds. Therefore, seeing the global picture and avoiding local minima is of significant importance. If we were dealing with a linear model, finding the global minimum would have been an easy task. With neural networks, the output as a function of the inputs is highly non-linear which results in a complex optimization process. To illustrate this problem, the error is plotted as a function of the weights as shown below

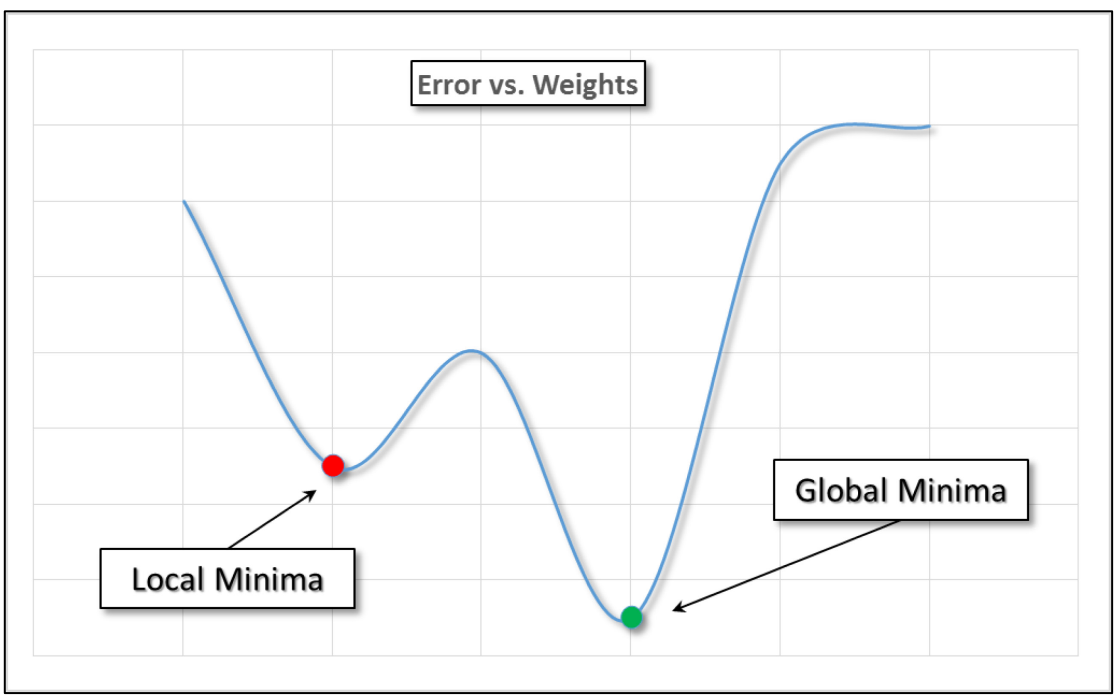

Figure 10 Example local/global minima

What we see is a rough surface with many local minima. It should be noted, that this is a highly simplified example, showing only a single weight value. In reality, a typical neural network will produce a 200-dimensional, rough surface with hundreds of local minima valleys.

Different methods are available, which deal with the problem of avoiding local minima. The easiest is to try a number of random starting points and take the one with the best value. More complex techniques, like the so called simulated annealing provide improved results by trying widely spread random values and slowly reducing the jumps with the hope that the location is getting closer to the global minimum. Typically, since the error space cannot be known a priori, neural network analysis often involves a number of individual runs to determine the best solution.

Neural network training algorithms mostly follow a certain iteration procedure (loops) in other to gain the optimal weight values. The first step is to run a set of values through the network using an initial random set of weights. The difference between the predicted value and the actual target value for this case is computed and the error information is averaged over the entire training set. The error is propagated backward through the network and the gradient of the change in error with respect to the changes in weight values is computed. Finally, the weights are adjusted to reduce the error. The complete cycle is known as an epoch. Since the error information is propagated backwards through the neural network, this kind of training technique is called backward propagation.

The quality of the training process is increased by normalizing the data. Both input and target vectors are scaled to match the input neuron range.

MATLAB's function mapminmax uses the following algorithm to scale inputs and targets to fall in a certain range:

$$y = \frac{(y_{max} - y_{min}) * (x - x_{min})}{(x_{max} - x_{min})} + y_{min} \qquad \text{Eq.(3-1)}$$

where:

$\mathbf{y_{max}}$ = maximum value after normalization (default value for the mapminmax function is 1)

$\mathbf{y_{min}}$ = minimum value after normalization (default value for the mapminmax function is -1)

$\mathbf{x}$ = value to be scaled.

$\mathbf{x_{max}}$ = maximum value in the range of interest

$\mathbf{x_{min}}$ = minimum value in the range of interest

3.4 Inputs

Real-time rig surface data transmission has been a widely covered topic in recent years and is way beyond the scope of this work. However, since the described model relies entirely on such data streams, a brief explanation regarding the current state of the technology will be given below. Furthermore, the data selection criteria and an introduction of an automatic operation recognition system will be presented.

3.4.1 Data exchange standards in the petroleum industry (WITSML History)

As the technologies evolve, data-mining processes become more common and find practical applications on every modern drilling rig. Rig sensors, data flows between data producers and data consumers, advanced data quality control algorithms etc. have all been assimilated and implemented into the design and operation of various oilfield services. On the other hand, the increased amount of data due to the greater availability of these technologies led to the necessity of new data transmission methods.

Currently, the standard for broadcasting technical data in the petroleum industry is given by WITSML (Wellsite Information Transfer Standard Markup Language). WITSML is a XML based language, in which data sets are encapsulated within single xml files. These files are transmitted between a WITSML server and a WITSML client (Deeks & Halland, 2008).

WITSML is an evolution of WITS (Wellsite Information Transfer Specification) which was designed and implemented into the oil and gas industry until the early 90's. WITS included 25 different data records, covering a wide variety of operations. The records were given in one of the two units' systems: FPS (foot, pound, second; common US oil field units) or metric units. Generally, WITS data streams were transmitted via serial interfaces, TCP/IP network sockets, or as discrete files on magnetic or optical media.

Despite its advantages, WITS also had several limitations. Among these, we should mention the outdated MWD data records, the restrictions on the number of drill strings and casing sections, the inflexibility for handling different units of measurement and the limitations when handling static well information.

Today, the improved WITSML technology opens greater possibilities in the rig data transfer. It also provides an application programming interface, known as “API”, which allows programmers and software developers to build custom data exchange capabilities. WITSML is object oriented, web based and built on WC3 standards. With all these capabilities, many companies are building centralized real-time operation centers with specialized teams working with real-time data (Oil & Gas Journal, 2013).

3.4.2 Input Data Selection

A precise analysis and selection of the input parameters is perhaps the most important part of the simulation process, more so even than the selection of the training algorithm. Since artificial neural networks rely on the quality and not on the quantity of the data, the major goal is to define input data which are not only generally available but also have sufficient quality for the training process.

In general, the following rules have been considered:

1. Get as much clean data as possible.
2. Conduct data analysis. You need to understand your data before using it.
    a. Use filter algorithms if necessary
    b. Fill/Delete missing values if necessary
    c. Correct/Ignore bad data whenever possible

Following the data selection requirements, and exchanging experience with other rig data mining research groups a preliminary list of nine data channels has been compiled. These nine input channels include:

- Bit measured depth
- Hole measured depth
- Block position
- Hook load
- Torque
- RPM
- Flow in
- Weight on bit
- Rate of penetration

After further analyzing the available data, a decision was made to drop out the weight on bit and rate of penetration channels. Weight of bit is typically calculated based on the hook load readings. Therefore, considering this correlation the data will have no direct influence on the performance since the neural network will have already registered this relationship. The same is valid for the rate of penetration which is directly related to the hole measured depth channel.

At the end seven data channels were the ones that could be used in most of the cases. Of course, as soon as a client ensures additional channels these could be easily added and such the quality of the simulation will be improved.

3.4.3 Automatic Operation Recognition

Most drilling hydraulics simulators have one common shortcoming – they assume full load on the bit and respond as if one was performing permanently drilling operations. However, when the bit is off bottom and performing wellbore conditioning jobs (e.g. reaming/washing in or out of hole, circulating) there is significantly less pressure losses as when drilling hole. In such cases, the calculated pressure losses are usually overrated and do not match the real values.

To cope with this disadvantage and to improve performance through separating such operations, the results on an automatic event recognition system were integrated into the primary basic parameters.

The automatic recognition system used for this work is a patented approach and is proven to work with a very high accuracy. Basically, it uses high frequency rig sensor data and provides very good results. The output of it are the so-called operation states, such as drilling rotary or sliding, circulation, ream in or out, washing in or out of hole, etc. To get proper results out of the operation recognition system, a data stream with a frequency of 0.1 Hz or better should be provided. The operation recognition runs in parallel as an additional service, and delivers the recognized states to a MySQL database from where these are then read and loaded in the hydraulic simulator. A total of ten operation states are being used for the simulations. These are considered as the main states and include:

- Drilling rotating
- Drilling sliding
- Ream upwards
- Ream downwards
- Wash upwards
- Wash downwards
- Run in hole
- Pull out of hole
- Circulate hole

- Make connection

The hydraulic simulator is adapted completely to the automated operation recognition system, allowing any custom configuration of operational states to be used as an input for various simulations and analysis.

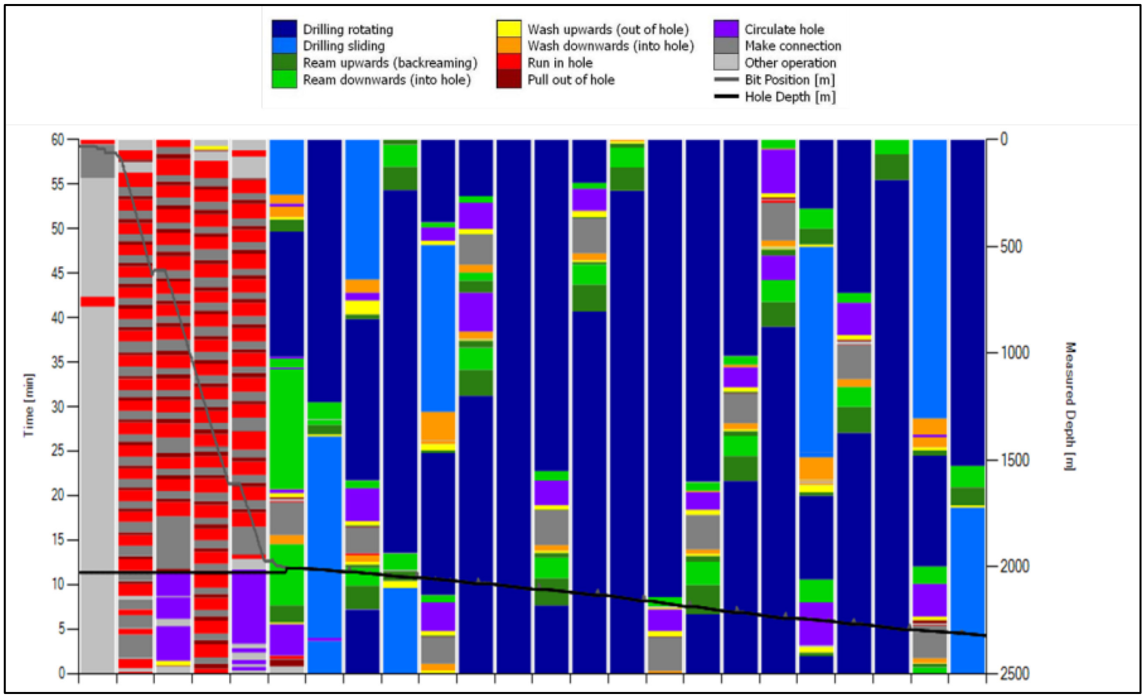

Figure 11 Automatic operation recognition example

The advantage of such a model over the traditional approach is that one can focus on the hydraulics during specific operations performed on rig as well as use the gathered information form the automated recognition algorithms to improve the result neural network results. With the introduction of the operation states, the system has been upgraded to the so called “State aware” setup which will be shown later in chapter 4.2.

4 Calculations and Results

The following chapters will demonstrate the procedures used to perform the hydraulic simulations. It should be noted that all units utilize metric units unless otherwise stipulated.

The tests are performed on onshore and offshore scenarios using anonymous source data.

Upon execution of the simulator the results will be graphically visible in the plot window. The proNova plot may also be switched in a real – time mode, configuring a predefined refresh rate. This option gives the user a live view of all drilling parameters plus the simulated theoretical standpipe pressure.

The additional calculations (incl. cross plots and histograms), which convey more information regarding the results are done separately in Microsoft Excel.

4.1 Basic Setup

As previously described, the basic setup includes 7 input channels. These seven channels are used as inputs for the neural network training and are mapped to the target stand pipe pressure. The network has one hidden neuron and the uses the Bayesian regulation backpropagation function trainbr. Trainbr is a network training function that updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination to produce a network that generalizes well (Demuth, Beale, & Hagan, 2009).

In this stage, the training mode is set to a moving window, meaning that the network uses a predefined time frame for training and then steps in to the prediction mode for a given period. Once the prediction period is over, the training window moves one prediction period further and proceeds with the second training cycle. This goes on until the complete data set is covered.

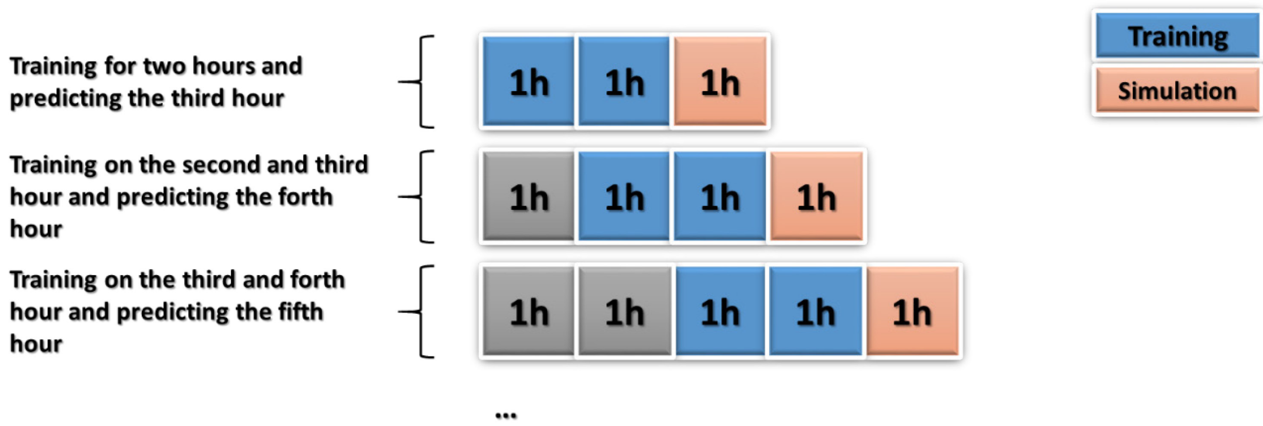

Figure 12 Moving window training mode

The neural network uses one hidden layer, one hidden neuron and a 70/15/15 setup (training / validation / testing). This configuration indicates that 70% of the data will be used for training, and the network will be adjusted according to its error. The 15% assigned for validation will be used to check whether the generalization stops improving. Once this happens, the training will be halted. The remaining 15% represent the part of the data set which is used for testing. This is an independent measure of the network performance and have no effect on the training itself.

Once the network is created, the actual Bit Measured Depth, Hole Measured Depth, Block Position, Hook Load, Torque, RPM and Flow In values are read from the data base and fed into the prepared network. Based on this, a theoretical stand pipe pressure can be obtained.

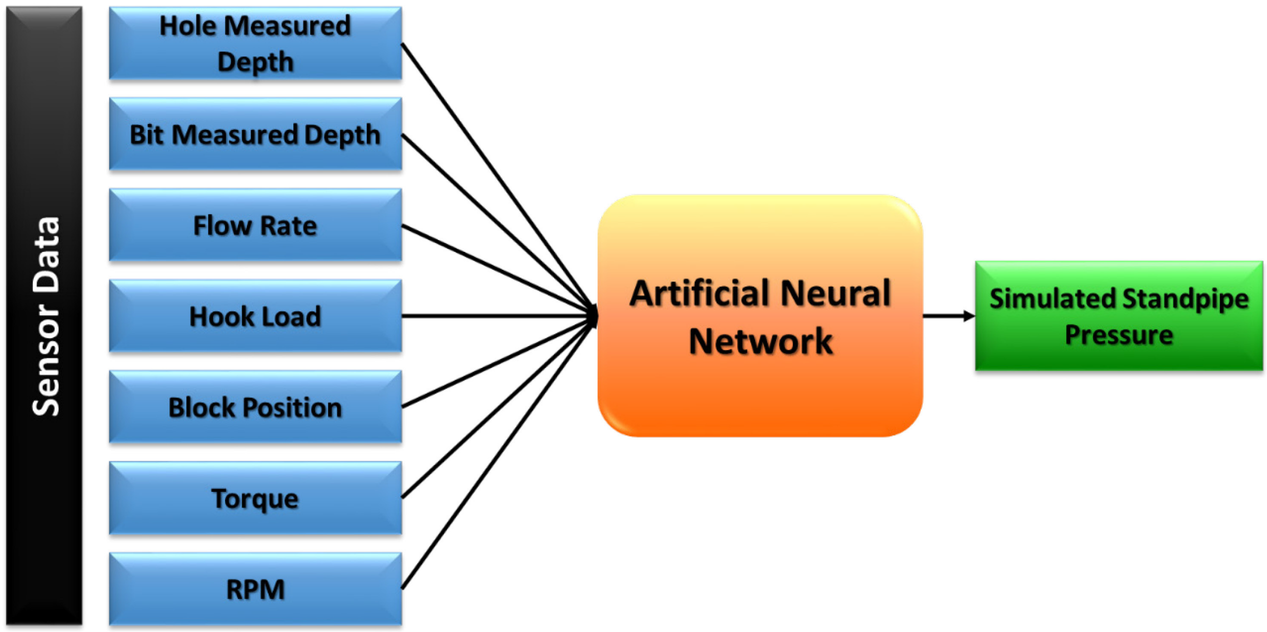

Figure 13 Initial model configuration

4.1.1 Land Rigs

The first test trials were done using the basic configuration on land rigs. Onshore exploration is generally economical, less complex and widely spread. Due to specificity of the equipment and operations, the sensor data from onshore wells is perfectly suitable for testing purposes due to its more stable parameter – standpipe pressure relationship. Such wells provided a perfect testing environment to tune up and calibrate the tool. Furthermore, these scenarios will add significantly to the overall understanding of the presented hydraulic monitor.

Another important task of these initial land rig trials is figuring out the exact influence of the particular input parameters on the output – the theoretical pressure loss.

The initial test was done on a land rig data set from a well, which during the contents of this work will be referred as “Well A”. In the selected time frame, the rig was drilling the 6.75” production hole. Throughout the selected interval a vertical section of approximately 1074m (from 1312.5m to 2386.2m) has been drilled.

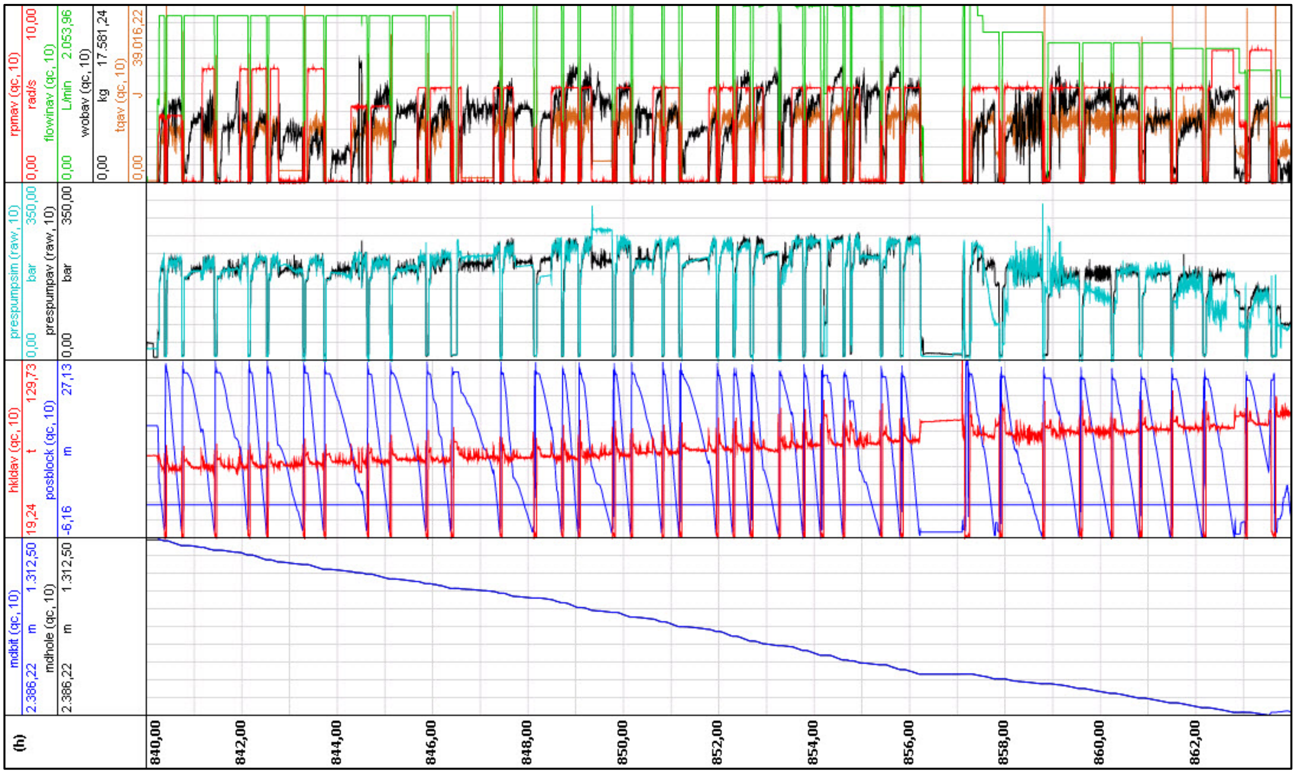

Figure 14 Data and results from well A using the basic setup

The plot in Figure 13 shows the main drilling parameters as well as both hole measured depth and bit measured depth. Additionally, the simulated stand pipe pressure is plotted in light blue on the second track. It must be noted that the focus of any hydraulic model is not necessarily mirroring the sensor data, but rather to be able to follow the trend of the real values. If this is achieved, the model can be easily calibrated to represent the real conditions.

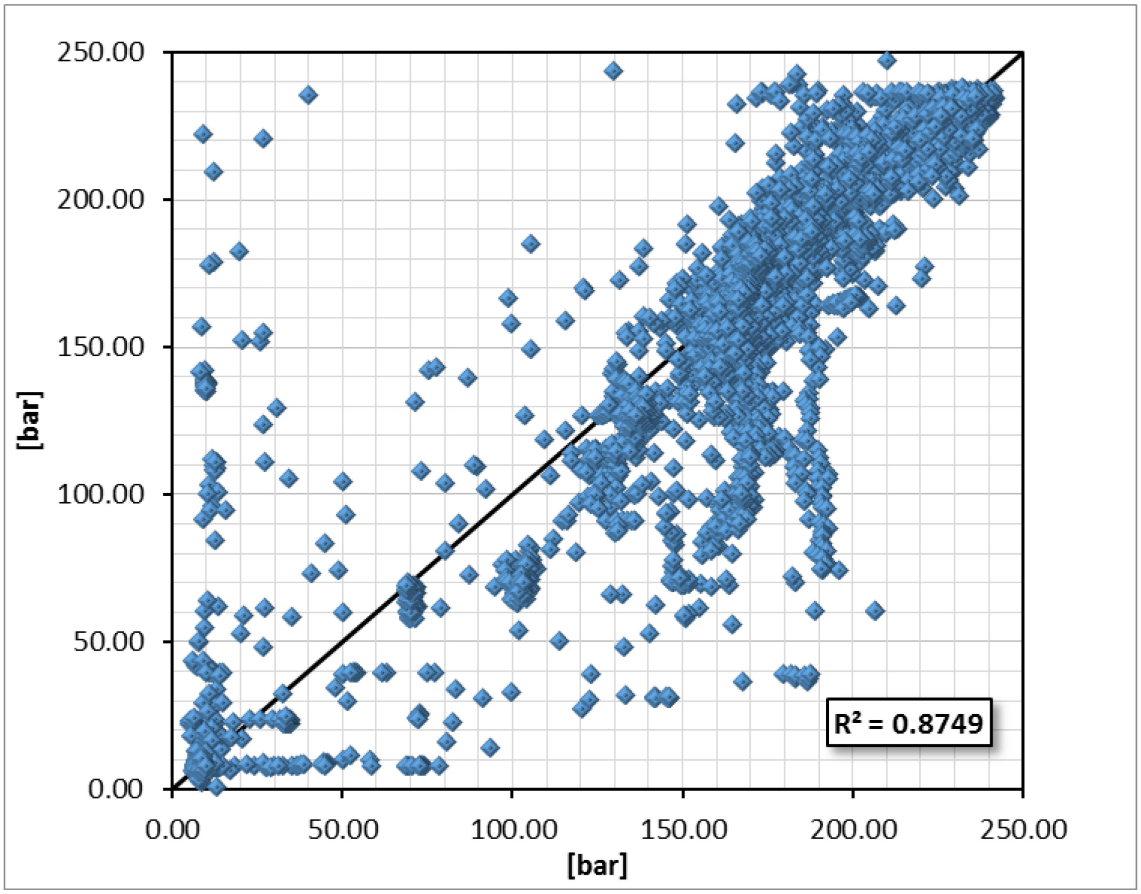

Figure 15 Well A - SPP/Simulated SPP cross plot

The standpipe pressure has been cross plotted vs. the simulated standpipe pressure. As it can be seen on Figure 14, the overall data fit, with some exceptions is satisfactory. To give a number to the results, the coefficient of determination or R-squared value has been generated. The R-squared number is a coefficient which demonstrates how well the data fits a statistical model. A value of 1 indicates that the regression line is a perfect fit, whereas a value of 0 will show that there is no fit at all. In the current case, the coefficient of determination has a value of 0.8749 which is a proof for the accuracy of the simulation.

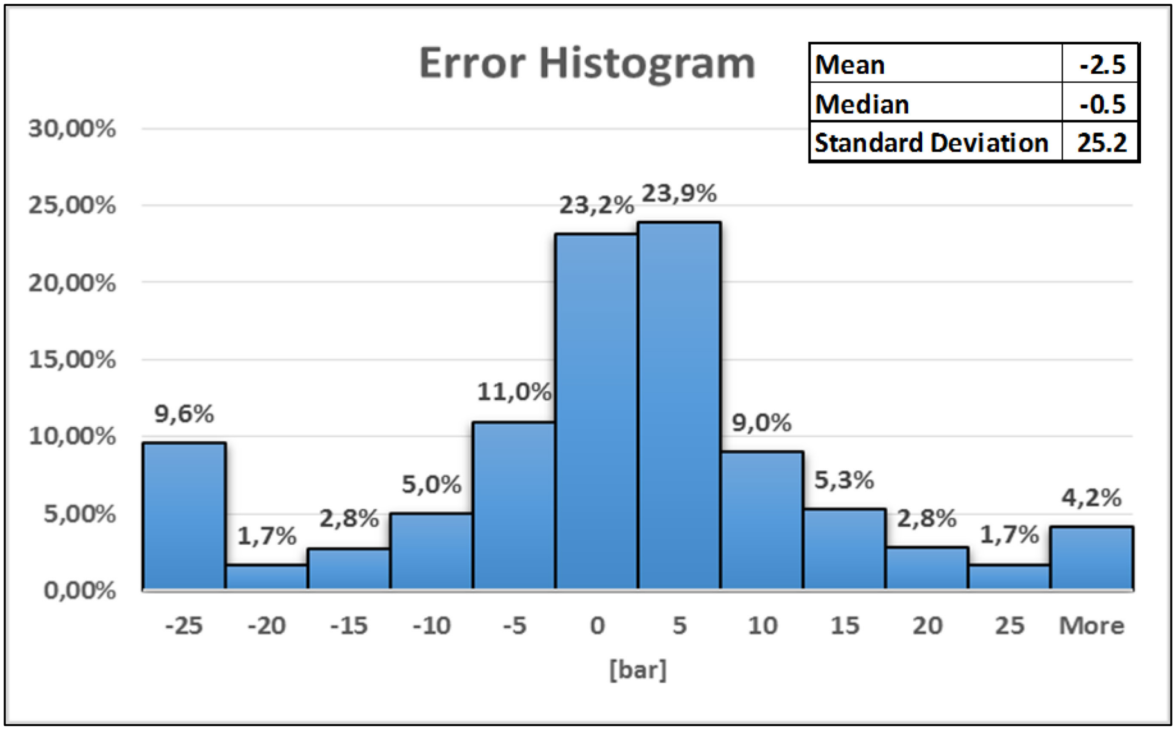

Figure 16 Error histogram - Basic setup/Land Rig/Moving Window

The data plot and the error cross plot express the results in general. With the data plot, we can visualize the results and note the sections where the hydraulic model performs better or worse. In other words, one gets a clear view about the exactness of the simulation. The cross plot, and especially the coefficient of regression delivered a numerical value to the results.

The final part of this first run's analysis involves plotting the error histogram. This chart shows the error distribution. The histogram has 11 bins, starting from -25 bar and increasing with a step of 5 bar to errors greater than 25 bar. Furthermore, the basic statistical methods: mean, median and the standard deviation are calculated.

The results after the first simulation on land rig data indicate an average error of -2.5 bar and a standard deviation of 25.2 bar. As it can be seen, the average error lies in acceptable ranges. On the other hand, the spread – determined by the standard deviation ideally should be more tightly clustered around the mean value.

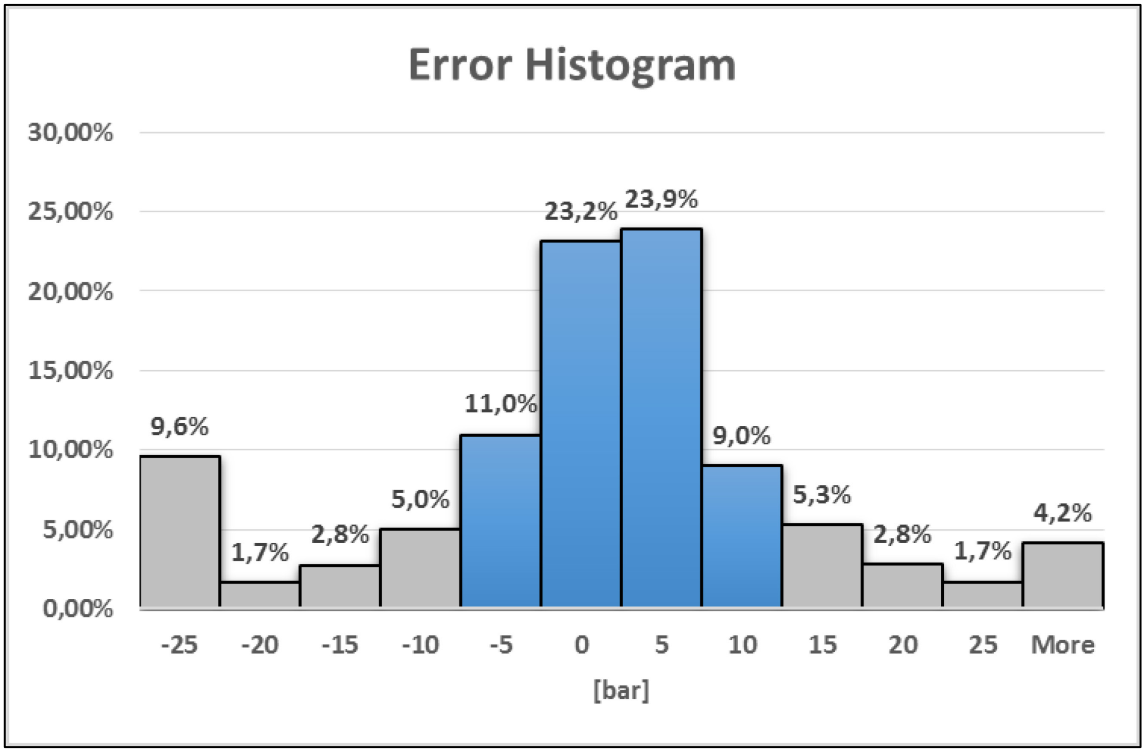

Figure 17 Error histogram highlighting errors between -9 and 10 bar

After a detailed look, highlighting the bins between -9 and 10 bar, we can see that the errors in this range, which are considered as a good reference for an accurate prediction, cover 67.1% of the results.

Overall, after looking at the first simulation, we can definitely conclude that there is a clear correlation between the sensor data channels and the simulated pressure losses. With some exceptions, the accuracy of the simulation is significant and proves the theory behind the model.

4.1.2 Offshore Rigs

Offshore drilling usually involves more complex well designs and state of the art equipment. The work is often performed under harsh conditions. It is common understanding that such wells can be a greater challenge than those drilled onshore.

Technologically, todays offshore drilling units are far more superior to those used 10-15 years ago. Thousands of meters of water depth can be conquered to ensure safe and reliable operations. The machinery has matured from a rough – and – ready approach to models that utilize performance and HSE standards.

There are a variety of units available today each involving different technical, economical or governmental requirements to accomplish a certain drilling program. The range of the mobile offshore drilling units includes floating rigs such as drill ships and semi-submersibles or bottom supported rigs like the fixed platforms, jack-ups or barges. No one type can satisfy all requirements for every drilling location.

Offshore drilling is much more expensive compared to drilling from an onshore facility. The extreme costs can be attributed amongst other things to the expensive subsea equipment, lost times due to trouble events or bad weather, complicated logistics and high transportation costs (supply boats, helicopters, etc.). A typical offshore unit in the North Sea may costs several hundreds of thousands per day. Since the costs for these units are so high the companies are anxious to reduce the drilling time and thus cut the spending wherever possible.

With all this said the introduction of a reliable real time hydraulic monitoring system may assist and be of huge advantage to an offshore unit and its crew. Being able to monitor and control the status of the wellbore at any moment can drastically reduce the risks of any unwanted hazardous events which may harm nature or personnel. Further than that it will have a positive impact the complete drilling performance, ensuring any trouble events are recognized and avoided in time.

The tests on offshore data followed the previous simulations done on land rigs. The selected 24 hours timeframe is from a Jack-up rig, drilling an 8.50” section with a standard RSS BHA on a well which we will refer to in this work as “Well B”. The total depth drilled during the selected timeframe is approximately 1418m – from 1812m to about 3230m.

For this testing stage, just as described in the previous chapter the basic setup was applied. A moving window training/predicting mode with seven data channels and the standard network configuration have been used. Once again three plots where generated to display the results including the data plot, showing the major drilling parameters with the simulated standpipe pressure included, a SPP/Simulated SPP cross plot with a regression analysis and the error histogram plot.

The data plot, shown in Figure 17 gives an outline of the mudlogging data. One can recognize the trip in hole at the beginning, the drilled stands, sections where the string is in slips as well as the corresponding weight-to-weight connections.

It can be seen that the simulated pump pressure, labelled *prespumpsim* on the second track closely follows the original standpipe pressure. Despite the overall positive results there are a couple of flaws are also observed. The model responds rapidly to data inaccuracies. Such data deceptions are a common issue with the huge volumes of data transferred from the rig site. However, since these are mostly sudden single events an algorithm for filtering these out may be implemented. Furthermore, the alarm triggering mechanism may be configured in a way that only events with a certain pattern or duration will be taken into account.

The next issue seen on the data plot occurs at approximately between timestamps 4084 and 4086 where the simulated results do not follow accurately the real data readings. This issue is assigned to the network as a result of the short training window. Obviously, the data pattern up to this point is quite different, as the operations switch from tripping to drilling with a short reaming interval in between. The network has no possibility to account for this difference at the beginning and need a while to adjust. Unlike the first issue, this problem can result in adverse action by an automatic safety system.

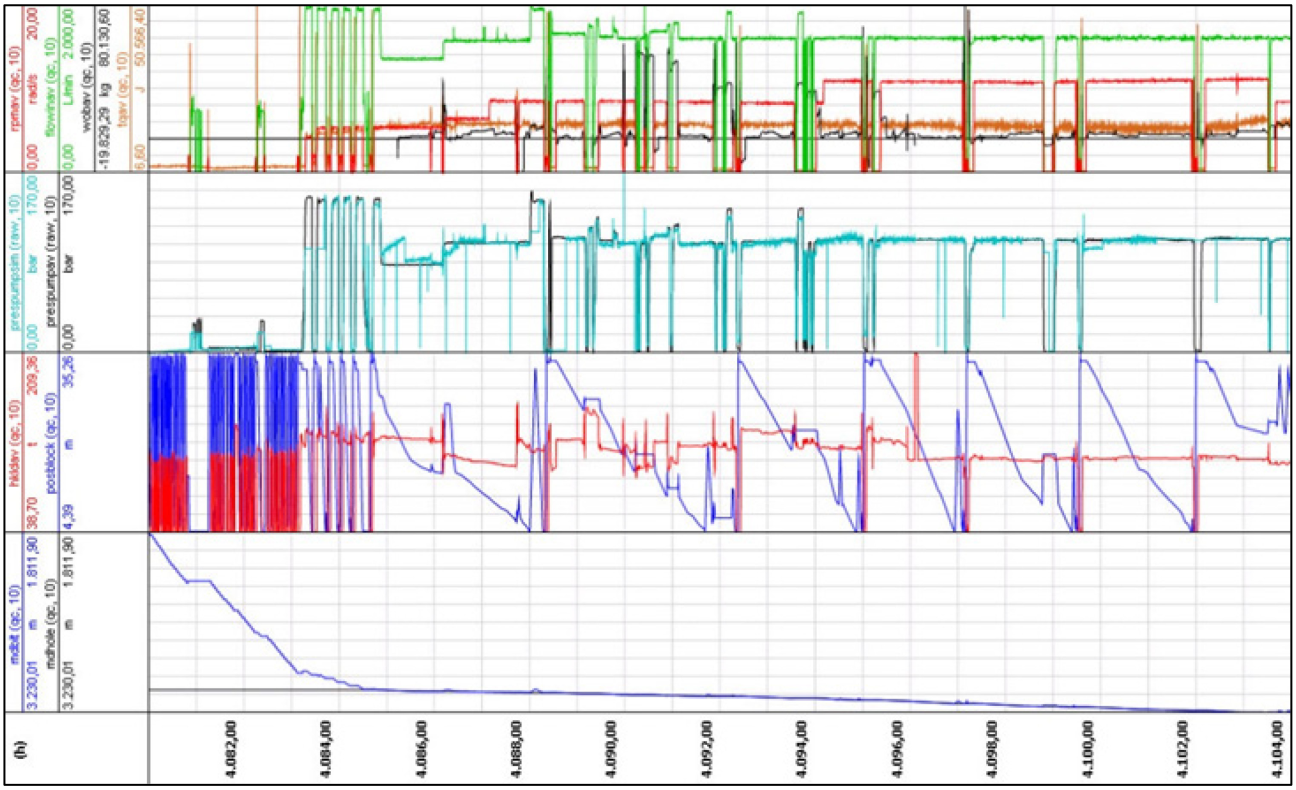

Figure 18 Data plot using the basic setup on an offshore rig

Figure 18 again displays the standpipe pressure data received from the mudlogging unit versus the simulated pressure data delivered by the model. The coefficient of determination has been once again calculated. In contrast to the onshore data, here much lower values were initially expected. This effect was awaited largely due to the above-mentioned issues – the data inaccuracies as well as the network training and prediction model limitations. However, after the first run, the simulated standpipe pressure showed a significant accuracy.

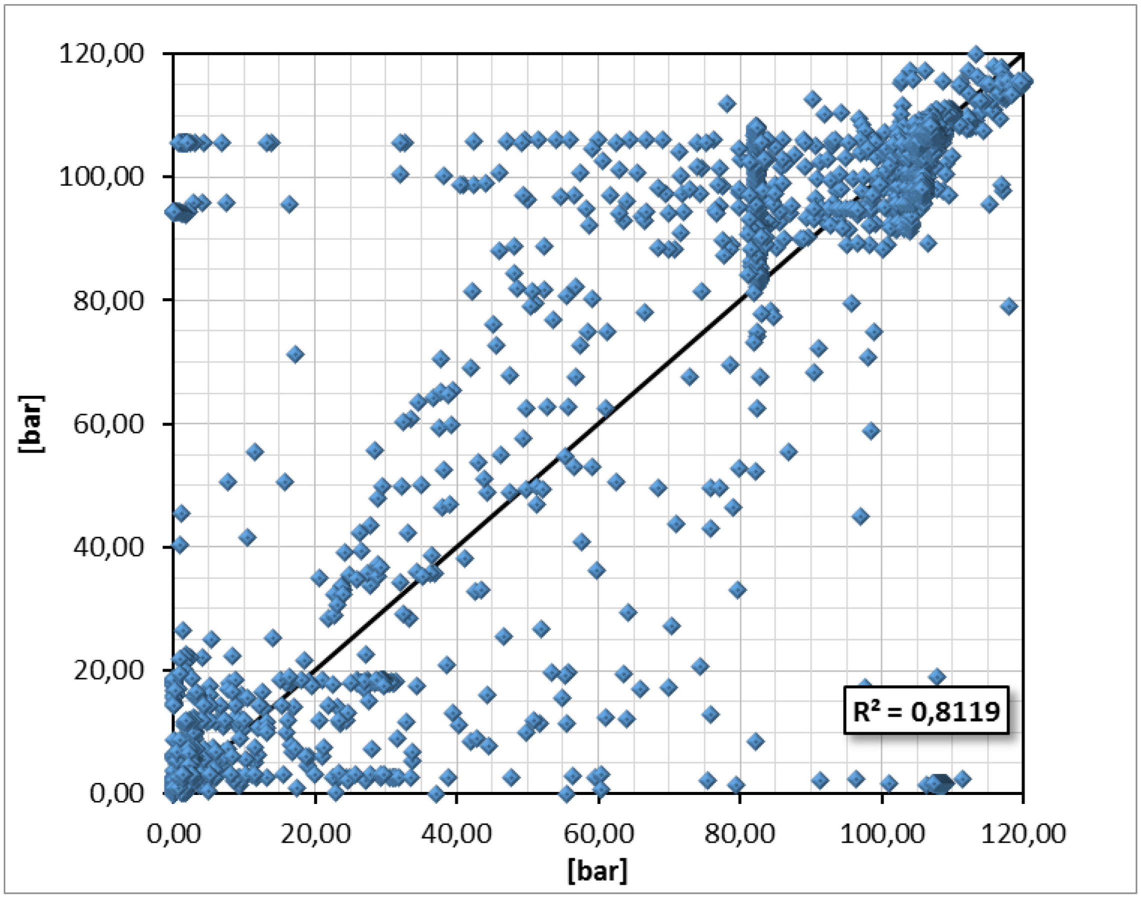

Figure 19 SPP/Simulated SPP - basic setup, offshore rig

As it can be seen on Figure 20, the cases in which the results are within the acceptable limits (-9 to 10 bar) cover 87.92% of the data.

After the first round of simulation tests on both onshore and offshore data sets the conclusion can be made that additional parameters are required in order to improve the results in the cases where complex data sets and technologies are present.

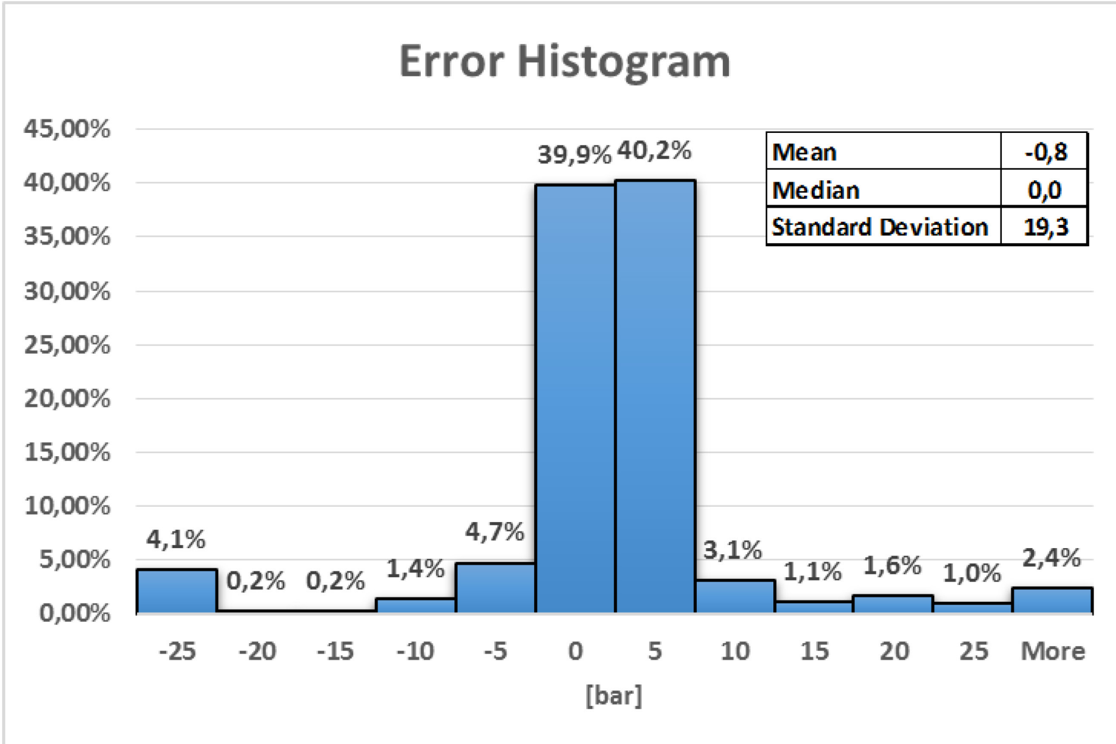

Figure 20 Error histogram - basic setup, offshore rig

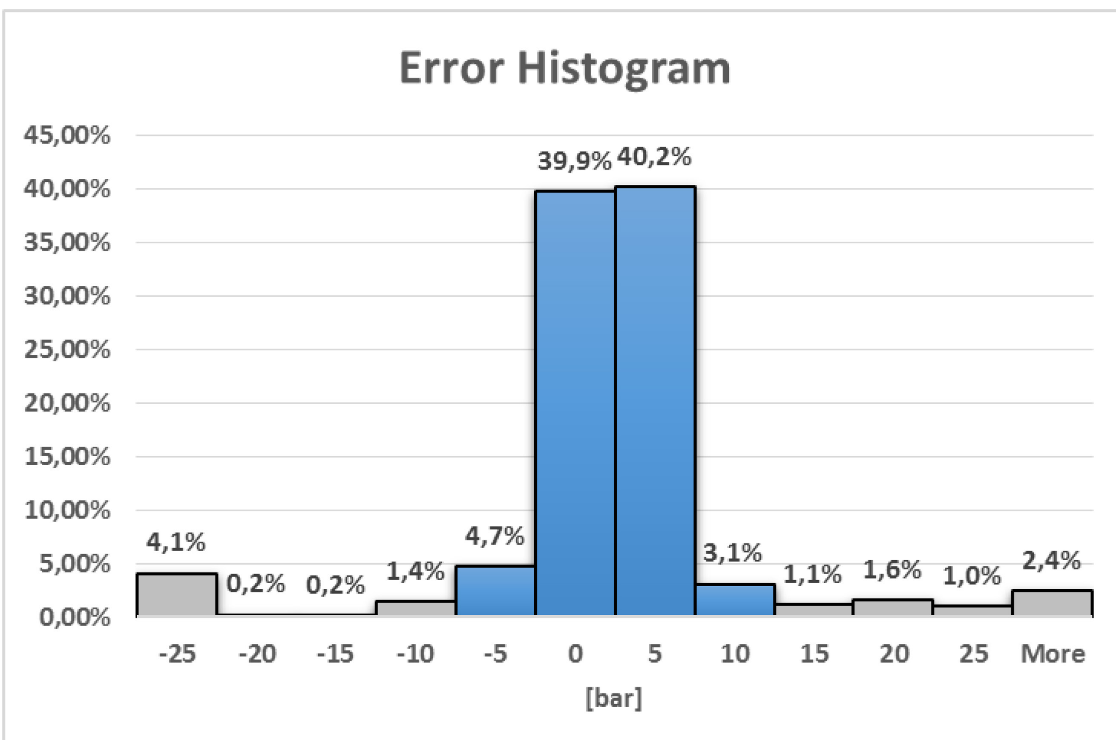

Figure 21 Histogram highlighting the errors between -9 and 10 bar

4.2 State Aware Setup

Using the basic setup described in chapter 4.1, the first preliminary tests have been performed. Generally, the results were promising and the performance was good. However, in order to further improved the quality and reduce the margin of error of the simulation a decision was made to include a classification system into the training configuration.

With this in mind, the model was upgraded by feeding the neural network additionally with operation recognition states. The automatic operation recognition system used in this thesis offers a wide variety of operation states. Beginning from the most typical drilling operations such as drilling rotary or sliding, making connections, main wellbore conditioning operations, running and pulling out of hole and extending further to more complex states like weight-to-weight connections, drilling stands, etc. the system has the capability to recognize a wide variety of states.

As described in chapter 3.4.3, the test cases shown in this work uses a reduced configuration set including the ten most general drilling operations. These operation states are added as an additional input to the training and prediction algorithms. Such, the system is upgraded to the so-called state aware setup.

4.2.1 Land Rigs

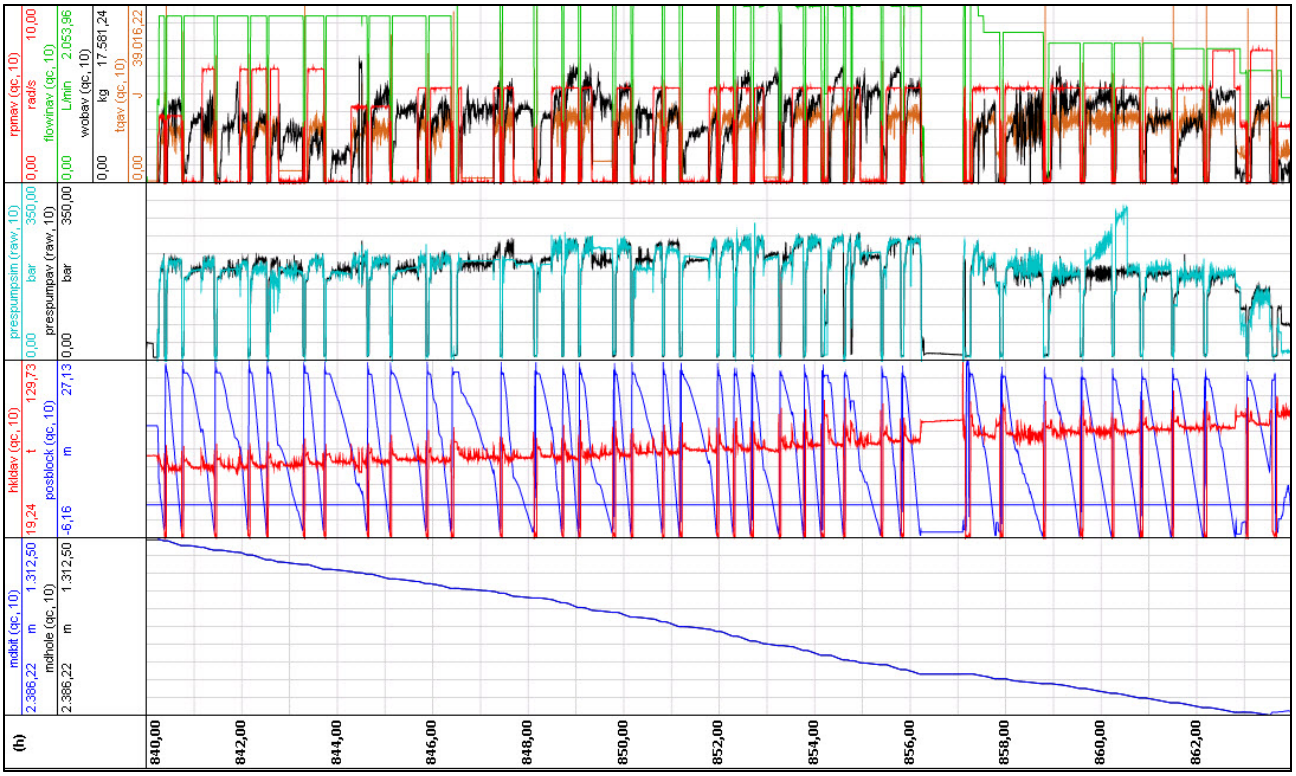

Figure 22 Data and results using the „state aware" setup

The second test trials on onshore rig data are done using the same data from "Well A" but adding the automatic operations recognition results to the training and prediction processes.

The results with the „state aware" setup show a slight improvement compared to those delivered using the basic configuration. However, with the onshore data set the level of improvement is almost negligible. The operations in the data set are quite homogeneous, including mostly rotary drilling, some short wellbore conditioning events during the weight-to-weight connections and the slip-to-slip connections. This explains the weak effect of the operation recognition system in the current example.

There is once section, around the 860 timestamp where the performance of the model is not as good as desired. The inaccurate simulation results during this range are accounted to data uncertainties in this part of the data.

The R-squared value of 0.88 is similar to the result achieved with the basic configuration. The cross plot shows well scattered data with a few outliers.

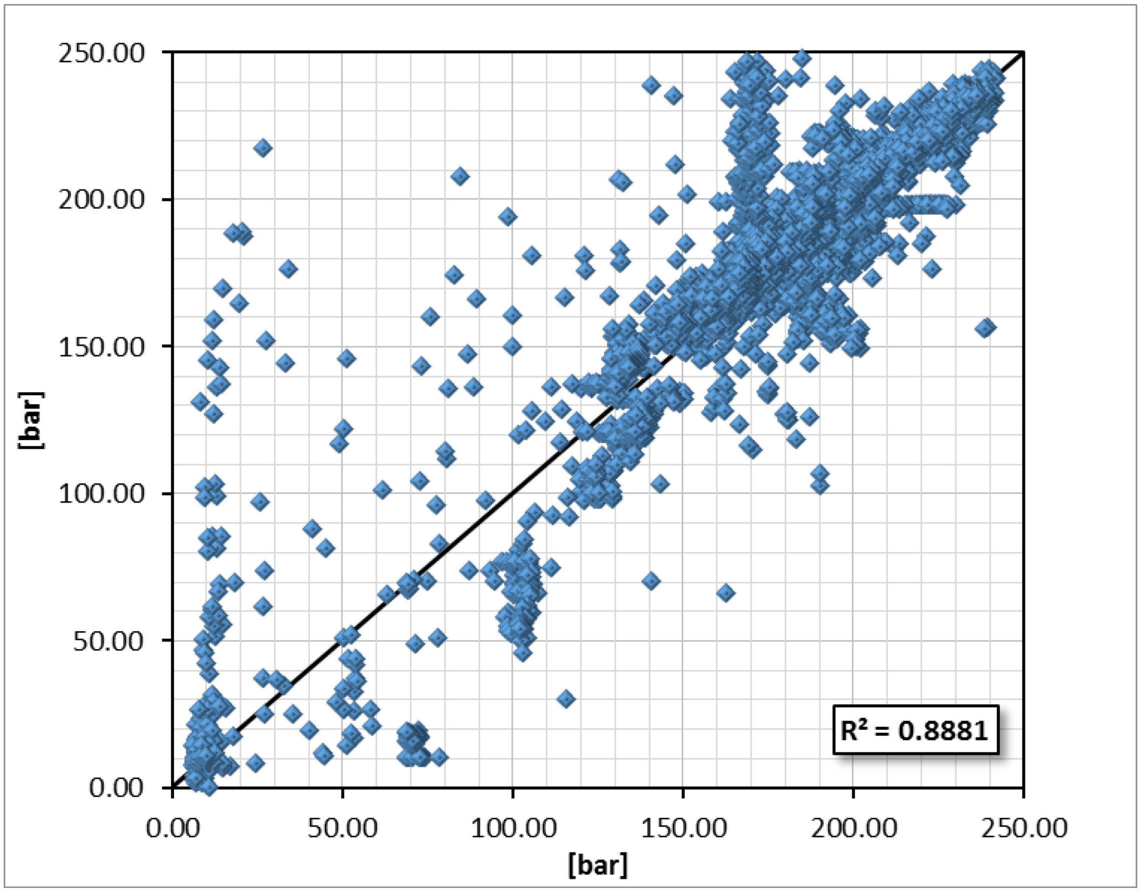

Figure 23 SPP/Simulated SPP cross plot after „state aware“ simulation

The slight impact of the automatic operation recognition system can be also confirmed by the following error histograms seen on Figure 23 and Figure 24. The state aware setup delivered 67.7% of the results with an error within the range of -9 and 10 bar. This gives less than 1% improvement compared to the basic configuration.

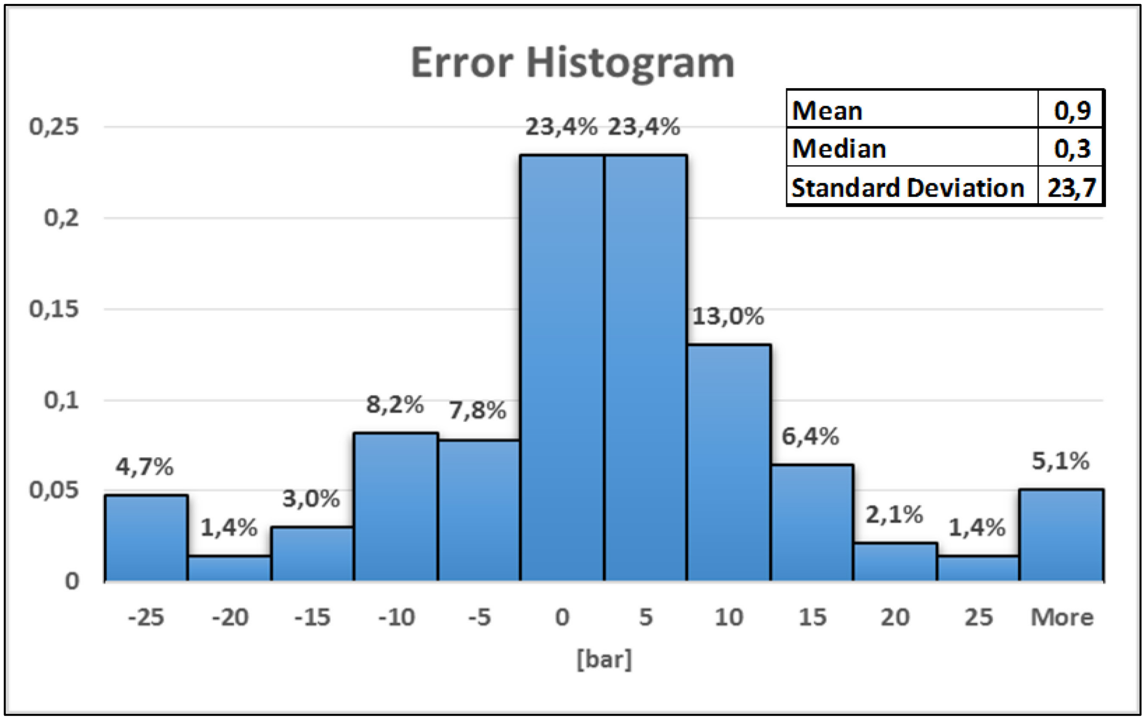

Figure 24 Land rig - „state aware" setup - error histogram

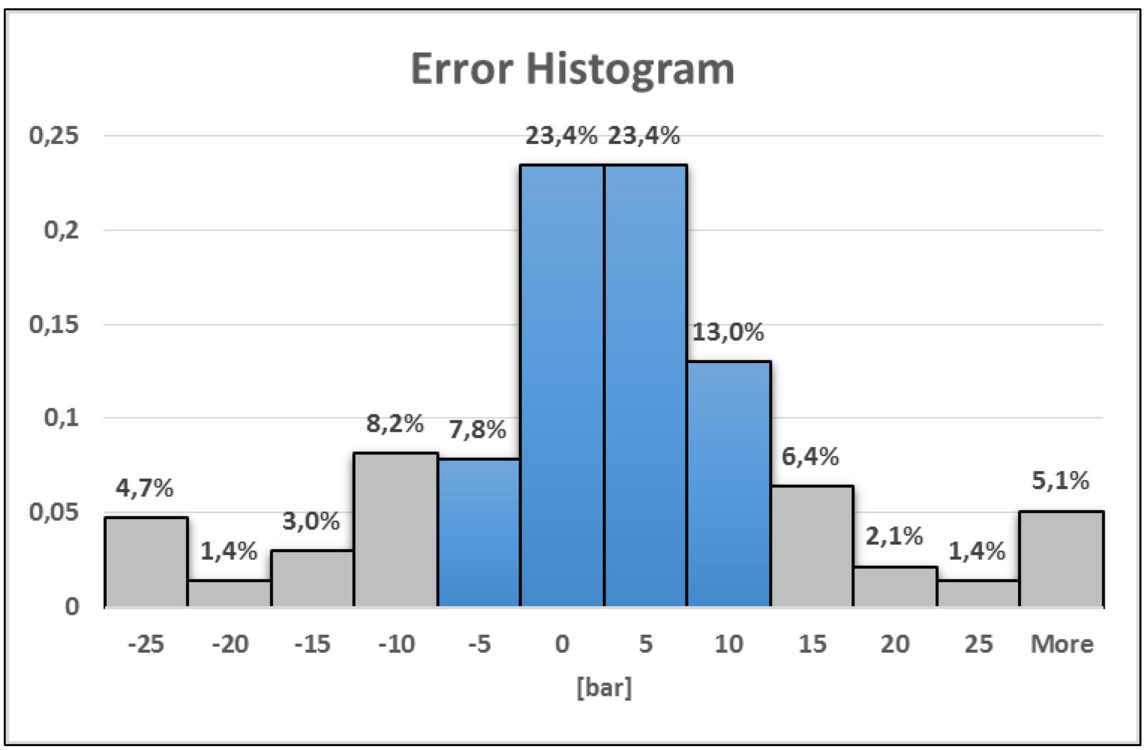

Figure 25 Land rig – „state aware" setup error histogram highlighting errors between -9 and 10 bar

4.2.2 Offshore Rigs

The same state aware setup was applied to the offshore data set. Using the chosen configuration, a simulation was performed. The results can be seen on the figures below.

As it can be seen on the plots, there hasn't been any improvement in the simulation accuracy. This can be assigned to the fact that the automatic operation recognition feature needs sufficient training data to be able to affect the simulation in a positive way. With the current setup, using a moving window with two hours for training and one hour for the subsequent simulation, the network can't cover many states during the training period. Thus, the network has a poor operation states library at the point where the prediction begins. To overcome this issue, one should reconsider the exact duration of the training and prediction windows.

The figures below represent the results of the „state aware" simulation on Well B.

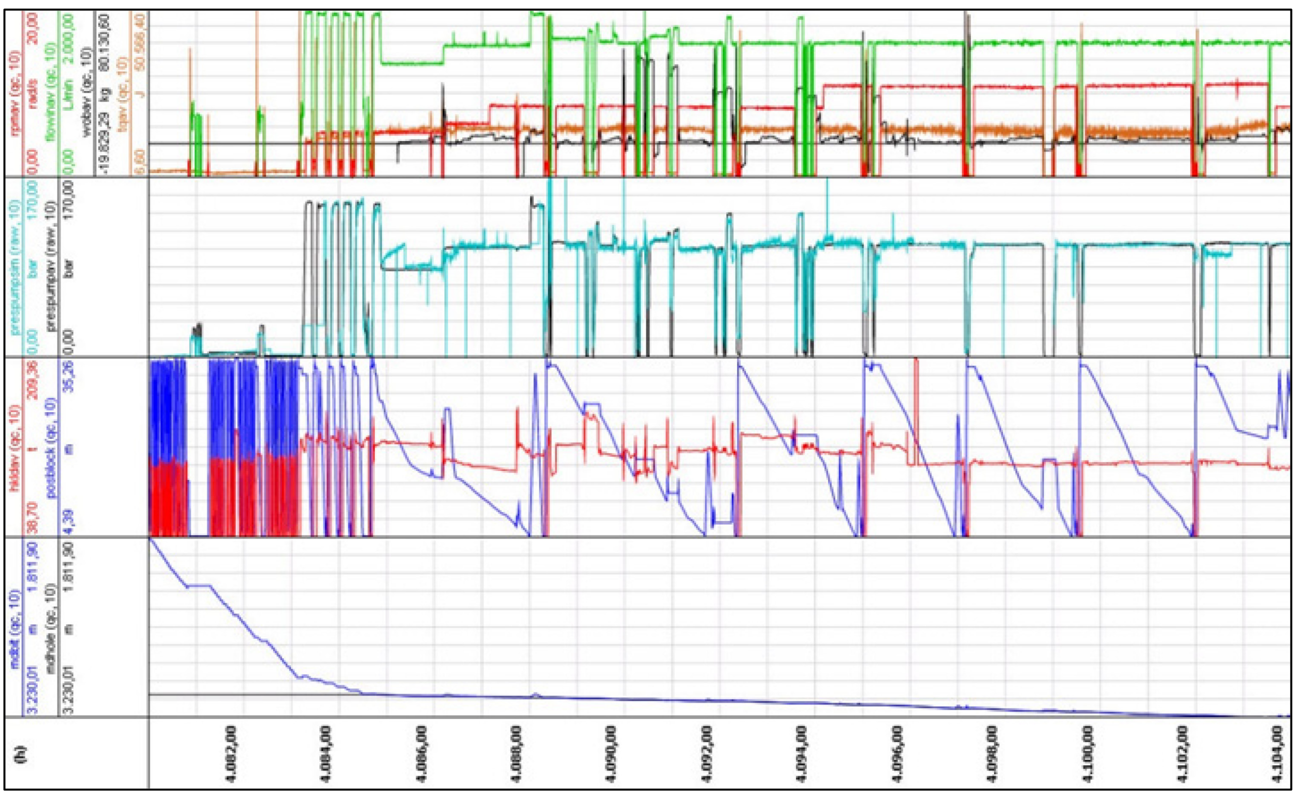

Figure 26 Data and results - Well B – "State aware" setup

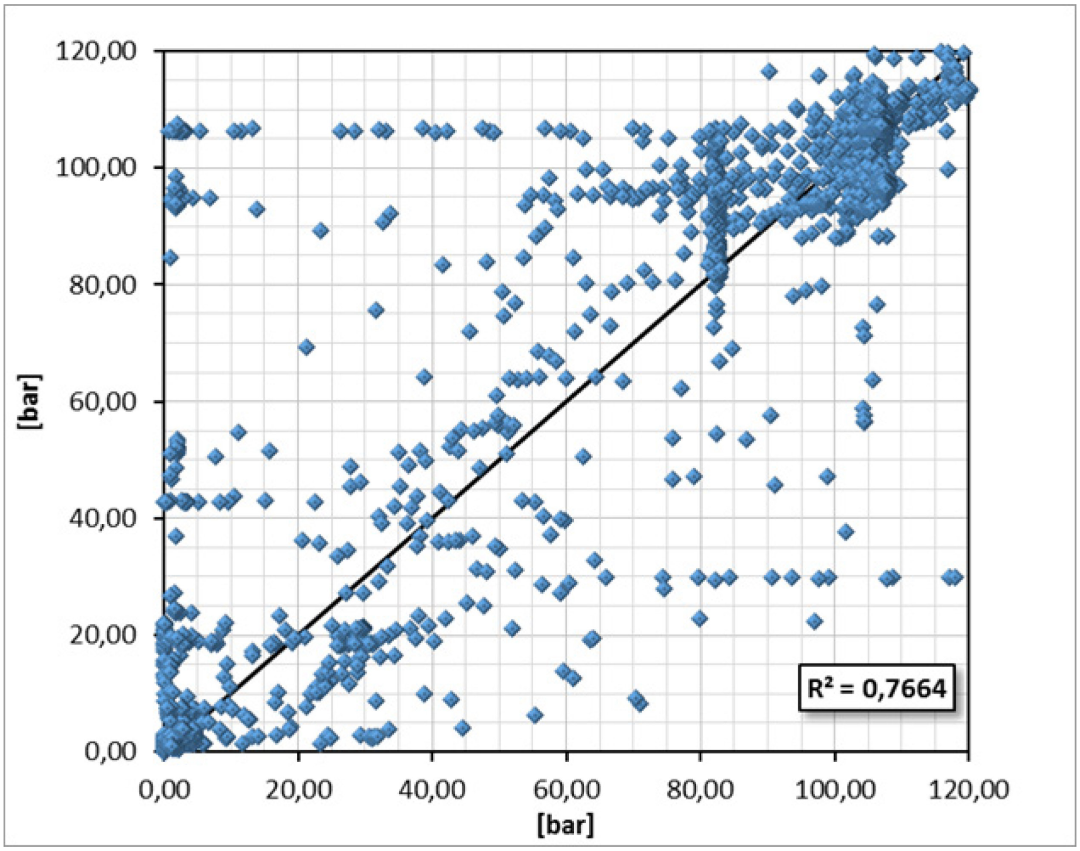

Figure 27 Error cross plot - Well B - „State aware“ setup

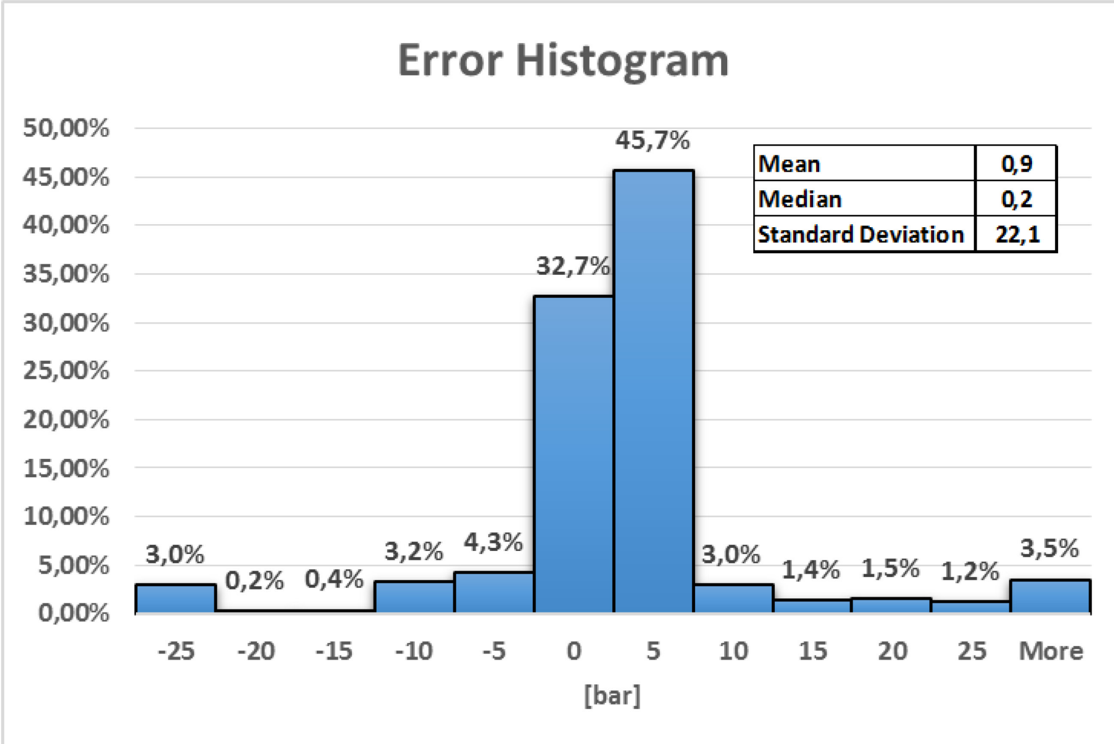

Figure 28 Error histogram - Well B - „State aware" setup

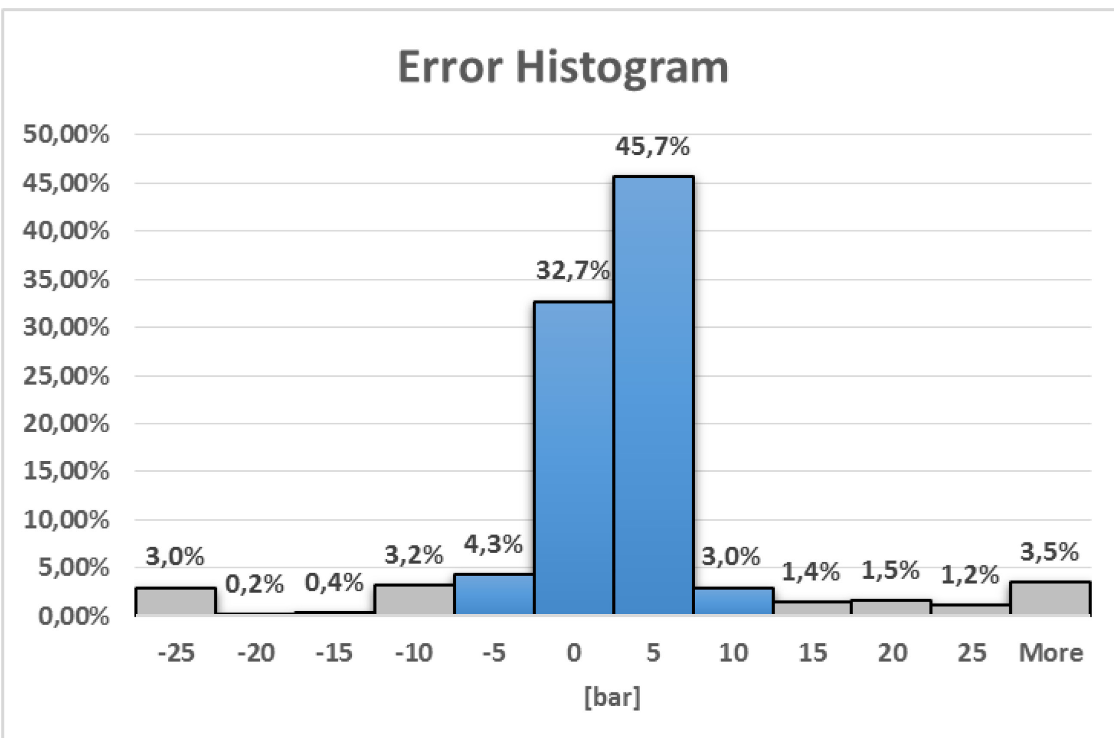

Figure 29 Highlighted error bins -9 to 10 bar for Well B

4.3 Incremental Training Setup

As shown previously, the configurations applied so far relied on a moving window training and prediction approach. This method worked sufficiently on both land and offshore data. It also coped with the basic and „state aware“ setup. Yet, the full advantage of the automatic recognition system couldn't be used, since either the operations were too homogenous and monotone (as in the land case on Well A) or the selected training window wasn't sufficient enough to gather information regarding states that occurred during the prediction period (as in the offshore case on Well B). Therefore, the next step was to develop a new method for training and predicting which will be able to deal with the drawback of the moving window approach.

Several options have been considered. At the end, the list came down to two approaches. The first one was based on the idea to train the network on offset well data and use the created network for real time predictions.

The second approach used an incremental training approach, adding more data to the training interval and such updating and improving the neural network.

The first approach required a sufficient volume of data, structured and organized in a way that the desired rig data may easily be extracted and prepared for training. This approach goes way beyond the framework of this thesis and may be an interesting topic for future research.

Figure 29 sketches the basic concept and idea behind the incremental training approach. Basically, the training routine starts with a predefined data range. Once the training process is completed the model steps into prediction mode for a certain time frame. As the simulation is over, the network is re-trained with the new data range. The process goes on until the bit is out of hole. A threshold was added additionally, with the function to indicate the start and end of the BHA run. This depth based threshold was used to reset the neural network and ensure that the next BHA run will start with a new network.

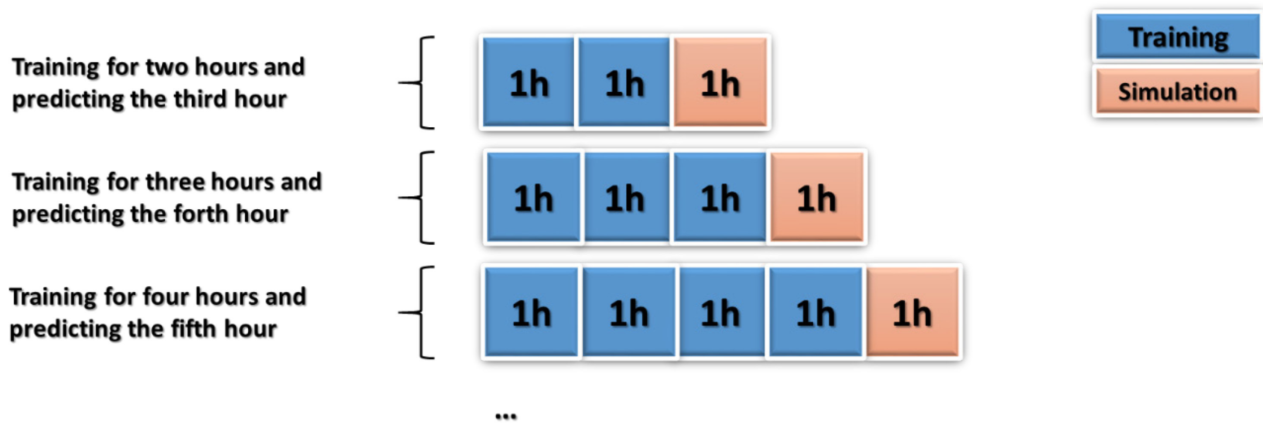

Figure 30 Incremental setup training and simulation concept

The incremental training model was tested on both land and offshore data and the results will be provided in the following chapters.

4.3.1 Land Rigs

The first test using the incremental training approach was once again performed on the onshore rig using the same data set from Well A. Since the training set used for this configuration will cumulatively increase, the "Out of Hole" threshold must be carefully set, to ensure that the network is built using information only from the current run. If this is not the case, the training will continue over the complete well and may take too long to ensure a desired speed. Thus, the real-time capability of the simulator might be impeded.

Figure 30 shows the simulated stand pipe pressure plotted along the other main drilling parameters. Compared to the Basic setup and the „state aware" setup, we can now see that the predicted pressure curve, almost exactly follows the real measured standpipe pressure. Since the training data continuously increases, the neural network engine can sort out the majority of the data issues and thus the spikes caused by the data quality, which were observed in the previous approaches, can are now sorted out and fixed.

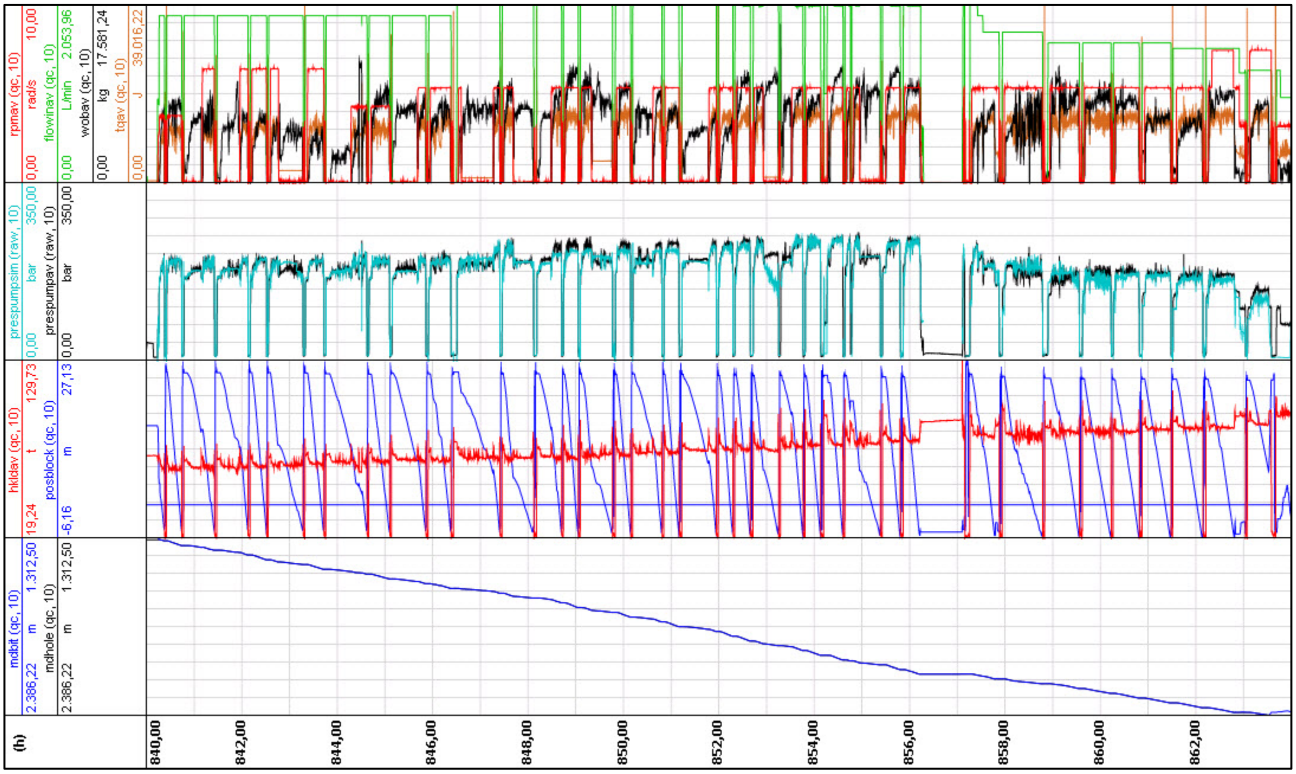

Figure 31 Data and results from Well A using the Incremental setup

The improved performance can also be seen on the cross plot given in Figure 31. The R-squared number rose from values in the ranges of approximately 0.88 for the previous tests to values in the order of approximately 0.92 for the current configuration.

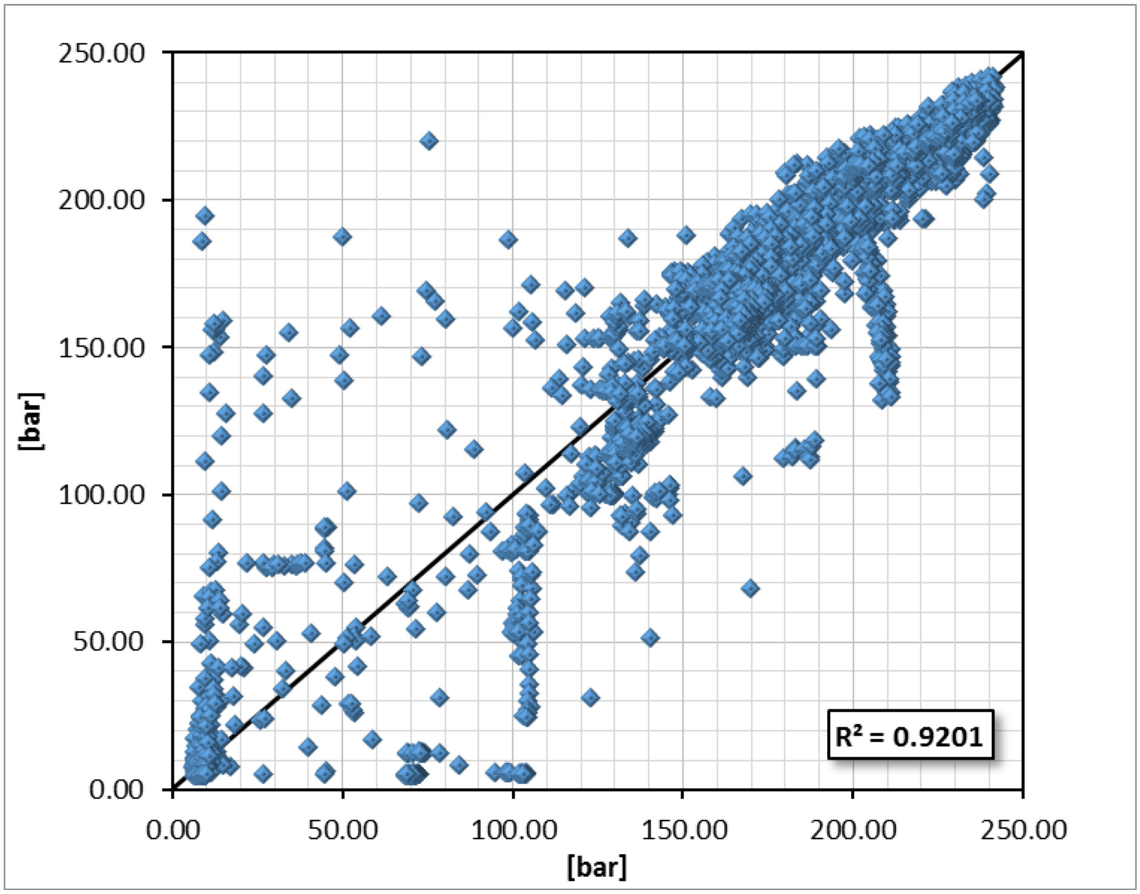

Figure 32 Well A - SPP/Simulated SPP cross plot after incremental simulation

The lower standard deviation indicates that the errors are less dispersed and are closer to the mean (also called expected value).

The highlighted bins in the histogram on figure 33 indicate that approximately 70% of the errors lie in the range between -9 and 10 bars. This is another signal that improvement has been achieved using an incremental training and simulation approach.

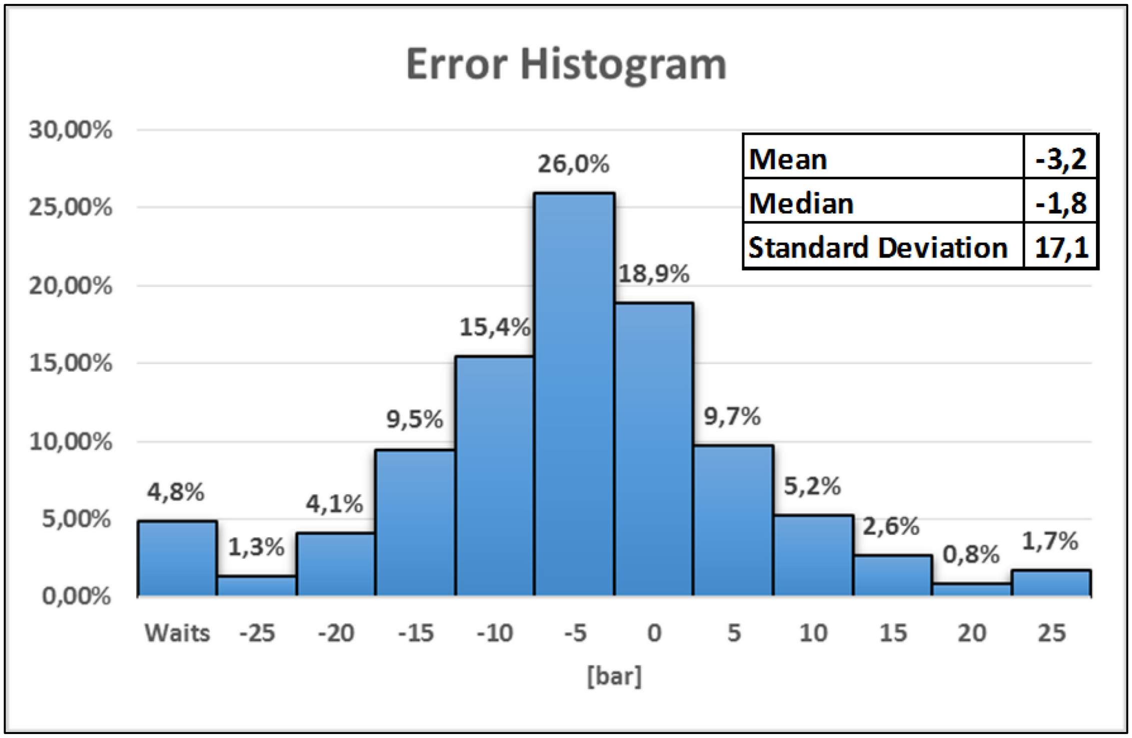

Figure 33 Land rig - incremental setup - error histogram

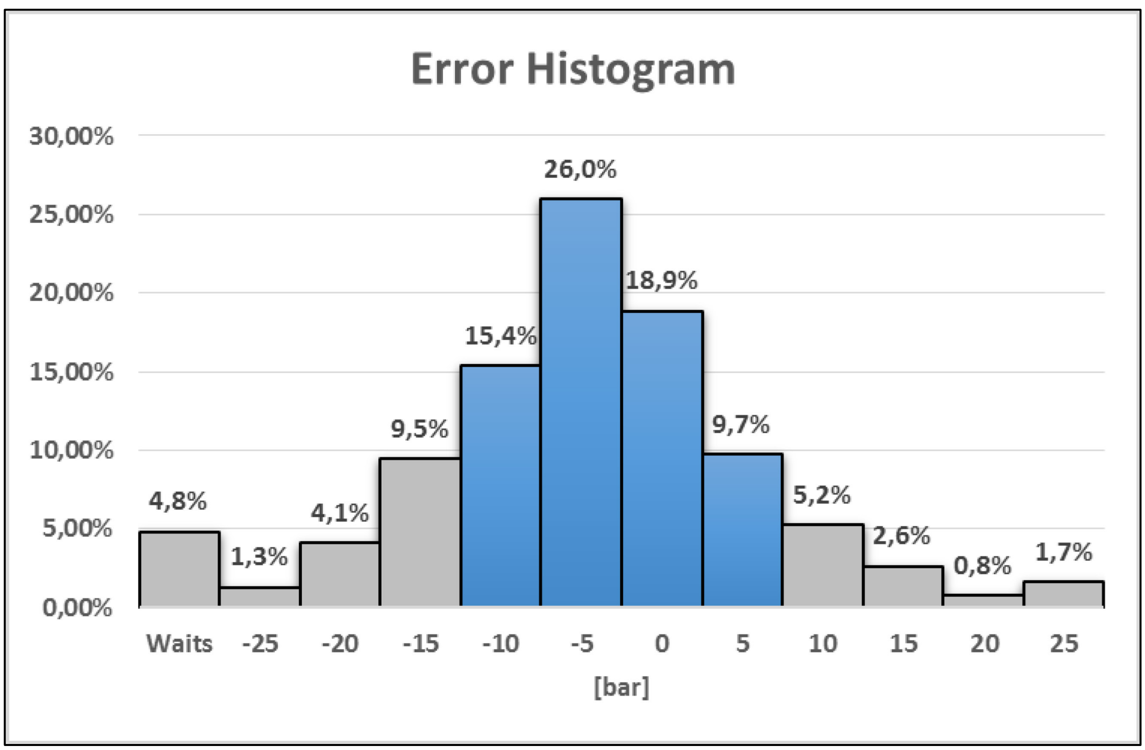

Figure 34 Land rig – incremental setup error histogram highlighting errors between -9 and 10 bar

4.3.2 Offshore Rigs

When looking back to the simulations on the offshore rig, no improvement has been made using the „state aware“ configuration so far. This was due to the fact that a small, 1 hour moving window, could not cover a wide range of operation states. Thus, the addition of the automatic recognition system didn’t add much to the simulator. Even more, the extension of the parameter set had a slightly negative effect on the neural network and thus on the overall performance.

The theory for overcoming this issue by using the incremental training and simulation method has indeed proved successful and the results are listed in the figures shown below.

One can immediately recognize the change in the performance, especially at the start and end section of the data set, where previous simulations struggled to perform well.

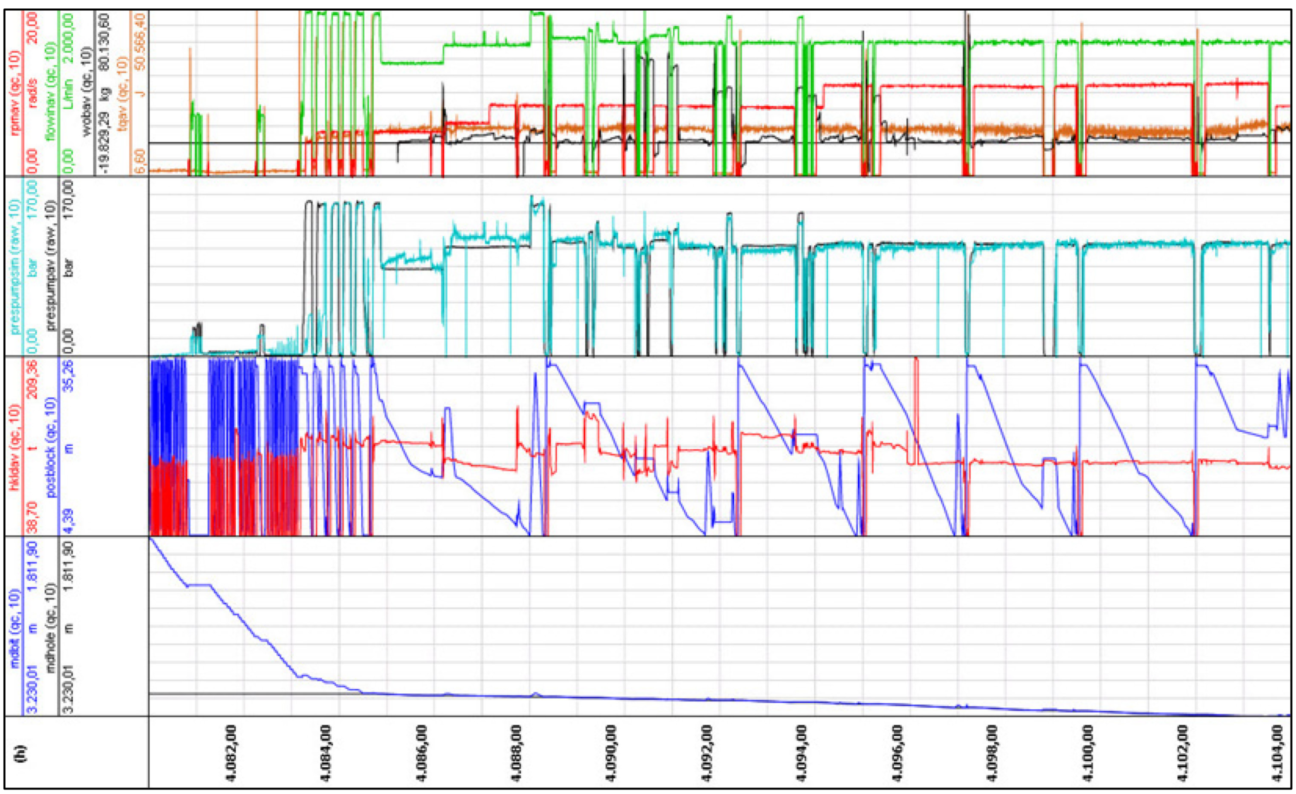

Figure 35 Data and results - Well B – Incremental setup

The linear regression analysis demonstrates that this new approach adds significantly to the overall quality of the simulation. The R-squared number rose from approximately 0.80 for the basic setup to above 0.87 when using the incremental training and simulation configuration.

A further sign for the importance of such a configuration is the improvement in the standard deviation values where a reduction of about 6 bar - from over 22 bar (for the „state aware“ setup) to around 16 bar has been achieved.

The mean lies in the range of 1.6 bar, which by itself is also a good indicator for the model performance.

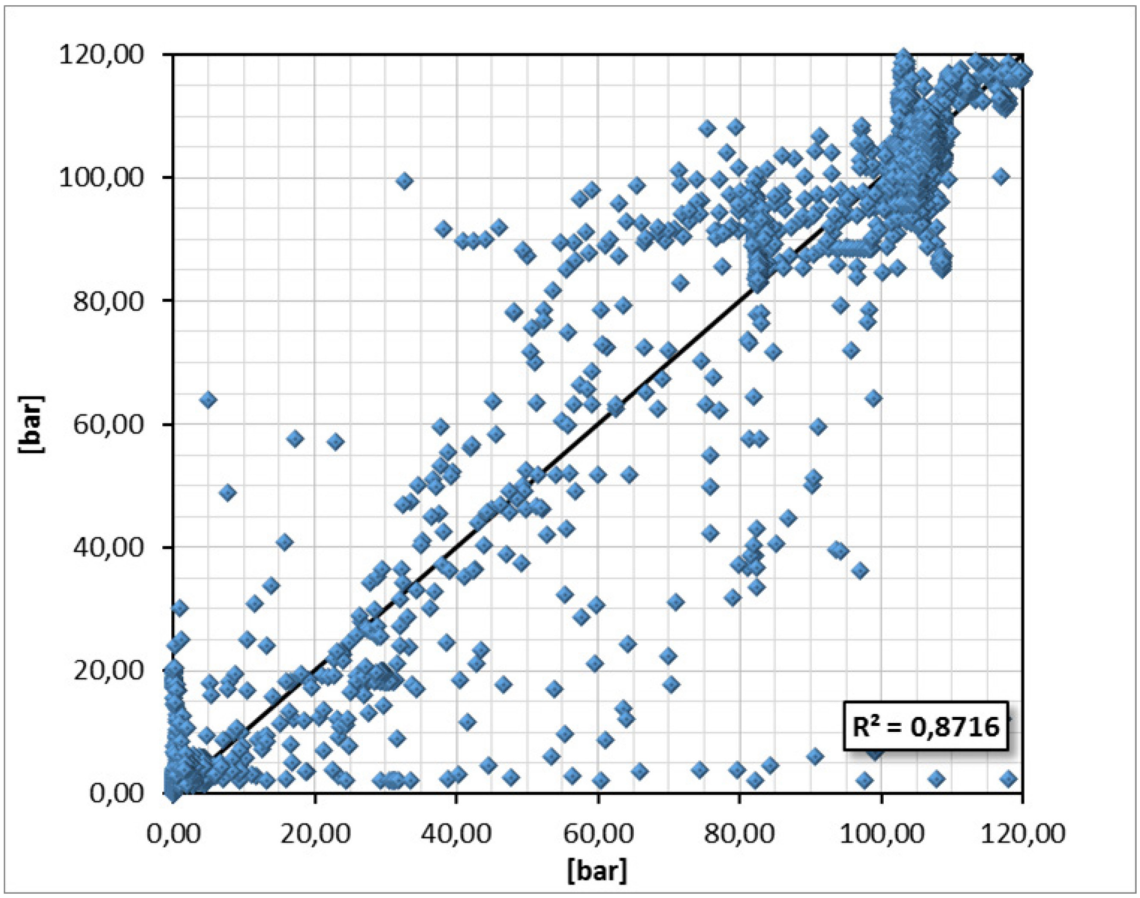

Figure 36 Error cross plot - Well B - Incremental setup

Consequently, the post-analysis showed that with this approach, the user is able to “flatten” the error peaks and achieve less dispersed and smoother results.

With all this being said, one can conclude that the incremental setup fulfils the requirements for this type of rigs and operations.

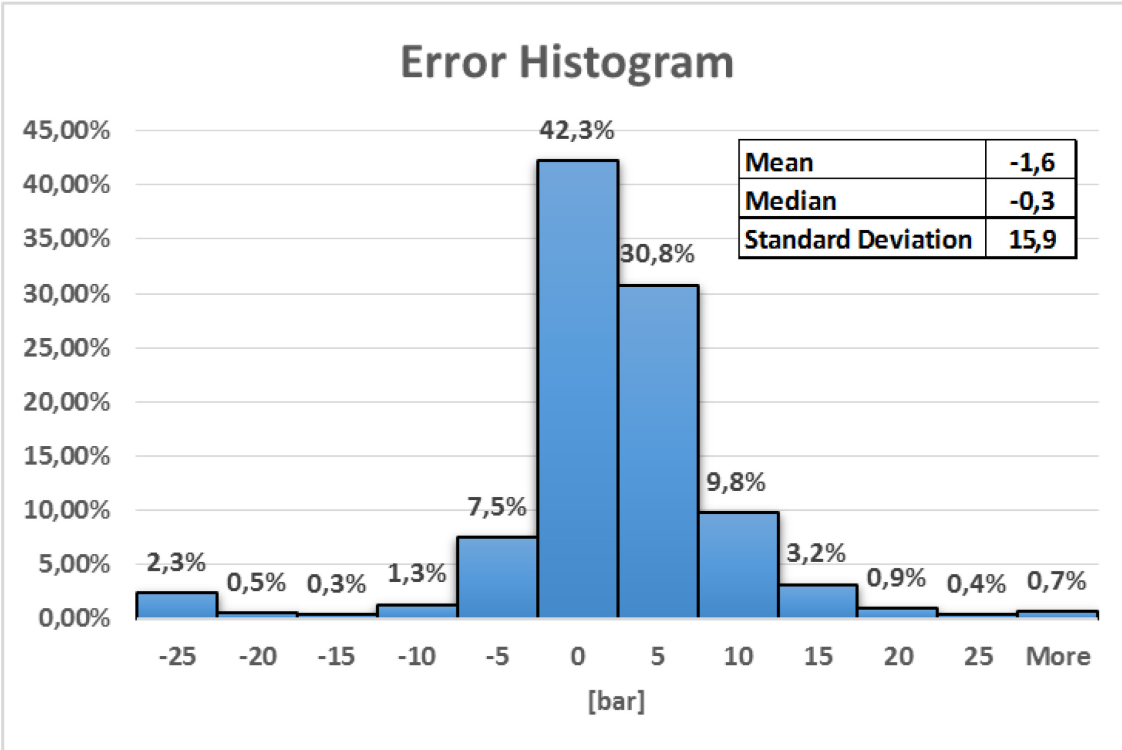

Figure 37 Error histogram - Well B - Incremental setup

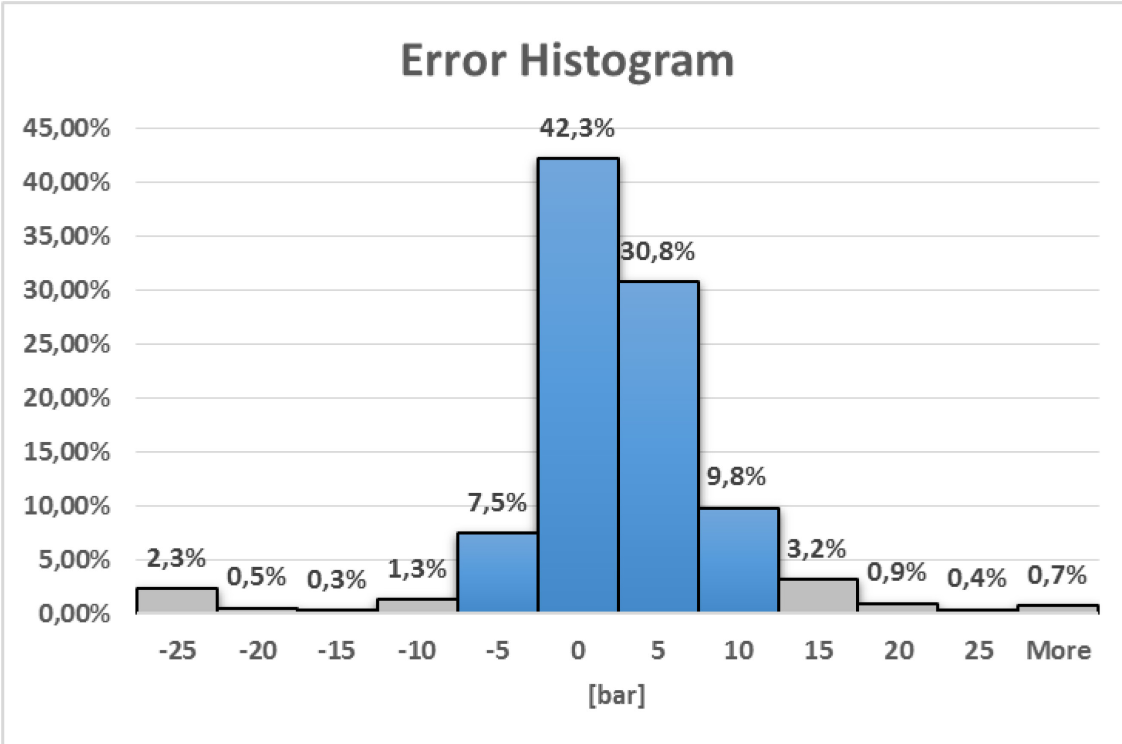

Figure 38 Highlighted histogram - Well B - Incremental setup

5 Output Interface

The chapters so far gave an overview of the methodology behind the hydraulic simulator covered in this thesis. Additionally, the system has been tested on two scenarios – an onshore- and an offshore well using different configurations.

The final part that needs to be illustrated is an output graphical interface that uses the described real-time hydraulic simulator and provides instant feedback to the driller thus giving him the option for immediate reaction if critical or suspicious wellbore conditions are observed.

Of course, the software used during the tests covered in this thesis, proNova Plot®, is sufficient for performing sophisticated analysis in office or laboratory environments. It provides the required real-time visualization capabilities plus various features and configuration options.

On the other side, using a complex software tool like this is probably not the optimal solution in regard to outdoor or rig floor conditions. For these harsh environments, where the time factor is of massive importance, one needs a simple-, user friendly and clear indicator showing the current downhole status. The driller should be aware of the situation by just throwing a look at the screen.

In this respect, a simplified hydraulic monitor will be presented together with an idea for a traffic light warning system. It should be noted that none of these were fully developed as software products. Some prototypes have been tested, however the full development remains outside the scope of this thesis.

5.1 Hydraulic monitor including simulated curves

The idea behind this concept is to define and visualize a safe operation window. The real-time standpipe pressure readings are overlaid on this safe operation window. The window is determined by plotting several operational parameters:

- The minimum flow rate required for cutting transport
- The maximum flow rate before fracturing the formation
- ECD
- Pump efficiency and limitations
- Simulated standpipe pressure

Depending on the operating parameters and the bit position, the safe operating window may shrink or expand.

Additionally, predefined abnormal event curves might be plotted which may be used to recognize the type of event that occurs. A library with different abnormal events may be defined and the actual pattern of the simulated curve can be compared with those stored in the database. The library may include a variety of technical issues such as: plugged bit nozzles, washed pipes, pump malfunctions, etc.

Additionally, different pre-sets can be also integrated in the tool, which can control and operate equipment on the rig floor. These routines ideally will be derived from operation practices or manufacture recommendations. Pump start-up sequences are a good example for such an application.

A sketch of a hydraulic monitor window is shown on Figure 38 below.

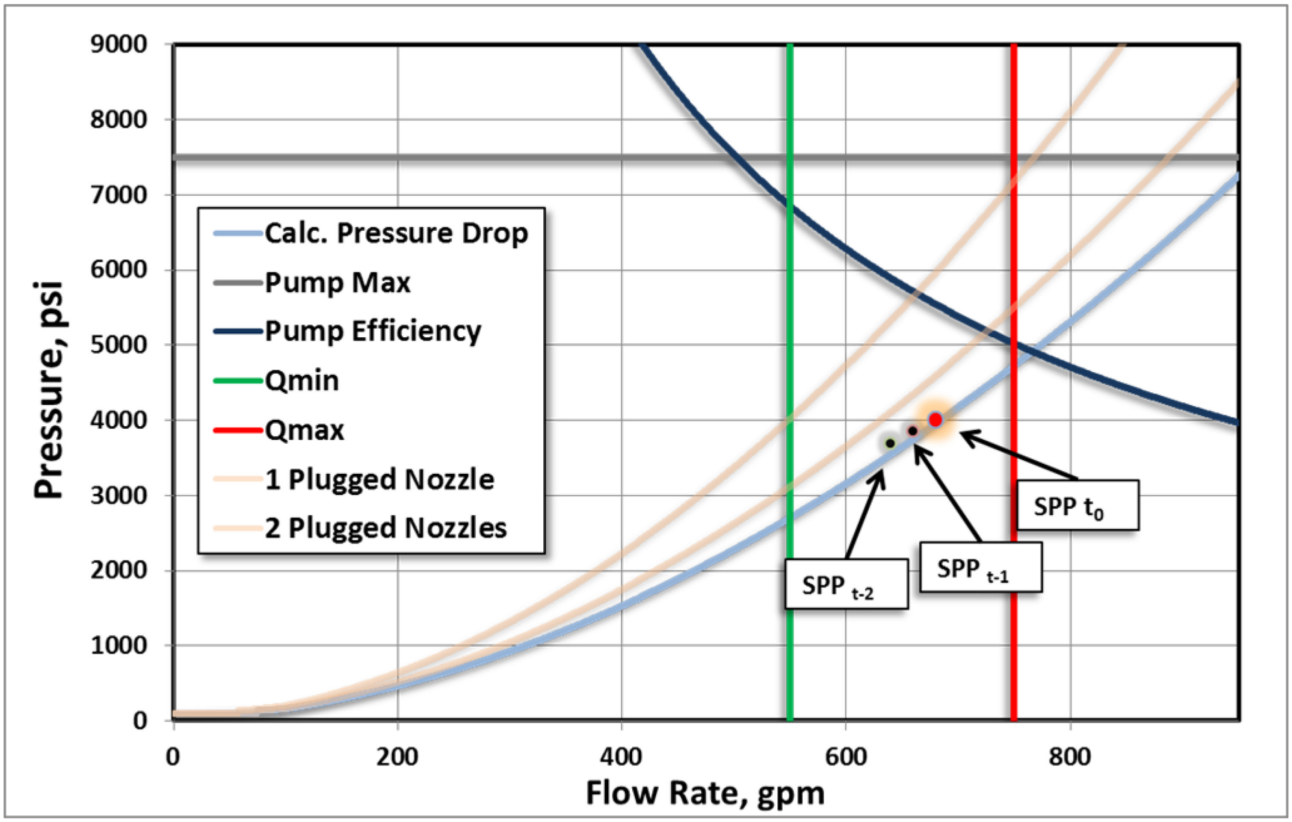

Figure 39 Hydraulic monitor concept

5.2 Simplified "traffic light" warning system

The driller's decision making can be assisted be the use of a simple "traffic light" warning system. The hydraulic simulator presented, might be implemented in such a system. Once again, the core of the warning system should consist of a comparison between actual and simulated values. Depending on specific deviation ranges, traffic light alarms will be triggered. These will indicate if the driller is operating in the safe zone (green light), is he is approaching critical conditions (yellow light) or immediate reaction is required (red light).

6 Conclusions and Recommendations

6.1 Conclusions

This thesis provides a concept and procedures to create a real-time drilling hydraulic monitor. Given the mud logging data normally available, the program is able to reasonably predict the theoretical stand pipe pressure without any sophisticated and long data input routines. Furthermore, the simulation is fully independent of morning reports, drill string and BHA descriptions, temperature profiles or any additional information.

The program shown in this work has been tested and quality controlled against the data from an offshore and an onshore drilling rig. Some of these test results are provided as examples in the thesis.

The core of the simulator is an artificial neural network with one hidden neuron. The network uses the Bayesian regulation backpropagation function. In addition to the neural network an automatic operation recognition system was introduced to enhance the simulation and to enable an operation based training and recognition mode.

Using this setup, the simulation was tested in three modes: using a moving window without the operation recognition, using a moving window and the operation recognition and finally using an incremental training and prediction approach including the operation states.

What can be concluded after these test trials is that the type of training and prediction model is crucial for some wells and less critical for others. The one hour moving window is way too short to cover a wide variety of states during training (the used data sets had relatively homogeneous operation recognition results), meaning that there is a high chance that the prediction will be made based on states that hasn't be trained for. Therefore, the best results were achieved using the incremental training and prediction mode.

Additionally, the automation recognition states add less to the simulation quality on onshore data, but have a major impact on offshore data.

With all this being said, the model presented provides a great approach for early abnormal event detection by comparing theoretical results with real data. The process can be run in real-time or historical mode. The simulation results can be visualized in different graphical interfaces. The program can also control and operate specific equipment (e.g. operate pumps, etc.) and can be part of an advanced rig automation system.

Last but not least, the type of training and prediction approach used in this work can be applied to other data channels which are often of interest.

6.2 Future work

Regarding features that might be considered in future developments the author would like to mention the following points:

- Graphical visualization

  The author mentioned two options in this work. However, the development of these hasn't been completed so far. These were considered prototypes and have been just provisionally programmed to test the concept.

- Library of abnormal events

  As mentioned already, the simulation can be performed in a way that the simulated theoretical pressure is artificially altered so that it mimics an abnormal event case. These manipulated values are compared to the actual ones and in case of a match, an alarm should be triggered. The option, for including these simulated events may be of great interest for future developments.

- Offset well training and simulation

  Another interesting approach will be if the training process is performed on an offset well instead of directly training and simulating on the current data set. For this to be possible, one must build or use a database, where the rig data is strictly organized and classified in a way that the appropriate data for training can be pulled anytime. This includes, rig, well, hole sections, depths, equipment etc.

The given ideas are just a part of the possibilities that can be created based on a good real-time hydraulic simulation. Of course, if thinking bigger, one may imagine it being part of an advanced rig automation system. Finding the optimal setup and parameters is still a challenge and will need systematic effort. The final results however, will be of great benefit to hydraulic aspect of the drilling process.

7 Nomenclature

A	Surface area
BHA	Bottom hole assembly
d_h	Hole diameter
$d_{in,pipe}$	Pipe inner diameter
$d_{out,pipe}$	Pipe outer diameter
ECD	Equivalent circulation density
FPS	Foot, pound, second
g	Gravitational acceleration
K	Consistency index
MD	Measured depth
MWD	Measurement while drilling
n	Non-Newtonian index
N_{RE}	Reynolds number
Q	Flow rate
R^2	Coefficient of determination
RPM	Revolutions per minute
TVD	True vertical depth
Va	Annular velocity
Vc	Critical velocity
V_n	Nozzle velocity

V_p	Pipe velocity
WITS	Wellsite Information Transfer Specification
WITSML	Wellsite information transfer standard markup language
γ	Shear rate
μ	Viscosity
ρ	Density
τ	Shear stress

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