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Extended Abstract

Self-adjusting, Real-time Virtual Flow Metering

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1 INTRODUCTION

Access to well rates forms the basis for both reservoir and production optimization. Nevertheless, continuous access to accurate well rates is not commonplace. Rather, intermittent information is often available through well testing. Virtual Flow Metering offers a supplement to well testing where software solutions estimate well rates in between well tests. However, many current Virtual Flow Meter (VFM) solutions are commonly calibrated manually based on the well tests. Consequently, the outcome from a VFM assumes that the well behavior remains stable in between recalibrations. This constitutes a significant drawback since the well rate estimates will not be reliable when the flowing characteristics of the well changes.

In this paper, we present a self-adjusting VFM concept which continuously updates itself based on existing sensor data. In addition to improved accuracy throughout the life of a well, this reduces the need for manual interventions and facilitates less frequent well testing, as well tests are rather used for validation than direct calibration.

2 METHODOLOGY

2.1 General

In this work, we address an approach to Virtual Flow Metering where physics-based simulations are key to the solution. Simulations may, when required, be augmented with Machine Learning (ML) models, resulting in a hybrid solution [1]. An underlying physics-based simulator is, however, always part of the solution.

To simulate the behavior of a well, boundary and operational parameters are required input. The upstream boundary constitutes the reservoir inflow, often represented by an Inflow Performance Relationship (IPR). The downstream boundary is a known pressure measurement, e.g., a pressure measurement downstream of the production choke or a known flowline pressure. In addition, information about operational setpoints is required, like choke openings, gas lift rates, and ESP frequencies, see Figure 1.

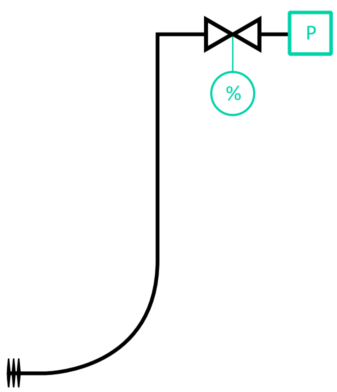

Figure 1 Illustration of sensors representing boundary conditions and operational set-points used to drive the physics-based simulation model for a VFM.

For such a simulation model, well tests provide reference data, which can form the basis for calibration of the fundamental physical closures in the simulator. Furthermore, these reference rates can be used to calibrate the IPR. Here, it is important to understand that there is a significant difference between these two types of calibration; the calibration of physical closures represent properties which are stable over longer periods whereas the IPR represents reservoir properties which may change fast and frequently.

2.2 Self-Adjustment

If we consider a well from reservoir inflow to a position downstream of the production choke, additional sensors are often available along the path, as illustrated in Figure 2.

Pressure and temperature sensors are common, but any sensors which represent physical properties addressed by the simulation model can be incorporated, e.g., phase fraction meters. For any such sensor within the realm of the simulation model, the equivalent output from the simulation can form basis for self-adjustment of the reservoir conditions and fluid properties.

Using the simulation model in conjunction with an optimizer, minimizing the deviation between the measured and simulated data for the additional sensors indicated in orange in Figure 2, reservoir parameters can be determined without a need for reference flow rates. This leads to an always up-to-date representation of the well, and, thus, accurate well rate predictions.

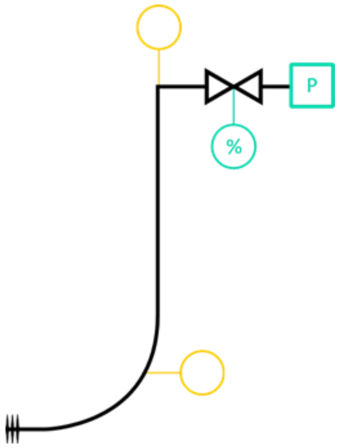

Figure 2 Illustration of additional sensors (orange) beyond boundary conditions and operational set-points (green) used to drive self-adjustment of the reservoir inflow parameters in a physics-based simulation model for a VFM.

2.3 Hybrid Modeling

The self-adjustment outlined above is attractive but still has its challenges. Firstly, there may be a shortage of available sensor data. To determine the unknown reservoir properties, sufficient sensors measuring independent parameters must be available. For an under-determined optimization problem, it will not be possible to uniquely determine the unknown parameters. Secondly, even if sufficient sensors are available, the problem may be of such a character that physics and mathematics alone cannot determine all unknown parameters accurately.

For example, we may consider a situation where the water cut exceeds 95%. While it is possible to determine the gas and total liquid flow rates accurately using pressure and temperature sensors, the differences in oil and water properties are commonly too small to accurately determine the oil/water split. When oil makes up a small fraction of the total liquid, an insignificant error in the water cut has a significant effect on the predicted oil rate: A water cut deviation of 1 percentage point results in 20% relative error in the oil rate. For such a situation, physics-based modeling can be augmented with machine learning to form a hybrid solution and offer a means to determine 3-phase well rates [1][2].

In the case where available sensors along the modeled flow path are insufficient, machine learning can offer a means to utilize other sensors to provide the information required to close the system. The additional sensors can be on the same well, e.g., parts of the gas lift system not included in the model or mechanical sensors on an ESP which can be converted into useful insights. Additional information can also be deduced from sensors connected to other, similar wells within the same asset, so-called transfer learning [1].

3 CASE STUDY

In this case study, Virtual Flow Metering is deployed to deliver three-phase flow rates for wells on an aging asset on the Norwegian Continental Shelf. The default sensor configuration illustrated in Figure 3 offers a good starting point and should suffice to deliver three-phase well rates, however two common challenges for aging assets are relevant in this case: malfunctioning sensors and high water cuts.

For wells with all sensors functioning, a purely physics-based solution is capable of accurately determining the gas and total liquid flow rates, see Figure 4. This may, however, be difficult in the case of a malfunctioning sensors. Under such circumstance, machine learning (ML) models can serve to synthetically generate required input data based on other sensors.

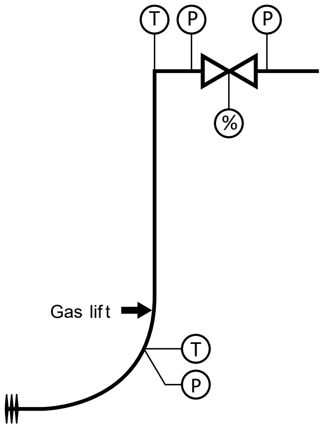

Figure 3 Illustration of the typical sensor configuration for wells on the asset.

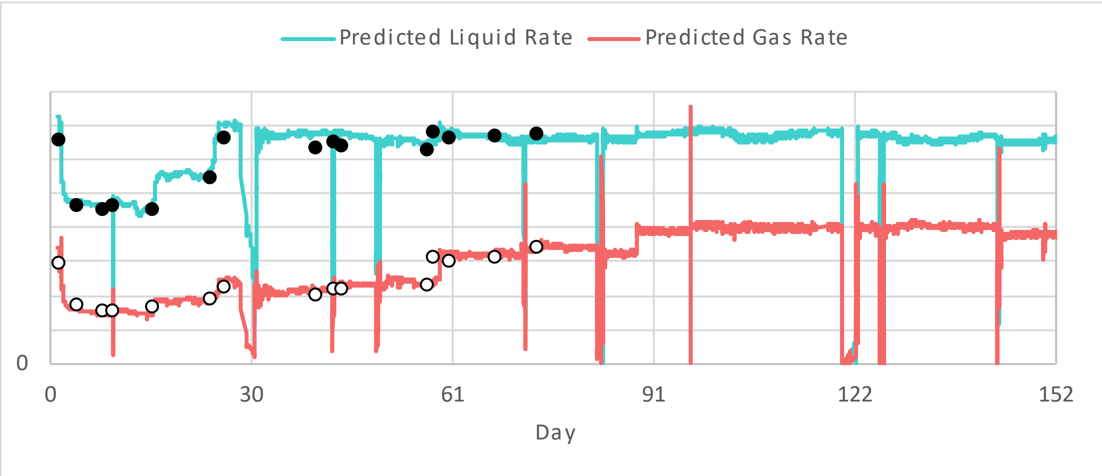

Figure 4 VFM predictions of gas and total liquid flow rates for a well with all sensors working. Self-adjustment is purely based on physics-based simulations. Field well test measurements are shown as circles.

Figure 5 illustrates the gas and total liquid rates for a well with malfunctioning sensors. The sensor data alone are not sufficient to deliver accurate gas and total liquid flow rates, however once augmented with synthetic data from machine learning, good accuracy can be achieved as shown.

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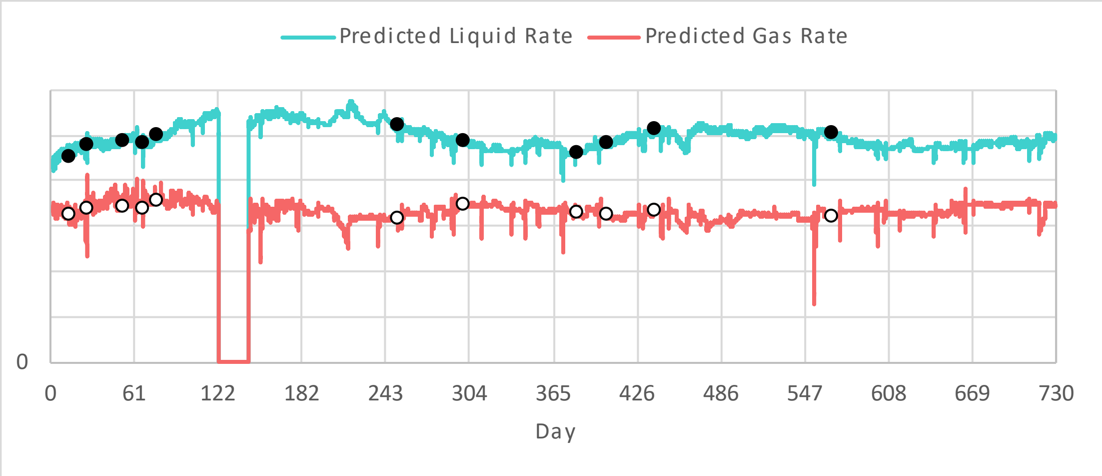

Figure 5 VFM predictions of gas and total liquid flow rates for a well with malfunctioning sensors. Self-adjustment is based on physics-based simulations augmented with synthetic data from machine learning models. Well test field measurements are shown as circles.

Above, we have demonstrated successful predictions of gas and total liquid flow rates. To go from two-phase to three-phase predictions, accurate estimates of the water cut are required. The determination of water cut based on physics and mathematics alone can be considered accurate within a few percentage points, and for very high water cuts this implies an unacceptable uncertainty on the oil rates.

Here, machine learning models which incorporate basic physical relations through feature engineering provides a means to accurately predict the water cut. The inclusion of physics through feature engineering also ensures some extrapolation capabilities, which in turn means that the model remains valid in between well tests. To maintain the best possible accuracy, the ML models are retrained after each approved well test. When combined with physics-based simulations, this results in a VFM which can deliver 3-phase well rates at required accuracy, see Figure 6.

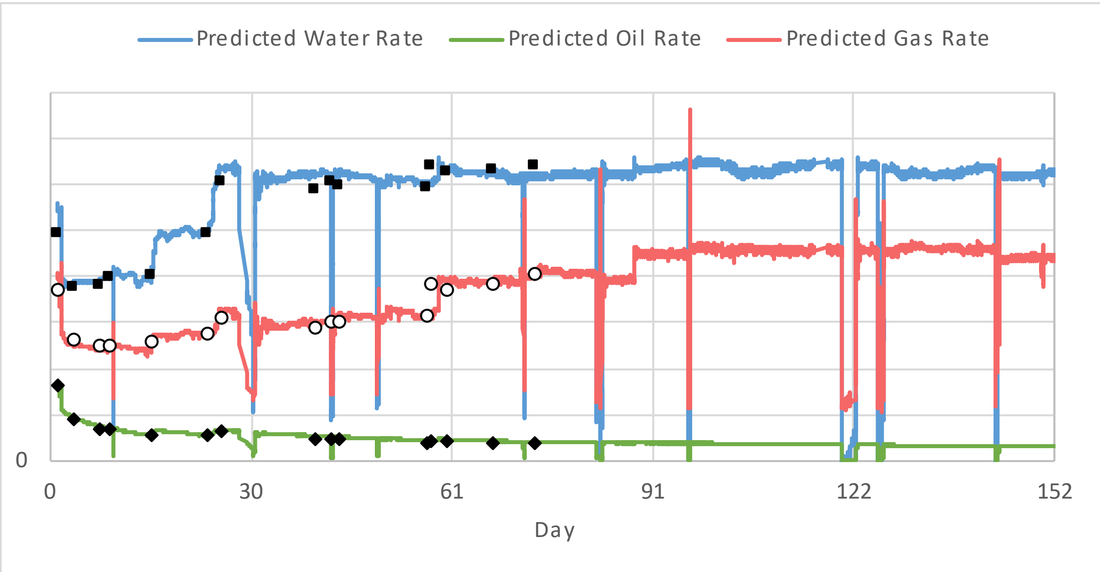

Figure 6 VFM predictions of gas, oil, and water flow rates for a well with all sensors working. Self-adjustment of gas and total liquid flow rates is purely based on physics-based simulations, see Figure 4, while the water cut is determined by machine learning models. Field measurements are represented with markers.

4 DISCUSSION

Virtual Flow Metering has been developed, tested, and deployed for decades [3]. Various solutions have attracted an increased interest with increasing access to sensor data, and the capabilities have even further increased with the entry of machine learning. However, there are still unresolved challenges, particularly in terms of maintenance and reliability. Whether based on first-principles physics or machine learning algorithms, regular recalibration/retraining is required, which often requires manual intervention. In this work, we have presented how a self-adjusting hybrid solution, which combines first-principles physics with machine learning, increases reliability and reduces the need for human intervention.

A Virtual Flow Meter (VFM) can deliver continuous well rates based on data from existing sensors. This can act as a supplement to well testing and offer continuous insights in between well tests. For assets with highly transient well behavior, we have demonstrated that a VFM combined with intermittent well testing can replace the need for continuous well flow measurements with maintained understanding of the well performance [2]. For assets already employing intermittent well testing, a reliable VFM solutions can extend the time in between well tests, and by that reduce both operational expenditure and deferred production.

With the self-adjustment methodology outlined in this work, where the VFM utilizes additional sensors to self-adjust and maintain accuracy, reference well rate measurements are no longer primarily for calibration, but rather a means for validation. In that, the presented approach is well suited to be deployed side-by-side with multiphase flow meters (MPFM) in case of failure.

It is important to emphasize that deviations between VFM predictions and field measurements do not necessarily mean a less accurate VFM solution, but may rather be an indication that attention is needed. Deviations may, e.g., be caused by drifting sensors, equipment operating outside their calibrated range, or changes in well performance. Furthermore, by proactive deployment of model components such as machine learning models to compensate for malfunctioning sensors, the solution offers fallbacks and will seamlessly deliver insights even if sensors fail.

Finally, by incorporating a physics-based simulator at the core of a VFM, the potential reach of the solution extends far beyond real-time well rates. Access to the underlying simulation model facilitates additional workflows on top, such as operations support and production optimization. One example is the possibility to run what-if scenarios to investigate how changes in operational setpoints impact operations ahead of their implementation. This in turn can facilitate optimization to, e.g., optimize use of gas lift and maximize utilization of limited resources.

Another use-case is to gain insights into flow assurance challenges such as the onset of water breakthrough, impending liquid loading, risk of solids deposition, etc. When preconfigured, automated, and combined with alerts, this caters for operational excellence.

5 SUMMARY

In this work, we outline a self-adjusting VFM solution based on a hybrid technology, combining a first-principles physics-based simulation model and data analytics, and its successful deployment on an aging oil field on the Norwegian Continental Shelf. We demonstrate that such a solution provides accurate predictions of three-phase well rates even at very high water cuts (exceeding 95%), and we also show how machine learning makes it possible to compensate for failing sensors. A comparison between predictions from the deployed hybrid VFM solution and intermittent well tests confirms that the predicted rates are within 10%.

6 REFERENCES

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[2] T. Vanvik, J. Henriksson, Z. Yang, and G. Weisz. "Virtual Flow Metering for Continuous Real-Time Production Monitoring of Unconventional Wells." Unconventional Resources Technology Conference, June 2022. URTEC-3723767-MS. https://doi.org/10.15530/urtec-2022-3723767.

[3] T. Bikmukhametov and J. Jäschke, "First Principles and Machine Learning Virtual Flow Metering: A Literature Review." Journal of Petroleum Science and Engineering vol. 184. 2019. https://doi.org/10.1016/j.petrol.2019.106487.