DEVELOPMENT OF A RANDOM-FOREST-BASED MODEL FOR PREDICTING LIQUID HOLD-UP AND SLUG FLOW REGIME CHARACTERISTICS IN VERTICAL TWO-PHASE FLOW USING MACHINE LEARNING TECHNIQUE

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Abstract

The development of heavy oil has attracted attention in recent times. With increasing fluid viscosity, slug flow has become the most common flow pattern in oil and gas pipeline flow which poses a challenge in flow assurance as the need for stability of system and production maximization. The accurate prediction of slug flow parameters is an urgent problem to be solved in heavy oil development for more efficiency in productivity. In this research paper, the analysis of experimental data for the Air-Silicon oil slug transition in a 67mm diameter and 6m long vertical pipe was carried out in this work. The superficial velocity ranges of gas and liquid obtained from the ECT were 0.047 – 4.727m/s and 0.05 – 0.284m/s respectively. This research makes use of Random-forest-based Machine learning technique to predict liquid hold up and slog flow regime characteristics at different time intervals due to as it uses random subspace method and bagging to prevent overfitting. From the investigated data, the liquid hold up, void fraction were obtained and other slug flow parameters obtained were; structural velocity, slug frequency, length of slug and

KEYWORDS: *Slug flow, Machine learning, Random-forest, Modeling, Multi-phase flow, vertical pipe, liquid hold-up*

film thickness. Comparison with the data from the proposed algorithm accurately predicts the liquid hold up, void fraction, and liquid film thickness. They were seen to have a good agreement with the Machine Learning based Random-forest prediction however slug frequency, structural velocity, and length of slug unit all had varying disagreement with the prediction leading to limitations in the use of the model algorithm in prediction of these flow parameters. The model was also tested against varying viscosity and a good agreement was seen from 5cP to 1000cP excluding high liquid viscosity of 5000cP. The random-forest based machine learning model can then be used in predicting liquid hold up, void fraction, and liquid film thickness in low viscosity fluids less 1000cP.

INTRODUCTION

Multiphase flow phenomenon is seen in many engineering fields such as, nuclear reactor engineering, power generation, food production, automobile, and majorly the oil and gas engineering. This phenomena deals with the concurrent flow of fluids within different phases (i.e. gas, liquid and solid) or the different chemical properties but in the same phase, for example gas-liquid, gas solid, liquid-solid, liquid-liquid and gas-liquid-solid (Abdulkadir, 2015)

Where the liquefied gas mixture moves along the pipe, it is observed that different difficulties are encountered in the flow, some of which are phase velocity differences and the existence of numerous flow regimes, flow rate and patterns. The exact nature of flow pattern depends on conduit size and geometry, fluid properties, and phase velocity. (Ganat and Hrairi, 2019). Although pipes are the safest means of transporting oil and gas products, pipelines can sometimes fail, resulting to hazardous consequences and large business losses. The decision to replace, repair, or rehabilitate depends mainly on the condition of the pipeline. (El-abbasy, *et al.* 2014). Among the flow patterns, slug flow is an unwanted multiphase flow system which regularly happens the most in various industrial processes, resulting in time-varying loads in pipes and supports, resulting in structural failure and stress. It has been observed that slug flow pattern frequently occurs in oils with high viscosity which

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is seen in varying superficial velocities range, indicating that slug flow expertise is a major advantage in oil and gas industries. (Mohammed, *et al*. 2019)

Experimental, and Numerical approaches in investigating multiphase flow has been significantly done with varying degree of accuracy, however analytical machine learning approach gives an even higher accuracy of prediction with advancement in technology, machine learning gives a very promising data analysis method for multiphase flowrate estimation. (Brunton, *et al*. 2020). In this study, Air-Silicone oil flow data from vertical pipes will be analyzed using a random-forrest based machine learning model in order to make predictions for slug flow parameters.

Materials and Method

Data Acquisition

The Data for analyses was gotten from experiments carried out by Abdulkadir (2015). "Experimental and Computational Fluid Dynamics (CFD) Studies of Gas-Liquid Flow in Bends" was carried out in the Chemical Engineering Laboratory of the University of Nottingham. The site were the experiment was carried out was made up of a testing section made from transparent acrylic glass pipes of 67 mm diameter pipes and 6 m long. The fluid mixture used was an air-silicone oil mixture using a state of the art instrument called a Wire Mesh Sensor (WMS).

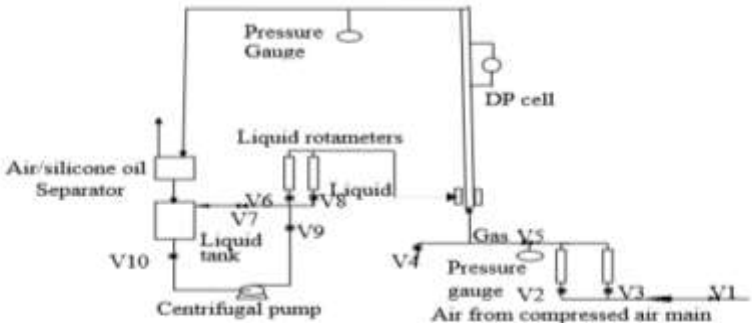

Figure 1: A Schematic Diagram of the Flow Facility (Abdulkadir *et al*., 2015)

Analysis of Acquired Data

The wire mesh sensor was used in obtaining the cross-sectional mean liquid hold up time series data. Superficial gas velocity (0.047- 4.727 m/s), at different superficial liquid velocities (0.05-0.378 m/s) on the liquid hold up, were obtained for vertical pipes. The time series raw data was processed to obtain the void fraction for different experimental runs. The void fraction data for planes 1 and 2 of each experimental run were used in a MACRO cross correlation template to obtain the structural velocity after inserting the total number of data (12000), sampling frequency (200Hz) and distance between the sensors (0.089m). Power spectral density (PSD) was ran in macro after inserting the total number of data (12000) and sampling frequency (200Hz) to obtain the dominant frequency in each run.

Model Generation and Validation

The Model generation was done with 70% of the collected data, 20% for testing and 10% for validation. Due to the random nature of the data it was trained and validate using a Random-Forrest-based model (Jupyter Notebook) was then used to predict the exact output of liquid hold up for all the various runs of data set.

The predicted Liquid Hold up for the various data sets were obtained, the Void fraction and slug flow parameters of (Structural velocity, slug frequency, length of slug unit and liquid film thickness) were obtained and plotted in a cross plot against the experimental for comparison.

Results and Discussion.

The results were obtained from the computation of the slug flow parameters after prediction of the liquid hold up and flow parameters, cross-plot comparison were made between the predicted and experimental data as shown below:

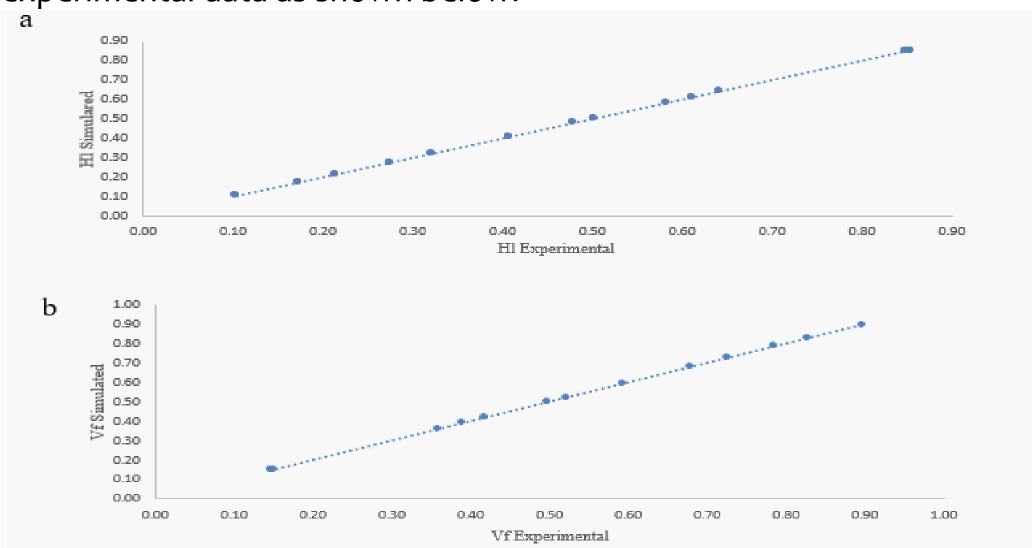

Figure 2: Cross plot of simulated vs experimental of (a) Liquid hold-up (b) void fraction at Usl = 0.05m/s

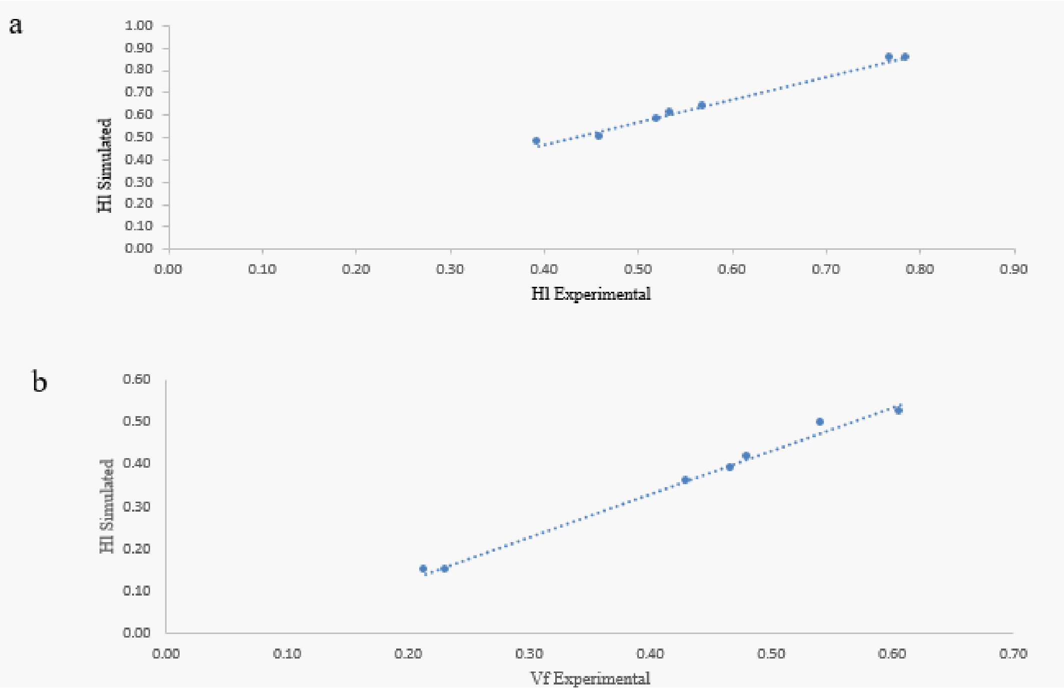

Figure 3: Cross plot of simulated vs experimental of (a) Liquid hold-up (b) void fraction at Usl = 0.071m/s

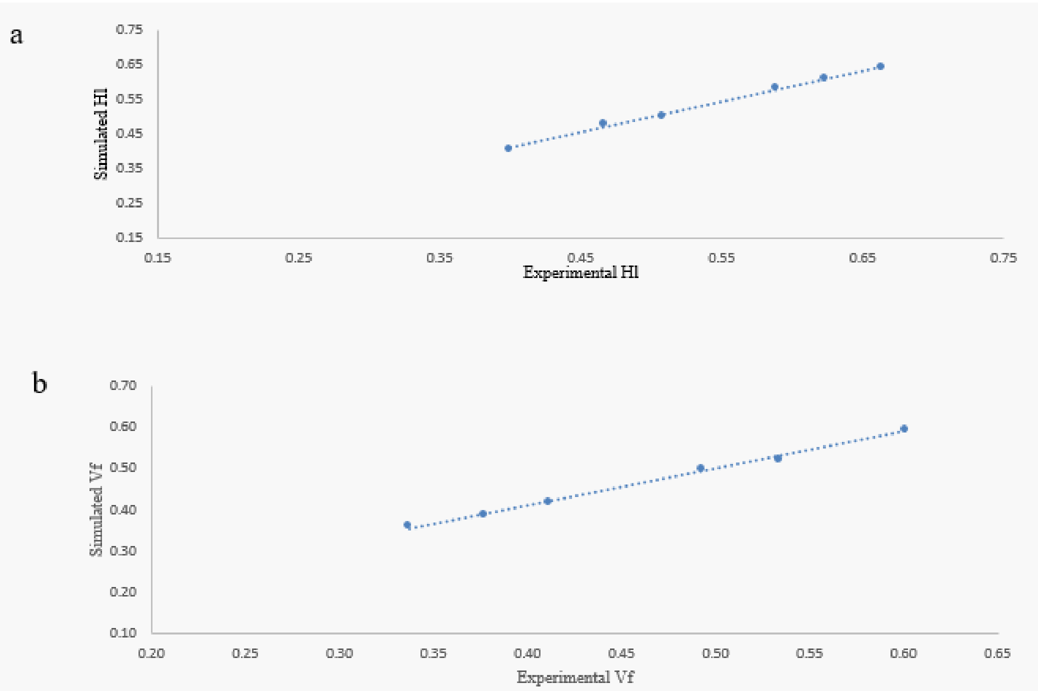

Figure 4: Cross plot of simulated vs experimental of (a) Liquid hold-up (b) void fraction at Usl = 0.095m/s

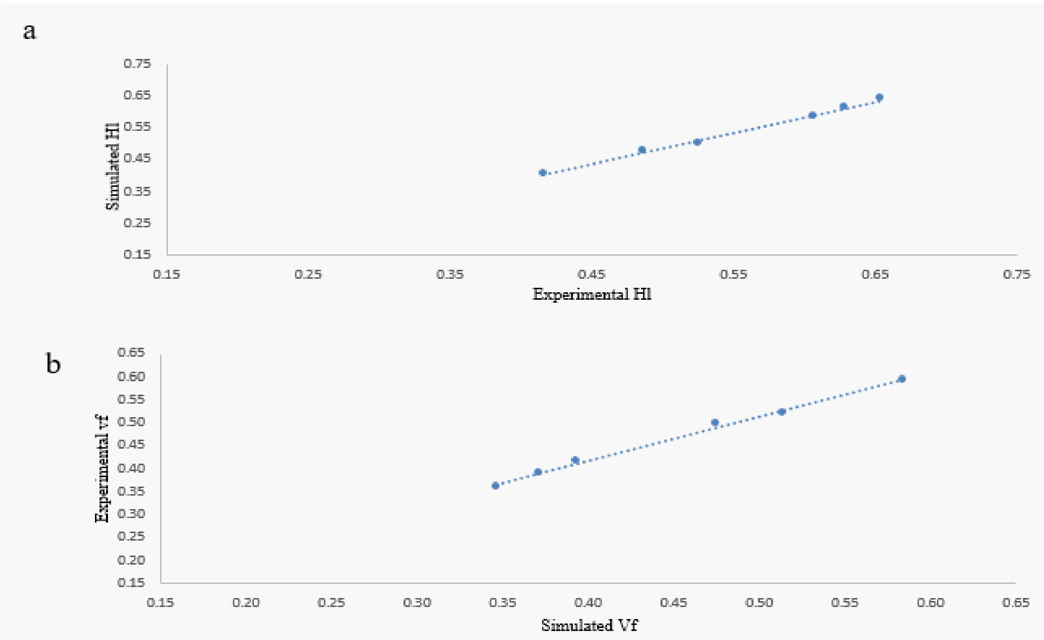

Figure 5: Cross plot of simulated vs experimental of (a) Liquid hold-up (b) void fraction at Usl = 0.142m/s

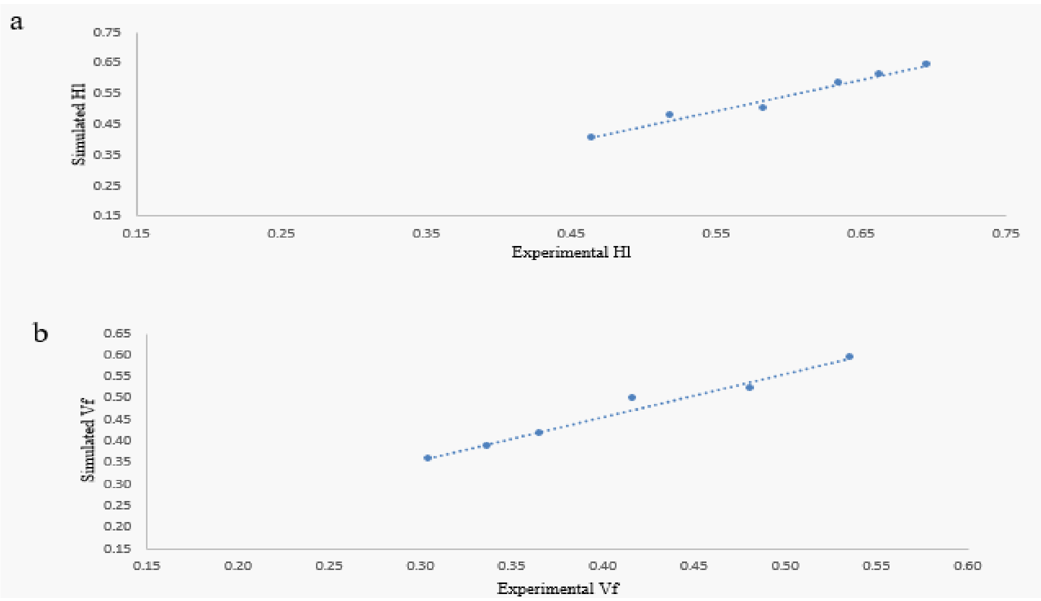

Figure 9: Cross plot of simulated vs experimental of (a) Liquid hold-up (b) void fraction at Usl = 0.284m/s

From figures 2-9 it was seen a perfect fit between the experimental and predicted liquid hold up and void fraction at Liquid superficial velocity of 0.05-0.284m/s, However there were slight over predictions and under predictions observed, which are neglible, given that with more training

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data the model could give a perfect fit. It can be seen that the Liquid hold up decreases with increasing gas velocity at constant liquid velocity, and vice versa for void fraction, this was the case in Abdulkadir (2010, 2011 and 2015), Kong *et al*., (2018) and Hernandez-Alvarado *et al*., (2017). The model could be seen to give a good fit for the predictions of liquid hold up and void fractions.

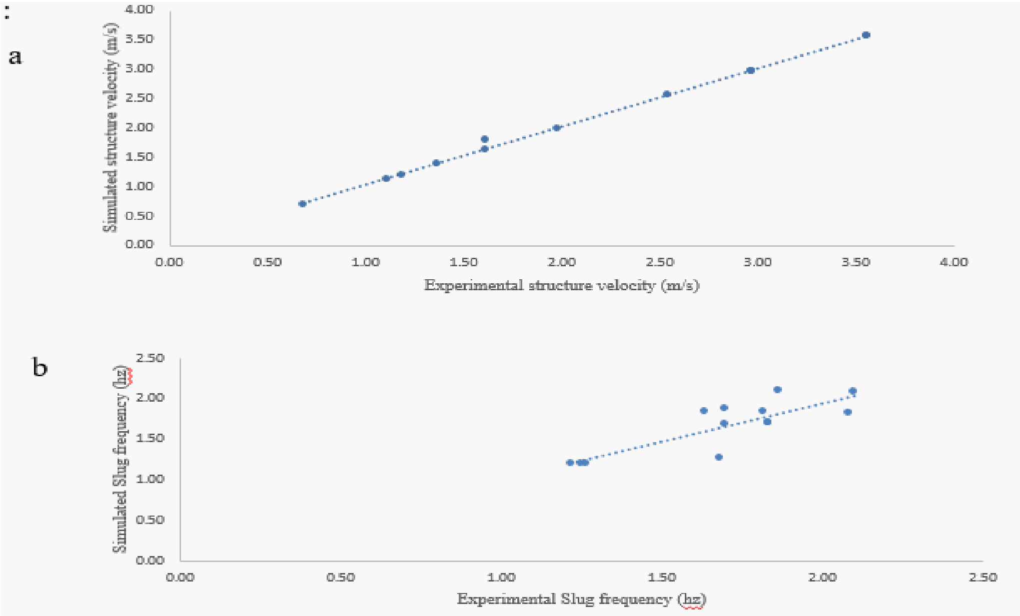

Figure 10: Cross plot of simulated vs experimental of (a) Structural velocity (b) slug frequency at Usl = 0.05m/s

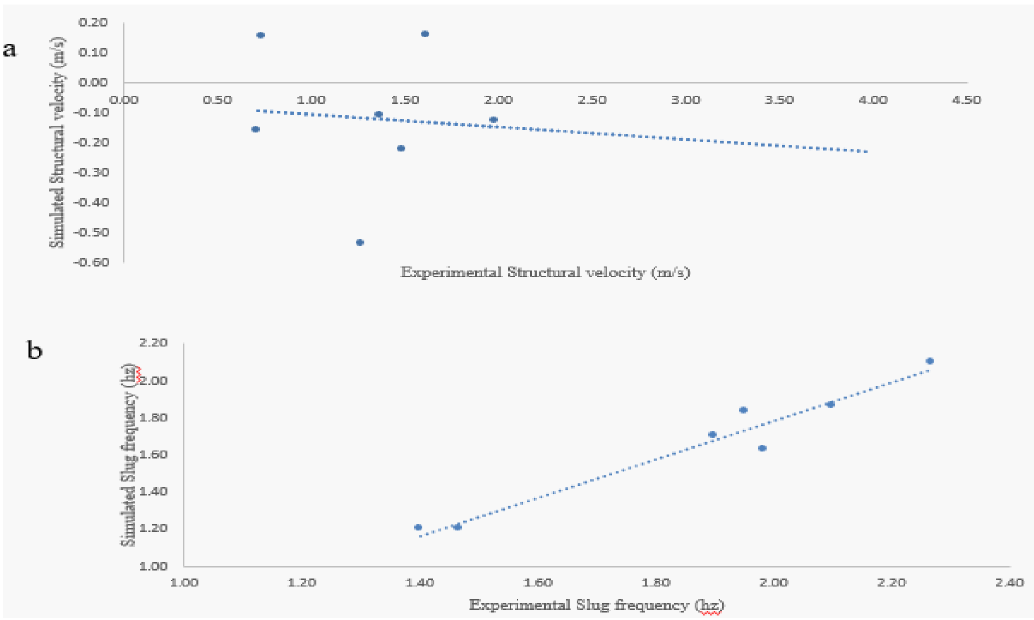

Figure 11: Cross plot of simulated vs experimental of (a) Structural velocity (b) slug frequency at Usl = 0.095m/s

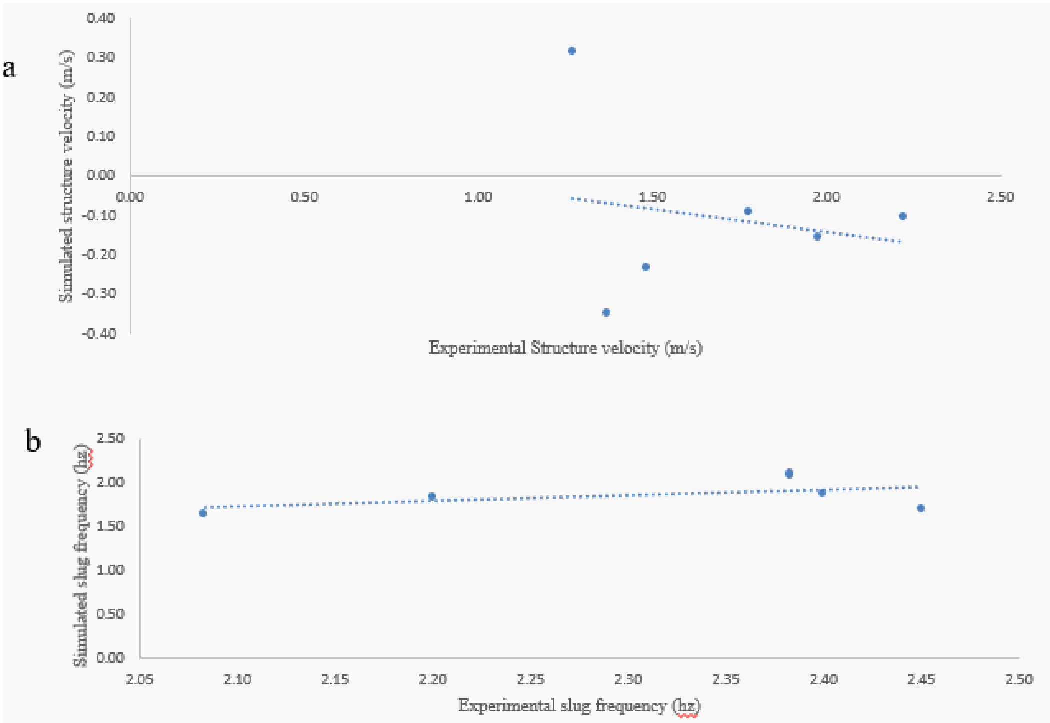

Figure 12: Cross plot of simulated vs experimental of (a) Structural velocity (b) slug frequency at Usl = 0.142m/s

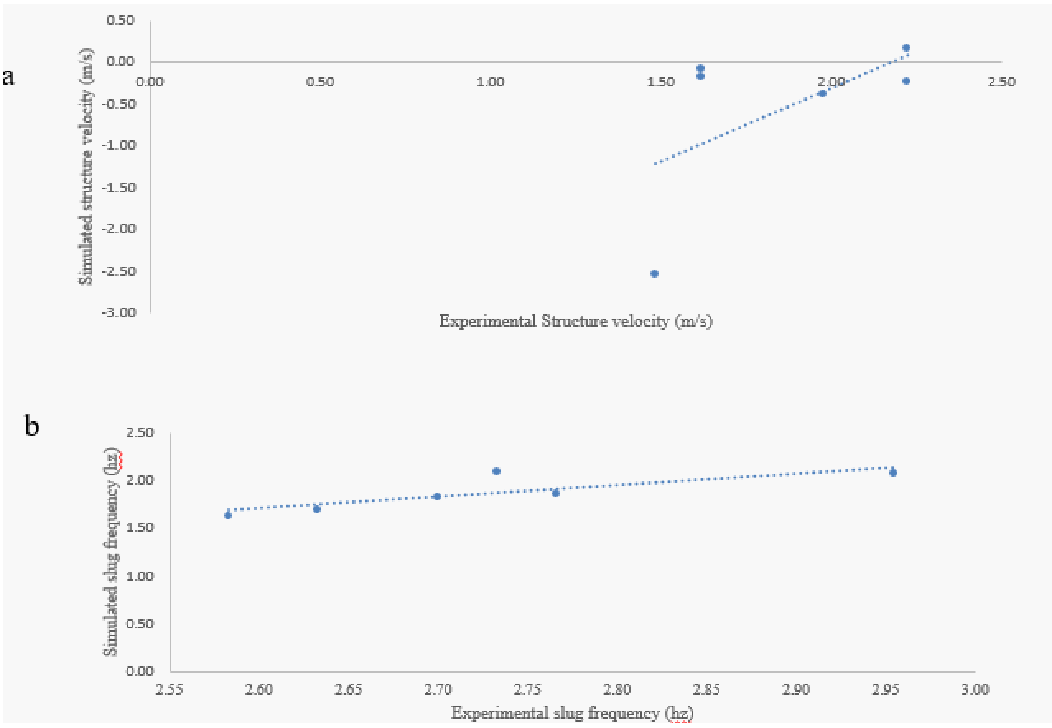

Figure 13: Cross plot of simulated vs experimental of (a) Structural velocity (b) slug frequency at Usl = 0.284m/s

From figure 10-13, wide over prediction is observed by the model as the liquid velocity increased for slug frequency from 0.05m/s to 0.284m/s while the structure velocity gave negative trends from figure 11-13, this could also be attributed to oscillation from flow transitions.

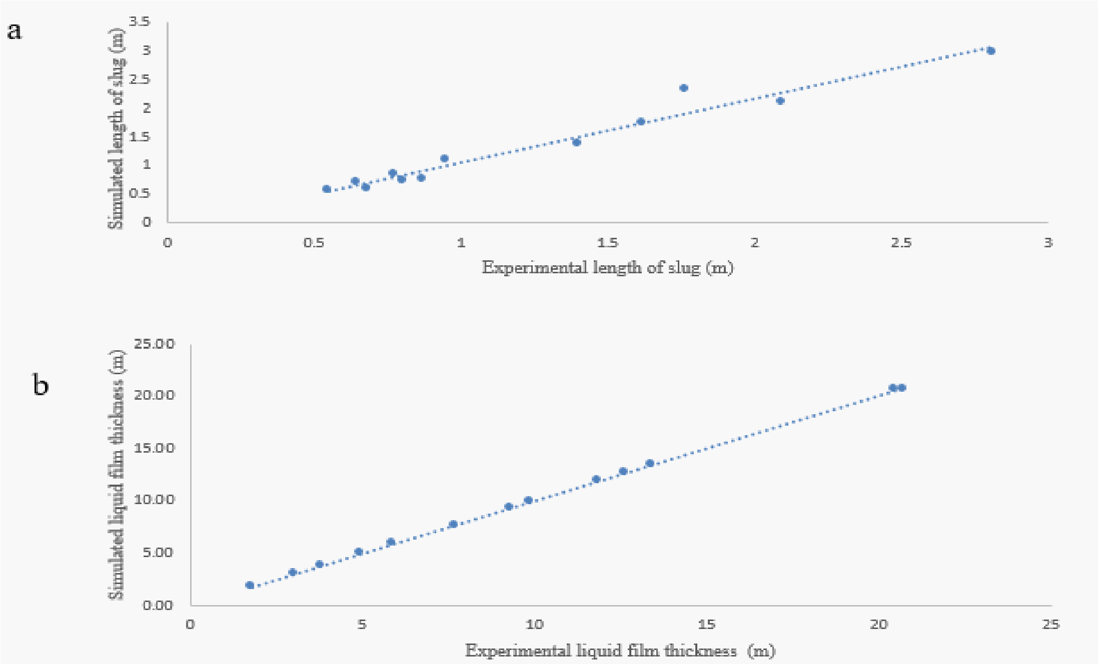

Figure 14: Cross plot of simulated vs experimental of (a) Length of slug (b) liquid film thickness at Usl = 0.05m/s

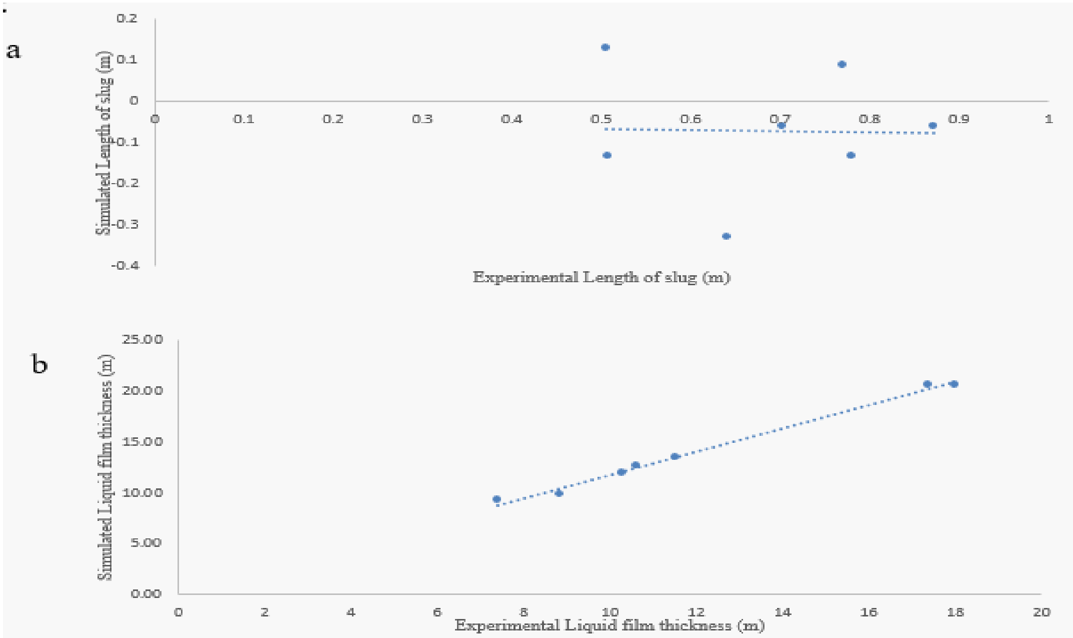

Figure 15: Cross plot of simulated vs experimental of (a) Length of slug (b) liquid film thickness at Usl = 0.071m/s

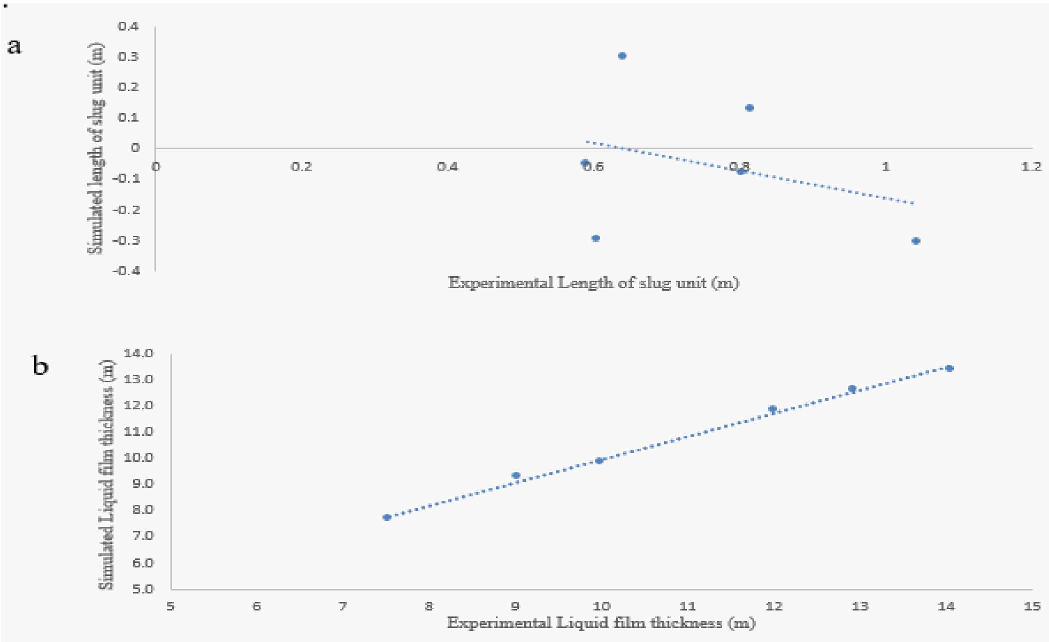

Figure 16: Cross plot of simulated vs experimental of (a) Length of slug (b) liquid film thickness at Usl = 0.095m/s

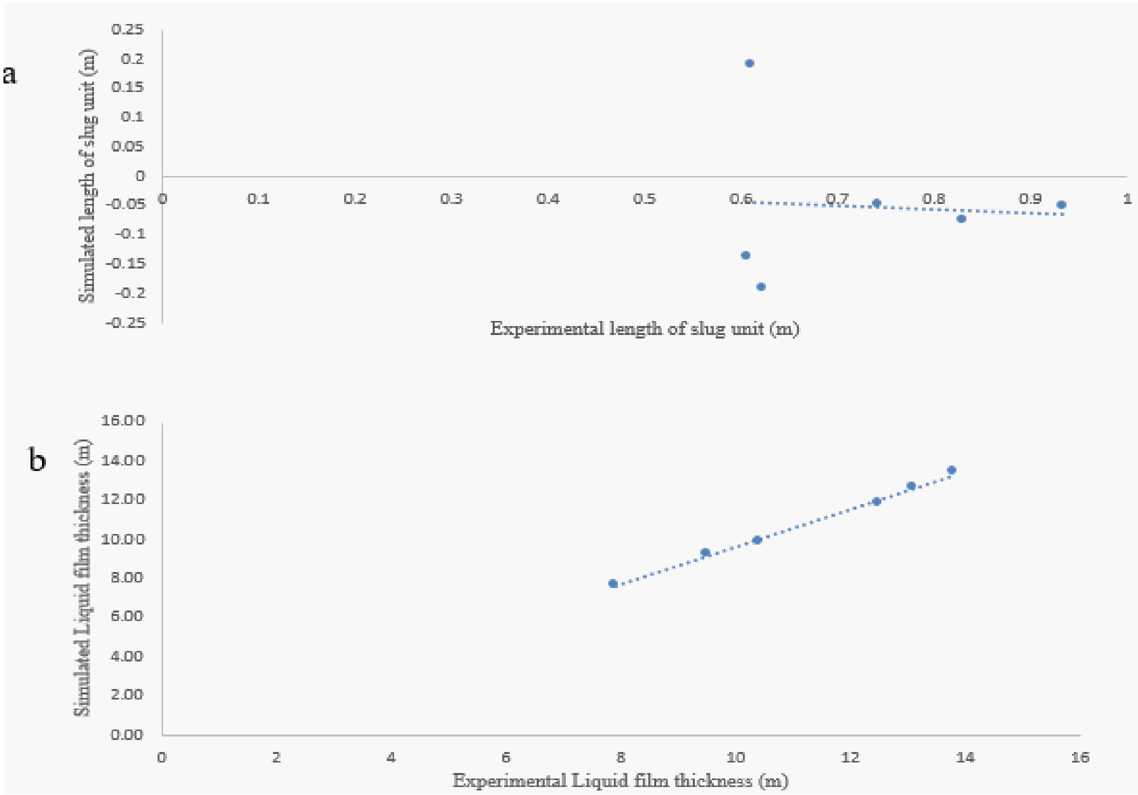

Figure 17: Cross plot of simulated vs experimental of (a) Length of slug (b) liquid film thickness at Usl = 0.142m/s

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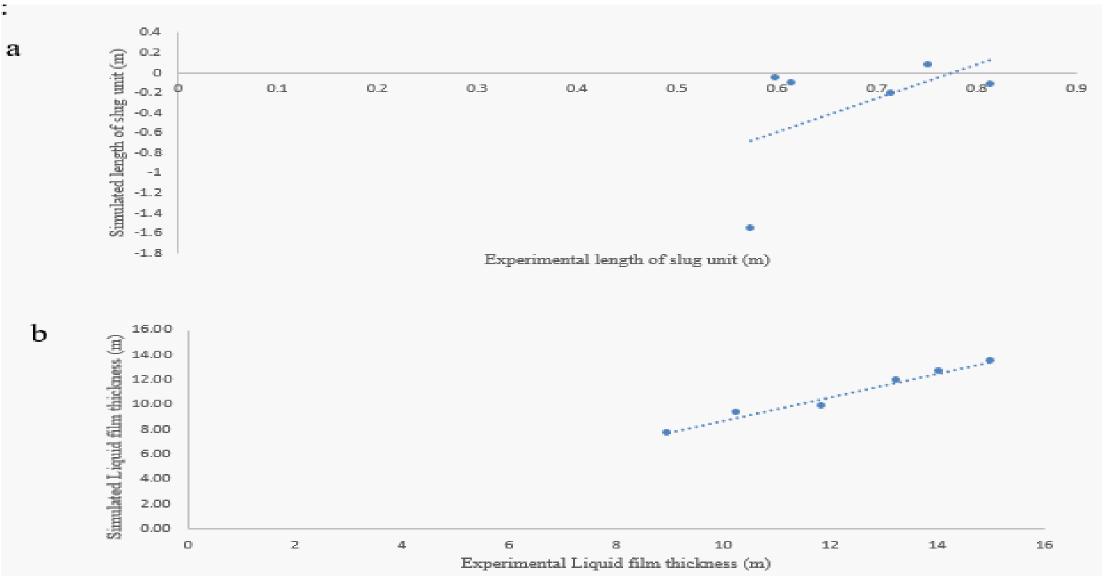

Figure 18: Cross plot of simulated vs experimental of (a) Length of slug (b) liquid film thickness at Usl = 0.284m/s

From figures 14-18 there were little correlation between experimental and simulated the length of slug unit except in figure 14, this is due to the fact that it is a function of mixture velocity and slug frequency, which the model limitations has been observed in slug frequency. While in figure 14-18 a good fit between the experimental and slight over predictions at superficial liquid velocity of 0.05-0.284m/s of film thickness of liquid was observed, this shows good estimation can be gotten using the model for liquid superficial velocities under the flow conditions.

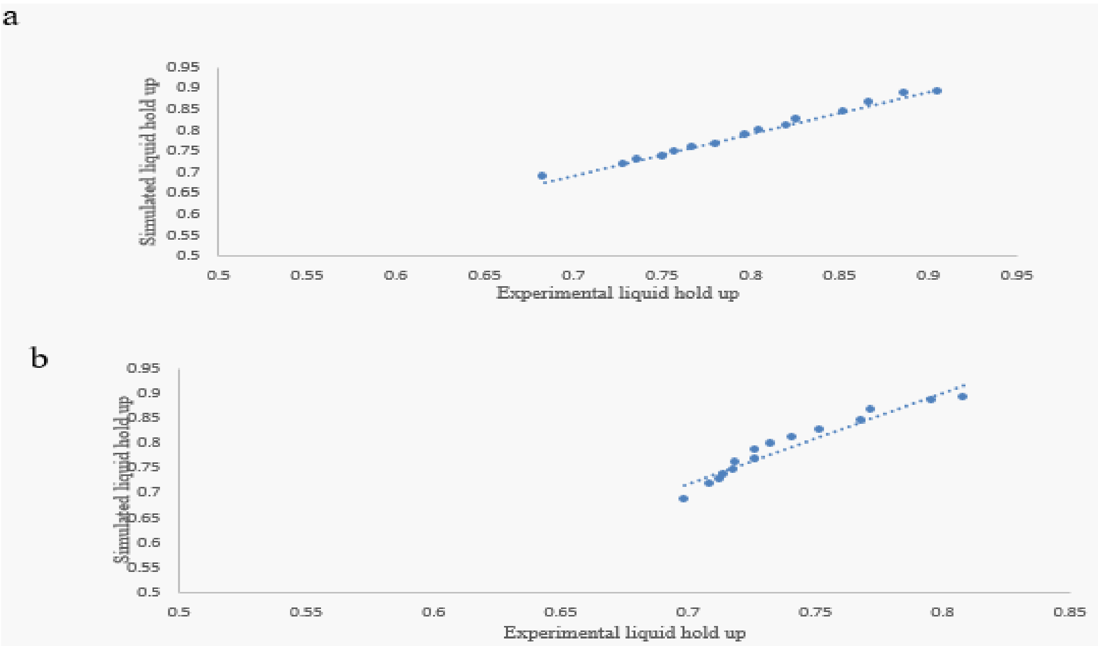

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Figure 24: Cross plot of simulated vs experimental of Liquid hold-up at (a) 100cp (b) 5000cp

From the figures 24 it is seen that the model gives a good plot at lower viscosity of 100cP while it becomes less stable as the viscosity gets to 5000cP. This follows the trend seen in Kora (2012).

It has been deduced that structural (translational) velocity is affected by increase in the fluid viscosity. In the work of (Al-kayiem *et al*. 2017), an analytical investigation of structural velocity and slug body length with water as the liquid phase, it was seen that for a static water velocity, the slug length and structural velocity rises with an increase in the superficial air velocity while the slug frequency reduces. Bendiksen *et al*. (1991) utilized oil of viscosity ranging from 240–730 cP in a 0.057-m ID horizontal pipe to investigate slug bubble velocity. The authors observed that liquid viscosity has a huge influence on bubble shape and velocity. This shows the machine learning model is good in estimating liquid hold-up, void fraction, and length of film thickness but has limitations in the slug frequency, slug unit length and structural velocity.

Conclusion

In this work, the experimental data obtained with a 67 mm diameter vertical pipe for air-silicone oil slug flow regime have been presented. Machine learning models developed and then used for prediction. Comparisons were made between the experimental and predicted data for liquid hold up, void fraction, structure velocity, frequency of the slug flow, slug unit length, and thickness of the liquid film.

The following conclusions has been reached:

1. The liquid hold up decreases with increasing gas superficial velocity at constant liquid superficial velocity as seen in (Kong *et al*., 2018), and (Hernandez- Alvarado *et al*, 2017)
2. The model generated showed a good fit in predicted slug flow parameters of liquid hold up, void fraction, and as well the width of liquid film under the flow conditions for the research.
3. The model showed high deviations in the slug frequency, slug unit length, and structure velocity this could be attributed to data leakage in the machine learning model creation based on the flow

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parameters considered. This leads to limitation in using the model to predict the above slug flow parameters.

4. Viscosity has a significant effect on the prediction of the liquid hold up as over and under predictions were observed when the model was used to predict high viscosity of 5000cP data. While at low viscosity of 100cP, a perfect prediction was observed.

The Machine learning random-forest model gives a very accurate prediction under the flow conditions and can be useful in multiphase flow prediction.

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