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Research Article

Prediction of frictional pressure loss for multiphase flow in inclined annuli during Underbalanced Drilling operations

Barati-Harooni Ali [a], Najafi-Marghmaleki Adel [a,*], Tatar Afshin [b], Arabloo Milad [b], Phung Le Thi Kim [c], Lee Moonyong [d], Bahadori Alireza [e,**]

[a] Department of Petroleum Engineering, Ahwaz Faculty of Petroleum Engineering, Petroleum University of Technology (PUT), Ahwaz, Iran
[b] Young Researchers and Elite Club, North Tehran Branch, Islamic Azad University, Tehran, Iran
[c] Department of Chemical Process and Equipment, Faculty of Chemical Engineering, Hochiminh City University of Technology, Hochiminh City, Viet Nam
[d] School of Chemical Engineering, Yeungnam University, Gyeungsan, Republic of Korea
[e] Southern Cross University, School of Environment, Science and Engineering, PO Box 157, Lismore, NSW, Australia

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Abstract

In Underbalanced Drilling (UBD) method, it is difficult to predict the equivalent circulation density due to co-existence of three phases which are air, cuttings and drilling fluid. This study presents the application of a developed model inspired from a novel intelligent algorithm namely radial basis function optimized by genetic algorithm (GA-RBF) algorithm to calculate frictional pressure loss of two-phase gasified drilling fluid flow along with cutting as the third phase in inclined wellbore portions. The suggested approach was conducted to extensive data reported in literature and was based on Rate of Penetration (ROP), wellbore inclination, pipe rotation and *in situ* flow rate of each phase. The results of this study show that the proposed model could reproduce the experimental frictional pressure loss data to an acceptable accuracy due to high correlation coefficient ($R^2 > 0.99$) and very small values of average absolute relative deviation (AARD) (2.166726), standard deviation (STD) (0.038222) and root mean square error (RMSE) (0.008783). Results of this study could couple with commercial drilling simulators to accurately predict the frictional pressure loss of three phase flow.

Keywords: Frictional pressure loss; Three phase flow; Radial basis function network; Rate of Penetration

1. Introduction

It is important to improve the process and techniques of drilling operations in order to get better results. The producible oil in place from a reservoir depends intensely on drilling operations and measurements. Cares must be taken to account in any action from drilling to production scenarios. Drilling fluids have a remarkable role in drilling operations, which could deeply effect on the efficiency and cost of drilling process and also could have very undesirable effects on productive formations. Over balance drilling (OBD) is a drilling technique in which the formation pressure is lower than the drilling fluid pressure. This over balance pressure results in invasion of drilling fluid into the formation. The invasion phenomenon causes lots of damages to formations. It could result in permeability reduction by penetration of mud particles into formation and plugging of pores [1]. Underbalanced Drilling (UBD) is a new drilling method resolved many of the invasion related problems [2]. This method is suitable for depleted pressure reservoirs because increases the penetration rate and bit life and prevents lost circulation, formation damage, pipe sticking, etc. [3–5].

* Corresponding author.
** Corresponding author.
E-mail addresses: adelnajafiput90@yahoo.com (Najafi-Marghmaleki A.), alireza.bahadori@scu.edu.au (Bahadori A.).
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In contrast with OBD method the drilling fluid pressure is lower than the formation pressure in UBD method. The effectiveness of this method depends largely on the type of drilling fluid, which is based on the formation pressure and its other properties. In this method, another important point in drilling fluid selection is the cleaning capability. Inadequate cleaning of borehole may lead to costly related drilling problems such as early bit wear or pipe sticking [6−8]. Aerated fluids are suitable and widely used in this method [9−11]. These fluids consist of two phase (i.e. liquid and gas phase) and as a result develop two phase flow pattern in annulus. In this type of drilling fluids the liquid phase serves to transport cutting and the gas phase is used to set pressure [12,13]. An important step in this method is the true detection of minimum required flow rate of each phase. The importance of this step is due to its contribution in effectiveness of wellbore cleaning and also better cutting transportation [14,15]. Well inclination and pressure distribution are two parameters that should be taken into consideration in modeling flow profile in annulus, especially in UBD method. An accurate estimation of equivalent circulation density is very important. The pressure drop and two-phase flow pattern effect this estimation in aerated type drilling fluid. The extent and profile of pressure drop should be regarded as an important factor in UBD [16]. The discussion on the carrying capacity and hydrodynamic behavior of gasified drilling fluids such as aerated fluids reveals the importance of an accurate knowledge of the procedure of cutting transport in inclined annuluses. Literature review shows that there are many researches on the hydrodynamic behavior of aerated drilling fluids [17−22]; however there is little report on the cutting transport modeling of three phase flow. Shahdi and Arabloo [23] studied the application of least square support vector machine (LSSVM) model for prediction of frictional loss in two-phase gas based drilling fluids in presence of cuttings. They concluded that the model reproduces the target data with an acceptable accuracy. They also showed that by changing input parameters, the model could simulate the actual physical trend of the total pressure loss. This study highlights the application of an intelligent approach model based on GA-RBF algorithm to calculate frictional loss of three phase flow (i.e. two-phase gasified drilling fluid along with cutting as the third phase) in inclined wellbore portions. This model used to calculate the frictional pressure loss according to Rate of Penetration (ROP), wellbore inclination, pipe rotation and *in situ* flow rate of each phase. This intelligent approach was based on extensive data reported in literature.

2. Details of intelligent model

Artificial neural networks (ANNs) have ability to take some evidences from a complex issue, developing a model approach to improve it and adopting to the changes in environment [24]. The main advantages of ANNs are the ability of effectively manipulating large amounts of data and capability to extend and generalize the results. ANNs have parallel interconnected and distributed nature. The basic components of ANNs are artificial neurons which are used as processing units. These units are present in layer(s) and are linked to each other by interconnected connections. Two common ANNs are Multilayer Perceptron (MLP) and radial basis function (RBF) networks. The application of both models is the same and they are used for pattern recognition and nonlinear approximation. However, the internal computational structure of two models is different. RBF networks have several advantages including the simple and fixed three layer architecture which causes them to be easy to design. They have high tolerance to input noise, ability of online learning and effective generalization and extension of results [24]. The good generalization of RBF networks makes them to be capable to strongly figure out the patterns that were not used for training [25]. The computational procedure of RBF network (RBFN) is based on localized basis functions and iteratively function approximation [26−29]. The RBFN is a feed-forward neural network which applies to distinct areas by using the supervised training technique [30]. The RBFN is a universal approximator with a solid nature which could effectively predict any reasonable continuous function with the best approximation [31]. The structure of RBF is much simpler than MLP; in addition the process of training data by RBF is much faster than MLP. Considering these advantages, the RBF could be a suitable alternative to MLP. The RBF is capable to exactly linearize and interpolate a set of data points in multidimensional space [32]. From the point view of similar layer by layer topology of RBF and MLP, it is often considered that RBF networks can be completed by MLP networks with increased input parameters [33]. The architecture of RBF network is similar to classical regularization network [34]. The fundamental properties of regularization network are as follows [34,35]:

1. The ability to accurately approximate any multivariate function on a compact domain in presence of sufficient number of units.
2. Considering the linearity of unknown coefficients, there is always a choice of coefficients with best-approximation property.
3. The network eliminates solutions that predict the data points but badly oscillate in domains without data points. This means that the solution is optimal.

Fig. 1 shows a schematic of architecture of RBF network. It consists of three input, output and hidden layers. The input layer contains an input vector. In hidden layer a nonlinear transformation is applied to this vector by means of RBF activation function (ϕ (r)). The RBF activation function takes the vector distance between its weight and input vector that is multiplied by its related bias. The output layer serves as a linear combiner and maps the nonlinearity into a new domain. The biases of output layer could be further modeled by an additional neuron in hidden layer which contains a Constant Activation Function ϕ_0 (r) = 1. The linear optimization method helps RBFN to develop a general optimal solution to the adjustable weights in the light of minimum mean square error (MSE) [31]. There are several important differences

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