AI-Based Evaluation of Homogeneous Flow Volume Fractions Independent of Scale Using Capacitance and Photon Sensors

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Abstract—**Metering fluids is critical in various industries, and researchers have extensively explored factors affecting measurement accuracy. As a result, numerous sensors and methods are developed to precisely measure volume fractions in multi-phase fluids. A significant challenge in multi-phase fluid pipelines is the formation of scale within the pipes. This issue is particularly problematic in the petroleum industry, leading to narrowed internal diameters, corrosion, increased energy consumption, reduced equipment lifespan, and, most crucially, compromised flow measurement accuracy. This paper proposes a non-destructive metering system incorporating an artificial neural network with capacitive and photon attenuation sensors to address this challenge. The system simulates scale thicknesses from 0 mm to 10 mm using COMSOL multiphysics software and calculates counted rays through Beer-Lambert equations. The simulation considers a 10% interval of volume variation in each phase, generating 726 data points. The proposed network, with two inputs-measured capacity and counted rays-and three outputs-volume fractions of gas, water, and oil-achieves mean absolute errors of 0.318, 1.531, and 1.614, respectively. These results demonstrate the system's ability to accurately gauge volume proportions of a three-phase gas-water-oil fluid, regardless of pipeline scale thickness.**

Index Terms—**Non-destructive metering, Scale thickness in pipelines, Multi-phase fluids, Artificial neural network, Capacitive sensors, Gamma-ray attenuation sensor.**

I. Introduction

Measuring the volume fraction (VF) of multiphase flows is a critical task and so important in a number of fields such as gas, oil, and water. This is because of many subjects, such as financial matters and environmental-oriented concepts. Hence, researchers have been strived a lot to present new and optimized methods to avoid making delay and separation in the process being the worst part of conventional methods. Among introduced techniques, gamma-ray attenuation and capacitance-based sensors are so intriguing and this is because of their natures, which are non-destructive, non-invasive, and applicable to be utilized in harsh conditions unlike mechanical solutions, such as turbo meters, sampling tubes, and vibrating densitometers, which are intrusive in measurement and complex in their structures (Mayet, et al., 2024a). Regarding the gamma attenuation sensor, many works can be found that authors have utilized this type of sensor to measure volume fractions of fluids. In 1999, Abro and his coworkers developed a technique that used multiple radiation beams to detect flow patterns in two-phase flow within a narrow pipe (Åbro, et al., 1999). In a sophisticated system, Salgado et al. employed dual-energy gamma emitter radioisotopes. They had an emphasis on investigations into the complex nature of gas-oil-water multiphase flow in mostly understanding and identification of different flow patterns (Salgado, et al., 2010). Roshani and his colleagues conducted an analysis of the performance of a radial basis function (RBF) neural network alongside a photon attenuation sensor to predict various phases' proportions in water, oil, and gas annular mixtures. They evaluated 3 different structures of the mentioned model. The first one aimed at predicting the proportions of water and oil, the second focused on gas and water, and the third on gas and oil. They reported that the first RBF model was the most accurate in forecasting proportions in the three-phase annular mixture (Roshani, et al., 2017a). In the aspect of capacitive sensors, many works have been published so far. Researchers have used capacitive plates to measure both the resistance and capacitance of a three-phase blended liquid without physical intrusion. The examined Plexiglas pipeline was equipped with two semi-cylindrical electrodes each one of them covered about half of the pipeline's circular perimeter (Sheikh, Hassan and Iqbal, 2019). Fouladinia et al. have employed a capacitive sensor in a three-phase homogeneous regime to measure volumes of all phases. They have concluded that just one capacitive sensor is unable to do this action and there is a need for other

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methodologies or using other types of sensors along with the utilized sensor. Hence, they measured the proportion of water, precisely (Mayet, et al., 2024b). Proposing new and optimized capacitance-oriented sensor is a hot topic and many papers can be found in this regard. For example, in (Syah, et al., 2023), a new sensor called arrow-shaped has been presented which has a good level of sensitivity for two-phase annular fluids. Similarly, a capacitive sensor called skewed has been proposed by authors which is able to measure volume fractions of oil and gas two-phase flows in stratified, annular, and homogeneous regimes (Iliyasu, et al., 2024). Scale layers that are formed within pipelines face oil and water industries with a number of challenges such as drilling tools, increasing the consumed energy, decreasing the efficiency, and the most important one, reducing the accuracy of flow measurement. Flowing water in pipes introducing some materials, such as calcium, barium, and strontium sulfate, leads to the forming of these challengeable layers. Therefore, many papers have been published to measure scale-oriented matters in pipelines. For instance, in (Oliveira, et al., 2015), authors have used a detector paired with a source to investigate the accumulation of scale within transmission channels. The authors collected gamma spectra at intervals of 0.5 cm. Their findings indicated that while gamma transmission scanning is capable of identifying the existence of scale in a pipe carrying a single-phase flow, it cannot accurately map the exact distribution of the scale. Salgado and his coworkers have employed a method for measuring the thickness of scale inside pipelines. Their introduced method included a source, a steel pipe, and a detector. The collected gamma spectra were given to an artificial neural network (ANN) resulting in the estimating of the scale thickness. The weakness of this approach is that it was able to measure the scale's thickness in pipelines with a one-phase flow, while in real conditions more phases inflows exist (Teixeira, et al., 2018). Authors in (Roshani, et al., 2021) tried to measure void fraction in two-phase gas and oil regardless of the effect of the scale layer in the measurement. This study was done by combining photon attenuation with artificial intelligence methods. They employed an ANN to classify the flow regimes and predict the void fraction. However, their outputs declared that the proposed method was unable to accurately identify all three flow regimes. Utilizing ANN in flow measurement is a popular tool that can be found in many studies such as (Mayet, et al., 2023), which has used a multilayer perceptron (MLP) ANN along with two capacitive sensors, ring, and concave, to measure void fraction of a two-phase water and gas fluid independent of temperature and pressure. Authors have utilized a combination of capacitive and gamma-ray attenuation sensors to measure volumes of oil, gas, and water by an ANN. They did this mission without any attention to the effect of scale in measurement accuracy (Fouladinia, et al., 2024). A gamma-based system including two sources and two detectors along with a couple of machine learning tools were used to analyze the water-airflow in a horizontal pipe. To do this mission, the cross-spectral density and 8 extracted parameters from the signal spectrum for one detector acted as input features for used machine learning (Hanus, et al., 2024). Authors have utilized a particle swarm optimization based feature selection system, and an ANN to detect a void fraction of a two-phase liquid-gas fluid. The used sensor was a gamma-based sensor with one source and two detectors (Iliyasu, et al., 2023). In the aspect of homogeneous two-phase fluids, a study was conducted being measuring void fraction independent of the liquid phase density changes by an MLP model (Iliyasu, et al., 2023). Authors have done this for an annular two-phase fluid (Veisi, et al., 2023). The same can be found for an annular regime while authors have utilized concave and TRFLC sensors to measure void fraction regardless of liquid type (Al-Fayoumi, et al., 2023). In another study, capacitive and photon attenuation sensors were used to collect data for an MLP ANN. The model was able to measure a void fraction of an oil-gas annular regime, precisely (Mohammed, et al., 2022). By employing two different capacitance-oriented sensors (concave and ring), the void fraction of a two-phase homogeneous regime was measured independent of temperature and pressure changes (Chen, et al., 2023). Moreover, a temperature-independent measurement was done for a two-phase fluid by employing an ANN and an 8-electrode sensor (Qaisi, et al., 2023). While these papers have reported good accuracies, they have not considered the impact of scale thickness.

In this paper, the main idea is to eliminate the impact of the scale layer in volume fractions measuring. Scale is a common phenomenon in pipelines and highly effects the accuracy of measurement. While in many previous published papers, the impact of this material is not applied, the proposed metering system's objective is to solve this challenge by measuring all phases' volume fractions independent of scale thickness, precisely. This mission is done by combining an MLP ANN, capacitive and gamma-ray attenuation sensors. Investigated fluid is a homogeneous regime containing gas, water, and oil. To generate data for the proposed network, the concave sensor is simulated in the COMSOL software and acts as the first input of the network. The second input is then produced by calculating Beer-Lambert equations to count gamma rays in each ratio of the materials mixture. Moreover, the scale's thickness is considered from 0 mm to 10 mm of $BaSO_4$ being one of the most common materials in pipelines. After investigating a number of networks with various hyperparameters, the best one is proposed which has a mean absolute error (MAE) of 0.318, 1.531, and 1.614, for the gas, water, and oil phases, respectively. These errors illustrate the novelty of the approach being able to measure the volume proportions of a three-phase gas-water-oil homogeneous fluid independent of the scale thickness. This study includes 4 more main sections. While in section 2 the details of simulations and calculations are presented, the proposed network's details are reported in section 3. In section 4, the obtained results are illustrated and discussed. Finally, the conclusion of the whole paper is done in section 5.

II. Describing Sensors Utilized in The Proposed Approach

As it was mentioned, the main aim of this paper is to present an approach being able to measure the VFs of all three phases, precisely. To do this mission, the first step is selecting an appropriate sensor. Capacitive and gamma-based sensors are highly popular among researchers to measure VFs of various fluids. One of the key reasons in this regard is their non-invasive nature. Another reason is their accuracy along with their installation being easy. The principle behind capacitive sensors is based on the variation in measured capacitance, which occurs due to changes in the material between the sensor's electrodes, referred to as the dielectric. In the case of a capacitance-based sensor, the material inside the pipe serves as the dielectric. Therefore, any alteration in the composition or ratio of the materials results in a change in the sensor's measured capacitance. This variation is attributed to the dielectric properties of the materials, with the most significant being their relative permittivity. Capacitive sensors are influenced by relative permittivity, and due to the similarity in the relative permittivity values of gas and oil, these sensors are unable to accurately measure the volume fractions of all three phases. As a result, an additional sensor based on a different physical property is required. A gamma-ray attenuation sensor, which operates based on density, is a suitable option. However, due to the similar densities of water and oil, it cannot effectively measure all three phases. While the gas phase has the lowest linear absorption coefficient, the challenge arises from the similarity between the liquid phases, making it difficult for the gamma sensor to differentiate between them. Therefore, both capacitive and gamma-ray sensors are used in conjunction to achieve the accurate measurement of all three phases. As it was mentioned before, the selected sensors must be non-destructive and non-invasive because the proposed approach is expected to do measurements without doing any separation or delay in the process. One critical point that must be considered is the parameters that impact the results produced by sensors. Since water and oil have close densities and oil and gas have close relative permittivity, the chosen sensors must be dependent on different parameters to generate various inputs to train and test the network much better and make it able to predict volumes. Density and relative permittivity are so important across various scientific and engineering disciplines. While density refers to the amount of mass contained within a specific volume, indicating how tightly matter is packed in a substance, relative permittivity indicates how effectively a material can save electrical-oriented energy within an electric-style field compared to empty space. Since capacitive and gamma-ray attenuation sensors are related to relative permittivity and density, respectively, they can be good choices for this research's purpose. Therefore, these sensors along with an MLP ANN are utilized to measure the volumes of the phases. It is to be noted that, fluids could be divided into three main regimes, annular, stratified, and homogeneous shown in Fig. 1. Due to the main aim of this investigation being independent of scale thickness measurement of a homogeneous flow, the scale can be seen in Fig. 1 with brown color.

Capacitance-based sensors have two electrodes with an insulating material in between. The mix of three phases in the fluid affects its overall dielectric properties, which in turn, alters the capacitive sensor's capacitance. This shows how much capacitive sensors depend on relative permittivity. These sensors have several perks, including a straightforward design, low-cost implementation, the use of non-ionizing radiation, fast response times, and easy, non-intrusive installation (Heindel, Gray and Jensen, 2008 and Hammer, et al., 2006).

As it is clear from equation (1), the capacity of the capacitance-based sensor (C) and relative permittivity or ε_r of material flowing inside the pipe are highly connected together. This parameter illustrates the amount of electrostatic energy that can be stored per unit of applied voltage. While A takes place as the area of electrodes, D is the gap between them. Finally, the permittivity of free space or ε_0 appears being about $8.854 \times 10^{-12} \frac{F}{m}$ (Cui, et al., 2021).

$$C = \frac{\varepsilon_r \times \varepsilon_0 \times A}{D} \tag{1}$$

Since both of the used sensors, capacitive and gamma-based sensors, have been utilized in a number of previously published papers to measure VFs of various fluids, their application is proved. Hence, in the current study, a combination of them along with an ANN is applied to reach the main goal of this study being measuring volumes of all three phases regardless of scale thickness. According to previous studies by authors. A static experimental study was conducted to validate the generated data by COMSOL software. After measuring sensor capacity in various VFs by an LCR meter, collected data were compared with that of simulated data. After comparing both data, it was observed that they have similar trends and generated data by the software are valid. This approach canbe found in a number of previous published studies (Veisi, et al., 2023 and Al-Fayoumi, et al., 2023 and Qaisi, et al., 2023).. Due

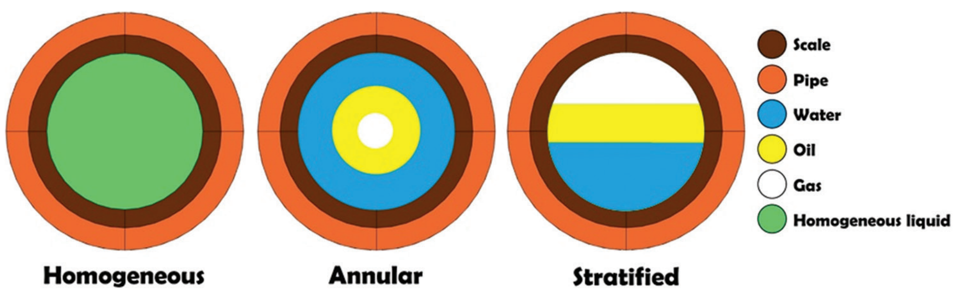

Fig. 1. Three main regimes of fluids.

to its good level of sensitivity and being easy to install on pipelines, the chosen sensor is concave being one of the most popular ones in this regard. To design and simulate this sensor the COMSOL software is utilized which is completely valid and has been benchmarked in a number of previous studies (Syah, et al., 2023 and Iliyasu, et al., 2024). The first stage of simulating this sensor in the mentioned software is creating an area to make an isolated condition for the study. Next, is the time for adding pipe followed by adding electrodes, both GND and VCC, to the surface of it. The liquid being a mixture of oil, water, and gas is then added inside the pipe. While (Fig. 2a) shows the 3D view of the simulated sensor, (Fig. 2b) do that of Mesh which was set on a Fine level before running the sensor for measuring capacities as much as accurate. In this figure, GND is gray and VCC is red. In Fig. 3, different lengths, radiuses, and the gap between electrodes are presented. While L_p is the length of the pipe and is equal to 180 mm, the length of the electrodes is depicted by L_e and is equal to 120 mm. Last but not least, the distance between electrodes is shown as G_e and is equal to 3 mm. Since the thickness of scale (R_s) made of $BaSO_4$ is alternative, R_l being the radius of the mixture is alternative, too. This happens while the radius of the pipe shown as R_p is equal to 32 mm. According to Fig. 4, various thicknesses of scale are considered for simulation ranging from 0 mm to 10 mm. The formula of R_l is 26 - R_s and is alternative from 26 mm to 16 mm based on each amount of scale. In this figure, pipe, scale, and liquid are shown with orange, brown, and green colors, respectively. There are 11 states of scale and by considering 10% of interval for changing in materials' volumes, 66 simulations are needed for each thickness of scale. Hence, by consuming a great amount of time, the simulations are done 726 times to generate the first input of the network.

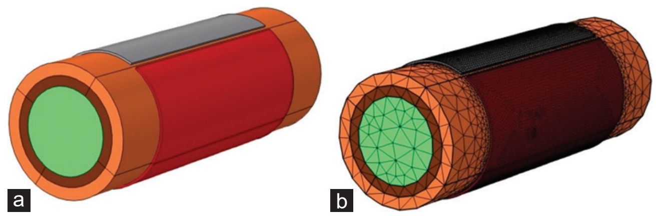

Fig. 2. (a) Simulated concave sensor and (b) Mesh view.

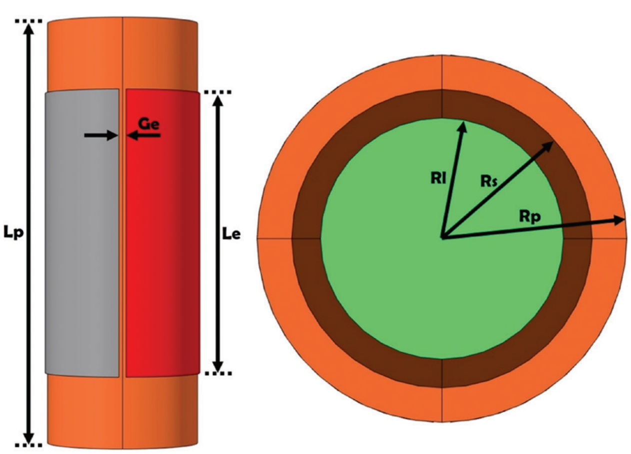

Fig. 3. Various dimensions of the simulated sensor.

As it was mentioned in (Mayet, et al., 2024b), just one capacitive sensor is unable to predict all phases and due to the closeness of the oil and gas phases' relative permittivity, this happens. To solve this problem, the solution is employing another type of sensor being sensitive to another physical parameter. Hence, a gamma-ray sensor could be a good choice because it is highly dependent on density and is non-destructive, too.

Since 1950s, gamma attenuation sensor has been utilized to measure volume fractions. The one-beam version of this density-dependent sensor works with the attenuation of the rays when cross the liquid. In fact, the ray starts from the source side and traverses the pipe (its diameter) to reach the detector side and be counted. It is obvious that the counted rays or the output of the sensor depends on the flow regime inside the pipe and for this reason, in this investigation, a homogeneous fluid of oil, gas, and water was considered. When gamma rays (like a narrow beam) move from a source has an initial intensity (I_1). After passing the first wall of the pipe (the wall near the source side) it penetrates to the fluid and after exiting from the second wall (the wall near the detector side) rays reach the detector with the final intensity (I_2). By these two intensities, the output of the sensor is calculated. Fig. 5 shows the details related to a gamma ray crossing the pipe and reaches to the detector to be counted.

The Beer-Lambert law is presented in equation (2) proving the fact of high impact of density on the gamma-ray attenuation sensor. In this equation, $I_1(E)$ and $I_2(E)$ are the energy of the ray emitted and the energy of the ray collected, respectively. While η is the absorption coefficient, ρ is the density of the material within the pipe and L stands for its thickness (Dong-hui, et al., 2005). By putting equation (3) being about the linear attenuation coefficients ($\mu(E)$) in equation (2), equation (4) is earned giving the amount of $\frac{I_2}{I_1}$, the second input for the network. Since the investigated fluid is a three-phase oil-water-gas flow, equation (5) is replaced in equation (4) to reach the final equation being equation (6). α, β, and γ in equation (6) are VF of oil, water, and gas, respectively. Finally, L is the thickness of materials inside the pipe and is equal to 52 mm.

$$I_2(E) = I_1(E)\ \exp(-\eta(\mathrm{ZE})\ \rho\mathrm{L}) \tag{2}$$

$$\mu(E) = \eta(\mathrm{ZE})\ \rho \tag{3}$$

$$I_2(E) = I_1(E)\ \exp(-\ (\mathrm{E})\mathrm{L}) \tag{4}$$

$$\mu(E) = \alpha\mu(E)_o + \beta\mu(E)_w + \gamma\mu(E)_g \tag{5}$$

$$Ln(\frac{I_2}{I_1}) = -[\alpha\mu(E)_o + \beta\mu(E)_w + \gamma\mu(E)_g] \times L \tag{6}$$

In this study, Cesium-137, emitting radiation at 0.662 MeV, was chosen. According to the linear attenuation coefficient of all three phases in (National Institute of Standards and Technology, 2023), equation (6) is calculated for various

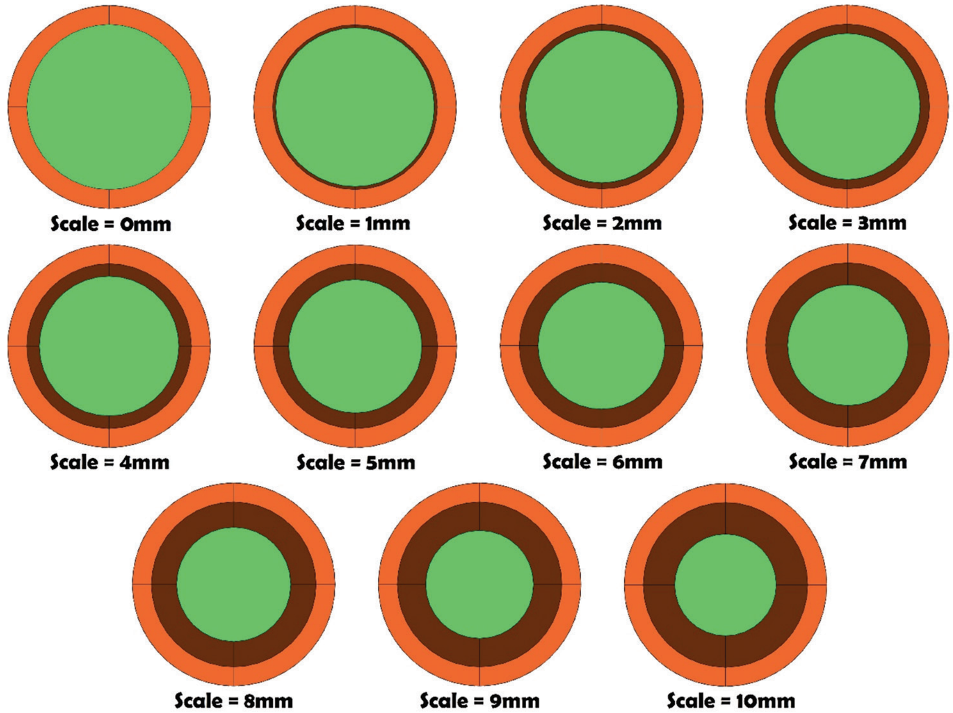

Fig. 4. Various thicknesses of the scale considered during simulations.

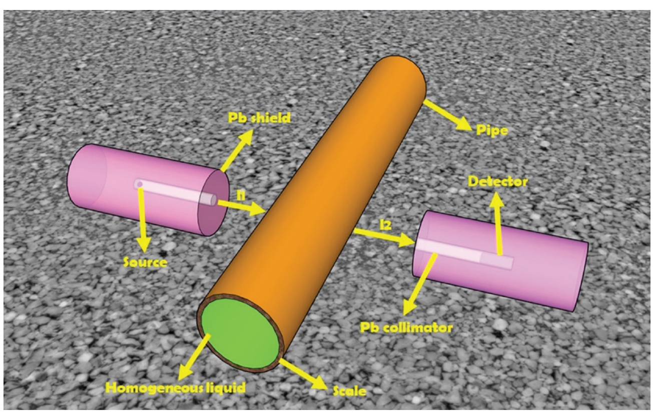

Fig. 5. The travel of gamma ray from source to detector to be counted.

TABLE I
CHARACTERISTICS OF THE SCALE AND PHASES OF THE INVESTIGATED FLUID

Characteristic	Value or Name
Utilized material for the scale	$BaSO4$
Relative permittivity of gas	1
Relative permittivity of water	81
Relative permittivity of oil	2.2
Relative permittivity of the used scale	11.4
Density of gas	0.001 g/cm^3
Density of water	1 g/cm^3
Density of oil	0.9 g/cm^3
Density of the used scale	4.48 g/cm^3
The range of volume fractions	0–100%
The step of volume fractions	10%
The number of simulations and calculations	11×66=726
Type of the investigated fluid	Homogeneous

ratios of materials and the second input of the network is generated. Table I presents all parameters and materials which are utilized in done simulations and calculations. Statistical analysis is a systematic process that involves selecting appropriate techniques, utilizing relevant software tools, and adhering to specific guidelines to facilitate the efficient collection and analysis of data. In this study, the statistical technique of data splitting was applied, where the dataset was randomly divided into training and testing subsets. Microsoft Excel, software offering basic statistical features useful for straightforward analyses, was employed. The criteria for data collection and analysis were based on data quality and sampling methods. Several steps were taken to process, clean, and prepare the data for analysis after extraction. First, the extracted data were examined to identify any missing values, outliers, duplicates, or inconsistencies, none of which were found. As the data were on the same scale, normalization and conversion were unnecessary. Subsequently, the data were randomly split into training and testing sets. Finally, the verified data were saved using Excel software for further analysis. Last but not least, since the used data are simulated-based data, there is nothing about unreliability to do with this data because they are generated by software and ideal conditions are considered and noise is not considered a brining error to the results and decreases the reliability of outcomes.

It is to be noted that, before a sensor can be manufactured, it must undergo calibration using a reliable reference. This is essential because the sensor is designed to measure dynamic values for which no prior data exists. To achieve this, several studies are conducted using a static model across various phase ratios to produce calibration points. These points are then used to calibrate the sensor and can be generated using advanced software, such as the validated COMSOL Multiphysics software.

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III. Utilizing Ann as A Powerful Tool to Predict Volumes

ANN are utilized in many areas, such as signal processing and pattern recognition. The selection of ANNs was based on their demonstrated effectiveness in handling complex, non-linear relationships between input variables, such as those encountered in multiphase fluid measurement. Multiphase flow systems are highly dynamic, and the capacitance and gamma-ray sensor outputs often exhibit non-linearity and interdependence, which ANNs are well-suited to model due to their ability to learn complex mappings from data. As it was mentioned, due to the inherent complexity of multi-phase fluids and the non-linear behavior between sensors' outcomes and volume proportions, ANNs are so intriguing for researchers in the aspect of flow measurement because they are so appropriate in non-linear-style systems. Among various types of ANN, such as Support Vector Machines (SVM) and XGBoost, Multi-Layer Perceptron (MLP) ANNs are widely used in measuring volumes. This is because of offering a more versatile framework, accommodating a wide range of configurations and activation functions being non-linear (Goodfellow, Bengio and Courville, 2016; Zhang and Suganthan, 2016). Another merit related to MLP ANNs is their flexibility in predicting continuous function providing enough data and appropriate architecture for modeling unpredictable systems, such as multi-phase fluids. Moreover, while some networks such as Gaussian process regression can become computationally challengeable in handling extensive data, MLP ANNs are compatible with advanced hardware such as GPUs resulting in enhancing training speeds (Hinton, et al., 2012; He, et al., 2016). Next, due to their learning and generalization capabilities of MLP ANNs, they exhibit robustness in dealing with noisy data. Hence, they are useful in the flow measurement industry (Bishop and Nasrabadi, 2006; Geman, Bienenstock and Doursat, 1992). According to all provided reasons, an MLP ANN is chosen and by using it, the metering of all phases of the investigated fluid is done. This kind of network has some layers, input, output, and hidden layers. Each one of these layers has neurons and activation functions, such as linear, sigmoid, tansig, and purelin. When the training process is in process, weights and biases are iteratively tuned to reach the lowest MAE. Convergence plays a crucial role in network performance, and its relationship with the learning rate is well-established. If the learning rate is set too high, it can cause instability or lead to oscillations in the algorithm, while a rate that is too low may result in extremely slow convergence. Therefore, determining the optimal learning rate often requires experimentation. In this study, the learning rate was set at 0.01 based on such considerations. Non-linear systems, such as multi-phase flow measurement, often prompt researchers to employ optimization algorithms to address complex challenges. One of the most commonly utilized algorithms is the Levenberg-Marquardt (LM) algorithm, which combines the features of both Gradient Descent and Gauss-Newton iteration, offering numerous advantages. For example, it reduces the demand for high-performance computing resources while ensuring a fast convergence rate. As a result, the learning process for the network in this study was based on the LM algorithm, which has a broad spectrum of engineering applications, making it well-suited for this research (Levenberg, 1944; Marquardt, 1963). Data were generated by simulating a concave sensor in the COMSOL Multiphysics software under varying ratios of oil, water, and gas, along with solving the Beer-Lambert equations for a gamma-ray attenuation sensor using Cesium-137. The collected data were then normalized before being fed into the MLP ANN. In the next phase, multiple iterations were implemented in MATLAB to explore and evaluate different combinations of hyperparameters, including the number of hidden layers, neurons per hidden layer, activation functions for the input, output, and hidden layers, as well as the number of epochs, among other parameters. Ultimately, the model with the lowest MAE was selected and is presented in this paper. The proposed network has 2 inputs generated from simulations of a concave sensor in COMSOL software to measure capacitance of various ratios and calculations of the Beer-Lambert equations related to counted rays with Cesium-137 in its source side. Since the scale from 0mm to 10mm is investigated and the volume interval is 10%, totally, simulations and calculations are done for 726 times. After normalizing all data, 70% of them being 508 data are considered for training and the rest of them belong to testing the network. This data consideration is done, randomly. This network has 2 hidden layers, both of them have 10 neurons and their activation function is tansig. The activation function of both input and output layers is purelin. In Equation (7) and Equation (8), the function of tansig and purelin is presented, respectively. Last but not least, the best network with the lowest desired MAEs trained over 2100 epochs. The proposed network is illustrated in Fig. 6.

$$Tansig\left(n\right) = \frac{2}{1+e^{-2n}} - 1 \tag{7}$$

$$Purelin\left(n\right) = n \tag{8}$$

In the measurement of volume fractions of a multiphase fluid using multiple sensors, such as a capacitance-based sensor and a gamma-ray attenuation sensor, the accurate and real-time transmission of sensor data are critical. The sensors generate continuous data regarding VFs of the fluid phases and this data can be transferred by various transferring protocols, one of the most popular ones is message queuing telemetry transport (MQTT). MQTT ensures that the sensor outputs are transmitted efficiently to the server in a way being lightweight, low-bandwidth, and reliable data transfer over networks with minimal latency. Once the data are received at the server, the modeled ANN starts to process and analyze the input, enabling the real-time estimation of the multiphase fluid's volume fractions. The combination of MQTT's protocol for data transmission and ANN's computational capabilities allows for robust and precise monitoring of the fluid composition, ensuring that the system is both scalable and adaptable to complex environments.

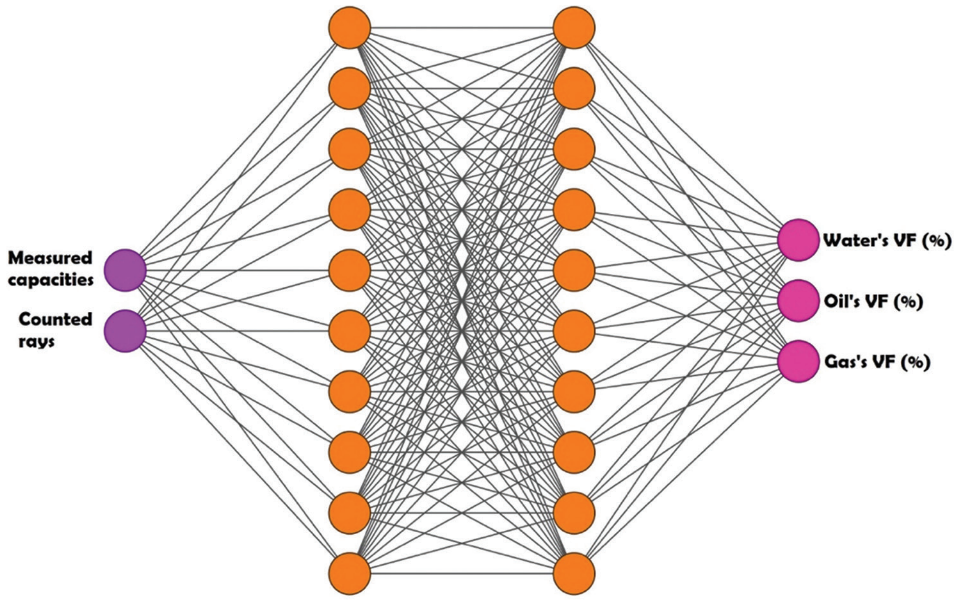

Fig. 6. Various layers of the proposed network.

IV. Results and Discussion

After doing all required simulations and calculations, the obtained results are presented in this section. The main aim of this investigation was to measure the volume proportions of all three phases of a homogeneous fluid including gas, water, and oil independent of scale thickness presented in the wall of pipelines. To achieve this task, an MLP ANN along with capacitive and photon attenuation sensors were employed. As it was mentioned before, the proposed network had 2 distinct inputs generated from simulating the concave sensor in the COMSOL software and calculating Beer-Lambert equations for a gamma attenuation sensor with Cesium-137 in its source part. All 726 obtained data were randomly divided between the test and train sets of the network. The proposed metering system had 3 outputs, a void fraction of gas, and volumes of water and oil having MAE equal to 0.318, 1.527, and 1.608, respectively. These errors illustrate the novelty of the system being able to gauge volumes of a three-phase gas-water-oil homogeneous fluid regardless of the scale thickness. The flowchart of the way that the presented approach combined sensors and network is illustrated in Fig. 7. As it was said before, the main reason for choosing two types of sensors was dependent on the very close relative permittivity of oil and gas resulting in an inability of the capacitive sensor in VFs of all three phases. Hence, another kind of sensor being sensitive to another parameter was employed and it was a gamma-ray attenuation sensor being highly dependent to density. The combination of these two different sensors along with an MLP could measure all three phases' volumes, precisely.

When just one capacitance-oriented sensor is utilized for measuring VFs, due to the closeness of materials' relative permittivity, similar capacities for different ratios of combinations are generated and this confuses the network to predict volumes. In fact, some ratios of combinations exist that are different in the amount of materials but similar in the measured capacity. Therefore, to make the network able to predict correct volumes, a gamma-ray attenuation sensor, being sensitive to density, can be used to generate another set of data being different with the first set, which were measured capacities. That is why; the combination of this sensor was used and made the proposed network able to measure all volume fractions regardless of the effect of scale thickness. The obtained results, test and train set from the proposed network for all phases are shown in Fig. 8. From the mentioned figure, it is clear that both overfitting and underfitting did not happen for the obtained outcomes.

After reaching the best network, the MAE of all three phases was calculated by Equation (9) (Chicco, Warrens and Jurman, 2021). The proposed metering system had 3 outputs, a void fraction of gas, and volumes of water and oil having MAE equal to 0.318, 1.527, and 1.608, respectively. These numbers were related to the test set, the train sets' MAE for gas, oil, and water was 0.304, 1.348, and 1.403, respectively. This very low error depicts the ability of the proposed metering system, a combination of two sensors and an MLP ANN, in gauging oil, gas, and water phases regardless on scale thickness in a homogeneous flow. In addition, other error metrics are also discussed in this paper. The formulas for root mean square error (RMSE), coefficient of determination (R-squared or R^2), and symmetric mean absolute percentage error (SMAPE) are provided in equations (10), (11), and (12), respectively, as referenced in (Chicco, Warrens and Jurman, 2021).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | X_i - Y_i | \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (X_i - Y_i)^2} \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (X_i - Y_i)^2}{\sum_{i=1}^{n} (X_i - Y)^2} \tag{11}$$

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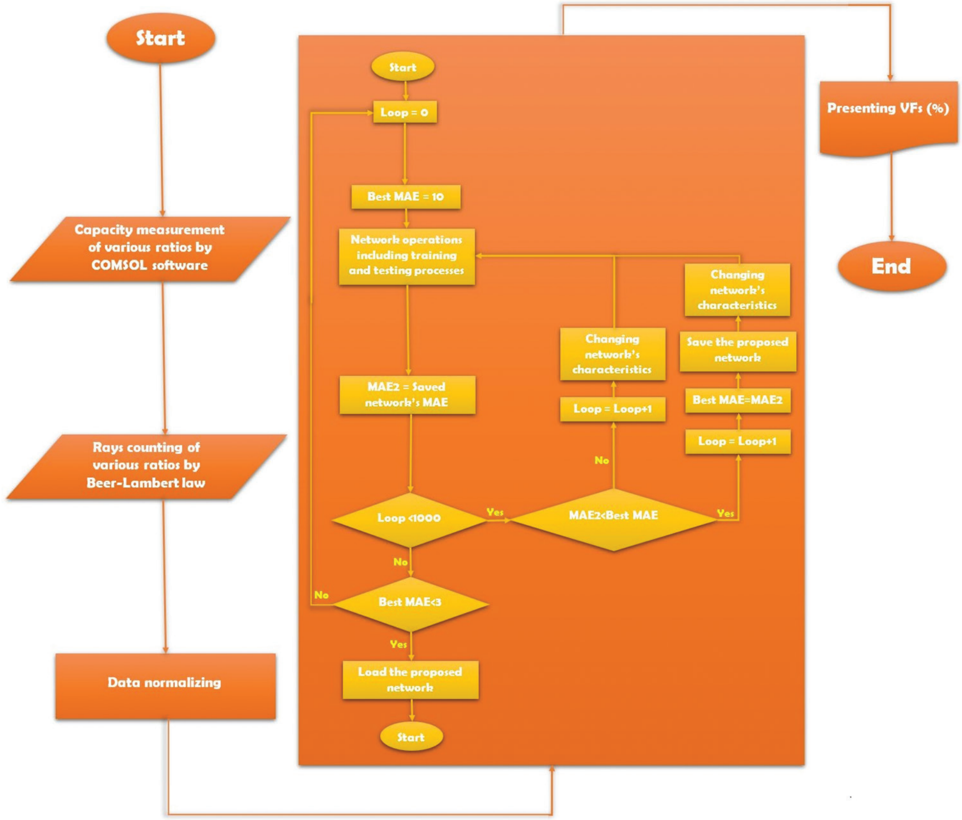

Fig. 7. The flowchart of the proposed approach contains an artificial neural network along with capacitive and photon attenuation sensors.

$$SMAPE = \frac{100\%}{n} \sum_{i=1}^{n} \frac{|X_i - Y_i|}{\left(|X_i| + |Y_i|\right)/2} \quad (12)$$

In the aforementioned equations, n represents the total number of data points, Xi refers to the actual value for the i^{th} data point, Yi is the predicted value for the i^{th} data point, and Y denotes the mean of all actual values. Similar to MAE, RMSE equals zero when the linear regression model perfectly matches the data, while a positive value indicates an imperfect fit. The R^2 metric ranges from 0 to 1, with 1 indicating a perfect fit and 0 representing the worst fit. On the other hand, SMAPE ranges from 0% to 100%, where a perfect alignment between actual and predicted values results in a value of 0%, while the worst alignment leads to SMAPE = 100%. For the proposed model, R^2 values were found to be 0.9997 for gas, 0.9908 for water, and 0.9897 for oil phases. In terms of SMAPE, the gas, water, and oil phases showed values of 0.0012%, 0.0057%, and 0.0060%, respectively. In addition, the RMSE for the gas phase was 0.4105, whereas it was 2.5706 for the water phase, which was 0.1474 lower than that of the oil phase. In Fig. 9, various Error illustrations regarding the obtained results are shown. Error histograms for gas, water, and oil are presented in (a), (b), and (c) parts of this figure showing a great distribution of data around 0. While errors of all three phases are depicted in (d), (e), and (f), the figure for target versus predicted is illustrated in (g), (h), and (i) parts.

To highlight the novelty and performance of the metering system, its details are compared to that of some similar previous published works in Table II.

In the above table, 6 previously published papers were compared with the proposed metering system. Except for the presented approach, just authors in (Roshani, et al., 2021) have tried to eliminate the impact of scale thickness in their measurement being measuring the void fraction of a two-phase annular system including oil and gas. However, the proposed system is able to measure all three phases of a three-phase flow regardless of the scale's impact with a lower amount of MAE for all phases in comparison with reference (Roshani, et al., 2021). Moreover, authors in (Roshani, et al., 2021) have utilized 2 sources and 2 detectors for their investigations, 2 times higher than that of the presented method. It is obvious that when the number of sources and detectors increases, a much more accurate result is expected but the problem is rising in both complexity and cost of the system. This point is another merit of the presented metering system in comparison with references (Roshani, et al., 2021) and (Salgado, Dam and Salgado, 2021). While all phases including gas, water, and oil were presented in the proposed approach, references (Mayet, et al., 2024b) and (Pan, et al., 2019) have reported just one phase's volume. Last but not least, reference (Mayet, et al., 2024a) have reported all three phases' volumes with a good level of accuracy. Aside from having a lower amount of MAE in gas and oil phases, the presented method measures volumes independent of scale thickness, the point that the reference (Mayet, et al., 2024a) is unable to do it. Finally, reference (Peyvandi and Rad, 2017) can be seen that not only is not able to measure volumes regardless of scale but also have a higher amount

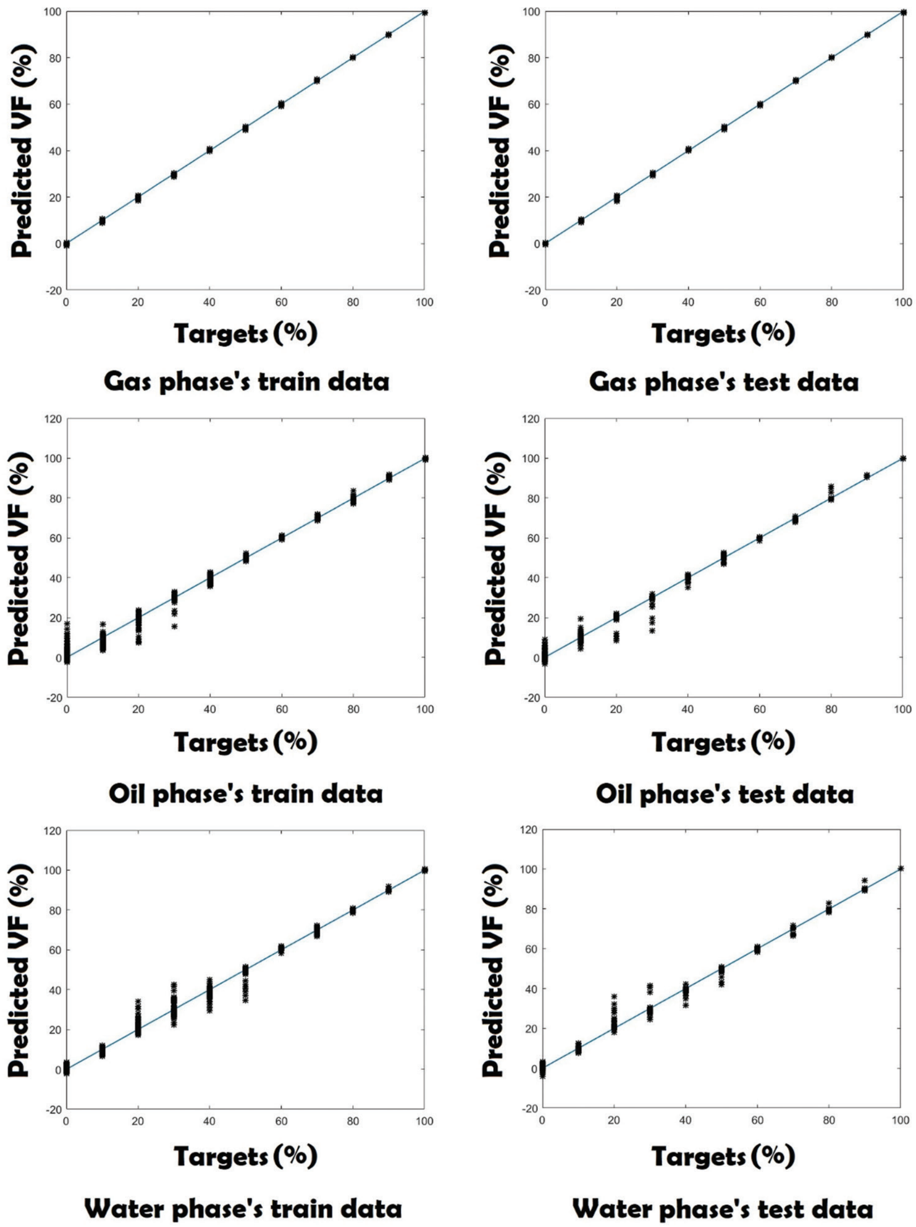

Fig. 8. The proposed network's test and train performance for all three phases.

Table II
Comparing The Proposed Approach With A Couple Of Similar Previous Works

Study	Presented phases	Utilized sensors	Utilized sources	Utilized detectors	Mean Absolute Error	Independent of scale thickness
(Mayet, et al., 2024a)	Gas Water Oil	Capacitive+Gamma attenuation	1	1	1.6 0.29 1.67	No
(Mayet, et al., 2024b)	Water	Capacitive	---	---	1.66	No
(Roshani, et al., 2021)	Gas Oil	Gamma attenuation	2	2	2.81 ---	Yes
(Salgado, Dam, Salgado et al., 2021)	Water Gas	Gamma attenuation	2	2	1.79 0.4	No
(Pan, et al., 2019)	Gas	Gamma attenuation	1	1	7.72	No
(Peyvandi and Rad, 2017)	Gas Water Oil	Gamma attenuation	1	1	1.87 1.88 ---	No
Proposed approach	Gas Water Oil	Capacitive+Gamma attenuation	1	1	0.318 1.531 1.614	Yes

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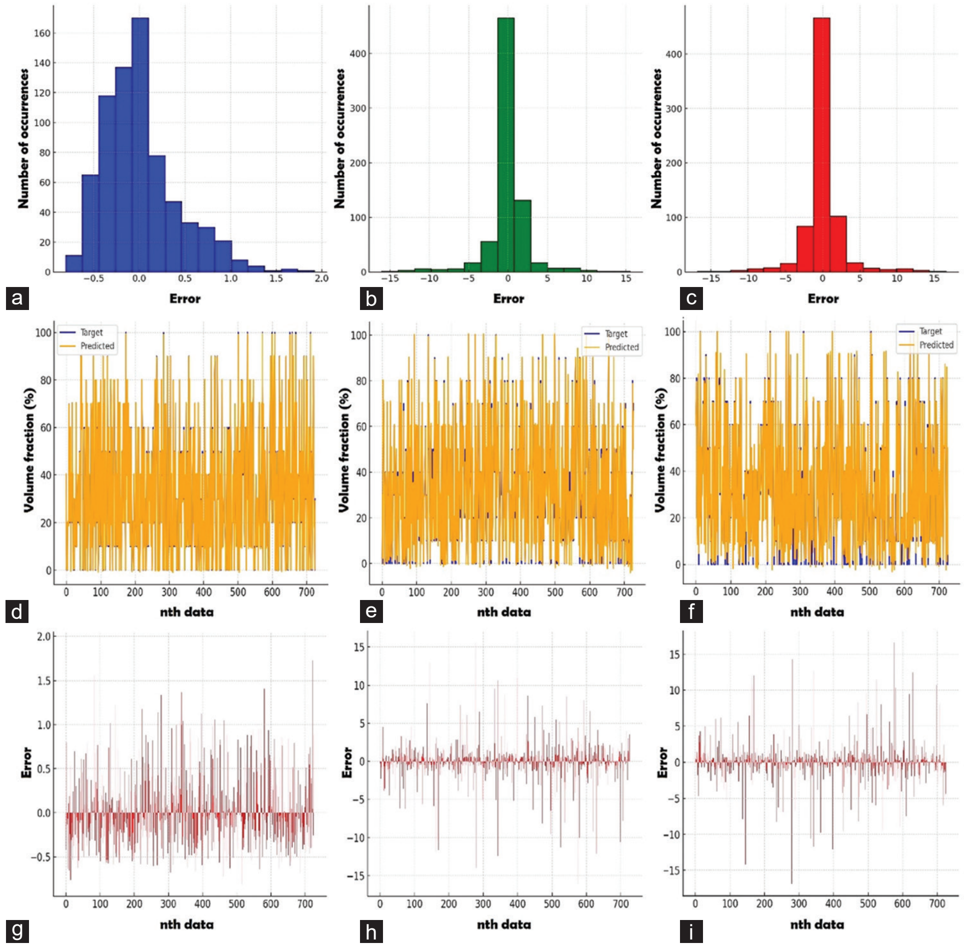

Fig. 9. Error illustration for the proposed metering approach, (a) Gas phase's Error histogram, (b) Water phase's Error histogram, (c) Oil phase's Error histogram, (d) target versus predicted values of gas phase, (e) target versus predicted values of water phase, (f) target versus predicted values of oil phase, (g) Gas phase's error, (h) Water phase's error, (i) Oil phase's error.

of MAE in comparison with this study. While the proposed metering system demonstrates accurate prediction of the volume fraction in all phases of a gas-oil-water homogeneous mixture, like any solution, it has certain limitations. One significant issue is the need to address radiation shielding, as it is critical to ensure the health and safety of personnel working with such systems. However, due to the flexibility in adjusting photon energy, the high intensity of photon emission, and the ability to switch X-ray tubes on and off, this method presents a viable alternative to the use of radioisotopes. In addition, the scope of this study is limited to homogeneous regimes and cannot measure VFs in other types of fluid mixtures. Finally, the effects of temperature and pressure variations, which significantly influence the liquid's relative permittivity and density inside the pipe, should also be considered.

V. Conclusion

In this paper, a metering approach was proposed that was able to measure all three phases of a multi-phase fluid independent of scale thickness, accurately. The presented approach had 2 employed sensors and an MPL ANN. Capacitive and gamma attenuation sensors were used to generate enough data for training and testing the network. After examining a numerous number of networks with various characteristics, the best one was presented in this study. This model had 2 inputs from sensors, and 3 outputs for phases' volume. The MAE of gas, water, and oil was 0.318, 1.531, and 1.614, respectively. It is to be noted that, just 1 source and 1 detector were employed to generate data by the gamma-ray attenuation sensor by calculating Beer-Lambert equations. Moreover, the simulated capacitive sensor was concave geometry. This metering system can be used in pipelines because they are faced with a scale during their processes and eliminating the effects of this material on measuring accuracy is a vital action. Variations in temperature and pressure significantly influence the capacitance-based method due to changes in liquids' relative permittivity and density. The experiments in this study were performed at room temperature (approximately 300 K), but future research should account for these variables and develop metering systems that are not dependent on them. To further reduce errors, enhancing feature extraction could lead to more accurate volume fraction predictions. In addition, experimenting with different learning algorithms or activation functions could offer further optimization for future studies. Although scale formation can be non-uniform in real-world conditions, uniform scale formation (ideal condition) is assumed to simplify the analysis. Moreover, while uniform scale is a simplifying assumption, it serves as a baseline for further investigations to address non-uniform scale distributions.

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