Intelligent Multimodal Sensor Multiphase Flow Meter using Machine Learning and Digital Twin Technologies

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Research Question

Can complementary sensors, machine learning and a digital twin make multiphase metering more accurate and more dependable?

117	3	9.0%	0.5 s
air–water operating points	**sensing modalities**	**water-rate MAPE after ML**	**fault detection latency**
50.8 mm horizontal loop	Acoustic • Optical • Vision	43.2% before ML	Injected acoustic-gain defect

A simulation-based framework demonstrates how feature-level sensor fusion and learned correction can address a systematic water-rate error, while an embedded digital twin monitors sensor health.

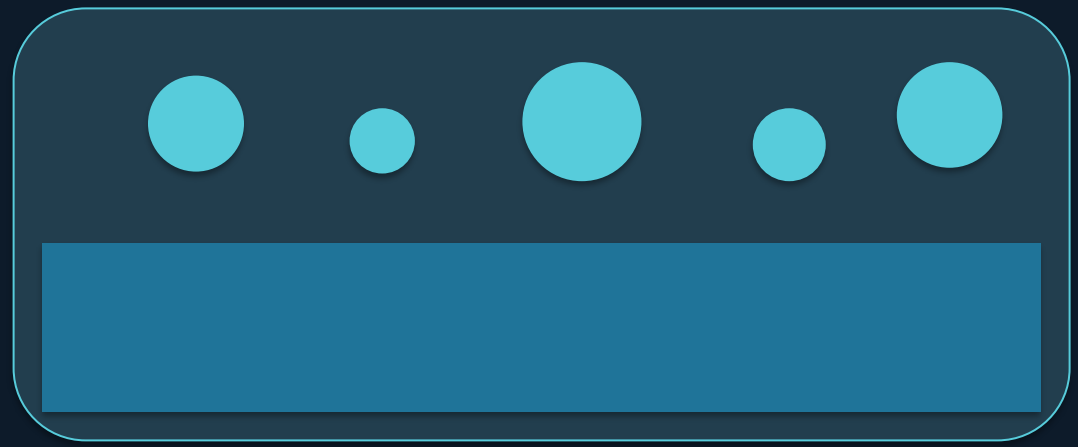
Important scope: The simulation was built on measured operating conditions: the flow conditions are experimental. results are reconstruction performance against known simulator references, not yet validated physical-meter accuracy.

Why multiphase flow measurement matters

Oil and gas production is rarely single-phase.

- Wells can produce gas, oil and water simultaneously.
- Operators need phase-specific rates for production allocation and reservoir management.
- Flow regime and changing operating conditions complicate phase-rate estimation.
- Measurement errors affect operational decisions and flow-assurance planning.

MULTIPHASE FLOW IN A PIPE



Gas phase

Liquid phase

The measurement task is to infer how much of each phase is flowing, not simply the total mixture.

Problem statement: where current approaches struggle

Conventional MPFMs

High capital and maintenance; calibration needs; some configurations use radioactive densitometry; performance can deteriorate at elevated gas volume fractions.

Virtual flow meters

Depend on model assumptions or historical training data; extrapolation beyond the training envelope remains difficult; phase partitioning, especially water rate is challenging.

Sensor reliability

A metering estimate can be compromised by sensor drift or gain changes; self-validation is not routinely embedded in the measurement pipeline.

THE SPECIFIC TECHNICAL CHALLENGE

How can the weaknesses of individual sensing channels be compensated, while maintaining phase-rate estimation and detecting sensor faults?

Research: non-radioactive acoustic + optical + vision sensing, feature-level fusion, machine learning correction and an embedded fault-detecting twin.

Reviewed Literature

Author(s) / Year	Title	Methodology	Identified Limitation/Research Gap
Yanjun et al. (2016)	Oil–air–water three-phase flow-rate measurement	Turbine flowmeter, conductance sensor and optical fibre sensor	Demonstrated under laboratory conditions; further investigation under field conditions is required to establish reliability.
Junpei et al. (2017)	Non-invasive monitoring of air–oil–water pipe flow	Ultrasonic pulse-echo and Doppler measurement	Assumes vertical phase stratification; multiple measurement lines are proposed to improve three-dimensional flow monitoring.
Heghedus et al. (2019)	Deep learning for upstream petroleum monitoring	NARX and LSTM neural networks using pressure–rate data	Requires larger datasets and further parameter optimisation to improve generalisation across wells and sensor types.

Reviewed Literature Cont'd

Author(s) / Year	Title	Methodology	Identified Limitation/Research Gap
Ünalmis (2023)	In-well multiphase flow measurement	Local and distributed acoustic sensing	Requires strategically positioned acoustic measurements and bulk velocity information to estimate phase fractions.
Wael et al. (2025)	Data-driven multiphase virtual flow metering	Ensemble machine learning and historical field data	Reported performance of approximately 85%; further improvement depends on incorporating additional field-test data.
Raka et al. (2026)	Real-time MPFM health monitoring	Sensor diagnostics, digital twin and surrogate sensors	Focuses on meter health and compensation for sensor failures; does not establish the proposed combined acoustic, optical and vision-based

Research gap and contribution

Prior work has advanced individual building blocks:

- Physical and virtual multiphase metering
- Machine-learning-based flow-regime and rate estimation
- Sensor fusion in perception-intensive applications
- Digital twins for process monitoring and fault detection

The integration gap addressed here:

One integrated metering pipeline

A non-radioactive tri-modal framework that uses the camera as a measurement channel, combines modalities at feature level, learns phase-specific corrections, and embeds sensor-residual monitoring.

Therefore, the study integrates multimodal sensing, learned phase-rate correction, regime identification, uncertainty estimates and sensor-fault detection in one framework.

Aim and specific objectives

AIM

To develop and evaluate an intelligent multimodal framework for multiphase flow metering using acoustic, optical and vision sensing, machine learning and digital twin technologies.

01 Integrate

Acoustic flow velocity, optical phase-fraction and camera-based flow-regime features.

02 Fuse

Combine modality-specific features into a unified feature representation.

03 Estimate

Infer flow regime, gas holdup, mixture velocity and phase flow rates.

04 Correct

Use machine learning to reduce s phase-rate reconstruction errors.

05 Monitor

Use a digital twin to identify sensor anomalies from residual behaviour.

Study design and operating envelope

117
steady operating points

50.8 mm
pipe internal diameter

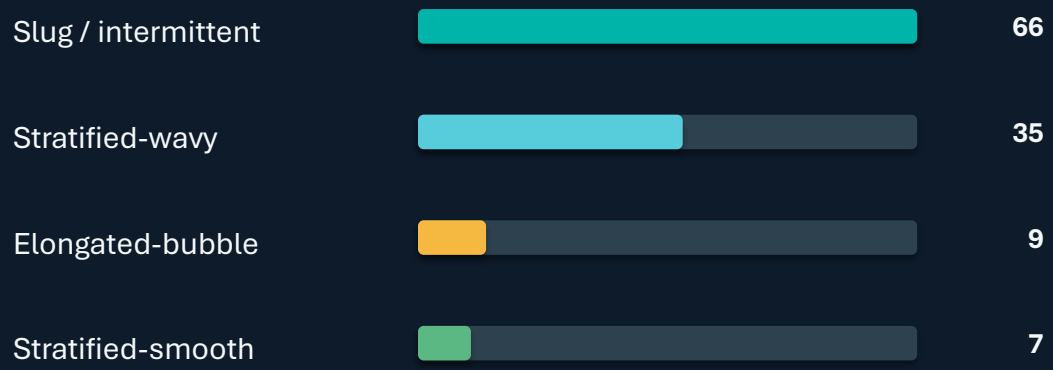
Air–water
two-phase system

4
flow regimes

SUPERFICIAL VELOCITY ENVELOPE

Air: $V_sg \approx 0.19–1.55$ m/s
Water: $V_sl \approx 0.19–0.50$ m/s

FLOW-REGIME DISTRIBUTION



The 117 operating points were derived from experimental pressure-sensor measurements; the tri-modal responses were synthesised by a physics-based forward model.

Multimodal sensing

ACOUSTIC

Four transit-time chords
Velocity-sensitive features
Bulk mixture velocity

Velocity channel

OPTICAL

Optical phase-fraction channel
Gas-volume-fraction information

Phase-fraction channel

VISION

High-speed camera images
Flow-pattern characteristics

Flow-regime channel

Each sensor contributes information that the other channels may not capture reliably.

Methodology framework: end-to-end architecture



Outputs: flow-regime class; gas holdup; bulk velocity; total, gas and water volumetric flow rates. The digital twin monitors expected-versus-observed sensor behaviour.

Feature-level fusion and machine-learning inference

9	4	5	18
acoustic features	optical features	visual features	fused features

FUSION WORKFLOW

- Standardise modality-specific features.
- Concatenate into an 18-dimensional feature vector.
- Use PCA to examine compact structure; three components explain 96.8% of variation.

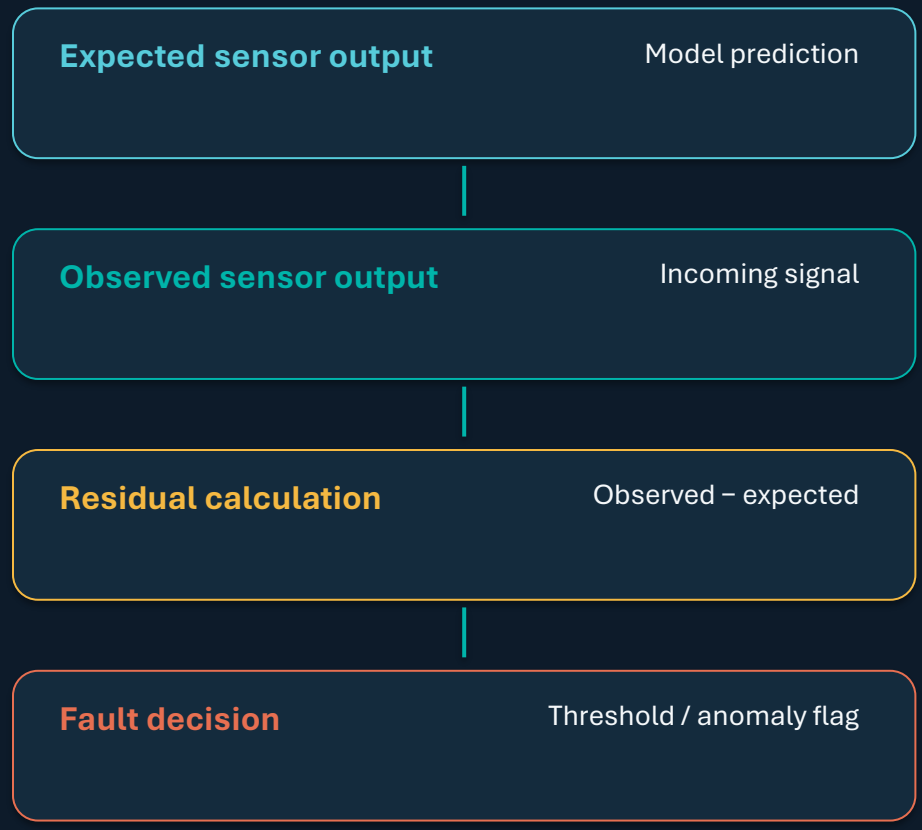
MACHINE-LEARNING TASKS

- Random Forest classifier: flow-regime identification.
- Random Forest regressors: holdup, bulk velocity and total/gas/water rates.
- Operating-point-based train/validation/test split to reduce leakage.

Digital twin: sensor-health monitoring

Principle: compare expected sensor behaviour with observed output.

- The twin maintains a model-driven expectation for each sensor.
- Residuals represent the difference between observed and expected sensor responses.
- A gain drift is injected into the acoustic channel to test fault detection.
- Detection latency and false-alarm behaviour are evaluated.



Results: reconstruction performance before and after ML

Mean absolute percentage error (MAPE), unless otherwise stated

Estimated quantity	Physics-based reconstruction	After ML
Total flow rate	5.2%	**3.0%**
Gas flow rate	3.9%	**3.5%**
Gas holdup (GVF)	1.7%	**1.0%**
Water flow rate	43.2%	**9.0%**

Main result: machine learning substantially reduces the systematic water-rate error while retaining low total-rate and gas-holdup reconstruction errors.

Key finding: diagnosing and correcting water-rate bias

BEFORE MACHINE LEARNING

43.2%

water-rate MAPE

Raw reconstruction

+43.1%

mean percentage error

Systematic over-read

AFTER MACHINE LEARNING

9.0%

water-rate MAPE

Learned correction

+4.3%

remaining mean bias

Bias greatly reduced

PHYSICAL INTERPRETATION

In dispersed and slug flow, the acoustic chordal array can confuse the slower in-situ water velocity with the faster bulk mixture velocity. This phase-slip mechanism drives a systematic overestimation of water velocity and therefore water rate.

Flow-regime classification and modality ablation

100%

reserved-test accuracy

Flow-regime classification

0.971

macro-F1

Grouped cross-validation

Full fusion outperformed every single modality on both regime classification and water-rate estimation. Vision contributed meaningful information beyond acoustic–optical sensing.

MODALITY ABLATION

	Macro-F1	Water MAPE
Acoustic only	**0.878**	**9.69%**
Optical only	**0.416**	**26.61%**
Vision only	**0.951**	**12.27%**
Acoustic + optical	**0.932**	**9.37%**
Full fusion	**0.971**	**9.08%**

Uncertainty quantification: conformal intervals

Split-conformal prediction intervals were evaluated at a 90% nominal coverage level.

88.4%

water-rate empirical coverage

Mean interval width: 35.6% of mean rate

87.4%

total-rate empirical coverage

Mean interval width: 31.1% of mean rate

Interpretation

Coverage is close to the 90% target, with modest under-coverage. Intervals communicate estimate uncertainty rather than presenting a point estimate alone.

Why it matters: metering decisions need both an estimated rate and an indication of how uncertain that estimate may be.

Digital-twin results: fault detection

0.5 s	≥3%	1%	~1.0
observed detection latency	**fault magnitude**	**false-alarm rate**	**ROC AUC**
At 5% acoustic-gain fault	Detection probability > 0.9	At evaluated operating point	At 5% gain error

DETECTION PERFORMANCE

- AUC rises from 0.83 at 1% gain error to 0.97 at 2%.
- AUC approaches 1.0 at 5% gain error.
- Detection latency falls from ~2.5 s at 1% to ~0.5 s at 5%.

INTERPRETATION

The twin reliably identifies moderate and larger injected acoustic-gain anomalies. Small faults (≤2%) remain more difficult to detect.

Fault characterisation is simulation-based and limited to acoustic gain drift; it is not yet a field fault-validation result.

What the results mean and what they do not yet prove

What this study demonstrates

A multimodel sensor architecture is feasible in simulation; fusion improves performance over individual modalities; learned correction reduces water-rate bias; the twin detects injected sensor-gain faults.

What remains unproven

Pjysical validation of the three sensing modalities in progress; Limited operating envelope and flow regimes.

KEY LIMITATIONS TO STATE CLEARLY

- Simulation uses model-generated multimodal signals; reported errors are against known simulator references.
- Air–water only; 117 steady points; churn and annular regimes are not represented.
- Minority regime classes are small; broader cross-validation and physical benchmark testing are required.

The results are promising evidence of framework capability, not a claim of a validated commercial meter.

Conclusion and Recommendation

A multimodal sensor, feature-fusion metering framework can combine complementary measurements, learned correction and sensor-health monitoring.

1 Performance

After ML: total 3.0%, gas 3.5%, water 9.0%, gas holdup 1.0% MAPE.

2 Diagnosis

Raw water-rate error was mainly systematic and associated with acoustic phase-slip.

3 Reliability

The digital twin detected injected acoustic-gain defects in ~0.5 s for the tested 5% fault.

NEXT RESEARCH STEPS

- Validate against physical rig measurements and benchmark meters.
- Expand fault types and test online adaptive correction.

Key Findings

The main contribution is the integrated architecture, and the diagnosis of a correctable water-rate error.

Q & A

Thank you

Questions?

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