Virtual flow-tool for monitoring and troubleshooting multiphase flow meters

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1 INTRODUCTION

In the oil and gas industry, accurately measuring the flow rates of oil, gas, and water from subsea wells is critical for production optimisation and allocation accounting. Physical Multiphase Flow Meters (MPFMs) [1] are complex sensor systems used for this purpose. Multiple subsea wells are often co-mingled into a single flowline, which transports the multiphase fluid to a topside processing facility. Here, separators divide the fluid into its constituent phases (oil, gas, water), which are then measured individually using more reliable single-phase meters.

Multiphase meters are inherently complex, necessitating significant time and effort for effective monitoring and maintenance. Apart from virtual measurement systems, there is a notable absence of tools designed to enhance the accuracy and quality of these systems. As fields mature and assets expand with increasing number of meters, the challenges associated with measurement systems escalate in both scale and complexity. Water production adds further complexity through slugging, lower oil fractions with higher relative measurement uncertainty, and sampling difficulties, underscoring the need for robust tools to address these issues proactively Manually monitoring these fields becomes highly intricate and time consuming and therefore there is an increased risk of undetected measurement errors or even the potential use of incorrect data for multiphase meter calibration.

This paper details the development of a Virtual Flow Metering (VFM) system to address this challenge and is tested on three flow streams operated by AkerBP with the aim of reducing undetected measurement errors and enhancing the quality of multiphase flow measurements. A machine-learning driven approach is used which utilises existing instrumentation data such as choke pressures, temperatures as well as internal multiphase instrumentation and separator data to monitor and troubleshoot topside MPFMs.

2.1 Problem Description and Test Setup

The aim of the project was to allow AkerBP to have further confidence in the multiphase flow rates coming from three top side multiphase meters (A, B and C) while decreasing the manual effort required to monitor and follow up on these meters.

Upstream of the topside multiphase meter (MPFM) is a series of subsea wells. Downstream of the topside meters, the three flow lines flow into a separator. From the separator, an ultrasonic meter for single phase gas, a magnetic meter for water and a turbine for oil is used. Each flowline transports multiphase flow from a series of subsea wells and is equipped with a physical topside MPFM located upstream of the separator. The MPFMs are from different vendors, provide real-time estimates for oil, gas, and water flow rates.

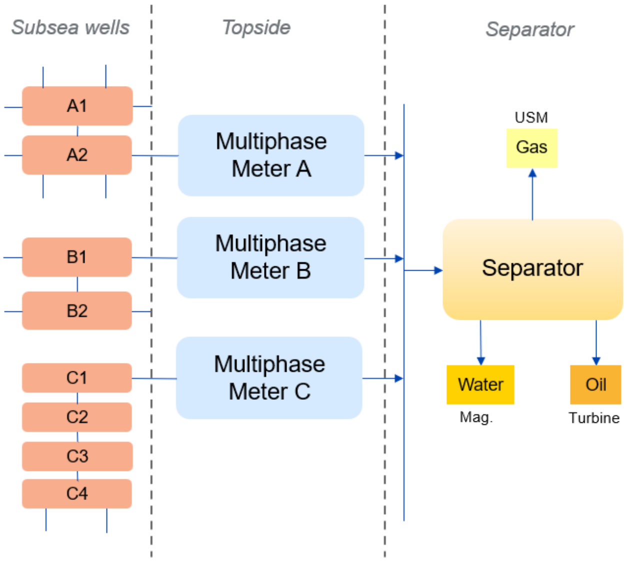

Fig. 1 - Schematic of the production system with flowlines, MPFM and separator.

All instrumentation and historical data is available through, AkerBP's Cognite Data Fusion (CDF) cloud platform. This includes pressure, temperatures, valve positions, sensor outputs and flow rates. For each multiphase meter, pressures, differential pressures, gamma densitometer, permittivity and conductance sensor outputs are also available.

2.2 Modelling Approach

Two primary modelling approaches are common for VFMs: physics-based (first principles) models and data-driven models [2]. A hybrid approach combining data-driven models with physics-based constraints could also be used.

2.2.1 Physics-based models

Physics-based models are based on first principles of flow measurement and require an understanding of the process and thermodynamic principles. For example, in an oil and gas application, valves are present in the process and the pressure drop across the valve is known, alongside pressure, temperature, density, composition and choke valve position, a correlation can be developed to provide a simple estimation of flow rate.

Whilst this is documented in standards for single phase flows such as ANSI/ISA-75.02.01-2008 [3], previous testing at TÜV SÜD showed that this can also be applied for multiphase flows but only if the mixture density is well understood [4]. TÜV SÜD previously tested a number of physics-based models such as Sachdeva, Al-Safran and Hydro models [5,6,7] in combination with over 11 different slip models against measurement on a commercial choke valve at TÜV SÜD's multiphase facility for over 400 test points [4]. Overall, predicted mass flow rates were within 10 % of the separator flow rates.

It is important to note that all of these models had to utilise some form of coefficient, which is a modifying factor to absorb errors due to assumptions within the model. An important finding was that single phase data could be used to calibrate the model in most scenarios. Improvements were also made when the valve was flow calibrated rather than using manufacturer datasheets. And further improvements were made when phase slip (where the phases move at different speeds) was included. In conclusion, a successful physics-based model required an extensive range of test data to verify and calibrate the model which including a variety of different choke positions, operating conditions, detailed information about piping geometry, cage sizes within the valve as well as detailed PVT model.

A physics-based model requires, similar to a physical meter, some form of calibration and testing as well as detailed knowledge of the valve geometry and fluid properties. An initial attempt to test some physics-based models resulted in a very sensitive model as there were insufficient variations in the data to tune the model.

2.2.2 Data-driven models

Data-driven models take a fundamentally different approach. Instead of relying on physical equations and detailed system knowledge, they learn patterns directly from the historical operational data. These models use machine learning algorithms to identify relationships between input sensor measurements and target flow rates.

The main advantage of data-driven VFM models is their flexibility. They can capture complex, nonlinear relationships that might be difficult or impossible to model using first principles, especially in multiphase flow where the interactions between phases are highly complex. VFMs also do not require detailed physical specifications of the equipment, instead can learn the system behaviour implicitly from the data.

However, a similar limitation of a data-driven model to a physics-based model is the quantity and quality of the data available to train and tests these models. There must be a sufficient diverse range of flow conditions to allow the model to adequately learn appropriate trends. Otherwise, the model will be highly biased towards one set of operating conditions. Operationally, this can be limiting so we have proposed a simplistic consideration for this in Section 4.2 that notifies the user when the model may be extrapolating and could benefit from some retraining. As fields evolve through their lifetime and operate in different manners, re-training of these models will always be necessary and should be expected, but having a set of conditions to allow the user to make informed decisions of when to re-train a model provides further valuable feedback.

2.2.3 Selected modelling approach

Single stream data, where only either Streams A, B or C flow into the separator, provides valuable training and test data to develop either a physics-based or data-driven model. Periods of time where single stream tests had been performed were provided by AkerBP. Stream A had two periods in 2025 of around 4-7 hours, Stream B had five periods of around 3-5 hours between 2022-2023 and Stream C had five periods between 2022-2024 of around 5-7 hours. If the data was analysed once a minute this would equate to around 500 data points for Stream A and approximately 1000 datapoints for Streams B and C.

Throughout the analysed periods, operating conditions remained broadly consistent. The choke valves were typically in a fully open position, and the separator flow rates for oil, gas, and water exhibited variations of no more than 10% across most scenarios. Additionally, the dataset lacked detailed information regarding the physical dimensions of the choke valves, and no data were available on the internal geometry of the multiphase flow meter. These limitations posed significant challenges to the development of a physics-based model. Although preliminary modelling efforts were undertaken, the number of assumptions required rendered the resulting model insufficiently reliable for practical application.

A data-driven modelling approach was therefore selected as operational time-series data could be used without the need for detailed physical specifications. Given the availability of extensive historical data from AkerBP's Cognite Data Fusion (CDF) cloud platform, additional datasets where there is confidence in the flow rates from all three streams could also be used and is discussed further in Section 2.3.

2.3 Data Acquisition and Feature Engineering

We utilised two primary datasets for model development:

- Single Flowline Calibration Data: This dataset was captured during periods when only one flowline was directed to a separator, as discussed in Section 2.2.3. In this scenario, the separator measurements could be used as the ground truth (target variables) for testing and validating the models.

- Stable MPFM Data: AkerBP's engineers identified historical periods where MPFM estimates were considered stable and reliable, with no operational changes like valve adjustments or flow diversions.

For each dataset, specific time periods were identified by AkerBP engineers, and the relevant sensor data was extracted from the Cognite cloud. We identified input features (sensor measurements) that were most correlated with the target flow rates.

Table 1 – Sensor measurements available as model inputs for the specific flowline

	Sensor Measurements - Inputs
Choke	valve position
	Upstream pressure
	Downstream pressure
	Upstream temperature
MPFM	Differential pressure (DP)
	Density
	Pressure
	Temperature
	Permittivity
	Conductivity

Table 2 – Targets for the model

Dataset	Targets for model training
Stable MPFM Data	MPFM Oil Mass Flow rates
	MPFM Gas Mass Flow rates
	MPFM Water Mass Flow rates
Single Flowline Calibration Data	Separator Oil Mass Flow rates
	Separator Gas Mass Flow rates
	Separator Water Mass Flow rates

2.4 Model Selection

An ensemble-based XGBoost (Extreme Gradient Boosting) model was chosen for the final implementation [8]. This model demonstrated superior average performance across both the smaller calibration datasets and the larger stable MPFM datasets. XGBoost also offers practical advantages for deployment, including lower latency for real-time predictions and built-in mechanisms for explainability, which help in identifying how individual input features contribute to the model's predictions.

XGBoost implements an ensemble of decision trees using gradient boosting, where each subsequent tree corrects errors made by previous trees. The algorithm optimises the following objective function:

$$Obj(t) = \Sigma_{\mathrm{i}} L(y_{\mathrm{i}}, \hat{y}_{\mathrm{i}}^{(\mathrm{t}-1)} + f_{\mathrm{t}}(x_{\mathrm{i}})) + \Omega(f_{\mathrm{t}}) \quad (1)$$

where:
- L is the loss function
- $\hat{y}_{\mathrm{i}}^{(\mathrm{t}-1)}$ is the prediction from previous iteration
- f_t is the new tree function
- $\Omega(f_t)$ is the regularization term

The implementation uses a pre-processing pipeline for input scaling and utilises a multi-output regression approach to handle the three target variables concurrently. Hyperparameter optimisation was performed using Bayesian optimisation with the Tree Parzen Estimator (TPE) algorithm to efficiently navigate the high-dimensional parameter space and carefully maximise model performance while avoiding overfitting.

Data preprocessing for the input data includes handling missing values through forward and backward filling techniques. In practice, there are often gaps in this type of data, as some sensor measurements are sampled at lower frequencies or may be missing entirely due to sensor downtime or communication errors. Given the time-dependant nature of flow measurements, the model training employs a time series cross-validation where data is chronologically split into multiple training-validation folds, ensuring predictions are always done on future data relative to the training set. The best model was chosen using the standard metrics commonly used for regression analysis such as RMSE to evaluate across training, validation and test datasets and ensure the model provides best overall performance while also providing strong generalisation across different flowline configurations.

3 CASE STUDIES

The VFM models were evaluated using separator mass flow rates as the ground truth. For each case, the combined predictions from all three flowlines were compared and evaluated against separator measurements for oil, gas, and water phases. Six configurations were tested to identify the optimal combination of input features and target variable formulations.

Table 3 – Configurations for the Case Studies

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Sensor Inputs	Valve position U/S Pressure D/S Pressure U/S Temp. MPFM DP MPFM Pressure MPFM Temp. MPFM Density	Valve position U/S Pressure D/S Pressure U/S Temp. MPFM DP MPFM Pressure MPFM Temp. MPFM Density MPFM Perm. MPFM Cond.	Valve position U/S Pressure D/S Pressure U/S Temp. MPFM DP MPFM Pressure MPFM Temp. MPFM Density	Valve position U/S Pressure D/S Pressure U/S Temp. MPFM DP MPFM Pressure MPFM Temp. MPFM Density MPFM Perm. MPFM Cond.	Valve position U/S Pressure D/S Pressure U/S Temp. MPFM DP MPFM Pressure MPFM Temp. MPFM Density MPFM Perm. MPFM Cond.	Valve position U/S Pressure D/S Pressure U/S Temp. MPFM DP MPFM Pressure MPFM Temp. MPFM Density MPFM Perm. MPFM Cond. (All flowlines)
Dataset	Single Flowline Calibration data	Single Flowline Calibration data	Stable MPFM Data	Stable MPFM Data	Reconciled MPFM Data	Stable MPFM Data

Targets for Model	Separator mass flow rates	Separator mass flow rates	MPFM mass flow rates	MPFM mass flow rates	MPFM mass flow rates	MPFM mass flow rates (all 3 flowlines)
Model Architecture	Individual flowline models	Individual flowline models	Individual flowline models	Individual flowline models	Individual flowline models	Single unified model (9 outputs)

3.1 CASE 1: Single Flowline Calibration Data

Models were initially trained on single flowline calibration data collected using the sensor inputs for the modelled flowline shown in Table 3. Permittivity and conductivity were excluded in this case. As discussed in Section 2.2.3, the available training dataset was limited because calibrations are typically conducted every 3-4 months for only a few hours per session, resulting in approximately one day's worth of aggregated data points across all flowlines. Three separate flowline models were developed for Streams A, B and C with the separator mass flow rates as the target variables. Each model split this data into an 80:20 ratio where 80% was used for training and cross-validation and 20% was used to verify and test the model on unseen data.

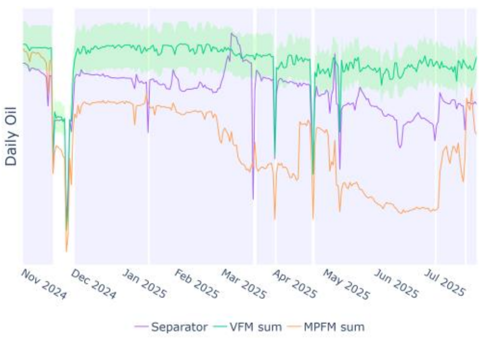

Fig. 2 - Daily Oil rates – VFM sum vs MPFM sum vs Separator

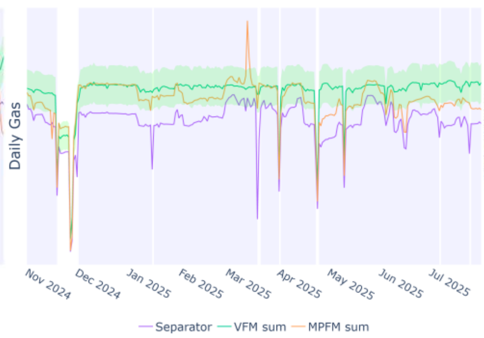

Fig. 3 - Daily Gas rates – VFM sum vs MPFM sum vs Separator

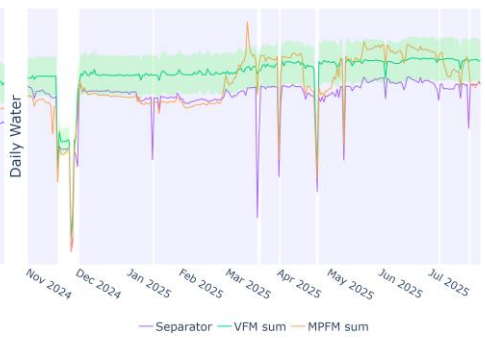

Fig. 4 - Daily Water rates – VFM sum vs MPFM sum vs Separator

Figures 2-4 compare the daily oil, gas and water mass flow rates from VFM predictions, MPFM measurements, and separator readings. The blue shaded regions show operational periods when all three flowlines are routed to the separator. The VFM predictions are shown with ±10% boundary highlighted by the green shaded area around the solid green line. Over an 8-month evaluation period, the mean absolute percentage error (MAPE), was 19.95%, 20.19% and 13.42% for oil, gas and water phases, respectively.

As seen across Figures 2-4, the VFM tends to overpredict the oil, gas and water flow rates compared to the total separator mass flow rates. The MPFM tends to underpredict the oil, overpredict the gas and both under and overpredict the water. The overprediction from the VFM and fairly linear trend across all flow rates could be due to two factors. The first is the variance of the training periods which did not exhibit enough process changes to train a model. Secondly, each flowline is co-mingled before leading to the separator so flowing a single stream compared to three streams may also have some back pressure effects on the streams. As a result, the pressures and temperatures experienced during a single stream calibration may not directly relate to those experienced during production when all three streams are flowing.

In Figures 2 and 4, there is a shift in oil and water rates from both the separator and the MPFM from March 2025 onward. The MPFM shows a reduction in oil but an increase in water whereas there appears to be an opposite trend in the separator output. From March 2025, there was a change in operation with other subsea wells flowing into the streams which appears to have resulted in a shift in the measurement of water-in-oil or the balance between oil-continuous and water-continuous flows. The VFM does not capture this effect and suggests further sensor data, or training data is required.

3.2 CASE 2: Single Flowline Calibration Data with Additional Inputs

Building on Case 1, the input feature set was expanded to include additional MPFM measurements: permittivity and conductivity. Saline water tends to have a much higher conductivity and permittivity than oil, so differences in these measurements should provide valuable information on the oil-water mix and its behaviour, for example to distinguish between oil-continuous and water-continuous flows [1].

Using the same single flowline calibration dataset as Case 1, three separate flowline models were retrained with the expanded input set (base inputs + permittivity + conductivity), with separator mass flow rates as target variables.

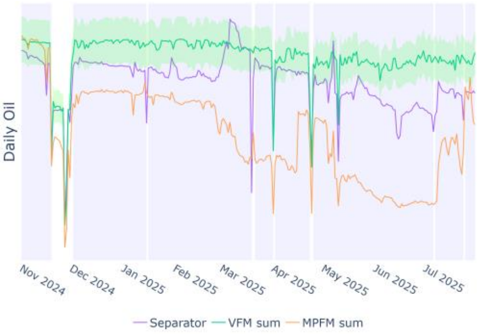

Fig. 5 - Daily Oil rates – VFM sum vs MPFM sum vs Separator

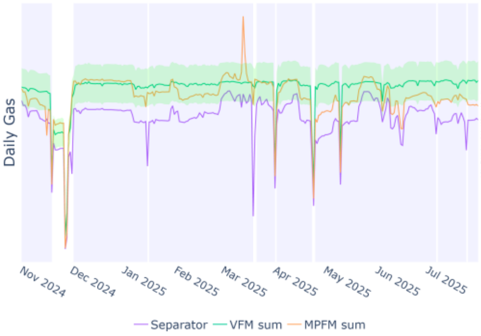

Fig. 6 - Daily Gas rates – VFM sum vs MPFM sum vs Separator

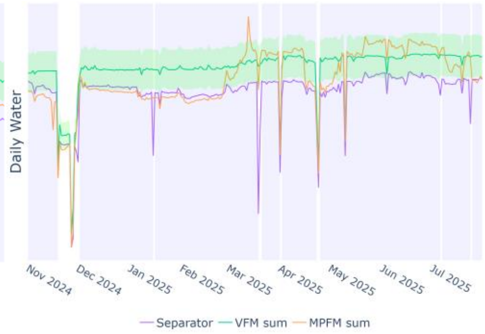

Fig. 7 - Daily Water rates – VFM sum vs MPFM sum vs Separator

Figures 5-7 compare the daily oil, gas and water mass flow rates from VFM predictions, MPFM measurements, and separator readings. Over an 8-month evaluation period, the mean absolute percentage error (MAPE), was 16.58%, 18.58% and 13.18% for oil, gas and water phases, respectively.

Adding the additional parameters appears to improve the prediction of oil by about 3% but minimal change to water. The trends appear similar to those of Case 1 for all three phases which suggests limitations of the operational variance in the single-flowline calibration data.

3.3 CASE 3: Stable MPFM Data

To address the limited availability of calibration data, models were trained on stable MPFM datasets identified by AkerBP engineers during historical periods of stable operations with no valve adjustments or flow diversions. Aggregation of multiple stable windows between June 2024 and January 2025 provided approximately 50 days of training data. The sensor inputs from Table 3 were used, with MPFM oil, gas, and water mass flow rate estimates serving as target variables. This approach provided access to extended operational windows with consistent system behaviour, expanding the training dataset compared to Cases 1 and 2.

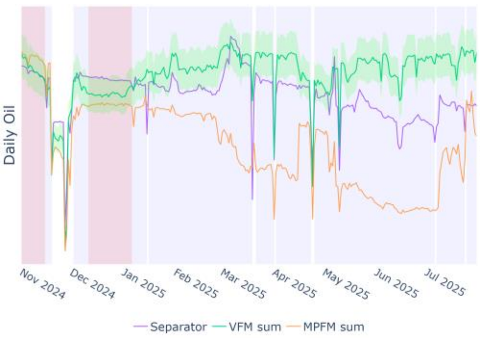

Fig. 8 - Daily Oil rates – VFM sum vs MPFM sum vs Separator

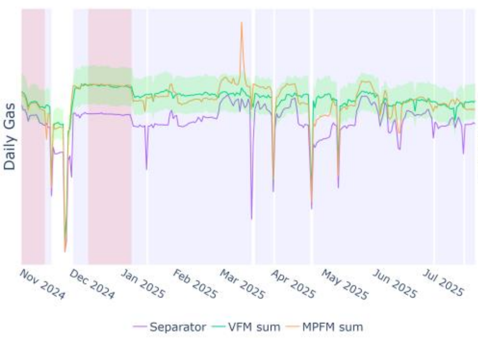

Fig. 9 - Daily Gas rates – VFM sum vs MPFM sum vs Separator

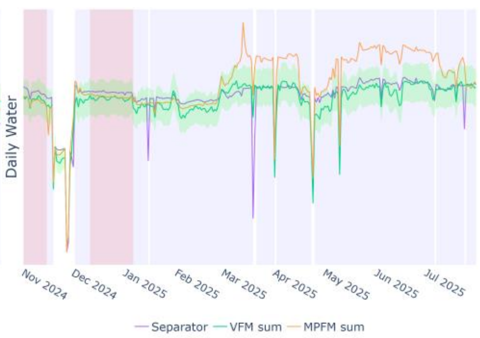

Fig. 10 - Daily Water rates – VFM sum vs MPFM sum vs Separator

Figures 8-10 compare the daily oil, gas and water mass flow rates, respectively, from VFM predictions, MPFM measurements, and separator readings. Red regions highlight the stable periods identified for model training. The blue regions show operational periods when all three flowlines are routed to the separator The VFM predictions are shown with ±10% boundary. Model performance improved for gas and water compared to Cases 1 and 2. Over the same 8-month evaluation period, the mean absolute percentage error (MAPE) was 18.43%, 13.41%, and 3.42% for oil, gas, and water phases, respectively, representing improvements across all three phases, except for relative to Case 2.

Comparing the results from the previous cases (Figures 2-7) with the current case (Figures 8-10), there is a clear difference in the overall trends from the VFM predictions. It is important to note that the model has been trained on the multiphase flow meter output of gas, oil and water as this information is available from each stream, yet the VFM does not completely replicate the MPFM despite utilising the majority of the raw measurements from the multiphase meter. The additional inputs of choke pressure and temperature in the VFM also provided additional information which helped capture different trends. These factors and the use of different modelling approaches appear to provide a much closer prediction of total oil and water, but the prediction of gas showed values similar to the multiphase meter.

3.4 CASE 4: Stable MPFM Data with Additional Inputs

Building on the stable MPFM data approach from Case 3, the input features included permittivity and conductivity measurements to evaluate whether these additional MPFM parameters could further enhance prediction accuracy when combined with the larger training dataset.

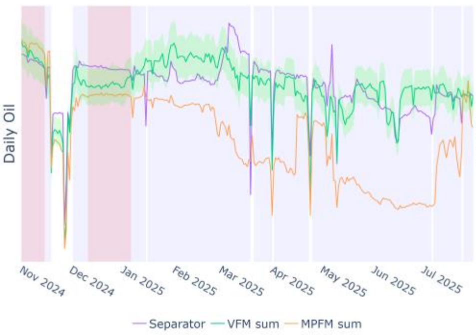

Fig. 11 - Daily Oil rates – VFM sum vs MPFM sum vs Separator

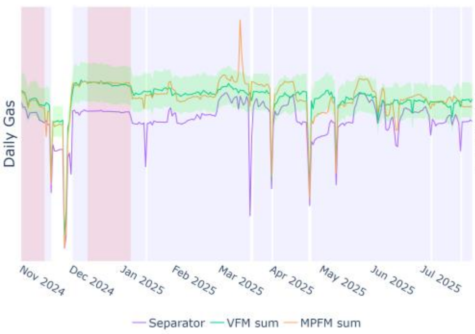

Fig. 12 - Daily Gas rates – VFM sum vs MPFM sum vs Separator

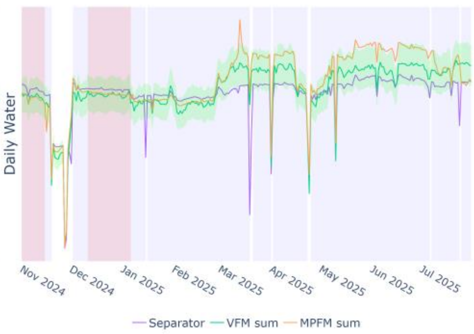

Fig. 13 - Daily Water rates – VFM sum vs MPFM sum vs Separator

Figures 11-13 compare the daily oil, gas and water mass flow rates, respectively, from VFM predictions, MPFM measurements, and separator readings. Model performance improved for oil and gas compared to Case 3. Over the same 8-month evaluation period, the mean absolute percentage error (MAPE) was 8.35%, 12.23%, and 5.93% for oil, gas, and water phases, respectively, representing the most significant improvement in the oil phase.

Comparing Figures 8-10 and 11-13, the addition of permittivity and conductivity, appears to have effects on the oil and water rates especially after March 2025. During these periods as discussed before there was a change in operation with other subsea wells flowing into the streams which appears to have resulted in a shift in the measurement of water in oil or balance between oil-continuous and water-continuous flows. Permittivity and conductivity readings increased during this period, suggesting increased water-in-oil, and the prediction of oil in the VFM begins to drop compared to Case 3. The VFM model seems to capture the trends in oil similar to the separator here, and also as evidently shown by the improvement in the oil metric from 18.43% to 8.35%. The water rates now slightly overpredict and the metrics changed from 3.42% to 5.93%. The metric for gas changed from 13.41% to 12.23%.

This highlights the value of multiple modelling approaches using similar inputs and improves confidence in the quality of the multiphase flow meter measurement by continuously monitoring these fields without the need for additional instrumentation. In this example, an acceptance criterion could be utilised between the two values to establish if there is a need for an intervention. If the uncertainty is known, a Zeta score approach or other means may be used [9].

Further improvement could be made if the data is reconciled and this is discussed in Case 5.

3.5 CASE 5: Reconciled MPFM Data with Separator Measurements

One major observation when considering stable periods was, the gas predictions needed to be improved. During the stable periods chosen, there was still a difference between the aggregated MPFM estimates and the separator rates, and the difference was highest for the gas phase as clearly seen in Figure 12. A reconciliation procedure was applied to align MPFM training data with separator measurements for each phase. The MPFM and separator rates were aggregated to hourly averages. For each hour h and phase p, let $S_{h,p}$ denote the separator total and $Q_{h,p}$ the combined MPFM total across the three flowlines. A phase-specific scaling factor was defined as:

$$f_{h,p} = S_{h,p}/Q_{h,p} \qquad (2)$$

Each flowline's MPFM rate was then scaled as:

$$Q'_{i,h,p} = f_{h,p} \cdot Q_{i,h,p} \tag{3}$$

where $Q'_{i,h,p}$ is the adjusted rate for flowline i in hour h and phase p. Each flowline's model was then trained on these scaled MPFM rates.

This procedure preserves the relative distribution among flowlines while ensuring mass balance with separator measurements. However, this approach assumes that MPFM measurement errors are proportionally distributed across flowlines within each hour and phase.

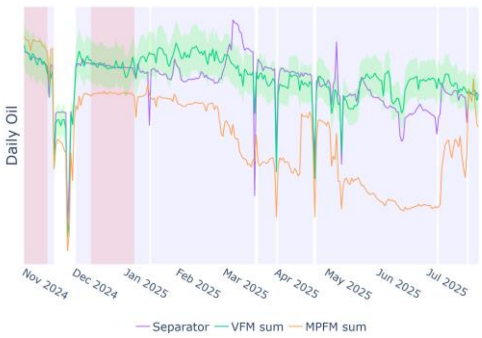

Fig. 14 - Daily Oil rates – VFM sum vs MPFM sum vs Separator

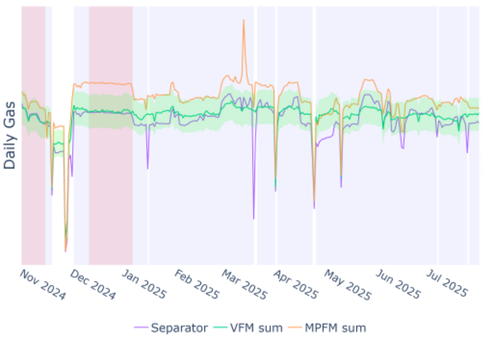

Fig. 15 - Daily Gas rates – VFM sum vs MPFM sum vs Separator

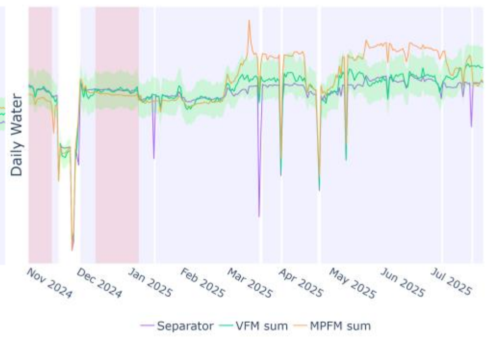

Fig. 16 - Daily Water rates – VFM sum vs MPFM sum vs Separator

Figures 14-16 demonstrate that this reconciliation approach yielded the most consistent results across all three phases. Gas predictions improved substantially, with water and oil also showing incremental gains. Over the same 8-month evaluation period, the mean absolute percentage error (MAPE) was 9.07%, 4.84% and 3.33% for oil, gas and water phases, respectively.

3.6 CASE 6: Unified Multi-Flowline Model

While Cases 1-5 employed separate models for each flowline, Case 6 explored a fundamentally different architecture: a single unified model that simultaneously predicts mass flow rates for all three flowlines.

Model Architecture:

- Inputs: All sensor measurements from all three flowlines (base inputs + permittivity + conductivity for Streams A, B, and C), resulting in total 30 input features
- Outputs: Nine predictions (oil, gas, and water mass flow rates for each of the three flowlines)
- Dataset: Stable MPFM data (same as Case 4)
- Targets: MPFM mass flow rates

This architecture was explored to evaluate whether it would enable the model to learn cross-flowline interactions and system-level patterns that the individual flowlines may not be able to capture.

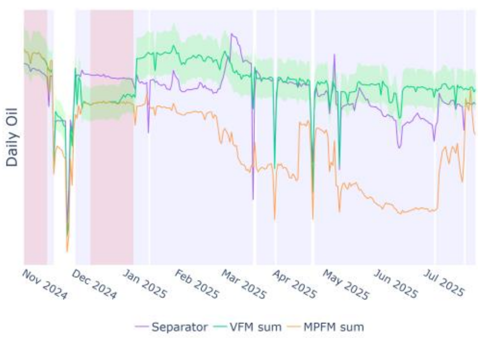

Fig. 17 - Daily Oil rates – VFM sum vs MPFM sum vs Separator

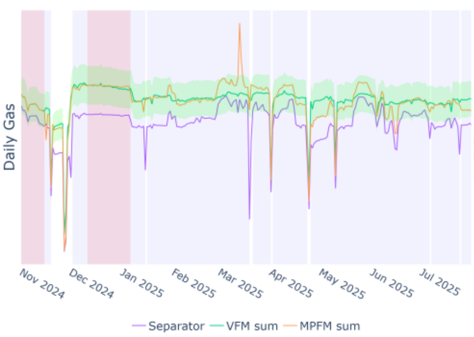

Fig. 18 - Daily Gas rates – VFM sum vs MPFM sum vs Separator

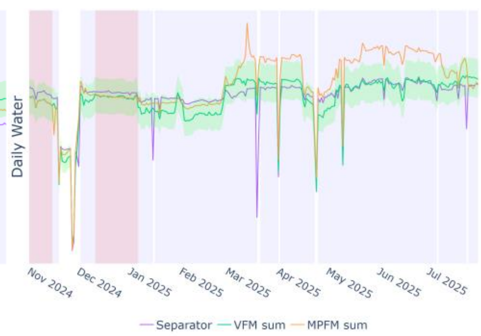

Fig. 19 - Daily Water rates – VFM sum vs MPFM sum vs Separator

Figures 17-19 compare the daily oil, gas and water mass flow rates from the unified VFM model, MPFM measurements, and separator readings. Over the same 8-month evaluation period, the mean absolute percentage error (MAPE) was 10.76%, 13.46%, and 3.95% for oil, gas, and water phases, respectively.

Compared to the individual models used in Case 4, the oil and gas metrics slightly increased from 8.35 to 10.76% and from 12.23 to 13.46%, with water metrics reducing from 5.93 to 3.95%. This indicates that the use of a unified architecture did not bring sufficient improvements.

4 RESULTS & DISCUSSION

4.1 Comparative Performance Analysis for All 6 Case Studies

Each model variant was evaluated over an 8-month period (January 2025 to August 2025), outside the training periods, using separator rates as the ground truth. Table 4 presents the evaluation metrics in terms of Mean Absolute Percentage Error (MAPE).

Table 4 – Evaluation metrics for combined flowline predictions (MAPE, %)

Phase	Oil	Gas	Water
VFM - Case 1	19.95	20.19	13.42
VFM - Case 2	16.58	18.58	13.18
VFM - Case 3	18.43	13.41	3.42
VFM - Case 4	8.35	12.23	5.93
VFM - Case 5	9.07	4.84	3.33
VFM - Case 6	10.76	13.46	3.95

Case 4 showed lower errors than Case 2 across all phases. The largest improvement was observed in the oil and water phases, with errors dropping from 16.58% and 13.18% to 8.35% and 5.93%, respectively. Case 5, which adjusted the data to match separator measurements, had the lowest errors for gas (4.84%) and water (3.33%). The oil phase error in Case 5 (9.07%) was comparable to Case 4 (8.35%). The inclusion of permittivity and conductivity proved important for predicting changes in water-in-oil content across all cases.

4.2 Operational drift monitoring

As previously noted, the reliability of both physics-based and data-driven models is fundamentally tied to the quality and relevance of the data used during their training. In operational settings, however, changes such as the opening or closing of subsea valves or the activation of wells not included in the original training dataset can introduce discrepancies. For example, in March 2025 additional wells were brought online that were not including in the original dataset.

To evaluate the performance of the model and detect when recalibration may be required, a distance function was formulated. Each subsea well has a corresponding valve with an activation status. For a flowline with n wells, the configuration at time t is expressed as an n-dimensional binary vector, x_t:

$$x_t \in 0{,}1^n \tag{4}$$

where $x_{t,i} = 1$ if well i is active and 0 otherwise.

During model training, all observed well configuration combinations are recorded as a reference set R for each flowline:

$$R = \{r^{(1)}, r^{(2)}, \ldots, r^{(K)}\},\ with\, r^{(k)} \in 0{,}1^n \tag{5}$$

For new data, the Hamming distance d_H to a training configuration is computed as:

$$d_H\left(x_t, r^{(k)}\right) = sum_{(i=1)}^{n} \left|x_{(t,i)} - r_i^{(k)}\right| \tag{6}$$

The drift score s_t is defined as:

$$s_t = min_{r \in R}\, d_H(x_t, r) \tag{7}$$

Operational conditions that differ substantially from the training set are flagged using a simple threshold-based rule with threshold τ: at time t, flag if $s_t \geq \tau$ (8)

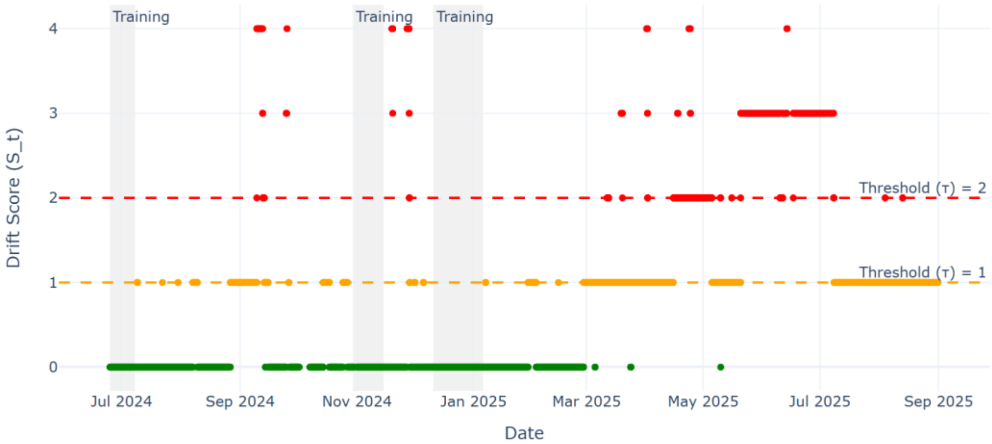

Fig. 20 – Drift score calculated for Stream A, with the thresholds set $\tau = 1, 2$ and Training periods shown.

This score s_t indicates the minimum number of well status changes observed for new data relative to known training states. Threshold rule (7) flags operational conditions that deviate significantly from the training states and can serve as an indication of potential for model degradation as well as initiate as one of the considerations for proactive retraining for the specific flowline. Figure 20 clearly shows that the majority of operation was similar to the training data prior to March 2025 and, and for flowline A, the drift score s_t exceeds 2 after March 2025, suggesting the model may need to be retrained for this new operating condition.

5 DEPLOYMENT

The best performing model for each flowline is deployed on TÜV SÜD National Engineering Laboratory's Azure cloud platform and exposed via encrypted and secure API endpoint. The REST API calls use a standard JSON format for data exchange, with model inputs and outputs structured according to a predefined schema. Each REST API call can process data from multiple timestamps at once.

AkerBP retrieves sensor measurements from their Cognite Data Fusion platform and can submit either real-time or batch requests to NEL's API endpoint depending on operational needs. The process has following steps: sensor data is extracted from Cognite, formatted into the required JSON structure, and sent to NEL's Azure cloud. The corresponding flowline model processes the request and returns flow rate estimates as a JSON response. AkerBP then writes these predictions back to the corresponding tags in Cognite.

This deployment architecture establishes a clear separation of responsibilities: NEL manages model maintenance and focuses on model improvements, while AkerBP handles the data acquisition and integration process. This approach ensures model updates are implemented seamlessly with minimal operational disruption.

6 CONCLUSIONS

This paper describes the development and deployment of a machine-learning based Virtual Flow Metering system for monitoring topside multiphase flow meters at AkerBP's facilities. Six case studies were conducted to evaluate different training data approaches and their impact on prediction accuracy.

The study shows data quality and quantity of the training dataset have a major impact for model performance. Models trained on limited calibration and input data (Case 1) showed MAPE of 19.95 %, 20.19 % and 13.42 % for oil, gas and water, respectively. Changes in oil and water levels in the separator were observed from March 2025 onward and therefore considered the inclusion of permittivity and conductivity measurements in Case 2. This can only marginally improve the MAPE with 16.58%, 18.58%, and 13.18% for oil, gas, and water, respectively, suggesting the calibration data was the limiting factor in the prediction of the multiphase flow rates.

Extended stable operation periods were therefore tested (Case 3 excluding permittivity and conductivity and Case 4, including permittivity and conductivity). The extended training period improved the oil, gas and water predictions against the separator measurement marginally for Case 3 but improved approximately 8%, 6% and 7% between Case 2 (single flowline calibration data) to Case 4 (stable operation data). Further reconciliation with separator measurements (Case 5) further improved predictions, particularly for gas phase (MAPE reduced from 12.23% to 4.84%). As each flowline flows into a header before entering the separator, it was hypothesised that there may be some backpressure effects between the streams, therefore an additional trial was made where a single model was used to predict all nine multiphase flow rates. No significant improvement was observed to the predictions which suggest the interaction between the streams does not have a significant impact on the flows from each of the streams.

In summary, the paper shows the value in multiple modelling approaches using similar inputs and helps improve the quality of the multiphase flow meter measurement by continuously monitoring these fields without the need for additional instrumentation.

Future work includes implementing automated retraining triggers based on VFM deviation from separator measurements, statistical drift in input features and detected changes in subsea well configurations using drift monitoring approach.

7 NOTATION

MPFM	Multiphase Flow Meter
VFM	Virtual Flow Meter
CDF	Cognite Data Fusion
MAPE	Mean Absolute Percentage Error
API	Application Programming Interface
JSON	JavaScript Object Notation
DP	Differential Pressure

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