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Best Real Time Model Development of an Oil Well Drilling System

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A drilling system consists of a rotating drill string, which is placed into the well. The drill fluid is pumped through the drill string and exits through the choke valve. During drilling, the pore pressure (minimum limit) and the fracture pressure (maximum limit) define mud density range and pressure operational window. Several disturbances affect bottom hole pressure; for example, as the length of the well increases, the bottom hole pressure varies for growing hydrostatic pressure levels. In addition, the pipe connection procedure causes severe fluctuations in well fluids flow, changing well pressure. Permeability and porous reservoir pressure governs native reservoir fluid well influx, affecting flow patterns inside the well and well pressure. The objective being tracked is operating under desired pressure levels, which assures process safety, also reducing costs. In this scenario, modelling techniques are important tools for narrow operational windows, commonly observed at deepwater and pre-salt layer environments. The major objective of this paper is real time building and comparing model performance for predicting annulus bottom hole pressure, using real time flow, choke index and ROP (rate of penetration) data, available from a drilling site. Neural Network (NN) based models were used successfully for on-line identification purposes, using an adaptive methodology. The proposed methodology can be employed at drilling sites, through the use of PWD (Pressure While Drilling) and mud-logging tools, providing real time data and helping operators to make important decisions concerning safety of the drilling process.

1. Introduction

A drilling system consists of a rotating drill string, which is placed into the well. The drill fluid is pumped through the drill string and exits through the choke valve. During drilling, the pore pressure (minimum limit) and the fracture pressure (maximum limit) define mud density range and pressure operational window. Several disturbances affect bottom hole pressure; for example, as the length of the well increases, the bottom hole pressure varies for growing hydrostatic pressure levels. In addition, the pipe connection procedure, causes severe fluctuations in well fluids flow, changing well pressure. Permeability and porous reservoir pressure governs native reservoir fluid well influx, affecting flow patterns inside the well and well pressure. The objective being tracked is operating under desired pressure levels, which assures process safety, also reducing costs. In this scenario, modelling techniques are important tools for narrow operational windows, commonly observed at deepwater and pre-salt layer environments.

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The major objective of this paper is real time building and comparing model performance for predicting annulus bottom hole pressure, using real time flow, choke index and ROP (rate of penetration) data. Neural network models were built using an adaptive framework. The proposed methodology can be employed at drilling sites, through the use of PWD (Pressure While Drilling) and mud-logging tools, providing real time data and helping operators to make important decisions concerning safety of the drilling process.

2. The process analyzed

The pressure balance between the well section and the reservoir is important. If the pressure in the well is higher than the reservoir pressure, it is referred to as over-balanced drilling. This condition causes the circulation fluids to penetrate into the reservoir formation, damaging porous formation. On the other hand, if the pressure in the well is lower than the reservoir pressure (under-balanced drilling), the reservoir fluids migrate into the well annulus. Over-balanced drilling is the most used method for drilling oil wells because nearly eliminates the risk for an uncontrolled blow-out. During a blow-out, as the pressure in the reservoir is higher than in the well annulus, large amounts of the reservoir fluids penetrate into the well and follow the well to the surface. Today, different type of blow-out preventers gives the possibility of reducing the well pressure lower than the reservoir pressure (Nygaard et al., 2006). Drilling the oil well using under-balanced conditions has the benefit that the porous formation is less damaged, for minimizing the particles from the drilling process to penetrate into the formation, improving production rate when the oil well is set into production.

During oil well drilling, the pore pressure (minimum limit) and the fracture pressure (maximum limit) define mud density range. As a result, the drilling fluid hydrostatic pressure needs to be higher than pore pressure, in order to avoid formation fluid invasion into the well. Simultaneously, the drilling fluid hydrostatic pressure needs to be smaller than fracture pressure, for avoiding formation damage. Modelling, optimization and control analysis of a drilling process constitutes a powerful tool for operating under desired pressure levels and simultaneously maximizing the penetration rate, which reduces costs, as oil derrick operation demands around 220,000.00 U$/d (Perez-Téllez et al., 2004). As a result, the main objective of this paper is implementing real time model development, based on NN, for oil well drilling sites using PWD measurements.

It is well known that the complexity of mathematical models used to describe actual processes strongly depends on its final use. Models are generally required to allow the best process description with the minimum mathematical complexity; however, these two objectives are normally exclusive. This is one of the reasons that make process modelling such a difficult task, sometimes more an art than a science. In the case of model based process control, simplicity is a very important required characteristic, as the model has to be solved many times at each sampling interval.

When all the important characteristics of the process to be modelled are known, building a phenomenological model by applying mass, energy and momentum balances to the process is normally an easy task. However, difficulties may emerge during the solution of the resulting system of equations. A disadvantage of the first principles modelling method is that the resulting dynamic model may be too complex to be employed for model based process control design. For this reason, a number of different model reduction techniques have been proposed in the literature.

Empirical linear modelling is well studied but, as pointed out by Pearson et al. (1997), a well-developed theory for nonlinear system identification is not available. The neural network (NN) approach has proved to be a useful tool and is the most popular framework for empirical model development, although estimating the huge number of parameters frequently present in the model may be regarded as a major problem to be solved (Su and McAvoy, 1997).

It is well known that the construction of an efficient NN is a function of many factors. The amount and appropriateness of the available training data is an important factor. In addition, the optimal NN structure is not easy to pre-specify; the optimization of the NN weights can result in contrasting generalization characteristics and alternative convergence criteria for training can also result in different solutions (Haykin, 2001). Neural network based identification involves model parameters selection, determination of the forcing function which is introduced into the plant to generate the output response, estimation of model parameters and comparison of plant information and model predictions for data not used in model development.

The main objective of this paper is building a methodology for the proper on-line construction and training of neural networks (NNs), which allow the development of confident models for use in the drilling environment. In order to train the NN model, PWD data were employed. Among the several sensors available, PWD (pressure while drilling) measurements gained popularity due to its potential for problem diagnosis (Hutchinson, 1998; Hedayatzadeh et al., 2010). PWD measurements are taken continuously every few seconds and stored in memory, being downloaded at surface after a trip.

3. Results

NN training and validation employed oil well drilling data from on-line PWD measurements. A three layer feedforward NN architecture was built, using 10 hidden neurons and sigmoid activation functions. The input NN data comprised depth, weight on bit, rate of penetration, RPM, pressure, density, flow, temperature (Figure 1). The NN output was annulus pressure and the algorithm for NN learning was back propagation with adaptive learning rate (Haykin, 1994). Figure 2 illustrates the error minimization during the learning process.

Systematic techniques for nonlinear model validation, characterization of the amount and type of process data required to build nonlinear empirical models with satisfactory predictive capability and the identification of nonlinear model structures which are capable of capturing a wide variety of process behaviours are important issues that need to be explored for non linear identification purposes. According to traditional literature methodology, the input-output data was normalized and random initial guesses for weights and bias were employed. Also, in accordance with standard cross-validation procedures, (Pollard et al., 1992), the NN empirical model employed two independent data (training and validation sets) containing two different data sets were used. As discussed by Pollard et al. (1992), cross-validation is expected to minimize the problem of scarce data. Besides, in actual industrial and laboratory process, data sets sometimes are insufficient, due to infrequent sampling times or basically during start up of the drilling system.

A very natural point to be investigated is the effect of the neuron activation function on the dynamic behaviour of the empirical model. Simulation studies carried out with both sigmoid and hyperbolic tangent functions led to very similar results. Therefore, changing the particular form of the neuron activation function was not enough to assure the development of efficient empirical models.

The influence of the initial guesses of the weights and bias of the NN, during the training phase, on the resulting dynamic behaviour was also investigated. Different empirical models were obtained for different initial guesses. Therefore, particular dynamic simulations obtained depend on the initial guesses. However, the dynamic patterns observed by the empirical model were qualitatively similar to the one shown by the drilling system when a set containing historical data points was employed.

As a result, the data for validation comprised historical data of drilling. As a result, the parameters of the on-line training with PWD measurements were analyzed using the historical available data, in order to avoid poor predictive capacity due to over fitting. The training procedure was made through a batch mode (Figure 3). As a result, the training data did not include past values, which were already learned and saved in the synapses. In fact, after the first iteration, the training procedure employed new data and the weights and bias from the previous iteration learning step. Therefore, the NN model was built using an adaptive structure. During NN training procedure, the NN predictive capacity was periodically tested with validation data set, and the NN parameters were saved, during the training procedure, until NN validation error reached a minimum value (Figure 4).

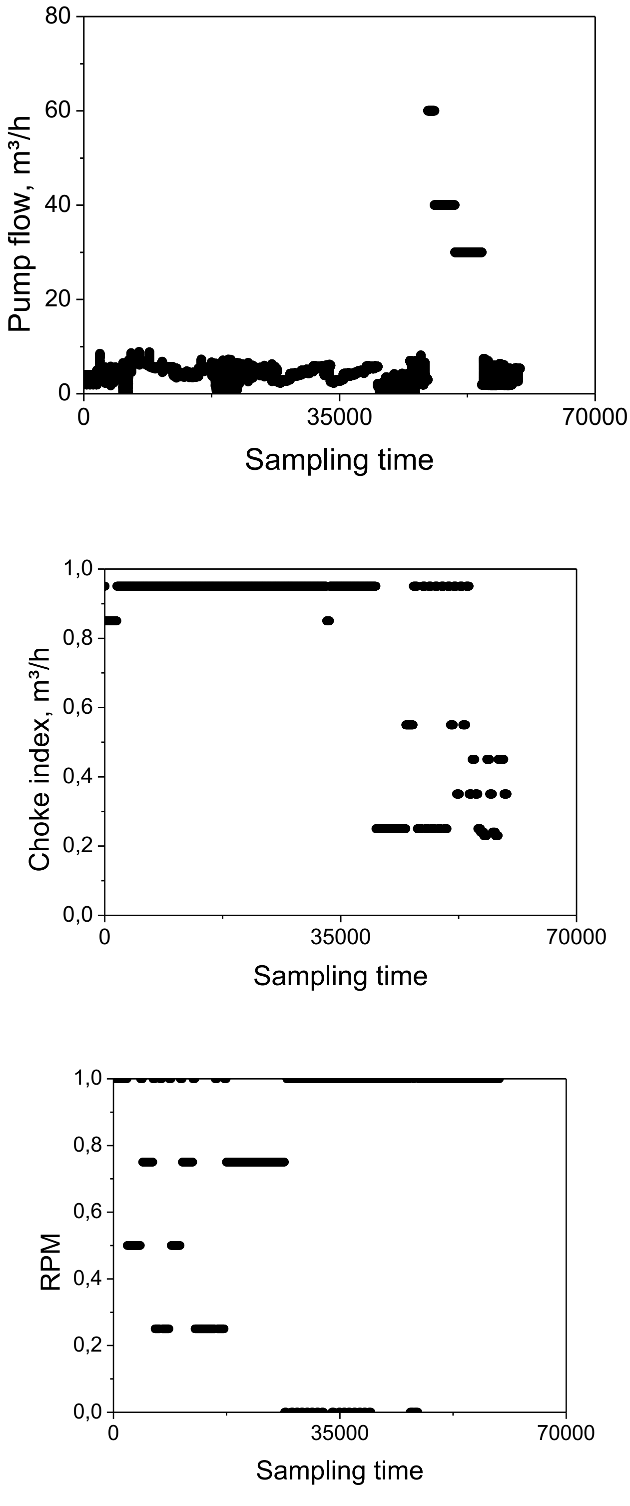

Figure 1: Examples of input data for NN training.

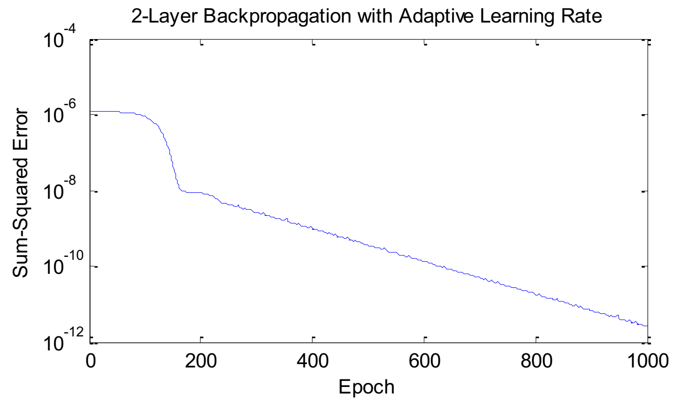

Figure 2: NN training algorithm.

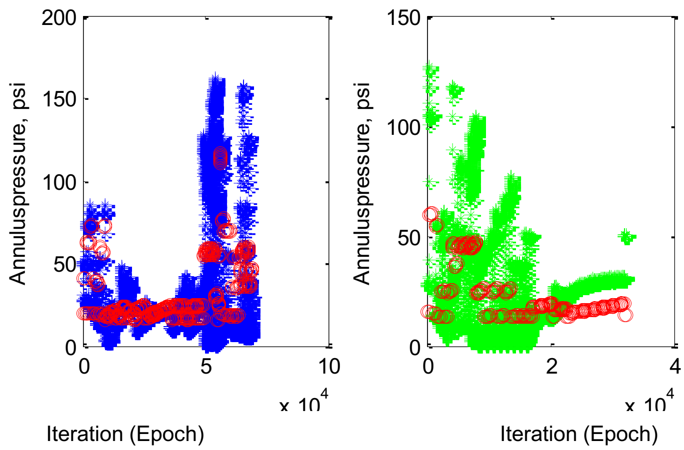

Figure 3: Adaptive NN training procedure with cross-validation (Neural network output (red), experimental training data – known (blue), experimental training data – unknown (green)).

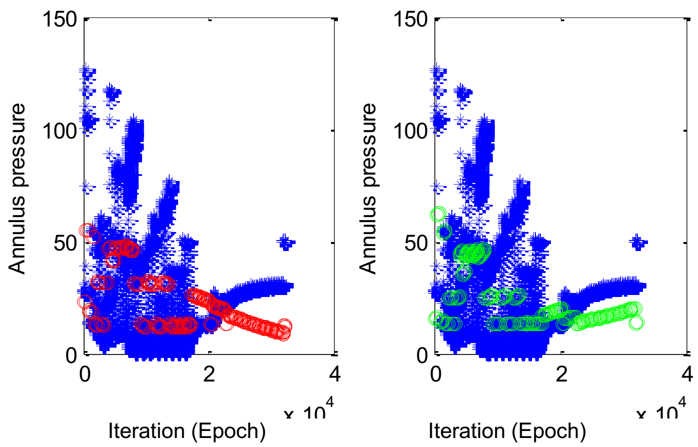

Figure 4: NN validation procedure (Blue: unknown experimental data, Red: NN output using the last training iteration, Green: NN output using cross-validation).

4. Conclusions

The paper presents a methodology for on-line identification of non linear models for use in the drilling environment. PWD data were employed for neural network modelling purposes. It may me concluded that NNs were used successfully for on-line identification purposes, using an adaptive methodology, which employed fresh data for the training procedure. In fact, the past data was assumed to be saved in the NN synapses, reducing computational effort, allowing on-line model building. The proposed methodology also uses best model identification methodology, through validation test, using historical data obtained previously from oil well drilling operations. This way, the validating of nonlinear models (NNs) was built in a supervisory fashion, using available experimental data from the drilling process.

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