UNIVERSITY OF MISKOLC

Faculty of Earth and Environmental Sciences and Engineering

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Forecasting of Intermittent Gas Lift Flow Parameters Using Computational Fluid Dynamics and Machine Learning Techniques

New Scientific Achievements of Ph.D. Thesis

by

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1 Summary

Despite the advance of the work proposed by previous researchers to study the intermittent gas lift system, the interaction operating parameters of the process remains poorly understood and need more investigation. A computational fluid dynamics model (CFD) and machine learning algorithms are used in this research to accurately predict the single and multiphase flow parameters of intermittent gas lift process.

The CFD simulation is conducted for a test section of 18 m vertical tube with 0.076 m in diameter using air as injected gas and oil as a formation fluid. Also, the well parameters are organized into dimensionless ratios to reduce the complexity of the system and the required computational time. The liquid production rate is noted to increase with increases the injection pressure, tubing size and submergence length and the results obtained from the simulation model were validated with the results from the literature. Pressure and velocity profile are often the most important parameter for the design and efficiency of the intermittent process and by using the present developed model, the pressure profile can be easily obtained for different positions and conditions along the production tube.

In intermittent producing system, the pilot gas-lift valve is extremely used to control the point of compressed gas entry into the production tubing and acts as a pressure regulator. A novel approach using computational fluid dynamics simulation was performed in this study to develop a dynamic model for the gas passage performance of a 1-in., nitrogen-charged, pilot gas-lift valve. This study investigates the effect of internal pressure, velocity and temperature distribution within the pilot valve that cannot be predicted in the experiments and mathematical models during the flow-performance studies. A general equation of the nonconstant discharge coefficient has been developed for 1-inch pilot valve to be used for further calculation in the industry without using CFD model.

Tubing pressure at gas injection depth in intermittent wells is one of the most critical parameters for production engineers to evaluate the performance of the system. However, monitoring of the tubing pressure is not usually carried out in real time. Machine learning (ML) algorithms is utilized in this research to develop a model that can accurately predict tubing pressure in artificial intermittent gas lift wells. All the tubing pressures obtained from ML models were compared with the actual field values to ensure the effectiveness of the work. The developed model shows that it can predict the pressure with more than 99.9% accuracy. This

is an interesting result, as such outcome accuracy has not been reported usually in the open literature.

2 Thesis Contribution

The contribution to research is the development of a computational fluid dynamic model to study the liquid production rate with different gas injection conditions. This model is a novel model to physically describe the transient flow in intermittent lift and predict the effect of intermittent parameters on the slug velocity and liquid production rate. The pilot valve, discharge coefficient correlation is developed in this study to calculate the actual gas flow rate through 1-inch pilot valve in the petroleum industry. This correlation is efficiently correct the gas rate from the analytical to actual flow because it based on the numerical model that consider the change in the velocity, temperature, and pressure gradient around the valve piston. Finally, machine learning model is developed in this research based on the field data to predict the tubing pressure at the gas injection depth.

3 Thesis Objectives

Intermittent gas lift is considered as complex process and contains many interaction parameters that required trial and error procedure to find the best and optimum operation conditions that is good on case by case. The work on the intermittent gas lift should be proceeded to find a good computer model which can accurately describe the whole intermittent cycle and the effects of interaction parameters on the system efficiency. The main objectives of this research are:

1- To construct a numerical simulation model using Computational Fluid Dynamics (CFD) that investigate the effect of injected time on the liquid production rate and to calculate the velocity and pressure profile of the slug flow in intermittent process.

2- Carry out a dimensionless analysis model to reduce the complexity of the system and the required computational time.

3- To develop CFD simulation procedure for pilot valves, based on the conditions similar to those find in the industry. This procedure is used to propose a numerical correlation equation of the discharge coefficient of 1-inch pilot valve.

4- To build artificial machine learning model using different algorithms to predict the tubing pressure at the gas injection depth.

4 CFD Model of Intermittent Two-Phase Flow

4.1 Numerical CFD Modelling Stages

There are three main stages for typical CFD model: pre-processing, solving, and post-processing. **Figure 1**. describe the CFD method used in this research.

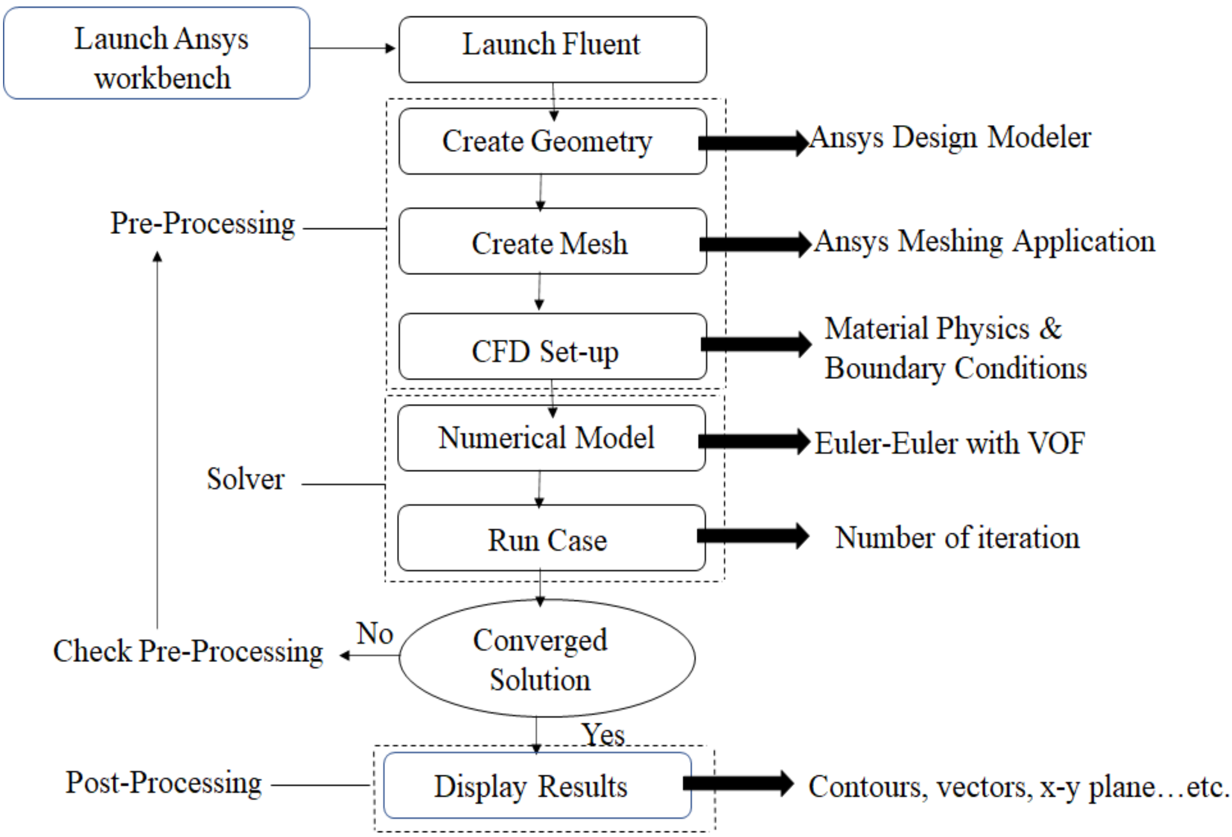

Figure 1. CFD simulation flow chart (edited by the Author)

4.2 Scenarios of CFD simulation

In this research two scenarios of intermittent gas lift have been studied and compared with experiment results. The geometry dimensions and the solution set up in each case are the same as those of the experiment conditions in order to validate the CFD model. **Table 1** shows the summary of different variables for the two cases.

Table 1. Parameters for Intermittent gas lift cases (edited by the Author)

Parameters	Tubing size	port size	Injected Gas	Liquid Slug	Injection pressure
Case 1	0.076 m (3 in)	0.025 m (1 in)	Air	Oil	2.7&3.5 bar (40&50 psig)
Case 2	0.051&0.060 m (2&2.375 in.)	0.013 m (0.5 in)	Natural gas	Water	2&3 times Pt (tubing pressure)

Figure 2 shows the details of the domain parts used in this study to simulate the intermittent gas lift process. In the industry, the gas injection is ceased when the liquid slug reaches the wellhead, user define function is written to set the pressure inlet based on the liquid volume fraction in the tubing outlet. Hexahedral computation mesh was created with enough mesh resolution near the wall as shown in **Figure 3** to capture the liquid film flow near the pipe wall.

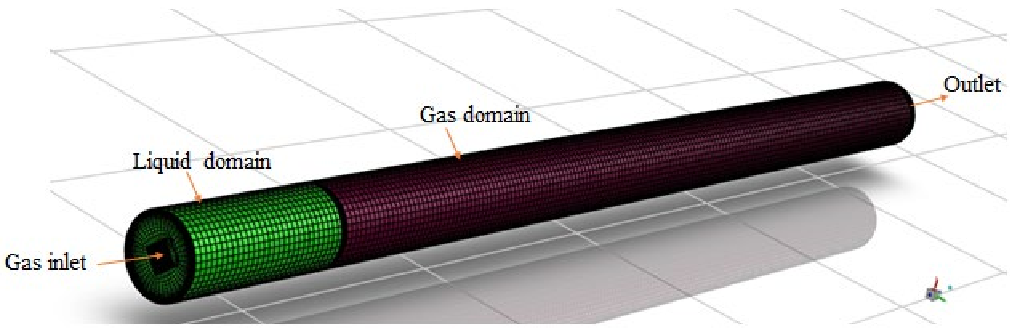

Figure 2. The different domain parts used for simulation. (edited by the Author)

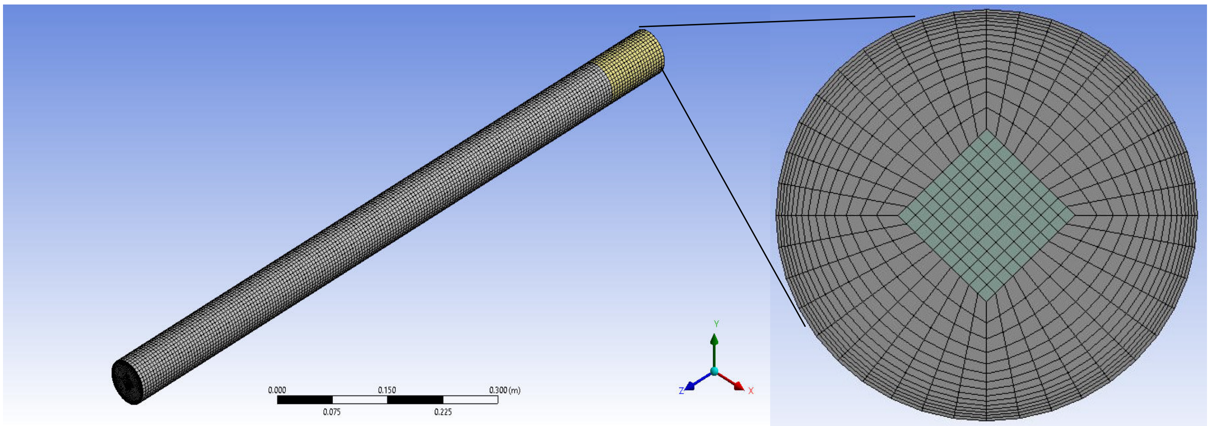

Figure 3. The structured mesh used for intermittent gas lift (Case 2) (edited by the Author)

5 CFD Simulation of Pilot Operated Intermittent Gas Lift Valve

The domain considered in this study is shown in **Figure 4.** The important part to be simulated is the power part, since the injected gas flows through this section to the production tubing and it is responsible for the gas flow rate. To simplify the geometry, the following assumptions are made.

(a) The gas flow through the bleed hole has not been modeled, in fact the gas flow through the bleed hole is not that much significant compared to the total gas flow rate.

(b) The inlet boundary condition is located on the wall that separates the piston seal ring and the gas entrance to the main part.

Mesh independence study is conducted, to establish the accuracy of the solution and reduce the simulation run time without affecting the calculation accuracy. Also, the effect of the distance that power piston travels inside the power section of the pilot valve on the gas flow rate had been studied. Three different travels measured from the boundary wall to the end of the piston had been studied as shown in **Figure 5** For each piston travel, the gas flow rate is measured. The results show that the piston travels of 32, 34, and 36 mm have no significant effect on the gas flow through the pilot valve for different production pressure.

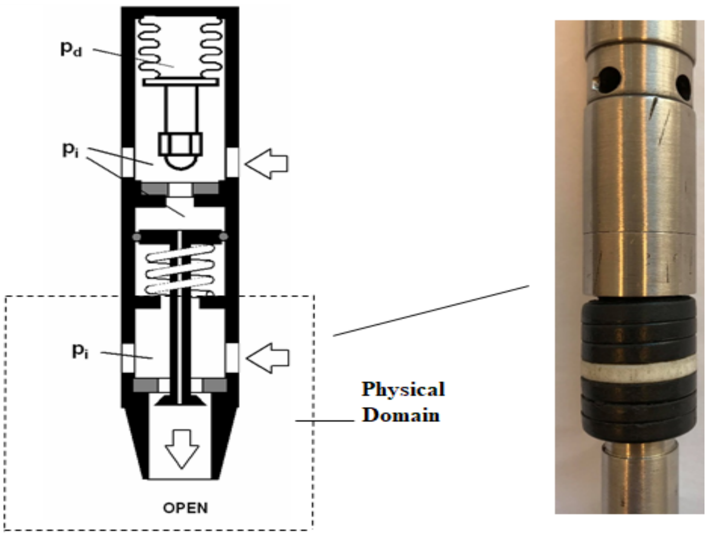

Figure 4. Physical pilot valve domain for CFD simulation (edited by the Author)

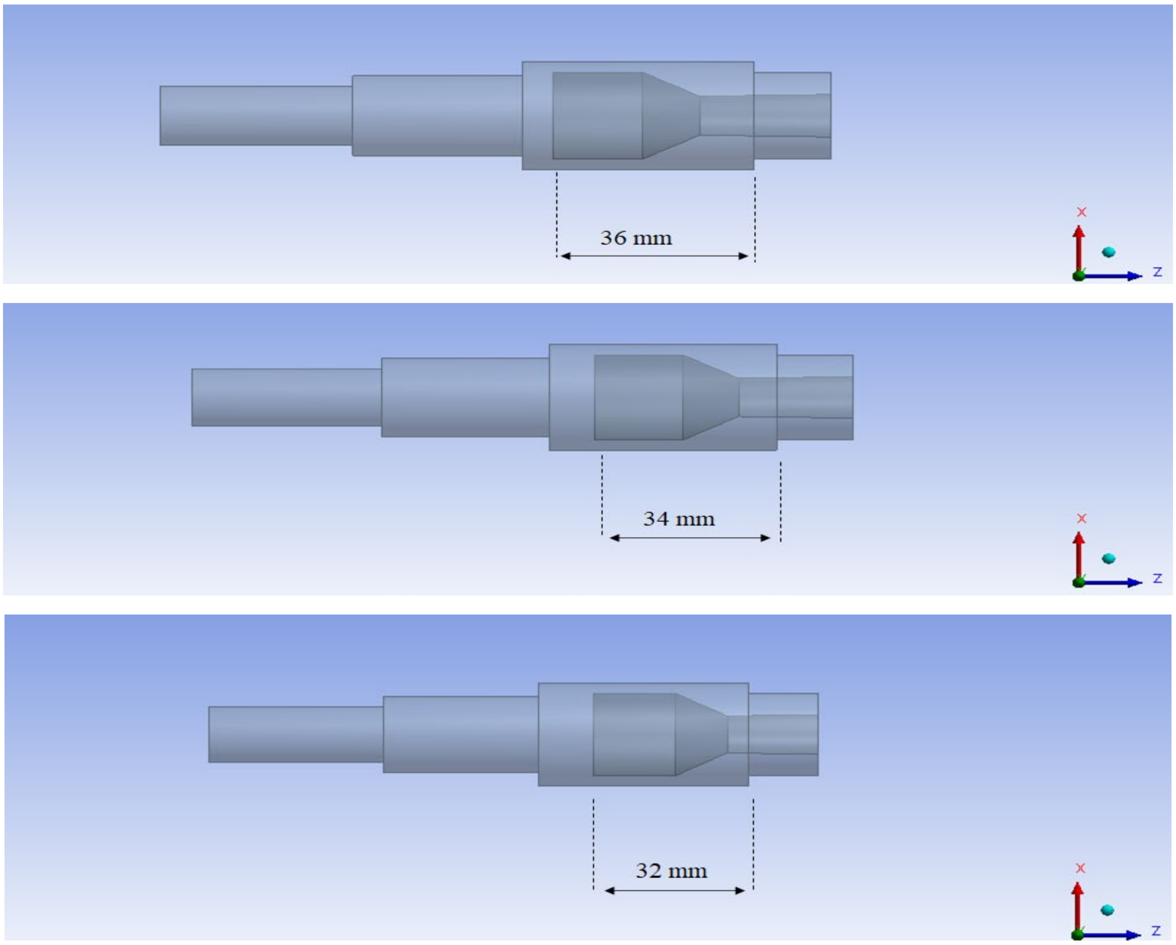

Figure 5. Different piston travel geometry for pilot valve (edited by the Author)

6 Machine Learning Algorithms for Predicting Tubing Pressure

A total of 9594 intermittent gas lift test data were obtained from Algyo oil wells located in the southern part of Hungary. These wells are artificially flow using intermittent gas lift process. The first most imperative step taken in the process of data analysis of this study was to plot the attributes correlation matrix as shown in **Figure 6.** The filter method is selected in this study to reduce the number of the input data. The correlation between each input parameters was calculated using Pearson's correlation coefficient method. The filter process based on correlated parameters reduces the number of elements from 105534 to 67158 and reduces the number of the independent variables from 10 to 6.

Data analysis and preprocessing performed carefully in this study since, the prediction performance of any machine learning models is highly depending on the quality of the data. **Figure 7** shows a summary of data preprocessing and models training used in this research.

Three different machine learning algorithms namely, Decision Tree (DT), Random Forest (RF)and K-Nearest-Neighbors (KNN) are used in order to predict the tubing pressure at the gas injection depth in intermittent gas lift wells.

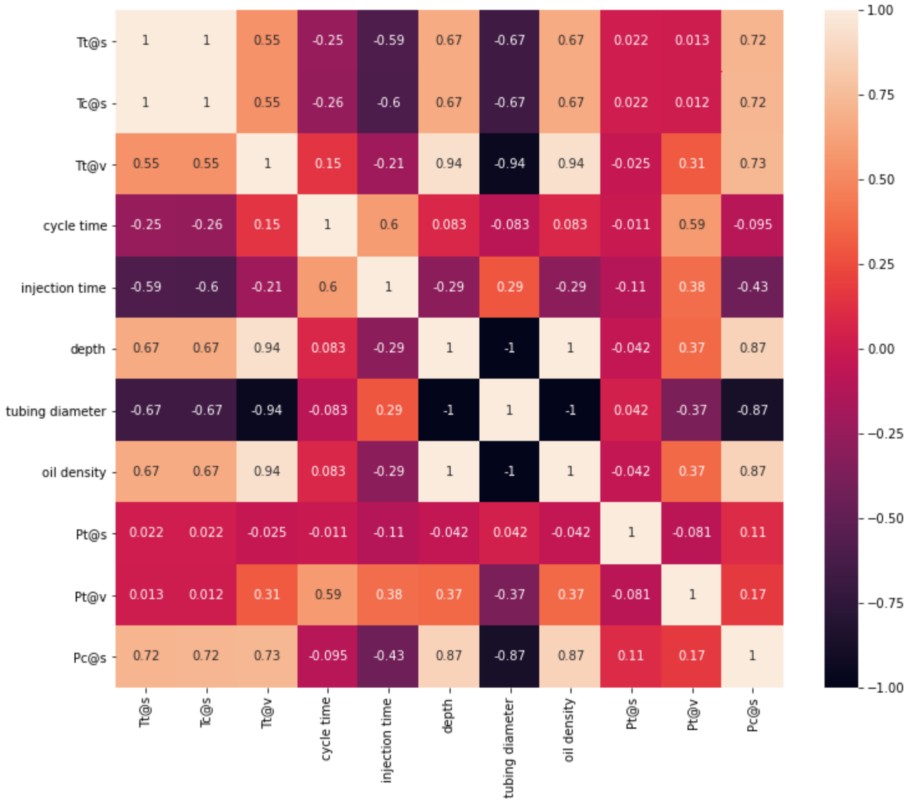

Figure 6. Correlation plot of all attributes in intermittent dataset. (edited by the Author)

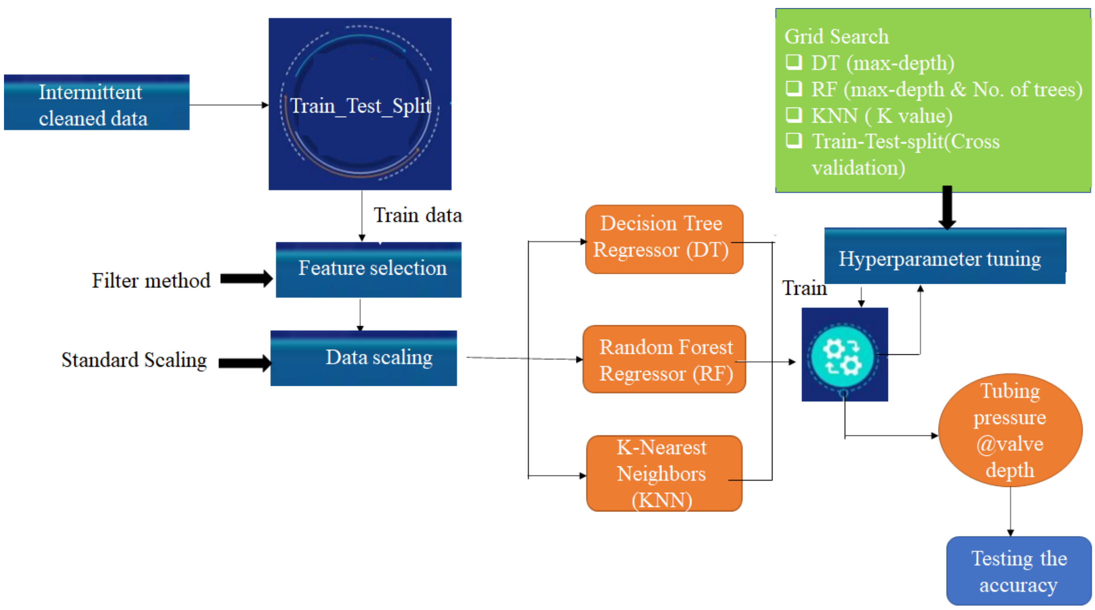

Figure 7. Flowchart of Machine learning models procedure. (edited by the Author)

Grid-search is used to find the optimal hyperparameters of a model which results in the most 'accurate' predictions. To select the optimum hyperparameters, each model is trained and evaluated for different set of parameters to select the optimum one. Cross validation technique is used to split the data for the train and test. In this technique the dataset is divided into K-folds, the model is train in K-1 folds and test in 1 K as shown in **Figure 8.** By iteration through the train/test comparison several times, a better estimation of the model performance is achieved. This checks that the model is not performing differently after being trained on new labeled data. The result of hyper parameters is shown in **Table 2**.

Table 2. Optimum Machine learning models parameters (edited by the Author)

Model	score	Best parameters
Decision Tree	0.99982	Max-depth=50
Random forest	0.99987	Bootstrap=True, max feature= auto
K-Nearest Neighbors	0.9992	K=2

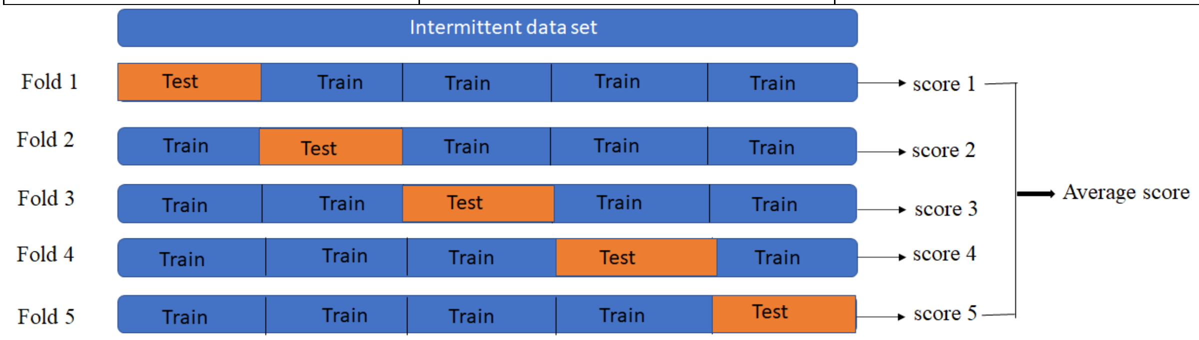

Figure 8. Cross validation of machine learning models using 5 K-Folds. (edited by the Author)

7 Scientific Results

7.1 Study the Slug Velocity Profile with Gas Injected Time

The slug velocity with the gas injected time is shown in **Figure 9.** for two different injection pressures (40 psig and 50 psig). As the injection pressure increases from 40 psig to 50 psig the slug velocity increase and this is due to the expansion of the gas injected under the slug which causes the slug to rise to the surface rapidly. Also, when the pressure of the injected gas increased, the time required for pushing the slug to the surface decreased.

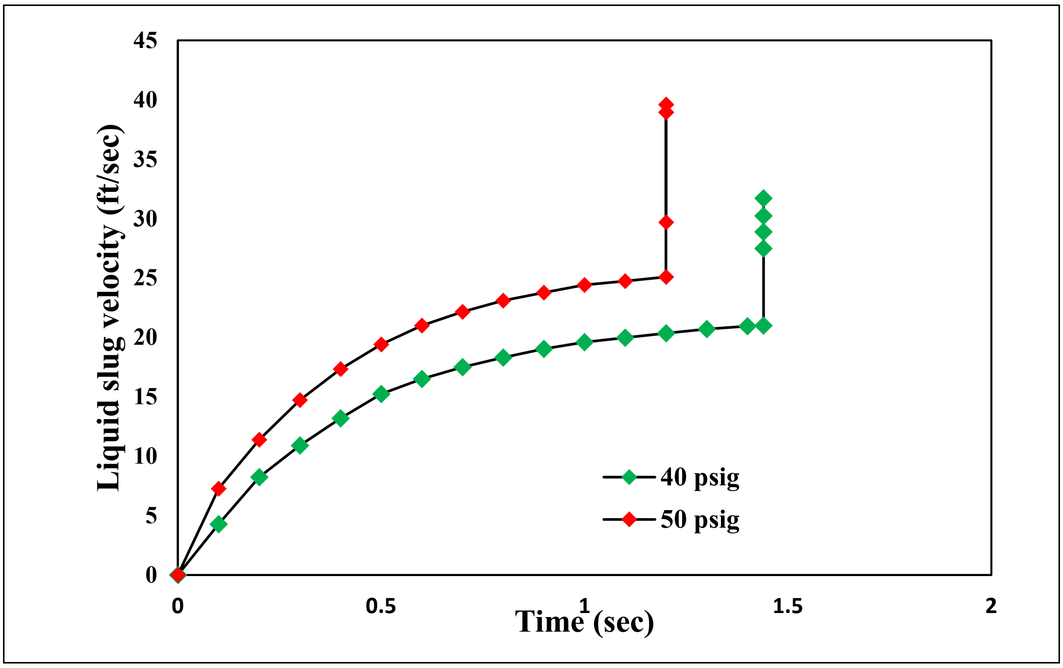

Figure 9. Liquid slug velocity vs. injection time, The CFD results developed in this study. (edited by the Author)

7.2 Study the Liquid production with Gas Injected Time.

The liquid recovery with gas injected time is obtained from two different gas injection pressures. **Figure 10** shows the fraction of liquid produced from the slug core is about 0.366 (36.6% of the total liquid) for injection pressure of 40 psig and about 0.392 (39.2 % of the total liquid) for injection pressure of 50 psig. It is observed that when the injection pressure increases the liquid production increase. Also, when the injection time increases, the liquid production increase because of the liquid production from the film. From the figure, it can be seen that the larger portion of production is coming from the liquid after flow.

7.3 Modeling of Gas Flow Rate Through the Pilot Valve

The valve performance curve describes the dynamic behavior of the pilot valve and represents the gas flow rate through the valve for different injection and production pressure. The gas flow rate is calculated for different conditions using CFD simulation as shown in **Figure 11.**

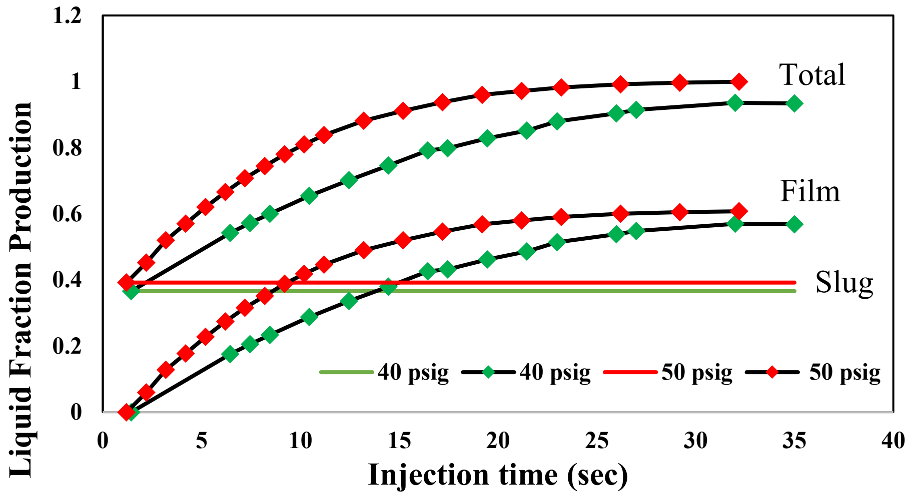

Figure 10. Liquid production vs. injection time, The CFD results developed in this study (edited by the Author)

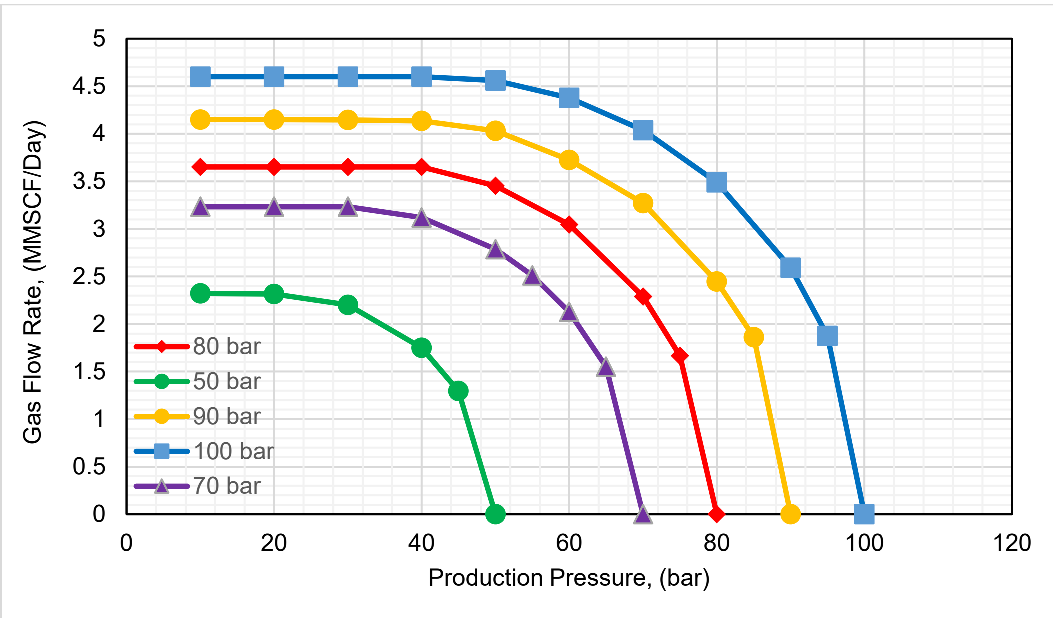

Figure 11. Pilot valve performance curve from CFD model. (edited by the Author)

Using CFD results the following steps are used to develop a general equation of the non-constant discharge coefficient (C_dY) of 1-inch pilot valve that can be used for further calculations without using CFD model:

1. Gas rate is calculated from CFD simulation for different conditions.

2. C_dY is back calculated for different values of gas flow rates using the following equation:

$$Q_{sc} = 1240.3 \cdot C_d Y \cdot A_v \cdot \sqrt{\frac{P_i \cdot (P_i - P_p)}{T_v \cdot z_v \cdot \gamma_g}}$$

3. C_dY is plotted against $(P_i - Pp)/P_i k$ as shown in **Figure 12.**
4. A general equation for C_dY is obtained using linear regression.

$$C_d Y = -0.217 \frac{(P_i - P_p)}{P_i k} + 0.322$$

Where CdY is the non constant discharge coefficient (dimensionless), A_v is effective flow area (in^2), P_i is injection pressure (psi), P_p is the production pressure (psi), k is ratio of specific heats (dimensionless), T_v upstream gas temperature (°R), z_v is gas compressibility factor at upstream condition (dimensionless), γ_g is gas specific gravity (dimensionless).

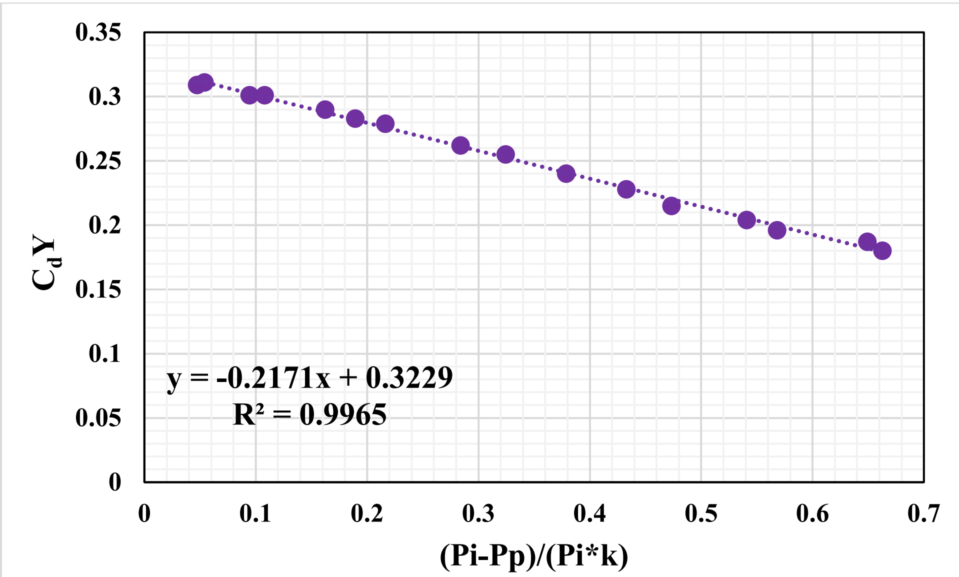

Figure 12. C_dY correlation of 1-inch pilot valve (edited by the Author)

7.4 Prediction of Tubing Pressure Using Machine Learning Algorithms

After the data preprocessing steps, the selected machine learning models were built on the training dataset. The evaluation of each algorithm was essential to ensure the quality of the employed model. The models are fit to the training dataset and then used to predict the tubing pressure for the training and testing dataset. A graphical description of the results is presented in **Figure 13**. which show a comparison between the actual tubing pressure and ML model predicted values for both the training and testing data and also the figure displays the correlation of determination (R^2) for each model.

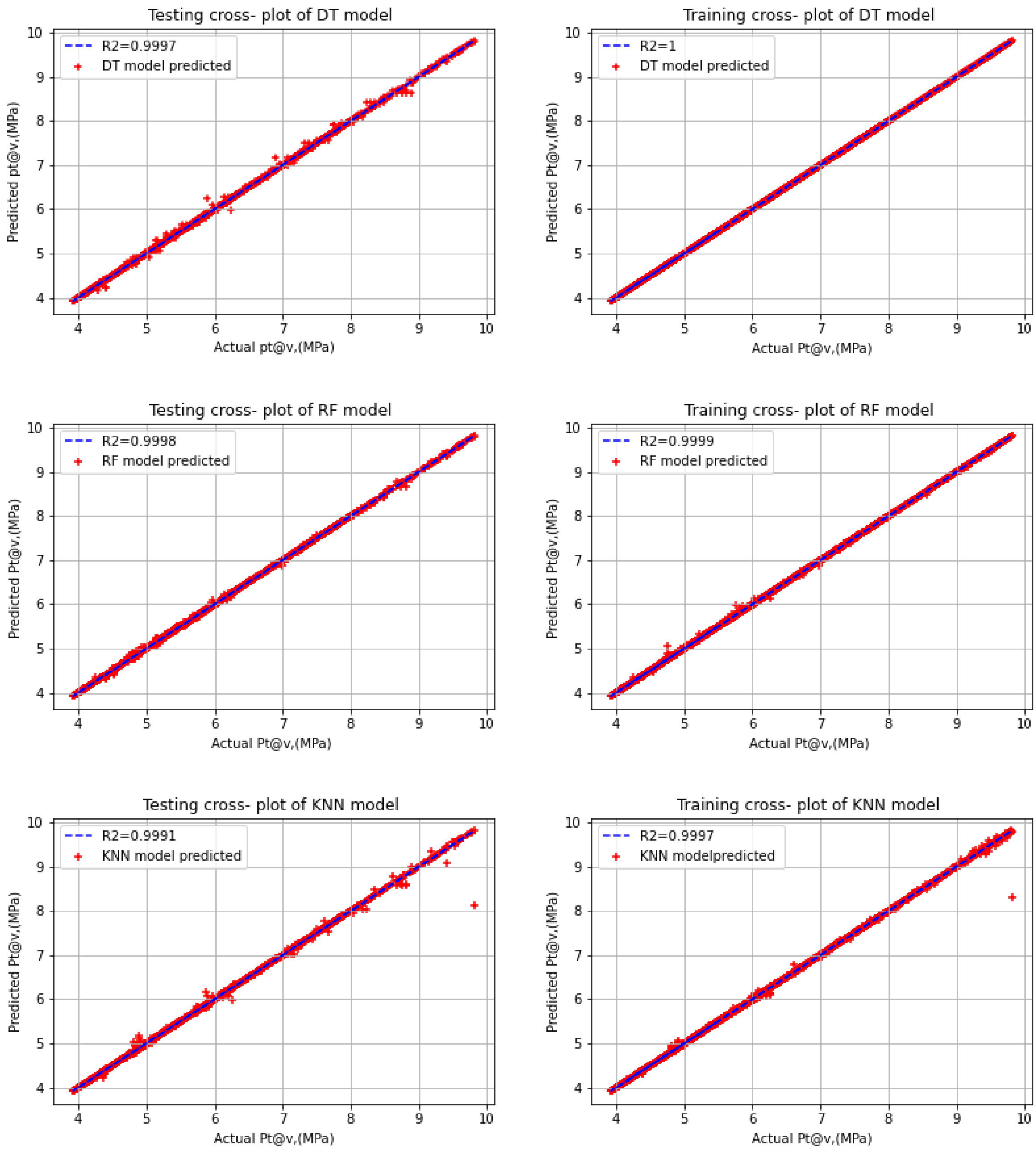

Figure 13 Cross-Plot between Actual and Predicted tubing pressure at the valve depth (edited by the Author)

The comparison between all the ML methods which were used in this study is based on minimum root mean square error (RMSE) and highest coefficient of determination. This comparison clearly shows the power of the ML models in predicting tubing pressure during intermittent process in our case. Figure 14 and Figure 15 show the comparison between the machine learning models based on RMSE and R2 respectively. From the values of the RMSE, R2 and the residuals, it can be concluded that the decision tree model performs better than the others model in the prediction the tubing pressure from training data set, whereas the Random forest model perform better than the others in the prediction of the testing dataset. The KNN model give the highest RMSE, lowest R2 and highest residual range than the other models.

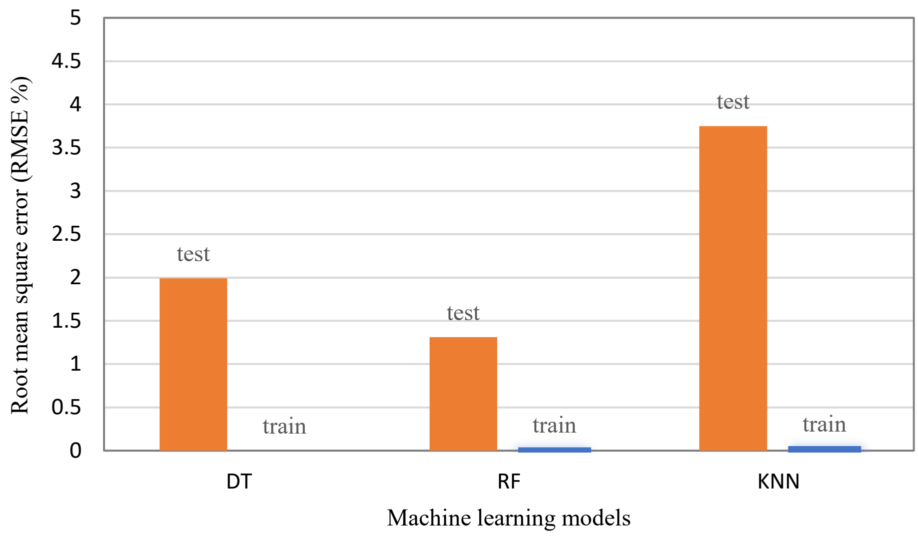

Figure 14. Root mean square error for the developed machine learning models. (edited by the Author)

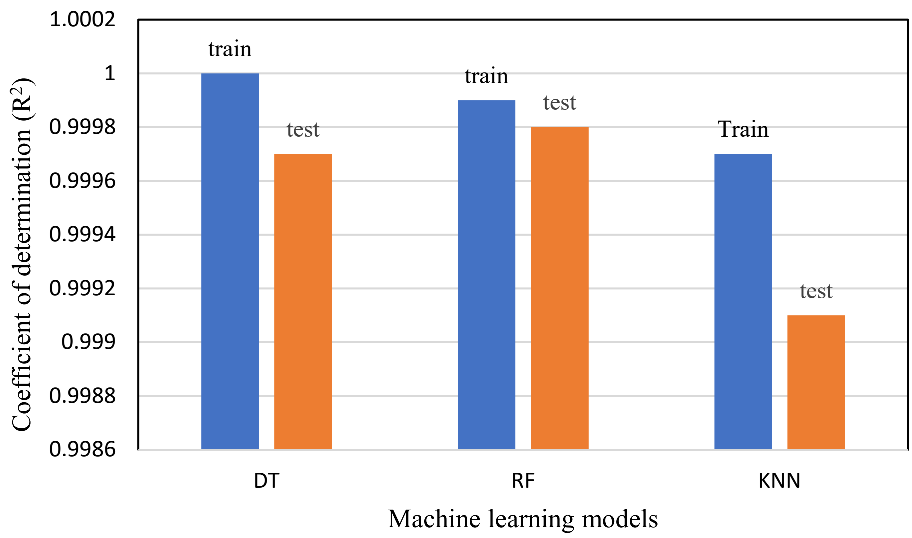

Figure 15. Coefficient of determination for the developed machine learning models. (edited by the Author)

8 NEW SCIENTIFIC RESULTS

Thesis #1

Developed a computational fluid dynamics model for intermittent gas lift systems, this simulation is a proven program for predicting intermittent gas lift characteristics and the transient flow parameters that are changing with time and position in the coordinate system. This model is applied for a long tubing string with a length of 236 times the diameter which is not yet reported in the open literature.

The velocity profile of the liquid slug is calculated using CFD simulation for two different gas injection pressures. Also, the pressure profile inside the tubing string is calculated for different positions with the gas injection time. These calculations using the developed CFD model show good agreement with the experiment results.

Thesis #2

The dimensionless analysis procedure is developed in this research by organizing the well parameters into dimensionless ratios to reduce the complexity of the system and the required computational time. The initial variables of injection pressure, tubing pressure, submergence length, and valve depth are related to the liquid production fraction for certain tubing sizes and valve diameters using CFD.

Thesis #3

A novel approach using computational fluid dynamics simulation was performed to develop a dynamic model for the gas passage performance of a 1-in., nitrogen-charged, pilot gas-lift valve. Dynamic performance curves were obtained by using methane as an injection gas with flow rates reaching up to 4.5 MMscf/day (127 em^3/day). This study investigates the effect of internal pressure, velocity, and temperature distribution within the pilot valve that cannot be predicted in experiments and mathematical models during the flow-performance studies.

Thesis #4

A successive procedure is introduced to develop a general equation of the nonconstant discharge coefficient for a 1-inch pilot valve to be used for further calculation in the industry without using the CFD model. The developed model calculates the nonconstant discharge coefficient taking into account the pressure, temperature, and velocity gradient around the piston. This model reduces the complexity of the data required to calculate the discharge coefficient.

Thesis #5

Machine learning (ML) algorithms are utilized to develop an artificial intelligence model that can accurately predict tubing pressure in intermittent gas lift wells. Intelligent algorithms built on the field data from Algyo wells in Hungary, provide a solution that is easy to use and universally applicable to calculate such a complex parameter in the industry. This model is capable of predicting the tubing pressure at the gas lift valve with high accuracy (~99%).

Filter method of feature selection is used to find the most variables that affect the tubing pressure at the gas lift valve. By using this method, the number of input variables is reduced from ten to six. It is found that temperature at the casing surface, injection depth, oil density, and tubing diameter are not necessary to be included in the machine learning algorithm since they are highly correlated with other input parameters.

9 List of Publications Related to This Thesis.

Sami N.A. and Turzo Z. (2020): Computational fluid dynamic (CFD) simulation of pilot operated intermittent gas lift valve, Journal of Petroleum Research. 5(3), 254-264.

Sami N.A. and Turzo Z. (2020): Computational fluid dynamic (CFD) modelling of transient flow in the intermittent gas lift, Journal of Petroleum Research. 5(2), 144-153.

Sami N.A. and Turzo Z. (2020): Tracking sequence of oil well production with artificial gas-lift installations. Műszaki Földtudományi Közlemények, 89(2), 83–91.

Sami N.A. and Turzo Z. (2021): CFD Modeling of Dynamic Flow Behavior of Intermittent Gas Lift Components. Journal Petroleum and Coal, 63(1), 106-115.

Sami N.A. and Dhorgham A. (2021): Forecasting multiphase flowing bottom-hole pressure of vertical oil wells using three machine learning techniques, Journal of Petroleum Research**,** 5(3)**,** 417-422.

Sami N.A. (2022): Application of machine learning algorithms to predict tubing pressure in intermittent gas lift wells, Journal of Petroleum Research, 7(2), 246-252.