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A Hybrid Approach to Virtual Flow Metering Using Physics Based Models and Machine Learning

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Abstract
The use of machine learning and big data is becoming increasingly important for optimizing production and ensuring operational efficiency in the upstream oil and gas industry. This paper presents a hybrid virtual metering solution aimed at supplementing and improving flow rate predictions. By leveraging the capabilities of a multiphase flow simulator (LedaFlow) and advanced machine learning techniques, we generate high-fidelity synthetic data to train a neural network model. This trained model is deployed in an online, real-time environment to predict gas, oil, and water flow rates using measured data available from typical well instrumentation.

This methodology was applied to an offshore field in the North Sea operated by Vår Energi, encompassing 15 wells, and its performance was evaluated against field measurements located on the offshore floating production unit. The results demonstrate enhanced prediction accuracy under highly varying well conditions, thereby supporting better decision-making in flow assurance and production operations.

Introduction
The upstream oil and gas industry is increasingly relying on advanced technologies to enhance production optimization and ensure operational efficiency. Machine learning and big data analytics are at the forefront of these technological advancements, offering significant potential for improving flow rate predictions. Accurate flow rate measurement is crucial for optimizing production, ensuring safety, and making informed operational decisions. Traditional metering techniques, while effective, can be complemented and enhanced through the integration of virtual metering solutions that utilize machine learning models. This paper introduces a hybrid virtual metering solution that leverages the capabilities of LedaFlow (transient multiphase flow simulation software) and advanced machine learning techniques. By generating high-fidelity synthetic data, we train a neural network model to predict gas, oil, and water flow rates in real-time. This model is deployed in an offshore field in the North Sea, encompassing 15 wells, and its performance is evaluated against field measurements from the offshore floating production unit.

Methodology
The hybrid virtual metering solution involves the integration of LedaFlow, a state-of-the-art multiphase flow simulation tool, with advanced machine learning techniques to generate synthetic data and train a neural network model.

Experimental Procedure
The methodology can be divided into several key steps depicted in Fig. (1).

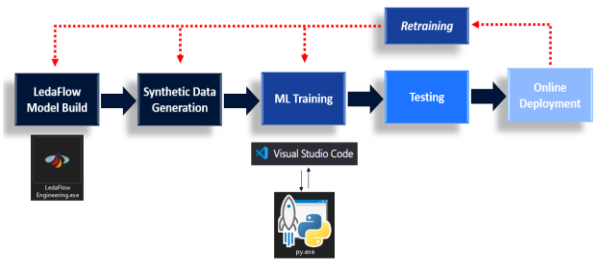

Figure 1: Hybrid Approach Workflow

1. **Data Collection and Preprocessing**: Field data from 15 wells in an offshore field in the North Sea is collected. This data includes well pressure, temperature, and flow rates of gas, oil, and water. Initial preprocessing involves cleaning the data to remove anomalies and fill in missing values to ensure data quality and consistency.

2. **Multiphase Flow Model Build and Initial Calibration**: Use of field data for initial

multiphase flow model benchmarking and calibration.

3. **Synthetic Data Generation**: The multiphase flow model is used to simulate various well conditions and generate high-fidelity steady-state synthetic data. This synthetic data is used to supplement the limited field data and enhance the training dataset for the neural network model. The data generated (given different model boundary inputs) is detailed in the next step and forms the input layer for the neural network.

4. **Neural Network Training:** The neural network model was trained using synthetic data. The model architecture was optimized to ensure accurate prediction of flow rates under varying well conditions. The architecture included:

   Input Layer: Featuring wellhead pressure (P_{WH}), bottom-hole pressure (P_{BH}), wellhead temperature (T_{WH}), bottom-hole temperature (T_{BH}), wellbore pressure drop (ΔP), wellbore temperature drop (ΔT) and well subsea choke (CV) opening. Noise could be introduced for certain machine learning features, when necessary, to prevent overfitting and address potential inaccuracies in measurements.

   Hidden Layers: Comprised of multiple layers of interconnected nodes (neurons), which processed the input features through nonlinear transformations to capture complex relationships.

   Output Layer: Provided the predicted flow rates of gas, oil, and water. The relationship modeled can be described by the Eq. (1):

$$Q_{gas}, Q_{oil}, Q_{water} = f(P_{BH}, P_{WH}, T_{BH}, T_{WH}, \Delta P, \Delta T, CV) \quad (1)$$

5. **Machine Learning (ML) Model Testing**: The trained ML model is tested on diverse synthetic test datasets, which include varying gas-oil ratios (GOR) and water cut (WC) ranges, to ensure its effectiveness and accuracy. By using synthetic data not previously utilized during the training phase, this evaluation phase assessed the model's ability to generalize to new, unseen conditions. The model's output was compared against these test sets, with key metrics such as the R^2 score (described in Eq. (2)) and comparisons of actual (y_i) versus predicted flow rates ($\hat{y}_i$). These evaluations quantified the model's accuracy and predictive power, ensuring its robustness and reliability.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (2)$$

   where,

$$SS_{res} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (3)$$

$$SS_{tot} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2 \quad (4)$$

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \quad (5)$$

6. **Real-time Deployment**: The trained neural network model is deployed in an online environment to predict gas, oil, and water flow rates in real-time. The model's performance is continuously monitored and evaluated against field measurements from the offshore floating production unit. Machine learning predicted rates are also used as boundary conditions for online dynamic simulations based on LedaFlow models, providing a pathway for real-time verification and accuracy monitoring of the ML predictions.

7. **Re-Training and Re-Calibration**: Based on comparisons with topside measurements, the multiphase flow model is re-tuned, particularly focusing on heat transfer coefficient to calibrate for uncertainties in wellbore heat loss, and synthetic data was re-generated. Machine learning model parameters are also tuned to prevent overfitting to test datasets (feature noise, epochs, number of hidden layers and nodes, etc.).

Results and Discussion

All wells in the project are characterized as low flow, late-stage wells. The individual multiphase flow meters (MPFMs) installed on these wells were found to be either faulty or have different ranges of inaccuracy, which necessitated the implementation of a virtual flow metering approach.

The summation of the machine learning-predicted multiphase flow rates is compared against the topsides inlet separator(s) single-phase meters (outlet lines) in Figs. (2-4). The comparison revealed an accuracy of 5-10% for all three phases, with variations attributed to changing operating conditions (e.g., changes in WC, GOR, choke position, or inlet flowline pressure due to well routing) not originally accounted for in the initial training iteration. Additionally, some discrepancies were due to faulty or incorrect measurement values from the field.

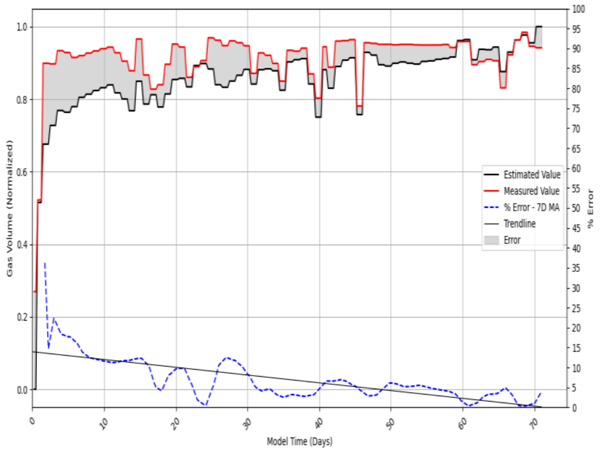

Figure 2: Measured vs Simulated Gas Daily Totalized Volumes

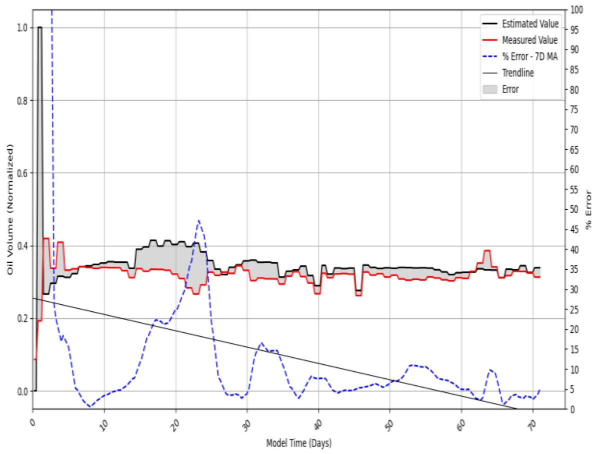

Figure 3: Measured vs Simulated Oil Daily Totalized Volumes

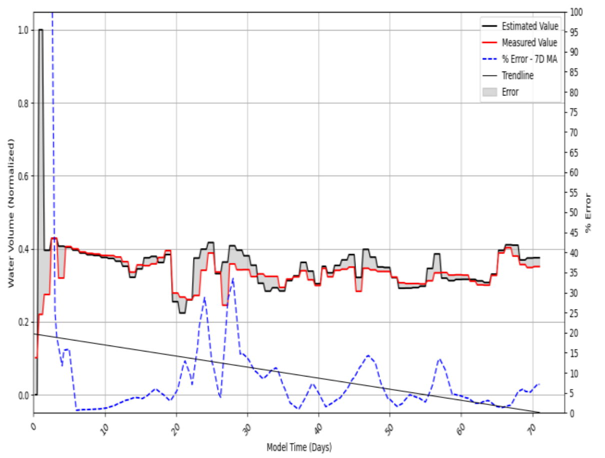

Figure 4: Measured vs Simulated Water Daily Totalized Volumes

Key findings from the results include:

1. **Improved Accuracy**: The integration of synthetic data with field measurements, along with ML model retraining as more historical data became available (e.g., pressure, temperature and choke CV operating ranges), significantly improved the neural network model's accuracy, as shown by the downward trend of the % error in Figs. (2-4). The model mostly provided flow rate predictions within a 5-10% error margin when compared to topsides single-phase measurements after initial training iterations were completed.

2. **Enhanced Reliability**: The virtual metering system proved to be a reliable alternative to the faulty or inaccurate individual well MPFMs, ensuring continuous and accurate monitoring of well performance. By utilizing advanced algorithms and integrating data from multiple sources, the system provided consistent measurements even in challenging operating conditions.

3. **Real-time Adaptability**: Integrating the ML VFM with the online dynamic simulator enabled continuous validation, facilitated the identification of recalibration needs, and provided accurate flow assurance insights.

Conclusions

The implementation of a hybrid virtual metering solution, which combines LedaFlow simulations with advanced machine learning techniques, has enhanced flow rate predictions for an offshore field in the North Sea. The neural network model, trained on a blend of field data (implicitly via model calibration) and high-fidelity synthetic data (explicitly), demonstrated notable accuracy improvements under a variety of well conditions. This innovative approach not only addresses the limitations of traditional multiphase flow meters but also supports better decision-making in flow assurance and production operations. Other benefits of this hybrid solution include GOR and WC predictability, less computational resources needed than traditional physics based virtual metering solutions and reduced online tuning requirements.

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