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Virtual Multiphase Flow Meter using combination of Ensemble Learning and first principle physics based

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Abstract

This paper describes a Virtual Flow Meter (VFM) to estimate oil, gas and water flow rate by combining two distinct approaches i.e., data-driven Ensemble Learning algorithm and first principle physics-based transient multiphase flow simulator. The VFM uses a common real-time sensor readings and the estimated flow rates were then combined using a new combiner approach which provides confidence decay and historical performance factors to assign confidence and contribution weights to the base estimators, and then aggregates their estimates to deliver more accurate flow rate estimates. This technique was tested for over 6 months at an offshore oil facility having two oil wells. The technique successfully delivered a 50% improvement in measurement performance compared to stand-alone VFMs. This combiner technique will be of great benefit to surveillance engineers by providing additional real-time production monitoring in addition to acting as a verification tool for physical multiphase flow meters (MPFMs).

Keywords

Combiner, Ensemble Learning, Multiphase flow meter, Virtual flow meter.

Introduction

Virtual flow meter (VFM) is a computational model which utilises the available distributed physical measurements (i.e. gauges and transmitters) in oil well installation, as shown in Figure 1 to provide real-time estimates of phase flow rates (Mokhtari Jadid, 2017). This is in contrast to a physical flow meter, known as multiphase flow meter (MPFM), which is shown in Figure 2 which has its own set of internal instruments and its own metrology principle that is well understood and governed by various industry standards (I. O. for S. ISO, 2003; American Petroleum Institute API, 2013; PETRONAS, 2013; Process Industry Practices PIP, 2015). Meanwhile, VFMs can be considered as a 'soft' sensor or inferential sensor. VFMs and similar soft sensor applications are useful to provide estimated real-time measurements in cases where a physical sensor or meter is not available or is faulty.

Both MPFMs and VFMs can be used for well-surveillance, performance tracking of individual well productivity, flow assurance, reservoir management, operational control and process optimization such as artificial lift optimization (American Petroleum Institute API, 2013). VFM also could be used alongside physical MPFM to provide backup (Mokhtari Jadid, 2017).

There are two types of VFM, namely, (i) physics-driven and (ii) data-driven. Physics-driven VFMs use first-principles modelling, based on the laws of physics and chemistry, to estimate multiphase flow rates. These models can be further classified into steady-state models and transient models (Ishak et al., 2020; Kim et al., 2020). The Physics-driven VFM was initially developed as an add-on to a transient multiphase flow simulator (i.e. OLGA, previously developed by SPT Group, later acquired by Schlumberger) developed as a tool to assist in the design of deepwater subsea development and later on as tool for flow assurance monitoring in deepwater oil & gas applications (Canon et al., 2015). Another common physics-driven VFM has been developed by Kongsberg Ledaflow. The performance evaluation for the type of VFM was

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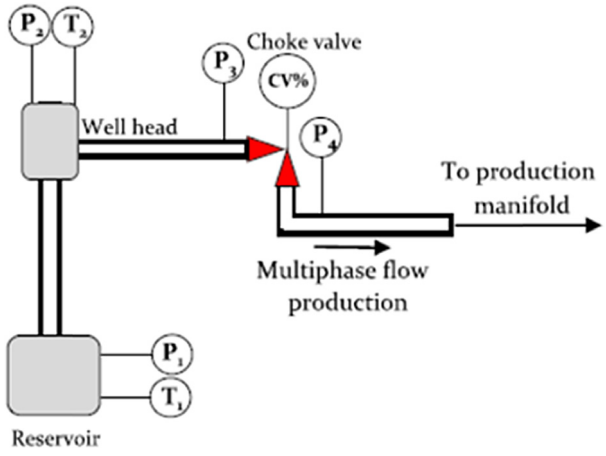


Figure 1: Typical real-time measurement devices installed in upstream production well.

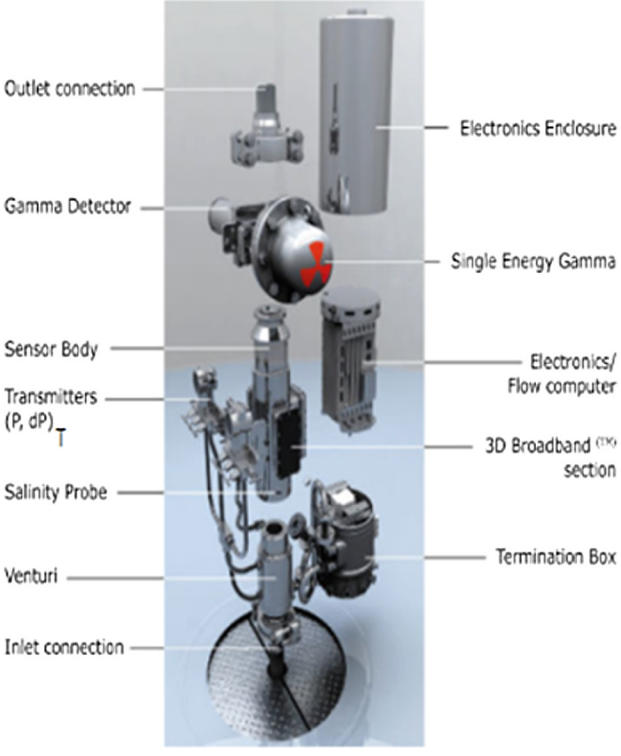


Figure 2: MPM (now TechnipFMC™) Multiphase Flow Meter.

conducted (Belt et al., 2011). The most recent transient multiphase flow simulator to be introduced to oil and gas industry is Flux Simulator by Turbulent Flux (Turbulent Flux, https://turbulentflux.com). Turbulent Flux's Flux Simulator is developed as a dedicated transient flow simulator for real-time monitoring application.

Data-driven VFMs use historical production data to enable machine learning and generation of regression models. Various machine learning models have been tested, including Neural Networks (Ahmadi et al., 2013; Andrianov, 2018; Grimstad et al., 2021) and ensemble learning (AL-Qutami et al., 2018; Bikmukhametov and Jäschke, 2019). A data-driven VFM, known as 'Production Universe', has been developed by Shell (PU) (Poulisse et al, 2006).

The potential of combining physics-driven and data-driven VFMs has been explored in work by Bikmukhametov (Bikmukhametov and Jäschke, 2020a). The performance evaluation comparing physics-driven and data-driven VFMs running in parallel has also been evaluated (Ishak et al., 2020). In this paper, we will introduce a new approach for combining the estimated flow rate outputs from physics-driven and data-driven VFMs. The proposed

Table 1. Pilot Experiment Parameters.

Parameter	Detail
Producing Wells	Well 101 and Well 102
Well-testing equipment	Shared MPFM
Flow type	Multiphase (3 phases)
Training data	6 weeks multi-rate well-tests
Online test duration	6 months
Measurements	Downhole P/T, Upstream P/T, downstream P/T, Choke opening
Data source	OSIsoft PI

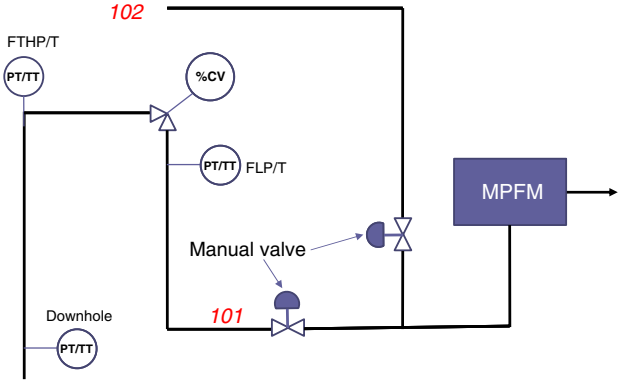


Figure 3: Well 101 and 102 is diverted manually through a common Multiphase Flow Meter (MPFM).

Table 2. Format for well test report to be for both training and testing dataset.

		INPUT							OUTPUT		
Date/Time	Well No	Flowing tubing head pressure (FTHP), psi	Flowing tubing head temperature (FTHT), °C	Differential pressure across the well (dPWell), psi	Differential temperature across the well (dTWell), °C	Choke opening (CV), %	Differential pressure across the choke (dPChoke)	Differential temperature across the choke (dTChoke)	Oil Flow Rate (bbl/day)	Gas Flow Rate (MMscf/day)	Water Flow Rate (bbl/day)
DD:MM:YYYY HH:MM:SS	101	–	–	–	–	–	–	–	–	–	–
DD:MM:YYYY HH:MM:SS	102	–	–	–	–	–	–	–	–	–	–
DD:MM:YYYY HH:MM:SS	101	–	–	–	–	–	–	–	–	–	–
DD:MM:YYYY HH:MM:SS	102	–	–	–	–	–	–	–	–	–	–

algorithm attempts to keep both types of models running in parallel and then introduces a meta optimal estimator that combines both of their predictions and tracks each VFM's performance over time. The proposed combiner will also provide an indication of confidence level on the final estimate, based on the underlying correlation between the individual estimates and the VFM's historical performance.

This study adds the following to the existing literature:

- A method to combine physics and data-driven approaches for virtual flow metering application
- A method to evaluate the confidence of VFM estimations over time
- Results of running different VFMs in an actual field for 6 months.

The rest of this paper is arranged as follows: the "Methodology" section explains the details of the experimental setup, the proposed approach and its underlying components and evaluation metrics. The "Results" section explains the outcomes and observations of the testing. The "Conclusion" section highlights the insights from this research.

Methodology

In this section, the overall experimental setup as well as the workflow and the performance criteria will be presented.

Experimental setup

The test pilot was set up to get real-time measurements from the OSIsoft™ PI server through PI web

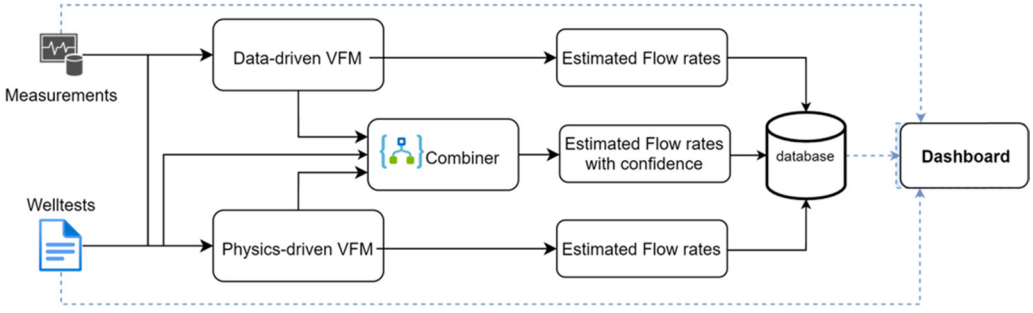


Figure 4: Overall Virtual Flow Meter architecture incorporating the combiner.

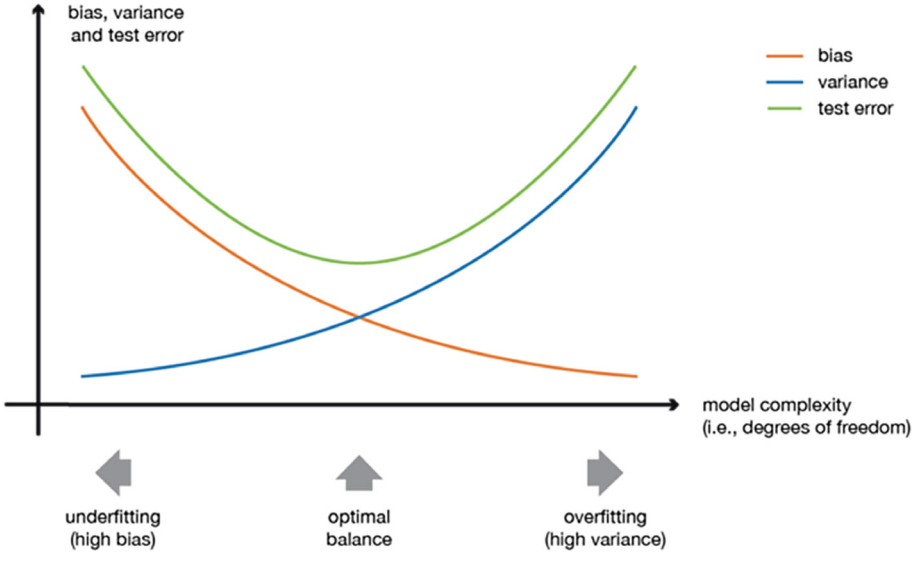


Figure 5: Illustration of bias-variance trade-off.

Application Program Interface (API). The developed system was tested in an online pilot in an offshore field with two oil-producing wells. The details of the pilot test are shown in Table 1.

Wells 101 and 102 together with physical multi-phase flow meter (MPFM) are shown in Figure 3.

Both of the wells were tested on a monthly basis by diverting the manual valve for an 8-hr duration. This data dataset is called a Well Test Report in a format shown in Table 2. Both wells have close to 2 years of historical Well Test data. Based on the dataset, well 101 flows only oil and gas while 102 also contains a significant amount of water.

System architecture

The VFM system architecture is shown in Figure 4. Sensor measurements come from OSIsoft™ PI, while the well-test dataset is uploaded from Excel sheets.

Both the measurements and the reference well-test results are fed into individual VFMs, and the outputs are stored in a database. The combiner subsystem uses the outputs from the individual VFMs to estimate flow rates along with the confidence level indicator. All the data is then stored in the database and visualized using a real-time dashboard. The system is flexible such that more than one VFM model can be running for the same asset. The combiner is also flexible as it can accept one or more models to run the combining algorithm and can also handle missing values correctly.

Data-driven VFM workflow

For this project, the chosen data-driven VFM (DD-VFM) uses ensemble learning methods as per developed previously using the same dataset by (AL-Qutami et al., 2018). This choice is supported independently by Bikmukhametov (AL-Qutami, 2017; Bikmukhametov and Jäschke, 2020b). Ensemble methods take multiple models which normally considered as “weak learners: and combine them together to form a more powerful model overall. There are 3 different approaches of Ensemble Learning i.e. Bagging, Boosting and Stacking (Opitz and Maclin, 1999).

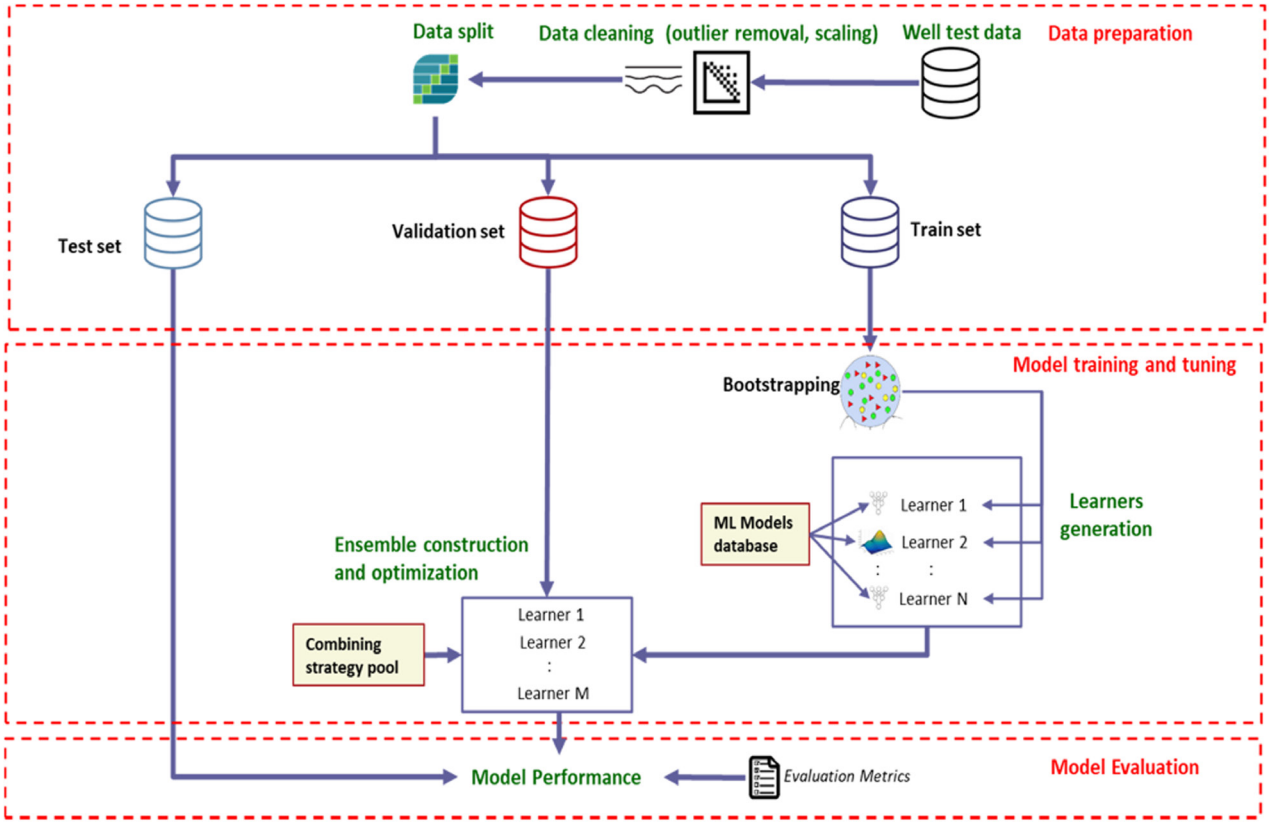


Figure 6: Data-driven VFM based on ensemble learning.

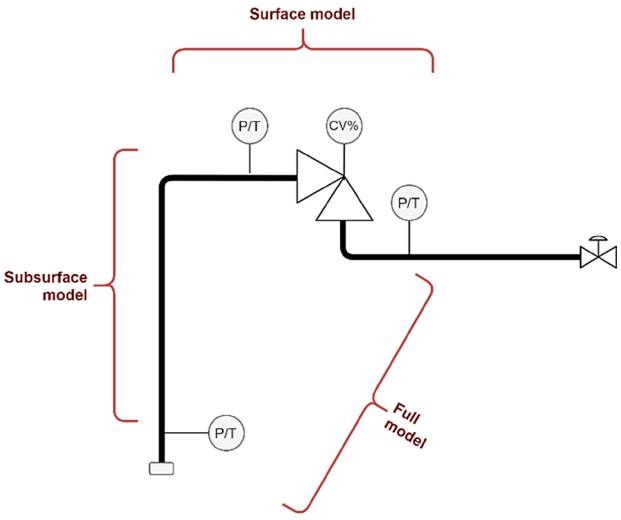


Figure 7: 3 Distinct models were developed namely subsurface model, surface model and complete model.

Bagging (also called bootstrap aggregating) combine homogenous "weak learners". Homogeneous means each earlier weak learner is of the same type (e.g. all decision trees) These weak learners are trained independently in parallel. The output from weak learners are then combined with some type of aggression technique like voting for binary classification or averaging regression use case. From this definition, Random Forest is indeed a type of Bagging (Naik, 2019a).

In Boosting, models are trained sequentially. Weak learners are therefore not independent. Model at the current step depends on models at previous steps. There are further 3 methods of Boosting i.e. AdaBoost (Adaptive Boosting), Gradient Boosting and XGBoost (Extreme Gradient Boosting) (Naik, 2019b). In AdaBoost, at each step, the weights of the observations that were previously misclassified are increased making the better the weak learner the higher its weight. The "strong learner" (final model) is a weighted sum of the weak learners.

With Gradient Boosting, the final model is also weighted sum of the weak learners, however, gradient descent is used to determine how to improve at each step in the sequence. Gradient boosting is a generalisation of boosting where optimization can be based on any arbitrary differentiable loss function.

Table 3. Data-driven model category with the associated inputs and outputs for each well.

Well	Model Category	Inputs	Output	Algorithm
101	full	CV, FTHP, FTHT, dPWell, dTWell, dPChoke, dTChoke	Qgas	AdaBoost
			Qoil	RandomForest
			Qwater	AdaBoost
	surface	CV, FTHP, FTHT, dPChoke, dTChoke	Qgas	RandomForest
			Qoil	RandomForest
			Qwater	AdaBoost
	subsurface	FTHP, FTHT, dPWell, dTWell	Qgas	AdaBoost
			Qoil	RandomForest
102	full	CV, FTHP, FTHT, dPWell, dTWell, dPChoke, dTChoke	Qgas	Bagging
			Qoil	RandomForest
			Qwater	AdaBoost
	surface	CV, FTHP, FTHT, dPChoke, dTChoke	Qgas	AdaBoost
			Qoil	RandomForest
			Qwater	AdaBoost
	subsurface	FTHP, FTHT, dPWell, dTWell	Qgas	RandomForest
			Qoil	AdaBoost
			Qwater	Bagging

COMPONENT	MOLE% WELLSTREAM
N_2	0.31
CO_2	0.84
C_1	31.17
C_2	2.10
C_3	0.18
i-C_4	0.50
n-C_4	0.03
i-C_5	0.01
n-C_5	0.01
C_6	0.05
C_7	0.28
C_8	0.44
C_9	0.54
C_{10}	2.59
C_{11}	4.72
C_{12}	5.42
C_{13}	6.91
C_{14}	6.98
C_{15}	9.14
C_{16}	5.40
C_{17}	4.79
C_{18}	4.24
C_{19}	2.90
C_{20+}	10.45
TOTAL	100.00

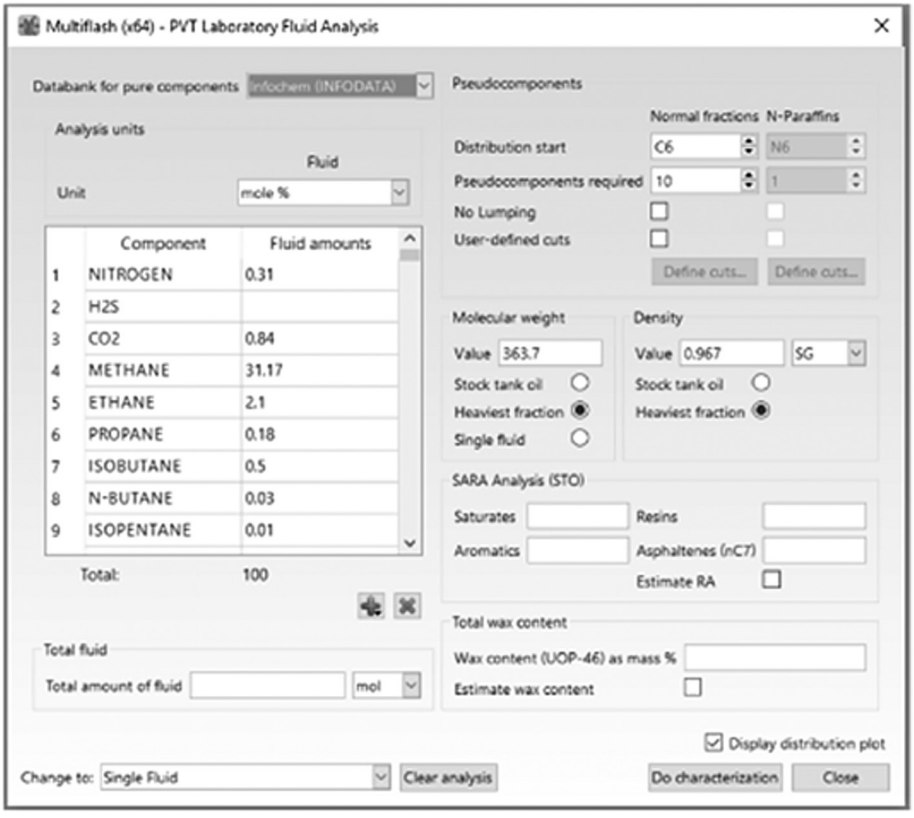


Figure 8: Fluid characterization in Multiflash®.

Theoretically, comparing the two methods using bias-variance trade off as shown in Figure 5; with bagging, the goal is to reduce the variance in model while with boosting, the goal is to increase the prediction accuracy or the bias of the model (Naik, 2020; Powerhouse, 2020). On the dataset partition, in bagging, the data partition is random, while in boosting, mis-classified data is given higher importance.

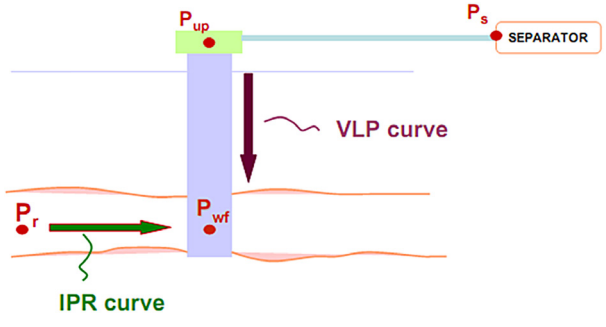


Figure 9: Inflow Performance Relationship (IPR) and Vertical Lift Performance (VLP) (Fetoui, [Online]).

Finally, stacking is ensemble method that combine heterogenous weak learners (Wolpert, 1992). For example, a combination of neural networks with decision trees, linear model and so on. Bagged or Boosted models could as well be used as those weak learners. For this reason,

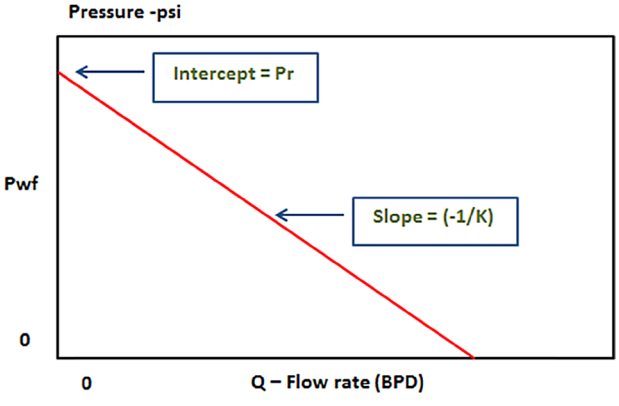


Figure 10: Inflow Performance Model (IPR) provide relationship between well flowing bottom-hole pressure, *Pwf* as a function of production rate, *BPD*.

stacked models can be very difficult to interpret meaningfully.

Ensemble Learning is preferred especially in this application for multiphase flow prediction because interpretability is not our top priority with high accuracy take higher precedence. The complete workflow of the data-driven VFM using ensemble learning is shown in Figure 6. The implementation of Ensemble Learning in Python is described by (Semicolon, 2017).

Three separate data-driven models were developed, as shown in Figure 7. The subsurface model uses measurements taken from downhole and from upstream of the choke valve. The surface model uses measurements from upstream of choke valve and downstream of choke. Lastly, the full model covers all the above, utilising measurements from downhole to downstream of the choke valve.

Each phase flow rate was modeled independently resulting in three ML estimators for the same production well. A further three categories of models were developed based on the measurements fed to each estimator. The summary of the different trained estimators is shown in Table 3.

The possible inputs to the machine learning model are Choke opening (C_V), Flowing tubing head pressure (FTHP), Flowing tubing head temperature (FTHT), differential pressure across the well (dP_{Well}), differential temperature across the well (dT_{Well}), differential pressure across the choke (dP_{Choke}), differential temperature across the choke (dT_{Choke}). dP_{Well} and dT_{Well} are the differences between downhole *P/T* and flowing tubing head *P/T*.

The outputs of the VFMs are gas flow rate (Q_{gas}), oil flow rate (Q_{oil}), and water flow rate (Q_{water}). Each model was trained using the pool of algorithms and a hyperparameter space to produce the best performing model.

Physics-based VFM workflow

In this project, the Physics-based virtual flow meter (VFM) uses Flux Simulator from Turbulent Flux (Turbulent Flux, https://turbulentflux.com) to construct the physics model. TF-VFM will be used as the abbreviation for the VFM from Turbulent Flux's Flux Simulator.

The workflow requires two general steps to work properly.

Physics and static tuning

As shown in Figure 8, static information about the well is used, such as well geometry, PVT, and choke characteristics to tune the physical and system parameters. Using description by Mokhtari Jadid (2017) and Figure 7 as reference, the Physics model can be constructed suing the following:

i. Fluid properties characterization
ii. Wellbore model
iii. Choke valve model
iv. Enthalpy model

Fluid properties characterization: From the supplied fluid property (also known as PVT data), Multiflash® software can be used to generate the model as shown in Figure 9.

Wellbore model: are represented by Inflow Performance Relationship (IPR) and Vertical Lift Performance (VLP), as shown in Figures 10 and 11. IPR

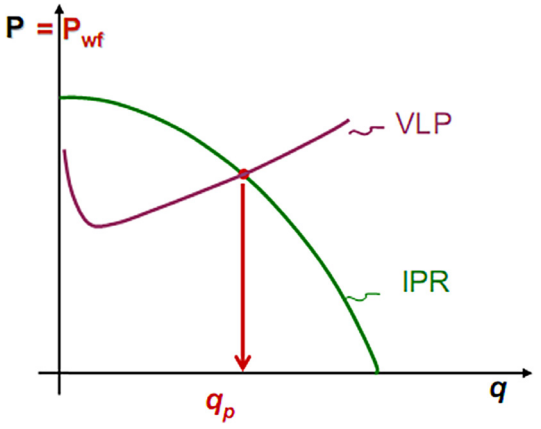


Figure 11: The intersection of the IPR with the VLP, called the operating point, yields the well deliverability.

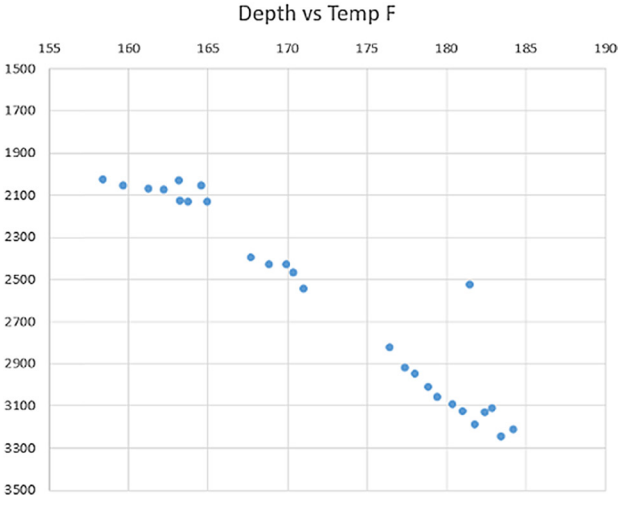


Figure 12: Geothermal profile along the vertical well (depth), ft vs. Temperature °*F*.

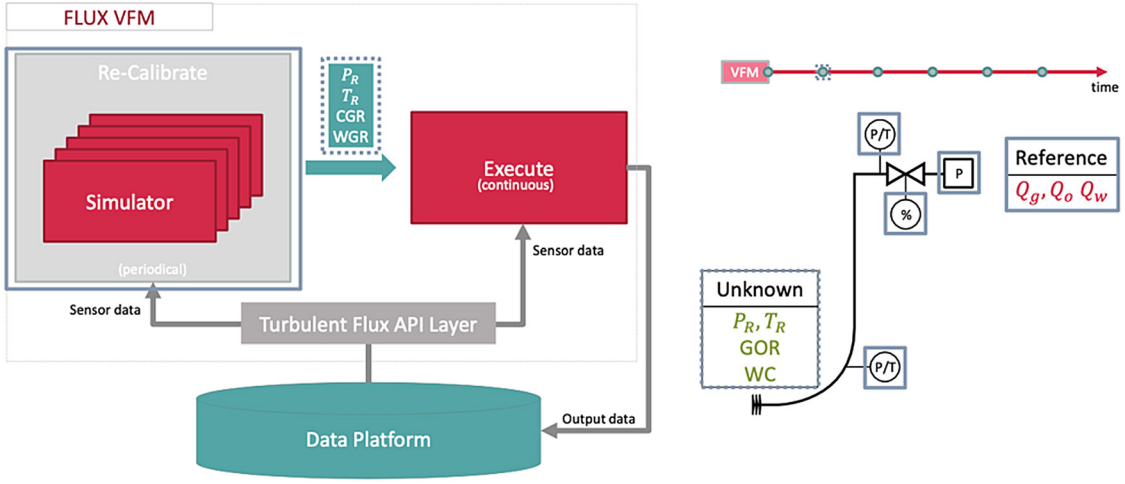


Figure 13: Initial calibration step in Flux Simulator.

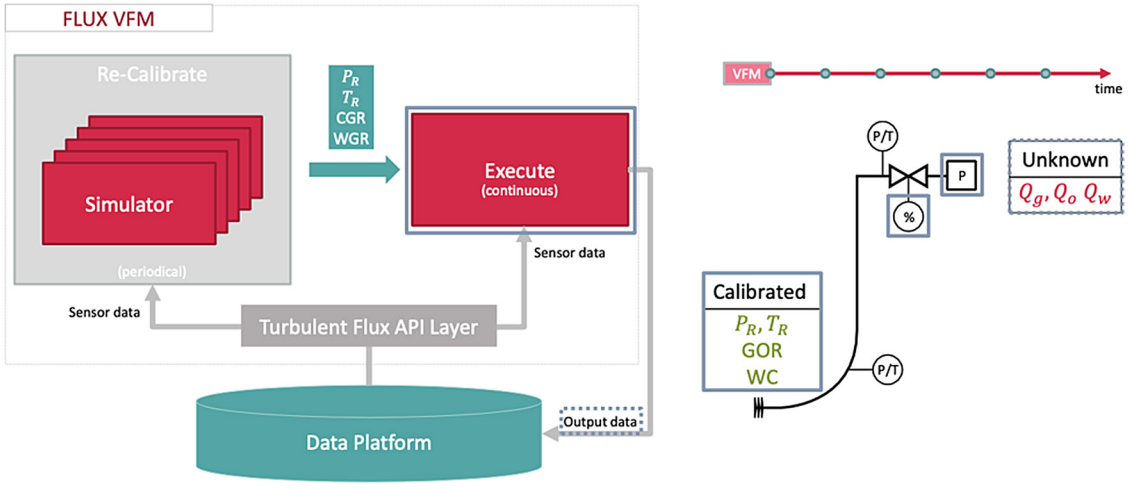


Figure 14: Flux Simulator in autonomous optimization.

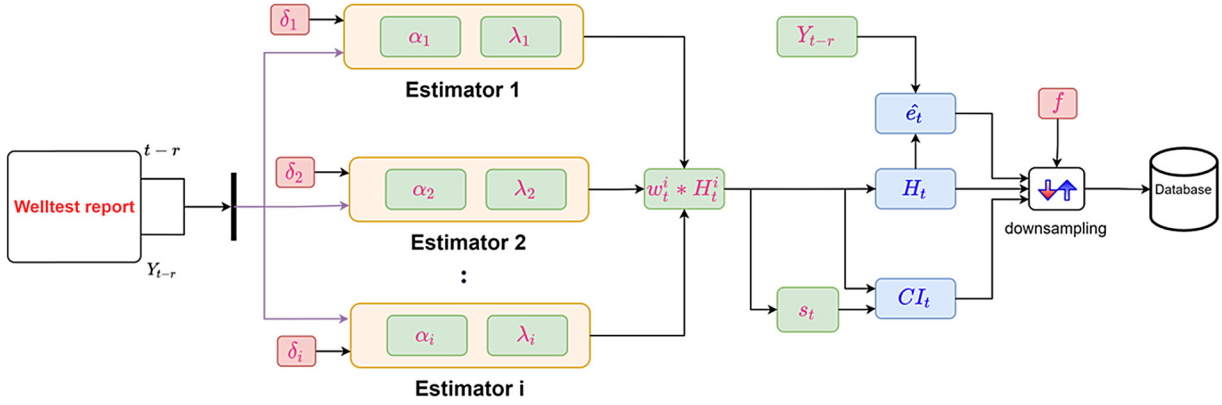


Figure 15: Combiner general workflow.

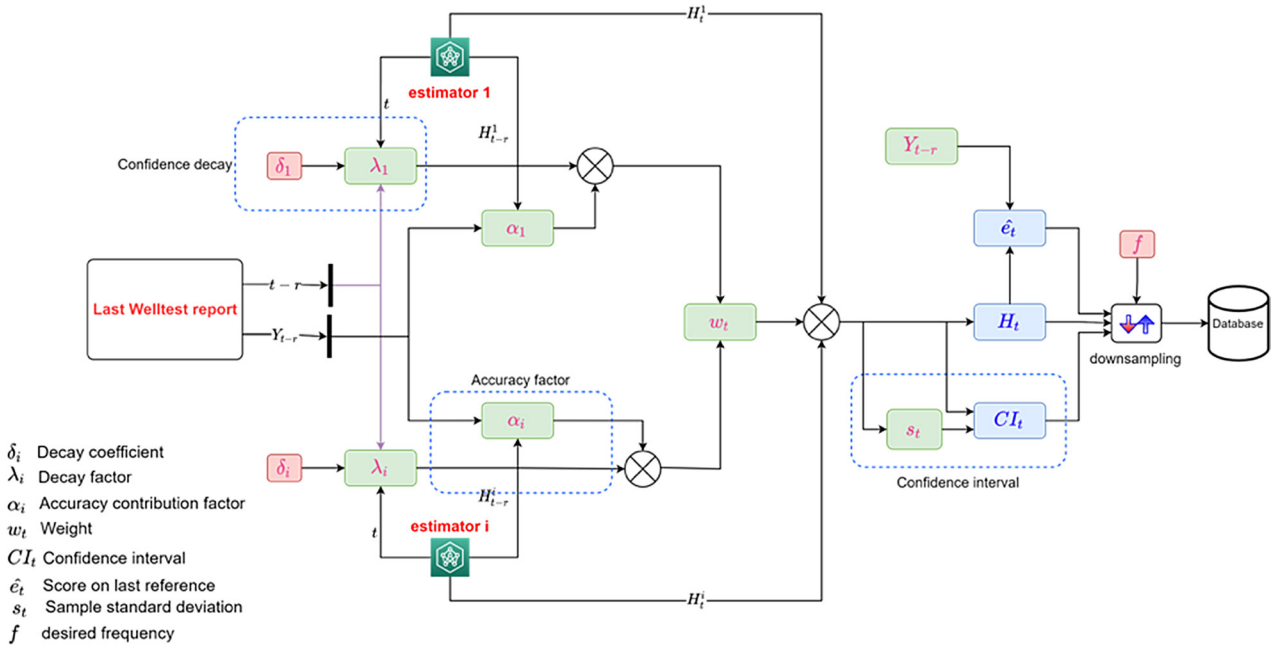


Figure 16: Detailed combiner algorithm.

is defined as the well flowing bottom-hole pressure (Pwf) as a function of production rate. It describes the flow in the reservoir. The *Pwf* is defined in the pressure range between the average reservoir pressure and atmospheric pressure.

Vertical Lift Performance Relationship (VLP) is name also Outflow, describes the bottom-hole pressure as a function of flow rate. The VLP depends on many factors including fluid PVT properties, well depth, tubing size, surface pressure, water cut and GOR. It describes the flow from the bottom-hole of the well to the wellhead. Both the Inflow Performance Relationship and the Vertical Lift Performance Relationship relate the wellbore flowing pressure to the surface production rate. While the IPR represents what the reservoir can deliver to the bottom hole, the VLP represents what the well can deliver to the surface. The intersection of the IPR with the VLP, called the operating point, yields the well deliverability, an expression of what a well will actually produce for a given operating condition as in Figure 12.

Choke Flow Model: the model represent an equipment used to regulate well production rate. Choke valve opening is regulated in such a way the opening is not too small to impede production and not too big causing sand, water accumulating at the well bore. No universal equation exists that can predict pressure drop across the Choke for different wells and fluid properties. Flow-through choke can be Sonic (critical) or Subsonic (subcritical). Sonic flow is the most common type and happens when fluid flow velocity reaches the speed of sound, hence upstream pressure is independent of pressure downstream the choke. Literatures are full of choke flow models that were designed for sonic and subsonic flow. Many empirical choke models are generally represented by the following: $P_{wh} = CR^m Q/S^n$ where P_{wh} is the upstream (wellhead) pressure (psia), Q is gross production rate (bbl/day), R is gas-liquid- ratio (Mcf/bbl), S is the choke size (in 1/64 of inch), C, m and n are empirical constants provided by each choke valve manufacturer.

Enthalpy Model: Application of energy conservation can also be used to predict the fluid temperature and used to correlate the flow rate in the wellbore as a function of depth versus temperature, as shown in Figure 13.

Autonomous calibration

As shown in Figure 14, Flux Simulator uses an optimizer that runs periodically and corrects the system based on measurements from the well. No reference flow rates are required to perform this step.

The combiner algorithm

The combiner is an algorithm that aggregates estimations from different VFM models (be it either

Table 4. Tested combiner VFM.

Well	Output	Hybrid-VFM	Input Estimators
101	Qgas	combiner-all	[full, surface, subsurface, TF]
		combiner-dd	[full, surface, subsurface]
		combiner-full	[full, TF]
		combiner-surface	[surface, TF]
	Qoil	combiner-all	[full, surface, subsurface, TF]
		combiner-dd	[full, surface, subsurface]
		combiner-full	[full, TF]
		combiner-surface	[surface, TF]
	Qwater	combiner-all	[full, surface, TF]
		combiner-dd	[full, surface]
		combiner-full	[full, TF]
		combiner-surface	[surface, TF]
102	Qgas	combiner-all	[full, surface, subsurface, TF]
		combiner-dd	[full, surface, subsurface]
		combiner-full	[full, TF]
		combiner-surface	[surface, TF]
	Qoil	combiner-all	[full, surface, subsurface, TF]
		combiner-dd	[full, surface, subsurface]
		combiner-full	[full, TF]
		combiner-surface	[surface, TF]
	Qwater	combiner-all	[full, surface, subsurface, TF]
		combiner-dd	[full, surface, subsurface]
		combiner-full	[full, TF]
		combiner-surface	[surface, TF]

Table 5. Combiner group description.

Type	Description
combiner-all	Combining the three DD-VFM estimator categories and TF-VFM
combiner-dd	Combining the three DD-VFM estimator categories only
combiner-full	Combining the full-type DD-VFM estimator and TF-VFM
combiner-surface	Combining the surface-type DD-VFM estimator and TF-VFM

data-driven or physics-driven), and finds the optimal flow rate estimates along with an indication of confidence level. The combiner tracks the performance of different models using periodically updated and validated well-tests. The contribution of each model to the final estimate is dependent on its performance compared to historical well-tests, and the confidence decay factor which indicates the model relevance over time and concept drift. The general combiner workflow is shown in Figure 15.

Confidence decay factor λ: is calculated based on the time difference between the last estimator

Evaluation Measure	Equation
Mean Absolute Percent Error	$MAPE = \frac{\sum \left\lvert \frac{Q_{meas} - Q_{calc}}{Q_{meas}} \right\rvert}{n} * 100\%$
Average flow rate deviation	$\overline{\Delta Q} = \frac{1}{n} \sum \lvert Q_{meas} - Q_{calc} \rvert$

Figure 17: Model performance evaluation metrics.

Table 6. MAPE performance summary for data-driven VFM estimators.

		DD-VFM			
Well	Output	Full	Surface	Subsurface	Combiner-dd
101	Qgas	16.6	19.2	16.9	13.9
	Qoil	9.7	10.0	15.7	9.8
102	Qgas	6.0	9.5	10.2	7.7
	Qoil	3.1	2.3	3.8	2.5

Table 7. Flow rate deviation (delta Q) performance summary for data-driven VFM estimators.

		DD-VFM			
Well	Output	Full	Surface	Subsurface	Combiner
101	Qgas	216	248	222	189
	Qoil	242	263	377	248
	Qwater	0.5	0.3	-	0.2
102	Qgas	68	135	106	90
	Qoil	35	25	40	27
	Qwater	12	16	6	10

tuning and the current sample time. Decay coefficient δ is a constant selected based on the estimator behaviors and the well conditions. For example, a physics-driven estimator can have a small δ since it can have a wider operating envelope compared to data-driven estimators which was trained on a small window of the operating envelope. Wells that are rapidly changing should also have a large δ since the estimator's performance tends to degrade rapidly over time due to the changing operating conditions and concept drift.

$$\lambda_i = 1 - |\Delta t|\delta_i : range[0,1]$$

Accuracy contribution factor α_i: for estimator i is calculated from Mean Absolute Percent Error (MAPE) of the estimator and the last known reference point at time $t - r$ where r is the time of last known reference data available. α_i is normalized by the sum of errors of all estimators such that $\sum_{N=1}^{N} \alpha_n = 1$, where N is the number of estimators involved.

$$MAPE_i = \left| \frac{Y_{t-r} - H^i_{t-r}}{Y_{t-r}} \right|$$

$$acc_i = 1 - \frac{MAPE_i}{\sum_{n=1}^{N} MAPE_n}$$

$$\alpha_i = \frac{acc_i}{\sum_{n=1}^{N} acc_n}$$

Confidence Interval (CI): of the combined flow rate is calculated from the pair-wise sample standard deviation s_t.

Table 8. MAPE performance summary for all VFM.

				Hybrid VFM (combiner)		
Well	**Output**	**DD-VFM**	**TF-VFM**	**All**	**Full+TF**	**Surface+TF**
101	Qgas	16.6	9.6	11.8	9.0	8.7
	Qoil	9.7	8.3	8.5	4.7	5.5
102	Qgas	6.0	5.6	4.9	3.6	5.4
	Qoil	3.1	17.5	1.3	1.2	1.3

Table 9. Flow rate deviation (delta Q) performance for all VFM.

				Hybrid VFM (combiner)		
Well	**Output**	**DD-VFM**	**TF-VFM**	**All**	**Full+TF**	**Surface+TF**
101	Qgas	214	155	186	148	146
	Qoil	278	221	220	126	146
	Qwater	0.2	15.4	0.6	0.6	0.7
102	Qgas	83	85	77	54	87
	Qoil	14	152	12.6	12	13
	Qwater	7	53	4	4	5

$$s_t = \sqrt{\sum_{i=1}^{N} \frac{\left(H_t - H_t^i\right)^2}{N-1}}$$

$$CI_t = \hat{H}_t \pm \frac{t^* s_t}{\sqrt{N}}$$

where $\hat{H}_t$ represents the outcome of the combiner and t is the student's t-distribution score which is a parameter based on the confidence level and degrees of freedom. If there are enough samples, the normal distribution can be used instead of t-distribution.

Downsampling by f: the results are passed through a downsampler to produce estimates at the desired frequency f which should be slower than the estimator frequency to introduce a smoothing effect.

Figure 16 shows the detailed block diagram and data flow of the combiner. Only two estimators (1 and i) are shown for simplicity.

The combiner is used to improve the overall performance of the VFM over time, by combining different estimators (data-driven and physics-driven), taking into consideration the weaknesses of these estimators, and performance degradation over time. A total of 24 Hybrid VFMs have been tested in this study. Each of them takes a different set of input estimators as shown in Table 4 with the explanation for each combiner group is described in Table 5.

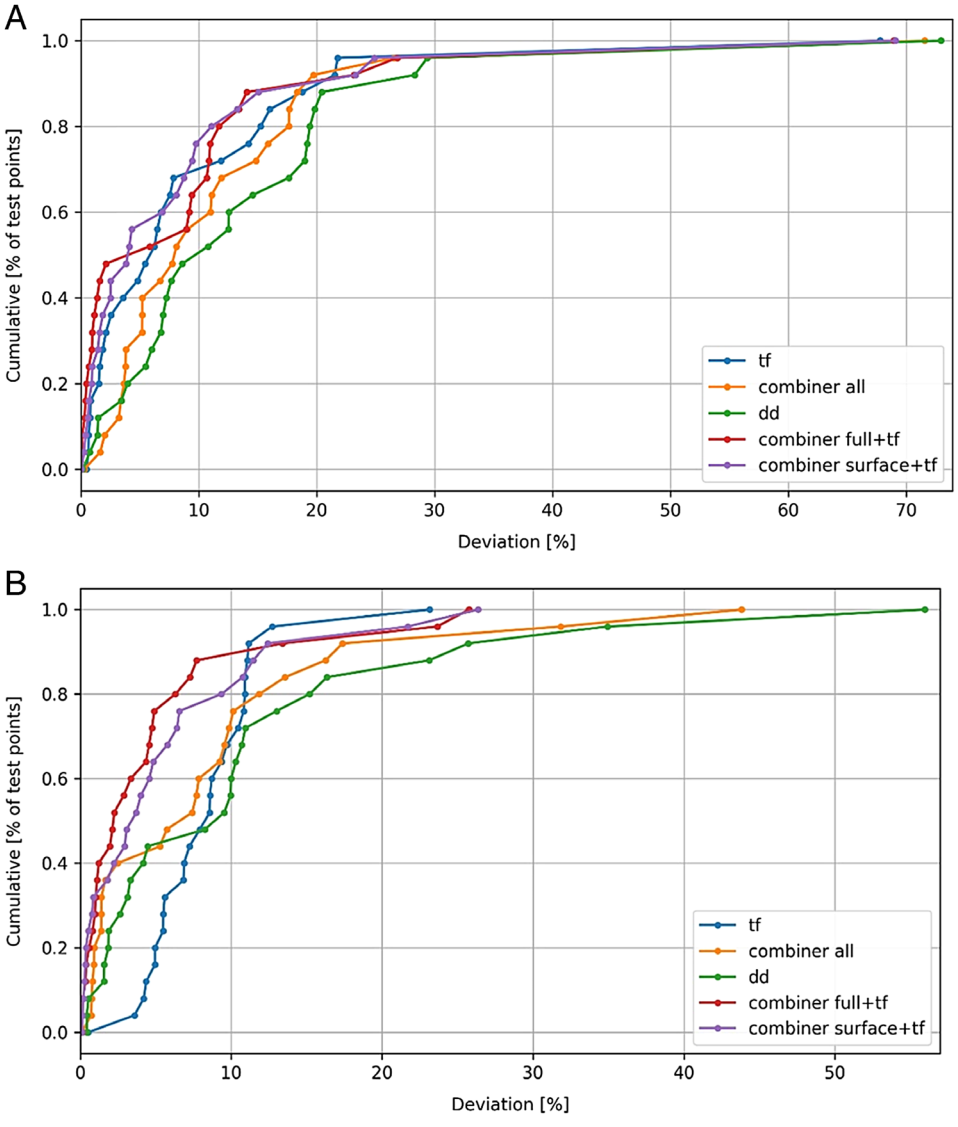


Figure 18: Cumulative deviation for well 101 (a) Qgas and (b) Qoil.

Performance metrics

To evaluate the developed VFMs and confirm they will perform satisfactorily; a set of evaluation metric must be devised. Following the published standards such as API MPMS (PETRONAS, 2015; Mokhtari Jadid, 2017), the metrics listed in Figure 17 are used to evaluate VFM performance. However, the main indicator will be the mean absolute percent error.

In addition to quantitative performance measures, there are also visual quality plots that are recommended by the Norwegian Society for Oil and Gas Measurement (Norwegian Society for Oil and Gas Measurement NFOGM, 2005). The two visual quality plots that will be used here are:

- *Cumulative deviation plot:* which will be used to indicate the percentage of test points that are below specified deviation criteria. The error percentage between actual and VFM estimates is calculated for each test sample. Then, the number of samples with error percentage below a specified deviation percentage (5%, 10%, 15%, etc.) are counted. The counts are then divided by the total number of test samples and plotted against deviation percentage.

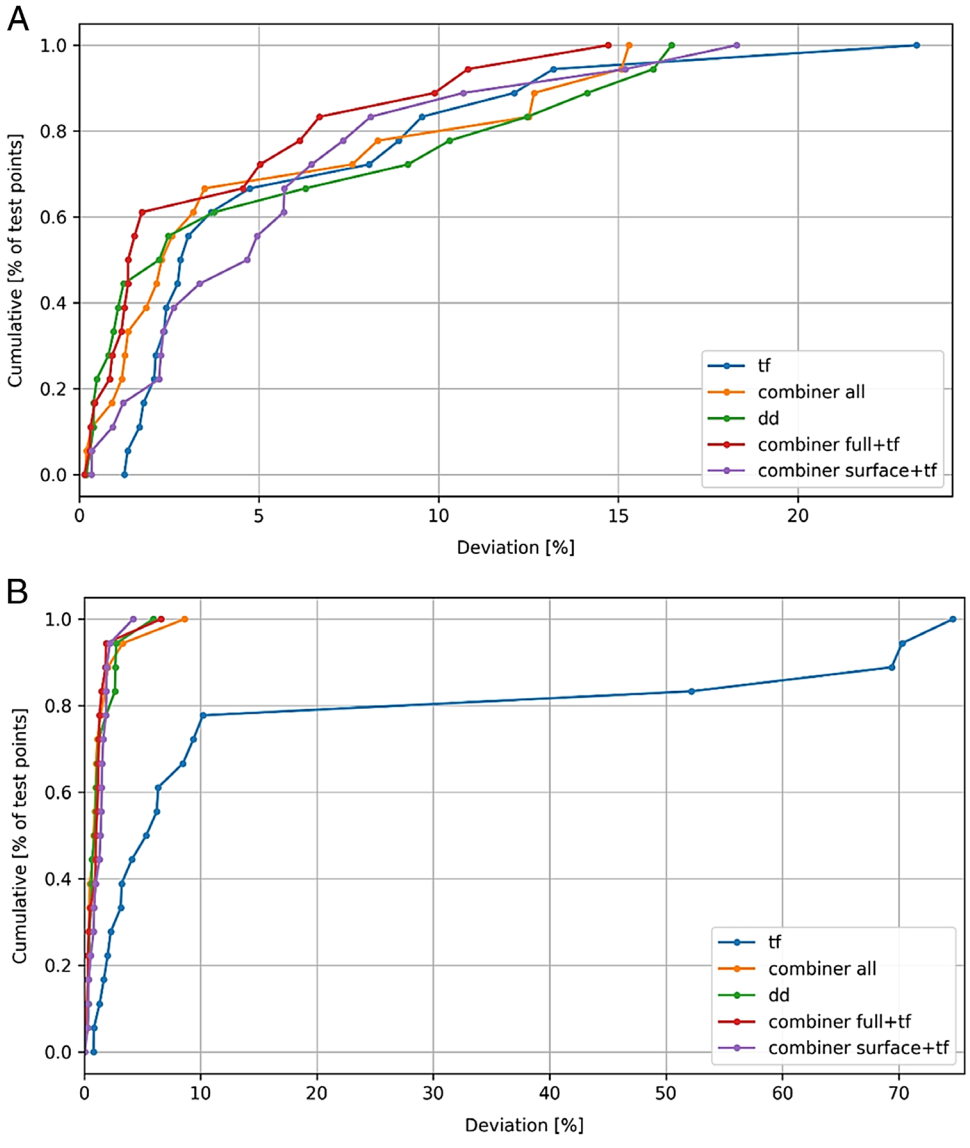


Figure 19: Cumulative deviation for well 102 (a) Qgas and (b) Qoil.

- *Error deviation plot:* which plots all errors as MAPE and draws horizontal lines to indicate the acceptable threshold (e.g., 10% or 20%).

Results

Now the results will be presented. Firstly, the results from the data-driven VFM will be shown, followed by the overall VFM (data-driven, physics-based and VFM combiner).

Data-driven VFM performance

In Tables 6 and 7, the performance of each data-driven VFM without combiner and with combiner are shown. MAPE of Q_{water} is not included since the water flow rate has zero values which would result in undefined MAPE. All models achieved a satisfactory performance. We can observe that data-driven VFM with combiner does not introduce much improvement over the individual estimators. Only when all the individual estimators have high errors will the combiner result have overall lower error than individual estimators.

Overall VFM performance

In this section the overall VFM performance (data-driven VFM, physics-based from Flux Simulator and VFM with combiner) will be presented. In Tables 8 and 9, we can see the MAPE and flow rate deviation performance of each VFM type. DD-VFM is using the full-type estimator in this comparison. The combiner (now called Hydrid VFM) combines all three DD-VFM types (full, surface and subsurface) along with TF-VFM. Full+TF Hybrid-VFM is combining the full-type DD-VFM with TF-VFM. Surface+TF Hybrid-VFM is combining the surface-type DD-VFM with TF-VFM (Table 9).

All models achieved a satisfactory performance i.e., deviation less than 20%. We can observe that,

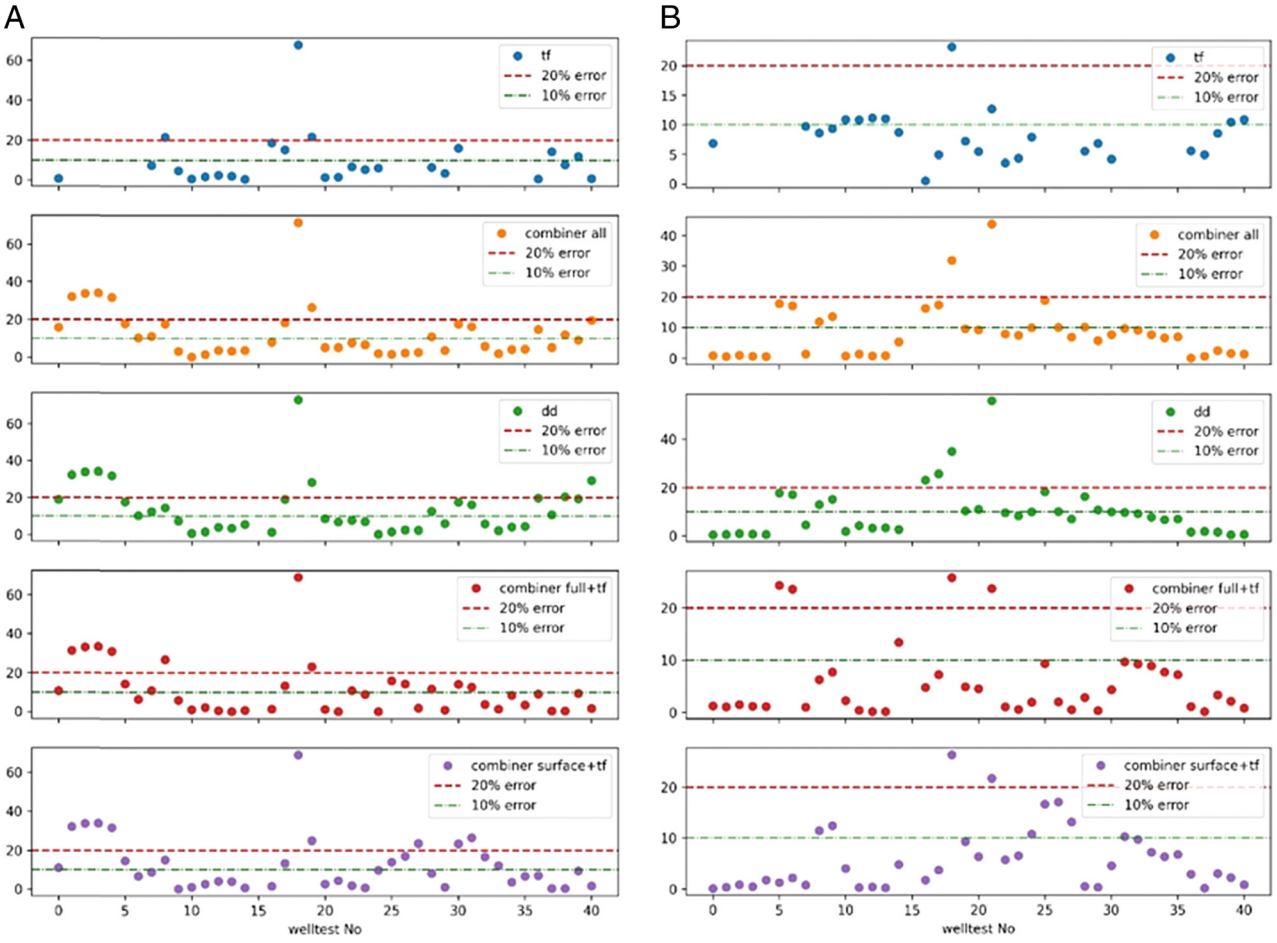


Figure 20: Error bands for well 101 (a) for Qgas (b) for Qoil.

in general, Hybrid-VFMs achieved better results compared to independent VFMs.

Cumulative deviation

Figures 18 and 19 show the cumulative percentage deviation for each VFM for both wells 101 and 102. Q_{water} is not shown here since the water flow rate has zero values and cannot be represented in MAPE. The performance of the best model (combiner) can keep over 90% of the samples within a deviation of 20%. Most of the deviations above 20% are justified and attributed to physical meter abnormalities, well-test abnormalities, or process upsets such as downstream process changes.

Error bands

Figures 20 and 21 show the percent deviation of estimations from the well-test test points. We can observe the following:

1. Performance of individual models is satisfactory,
2. Hybrid models perform better on average throughout the online test period,
3. The error band is mostly below 10% for Q_{oil} and 20% for Q_{gas},
4. Q_{gas} has a higher error due to MPFM's large oscillations in gas readings as confirmed by field engineers.

Flow rate trends

In this section, we show a visual trend of well-test flow rates over the pilot period. We can observe from Figures 22–24 that DD-VFMs try to estimate the confidence interval but the confidence is very poor. TF-VFMs don't provide any confidence indicators. Hybrid-VFMs through the combiner provide both better flow rate estimations and better confidence interval indicator. Notice here that the confidence band increases when the base estimators disagree but otherwise will decrease.

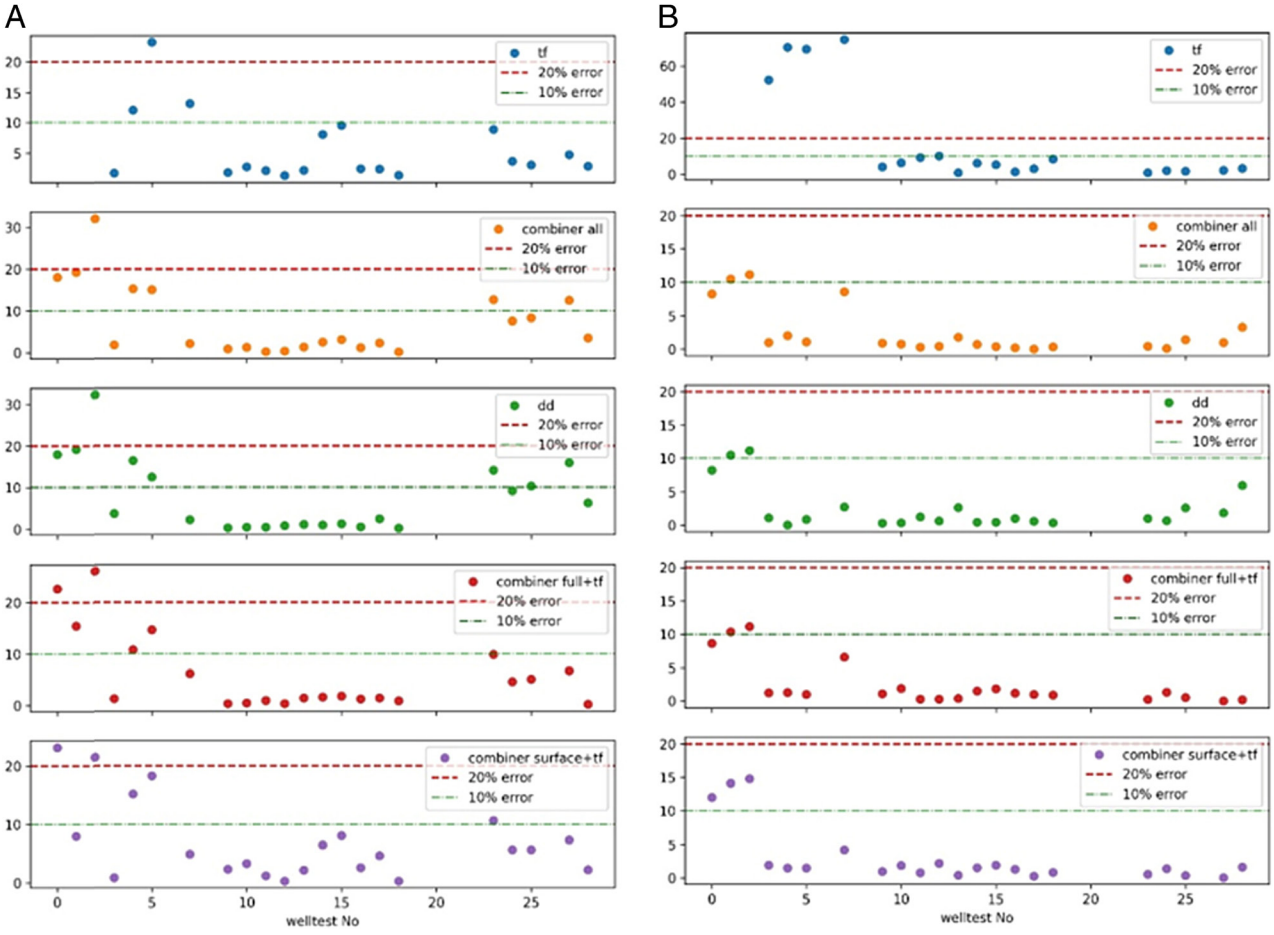


Figure 21: Error bands for well 102 (a) for Qgas, (b) for Qoil.

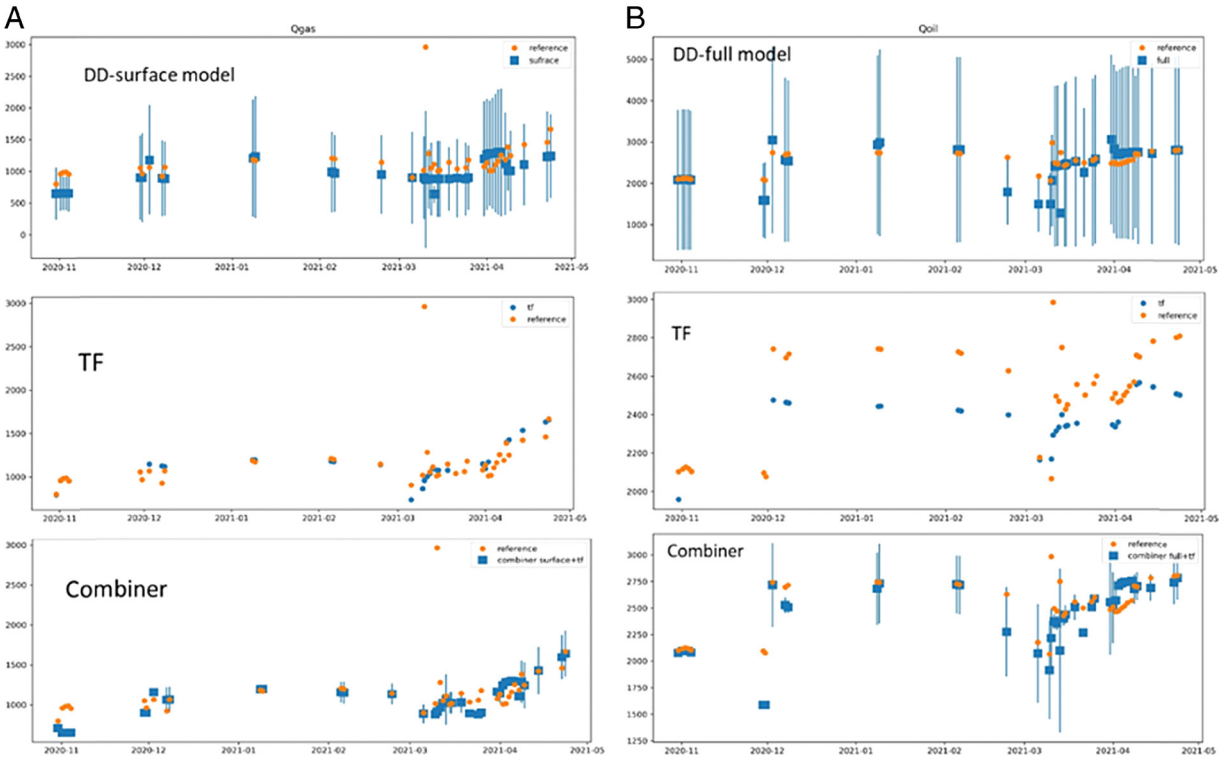


Figure 22: Flow rates with confidence intervals for well 101 (a) for Qgas, (b) for Qoil.

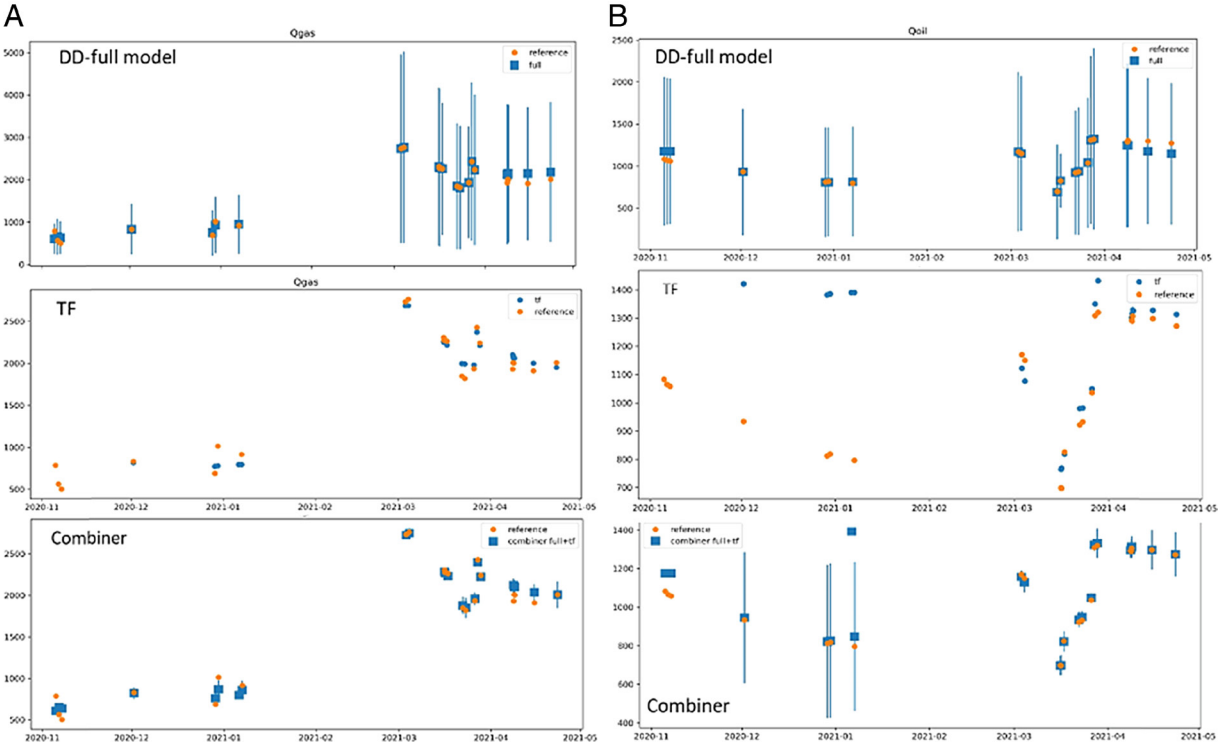


Figure 23: Flow rates with confidence intervals for well 102 (a) for Q_{gas}, (b) for Q_{oil}.

Results observations

In summary the following observations can be made by comparing the standalone VFM versus the combiner (Hybrid VFM):

- Combiner VFM indeed produces good confidence interval indication,
- The more the base models disagree about the estimate, the higher the confidence interval band,
- Combiner VFM varies the weights of base models based on their performance history which results in robust estimates over time,
- Combiner VFM can handle missing values from some base models.

Conclusion

Based on the results presented and the observations made during the six months real-time online pilot, we can conclude that the individual VFM model performance fluctuated over time. By using a combiner technique, as presented in this paper, we could improve the performance by almost 50% as observed throughout the pilot. The MAPE error of the combined VFM was less than 50%. The combined

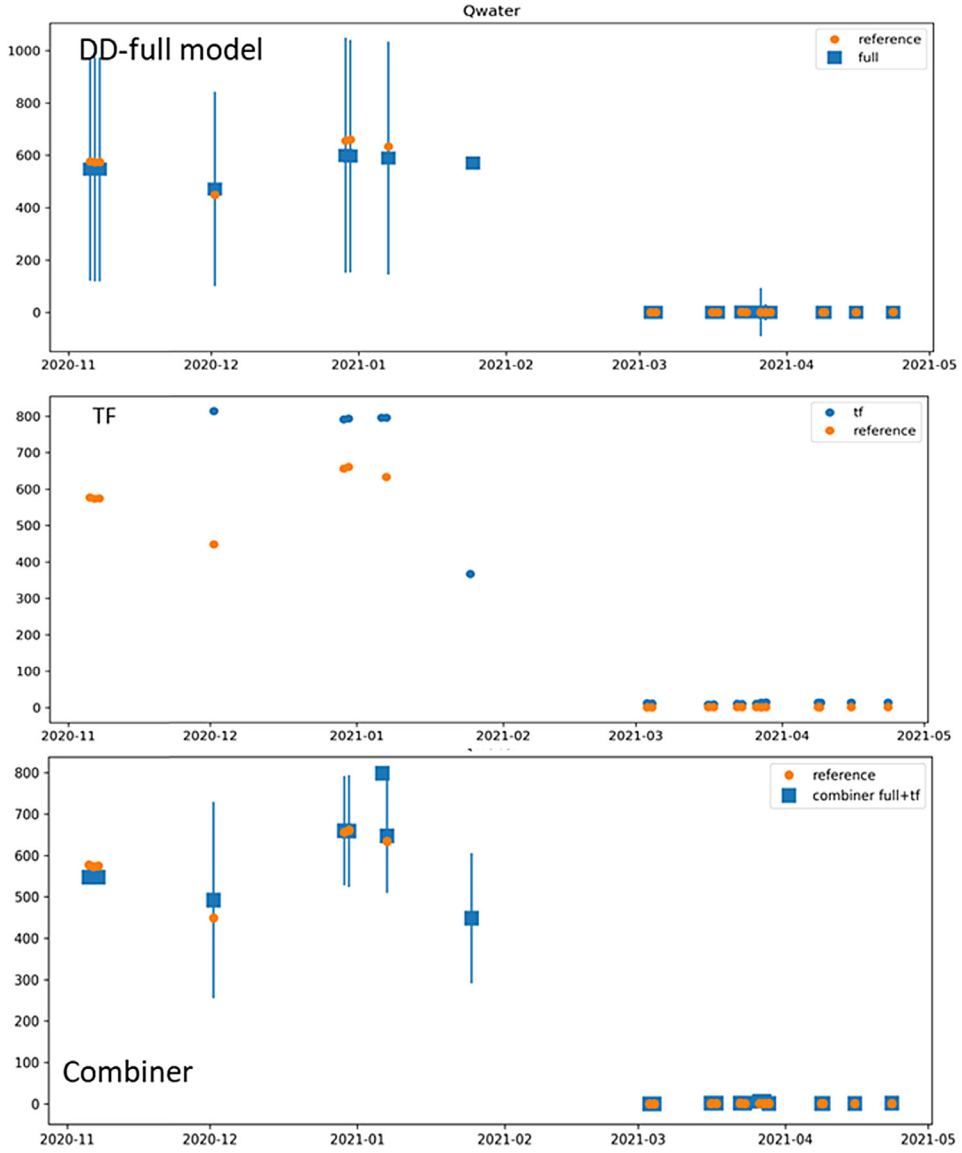


Figure 24: Flow rate with confidence interval for Q_{water} well 102.

Hybrid VFM also actually helped the operator to identify an instrument failure (a differential pressure transmitter) in the physical Multiphase Flow Meter (MPFM). Both the performance and the successful demonstration of identifying the instrument failure clearly demonstrated the effectiveness of the combined VFM developed in this project. VFM therefore was proven to help the operator as a great diagnostic, verification and troubleshooting tool for physical MPFMs as well as an additional real-time production monitoring.

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