Transformer Neural Network based Virtual Flow Meter for Oil Well Production Optimization

Priyanka Perera
Dept. of Computer Science, University Of Moratuwa, Sri Lanka
priyanka.23@cse.mrt.ac.lk

***Index Terms*—oil and gas well optimization, neural networks, virtual flow meter, transformer neural networks**

I. Introduction

An oilfield refers to a geographical area that encompasses one or more oil or gas reservoirs equipped with the necessary infrastructure for exploration, extraction and production. An oilfield consists of many oil wells drilled into the Earth's surface to extract oil and natural gas from underground reservoirs. Petroleum Engineers need to make informed decisions about production strategies based on the performance of the wells in the oilfield. Oil, gas and water flow rates of the wells are reflection of the performance of the wells. Accurate knowledge about the oil, gas and water flow rates of wells are therefore required to arrive at informed production decisions. Through accurate prediction of flow rates, Petroleum Engineers can diagnose production inefficiencies and constraints, implement solutions to optimize production, project future investment and decommission nonproductive wells. Objective of the author is to develop a physics informed transformer based neural network model for accurate prediction of flow rates in oil and gas wells.

Acronym	Description
BNN	Bayesian Neural Network
LSTM	Long Short-Term Memory
ML	Machine Learning
MPFM	Multi-Phase Flow Meter
PINN	Physics-Informed Neural Network
NN	Neural Network
RNN	Recurrent Neural Network
VFM	Virtual Flow Meter

TABLE I Acronyms

II. Literature Survey

[1] have done a detailed literature study on the oilfield production and different types of flow meters. The area that contains the deposit of oil and/or natural gas is called the oil reservoir. There can be multiple wells connected to the same reservoir. Fluid flow in the piping network in a oil well is a multi-phase flow containing oil, gas and water. Piping network in a oil and gas well can be a combination of horizontal, vertical or inclined pipes. Therefore the flow of fluid in the piping can occur at any direction including upward and downward flows. Flow of fluid in the well can transit between the steady state and unsteady state. The steady state refers to the situation when the flow rates of the phases of the flow remains approximately uniform over time. Unsteady state on the other hand refers when the flow rates of individual phases rapidly varies over time. There are two mechanisms of measuring the flow rates of the oil well. They are physical flow meters and virtual flow meters (VFM). They physical flow meters can be of two types. They are multi-phase flow meter and single phase flow meter. Even in the physical flow meters, flow rates are calculated indirectly using physics based mathematical model. Multi-phase flow meter measure the flow rates of different phases simultaneously without separation. Multi-phase flow meters can provide continuous measurement of flow rates at sensor locations with decent accuracy but they are considered extremely expensive and requires regular calibration. Multi-phase flow meters are however considered to be less accurate outside of normal operational ranges. Physical flow meters in general also have the limitation of not being able to back-fill historical flow rates prior to the installation of the instrument. Single phase flow meters in contrast measure the flow rate of each phase individually, therefore multi-phase flow should be separated through a separator prior to feeding the single phase flow meter. Single phase flow meters are considered more accurate than multi-phase flow meter. Although not as advanced as multi-phase flow meters, the single phase flow meters are also considered expensive and its usage is extremely costly due to production deferment. This is because the well has to be disconnected from the production and needs to be connected with the separator prior to feeding the single phase flow meter. Single phase flow measurement is often called a well test. Some wells cannot be measured from a well test because the distance from the well to the separator can be very long. Both VFMs and physical flow meters measure the flow rates indirectly [1]. Physical flow meters bring their own set of sensors whereas VFMs use the existing sensors in the well. Physical flow meters use physics based mathematical models to calculate the flow rates whereas VFM can use physics models and/or ML based models for prediction. VFMs, therefore can be categorized into 3 types; physics based, ML based and hybrid flow meters. Physics based VFMs are also called first principle VFMs or physics simulator based VFMs. Physics based VFMs are generally considered expensive due to licensing costs of the simulator and slow in prediction due to processing of high complexity mathematical models. Physics based VFMs require very accurate descriptions of the well, fluids, trajectory,

production choke and installation parameters for modeling the simulator based on the principles of physics. ML based VFMs on the other hand are purely data driven. Hybrid VFMs implement combined physics based and ML based models. All 3 types of VFMs rely on pressure and temperature sensor data in the well. ML based VFM and hybrid VFM also rely on physical well-test measurements for model training. More the well-test measurements available, higher the accuracy of the model within the operating conditions of the well-test measurements. They are however said to have higher degree of uncertainty outside the operating conditions of the well-test measurements. Oilfields are required for perform well-tests at some point based on regulatory requirements of the jurisdictions. It is however not economically feasible to run regular well-tests as they cause production deferment. All types of VFMs have the limitation of being restricted to steady state, meaning that if there are rapid transient changes in the flow, VFMs will not predict them accurately. Therefore VFMs cannot predict startup, shutdown and other transient scenarios. ML and hybrid VFMs also cannot accurately handle advanced what-if predictive scenarios. Physics based VFMs in contrast can accurately handle advanced what-if predictive scenarios.

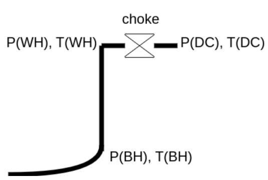

Fig. 1: Well Sensors

In a typical well, pressure and temperature sensors are deployed in the well bottom-hole (BH), well-head (WH) and downstream of the choke (DC) [1]. The choke is used to control the produced flow in the well for situational requirements. The six pressure and temperature sensors along the the choke position is generally used as independent variables for predicting the flow rates in ML based VFMs. [2] more recent work published in 2022, similar to [1] performs a detailed study on the physical and virtual FMs with overlapping content.

The hybrid VFM proposed by [3] uses ensemble learning to develop the data driven model by incorporating multiple ML models. The data driven model is then combined with the physics model using a combiner. They have achieved a 50% improvement in performance using the combiner compared to their stand-alone performance of physics based and ML based VFMs. [4] too proposes a VFM based on ensemble learning but instead of a hybrid VFM they propose ML based model. The model consumes bottom-hole, well-head, downstream choke pressure and sensor data. The proposed method generates diverse NN learners by manipulating training data, NN architecture and learning trajectory. They have evaluated the proposed method using actual well-test data and achieved a remarkable performance with average errors of 4.7% and 2.4% for liquid and gas flow rates respectively. The accuracy of the developed VFM was also analyzed using cumulative deviation plot where the predictions are within a maximum deviation of ± 15%. [5] have successfully developed a LSTM-RNN based model not only to predict multi-phase rates at present but also to predict future flow rates as a time-series. This is because unlike feed-forward NN, which process input data in a one-way, LSTM-RNN are designed to process sequential data, such as time series. [5] has achieved the best accuracy when the lengths of the input and output sequences to LSTM are equal. [6] develops a ML based VFM, implemented on BNN. BNNs provide a probabilistic distribution over weights and predictions unlike traditional neural networks, which produce point estimates for weights and predictions. [6] have trained the model on a large and heterogeneous data-set, consisting of 60 wells across five different oil and gas assets. The predictive performance is analyzed on historical and future test data, where an average error of 4%–6% and 8%–13% is achieved for the 50% best performing models, respectively. [7] proposes a hybrid VFM combining PINN based physics model and LSTM-RNN based ML model. Their resulting hybrid model is capable of predicting the average flow rate some time-steps ahead using the measurements available in the oil well information system. Unlike the ML based LSTM-RNN model proposed by [5], the system proposed by [7] is hybrid model using NN for physics based model as well as the ML based model.

Hybird VFM models have become increasingly popular since 2018 and increase usage of NNs seen for developing both physics and ML based models. Although many types of NNs have been evaluated, author at the time did not discover Transformer based NN for implementing VFM. Transformers, with the ability to capture long-range patterns in sequential data, can be applied to time-series data obtained from sensors.

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Annex : Summary Table

#	Title	Year	Authors	Research Type	Contributions	Flow Meter Type
1	First Principles and Machine Learning Virtual Flow Metering: A Literature Review	2020	Bikmukhametov, Jäschke	Literature research	Comprehensive literature study of Virtual Flow Meters (VFM) and provides related domain knowledge on petroleum industry and oil well sub-system ● Types of physical flow meters ● Types of virtual flow meters ● Types of sensors ● Review of physical flow meters ● Review VFM models ● Performance and economical evaluation of physical and virtual FMs Highlights machine learning as a strong alternative to first principles VFM and the importance of computing uncertainty in machine learning estimates is vital for future development.	NA
2	Modelling oil and gas flow rate through chokes: A critical review of extant models	2022	Agwu, Okoro, Sanni	Literature research	Comprehensive literature study similar to [1]. This research further goes on to summarise most empirical research done since 1950 in-terms of methodology, data-size, data source and independent variables. Provides related domain knowledge on petroleum industry and oil well sub-system similar to [1].	NA
3	Virtual Multiphase Flow Meter using combination of Ensemble Learning and first principle physics based	2022	A. Ishak et al.	Quantitative research	Uses ensemble learning to develop the data driven model by incorporating multiple ML models. Data driven model is combined with the physics model using a combiner. Achieves a 50% improvement in performance using the combiner compared to their stand-alone	Hybrid VFM

					performance of physics based and ML based VFMs.	
4	Virtual multiphase flow metering using diverse neural network ensemble and adaptive simulated annealing	2018	T. A. AL-Qutam et al	Quantitative research	ML VFM based on ensemble learning.	ML VFM
5	A Machine Learning Approach for Virtual Flow Metering and Forecasting	2018	N. Andrianov	Quantitative research	**Principle** Estimate future values of multiphase rates based on the previous behaviour of the system. **Model** Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) model. Not only to accurately estimate the multiphase rates at current time but also to forecast the rates for a sequence of future time instants.	ML VFM
6	Bayesian neural networks for virtual flow metering: An empirical study	2021	B. Grimstad et al	Quantitative research	ML based VFM, implemented on Bayesian Neural Network (BNN).	ML VFM
7	A Physics-Informed Neural Networks (PINN) oriented approach to flow metering in oil wells: an ESP lifted oil well system as a case study	2022	T. S. Franklin et al	Quantitative research	A hybrid VFM combining Physics Informed Neural Network (PINN) model and LSTM-RNN based ML model.	Hybrid VFM