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

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I. Introduction

Oil and gas production is a complex process that involves the extraction of hydrocarbons from underground reservoirs. Oilfield is a geographical area that encompasses one or more oil or gas reservoirs equipped with the necessary infrastructure for exploration, extraction and production. The fluid mixture flowing out of the well consists of oil, natural gas and water. The flow rates of oil, gas and water reflect the performance of the well. Petroleum Engineers need to make informed decisions regarding the production strategies based on the performance of the wells. Through accurate predictions of flow rates, petroleum Engineers can diagnose production inefficiencies and constraints, implement solutions to optimize production and project future investments. Physical flow meters and virtual flow meters are used to predict flow rates in the oil wells. Physical flow meters are often very expensive, require regular maintenance, and are prone to failure in harsh operating conditions. Physical flow meters use in-built sensor data and physics based mathematical equations to predict the real-time flow rates. Virtual flow meters in contrast, can use physics based mathematical models, machine learning based models or hybrid models to predict the flow rates [1]. Oil wells are installed with temperature, pressure and valve sensors in well-bottom-hole (BH), well-head (WH) and downstream choke (DC) and the time series data produced by sensors are consumed by VFMs for modeling and predictions.

A. Research Problem

Well flow rate prediction is a challenging problem due to the complex design of the well and the complicated physics of the fluid mixture flowing out of the well. These challenges affect accurate predictions regardless of the type of flow meters used. Physical flow meters are the most common method of measuring oil and gas well rates. They are however extremely expensive to install and maintain. The accuracy of the physical flow meters gradually reduces over time and requires re-calibration. Virtual flow meters (VFMs) are a growling alternative to physical flow meters. VFMs are less expensive than physical flow meters and can be used when physical flow meters are not financially viable. VFMs are typically less accurate than physical flow meters, and they they are often complex to develop and implement. The hybrid VFM models which use physics and machine learning have become increasingly popular since 2018. Increase usage of neural networks including RNN and LSTM also seen for developing both physics and ML based models [2].

Although many types of neural networks have been evaluated in literature, author at the time of writing did not discover any experimentation or implementation of transformers for VFMs. Transformers [3], originally designed for natural language processing tasks, have shown remarkable performance in capturing complex and long range dependencies in sequential data. Temporal Fusion Transformer (TFT) [4] a type of a transformer network, on a variety of real-world datasets have demonstrated significant performance improvements over existing benchmarks for predicting time-series data. The author therefore argues that developing a VFM based on promising transformers holds potential for accurate and cost-effective flow rate prediction leading to greater production optimization and profits.

B. Research Objectives

1) Investigate the feasibility and effectiveness of the TFT architecture in capturing the complex relationships and dependencies present in oil flow data.
2) Develop a virtual flow meter based on TFT neural networks to accurately estimate oil flow rates in real-time for oil well production optimization.
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) Provide recommendations and guidelines for implementing and deploying the TFT-based virtual flow meter in real-world oil production scenarios.
8) Assess the scalability and potential for integration with existing oil production systems, considering computational requirements and data management aspects.
9) 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.

C. Methodology

The author proposes a novel approach to address the accuracy challenges by leveraging the capabilities of the TFTs and exploring transfer learning techniques to generalize across different well configurations and operating conditions.

1) Data collection: Real-world well sensor data will be provided by the author's employer based in Scandinavia.
2) Data preprocessing: Clean and prepare the data for training the TFT model. This may involve removing outliers, imputing missing values, and scaling the data.
3) Feature engineering: Extract relevant features from the data that can be used to predict the flow rates. This may involve using statistical methods, such as time series analysis, or machine learning algorithms, such as principal component analysis.
4) Model training: Train the TFT model on the preprocessed data. This involves tuning the model hyperparameters and training the model until it converges.
5) Transfer learning: Explore transfer learning techniques to enhance the generalization capabilities of the virtual flow meter across different well configurations and operating conditions.
6) Model evaluation: Evaluate the performance of the trained model on a held-out test set. This involves calculating metrics such as mean absolute error (MAE) and mean squared error (MSE).
7) Model deployment: Deploy the trained model to production so that it can be used to predict flow rates in real time.

References

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