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First Principles and Machine Learning Virtual Flow Metering: A Literature Review

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ABSTRACT

Virtual Flow Metering (VFM) is an increasingly attractive method for estimation of multiphase flowrates in oil and gas production systems. Instead of using expensive hardware metering devices, numerical models are used to compute the flowrates by using readily available field measurements such as pressure and temperature. Currently, several VFM methods and software are developed which differ by their methodological nature and the industry use. In this paper, we review the state-of-the-art of VFM methods, the applied numerical models, field experience and current research activity. In addition, we identify gaps for future VFM research and development. The review shows that VFM is an active field of research, which has the potential to be used as a standalone metering solution or as a back-up for physical multiphase flow meters. However, to increase the value of VFM technology for oil and gas operators, future research should focus on developing auto-tuning and calibration methods which account for changes of fluid properties and operation conditions. In addition, the review shows that the potential of machine learning methods in VFM is not fully revealed, and future research should focus on developing robust methods which are able to quantify flow estimation uncertainties and incorporate first principle models that will result in more accurate and robust hybrid VFM systems. Finally, our review reveals that dynamic state estimation methods combined with first principles and machine learning models could further improve the VFM accuracy, especially under transient conditions, but implementation of these methods can be challenging, and further research is required to make them robust.

1. Introduction

An oil and gas production system typically consists of a number of wells which are connected to a flowline which carries the produced fluid from wellheads to an inlet separator of a processing facility. If the field is subsea, the flowline is connected with the inlet separator via a riser. The flowrate of the produced fluid is controlled by choke valves installed at the wellheads. A schematic representation of a typical subsea production system is shown in Fig. 1, where an example with two wells is shown for simplicity. In the vast majority of cases the production field consists of more wells. In this example, we also include an electric submersible pump (ESP) as an example of artificial lift, however, other methods may also be used for this purpose, for instance, gas lift (Rashid et al., 2012). Typically, the produced fluid is a multiphase mixture of oil, gas, water and solids such as sand or asphaltenes (Falcone et al., 2009). This mixture is split into single phases in the inlet separator and further processed at a processing facility.

For economic operation of the production systems, it is important to know the oil, gas and water flowrates from each well. It allows operators to make critical decisions in production optimization, rate allocation, reservoir management and predict the future performance of the field (Retnanto et al., 2001; Morra et al., 2014; Falcone et al., 2001). At the early stage of the industry, the main method to estimate well flowrates was well testing. Here, a well stream is directed into a test separator where it is split into oil, gas and water. These flow streams are then measured by single-phase meters at the separator outlet (Corneliussen et al., 2005). The test separators require a separate flowline, so that each well can be routed to the test separator and tested without shutting-down the entire field. As an alternative, the flowrates can be estimated by the use of an inlet separator. In this case, two options are possible. The first option is to shut-down all the wells except the tested one, so that the flowrates of this well can be estimated. This option is associated with a large production loss and often economically undesirable. Another possibility is to close the well of interest, measure the flowrates of the producing wells at the separator conditions and then back-calculate the flowrates of the closed well. This is done by subtracting the obtained flowrates from the ones recorded before the well test. This method is called deduction well testing (Idso et al.,

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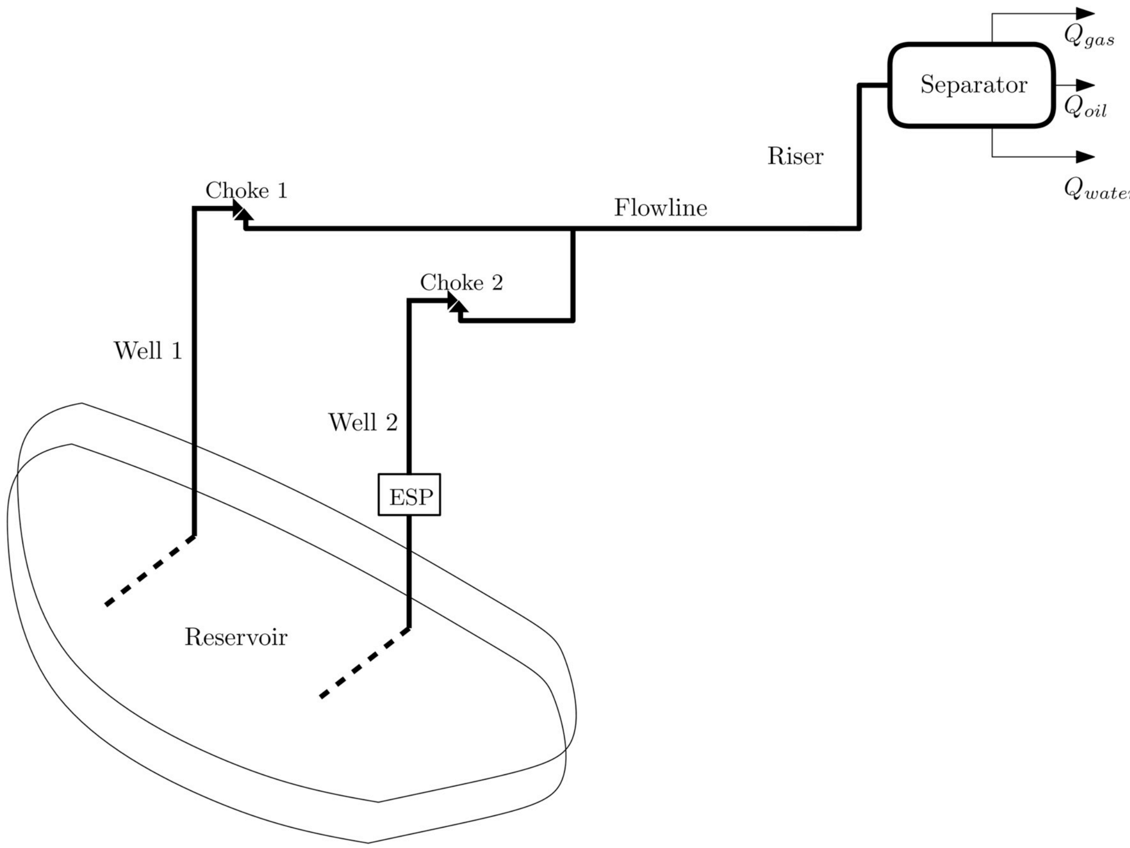

Fig. 1. Schematic representation of a typical subsea oil and gas production system.

2014). In all the described options, stable operating conditions need to be achieved in order to measure the flowrates, which might require several hours depending on the distance between the well and separator. In addition, the act of closing one well affects the performance of other wells which may result in inaccurate flowrate estimations (Falcone et al., 2001; Idso et al., 2014).

Over the last 25 years, physical multiphase flow meters (MPFMs) have been developed as an alternative solution to well testing to measure well multiphase flowrates and were first commercialized in the early 1990s (Falcone et al., 2001). The core idea behind MPFMs is to estimate oil, gas and water flowrates without separating the phases. These meters are usually installed at the wellhead, so that the multiphase flowrates from a particular well can be tracked in real-time. The flowrates are calculated indirectly using supplementary measurements of fluid phase properties such as velocities and phase fractions inside the device (Falcone et al., 2001; Gryzlov, 2011). An extensive effort was made to develop accurate multiphase flow meters and several technologies have been used for this purpose such as acoustic attenuation, impedance and gamma densitometers (Falcone et al., 2001). A number of review articles exist, in which the applied methods, principles, governing equations and measurement strategies are discussed in details (Corneliussen et al., 2005; Falcone et al., 2009; Thorn et al., 2013).

Both aforementioned flowrate measurement techniques have their advantages and disadvantages. First of all, well testing requires a separate flowline and a separator, which results in high capital costs of the field development (Falcone et al., 2001). If the inlet separator is used as a test separator, the cost associated with the production loss can be significant due to closing the well of interest. Sometimes, deduction testing may be impossible to perform due to potential flow assurance problems (Melbø et al., 2003). Despite these facts, well testing measurements are still widely used in oil and gas production monitoring, even if multiphase flow meters are installed in the field. The reason for this is that the flowrate measurements from well tests are used as a reference to calibrate multiphase flow meters and extract information about the fluid properties (Corneliussen et al., 2005).

In contrast to well testing, MPFMs provide real-time information about the well flowrates. This is definitely advantageous from an operational point of view. However, MPFMs are quite expensive and require an intervention in case of a failure, which adds a significant operational cost (Falcone et al., 2001; Patel et al., 2014). Moreover, MPFMs have a specific operation range beyond which the accuracy of the flowrate estimates can decrease significantly. Apart from this, the meters may face degradation due to sand erosion or partial blockage which also has an impact on the measurement accuracy (Marshall and Thomas, 2015).

Considering the discussed challenges as well as associated costs for both flow measurement approaches, an alternative solution is Virtual Flow Metering (VFM). The idea behind VFM is to collect available field data and use it in a numerical model to estimate flowrates (Rasmussen, 2004; Toskey, 2011). The measurement data usually include:

- Bottomhole pressure and temperature (P_{BH} and T_{BH}).
- Wellhead pressure and temperature upstream of the choke (P_{WHCU} and T_{WHCU}).
- Wellhead pressure and temperature downstream of the choke (P_{WHCD} and T_{WHCD}).
- Choke opening (C_{op}).

In contrast to well testing and MPFMs, VFM systems do not require installation of an additional hardware, as such they can reduce the capital and operational costs of the field development. At the same time, VFM systems have capabilities to estimate the flowrates in real time and reflect changes of flow conditions accordingly. This is a clear advantage compared to the well testing approach which assumes constant well flowrates between the tests (Marshall and Thomas, 2015). Moreover, VFM can be used as a standalone solution, or in a combination with a MPFM as a back-up system such that it can use the information from a MPFM to further improve the flowrate estimates (Holmås et al., 2013).

Despite the amount of work done on Virtual Flow Metering and the diversity of applicable methods and models, there is a lack of an overview of this. In this paper, we fill this gap and cover the following objectives:

- Summarize and classify VFM methods, models and computational procedures.
- Distinguish the differences among the VFM vendors based on publicly available resources.
- Review the reported VFM field experience and the research activity.
- Identify gaps and propose directions for future VFM research and development.

We believe that this paper will be an asset for readers who want to get an overview of available VFM solutions, implement the existing commercial VFM solutions in the field, construct an own VFM or improve the already created one.

Our paper is organized as follows. First, we introduce the main VFM approaches which are applied in industry or developed for research purposes. Then, we explain each VFM method in detail by providing the main concepts behind it, the models used, the available market products as well as reported field experience and the current status of the academic research. Finally, we compare the methods and specify their advantages and disadvantages and propose directions for the future research and development of the VFM systems.

2. VFM methods

Over the last 20 years, the concept development of VFM resulted in various methods to estimate the multiphase flowrates using available field data, and several companies have developed commercial VFM systems which are used by oil and gas operators around the world. Some methods are currently emerging and aiming to improve the accuracy of the flowrate predictions, while yet other methods are currently not used in the industry but have a good potential to move the VFM development forward in the future.

Based on modeling paradigms, two main Virtual Flow Metering approaches can be distinguished:

- First principles VFM
- Data-driven VFM

The first principles VFM systems are based on mechanistic modeling of multiphase flows in the near-well region, wells, pipelines and production chokes (Holmås and Løvli, 2011). The models are used together with the measurements such as pressure and temperature to find accurate estimates of the flowrates. An optimization algorithm adjusts the flowrates and other tuning parameters to minimize the mismatch between the model predictions and real measurements (Holmås and Løvli, 2011). The production system can be modelled as a whole from the reservoir to the processing facility, or it can be separated into submodels depending on the available measurement data. First principles models are currently used in most commercial Virtual Flow Metering systems.

The data-driven VFM approach is based on collecting the field data and fitting a mathematical model to it without the exact description of the physical parameters of the production system such as a wellbore and choke geometry, flowline wall thickness, etc. This approach is also referred to as “machine learning” modeling and it has become very popular in the past several years, not only for oil and gas applications but for many other applications as well. In this paper, we will call this approach “data-driven” modeling because in many VFM related publications it was named with this definition. In data-driven modeling, the fitting process is often called training (Hastie et al., 2009). If the model is well trained and the exposed conditions are within the range used for the training, the data-driven model can perform fast and accurate real-time metering. In this approach, deep domain knowledge of production engineering is not as important as in the first principles models and the model can be constructed at a lower cost.

In addition to the classification based on the modeling principles, we may classify approaches based on how time dependency is included in the model. Based on this, the following sub-classification can be performed:

- First principles VFM – steady state and dynamic models
- Data-driven VFM – steady state and dynamic models

In the first principles VFM, conservation equations often have a dynamic form, however, the formulation of the optimization problem is steady state or quasi-steady state, so that an optimization solver finds the solution for only one point in time or takes the solution from the last step as an initial guess for the current time step prediction. In some cases, even the conservation equations take steady state form or do not consider time because of its nature, for instance, a choke model (Perkins, 1993). While it is possible to formulate the VFM optimization problem in a dynamic way, in the available literature on the first principles VFM does not consider this approach. The main reason for this may be the fact that dynamic optimization for first principles VFM systems is computationally very expensive (Lew and Mauch, 2006). On the other hand, such methods may have been utilized but not discussed in the literature.

Apart from dynamic optimization, state estimation techniques such as Kalman filter approaches can be used in order to create a dynamic VFM (De Kruif et al., 2008). This approach has been covered in the research as we will show in the future sections, however, it is not implemented in the commercial software yet. The main reason for this may be that it requires a high expertise for setting up and using, and it can be difficult to tune in a robust manner for real field data.

For the large majority of data-driven algorithms used for VFM, the model formulation is steady state, so that the algorithms consider pressure and temperature measurements in one point in time to predict the flowrates at the same time step. At the same time, there are data-driven algorithm structures which have a dynamic formulation, so that measurements from the past may also be used to estimate the flowrate at the current time step and some of these algorithms have recently been studied for VFM applications. In the next sections, we consider each VFM paradigm in more detail and explain the considerations of dynamic system behavior by each method based on the used models and algorithms.

3. First principles VFM systems

3.1. An overview of the concept

The first principles VFM systems are the most widely used Virtual Flow Meters in the industry. This is because a tremendous effort was made over the past 50 years in order to describe each part of this VFM approach. This resulted in a quite good understanding of the mechanistic modeling of production systems, fluid properties and optimization techniques. As such, first principles modeling can be considered as a reliable way to describe the production system behavior in general, and multiphase flow phenomena in particular. In this section, we will describe the main concept behind the first principles VFM. In the later sections, each model used in the concept is discussed in more detail.

A current state-of-the-art first principles VFM system consists of the following main components:

- Fluid properties model.
- Production system model including:

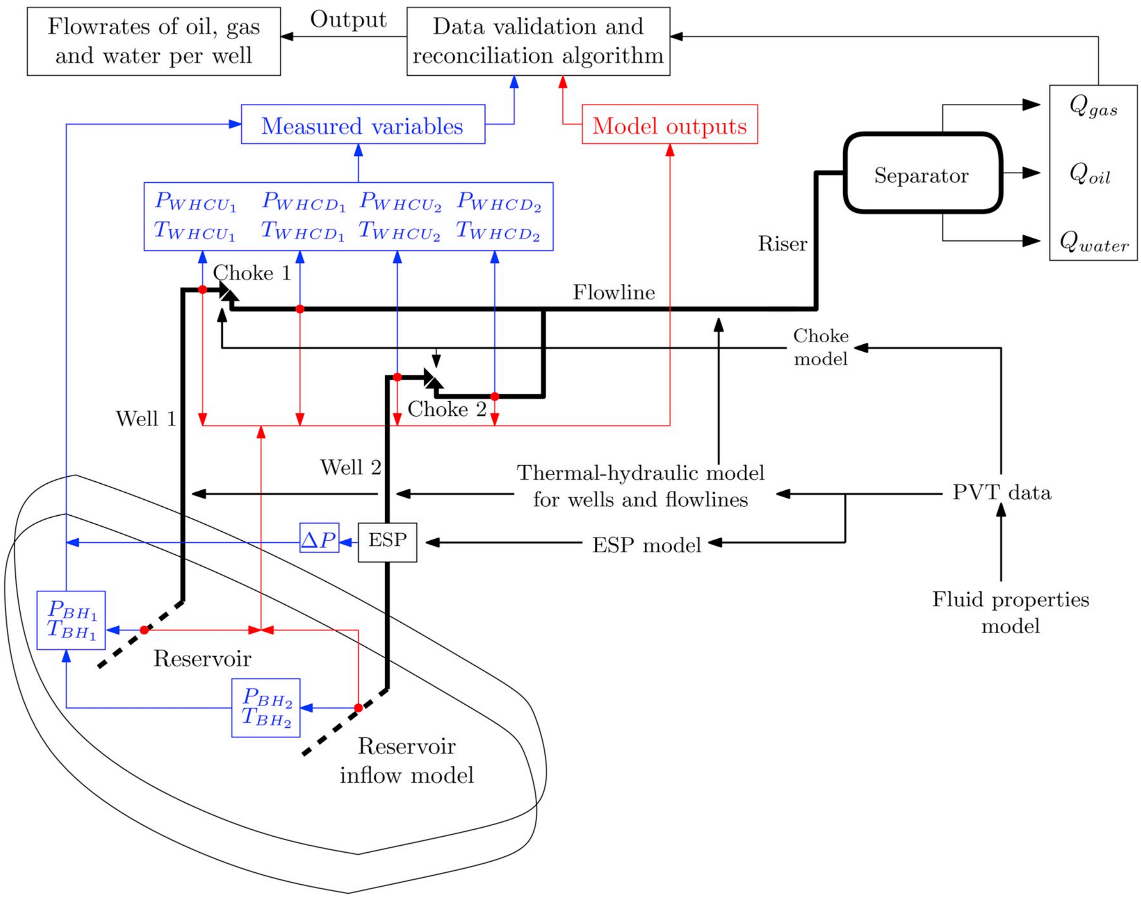

Fig. 2. Schematic overview of a first principles Virtual Flow Metering system. Thermal-hydraulic, choke, ESP and reservoir inflow models use pre-generated PVT data in order to predict the system variables such as pressures and temperatures along the system. The data validation and reconciliation algorithm adjusts the model parameters (flowrates, choke discharge coefficient, etc.) such that the model outputs (red color) match the measurements from the physical system (blue color) and the overall material balance (flowrates measured at the separator outlet). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

  - Reservoir inflow model
  - Thermal-hydraulic model
  - Choke model
  - Electric submersible pump (ESP) model
- Data validation and reconciliation (DVR) algorithm.

The main idea behind the first principles VFM system is depicted in Fig. 2 where the concept is applied for the production system shown in Fig. 1. First, the thermal-hydraulic, choke, ESP and reservoir inflow models produce model outputs which can be pressures and temperatures along the production system. To do that, the models require pre-generated pressure-volume-temperature (PVT) data which describe the fluid properties under given conditions and generated using fluid properties models. The popular forms of the fluid properties model are Equations of State (EoS) and Black Oil model (BOM) which will be described further below.

Next, the measured field data is processed by the data validation and reconciliation algorithm. In the DVR, first, the data are validated which can include removal of outliers and noise filtering. Then, in the reconciliation step the model parameters (e.g. flowrates, choke discharge coefficient, gas and water fractions, friction and heat transfer coefficients, slip relation, etc.) are adjusted such that the model outputs (in red in Fig. 2) match the measurements from the physical system (in blue in Fig. 2) and the overall material balance (flowrates measured at the separator outlet).

In summary, for VFM using the first principles models, the following steps are taken:

1 Create a fluid properties model which represents the fluid data accurately.
2 Choose appropriate production system models based on the available measurements.
3 Read and validate the measurement data, remove outliers and filter noise.
4. Select appropriate tuning parameters, for instance, flowrates, choke discharge and heat transfer coefficients, etc. and make a guess of the initial parameter values.
5. Simulate the models selected at step 2 using the fluid properties from step 1 and initial values of the tuning parameters from step 4.
6. Select the model outputs from step 5 for which the measurements are available, for instance, pressures and temperatures at the bottomhole and the wellhead.
7. Run the data reconciliation algorithm to minimize the mismatch between the model outputs from step 6 and the validated measurement data from step 3 by adjusting the tuning parameters selected at step 4.
8. Report the oil, gas and water flowrates for each well from the solution from step 7.

3.2. Commercial first principles VFM systems

To discuss the details behind each component of the first principles VFM, we consider commercial VFM systems which are based on this approach. The reason for this is that these systems use the most advanced methods and models which are currently applied in VFM

Table 1
Commercial first principles VFM systems.

Virtual Flow Metering system	Vendor
OLGA Online	Schlumberger
K-Spice Meter (K-Spice + LedaFlow)	KONGSBERG
FlowManager	FMC
Well Monitoring System (WMS)	ABB
Virtuoso	WoodGroup
FieldWatch + METTE	Roxar
ValiPerformance	Belsim
Rate&Phase	BP

technology. At the same time, the discussion gives an overview of the model variations among the software as well as the available products on the market. As such, we believe by describing the models and capabilities of the commercial software, we will be able to better evaluate the current state of the VFM technology development.

In our review, we will consider the methods and models of the commercial VFM systems listed in Table 1. All these products have conceptually the same structure, i.e. utilize fluid properties and production system models together with the data validation and reconciliation algorithm to estimate the multiphase flowrates. It is also important to mention other VFM suppliers which are not included in the list. Ensys Yocum delivers VMSS3 Virtual Flow Meter but the information about it in the literature is very limited, so that it is hard to evaluate software's features precisely. TurbulentFlux is currently an emerging company which supplies a state-of-the-art VFM product. As the company is at the starting phase, the information about the software is not publicly available yet, as such we do not consider it in the further analysis.

In addition to the listed software, there are several other software which could potentially be considered as a VFM system, but they are not considered in this paper in details. For instance, Amin (2015) used Prosper (PETEX, 2017) as a Virtual Flow Meter. Prosper is a software which describes performance of wells and production systems under various conditions and extensively used in the petroleum industry. The software has a variety of reservoir inflow, choke and hydrodynamic models linked to PVT data to evaluate production performance of wells (PETEX, 2017) However, in this paper we do not consider Prosper as a fully integrated VFM system because, according to the software description, it does not include the DVR algorithm to fit specific field measurement conditions. In addition, there are no other studies or papers which evaluate Prosper as a VFM system. Mokhtari and Waltrich (2016) used PIPESIM as a Virtual Flow Metering system to evaluate different models for VFM purposes. PIPESIM is a steady state multiphase flow simulator supplied by Schlumberger which delivers OLGA Online as a VFM product which we consider in this study. As such, PIPESIM is not considered as Schlumberger's VFM system in this study, but potentially can be utilized for VFM purposes.

In the next section, we will consider the components of the first principles VFM products from Table 1 in more detail. More specifically, we will emphasize the mathematical description of the models and the usage of a particular model type in a particular VFM product.

3.3. Description of the first principles VFM components and applied methods

In this section, we consider the components of the first principles VFM systems in more detail. First, we will discuss the fluid properties model together with subsequent PVT data generation. Then, we will show what the principles behind the production system models are and how the PVT data is used for in these models. Finally, we will discuss how the data validation and reconciliation algorithm finds optimum flowrate estimates. Throughout the description of the models, we will discuss its implementation in the commercial VFM products.

3.3.1. Fluid properties model

Hydrocarbon mixtures are complex substances whose properties vary with local pressure and temperature conditions along the production system. In order to take these variations into account, fluid characterization is carried out based on fluid samples taken at different points such as downhole or at the separator (Whitson and Brule, 2000). Based on the characterized fluid, a pressure-volume-temperature (PVT) data can be generated which is then used by VFM systems for two purposes (Falcone et al., 2009):

- Calculating local phase properties of the hydrocarbon mixtures such as density, viscosity, thermal conductivity, etc. for using in the first principles models.
- Reconciling reference flowrate measurements (e.g. at separator or standard conditions) with flowrate measurements/estimates at local conditions (e.g. at the wellhead).

As for the first point, the local fluid properties have a direct influence on the flowrate predictions by a VFM system because they are included in thermal-hydraulic conservation equations as well as the models of choke, ESP and reservoir inflow. As such, giving incorrect phase densities or enthalpies for certain pressures and temperatures to the VFM system will result in deviations between the predicted and actual flowrates. This in turn will cause problems in finding a good solution by the data validation and reconciliation algorithm when tuning flowrates and other model parameters.

Regarding the second point, when the local flowrates are calculated, they are usually reported at reference conditions for reconciliation, production and sales reporting purposes (Pinguet et al., 2005). Reconciliation is especially important in fields with commingled wells, so that the overall measured production rates at the separator conditions can be back-allocated (reconciled) to the individual wells as shown in Fig. 2.

Fluid characterization is typically done by two approaches separator (Whitson and Brule, 2000; Falcone et al., 2009):

- Black Oil model.
- Compositional model.

These two models are discussed below.

3.3.1.1. Black Oil Model (BOM). Black Oil model is a simple, yet useful approach for petroleum fluid characterization. In this approach, oil and gas are treated as two separate substances and their properties are calculated based on correlations (Whitson and Brule, 2000). In the traditional formulation of the BOM, three main PVT properties are considered: oil formation volume factor, gas formation volume factor and solution gas-oil ratio. For volatile hydrocarbon mixtures, modified Black Oil models (MBOM) are developed which introduce another core variable called solution oil-gas ratio. If water is present in the produced fluid, additional properties such as water formation volume factor, solution gas-water ratio and water content in gas are introduced into calculations. The full description of both traditional and modified black oil models for volatile oils and water/hydrocarbon systems are well described in the SPE monograph by Whitson and Brule (2000).

3.3.1.2. Compositional model. A compositional fluid model is described by Equations of State (EoS) which are relations between pressure, volume and temperature which is a basis for calculating phase and volumetric behavior of the produced fluid (Whitson and Brule, 2000). The history of the EoS development starts from the fundamental work by Van der Waals (1870). Later, various modifications and improvements of the van der Waals' equation were proposed. For the majority of oil and gas applications, the following modifications are used (Whitson and Brule, 2000; Falcone et al., 2009):

- Peng-Robinson (PR) (Peng and Robinson, 1976).
- Redlich-Kwong (RK) (Redlich and Kwong, 1949).
- Soave-Redlich-Kwong (SRK) (Soave, 1972).

State-of-the-art VFM systems support both compositional and BOM approaches for PVT modeling (Bendiksen et al., 1991; Haldipur and Metcalf, 2008; Kongsberg, 2016; Løvli and Amaya, 2016; Melbø et al., 2003). Even though the current trend in the first principles VFM is to use the compositional approach [e.g. VFM evaluation study by Letton-Hall Group (Toskey, 2011)], simplified VFM systems based only on one model (e.g. choke/orifice model) tend to utilize the Black Oil model because of its simplicity (Campos et al., 2014; Da Paz et al., 2010).

3.3.1.3. PVT data development. In order to simplify the simulation process, the obtained fluid properties models (BOM or compositional model) are typically stored in the form of PVT tables which are then used by the VFM models. In principle, the fluid properties models could be used directly in the VFM systems, however, this would lead to a high computational cost. Therefore, before performing the simulations, the fluid properties data are stored in PVT tables which are then used by the models to find the fluid properties values by interpolating between the generated data points.

Prior to the PVT table construction, it is first required to tune the fluid properties models to the specific petroleum fluid. This is because the default model parameters usually do not predict precisely the fluid properties from a specific field (Coats and Smart, 1986). Moreover, during the field life-cycle, fluid properties are changing which also require model calibration (Falcone et al., 2009). This tuning/calibration can be performed by applying non-linear regression (Agarwal et al., 1990; Coats and Smart, 1986) or by an iterative adjustment of EoS parameters (Pedersen et al., 1988; Whitson and Torp, 1983). The calibration is performed based on the data obtained in the laboratory tests. For the EoS model, the tests may include compositional analysis (gas chromatography), constant composition expansion, multistage surface separation, constant volume depletion and differential liberation expansion (Whitson and Brule, 2000). If BOM is used, the laboratory tests are used in order to estimate the main model parameters. An example of BOM parameters estimation based on the lab data is Whitson-Torp method (Whitson and Torp, 1983).

When the fluid models are tuned to the specific fluid properties, the PVT tables for the expected range of pressure and temperature conditions is generated and uploaded into a VFM system. Using these data, the system can interpolate the computed properties (e.g. phase density and viscosity) to local pressure and temperature (e.g. at the wellhead) based on the specified table values (Bendiksen et al., 1991).

3.3.1.4. Importance of fluid properties model tuning. Regardless the fluid model used for the PVT properties characterization, the fluid properties model accuracy has to be addressed with a particular attention. PVT related deviations in flowrate metering have been typically observed in MPFMs which have been found to be very sensitive to PVT data (AlDabbous et al., 2015). The sources of the PVT related deviations in MPFMs may originate from incorrect phase properties estimation or inaccurate usage of EoS (Åbro et al., 2017). EoS estimates of the fluid properties are consistent only within the tuning range of pressures and temperatures. If the fluid properties values are extrapolated outside the tuning range, the error of the estimates may be significant (Joshi and Joshi, 2007).

Similar to MPFMs, first principles VFM systems strongly rely on the PVT data. This means that accurate flowrate estimations require well characterized fluid properties data (Petukhov et al., 2011; Zhang et al., 2017). It has been found that when VFM is applied in a pilot case study or a field, PVT data is one of the most critical system parameters (Haouche et al., 2012a). Inaccurate PVT characterization results in the increase of the uncertainty of the VFM estimates (Ausen et al., 2017). The reason for such a large influence is the fact that the PVT data defines the local fluid properties, hence the discrepancies in fluid properties will directly influence the local flowrate estimates. Also, it will affect the reconciliation algorithm outputs because the fluid properties are directly involved in converting the rates from local to reference conditions which are used in the algorithm.

3.3.2. Production system model

The production system model typically consists of different components that are given by the measurements available in the field as well as the installed equipment. Below, we present the most relevant models which may be included into the first principles VFM system.

3.3.2.1. Reservoir inflow model. The reservoir inflow model is usually represented by an Inflow Performance Relationship (IPR) model which defines the well production rate as a function of pressure difference at reservoir and bottomhole conditions. The data for IPR curves are collected during multi-rate well testing (Golan and Whitson, 1991). This method has been extensively used in the industry to calculate the performance and production potential of wells and many models have been developed which are currently implemented in the state-of-the-art VFM systems. The most frequently used models are:

- Linear
- Backpressure/Backpressure normalized
- Undersaturated
- Vogel
- IPR table
- Forchheimer/Single Forchheimer

The linear model assumes that the well rate is proportional to the pressure difference between the reservoir and bottomhole (Bradley, 1987). This model is typically used for undersaturated oil wells and can be expressed in the following form (Cholet, 2008; Schlumberger Limited., 2014):

$$q_0 = PI\cdot(P_R - P_{BH}) \tag{1}$$

where q_0 denotes the oil flowrate, PI– the productivity index, P_R – the reservoir pressure, P_{BH} – the bottomhole pressure. The productivity index PI is estimated during a well test and then used in subsequent calculations.

The backpressure model is suitable for gas wells and can be written as follows:

$$q_g = C_b(P_R^2 - P_{BH}^2)^n \tag{2}$$

where q_g denotes the gas flowrate, C_b and n – the tuning coefficients which are estimated during well tests.

A normalized form of Eq. (2) is used for saturated oil wells and can be expressed as:

$$q_o = q_{o,\max}\left[1 - \left(\frac{P_{BH}}{P_R}\right)^2\right]^n \tag{3}$$

where $q_{o,\max}$ denotes the maximum oil flowrate.

For the full description of the backpressure model, please see Bradley (1987).

The undersaturated model is often used to model oil wells with the static reservoir pressure for which the bottomhole pressure drops below the bubble point during production (Schlumberger Limited., 2014).

$$q_o = PI\cdot(P_R - P_B) + \left(\frac{PI}{2P_B}\right)(P_B^2 - P_{BH}^2) \tag{4}$$

where P_B denotes the bubble point pressure.

The Vogel model (Vogel, 1968) is commonly used in solution-gas-drive reservoirs and expressed as the following:

$$q_o = q_{o,\max}\left[1 - 0.2\left(\frac{P_{BH}}{P_R}\right) - \left(\frac{P_{BH}}{P_R}\right)^2\right] \tag{5}$$

To compute the gas flowrate using the equations above, the obtained flowrate must be multiplied by GOR.

IPR table, as the name states, represents the tabulated relationship between the flowrate and pressure difference. Based on the user-specified data and a calculated pressure difference value, the flowrate is interpolated by a linear or polynomial method (Schlumberger Limited., 2014).

For gas reservoirs with high flowrates, the inertial effect can be important to be accounted. In this case, a non-Darcy's law model called Forchheimer model is applicable (Bradley, 1987) which has the following form (Schlumberger Limited., 2014):

$$P_R^2 - P_{BH}^2 = B_f q_g + C_f q_g^2 \tag{6}$$

where B_f and C_f denote the tuning coefficients, which are estimated during well tests.

In case of high pressure gas wells, the single Forchheimer model can be used instead. It has a linear form of the pressure difference as follows:

$$P_R - P_{BH} = B_f q_g + C_f q_g^2 \tag{7}$$

Except for the Forchheimer's models, all the models are currently implemented in K-Spice Meter, while OLGA-Online currently incorporates all the listed models (Kongsberg, 2016; Schlumberger Limited., 2014). For other VFM software the information about implemented IPR models is rather limited. In ValiPerformance (Belsim), Vogel's model was utilized and tested (Haouche et al., 2012a, 2012b), while in Petukhov et al. (2011) and Wising et al. (2009). IPR model is mentioned as a part of the system but the type is not specified. In both FieldWatch and FlowManager, the reservoir inflow model can be specified by IPR tables (Gunnerud, 2011; Roxar, 2015). WoodGroup's Virtuoso and BP's Rate&Phase also use the IPR models, however, the exact models are not specified (Haldipur and Metcalf, 2008; Heddle et al., 2012).

As we can see, the IPR models have variety of forms depending on the well production conditions. In VFM, IPR models can be used in different purposes. First, it can be used as a separate model to estimate the production potential of a well. Secondly, the IPR models can be used in a combination with the thermal-hydraulic and choke models as a boundary condition of the system representing reservoir inflow to the well. In this case, it adds additional variables to the tuning process described in Fig. 2 which can further be used to tune the VFM system to the historical data. Apart from that, IPR equation can be combined with a thermal-hydraulic model (vertical lift performance curve) to estimate multiphase flowrate under steady state conditions, please, see, for instance, Lansagan (2012).

3.3.2.2. Thermal-hydraulic model. Multiphase flows in wells and pipelines in oil and gas fields have existed for more than a hundred years (Shippen and Bailey, 2012). The first attempt to model the multiphase flow was made by Lockhart and Martinelli (1949). At that time, the approach for multiphase flow modeling was based on empirical correlations obtained from experiments and available field data. With time, a more fundamental modeling approach replaced pure empirical models by including the physics behind the multiphase flow phenomena. An excellent review of the history of multiphase flow models development can be found in Shippen and Bailey (2012).

In this work, we will focus on the models currently used in commercial Virtual Flow Metering systems. Based on the literature, the following types of thermal-hydraulic multiphase models are currently implemented in the first principles VFM products:

- Two-fluid model.
- Drift-flux model.
- Steady state mechanistic model.

In the two-fluid model (often referred as the multi-fluid model), the conservation equations are written for each phase which can be continuous or dispersed. In a simplified manner, the general form of mass, momentum and energy equations respectively can be written as follows (Goldszal et al., 2007; Nydal, 2012):

$$\frac{\partial \alpha_k \rho_k}{\partial t} + \frac{\partial \alpha_k \rho_k u_k}{\partial x} = \Psi \tag{8}$$

$$\frac{\partial \alpha_k \rho_k u_k}{\partial t} + \frac{\partial \alpha_k \rho_k u_k u_k}{\partial x} = -\frac{\partial \alpha_k p_k}{\partial x} - \alpha_k \rho_k g \sin\theta - F_{kw} \pm F_{ki} + O_k \tag{9}$$

$$\frac{\partial \alpha_k \rho_k h_k}{\partial t} + \frac{\partial \alpha_k \rho_k u_k h_k}{\partial x} = \frac{\partial}{\partial x}\alpha_k k_k \frac{\partial}{\partial x} T_k + \alpha_k \frac{Dp}{Dx} + Q_{kw} + \sum_{i \neq k} Q_{ki} + Q_{ext} \tag{10}$$

where α_k denotes the phase volume fraction, ρ_k – the phase density, t – the time, u_k – the phase velocity, x – the pipe axial dimension,Ψ – the mass transfer sources (e.g. phase change and mixing), p_k – the phase pressure, θ – the pipe inclination angle, F_{kw} – the wall friction, F_{ki} – the interphase friction, O_k – the other momentum exchange terms (e.g. phase change, droplet-exchange, level-gradient term), p – the system pressure, k_k – the effective phase thermal conductivity, Q_{kw} – the phase transfer rate at pipe wall, Q_{ki} – the interfacial heat transfer rate of k-phase with other fields, Q_{ext} – the other net external heat transfer sources.

In the drift-flux model, the momentum and energy equations are written for the mixture while the mass conservation equations can be written for each phase. It can be expressed as the following (Holmås and Løvli, 2011):

$$\frac{\partial \alpha_k \rho_k}{\partial t} + \frac{\partial \alpha_k \rho_k u_k}{\partial x} = \Psi \tag{11}$$

$$\frac{\partial}{\partial t}\sum_k \alpha_k \rho_k u_k + \frac{\partial}{\partial x}\sum_k \alpha_k \rho_k u_k u_k + \sum_K \alpha_k \rho_k g + \frac{\partial p}{\partial x} = -F_{tot} - O_{tot} \tag{12}$$

$$\frac{\partial}{\partial t}\sum_k \alpha_k \rho_k E_k + \frac{\partial}{\partial x}\sum_k \alpha_k \rho_k u_k E_k + \frac{\partial}{\partial x}\sum_k \alpha_k \rho_k p + U_{tot} = 0 \tag{13}$$

where F_{tot} denotes the total wall friction, O_{tot} – the source term,E_k – the total energy, U_{tot} – the total source term including wall heat transfer, mass transfer and sources.

The drift-flux model requires a slip relation in order to take the difference between the phase velocities into account. The most famous and commonly used form is developed by Zuber and Findlay (1965):

$$u_g = C_0 u_m + u_d \tag{14}$$

where u_g denotes the gas velocity, u_m – the mixture velocity, u_d – the drift velocity, C_0 – the profile parameter.

Both multiphase flow model formulations above are transient which means they reconstruct the flow behavior in space and time. If the time derivative term $\frac{\partial}{\partial t}$ is set to zero, the model becomes steady state and resolved only in space. With a steady state model, it is not possible to properly describe an unstable behavior in wells, for instance, liquid loading or severe slugging as it is transient in nature (Waltrich and Barbosa, 2011).

Some VFM systems use only one specific formulation of the thermal-hydraulic model, while others utilize a combination of them. For instance, in OLGA the two-fluid formulation of the momentum equation is combined with a mixture energy equation (Nydal, 2012). In total, OLGA includes five mass and three momentum equations as well as one mixture energy equation (Shippen and Bailey, 2012). In K-Spice Meter which uses LedaFlow for resolving multiphase flows in wells, nine mass, three momentum and three energy equations are used (Kongsberg, 2016; Shippen and Bailey, 2012). As such, it is classified as a two-fluid model which have nine fields: 3 continuous and 6 dispersed.

In contrast to OLGA and K-Spice Meter, FlowManager utilizes the transient drift-flux model with one mixture momentum and one energy equation. The mass balances are solved for each phase (Holmås and Løvli, 2011). A similar approach is used in METTE which is a multiphase flow solver in FieldWatch. The software uses the transient drift-flux model with the mixture momentum and energy equations with a possibility to include and exclude the slip effect between the phases (Roxar, 2015).

Based on the literature available on Well Monitoring System by ABB, it is difficult to relate the software model to any of the formulations above. van der Geest et al. (2000) formulated the momentum equation in a very generic way as the following:

$$-\frac{dp}{dx} = f_{fric}\frac{2\rho u^2}{D} + \rho g \sin\theta \tag{15}$$

where p denotes the system pressure, f_{fric} – the friction factor, u – the fluid velocity, ρ – the fluid density, D – the pipe diameter, x – the pipe axial dimension, θ – the pipe inclination angle.

The equation basically states that the pressure drop along the well depends on friction and gravity. In this case, the multiphase flow is resolved as follows. First, the flow pattern is identified based on the method developed by Barnea (1987). Based on the local flow pattern, the respective closure laws and correlations are identified and the momentum equation is solved. Given the solution of the momentum equation, the temperature gradient is solved which has the following form (van der Geest et al., 2000):

$$\frac{dT}{dx} = \frac{\frac{e+w}{dx} - u\frac{du}{dx} - g\sin\theta - \frac{\partial h}{\partial P}\frac{dp}{dx}}{\frac{\partial h}{\partial T}} \tag{16}$$

where e denotes the specific heat exchange with the environment, T – the fluid temperature, h – the specific fluid enthalpy, w – the specific work done on the system.

This is a similar approach to the Unified Model developed at the University of Tulsa, see Zhang et al. (2003). However, since the literature on the model applied in Well Monitoring System is limited, it is not possible to surely state that the Unified Model is applied. On the other hand, it is possible to conclude that this model uses a mechanistic steady state approach as there is no time derivative in the model as well as flow is modelled based on the physics behind including force balances and correlations based on the flow pattern. This classification is also in correspondence with the one provided by Shippen and Bailey (2012).

As for the rest of the commercial VFM systems, based on the available sources, we have not been able to identify the type of the implemented thermal-hydraulic model. However, the software definitely use one, please see Haouche et al. (2012b) for Vali-Performance, Haldipur and Metcalf (2008) for Virtuoso and Heddle et al. (2012) for Rate&Phase.

3.3.2.3. Choke model. Over many years, choke valves at the wellheads have been used in oil and gas production for safety and control purposes (Buffa and Baliño, 2017). In addition to this, because the pressure drop over the choke depends on the flowrate, the choke valve can be used to estimate the flow. As such, a choke valve model can be considered as a simple Virtual Flow Meter because the flow is not measured directly but rather estimated. However, estimating the flow over the choke is not a straightforward task due to the multiphase flow complexity.

As in many other fluid dynamics applications, the first attempts to estimate the flow through the choke were made using empirical correlations. For example, see the model developed by Gilbert (1954). At the later development stage, mechanistic models were proposed which are currently implemented in Virtual Flow Meters.

Based on the available literature, we found that four models are currently implemented in commercial VFM systems. It can be the case that there are more utilized models, but, unfortunately, the literature published by VFM suppliers on this topic is rather limited.

As for the implemented models, they are:

- Modified Bernoulli
- Hydro (Long and Short)
- Perkins

The Modified Bernoulli model is implemented in Roxar's FieldWatch. The model is derived from the famous Bernoulli equation which was originally applied for a single-phase flow. In order to adjust the model to specific choke parameters, the choke discharge coefficient and mixture density are introduced. The Modified Bernoulli model can be written as follows:

$$\dot{m} = A_1 C_D \left[\frac{2\Delta p \rho_m}{\frac{A_1}{A_2} - 1}\right]^{1/2} \tag{17}$$

where $\dot{m}$ denotes the mass flowrate, C_D – the choke discharge coefficient, A_1 – the inlet choke area, A_2 – the choke throat area, ρ_m – the fluid mixture density, Δp – the pressure drop over the choke.

The Hydro model developed by Selmer-Olsen (1995) is used in OLGA Online. This model has two versions: Long and Short. In the Long version, it is assumed that vena contracta is located inside the throat while in the Short model it is located downstream of the throat. In both models, sub-critical and critical flows are calculated and then the smallest one is selected since the critical flow is the largest possible. In comparison with many other models, the Hydro model considers irreversible losses in the choke in a mechanistic manner, thus, the discharge coefficient is not involved in calculations. For the full Hydro model description with the derivation details, an improved slip relation as well as testing results by experimental data, please see Schüller et al. (2003) and Sampath et al. (2006).

The Perkins model (Perkins, 1993) is implemented in Rate&Phase. The model is derived from the energy equation applied on a control volume of a fluid. It calculates the mass flowrate for sub-critical and critical flows and then adjusts it to the actual flow by multiplying with a discharge coefficient (Perkins, 1993). In contrast to the Hydro model, this model does not consider the slip effect between the phases as well as frictional losses in the throat. However, Sampath et al. (2006) found that this is a disadvantage of this model and that the Hydro model outperforms Perkins model by accounting the slip effect. K-Spice Meter includes both Hydro and Perkins models, so that the user may choose a preferable option (Kongsberg, 2016).

Apart from the models implemented in the commercial simulators, there are many other models suitable for estimating the mass flowrate over the choke. Ashford (1974) derived a model for the total mass flowrate based on the fluid properties, choke size and discharge coefficient. With the computed total mass flowrate, the oil flowrate can be estimated based on Black Oil properties.

By considering a no-slip frozen two-phase flow, Sachdeva et al. (1986) developed a model which has been popular in the literature. As in the Perkins model, they consider the discharge coefficient to adjust the flowrate to the actual conditions. Sampath et al. (2006) showed that the no-slip assumption makes this model to be less accurate than the Hydro model. Despite this drawback, the Sachdeva et al. (1986) model is one of the first mechanistic choke models and often considered in the literature for the analysis and comparison with new models.

Al-Safran and Kelkar (2009) developed a mechanistic choke model which accounts for the slip between phases. The idea behind the model development was to create a simple (as Sachdeva and Perkins) and accurate (as Hydro) model. As such, the basis of the model is taken from Sachdeva and Perkins models with an implementation of the slip model developed by Schüller et al. (2003) for a modified version of the Hydro model (Sampath et al., 2006). Based on experimental tests, Al-Safran and Kelkar model outperformed Sachdeva and Perkins models and decreased the average percent error by 5–10%.

As the field of choke models for flowrate estimation is wide, in addition to the aforementioned models, there are some less popular and general models available in the literature and utilized for real field cases. Several review papers study the history of the choke models' development and evaluate performance of different models. So, if the validation of the discussed models as well as description of other developed ones is of interest, see the works by Rastoin et al. (1997), Buffa and Baliño (2017) and Sampath et al. (2006).

3.3.2.4. Electric submersible pump (ESP) model. An electric submersible pump is a widely used artificial lift equipment which is used to produce oil where natural production is not possible due to various reasons, for instance, low bottomhole pressure, liquid loading, heavy oil presence, etc. ESPs have a long application history in the oil and gas industry, for example, see Lea and Bearden (1999) for a review of ESP applications in onshore and offshore oil and gas production. Due to its popularity, there have been a numerous amount of attempts to make a first principles model which describes ESP operation which are not possible to cover within this paper. The general idea behind an ESP model is to link the pump pressure increase with the pump inlet pressure, the flow and the pump speed (Schlumberger Limited., 2014):

$$\Delta P = f(q, \xi, \alpha_l, P_{inlet}) \tag{18}$$

where q denotes the flowrate, ξ – the pump speed, α_l – liquid fraction, P_{inlet} – pump inlet pressure.

By measuring the pressure before and after the pump and using a model described in a form of Eq. (18), it becomes possible to compute flowrates of the multiphase flow mixture which is pumped by an ESP. In this paper, we do not describe the exact differences between the models which are used by the commercial VFM systems. First of all, it is in general difficult to group the ESP models as it was done, for instance, for the thermal-hydraulic and choke models. In addition, some VFM suppliers do not provide specifics of the used models and mention only the fact that these models exist. What is important to note is the fact that these systems use ESP models and it can be a good source for multiphase flowrate estimation without additional hardware installations.

3.3.3. Data validation and reconciliation (DVR) algorithm

Another important part of the state-of-the-art first principles VFM systems is a data validation and reconciliation algorithm. In some papers and software, this VFM part is called simply "optimization algorithm" (Heddle et al., 2012; Holmås and Løvli, 2011), while in others it is mentioned as DVR (Haouche et al., 2012a; Patel et al., 2014). In case of Well Monitoring System by ABB, Melbø et al. (2003) defines it as the optimization algorithm, while van der Geest et al. (2001) defines it as DVR. In this paper, we use the term "data validation and reconciliation" to describe the process of adjusting the VFM model parameters such that the VFM model outputs match the measured field data.

As the technique name states, DVR consists of two parts: (1) validation and (2) reconciliation. In the data validation part (1), the goal is to remove erroneous and noisy data. This step can be done by means of statistical analysis and filtering techniques, for example, exponential filters or moving averages (Stanley, 1982).

When the data is validated, the reconciliation part (2) takes place. Here, an optimization algorithm adjusts the model parameters, for instance, flowrates, choke discharge coefficient, gas and water fractions, and friction and heat transfer coefficients such that the model outputs match the validated measured data being constrained to process conditions, for instance, the material balances (Câmara et al., 2017). In Virtual Flow Metering systems, the reconciliation algorithm is often written in the constrained least-squares form (Petukhov et al., 2011):

$$\min_{x} \sum_{i}^{N} \left(\frac{y_{meas\ i} - y_{predicted\ i}}{\sigma_i} \right)^2 \tag{19}$$

subject to the following constraints:

$$F(s, y) = 0 \tag{20}$$

$$y_{\min} \le y_{predicted\ i} \le y_{\max} \tag{21}$$

$$s_{\min} \le s_i \le s_{\max} \tag{22}$$

where i denotes the measurement index, $y_{meas\ i}$ – the measured value, $y_{predicted\ i}$ – the reconciled (predicted) value, σ_i – the measurement uncertainty, s_i – the unmeasured variable, $F(s, y) = 0$ – the process equality constraints (e.g. mass and energy balances).

In VFM applications, the problem formulation is usually non-linear due to the complexity of the system. In order to find the solution of a non-linear data reconciliation problem, different methods can be applied. If inequality constraints are not present, the method of Lagrangian multipliers may be used to obtain the solution (Câmara et al., 2017). If constrains are included, typically gradient based optimization methods are used such as Levenberg-Marquardt, SQP or Gauss-Newton (Câmara et al., 2017; Holmås and Løvli, 2011). In the outcome, the algorithm estimates the flowrates which give a local or global minimum error.

When the reconciliation process is finished, the results can be validated. In this step, statistical tests are conducted in order to further detect unreliable measurements and estimates and probability of a gross error existence. This can be achieved by performing individual (e.g. penalty) and global (e.g. chi-squared) tests (Petukhov et al., 2011).

3.4. Reported field experience with first principles VFM systems

The VFM systems derived from the first principles have been used in the industry as standalone solutions as well as back-up systems for physical multiphase flow meters. Unfortunately, not many examples of using a particular VFM solution are published. Despite this fact, some examples are still available in the open literature and are summarized in this section.

3.4.1. Reported field experience with commercial first principles VFM products

One of the most widely spread first principles VFM systems is Rate&Phase which was reported to be installed in more than 300 production and injection wells by 2011(Heddle et al., 2012). The authors reported that the average error of this VFM is usually recorded at the level of less than 5%.

In 2004, FlowManager was in operation in a subsea field with three wells which had challenges with downhole pressure sensors and unreliable choke information. Despite these difficulties, the software was able to identify erroneous flowrate measurements at the separator that emphasized possible features of the VFM technology (Rasmussen, 2004). FlowManager is also successfully utilized as a flow assurance system in Ormen Lange and Vega fields in the North Sea and used as a back-up system to the MPFMs (Holmås et al., 2013; Holmås and Løvli, 2011). Løvli and Amaya (2016) showed six cases of FlowManager implementation for VFM applications including gas condensate and oil fields. The software was used during normal conditions as well as start-up operations. These examples showed usefulness of VFM not only as a standalone solution but also for performance monitoring of physical flow meters. Overall, by 2018, FlowManager is in operation of 700 wells around the world (Escuer et al., 2018).

Application of Well Monitoring System in the British sector in the North Sea is discussed in Melbø et al. (2003). In this application, the information from the sensors was limited and not reliable but the flowrate estimations were close to the true values. van der Geest et al. (2001) presented the tests of WMS in Troika Field in the Gulf of Mexico and emphasized the ability of the simulator to predict the flowrates as well as other system parameters when necessary. Another example of installation is Bonga field in Nigeria (ABB, 2004; Bringedal et al., 2006).

An example of VFM as a standalone metering solution is the implementation of K-Spice meter in Alta field in Norway which is a small field tied-in to the existing infrastructure (Patel et al., 2014). In this case, the MPFM solution would have significantly increased CAPEX and OPEX, so that it was decided to apply the VFM solution which showed a good performance during the tests.

ValiPerformance was successfully tested and suggested for further use in Ceiba oil field in Equatorial Guinea (Petukhov et al., 2011). It was also installed in an offshore field in the Middle East operated by Total with 16 wells with ESPs (Couput and Renaud, 2010). During the tests and operation, the ESP model was tested and improved by "density correction factor" (Haouche et al., 2012a, 2012b). Couput et al. (2008) showed examples of the software installation in an onshore field in France and a complex subsea field as a back-up and reduction uncertainty system.

Virtuoso was successfully used as a standalone multiphase flow metering technology in gas condensate and black oil systems in Asia Pacific, the Gulf of Mexico and Southern North Sea (Haldipur and Metcalf, 2008). The system was also linked to the implemented pipeline flow simulators that resulted in an integration flow assurance system used for multiple purposes such as flow metering, detection of hydrates, asphaltene and wax depositions and leak detection. Parthasarathy and Mai (2006) showed two other examples of Virtuoso implementation. In the examples, Virtuoso was used as a back-up for wet gas meters initially but after ones' failure it was used as primary metering information for the flow assurance system. In another example, the software revealed inconsistent performance of topside meters which then was successfully fixed.

Couput et al. (2017) summarized the operational experience with ValiPerformance and K-Spice VFM systems in Total providing examples from Couput and Renaud (2010) and Patel et al. (2014). They emphasized that despite the advantages of the VFM costs, this technology still needs skilled people to tune and calibrate the software which can be a challenge for operator companies.

3.4.2. Reported field experience with patchwork first principles VFM solutions

Apart from the commercial first principles VFM products discussed above, there were several examples of combining commercial software with an optimization algorithm to create a VFM solution. Acuna (2016), Omole et al. (2011) and Ma et al. (2016) combined the software packages Prosper and GAP as an engine for VFM in real field cases and then combined it with external optimization techniques to estimate the flowrates continuously and optimize the field production.

In addition, smaller VFM solutions have also been utilized for flow metering. Usually, these systems rely on a particular model rather than on an integrated approach as the systems described above. For example, Ajayi et al. (2012) and Allen and Smith (2012) used the models of downhole inflow control valves (ICV) to construct a Virtual Flow Metering system. Campos et al. (2010), Hussain et al. (2016), Moreno et al. (2014), Loseto et al. (2010) and Espinoza et al. (2017) used choke valve models in order to estimate the flowrate at the field conditions. Delarolle et al. (2005) and Faluomi et al. (2006) from TEA Sistemi also developed a choke model, validated it with experimental data and CFD analysis and applied the model at field conditions in Italy, North and West Africa and the Gulf of Mexico. They also tried to implement the hydraulic tubing model, but it showed a less accurate performance than the choke model.

Cheng et al. (2018) created a VFM system based on not a particular model but a combination of the discussed models such as IPR, steady state thermal-hydraulic and choke models and successfully applied in real operation of an offshore field in China. Similarly, Mursaliyev (2018) used a steady state thermal-hydraulic model together with tuned PVT model to construct a VFM system and applied it for real time production monitoring in Kashagan field achieving the error of less than 5%.

Apart from the choke model based VFM solutions, the ESP model has also been used for flow metering. Camilleri and Zhou (2011) and Camilleri et al. (2016a, 2016c, 2016b, 2015) showed field case studies in which ESP first principles models act as Virtual Flow Meters and able to estimate the flowrates as well as other production system parameters such as productivity index.

3.5. Evaluation studies of the first principles VFM systems in the literature

In order to improve accuracy of VFM systems, it is important to critically evaluate it against various input data. This is because each single field may differ from one to another in terms of sensor availability and accuracy, frequency of well testing, presence of an additional equipment (e.g. Venturi meters), etc. The critical evaluation of the existing VFM solutions is beneficial for both operators and software vendors. The operators might understand the applicability of VFM systems for a particular case and/or a necessity for installing the required instrumentation to improve the accuracy of the flowrate estimates. The vendors in turn could understand the direction for further improvements of the software.

In the literature, there are several evaluations of the commercial first principles VFM systems. Among the others, the evaluations by Toskey (2011) and Amin (2015) are of a particular interest. This is because they compare several VFM systems and evaluate the relative error depending on the input data. Even though the works are conducted by the same company and within a similar strategy, some major differences exist. Toskey (2011) used OLGA to simulate the field data while Amin (2015) used real field data. For tuning purposes, the vendors in Toskey (2011) were provided with phase flowrates, while in Amin (2015) the vendors were given Water-Liquid-Ratio at first and total mass flowrates with Gas-Volume Fractions later. Last but not least, Amin (2015) also included a short but important study of the VFM products sensitivity to the PVT data. In addition to the mentioned studies, a smaller but similar work was performed by Varyan et al. (2015). They evaluated the performance of FlowManager software using a similar approach, so that some conclusions may be compared with the ones by Toskey (2011) and Amin (2015).

As the studies are extensive, we will not give a thorough description of them here. Instead, we will summarize the main common conclusions and disagreements. From the studies, the following common conclusions can be made:

- VFM tuning is required for accurate estimations.
- Tuning frequency depends on the local field conditions.
- Tuning is essential when the pressure drops below the bubble point at well conditions.
- When GOR increases, more attention must be paid to carefully tune the VFM system
- Total mass flowrate is a reliable tuning parameter.
- Increase in choke opening decreases the estimates accuracy.
- Additional devices such as Venturi, densitometer or partly working MPFM may help to improve the VFM system accuracy.
- Importance of adding measurements to the model depends on the VFM strategy.

At first, the last conclusion may seem not very clear. This is because it comes from a disagreement between the studies. Toskey (2011) concluded that adding bottomhole sensors data to the VFM system does not improve the flowrate predictions while the results from Amin (2015) and Varyan et al. (2015) state opposite conclusions. Comparing these statements and looking at the results, it can be said that the importance of adding the measurements depends on the strategy used for Virtual Flow Metering. This means that if the VFM strategy initially relies on the choke model, then adding the bottomhole measurements will not add much value because the final estimates still rely on the choke model. On the other hand, if adding the measurement adds a separate model into the VFM and the estimates are made based on both the choke and tubing models (e.g. weighted average value), the results might improve.

Another important point is that using the total mass flowrate and mixture densities as tuning parameters may allow some errors in PVT data while still maintaining a high accuracy of the flowrate estimates (Amin, 2015). This is a very important conclusion since it may be the case that the PVT data is tuned with some errors or not being tuned continuously. However, this conclusion is made based only on the case considered in one study and may not be generalized for other cases. Definitely, more studies are needed on this topic.

Finally, an attempt was made to evaluate the sensitivity of the VFM systems to the errors in pressure and temperature readings. Amin (2015) showed that with the measurement error the VFM systems were unable to estimate the flowrate within a high accuracy. Toskey (2011) found that the VFM suppliers were able to eliminate the measurement

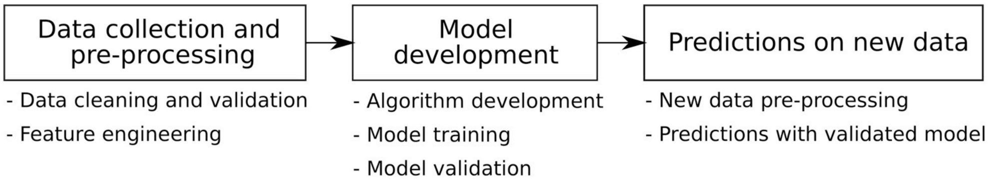

Fig. 3. A typical workflow of data-driven model development.

error and provide accurate estimates. However, both authors concluded that more investigation on this topic is required because these results were highly dependent on the studies conditions.

Additional investigations on the measurement errors influence were conducted by Tangen et al. (2017) and Lansagan (2012). Tangen et al. (2017) used K-Spice meter to test the sensitivity of the VFM software to the errors in the pressure and choke opening measurements as well as in GOR and WC. To do that, a digital twin approach was used where one model represented a plant while the second one represented the VFM model. Lansagan (2012) used two different approaches to test the sensitivity of a VFM system. The first one relies on the intersection method between the inflow and outflow performance of the well while the second one is the same as in Tangen et al. (2017): using a transient multiphase flow simulator. From the studies, some common and distinct conclusions can be drawn:

- Redundant measurements are preferable to improve VFM accuracy.
- Wellhead pressure measurements are more important than bottomhole ones.
- Validated choke model makes the predictions more accurate.
- Oil wells are more sensitive to WC input.
- Gas wells are more sensitive to GOR input.
- Increase in choke opening decreases the estimates accuracy.
- If the intersection method is used, reservoir and bottomhole pressures are more sensitive parameters than wellhead pressures.

Considering all the aforementioned studies on the VFM systems sensitivity, the following general conclusions can be made. First principles VFM is a sophisticated system which aims to simulate complex nonlinear multiphase flow phenomena by combining several computational approaches. This leads to the difficulty of a comprehensive VFM evaluation since it highly depends on the selected strategy and applied computational methods. From the studies we see that some conclusions agree with each other while the others may be totally contradictive. Hence, we conclude that more studies on this topic are required in order to better understand the behavior of the VFM under different conditions. Future studies can take the discussed works into account and go deeper in terms of the evaluation of critical system parameters such as measurements and PVT data. An attempt to address some of these points was done by Bikmukhametov et al. (2018). They conducted a statistical analysis of the sensor degradation effect on a first principles VFM system and revealed that drift errors in pressure and temperature measurements may lead to a big systematic error in flowrate estimated from a VFM system. They also conducted a sensitivity study on heat transfer modeling approaches of the wellbore and found that the detailed heat transfer modeling is not necessary for VFM in oil wells with middle range values of GOR. Despite this attempt, further sensitivities studies are required for a deeper understanding of first principles VFM systems and suggestions for the future work are discussed later in the respective section.

4. Data-driven VFM systems

4.1. An overview of the concept

Data-driven modeling is a technique which is based on analyzing the system data and finding relationships between the system state input and output variables without exact knowledge about the physical behavior of the system (Solomatine et al., 2009). The main advantage of this approach is that it allows to skip the detailed physical modeling of systems or processes for which the exact solution can be difficult to find numerically, for example, multiphase flows in pipes. Data-driven methods rely on the fact that experimental or industrial data represent the system well and attempt to learn the physics relationship which describe the system directly from data. A typical workflow process of data-driven modeling is shown in Fig. 3.

In order to start the modeling process, first, the data must be collected. Any data related to the process can be relevant, for instance, historical system data, current system data or even historical data from a similar system. In the next step, the data must be pre-processed. This may include different operations. First, we ensure that the collected data is suited for modeling by removing outliers, treating missing values or removing noise. Also, additional insights about the information contained in data can be obtained through data transformation and feature engineering. Feature engineering get its name from the fact that in the machine learning community the input data are often called features, so that feature engineering is the process of manipulating the input data to reveal useful information which can help in the model training process.

When the data is pre-processed, the model development is performed. At this step, a data-driven model is developed and trained on the pre-processed data. The training process is basically fitting a mathematical function which describes the data well. In some cases, this function has an analytical form, for instance, in a linear regression model, but it can also be a black-box model, for instance, a neural network (NN). The obtained model must be validated on a separate dataset to ensure the capability of the model of making accurate predictions on the new data. After the model has been validated, it can be used to make predictions on newly obtained data.

In Fig. 4, a schematic overview of the data-driven modeling application for Virtual Flow Metering is shown for the production system shown in Fig. 1. In a data-driven VFM system, the collected data typically includes the pressures and temperatures at the bottomhole and wellhead, the choke opening values as well as the parameters of the ESP and the corresponding measurements of oil, gas and water flowrates. The measurements of the flowrates can come from different sources. One possibility is to use well test data and another possibility is to use the data from hardware multiphase flow meters. In the latter case, if MPFMs are installed at each wellhead, the data-driven model becomes a back-up metering system for each well. However, if one MPFM is installed for a cluster of wells, its data can be used similar to well test and separator data, so that the flowrate measurements from each well are collected according to the well testing schedule. In this case, after training and validation, the data-driven model can be used as a standalone VFM system. In the next section, we will describe the data-driven workflow process in more detail.

4.2. Description of the data-driven VFM components and applied methods

4.2.1. Data collection and pre-processing

Before developing any data-driven model, the data must be collected and pre-processed. In Virtual Flow Metering systems, the data may include sensor readings from wells and processing facilities. In addition, historical data from similar wells or fields can potentially be used for model development. In the next step, the data is pre-processed prior to training. Typically, the collected data are noisy, corrupted, may include missing values, outliers and irrelevant inputs (Famili et al., 1997). As such, the data needs to be cleaned and validated before

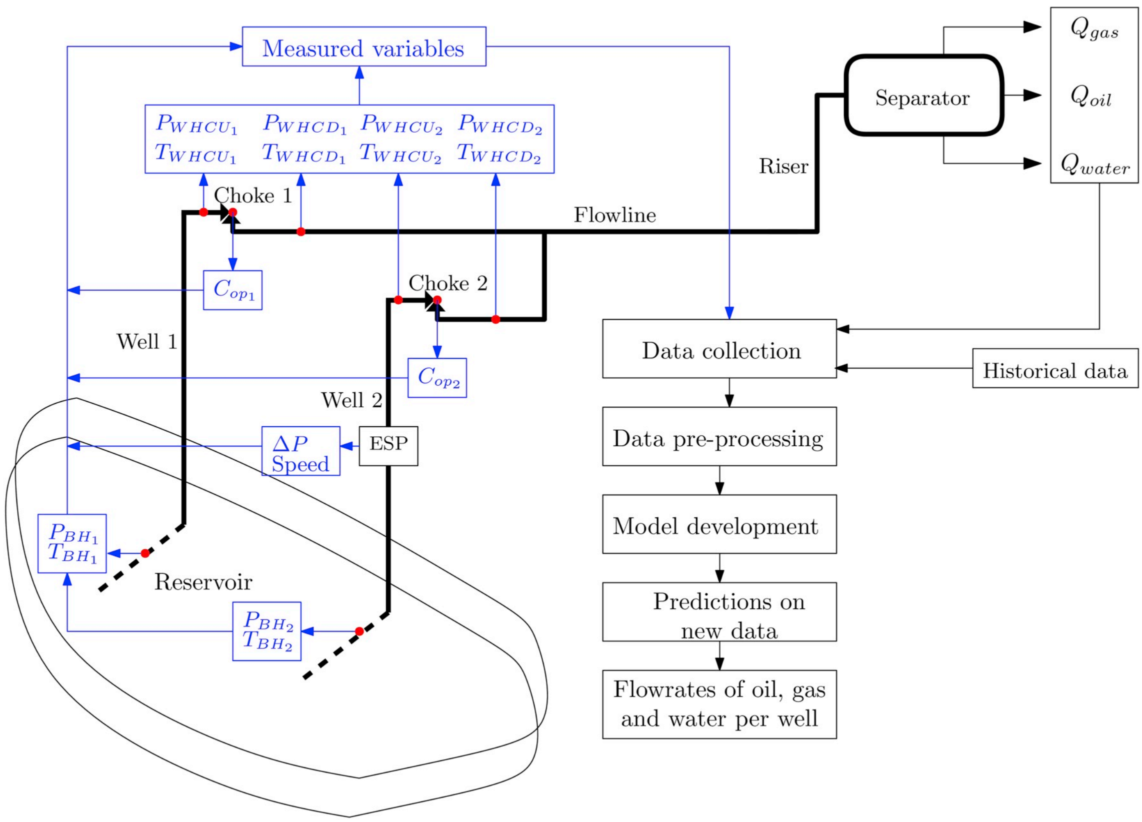

Fig. 4. A schematic overview of a data-driven Virtual Flow Meter. First, the production system data is collected and pre-processed. Then, the pre-processed data is used for model development and validation. When new measurement data is obtained, the validated model is used to estimate the well flowrates of oil, gas and water.

further usage. In principle, this is the same validation process as in the data validation and reconciliation algorithm which is used in the first principles VFM systems discussed before.

In the pre-processing step, data may also be transformed and additional insights about the information contained in the data can be obtained. This process is usually called feature engineering. Typical raw features in VFM are shown in Fig. 4, i.e. pressures and temperatures along the production system, choke openings and the information from the ESP. There are many techniques which are used in feature engineering, for instance, dimensionality reduction algorithms by Principal Component Analysis (PCA), feature selection methods or linear and non-linear combination of the raw features. A good overview of the feature engineering methods is provided by Cunningham (2008). In general, feature engineering may help the data-driven algorithm to find complex relationships between the original data and the output variable or remove redundant features which leads to lower computational cost during training and prediction steps. In most of the cases, domain knowledge of the field of interest is important to construct informative features for further algorithm training and Virtual Flow Metering is not an exception. Creating good features using the input data which can describe the multiphase flow transport process may help to obtain better predictions. However, as we will see in the next sections, in most of the literature resources the production system sensor data are often used as it is and the potential of good feature engineering for VFM applications is not explored yet.

4.2.2. Model development

Model development is the process of developing an algorithm which is able to map input features and output (target) variables. The mapping process is also called training or learning during which the algorithm adjusts the parameters in such a way that it estimates the target variables accurately. The adjusted parameters depend on the algorithm in use. For instance, in case of a neural network, the parameters are typically weights, which connect the neurons, while in case of regression trees the parameter can be the tree depth. The process of training is achieved by minimizing a cost function which is formulated as the difference between the algorithm predictions and true (measured) values. For regression problems as Virtual Flow Metering, the mean squared error (MSE) is often used as a cost function which has the following form:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_{meas\ i} - y_{predicted\ i})^2 \tag{23}$$

where MSE denotes the mean squared error (cost function), $y_{meas\ i}$ – the measured (true) value of the *i-th* training example, $y_{predicted\ i}$ – the predicted value of the *i-th* training example, N – the number of training examples, i – the index of the training example.

This expression resembles Eq. (19) for the data reconciliation algorithm in the first principles VFM systems except for the fact that the data-driven model training is typically an unconstrained optimization problem while in data reconciliation the problem includes constrains as well as uncertainty in the cost function. As such, the main idea behind the first principles and data-driven VFM systems is the same – adjust the model parameters such that the difference between the predictions produced by the mathematical model and the measurement data is small. However, the major difference is the mathematical formulation of the model where the first principles models try to explain the multiphase flow transport using the physics behind the phenomenon while the data-driven models try to learn the multiphase flow behavior directly from data.

After the model is trained, it must be validated and tested on a different dataset to ensure that the trained model will perform well on the data which the model has not seen during the training. The model ability of producing accurate predictions on new data is called model generalization (Abrahart et al., 2008). Another purpose of validation is to select accurate hyperparameters of the model to fit the data well. Hyperparameters are the model parameters which are set prior to training and are not learned during the training process. For instance, in case of neural networks, the hyperparameters are the number of layers, number of nodes in the hidden layers, regularization parameters, etc. The regularization parameters are the hyperparameters which allow to reduce the effect of noise and outliers on the final algorithm predictions, so that the algorithm does not overfit the data. Bishop (2006) provides a rigorous discussion on the influence of hyperparameters on the model performance including its more detailed definitions.

There are different methods for validation. One of the most widely used approach is standard K-fold cross-validation (Hastie et al., 2009) which is shown in Fig. 5 (left). In this method, the available data is divided into training and test parts. Then, the training set is again divided into K-folds. Prior to training, a set of hyperparameters is selected and then the model is trained with these parameters on K-1 folds and the error between the actual values and the algorithm predictions is checked on the remaining fold. This process is repeated K times and the error is averaged over K folds. The obtained error corresponds to the model error with the selected hyperparameters. Then, the hyperparameters can be changed and the averaged error over K folds is computed again. The best set of hyperparameters is the one which corresponds to the lowest obtained error over K folds. The model with the best hyperparameters set can be re-trained on the entire training set to utilize all the available data.

One of the main assumptions behind the K-fold cross-validation is that the data points are independent from each other. However, in case of Virtual Flow Metering this is an inadequate assumption because, for instance, the bottomhole pressures at time instance *t* are dependent on conditions at time instance *t-1* unless the time difference between the instances is large or during steady state operation with no pressure variations. However, in most of the reported applications of data-driven models in VFM, this fact has not been considered and the standard K-fold cross-validation was performed as shown in Fig. 5 (left), see, for instance, the works by Al-Qutami et al. (2017c, 2017a).

An alternative to the standard K-fold cross-validation can be nested K-fold cross-validation, see Fig. 5 (right). In this case, the training set is again divided into K-folds, however, the model is trained and validated in a nested manner, for instance, trained on fold 1 and validated on fold 2, trained on folds 1 and 2 combined and validated on fold 3. In this case, the algorithm does not use the future data in order to predict the past outputs and misleading conclusions about the model performance can be avoided. An application of the nested K-fold cross-validation in data-driven VFM is described by Bikmukhametov and Jäschke (2019).

Ideally, the performance of the obtained validated model is checked on a separate test dataset to make conclusions about the model generalization. Typically, two situations can happen when testing the model performance:

- The errors on the training and test sets are large.
- The error on the training set is small but large on the test set.

The first situation is called underfitting and often referred as the fact that the trained algorithm has high bias. The second situation is called overfitting and often referred as the fact that the trained algorithm has high variance. In fact, finding an optimum value of both bias and variance is the overall goal of the data-driven algorithm training and called *a bias-variance trade-off* (Hastie et al., 2009). So, in summary, *the validation and testing are conducted in order to find the best set of hyperparameters which provides an optimal value of bias and variance.* In this case, the algorithm has good generalization and can be used for future predictions with greater confidence. For a more detailed explanation and the rigorous mathematical formulation of the data-driven model assessment, we recommend the book by Hastie et al. (2009).

An alternative to K-fold cross-validation is early stopping approach which has been extensively used for data-driven models training including VFM applications (Al-Qutami et al., 2017b; Bikmukhametov and Jäschke, 2019; Prechelt, 2012). In this case, the dataset is divided into training, validation and test sets. During training, the error is monitored on the training and validation sets. The training continues until the error on the validation set keeps increasing a specified number of training steps. The model can be further re-trained on the combination of the training and validation sets and evaluated on the test set. Prechelt (2012) provides a thorough explanation of this approach and the methodology for selecting the stopping criteria.

4.2.3. *Applied methods for data-driven VFM systems*

Having considered how data-driven model can be developed, in this section, we will discuss data-driven methods which have been reported to be used for VFM systems. Because VFM is a non-linear regression problem, most of the data-driven VFM approaches are based on artificial neural networks alone or with some modifications, for instance, ensemble algorithms. As such, we will separate the ANNs applications from the other used methods. In addition, we distinguish recurrent neural networks which are able to model dynamic problems.

4.2.3.1. Steady state artificial neural network VFM solutions. Feed-forward neural networks (also often referred as Multilayer Perceptrons (MLPs)) are a type of artificial neural networks which aims to approximate a function based on a certain number of input features without any recursive feedback connection between the network outputs and inputs. They are inspired by cognitive abilities of biological neural networks. The network is constructed using interconnected cells (neurons). These neurons are structured in a layered manner, so that the network usually consists of an input, hidden and output layers (Goodfellow et al., 2016). The input layer is required to read the variable (feature) values which are used for

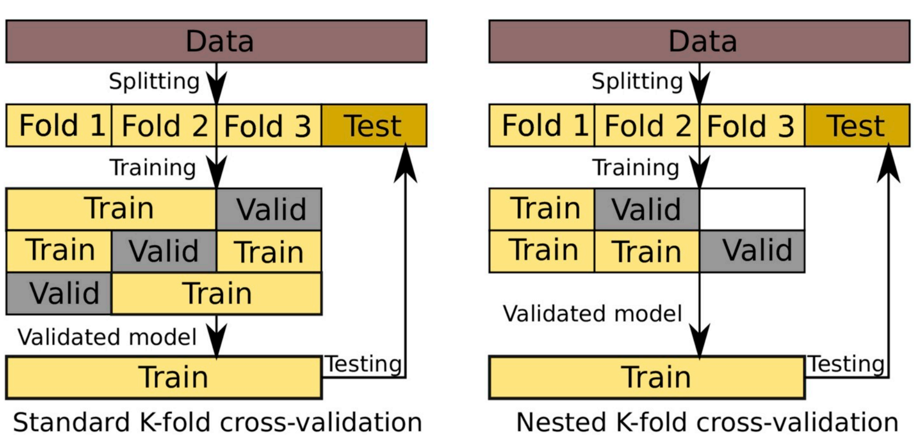

Fig. 5. Standard (left) and nested (right) K-fold cross-validation schemes for data-driven models.

training and for future predictions after training. In a VFM case, this can be pressure and temperature measurements, choke opening or other production system parameters. The hidden layers are used to produce non-linear relationships between the input parameters and approximate the function which describes the system behavior. In the output layer, the values produced in the hidden layer go through an activation function and then the network estimates the output variables (e.g. flowrates). This type of neural networks has been a popular choice for VFM technology because its key advantage is that it can approximate any relationships and patterns between variables, so that it can be considered as a universal approximator (Hornik et al., 1989). However, in case of transient flow behavior, steady state solution provided by a feed-forward neural network may not be accurate (Omrani et al., 2018).

One of the earliest attempts to estimate the multiphase flowrates based on pressure sensor data using neural network models was done by Qiu and Toral (1993). They used laboratory pressure transducers data as an input to the neural network and predicted gas-liquid rates as outputs. Since then, several examples of neural networks for VFM were reported.

A noticeable effort in applying neural networks for Virtual Flow Metering systems is done by Al-Qutami et al. (2018, 2017a, 2017c, 2017b). Al-Qutami et al. (2017b) used a neural network trained by Levenberg-Marquardt optimization algorithm. K-fold cross validation technique was used to select the number of neurons. The model was validated over 1.5 years of well test data. In order to avoid problems with overfitting, the early stopping technique was utilized. In addition to the evaluation of the trained model on the test data set, a sensitivity study was performed. The study revealed that the estimated gas flowrate is the most sensitive to the choke position value while bottomhole pressure is the most critical parameter for the oil flowrate predictions.

Al-Qutami et al. (2017a) discussed a hybrid ensemble learning by combining the neural network and regression tree (RT) approaches (NN-RTE). The idea behind the method is to generate a certain number of learners using different algorithms (in this case NN and RT), use a pruning technique to optimize this number (in this case simulated annealing (SA)) and then use a combining strategy (in this case simple averaging) to produce the final output. The paper compared the hybrid approach (NN-RTE) with homogeneous ensemble approaches (NN and RTE) and revealed a more accurate performance of the hybrid one.

Al-Qutami et al. (2017c) implemented a radial basis function network (RBFN) which uses a Gaussian transfer function in the hidden layer instead of a sigmoid function used in Al-Qutami et al. (2017a). The advantage of this method is the fact that it generally results in a faster training. In order to train the RBFN, Orthogonal Least Squares algorithm was used which is a common technique applied for RBFNs. A sensitivity study was carried out by excluding bottomhole pressure and choke opening form the model inputs. The results showed that the bottomhole pressure did not change much the resulting estimates while the choke opening was crucial for the network performance. This is a similar conclusion to the one in Al-Qutami et al. (2017b) for the gas rate. The authors concluded that further investigations in neural network sensitivity are required to make a solid argument on robustness of the method.

Al-Qutami et al. (2018) considered a modified version of the ensemble learning if compare to Al-Qutami et al. (2017b). In this case, the homogeneous approach with neural network ensemble was used. Instead of using another algorithm for learners, the diversity was achieved by implemented different regularization criteria such as scaled conjugate gradient and Bayesian regulation. In addition to the simple averaging, weighted average and NN meta-learner combining strategies were used. The results were compared before and after adaptive simulated annealing with bagging and stacking ensemble methods.

Omrani et al. (2018) performed a rigorous study of applying feed-forward neural networks to simulated and real field data. First, they considered a NN for predicting oil and gas flowrates in steady state operation and showed that the algorithm produces a good performance while during transient operation the NN may give inaccurate results. In addition, they considered sensitivity studies of the target variables with respect to uncertainty of the input data and revealed that in general NNs are capable to produce accurate flowrate predictions even under noisy input features unless the uncertainty increases dramatically. Finally, they proposed a method for back-allocation of well flowrates using total flow measurements from a separator, and the method showed a reasonable performance and can be addressed in future research.

AlAjmi et al. (2015) used a neural network to predict the oil flowrate through the choke. In addition to pressure, temperature, choke size and WC data, they used some additional parameters for inputs including an empirical correlation for the critical choke flow. When compared with flowrate estimations obtained by using the choke empirical correlations, the NN showed a reasonably better performance. It has to be noted that the choke models used in the study were purely empirical and not mechanistic which usually make better flowrate predictions.

Berneti and Shahbazian (2011) and Ahmadi et al. (2013) compared a conventional neural network approach with a hybrid approach by introducing Imperialist Competitive Algorithm (ICA) to optimize the initial values of weights in the network. Ahmadi et al. (2013) compared also considered Particle Swarm Optimization (PSO) and Genetic Algorithm for this purpose as well as utilized Fuzzy Logic approach to estimate the flows. Based on the study, superior capabilities of NN with ICA were revealed compared to other hybrid methods and the conventional NN training approach.

Zangl et al. (2014) constructed a neural network to estimate oil and water rates by the use of multi-rate well tests. They trained the network with a gradient descent method and the resulted network produced good predictions on a test dataset. A similar work by Hasanvand and Berneti (2015) shows a successful application of a three layers feed-forward neural network trained by Levenberg-Marquardt algorithm to predict oil flowrates using real field well test data from 31 wells collected over 8 years of production.

Xu et al. (2011) and Shaban and Tavoularis (2014) used Principal Component Analysis (PCA) in order to extract features from the experiemntal data sets to produce input variables to neural networks. The output flowrate estimates from the networks were in a good agreement with the measured values.

In addition to the research oriented neural network VFM applications, Baker Hughes has developed NeuraFlow software which is based on the neural network model (Baker Huges, 2014; Denney et al., 2013). This software is used to estimate the flowrates in systems with electric submersible pumps by applying the neural network approach. Similar to the previously discussed NNs, this system takes pump intake and discharge pressures as well as other measured parameters such as pump frequency as an input and produces the flowrate estimates as the network output.

4.2.3.2. Dynamic artificial neural network VFM solutions. In addition to the steady state feed-forward neural networks discussed above, there are different NN modifications which are capable to model transient phenomena. One example are recurrent neural networks (RNN) which are extensively used in many applications such as speech recognition and machine translation (Graves et al., 2013). The main idea behind this approach is to use the data from the past to predict the current target variable. For instance, in case of VFM, it takes the pressure and temperature measurements from the previous time step in order to estimate the flow at the current time step. In contrast, the feed-forward neural networks typically consider the data from the current time step only, so it performs steady state mapping only. In principle, it is possible to also include the past data into the feed-forward neural network, however, this approach has not been considered in the literature so far. At the same time, the RNN approach has been used in Virtual Flow Metering for transient flow estimation, and it is important to emphasize this in a separate section.

One example of utilizing RNNs for VFM is the work by Andrianov (2018). He used Long-Short Term Memory (LSTM) model which is a type of recurrent neural networks. Using synthetic well test data, he showed the capabilities of the LSTM method not only for estimating but also forecasting the flowrates in the future time. In addition, he also considered the LSTM model for severe slugging prediction which is a highly dynamic multiphase flow phenomenon which typically occurs in risers. The results showed that the model was able to make accurate predictions of the volumetric flowrate of the periodic slugging flow in the riser.

Another example of RNN VFM system is the work by Loh et al. (2018). They also used an LSTM model for gas rate predictions for two natural gas wells. They trained the algorithm on the data of one well and made predictions on the new data for both wells. The results showed that the model is capable to predict the gas flowrates well in general, however, for the well whose data was not used in training, the predictions sometimes were not accurate. In addition to this analysis, they also combined the LSTM model with ensamble Kalman filter which we will discuss in the next chapter, and showed that adding the method of combining the two approaches allows to obtain more accurate flow estimates for both wells.

Omrani et al. (2018) compared performance of an LSTM neural network with a feed-forward NN and showed that under dynamic conditions such as shut-in and start-up of the well, the LSTM model has a better performance and even able to track changes of liquid-gas ratio during production.

Sun et al. (2018) used an LSTM NN for predicting oil, gas and water flowrates from shale wells. Such an application is very promising because, in general, shale wells have highly transient behavior which can be difficult to capture with feed-forward NNs and other steady state data-driven algorithms. The authors showed that the LSTM model is capable not only to predict the flowrates for the well whose historical data was used for training but also it is possible to predict the flow for a new well using the historical data from neighboring wells.

4.2.3.3. Other data-driven VFM solutions. In addition to the neural networks, some other methods were used to estimate multiphase flowrates from the collected measurements. One of the methods has been developed and applied in actual oil and gas production systems. FieldWare Production Universe (FW PU) is a data-driven VFM software which is used in Shell's fields around the world. The idea for the development of this software came from the Smart Fields initiative which aimed to use smart equipment, technologies and processes to optimize field production in Shell's fields (Bogaert et al., 2004; Poulisse et al., 2006). By 2011, the system had been running on around 60% of Shell's producing fields covering America, Europe, Africa, the Middle and Far East (Cramer and Goh, 2009; Dolle et al., 2007; Gerrard et al., 2007; Goh et al., 2008).

The data required for FW PU data-driven model is collected during Deliberately Disturbed Well Test (DDWT). DDWT is a well test procedure in which a well is routed to a test separator and then an operator deliberately changes the parameters in a stepwise manner, track it with the equipment and measures the single-phase flow at the test separator. By testing the well at various conditions, it is possible to construct a function which describes a well model. The function may have a general form as the following (Poulisse, 2009):

$$q_i(t) = f_i(g_{1i}(t), g_{2i}(t), .. g_{Ni}(t)) \tag{24}$$

where i – well number, $q_i(t)$ – flowrate, g_{Ni} – system parameter (e.g. wellhead pressure).

By performing DDWTs for each well, the well models can be constructed for each well and then combined in the estimation of the total field flowrate as:

$$q(t)_{estimated} \cong \sum_{i=1}^{N} \gamma_i g_i(t) \tag{25}$$

In this expression, γ_i is an unknown weight coefficient which must be iteratively found from the fact that the estimated and monitored (measured) flowrates should be substantially equal (Poulisse, 2009).

In order to apply the FW PU data-driven models for a field start-up phase, multiple runs of physical multiphase flow models can also be used. These pre-generated synthetic production data are then used to create the data-driven models (Poulisse et al., 2006). These models can then be re-trained when actual production data become available.

Apart from the widely used method applied in FW PU, some other data-driven methods have been used for VFM, mostly for research purposes. For instance, Xu et al. (2011) utilized Support Vector Machine approach to predict the flowrates based on the Venturi pressure difference values from the experiments which outperformed the neural network approach.

Zangl et al. (2014) considered linear regression (LR) and random forest (RF) for flowrate estimation, in addition to the backpropagation neural network. All the methods showed a reasonable performance with low average errors. The authors also used the models to perform Monte Carlo analysis in order to test the sensitivity of the model to input parameters. This study showed an advantage of using data-driven models for flowrate predictions as the run time is quick which makes it possible to perform many simulations for a reasonable time period. Bello et al. (2014) also used a linear regression model with a preliminary extraction of the training features using PCA. The resulted hybrid intelligence system produced good oil and gas rate predictions.

Grimstad et al. (2015) applied B-spline surrogate models for the flowrate estimation. In order to obtain the data for the algorithm, they used the pressure drop, choke and inflow performance models from Prosper and then fitted the results with the cubic spline interpolation function. The estimation results were compared to OLGA and showed a good performance.

Bikmukhametov and Jäschke (2019) applied gradient boosting algorithm with regression trees as a VFM system to predict oil flowrates in different field development cases. They considered the cases when VFM is used as a back-up system for a MPFM and as a standalone solution. The algorithm was trained on the data generated by OLGA software. The results showed that the algorithm has a good potential for multiphase flowrate predictions even having relatively small datasets from the well tests and the measurements from the MPFM. In addition, the algorithm can further be combined with neural networks within ensembles to improve the flowrate prediction accuracy.

4.3. Field experience with data-driven VFM systems

In this section, we describe the real operational experience reported in the literature using the data-driven models discussed in the previous section. The number of field applications with data-driven models is lower than with the first principles methods. The main reason for this is the fact that the industry effort over the past 50 years was mostly focused on the development of the first principles models, so that many vendors offer the products based on this approach. However, currently the industry is also trying to utilize the enormous amount of data collected in the fields every day and the research effort in this area has also increased over the past several years as we observed in the previous section.

Regarding the actual applications of data-driven methods in oil and gas production, the FW PU showed a robust and accurate performance for conventional and multizone wells and capable to track the dynamic changes in production systems. The estimates produced by the software can further be used for optimization and forecasting purposes (Cramer et al., 2011; Goh et al., 2008; Poulisse et al., 2006). Law et al. (2018) used FW PU Virtual Flow Meter for chemical injection optimization.

Denney et al. (2013) showed performance of NeuralFlow in a field over nine months period without a need to be re-calibrated. There are also some examples of applying data-driven VFM systems in fields which were developed for a specific field case. Garcia et al. (2010) developed a neural network to estimate the production and injection rates in fields in Brazil using a typical set of pressure, temperature and choke measurements for the network input and obtained the error level of 4–7%. Olivarez et al. (2012) overcame problems with empirical choke flowrate estimations by developing a neural network solution which improved reliability of the field metering system. Ziegel et al. (2014) used a VFM system based on a neural network to predict oil and gas flowrates in a field with gas coning in the North Sea using the data from well tests. Al-Jasmi et al. (2013) developed a radial basis neural network able to predict the flowrates 30 days ahead with 90% confidence in wells with ESPs.

4.4. Summary of data-driven VFM applications

In Table 2, we give an overview of the discussed applications of data-driven modeling in Virtual Flow Metering systems. The table emphasizes the models features used in the works, the predicted variables, the input data for the training and the respective paper. In addition, we point out the origin of the training and test data and the fact if the sensitivity analysis to the input data was conducted.

5. Application of state estimation for transient modeling in VFM systems

5.1. Introduction

So far, we have discussed the first principles and data-driven modeling methods applied for Virtual Flow Metering. Most of the discussed methods describe steady state solutions meaning that they do not accurately estimate transient flows. In order to estimate flows under transient conditions, the time dependency of the system must be considered. This requires two necessary conditions: (1) dynamic models that accurately describe the transient behavior of the production system that may be based on the first principles or data-driven approach; (2) dynamic formulation of the training/optimization algorithm which considers the past states of the system. As we saw in the description of the first principles VFM systems, requirement (1) is typically satisfied, however, the requirement (2) is not, because typically the data validation and reconciliation algorithm has a steady state formulation. In the data-driven VFM systems, most of the methods do not satisfy both requirements.

One solution to this problem is using state estimation approach together with first principles or data-driven models to estimate the transient flows. In the literature, several application examples of state estimation for Virtual Flow Metering are described, in which the authors use first principles models and data-driven models together with state estimation techniques to estimate the oil and gas flowrates under transient conditions using the available measurement data. In this section, we will describe the main idea behind the most often used state estimation techniques for VFM such as Kalman filter modifications and then consider its applications in Virtual Flow Metering.

5.2. Description of the state estimation techniques applied for dynamic VFM systems

One of the most common state estimation techniques is the Kalman filter (Kalman, 1960). The Kalman filter is an optimal estimator meaning that, under some assumptions, the mean value of the estimation errors sum goes to a minimum value (Singh and Mehra, 2015). Despite the fact that the Kalman filter is extensively used in various applications, it is not widely spread in the petroleum industry. This is because most of the systems in this industry have non-linear behavior which restricts the usage of the Kalman filter. To overcome this, several extensions were developed to apply the Kalman filter concepts to non-linear systems. Some of the most common extensions are extended Kalman filter (EKF) (Jazwinski, 1970), ensemble Kalman filter (EnKF) (Eversen, 2003) and unscented Kalman filter (UKF) (Julier et al., 2000). For estimation of multiphase flowrates, the first two options have been considered.

The Kalman filter and its variants are algorithms that use a dynamic model to propagate estimates of the states together with the variance-covariance matrices in time. While the original Kalman filter was developed for linear systems, the extended Kalman filter uses a linearization of the non-linear model around the current estimate. Given the system with available measurements, the idea behind the state estimator is to predict the state values based on the noisy measurements obtained from the system. To construct the EKF, we need to discretize a state-space model of a non-linear system in time. The states of the system typically include variables which we would like to estimate, for example, in case of VFM, pressure, holdup or flowrates. The EKF will integrate the discretized model over time considering the process noise and the measurements. A good example of the adaptation of the conservation equations in the context of flow estimation to the state space form is described by (Gryzlov et al., 2013).

The Ensemble Kalman filter allows to avoid linearization but generate the estimates of the state vector and the covariance using so-called ensembles. The EnKF is able to solve highly non-linear problems more accurately compared to the EKF, while for problems with small non-linearities their performance is approximately the same. The computational time depends on the order of the system under consideration. For higher order systems, the EnKF is usually the fastest option (Leskens et al., 2008). More discussions about the comparison of the EKF and EnKF can be found in Leskens et al. (2008) and Reichle et al. (2002).

Another estimation technique which has been used for VFM is Moving Horizon Estimation (MHE). This approach is based on formulating an optimization problem to find the states of a dynamic model that best match measurement data during a specified time period (horizon) in the past. When new measurement data become available. The horizon is shifted, such that the oldest data point is discarded and the newest point is included. This procedure is repeated at given sample times. MHE is becoming a popular estimation technique for many industrial applications and a vast amount of literature is available on this method. For a more detailed description about the method, please see Rao et al. (2001).

5.3. Reported research on state estimation methods applied for dynamic VFM systems

Despite the fact that state estimation methods for VFM applications are not widely used in industry, there have been several research efforts in this area. Bloemen et al. (2006) considered the extended Kalman filter to predict the flowrates in gas-lift wells. To estimate the flowrates of a two-phase flow, they assumed that noisy pressure measurements are taken along the wellbore. For the model part, the drift-flux formulation was considered. It was shown that under dynamic conditions caused by the choke opening, the model was able to estimate the gas and liquid flows accurately.

Leskens et al. (2008) considered a three-phase flow in a unilateral horizontal well and applied the EKF for flowrate estimation. It was assumed that five downhole pressure and four temperature sensors were available for the EKF. The wellhead measurements were not considered. The authors showed that without the noise the model worked well while with the noise the method was unable to track the flowrate changes.

To extend the work by Leskens et al. (2008), De Kruif et al. (2008) considered both two and three-phase flows in unilateral and multilateral wells using the EKF. In the two-phase case in the unilateral well, six downhole pressure and temperature measurements were sufficient to estimate the flow accurately. For the three-phase case, downhole data were not enough for good estimations. However, wellhead pressure sensors helped to improve the predictions. Another interesting finding was the fact that using only wellhead data was sufficient to predict the flowrates. However, the model was not able to track the changes of the inflow in time. Instead, the time delay response was observed. This led to the conclusion that the downhole sensors are necessary in order to track flowrate changes accurately. As for the multilateral case, the authors showed that even with the downhole and

Table 2
Summary of data-driven models for VFM applications.

Method	Method features	Predicted flowrate	Data origin	P_{BH}	T_{BH}	P_{WH}	T_{WH}	C_V	Gas lift rate	WC	P_{FL}	Other	Sensitivity to input	Paper
	Conventional NN trained by L-M and NN with ICA/PSO/GA for weights optimization	Oil	Field	✓	✓	✓	✓							Ahmadi et al. (2013)
	NN trained by L-M with early stopping	Oil/Gas	Field	✓		✓	✓	✓					✓	Al-Qutami et al. (2017b)
Feed-forward NN	RBFN with Gaussian radial basis function. Trained by Orthogonal Least Squares	Gas	Field	✓		✓	✓	✓					✓	Al-Qutami et al. (2017c)
	NNE trained by L-M with early stopping and NN with regression tree learners	Oil/gas/water	Field	✓	✓	✓		✓	✓	✓	✓			Al-Qutami et al. (2017a)
	NNE trained by L-M with scaled conjugate gradient and Bayesian regulation. Applied simple and weighted averaging and NN meta-learner for the output layer	Liquid/Gas	Field	✓		✓	✓	✓						Al-Qutami et al. (2018)
	NN for critical choke flow; compared to empirical choke models	Oil/Gas	Field			✓		✓		✓		✓		AlAjmi et al. (2015)
	NN applied to real operation in a field with ESPs	Liquid	Field			✓						✓		Al-Jasmi et al. (2013)
	NN integrated with Fuzzy Logic to select the best performing model	Oil	Field			✓	✓							Alimonti and Falcone (2004)
	NN with Imperialist Competitive Algorithm for weights optimization	Oil	Field	✓	✓	✓	✓							Berneti and Shahbazian (2011)
	NN applied in real field operation	Oil	Field	✓	✓	✓	✓	✓	✓	✓		GOR		Garcia et al. (2010)
	NN trained with L-M	Oil	Field	✓	✓	✓	✓							Hasanvand and Berneti (2015)
	NN trained using ESP data	Oil	Field									✓		Denney et al. (2013)
	NN trained with L-M using simulated and field data and tested for sensitivity to data uncertainty	Oil/Gas	Synthetic/Field	✓	✓	✓	✓	✓			✓	✓	✓	Omrani et al. (2018)
	NN applied in real field operation	Oil	Field	✓	✓	✓	✓	✓		✓	✓	✓		Olivarez et al. (2012)
	NN with PCA for dimensionality reduction	Gas/Water	Experiment									RDP		Shaban and Tavoularis (2014)
	NN with PCA for dimensionality reduction	Gas/Water	Experiment									VDP		Xu et al. (2011)
	NN trained by the gradient descent method on multi-rate well test data	Oil/Water	Field			✓	✓		✓		✓		✓	Zangl et al. (2014)
	NN trained on well test data	Gas/Liquid	Field			✓		✓	✓			✓		Ziegel et al. (2014)
Recurrent NN	LSTM NN to estimate dynamic current and future flowrates	Oil/Gas/Water	Synthetic			✓	✓				✓			Andrianov (2018)
	LSTM NN and LSTM NN with ensemble Kalman filter to predict transient oil flowrate	Gas	Field	✓	✓	✓	✓	✓						Loh et al. (2018)
	LSTM and feed-forward NN trained on steady state and dynamic conditions	Oil/Gas	Synthetic/Field	✓	✓	✓	✓	✓			✓	✓	✓	Omrani et al. (2018)
	LSTM for multiphase flows estimation in unconventional wells	Oil/Gas/Water	Field			✓						✓		Sun et al. (2018)
Model identification with DDWT	Model identification using data from DDWT	Oil/Gas/Water	Field	✓	✓	✓	✓	✓				✓		(Gerrard et al., 2007; Poulisse, 2009) and therein references
B-spline	B-spline surrogate model which approximates simulated data	Liquid	Synthetic	✓	✓	✓	✓	✓						Grimstad et al. (2015)
Gradient Boosting with RT	Gradient boosting algorithm with regression trees as weak learners	Oil	Synthetic	✓	✓	✓	✓	✓						Bikmukhametov and Jäschke (2019)
RTE	Regression trees ensembles. Minimum leaf size or early stopping used for stopping	Oil/Gas/Water	Field	✓	✓	✓		✓	✓	✓	✓			Al-Qutami et al. (2017a)
FL	Automatic selection of the membership function	Oil	Field	✓	✓	✓	✓							Ahmadi et al. (2013)
SVM	SVM models trained to predict gas and water flowrates	Gas/Water	Experiment									VDP		Xu et al. (2011)
LR	Multiple Linear Regression method	Oil/Water	Field			✓	✓		✓		✓		✓	Zangl et al. (2014)
RF	Decision tree approach with 700 nodes	Oil/Water	Field			✓	✓		✓		✓		✓	Zangl et al. (2014)
PCR	Linear regression with Principal Component Analysis	Oil/Gas	Field	✓	✓	✓	✓	✓		✓		GOR		Bello et al. (2014)

wellhead sensors, the model was not good enough to estimate the flow correctly. This is because the model needs correction for the specific branch of the multilateral well at the wellhead which is not possible as the flows from all the branches commingle inside the wellbore.

Lorentzen et al. (2010a) used the ensemble Kalman filter to predict the gas inflow at four different zones in the wellbore. To do this, downhole temperature sensors were used together with the transient drift-flux model. The model showed promising results by estimating the flows accurately. In a similar work, Lorentzen et al. (2010b) considered a well with two branches and used temperature measurements with and without pressure sensor data to estimate the flow by use of the EnKF. They showed that using only temperature sensors can be sufficient to estimate the gas flowrate from a particular well branch.

Gryzlov et al. (2013) utilized the extended Kalman filter for the flowrate estimation problem. Several cases were considered including flowrate and holdup estimation. At first, it was assumed that in each of 50 discretization blocks the pressure measurements were available. Then, the number of sensors were reduced by a factor of three and six. The results showed that by reducing the number of sensors, the estimation error increases. The conclusion was that each inflow point must be equipped with at least two pressure sensors, however, this requires a closer investigation.

Muradov and Davies (2009) applied the extended Kalman filter for zonal rate allocation in synthetic and real multizone wells and compared its performance with optimization techniques. The results showed that even though all the methods were suitable for the application, the EKF was the most suitable for noisy measurement data.

Binder et al. (2015) consider Moving Horizon Estimator for flowrate estimation in a well with an ESP. For the input, bottomhole, downhole and pump pressure sensors were considered together with pump parameters. The method showed an accurate performance and was suggested to be used for industrial applications.

In the works described above, the state estimation methods are applied to the first principles models. However, it can also be applied to the data-driven model if the model is dynamic, for instance, a recurrent neural network. Loh et al. (2018) applied the ensemble Kalman filter together with an LSTM network and compared the performance with a pure LSTM model. The results showed that the ensemble Kalman filter gives an opportunity for the LSTM model to better capture the flow behavior and preform more accurate multiphase flowrate estimation.

In addition to the aforementioned studies, there are several works which do not consider estimation methods for VFM directly but describe models which can be suitable for this purpose. Aarsnes et al. (2016) conducted a review work on multiphase flow models which can be used for estimation algorithms. Some aspects of implementing the Kalman filter variations for drilling applications can be also accounted when constructing a state estimator for VFM purpose. For such examples, please see Aarsnes et al. (2014a, 2014b) and Nikoofard et al. (2017). The state estimation techniques can also be used to estimate the multiphase flow model parameters such as slip and friction coefficients (Lorentzen et al., 2003, 2001).

5.4. Discussion on using state estimation in dynamic VFM systems

State estimation methods can be a promising tool for dynamic estimation of multiphase flowrates in VFM systems. These methods have the following advantages for VFM applications:

- Have a potential to use additional data from the production to improve estimates in a simple manner
- Filter noisy measurements and solve the estimation problem within one algorithm
- Have a potential in accurate flow estimation using MHE and data-driven models that are fast to evaluate
- Can be used to estimate unmeasured variables

However, apart from the positive sides, there are disadvantages which make application of these methods in VFM systems challenging:

- The methods have not been used in the industrial VFM applications, so that operational experience is absent
- It is a complex approach which includes physical and statistical modeling, so the model development cost is high
- Difficult tuning

Taking the aforementioned points into account, we conclude that the state estimation methods are a promising approach for VFM, but the challenges with its construction complexity have to be overcome in order to make these methods applied for VFM more often.

6. Comparison of VFM methods

In the previous sections, we described the VFM methods which have been developed for industrial and academic applications. In this section, we would like to emphasize the advantages and disadvantages of using a particular VFM solution and also compare it with physical multiphase flow meter. Marshall and Thomas (2015) compared VFM in general with MPFM and test separators but did not distinguished the difference between the VFM methods. In this section, we add the comparison between the VFM methods and also specify other additional points of interest. Table 3 shows the methods comparison. In addition to this table, please see Bringedal and Phillips (2006) and Varyan (2016) for more detailed discussions about potential savings and cost reduction using VFM.

7. VFM literature summary

In this section, we give an overview of the available contributions on Virtual Flow Metering. In Table 4, the material summary is structured in such a way that all the relevant papers can be found based on a topic of interest. Here we aim to include all the works which contributed to the VFM development. The works under each sub-section of the table is presented by the published date order.

8. Challenges and opportunities for VFM development

Even though a vast research effort in the development of Virtual Flow Metering systems has been conducted, there are still many opportunities for this technology to improve and become a more reliable source of multiphase flowrates estimates. Based on the revised literature, in this section we propose several possible directions for the research and development of first principles and data-driven VFM systems.

8.1. First principles VFM systems

A further evaluation of the VFM sensitivity to the input parameters is required. As a starting point, one can take the evaluation by Amin (2015), Toskey (2011), Varyan et al. (2015), Tangen et al. (2017) and Lansagan (2012) and address the revealed contradictive points from the studies which we emphasized before. In addition, a systematic evaluation of the accuracy of sub-models under various conditions can be conducted. It can useful to see how separate models perform (e.g. choke and thermal-hydraulic models) with changing GORs and sensor accuracy. This can lead to selecting a correct VFM strategy at different stages of the field life cycle.

Another question is how accurate the models must be in order to construct an accurate VFM system? Can the required accuracy of the models be reduced by robust data validation and reconciliation techniques? We saw that there are several commercial VFM systems available and each has its own accuracy level of the used models. Some systems mostly rely on high fidelity multiphase models (e.g. OLGA and

Table 3
Comparison of VFM methods, MPFM and test separators.

Metering method		Advantages	Disadvantages
Virtual Flow Metering	VFM in general	- Real-time or near-real-time monitoring - Low cost solution - Does not require physical intervention to fix the problem unless most of the sensors fail - May be well integrated with other software to maximize production	- Depends on the sensor accuracy - Requires periodical tuning - Depends on the model accuracy
	First principles VFM	- Uses well-proven and known modeling methods - Operational experience is relatively long - Well suited for steady state or near-steady state situations - Many vendors available - Can be used to model other operational problems such as slugging, erosion, hydrates occurrence - Can be used to estimate unmeasured variables	- Require deep knowledge about the physics which describes the system - Quasi-steady state. Fit parameters in a certain point in time having the previous solution, hence might have a delay to capture dynamic situations - Highly depends on PVT data accuracy - Tuning process is not straightforward - High computational cost compared to data-driven VFM
	Data-driven VFM	- Does not require deep knowledge about the physics which describes the system - When the model is trained, it has low computational cost for flowrate predictions compared to other VFM methods - Easy to update continuously with newly obtained data - Easy to combine different parameters from different parts of the production system without constructing a complex physical model	- Not suitable when limited historical data is available - Most of the methods are steady state. Research on using this VFM approach for dynamic situations is required. - Limited operational experience - Can be applied to data within or near the training data range, otherwise calibration and re-training is required - Advanced feature engineering requires process insights
Physical Flow Metering	MPFM	- Vast operational experience because widely used in the industry - Real-time monitoring - Handles dynamic multiphase flow metering - Many vendors are available	- High cost technology - Requires periodical calibration and accurate PVT data - Exposed to failures, erosion and blockage - Requires expensive physical intervention to fix problems - May produce inaccurate measurements if conditions are out of the operational range
	Test separator	- Accurate flowrate estimation - Can be used as the reference with high confidence - Allows to estimate other important parameters such as fluid and reservoir properties	- No real-time monitoring - Loss of production which leads to high cost of operation - Requires vast experience of operators to make accurate well tests - Performance of other wells may be affected during the well test

K-Spice VFM systems) while the others on the reconciliation techniques (e.g. ValiPerformance). By answering these questions, we could understand what we should focus on in the future VFM development: an accurate tuning and optimization strategy or accurate system models, for instance, tubing and choke models.

Even when the VFM is tuned well, it will be necessary to re-tune the model after some production time. The tuning requires the knowledge about both operational and software features which make the process complicated. As such, an auto-tuning strategy would be a valuable asset in order to make VFM to be a standalone flow metering solution in the fields.

One of the issues influencing the VFM performance is the accuracy of PVT data which has to be continuously updated. This is linked to the tuning strategy discussed above. As such, one could also think of a more robust implementation of the VFM system in terms of the PVT change. If the system becomes less sensitive to the PVT error, this will result in less frequent well testing for model tuning and the tuning in general. One possible way may be measuring total mass flowrate, mixture densities and water cut at wellhead conditions and using it as a tuning parameter.

We saw that state estimation methods can be a promising tool for constructing an accurate dynamic first principles VFM system. The methods may be useful in solving the following problems: flowrate estimation under transient conditions; removing the influence of noise and even drift of measurement data on the VFM estimates; estimation of zonal well inflow and flow from multilateral wells. However, to proceed in incorporating these methods into the first principles VFM systems, the following questions have to be answered first: how to perform a robust tuning of the estimation methods; is the typical well configuration with downhole and wellhead sensors enough for accurate estimation or more sensors are needed; can the models be easily recalibrated for new field conditions. In addition, more investigations using real field data are required. In this way, the potential of utilizing the state estimation methods for the first principles VFM systems will actually be revealed.

In order to proceed in developing accurate transient flow estimation using first principles VFM systems, it can be promising to develop methods for numerical optimization of large-scale complex high-fidelity dynamic models that provide real-time derivatives that can be used by an optimization solver.

8.2. Data-driven VFM systems

Various data-driven models are considered in this work. One of the emerging data-driven models in VFM is based on neural networks which seems to have a big application potential. Despite the fact that the academic results are promising, a lot of work has to be done in order to make NNs to be widely applicable as an industrial VFM solution. In addition to consideration of neural networks applications, other more general research directions are given below.

Performance of data-driven models in general and neural networks in particular is highly dependent on feature engineering. Oil and gas productions systems include many parameters which influence a particular well, so may be potentially used as input features to the neural network. At the same time, finding an optimal set of features as well as hyperparameters of the neural network is a challenging task which is an ongoing research in the field of machine learning. As such, development of the approach which could identify the most informative features and optimal set of neural network hyperparameters at the same time will be a strong contribution towards accurate and robust flowrate estimates from a data-driven VFM model.

So far, only maximum likelihood estimation approach has been used for VFM modeling meaning that only the most likely value of the

Table 4
Summary of VFM manuals and literature contributions.

First principles VFM systems

Commercial VFM systems (description of models and field experience)

OLGA Online:
(Schlumberger Limited., 2014) – description of models used in OLGA Online VFM (manual)
K-Spice:
(Patel et al., 2014) – implementation of K-Spice VFM in Alta field which showed a good performance during the tests
(Kongsberg, 2016) – description of models used in K-Spice VFM system (manual)
(Tangen et al., 2017) – sensitivity analysis of K-Spice VFM system under various conditions with a digital twin approach
(Couput et al., 2017) – summary of Total experience with K-Spice VFM. Emphasized that despite the advantages of the VFM costs, it still needs skilled people to tune and calibrate the software which can be a challenge for operator companies
FlowManager:
(Rasmussen, 2004) – discusses principles and possible applications of VFM as well as field experience with FlowManager
(Holmås and Løvli, 2011) – describes models and numerical schemes used in FlowManager as well as field applications
(Holmås et al., 2013) – discusses applications of FlowManager as a flow assurance system in Ormen Lange and Vega fields in the North Sea and used as a back-up system to the MPFMs
(Varyan et al., 2015) – performed several sensitivities studies with FlowManager and compared performance with MPFMs
(Løvli and Amaya, 2016) – shows six cases of FlowManager VFM applications including gas condensate and oil fields during normal conditions as well as start-up operations.
WMS:
(van der Geest et al., 2000) – describes the models used in WMS and its performance on synthetic data
(van der Geest et al., 2001) – discusses successful WMS applications in Troika field in the Gulf of Mexico
(Melbø et al., 2003) – discusses application of WMS in the North Sea including cases with unreliable sensor information
(ABB, 2004) – application of WMS VFM in Bonga field, Nigeria.
(Bringedal et al., 2006) – application of WMS VFM in Bonga field, Nigeria.
Virtuoso:
(Haldipur, 2011; Haldipur and Metcalf, 2008) – describes models and computational methods used in Virtuoso as well as various field applications
(Parthasarathy and Mai, 2006) – presents Virtuoso applications as a back-up, monitoring and substitute system for MPFMs
ValiPerformance:
(Couput et al., 2008) – discusses examples of the software installation in an onshore field in France and a complex subsea field as a back-up and reduction uncertainty system
(Wising et al., 2009) – discusses the models used in ValiPerformance and its implementation with DVR algorithm
(Couput and Renaud, 2010) – describes an example of the software performance in the Middle East operated by Total with 16 wells with ESPs
(Petukhov et al., 2011) – describes the software models and successful testing in Ceiba oil field in Equatorial Guinea
(Haouche et al., 2012a; 2012b) – describe the software models including ESP with density correction factor as well as field tests and operation
(Couput et al., 2017) – summary of Total experience with ValiPerformance VFM.
Rate&Phase:
(Foot et al., 2006; Heddle et al., 2012) – describe types of software models and its performance on more than 300 production and injection wells
FieldWatch:
(Roxar, 2015) – description of models used in FieldWatch VFM (manual)
Prosper:
(Acuna, 2016; Ma et al., 2016; Omole et al., 2011) – used Prosper as an engine for VFM in real field cases and then combined it with external optimization techniques to estimate the flowrates continuously and optimize field production
(PETEX, 2017) – description of models used in Prosper (manual)
Sensitivity, comparative and economic studies:
(Bringedal and Phillips, 2006) – compares VFM with test separator and MPFM solutions from technological and economic points of view
(Toskey, 2011) – performs comparison of several VFM software based on synthetic data from OLGA which included several case studies with different set of parameters for flowrate estimation. In addition, conducted a survey of vendors about the VFM product features
(Lansagan, 2012) – considers sensitivity study on influence of measurement degradation, input uncertainty and availability on VFM estimates
(Amin, 2015) – describes comparison of several VFM software based on real field data. In addition, performs a sensitivity study of VFM to the input PVT data
(Varyan et al., 2015) – describes a sensitivity study of FlowManager VFM with respect to the input parameters
(Mokhtari and Waltrich, 2016) – compares different wellbore and choke models for VFM
(Varyan, 2016) – discusses potential cost savings using VFM compared to test separators and MPFMs
(Tangen et al., 2017) – sensitivity analysis of K-Spice VFM under various conditions with a digital twin approach
(Bikmukhametov et al., 2018) – describes statistical analysis of effect of sensor degradation and failure as well as heat transfer modeling methods on VFM flowrate estimates

Choke model VFM

(Delarolle et al., 2005; Faluomi et al., 2006) – developed a choke model, validated it with experimental data and CFD analysis and applied the model at field conditions in Italy, North and West Africa and the Gulf of Mexico
(Campos et al., 2010) – used a choke model as a VFM tool in an integrated production model of Urucu field
(Loseto et al., 2010) – used a choke model as a VFM tool in an integrated production model of Don fields
(Ajayi et al., 2012; Allen and Smith, 2012) – used models of downhole inflow control valves to construct a VFM system
(Moreno et al., 2014) – used a choke model as a VFM tool together with an optimization algorithm to optimize field production
(Espinoza et al., 2017; Hussain et al., 2016) – used empirical choke models to estimate the flowrate at field conditions
(Cheng et al., 2018) – combined choke model with thermal-hydraulic and IPR models for creating a VFM system which used in real field application in an offshore field

ESP model VFM

(Camilleri et al., 2016b; 2016c; 2016a; 2015; Camilleri and Zhou, 2011) – consider ESP models with various modifications and field case studies in which ESP first principles models act as Virtual Flow Meters
(Haouche et al., 2012a; 2012b) – describe the software models including ESP with density correction factor as well as field tests and operation

(*continued on next page*)

Table 4 (*continued*)

First principles VFM systems

Commercial VFM systems (description of models and field experience)

Data-driven VFM systems

Industrial applications (neural networks)

NeuraFlow:

(Denney et al., 2013) – describes the performance of NeuraFlow in field conditions
(Baker Huges, 2014) – describes the approach used for NeuraFlow software

Patchwork applications:

(Garcia et al., 2010)– describes a neural network application for production and injection rates estimation in fields of Brazil using a typical set of pressure, temperature and choke opening measurements
(Olivarez et al., 2012) – describes a neural network for production estimation when choke models showed unsatisfying performance
(Al-Jasmi et al., 2013) – used a radial basis neural network to forecast oil production 30 days ahead in wells with ESPs
(Ziegel et al., 2014) – used a neural network as a VFM system to predict oil and gas flowrates in a field in the North Sea

Industrial applications (other methods)

FieldWare Production Universe:

(*Bogaert* et al., *2004*; *Poulisse* et al., *2006*) – discuss the first ideas of developing a data-driven VFM system as a part of Smart Fields production technologies
(*Cramer* et al., *2011*; *Cramer and Goh, 2009*; *Dolle* et al., *2007*; *Gerrard* et al., *2007*; *Goh* et al., *2008*; *Law* et al., *2018*; *Poulisse, 2009*; *van Den Berg* et al., *2010*) – describe FieldWare application in many production examples from America, Europe, Africa and the Middle East to estimate the flowrates and optimize production

Research works (neural networks)

Feed-forward neural networks

(*Qiu and Toral, 1993*) – considers a neural network for oil and gas flowrates estimation using experimental data with pressure transducers
(*Berneti and Shahbazian, 2011*) – describes application of Imperialist Competitive Algorithm for initial weights optimization in a neural network for estimation of oil production
(*Hasanvand and Berneti, 2015*) – trained a neural network by Levenberg-Marquardt algorithm for oil rate predictions
(*Xu* et al., *2011*) – used Principal Component Analysis in order to reduce dimensionality of the feature space from the experiemntal data sets to produce input variables for neural networks
(*Ahmadi* et al., *2013*) – describes application of various derivative free algorithms for weights optimization of a neural network to make accurate estimates of oil production
(*Zangl* et al., *2014*) – constructed a neural network to estimate oil and water rates by the use of multi-rate well tests
(*Shaban and Tavoularis, 2014*) – used Principal Component Analysis in order to extract features from the experiemntal data sets to produce input variables for neural networks
(*AlAjmi* et al., *2015*) – describes application of a neural network to predict the flow through a choke by including not only pressure and temperature measurements but also WC and a choke model for critical flow
(*Al-Qutami* et al., *2017a*) – describes ensemble learning by combining neural networks and regression trees to estimate oil production and compares the model performance with homogeneous neural networks
(*Al-Qutami* et al., *2017b*) – developed a neural network to estimate the flowrates based on real production data as well as performed sensitivity studies of input parameters
(*Al-Qutami* et al., *2017c*) – used a radial basis neural network for the flowrate estimates as well as performed sensitivity studies of input parameters
(*Al-Qutami* et al., *2018*) – considers different methods for ensemble learning with neural networks for production estimation

Recurrent neural networks

(*Andrianov, 2018*) – used LSTM recurrent neural networks on synthetic well test data to estimate and forecast oil production
(*Loh* et al., *2018*) – compared performance of LSTM NN and LSTM NN combined with ensemble Kalman filter to predict transient oil flowrates
(*Omrani* et al., *2018*) – compared LSTM with feed-forward NN under transient conditions, performed sensitivity analysis of NN predictions with respect to data uncertainty and proposed a method for back-allocation of well flowrates using total flowrate measurements from a separator
(*Sun* et al., *2018*) – used LSTM models for predicting oil, gas and water flowrates from unconventional shale production

Research works (other methods)

(*Xu* et al., *2011*) – describes application of Support Vector Machine for flowrate estimation based on Venturi pressure difference from experiments
(*Zangl* et al., *2014*) – describes comparison of neural networks with linear regression and random forest methods
(*Bello* et al., *2014*) – describes a linear regression model with a preliminary extraction of the training features using PCA for flowrate estimation
(*Grimstad* et al., *2015*) – used B-spline models to approximate models from a commercial simulator which are then used for VFM purposes
(*Bikmukhametov and Jäschke, 2019*) – used gradient boosting with regression trees to estimate oil flowrates for different field development cases

Application of state estimation methods for VFM

(*Bloemen* et al., *2006*) – describes application of extended Kalman filter (EKF) for flowrate prediction in gas-lift wells
(*Leskens* et al., *2008*) – shows application of EKF for three-phase flowrate estimation in a unilateral horizontal well
(*De Kruif* et al., *2008*) – discusses EKF for two and three-phase flow estimation in unilateral and multilateral wells using different number and placement of measurements
(*Muradov and Davies, 2009*) – considers EKF for zonal rate allocation in synthetic and real multizone wells and compared its performance with optimization techniques
(*Lorentzen* et al., *2010a*) – discusses application of EKF to predict the gas inflow at four different zones in the wellbore
(*Lorentzen* et al., *2010b*) – considers a well with two branches and used temperature measurements with and without pressure sensor data to estimate the flow by use of the ensemble Kalman filter
(*Gryzlov* et al., *2013*) – considers different cases including flowrate and holdup estimation using EKF
(*Binder* et al., *2015*) – consider Moving Horizon Estimation for flowrate estimation in a well with an ESP

flowrates is estimated by a data-driven algorithm. However, these estimates will always have uncertainty due to different distributions of training and actual production data, noise in data, errors in reference measurements of flowrates from well tests and sensors, etc. Accurate estimation of these uncertainties in VFM applications may be valuable. It will allow using reconciliation techniques for better flowrate estimates using separator measurements as well as incorporating these uncertainties into daily and long-term production optimization.

Most of the data-driven algorithms described in this paper are able to model steady state systems and might fail to model transient fluid flow accurately. As Andrianov (2018), Loh et al. (2018) and Omrani et al. (2018) showed, there are neural network architectures which are able to capture the dynamic systems behavior. However, it is likely to happen that recurrent neural networks will not always outperform other data-driven methods even under transient conditions. As such, more work should be done in this direction to reveal the full potential of recurrent neural network architectures for making more accurate multiphase flowrate estimations, especially under transient conditions. For instance, identifying the required time frequency of the measurements and strategy for tuning the time window size can be a valuable asset.

As the industry has good knowledge of the first principles models for multiphase flow, it can also be valuable utilize this knowledge for making hybrid solutions together with data-driven models. There are different research directions to investigate. First, ensemble learning with data-driven and first principles models can be used. Another possibility may be applying physical models for training purposes, for example, in transient or lack of data situations. In addition, creating input features based on the first principles of multiphase flow may help the algorithm to map the input with output variables and produce better predictions.

Only a few works have been done on the ensemble learning of data-driven algorithms for VFM, while it has been well investigated for many other applications. With ensemble learning the model the behavior of the model becomes less explainable, but it may produce better estimates. At the same time, the model explanation may not always be necessary for flow monitoring. The potential of ensemble learning for VFM applications is certainly unrevealed and can be addressed in the future research work in this area.

As Loh et al. (2018) showed, the state estimation methods can be used not only with the first principle models but also with dynamic data-driven models, for instance, an LSTM neural network. Using the state estimation methods in this case can help the data-driven model produce accurate flowrate estimates having even a small training dataset or noisy input data. However, since only one attempt has been made in incorporating the state estimation methods in data-driven models, this research direction has many opportunities for revealing additional advantages of utilizing this approach.

9. Conclusions

Virtual Flow Metering is a promising approach for flowrate estimation due to its low cost, real-time monitoring capabilities and an easy integration with other software solutions. There are different approaches to estimate multiphase flowrates which are used in the industry or are at the research phase. Currently, the first principles approach is the most often used Virtual Flow Metering tool in operation as a standalone solution or as a back-up system for physical multiphase flow meters. Despite an active use of the first principles VFM systems, this approach still has many challenges to solve, such as model and PVT data tuning and handing transient flow behavior using dynamic optimization or state estimation techniques.

Data-driven methods are becoming more and more popular due to an increasing amount of field data and recent advances in development and understanding of data-driven algorithms as well as increase of computational power used for algorithm training. State estimation methods are still not often used in the industry and have mostly academic applications, however, the methods have several strong advantages, for instance, transient flow modeling integrated with noisy measurement data. The main challenge associated with this method is that it typically requires good models and is difficult to tune and these points have to be addressed on the future research. In addition, there is a potential in combining state estimation methods with data-driven models where a detailed physical model is not required, while the advantage of incorporating noisy measurement data still holds.

Independently on the applied VFM approach, systematic model tuning is one of the main reasons why VFM is not the main multiphase flow metering solution. The first reason for this is the fact that obtaining accurate flowrate measurements for tuning is difficult, especially in subsea fields, so it is challenging to establish a robust procedure for VFM tuning. Also, the model tuning itself is a hard task and requires a deep understanding of the models and other underlying principles. As such, developing auto-tuning strategies is an important task which has to be solved by VFM vendors to increase popularity of VFM solutions for multiphase flow metering.

Another problem is estimating uncertainty of VFM predictions and taking it into account to make accurate predictions. Depending on the applied method, this includes uncertainty of models, measurements, PVT data and reference flowrates. Accurate estimating and reducing these uncertainties is an important issue which has to be addressed in the future research for all the VFM methods.

A promising direction for research can be development of a VFM system which uses approaches of first principles and data-driven modeling together and takes advantages of each method. This approach can be called a hybrid VFM system. A hybrid model should be able to adapt to conditions of a particular field such as measurement data availability, stage of the field development, frequency of well tests for model tuning, uncertainty of the measurements, etc. In addition, by combining several VFM methods it will be possible to obtain several estimates of the same quantity which can increase the estimation confidence.

Irrespectively of the method, VFM is one of the steps towards low cost field development solutions which is steadily being integrated in subsea oil and gas fields around the world. The trend of an efficient data use in the industry also supports the concept of VFM. We believe that the future research and pilot tests may strengthen capabilities of VFM methods which will provide more trust for the operators to utilize VFM technology in a reliable and effective manner.

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Abbreviations

ANN: Artificial Neural Network
BOM: Black Oil Model
CAPEX: Capital Expenditure
DDWT: Deliberately Disturbed Well Test
DVR: Data Validation and Reconciliation
EKF: Extended Kalman Filter
EnKF: Ensemble Kalman Filter
EoS: Equation of State
ESP: Electric Submersible Pump
FL: Fuzzy Logic
FW PU: FieldWare Production Universe
GOR: Gas-Oil Ratio
GA: Generic Algorithm
ICA: Imperialist Competitive Algorithm
IPR: Inflow Performance Relationship
L-M: Levenberg-Marquardt
LR: Linear Regression
LSTM: Long-Short Term Memory
MHE: Moving Horizon Estimation
MPFM: Multiphase Flow Meter
MSE: Mean Squared Error
NN: Neural Network
NNE: Neural Network Ensemble
OPEX: Operating Expenditure
PCA: Principle Component Analysis
PCR: Principle Component Regression
PR: Peng-Robinson
PSO: Particle Swarm Optimization
PVT: Pressure Volume Temperature
RBFN: Radial Basis Function Network
RDP: Rotameter Pressure Drop
RF: Random Forest
RK: Redlich-Kwong
RNN: Recurrent Neural Network
RT: Regression Tree
RTE: Regression Tree Ensemble
SA: Simulated Annealing
SQP: Sequential Quadratic Programming
SRK: Soave-Redlich-Kwong
SVM: Support Vector Machine
UKF: unscented Kalman filter
VDP: Venturi Pressure Drop
VFM: Virtual Flow Meter/Virtual Flow Metering
WC: Water Cut
WMS: Well Monitoring System

Nomenclature

A_1: cross-sectional area upstream the choke, m^2
A_2: cross-sectional area at the choke throat, m^2
B_f: linear Forchheimer equation constant
C_0: profile parameter
C_b: backpressure equation constant
C_D: choke discharge coefficient
C_f: quadratic Forchheimer equation constant
C_{op}: choke opening
D: pipe diameter, m
e: specific heat exchange with the environment, m^2/s^2
E_k: total energy, m^2/s^2
f_{fric}: friction factor
F_{ki}: interphase friction, $kg/(m^2 \cdot s^2)$
F_{kw}: wall friction term, $kg/(m^2 \cdot s^2)$
F_{tot}: total wall friction, $kg/(m^2 \cdot s^2)$
g: gravitational constant, m/s^2
g_i: system parameter
h: fluid specific enthalpy, m^2/s^2
h_k: k-phase specific enthalpy, m^2/s^2
i: index of the training example/well number
k_k: effective phase thermal conductivity, $kg \cdot m/(s^3 \cdot K)$
$\dot{m}$: mass flow rate, kg/s
n: power constant
N: ensemble/training dataset size
O_k: additional momentum exchange terms, $kg/(m^2 \cdot s^2)$
O_{tot}: total source term, $kg/(m^2 \cdot s^2)$
p: system pressure, Pa
P_B: bubble point pressure, Pa

P_{BH}: bottomhole pressure, Pa
P_{FL}: flowline pressure, Pa
P_R: reservoir pressure, Pa
P_{WHCU}: wellhead upstream choke pressure, Pa
P_{WHCD}: wellhead downstream choke pressure, Pa
PI: productivity index, Pa·s/ m^3
$q_{estimated}$: estimated volumetric flowrate, m^3/s
q_i: volumetric flowrate of i-well, m^3/s
q_g: gas volumetric flowrate, m^3/s
q_o: oil volumetric flowrate, m^3/s
$q_{o,\max}$: maximum oil volumetric flowrate, m^3/s
Q_{ext}: additional net external heat transfer sources, $kg/(s^3{\cdot}K)$
Q_{ki}: interfacial heat transfer rate of k-phase with other fields, $kg/(s^3{\cdot}K)$
Q_{kw}: phase transfer rate at pipe wall, $kg/(s^3{\cdot}K)$
s_i: unmeasured variable
$s_{\max}$: minimum unmeasured value constraint
$s_{\min}$: minimum unmeasured value constraint
t: time, s
T: system temperature, K
T_{BH}: bottomhole temperature, K
T_k: k-phase temperature, K
T_{WHCU}: wellhead upstream choke temperature, K
T_{WHCD}: wellhead downstream choke temperature, K
u_d: drift velocity, m/s
u_g: gas velocity, m/s
u_k: k-phase velocity, m/s
u_m: mixture velocity, m/s
U: total heat source term, $kg/(m{\cdot}s^2)$
U_{tot}: total source term including wall heat transfer, mass transfer and sources, $kg^2/(s^2{\cdot}\ m^4)$
w: specific work done on the system, m^2/s^2
w_t: measurement noise
x: pipe axial coordinate, m
$y_{meas\ i}$: measured value
$y_{predicted\ i}$: predicted value
$y_{\min}$: minimum measured value constraint
$y_{\max}$: maximum measured value constraint
α_k: k-phase volume fraction
γ_i: weight coefficient
Δp: pressure drop across the choke/electric submersible pump, Pa
θ: pipe/wellbore inclination angle
ρ: fluid density, kg/m^3
ρ_k: k-phase density, kg/m^3
ρ_m: mixture density, kg/m^3
σ_i: measurement uncertainty
Ψ: mass transfer source, $kg/(m^3{\cdot}s)$
ξ: pump speed, rpm