Application of SVM Algorithm for Frictional Pressure Loss Calculation of Three Phase Flow in Inclined Annuli

Arya Shahdi1 and Milad Arabloo2*
1Department of Petroleum Engineering, Islamic Azad University, Science and Research Branch, Tehran, Iran
2Department of Petroleum Engineering, Petroleum University of Technology, Ahwaz, Iran

Abstract

In Underbalanced Drilling (UBD) operation, the presence of three phases including, drilling fluid, air and cuttings, makes the estimation of equivalent circulation density more difficult. This study presents a novel computer-based model namely Lease Square Support Vector Machine (LS-SVM), for frictional loss calculation of two-phase gas based drilling fluids with the presence of cuttings as the third phase in inclined section of wellbore. This model is based on extensive experimental data collected from published literature. This model is account for in situ flow rate of each phase, Rate of Penetration (ROP), pipe rotation, and hole inclination. The results show that the proposed model is predicting frictional pressure losses in acceptable agreement with experimental data with very high correlation coefficient (>0.99) and small average relative error. Moreover, a trend analysis was carried out to check the validity of the developed model. Results of the present study show that implementation of this developed model can be incorporated in drilling simulators for accurate estimation of frictional pressure loss of three phase flow.

Keywords: Pressure loss; Three phase flow; LS-SVM; Sensitivity analysis

Introduction

Drilling operations and techniques are effectively improving in order to get into better results with avoidance of any unfortunate incidents. Extractable hydrocarbon is highly dependent on drilling operations and measurements. Every action should be precisely taken in total steps from drilling to production. Drilling fluids play pivotal role in drilling operations while could be highly deleterious to productive formations. Unavoidably, the phenomenon of invasion occurs during Over Balanced Drilling (OBD) which causes lots of damages to the formations [1]. These damages could result in less possible recoverable oil friction with the consequences of losing natural energy source and money. A relatively new drilling method resolved many damaging related problems which is called UBD [2]. It applies mostly in reservoirs with depleted pressure in order to prevent lost circulation, pipe sticking, formation damages, etc [3-5].

In UBD method, the formation pressure is higher than drilling fluid pressure. Choosing the best drilling fluid is crucially significant. Aerated fluids are widely acceptable to the procedure and broadly used as light fluid in UBD [6-8]. Cleaning capability is one the most important criteria in drilling fluid efficacy [9-11]. Thus, a comprehensive understanding of whole cleaning related functions is required. Aerated drilling fluid, is used in UBD, has two phases (gas and liquid) and consequently includes two flow patterns in the annulus. In aerated drilling fluids, each phase is supposed to do a specific job, cuttings should be transported by one flow rate of each phase, Rate of Penetration (ROP), pipe rotation, and hole inclination. The results show that the proposed model is predicting frictional pressure losses in acceptable agreement with experimental data with very high correlation coefficient (>0.99) and small average relative error. Moreover, a trend analysis was carried out to check the validity of the developed model. Results of the present study show that implementation of this developed model can be incorporated in drilling simulators for accurate estimation of frictional pressure loss of three phase flow.

Methodology

Background of the model

The least square version of the SVM (LS-SVM) which widely used in complex system studies for modeling, regression or parameter prediction was described in Suykens and Vandewalle (1999). The theory of LS-SVM is well described by previous researches [23-26].

Considering the problem of approximating a given dataset \( \{(x_1,y_1),(x_2,y_2)\ldots(x_N,y_N)\} \) with a nonlinear function:

\[
    f(x) = \langle w, \phi(x) \rangle + b
\]

where \( \langle \cdot, \cdot \rangle \) represent dot product; \( \Phi(x) \) represents the nonlinear function that maps \( x \) into \( n \)-dimensional feature space and performs

*Corresponding author: Milad Arabloo, Department of Petroleum Engineering, Petroleum University of Technology, Ahwaz, Iran, Tel: 982147911; E-mail: milad.arabloo@gmail.com

Received May 26, 2014; Accepted July 16, 2014; Published July 23, 2014


Copyright: © 2014 Shahdi A, et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.
linear regression; $w$ and $b$ are vector and bias terms. In LSSVM for function estimation, the optimization problem is formulated as [24]:

$$\min_{w,b,\epsilon} J(w,\epsilon) = \frac{1}{2} \|w\|^2 + \frac{1}{2} \sum_{i=1}^{N} \epsilon_i^2$$

s.t. $y_i = \langle w, \phi(x_i) \rangle + b + \epsilon_i$, $k = 1, ..., N$

Where $\epsilon_i \in \mathbb{R}$ are error variables; $\gamma \geq 0$ is a regularization constant. The Lagrangian is given by [24]:

$$L_{\text{LS-SVM}} = \frac{1}{2} \|w\|^2 + \frac{1}{2} \sum_{i=1}^{N} \epsilon_i^2 - \sum_{k=1}^{N} \alpha_k \left( \langle w, \phi(x_k) \rangle + b + \epsilon_k - y_k \right)$$

With Lagrange multipliers $\alpha_k \in \mathbb{R}$. The condition for optimality are given by [24]:

$$\frac{\partial L_{\text{LS-SVM}}}{\partial w} = 0 \rightarrow w = \sum_{i=1}^{N} \alpha_i \phi(x_i)$$

$$\frac{\partial L_{\text{LS-SVM}}}{\partial b} = 0 \rightarrow \sum_{i=1}^{N} \alpha_i = 0$$

$$\frac{\partial L_{\text{LS-SVM}}}{\partial \epsilon_i} = 0 \rightarrow \alpha_i = \gamma \epsilon_i$$

$$\frac{\partial L_{\text{LS-SVM}}}{\partial \alpha_i} = 0 \rightarrow \langle w, \phi(x_i) \rangle + b + \epsilon_i - y_i = 0$$

By defining $Y = [y_1, ..., y_N]$, $I = [I_1, ..., I_N]$ and eliminating $w$ and $e$, following linear equations are obtained [24]:

$$I_x^T \Omega^{-1} I_x \alpha = I_y$$

Where $I_x$ is an $N \times N$ identity matrix, and $\Omega \in \mathbb{R}^{N \times N}$ is the kernel matrix defined by

$$\Omega_{kl} = \Phi(x_k) \Phi(x_l) = K(x_k, x_l), \ k, l = 1, ..., N$$

As mentioned earlier, there is a tuning parameter $\gamma$. From the other point, as the LS-SVM is a kernel based method, parameters of kernel function should be considered. For LS-SVM, there are many kernel function including linear, polynomial, Radial Basis Function (RBF), etc [23,24]. However, most widely used kernel function is RBF (Eq. 26) [25,27,28].

$$K(x_k, x_l) = \exp(-\|x_k - x_l\|^2 / \sigma^2)$$

Where, $\sigma^2$ is the squared variance of the Gaussian function. In the case of RBF kernel, we have another tuning parameter $\gamma$. As the result, the LS-SVM model with the RBF kernel function has two tuning parameters which should be obtained by minimization of the deviation of the LS-SVM model from experimental values [29,30].

### Results and Discussion

To find the optimum values of the model’s parameters including $\gamma$ and $\sigma^2$, Coupled Simulating Annealing [32] technique has been employed. The optimized values of these parameters are as follows:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{ROP}$</td>
<td>80</td>
<td>120</td>
<td>98.52</td>
</tr>
<tr>
<td>$\text{RPM}$</td>
<td>0</td>
<td>75</td>
<td>32.18</td>
</tr>
<tr>
<td>$V_s$</td>
<td>2.0</td>
<td>5.0</td>
<td>2.69</td>
</tr>
<tr>
<td>$V_g$</td>
<td>0.2</td>
<td>33.86</td>
<td>13.55</td>
</tr>
<tr>
<td>$\text{Dp}$</td>
<td>0.05</td>
<td>0.70</td>
<td>0.33</td>
</tr>
</tbody>
</table>

Table 1: Descriptive statistics of the applied data sets.
\[ \gamma = 1.0549 \times 10^4 \]
\[ \sigma^2 = 6.00152 \]

Cross plots of the proposed LSSVM model estimations versus the corresponding target values for all three phases of training, validation, and test sets are shown in Figure 1. A tight cloud of points about 45° line for training, validation and testing data sets indicate the robustness of the proposed models. In addition, for representing a better visual comparison, relative deviations of estimated values are plotted versus the target (reported) data in Figure 2 for all data. As illustrated, predictions are in a satisfactory agreement with the reported data Table 2.

![Figure 2: Relative deviations of predicted pressure drops versus target data.](image1)

A trend analysis was also carried out in order to examine whether the developed model is physically accurate or not. To this end, the model responses to various input parameters. Figure 3 illustrates the trend of changes of pressure drop as a function of superficial gas velocity for typical values of RPM. As shown in this Figure 3, the model has captured the trend of increasing pressure drop with increasing drill pipe rotation. Rate of penetration causes an increase in total pressure drop at low gas flow rates (Figure 4). As expected, the developed model also captures this trend. Moreover, Figure 5 shows the effect of liquid velocity on pressure loss for three phase flow in nearly vertical annuli. The model response is entirely consistent with increasing trend of pressure loss versus liquid superficial velocity.

### Conclusions

The application of a novel machine learning method namely...
Least Square Support Vector Machine (LS-SVM) model for improved prediction of frictional loss of two-phase gas based drilling fluids with the presence of cuttings was studied in this work. Various influencing parameters including in situ flow rate of liquid and gas phases, Rate of Penetration (ROP), pipe rotation, and hole inclination were considered as the correlating parameters. The model was developed and tested using a total set of 216 experimental datasets covering a wide range of variables. The results show that the developed model provides predictions in acceptable agreement with target data. Also it was shown that the model is capable of simulating the actual physical trend of the total pressure loss versus changing input parameters.

References