An Improved Data-Driven Model for the Prediction of Minimum Transport Condition for Sand Transport in Multiphase Flow Systems

1 INTRODUCTION

Production of hydrocarbon from oil/gas reservoir usually comprises of sand when produced hydrocarbon from the unconsolidated formation is brought to surface. The transportation of multiphase fluid (hydrocarbon) in a safe and cost-effective manner without the presence of solid particles is unusual because most hydrocarbons are produced from an unconsolidated formation (reservoir with low formation strength). Also, human imposed activities on the well like acidization of the wellbore, production, injection (water and chemicals, enhanced oil recovery (EOR) and so on can contribute to disturbance of loose granular material of the formation to break from rock grains which leads to co-production of sand with hydrocarbon. (Ikporo & Sylvester, 2015). The produced sand in multiphase flow may be deposited in the transport medium due to the flow characteristics of the mixture. Therefore, there is a need to detect and monitor sand flow in multiphase pipelines.

This can be done using sand sensors like the Acoustic emission (AE) sensor (El-alej, Elforjani, & Mb, 2014). If rate of deposition of produced sand in the pipeline is high, there is a significant reduction in pipe internal diameter and this reduces the flow rate of produced fluid to surface separator and might as well damage the pipeline due to corrosion. The presence of sand in hydrocarbon transit media is a problem faced in the petroleum industry and can be minimized through proper sand management (Bello, 2008; Bello et al., 2011). Significant efforts have been devoted to sand transport prediction and management (Kinan, 2017). Researchers have employed experimental studies and correlations have been developed for MTC prediction (Yan, 2010; Fajemidupe, 2016; Archibong-Eso et al., 2020; Fajemidu et al., 2019a; Fajemidu et al., 2019b). However, it appears the use of data-driven approaches has not been explored for MTC despite its versatility.

This paper focuses on the development of data-driven models for the prediction of MTC. An improved prediction of sand transport condition for multiphase flow will help in the predictive control of loose sand granules, this would minimize challenges of settling of sand and stratum of sand formed, sand corrosion and erosion, low efficiency of transmitting medium, productivity impairments, failure of surface gathering equipment, the high operating cost of the production and transport systems.

2 METHODOLOGY

In this study, data-driven modelling techniques were employed for the development of models for MTC prediction. The adopted techniques are ANN, ANFIS and Response Surface Methodology (RSM). ANN & ANFIS were carried out using matrix laboratory software (MATLAB) and RSM was done using MINITAB software. Factors like liquid superficial velocity, pipe diameter, sand particle diameter, concentration of loose sand...
granules and pipe inclination were the input parameters and the output parameter to be predicted is the minimum transit speed commonly known as MTC.

2.1 Experimental Data Collection

The data used in this work were obtained using the experimental set up (flow loop) reported in Archibong-Eso et al. (2020). Their experimental study involves the evaluation of the concentration of loose sand granules, pipe diameter, liquid superficial velocity, pipe inclination and particle diameter under two-phase flow condition (sand-water) to establish sand MTC. Details about the rig and experimental procedure can be obtained from Archibong-Eso et al. (2020).

The total number of data obtained from this test loop was 182 and the range of each of the selected variables are presented in Table 1.

Table 1. Range of Experimental data used

| Factor          | Low          | High         |
|-----------------|--------------|--------------|
| $V_{SL}$ (m/s)  | 0.070076     | 8.3715750    |
| $D_p$ (m)       | 0.0001       | 0.0037       |
| $D$ (m)         | 0.009398     | 0.701040     |
| $C_v$ $(v/v)$   | 0.0000161    | 0.600000     |
| $\theta$ (%)    | -25          | 30           |
| $V_{MTC}$ (m/s) | 0.07         | 4.40         |

2.2 ANN Model Development

ANN model structure is determined by the selection of the number in the input, hidden and output layers. Also, the choice of the ANN properties such as network type, number of neurons, transfer function and adaption learning function determine the model. Three different training functions were used to train, test and validate the ANN model using feed-forward back-propagation as their network type. The machine learning toolbox of matrix laboratory software (MATLAB) was used and the networks were trained using 70% of 182 experimental datasets while 15% each was used for testing and validation. Average mean square error and regression was used to critic the performance of the created networks. However, the network output and target are correlated by the coefficient of Regression, $R$ whereby an $R$-value of 0 means a random relationship and an $R$-value of 1 mean a close relationship. The number of neurons used in fitting the network’s hidden layer was 14 and the transfer functions used was Hyperbolic tangent sigmoid (TANSIG).

The input layer refers to the several factors influencing the minimum transport condition while the output refers to the predicted minimum transport condition. The proposed functions of these variables can be shown in the following mathematical forms:

$$V_{MTC} = f(V_{SL}, D_p, C_v, D, \theta)$$

Where $V_{SL}$ = Liquid superficial velocity, $D_p$ = diameter of particle size, $C_v$ = Sand Concentration, $D$ = diameter of pipe and $\theta$ = pipe inclination angle

2.3 ANFIS Model Development

In the development of an ANFIS model, 80% of the total data set was used for training while 20% was used for testing. This was carried out using the fuzzy inference toolbox embedded on MATLAB, grid partitioning technique with Gaussian membership functions and 3 input membership functions (mf) was used for each input to create the Fuzzy inference system (FIS) while hybrid and back-propagation learning computation were used to train the FIS.

Figure 1 illustrates the ANFIS model, where there are five input variables which are liquid superficial velocity ($V_{SL}$), sand concentration ($C_v$), particle diameter ($d_p$), pipe diameter ($D$), and pipe inclination ($\theta$), the output is the minimum transport condition ($V_{MTC}$). Average error for training and testing data was used to critic the performance of the Adaptive Neuro-Fuzzy Inference System (ANFIS).

2.4 Development of Surface Response Models

Developing this model, response surface design was created using a total of 182 data set which were variables influencing MTC i.e., Sand concentration, pipe diameter, particle diameter, liquid superficial velocity and pipe inclination, these variables are referred to as the continuous factors while the variable to be predicted is referred to as the response. After loading the data appropriately using MINITAB software, a “linear” term and “linear + square” term response surface design using a forward selection stepwise-type procedure was used to run the data and a suitable regression model equation was generated based on the term used, the regression value and standard error were established as well.

2.5 Statistical Performance Indices for the Developed Models

In this work, the statistical parameters used to ascertain the performance of the models are as given in equations (2) to (8).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (V_{MTC,exp} - V_{MTC, pred})^2$$

$$APD = \sum_{i=1}^{n} PDi$$

$$PDi = \frac{(V_{MTC,exp} - V_{MTC, pred})}{V_{MTC,exp}}$$
Fig. 2: (a) Regression plots using Levenberg Marquardt, (b) Bayesian Regularization, and (c) Scale Conjugate Gradient for predictive analysis of MTC.

Table 2. Performance parameters of ANN Models

| Training Algorithms                  | Mean Squared Error (MSE) | Average Percent Deviation (APD) | Absolute Average Percent Deviation (AAPD) | Root Mean Squared Error (RMSE) | Standard Deviation (SD) | Regression Coefficient (R-sq.) |
|------------------------------------|--------------------------|--------------------------------|------------------------------------------|--------------------------------|-------------------------|-----------------------------|
| Levenberg Marquardt                | 0.039421                 | -0.01465                       | 0.021458                                 | 0.198547                        | 0.19800468               | 0.989454                    |
| Bayesian Regularization            | 0.002081                 | 0.005372                       | 0.00679                                  | 0.04561                         | 0.045494                | 0.999422                    |
| Scale Conjugate Gradient          | 0.014692                 | -0.0084                        | 0.091721                                 | 0.12121                         | 0.120876                | 0.95973                     |

\[ \text{AAPD} = \frac{\sum_{i=1}^{n} |PD_i|}{n} \]  
\[ \text{RMSE} = \sqrt{\frac{\text{MSE}}{n}} \]  
\[ \text{SD} = \sqrt{\frac{\sum_{i=1}^{n} (D_i - D_{\text{mean}})^2}{n-1}} \]  

Where \( D_i = (V_{\text{MTC,exp}} - V_{\text{MTC,pred}}) \) and \( D_{\text{mean}} \) is the mean of the \( D_i \) values.

\[ R^2 = 1 - \frac{\sum_{i=1}^{n} (V_{\text{MTC,pred}} - V_{\text{MTC,exp}})^2}{\sum_{i=1}^{n} (V_{\text{MTC,exp}})^2} \]  

3 RESULTS AND DISCUSSION

Three different training functions were tested to develop the neural network models. The results showed that Bayesian Regularization performed best for this predictive analysis with an average MSE of 0.002081 and R-value of 0.99998 while Levenberg Marquardt and Scale conjugate had R-value of about 0.9983 and 0.9971, as shown in Figure 2. This is similar to the results obtained from Ehinmowo et al. (2017). Bayesian Regularization was then used for the rest of the study.

In this study, the Sugeno ANFIS structure model was developed using two different optimization method. From the results, the Hybrid optimization method gives the best prediction of the output with an average error value of 0.00035836 and regression value of 0.99974 while the back-propagation method gives an average error value of 0.11912 and regression value of 0.9783 as shown in Table 3.

Table 3. Performance parameters of ANFIS Models

| Optimization method | Regression coefficient | Average error values |
|---------------------|------------------------|----------------------|
| Hybrid              | 0.999974               | 0.00035836           |
| Back Propagation    | 0.9783                 | 0.11912              |

The Hybrid optimization approach has the overall best performance for the prediction of minimum transport condition (MTC). Figure 3a and Figure 3b display the regression plot for Back-propagation and Hybrid Optimization used for this study. The Hybrid optimization approach has the overall best performance for the prediction minimum transport condition (MTC).

The RSM generates a regression model equation which can be used to describe the relationship between the predicted MTC and the various factors influencing MTC, equation (9) and equation (10) describes this relationship. These are regression model equation generated using the “linear + square” term and linear term respectively.
The response surface model using “linear” and “linear + square” term obtained had Regression value of 89.48% and 99.73%, and from the model summary, forward Selection of a linear + square term gives a better regression model with a regression value of 99.73% and standard error of 0.0540751. This shows there is a strong correlation between the continuous factors and the response, it also shows the coherence between the experimental and predicted MTC values. Also, the regression models incorporate all the variables under consideration, removing the need for mechanistic models to experimentally evaluate the conceptual parameters.

A comparison between RSM, ANN and ANFIS performances showed that ANFIS outperforms ANN and RSM models with $R^2$ values of 0.9973, 0.99998 and 0.99997 respectively. This is expected since ANFIS combines the strength of both traditional neural networks and fuzzy logic systems.

The data-driven models developed in this work were compared with published correlations and models. Table 5 shows that the ANFIS and ANN models performed better amongst other correlations, with values of the MSE of $1.284*10^{-7}$ and RMSE of 0.00035836 for the ANFIS model. This aligns with the previous work of Ighose et al. (2017) which reported that ANFIS outperformed RSM and ANN. The next best performing is ANN correlation which estimated values of MSE and RMSE of 0.002081 and 0.04561, also has a good correlation compared to ANFIS and ANN.

These findings suggest that ANFIS and ANN can be veritable techniques for MTC prediction in multiphase transport systems.
4 CONCLUSION

Neural networks, Neuro-Fuzzy inference system and RSM models have been developed for the prediction of minimum sand velocity in a multiphase flow system. The models developed were compared with existing models. The results showed that the three techniques performed creditably well in the prediction of MTC with ANFIS having the highest predictive capability with an R² value of 0.99997 and an average error value of 0.00353836 compared with ANN and RSM having R² value of 0.9998 and 0.9973 respectively. The three data-driven techniques investigated in this study also outperformed published correlations for the prediction of MTC. The results from this research provide a better insight into factors affecting MTC in a multiphase flow system. The use of data-driven approaches provides a reliable means for the prediction of MTC in a multiphase system. Other data-driven methods may be explored for MTC prediction and this is a subject for further research.

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