

Temporal Fusion Transformer driven Virtual Flow Meter for Oil Well Production Optimization

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Abstract—The accurate measurement of oil flow rates is critical for optimizing oil well production. Traditional physical flow meters are often costly, require regular maintenance, and are prone to failure in harsh operating conditions. This research proposes a novel approach to address these challenges by leveraging TFT neural networks for virtual flow metering in oil well production. The Transformer architecture, known for its success in natural language processing tasks, is adapted to capture the complex relationships and dependencies in the oil flow data using TFT. This research presents a detailed methodology for training the virtual flow meter using historical production data and demonstrate its performance on a real data-set. Additionally, this research explores the potential of transfer learning techniques to enhance the generalization capabilities of the virtual flow meter across different well configurations and operating conditions. The findings of this research contribute to the advancement of oil well production optimization by providing an accurate, cost-effective, and reliable alternative to traditional flow meters.

Index Terms—oil well optimization, neural networks, virtual flow meter, temporal fusion transformer, transfer learning

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 TFT based neural network model for accurate prediction of flow rates in oil and gas wells.

A. Background and Motivation

The optimization of oil well production plays a vital role in the efficient extraction and utilization of oil reserves. Traditional flow meters, although widely used, have limitations such as high cost, regular maintenance requirements, and vulnerability to harsh operating conditions. These challenges hinder efficient oil well production management and can result in sub-optimal resource utilization and increased operational

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
TFT	Temporal Fusion Transformer
VFM	Virtual Flow Meter

TABLE I Acronyms

costs. To address these issues, there is a growing interest in exploring alternative methods for flow rate measurement in oil well production. Machine learning and artificial intelligence techniques have demonstrated great potential in various domains, and there is a need to investigate their applicability in the field of virtual flow metering. The development of a virtual flow meter, based on advanced neural network architectures such as TFT, holds promise for accurate and cost-effective flow rate estimation. The Transformer neural network [1], originally designed for natural language processing tasks, has shown remarkable performance in capturing complex relationships and dependencies in sequential data. [2] On a variety of real-world data-sets have demonstrated significant performance improvements for TFT over existing benchmarks for predicting time-series data. Applying the TFT architecture to oil flow data can potentially unlock new insights into the underlying patterns and dynamics of oil well production. By training a virtual flow meter using historical production data, we can leverage the power of deep learning to create a robust and adaptable model capable of accurately estimating flow rates. The motivation behind this research proposal is to explore the feasibility and effectiveness of a TFT-based virtual flow meter for oil well production optimization. By developing an accurate and reliable alternative to traditional flow meters, this research aims to contribute to the advancement of oil production management practices. A successful implementation of this virtual flow meter has the potential to significantly reduce operational costs, enhance resource allocation, and improve decision-making in the oil and gas industry. By leveraging the capabilities of the TFT neural network and investigating transfer learning techniques, we aim to create a virtual flow meter that can generalize across different well configurations and operating conditions. The findings of this research will not only benefit oil production companies but also contribute to

the broader field of machine learning in industrial applications. Overall, this research proposal seeks to address the limitations of traditional flow meters in oil well production optimization by harnessing the power of TFT neural networks. By providing an accurate, cost-effective, and reliable alternative for flow rate measurement, this research has the potential to revolutionize the way oil well production is managed, ultimately leading to increased efficiency and profitability in the industry.

B. Problem Statement

Accurate measurement of oil flow rates is vital for optimizing the production of oil wells. Traditional flow meters, although widely used, pose several challenges that hinder efficient oil well production management. These challenges include high costs, regular maintenance requirements, and vulnerability to harsh operating conditions. Additionally, traditional flow meters may not provide real-time measurements or adapt to varying well configurations and operating conditions. As a result, suboptimal resource utilization, increased operational costs, and inaccurate decision-making can occur. To address these challenges, this research proposal aims to develop a TFT Neural Network-based virtual flow meter for oil well production optimization. The goal is to create an accurate, cost-effective, and reliable alternative to traditional flow meters that can estimate flow rates in real-time, adapt to different well configurations, and operate effectively in harsh conditions. The proposed virtual flow meter leverages the power of the TFT neural network, known for its ability to capture complex relationships and dependencies in sequential data. By training the virtual flow meter with historical production data, the model can learn and predict oil flow rates based on various input parameters such as pressure, temperature, and well characteristics. The problem at hand is twofold: firstly, the development of a virtual flow meter that accurately estimates flow rates in real-time, overcoming the limitations of traditional flow meters. Secondly, the virtual flow meter should be capable of adapting to different well configurations, operating conditions, and variations in production patterns. Addressing these challenges will enable accurate and timely flow rate estimation, leading to improved oil well production optimization. Solving these problems will have significant implications for the oil and gas industry. The proposed virtual flow meter has the potential to reduce operational costs by eliminating the need for expensive traditional flow meters and their associated maintenance. Additionally, the virtual flow meter can provide valuable insights into production patterns, enabling better decision-making and resource allocation. By developing a TFT Neural Network-based virtual flow meter for oil well production optimization, this research proposal aims to contribute to the advancement of oil production management practices. The resulting solution has the potential to revolutionize the industry by providing an accurate, cost-effective, and adaptable alternative for flow rate measurement, leading to improved efficiency, reduced costs, and enhanced decision-making in oil well production operations.

C. Research Objectives

- 1) Develop a virtual flow meter based on TFT neural networks to accurately estimate oil flow rates in real-time for oil well production optimization.
- 2) Investigate the feasibility and effectiveness of the TFT architecture in capturing the complex relationships and dependencies present in oil flow data.
- 3) Explore the use of historical production data to train the virtual flow meter and establish its accuracy and reliability compared to traditional flow meters.
- 4) Evaluate the performance of the TFT-based virtual flow meter in various well configurations and operating conditions, ensuring its adaptability and versatility.
- 5) Investigate transfer learning techniques to enhance the generalization capabilities of the virtual flow meter across different oil well production settings.
- 6) Compare the performance of the proposed virtual flow meter with existing flow metering methods, quantifying the advantages in terms of cost, accuracy, and maintenance requirements.
- 7) Analyze the impact of the virtual flow meter on oil well production optimization, including resource allocation, decision-making, and operational cost reduction.
- 8) Provide recommendations and guidelines for implementing and deploying the TFT-based virtual flow meter in real-world oil production scenarios.
- 9) Assess the scalability and potential for integration with existing oil production systems, considering computational requirements and data management aspects.
- 10) Contribute to the broader field of machine learning in industrial applications by showcasing the applicability of TFT neural networks in optimizing oil well production processes.

D. Preliminary Suppositions and Implications

- 1) Accuracy of Virtual Flow Meter: It is assumed that the TNN-based VFM will accurately estimate the flow rate of oil wells by leveraging the inherent patterns and relationships present in the operational data. The TNN's ability to capture complex dependencies and generalize from the available data will be a critical factor in achieving accurate flow rate predictions.
- 2) Data Availability and Quality: It is assumed that sufficient historical data on oil well production, including flow rates and associated parameters, is available for training and evaluating the TNN-based VFM. Additionally, the data is expected to be of good quality, ensuring that the model can effectively learn the underlying patterns and relationships.
- 3) Generalizability of the Model: The TNN-based VFM is expected to demonstrate generalizability across different oil well configurations and production conditions. The model's ability to adapt to varying well geometries, fluid properties, and operating conditions is crucial to ensure its effectiveness in real-world applications.

- 4) Optimization of Production: The successful implementation of the TNN-based VFM is assumed to enable optimization of oil well production. By providing accurate and real-time flow rate estimations, the virtual flow meter can facilitate decision-making processes related to production optimization, such as adjusting choke valve settings, identifying well performance issues, and maximizing production efficiency.
- 5) Computational Efficiency: The proposed TNN-based VFM is expected to demonstrate computational efficiency, allowing for real-time or near real-time flow rate predictions. The inherent parallelism and scalability of TFT models will be leveraged to develop an efficient solution that can handle the computational demands of processing large volumes of data in a time-sensitive production environment.

The implications of this research are significant for the oil and gas industry. If successful, the development and implementation of a TNN-based VFM could lead to substantial benefits, including enhanced production optimization, improved reservoir management, and reduced operational costs. Additionally, the virtual flow meter has the potential to mitigate risks associated with physical flow meters, such as maintenance requirements, measurement errors, and equipment failures.

It is essential to address these preliminary suppositions and implications through rigorous research, model development, and comprehensive evaluation. By doing so, we can contribute to the advancement of oil well production optimization techniques and provide a valuable tool for the industry.

II. LITERATURE SURVEY

[3] 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 VFM and physical flow meters measure the flow rates indirectly [3]. Physical flow meters bring their own set of sensors whereas VFM 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. VFM, therefore can be categorized into 3 types; physics based, ML based and hybrid flow meters. Physics based VFM are also called first principle VFM or physics simulator based VFM. Physics based VFM 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 VFM 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 VFM on the other hand are purely data driven. Hybrid VFM implement combined physics based and ML based models. All 3 types of VFM 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 to 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 VFM have the limitation of being restricted to steady state, meaning that if there are rapid transient changes in the flow, VFM will not predict them accurately. Therefore VFM cannot predict startup, shutdown and other transient scenarios. ML and hybrid VFM also cannot accurately handle advanced what-if predictive scenarios. Physics based VFM in contrast can accurately handle advanced what-if predictive scenarios.

In a typical well, pressure and temperature sensors are deployed in the well bottom-hole (BH), well-head (WH) and

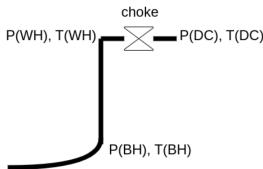


Fig. 1: Well Sensors

downstream of the choke (DC) [3]. 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 VFM. [4] more recent work published in 2022, similar to [3] performs a detailed study on the physical and virtual FMs with overlapping content.

The hybrid VFM proposed by [5] 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. [6] 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 $\pm 15\%$. [7] 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. [7] has achieved the best accuracy when the lengths of the input and output sequences to LSTM are equal. [8] 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. They 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. [9] 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 [7], the system proposed by [9] is hybrid model

using NN for physics based model as well as the ML based model. [10] employs Back Propagation (BP) neural network, Long Short-Term Memory (LSTM) network, and Random Forest algorithm to develop an intelligent data-driven model for virtual flow meters in oil and gas development. Their data-set is constructed using actual data from two oil wells in an offshore oil field in the South China Sea. Among the three models, the LSTM model has demonstrated the highest accuracy, with a Mean Absolute Error (MAE) of 3.9%. LSTM has also demonstrated the highest stability and requires a moderate amount of data volume. BP network on the other hand have exhibited the lowest accuracy, with a MAE of 12.1%, as well as the lowest stability. BP however has shown the smallest data volume requirement. The Random Forest model has shown moderate accuracy, high stability, but has required the highest data volume.

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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