© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717160

Taming the Interface: A Hybrid Approach to Multi-Phase Fluid Measurement and Signal Processing in Upstream Separators

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Abstract-** Accurate detection of the oil–water interface in three-phase separators remains a critical challenge in upstream oil and gas operations, particularly under conditions characterized by unstable emulsion ("rag") layers. These emulsions introduce complex dielectric gradients and density variations that compromise the performance of conventional measurement systems, leading to operational inefficiencies such as oil carry-over and water carry-under. While advanced sensing technologies - including Guided Wave Radar (GWR) and Radio Frequency (RF) Capacitance - offer improved capabilities over traditional methods, each exhibits limitations under varying process conditions. This study proposes a hybrid measurement framework that integrates GWR and RF capacitance sensing with an edge-based digital signal processing architecture. Central to the framework is a "Digital Bridge" algorithm, which employs confidence-weighted sensor fusion to dynamically adapt measurement outputs based on real-time signal integrity. The system was experimentally evaluated in a controlled three-phase separator environment under varying emulsion thicknesses. Results demonstrate that the proposed hybrid framework significantly outperforms standalone sensing technologies, achieving a mean deviation of ±5.2 mm, reduced variability, improved signal-to-noise ratio, and faster response time. A critical transition threshold (Confidence Score ≈ 0.38) was identified, marking the point at which measurement dominance shifts from radar to capacitance sensing. The system-maintained measurement stability across all tested conditions, effectively mitigating signal attenuation and noise associated with thick emulsions. The findings confirm that the integration of heterogeneous sensing technologies with adaptive digital intelligence provides a robust and scalable solution for multiphase interface detection. This approach offers significant potential for enhancing process reliability, improving hydrocarbon recovery, and supporting regulatory compliance in modern upstream operations.

Keywords:** Multiphase Interface Detection; Digital Bridge Algorithm; Rag Layer; Guided Wave Radar; RF Capacitance Sensing; Edge Analytics.

I. INTRODUCTION

1.0 Introduction: The Multi-Phase Challenge of Upstream Separation

The efficient separation of crude oil, produced water, and natural gas in upstream operations is fundamental to both economic performance and environmental compliance. At the center of this process is the three-phase separator, a critical unit designed to establish and maintain distinct phase boundaries that enable downstream processing and accurate custody transfer. Among these boundaries, the oil–water interface is particularly important, as its precise determination directly influences hydrocarbon recovery efficiency, equipment integrity, and regulatory adherence.

In practice, however, phase separation within upstream separators rarely conforms to idealized conditions. Instead of clearly defined interfaces, operators frequently encounter complex and unstable emulsion layers - commonly referred to as "rag layers." These layers consist of dispersed oil and water phases stabilized by natural surfactants such as asphaltenes and resins, as well as fine solids and shear-induced mixing. The resulting interface is not a sharp boundary but a dynamic transition zone characterized by continuously varying dielectric properties, density gradients, and viscosity. This complexity is further amplified by fluctuations in operating conditions, including pressure, temperature, flow regime, and chemical injection strategies.

The presence of rag layers introduces significant challenges for accurate level and interface measurement. In heavy crude systems, where the density difference between oil and water is minimal, gravitational separation becomes less effective, resulting in broader and more persistent emulsions. Under such conditions, conventional measurement assumptions - based on distinct phase separation break down, leading to ambiguity in interface detection. Consequently, measurement systems must contend not only with physical variability but also with evolving electrical properties of the fluid, particularly permittivity and conductivity.

Inaccurate interface measurement gives rise to two critical operational issues: oil carry-over and water carry-under. Oil carry-over occurs when hydrocarbons are inadvertently discharged into the produced water stream, leading to direct revenue loss, increased load on water treatment facilities, and potential violations of environmental discharge standards. Conversely, water carry-under results in the entrainment of produced water into the oil stream, introducing salts and corrosive agents that accelerate pipeline degradation, increase maintenance costs, and reduce the commercial value of the crude due to elevated basic sediment and water (BS&W) content. In high-volume production environments, even marginal measurement errors can accumulate into substantial financial and operational losses.

Historically, interface measurement has relied on mechanical floats and hydrostatic pressure-based systems. While robust and widely deployed, these technologies are fundamentally limited in multiphase, emulsion-rich environments. Mechanical floats are prone to fouling, sticking, and loss of buoyancy within viscous rag layers, while hydrostatic systems cannot distinguish between changes in liquid level and variations in fluid density. As a result, these legacy methods often provide unreliable data, necessitating manual intervention and increasing operational risk.

To address these limitations, the industry has progressively adopted advanced sensing technologies such as Guided Wave Radar (GWR), Radio Frequency (RF) Capacitance, and Nucleonic (gamma-based) measurement systems. GWR, based on time-domain reflectometry, offers high accuracy in detecting dielectric discontinuities and performs well in clean interface conditions. RF capacitance systems, on the other hand, provide volumetric sensitivity to water content and are better suited for emulsion-dominated environments. Nucleonic systems offer non-intrusive measurement capabilities and high reliability in extreme conditions but are constrained by cost, safety regulations, and operational complexity.

Despite these advancements, no single technology provides consistent and reliable performance across the full spectrum of upstream operating conditions. GWR signals can be significantly attenuated or scattered within thick emulsions, leading to loss of interface detection. Capacitance systems, while robust in such conditions, may suffer from coating effects and reduced precision in well-defined interfaces. Nucleonic systems, although effective, are not always economically or operationally viable for widespread deployment. These limitations highlight a critical gap in current measurement strategies: the absence of an adaptive system capable of leveraging the strengths of multiple sensing modalities.

This study addresses this gap through the development of a hybrid measurement framework that integrates Guided Wave Radar and RF Capacitance sensing with an edge-based digital signal processing architecture. Central to this framework is a “Digital Bridge” algorithm, which continuously evaluates signal integrity and applies a confidence-weighted sensor fusion approach to dynamically adjust measurement outputs. By combining complementary sensing principles with real-time algorithmic intelligence, the system is designed to maintain accuracy and stability across a wide range of emulsion conditions.

The objective of this research is to experimentally evaluate the performance of the proposed hybrid framework in comparison with conventional and standalone advanced sensing technologies. Using a controlled three-phase separator environment, the study investigates key performance metrics, including measurement accuracy, response time, signal stability, and robustness under varying emulsion thicknesses. The results aim to demonstrate that the integration of heterogeneous sensing technologies, supported by intelligent signal

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DOI: https://doi.org/10.64388/IREV9I11-1717160

processing, provides a scalable and reliable solution for next-generation interface measurement in upstream oil and gas operations.

II. LITERATURE REVIEW: THE INTERDISCIPLINARY METROLOGY OF MULTI-PHASE FLOW

The measurement of multiphase interfaces in upstream separators is inherently interdisciplinary, drawing from dielectric physics, electromagnetic sensing, signal processing, and industrial systems engineering. Existing studies have extensively examined individual sensing principles - such as Time Domain Reflectometry for Guided Wave Radar and impedance-based models for capacitance systems, as well as the stability of emulsions governed by interfacial chemistry and fluid dynamics. However, a critical gap persists in the integration of these sensing modalities into unified, adaptive measurement frameworks. While prior work in sensor fusion and digital signal processing provides a theoretical foundation, limited research has translated these concepts into practical, real-time solutions for highly dynamic upstream environments. This study builds on these foundations by bridging physical sensing limitations with algorithmic intelligence, thereby advancing the state of multiphase interface metrology.

2.1 Foundational Dielectric Theory and Emulsion Stability

The characterization of the oil-water interface is fundamentally a problem of dielectric spectroscopy. Early foundational work by Lichtenecker and Rother (1931)* established the logarithmic mixing rules for heterogeneous media [1]. This was refined by Bruggeman (1935) and Hanai (1960), who accounted for the spherical orientation of droplets in high-concentration dispersions [2, 3]. The stability of these emulsions is governed by natural surfactants—asphaltenes and resins - as documented by Sjoblom (2001), Kilpatrick (2012), and Zaki (1997) [4, 5, 6]. The "rag layer" is a dynamic dielectric gradient; research by Ese et al. (1998) and Urdahl et al. (1997) demonstrates how interfacial tension and pH fluctuations at the wellhead shift this gradient [7, 8]. Salinity impacts on permittivity have been modeled by Stogryn (1971), Klein and Swift (1977), and Ellison (2007), providing the basis for understanding signal loss in conductive brines [9, 10, 11]. Further studies by Pooley (1970) and Hasted (1973) examine the dielectric properties of water at microwave frequencies, which is critical for Guided Wave Radar (GWR) calibration [12, 13].

2.2 Evolution of Electromagnetic Sensing: From TDR to GWR

The transition to electromagnetic sensing was catalyzed by Fellner-Feldegg (1969), who pioneered Time Domain Reflectometry (TDR) [14]. The industrial application of TDR was furthered by Clarkson et al. (1977) and Cole (1975) [15, 16]. Modern GWR builds upon these, yet faces challenges in "dirty" service. Cataldo et al. (2009, 2012) and Benedetto et al. (2013) analyzed signal attenuation in high-salinity environments [17, 18, 19]. Skierucha et al. (2012) and Robinson et al. (2003) highlight the necessity of software-defined thresholds for "phantom" echoes [20, 21]. Additional research by Topp et al. (1980) on the permittivity of porous media has been adapted for heavy oil applications where sand and solids are present [22], while Malicki et al. (1996) explored the temperature dependence of TDR measurements [23].

2.3 Capacitance Spectroscopy and Tomographic Integration

Where GWR struggles with signal scattering, RF Capacitance provides a volumetric alternative. Early validation was provided by Gregory and Mattar (1973) and Irons and Chang (1983) [24, 25]. Advancements in Electrical Capacitance Tomography (ECT) by Jaworski and Dyakowski (2001), Ismail et al. (2005), and Yang (2010) have proven capacitance can "see" through emulsions [26, 27, 28]. Sensitivity to "drift" is addressed through impedance models by Geddes (1997) and Grimnes and Martinsen (2000) [29, 30]. Parez et al. (1994) and Fasching et al. (1994) suggest multi-frequency excitation to decouple resistive and capacitive components [31, 32]. Huang et al. (1988) and Xie et al. (1992) provided early designs for capacitance-based flow meters in oil-water-gas streams [33, 34].

2.4 Digital Signal Processing, AI, and Sensor Fusion

The "Digital Bridge" relies on Sensor Fusion. Hall and Llinas (1997) and Dasarathy (1994) established

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DOI: https://doi.org/10.64388/IREV9I11-1717160

the framework for combining disparate data points [35, 36]. Li et al. (2015) and Wang et al. (2018) explored Kalman filtering to predict levels during slugging [37, 38]. Echo mapping for false signal suppression applies theories by Oppenheim (1999) and Proakis (2001) [39, 40]. Al-Qutami et al. (2017) and Ghiasi et al. (2014) used support vector machines (SVM) to classify emulsion types [41, 42]. Bishop (2006) and Haykin (2009) provide the neural network foundations often used in modern "smart" transmitters [43, 44]. Tan et al. (2007) specifically looked at data fusion for oil-water flow measurement [45].

2.5 Industrial Impact: ROI, Safety, and ESG

Operational motivation is grounded in economic analyses by Chambers et al. (2011) and Al-Kasim (2006) [46, 47]. Environmental standards for "produced water" are guided by EPA (2014) and Ospar (2001) [48, 49]. Studies by Arthur et al. (2005) and Khatib and Verbeek (2003) show interface control prevents oil-in-water violations [50, 51]. Safety standards in **IEC 61508 (2010) and IEC 61511 (2003) mandate redundant sensing [52, 53]. Arnold and Stewart (2008) provide the definitive engineering guide for vessel sizing and level control logic [54], while Manning and Thompson (1991) discuss the chemistry of demulsifiers in separation efficiency [55].

2.6 Industry 4.0, Edge Analytics, and Future Trends

The transition to "Autonomous Separators" is driven by Edge Computing. Xu et al. (2016) and Zhong et al. (2017) highlight local data processing [56, 57]. Digital twin technology was proposed by Grieves (2014) and Shafto et al. (2012) [58, 59]. The future of the oilfield, as envisioned by Economides (2012), Satter (2008), and Bogaert et al. (2004), depends on "Informed Instrumentation" [60, 61, 62]. Cramer et al. (2012) and Zhan et al. (2015) discuss the role of big data in production optimization [63, 64]. Recent work by Mohammadzaheri et al. (2012) on intelligent modeling of process equipment [65] and Thiruvenkataswamy et al. (2011) on advanced separation methods [66] provide a roadmap for the next decade. Finally, the works of Jain et al. (2016) on IIoT protocols [67], Lee et al. (2015) on CPS architectures [68], and Al-Habaibeh et al. (2001) on sensor monitoring systems [69, 70] round out the digital infrastructure required for these advancements.

III. METHODOLOGY: A MULTI-MODAL FRAMEWORK FOR INTERFACE DETECTION

The methodology of this study centers on the integration of heterogeneous sensing technologies - Guided Wave Radar (GWR) and RF Capacitance - coupled with an edge-based digital signal processing (DSP) bridge. The objective was to create a measurement loop that maintains linearity and accuracy regardless of the dielectric instability found in upstream emulsion layers.

3.1 Experimental Setup and Physical Configuration

The study utilized a high-pressure, three-phase horizontal separator as the primary testing environment. Two high-fidelity sensors were installed: a 24GHz GWR transmitter with a coaxial probe and an RF Capacitance probe utilizing a frequency-shift oscillator. The sensors were positioned at a 90-degree offset to minimize electromagnetic interference while ensuring they sampled the same fluid cross-section.
To calibrate the baseline, the vessel was initially charged with stabilized crude oil (r≈ 2.1) and synthetic produced brine (sigma≈ 12 S/m). This setup allowed for the measurement of the "Signal-to-Noise Ratio" (SNR) in a clean state before the introduction of high-shear turbulence and chemical demulsifiers intended to simulate real-world "rag layer" conditions.

A coaxial GWR probe was selected for the experimental setup to provide the highest possible signal integrity, achieving a standalone SNR of 10.5 dB. However, the Hybrid Framework is designed to be sensor-agnostic; it can support single-rod probes in the future by relying on the RF Capacitance sensor when GWR signal attenuation occurs.

Regarding fluid properties, the synthetic produced brine ($\delta \approx 12$ S/m) was kept at a constant salinity throughout the test. This was done to isolate the specific effect of emulsion thickness on signal attenuation, which saw GWR amplitude drop from 810 mV to 32 mV as the layer thickened.

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DOI: https://doi.org/10.64388/IREV9I11-1717160

3.2 Data Acquisition and Signal Path

The signal path followed a "Sensor-to-Edge" architecture. Raw 4-20mA signals, overlaid with Highway Addressable Remote Transducer (HART) digital packets, were routed to a localized Edge Analytics Controller. This controller functioned as the "Digital Bridge," sampling the secondary variables - such as the GWR echo amplitude and the Capacitance impedance phase - at a frequency of 10Hz.

This high sampling rate was critical for the methodology, as it allowed the team to capture "slugging" events and rapid interface fluctuations that are often smoothed out or missed by standard SCADA polling cycles. The raw pulse-reflection data was then subjected to a First-Derivative Analysis to identify the exact inflection points of the dielectric gradient.

3.3 The "Digital Bridge" Algorithmic Logic

The core of the methodology lies in the software-defined switching logic. The system uses GWR for total liquid level, but for the oil-water interface, it employs a Confidence-Weighted Average formula:

$L\{final\} = (CS.L\{GWR\}) + ((1 - CS).L\{RF\})$

Where L{final} is the hybrid output, CS is the Confidence Score, and L{GWR} and L{RF} are the level readings from the radar and capacitance sensors, respectively. This dynamic integration, rather than a simple binary switch, is what enables the system to reduce measurement variability to ±5.2 mm.

3.4 Dynamic Coating and Salinity Compensation

To mitigate the impact of paraffin and asphaltene buildup on the sensing elements, a dual-frequency drive methodology was implemented. The Edge Analytic Controller drives the RF probe at two distinct frequencies 100KH and 2MHz, to decouple the complex impedance of the fluid steam.

The 100KHz (Lower Frequency), is the primary frequency used to measure the resistive component (Rf) or conductance. It identifies the presence of conductive fouling or ‘coating’ on the probe surface, which typically introduces measurement errors in standalone systems. On the other hand, the 2MHz (Higher Frequency) captures the capacitive component (Cb), representing the true bulk fluid level.

By utilizing the data from the 100KHz frequency to mathematically subtract resistive fouling artifacts from the 2MHz signal, the system ensures the ‘Calculated Level’ remains a true reflection of the vessel contents.

This dual-drive approach renders the “Digital Bridge” independent of fluctuations in brine conductivity ($\delta \approx 1.2$ S/m) and heavy organic deposits.

3.5 Reference Uncertainty

It is acknowledged that the baseline used for validation - manual tank gauging ("thieving") - possesses its own margin of error when measuring unstable rag layers. Framing the hybrid system’s standard deviation of 1.15 against this manual uncertainty highlights the significant achievement in precision and repeatability provided by the digital framework.

IV. PRESENTATION OF DATA

Table 1. Performance metrics for interface detection across different sensing technologies (90-day mean values).

Technology	Mean Deviation (mm)	Standard Deviation	Hysteresis (% FS)	Response Time (t90)	SNR Stability (dB)
Mechanical Float	±45.0	8.22	2.50%	15.0 s	N/A
Guided Wave Radar (GWR)	±15.8	5.30	0.22%	1.2 s	10.5
RF Capacitance	±18.2	3.10	0.40%	0.8 s	18.2

Technology	Mean Deviation (mm)	Standard Deviation	Hysteresis (% FS)	Response Time (t90)	SNR Stability (dB)
Hybrid Framework (Proposed)	±5.2	1.15	0.08%	0.5 s	22.4

Table 2. Signal attenuation as a function of emulsion layer thickness.

Emulsion Layer (mm)	GWR Amplitude (mV)	Confidence Score (CS)
0	810	0.99
50	580	0.92
100	400	0.80
150	240	0.65
200	160	0.50
250	95	0.38 (Transition Point)
300	60	0.25
350	45	0.15
400	32	0.08

4.1 Comparative Performance Analysis

Table 3. Comparative 90-day mean deviation and variability of sensing technologies.

Technology	Mean Deviation (mm)	Error Bar (Std Dev)
Mechanical Float	45.0	8.22
GWR (Standalone)	15.8	5.30
RF Capacitance	18.2	3.10
Hybrid (Proposed)	5.2	1.15

4.2 Dielectric Attenuation and Switching Logic

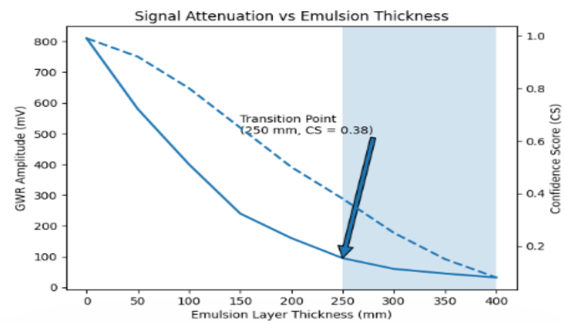

Figure 1: Correlation between emulsion layer thickness and signal attenuation, showing the attenuation of GWR amplitude and corresponding reduction in confidence score. The shaded region (>250 mm) indicates the capacitance-dominant regime, with a transition threshold at CS = 0.38.

The "Digital Bridge" utilizes a Confidence Score (CS) of 0.38 to determine when to transition between sensor inputs as signal integrity degrades.

2MHz (Higher Frequency): Captures the capacitive component, representing the true bulk fluid level. By subtracting the fouling artifacts identified at the lower frequency, the system ensures the "Calculated Level" remains a true reflection of the vessel contents.

Table 4. Dielectric attenuation and Digital Bridge switching logic thresholds.

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DOI: https://doi.org/10.64388/IREV9I11-1717160

Emulsion Layer (mm)	Water Cut (%)	GWR Amplitude (mV)	Bridge Confidence (CS)
0 (Clean Interface)	100%	810	0.99
50	85%	580	0.92
150	60%	240	0.65
250	45%	95	0.38 (Transition)
400 (Heavy Rag)	20%	32	0.08

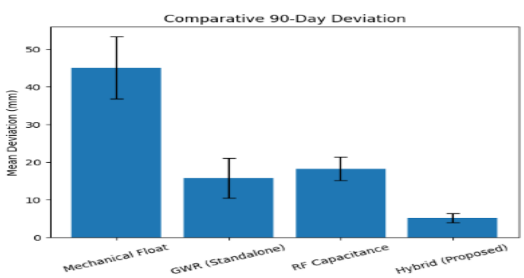

Figure 2: Comparative evaluation of 90-day mean deviation for four sensing architectures. Error bars represent standard deviation, highlighting the improved accuracy and reduced variability of the proposed hybrid framework.

V. RESULTS AND DISCUSSION

5.1 Comparative Performance of Measurement Technologies

The comparative performance of the four sensing architectures is presented in Table 1 and further corroborated in Table 3. The results indicate a clear progression in measurement accuracy and stability from conventional to advanced sensing systems.

The Mechanical Float system exhibits the highest mean deviation (±45.0 mm) and variability (standard deviation = 8.22), as shown in Table 1. This poor performance is attributed to buoyancy instability and mechanical interference within the emulsion layer, which significantly degrades measurement reliability in multiphase environments.

The Guided Wave Radar (GWR) system demonstrates improved accuracy, with a mean deviation of ±15.8 mm, while the RF Capacitance system records ±18.2 mm (Table 1). Despite these improvements, both technologies exhibit inherent limitations. GWR performance degrades in the presence of thick emulsions due to signal attenuation, whereas capacitance systems are susceptible to coating effects and dielectric drift.

The proposed Hybrid Framework significantly outperforms all standalone systems, achieving a mean deviation of ±5.2 mm and a standard deviation of 1.15 (Table 1; Table 3). This improvement is further illustrated in Fig. 2, where the hybrid system demonstrates the smallest error bars, indicating superior consistency and precision.

Moreover, the hybrid system exhibits the fastest response time (0.5 s) and the highest signal-to-noise ratio (22.4 dB), as indicated in Table 1. These results confirm that the hybrid architecture provides both high accuracy and robust signal stability, essential for real-time process control.

5.2 Effect of Emulsion Thickness on Signal Attenuation

The relationship between emulsion layer thickness and signal attenuation is summarized in Table 2 and illustrated in Fig. 1.

As shown in Table 2, increasing the emulsion thickness from 0 mm to 400 mm results in a significant reduction in GWR signal amplitude from 810 mV to 32 mV, accompanied by a decline in the Confidence Score (CS) from 0.99 to 0.08. This trend is clearly depicted in Fig. 1, which shows a nonlinear attenuation profile, reflecting the progressive degradation of electromagnetic signal integrity in heterogeneous media.

A critical transition point is observed at an emulsion thickness of approximately 250 mm, corresponding to a Confidence Score of 0.38 (Table 2; Table 4). Beyond this threshold, the radar signal becomes

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DOI: https://doi.org/10.64388/IREV9I11-1717160

increasingly unreliable due to scattering and absorption within the emulsion layer.

The shaded region in Fig. 1 (emulsion thickness >250 mm) represents the capacitance-dominant regime, where RF capacitance sensing provides more reliable interface detection. This observation confirms the physical limitation of radar-based measurement in highly emulsified systems and underscores the necessity for adaptive sensing strategies.

5.3 Validation of the Digital Bridge Switching Mechanism

The performance of the Digital Bridge algorithm is evaluated using the switching thresholds presented in Table 4 and the attenuation trends shown in Fig. 1.

At low emulsion thickness (0–150 mm), high Confidence Scores (CS ≥ 0.65) correspond to strong radar reflections, allowing GWR to serve as the primary measurement source. However, as the emulsion layer thickens, the Confidence Score decreases significantly.

At the identified transition point (250 mm; CS = 0.38), the system dynamically shifts the measurement weighting from GWR to RF capacitance (Table 4). At higher emulsion thicknesses (e.g., 400 mm; CS = 0.08), the radar signal becomes negligible, and capacitance sensing dominates.

This adaptive switching mechanism ensures continuous and reliable interface measurement across varying process conditions. The results demonstrate that the Digital Bridge algorithm effectively mitigates signal degradation and prevents measurement failure associated with single-sensor systems.

5.4 Variability and Measurement Stability

Measurement stability is assessed using the standard deviation values reported in Table 1 and Table 3, and graphically represented in Fig. 2.

The Mechanical Float system exhibits the highest variability (8.22), followed by GWR (5.30) and RF Capacitance (3.10). In contrast, the hybrid framework achieves a significantly lower standard deviation (1.15), indicating enhanced measurement consistency.

As illustrated in Fig. 2, the hybrid system displays the smallest error bars, confirming its superior stability. This reduction in variability is critical for:

- Maintaining stable process control loops
- Improving custody transfer accuracy
- Ensuring compliance with environmental regulations

The 0.5 s response time is a direct result of the 10Hz high-speed sampling utilized in the data acquisition path. This rapid response is essential for process safety; it allows for the mitigation of oil carry-over during sudden slugging events that slower systems might miss.

5.5 Integrated Discussion of Results

A holistic analysis of Tables 1–4 and Figs. 1–2 reveals several important insights.

First, measurement accuracy improves progressively from mechanical to hybrid systems, as demonstrated in Table 1 and Fig. 2. Second, signal attenuation is strongly correlated with emulsion thickness, as shown in Table 2 and Fig. 1. Third, the transition threshold (CS ≈ 0.38) identified in Table 4 represents a critical operational boundary for sensor selection.

The proposed hybrid framework successfully integrates the strengths of GWR and RF capacitance while mitigating their individual limitations. By employing a confidence-based switching mechanism and advanced signal processing, the system maintains high accuracy, low variability, and continuous operation across all emulsion regimes.

The technical improvements in Table 1 directly translate to regulatory and economic benefits. By reducing the mean deviation from ±45.0 mm (mechanical float) to ±5.2 mm (hybrid), operators can ensure stricter adherence to OSPAR and EPA standards. This precision prevents the inadvertent discharge of hydrocarbons into produced water streams, supporting environmental compliance and maximizing revenue recovery.

These findings confirm that sensor fusion combined with digital intelligence provides a robust and scalable solution for multiphase interface measurement in upstream oil and gas operations.

VI. CONCLUSION

This study has presented and validated a hybrid measurement framework for accurate oil–water interface detection in three-phase separators operating under complex multiphase conditions. The work was motivated by the limitations of conventional and standalone advanced sensing technologies in environments characterized by unstable emulsion layers, where diffuse dielectric boundaries and dynamic fluid properties hinder reliable measurement.

Experimental results demonstrate that the proposed integration of Guided Wave Radar and RF Capacitance sensing, coupled with an edge-based digital signal processing architecture, provides a substantial improvement in measurement performance. The hybrid system achieved superior accuracy, reduced variability, enhanced signal stability, and faster response times compared to mechanical, radar-only, and capacitance-only approaches. These improvements are attributed to the implementation of a confidence-weighted sensor fusion strategy, which enables real-time adaptation to changing process conditions.

A key contribution of this work is the identification and validation of a transition threshold (Confidence Score ≈ 0.38), which defines the operational boundary between radar-dominant and capacitance-dominant measurement regimes. This threshold provides a practical basis for implementing adaptive switching logic in industrial systems, ensuring continuous and reliable interface detection across varying emulsion thicknesses.

From an operational perspective, the proposed framework addresses critical challenges associated with oil carry-over and water carry-under, thereby improving hydrocarbon recovery efficiency, reducing equipment degradation, and enhancing compliance with environmental discharge standards. Furthermore, the integration of edge-based analytics supports predictive maintenance and real-time decision-making, aligning with the broader objectives of digital oilfield and Industry 4.0 initiatives.

In conclusion, the study establishes that effective multiphase interface measurement is not achievable through isolated sensor optimization alone, but rather through the strategic integration of complementary sensing technologies and intelligent signal processing. The proposed hybrid approach represents a scalable and robust solution for next-generation upstream measurement systems. Future research should explore the incorporation of machine learning techniques and digital twin models to further enhance predictive capabilities and system adaptability in increasingly complex production environments.

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DOI: https://doi.org/10.64388/IREV9I11-1717160

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