An Enhanced Model for the prediction of Minimum Transport Conditions in Multiphase Flow Systems

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Abstract- Hydrocarbon production accompanied by the flow of sand from reservoirs is unavoidable as many of the formations are poorly consolidated. The deposition of the produced sand at low velocities or production of sand at very high velocity can pose serious challenges to the condition of the petroleum pipeline as it can lead to pipeline capacity reduction and degradation respectively. It is therefore important to investigate the minimum transport velocity that prevents sand deposition in the pipelines. In this study, the firefly optimization algorithm (FFA) was used in the development of the improved model for the prediction of minimum transport condition (MTC) in a multiphase pipeline. The model development was implemented using the MATLAB software package. The input parameters were sand concentration, particle diameter, viscosity, density and superficial velocity of the hydrocarbons. The developed model was observed to perform better than the base model with a R^2 value of 0.9845 and 0.8149 for the developed model and base model respectively. The newly developed model was also compared with some existing models and the statistical measures show that the developed model gave a better performance. This enhanced model can be used for the prediction of MTC in multiphase pipelines

Keywords- Algorithms, Artificial Neural Network (ANN), Firefly algorithm (FFA), Minimum Transport Condition (MTC)

1 INTRODUCTION

The flow of sand during the production life of a reservoir is inevitable. This sand is produced because of the unconsolidated nature of most reservoirs from where the oil is produced. Flow assurance and corrosion problems come into play as more sand gets deposited in the pipeline thereby reducing the internal diameter of the pipe and also the possibility of an increase in pressure loss and so on (Fajemidupe *et al.* 2019). The existence of sand in pipelines can also cause both erosion and corrosion problems at a high production rate, as well as the possibilities of high-pressure loss from the deposition of sand at a low flow rate which would require expensive cleaning operations occasionally for optimal production. It can also damage down-hole tubular, subsea hardware and possibly cause catastrophic well failure. It is very important to prevent sand settling, that is why the critical velocity of the hydrocarbons must be monitored to allow it to disperse the sand particles and reach the surface processing facility without any deposition in the pipeline.

There are several methods used to control sand production such as gravel packing, the use of screens and filters, the use of chemicals to consolidate the formation etc. Although all these methods are effective on the loose granular particles, the pipeline still gets degraded along the line. There is therefore the need for the prediction of the minimum transport condition (velocity) at which the sand particles will continue flowing as a result of the combination of the hydrocarbons flowing energy (El-alej, Elforjani, & Mba, 2014).

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Various authors have different definitions for minimum transport conditions and have performed experiments and developed correlations for the prediction of minimum transport conditions (MTC). Thomas (1962) defined critical velocity as the minimal transfer velocity at which a stratum of stationary loose particles form at the bottom of a horizontal pipe. However, Oroskar & Turian (1980) described MTC as sand transport velocity which is the minimal transfer velocity needed to ensure that sand particles are embedded in uniform suspension. Holte *et al.* (1987) was one of the earliest studies that gave insight into sand transport prediction. It was an extension of Wick (1971) model to stratified air-water flow system.

Angelsen *et al.* (1989) further developed the model to account for particle diameter. Other authors including Oudeman (1993) and Gillies & Shook (1991) also developed experimental based models for MTC. In the last decade, efforts have been made to use software packages to predict MTC and expand studies into more multiphase systems. Salama (2000) compared Wick (1971) and Oroskar & Turian (1980) and developed a correlation based on similar parameters and found the empirical constants by using the DNV Corroline software.

King *et al.* (2001) made use of Thomas (1962) model to model minimum frictional pressure drop in multiphase systems. They suggested that the particle would be transported if the normal pressure drop is greater than that due to the friction across the pipeline. Stevenson *et al.* (2002) developed a correlation for the prediction of critical velocity in a multiphase stratified flow regime based on an experiment done by using particle sizes of 150-1180μm, the pipe diameter of 0.04-0.07m with a 1^0-angle inclination. Danielson(2007) modified and extended a single-phase model to a multiphase using a drift flux model and assumed that there is a slip between the liquid and particle velocity. However, it was observed that gas rate had no impact on the slip velocity between the liquid and particle.

Bello (2008) developed a phenomenological model for predicting MTC in 3-phase flow in pipelines. The model was derived from continuity equations of mass and momentum laws which were numerically solved using fourth-order Runge-Kutta method. The model was also validated with experiment work which involved the use of a non-intrusive high speed charged coupled device (CCD- particle image velocimetry and particle charging velocimetry) to show visualization and investigation of sand particles characteristics in multiphase flow in pipelines. However, due to a lot of assumptions in the continuity equations, the application of this model may be limited. Yan (2010) investigated sand transport conditions in air-water-oil flow using different sand concentrations and pipe internal diameter as well as observing pipe orientations (angle of inclination) with different oil viscosity. It was reported that MTC increases as concentration and diameter increased with pipe orientation contributing little or no effect in vertical movements. However, in upwardly inclined flow, Slug flow which was prevalent caused the backward movement of sand along with the continuous phase (air and water). It was reported that MTC increased with fluid viscosity in turbulent flow and decreased also with viscosity in bulk laminar flow.

Ibarra *et al.* (2014) considered particle concentration and developed a new correlation for MTC by combining Salama (2000) with Oroksar and Turian (1980) models. Najmi (2016) proposed a model to predict critical velocity in both intermittent and stratified flow regimes by extending Oroksar and Turian (1980) model and using actual liquid velocity which is gotten by the ratio of superficial velocity to liquid hold-up. The liquid hold up was estimated using Fan's model and Zhang's model for stratified and intermittent flow regimes respectively. The model also accounted for the effect of particle concentration. The study by Kinan (2017) showed the use of computational fluid dynamics in the prediction of the critical velocity of hydrocarbons. He used the combination of DPM and ANSYS to simulate data derived. The ANSYS DesignModeller software was used to design the pipe while the DPM was used for the actual simulation. The result achieved was compared with other works and result obtained was very much comparable.

Leporini *et al.*(2019) used OLGA software to model experimental data implemented on a one-dimensional dynamic multiphase code. There was good agreement reported in numerical prediction and experimental data. The study gave an insight into the effect of concentration, particle size and pipe diameter. Though there was agreement between the data obtained from SINTEF laboratory, OLGA did not predict the critical velocity well at turbulent conditions. Fajemidupe *et al.* (2019) carried out an experiment on a small-scale rig flowing air, water and sand particles of different diameters and different concentrations. It was shown that there is an increase in the needed critical velocity as the diameter increases as well as the concentration. This study gave a better insight into Thomas (1962) model which did not account for effect of concentration. In this paper, the correlation developed by Fajemidupe *et al.* (2019) is optimized to gain new constants that will be stable for a wide range of conditions. The model is given in equation 1.

$$u_c^* = u_0^* + 0.7C_v^{0.3977} \tag{1}$$

Where u_0^* is Thomas's (1962) lower model:

$$u_0^* = \left[100u_t\left(\frac{v}{d_p}\right)^{2.71}\right]^{0.269} \tag{2}$$

Despite all these efforts at MTC, data-driven approaches have not been well explored. Recently, Ehinmowo *et* al. (2021) developed a model using ANN (Artificial neural network), ANFIS (Adaptive neuro-fuzzy inference system) and RSM (response surface methodology) to predict MTC conditions in multiphase systems. It was reported that the ANFIS model gave the best prediction with an accuracy of more than 99% compared to ANN and RSM. Correlation for RSM was also developed for both linear and linear + square terms. Although Ehinmowo *et al.*(2021) used ANN, ANFIS and RSM methods to achieve good accuracy in the prediction, the use of FFA for MTC predication has not been previously explored. This study aims at extending the envelope of MTC prediction using FFA, a metaheuristic algorithm.

FFA has been used in many areas. Ehinmowo et al. (2019) explored the use of firefly algorithms for reservoir modelling and history matching while Hosseini-Moghari and Banihabib (2014) used FFA in optimizing the operation of reservoir for agricultural water supply, Ghorbani *et al.* (2017) used FFA to predict the gas flow rate from gas condensate reservoir through wellhead chokes. Some other studies combined the use of SVM and FFA. For example, Moazenzadeh *et al.* (2018) coupled FFA and SVM algorithms to predict evaporation components at two meteorological stations in Northern Iran. Chao & Horng (2015) fine-tuned the Support vector machine classifier parameters using the firefly algorithm. Firefly algorithm is a metaheuristic nature-inspired intelligent technique. It was developed by Yang in 2008 drawing from the characteristics of firefly. Following Ghorbani *et al.* (2017), Firefly algorithm can be represented by equations 3 and 4. These define the position and the movement of the by Yang firefly respectively.

$$r_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{3}$$

$$x_1^{(t+1)} = x_1^{(t)} + \beta_0 e^{-\Gamma\gamma_0^2}\left(x_i - x_j\right) + \alpha\left(rand\ n - \tfrac{1}{2}\right) \tag{4}$$

Where: (t) is the value of x_i used in the current iteration
$(t+1)$ is the value of x_i used in the next iteration

The component of change related to increased firefly j attractiveness is the second right-side term (exploitation). The component of change owing to random movement is the third right-side phrase (exploration) α is the randomized parameter $rand\,n$ is a uniform random number [0,1]. Fig. 1 shows the firefly algorithm workflow.

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Fig. 1: Firefly algorithm flow chart (Ajala *et al.* 2022)

2 METHODOLOGY

In this paper, the data acquired from Fajemidupe *et al* (2019) was used to develop a new correlation using Firefly Algorithm (FA). The FA technique was implemented in the Matrix laboratory software (MATLAB) package. The model developed by Fajemidupe et al. (2019) has been adopted as the base model. This is because of its robustness and the use of multivariate factors including concentration term which has only been considered previously by few authors.

2.1 EXPERIMENTAL DATA USED IN THIS STUDY

The data used in this work were obtained using the experimental set-up (flow loop) shown in Figure 2 and have been reported in Fajemidupe *et al*. (2019). The study investigated MTC as a function of sand concentration, liquid velocity, pipe diameter and inclination as well as particle diameter under two-phase flow conditions (sand-water). Details about the rig and experimental procedure can be obtained from Fajemidupe *et al.* (2019). 182 data point obtained from this test loop and the summary of the statistics is presented in Table 1.

Table 1. Summary of data used for this work

	V_{SL} (m/s)	d_P(m)	C_V(v/v)	Viscosity (Pa.s)	V_{MTC} (m/s)
Minimum	0.0700	0.0001	0.00002	0.0010	0.070
Maximum	8.3716	0.0037	0.6000	0.0270	4.400
Mean	2.1179	0.0004	0.1201	0.0013	1.630
Median	1.5215	0.0004	0.1000	0.0010	1.430
Range	8.3016	0.0036	0.6000	0.0260	4.330
Variance	3.2408	1.4E-07	0.0203	5.5E--06	1.010
Std. Deviation	1.8002	0.0037	0.1423	0.0023	1.000

2.2 FIREFLY ALGORITHM MODEL DEVELOPMENT

The steps taken in the implementation of the Firefly algorithm are summarised below following Ghorbani *et al.* (2017).

Step1: The initial firefly algorithm control parameters β_0, γ, α, the number of fireflies to be used N and the number of iterations (T) to be executed, the minimum and maximum values of the variables (Xmin, X_{max}) were selected and the best parameters were chosen based on sensitivity analysis.

Step2: The variable data for each sample data point involving five (5) variables to be evaluated by Equation 4 were inputted.

Step 3: Initial set of random solutions for the *b to f* coefficients values between the maximum and minimum limits were generated.

Step 4: Equation 4 was solved for each data set sample applying randomly selected values of *b to f* for each firefly.

Step 5: A comparison study was done for the main objective function. i.e., calculating the mean squared error (MSE) between the predicted values and the actual values

Step 6: Equation 4 was applied to modify the values of the *b to f* coefficients of each firefly towards only those with higher brightness i.e., a less bright firefly will randomly move towards a brighter firefly. This makes a new population of N fireflies to carry forward to the next iteration. Steps 4 to 6 was repeated until convergence was achieved.

Step 7: The optimum solution space ("**BestSol**") and lowest MSE were obtained from the converged solution.

The algorithm was repeated several times for verification. The firefly algorithm control parameters $B_0, \propto, \gamma$ (brightness coefficient), T (the total number of iterations to be run), N (number of fireflies), X_{min} *and* X_{max} (the minimum and maximum range foisted on the five *b to f* values, have a significant impact on the performance of the algorithm. After using different values to run the algorithm (sensitivity analysis), the chosen values of these parameters to minimize the objective function (the MSE) are listed in Table 2.

Table 2. Firefly algorithm parameters

Parameter	Values
B_0	2.00
$\propto$	0.20
γ	1.00
T	500
X_{min}	-10.00
X_{max}	+10.00
N	25.00

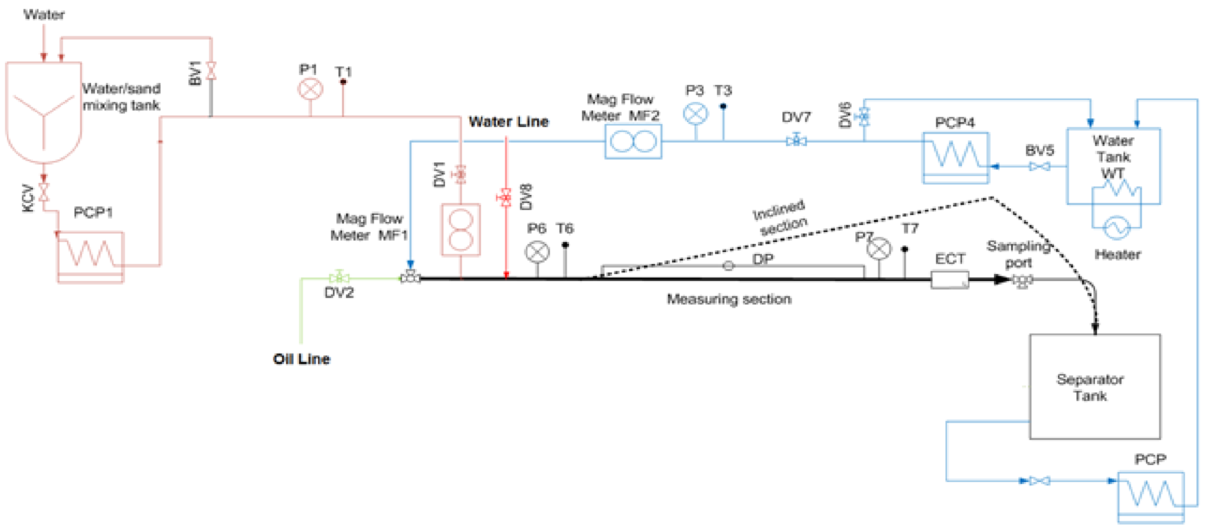

Fig. 2: Schematic of experimental flow loop (Fajemidupe *et al.*,2019)

2.3 Statistical Performance Indices for the Developed Model

The statistical parameters used in this study to validate the results are given as equations (5)-(11)

Percentage average absolute Error (PAE%)

$$= \frac{1}{N}\sum_{i=1}^{N}\left|\frac{V_{MTC,pred} - V_{MTC,Actual}}{V_{MTC,Actual}}\right| \times 100 \qquad (5)$$

Standard Deviation (SD)

$$= \sqrt{\frac{\sum_{i=1}^{n}(D_i - D_{imean})^2}{n-1}} \qquad (6)$$

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

Correlation coefficient (R^2)

$$= 1 - \frac{\sum_{i=1}^{n}\left(V_{MTC,pred} - V_{MTC,exp}\right)^2}{\sum_{i=1}^{n}(V_{MTC,pred} - \frac{V_{MTC,exp}}{n})^2} \qquad (7)$$

Root mean square error (RMSE)= $\sqrt{MSE}$ (8)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(V_{MTC,pred} - V_{MTC,Actual})^2 \qquad (9)$$

Average Absolute Relative Deviation (AARD%)

$$= \frac{1}{N}\sum_{i=1}^{N}\left|\frac{V_{MTC,pred} - V_{MTC,Actual}}{V_{MTC,Actual}}\right| \times 100 \qquad (10)$$

Mean relative percentage deviation (MRPD%)

$$= \frac{100}{n}\sum_{i=1}^{n}\frac{|V_{MTC,pred} - V_{MTC,Actual}|}{|V_{MTC,Actual}|} \qquad (11)$$

3 Results and Discussion

3.1 Proposed Model

The improved model is given as equation 12. The new optimized co-efficient obtained from the algorithm was used to calculate new values for the critical velocity and compared with that of Fajemidupe *et al.* (2019) which is the base model. The new model shows that the coefficient of the particle concentration is far less than that of Fajemidupe *et al.* (2019) and Danielson (2007). This suggests that the contribution of particle canticle concentration has been previously overestimated by previous models.

$$U_c^* = \left[0.9896u_t\left(\frac{v}{d_p}\right)^{0.000010513}\right]^{0.0029} + 0.0340C_v^{1.000} \qquad (12)$$

Where $U_c^* =$ *critical velocity* , m/s
$u_t =$ *Superficial velocity* , m/s , $v =$ *viscosity*, $Pa.s$
$d_p =$ *particle diameter*, mm ,
$C_v =$ *particle concentration* , v/v

3.2 Model Prediction and Performance

The prediction of the model was compared with the actual sand rate as shown in Figure 3. The model was shown to perform creditably well and some model performance indices well employed to further quantify the validity of the developed model as shown in Table 3.

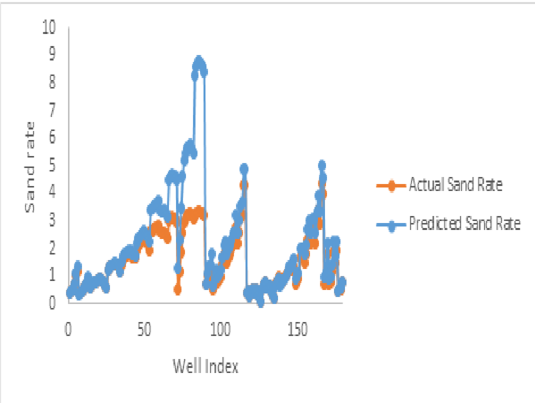

Fig. 3: Actual versus predicted trend

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Figure 4 shows the prediction of the base-model, developed model compared with the actual data. The trend shows that the new model follows the actual data more closely than the base-model. Between 83-89 well indexes, the new model over predicted the deposition rate while the base-model under predicted same. A detailed statistical performance measure is presented in Table 3 for the base-model, developed model and some existing models.

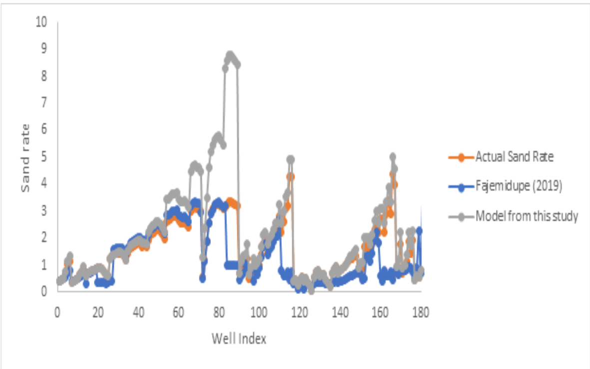

Fig. 4: Comparison of developed model, base-model and actual data

Table 3. Statistical performance of the developed model compared with existing models

	FFA	Fajemidupe *et al.* (2019)	Yan (2010)	Danielson (2007)
R^2	0.99	0.82	0.80	0.800
PAE (%)	22.97	24.00	26.20	25.01
AARD (%)	6.32	20.32	22.13	22.04
SD	1.89	7.00	9.03	9.56
RMSE	7.07×10^{-9}	0.030	0.267	0.29
MRPD (%)	3.56	9.34	18.88	19.04

Table 3 shows that the new optimized model gives a better prediction than the base model. The R^2 values obtained were 0.9845, 0.8149, 0.8030 and 0.8003 for the developed model in this study, Fajemidupe et al. (2019), Yan(2010) and Danielson(2007) respectively. Percentage absolute error (PAE%) from the Firefly algorithm gave a better value of 22.97% compared to that of 24.00% reported in Fajemidupe *et al.*(2019) and higher values previously reported in Danielson(2007) and Yan(2010). Also, a less deviated mean value of velocity and regression coefficient was reported to be better than that gotten from Fajemidupe(2019), Yan(2010) and Danielson(2007). The firefly algorithm-based model outperforms these models. However, using ANFIS, ANN and RSM, Ehinmowo et al. (2021) models have shown superior performances with R^2 values of 0.99997,0.9998 and 0.9973 for ANFIS, ANN and RSM respectively. The result in this work further strengthens the application of the data-driven modelling approach in MTC prediction.

4 Conclusion

In this study, an improved model for the prediction of MTC has been developed based on the firefly algorithm. The model expresses the V_{MTC} in terms of particle diameter, viscosity, superficial velocity, and concentration of the sand particles. The developed model outperforms the base model and some existing models. An increased performance of up to 17% above the base model was obtained. Metaheuristic algorithms may be a veritable tool for the prediction of MTC in multiphase flow. Other machine learning techniques such as Genetic Algorithms and Particle Swarm optimization might be explored for possible enhanced performance.

Nomenclature

C_V: Sand Concentration, v/v
d_P: Particle diameter, m
D: Pipe diameter, m
V_{SL}: Superficial Liquid velocity, m/s
V_{MTC}: Actual Minimum Transport Condition, m/s
V_{PMTC}: Predicted Minimum Transport Condition, m/s
θ: Pipe Inclination, °

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