Physics-Informed Neural Networks for the Prediction of Critical Sand Transport Velocity in Oil and Gas Pipelines

A. B. Ehinmowo[1*], B. Ofum[2], J.O. Olaide[3]
[1,2,3]Department of Petroleum and Gas Engineering, University of Lagos, Nigeria
Email: *aehinmowo@unilag.edu.ng*

Abstract
Many reservoir formations are poorly consolidated therefore generation of sand with hydrocarbons from them cannot be avoided. The petroleum pipeline's condition may be seriously jeopardized by the creation of sand at very high velocities or by the deposition of that sand at low velocities, which can cause degradation and reduced capacity, respectively. Thus, it's critical to look into the minimal transport velocity that keeps sand from building up in the pipelines. In this study, two machine predictive tools, Physics informed neural network (PINN) and Multilayer perceptron (MLP) regressor were used for the estimation of the minimum transport condition in a solid-liquid-gas pipeline. The models were developed using 182 experimental data points containing superficial velocity, pipe diameter, particle diameter, sand density, sand concentration, liquid density, viscosity, pipe angle of inclination, and critical velocity parameters. The results showed that the physics-informed neural networks performed better than the MLP Regressor with an R^2 coefficient of 0.9999 and RMSE of 0.00465. The MLP Regressor achieved an R^2 coefficient of 0.9992 and RMSE of 0.0295. The developed models were compared with existing empirical models and data-driven models and from the outcome, the two models performed better in predicting the minimum transport velocity with PINN performing best. A sensitivity analysis was conducted and from the results, the most influential parameter for the minimum transport velocity prediction is the superficial velocity, followed by pipe diameter, sand concentration, and pipe angle. This research showed the potential of incorporating physical laws in the machine learning training process for a more accurate estimation of the minimum transport velocity in multiphase pipelines.

Keywords: Minimum Transport Condition, Minimum Transport Velocity, Physics Informed Neural Networks, Multiphase System

1.0 INTRODUCTION

Trace amounts of solids like sand and debris sometimes get transported with fluids from a reservoir due to fractures in loosely packed formations and poorly consolidated reservoirs. This sand, along with oil, flows through pipelines but can create significant flow issues.

The key challenge here is flow assurance: which is the need to ensure hydrocarbons flow well from the reservoir to the processing facilities. Deposition of sand may block pipelines and disrupt oil and gas transport. Furthermore, sand particles may be responsible for abrasive wear, erosion, and even corrosion of the pipe surface, either by mechanical action or microbial activity under sand layers. All these effects weaken pipeline integrity and reduce the efficiency of production and transport.

Sand production happens when formation stress surpasses formation strength and leads to rock failure, which occurs as a result of geological movements, ground stress, pressure-induced, and flow resistance force. Sand particle production can consist of load-bearing solids and formation fines (Mahmud et al., 2020). If the production of sand is likely to occur, sand penetration into the system can be avoided by the use of some methodologies including the subsurface sand rejection mechanism such as gravel packs and screens; however, these methods may cause a major decline in productivity (Leporini et al., 2019). To stop sand from settling in pipelines when transporting hydrocarbons, sand particles need to move fast enough. This means we have to figure out the minimum transport conditions (MTC) or minimum

transport velocity (MTV) that keep sand floating. MTV also known as critical velocity; makes sure sand particles keep moving along the pipe. Experts use different ways to estimate this velocity, including mechanistic models, Computational Fluid Dynamics (CFD) models, and experimental studies. Several studies have focused on developing models to estimate minimum transport velocity. Al-Mutahar (2006) proposed a mathematical model for the critical transport velocity based on the equilibrium condition under which the net force equals zero, using the two irregular flow theories of Oroskar and Turian (1980) and Davies (1987). In developing this mathematical model, Al-Mutahar made the following three steps. The model first calculates the turbulent velocity changes that are necessary to keep solids in suspension, then estimates the actual turbulent changes caused by the moving fluid, and finally determines the critical transport velocity. This model assumes that when the required and produced turbulent changes are equal, the solids remain in suspension.

Tebowei et al. (2018) presented a 3D CFD model that simulated fluid behavior in the Eulerian-Eulerian process with the dynamic principle of particle flux to investigate the transportation of sand in turbulent pipelines and flow lines. The model considered inter-particle collision and friction forces to capture various regimes of particle movement. Results indicated that the inclined pipe had an effect on the minimum transport velocity and properties of sand. The model considered that the use of correlations (empirical or semi-empirical) to determine the minimum sand transport velocity from inclined pipes, including horizontal pipes, could be unreliable for the inclined sections. Unlike the case of horizontal pipes, the V-inclined curve needed a far larger threshold velocity in order to keep the sand in suspension within the liquid.

Archibong-Eso et al. (2020) studied sand transport in horizontal and inclined pipes under Minimum Transport Condition (MTC) requirements, using experiments with pipes of 0.0127 m diameter and sand concentrations from 0.1% to 10%. The results showed that increasing either mixture velocity or sand concentration raised both MTC and pressure gradients, with the pressure gradient stabilizing at higher sand concentrations near MTC.

Several studies have explored data-driven approaches, such as machine learning, to model minimum transport conditions (MTC). Bhattacharya et al. (2007) simulated sand transport using experimental data, applying model trees and artificial neural networks (ANNs). Salam et al. (2018) used response surface methodology to create a regression model for predicting MTC based on a double-factor synergy, which they validated and refined. An improved approach by Sarraf Shirazi and Frigaard (2021) combined ANN and support vector machines (SVM) to predict the minimum velocity for transitioning from laminar to turbulent slurry flow, also calculating frictional pressure drops in pipes. Ehinmowo et al. (2021) assessed ANN, adaptive neuro-fuzzy inference system (ANFIS), and response surface methodology models for predicting MTC in multiphase pipelines, finding them superior to earlier methods. Further improvements by Ehinmowo et al. (2022) involved applying the firefly optimization algorithm to enhance a model for predicting the minimum velocity needed to keep sand particles suspended in multiphase flow, achieving over 98% accuracy, a 17% improvement over the benchmark. Stachurska et al. (2022) introduced new machine learning techniques to predict the velocity of loose tidal grains over dunes using particle visual velocity measurements. They did this by applying the Student Psychology-based Optimization (SPBO) algorithm which included linear, nonlinear, and exponential regression methods as the training models, as well as the Classification and Regression Tree (CART) and ANFIS.

Most studies have identified viscosity, size, density, and velocity as the factors affecting MTC for sands. Most of the studies on sand transport have focused on flows that are horizontal or nearly horizontal, with very few on vertical, curved, or inclined ones. Machine learning opens

up new avenues to address some of these challenges. Previous machine learning implementations for MTC have outperformed the traditional approaches many times. However, most models, while training, hardly consider physical laws that may enhance the precision of a model, its generalization capability, and adherence to MTC principles. Having this in mind, this study will develop a Physics Informed Neural Network and a Multilayer Perceptron Regressor using experimentally obtained data in modeling minimum transport velocity.

2.0 MATERIALS AND METHOD

This study aims to predict the minimum transport velocity in multiphase flow systems based on factors like viscosity, fluid and gas density, pipeline diameter, angle of inclination, sand concentration, and sand particle size. Two nonlinear machine learning methods are used: physics-informed neural networks (PINN) and a multilayer perceptron (MLP) regressor. The minimum transport velocity is the speed needed to keep sand in continuous motion, making this a regression problem since it involves predicting a continuous variable.

2.1 *Machine Learning and Algorithm used*

Physics Informed Neural Networks (PINNs): Physics-informed neural networks are a class of neural networks that solve problems in which data and physical laws are important. Unlike regular neural networks, PINNs incorporate known physical equations into their training process. A typical PINN network is shown in Figure 1.

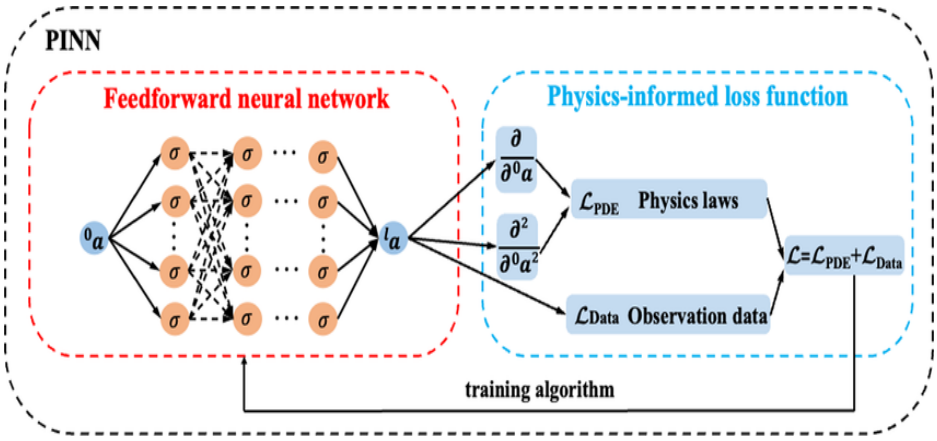


Figure 1: Physics informed neural network diagram (Li et al., 2024)

The Turian et al. (1987) equation was implemented in this study for the incorporation of a physics-based model for the critical velocity in pipelines, which it uses as a guiding principle for training the neural network. It factors in pipe diameter, particle size, sand concentration, and fluid viscosity to estimate transport velocity. The Turian equation is incorporated into the loss function of the PINN modeling process. This addition helps the model learn not just the patterns in the data but also the principles that govern the Turian equation.

The Turian et al. (1987) equation is shown below in equation 1.

$$V_c = 1.7951\, C_v^{0.109} (1 - C_v)^{0.25} \left[\frac{D\ \rho_l \sqrt{gD(s-1)}}{\mu}\right]^{0.018} \left(\frac{d}{D}\right)^{0.06623} \sqrt{2gD(s-1)} \quad (1)$$

Where Vc is the critical transport velocity, μ is liquid viscosity, Cv is sand concentration, d is particle diameter, g is gravitational acceleration, D is pipe diameter, ρ_l is liquid density, and s is the ratio of particle density to liquid density

Multilayer Perceptron (MLP) Regressor: The major components of a multilayer perceptron include an input layer, a number of hidden layers, and an output layer. Neurons form layers and are completely connected between layers, meaning that every neuron in a particular layer is linked to every neuron in the layer directly past it. An activation function is assigned to all neurons, except those from the input layer. This activation function decides the output of the neuron based on the input provided. MLP is trained using a backpropagation method of adjustment in the neuron connections such that the training error is minimized and thus increases the accuracy.

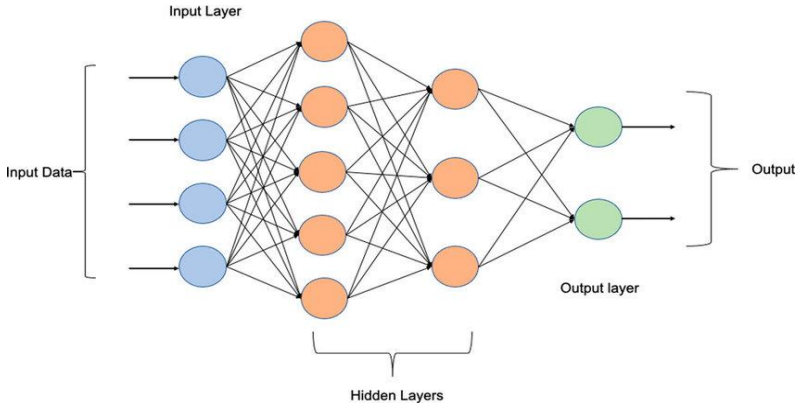


Figure 2: MLP Regressor Schematics (Afan et al., 2021)

2.2 Model Evaluation Metrics

For this study, mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and regression coefficient (R^2) were used to evaluate the performance of the models developed.

1. Coefficient of Determination or Performance (R-Squared)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(V_{MTC,\ actual} - V_{MTC,\ prediction})^2}{\sum_{i=1}^{n}(V_{MTC,\ actual} - V_{MTC,\ mean})^2} \quad (2)$$

Where,

$V_{MTC,\ actual}$ = experiment minimum transport velocity values

$V_{MTC,\ predict}$ = predicted minimum transport velocity values

n = number of records

$V_{MTC,\ mean}$ = mean of minimum transport velocity values

2. Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(V_{MTC,\ actual} - V_{MTC,\ prediction})^2}{n}} \quad (3)$$

3. Mean Squared Error (MSE)

$$MSE = \frac{\sum_{i=1}^{n}(V_{MTC,\ actual} - V_{MTC,\ prediction})^2}{n} \quad (4)$$

4. Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{i=1}^{n}|V_{MTC,\ actual} - V_{MTC,\ prediction}|^2}{n} \quad (5)$$

5. Mean Absolute Percentage Error (MAPE)

$$MAPE = \left|\frac{V_{MTC,\ actual} - V_{MTC,\ prediction}}{V_{MTC,\ actual}}\right| * 100 \quad (6)$$

2.3 Data Collection and Preparation

This study uses data from the experimental work of Archibong-Eso et al. (2020). The experiments were conducted at the Oil and Gas Engineering Centre of Cranfield University with a 0.0254-meter diameter pipe placed horizontally and at a 30-degree incline. The summary of the data is shown in Table 1.

Table 1: Summary of statistics of the experimental data used in this study

Features	Minimum	Maximum	Mean	Median	Standard Deviation
Superficial Velocity (ms^{-1})	0.07	8.37	2.12	1.52	1.81
Pipe Diameter (m)	0.009	0.70	0.100	0.100	0.091
Particle Diameter (mm)	0.10	3.70	0.37	0.36	0.37
Sand Density (kgm^{-3})	2650	2650	2650	2650	0
Sand Concentration (vol %)	0.002	60.00	12.07	10.00	14.27
Liquid Density (kgm^{-3})	850.0	1000.0	997.9	1000.0	16.6
Liquid Viscosity (mPa·s)	1.00	17.00	1.15	1.00	1.37
Pipe Angle (ø)	-25.00	30.00	4.54	0.00	11.39
Critical Velocity (ms^{-1})	0.07	4.40	1.64	1.44	1.01

In all, 182 data points were acquired for superficial velocity, pipe diameter, particle size, sand concentration, liquid density and viscosity, and pipe angle.These experiments were carried out with the help of video recordings and pressure sensors to track sand transport through the liquid stream, focusing on minimum transport conditions. Before developing the model, the data was cleaned and scaled. It was then split into three sets: 70% for training, 15% for validation, and 15% for testing.

3.0 RESULTS AND DISCUSSION

A model evaluation study was done after modeling in order to test the performance of PINN and MLP models in the test or future scenarios. Results in Table 2 present the performance of each model evaluated in terms of MAE, MSE, RMSE, MAPE, and R^2 metrics. The PINN had superior prediction in comparison with the MLP regressor. For PINN and MLP models, R^2 and RMSE values were equal to 0.9999 and 0.9992 and 0.0047 and 0.03, respectively.

Table 2: Performance evaluation of PINN and MLP Regressor

	R^2	MSE	RMSE	MAE	MAPE (%)
PINN Model	0.99998	0.00002	0.00469	0.00367	0.24904
MLP Model	0.99920	0.00087	0.02950	0.01974	1.54660

3.1 Model Evaluation Visualization

Figure 3 below shows the plots of prediction error for the PINN and MLP models. A prediction error plot is a plot of the expected values of MTC from the dataset against the MTC values predicted by the model. The plot helps in determining how well the predictions correspond to the actual values.

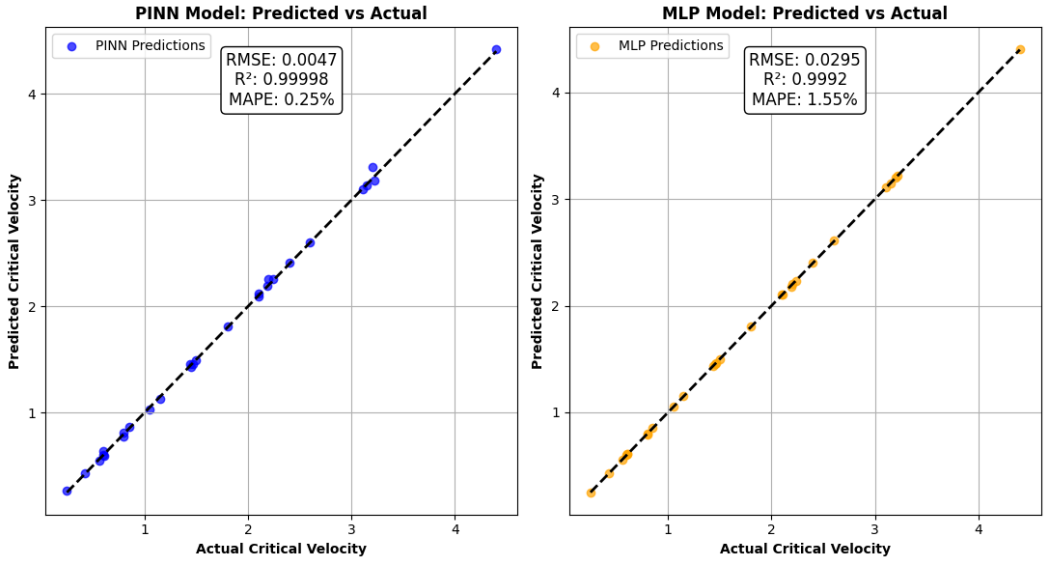


Figure 3: Prediction error plot for PINN and MLP regressors

3.2 Comparative Analysis with Existing MTC Models

Table 3 gives the results of the developed model with other published models. Comparison shows that PINN and MLP regressor models performed better than the other literature models using the R^2, MSE, RMSE, and MAPE metrics.

Table 3: Numerical comparison between the developed models and published models

Correlation	R^2	MSE	RMSE	MAPE (%)
Turian et al. (1987)	0.6932	0.3315	0.5758	27.4
Danielson (2007)	0.8003	0.17448	0.4170	60.3
Yan (2010)	0.803	0.07129	0.2670	26.2
Fajemidupe et al. (2019)	0.8149	0.00090	0.0300	24.0
Ehinmowo et al (2021)	0.9994	0.00208	0.0456	2.15
Ehinmowo et al (2022)	0.9845	4.99×10^{-17}	7.07×10^{-9}	22.97
PINN Model	0.99998	0.00002	0.0047	0.2
MLP Model	0.99920	0.00087	0.0295	1.5

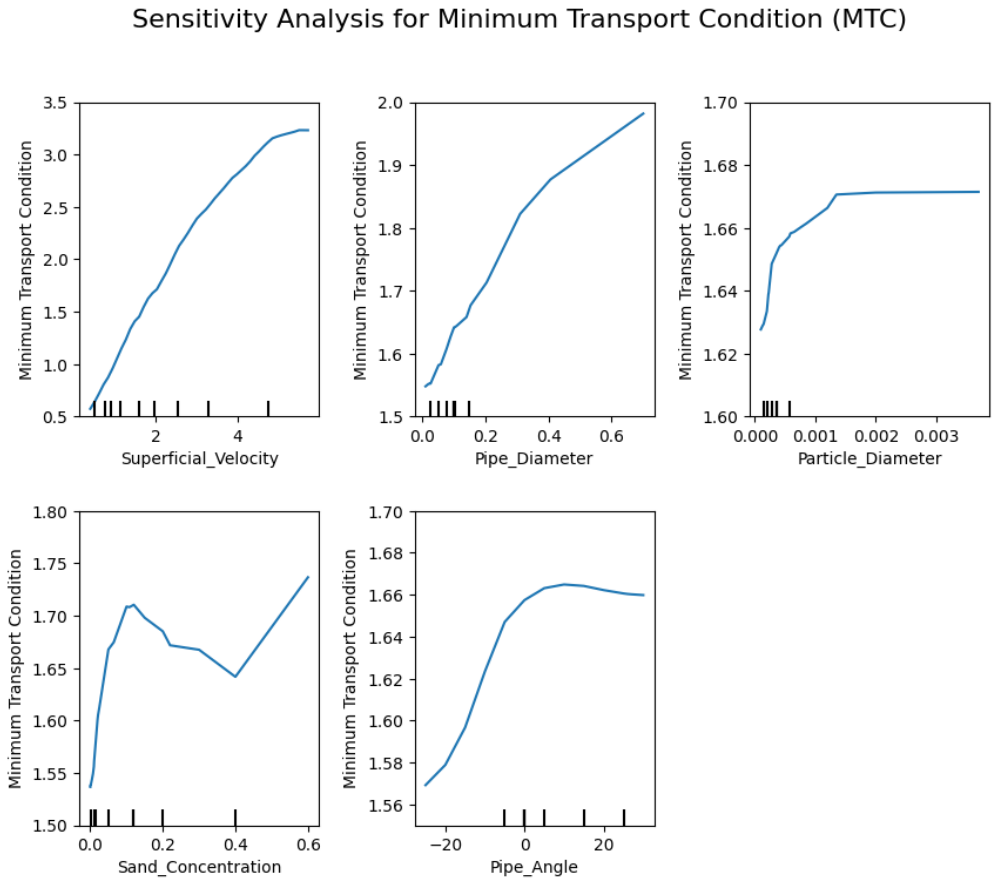


Figure 4: Sensitivity analysis for minimum transport condition prediction

Figure 4 shows the visualization of the sensitivity analysis conducted to evaluate how different factors affect the minimum transport velocity of sand using the PINN model.The results showed that superficial velocity has a strong positive correlation with the sand's critical transport velocity. As superficial velocity increases, the critical velocity of the fluid rises as well. This is because higher fluid velocities would exert more drag on sand particles, thus providing the required energy to keep them suspended and not deposited on pipeline walls (Dabirian et al., 2016; Yao et al., 2022). The pipe diameter also has a positive relationship to the sand's critical transport velocity. When the pipe gets bigger, you need a higher critical velocity to keep sand particles floating in the fluid. This happens because, with the same flow rate fluid moves slower in bigger pipes due to more area inside. To prevent sand from settling, the critical velocity must be higher to ensure suspension in these larger pipes (Yao et al., 2023).Although particle diameter shows a slight positive trend, its effect on critical velocity is relatively weak.

The relationship between sand concentration and critical velocity is non-linear, with noticeable changes as concentration increases. An increase in sand concentration results in a greater degree of particle-particle interactions, which in turn can cause an increase in the effective viscosity of the fluid, thus a greater critical velocity is to be used in order to prevent deposition (Zhang et al., 2022). The pipe's inclination angle also has a non-linear effect on critical velocity. For upward-inclined pipes, the flow has to work against gravity; hence, higher velocities are required in order to prevent sand from settling. In contrast, gravitational effects become smaller for horizontal or downward-sloping pipes, and thus a lower critical velocity is needed to keep particles in suspension (Vlasak et al., 2019). However, beyond a certain angle,

the effect of the pipe's inclination angle becomes negligible, showing diminished effects of gravity.

This analysis underlines that the most influential parameter for the minimum transport velocity modelling is the superficial velocity, followed by pipe diameter, sand concentration, and pipe angle. The particle diameter has the least effect. To understand conditions of minimum sand transport, all these parameters have to be taken into account because their effects are so strongly interdependent.

4. CONCLUSION

Physics informed neural network and Multilayer perceptron regressor were developed in this study for the prediction of the minimum transport velocity that will keep sand particles in motion in multiphase solid-liquid-gas flow lines and pipelines. The models correlate the critical velocity in terms of sand particles concentration, diameter of the pipe, superficial velocity, inclination angle, and diameter of the sand particle. The physics informed neural networks showed a better prediction capability than the MLP Regressor with a R^2 score of 0.9999 and RMSE of 0.00465. The MLP Regressor also performed well with a R^2 scores of 0.9992 and RMSE of 0.0295 respectively. The developed models were compared with existing empirical models and data-driven models and from the outcome it was seen that the two models performed better in predicting the minimum transport velocity with PINN performing best. For further research, machine learning models that incorporate physical laws may be explored for prediction of the minimum transport condition. Additionally, more accurate physical laws can be investigated with more experimental data and parameters collated for a more robust modelling of the minimum transport condition.

NOMENCLATURE

T MTC - Minimum Transport Condition
PINN - Physics-Informed Neural Network
MLP - Multilayer Perceptron Regressor
CFD - Computational Fluid Dynamics
ANN - Artificial Neural Network
SVR - Support Vector Regression
ANFIS - Adaptive Neuro-fuzzy Inference System
RSM - Response Surface Methodology
RMSE - Root Mean Squared Error
MAE - Mean Absolute Error
MAPE - Mean Absolute Percentage Error
R^2 - Coefficient of Determination
FFA - Firefly Optimization Algorithm
SPBO - Student Psychology-Based Optimization
SVM - Support Vector Machine
CART - Classification and Regression Tree
KAN - Kolmogorov Arnold Networks
PG - Pressure Gradient

REFERENCES

Afan, H.A., Ibrahem Ahmed Osman, A., Essam, Y., Ahmed, A.N., Huang, Y.F., Kisi, O., Sherif, M., Sefelnasr, A., Chau, K.W. and El-Shafie, A., (2021). Modeling the fluctuations of groundwater level by employing ensemble deep learning techniques. *Engineering Applications of Computational Fluid Mechanics*, *15*(1), 1420-1439.

Al-Mutahar, F. (2006). *Modeling of critical deposition velocity of sand in horizontal and inclined pipes* (Master's thesis). The University of Tulsa, Tulsa, OK.

Archibong-Eso, A., Aliyu, A. M., Yan, W., Okeke, N. E., Baba, Y. D., Fajemidupe, O., & Yeung, H. (2020). Experimental study on sand transport characteristics in horizontal and inclined two-phase solid-liquid pipe flow. *Journal of Pipeline Systems Engineering and Practice*, *11*(1), 04019050. doi:10.1061/(asce)ps.1949-1204.0000427

Bhattacharya, B., Price, R. K., & Solomatine, D. P. (2007). Machine learning approach to modeling sediment transport. *Journal of Hydraulic Engineering*, *133*(4), 440-450.

Danielson, T. J. (2007, April). Sand transport modeling in multiphase pipelines. In *Offshore Technology Conference* (pp. OTC-18691). OTC. doi:10.4043/18691-ms

Dabirian, R., Mohan, R. S., Shoham, O., & Kouba, G. (2016, July). Sand flow regimes in slightly upward inclined gas-liquid stratified flow. In *Fluids Engineering Division Summer Meeting* (Vol. 50299, p. V01BT28A003). American Society of Mechanical Engineers.

Davies, J. (1987). Calculation of critical velocities to maintain solids in suspension in horizontal pipes. *Chemical Engineering Science*, *42*(7), 1667–1670.

Ehinmowo, A. B., Talabi, O. O., Ajala, E. O., Olamigoke, O. & Ojewumi, M. E. (2022). An Enhanced model for the prediction of Minimum Transport Conditions in Multiphase flow systems. FUOYE Journal of Engineering and Technology, 7(1). doi: 10.46792/fuoyejet.v7i1.730

Ehinmowo, A. B., Ariyo, O. O., Ohiro, O. A., Fajemidupe, O. T., & Salam, K. K. (2021). An Improved Data-Driven Model for the Prediction of Minimum Transport condition for sand transport in Multiphase Flow Systems. *FUOYE Journal of Engineering and Technology*, *6*(1). doi: 10.46792/fuoyejet.v6i1.618

Fajemidupe, O. T., Aliyu, A. M., Baba, Y. D., Archibong-Eso, A., & Yeung, H. (2019). Sand minimum transport conditions in gas–solid–liquid three-phase stratified flow in a horizontal pipe at low particle concentrations. *Chemical Engineering Research and Design*, *143*, 114-126. doi: 10.1016/j.cherd.2019.01.014

Leporini, M., Marchetti, B., Corvaro, F., di Giovine, G., Polonara, F., & Terenzi, A. (2019). Sand transport in multiphase flow mixtures in a horizontal pipeline: An experimental investigation. *Petroleum*, *5*(2), 161-170. doi: 10.1016/j.petlm.2018.04.004

Li, Z., Bai, J., Ouyang, H., Martelli, S., Tang, M., Yang, Y., ... & Gu, Y. (2024). Physics-informed neural networks for friction-involved nonsmooth dynamics problems. *Nonlinear Dynamics*, *112*(9), 7159-7183.

Mahmud, H. B., Leong, V. H., & Lestariono, Y. (2020). Sand production: A smart control framework for risk mitigation. *Petroleum*, *6*(1), 1-13.

Oroskar, A. R., & Turian, R. M. (1980). The critical velocity in pipeline flow of slurries. *AIChE Journal*, *26*(4), 550-558. doi:10.1002/aic.690260405

Salam, K. K., Arinkoola, A. O., & Aminu, M. D. (2018). Application of response surface methodology (RSM) for the modelling and optimization of sand minimum transport condition (MTC) in pipeline multiphase flow. *Petroleum & Coal*, *60*(2).

Sarraf Shirazi, A., & Frigaard, I. (2021). SlurryNet: Predicting critical velocities and frictional pressure drops in oilfield suspension flows. *Energies*, *14*(5), 1263.

Stachurska, B., Mahdavi-Meymand, A., & Sulisz, W. (2022). Machine learning methodology for determination of sediment particle velocities over sandy and rippled bed. *Measurement*, *197*, 111332.

Tebowei, R., Hossain, M., Islam, S. Z., Droubi, M. G., & Oluyemi, G. (2018). Investigation of sand transport in an undulated pipe using computational fluid dynamics. *Journal of petroleum science and engineering*, *162*, 747-762. doi: 10.1016/j.petrol.2017.11.003

Turian, R. M., Hsu, F. L., & Ma, T. W. (1987). Estimation of the critical velocity in pipeline flow of slurries. *Powder Technology*, *51*(1), 35-47.

Vlasak, P., Chara, Z., Matousek, V., Konfrst, J., & Kesely, M. (2019). Effect of pipe inclination on flow behaviour of fine-grained settling slurry. In *EPJ Web of Conferences* (Vol. 213, p. 02094). EDP Sciences.

Yan, W. (2010). Sand transport in multiphase pipelines. PhD Thesis, Cranfield University, UK.

Yao, R., Qi, D., Zeng, H., Huang, X., Li, B., Wang, Y., ... & Wang, Z. (2022). Study on Critical Velocity of Sand Transport in V-Inclined Pipe Based on Numerical Simulation. *Water*, *14*(17), 2627.

Yao, R., Wang, Z., & Huang, X. (2023). Design Parameters Investigation on Sand Transportation Characteristics of V-Inclined Pipe Based on Eulerian–Eulerian Two-Phase Flow Model. *Water*, *15*(24), 4266.

Zhang, L., Guan, J., Zhong, D., & Wang, Y. (2023). Effect of sediment particles on the velocity profile of sediment–water mixtures in open-channel flow. *International Journal of Sediment Research*, *38*(3), 361-373.