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Original Article

Cloud-based virtual flow metering system powered by a hybrid physics-data approach for water production monitoring in an offshore gas field

Rafael H. Nemoto, Roberto Ibarra, Gunnar Staff, Anvar Akhiiartdinov, Daniel Brett, Peder Dalby, Simone Casolo, Andris Piebalgs *

Cognite AS, Oksenøyveien 10, Lysaker 1366, Norway

A R T I C L E I N F O

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A B S T R A C T

This work presents a cloud-based Virtual Flow Metering (VFM) system powered by a hybrid physics-data approach to estimate the water production per well in a gas field. This hybrid approach, which allows accurate calculations near real-time conditions, is based on the description of the flow through the wellbore using physics-based models pertaining to gas-liquid flows with high gas volume fraction. A data-driven approach is implemented to tune the flow model using well test data. This implementation accounts for changes in the well performance and increase in water production, resulting in a self-calibrating solution. This means that the model will remain accurate and relevant as production and well conditions change. Results from the VFM show good agreement with the well test data for steady-state conditions. The VFM calculations are performed remotely using a cloud-based DataOps platform where results are also stored. This allows continuous access to live sensor data to be used as input to other applications or visualized through a web interface. The VFM system uses a set of readily available sensors installed in the wells. Thus, it represents cost reduction in both capital and operating expenditures when compared to the installation of multiphase flow meters or separators.

Introduction

In oil and gas wells, the production fluid often consists of a mixture of oil, gas and water flowing from the reservoir to the topside separation facility via a network of piping and valves. The fluid phase composition changes over time and its variation introduces a challenge in optimizing oil and gas production: for this reason the volume and proportion of all phases are monitored for each well throughout the life of the oilfield.

In gas fields, water production monitoring per well allows production and reservoir engineers to (a) identify water breakthrough, (b) allocate produced water, (c) evaluate water reinjection rates, (d) monitor the fluid composition over time, (e) plan inhibitors' usage, (f) plan for future interventions, such as the installation of water-shutoff plugs to specific perforations, and (g) adjust the water handling capabilities, namely, water transport, storage, treatment, and disposal. In some cases, offshore gas wells may not be routed to separation facilities (neither production nor testing). This means that water rate metering can only be performed in the onshore processing plant, after the commingled field production flows through a long transportation pipeline. This configuration leads to challenges regarding water rate monitoring per well and water production allocation.

Water rate monitoring per well can be performed using different alternatives (Falcone et al., 2009), namely, separators, multiphase flow meters (MPFM), and virtual flow meters. The installation of a test separator or a MPFM incurs significant costs due to mobilization of specialized personnel to the offshore platform, deferred production associated with the interventions, and equipment procurement. VFMs provide a simple and low-cost solution to monitor the flow rates of individual wells using readily available sensors in wells and flowlines (da Paz and Baliño, 2010; Bikmukhametov and Jäschke, 2020a), such as pressure and temperature gauges, and reference flow rates obtained through well tests.

Different approaches might be used when deploying a VFM, namely, physics-based, data-driven, and hybrid physics-data (Staff et al., 2020; Zarruk, 2020). A VFM that relies solely on a physics-based approach requires a high-fidelity multiphase flow model. Such models are

* Corresponding author.
E-mail address: andris.piebalgs@cognite.com (A. Piebalgs).

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generally computationally demanding and use default closure laws, which might not reflect the system's actual operating envelope. A VFM based on a purely data-driven approach, such as a machine learning (ML) model (Andrianov, 2018; Bikmukhametov, 2019; Akhiiartdinov et al., 2020), requires a large set of relevant reference data; however, well tests are generally scarce, and might cover only a narrow range of flow conditions. Moreover, the machine learning model might drift due to the continuous changes in production conditions, such as reservoir pressure decline and water cut increase. As such, hybrid VFM models are seen as a good alternative that can combine the best of both worlds by integrating physics knowledge into machine learning methods for increased performance and flexibility.

There have been relatively few examples of academic applications of hybrid VFMs in the literature thus far. Initially, such models were based on laboratory (Kanin et al., 2019, Quintino et al., 2021) or test rig data (Xu et al., 2010, Al-Rawahi et al., 2012, Soedarmo 2023), and only more recently were applied on data from operating production facilities (Mohammadmoradi et al., 2018; Staff et al. 2020; Andrade et al., 2022; Hotvedt et al., 2022b; Akhiiartdinov et al., 2023, Henriksson et al., 2022).

One such example is the work of Hotvedt et al. (2020), who created a hybrid VFM by incorporating a feed-forward neural network to calculate the choke coefficient of the production choke, based on a mechanistic choke model established by Kittilsen et al. (2014). The resulting value was subsequently utilized as input into the mechanistic model to predict production data on the Edvard Grieg platform. In another study, Hotvedt et al. (2022a) employed the Sachdeva model for the production choke, using various levels of hybridization to evaluate the advantages of gray-box modeling. They attained comparable accuracy to fully data-driven models, indicating that in certain circumstances, hybridized VFM models can perform well.

The performances of hybrid models compared with those of physics models have been recently studied in a large variety of operational scenarios by Bikmukhametov and Jäschke (2020b). In general, it has been recently shown that hybrid approaches outperform pure first principles models whenever there is a mismatch between a simulated and measured flow rates. As well, hybrid models can achieve higher accuracies than ML VFM data models in regimes with limited amounts of historical data (Hotvedt et al., 2022a).

The herein proposed VFM, powered by a hybrid physics-data approach, relies on a simplified multiphase flow model based on a steady-state point model with closure laws adjusted using reference data (well tests). Unlike previous studies, this VFM uses a simplified fluid flow equation in the wellbore instead of the choke model and measurements from a wet gas flow meter to predict production flow rates. A machine learning proxy model is used for determining the friction factor for the well which is then subsequently used in the flow equation. This approach allows accurate near-real-time calculations, works with a limited amount of reference data, and accounts for changes in the operating envelope and well performance. In addition, the VFM presented in this work is coupled with an efficient cloud-based architecture, where field sensor data is made available in real time. This system allows for an automatic update of the flow rate predictions and for re-training of the machine learning models regularly, either on a scheduled basis or whenever new well test data is available. This combination is particularly useful in production environments with large volumes of sensor data streaming to a cloud environment where, in order to avoid the models drifting, a regular update of the VFM model is required. While modeling the flow models in a physics simulator would require an input setup and possibly human intervention and domain knowledge, having a hybrid model and a robust data pipeline allows for a regular and more agile model update. Moreover, such data architecture allows for building models which can be updated continuously, training on a continuous influx of live sensor data. Such techniques are known as passive learning approaches, and online learning (Hotvedt et al., 2022b).

The rest of this paper is structured as follows. Section 2 describes the production system. Section 3 details the characteristics of the reference data used to tune the model. The cloud-based architecture and the VFM system are presented in Section 4 and 5, respectively. The VFM results and analysis is described in Section 6. Finally, Section 7 presents the main conclusions of this work.

Production system description

The gas field is located offshore in shallow water and consists of three dry-tree production wells, which are connected to an unmanned offshore platform. Wells produce gas, condensate, and water where only gas flow rates (for each well) are measured at the offshore platform (FT_G in Fig. 1). The produced fluids are commingled in the production manifold at the platform to then be exported through a single flowline, with a length of more than 100 km, to the onshore processing plant. There, the three-phase mixture is separated, and each phase is measured individually (see Fig. 1). The total water flow rate, Q_{WT}, is estimated once a day using the level change in buffer tanks and readings from a flow meter connected to a water tank's drainage outlet.

Wells instrumentation

Each well is equipped with downhole and wellhead pressure and temperature sensors. The gas rate is measured using an annubar flow meter, also called averaging pitot tube, which is an intrusive meter based on differential pressure. The gas meter is installed downstream of the production choke valve, as presented in Fig. 2.

Well geometries

The tubing internal diameter for the three wells is 0.1571 m. The distance between the wellhead and downhole pressure and temperature gauges in terms of the True Vertical Distance (TVD) and Measured Distance (MD) is presented in Table 1 for the three wells. An absolute pipe roughness of 0.01524 mm is assumed for the tubing.

Fluid composition

The three wells produce wet gas and have experienced water breakthrough. Water-shutoff plugs were installed to perforations in some of the wells to reduce the water production. Pressure and temperature conditions along the wellbore are such that negligible gas condensate or condensed water-vapor are present in the wells. Condensed water-vapor and gas condensate from the wet gas are formed as pressure and temperature drop along the long export flowline connecting the offshore platform to the onshore processing plant. Hence, the aqueous phase arriving at the onshore processing plant is formed of water-vapor condensation and formation water. Table 2 presents the fluid properties and composition used to generate a PVT look-up table using black-oil correlations (McCain, 1990).

Reference data

The reference data consists of steady-state flow parameters that

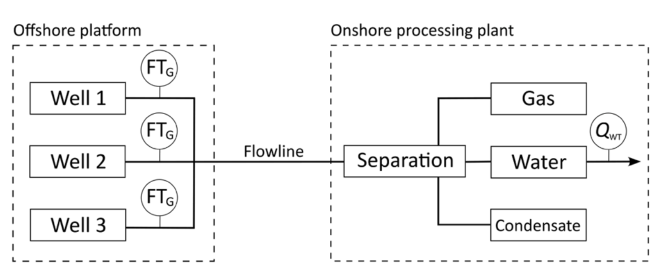

Fig. 1. Production system overview.

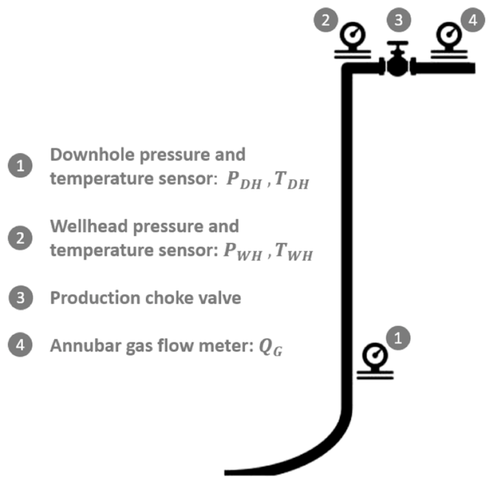

Fig. 2. Instrumentation available in the wells.

Table 1
Wells' distance between wellhead and downhole sensors.

	Well 1	Well 2	Well 3
TVD (m)	2266	2264	2200
MD (m)	2416	2534	2535

Table 2
Fluid properties and composition.

Property	Value
Gas gravity	0.623
Separator pressure (psia)	514.7
Condensate-gas-ratio (stb/MMscf)	3.93
Condensate gravity (API)	61.6
Condensate water vapor-gas-ratio (stb/MMscf)	1
Water salinity (ppm)	20,000
H_2S content (mole%)	0.000
CO_2 content (mole%)	3.590
N_2 content (mole%)	0.527

represent the flow system characteristics for each well. These are commonly known as well tests. A well test refers to a period of time during which a well's flow rate is kept constant by setting a choke position of interest. During a well test campaign, a multi-rate well test is obtained by varying the choke position. The resulting individual phase flow rates along with other relevant parameters, such as pressure and temperature, are obtained. Well tests in producing wells are generally performed to evaluate well permeability, skin factor, and reservoir parameters; they are also valuable as reference data for flow metering calibration purposes, e.g. tuning VFMs.

Well test restrictions

The ideal setup to measure phase flow rates during a well test is to separate the multiphase flow mixture for each well flow stream using a test separator and measure the pure phase flow rates (single-phase flow) at the separator outlets. In this study, only the water rate is the flow rate of interest during a well test given the system and fluid characteristics in the well, i.e. gas flow rate is measured using the annubar meter, and negligible gas condensate is present in the wellbore based on the pressure and temperature conditions.

Directly measuring the water flow rate per well is not possible as no test separator is available in the offshore platform. Thus, the water production per well can only be measured in the onshore facility. During low gas rates, liquids accumulate in the long flowline connecting the offshore platform to the onshore facility, whereas during high gas flow rates, liquid is flushed from the flowline into the onshore facilities. Due to these circumstances, a well test is performed by having a single water-producing well opened at a constant choke position for a time interval that allows reaching dynamic equilibrium for water transportation in the flowline before the measurements are taken.

Although not ideal, gas demands might require the conduction of a well test with an additional operating well, provided that the additional well does not produce formation water. The choke position of the additional well is commonly changed due to varying gas output demands. Consequently, the dynamic equilibrium might be disturbed due to varying gas rates, which leads to increased uncertainty to the well test results. In the future, well tests might not be feasible as increased water production and resultant greater liquid holdup in the flowline could cause transient phenomena, such as terrain-induced slugging. In this case, the lack of recent well tests might prevent re-tuning closure relationships to reflect the latest operating envelope.

Due to its long duration and stringent requirements, performing a well test is onerous and cannot be performed with high frequency. Consequently, very few data points are available to tune the model closure relationships. A solution to overcome the lack of reference data (well test data per well) was to group together the well tests for different wells in a single pool of reference data. This procedure is acceptable since the wells have similar completions and fluid properties.

Automatic well test detection and data processing algorithm

The previous process to detect a well test campaign consisted of adding the approximate start and end dates of the test period manually to a log file. Then, operational parameters were manually extracted based on the logged period. However, this process considers neither the verification of data quality nor the correctness of the methodology.

An automatic detection algorithm was developed to identify the occurrence of new well tests as well historic campaigns. The algorithm identifies a time interval as a new well test once the following conditions are fulfilled:

- One single water-producing well is open
- Constant choke position for the tested well
- Steady-state condition for the total daily water rate measured at the onshore processing plant
- The three conditions mentioned above must be fulfilled simultaneously for a time interval of at least three days for data averaging purposes

The algorithm runs once per day and if a new well test is detected, it performs the integral average of the relevant sensor data for the identified time interval (see Fig. 3) and stores the results as a new data point in the well test dataset (see Table 3). The following information is stored for each well test: (a) start and end dates, (b) name of the tested well, (c) downhole temperature (DHT), (d) wellhead temperature (WHT), (e) downhole pressure (DHP), (f) wellhead pressure (WHP), (g) choke position, (h) gas rate per well, (i) onshore (total) water rate, and (j) water-gas ratio (WGR).

Cloud-based architecture

The cloud-based architecture that enables the VFM system is presented in Fig. 4. The core component is Cognite Data Fusion (CDF), an industrial data operations (DataOps) platform (Vainikka et al., 2021, Cognite, 2022) for the analysis and management of industrial data. CDF ingests data from the following source systems: (a) conventional information technology (IT) systems, such as databases and assets/equipment hierarchy, (b) operational technology (OT) systems, such as time-series and events from control and monitoring systems, (c) engineering technology (ET) systems, such as fluid properties table files (e.g.

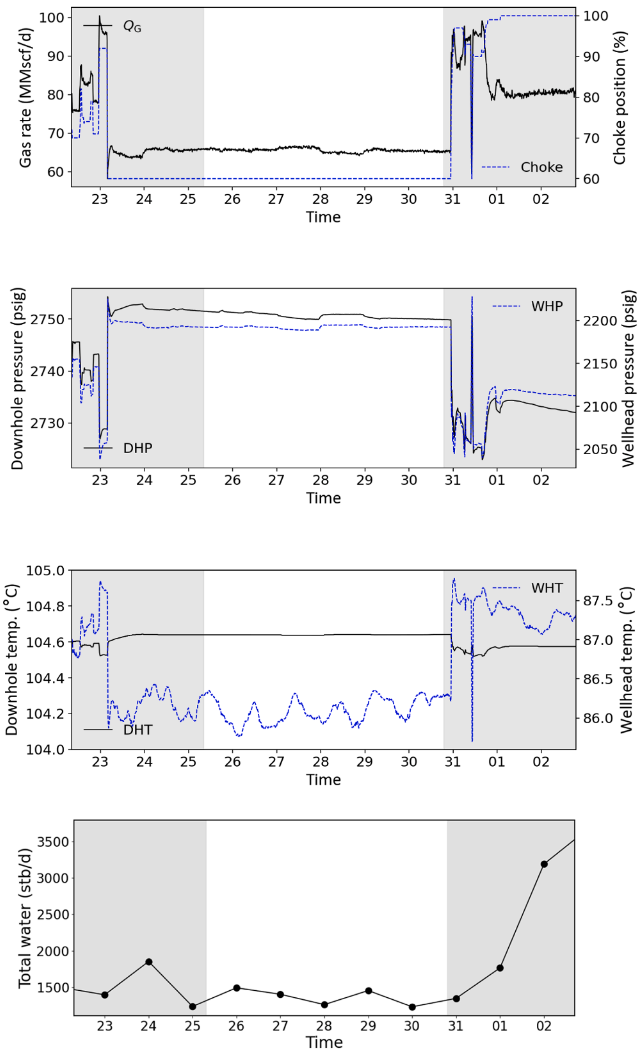

Fig. 3. Example of relevant time-series trends during a well test (well test number 6 for well 1 as shown in Table 3). From top to bottom: gas rate and choke position, downhole and wellhead pressure, downhole and wellhead temperature, total daily water rate measured at the onshore facility. The time interval (in days) identified as a well test is presented with a white background, whereas the gray surrounding area shows the conditions 3 days before and after the test period.

PVT tab), process and instrumentation diagrams (P&ID), process flow diagrams (PFD), and well completion diagrams.

Extractors connect to source systems and push data in its original format to a staging area in CDF as part of the data integration workflow. After data from different source systems are ingested, CDF performs data contextualization, which consists of mapping resources from different source systems to each other in the CDF data model (Caso et al., 2020; Laborie et al., 2019); as an example, the contextualization tool allows the automatic identification of the sensor tags depicted in P&IDs and the ready visualization of the associated time-series. This process facilitates data identification and consumption by subject matter experts when building customized solutions, such as the VFM system described here.

The VFM algorithms are implemented using the Python programming language and the source code resides in a GitHub repository. Development operations (DevOps) are enabled using GitHub's continuous integration and continuous deployment (CI/CD) pipeline, which consists of a series of automated workflows to facilitate code development, testing, and deployment. One of the workflows automatically packages files and components into standalone software artifacts, which are deployed to CDF as Cognite Functions, a schedule or trigger based serverless compute environment. Cognite Functions perform calculations on data retrieved from CDF, such as time-series and events from operations, and write results back to CDF, such as artificial time-series and data in tabular format (sequences). Specifically, two Cognite Functions are deployed. One function for training and model selection, and another function for performing the VFM predictions. The training function runs daily and, (re-)trains and evaluates the different VFM model options, described in Section 5.4, on any new training data. The VFM model option that performs the best is stored in CDF and subsequently retrieved by the prediction function. This allows for automatically switching between the VFM implementations as production conditions change. The prediction function runs hourly and retrieves the most recent VFM model stored in CDF. Predictions are performed on any new data since the previous run and are written back as time series to CDF.

An interactive dashboard for visualizing VFM predictions and other relevant operational data for the wells was developed using the Plotly-Dash web application framework and made accessible through a web browser. All the components of the VFM system reside in the cloud - both CDF and the dashboard are hosted on the Google Cloud Platform.

VFM system

A hybrid physics-data VFM system is implemented to estimate the water production per well for production allocation purposes. The flow in the wellbore is described using physics-based models pertaining to gas-liquid flows with high gas volume fraction (GVF). The mixture friction factor is tuned using reference data from well tests. The available wellbore instrumentation is used, namely, downhole and wellhead pressure and temperature sensors.

In summary, the gas field has the following features: (a) the phases present in the tubing are wet gas and formation water with a high GVF, (b) gas condensate and condensed water-vapor are negligible in the tubing given the in-situ pressure and temperature conditions, (c) the condensate-gas ratio (CGR) is known and constant, (d) the GVF is expected to decrease with time as the wells might produce more water and less gas, (e) the available sensors allow measuring both the pressure drop and temperature difference along the tubing, and (f) a limited reference dataset (well test dataset) of only nine data points is available. The objective of the VFM system for the gas field is to estimate the

Table 3
Well test dataset.

No.	Tested well	DHT (°C)	WHT (°C)	DHP (psig)	WHP (psig)	Choke (%)	Gas rate (MMscf/d)	Onshore water rate (stb/d)	WGR (stb/MMscf)
1	Well 1	105	87	2798	2185	70	88	1164	13
2	Well 1	105	79	2832	2394	25	32	137	4
3	Well 1	105	79	2830	2391	25	32	121	4
4	Well 1	105	87	2758	2116	78	93	1664	18
5	Well 1	105	87	2757	2127	78	90	1597	18
6	Well 1	105	86	2751	2192	60	65	1288	20
7	Well 3	104	86	2684	2059	74	87	2252	26
8	Well 3	104	87	2651	2003	86	91	2978	33
9	Well 3	104	87	2719	2058	84	99	2188	22

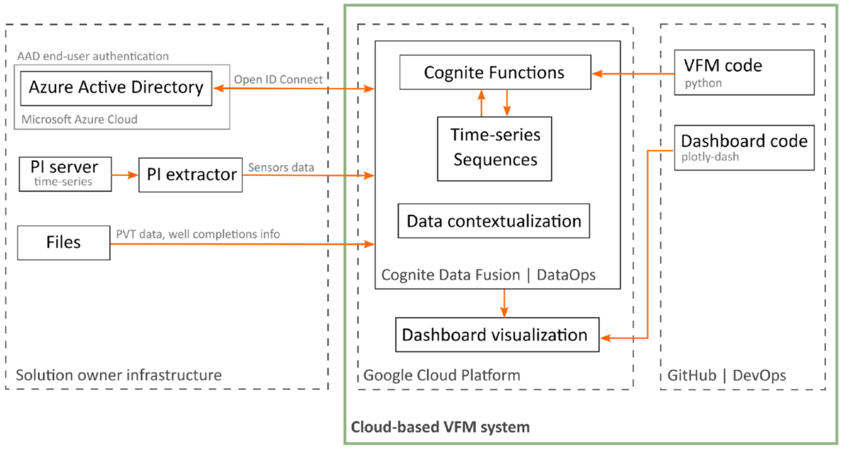

Fig. 4. Cloud-based architecture related to the VFM system.

formation water flow rate per well, whereas the wet gas rate is measured by gas meters for each well.

Pressure drop along the tubing

A simplified steady-state point model based on the mass and momentum conservation is used to describe the pressure drop in the tubing between the downhole and wellhead gauges. The pressure drop can be calculated considering a homogeneous mixture (pseudo single-phase flow) with average velocity and fluid properties (Wallis, 1969; Shoham, 2005). Thus, the pressure difference in the well is related to the hydrostatic and frictional pressure drop, as follows:

$$dP = \frac{L}{2D}\, f\, \rho_M\, U_M^2 + \rho_M\, g\, H \tag{1}$$

where dP is the pressure difference between downhole and wellhead ($dP = P_{DH} - P_{WH}$), L is the tubing length measured between gauges, D is the tubing internal diameter, f is the friction factor, ρ_M is the mixture density, U_M is the mixture velocity, g is the gravitational acceleration, and H is the vertical distance between gauges.

The mixture velocity U_M for the two-phase flow, i.e. wet gas and formation water, is defined as:

$$U_M = \frac{Q_w + Q_G}{A_P} \tag{2}$$

where Q_W is the water volumetric flow rate, Q_G is the wet gas volumetric flow rate, and A_P is the cross-sectional area of the tubing.

The mixture density is defined as follows:

$$\rho_M = \rho_W\, H_L + \rho_G\, (1 - H_L) \tag{3}$$

where ρ is the density, subscripts W and G correspond to water and wet gas phases, respectively, and H_L is the liquid holdup in the tubing. The liquid holdup is defined as the fraction of a volume element occupied by the liquid phase.

Since a point model is used to calculate the pressure drop between the downhole and wellhead gauges, the parameters used in the analysis (e.g. f, ρ_M, U_M, H_L) are averaged along the tubing. This means that the referred parameters are calculated for the in-situ pressure and temperature conditions at the downhole and wellhead gauges; next, the parameter's arithmetic average is calculated to obtain a representative value for the entire tubing.

Liquid holdup

Two variations of liquid holdup are used, namely, no-slip liquid holdup and slip liquid holdup. No-slip implies that both phases flow at the same velocity, whereas the slip assumption allows for slippage between the phases, i.e. the gas and liquid phases might have different velocities. The no-slip liquid holdup is defined as the ratio of the water volumetric flow rate to the total volumetric flow rate, as follows:

$$H_{L,ns} = \frac{Q_W}{Q_W + Q_G} \tag{4}$$

The slip liquid holdup can be calculated using the Gray's correlation developed for the vertical flow of gas and liquid with a high gas-liquid ratio (Gray, 1974). The slip liquid holdup is given as:

$$H_{L,s} = 1 - \frac{1 - e^{-2.314\left[N_V\left(1+\frac{205}{N_D}\right)\right]^B}}{R+1} \tag{5}$$

where the dimensionless parameters R, B, N_V, and N_D are given as follows:

$$R = \frac{Q_W}{Q_G} \tag{6}$$

$$B = 0.0814\left[1 - 0.0554\, ln\left(1 + \frac{730\, R}{R+1}\right)\right] \tag{7}$$

$$N_V = \frac{\rho_{M,ns}^2\, U_M^4}{g\, \sigma_W\, (\rho_W - \rho_G)} \tag{8}$$

$$N_D = \frac{g\, (\rho_W - \rho_G) D^2}{\sigma_W} \tag{9}$$

where $\rho_{M,ns}$ is the mixture density calculated using Eqs. (3) and (4), and σ_W is the gas-water surface tension.

Friction factor

The friction factor along the wellbore is estimated based on two approaches: (a) using an explicit approximation to the solution of Colebrook's friction factor equation (Zigrang and Sylvester, 1982), and (b) a Blasius-type equation with adjustable coefficients β_1 and β_2, as follows:

$$f = \beta_1\, Re_M^{-\beta_2} \tag{10}$$

where Re_M is the mixture Reynolds number,

$$Re_M = \frac{\rho_M D\, U_M}{\mu_M} \tag{11}$$

and μ_M is the dynamic viscosity of the mixture, with μ_W and μ_G the viscosities of the water and gas phases, respectively.

$$\mu_M = \mu_W \, H_L + \mu_G \, (1 - H_L) \tag{12}$$

The Blasius-type friction factor equation will be used as a machine learning proxy model for the friction factor where the Blasius coefficients are determined using parametric regression on the training data. More details on the training are provided in Section 5.5.

Model options

Three model options are defined to calculate the pressure drop in the tubing, using Eq. (1), combining different flow (holdup) and friction models as shown in the following Table.

The above approaches are intended to account for increasing water production, in which slippage between the phases might become significant. Note that there is no explicit threshold on the liquid holdup for when to switch between the flow models. It will happen automatically during subsequent VFM re-training as soon as the flow model using slippage starts performing better than the no-slippage models. The model option to be used for calculating the water flow rate will be defined by the VFM training algorithm.

VFM training algorithm

To solve for 2 phases (water and gas), 2 independent equations are needed. In this work, one equation is substituted with the measurements from the wet gas meter. Therefore, only the flow equation needs to be considered. The VFM training algorithm involves the following steps:

- Step 0: The latest data is taken from CDF to check if a new well test value is available. If there is a new well test, then the training algorithm is triggered.
- Step 1: Calculate fluid properties (at well head and bottom hole conditions) using the black-oil model look-up tables (as detailed in Section 2.3)
- Step 2: Calculate coefficients β_1 and β_2 in the Blasius-type friction factor equation, Eq. (10) for model options 2 and 3. Note that no parameter estimation is needed for model option 1 since a friction factor equation from the literature is used. The calculation starts by rearranging Eq. (1) to compute the friction factor f and the mixture Reynolds number Re_M from Eq. (11) for each data point in the well test dataset (see Table 3). The coefficients β_1 and β_2 are estimated using a curve-fitting algorithm, such as the non-linear least-squares method. This procedure is performed for model options 2 and 3, with each option using its respective liquid holdup assumption, i.e. no-slip, Eq. (4), and slip, Eq. (5).
- Step 3: The water rate for each data point of the well test dataset is calculated for each VFM model option highlighted in Table 4. This calculation is performed by using Eq. (1) and Eq. (2) by considering the measured pressures and temperatures from the well test data, and the gas flow rate from the wet gas meter. To solve the equations for the water rate, an iterative process is employed with a solver, such as a root-finding algorithm.
- Step 4: A comparison is made between the WGR calculated by each type of VFM and the WGR obtained from the well test data points. The model option that yields the lowest mean absolute error (MAE) is selected and stored in CDF for later use in the VFM prediction algorithm.

Table 4
VFM model options.

Model option	Flow model	Friction model
1 (base case)	No-slip liquid holdup, Eq. (4)	Explicit approximation of Colebrook's friction factor equation
2	No-slip liquid holdup, Eq. (4)	Blasius-type equation with adjustable coefficients, Eq. (10)
3	Slip liquid holdup, Eq. (5)	Blasius-type equation with adjustable coefficients, Eq. (10)

The training algorithm workflow diagram is shown in Fig. 5. The algorithm selects the best performing model option and accounts for changes in the operating envelope and well performance.

VFM prediction algorithm

The VFM prediction algorithm, presented in Fig. 6, is scheduled to run every hour and each runtime provides water rate calculation with a granularity of 10 min. The algorithm follows the steps outlined below:

- Step 1: The process begins with reading and pre-processing raw sensor data to assure data quality. The pre-processing involves removal of anomalous data based on predefined ranges, detection of missing data points, data interpolation, and data averaging over the time interval of 10 min.
- Step 2: The latest selected model in the VFM training algorithm is used to calculate the water flow rate, along with the corresponding WGR. The calculation process involves using the machine learning proxy model developed to estimate the friction factor (created during Step 2 of the training phase) and then resolving Eq. (1) for the water flow rate given the pressure, temperature, and gas flow rate measured during normal well operation. The water rate is calculated through an iterative process using a solver, such as a root-finding algorithm.
- Step 3: Upload the results from the prediction algorithm to CDF.

Limitations to VFM approach

The VFM methodology outlined in this paper possesses a certain level of universality, allowing its application to various systems. Nevertheless, certain modifications are necessary to adapt it to the availability of training data and the suitability of assumptions (e.g. phase behavior). These factors influence the feasibility of implementation and overall performance in different scenarios. Some of the assumptions and limitations include:

- Sensor Requirements: The hybrid method relies on the availability of specific sensors for each well, such as bottomhole pressure and well head pressure, to estimate the flow rates. However, not all wells may have these sensors installed, which restricts the application of the method.
- Steady State Assumption: The method requires steady state conditions to be maintained during the estimation process.
- Data requirements: Additionally, reliable well test data is necessary to fine-tune the closure law. While the hybrid approach strikes a balance between data-driven and physics-based methods, it still relies on some well test data for accurate calibration.
- Flow Regime Specificity: The physical correlations utilized in the method are tailored to the flow regime present in the system under consideration. This means that the correlations may not be universally applicable and may need to be adjusted or modified for different flow regimes encountered.
- Phase Behavior: In this instance, it was known that hydrocarbon liquid would not be present at any condition in the wellbores and therefore all liquid in the well bore attributable to aqueous phase.
- Similarity: In this instance, since the wells were of similar completions and fluid composition, test data could be shared. Without this, test data may have been too sparse.

In summary, there are parts of the approach that are universal but the availability of the data and applicability of the assumptions (e.g. phase behavior) will impact feasibility of deployment and/or performance in other instances.

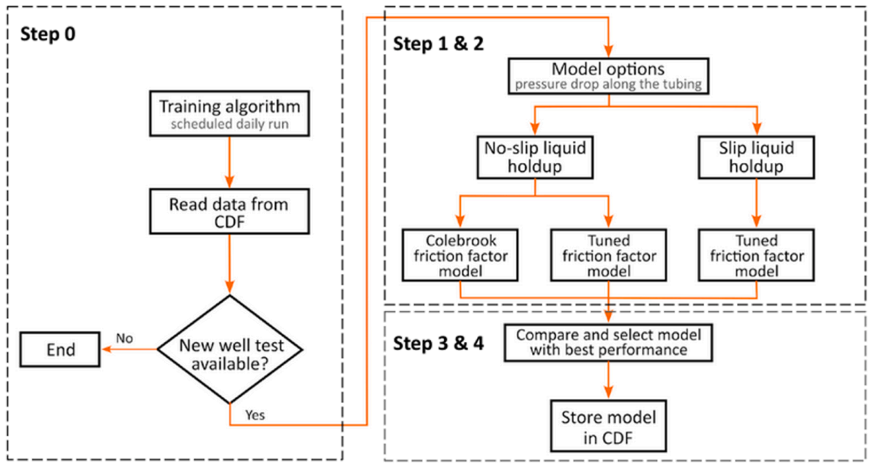

Fig. 5. Schematic of the VFM training algorithm.

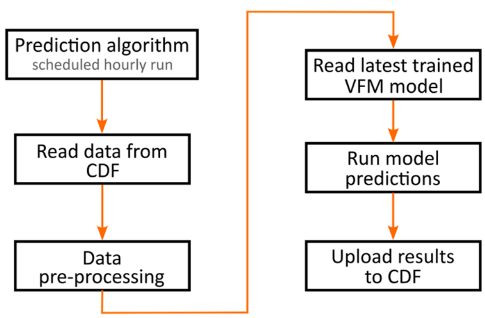

Fig. 6. Schematic of the VFM prediction algorithm.

Note that since the algorithm is based on the fundamental flow equations, it has the ability to predict water rate beyond the training range.

Results

This section presents the results for the liquid holdup, using both the no-slip and slip assumptions, and the results related to the VFM training and prediction algorithms.

Liquid holdup

Fig. 7 shows a comparison of the calculated no-slip and slip liquid holdups in the tubing (averaged) using the available well test dataset. The no-slip holdup considers a homogeneous gas-liquid mixture that flows with the same phase velocity (Eq. (4)). The slip holdup is calculated using Gray's correlation, according to Eq. (5), and considers the slippage between the gas and liquid phases. The operating conditions reflected by the well tests refer to a gas-dominant system with a maximum WGR of 33 stb/MMscf (see Table 3). Consequently, the slip liquid holdup values are similar to no-slip counterparts, implying that phase slippage is currently not relevant. Note that phase slippage might become more relevant as water rate or WGR increases. In which case the model option including slippage is expected to start performing better than the other model options, and thus be selected for doing predictions by the VFM training algorithm.

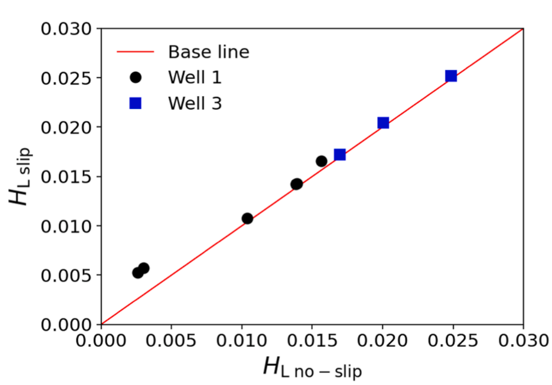

Fig. 7. Comparison of the no-slip and slip liquid holdup using the available well test data.

VFM training

As output of step 1 of the VFM training algorithm (i.e. calculating coefficients β_1 and β_2 in the Blasius-type friction factor equation), Fig. 8 shows the friction factors calculated according to the different model options. As a result of step 2 of the VFM training algorithm, Fig. 9 shows a comparison of the WGR values from the reference data (well tests dataset) on the x-axis and the WGR values calculated by the VFM system on the y-axis for the different model options. WGR_{total} refers to the WGR calculated using the water rate originated from the condensed water-vapor and formation water.

The performance of the VFM system powered by the different model options against the well test dataset is quantified by three metrics (see Table 5), namely (a) mean relative error (MRE), (b) mean absolute error (MAE), and (c) coefficient of determination (R^2) (see Appendix A). Model option 2 has the lowest MAE and the highest R^2 value, meaning that this model option is selected to power the VFM system as part of the VFM prediction algorithm.

The selection of model option 2 shows that the tuning of the friction factor equation improves the water rate prediction and that a no-slip holdup model, i.e. assumption of homogeneous gas-liquid flow, provides better performance. This is due to the currently high GVF observed in the tubing.

VFM prediction

Prior to the provision of a VFM, the water rate for each well was not measured. The only available reference for water production was total water flow rate, i.e. the combination of the water production from the three wells, measured once a day in the onshore processing plant. As described in the Section 5.6, the VFM system estimates the produced water flow rate for each well every 10 min. In order to compare the VFM predictions with the reference daily total accumulated water rate, it is necessary to integrate the estimated water volumetric flow rate over the time interval of one day.

Fig. 10 shows the daily total accumulated water rate from the three

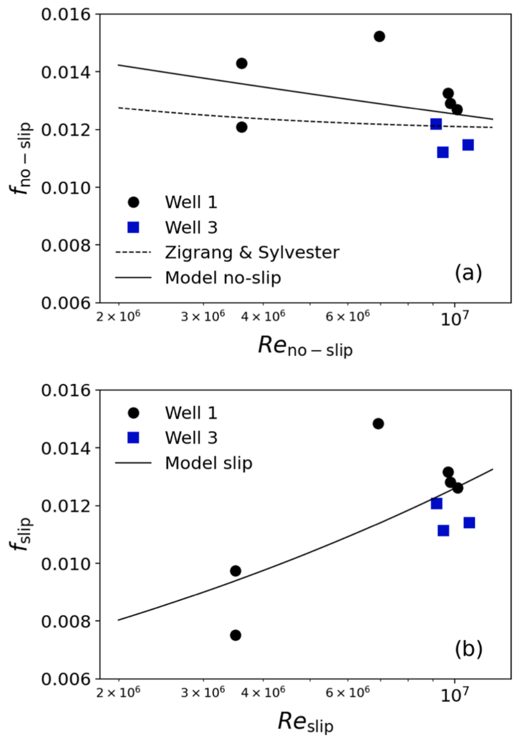

Fig. 8. Friction factor, *f*, as function of the Reynolds number, for the well test data along with the fitting curves for: (a) no-slip liquid holdup approach and (b) slip approach.

wells estimated by the VFM system (red curve) and the daily total accumulated water rate measured at the onshore processing plant (black curve). The VFM predictions follow the trend of the total water rate measured onshore. The VFM system provides better results under steady-state operation, when the production choke valve operates with a constant position.

The deviation between the measured and calculated total water rates occur due to: (a) transients in the wells induced by changes in the production system, such as modifications in choke valve position, (b) transients in the long export flowline, such as water accumulation and flushing, depending on the gas rates, (c) time delay between the moment in which the water rate is calculated by the VFM system using the well's parameter (near real-time) and moment in which the total water rate is measured at the onshore facility after being transported through the long export flowline, (d) residual error from the simplified flow model (see Table 4), and (e) error in the water metering system in the onshore processing plant, which is calculated from changes in buffer tanks level over one day.

Fig. 11 presents the pro-ration factor for the water phase, which is defined by the ratio of the daily total accumulated water rate measured at the onshore facility to the daily total accumulated water rate estimated by the VFM system. Here it is used to qualitatively evaluate the efficacy of the system. Treating the measured rate as the ground truth, a pro-ration factor of 1 would signify perfect accuracy. A pro-ration factor smaller than 1 indicates over-prediction of the total water; and conversely, a pro-ration factor higher than 1 indicates under-prediction. With a few exceptions, the pro-ration fluctuates between 0 and 2, with an average value of 0.89 for the time interval between March of the first year and January of the second year. The water proration factor was used as a qualitative performance metric against a previous method which it significantly out-performed. The outlier data-points correspond

Table 5
Performance of the VFM predictions for the different model options in terms of the total WGR.

Model option	MRE (%)	MAE (%)	R^2
1: no-slip liquid holdup, Colebrook friction factor	12.64	20.61	0.77
2: no-slip liquid holdup, tuned friction factor	0.43	17.43	0.80
3: slip liquid holdup, tuned friction factor	−0.23	20.10	0.64

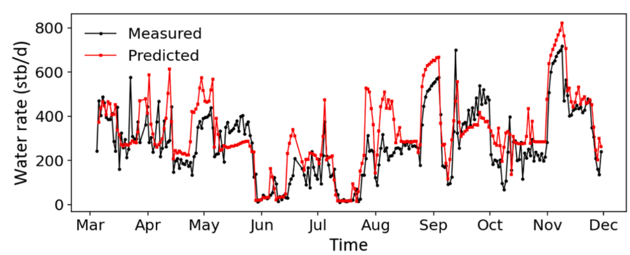

Fig. 10. Comparison of the measured and predicted total water production (predictions corresponds to daily total accumulated).

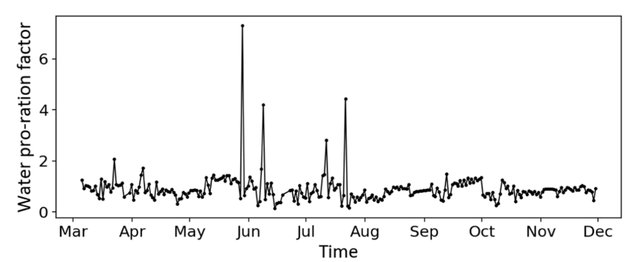

Fig. 11. Water pro-ration factor.

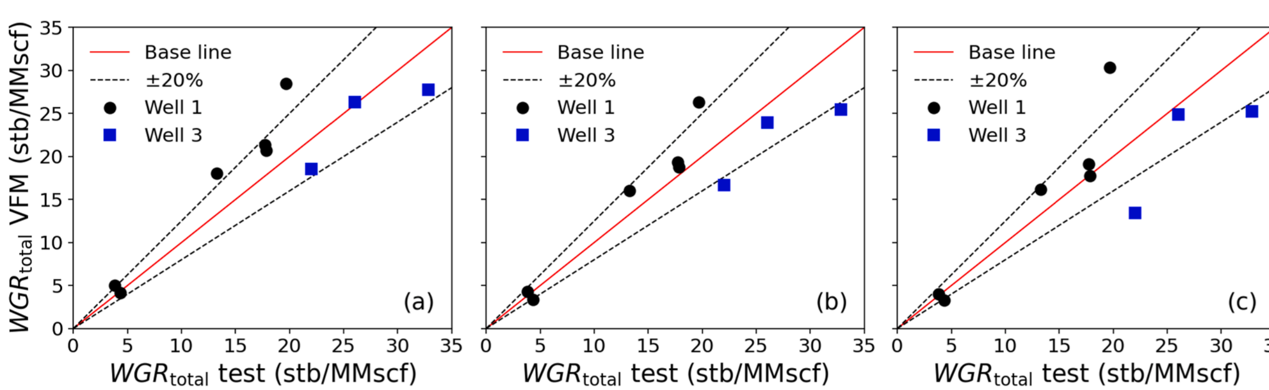

Fig. 9. Comparison of the well test and predicted WGR for the model options (a) no-slip liquid holdup and Colebrook friction factor (model option 1), (b) no-slip liquid holdup and tuned Blasius-type friction factor (model option 2), and (c) slip liquid holdup and tuned Blasius-type friction factor (model option 3).

to conditions with low total water rate.

Conclusions

The proposed cloud-based VFM system powered by a hybrid physics-data approach allows for water production monitoring in an offshore gas field with no offshore separation. By using the water rate per well estimated by the VFM system, it is also possible to perform production allocation having as input the daily total water production measured at the onshore facility.

The VFM system uses a set of readily available sensors installed in the wells and the calculations are performed remotely using a cloud-based DataOps platform, known as Cognite Data Fusion (CDF). This way, the VFM system represents cost reduction in both capital and operating expenditures when compared to the installation of MPFMs or separators.

The VFM system was implemented by a team involving data scientists, solution architects, project managers, and front-end developers working remotely. Furthermore, the VFM system relies on an efficient cloud-based architecture, allowing for the automatic identification of new well tests and triggering the tuning of the flow model, resulting in a self-calibrating solution based on the incoming live sensors data. Therefore, the VFM system eliminates the need for specialized personnel to install and maintain hardware in the offshore platform, leading to reduced exposure to hazards. Moreover, the cloud-based implementation of the VFM system did not demand interruptions in the operation of the wells, avoiding production deferrals and thus maximizing asset productivity.

Furthermore, this study has shown a novel hybrid physics-data approach to VFM training and prediction that can combine the strengths of data-driven methods with the physics based ones. The VFM utilizes a simplified multiphase flow model based on a steady-state point model with the friction factor adjusted by reference data (well tests). The closure law is determined with a machine learning model which is used to estimate the friction factor coefficient. The combination of these 2 approaches allows for the creation of VFM models that can leverage fluid mechanics knowledge to limit the number of data points needed for training and machine learning methods to compute closure relations. Different VFM model options are tested during the VFM training algorithm, involving a flow model that considers no-slip liquid holdup (homogeneous model) and slip liquid holdup (Gray's correlation). The model option with best performance is then selected to calculate the water rates at the VFM prediction algorithm.

In summary, this study demonstrates the implementation of a hybrid physics data approach to VFMs for monitoring water production in an offshore gas field. The VFM system accurately estimates the water rates of individual wells, even when there is a limited amount of well test data available. Furthermore, the study highlights the deployment of the VFM system on cloud infrastructure, enabling continuous prediction, self-calibration, and minimal maintenance requirements.

Further work

As a next step, the effect of tuning other closure laws will be investigated, such as the phase slippage. As an alternative to calculating the slip liquid holdup using a correlation, as in Eq. (5), it is possible to tune the slip liquid holdup as a function of the no-slip liquid holdup, given by Eq. (4), using reference data. This approach becomes more relevant as water production significantly increases.

Declaration of Competing Interest

The authors Rafael H. Nemoto, Roberto Ibarra, Gunnar Staff, Anvar Akhiiartdinov, Daniel Brett, Peder Dalby, Simone Casolo and Andris Piebalgs are/were employees of Cognite AS at the time that this study was performed. Cognite AS develops and delivers VFM solutions for the O&G industry and as such may gain financially by publishing favorable results. The authors would like to state that they are against any unethical research practice and stress their commitment to fair and unbiased scientific research.

Acknowledgements

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Appendix A. Error statistical parameters

The percentage mean relative error, MRE, between the WGR from well tests, $WGR_{\mathrm{well\ test}}$, and VFM predictions, WGR_{VFM}, for a total number of data-points, N, is

$$MRE(\%) = \left(\frac{1}{N} \sum_{i}^{N} \frac{WGR_{VFM,i} - WGR_{well\ test,i}}{WGR_{well\ test,i}} \right) \times 100. \tag{A.1}$$

The percentage mean absolute error, MAE, is

$$MAE(\%) = \left(\frac{1}{N} \sum_{i}^{N} \frac{\left| WGR_{VFM,i} - WGR_{well\ test,i} \right|}{WGR_{well\ test,i}} \right) \times 100. \tag{A.2}$$

The coefficient of determination, R^2, is

$$R^2 = 1 - \frac{\sum_i^N \left(WGR_{well\ test,i} - WGR_{VFM,i} \right)^2}{\sum_i^N \left(WGR_{well\ test,i} - \langle WGR_{well\ test,i} \rangle \right)^2}, \tag{A.3}$$

where the mean WGR from well tests is $\langle WGR_{well\ test} \rangle = \frac{WGR_{well\ test}}{N}$.

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