IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 13 May 2024, accepted 28 June 2024, date of publication 3 July 2024, date of current version 24 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3422610

RESEARCH ARTICLE

Design of a Novel Predictive Technique to Estimate Liquid Level and Concentration Using Multi-Sensor Data Fusion

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ABSTRACT Level is one of the important parameters to be measured in many of the industrial applications, in which Capacitance Level Sensors (CLS) play an important role in measuring liquid level because of its ruggedness. But CLS is inept at measuring levels irrespective of liquid types hence this work proposes a novel technique to overcome the demerits of conventional measurement of CLS. This paper aims to develop a novel predictive technique to measure the liquid level along with its concentration. The predictive technique comprises a Level Predictive Model (LPM) and a Concentration Predictive Model (CPM). LPM predicts an accurate level for the change in liquid type and CPM predicts the change in sugar concentration of a liquid. An experimental setup was established for the model development. LPM was developed by infusing the data fusion technique from the data obtained by three different sensors CLS, Pressure Level Sensor (PLS) and Ultrasonic Level Sensor (ULS) for adaptive level measurement. CPM was developed using a Support Vector Machine (SVM) model for predicting the changes in sugar concentration in a liquid. The work was validated by implementing the developed LPM and CPM on a real-time system. System validation results showed that LPM detected the level with an error of −6 to 0.0001 cm, and CPM gave an accurate result for predicting the sugar concentration in liquid with an error between +/− 0.8%. The obtained results of models catered to the objectives of the work with enhanced accuracy and avoided the re-calibration of CLS-based Liquid Level Measurement Systems (LLMS).

INDEX TERMS Calibration and fitting methods, concentration measurement, data analysis, liquid level measurement, multi-sensor data fusion.

I. INTRODUCTION

The level and concentration of liquids are important process parameters to be precisely measured in many process industries, such as the petrochemical and fuel industries, pharmaceutical and chemical industries, milk, dairy and oil industries, and dye manufacturing industries [1]. Accurate Liquid level measurement (LLM) is important for many process control industries [2]. Incorrect representation of the liquid level may cause an overflow leading to a hazardous environment or fetching a defective byproduct [3]. Also, in many process industries, finding the concentration of additives in liquids, such as salt, sugar, powder, chemicals, oil-water mixtures, and detergents, has become an important task to attain an accurate byproduct [4].

The level measurement process involves finding the trace of the liquid surface inside the process container [5]. Finding

The associate editor coordinating the review of this manuscript and approving it for publication was Bo Pu.

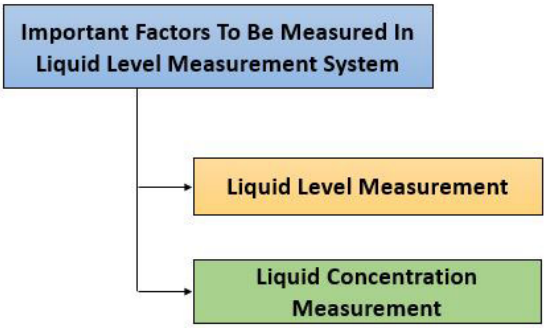

FIGURE 1. Important factors of LLM.

the concentration determines the process of detecting an additive in the liquid. Generally, a measurement system consists of a level sensor, a data conversion circuit, a data conditioning circuit, a data representation unit and predictive models [6]. Figure 1 shows the important factors to be measured in the LLM system.

Accurate measurement of level and concentration in industrial settings saves time and money and optimizes the performance of processes, plants as well as products [7]. The process of liquid level measurement and liquid concentration measurement by a wide range of measurement techniques are detailed in the below subsections.

A. LIQUID LEVEL MEASUREMENT

LLM is mainly carried out by a level sensor - A device that is used for finding the quantity or level of fluids, powder, slurry, etc. [8], [9], and [10] in a closed or open structure. In this context, a wide range of such sensors are available for measuring the levels of various liquid types and liquid parameters for different applications of LLMs [11], [12], [13]. For example, the capacitance level sensor (CLS) measures the water level irrespective of the contaminants of water by the structure of comb electrodes [14], [15]. Ultrasonic and radar sensors measure the level of any liquid type by determining the travel time of an ultrasonic and radio wave from the transmitter to the receiver [16], [17], [18]. The resistive sensor measures the level by an electrical method by detecting the change in resistance with the change in level [19]. The optical sensor measures the level by monitoring the reflection time [20], [21], [22]. The pressure sensor measures the level and density of the liquid related to its height [23], [24], [25]. Conductive probes are used in point measurement of the liquid level [26], [27], [28]. Measurement of the liquid level is affected by changes in the liquid temperature, liquid type, and additives in the liquid. Basically, LLM is dependent on the following factors.

1) LIQUID TYPE

LLM depends on the type of liquid used for the measurement. A change in liquid type affects the sensor performance, as sensors are calibrated for certain liquid types.

2) CONCENTRATION OF LIQUID

LLM is also dependent on changes in additives in liquid. Sensor characteristics such as accuracy, precision, repeatability, and stability are affected by the change in additives in a liquid.

B. LIQUID CONCENTRATION MEASUREMENT

Measuring the concentration of liquid is an important parameter in LLM, among which various sensors measure different concentrations using different techniques that are reported in various sets of papers. For example, the contents of droplets and moisture content are detected by microfluidic capacitive and capacitive throughput sensors [29], [30], [31]. The measurement of solid-liquid, i.e., deionized water along with glass beads, is measured with stirring speed by CLS [32], [33]. Air-water volumetric concentration, conductive liquids, and oil are measured by a capacitive sensor [34], [35], [36]. CLS is used to measure the contents of mixtures of two liquids with different ratios [36], [37] and detect the oil level in a fuel tank [38], [39], [40].

In this paper, we propose a novel predictive technique that detects the level and concentration of liquid by developing a level prediction model (LPM) and concentration prediction model (CPM) using multisensor data fusion (MSDF) and support vector machine (SVM) techniques. As per the above discussions, CLS is mainly dependent on the change in the type of liquid, liquid temperature, and types of additives used in the liquid [41]. This work comprises measuring the level and concentration of liquid by using CLS and considering various factors, such as liquid type, liquid temperature, and change in concentration of sugar in liquid.

C. MOTIVATION

However, much scholarly work provides research contributions in the field of measurement of the liquid level and its concentration by using various techniques and different sensors. Additionally, the performance of sensors that are used to measure the level is enhanced for changes in liquid type and changes in additives in liquid by re-calibrating the sensor for every change. Additionally, the concentration and content of the liquid were detected by the sensors by changing the sensor characteristics and by re-calibrating the sensor. Nevertheless, there exists a challenge in detecting the level and concentration of liquid by enhancing the sensor characteristics and by avoiding re-calibration of the sensor. Therefore, it is essential to provide an effective novel technique consisting of LPM and CPM. This work attempts to provide a novel predictive technique by designing an LPM using the MSDF-based neural network (NN) technique to predict an exact level of changes in liquid type, liquid temperature and the change in concentration of sugar in liquid. Additionally, the development of CPM using the SVM technique to detect the concentration of sugar in liquid has been reported in this paper. The implementation of the LPM and CPM on a real-time system is detailed in this paper.

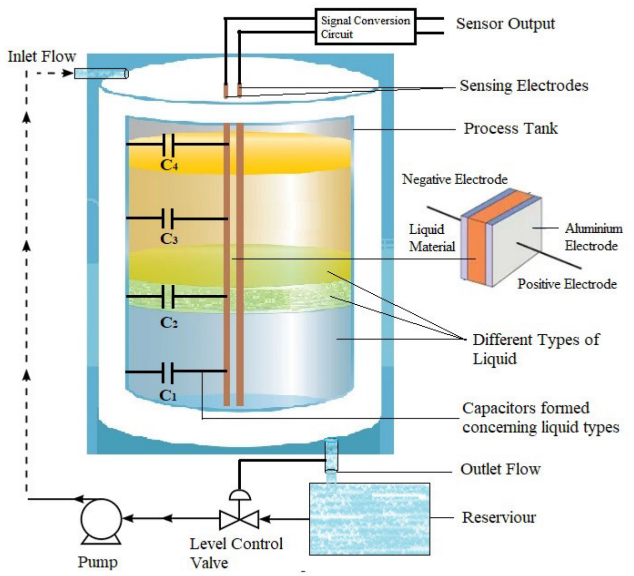

FIGURE 2. CLS working principle.

D. PAPER ORGANIZATION

This paper is organized as follows. Section II discusses the analysis of the LLM using CLS and the working principle of CLS. Section III provides a need for the development of a level and concentration predictive model for LLM using CLS. It also analyses the effect on sensor output for the change in liquid type and changes in concentration of sugar. In Section IV, focuses on the solution to the problem by designing and developing models to cater to the requirement of level and concentration measurement. A detailed description of both predictive techniques for developing LPM and CPM is presented. Additionally, both models are validated on a real-time system. Sections V and VI conclude the paper by discussing the results obtained by the models. Also, the advantages of designing a predictive technique of CLS-based LLMs are highlighted.

II. ANALYSIS OF LLM USING CLS

Capacitance-based LLM system is one of the prominent measurement techniques because of its ruggedness [42]. This work precises to measure liquid levels using CLS [43]. The working principle of CLS is based on measuring the change of capacitance value for the change in the dielectric medium (i.e., liquid) between two electrodes [44]. The capacitance equation of CLS in Eq. 1 states the capacitance output's dependency on the liquid's relative permittivity [45].

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

where, surface area and distance between the electrode plate are defined as A and D, ε_r are relative Permittivity of the dielectric medium, ε_o is absolute Permittivity i.e. 8.854×10^{-12} [46]. Generally, CLS is built by immersing sensing electrodes in a liquid process tank [47]. CLS works on the principle of capacitors formed in parallel concerning liquid and air in a tank [48] as shown in Figure 2.

The total resultant capacitance of the sensor is obtained by the summation of parallel capacitors formed within the process tank [49] as given in Eq.2.

$$C_T = C_1 + C_2 + C_3 + C_4 \tag{2}$$

where C_T is total output capacitance of a sensor, C_1, C_2, C_3 and C_4 are capacitors formed with respect to different types of liquid [50].

In this work we tend to use novel helical structured CLS for analysis [51], [52] consisting of a tank height 'H', containing level liquid at height 'h' and the total capacitance of helical CLS (C_{Th}) expressed in the Eq.3, Eq.4 and Eq.5 below.

$$C_{Th} = C_{h(air)} + C_{h(liquid)} \tag{3}$$

$$C_{Th} = C_{h1} + C_{h2} \tag{4}$$

$$C_{Th} = \frac{2\pi\varepsilon_o\varepsilon_{ra}(H-h)}{ln\left[\frac{b}{a}\right] + ln\left[\frac{P+\sqrt{P^2+(2\pi a)^2}}{P+\sqrt{P^2+(2\pi b)^2}}\right]} + \frac{2\pi\varepsilon_o\varepsilon_{rl}(h)}{ln\left[\frac{b}{a}\right] + ln\left[\frac{P+\sqrt{P^2+(2\pi a)^2}}{P+\sqrt{P^2+(2\pi b)^2}}\right]} \tag{5}$$

where, C_{Th} is total capacitance, C_{h1} is a capacitor formed with respect to air, C_{h2} is a capacitor formed with respect to liquid, ε_{ra} relative permittivity of air and ε_{rl} is the relative permittivity of liquid, H is the total height can also be determined as $(n \times P)$, a is radius of inner helical electrode, n is number of turns, b is radius of outer helical electrode, P is pitch i.e. distance between one turn to other.

The research gaps in using CLS for the measurement of the level and concentration of liquid are detailed in the section below.

III. PROBLEM STATEMENT

Detecting the liquid level and its concentration are important parameters to be measured in the LLM system. The measurement of the level and concentration of liquid by using CLS [53] includes certain factors that affect the output of CLS. In essence, the output of CLS depends on the liquid permittivity of the liquid, increase in permittivity increases the capacitance output [54]. To analyze the effect of change in liquid type and concentration of sugar on the CLS output, experiments were conducted for change in liquid type and changes in 20%, 40%, and 60% of sugar concentration in liquid. Hence, the following tests were carried out to analyze the effect of the sensor output on the detection level [55].

- [1]Effect of change in liquid type on sensor output.
- [2]Effect of the change in the concentration of liquid on the sensor output.

A. EFFECT OF CHANGE IN LIQUID TYPE

To measure the liquid level using CLS, it is essential to analyze the effect of the change in liquid type on the sensor

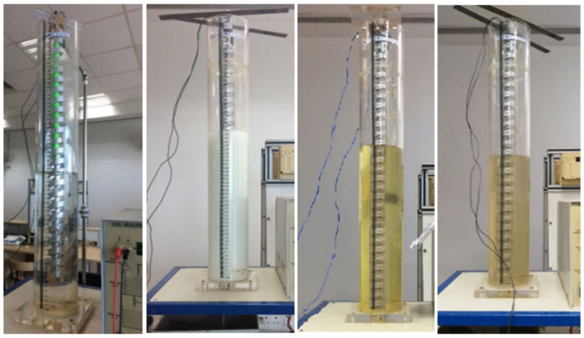

FIGURE 3. Experimental setup of the effect of different types of liquids on CLS.

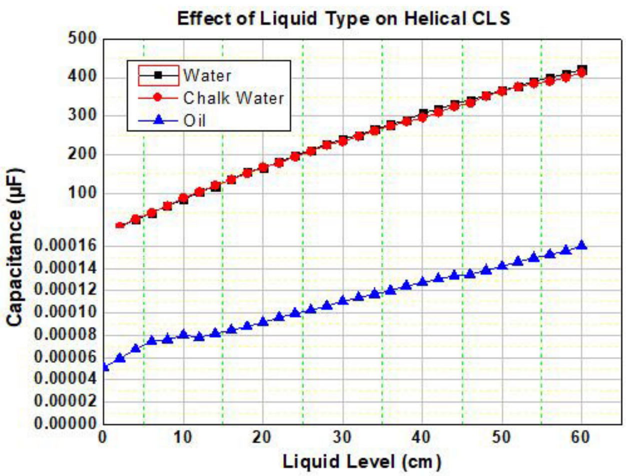

FIGURE 4. Effect of different types of liquid on helical CLS.

output. Generally, CLS works on the principle of measuring the change in capacitance with respect to the change in liquid level [56], [57], [58]. The capacitance equation in Eq. 1 above shows the dependency of the capacitance on the relative permittivity of the liquid.

To analyze the effect the different types of liquids, such as water, chalk, water, and edible oil, have been considered for the experiments [38], [60], [61], [62], [63]. And a change in the output of helical CLSs was observed. The experimental setup of CLS with different types of liquids is shown in Figure 3.

The helical CLS output depends on the dielectric medium of the liquid, as the liquid type changes, the dielectric constant changes, and hence, there is a change in the output of CLS. Figure 4 shows the effect of different types of liquid on helical CLS.

The list of liquid types and dielectric constants are mentioned in Table 1. It was observed that a higher sensor output (capacitance) was obtained for a higher relative permittivity (ε_r) of liquid, as noted in Table 1.

The sensor output is also dependent on the concentration of liquid used. As the liquid concentration changes, the permittivity is changed, and the sensor outputs. The following subsection describes the effect of the change in liquid type on the sensor output.

TABLE 1. Permittivity of different types of liquid.

Types of Liquid	Permittivity (ε_w) (F/m)	Level (cm)	Helical CLS (μF)
Chalk water	74.1	60	413
Water	80.1	60	421
Edible oil	2.9	60	160.1

TABLE 2. Dielectric constant of the sugar solution with respect to its concentration.

Concentration (%)	Volume of water (L)	Sugar (Kg)	Permittivity (F/m)
20	6	1.2	74.4834
40	6	2.4	67.6642
60	6	3.6	59.2178

B. EFFECT OF CHANGE IN THE CONCENTRATION OF SUGAR

The LLM of CLS depends on the change in the concentration of sugar in the liquid. As discussed in the above section, a change in permittivity affects the sensor output [64].To reach the objective of this work, sugar solutions with varying concentrations were tested. As the concentration of sugar in the sugar solution changes, the permittivity of the solution also changes [65]. The permittivity of sugar solutions with different concentrations is calculated as shown in Eq. 6. Using this, the dielectric constant of solutions with different concentrations was determined [66].

$$\begin{aligned}\varepsilon_s &= \varepsilon_w - 0.226 \times C \\ &\quad - [6.75 \times 10^{-4} - 1.5 \times 10^{-5}(t - 25)] \times C^2 \\ &\quad - [1.09 \times 10^{-5} + 4 \times 10^{-8}(t - 25)] \times C^3 \qquad (6)\end{aligned}$$

where ε_s is permittivity of sugar solution, ε_w is Permittivity of water and t is the solution temperature at ° C, C is the weight of sugar in %. The concentration of sugar solution is obtained by calculating a number of liters in a storage tank by converting volume into liters and mixing % of sugar into water. Table 2 below shows the calculated sugar solution with its permittivity.

Experiments were conducted to analyze the effect of changes in sugar solution with varying concentrations on helical CLS. Figure 5 shows the effect of the sugar solution on helical CLSs. It was observed that varying the concentration of the sugar solution affected the sensor output.

As the concentration of sugar increases, the permittivity of the solution decreases, and thus, the sensor output decreases. The results of the analysis are shown in Table 3.

As per the analysis conducted, the output of CLS depends on the change in liquid type, liquid temperature and variation in the concentration of sugar in liquid. Hence, to overcome the re-calibration of the sensor for the above-mentioned changes,

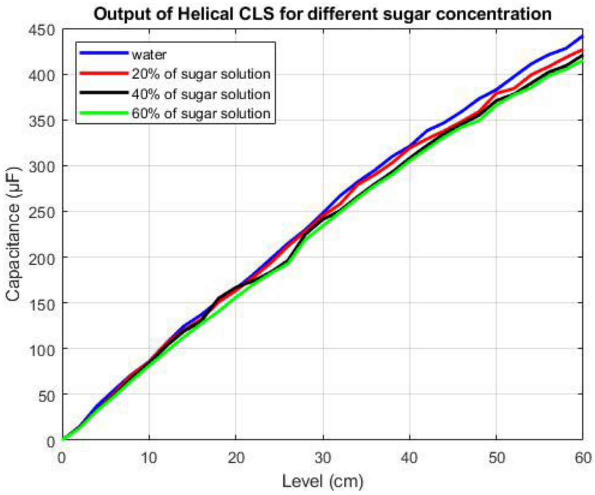

FIGURE 5. Effect of change in % of sugar solution on Helical CLS.

TABLE 3. Test results of the effect of sugar solution on sensor output.

Concentration (%)	Level (cm)	Helical CLS (μF)
Water	60	421
20	60	420
40	60	417
60	60	415

a predictive technique has to be developed for level and concentration. The solution is discussed in the below section.

IV. PROBLEM SOLUTION

The main objective of this work is to develop a novel technique to measure the level and concentration of liquids using a CLS. The work aims to measure the level and concentration of liquid accurately even with variations in liquid types, liquid temperature, and concentration of sugar in a solution. Hence, it is important to develop a predictive technique to make the level measurement system independent. The following subsection details the design and development of a predictive model for level and concentration measurement.

A. DESIGN OF THE PREDICTIVE TECHNIQUE

The LLM system comprises a level predictive model (LPM) and concentration predictive model (CPM), which intend to accurately detect the level and concentration of liquid. The capacitance level measurement depends on sugar concentration variations and liquid type [67]. The output of CLS varies with respect to changes in the concentration of sugar solution, liquid type, and liquid temperature. Hence, a predictive technique is designed to compute the liquid level and concentration of additives in the liquid [68]. A predictive model to measure the level and concentration of sugar solution is developed by using a capacitive level sensor (CLS), ultrasonic level sensor (ULS), and pressure level sensor (PLS) to acquire information on the liquid and concentration. The data acquired from all these sensors are processed using a multisensor data fusion technique to compute the level of liquid along with the SVM model to analyse the concentration of additives added to the solution [69]. The adaptive technique incorporates the following models.

- [1] The level predictive model is developed by the multisensor data fusion (MSDF) technique using neural networks (NNs) by training the output data from CLS, ULS, and PLS to predict the actual level.
- [2] concentration predictive model was developed using the support vector machine (SVM) algorithm to trace the level and variation in sugar concentration.
- [3]LPM and CPM are validated in a real-time system.

B. LEVEL PREDICTIVE MODEL

The level predictive model aims to determine liquid level irrespective of liquid type. It is developed using a multi-sensor data fusion technique based on neural networks. The model is achieved by fusing the responses of three different sensors CLS, PLS and ULS concerning level. As the model trains to the target data, which is set to CLS output for a specific level and a certain concentration [70]. The output of the model determines the liquid level [71].

Multi-sensor data fusion (MSDF) is the process of combining observations, information and data that are acquired from multisensors from a specific process [72]. The fusion process provides more informative results and reduces the uncertainty of the process than compared with the results of the single sensor [73]. An MSDF is a technique of combining various sensory data [74].

In this research work, as the representation of the level is changed by its liquid type using CLS. The LPM is designed to make the CLS level measurement process adaptive to changes in sugar concentration. Hence it is intended to consider the fusion across multi-sensors such as CLS, PLS, and ULS to measure the liquid level, focusing on different parameters or attributes such as the density and permittivity of the liquid [75]. The principal motivation for the MSDF of this research work is to make the CLS-based level measurement process adaptive for the change in sugar concentration [76] operated in the same conditions as the level measurement process. Employing multiple sensors enhances the accuracy in level representation irrespective of the concentration of sugar in the solution [77].

The research work comprises developing the sensor model (SM) by distinguishing between the variables of liquid level and concentration with a measured multisensor output [78]. The task of SM is to optimize the MSDF process by obtaining the maximum information about the process from multiple sensors as shown in Figure 6.

Observation of the effect of changes in the liquid level and concentration of sugar in solution on the output of CLS, PLS,

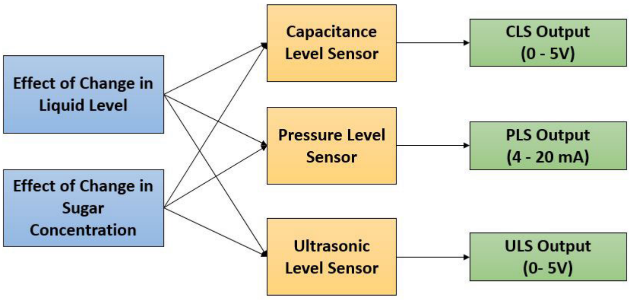

FIGURE 6. Sensor model.

and ULS are analyzed [79]. The sensor characteristics are shown in Figure 7.

Additionally, three different sensors are used to measure the liquid level and sugar concentration of the measurement system individually, but the responses of all sensors are taken into account for the MSDF [80]. In the construction of the MSDF technique, sensor normalization is a primary step. In this research work, the multi-sensor output concerning the change in liquid level and change in sugar concentration are normalized to the scale of 0-1 to develop an MSDF system [81]. An MSDF system is classified based on its input-output characteristics.

The use of MSDF helps to make the LLM system more adaptive to the change in sugar concentration in solution [72]. MSDF systems hold a large area of complexity that requires knowledge of the type of data acquired from multiple sensors in the process. The MSDF system can be analysed as shown in Figure 8.

- [1] Physical Domain (Sensors): This domain consists of multi-sensor modules representing a sensor that interacts with the process. The module provides the data, information and description of the measurements made by the sensor.
- [2]Information Domain (Software): The domain consists of operating blocks: the data fusion block, which is responsible for combining all multi-sensor data to derive process information and determines a fusion technique that is used for the process [67].
- [3] Cognitive Domain (Human Operator): It is most important to develop a system to transform all the information that is transferred to the human operator into a usable form such that it can be used for the decision-making process [67].

C. CONCENTRATION PREDICTIVE MODEL

To determine the concentration of sugar in the solution, the CPM was developed using the support vector machine (SVM) algorithm. Multi-sensor output with respect to the change in level and concentration is fed as an input to the model, and the model trains to the target data, which is set to CLS output for a specific level and for a certain concentration. The output of the predictive model determines the concentration of sugar in the liquid. Predictive modelling can be defined as a method of predicting future outcomes of the process by using data. The prediction method attains high accuracy, so it is widely used. Several prediction models have shortcomings; hence, we choose support vector machine (SVM) regression analysis to predict the concentration of sugar in the solution and the level concerning the given CLS output. The design of LPM and CPM are discussed in the below section.

TABLE 4. Permittivity and capacitance of different concentrations of sugar solution.

Concentration (%)	Level (cm)	Permittivity (F/m)	Capacitance (μF)
Water	60	80.180	442
20	60	74.4834	427
40	60	67.6642	421
60	60	59.2178	415

V. DEVELOPMENT OF MODEL

To achieve the objective of this work, i.e., to predict the level accurately irrespective of the change in sugar concentration and to measure the concentration of sugar in solution certain analyses are carried out. All sensors were tested for varying sugar concentrations in a solution. The obtained output data are fused to make the system adaptive. The experimental setup of the multi-sensor level measurement is shown in Figure 9.

Helical CLS: The helical CLS works on the principle of measuring the change in capacitance by the change in the dielectric medium (i.e., liquid) between the electrodes. The change in the dielectric constant of the liquid affects the sensor capacitance and intern changes the sensor voltage output. Different concentrations of sugar solution exhibit different permittivities, so the sensor output varies. Experiments were conducted to analyse the effect of changes in sugar solution with varying concentrations on the output of novel helical CLSs, and the experimental setup is shown in Figure 9. Figure 5 shows the effect of varying concentrations of sugar solution on the helical CLS. It is observed that varying the concentration of the sugar solution affects the sensor output. As the concentration of sugar increases, the permittivity of the solution decreases, and thus, the sensor output decreases. The results of the analysis are shown in Table 4.

Ultrasonic Level Sensor: An ultrasonic sensor is a device that is used to measure the liquid level by emitting ultrasonic sound waves. It works on the principle of converting the reflected sound into an electrical signal. In this research, an ultrasonic sensor is used with a ranging distance of 0-90 cm, resolution of 0.1 cm, supply voltage of +5 Vdc, and frequency of 40 kHz. Subjects whose dimensions are longer than the wavelength of the impinging sound waves reflect them, and the echoes are received by the transducer. The ultrasonic sensor mounted on the top of the tank is shown in Figure 9. The liquid level is measured by using Eq. 7 below. The ultrasonic sensor is independent of the liquid type. Varying the concentration of the sugar solution does not affect

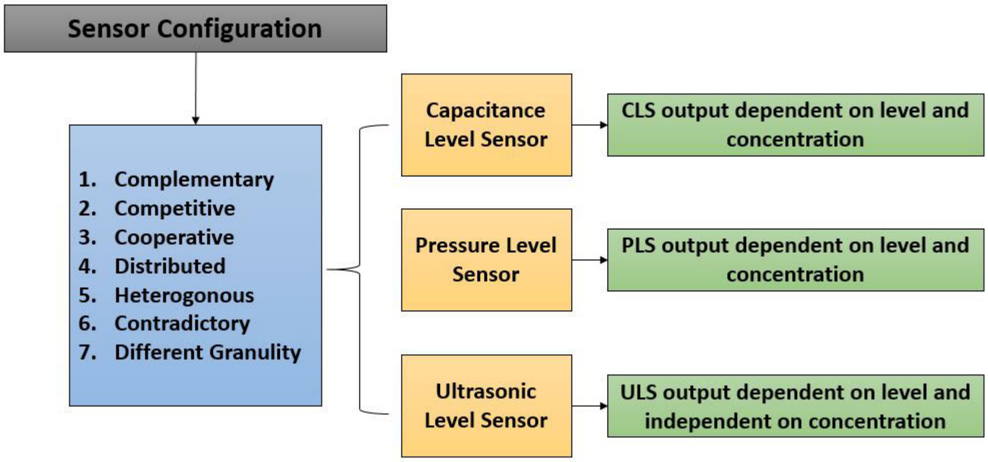

FIGURE 7. Sensor configuration.

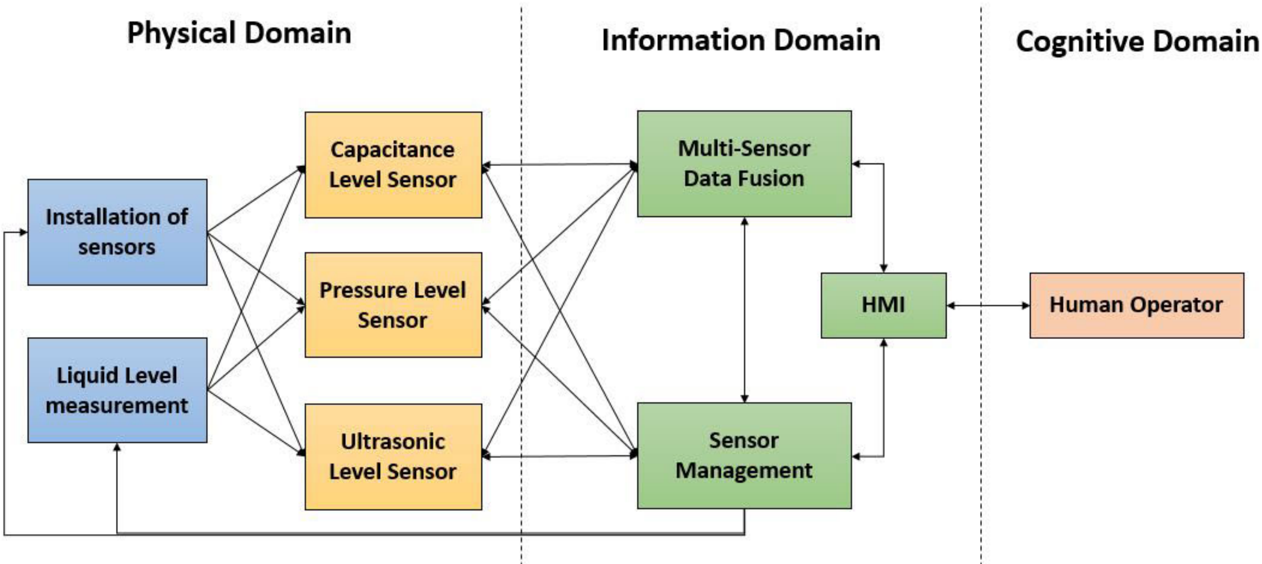

FIGURE 8. Sensor fusion functionality.

the output of the ultrasonic sensor.

$$Distance = \frac{T}{2} \times C \tag{7}$$

where T is the time taken by the sound wave to travel from emitter to receiver of the sensor in μs and C is the speed of sound i.e. 343 m/s or 0.0343 cm/μs. The output of the sensor is shown in Figure 10. It is observed that sensor output is unaffected by varying concentrations of sugar solution i.e. the output of ULS is given as 5.03 V for 60 cm of level for all different concentrations of sugar solution. It can be concluded that the output of an ultrasonic level sensor is independent of liquid type as shown in Table 5.

Pressure Level Sensor: Level measurement using a pressure sensor is an indirect method of measurement. Pressure sensors measure the liquid level by measuring the liquid density at a certain height. A continuous pressure sensor is fixed at the bottom of the tank to monitor the level, as shown in Fig. 9. Pressure exerted by liquid on the sensor is used to calculate the level of liquid. The sensor output depends on the density and height of the liquid placed in the tank. As given by Eq. 8 below.

$$Distance = \rho g H \tag{8}$$

TABLE 5. Concentration of sugar solution and ULS output.

Concentration (%)	Level (cm)	ULS Output (V)
Water	60	5.03
20	60	5.03
40	60	5.03
60	60	5.03

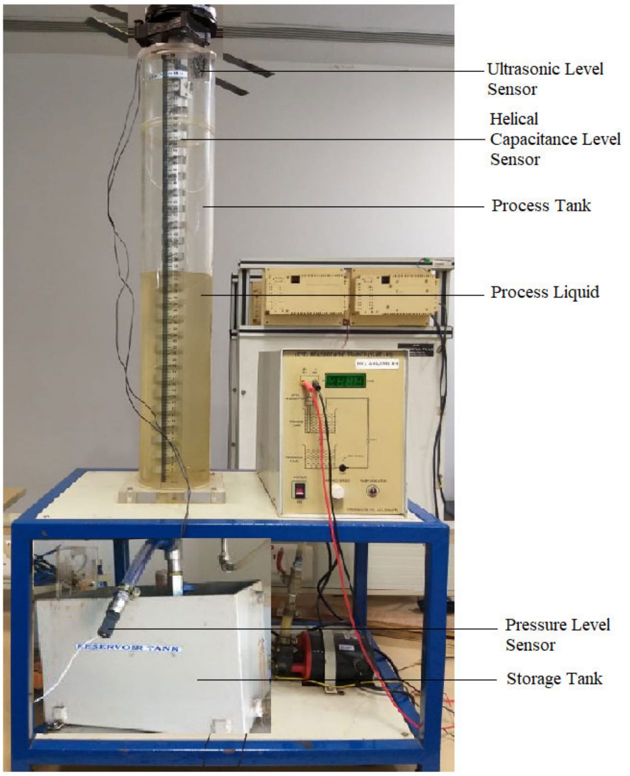

FIGURE 9. Experimental set-up of multi-sensor level measurement fusion technology.

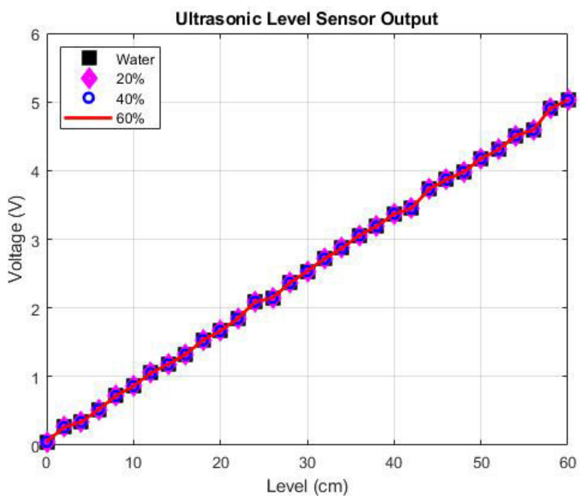

FIGURE 10. Effect of change in % of sugar solution on ultrasonic sensor.

where ρ is the density of liquid and g is the gravitational force i.e. 9.8 m/s^2 and H is the height of liquid present in the tank. For this work densities (ρ) of varying concentration of sugar solution is calculated using Eq.9 below.

$$\rho = \frac{m}{V} \tag{9}$$

where m is the mass of liquid and V is the volume of tank. Here volume of tank is 0.005704 m^3. Densities and

TABLE 6. Density and pressure of sugar solution.

Concentration (%)	Mass (Kg)	Density (Kg/(m^3)	Pressure (KPa)
Water	6	1000	5.9
20%	7.2	1262.3	7.42
40%	8.4	1472.7	8.67
60%	9.6	1683.02	9.89

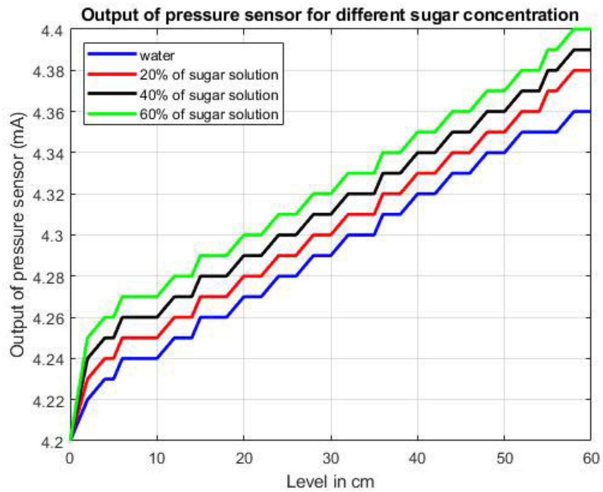

FIGURE 11. Effect of change in % of sugar solution on pressure sensor.

TABLE 7. Output of the pressure sensor for different concentrations of sugar solution.

Concentration (%)	Mass (Kg)	Density (Kg/(m^3)	Pressure (KPa)	Sensor output (mA)
water	6	1000	5.9	4.36
20%	7.2	1262.3	7.42	4.38
40%	8.4	1472.7	8.67	4.39
60%	9.6	1683.02	9.89	4.41

pressure of different concentration of sugar solution and water is calculated and measured using above equations and is mentioned in Table 6.

As the density of the liquid increases, the sensor output also increases. The sensor output is completely dependent on the liquid density and height [82]. The pressure sensor is mounted at the bottom of the tank, and all connections are made in series. The specifications of the sensor are as given: the supply voltage is 8-30 Vdc, the output range is (4-20) mA, and the operating pressure range is (0-7) bar. The output of the sensor is shown in Figure 11.

The results are discussed in Table 7. It is observed that an increase in the density of the liquid increases the sensor output. We can conclude that the sensor output depends on the liquid type.

Tests were conducted to analyse the effect of varying concentrations of sugar solution on CLS, ultrasonic and pressure sensor output. The results show that CLS is affected by a change in sugar concentration due to a change in the permittivity of the liquid [83]. The ultrasonic sensor is independent of the liquid type. The pressure sensor depends

TABLE 8. Test results of the effect of sugar solution on sensor output.

Concentration (%)	Level (cm)	Capacitance (μF)	Pressure (KPa)	Sensor output (mA)
Water	60	442	5.03	4.36
20%	60	427	5.03	4.38
40%	60	421	5.03	4.39
60%	60	415	5.03	4.41

on the height and density of the liquid; as the density and height of the liquid increase, the output of the sensor also increases, as shown in Table 8.

Experiments were conducted to analyse the effect of changes in the concentration of the sugar solution on CLS, ultrasonication and pressure sensor output. The output of the helical CLS and pressure sensor varies with respect to the change in concentration. Hence, the tests conclude that helical CLSs and pressure sensors depend on the concentration of the sugar solution and that ultrasonic sensors are independent of the concentration of the sugar solution. Furthermore, the output of all sensors is fused to achieve an adaptive technique, as discussed below.

A. LPM DEVELOPMENT

A data fusion system is a framework in which an MSDF system is represented as a distributed system of various modules. In this work, we consider an MSDF for the LPM. The major operating blocks that are required to design the MSDF are known as modules, which are commonly called fusion nodes [83]. The information about the process is transferred from one node to another. An algorithmic description of the MSDF block is provided by the neural network, which is embedded in the nodes, determining the behaviour and activities of the block, and the data are collected from the individual nodes.

Each fusion node or module receives one or more sensor data that are acquired from the process. The multisensor data are converted to a common representational format by sensor alignment, and then they are fused together to attain a target parameter of the model. Here, we use a single fusion cell to develop the MSDF system. Figure 12 shows the operation of a single fusion node.

The fusion node receives input data from sensor information in which the information is directly attained from the sensors and inputs produced by other fusion nodes. Data from auxiliary information in additional data are derived by specific processing of the sensor information. Data from external knowledge, which includes additional data and consists of all elements related to the process [84]. The MSDF network consists of a single fusion cell that is used to fuse all sensor measurements. The MSDF system fuses data from the CLS, PLS, and ULS.

In this work, we propose an adaptive fusion technique that aims to define a deterministic fusion operation, such as concatenation for the neural network. We let the neural

TABLE 9. Specifications of the neural network model for LPM using the MSDF technique.

Specifications	Descriptions
Model	Feed-forward back propagation
Training function	Levenberg Marquardt
Performance function	Mean Square Error
Transfer function	Transig
Hidden layers	2
Neurons	10
No. of inputs	3 set (12 inputs)

network decide "how" to combine a given set of multisensor data more effectively. NN, distributed information processing system. The network analyses the dynamic behaviour of the process with varying liquid levels and concentrations of sugar in a solution. An NN is a computational model that is composed of the number of neurons connected to each other. This work discusses data fusion methods to combine the data obtained from CLS, ULS, and PLS for changes in sugar concentrations of 20%, 40%, and 60%. All sensors are mounted on a tank, and the data are obtained. Figure 13 shows the effect of changes in sugar concentration on the CLS, ULS, and PLS output.

The obtained data are trained in a neural network to fuse all data. All values are given at once to the network with target data independent of the concentration. The NN model is trained using the feedforward backpropagation model, the Levenberg-Marquardt training function, and the MSE performance function. It consists of weights, neurons, hidden layers, and neuron transfer functions, which are varied to obtain the desired MSE and regression. It is always desired to have 0 MSE and a regression value of 1. In the proposed work, for the constraints subjected, the NN model is obtained with 2 hidden layers having 10 neurons in each of the hidden layers, and the Tansig transfer function is used, as shown in Table 9. The design of the NN model is shown in Figure 14.

Figure 15 shows the trained neural network with the best performance with a minimum MSE of 0.000001. The regression values are shown in Figure 16, which are almost equal to 1, and the error is less than 0.05, as shown in Figure 17. The trained network is checked with a different set of inputs with respect to liquid type and is analysed with the target output to ensure the accurate training of the multisensor fusion network. The results showed that all data were perfectly mapped to the target data, as shown in Figure 18.

The multisensor fusion model is obtained after training the network, as shown in Figure 19. The model provides an effective method for the data fusion technique catering to all requirements of the objective. The results showed that CLS measures the liquid level accurately irrespective of the change in the concentration of the sugar solution.

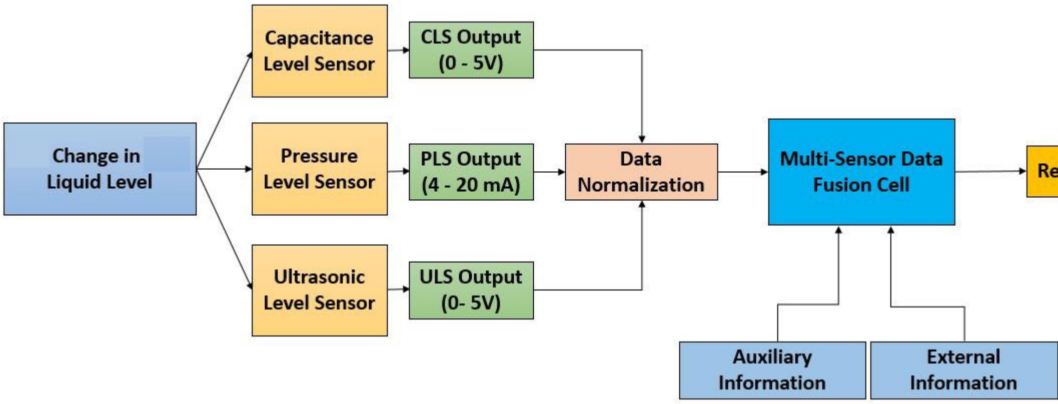

FIGURE 12. Operation of signal fusion node.

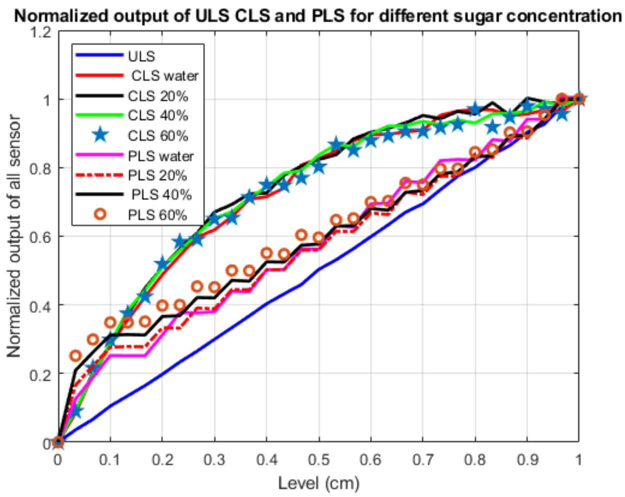

FIGURE 13. Effect of change in sugar concentration on CLS, PLS and ULS.

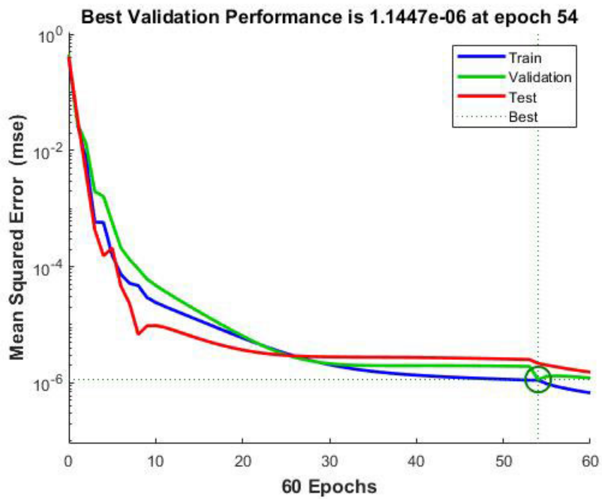

FIGURE 15. Performance plot of MSDF-NN LPM.

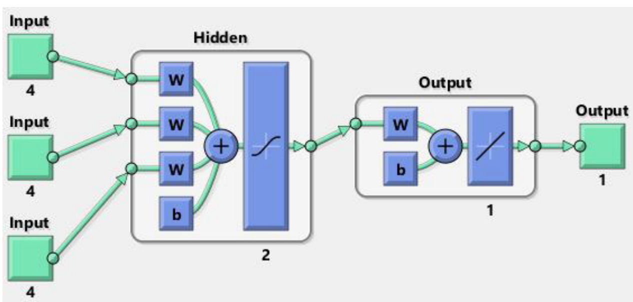

FIGURE 14. Multi-sensor data fusion using neural networks.

All sensor data obtained with respect to the change in sugar solution are given to the model to obtain the accurate level. The CLS measures the liquid level accurately irrespective of the variation in sugar concentration, as shown in Figure 20.

The level prediction model using multisensor data fusion made the system adaptive and accurately measured the level of change in the concentration of the sugar solution. Hence, the novel predictive model for the change in variation of liquid level in a tank by training the neural network. A further prediction model is developed using SVM to find the concentration of liquid, as discussed below.

B. CPM DEVELOPMENT

A concentration prediction model is developed using SVM. It is one of the most important algorithms with strong theoretical foundations. SVM is applicable for both linear and nonlinear types of regression [85], [86], [87]. The parameters used for developing the CPM using the SVM model are given in Table. 10. The model is developed by feeding the output of multi-sensors, i.e., CLS, PLS, and ULS, along with the predicted level data from the LPM model with respect to the change in level and concentration to the model [36]. The model trains all data to the target data, which is set to the CLS output for a specific level and for a certain concentration [68], [88], [89], [90], [91]. The classifier was designed to remove information related to the level of CLS, and the remaining

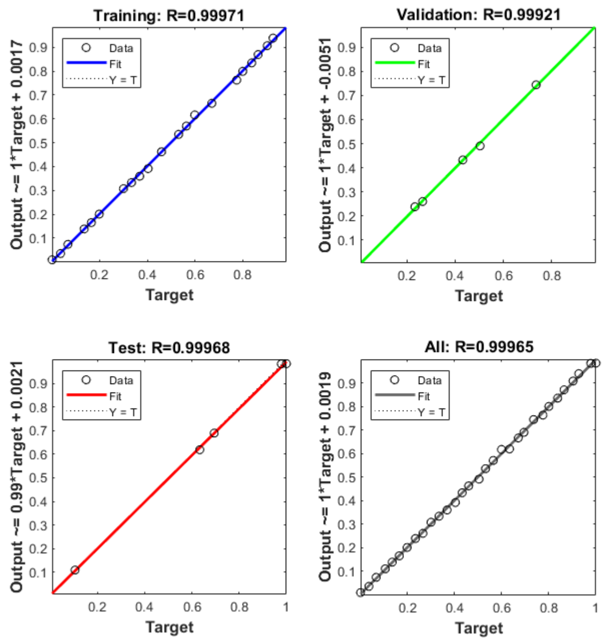

FIGURE 16. Regression value of MSDF-NN LPM.

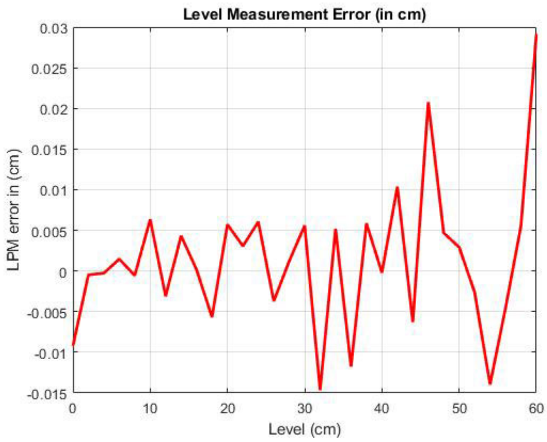

FIGURE 17. Error value of LPM.

TABLE 10. Training parameters of CPM using SVM.

Parameters	Values
Input to the model	Data from CLS, PLS, ULS and output data from LPM
Kernel	RBF

information of CLS was related to concentration. The output of the predictive model determines the concentration of sugar in the liquid.

It is robust and has excellent generalization capability and high prediction accuracy. The CPM using the prediction model is shown in Figure 21.

The concentration of sugar in the solution was detected using the level and output of multisensor data. The obtained results are shown in Table 11 below. The error is calculated

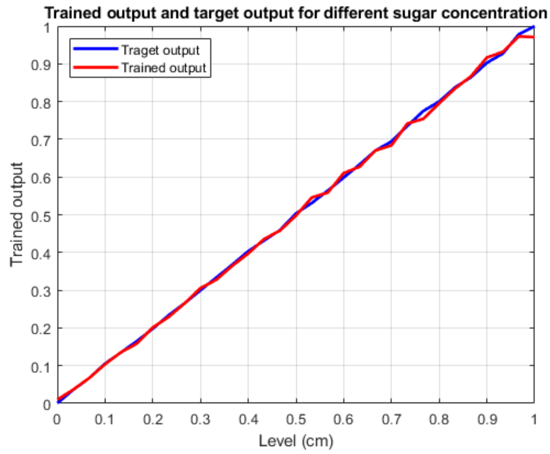

FIGURE 18. Trained and target output of LPM.

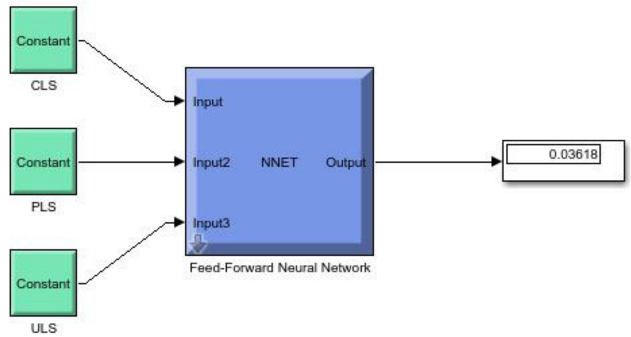

FIGURE 19. Multi-sensor data fusion based LPM.

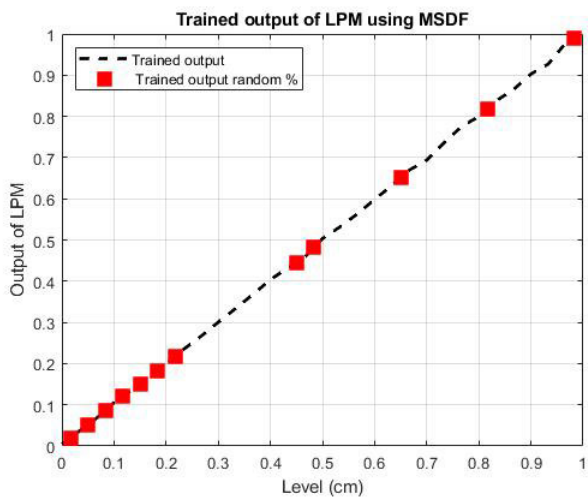

FIGURE 20. Multi-sensor data fusion using neural networks.

using Eq. 10 below.

$$Error = ActualValue - MeasuredValue \tag{10}$$

The concentration was detected with an error of the CPM between +/− 0.80% of sugar concentration. The system was validated in real time by mounting all CLS, PLS, and CLS in

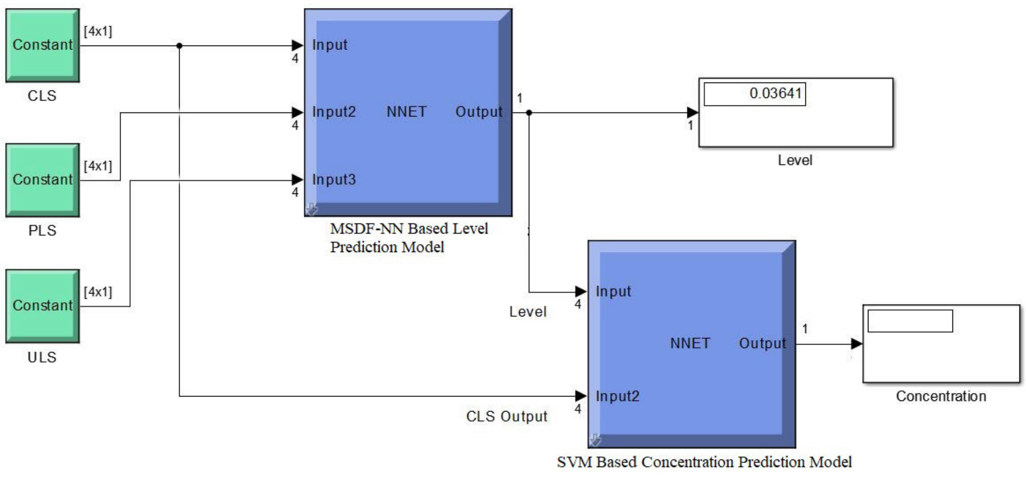

FIGURE 21. Development of CPM.

TABLE 11. Output of CPM using SVM model.

Actual Concentration (%)	Predictive Concentration (%)	Error (%)
10	9.98	0.02
15	15.20	-0.20
20	19.50	0.50
30	30.80	-0.80
45	44.50	0.50
60	59.20	0.80

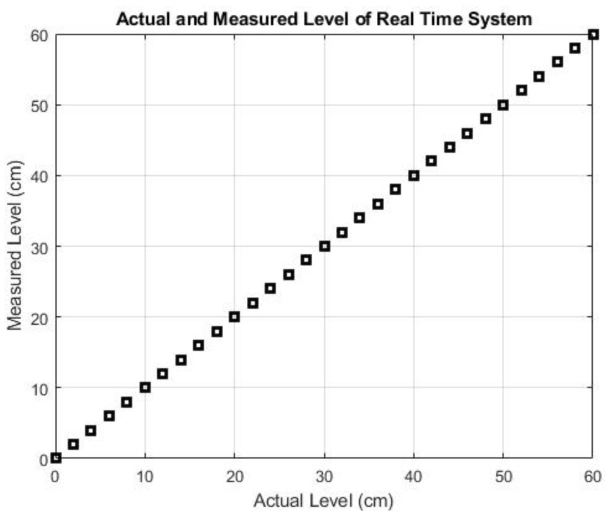

FIGURE 22. Actual level and measured level.

the tank with respect to the change in the concentration of the liquid level, as discussed below.

C. SYSTEM VALIDATION

The adaptive technique was validated using a real-time system with the NN model and SVM model. The sugar concentration was varied to 20%, 40%, and 60%, and the output of all CLS was given to the network. The multisensor

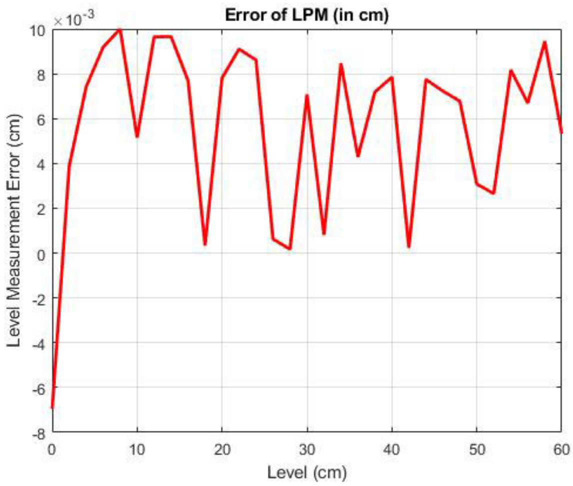

FIGURE 23. Real time error of LPM.

TABLE 12. Model errors.

Models	Errors
LPM	+0.03 to -0.015 cm of level
CPM	+/- 0.8% of concentration

fusion network gave an accurate result, which measured the level of variation in concentration, as shown in Figure 22, and the error is shown in Figure 23.

Additionally, the prediction model accurately determined the concentration of sugar in the liquid, as shown in Figure 24. The concentration was detected with an error of the CPM between +/− 0.80% of the sugar concentration, as shown in Figure 25.

The errors of the LPM and CPM are given in Table 12.

As a result, the fusion and prediction network made CLS adaptive to the variation in sugar concentration and predicted the concentration with high accuracy, which achieved the objective of the work.

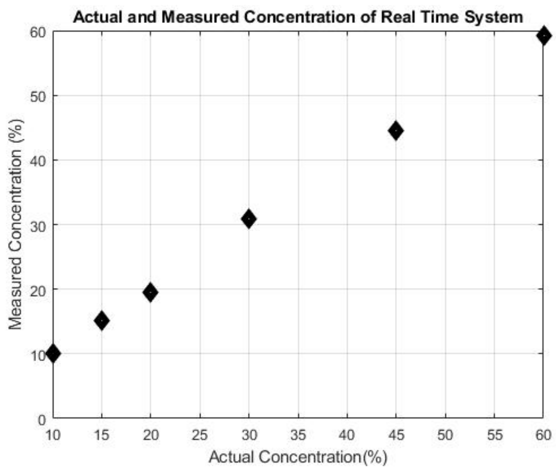

FIGURE 24. Actual concentration and measured concentration.

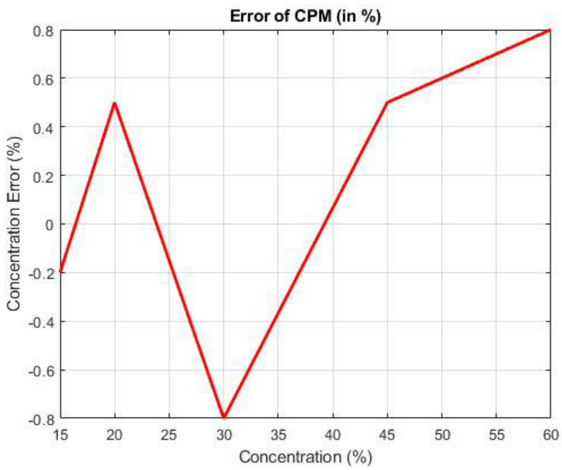

FIGURE 25. Real time error of CPM.

VI. RESULTS AND DISCUSSION

To develop a predictive technique to measure the liquid level for the change in sugar concentration and to measure its concentration using the capacitance level measurement, the LPM and CPM models were developed, and the results are discussed below.

- [1] Level prediction system that predicted the level using the NN multisensor data fusion technique. The model predicted the level of training the neural networks with an MSE of 0.000001, and the regression value of the trained network was 0.9996, which showed that all data were trained accurately and that the error obtained was between $+0.03$ and -0.015 cm.
- [2] Concentration prediction system that predicted the concentration of sugar in the solution using the SVM technique. The CPM predicted concentration by training the SVM model with the actual level and output of the multisensor as an input and concentration as an output, which showed that all data were trained accurately, and the error obtained was between $+/-0.80\%$.

VII. CONCLUSION

The main objective of the work was to develop an LPM to accurately measure the liquid level independent of the liquid type and a CPM to measure the concentration of liquid using CLS. The models were designed by analyzing the effect of the change in the level and concentration of sugar on helical CLS. Specifically, the effect of the change in sugar concentration in the liquid was analyzed with multiple sensors as CLS, PLS and ULS. The results showed that CLS and PLS were affected by the variation in concentration and that ULS was independent of the change. Hence, the LPM was developed by a multi-sensor data fusion technique using a neural network. The fusion network measured the liquid level accurately and the error obtained to measure the level was between $+0.03$ and -0.015 cm. The CPM was developed using SVM to measure the concentration of liquid concerning a specific level of 70 cm and the error obtained to measure the concentration of sugar in liquid was in between $+/-0.80\%$. The models were tested on a real-time system for varying liquid levels and additives. The results showed that the successful implementation of the proposed objective produced a root mean square of a percentage error of 0.000001% over the full scale. The obtained results of models catered to the objectives of the work with enhanced accuracy and avoided the re-calibration of CLS-based Liquid Level Monitoring Systems (LLMS).

ACKNOWLEDGMENT

Two patents are filed on this research work, among which one is granted in India Patent Office (IPO) holding patent details as follows: 1)patent granted with the CLS Based Level Prediction and the details are, Invention Title: Helical Capacitance Level Sensor with Adaptive Sensing, Applicant Name: Manipal Academy of Higher Education, Application No.: 201941014455, Date of Filing: April 10, 2019 [92]; and 2) patents filed on the Adaptive technique and the details are Invention Title: System and Method for Detecting Liquid Concentration Using Multi-Sensor Data, Applicant Name: Manipal Academy of Higher Education, Application No.: 202241018269, Date of Filing: March 29, 2022 [93].

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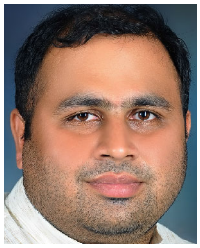

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