

Application and Complexity of AI VFM Well Testing Technology (LAMFlow Tool)-Field Trial

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1 INTRODUCTION

Well-testing is one of the most fundamental processes of oil and gas production procedures. It is used for evaluating reservoir properties and performance, but it can also be challenging. Every day conventional well testing becomes more difficult and challenging for the operation [1].

Start The fluid flow profile from individual wells can change over time, sometimes unpredictably; as the reservoirs become depleted, changes in hydrocarbon properties occur, and water cut begins to increase.[2] Thus, the existing well-testing unit will not be efficient in testing the new composition as it is not designed to measure that profile, so an upgrade will be required for that unit.

Traditional well-testing is also time-consuming and costly, which has led to an increase in the development of Virtual flow meters (VFMs) [3]. VFMs can be categorized into two groups: First Principles (Physics Based) and Machine Learning. This paper covers the application of the Machine Learning Principle named LAMFlow, which is based on Artificial Intelligence (AI) to overcome the fundamental challenges of well-testing.

LAMFlow can be used to produce live well testing minute by minute, which increases well testing availability by more than 95%. It also reduces well-testing operational and maintenance costs by almost eight times on a yearly basis. Compared to LAMFlow, traditional well-testing methods such as test separators are deemed time-consuming and costly. Test separators require a significant amount of time to set up and operate, and they can also be expensive to maintain. LAMFlow, on the other hand, is a software-based solution that does not require any additional hardware or spares.

Overall, the paper presents an innovative approach to well-testing that has the potential to significantly reduce costs and improve efficiency.

2 IMPORTANCE OF WELL TESTING

Surface well testing provides valuable insights into reservoir performance. This data is essential for understanding how the reservoir behaves and for developing optimal production strategies [4]. Also, it allows for the characterization of produced fluids, including their API gravity, gas-to-oil ratio (GOR), and water cut. This data is essential for designing processing facilities and ensuring product quality [5].

Accurate surface well testing can have a significant economic impact by reducing operational costs, optimizing resource extraction, and ensuring efficient production operations [6].

2.1 Current Status of Well-Testing Techniques

As explained earlier every day conventional well testing becomes more difficult and challengeable to the operation. The number of drilled wells increases intensely and scatters geographically which makes it difficult to use a common well testing unit for each group of new wells. In practice, the well's behavior changes through its lifecycle. For example, gas may appear in an oil well with zero 'gas to oil ratio' (GOR) after 10 to 15 years. Thus, the existing well testing unit will not be efficient to test the new composition as it is not designed to measure that gas, so an upgrade will be required for that unit. Moreover, the available technologies for accurate measurement of high water cut and low gross flow wells are limited and rather expensive. On the other hand, well-testing by mean of traditional methods such as Test separators are deemed time-consuming and costly in terms of CAPEX and OPEX.



3 VIRTUAL WELL TESTING AND LAMFLOW

Artificial intelligence (AI) is being used to develop more accurate and reliable virtual flow meters (VFMs) (or in our case Well Testing). AI-powered VFMs can learn from data to improve their accuracy over time. They can also be used to estimate flow rates in more complex and challenging environments.

Virtual Flow Meters (Well Testing) can help on presenting an average property of the whole reservoir as the reservoir responds to the perturbation caused during the test period [4]. As expressed by [3] Most Virtual Meter research work focuses on using either Artificial Intelligence or Physics Principles and tries to automatically determine the values of the individual flow phases, the gross together with water cut (BS&W). BS&W is a measure of the non-hydrocarbon impurities in crude oil, typically consisting of water, sediment, and other solids. BS&W is expressed as a percentage of the total volume of the crude oil. [7]

3.1 LAMFlow Definition

LAMFlow tool is a solution based on artificial intelligence (AI) developed to alleviate such challenges. The LAMFlow is a machine learning application that utilizes well-test backlog history and the live well parameters to predict gross flow, net oil, and water cut of flowing wells in real-time. The tool is capable of correlating the prediction to the inferred values by physics and math to calibrate itself to provide a more accurate prediction during runtime. It is worth mentioning that the AI algorithms are Neural Nets, Ensemble Learning, and Reinforced Learning supported with mathematics models and API, ISO, and GUM standards.

LAMFlow obtains its required dataset from multiple locations with different weighting which is carefully tuned during the mathematical modeling phase. These values are collected in real-time and defined as d(number)x and d(number)y (see Fig 1) as metrics into the formula.

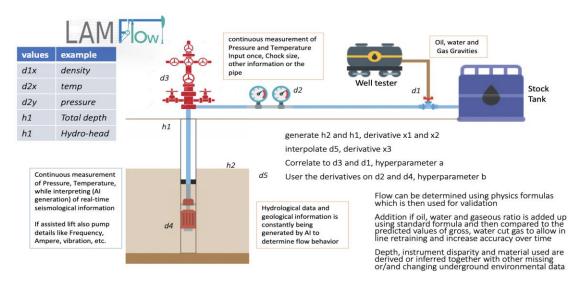


Figure 1. Data flow for LAMFlow system

Thus, LAMFlow is an Artificial Intelligence (AI) product for virtual metering. It reads from various metering hardware via OSISoft PI system where the Artificial Intelligence provides the flow of the 3 phases (initial only 2 phases – water and oil). The main function and observed main benefits of LAMFlow are:

- 8 times of well testing cost per year is reduced.
- Availability of well testing is increased to more than 95%.
- No hardware, no spare parts is required.
- Tested period is open and available, Live result minute by minute.



3.2 Validation Data

Fixed well-testing units test results are required to be validated and accepted. For this purpose a single source was determined to be suitable, the Mobile Well Testing Units (referred here as MWT). The MWT is also considered the gold standard in the well-testing area [8]. Various other sources (like MPFMs) were compared to determine the closeness to the MWT so we could increase the data size, but these were eventually discarded after determining that the accuracy can via off by 20%, and in very complex wells it could go over that [9]. Therefore, initially, we trained the system using 14 wells with each having more than 5 historic MWT. These were eventually expanded to 60 which eventually selected 10 wells that had good historical data to work with.

4 METHODOLOGY

As a novelty running experiments to determine the usability of LAMFlow is required. Thus together as developers and partnering with field experts and industrial users, we have developed a mechanism to test its efficiency. The main testing methodology and data exploration was using field experiments where real-time data collection was done while in parallel running the most accurate well-testing tool available. In this case, Process Instruments (PI) mobile well test equipment was used, and using totaled value of the day (this was round as close as possible to the physical testing hours).

4.1 Validation Criteria

Verification is an essential part of any technology trial. By using the right verification methods, end-users can ensure that products meet their requirements.

The mobile well testing unit (PI) was used as validation for the LAMFlow predictions. Its uncertainty is about 5% for Gross and 1% for water cut. The trial target will be calculated as described in below table 1. The evaluation process was agreed (by the 3rd party involved: developers, field experts, and users) to be with the values shown in Table 1.

Table 1- Evaluation Criteria

Parameter	Trial Target	Paramet	Score		
		Method/Sys	Freq./when?	Pass	Fail
System	100%	observation	At any time of testing		
availability					
Predicted testing	+/-10%	Deviation = (A-	At any time of testing.		
parameters within		B)/ MAX(A,B)			
+/-10%.					
Predict water cut	< +/-2%	Deviation = A-B	At any time of testing		
The tool is	Minimum to	Observation	At any time of testing		
expected to have	zero.				
minimum human					
intervention or					
adjustments.					
Testing period	Online.	observation	At any time.		

The validation process was conducted in two phases using wells with different behaviors. The water cut range and flow target range for the experiments are shown in Tables 2 and 3.



The first phase of the experiment addressed the operational pain point of high BS&W (>94%). The 10 wells were selected to ensure full coverage of the issue, as shown in Table 2.

Table 2. Phase 1 experiment values

Process	Range				
Gross	30 - 800 Sm3/d				
BS&W	94% - 99%				
Net Oil	0.5 - 20 Sm3/d				
Water Flow	20 - 800 Sm3/d				
Gas Flow	0				

The second phase focused on wells with BS&W below 95%, as the findings from phase one showed a high deviation in net oil of more than 20% between LAMFlow prediction and PI reference. Four wells were selected in this phase to verify the findings from phase one.

Table 3. Phase 2 experiment values

Process	Range				
Gross	30 - 133 Sm3/d				
wc	56% - 95%				
Net Oil	3 - 11 Sm3/d				
Water Flow	15 - 79 Sm3/d				
Gas	0				

4.2 Experiment Setup

A three-year, two-phase trial was conducted on multiple wells with varying behaviors. The trial involved collecting and analyzing data, training a model, installing the tool, and results evaluation.

The first phase of the test was to assess the feasibility of using the LAMFlow to test wells with a very high water cut and low gross, which are challenging to test using conventional permanent well testing units.

The second phase of the trial was to assess the full range of water. The system is first trained on a set of well-test data from a separator. The separator is the most accurate measurement of well-test parameters. This data is used to create a well profile for each well. The system is then able to use this profile to generate well-test readings without the need for a separator.

The system is designed to be adaptive and self-learning. If the system detects a major change in a well's behavior, it will request more information through a well test through the separator. This additional data is used to update the well profile and improve the accuracy of the system's predictions.

4.3 Problems and Solutions to External Behavior Affecting LAMFlow Results

LAMFlow is an AI-based system that mimics a mobile well test. Therefore, it should only be compared to a mobile well test. Since two tests can differ from each other, LAMFlow should be given a lenient scope when tested against a type of mobile well test that was not used during training. In this regard, the target values are as follows:

• Oil and Water flow phases are the core testing criteria. They are expected to be 20% plus or minus to the Mobile Test results with up to 10% threshold. In addition, the water cut is about +/-2%.

Furthermore, during this research, it was observed that even the physical Well Test is often considered invalid. This seems to be due to the behavior and effects of the well. Sometimes, the discrepancies are



observed to originate from the mobile well test itself. For these reasons, the expected passing rate is 70% of the tests (dataset) for each of the two phases considered in this study.

Depending on the well behavior the flow in one day could be very different to another day. In this regard, it is imperative to compare the results of LAMFlow to the Mobile Well Test of the same day. Furthermore, a Mobile Well Test can be run across 2 days (the test could run from 14:00 of day one and end at 14:00 of day 2). In these circumstances, the results have to be matched to the day before and the day after. This can be observed when the system is compared to a physical Well Test results as such or can be further confirmed by the data at hand. The important factor is that LAMFlow results should match the Mobile Well Test accurately according to the expected threshold with the same day or plus/minus a day.

The system has a mechanism to adjust itself to the well's behavior changes. However, when the changes are induced externally (change of pump, periodic chemical injection), and their effect is significant to change the flow pattern completely the system will require retraining for the said well. The system will cope with continuous reservoir injection when done at set rate and is reported to LAMFlow. In the later circumstance LAMFlow will have a schedule retrain to fit the pattern. Ultimately, LAMFlow is a system that uses AI and physics and therefore it has to adhere to the law of physics.

5 RESULTS AND OBSERVATION

Two phases of tests were performed on 14 wells over several months to understand and track their performance. Once tracking was confirmed, a one-year evaluation and performance monitoring period was initiated as phase one. Then,2nd phase was conducted as a recommendation from the first phase to further verify the net oil deviation. The results will be presented in two sets:

5.1 Phase 1

The gross prediction from LAMFlow on multiple runs (4 cycles) exhibited the highest level of accuracy when compared to other parameters. Approximately 80% of the dataset for gross fell within a deviation of +/-10% in comparison to the results from mobile well testing. These results are illustrated in Graph 2 below.

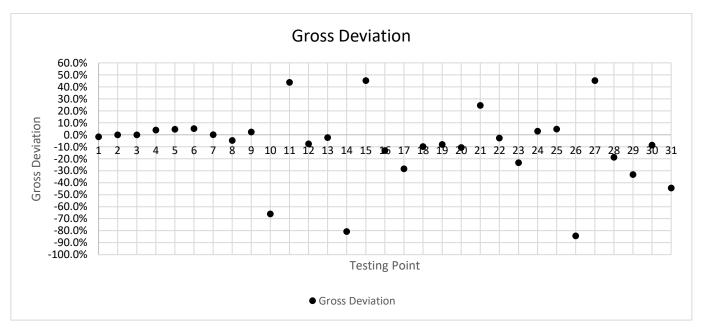


Figure 2. Phase 1: Gross Evaluation

The water cut data (BS&W) showed a high degree of accuracy, with 88% of the data points falling within a deviation of +/-2% of the mobile well testing results, and 72% of the data points falling within a deviation of +/-1%. These results are illustrated in Graph 3 below.



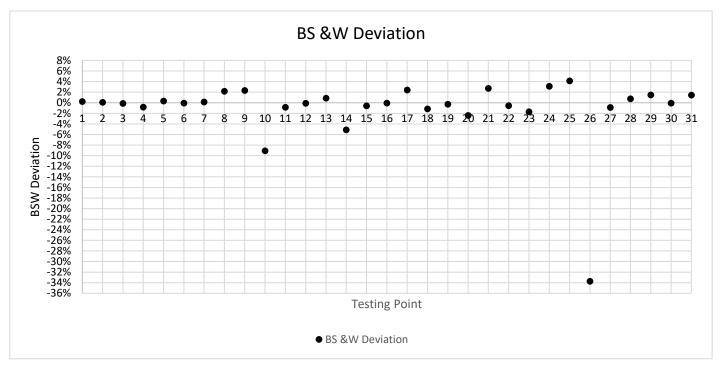


Figure 3. BS&W Evaluation

LAMFlow's net oil predictions deviated significantly from mobile well testing results, with 68% of the dataset falling outside of a +/- 10% margin of error. As a result, the trial was extended to another phase to further verify the net oil prediction using different operating envelopes of water cut. The results are plotted in graph 4 below.

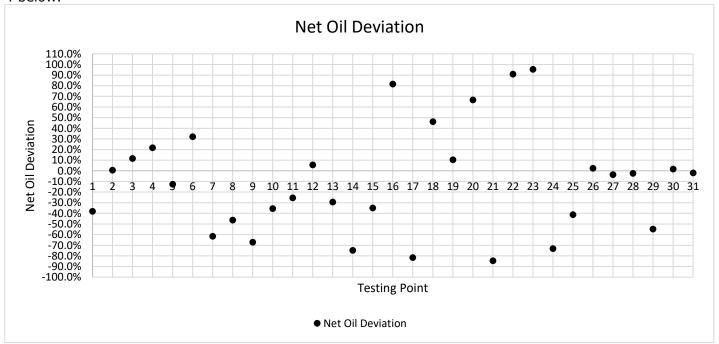


Figure 4. Phase 1: Net Oil Evaluation

5.2 Phase 2

Phase two was conducted in a shorter period and covered the operating envelope tabulated in Table 3. Two cycles of mobile well testing were performed for verification. The results showed that 95% of the gross data was within $\pm 10\%$ deviation of mobile well testing results. This percentage confirms that the tool is learning and improving its prediction accuracy over time. The results are plotted in graph 5 below.



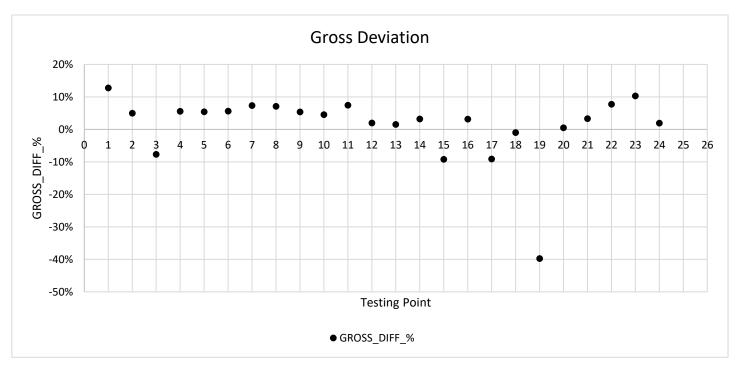


Figure 5. Phase 2: Gross Evaluation

In contrast, around 71% of the water cut data fell within a deviation of \pm 0 of the mobile well testing results. These results are illustrated in Graph 6 below.

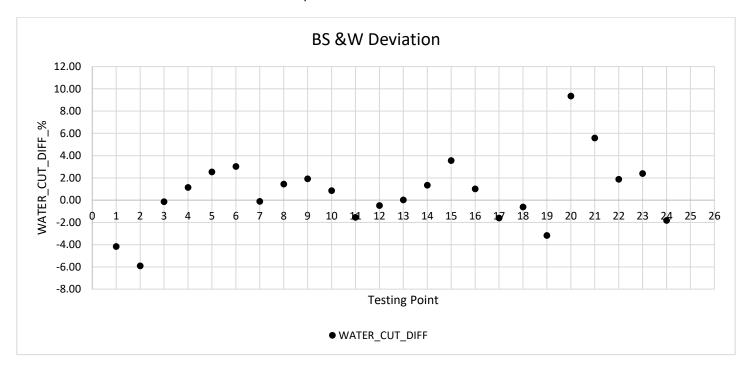


Figure 6. Phase 2: BS&W Evaluation

Net oil predictions were highly consistent with mobile well testing results, with 88% of the dataset falling within a +/- 20% margin of error and 76% falling within a +/- 10% margin of error. The results are presented in the below graph 7.



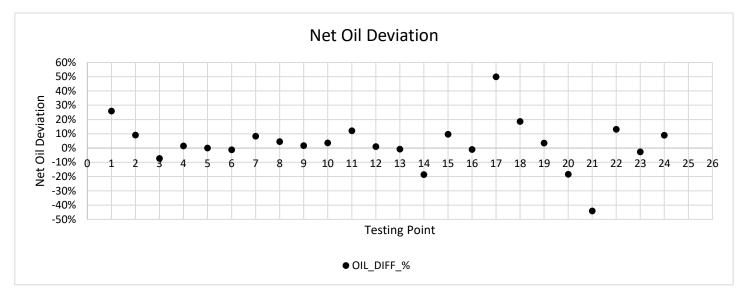


Figure 7. Phase 2: Net Oil Evaluation

5.3 Understanding the deviations

There were *three* reasons observed to cause the deviations during evaluation. The first was due to uncertainty, the *second* due to instrument disruption during well testing hookup, and the *third* due to causes in the production process (there are multiple root causes but all with the same outcome).

In case 1, the uncertainty of extreme values issue, it is mathematically not possible to predict extreme values with accuracy as a very small difference will have a very high impact on the percentage, for example, the difference of 1.6 to 2.8 is around 60%. But in real life, this is only 1 one-barrel difference, and it should not make any difference in real monetary and technical allocation. In this light on this, the following is true in mathematical theory "Uncertainty increases below 20% and above 80%". Therefore. LAMFlow is designed to follow the following rules:

- 1. If the water cut is above 85% then Lamflow predicts the oil readings with high uncertainty and any oil readings recorded with an 85% water cut or above can be highlighted in a different color.
- 2. Whereas if the water cut is 15% or below then Lamflow predicts the water with higher uncertainty and any water readings recorded with a 15% water cut or below can be highlighted in a different color.
- 3. Lamflow works best when the water cut is between the range of 15-85%.

This is a logical problem that has no effect on the actual usable results. It is only observable in the percantage difference but in terms of real outcome, the difference is negligible.

In case 2, the deviation was due to instrumentation disruption during the connection of MWT.



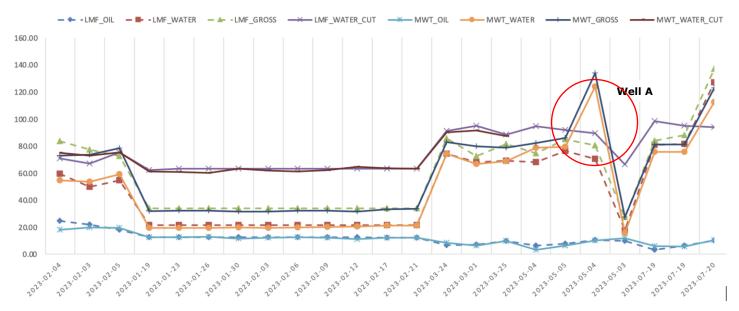


Figure 8. 3 phase comparison of LAMFlow to MWT

Figure 8 shows the the point marked **Well A** having a major drop in the readings indicating there is a change of flow on the 4^{th} . The graph in Figure 9 and the data in Table 4 clearly show that there is a change in the instrumentation. By interpolation, the results of MWT actually match both days before and after the 4^{th} .

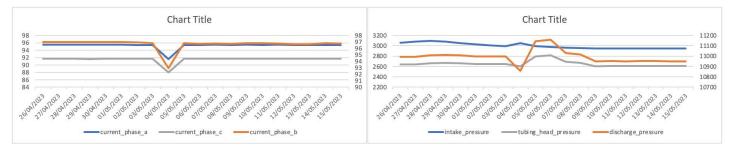


Figure 9. Instrument reading of the deviated well

Table 4. Instrument reading of the deviated well

process_time	intake_pressure	discharge_pressure	intake_temp	tubing_head_pres	current_phase_b	voltage_phas	current_phase_a	current_phase_c	voltage_phas	voltage_phase_b_c
02/05/2023	3008.722222	10996.42361	52.5052083	2645.670749	96.94027778	408.808333	95.45	91.67291667	408.808333	408.8097222
03/05/2023	2992.761134	10997.94332	52.5066397	2647.087924	96.82834008	408.821862	95.40890688	91.65668016	408.821862	408.817004
04/05/2023	3049.159138	10859.28423	52.680959	2600.175189	92.90548992	392.060459	91.60736623	87.96733843	392.060459	392.0618485
05/05/2023	2994.601113	11143.45083	52.5108534	2795.292258	96.82653061	408.843228	95.39517625	91.66512059	408.843228	408.8450835
06/05/2023	2977.158385	11157.59317	52.5017081	2813.402613	96.66925466	408.852484	95.42080745	91.67624224	408.852484	408.8486025

In case 3, it was observed that disruption due to sludge or more complex issues like a gas bubble to well intervention on the day of testing (LAMFlow does not have the capability of identifying the reason with high confidence). In fact, this finding is very good as it will be used as a feature that would be implemented in the future to be able to find well performance and optimization.

6 CONCLUSION

LAMFlow is a system made of microservices and centered on Artificial Intelligence that is supported by Physics. It offers continuous live well testing, available 24/7, directly at the client's desktop. This not only ensures convenience but also enhances safety while conducting well testing, all while remaining cost-



effective. With our system, users can access real-time readings of flow components such as oil, gas, and water, allowing for precise monitoring and analysis. Moreover, the system provides valuable insights into the trends of individual flow components, such as oil, gas, and water, enabling users to make informed decisions. Additionally, the system tracks trends in gas-oil ratio (GOR), gas volume fraction (GVF), and water cut, offering a comprehensive view of well conditions and performance. Users can easily access a summary of flow production data for all their wells, streamlining their monitoring efforts. To facilitate further analysis and reporting, our system allows for seamless well-tested data export to Excel, empowering users with the tools they need for in-depth evaluation and decision-making.

LAMFlow tool results are evaluated with the most accurate reference mobile well testing unit available in PDO. Ten wells are selected based on the operational challenges to be under the testing of LAMFLow. More than 20 points for each assessed parameter are entered in the analysis. It achieved 80% to 90% of tested points within acceptable limits in gross flow, oil flow and water cut testing results. The Enhanced availability is 95% compared to the conventional units which is may available every 2 weeks to 3 months based on oil production level. Moreover, LAMFLow tool provides instantaneous test results minute by minute unlike to test separator which may need at least 8 hours to finalize the results.

7 REFERENCES

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