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Multiphase Measurement, Soft Sensors, Digital Twins: A Systematic Literature Review

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Abstract. Accurate multiphase flow measurement (MPFM) is essential in the oil and gas industry to optimize production, manage reservoirs, and ensure operational safety. Conventional MPFMs, such as Venturi, Coriolis, and positive displacement meters, remain costly and often unreliable under complex flow conditions, limiting their widespread application. In recent years, artificial intelligence (AI), soft sensors, and digital twins have emerged as promising alternatives to improve accuracy, reduce costs, and enable real-time monitoring. This paper presents a systematic review of multiphase measurement technologies, soft sensors, and digital twin applications in hydrocarbon production. Following a structured protocol, we analyze 150 publications from the past decade, addressing three research questions: (i) the current state, challenges, and limitations of MPFM technologies; (ii) the role of soft sensors and data-driven modeling, including statistical methods, machine learning algorithms, and hybrid physics-guided approaches; and (iii) methodological and industrial applications of digital twins in oil and gas operations. The review shows that while traditional MPFMs have reached technological maturity, their costs and operational constraints remain significant barriers. Soft sensors and AI-based methods offer high predictive capacity, although the challenges of interpretability and data quality persist. Digital twins demonstrate potential for integration of real-time monitoring and predictive analytics, but require clearer frameworks distinguishing theoretical models from industrial practice. In general, the findings highlight opportunities to advance multiphase measurement through the integration of AI, soft computing, and digital twin paradigms, and outline directions for future research in this field.

Keywords: Digital twin; machine learning; multiphase flow measurement, data-driven models, soft computing techniques, soft sensors.

1 Introduction

The simultaneous flow of materials in two or more different phases is referred to as multiphase flow [Baker, 2000; Yan *et al.*, 2018]. In some industrial processes, accurate multiphase flow measurement is highly desirable for flow quantification, operation monitoring, process optimization, and product quality control [Yan *et al.*, 2018]. The fluid properties of a multiphase mixture cannot be determined by simply combining the properties of the individual components. It must be taken into account that mass transfer occurs between the phases of a multiphase mixture [Bahrami *et al.*, 2019; Sun *et al.*, 2017]. Meters have been developed to determine the flow of the different phases without separating them, which are called multiphase flow meters (MPFM) [Bahrami *et al.*, 2019; Falcone *et al.*, 2009].

One of the most important applications of MPFMs is the determination of the quantities of oil, gas, and water produced from an oil well. If an MPFM is not used, making this determination requires separation of the three phases and subsequent measurement of each phase with a suitable flow meter. Although the oil treatment process requires the removal of water and gas coming in the production stream, many times this process is performed in facilities that receive production from different wells, so this process separation does not allow individualizing (allocating) the production of oil, water and gas from each well. Thus, production allocation is done with one of two methods: the temporary installation of a separator at the wellhead (test separator), the assumption that the productions of the three streams remain constant until the next test, and the use of a permanent MPFM. An appropriate combination of techniques must be used to determine the flow rates of oil, water and gas, as one technique alone is not sufficient to determine the flow rates of the three streams [Bahrami *et al.*, 2019; Busaidi and Bhaskaran, 2003].

In order to improve production strategy, monitor reservoir performance and improve economic recovery of oil and gas reservoirs, it is crucial to accurately quantify the flow of each fluid in multiphase flow. Achieving this determination using an MPFM is a technological challenge due to the complexity of multiphase systems and the challenge of accurately distinguishing and quantifying each phase. Various technologies exist to calculate the flow of the rate phase, including orifice plates, Venturi meters [dos Santos *et al.*, 2023], turbine-type meters, rotary meters, Coriolis meters [Ganat, 2024], gamma density meters [Álvarez Pacheco *et al.*, 2024], and ultrasonic meters [Suryana and Yudono, 2023]. Although technologies have reached a stage of maturity and there are ideal methods, flow measurement technologies continue to be the subject of study and development in constant evolution. For their part, MPFMs can be classified into direct and indirect measurements based on the measurement characteristics implemented. Direct measurement of a phase flow is often performed using a Venturi flowmeter, Coriolis flowmeter, and cross-correlation techniques, among others; while a phase fraction is usually determined from radiation absorption, electrical impedance and microwave techniques, etc. [Albion *et al.*, 2011].

An indirect measurement method determines the individual phases through the analysis of time-varying signals acquired from a set of sensors. In general, the relationship between the sensor outputs and the flow rate or fraction of each phase cannot be deduced theoretically. With the increasing development of artificial intelligence, machine learning and soft computing techniques, the capabilities of empirical models can be extended [Yan *et al.*, 2018].

In terms of MPFM approaches, there are currently four main measurement techniques: flow pattern detection [Ganat *et al.*, 2023; Liang *et al.*, 2021; Wu *et al.*, 2022; Brauner and Ullmann, 2023; Zhang *et al.*, 2023] visual flow representation [Kumara *et al.*, 2010; Santos *et al.*, 2019; Zhou and Niu, 2020; Wu *et al.*, 2023], retention assessment [Bhosale *et al.*, 2023; Kareem *et al.*, 2023; Porter *et al.*, 2023], and flow measurement [Kim *et al.*, 2015; Chang *et al.*, 2023; Song *et al.*, 2024]. The latter technique is designed to directly measure multiphase flow.

Recent advances in artificial intelligence (AI), data-driven modeling, and soft computing techniques have introduced promising alternatives. Virtual sensors (or soft sensors) aim to estimate flow variables such as phase fractions and flow rates using easily measurable process parameters, reducing costs and enabling real-time monitoring. Similarly, the emerging paradigm of digital twins integrates physical models, sensor data, and AI algorithms to provide dynamic, virtual representations of assets and processes in oil and gas operations [Rasheed *et al.*, 2020]. These approaches offer the potential to address some of the key shortcomings of conventional MPFMs, particularly in terms of adaptability, predictive capability, and cost efficiency.

Although reviews exist on multiphase flow metering technologies [Yan *et al.*, 2018; Bikmukhametov and Jäschke, 2020; Ali, 2025], few works have systematically examined the intersection between MPFMs, soft sensors, and digital twins, particularly with a focus on AI-based approaches. To the best of our knowledge, no consolidated review has addressed how classical statistical methods, machine learning algorithms, and hybrid physics-guided approaches are being applied to multiphase measurement challenges. Moreover, the application of digital twins to the hydrocarbon sector remains fragmented, with limited analyses of methodological proposals versus industrial implementations.

This article addresses these gaps by conducting a systematic literature review guided by three research questions.

This article is organized as follows: section 2, presents the review methodology, including the search strategy, inclusion/exclusion criteria, and the selection process. Section 3 presents the background to understand the problem. Section 4 presents traditional multiphase measurement technologies and their limitations. Section 5 discusses soft sensors and data-driven approaches. Section 6 analyzes digital twins, distinguishing between methodological proposals and industrial applications. In this section, the implications for the research questions are synthesized, and Section 7 concludes with identified trends and future research directions.

2 Review Methodology

The present work focused on the review of MPFM technologies and on the application of soft sensors and digital twins in multiphase measurement. For the development of the systematic review of the literature, a clearly defined protocol was followed and follows a methodology that proposes a fixed sequence of steps. The schema applied for the systematic review of the literature is summarized in **Figure 1**.

Considering the objective of the review and in order to detect opportunities to implement new ways of working that could be used for the creation of digital twins of multiphase flow measurement. Therefore, it is very important to understand what methods have been applied and for what type of measurement. Based on this information, the following questions were raised:

- **RQ1**. What soft computing techniques have been applied for multiphase flow measurement processes in the oil and gas industry?

- **RQ2.** How to use soft sensors for multiphase measurement data management?

- **RQ3.** What methodologies have been proposed for the creation of digital twins for multiphase flow measurement?

To address the questions asked, search keywords were determined to identify studies that answer the research questions. Some of the keywords were: multiphase flow meter, digital twin, machine learning oil and gas, multiphase three phases, data-driven models, and soft sensors.

For the development of the search for research published in recognized journals, conference proceedings, systematic literature review articles, theses, academic databases, and journals related to the topic were consulted. For journals, it was necessary to limit the search, due to the specificity of the topic and in order to take the most significant works for the study; for this reason, analysis of topics and trends was used, taking as a reference the frequency of key words. For the analysis using global and local documents, the number of citations was used as a parameter, together with the year of publication. Among the databases consulted were: Google Scholar, Lens, IEEE Xplore, Scopus, and Elsevier. The databases of some publishers such as Science Direct and Springer were also consulted. All defined search equations were applied to each of the related databases to identify primary studies.

Following [Toledo *et al.*, 2022], the review process was structured into sequential stages including (i) planning, (ii) conducting, and (iii) reporting the review. Murugesan *et al.* [2015] provided complementary guidelines for defining research questions, inclusion and exclusion criteria, and classification categories. This study integrated both approaches: from Toledo (2022) PRISMA-like flow structure was adapted, while from Murugesan (2015) the categorization of methods and applications was used. This ensured both methodological rigor and domain-specific relevance for multiphase measurement studies.

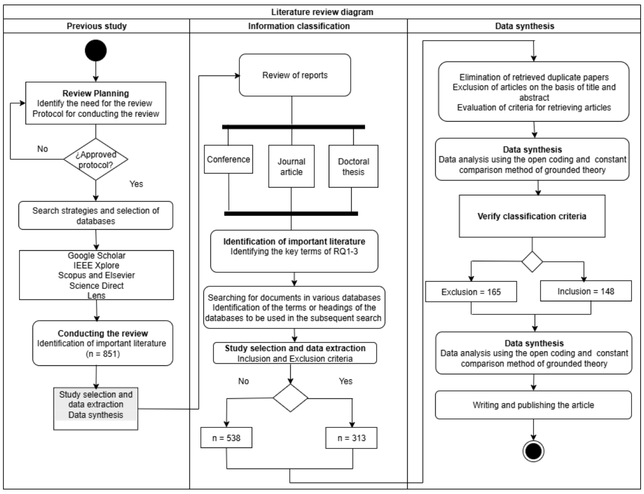

Figure 1. Schematic of the systematic literature review procedure. Adjusted from [Toledo *et al.*, 2022; Murugesan *et al.*, 2015].

The use of the articles identified in the review depended on a series of inclusion criteria, among which were the number of citations in the article, trend analysis and writing in English, and exclusion criteria, such as excessive age, the article dealing with single-phase measurement, or not related to the hydrocarbon industry.

The **Figure 2**, shows the number of publications related to multiphase measurement for the oil industry, with the search equation (TITLE-ABS-KEY (multiphase AND meas* AND oil* AND pha*) AND PUB-YEAR > 1869 AND PUB-YEAR < 2025). A total of 2204 papers published in Scopus were found. For this same search, the six countries with the most publications on the subject are the United States with 623 articles, China 378, United Kingdom 280, Norway 130 and Saudi Arabia 104.

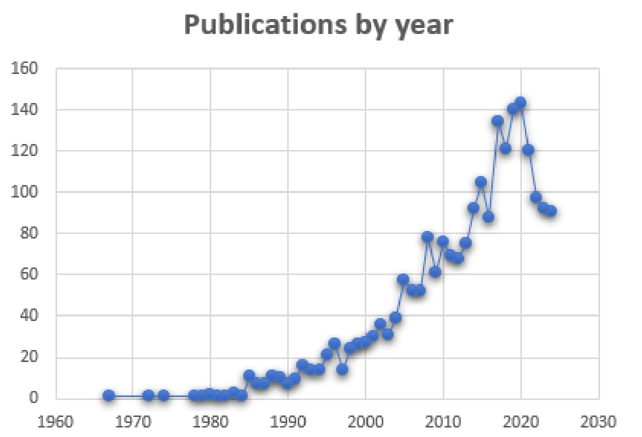

Figure 2. The graphs show the number of published papers related to multiphase measurement per year

In relation to digital twins, 850 publications on digital twins were found in Scopus, with the following search equation: (TITLE-ABS-KEY (*digital AND twin* oil*) AND PUB-YEAR > 1869 AND PUB-YEAR < 2025). **Figure 3**, shows the progression over time of these publications. In relation to the papers published by country, the largest volumes correspond to China (163), the United States (139), the Russian Federation (65), Norway (61), the United Kingdom (48)

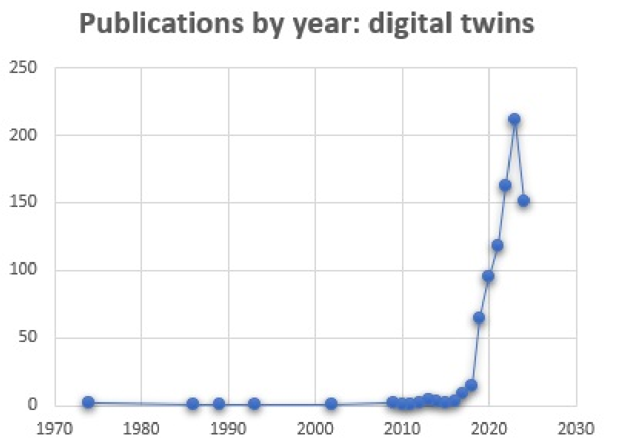

Figure 3. The graphs show the number of published papers by year related to digital twins for the oil industry.

and Brazil (39).

The selection process ended with 313 articles published in the last five years. The selected articles were reviewed and registered in a database to keep a log of the articles. For each paper, the following information was recorded: identifier code, article title, author(s), year of publication, journal/conference, DOI, URL, country or region, type of study, method or algorithm, measurement categories, application or industry, main results, limitations, relevant citations, database and sampling time.

The articles were then classified by topic, selecting the most recent articles that serve as a review of the state-of-the-art, and for theoretical support, references to published works older than five years were included, as well as some books. Table 1 presents the classification of the articles (see **Table 1**).

Table 1. Number of articles reviewed, classified by topic

Topic	Number of articles
Multiphase measurement	55
Three phases	19
Digital twin	35
Data-driven models	93
Soft sensors	29
Machine learning	73
Soft computing	9

3 Background

The soft sensor is the result of the construction of predictive models taking advantage of the large amounts of measured and stored data in the process industry [Kadlec *et al.*, 2009]. In this way, they offer real-time monitoring and control of industrial processes through the projection of the prediction of fundamental variables involved in the process. Soft sensors seek to solve challenges posed by physical sensors, such as difficulty of installation, high calibration and maintenance costs [Hucko *et al.*, 2023], as well as long measurement periods, among others [Hucko *et al.*, 2023; Jiang *et al.*, 2021].

Two types of soft sensors can be considered. The first type, called model-driven, is based on mathematical models, acquired through physical understanding of the system. In some situations, the elaboration of mathematical models is excessively complex and requires considerable effort to develop. In addition, their use requires precise knowledge of all the parameters of the created model [Jiang *et al.*, 2021; Liu and Xie, 2020]. The second, called data-driven, consists of sensors based on measurements obtained from the system in its actual operation [Yan *et al.*, 2018; Bahrami *et al.*, 2019]. Generally, the number of these process variables is much larger than their effective dimension, which is called data-rich but information-poor [Sun *et al.*, 2017].

In such a case, latent variable models are particularly suitable for describing low-dimensional subspaces with little information loss, which give explanations for the main variations of process data [Falcone *et al.*, 2009]. The original application of data-driven soft sensors is known as online prediction and consists of obtaining information with a higher frequency or lower cost of key variables in the process, which normally can only be calculated off-line or with low frequency [Kadlec *et al.*, 2009]. Applications oriented to process monitoring and process fault detection have also been developed.

Techniques such as principal component analysis (PCA), regression, artificial neural networks (ANN), and support vector machines (SVM) are used to create soft data-driven models [Kadlec *et al.*, 2011]. Data-driven modeling is defined as a technique that analyzes system data to find relationships between system input and output variables without exact knowledge of the physical behavior of the system [Solomatine *et al.*, 2009], and relies on the fact that experimental or industrial data accurately represent the system [Bikmukhametov and Jäschke, 2020; Hurtado, 2006]. This concept comes from data science, which is a discipline that deals with the extraction of knowledge from data and is in full expansion. Data science incorporates methods, techniques, and tools from numerous fields, including mathematics and statistics, computer science, data storage and processing, visualization, pattern recognition, machine learning, deep learning, and algorithms, among others [Aguilar, 2019].

Model creation begins by using a machine learning algorithm to determine the relationship between inputs and outputs of a system using a training data set representative of all system behaviors. Once the model is trained, it can be tested using an independent data set to determine the generalization to unobserved data [Solomatine *et al.*, 2009]. In some occasions, drawbacks have been detected, such as noncompliance with some physical principles; for this reason, new procedures based on physical data are being introduced [Montáns *et al.*, 2019].

Some authors consider data-driven models to be a robust tool for transforming data into knowledge [Balaji *et al.*, 2018]. Due to the advances and application of data-driven methods, data-driven models are increasingly used for the analysis, predictive modeling, control, and optimization of various processes. For successful use of data-driven models in the hydrocarbon industry, a solid understanding of petroleum engineering processes and conventional physics-based methods is required, along with a good command of traditional statistics, data mining, artificial intelligence, and machine learning. Some of the techniques that are applied to obtain a data-driven model belong to a category called soft computing techniques, a branch of artificial intelligence that deals with solving problems with incomplete or inaccurate information, and includes techniques such as neural networks, fuzzy logic, genetic algorithms, swarm intelligence, and metaheuristic algorithms based on probability and randomness [Mohammadi and Sheikholeslam, 2023].

One application of data-driven models and soft sensors is the construction of digital twins. These aim to be virtual representations of physical objects, with such high similarity that they produce the same results when fed with the same input information [Fu *et al.*, 2022; Attaran and Celik, 2023]. Among their applications is their use in industrial manufacturing companies, where they are used to optimize the manufacturing life cycle and promote smart manufacturing improvement [Liu *et al.*, 2021; Zhong *et al.*, 2023]. Some authors differentiate three levels of integration: the digital model, the digital shadow and the digital twin [Attaran and Celik, 2023]; [Kritzinger *et al.*, 2018; Grieves, 2015].

A digital twin consists of three parts 1) the information model of the physical entity, 2) the data communication mechanism between digital twins and physical entities, and 3) the data processing module that can extract information from heterogeneous data from multiple sources and construct a real representation of the physical entities [Lu *et al.*, 2020]. The information model usually includes the appearance model and the mechanism model of the physical entity, so that the data transmitted to cyberspace retain their meaning and context. For its part, the communication mechanism enables the passage of data between the digital entity and the physical entity; in physical space, the state synchronization between the digital entity and the physical entity depends on the bidirectional communication of data in real time. As for data processing, it should be noted that the system has many equipment parameters and large data redundancy, with strong coupling, nonlinearity and high temporal variability, which directly affects the data quality [Zhong *et al.*, 2023]. Through the cooperation of these three parts, the digital twin can work properly. A graphical schema for the general reference model of a digital twin can be seen in **Figure 4**.

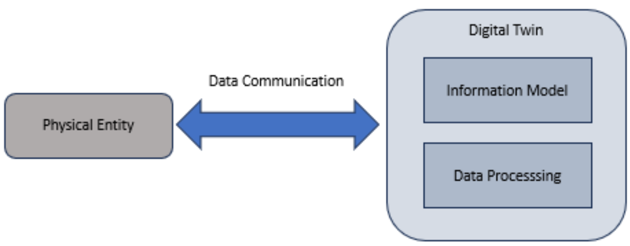

Figure 4. General reference model for a digital twin. Taken from [Zhong *et al.*, 2023].

4 Multiphase Measurement in the Oil and Gas Industry using Computational Intelligence

4.1 Multiphase Measurement in the Oil and Gas Industry

Crude oil, during the production phase, is normally a mixture of gas, oil, and water. Thus, the flow through the pipelines is not homogeneous, which means that the physical properties of the mixture vary along the cross-section of the pipe. Depending on the relative amounts of each phase, the average velocity of the fluid, and the orientation of the pipe, different flow patterns can occur. Prediction of flow patterns is a necessary prerequisite for predicting two-phase mass transfer, heat transfer, and pressure gradient in pipes [Eissa and Al-Safran, 2017]. In the case of flow in vertical pipes, patterns such as bubble flow, slug flow, churning flow, and annular flow can be found, which are shown in **Figure 5**. [Sun, 2016]. The **Figure 6**, shows some of the multiphase flow patterns in horizontal pipes: bubble, slug, stratified, wavy and annular flow [Sun, 2016].

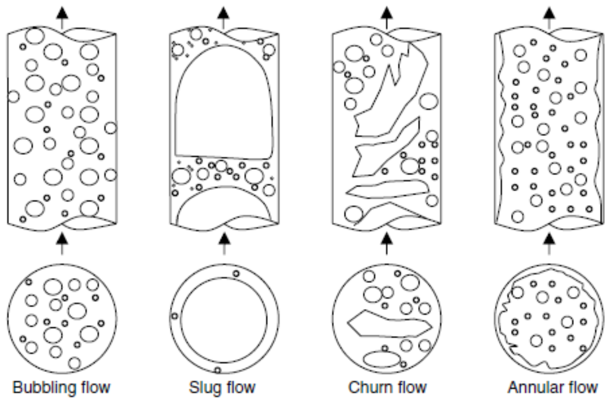

Figure 5. Continuous phase low-flow gas-liquid flow regimes in standpipes. [Sun, 2016]

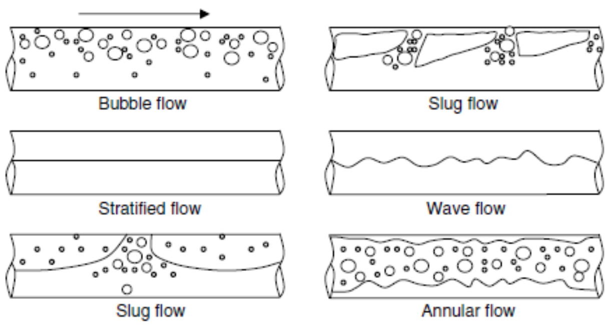

Figure 6. Gas-liquid flow patterns in horizontal pipes. [Sun, 2016]

The purpose of a multiphase flowmeter MPFM is to determine the individual flow rates of oil Q_{O}, water Q_{W} and gas Q_{G} [Meribout *et al.*, 2020a].

This requires the use of multiple sensors to measure the flow fractions of oil (α), water (β) and gas (γ) and another set of sensors to measure the oil, water and gas velocities. This schema can be seen in **Figure 7**.

Some MPFMs, for example, from Schlumberger, Emerson and Weatherford, use a flow homogenizer, which is a blind tee (T), that is placed upstream of the meter to reduce the slip velocity between the liquid and gas phases, and to assume that the flow velocities of the three phases are equal. For this reason, these MPFMs should be placed vertically, immediately downstream of a T-junction. This allows the number of unknown parameters to be reduced by measuring only the total volumetric flow rate Q_{T}, using either volumetric flow meters such as orifice, V-cone, or Venturi meters, which are more commonly used. The MPFM equations are defined as follows [Meribout *et al.*, 2020a]:

$$Q_{\mathrm{O}} = \alpha Q_{\mathrm{T}} \tag{1}$$

$$Q_{\mathrm{W}} = \beta Q_{\mathrm{T}} \tag{2}$$

$$Q_{\mathrm{G}} = \gamma Q_{\mathrm{T}} \tag{3}$$

It is possible to use a mass flow meter, such as the Coriolis flow meter, to measure the MT mass flow rate. Consequently, to determine the individual volumetric flow rates, the following equations are used:

$$Q_{\mathrm{O}} = (\alpha M_{\mathrm{T}})/\rho_{\mathrm{O}} \tag{4}$$

$$Q_{\mathrm{W}} = (\beta M_{\mathrm{T}})/\rho_{\mathrm{W}} \tag{5}$$

$$Q_{\mathrm{G}} = (\gamma M_{\mathrm{T}})/\rho_{\mathrm{G}} \tag{6}$$

Where ρ_{O}, ρ_{W}, and ρ_{G} are the densities of oil, water, and gas, respectively. The determination of the flow fractions α, β and γ, requires the measurement of two properties of the fluid x and y, which can be the density of the mixed fluid and/or the dielectric value of the mixture, generating three equations with three unknowns:

$$x = \alpha x_{\mathrm{O}} + \beta x_{\mathrm{W}} + \gamma x_{\mathrm{G}} \tag{7}$$

$$y = \alpha y_{\mathrm{O}} + \beta y_{\mathrm{W}} + \gamma y_{\mathrm{G}} \tag{8}$$

$$\alpha + \beta + \gamma = 1 \tag{9}$$

Where $(x_{\mathrm{O}}, x_{\mathrm{W}}, x_{\mathrm{G}})$ and $(y_{\mathrm{O}}, y_{\mathrm{W}}, y_{\mathrm{G}})$ represent the fluid properties corresponding to oil, water and gas, respectively, as defined in this article [Meribout *et al.*, 2020a].

In multiphase flow, the mass flow rate, volume fraction, and velocity of each phase are required to characterize the flow. The methods for measuring the velocity and volume fraction of each phase include the following: separation of all phases (based on measurement of each phase flow rate under single-phase flow conditions, using conventional instruments), partial separation (where excess gas is separated from the multiphase main stream, prior to determination of phase flow rates), homogenization of the mixture (which makes the velocity the same for all phases and is based on measurement of velocity and phase fractions), fluid sampling at representative flow conditions (which provides an estimate of the phase fractions and must be combined with the velocity measurement to allow determination of phase flow rates, and Leave-as-it-is, which aims to be completely non-intrusive in the flow, that is, no separation, no homogenization, in general, no alteration of the original flow regime) [Busaidi and Bhaskaran, 2003].

The above options for measurement can be reduced to three main categories of Multiphase Flow Measurement techniques, such as 1) flow homogenization-dependent techniques, 2) non-homogenization-dependent techniques, and 3) techniques that rely on total flow separation and separate measurements. In **Table 2** and **Table 3**, the description of each variable is extended to include the equations that define them.

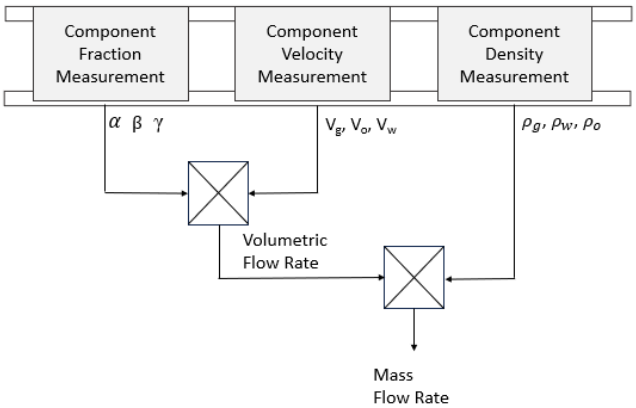

Figure 7. Typical measurement algorithm for a MPFM. [Meribout *et al.*, 2020a]

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To measure the flow rates of each phase of a three-phase flow of oil, gas, and water, there are two possible methods. With the first approach, three independent flow parameters (functions of the three flow rates) and the relationships between them and the flow rates of the respective phases are obtained. The main problem with this approach is that these relationships cannot be predicted theoretically but must be established by calibration. With the second approach, the basic parameters of the phase velocities (or quantities that can be unambiguously related to them) are measured. Subsequently, the velocities and phase holdups were combined to obtain the phase flow rate. For a three-phase flow, three average velocities and three-phase cross sections are required. Thus, five measurements are needed, namely: three velocities and basic fractions (the three-phase fraction is obtained by difference between unity and the sum of the two measured fractions) [Falcone *et al.*, 2009].

The number of measurements required can be reduced by separation or homogenization. By separating the phases, the need for cross-sectional retention measurements disappears and the three volumetric flows can be established by conventional single-phase measurement technology. However, it should be noted that in many cases it is difficult to achieve complete separation of the three phases, due to liquid entrainment in the gas phase or gas remaining trapped in the liquid phase, or the formation of emulsions or foams [Falcone *et al.*, 2009].

Some of the most commonly used commercially available MPFMs, along with the technology used for flow and phase fraction measurement, are Weatherford (Venturi meter, NIR probe), Abril Inc. (Coriolis and Venturi Meter, Microwave), Roxar/Emerson Flow Measurement, Schlumberger (Cross Correlation/Venturi, Impedance, and Capacitance). It is noted that, despite using the same sensing technology, there may be design differences between manufacturers in how flow can be conditioned and the type of algorithms used [Meribout *et al.*, 2020a].

From an algorithmic perspective, due to the complexity and high dimensionality of the input parameter space derived from various sensors, soft computing techniques, including machine learning and artificial intelligence (AI) algorithmics, are typically employed in MPFMS. Including ANN [Bahrami *et al.*, 2019; Meribout *et al.*, 2009], radial basis function neural network (RBFN) [Chunguo and Qiuguo, 2009] and SVM + k-Means [Hanus *et al.*, 2018]. These models have been used to determine the phase fractions and individual flow rates, which allow solving a function approximation problem, or to determine the multiphase flow regime corresponding to a classification problem [Meribout *et al.*, 2020a].

4.2 Multiphase Measurement Techniques

The purpose of multiphase measurement is to determine the individual flow rates and phase fractions that characterize complex oil and gas flows. During the past three decades, substantial progress has been achieved in the development of techniques capable of addressing industrial measurement challenges [Thorn *et al.*, 1997] [Thorn *et al.*, 2013] [Falcone *et al.*, 2002]. Non-intrusive methods have been increasingly adopted to capture flow dynamics and monitor flow conditions without disturbing the process.

These measurement techniques can be broadly grouped into six categories: electrostatic sensing, acoustic emission and vibration analysis, visualization, particle tracking, laser Doppler anemometry, and pressure fluctuation methods [Sun and Yan, 2016]. Such approaches provide accurate and valuable data for understanding flow hydrodynamics, validating computational fluid dynamics (CFD) models, and defining operational parameters in multiphase systems.

Since no single technique can capture all relevant aspects of multiphase flow, selecting an appropriate measurement approach requires careful consideration. Factors such as measurement scale, ease of operation, data interpretability, cost, and suitability for industrial environments must be evaluated. Despite the wide range of sensor and instrumentation principles available, relatively few systems have reached full industrial deployment. Nevertheless, continuous advances in materials, electronics, and computational methods are enabling the development of sensors with multiple measurement functions. Consequently, modern systems increasingly integrate various data processing techniques to analyze signals associated with different flow regimes and behaviors [Sun and Yan, 2016] [Yan, 2000] [Zheng and Liu, 2010].

Four parameters are measured by MPFMs, such as density, velocity, mass flow rate, and momentum [Daniel Industries, 2023; Fadaei *et al.*, 2021]. For example, the multiphase flow

Table 2. Variables used to describe multiphase flow [Sun, 2016]

Parameter	Description	Equation
Mass Flow Rate (G)	It is defined as the mass of fluid passing through the cross section per unit of time. G_g, G_l y G_s represent the mass flow rate of gas, liquid and solid respectively.	$G = G_{\mathrm{g}} + G_{\mathrm{l}} + G_{\mathrm{s}}$ (10)
Volumetric Flow Rate (Q)	It is defined as the volume of fluid passing through the cross section per unit time. Q_{g}, Q_{l} and Q_{s} represent the volumetric flow rate of gas, liquid and solid respectively	$Q = Q_{\mathrm{g}} + Q_{\mathrm{l}} + Q_{\mathrm{s}}$ (11)
Actual velocity of gas, liquid and solid phase (mean velocity)	Defines the actual velocity of the gas, liquid and solid phases (average velocity). For the equations, v_{g} is the real velocity of the gas phase, measured in m/s; A_{g}, is the cross-sectional area of the gas flow, measured in m^2. v_{l}, is the real velocity of the liquid phase, measured in m/s; A_{l} refers to the cross-sectional area of the liquid flow, measured in m^2. Finally, v_{s} is the real velocity of the solid phase, measured in m/s. As is the cross-sectional area of the solid flow, measured in m^2.	$v_{\mathrm{g}} = Q_{\mathrm{g}}/A_{\mathrm{g}}$ (12) $v_{\mathrm{l}} = Q_{\mathrm{l}}/A_{\mathrm{l}}$ (13) $v_{\mathrm{s}} = Q_{\mathrm{s}}/A_{\mathrm{s}}$ (14)
Superficial velocity of gas and liquid phase	The Surface velocity of a phase is the volumetric flow rate of the phase, which represents the volumetric flow rate per unit area. In the equations, v_{ag} is the surface velocity of the gas phase, in m/s. A is the cross-sectional area of the flow, in m^2. v_{al} is the surface velocity of the liquid phase, units m/s. v_{as} is the surface velocity of the solid phase, measured in m/s.	$v_{\mathrm{ag}} = Q_{\mathrm{g}}/A$ (15) $v_{\mathrm{al}} = Q_{\mathrm{l}}/A$ (16) $v_{\mathrm{as}} = Q_{\mathrm{s}}/A$ (17)
Mixture velocity	It is defined as the ratio of the volume of mixture flowing through the cross section per unit time to the cross-sectional area. In the equation, V is the velocity of the slurry, unit's m/s	$v = (Q_{\mathrm{g}} + Q_{\mathrm{l}} + Q_{\mathrm{s}})/A = v_{ag} + v_{al} + v_{as}$ (18)
Drift velocity of gas phase	The lower the density of the gas phase, the greater the velocity difference between the gas and the mixture, and the actual velocity of the gas phase differs significantly from the actual velocity of the liquid phase or gas-liquid mixture. The velocity difference is called the drift velocity of the gas phase. In the equation, Δv is the drift velocity, measured in m/s. v_{H} is the average velocity of the mixture, in m/s. The slip coefficient is the ratio of the real gas phase velocity to the actual mixture velocity. Where S is the slip coefficient.	$\Delta \mathrm{v} = v_{\mathrm{g}} - v_{\mathrm{H}}$ (19) $S = v_{\mathrm{g}}/v_{\mathrm{H}}$ (20)
Solid phase slip velocity	In the case of liquid-solid two-phase flow in a well or pipe, slippage will occur due to the difference in velocity of each phase. The concentration of solid phase at different points also differs due to the retention effect of the solid phase.	$v_{\mathrm{sH}} = v_{\mathrm{H}} - v_{\mathrm{s}}$ (21)
Mass fraction (x_{i})	It is defined as the ratio of the mass of a phase to the total mass of the mixture passing through the cross section per unit time.	$x_{\mathrm{i}} = G_{\mathrm{i}}/G = G_{\mathrm{i}}/(G_g + G_l + G_s)$ (22)
Volumen fraction (β_{i})	It is defined as the ratio of the volume of a phase to the total volume of mixture passing through the cross section per unit time.	$\beta_{\mathrm{i}} = Q_{\mathrm{i}}/(G_g + G_l + G_s)$ (23)

Table 3. Continuation of Variables used to describe multiphase flow [Sun, 2016]

Parameter	Description	Equation
Actual or cross-sectional fraction (φ)	The actual or cross-sectional fraction is defined as the ratio of the area of a phase occupied to the entire cross-sectional area as the mixture flows through the section. For example, in gas-liquid-solid multiphase flow, the ratio of the area occupied by the gas phase to the total cross-sectional area is the gas volume fraction. φ is the real gas volume fraction.	$$\varphi = \frac{A_g}{A} = \frac{A_g}{A_g + A_l + A_s} \quad (24)$$
Flowing density (ρ')	It refers to the ratio between the mass and volume of mixture flowing through the cross section per unit time.	$$\rho' = \frac{G}{Q} \quad (25)$$
Phase volumen fraction (E_k)	It indicates the volume fraction of a phase with respect to the total volume, or the area occupied by a phase with respect to the total cross-sectional area. This is the measure of the distribution characteristics of the phases. Where V is the volume of the mixture, measured in m^3, V_k is the volume of a phase (m^3) and A_d is the cross-sectional area of a phase, measured in m^2.	$$E_k = \frac{V_k}{V} = \frac{A_d}{A} \quad (26)$$

meter that measures phase density is the gamma multiphase flow meter, or a flow meter that measures phase velocity is the turbine flow meter [Henry *et al.*, 2011]. Although the mass flow of each component cannot be measured directly, the total mass flow can be obtained using a Coriolis flow meter [Green, 2019]. Another parameter is the fluid momentum. This category includes classical pressure drop instruments, such as Venturi and Orifice flow meters [Fadaei *et al.*, 2021].

4.2.1 Multiphase flow Coriolis meter

In a Coriolis meter, the flow is usually divided into a pair of flow tubes, which vibrate at frequencies on the order of a few hundred Hz [Mahalingam and Arsalan, 2020]. There are two sensors, one at each end of the meter, that continuously measure the motion of the tubes [O'Banion, 2013]; [Wang and Baker, 2014]; [Smith and Cage, 1985]. The resonant frequency of the tubes is altered as a result of the presence of fluids inside the tubes, and this relationship is used to measure the fluid density. Fluid flow causes additional out-of-plane torsion in the tubes as a result of the Coriolis effect. This results in an offset between the two samplers and is used to measure the mass flow rate of the fluid. In multiphase flow, when the liquid and gas flow together, the center of mass of the fluid inside the tubes and the proper center of mass of each tube no longer coincide. This is one of the assumptions built into the meter calibration and any deviation from this assumption causes errors in the measured density and mass flow rate. There are two main problems with entrained gas flowing through Coriolis meters: a) compressibility of the gas and b) phase decoupling [Basse, 2014; Hemp and Kutin, 2006]. Since the gas is compressible, the motion of the tubes can cause them to squeeze against the outlet wall of the vibrating tube. The Coriolis meter calculates and reports the density and mass flow rate as two independent measurements. Subsequently, there are other measurements that have an indirect effect on the meter, such as the temperature and drive power required to maintain vibrations. These are useful for diagnosing the meter and its performance. Based on this situation, the design of a digital twin of the Coriolis meter has been proposed [Mahalingam and Arsalan, 2020].

4.2.2 Pressure Differential (PD)

The PD flowmeter consists of two inlets that are connected to pressure points upstream and downstream of the meter through 0.5" flow lines containing the process fluid. According to ISO-5167-1, the associated mass flow rate for a multiphase fluid of density ρ passing through a diameter restriction d can be determined by the following equation.

$$Q_m = \frac{C}{\sqrt{1-\beta^2}} \cdot \frac{\pi}{4} d^2 \cdot \sqrt{2\rho\Delta p} \tag{27}$$

Where β is the ratio of diameters between the throat and the pipe, Δ_p is the measured differential pressure and C the discharge coefficient, which is a calibration constant that depends on the Reynolds number, R_e, of the multiphase fluid [Atkinson *et al.*, 2000]. In case of having a high value of R_e, which is common in oil and gas reservoirs, due to lower energy losses of the multiphase fluid, the discharge coefficient usually ranges from 0.98 to 1.0 [Wee and Gundersen, 2017]. This value can be used in the equation 27 without causing significant errors. However, in the case of highly viscous oils (e.g., >10 cP) or heavy crude oil, R_e, may be reduced so that the meter operates in a zone appreciably below 1.0. In practice, it is necessary to estimate the Reynolds number value to provide a reliable flow measurement. The FMC company proposed a WC device that predicts whether the multiphase flow is continuous oil or continuous water in order to accurately determine the Reynolds number and consequently the discharge coefficient [Wee and Gundersen, 2017].

V-Cone, orifice plate, Dall tube along with Venturi meters are most commonly used to determine the volumetric flow rate of multiphase flow. These use the principle that any restriction in the pipe will cause a pressure change and generates a pressure drop across the restriction [Meribout *et al.*, 2020a].

4.2.3 Cross Correlation

This technique uses two receiver sensors of the same type that are placed along the pipe, at a given distance, to generate two signals, x(t) and y(t). The cross-correlation of the two signals $R_{xy}(\tau)$, is calculated for different delays(τ) within a time window τ by the following equation:

$$R_{xy}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_0^T x(t)\, y(t+\tau)\, dt \tag{28}$$

In turn, the flow velocity can be determined through the following equation $v_T = \frac{L}{\tau_0}$. Where τ_0 is the time delay that maximizes the correlation function $R_{xy}(\tau)$.

In practice, the use of a pair of pressure or temperature sensors is not usually adopted, because the physics relating the few pressure and temperature measurements to the flow system is quite complex and depends on the estimation of several, often ill-defined parameters such as flow system properties, viscosity and wall surface roughness. For the cross-correlation flow measurement technique, acoustic, ultrasonic and impedance sensors were the most commonly used devices. This technique requires that the flow is not laminar, but turbulent to some extent. Otherwise, it is not possible to extract features from the two signals. This goal can be achieved by implementing an optimal piping system design, so that the Reynolds number exceeds a certain value (e.g., 3,000 in several of the cases), thus setting a lower limit for the Reynolds number and determining a low limit value on the fluid flow rate [Meribout *et al.*, 2020a].

In another configuration, few transmitters are used to transmit a carrier signal in the stream. In this context, a small number of receivers, strategically placed to measure amplitude loss, phase or frequency modulation of the transmitted signals, play a crucial role. These receivers, arranged in a preset manner, allow the measurement of disturbances in the flow, resulting in the frequency modulation of the transmitted signals. Once the data has been obtained, the flow rate can be determined by searching for more correlated patterns in both signals.

The main advantage of cross-correlation based flowmeters compared to pressure differential (PD) flowmeters lies in their ability to avoid flow pressure drop and their ability to be attached to the pipe, thus causing no disturbance to the flow. This can be significant in applications where the use of pumps and compressors is costly, such as in offshore fields. In addition, these devices are capable of operating over a wide a range of flow rates [Meribout *et al.*, 2020a].

4.2.4 Pitot tube

The Pitot tube, which is the simplest dynamic pressure differential gauge, basically measures dynamic pressure differential , which is the pressure produced by the velocity of the fluid. Its main advantage is that it causes a very small pressure drop. However, it has never been used in MPFM. This is because it is much less accurate than other DP sensors. This is because the area of the diaphragm, where the sensor is located and the measurement is made, is relatively low, which considerably alters its sensitivity. For this reason, it is often used as a stand-alone meter to quickly estimate the flow rate of a fluid with a known density [Meribout *et al.*, 2020a].

4.2.5 Venturi meter

The operating principle of the Venturi meter is based on the presence of a constricted zone (throat) which causes an increase in velocity and, consequently, a decrease in pressure. From the throat, there is a diverging tube which allows the pressure to be recovered. Pressure taps at the inlet and throat are used to measure the pressure differential produced by the meter, which can be applied to Bernoulli's principle and conservation of mass to calculate the flow rate using the appropriate flow equation.

Research and manufacturing capabilities have led to several modifications of the classic Venturi meter. Among the most common are the universal Venturi tube (UVT), the Halmi Venturi tube (HVT), the Dahl tube, and the nozzle Venturi [Nalulu, 2021].

4.2.6 V-Cone meter

It consists of a V-cone shaped object that creates an obstruction in the flow and generates a differential pressure (DP = P1-P2) across the meter, which is proportional to the multiphase fluid flow exponentially. Instead of the flow contracting, the fluid flows around a central cone. Like the Venturi meter, its associated flow equation assumes that the energy conservation condition is met, which requires the flow to be turbulent. An advantage of this meter is that only 1 to 3 diameters of straight pipe in both directions are required for efficient operation. In addition, it can operate at very high pressures and is more accurate than the Venturi meter for steam flow rates. Therefore, it is suitable for clean energy applications [Meribout *et al.*, 2020a].

4.2.7 Vortex flow meter

The meter comprises a bluff body that obstructs the flow, causing a generation of vortices when the multiphase flow passes through it. The vortices are alternately induced and expelled from opposite sides of the obstructions, according to the Karman effect. The frequency of vortex shedding is proportional to the width and also to the velocity of the multiphase flow, V, according to the following equation:

$$f = \frac{S_t \cdot V}{d} \tag{29}$$

Where S_t is the Strouhal number, which is constant for relatively low Reynolds numbers and increases exponentially for high Reynolds numbers, requiring proper calibration.

Acoustic sensors, usually piezoelectric sensors, which are evenly distributed downstream and on both sides of the cliff body pick up the acoustic signals generated by the vortices. The flowmeter can be flanged or threaded type and must be inserted inside the pipe section. It can also be of the insert type, in which the bluff body is inserted directly inside the probe. This has the advantage of facilitating maintenance of the probe body, which is the only intrusive part of the meter. In addition, it is an economical solution, since the same body can be inserted into any pipe, regardless of its diameter.

The electronics associated with the transmitter of a vortex flowmeter usually consist of a Schmitt trigger or digital comparator followed by a counter, usually embedded within a microcontroller that counts the number of pulses in a given period of time, usually on the order of milliseconds. This is different from Venturi transmitters that require an analog-to-digital converter followed by a processor to perform square root and division calculations. Therefore, a higher number of positive pulses from the comparator provides higher accuracy in the flow measurement. From Eq. 30, it follows that the counter is more accurate for high flow measurement. Furthermore, it is more accurate for turbulent flows than laminar turbulent flows, since the Strouhal constant, S_t is higher for higher Reynolds numbers [Meribout *et al*., 2020a].

4.2.8 Positive Displacement flow meter

Positive displacement flowmeters are another type of flowmeters used for oil custody measurement applications, where they sometimes replace the turbine meter. This is because the turbine flowmeter equations can be altered because the WC value during oil export is unknown and may even fluctuate during loading. However, to estimate the actual amount of oil exported, periodic sampling and analysis in specialized laboratories is necessary. This meter measures volumetric flow rates of liquid or gas by separating the flow stream into known volumes, using few gears and counting them over time. Paddles, pistons and diaphragms can also be used to separate the fluid.

An advantage of this flowmeter is the ability to measure reverse flow rates, which may be needed in various applications, including custody transfer and enhanced oil recovery (EOR). This meter is also used in other industries, such as pharmaceuticals, when it is necessary to accurately measure the mixture of two flowing fluids [Eugene, 2019]. However, the main disadvantage of these meters is that they include moving parts, so they are prone to failure when solids are present in the multiphase fluid [Meribout *et al*., 2020a].

4.3 Historical Evolution of Multiphase Flow Measurement

The evolution of multiphase flow technologies has advanced from pressure-differential meters to model-based systems and AI-assisted systems. Unlike traditional devices that directly measure flow variables, digital twins do not perform physical measurements but rather estimate them through virtual representations of the system. **Figure 8** summarizes this progression, showing the shift from direct sensing to intelligent modeling.

- **Early 1900's**: The first experimental and theorical studies on multiphase flow focused on understanding gas-liquid flow patterns and pressure drops in pipelines [Sun, 2016; Wallis, 2020]. These foundational investigations provided the basis for characterizing phase behavior and modeling complex flow dynamics.
- **1950's–1970's:** This period marked the consolidation of classic flow-measurement technologies. Differential pressure-based devices, such as orifice plates and Venturi meters, became the standard for single-phase flows, although they proved to be unreliable under multiphase conditions. At the same time, positive-displacement meters and turbine meters were already mature technologies, widely used for liquid measurement and custody transfer, but they also showed limitations when applied to complex multiphase environments [Miller, 1996; Reader-Harris, 2015].
- **1980's–1990's:** During this period, Coriolis meters and the first commercial multiphase flow meters (MPFMs) emerged, significantly improving measurement accuracy but requiring complex calibration and flow-regime characterization. Companies such as Framo, and Roxar developed the first industrial prototypes integrating differential-pressure, gamma-ray densitometry, and electrical-impedance sensors [Falcone *et al*., 2009; Anklin *et al*., 2006; Meribout *et al*., 2020a].
- **2000's–2010's:** The expansion of offshore oil production increased the demand for reliable multiphase metering systems for subsea environments. Non-intrusive techniques such as ultrasonic, capacitance, microwave, and impedance sensors gained attention, often combined with computational fluid dynamics (CFD)-based signal-processing approaches [Da Silva *et al*., 2007; Sun, 2016; Thorn *et al*., 2013]. Hybrid systems that combined empirical and mechanistic models also emerged to address complex flow-regime transitions.
- **2020's:** The integration of artificial intelligence, machine learning, and digital twins technologies reshaped the field, enabling real-time monitoring, data-driven diagnostics, and predictive maintenance [Sircar *et al*., 2021; Mu *et al*., 2023; Manami *et al*., 2023]. These developments have not replaced physical flow meters, but rather complement them through virtual sensing and hybrid digital representations. In particular, data-driven and physics-informed neural-network models have shown great potential for to improve measurement accuracy and generalization capability.

This historical evolution has been extensively documented in both early reviews [Thorn *et al*., 1997; Whalley, 1996] and recent analyzes [Bikmukhametov and Jäschke, 2020; Ali, 2025], evidencing a consistent research trend toward integrating traditional metering technologies with AI-enhanced modeling and soft-sensing strategies, rather than replacing them entirely.

4.4 Challenges and Limitations of Multiphase Measurement

There are several factors that affect multiphase flow, including phase characteristics, composition, velocities, velocities, pressure, temperature, pipe diameter, pipe slope, roughness, and the presence of valves in pipes [Falcone *et al*., 2009;

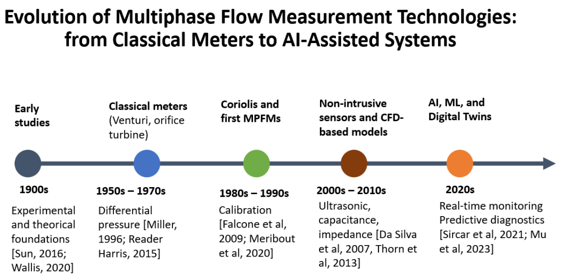

Figure 8. The chronological evolution of these technologies is illustrated in this figure, which highlights the transition from classical devices to hybrid and AI-driven approaches.

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Fadaei *et al.*, 2021]. The complexity of the nature of multiphase flow makes the development of multiphase flow models challenging. Artificial intelligence has been used to observe different two-phase flow regimes. For example, Kohonen's self-organizing neural network was applied for this purpose [Green, 2019]. In the neural network approach, the optimal selection for the number of hidden layers is very important as it leads to accurate results and reduces the computational time.

Other studies have focused on the determination of the two-phase flow through an orifice plate; a mesh sensor was used to determine the volume fraction of each phase, based on 260 experimental data [Oliveira *et al.*, 2009]. Vertical and horizontal flow data were validated using the equations of Hewitt et al. [Hewitt and Roberts, 1969] and Baker [Baker, 1953], respectively. A comparative study was performed between Venturi and Orifice in a two-phase flow with quality less than 0.011. This Work has also been done on the investigation of bubble and slug flow patterns in an air-water mixture through an orifice plate, and the comparison of pressure drop coefficients for two-phase flows through valves [Alimonti *et al.*, 2010]. Other works have focused on the experimental determination of the pressure drop and the characteristics of two-phase flow through an orifice plate [Bertola, 2004; Jones and Zuber, 1975; Roul and Dash, 2012]. In [Meng *et al.*, 2010], they proposed more comprehensive studies on the measurement of two-phase flow using Venturi and electrical resistive sensors. In this study, the composition of each phase was determined using an electrical resistive sensor. The total two-phase flow rate was then determined using the pressure drop generated at the Venturi meter. The calculation error of the proposed method is less than 5% for bubble and slug flow patterns and less than 10% for annular and stratified flow regimes. In [Hollingshead *et al.*, 2011], the performance and discharge coefficients of the orifice plate and Venturi meter were investigated for low two-phase flow rates. According to the results, as the Reynolds number increases, the discharge coefficients of orifice plates and Venturi meters also increase.

In [Shaban and Tavoularis, 2014], machine learning methods were used to estimate water and gas flow rates in a vertical multiphase flow through the orifice plate. In [AL-Qutami *et al.*, 2017], this paper presents a soft sensor that uses common measurements in oil and gas production wells to estimate gas and oil phase flow rates in multiphase production wells. This sensor was developed using a Feed-Forward neural network trained using the Levenberg Marquardt algorithm, whose generalization and complexity are regulated by K-fold cross-validation and an early stopping technique. The results showed promising performance, with a mean absolute percentage error of about 4% and a deviation of less than 10% in 90% of the samples. In [Meribout *et al.*, 2020b], a new Coriolis-based two-phase flowmeter is presented using a flow conditioner to separate liquid from gas. The flowmeter has two outlets, one for gas and one for liquid, each with its respective Coriolis flowmeter and regulating valve to measure and control the gas void fraction (GVF). In addition, a new measurement algorithm based on an artificial neural network combining pressure-volume-temperature models and bubble theory is proposed to estimate the amount of gas or liquid dissolved in the corresponding phase. Experimental results show that the proposed flowmeter has a maximum relative error of 2.5% in mass flow rate and density over the entire GVF range. These findings suggest that the two-phase flowmeter presented may be a safe and accurate alternative to the two-phase flow measurement.

In the study of [Fadaei *et al.*, 2021] conducted in 2021, several methods were introduced to measure multiphase flow. These included measurement of the gas-liquid mean density using a Coriolis flowmeter and gas volume fraction using the discharge coefficient of an orifice plate. The principle of using instruments such as single-phase flowmeters for two-phase flow measurement was included; a soft sensor was also used to predict the gas volume fraction, then the variation of the Coriolis meter factor with gas volume fraction and Reynolds number was studied, along with the variation of pressure drop and orifice discharge coefficient with Reynolds number. Moreover, 250 data sets were collected to develop the soft sensor using 2 and 3 layer neural networks optimized through a genetic algorithm and a least-squares support vector machine. The increase in Reynolds number generated a decrease in the Coriolis meter factor.

Table 4 provides a comparative overview of the most relevant multiphase measurement technologies. The analysis considers their decade of introduction, the measurement principle, the main advantages, limitations, and the current level of adoption. Classical approaches such as orifice plates and Venturi meters remain robust but limited in complex multiphase conditions. Coriolis meters represent a major advance in providing direct mass flow measurement, although they are still challenged by gas entrainment. Modern MPFMs combine several sensing techniques to achieve higher accuracy, yet their high cost and calibration requirements hinder widespread deployment. Emerging solutions that integrate AI, ML, and digital twins demonstrate the shift toward hybrid, data-driven approaches capable of real-time adaptation and predictive diagnostics. Together, the timeline and comparative table enrich the discussion of RQ1 by offering both a historical and analytic perspective on multiphase measurement technologies.

Table 4. Comparative overview of multiphase measurement technologies (adapted from [Falcone *et al*., 2009; Thorn *et al*., 2013]

Technology / Method	Period	Measurement Principle / Role	Main Advantages	Key Limitations	Current Adoption Level	Representative Reference
Orifice /Venturi	1950's–1970's	Differential pressure (Bernoulli principle)	Robust, low cost, standardized, easy to implement	High sensitivity to flow regime; low accuracy for gas–liquid flows	Still widely used for single-phase and hybrid systems	Miller [1996]; Reader-Harris [2015]
Positive Displacement /Turbine	1950's–1970's	Volumetric (gears, pistons, diaphragms)	High accuracy in liquid custody transfer; proven design	Poor performance with entrained gas or solids; maintenance required	Common for single phase liquid; limited in MPFM	[Miller, 1996; Eugene, 2019]
Coriolis	1980's–1990's	Tube vibration (Coriolis effect → mass flow and density)	Direct mass flow measurement; high single-phase accuracy	Performance degrades with gas phase; calibration complexity	Widely used in liquids; adapted versions for multiphase pilots	Falcone *et al.* [2009]; Wang and Baker [2014]
Commercial MPFMs (multi-sensor)	1990's–2000's	Combination of pressure, gamma-ray, capacitance, impedance, and cross-correlation	In-line measurement of phase fractions and flow rates	High cost, complex calibration, performance depends on flow regime	Standard in high-cost or offshore environments	Falcone *et al.* [2009]; Meribout *et al.* [2020a]; Anklin *et al.* [2006]
Ultrasonic /Capacitance /Impedance (non-intrusive)	2000's–2010's	Dielectric, acoustic, or electrical property analysis	Non-intrusive; suitable for extreme conditions and multi-parameter data	Sensitive to mixture composition and regime variability	Increasing use in hybrid and research systems	Da Silva *et al.* [2007]; Sun [2016]
Cross-Correlation /Signal Processing	2000's	Time-domain correlation of sensor signals	Allows detection of flow regime transitions; supports diagnostics	Indirect; requires advanced data processing and calibration	Used in diagnostics; increasingly integrated into MPFMs	Meribout *et al.* [2020a]
Data-Driven Models /Soft Sensors (AI/ML)	2010's–2020's	Statistical and machine learning models using indirect sensor data	Cost-effective; adaptable, capable of nonlinear modeling; improved flexibility	Data dependency; generalization challenges; need for validation	Active research; several field and pilot implementations	Goodfellow *et al.* [2016]; Bikmukhametov and Jäschke [2020]
Digital Twins (DTs)	2020's	Virtual representations of physical systems integrating real-time data and physics/data-driven models	Predictive diagnostics, performance optimization, fault detection; complement physical sensors	Do not perform direct flow measurement; require high data quality and validation	Emerging in R&D and pilot-scale applications; focus on system diagnostics	Rasheed *et al.* [2020]; Sircar *et al.* [2021]; Mu *et al.* [2023]; Sun and Ge [2021]; Manami *et al.* [2023]

5 Use of Soft Sensors in Multiphase Measurement

Soft sensors, also known as virtual sensors or virtual flow meters (VFM), estimate difficult-to-measure variables such as multiphase flow rates from easily available process data such as temperature, pressure and level [Cote, 2017]. These methods have become increasingly relevant for hydrocarbon production systems, where accurate and cost-effective flow measurement remains a major challenge. Over time, research has evolved from classical statistical models to machine learning approaches and, more recently, hybrid and physics-guided frameworks. This section reviews the main methodological lines and practical applications.

5.1 Classical Statistical Models

The early developments in soft sensing were based on statistical and regression techniques. Methods such as principal component analysis (PCA) and partial least squares (PLS) were widely used to reduce dimensionality [Kourti and MacGregor, 1995; Joe Qin, 2003; Wold *et al*., 2001], identify correlations among process variables, and build predictive models. These approaches offered transparency and interpretability [Wise and Gallagher, 1996; Jackson, 2005], which facilitated their adoption in industrial practice. However, they generally required strong linearity assumptions and were sensitive to noise and outliers, limiting their performance under the nonlinear and highly dynamic conditions typical of multiphase flows [Adhi, 2018]. Statistical models remain valuable for preliminary analysis and feature selection, but they often lack the predictive accuracy needed in real-time industrial applications.

5.2 Machine Learning Methods

With the growth of computational power and data availability, machine learning (ML) became a dominant field of research. Artificial neural networks (ANN) were among the first algorithms applied to multiphase flow estimation [Sheppard and Russell, 1993; Yan *et al*., 2018], and they continue to play a central role due to their ability to capture nonlinear dynamics. Later, support vector machines (SVM) [Vapnik, 1998], random forests (RF) [Breiman, 2001], and ensemble methods were introduced, offering strong predictive performance with relatively small datasets.

More recently, deep learning architectures such as convolutional neural networks (CNN) and long-short-term memory networks (LSTM) have been applied to extract temporal and spatial features from multiphase signals [LeCun *et al*., 2015; Goodfellow *et al*., 2016; Manami *et al*., 2023]. Although these models achieve high predictive accuracy, they act as ”black boxes” and require extensive, high-quality datasets, making generalization outside of training conditions a persistent challenge.

ML methods currently achieve state-of-the-art performance in nonlinear estimation tasks, but the issues of interpretability and data dependency remain significant barriers for industrial deployment.

5.3 Hybrid and Physics-Guided Approaches

To overcome the limitations of purely data-driven or purely physics-based methods, hybrid approaches have emerged. These combine physical flow models with machine learning techniques to ensure that predictions remain accurate and physically consistent [Zhang *et al*., 2023]. Examples include physics-guided neural networks (PGNN), in which physical constraints are embedded in the training process, and data fusion strategies that combine sensor measurements with AI models to enhance robustness [Ma *et al*., 2024].

Such methods have shown improved generalization across varying operational conditions and offer a compromise between interpretability and predictive power. This trend reflects a broader shift in the literature toward *hybrid digital twin architectures*, where soft sensors play a critical role in linking physics-informed models with real-time operational data.

5.4 Industrial Applications of Soft Sensors

Soft sensors have been applied across multiple use cases in multiphase flow measurement:

- **Flow regime identification:** ANNs combined with ultrasonic or conductance sensors have been used to classify flow patterns and estimate gas volume fractions [Figueiredo *et al*., 2016; Fan and Yan, 2014].
- **Volumetric flow estimation:** Differential pressure devices integrated with soft computing models (e.g., BP-ANNs, SVMs) improve wet gas and two-phase flow measurement [Xu *et al*., 2011; Zheng *et al*., 2008].
- **Sensor fusion:** Data-driven fusion of signals from capacitive, electrostatic, and turbine meters enhances reliability and provides confidence intervals for predictions [Barbariol *et al*., 2020; Wang *et al*., 2014].
- **Coriolis-based measurement:** ANNs and correction models integrated with Coriolis flowmeters have improved mass flow accuracy in gas-liquid systems [Liu *et al*., 2001; Mattar *et al*., 2006; Henry *et al*., 2006; Green *et al*., 2008].
- **Three-phase flow:** ANNs and fuzzy inference systems have been applied to estimate oil, water, and gas flow rates using pressure and conductance data [Bahrami *et al*., 2019; Bhatt, 2002].

Recent studies emphasize the potential of combining soft sensors with anomaly detection [Barbariol, 2023], genetic algorithms [Fadaei *et al*., 2021], and ensemble learning methods [Cao *et al*., 2022], confirming their industrial relevance for multiphase flow monitoring and production optimization.

In summary, the literature on soft sensors for multiphase measurement shows a clear evolution: from transparent but limited statistical models to highly accurate but opaque machine learning approaches, and finally toward hybrid frameworks that balance accuracy with physical interpretability. Industrial applications confirm their value for tasks ranging from flow regime identification to predictive maintenance. However, challenges remain with respect to data quality, robustness between operating conditions, and the scalability of these solutions in real production environments.

To synthesize the main findings, **Table 5** provides a comparative overview of classical statistical models, machine learning methods, and hybrid physics-guided approaches applied to soft sensing in multiphase flow measurement. The table highlights their representative techniques, strengths, limitations, and industrial relevance, thereby reinforcing the critical perspective discussed throughout this section. This comparison illustrates the methodological evolution from transparent but limited models, to highly accurate but opaque ML algorithms, and finally to hybrid solutions that seek a balance between accuracy and physical interpretability.

Table 5. Comparison of approaches for soft sensing in multiphase measurement.

Aspect	**Classical Statistical Models**	**Machine Learning Methods**	**Hybrid / Physics-Guided Approaches**
Representative Techniques	PCA, PLS, Multivariate regression	ANN, SVM, RF, CNN, LSTM	PGNN, Data fusion, Physics-informed ML
Strengths	Transparent and interpretable; useful for variable selection and preliminary analysis	High accuracy for nonlinear problems; strong pattern recognition capabilities	Combines accuracy of ML with physical consistency; improved generalization across conditions
Limitations	Assumes linearity; sensitive to noise/outliers; low accuracy in dynamic nonlinear flows	Black-box nature; requires large, high-quality datasets; limited extrapolation beyond training data	Higher complexity; still under development; may require domain expertise and high computational cost
Industrial Relevance	Early adoption in process monitoring; still used for diagnostics and validation	Widely applied for flow regime identification and flow rate estimation; basis for many VFM	Increasingly adopted in advanced monitoring and digital twin frameworks

6 Digital Twins in the Hydrocarbon Industry

The oil and gas sector has increasingly embraced *digital twin* (DT) technologies as a means to integrate real-time data, computational models, and predictive analytics into decision making. This section reviews methodological contributions from the academic literature and reported industrial applications, providing a clearer distinction between conceptual frameworks and field implementations.

6.1 Methodological Proposals in the Literature

Digital twins were originally conceptualized as a virtual replica of physical assets, integrating physical and virtual entities through continuous data exchange [Grieves, 2015; Tao *et al*., 2019]. In oil and gas production, DT extends beyond 3D representations to encompass complex workflows, integrating IoT, cloud platforms, and simulation tools in multiple business domains [Shen *et al*., 2021]. The architecture typically includes the following.

- A **physical layer**, built by integrating information technologies, virtual reality, and IoT-based infrastructures.
- A **data and transmission layer**, relying on cloud storage and exchange services for scalability.
- A **virtual layer**, incorporating simulation, AI, and predictive models.

Methodological studies emphasize the value of DTs in predictive maintenance [Zhong *et al*., 2023], flow assurance, and integrity management. Different modeling approaches have been proposed:

- **Analytical models**, useful in early developments but limited under modern DT paradigms.
- **Timoshenko beam models**, applied to Coriolis meters, allowing a detailed study of flow tube deformation and shear effects [Mole *et al*., 2008].
- **3D finite element models**, offering high-fidelity coupling of fluid and solid elements, though computationally expensive [Mole *et al*., 2008].

Recent reviews highlight challenges in data quality, interoperability, and computational demands, as well as enablers such as cloud computing and hybrid modeling strategies [Rasheed *et al*., 2020; Fuller *et al*., 2020; Jones *et al*., 2020]. Hybrid frameworks, where DTs integrate data-based and physics-based approaches, are gaining prominence in the context of multiphase measurement [Ma *et al*., 2024; Manami *et al*., 2023].

6.2 Reported Industrial Applications

Several industrial applications of DTs in hydrocarbons illustrate their potential and limitations.

Exploration and Production: Cenovus Energy and CNOOC deployed one of the first DTs in the South China Sea (Liwan field), where the system simulated dynamic multiphase flows in wells, pipelines, and mud traps. This collaborative platform supported flow assurance, leak detection, and reservoir optimization by integrating field measurements with dynamic models [Zhou *et al*., 2023]. Subsea wet gas flow meters (WGFMs) initially provided real-time data, but performance degradation prompted the integration of DT-based calculations to maintain operational reliability [Zhou *et al*., 2023].

Predictive Maintenance: Digital twins have been applied to develop predictive maintenance workflows in sectors such as energy, aerospace, and shipbuilding, with increasing penetration in oil and gas [Zhong *et al*., 2023]. These approaches enable anomaly detection, event prediction, and optimized intervention strategies.

Multiphase Metering and Coriolis Applications: DTs are increasingly coupled with multiphase flow meters. For Coriolis meters, DT models incorporate variables such as density, mass flow, temperature, and damping to diagnose performance [Emerson Micro Motion, 2019]. Three levels of modeling are possible: analytical, beam element, and full finite element. Comparative studies show that cloud-based FEM approaches enable higher accuracy but require more computational power, whereas beam models provide faster approximations [Mole *et al*., 2008]. Additional integration of pressure, water cut, pipe wall thickness, and corrosion sensors has been proposed to extend Coriolis meters to reliable multiphase devices based on DT [Mahalingam and Arsalan, 2020; Edwards, 2019].

Methodological contributions emphasize DT architectures, modeling strategies, and hybrid approaches for multiphase measurement, while industrial applications demonstrate the tangible benefits of DTs for production optimization, predictive maintenance, and flow assurance. This separation clarifies the progression from research to practice and strengthens the response to RQ3, underscoring that while the potential of digital twins is widely acknowledged, successful deployment requires balancing methodological rigor with the practical constraints of industrial environments [Tao *et al.*, 2019; Rasheed *et al.*, 2020].

To provide a clearer overview of academic and industrial perspectives, **Table 6** summarizes the main methodological approaches to digital twins and their reported applications in the hydrocarbon industry. The comparison highlights the distinction between analytical and computational models, hybrid strategies, and practical implementations such as predictive maintenance, reservoir optimization, and multiphase metering.

As shown in the table, the methodological proposals emphasize modeling accuracy, computational efficiency, and integration with machine learning, while industrial cases illustrate how DTs have been applied to address operational challenges such as flow assurance, equipment monitoring, and production optimization. This comparative view reinforces the critical insight that the success of digital twins depends not only on technological sophistication but also on their adaptability to the specific constraints of oil and gas environments.

6.3 Implications for Research Questions (RQ1–RQ3)

The synthesis of the reviewed literature allows a critical reflection on the three guiding research questions.

For **RQ1**, concerning traditional multiphase measurement technologies, the evolution from Venturi and turbine meters to Coriolis-based systems has demonstrated significant improvements in accuracy and robustness. However, their high costs and limitations under real operational conditions remain persistent barriers [Falcone *et al.*, 2009]. This indicates that, although hardware-based MPFMs are mature, their applicability in complex production environments continues to face unresolved challenges.

For **RQ2**, regarding soft sensors and data-driven models, the literature highlights how statistical approaches such as PCA and PLS [Kadlec *et al.*, 2009] have provided transparency and interpretability, while machine learning and deep learning methods offer superior predictive capacity in non-linear environments [Goodfellow *et al.*, 2016; Ma *et al.*, 2024]. The main implication is the trade-off between interpretability and accuracy, which suggests that hybrid and physics-guided approaches may be the most promising direction for future applications.

For **RQ3**, on the role of digital twins in the hydrocarbon industry, evidence suggests that their successful deployment requires a clear distinction between methodological frameworks and industrial implementations. Conceptual studies emphasize the integration of IoT, real-time monitoring, and predictive analytics, while industrial applications report challenges in data availability and model validation [Rasheed *et al.*, 2020; Tao *et al.*, 2019]. This highlights the need for frameworks that combine methodological rigor with scalability and adaptability in operational contexts.

In general, the implications of the three research questions converge toward the idea that integrating data-driven methods, soft sensors, and digital twin paradigms can help overcome many of the limitations of current MPFM technologies. However, achieving this integration requires careful consideration of accuracy, interpretability, and industrial feasibility, which remain open research and engineering challenges. These insights directly inform the future research directions discussed in the next section.

6.4 Future Research Directions

Based on the analysis of the reviewed literature, several opportunities for future research in multiphase flow measurement can be identified. Among the most promising lines of development are sensor fusion, hybrid modeling, and the integration of soft computing and digital twin technologies.

Sensor Fusion and Instrument Integration: Future systems are expected to combine multiple sensing principles, such as conductance, capacitance, ultrasonic, positive displacement, and Venturi sensors, to increase accuracy and measurement range. Sensor fusion can expand the operational envelope of traditional flow instruments and enable robust data acquisition under complex multiphase flow conditions [Yan *et al.*, 2018].

Soft Computing and Data-Driven Modeling: Significant progress is anticipated in the application of soft computing and machine learning techniques for multiphase flow measurement. Semi-supervised and incremental learning approaches [Yi *et al.*, 2020; Yu and Zhao, 2019] can address the challenges of limited labeled data and model retraining in dynamic industrial environments. Similarly, ensemble and broad convolutional neural network (BCNN) structures offer promising results for online adaptation and small-sample problems.

Integration with Digital Twins: Digital twins will not replace flow meters but will complement them by enabling diagnostic, predictive, and optimization capabilities. They can provide continuous virtual monitoring, allowing early detection of anomalies and improved maintenance strategies. Research should focus on coupling high-fidelity models (e.g., full 3D finite-element approaches) with real-time measurements to strengthen the link between physical and virtual representations [Mahalingam and Arsalan, 2020; Werneck *et al.*, 2021].

Hybrid and Physics-Guided Approaches: The combination of data-driven and physics-based modeling remains a key research frontier. Hybrid models can exploit the interpretability of physical laws and the adaptability of AI methods, improving predictive accuracy while maintaining robustness. Future studies are encouraged to develop generalized frameworks that integrate neural networks, fuzzy logic, support vector machines, and genetic algorithms [Bahaloo *et al.*, 2023].

Table 6. Comparative overview of Digital Twin approaches and applications in the hydrocarbon industry.

Category	Methodology	Examples
	Modeling Approaches	
Analytical models	Simplified mathematical formulations of flow and equipment behavior. Useful in early developments but limited under modern DT paradigms.	Early Coriolis meter models [Mole *et al*., 2008].
Timoshenko beam models	Structural modeling of Coriolis flow tubes, including shear deformation and actuator mass effects. Faster but less detailed than FEM.	Applied in multiphase flow metering [Mole *et al*., 2008].
3D Finite Element Models (FEM)	High-fidelity coupling of fluid and solid dynamics. Computationally expensive but accurate for complex flow profiles.	Coriolis meter digital twin with FEM on cloud platforms [Mole *et al*., 2008].
Hybrid DT approaches	Integration of physics-based models and machine learning for multiphase measurement. Enhance robustness under variable conditions.	Hybrid DTs for reservoir and flow assurance [Ma *et al*., 2024; Manami *et al*., 2023].
Physics-informed DTs	Combine governing physical equations with neural networks to ensure consistency between simulations and real-world behavior. Enhance interpretability and generalization.	Physically Guided Neural Networks (PGNN) for two-phase flow [Li and Bai, 2023].
Real-time operational twins	DTs integrated with IoT and edge computing for continuous monitoring, adaptive control, and decision support.	Offshore production optimization and smart asset management [Rasheed *et al*., 2020].
	Industrial Applications	
Exploration and production DTs	Dynamic models simulating multiphase flows, leak detection, and reservoir optimization.	Liwan field project by Cenovus Energy and CNOOC [Zhou *et al*., 2023].
Predictive maintenance	DT-based anomaly detection, event prediction, and intervention optimization.	Applications in energy, aerospace, shipbuilding, extended to oil & gas [Zhong *et al*., 2023].
Multiphase metering applications	DT-enhanced multiphase flowmeters. Integration of density, mass flow, temperature, damping, and additional sensors.	Coriolis meter DT models [Mahalingam and Arsalan, 2020; Edwards, 2019; Emerson Micro Motion, 2019].

Overall, the evolution of multiphase flow measurement will depend on multidisciplinary advances in sensing technologies, artificial intelligence, and computational modeling. The convergence of these areas is expected to lead to the next generation of intelligent, adaptive, and cost-effective metering systems for the hydrocarbon industry.

7 Conclusion

This systematic review analyzed the evolution of multiphase flow measurement technologies and their convergence with data-driven models, soft sensors, and digital twins. The study identified how these three areas complement each other and collectively contribute to advancing metering reliability, adaptability, and cost efficiency in the hydrocarbon industry.

Traditional multiphase flow meters, while technologically mature, remain limited by cost, calibration complexity, and operational uncertainty in harsh production environments. Data-driven soft sensors have emerged as a valuable complement, offering virtual estimation capabilities that enhance monitoring and reduce dependence on physical instrumentation. Meanwhile, digital twins extend these capabilities toward process-level integration, enabling predictive diagnostics, optimization, and decision support rather than direct measurement.

The synthesis of evidence across RQ1–RQ3 demonstrates that the future of multiphase flow measurement lies not in replacing hardware-based systems but in integrating them with intelligent modeling approaches. The evolution toward hybrid, physics-informed, and data-driven frameworks represents a paradigm shift from measuring flow variables to understanding and predicting flow behavior.

Overall, this review underscores the growing role of artificial intelligence and digitalization in transforming industrial measurement practices. Continued collaboration among experts in metrology, computation, and process engineering will be essential to achieve scalable, interpretable, and reliable solutions for next-generation multiphase metering.

Declarations

Authors' Contributions

LYCC conceptualization, original draft writing, SRP contributed in supervision, writing-review & editing, CEGS made contributions in conceptualization, supervision and writing – review & editing. All authors read and approved the final manuscript. All of these authors have made substantial contributions to the final manuscript and have approved this submission.

Competing interests

The authors declare that they have no competing interests.

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