Oil And Gas Flow Rate Prediction for African Oilfields: An Overview of Existing Models, Data and Uncertainties

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Abstract

An essential task that connects hydrocarbon estimation and operational decision-making especially for oilfields in Africa is the forecast of oil and gas flow rates. The reason for the focus on African oilfields is partly due to the rising concerns of poor metering of oil wells in the continent and partly due to the difficulties oil producers in the region face as a result of the lack of a universal model and scarcity of data. The methods, data sources, and difficulties of estimating oil and gas flow rates in this situation are discussed in this paper. To estimate flow rates based on reservoir features and production factors, numerous prediction models, including empirical, analytical, and numerical techniques, have been developed. To improve prediction accuracy, these models frequently include geological, geophysical, and engineering data. The prediction process, however, is rife with uncertainties brought on by complex geology, heterogeneity in the reservoir, fluid behaviour, and technical restrictions. Improving the accuracy of flow rate projections and the ensuing reservoir management techniques requires addressing these uncertainties. To improve prediction accuracy and decision-making, advanced data analytics, machine learning, and uncertainty quantification methodologies can be integrated. This paper emphasizes the value of high-quality data integration and data collecting to improve model correctness. Additionally, it underlines the significance of including uncertainty in projections and provides guidance on how decision-makers can make informed choices while taking into account probable changes in expected flow rates. Stakeholders in the oil and gas sector may improve production methods, reduce operational risks, and support the sustainable development of energy resources across the African continent by addressing these crucial factors.

Keywords: *Oil flow rates; Predictive Models, Machine learning; Data; Uncertainties*

1. Introduction

Hydrocarbons domiciled on the continent of Africa have long been explored and extracted, and this has had a significant impact on regional economies as well as the global energy environment (Obukohwo *et al*., 2015). Countries like Nigeria, Algeria, Ghana, Angola, South Sudan, Libya etc. all playing host to giant oil reserves had long been exploited and continues to be exploited. These African oilfields are becoming major contributors to the world supply of energy as energy demand continues to rise (Amaechi *et al*., 2019). An essential component of effective hydrocarbon management, operational planning, and decision-making in these oilfields is the correct prediction of oil and gas flow rates (Zhou, 2017). Predicting these flow rates are particularly difficult because of how dynamically complicated the geology, reservoir characteristics, and how the production parameters interact (Nazari and Alshafloot, 2019). The capacity to accurately estimate the amount of hydrocarbons that can be collected from the subterranean reservoirs is crucial for realizing the economic potential of these oilfields (Marshall and Thomas, 2015). Accurate flow rate forecasts equally help with infrastructure planning, investment selection, and resource exploitation that is sustainable (Nguyen *et al.*, 2022). To ensure the accuracy of projections, however, the complex character of oil and gas reservoirs—influenced by geological formations, fluid behaviour, and reservoir heterogeneity—engenders complications that must be carefully handled.

The cornerstone for computing oil and gas flow rates is a predictive model (Naseri et al., 2017). These models include a wide range of methodologies, from complex numerical simulations to empirically determined equations (Agwu *et al*., 2022). To make their estimates, they combine a variety of data sources, such as geological surveys, geophysical measurements, well logs, and information on previous production (Choubineh et al., 2017). But uncertainty—a significant obstacle—lies inside this complex system. Prediction accuracy can be affected by the inherent uncertainties brought on by inadequate data, geological ambiguity, and poor parameterization (Khan *et al*., 2019; Kalam *et al*., 2019).

African oilfields offer a particularly fascinating environment for predicting flow rate. Accurate flow rate estimation is further complicated by the fact that different places have different levels of access to extensive data (Marfo and Kporxah, 2020). As a result, to fully utilize African oilfields while reducing operating risks, a comprehensive understanding of the models, data integration methodologies, and strategies for controlling uncertainties is crucial.

This work on oil and gas flow rate prediction in African oilfields attempts to sort through the existing empirical and machine learning based models, data sources, and predictive uncertainties. This study aims to offer light on the approaches used to address the difficulties brought about by the lack of a universal model for flow rate prediction, a dearth of data, and the general requirement for accuracy in forecasts. In the end, having a thorough understanding of these concepts is crucial not only for the energy sector but also for resource management and sustainable development on the African continent.

2. Overview of some Oil Producing Regions of the World

In 2021, the majority of the oil worldwide was produced in the Middle East, which accounted for around 31.1% of the global output that year. North America was second followed by the common wealth of independent States (Aizarani, 2021). The petroleum is not distributed evenly around the world. The amount of oil and natural gas a given region produces is not always proportionate to the size of its proven reserves. Example middle east contain approximately 50% of the world's proven reserve, but account only for about 30% of global oil production. The US by contrast lays claim to less than 2% of the world's proven reserves but produces roughly 16 % of the world's oil. The regions of the world considered in this work are: Middle East, North America, North Sea, South America, Sub-Saharan Africa and North Africa.

1. The Middle East: this region includes five of the top ten oil producing countries and is responsible for producing about 27% of world production (Carpenter, 2022). The top

five oil producers in the Middle East are: - Saudi Arabia, Iran, Iraq, Kuwait and UAE others are Qatar and Oman. Some of the giant oil companies operating in the middle East are:- Saudi Aramco, Abudhabi oil Company, National Iranian oil company, Iraq National oil company and Sonatrach oil Company.

2. The North Sea: North Sea oil is a mixture of hydrocarbons, comprising liquid petroleum and natural gas produced from petroleum reservoirs beneath the North Sea. In the petroleum industry the term north sea often include areas such as the Norwegian sea and the area known as west Shetland, the Atlantic frontier or Atlantic margin that is not geographically part of the north sea. From 1960 to 2014, 42 billion barrels of oil equivalent (BOE) had been extracted from the North Sea and there is still a potential of 24 billion BOE left remaining. The countries in the North Sea are Norway, UK, some fields are belonging to Denmark, the Netherland and Germany. It is estimated that the Norwegian sector alone contains 54% of the Seas' oil reserves and 45% of its gas reserves.

3. The North America: the top oil producing countries in the North American region includes USA, Mexico and Canada. USA: has the production rate of 15,3 million bpd, which is the leading producers in the Americas. The North American nation has proven oil reserves of 61,200 million bpd. Some of the major oil companies are the Exxon Mobil, Chevron and Conoco phlips. Its daily consumption of oil was 20.45 million bpd in 2018. Canada: This is the second largest producer with production rate of 5.2 million bpd. Oil sands deposits in the province of Alberta account for more than 95% of the countries reserve. Canada proven reserves 167,800 million barrels around 2018.
4. South America: this region includes countries such as Brazil and Venezuela. In 2021, Brazil was the largest crude oil producing country in Latin America and Caribbean, with an average output of over 2.9 million bpd, Mexico followed with around 1.7 million bpd. (EIA, 2021 and Statista, 2023).
   Venezuela: the country has a producing capacity of 1.5 million bpd and the fifth largest oil producer in Americas.
5. Sub-Saharan Africa: Africa is rich in oil resources, yet most African countries have poor energy access. 9.5% of global crude oil reserves and 8% of gas reserves are in Africa. 12% of global production is from Africa but it only consumes 3.4% of global oil.
   Africa consumes less than 30% of its oil and gas. It exports the rest. Oil resources are concentrated in a relatively small number of countries and sub-regions (North and Western Africa). Nigeria, Algeria, Libya, Angola are the major producers. Other producers are Egypt, Sudan, Equatorial Guinea, Congo Republic, Chad, Gabon, Tunisia and Cameroon. However, in the last decade there has been noticeable changes in the geography of oil and gas in Africa. Several new producers have joined the league of oil producers, notable among these are Sudan, Equatorial Guinea, and Chad (Sahu, 2008). Nigeria is the top producer of crude oil in Africa with crude oil production is 1.36 million bpd. Nigeria is set to grow its hydrocarbon sector with the launch of more than 100 oil and gas projects over the next five years, including 25 upstream projects. The Nigerian Petroleum Development Corporation has pledged to boost production by 250,000 bpd over the next two years; meanwhile, the Nigerian National Petroleum Corporation recently signed a deal with

Shell, ExxonMobil, Total and Eni to develop an offshore oil block that includes the deep-water Bonga Field, unlocking up to $10 billion in new investment and adding 150,000 bpd to domestic output.

2. Method Adopted for the Review

This review was done based on the following criteria:

(i) Articles assessed: Articles for the study were chosen from various sources including Society of Petroleum Engineers (SPE) conference papers, journal articles, oil and gas production manuals, textbooks etc. Particular attention was given to articles that focused on modelling flow rate for oil and gas especially in African oilfields.

(ii) Time frame: The articles chosen for the review had no specific time frame. This was to ensure that most of the materials on the subject were covered.

(iii) Critique: The existing models for oil and gas flow rate estimation were critiqued based on: model replicability, generalizability, model complexity and computational burden, model performance assessment, Input parameter selection and field applicability

2.1 Comparison of Oil flow rate determination methods

Table 1 shows comparative between test separator, MPFM, and predictive models in terms of cost, space occupied, durability, safety, speed, input data, validation, replicability and reliability etc.

Table 1: Comparison of oil flow rate measurement methods

Factors	Test Separator	Multiphase Flow Meter (MPFM)	Predictive Models
Cost	$60,000 - $90,000	$100,000 - 50,0000	Cheap
Space occupied	Occupies large space	Not feasible	No Space
Durability	durable	Rarely	durable
Speed	Very slow	Slow	High speed
Safety	No	Unsafe due to radioactive effect	safe
Operation Time	Long retention time	Consumes time	Very fast
Accuracy	Not precise	Not precise for High GOR	Accurate
Reliability	rarely	Unreliable in high WC	reliable
Input data	No	No	Yes
Validation	No	No	Cross validate
Replicability	No	No	Replicate
Generalization	No	No	Always generalize

In Table 1, a comprehensive comparative among all the methods used for flow rate measurement in oil industries was analyzed. By examining the required factors it should be considered that only Predictive models has no challenges in terms of cost which is one of the most critical factor to be considered in running of oil and gas firm. Other factors such as safety, operation time, accuracy and reliability, any challenges in the aforementioned factors the company must shut down or continue running at a loss. Therefore, predictive models are highly recommended for implementations in oil and gas industries.

2.2 Highlights of previous review articles on oil prediction flow rate modelling

This section highlights previous review studies on oil prediction flow rate modelling. Three major reviews are available in literature. The focus of each review and the major findings of each review work are presented in Table 2. It is clear from the above, that though the reviews were comprehensive, they were focused in one direction i.e. mostly on soft computing techniques whereas techniques such as empirical, theoretical ensemble modeling techniques abound. A review of studies only from one area of the subject would result in conclusion that is applicable only to that area in question. On the contrary, a robust review such as the one discussed in this paper which assesses a wide range of modelling methods would provide a new and useful platform where the model user can make informed choices on which method offers the most advantages. According to Agwu et al. (2021). Of all the review papers where the reviewer identifies studies in particular areas, summarizes their findings and reports a conclusion in a narrative form, while the useful of such review are mainly subjective. This work is not meant to replace the already existing valuable review articles on this subject such as the ones in Table 2. But to provide a complementary assessment with particular focus on critiques of the extant models with the intent to deepen knowledge on the subject. This is what makes this review very unique, from other existing ones in the literature.

Table 2: Previous Review works on oil prediction flow rate in summary form

Author (year)	**Area of the review work covered**
Williams (1994)	The advantages of multiphase methods utilized for multiphase measurement to date
Rastoin et al. (1997)	A review of the performance of three mechanistic models
Oddie and Pearson (2004)	An overview on some technique used for flow rate measurement in two phase flow
Thorn et al. (2013)	The extant measurement approaches and a description of the main technologies currently used by commercial manufacturers
Zhou (2017)	Evaluation of several flow rates model and seven slip models
Buffa and Ballino (2017)	The basic assumptions of two models were reviewed.
Yan et al. (2018)	A review of the soft computing techniques for multiphase flow metering
Zhou et al. (2018)	Evaluated several models and correlation and compared their relative performances and their potential for field applicability
Hansen et al. (2019)	Currents trends and technologies within multi- phase flow measurement
Bikmukhametov and Jaschke (2020a)	First Principles and Machine Learning Virtual flow metering
Meribout et al. (2020)	A critical review on most existing multiphase flow meter technologies
Liu et al. (2020)	A comprehensive evaluation of established correlations for two phase (gas- liquid) flow through venture tube
Agwu et al. (2021)	Collated models on oil and gas flow rate prediction

2.3 Models for flow rate prediction in African Oilfields

Table 3 showcases the available research on predicting oil flow rates using empirical models for African oilfields. Empirical modelling essentially involves developing mathematical relationships based on experimental data to estimate the rate at which oil flows through a system. Here's a summary of the key aspects and findings related to empirical modelling of oil flow rate for African oilfields:

Table 3: Summary of research on oil flow rate prediction using empirical models

Authors	Method	Data size	Input parameters & Correlation
Ghareeb and Shedid (2007)	Least squares method	1750 data points from 352 producing wells	$Q = \frac{9.2 * 10^{-4} T_{th}^{3.27} H^{1.2} A^{0.81} GOR^{0.041}}{T_{bh}^{1.2} WC^{0.046}}$ Inputs: Wellhead temperature, bottom hole temperature, tubing cross-sectional area, producing gas/oil ratio, water cut Where Q = flow rate (STB/D); T_{th} = = wellhead temperature(◦F); T_{bh} = bottom hole temperature (◦F); A = tubing cross sectional area; WC = water cut (%); GOR = gas oil ratio (SCF/STB); H = well producing depth (ft)
Ganat and Hrairi (2018)	Non-linear regression	96 data points	$Q_0 = 0.002236(WHP_a - WHP_b)^{0.976949} WHT^{1.013912} t^{-0.97168} GOR^{0.634736} (100 - WC) Pb^{0.11189}$ Inputs: Wellhead temperature, bubble point pressure (pb), producing gas-oil ratio, WHP, overall shut in time (t), and water cut Where: Qo = oil flow rate (STB/D); WHP = wellhead pressure (psi); WHT = wellhead temperature (◦F); GOR = gas oil ratio (SCF/STB); WC = water cut (%)

Artificial Intelligence (AI) has gained significant attention in the oil and gas industry, including in African oilfields, for its potential to enhance decision-making, optimize operations, and improve production efficiency. Table 4 showcases AI-based flow rate models developed for oilfields in Africa. The table shows the method used, the data size and the input parameters as well as the gaps in each study.

Table 4: Flow rate models based on Artificial Intelligence

Authors	**Method/ architecture**	**Data size & country**	**Input**	**Gaps**
Elhaj et al. (2015)	ANN Fuzzy logic SVM Functional Network Decision Tree	162 data points [Sudan]	Choke size (1/64 in.), Upstream tubing pressure (psi), downstream tubing pressure (psi), upstream tubing temperature (◦F), gas gravity	No explicit models developed
Okon and Appah (2016)	ANN [3–6 – 5–1 - 1] [5–6 – 6–1 - 1]	64 data points, [Nigeria]	Flowing wellhead pressure (psi), choke size (1/64 in.), gas-liquid ratio (SCF/STB), flowing temperature (◦F) and basic sediments and water (BS&W)	No test for generalizability
Marfo and Kporxah (2020)	ANN [4–2 – 1]	1600 data sets [Ghana]	Gas production rate (Q_g)(MMSCF/D), tubing head pressure (THP)(psi), flowing bottom-hole pressure (FBHP)(psi), production time (t) $Q_o = 766.65 - 0.32t + 738.82Q_g - 0.67THP + 0.33FBHP$	No sensitivity analysis

2.4 Critique of the flow rate models

(a) Empirical models

Empirical correlations are limited in range of data used in their development stage. This means that empirical correlations may yield acceptable result only in similar circumstances (Mirzaei and Salavati, 2012).

(i) Model flexibility: This is defined as the amount of influence data features has on the behaviour of a model (Johnson, 2017). The critique against the usefulness of Gilbert type models is linked to the element causing inflexibility in the models. One of the causes of inflexibility of Gilbert model is the fixed analytic form. It is fair to say that in most of the contributions by the researcher in developing Gilberts Model, the emphasis has been on the modification of gilbert model rather than charting new course. There is little difference between the models in terms of the novelty of their contributions.

(ii) Model results replicability: the determination of the explicit form of a regression equation is the ultimate objective of regression analysis. Obtaining the estimates of the model's parameters involves in iterative process without the numerical coefficients of these parameter and or the associated constants, the model would limit its usefulness.

(b) Artificial Intelligence Models

(i) Model Replicability: This is the ability to reproduce the results of a scientific model & it enables the independent validation of the results of a research (Dou et al., 2018). The necessary details for ANN model replicability, i.e. the weights and biases of the network which can be used for reproducing the results of the models were not presented by most of the researchers. Only a few included these details in their work.

(ii) Model Generalizability: This refers to the consistency in which a model predicts when unseen data is supplied to it (Kronberger, 2010). most researchers failed to subject their models to unseen data.

(iii) Model Complexity and computational burden: Though several ANN architectures have been proposed by diverse authors in the literature for predicting oil and gas flow rates, however, to the best of the authors' knowledge, there is no mention of the computational burden of these architectures by any of them; hence the computational cost of the ANNs are missing points in the literature.

(iv) Sensitivity analysis: Most of the reviewed articles did not perform sensitivity analysis on the input variables they used. Therefore there is no clarity in the choosing the best combination of parameters as inputs for the models

3.1 Data Sources for oil flow rate estimation

Instrumentation: Flow rate data is typically collected using flow meters and sensors installed in oil and gas production facilities, pipelines, and wellheads. These instruments directly measure flow rates and provide real-time data.
SCADA Systems: Supervisory Control and Data Acquisition (SCADA) systems are commonly used in the oil and gas industry to monitor and control various processes. They can capture and store flow rate data.
Production Reports: Oil and gas companies maintain production reports that include flow rate measurements at different stages of the production process.
Historical Data: Long-term historical data from previous operations can be valuable for modeling purposes. This data may include flow rates, pressure differentials, fluid properties, and other relevant parameters.
Research and Publications: Academic studies, research papers, and industry publications can provide valuable insights and data on flow rate modeling in specific regions or for specific types of reservoirs.

3.2 Uncertainties in oil and gas flow rate data

Measurement Errors: Flow rate measurements can have inherent inaccuracies due to instrument limitations, calibration issues, or maintenance problems.
Sampling Frequency: The frequency at which flow rate data is sampled can impact accuracy. Insufficient sampling can lead to missed transient flow events or fail to capture short-term flow rate variations.

Fluid Composition: Accurate flow rate modeling requires knowledge of the fluid composition, including gas-to-oil ratios, water cut, and other relevant parameters. Uncertainties in fluid composition can affect flow rate predictions.
Reservoir Complexity: Predicting flow rates accurately relies on understanding the complex behaviour of oil and gas reservoirs. Variations in reservoir characteristics, such as permeability, porosity, and heterogeneity, can introduce uncertainties in modelling.

3.3 Availability of oil and gas flow rate data for African Oilfields

Accessibility: Within the oilfield sector, data on flow rates may be easily available, particularly for operations that are still in progress. The availability of historical data from abandoned or decommissioned facilities, however, may be restricted or difficult to obtain.

Data Sharing: Collaboration and data-sharing agreements among industry stakeholders can enhance the availability of flow rate data. However, sensitive or proprietary information may restrict data sharing.
Data Management: The accessibility and utility of flow rate data can be facilitated by effective data management techniques, such as appropriate storage, documentation, and archiving. For oil and gas flow rate modeling, interacting with subject matter experts, consulting industry databases, and working with pertinent stakeholders can assist reduce risks and enhance the availability of data.

3.4 Oil flow rate data validation

Validating data for oil flow rate from oil wells is crucial to ensure the accuracy and reliability of the information. Here are some common approaches to validate such data:

i. *Calibration*: Regular calibration of flow meters and sensors used for measuring oil flow rates is essential. Calibration involves comparing the instrument readings against a known reference standard to identify and correct any measurement errors or inaccuracies. Calibration should be performed by qualified technicians following recognized industry standards.
ii. *Field Testing*: Conducting field tests can help validate oil flow rate data. This involves physically measuring the flow rate using alternative methods, such as test separators or portable flow meters, and comparing the results with the readings from the installed instrumentation. Field tests can be performed periodically or during specific operations, such as well testing or production optimization studies.
iii. *Cross-Verification*: Cross-verifying flow rate data with other production parameters can provide additional validation. For example, comparing the oil flow rate with water cut (percentage of water in the produced fluid) can help identify any inconsistencies or anomalies. Additionally, cross-checking with other well performance indicators like pressure differentials or gas-oil ratios can provide further validation.
iv. *Data Reconciliation*: Data reconciliation techniques can be employed to validate oil flow rate data by ensuring mass balance across the production system. This involves comparing the measured flow rates at different stages of the production process, including wellhead, separators, and tanks, and reconciling the differences. Any significant discrepancies indicate the need for further investigation or adjustment.
v. *Historical Analysis*: Analyzing historical production data can help identify trends, patterns, and outliers in oil flow rate measurements. Comparing the data from different

time periods, similar wells, or neighbouring fields can provide insights into the accuracy and consistency of the flow rate measurements. Any unusual or unexpected behaviour can be investigated to validate the data.

4. Findings from the Review

i. The industry generates data for oil flow rate modeling from well tests, production history, sensors, flow meters, and surveillance technologies.

ii. Sparse models and data exist for oil flow rate for African oilfields

iii. Uncertainties in data cannot be eliminated entirely, but they can be mitigated through rigorous measurement practices, calibration standards, and advanced analytical techniques. By embracing uncertainty quantification as an integral part of flow rate modeling, engineers can make informed decisions, manage risks effectively, and optimize production outcomes.

iv. The future of data-driven flow rate modeling lies in embracing innovative approaches such as machine learning, artificial intelligence, and advanced data analytics. These techniques can unlock valuable insights from vast and complex datasets, empowering engineers and analysts to extract meaningful patterns, optimize operations, and forecast production performance more accurately.

v. Finally, the challenges associated with data for oil and gas flow rate modeling are substantial, but they are not insurmountable. By addressing the sources, uncertainties, and availability of data, the industry can elevate its modeling capabilities, improve operational efficiency, and optimize production outcomes.

5. Conclusion

Accurate oil and gas flow rate forecast for African oilfields is a critical step towards efficient operations, responsible resource management, and well-informed decision-making in the continent's energy sector. The importance of customized prediction models is highlighted by the complexity of African oilfields, which results from geological diversity, varied reservoir characteristics, and frequently difficult logistical circumstances. The combination of artificial intelligence and data-driven approaches offers a viable route forward as technology develops. These models may extract complex correlations between numerous factors by utilizing machine learning algorithms and data analytics, which finally results in accurate flow rate calculations. Although AI models have great potential, they must be developed using extensive, specialized datasets that take into account the specifics of African oilfields.

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