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# Integrated Ultrasonic Flow Meter and Microwave Sensing Technology for Wet Gas Measurement: Development and Validation of Over-Reading Correction Models

Ishigita Lucas Shunashu[1] | Osmund Kaunde[2] | Duncan Mwakipesile[3]

[1]Department of Mechanical and Industrial Engineering, Mbeya University of Science and Technology (MUST), Mbeya, Tanzania | [2]College of Engineering and Technology, Mbeya University of Science and Technology (MUST), Mbeya, Tanzania | [3]Department of Engineering, St. Joseph University in Tanzania (SJUIT), Dar es Salaam, Tanzania

**Correspondence:** Ishigita Lucas Shunashu (ishigitalc@gmail.com)

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## ABSTRACT

Accurate wet gas flow measurement is essential for production optimisation, custody transfer, and regulatory compliance in the energy and chemical industries. Conventional ultrasonic flow meters often overestimate gas flow rates due to liquid entrainment, while microwave sensors alone struggle with phase discrimination under dynamic conditions. This study introduces a hybrid metering system, Ultrasonic Flow Meters and Microwave Sensing Measurement of Wet Gas (USMMW), that integrates transit-time ultrasonic flow measurement with microwave dielectric sensing to correct over-reading errors. Experimental data were collected from a controlled multiphase flow loop using a 2-inch pipeline equipped with an ultrasonic meter and a 2.7 GHz microwave sensor. A data-driven over-reading correction model (OR) was developed using detected liquid volume fraction (LVF) and eight dimensionless parameters derived via the Buckingham Pi theorem. Multiple regression and machine learning techniques, including multilinear regression (MLR) and random forest regression (RFR), were applied to optimise model performance. Validation results showed that the USMMW system achieved corrected gas flow rates with an average relative absolute error (RAE) of 3.02%, outperforming conventional differential pressure models. The findings demonstrate that USMMW offers a robust, non-intrusive solution for real-time wet gas metering under mist and stratified flow regimes, with potential for scalable industrial deployment.

## 1 | Introduction

Accurate measurement of wet gas flow remains a persistent and technically demanding challenge across the oil, gas, and energy sectors. Wet gas, typically defined as a gas-liquid two-phase mixture with a gas volume fraction (GVF) exceeding 90%, is commonly encountered in natural gas extraction, subsea transport systems, and petrochemical processing environments [1, 2]. Its prevalence in upstream and midstream operations makes reliable metering essential for production optimisation, custody transfer, fiscal accountability, and regulatory compliance.

However, the presence of entrained liquid droplets and condensates introduces significant metrological complexity. These liquid phases distort sensor readings, particularly in velocity-based and pressure-based meters, leading to systematic over-reading of gas flow rates. Such inaccuracies can compromise operational safety, skew production data, and result in substantial financial discrepancies [3, 4]. The challenge is further exacerbated under mist and annular flow regimes, where droplet entrainment and phase slip effects become dominant.

Traditional metering technologies such as differential pressure (DP) meters, Venturi tubes, and orifice plates have long been used due to their simplicity and robustness. Yet, under wet gas conditions, these devices exhibit pronounced over-reading errors, often requiring empirical correction models that are limited in scope and generalisability [5–7]. While multiphase flow meters

(MPFMs) offer improved accuracy by directly quantifying phase fractions, they are typically expensive, intrusive, and operationally complex, often relying on radioactive sources or bulky separation mechanisms [8].

In response, ultrasonic flow meters (USMs) have emerged as attractive alternatives for measuring gas flow due to their non-intrusive design, wide turndown ratio, and capability to provide real-time monitoring without causing additional pressure drop. However, USMs consistently overestimate gas flow in wet conditions, with reported errors ranging from 3% to 20%. This is particularly problematic under mist and annular flow regimes, where droplet entrainment distorts the acoustic signals [9, 10].

In parallel, microwave sensors have been explored for their potential to detect liquid content by exploiting the differences in dielectric properties between gas and liquid phases. These sensors can achieve high sensitivity to water content, with detection accuracies as fine as 0.1–0.2% under controlled conditions [11]. However, their performance is significantly affected by factors such as salinity, turbulence, and calibration requirements. Conventional mixture models, like Bruggeman-Hanai, often fail to capture the complexities of actual wet gas flows [8, 12].

Efforts to combine these technologies into hybrid approaches, such as integrating ultrasonic velocity measurement with microwave-based liquid detection, have shown promise for reducing overestimation and improving overall reliability. Nevertheless, many of these approaches are limited by the need for empirical correction factors, lack of adaptability across diverse flow regimes, and insufficient validation under relevant industrial conditions [13].

Recent advancements in wet gas metering have increasingly turned toward data-driven and hybrid modelling approaches that integrate physical principles with machine learning (ML) and regression techniques. Iliyasu et al. [14] demonstrated that combining ML algorithms with physical flow models significantly enhances the adaptability of wet gas meters across varying flow regimes, reducing calibration dependency and improving reliability in mist and annular conditions. Similarly, Li et al. [15] applied gradient-boosted regression to optical flow data for gas-liquid two-phase measurement, achieving high predictive accuracy ($R^2$ = 0.97) and showcasing the potential of ML-optimised regression frameworks for industrial monitoring.

Numerous single-phase metering techniques for wet gas have been studied based on ultrasonic and microwave technologies, as summarised in Table 1 below. Existing measurement systems that rely on a single sensing modality often struggle to capture the full complexity of wet gas flows. Traditional correction models, whether empirical or semi-analytical, frequently lack adaptability across varying operating conditions, particularly in low liquid loading scenarios. Furthermore, these models can be either too rigid or too expensive for scalable industrial applications [3, 16]. The nonlinear interactions among flow parameters, sensor responses, and environmental conditions necessitate a more dynamic and integrated approach.

The purpose of this research is to design, develop, and validate a hybrid Ultrasonic-Microwave (USMMW) metering system for wet gas measurement that integrates transit-time ultrasonic flow measurement with microwave dielectric sensing, supported by regression and machine learning techniques. The study specifically seeks to formulate an empirical over-reading (OR) correction model using liquid volume fraction (LVF) and dimensionless parameters derived from multiphase flow dynamics; implement and compare regression methods, including multilinear regression (MLR) and random forest regression (RFR), to optimise correction accuracy; experimentally validate the USMMW system using controlled multiphase flow loop data; and benchmark the proposed model against conventional differential pressure (DP) correction methods such as those of Murdock, Chisholm, and de Leeuw.

## 2 | Material and Methods

### 2.1 | Measurement Principle

The hybrid Ultrasonic Flow Meters and Microwave Sensing Measurement of Wet Gas (USMMW) system was developed by integrating two complementary sensing principles: (i) transit-time ultrasonic flow measurement, which determined the bulk velocity of the gas-liquid mixture, and (ii) microwave transmission line sensing, which estimated the LVF by exploiting dielectric property contrasts between phases. Together, these principles provided the necessary parameters for constructing the OR model.

#### 2.1.1 | Transit-Time Ultrasonic Flowmeter (TT-USM)

Ultrasonic transit-time the ultrasonic flowmeter (TT-USM) operates on the transit-time principle, where two transducers alternately transmit and receive ultrasonic pulses across the flow path. The difference in transit times between upstream and downstream signals is used to calculate the average flow velocity. This technique is well-established and widely adopted in industrial gas metering applications [13, 22]. To maintain academic conciseness, detailed derivations are not included here. Readers seeking foundational theory are referred to American Gas Association (AGA) Report No. 9 [22], International Organization for Standardization (ISO) TR12748 [23], and van Putten and Dsouza [13].

The core velocity function used in this study is:

$$v = \frac{L}{2\cos\theta} \cdot \left(\frac{t_2 - t_1}{t_2 t_1}\right) \tag{1}$$

Where, $L$ is the distance between transducers, $\theta$ is the inclination angle, $t_1$ and $t_2$ are the upstream and downstream transit times, respectively.

The volumetric flow rate $Q$ is then computed as:

$$Q = A \times v = A \times \frac{L}{2\cos\theta} \cdot \left(\frac{t_2 - t_1}{t_2 t_1}\right) \tag{2}$$

This function forms the basis for ultrasonic flow rate estimation in the hybrid USMMW system. In this study, the ultrasonic module provides baseline flow measurements, which are corrected using

**TABLE 1** | Existing studies on wet gas measurement using ultrasonic and microwave technologies.

| Technology | Main objective/approach | Performance highlights | Limitations | Reference |
|---|---|---|---|---|
| FLEXIM Clamp-on USM | Evaluate clamp-on USM accuracy under varying wetness and pressure | Errors <8% at high pressure; non-intrusive installation | Susceptible to turbulence-induced attenuation; reduced accuracy at low flow velocities | [17] |
| USM model | Develop flow models for stratified and annular flows using ultrasonic TOF | Errors between 3.7 and 19% depending on the void fraction model used | Accuracy declines under mist flow; sensitive to pressure fluctuations | [18] |
| Multi-path USM | Assess USM performance across flow orientations and regimes | Reliable in stratified flow; OR < 1.15 in controlled conditions | Increased error under mist flow; limited vertical pipe data | [19] |
| TOF USM model | Model OR using dimensionless parameters and ultrasonic TOF theory | Introduced dimensionless OR model; RAE < 5% in mist flow | Assumes negligible wall roughness and velocity profile variation | [10] |
| DP + SONAR Hybrid | Combine DP and SONAR sensing for improved wet gas accuracy | Improved accuracy over DP alone; ensemble sensing reduces OR | Complex installation; limited robustness under transitional regimes | [3] |
| Microwave + DP | Integrate microwave water detection with DP metering for subsea applications | Water detection accuracy 0.1–0.2% at GVF > 98.5%; effective in subsea fields | Performance drops at WLR >50%; sensitive to salinity and water-continuous phases | [11] |
| Microwave mixture model | Analyse the dielectric behaviour of wet gas using mixture models | Explored dielectric behaviour in condensate-rich gas | Model underperforms in gas-dominant flows; limited by mixture assumptions | [12] |
| Non-intrusive microwave system | Design patch-based microwave sensors for multiphase flow detection | Achieved < ±10% error across GVF and WLR ranges using patch sensors | Hardware sensitivity to salinity; limited temporal resolution | [20] |
| Microwave Doppler sensor | Use Doppler shift to detect velocity and phase fractions in wet gas | Demonstrated velocity and phase fraction detection via Doppler shift | Affected by penetration depth, turbulence, and noise interference | [21] |

microwave-derived liquid volume fraction and dimensionless parameters to account for over-reading in wet gas conditions.

### 2.1.2 | Microwave Transmission Line Sensor

This study employed a transmission line microwave sensor for liquid detection. The microwave transmission line sensor operates by exploiting the electromagnetic field interactions described by Maxwell's equations. Starting from the constitutive relation $D = \varepsilon E$, the wave equation in a homogeneous, isotropic medium was derived from the curl equations of Maxwell. In the frequency domain, the propagation constant $\gamma$ was expressed as:

$$\gamma = \alpha + j\beta = j\omega\sqrt{\mu\varepsilon^*} \tag{3}$$

where $\alpha$ is the attenuation constant, $\beta$ the phase constant, $\omega$ the angular frequency, $\mu$ the magnetic permeability, and $\varepsilon^* = \varepsilon' - j\varepsilon''$ the complex permittivity of the medium [24]. Under the low-loss approximation, the real part of the permittivity dominated, and the effective dielectric constant of the wet gas mixture, $\varepsilon_m$, was obtained from the measured propagation constants as:

$$\varepsilon_m = \frac{\left(\beta^2 \; - \; \alpha^2\right) c^2}{\omega^2} \tag{4}$$

where $c$ is the speed of light in free space. The transmission line sensor measured the amplitude attenuation ($\Delta A$) and phase shift ($\Delta\theta$) of the microwave signal over a known propagation distance $x$. These were related to the propagation constants by:

$$\Delta A = -8.68\,\alpha x, \;\; \Delta\theta = \beta x \tag{5}$$

From these relations, the effective permittivity $\varepsilon_m$ of the wet gas mixture was determined [8]. To relate the effective permittivity to the phase composition, the Bruggeman effective-medium model was applied. This model accounted for the contributions of both gas and liquid phases to the overall dielectric constant of the mixture and was expressed in closed form (inverted to estimate LVF) as:

$$\left(\frac{\varepsilon_l \; - \varepsilon_m}{\varepsilon_l \; - \varepsilon_g} \times \frac{\varepsilon_g}{\varepsilon_m}\right)^{A_0} = 1 - \mathrm{LVF} \tag{6}$$

where $\varepsilon_l$ and $\varepsilon_g$ are the dielectric constants of the liquid and gas phases, respectively, $A_0$ is the shape factor (taken as 1/3 for spherical droplets), and LVF is the liquid volume fraction [11, 12]. Because the equation is nonlinear, LVF was obtained iteratively from the measured $\varepsilon_m$.

## 2.2 | Over-Reading Correction for Ultrasonic Flow Meter

The presence of a liquid phase in wet gas flow leads to systematic over-reading in ultrasonic flow meters. This over-reading occurred because the entrained liquid increased the apparent gas velocity, thereby causing the measured volumetric flow rate to exceed the actual dry gas flow rate [10, 13]. Here, the empirical OR is defined as the ratio of the measured wet gas volumetric flow rate ($Q_{tp}$) to the actual dry gas volumetric flow rate ($Q_g$):

$$OR = \frac{Q_{tp}}{Q_g} = \frac{1}{\alpha_g} \tag{7}$$

where $\alpha_g$ denoted the gas void fraction. Since the void fraction was related to the liquid hold-up ($\alpha_l$) by the normalisation condition $\alpha_g + \alpha_l = 1$, the OR was directly proportional to the liquid content in the mixture.

To generalise the correction model, dimensional analysis was applied using the Buckingham Pi theorem, which reduced eleven independent flow variables into a set of eight dimensionless parameters [25]. These parameters captured the dominant physical effects influencing over-reading and were therefore incorporated into the correction model. The Lockhart–Martinelli parameter ($X_{lm}$) was used to represent the ratio of liquid to gas mass flow rates, adjusted for density differences. The Reynolds numbers of gas and liquid ($\mathrm{Re}_g$ and $\mathrm{Re}_l$) characterised the relative contributions of inertial to viscous forces in each phase, while the Weber number (We) quantified the balance between inertial and surface tension forces. The Froude number ($\mathrm{Fr}_g$) accounted for gravitational influences on multiphase flow regimes, particularly in distinguishing stratified from dispersed flow. In addition, the density ratio ($\mathrm{DR} = \rho_l\,/\rho_g$) captured the disparity between liquid and gas densities, and the slip ratio ($S = U_{sg}\,/U_{sl}$) represented the relative velocities of the gas and liquid phases. Together, these dimensionless parameters provided a systematic framework for modelling the complex hydrodynamic interactions that contributed to ultrasonic over-reading in wet gas measurement.

The critical Froude number ($\mathrm{Fr}_g^*$) is particularly important in distinguishing flow regimes. When $\mathrm{Fr}_g < \mathrm{Fr}_g^*$, the flow was stratified, whereas $\mathrm{Fr}_g > \mathrm{Fr}_g^*$ indicated dispersed or mist flow conditions (Xu et al., 2017). Under mist flow, the void fraction approached the gas volume fraction ($\alpha_g \approx \mathrm{GVF}$), simplifying the correction model. The generic functional form of the over-reading correction model was therefore expressed as:

$$\mathrm{OR} = f\left(\mathrm{LVF}, X_{LM}, \mathrm{Fr}_g, \mathrm{We}, \mathrm{DR}, \mathrm{Re}_g, \mathrm{Re}_l, S\right) \tag{8}$$

where $f$ represented the dependence on liquid volume fraction and the influence of multiphase dimensionless parameters.

## 2.3 | Hybrid OR Correction

The OR correction model for the integrated ultrasonic-microwave metering system (USMMW) for wet gas was developed by combining the velocity measurement from the ultrasonic flow meter with the phase fraction detection from the microwave sensor. The ultrasonic flow meter measured the total volumetric flow rate of the wet gas mixture ($Q_{tp}$), while the microwave sensor provided the LVF by estimating the effective dielectric constant of the mixture using the Bruggeman model. The gas void fraction ($\alpha_g$) was then obtained as 1 − LVF, which was substituted into the OR formulation as expressed in Equation (9), and hence the OR relationship is expressed as:

$$\mathrm{OR} = \frac{1}{1 \; - \; LVF} \tag{9}$$

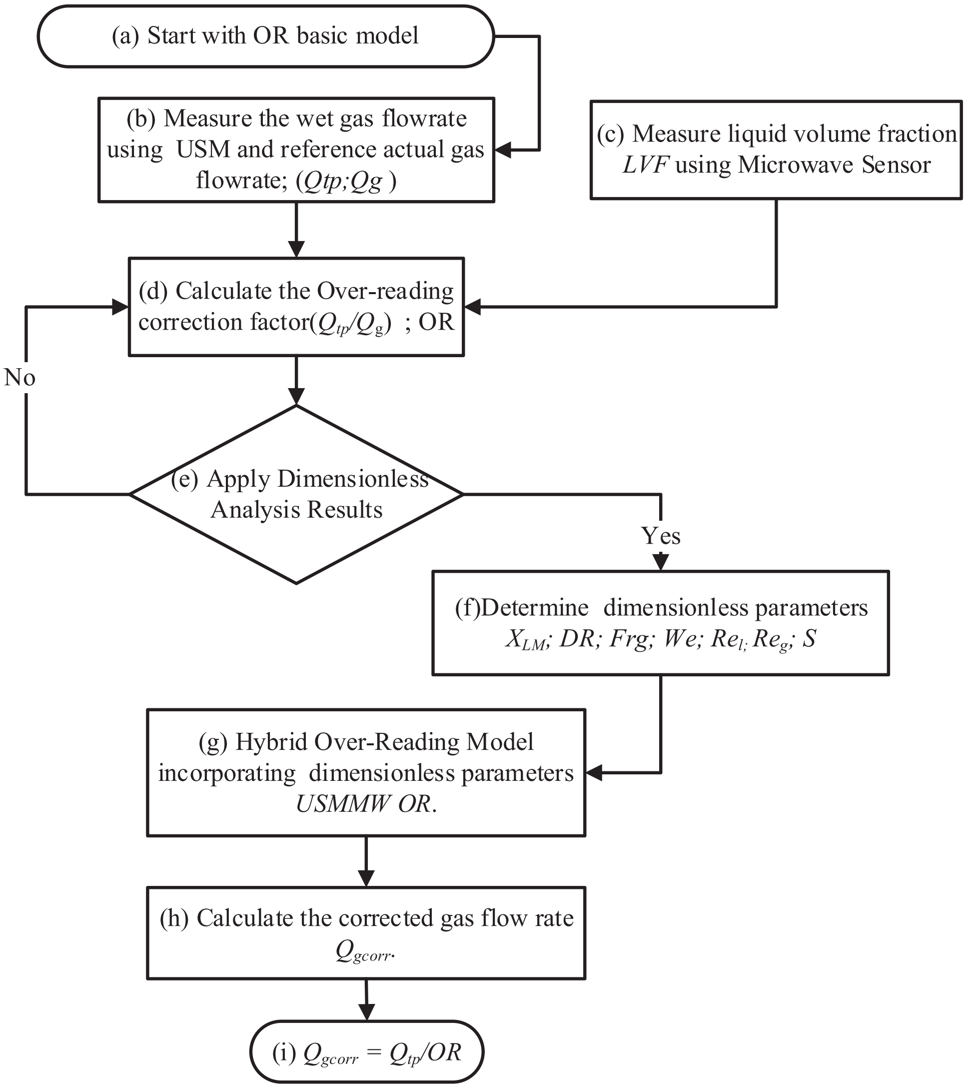


**FIGURE 1** | Modelling approach for USMMW over-reading correction factor.

The microwave sensor calculated the effective dielectric constant of the mixture, which was linked to the LVF through the Bruggeman mixture rule, as expressed in the closed function in Equation (8). By solving Equation (8) iteratively, the LVF was determined and subsequently used to refine the OR model.

To account for the influence of multiphase flow dynamics, the hybrid model incorporated the dimensionless parameters derived in Section 2.2, including the Lockhart–Martinelli parameter ($X_{lm}$), Reynolds numbers ($\mathrm{Re}_g$, $\mathrm{Re}_l$), Weber number (We), Froude number ($\mathrm{Fr}_g$), density ratio (DR), and slip ratio ($S$). The generic hybrid correction model was therefore expressed as:

$$\mathrm{OR} = \frac{1}{\left(\frac{\varepsilon_l - \varepsilon_m}{\varepsilon_l - \varepsilon_g} \cdot \frac{\varepsilon_g}{\varepsilon_m}\right)^{A_0}} \times f\left(X_{lm}, \mathrm{Fr}_g,\ \mathrm{DR},\ \mathrm{Re}_l/\mathrm{Re}_g,\ \mathrm{DR},\ \mathrm{We}, S\right) \tag{10}$$

where $\varepsilon_l$ and $\varepsilon_g$ represented the dielectric constants of the liquid and gas phases, respectively, and $A_0$ was the shape factor (assumed to be 1/3 for spherical droplets). Finally, the corrected wet gas flow rate ($Q_{g,corr}$) is then estimated using the equation:

$$Q_{g,corr} = Q_{tp} \ \times \ \mathrm{OR} \tag{11}$$

Figure 1 below illustrates the modelling framework of the over-reading correction factor for wet gas metering using integrated ultrasonic-microwave (USMMW).

## 2.4 | Data Collection and Feature Computation

### 2.4.1 | Experimental Facility and Setup

Experiments were carried out in the Process Systems Engineering (PSE) Laboratory at Cranfield University using a closed multi-phase flow loop specifically designed for wet gas testing. The 2-inch pipeline was fitted with a FLEXIM Fluxus ultrasonic meter and a 2.7 GHz microwave sensor. As depicted in Figure 2, the facility consisted of three interconnected loops: a gas loop (FL01), a liquid loop (FL02), and a wet gas loop (FL03). Gas and liquid were injected at controlled rates and combined upstream of the metering section, which housed a clamp-on ultrasonic

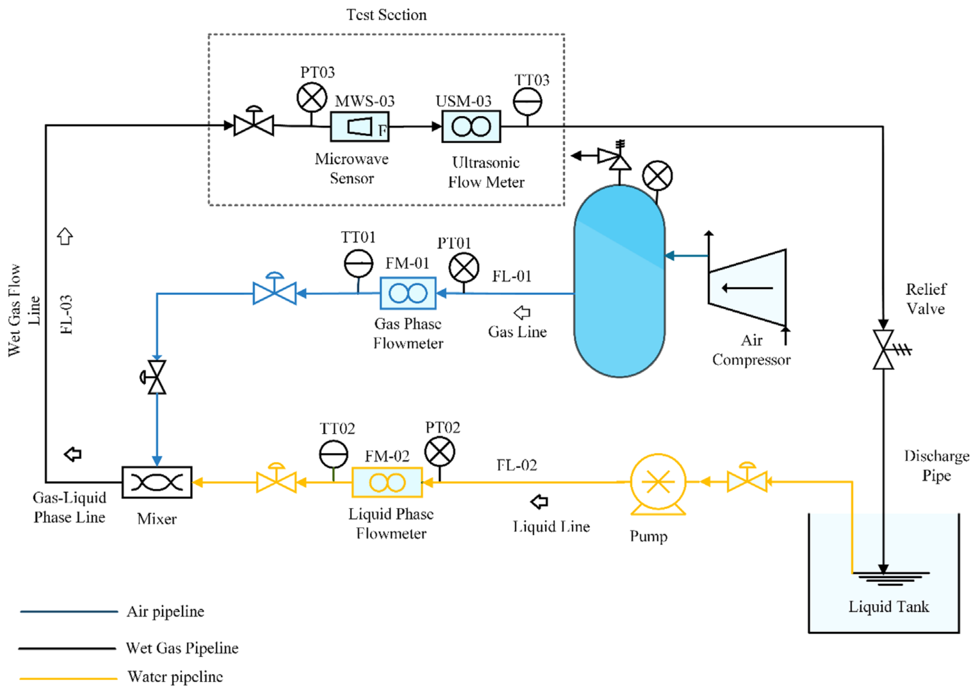


**FIGURE 2** | Test rig comprising the metering section, wet gas, actual gas and liquid flow.

**TABLE 2** | Summary of experimental ranges.

| Parameter | Symbol | Range/Value | Measurement method |
|---|---|---|---|
| Wet gas volumetric flow rate | $Q_{tp}$ | 25–550 $m^3$/h | Ultrasonic flow meter (USM03) |
| Superficial gas flow rate | $Q_g$ | 20–500 $m^3$/h | Coriolis meter (FM01) |
| Superficial liquid flow rate | $Q_l$ | 0.05–25 $m^3$/h | Coriolis meter (FM02) |
| Liquid volume fraction | LVF | 0.1–5% | Microwave sensor (MS03) + Bruggeman |
| Pressure | $P$ | 1.25–30 bars | Rosemount 3051 PT |
| Temperature | $T$ | 20–40°C | Calibrated TT |
| Density ratio | DR | 720–850 ($\rho_l/\rho_g$) | From reference data |
| Reynolds number (gas) | $\mathrm{Re}_g$ | 1000–31,000 | Computed |
| Reynolds number (liquid) | $\mathrm{Re}_l$ | 500–6000 | Computed |
| Weber number | We | 2–10 | Computed |
| Froude number (gas) | $\mathrm{Fr}_g$ | 0.1–1 | Computed |
| Slip ratio | $S$ | 200–350 | Computed |
| Flow regimes observed | – | Stratified, annular, mist | Sight glass |

flow meter (USM03) and a microwave dielectric sensor (MS03). Reference measurements for superficial gas and liquid flow rates were obtained using calibrated Coriolis meters (FM01 for gas and FM02 for liquid), which had uncertainties of ±0.2% FS and ±0.25% FS, respectively, adhering to AGA Report No. 11 and ISO/TR12748 guidelines. These reference meters provided an accurate determination of the actual gas and liquid superficial velocities, while the ultrasonic flow meter measured the total wet gas flow rate.

The test matrix was designed to systematically vary operating conditions across industrially relevant ranges as summarised in Table 2 below. The wet gas flow rate was varied between 25 $m^3$/h and 550 $m^3$/h, while the superficial gas and liquid flow rates were independently controlled by the Coriolis meters to achieve liquid volume fractions (LVF) between 0.1% and 5%. The operating temperature was maintained between 20 to 40°C, and pressure was varied from 1.25 bar to 30 bar. These conditions corresponded to a reasonable slip ratio, ensuring realistic wet gas hydrodynamics. Each test point was held for at least 10 min to ensure steady-state operation and repeated three times to assess repeatability. Flow regime transitions (stratified, annular, mist) were visually confirmed through a sight glass section. Figure 3 below shows the test section and the sight grass section used to monitor the flow transition regime.

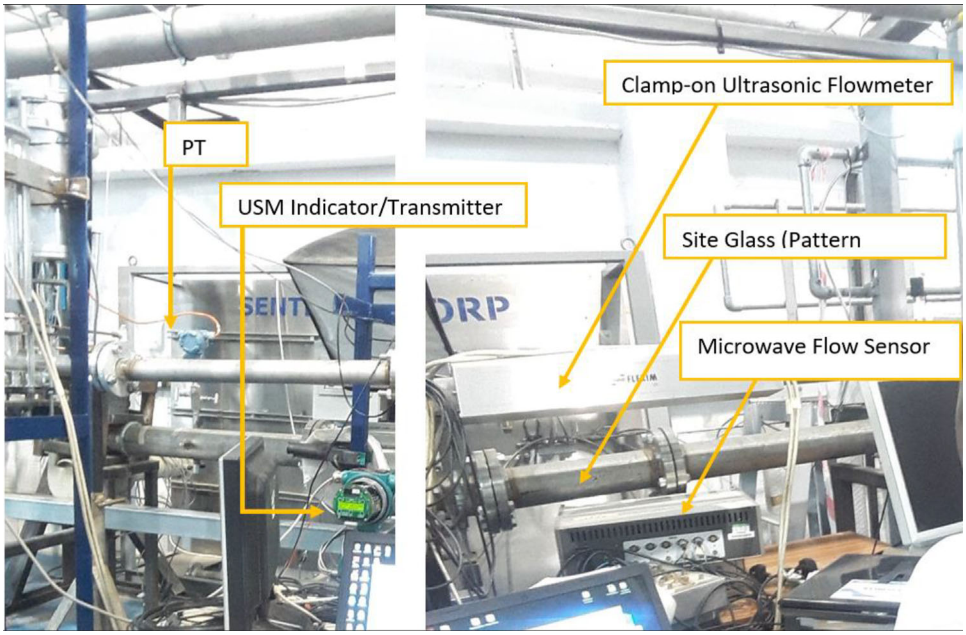


**FIGURE 3** | Metering section in the test rig at Cranfield PSE Laboratory.

### 2.4.2 | Calibration and Baseline Measurements

Baseline dielectric constants for both the pure gas phase ($\varepsilon_g$) and the liquid phase ($\varepsilon_l$) were determined using dedicated single-phase lines prior to conducting wet gas testing. The microwave sensor, operating at a frequency of 2.7 GHz, measured phase shift ($\Delta\theta$) and amplitude attenuation ($\Delta A$), which were then converted into the dielectric constant of the wet gas flow ($\varepsilon_m$) using propagation relations. The LVF was subsequently calculated iteratively utilising the Bruggeman effective-medium model. Meanwhile, the ultrasonic flow meter measured the total volumetric flow rate of the wet gas ($Q_{tp}$). The actual dry gas flow rate ($Q_g$) was obtained from the reference Coriolis meter, allowing for the calculation of the over-reading factor (OR), defined as ($Q_{tp}/Q_g$).

### 2.4.3 | Data Acquisition and Processing

All instruments were connected to a centralized flow computer via Modbus protocol to enable synchronized data acquisition across the metering system. Measurements were recorded at a sampling rate of 1 Hz, equivalent to 60 samples per minute. To ensure flow stabilisation and steady-state operation, each test condition was maintained for 10 min prior to data capture. This protocol yielded approximately 600 time-resolved data points per experimental run, providing sufficient resolution to characterize transient flow behaviour and regime-dependent variability.

The experimental matrix was systematically designed to vary key multiphase flow parameters across industrially relevant ranges. Specifically, LVF and GVF were used as primary set points to control phase composition. LVF varied between 0.1% and 5%, while GVF was maintained above 90%, consistent with wet gas flow definitions. These set points were achieved by independently adjusting the superficial gas and liquid flow rates using calibrated Coriolis meters (FM01 and FM02) and verified through microwave dielectric measurements.

The acquired dataset comprised both direct measurements and derived quantities essential for multiphase flow characterization. Primary measured parameters included the wet gas volumetric flow rate ($Q_{tp}$) from the ultrasonic flow meter (USM03), superficial gas and liquid flow rates ($Q_g$, $Q_l$) from calibrated Coriolis meters (FM01 and FM02), and the microwave dielectric constant of the wet gas mixture ($\varepsilon_m$) from the transmission line sensor (MS03). Pressure and temperature readings were obtained using Rosemount 3051 transmitters and calibrated thermocouples, while pipe diameter ($D$) was fixed at 2 inches throughout the test campaign.

Additional fluid properties required for dimensionless analysis were determined from reference data and validated under test conditions. These included gas and liquid densities ($\rho_g$, $\rho_l$), dynamic viscosities ($\mu_g$, $\mu_l$), and surface tension ($\sigma$) of the liquid phase. These values were used to compute derived parameters such as detected liquid volume fraction (LVF), Lockhart–Martinelli number ($X_{LM}$), Reynolds numbers for gas and liquid phases ($Re_g$, $Re_l$), Weber number (We), Froude number ($Fr_g$), density ratio (DR), and slip ratio ($S$). All calculations adhered to standard fluid dynamics principles. Figure 4 illustrates the data extraction for modelling the USMMW over-reading correction, while Figure 5 provides a visualisation of parameters against the calibration liquid volume fraction.

### 2.4.4 | Modelling Framework for OR Correction

The empirical OR correction model for the USMMW system was developed utilizing the experimental dataset outlined in Section 2.4. Initially, based on Equation (7), the OR was defined as the ratio of the ultrasonic flow meter's measured wet gas flow rate to the actual gas flow rate obtained from the calibrated reference meter (refer to Section 2.4.2). The liquid volume fraction (LVF) was estimated from the microwave dielectric constant of the wet

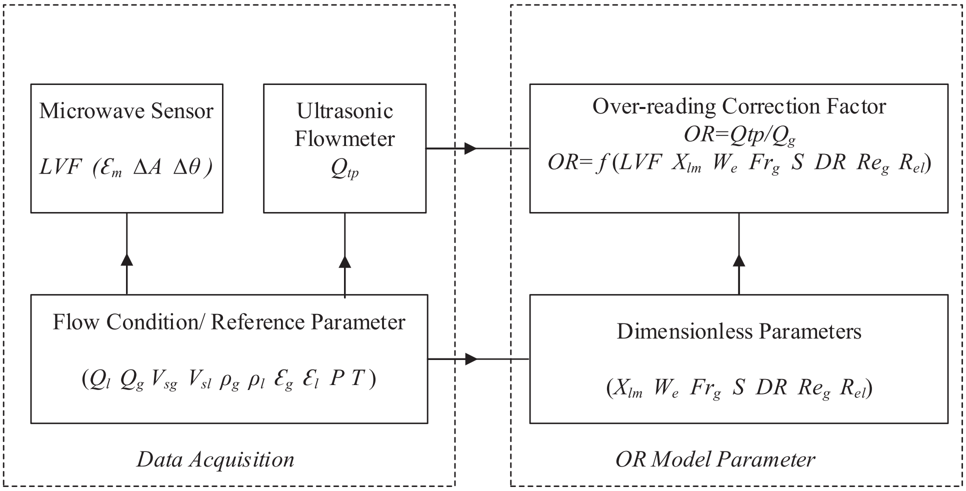


**FIGURE 4** | Modelling parameters acquired from the wet gas flow rig.

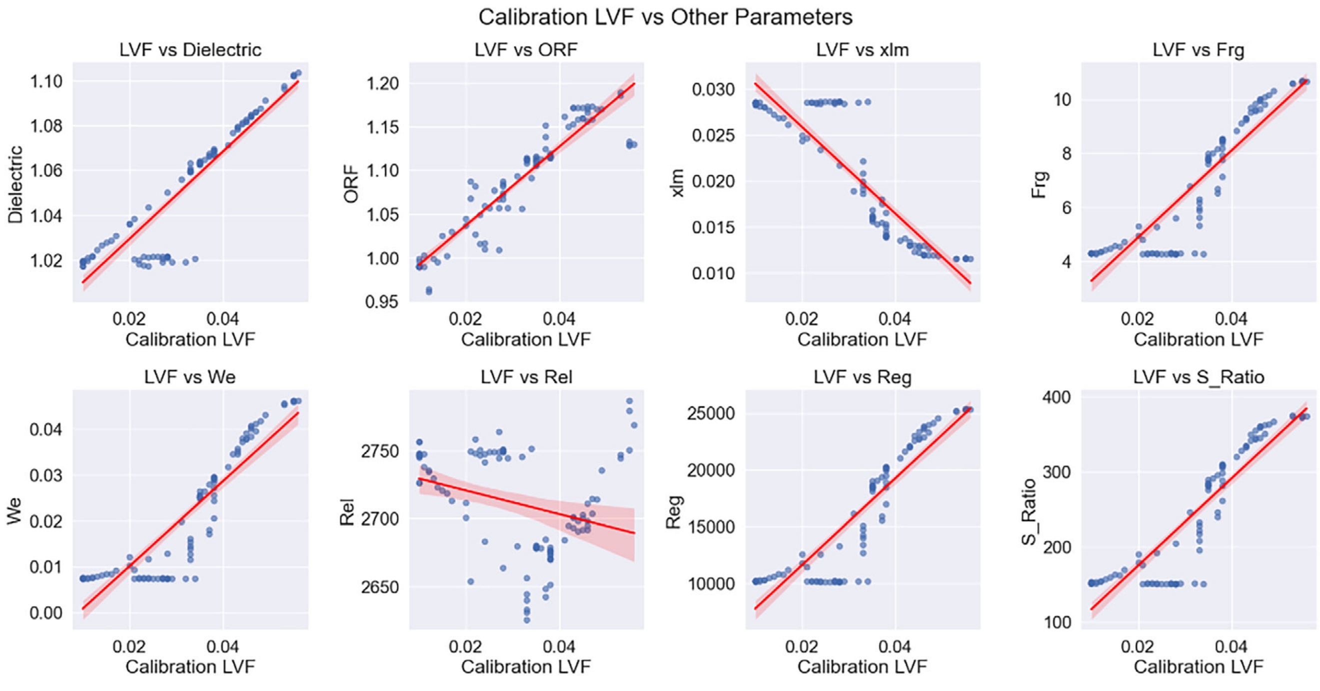


**FIGURE 5** | Data visualisation indicating the relation of parameters to the variation of calibration liquid volume fraction (LVF).

gas flow ($\varepsilon_m$) using the Bruggeman effective medium model, as described in Section 2.1.2.

To capture the hydrodynamic influences on ultrasonic over-reading, the model integrated the dimensionless parameters derived in Section 2.2, specifically $X_{LM}$, $\mathrm{Re}_g$, $\mathrm{Re}_l$, We, $\mathrm{Fr}_g$, DR, and $S$. These parameters were calculated from the experimental data as detailed in Section 2.4.3. Alongside detected LVF, they constituted the predictor variables for the regression and machine learning models.

The dataset was pre-processed as described in Section 2.4.3, with raw dynamic time-series data retained without averaging or imputation to preserve transient flow characteristics. The final dataset was partitioned into 70% training, 20% validation, and 10% testing subsets, stratified to maintain the distribution of LVF and flow regimes (stratified, annular, and mist). Two complementary modelling approaches were then implemented: Multilinear Regression (MLR) and Random Forest Regression (RFR).

**2.4.4.1 | Multilinear Regression (MLR).** MLR was employed as the baseline model due to its transparency in quantifying the additive contributions of predictor variables. The regression model was expressed as:

$$\mathrm{OR} = \beta_0 + \beta_1\mathrm{LVF} + \beta_2 X_{lm} + \beta_3\mathrm{Fr}_g + \beta_4\mathrm{We} + \beta_5\mathrm{Re}_g + \beta_6\mathrm{Re}_l + \beta_7 S + \beta_8\mathrm{DR} + \varepsilon \tag{12}$$

where $\beta_i$ are regression coefficients and $\varepsilon$ is the residual error. Multicollinearity among predictors was assessed using the variance inflation factor (VIF) analysis, and regularisation techniques such as ridge and lasso regression were evaluated to mitigate potential overfitting. This ensured that the MLR model provided a statistically robust and interpretable baseline for OR correction.

**2.4.4.2 | Random Forest Regression (RFR).** RFR was implemented as a complementary approach to capture nonlinear interactions beyond the scope of linear regression. As an ensemble learning method, RFR constructs multiple decision trees on bootstrapped subsets of the training data and averages their predictions:

$$\hat{y}\ (x) = \frac{1}{T}\ \sum_{t=1}^{T} h_t\,(x) \tag{13}$$

where $\hat{y}(x)$ is the predicted OR, $T$ is the number of trees, and $h_t(x)$ is the prediction from the $t^{th}$ regression tree trained on a random subset of features and samples. The same 70:20:10 split was applied as for MLR, ensuring consistency in model evaluation. Hyperparameter tuning was performed using grid search with cross-validation to optimise the number of trees ($n_{estimators}$), maximum depth, minimum samples per split, and feature selection strategy. The final configuration employed 500 trees with a maximum depth of 12, which provided stable predictions across diverse flow regimes while balancing bias and variance. Performance was assessed using the same statistical indicators as MLR, allowing for direct comparison between linear and nonlinear modelling strategies.

**2.4.4.3 | Model Performance Metrics.** Model performance was evaluated using statistical indicators widely applied in wet gas metering studies. These included the coefficient of determination ($R^2$) to assess goodness of fit, mean squared error (MSE) and root mean squared error (RMSE) to quantify prediction accuracy, mean absolute error (MAE) to measure average deviation, and the Durbin–Watson statistic (DW) to test for autocorrelation in residuals. Using a consistent set of metrics allowed for direct comparison between the linear (MLR) and nonlinear (RFR) modelling strategies, ensuring both statistical rigor and reproducibility.

## 3 | Results

### 3.1 | Performance Overview

The empirical OR correction model for the USMMW system was evaluated using the regression and machine learning approaches described in Section 2.4.4. The results presented here focus exclusively on model performance outcomes.

On one hand, the MLR model achieved exceptionally high predictive accuracy, with a coefficient of determination ($R^2$) of 0.9991, MSE of 0.000293, RMSE of 0.0171, and MAE of 0.0082. Residual analysis confirmed the absence of significant autocorrelation (Durbin–Watson = 1.72), and errors were symmetrically distributed around zero. These results demonstrate that MLR provided a statistically robust and transparent baseline for OR correction, effectively capturing the additive contributions of dimensionless parameters.

On the other hand, the optimised RFR model achieved an $R^2$ of 0.9968, an RMSE of 0.0184, and an MAE of 0.0091. Residuals were symmetrically distributed around zero, confirming the absence of systematic bias. While its overall accuracy was comparable to MLR, RFR demonstrated superior robustness under mist and transitional regimes, where nonlinear interactions among LVF, DR, and Reynolds number ratios dominate.

The complementary strengths of MLR and RFR highlight the value of a dual-model framework. MLR provided interpretability and statistical transparency, making it particularly useful for controlled flow regimes. RFR, by contrast, captured nonlinear interdependencies involving LVF, $X_{LM}$, DR, and the dielectric constant of wet gas ($\varepsilon_m$), ensuring stability under complex multiphase conditions. Together, these models form a correction framework that balances interpretability with predictive power, thereby strengthening the reliability of the USMMW system.

### 3.2 | Validation and Comparative Assessment of the USMMW Over-Reading Correction Model

Following the identification of MLR and RFR as the most effective modelling strategies (see Section 2.4.4), the predictive capability of the USMMW over-reading (OR) correction model was validated against independent experimental data and benchmarked against conventional differential pressure (DP) correlations. Validation focused on four aspects: (i) the accuracy of OR prediction, (ii) the average error performance across flow regimes, (iii) the corrected wet gas flow rate ($Q_{gcorr}$) relative to the reference gas flow rate ($Q_g$), and (iv) comparative performance against established DP models.

#### 3.2.1 | Validation of OR Prediction and Corrected Flow Rates

As illustrated in Figure 6, the USMMW over-reading derived from both MLR and RFR models demonstrated strong one-to-one correlations between predicted and experimental OR values across the full range of liquid volume fractions (LVF) and flow regimes. The RFR model exhibited slightly superior robustness under mist and transitional conditions, where nonlinear interactions between LVF, density ratio (DR), and Reynolds number ratios ($\mathrm{Re}_l/\mathrm{Re}_g$) dominate. In contrast, MLR provided highly transparent parameter contributions, with residuals symmetrically distributed around zero and no evidence of autocorrelation (Durbin–Watson $\approx$ 2). These findings confirm that while MLR offers interpretability, RFR captures nonlinearities more effectively, consistent with earlier reports [10, 13].

As shown in Figure 7, the error analysis confirmed that USMMW over-reading correction models based on both MLR and RFR achieved relative absolute errors (RAE) consistently below ±5%, with average values of 3.02% for MLR and 3.20% for RFR. This level of accuracy is comparable to, and in some cases surpasses, the performance of established wet gas correction models reported in the literature. Residual analysis further

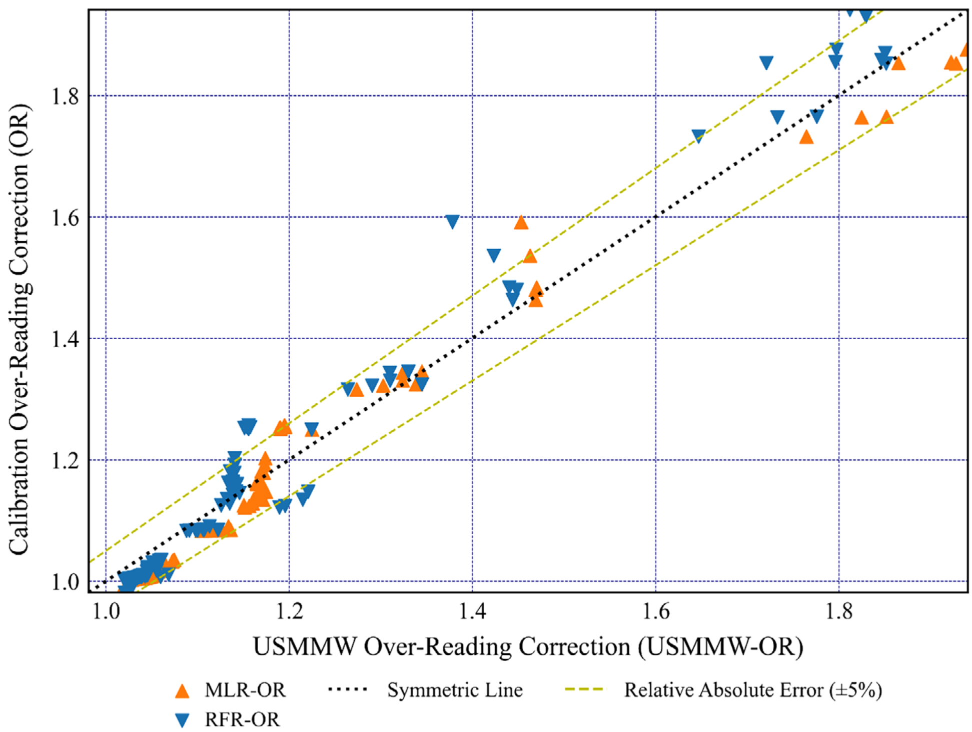


**FIGURE 6** | Correlation of calibration over-reading to the USMMW over-reading correction.

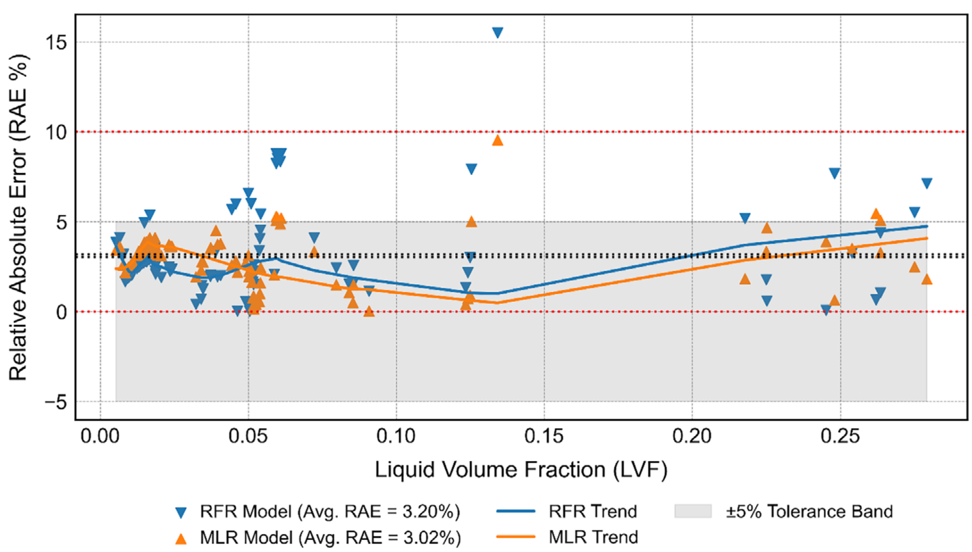


**FIGURE 7** | Relative absolute error for USMMW over-reading models based on random forest regression and multilinear regression.

demonstrated the absence of systematic bias, with errors symmetrically distributed around zero for both models.

The ultrasonic flow meter's over-reading flow rate ($Q_{tp}$) was corrected using the USMMW OR model, yielding a corrected gas flow rate ($Q_{gcorr}$) that closely aligned with the actual reference gas flow rate ($Q_g$). As illustrated in Figure 8, the corrected flow rates consistently fell within ±5% of the reference values, with a clear positive correlation across all operating conditions, especially in the stratified and mist flow regimes. This demonstrates the ability of the USMMW system to provide accurate wet gas flow measurements while accounting for influencing factors such as pressure, temperature, dielectric variability, and calibration uncertainties.

#### 3.2.2 | Benchmarking Against Conventional DP Models

To situate the USMMW correction model within the broader context of wet gas metering, its predictions were compared with conventional DP-based OR models, including those of Murdock [5], Chisholm [6], de Leeuw [7], and Smith and Leang [26]. Although no physical DP meter was installed in the present test

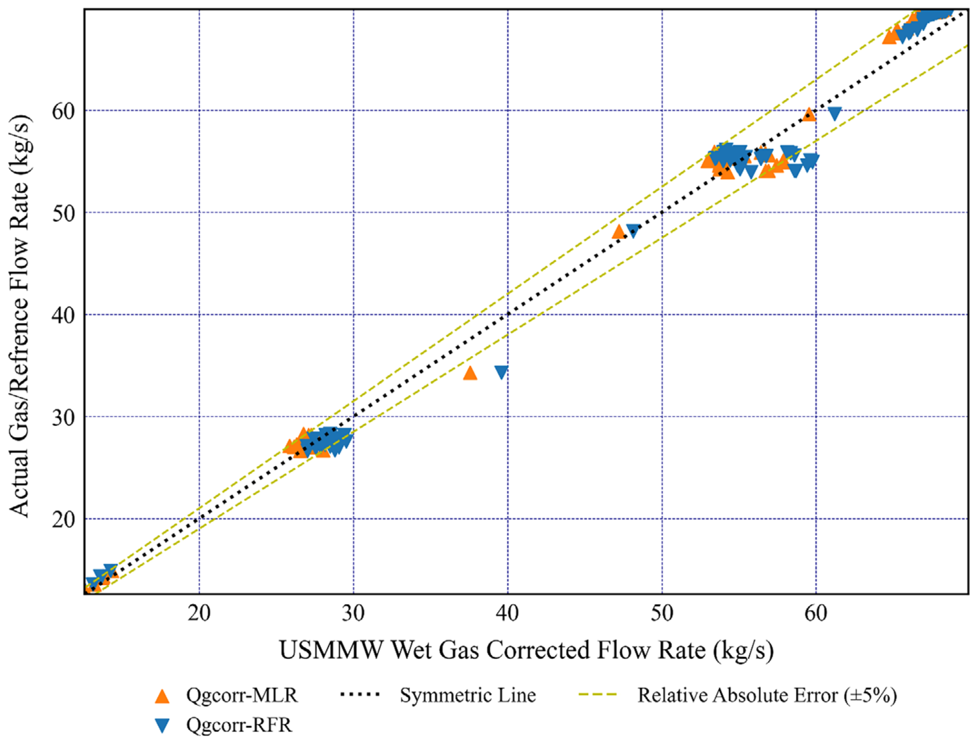


**FIGURE 8** | Correlation of actual flowrate with the predicted flowrate determined by the USMMW over-reading correction model.

loop, the comparison remains valid because the functional forms of these DP correlations are well established and expressed in terms of parameters such as LVF, Lockhart–Martinelli number ($X_{LM}$), density ratio (DR), and Reynolds numbers, all of which were directly available from the USMMW dataset. This benchmarking approach, where DP model predictions are computed from existing flow loop data rather than repeating full DP experiments, has been widely employed in wet gas metering studies such as van Putten and Dsouza [13] and Collins et al. [4].

The comparison based on LVF, as illustrated in Figure 9, shows that the USMMW model consistently maintained OR values below 1.13 across the full range of LVF estimated from microwave dielectric measurements. In contrast, conventional DP models exhibited significantly higher OR values, in some cases approaching 2.0 under equivalent wet gas conditions. This divergence reflects the inherent sensitivity of DP meters to liquid loading, where hydrodynamic disturbances and pressure drop effects amplify over-reading errors. The USMMW system, by integrating ultrasonic velocity measurement with microwave-based LVF detection, demonstrated superior resilience to liquid entrainment, thereby reducing error propagation across varying LVF levels.

The influence of the Lockhart–Martinelli parameter on OR predictions is shown in Figure 10. The USMMW model exhibited a stable and near-linear response to increasing $X_{lm}$, with corrected OR values remaining within ±5% of the reference across the tested range. In contrast, conventional DP models displayed greater variability, with over-reading errors escalating as $X_{lm}$ increased beyond 0.2. This trend highlights the limitations of empirical DP correlations, which often lack adaptability across diverse flow regimes. By contrast, the USMMW model, supported by regression-based correction (MLR and RFR), effectively captured the nonlinear interactions between $X_{LM}$, LVF and density ratio (DR), ensuring robust performance under both low- and high-liquid loading conditions.

Overall, the comparative analysis underscores the reasonable performance of the USMMW model over conventional DP-based OR models. While DP correlations remain widely used due to their simplicity, they are prone to significant over-reading under elevated LVF and $X_{lm}$ conditions. The USMMW system, by contrast, leverages sensor fusion and data-driven correction to deliver consistently lower OR values and reduced uncertainty. These findings confirm that the hybrid ultrasonic-microwave approach not only mitigates the limitations of DP meters but also provides a scalable, non-intrusive, and more accurate solution for industrial wet gas metering.

## 4 | Discussion

The central challenge addressed in this study was the persistent problem of OR in wet gas measurement, particularly in ultrasonic flow meters, and the limitations of conventional correction approaches such as differential pressure (DP) correlations and baseline microwave dielectric models. The objective was to develop and validate a hybrid USMMW system that integrates ultrasonic velocity measurement, microwave-based liquid detection, and data-driven correction models to improve accuracy, robustness, and field applicability.

An empirical OR correction model was constructed using LVF and dimensionless parameters, including the Lockhart–Martinelli parameter ($X_{LM}$), density ratio (DR), Froude number

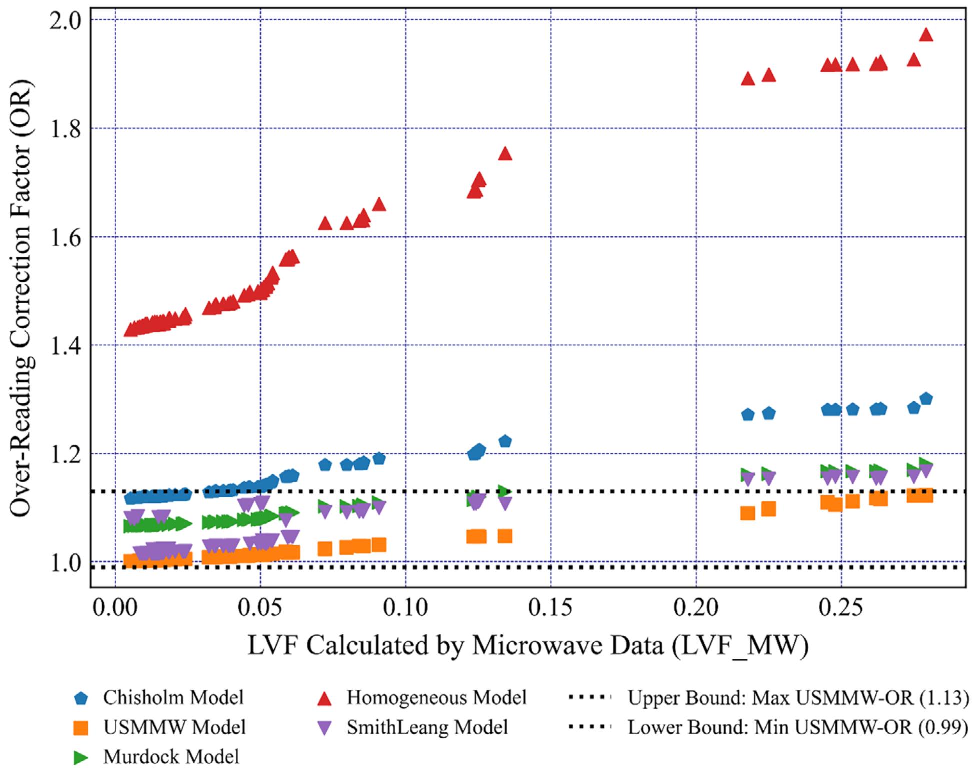


**FIGURE 9** | Comparison of conventional DP over-reading correction models and USMMW over-reading Model in varying liquid volume fraction.

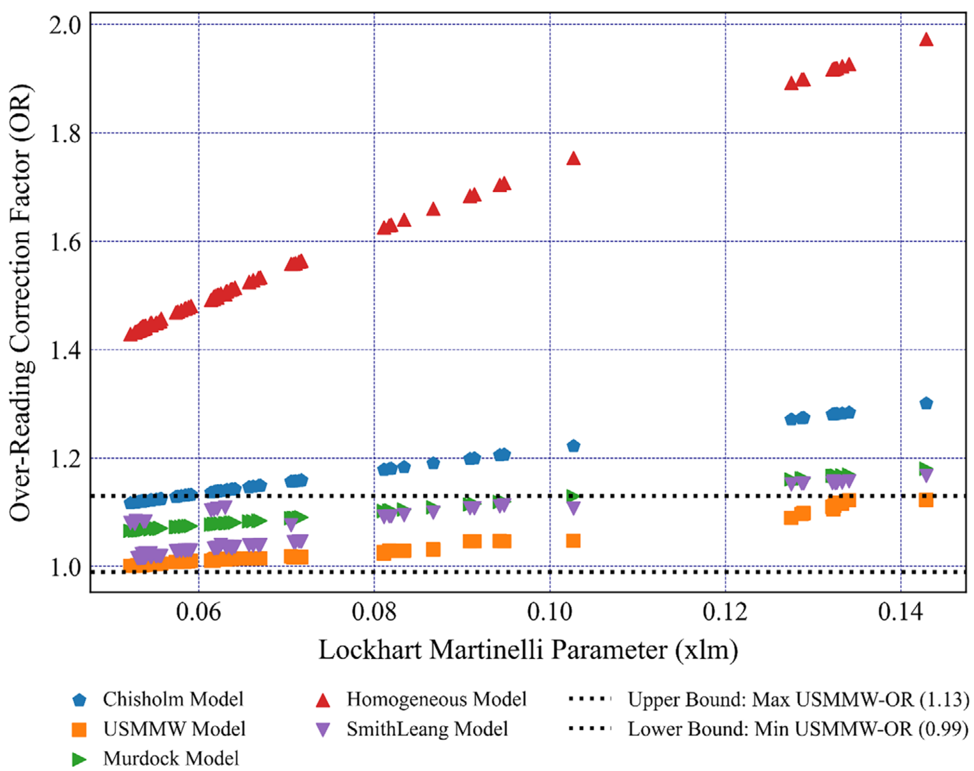


**FIGURE 10** | Comparison of conventional DP over-reading correction model (computed using experimental data) with USMMW over-reading model in varying Lockhart–Martinelli Parameter ($X_{\mathrm{LM}}$).

($Fr_g$), Reynolds numbers ($Re_l$, $Re_g$), Weber number (We), and slip ratio ($S$). The integration of microwave dielectric sensing ($\varepsilon_m$) with ultrasonic OR measurements provided the necessary inputs for regression-based modelling. Both multilinear regression (MLR) and random forest regression (RFR) were applied. MLR effectively captured additive linear contributions of the predictor variables, while RFR successfully modelled nonlinear interdependencies. Together, these approaches established a dual-model framework that balances interpretability with predictive power.

Validation against independent datasets confirmed that the USMMW system consistently corrected ultrasonic over-reading, yielding corrected gas flow rates ($Q_g$) within ±5% of reference Coriolis measurements. The average relative absolute error (RAE) was 3.02% for MLR and 3.20% for RFR, demonstrating high accuracy and robustness. Residual analysis confirmed the absence of systematic bias, and importantly, RFR maintained stability under mist and transitional regimes where conventional linear models typically degrade. These findings directly address the research problem of ultrasonic over-reading in wet gas metering.

Comparative analysis with established DP-based correlations (Murdock [5], Chisholm [6], Homogeneous [7], and Smith and Leang [25]) further demonstrated the superiority of the USMMW approach. As shown in Figures 8 and 9, the USMMW model maintained OR values below 1.13 across increasing LVF and $X_{lm}$, while DP models exhibited OR values approaching 2.0 under equivalent conditions. This confirms that DP meters, though widely used, are inherently sensitive to liquid loading and pressure drop effects, leading to systematic overestimation. By contrast, the USMMW system, through sensor fusion and regression-based correction, provided stable and accurate performance across regimes. However, when positioned relative to earlier hybrid methods such as Contra-Propagated Transmission Ultrasonics (CPTU) and Time-Averaging Transmission Intensity Ultrasonics (TAITIU), which rely on static empirical corrections [16, 19], the USMMW system advances the field by incorporating dimensionless parameters and machine learning. The USMMW resulting average RAE of 3.02% outperformed the ±3–8% errors typically reported for CPTU/TAITIU under high-LVF conditions.

The effectiveness of the model hinges on the optimisation parameters; as these parameters are optimised, the accuracy of predictions improves. The USMMW model initially utilised 12 optimisation parameters, which were later scaled down to eight for dimensional analysis. This approach is supported by Collins et al. [4], who evaluated various traditional corrections and reported the following apparent uncertainties: Homogeneous at 5.43%, de Leeuw at 3.70%, Murdock at 7.03%, and Chisholm at 10.30% for Lockhart–Martinelli parameters ≤0.3. Most models employed fewer than three optimisation parameters, whereas ISO TR11583:12 achieved a superior over-reading uncertainty of 2.34% using 12 optimisation parameters.

Beyond benchmarking against conventional DP correlations and earlier hybrid ultrasonic methods, it is equally important to position the present work within the context of recent data-driven advances in wet gas metering, where machine learning and regression frameworks have begun to redefine accuracy standards. Li et al. [15] demonstrated that gradient-boosted regression applied to multiphase flow prediction achieved $R^2 > 0.97$ and reduced RMSE by nearly 40% compared to conventional empirical correlations, highlighting the strength of ensemble learning in capturing nonlinearities in gas-liquid interactions. Similarly, Hosseini et al. [27] applied multiple machine learning algorithms to Venturi-based wet gas metering and showed that direct ML prediction of gas and liquid flow rates consistently achieved errors below 5%, outperforming traditional Lockhart–Martinelli based correlations. These independent findings reinforce the present study's results: regression- and ML-based correction frameworks not only mitigate ultrasonic over-reading but also provide robustness across mist and transitional regimes where empirical models typically degrade.

Taken together, these findings confirm that the USMMW system meets the stated objectives: it develops a robust OR correction model, validates it experimentally, benchmarks it against conventional DP models, and demonstrates resilience under industrially relevant conditions. By embedding both interpretability (via MLR) and nonlinear adaptability (via RFR), the USMMW system aligns with and extends recent advances in data-driven wet gas metering, offering a scalable, accurate, and non-intrusive solution that enhances measurement accuracy, safety, and operational reliability.

## 5 | Limitations

While the present study demonstrates the potential of the USMMW correction framework, several limitations should be acknowledged. The experiments were conducted using a single pipe diameter under controlled laboratory conditions, and no systematic variation of upstream disturbances was introduced. As such, the results are valid within the tested operating envelope and should not be generalised without caution. Broader applicability will require validation across multiple pipe diameters, pressure ranges, and flow regimes, including field-scale conditions where installation effects and upstream disturbances are more pronounced. In addition, although the benchmarking against conventional DP correlations provides a transparent and widely accepted comparative framework, future studies should incorporate direct DP meter measurements under identical conditions to further strengthen the comparative analysis. Finally, while the regression and machine learning models demonstrated strong predictive capability, their robustness under varying gas compositions, salinity levels, and condensate fractions remains to be tested. Addressing these aspects in future work will not only enhance the physical validity of the correction framework but also accelerate its readiness for industrial deployment.

## 6 | Conclusion

The present study establishes a compelling benchmark in the development of non-intrusive, hybrid metering technologies for wet gas applications by successfully integrating Ultrasonic and Microwave (USMMW) sensing systems. Through the creation of a data-driven OR correction model, the system demonstrated high accuracy, achieving an average of 3.02% RAE, and proved resilient under mist and stratified flow regimes. The complementary strengths of ultrasonic flow rate measurement and microwave-based LVF detection enable real-time flow monitoring without the operational constraints of traditional intrusive or radiometric techniques. Critically, this work not only validates the theoretical framework and regression modelling strategies but also highlights the robustness and scalability of the USMMW approach in multiphase environments characterised by hydrodynamic complexity.

To build on this achievement, future work should extend validation beyond mist regimes to stratified and annular flows, ensuring broader generalisability across industrial operating envelopes. Field-scale trials under high-pressure, high-temperature conditions are essential to confirm long-term reliability and compliance with international custody transfer standards. Methodologically, further research should focus on adaptive dielectric models that explicitly account for salinity, temperature, and pressure effects, as well as hybrid modelling strategies that combine the interpretability of linear regression with the nonlinear learning capacity of ensemble methods. Overall, the USMMW system represents a transformative advancement in wet gas metering, offering a scalable, safe, and high-fidelity alternative for subsea, high-pressure, and remote gas monitoring environments.

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### Author Contributions

**Ishigita Lucas Shunashu:** conceptualisation, methodology, data curation, formal analysis, software, visualisation and writing – original draft. **Osmund Kaunde:** supervision, validation, writing – review and editing. **Duncan Mwakipesile:** supervision, writing – review and editing.


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The authors have nothing to report.


### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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