Design and evaluation of a low-cost real-time fluid-level monitoring system for fuel stations

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ABSTRACT

Accurate fluid level management in fuel stations is hampered by inventory errors, delayed shortage detection and costly proprietary sensors. We designed and built a low-cost, open-source monitoring system using an Arduino Uno, an HC-SR04 ultrasonic sensor, a NodeMCU ESP8266 and a DHT11 temperature sensor. Validation was restricted to static short-term conditions, with a prototype tested in a 200 cm tank over 62 hours and 32 paired measurements collected at two-hour intervals. Prototype readings were compared with dipstick measurements after temperature compensation. The system achieved a mean error of 0.03 cm, a mean absolute error of 0.91 cm, a standard deviation of 1.06 cm and a root-mean-square error of 1.05 cm, with a 95 % confidence interval of ±0.37 cm. These results demonstrate that a calibrated and temperature-compensated ultrasonic sensor can deliver centimetre-level accuracy suitable for inventory management in resource-constrained fuel stations. Future work will extend validation to dynamic transfers, sloshing/vibration, humidity effects, and long-term drift in operational tanks.

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1. INTRODUCTION

Efficient fluid-level monitoring at fuel stations is essential for ensuring inventory accuracy, service continuity, and cost efficiency. Traditional approaches, such as manual dipstick readings or basic electronic gauges, lack real-time capabilities and are prone to human errors, measurement delays, and operational inefficiencies [1]. These limitations can lead to inaccurate stock estimations, unexpected shortages, and service disruptions. Existing commercial systems, such as resistive or pressure-based probes, are often costly and complex to deploy, and their integration with modern internet of things (IoT) platforms remains challenging, as highlighted in recent reviews of level-sensing technologies and IoT connectivity [2]. Consequently, there is growing interest in affordable, modular, and open-source solutions based on microcontrollers such as Arduino [3], [4].

There are multiple sensing technologies for continuous fluid-level monitoring, each with trade-offs in cost, accuracy, installation complexity, and environmental robustness. Among the most commonly evaluated are pressure-based sensors, radar sensors and ultrasonic sensors [2], [5]–[7]. Pressure sensors provide high precision and have recently become more compact and cost-effective due to advances in micro-electro-mechanical systems (MEMS) technology, yet their performance remains affected by temperature drift and packaging constraints, and the most accurate designs still rely on complex and costly fabrication processes [6].

The latest generations, such as silicon carbide (SiC)-based and through-silicon vias (TSV)-integrated MEMS devices, demonstrate remarkable robustness in harsh environments but still rely on complex and costly fabrication processes, making them less attractive for low-cost fuel-level monitoring applications [8], [9]. Radar sensors, for their part, enable non-contact measurement and perform reliably under varying environmental conditions, yet they remain prone to multipath reflections and clutter that can generate false readings [10], while surface dynamics such as turbulence further affect stability [11]; moreover, achieving high resolution and robustness often requires advanced mmWave hardware and sophisticated signal processing, which increases system complexity and cost [12], making integration into low-cost open-source platforms challenging.

Ultrasonic sensors thus emerge as a compelling option because they are inexpensive, easy to integrate and non-contact; however, they require regular calibration and are sensitive to temperature and humidity [13]-[15]. Interestingly, Recent studies have highlighted that incorporating environmental parameters such as temperature can enhance the accuracy of ultrasonic measurements [16].

Embedding ultrasonic sensors into IoT environments enables continuous, autonomous data acquisition and more responsive decision-making. Operating on time-of-flight (ToF) principles, these sensors are well suited for non-contact liquid-level measurement. They typically achieve ±1% accuracy over their effective range and are unaffected by fluid colour or opacity, making them well adapted to heterogeneous tank conditions [17]. They have been widely adopted in IoT-enabled water monitoring systems that leverage low-cost microcontrollers [18].

This study presents the design and prototyping of an ultrasonic-based, real-time fluid-level monitoring system using Arduino. The aim is to deliver a cost-effective, reliable solution suitable for fuel stations where commercial systems are either unaffordable or operationally unsuitable. The proposed prototype lays the groundwork for broader adoption in fluid-management sectors, particularly in socio-economically disadvantaged regions where infrastructure constraints limit the deployment of traditional technologies.

2. METHOD

2.1. System architecture

The fluid-level monitoring system was developed around the Arduino Uno R3 microcontroller, chosen for its low-cost, modular hardware design, and strong support from the open-source community [19], [20]. These features make it suitable for embedded sensing prototypes in situations where budget and flexibility are critical.

To measure distance, the HC-SR04 ultrasonic sensor emits a 40 kHz acoustic pulse and measures the time elapsed until the echo returns from the fluid surface [21]. This non-contact method can reach an accuracy of ±1% of the full measurement range when the sensor is calibrated correctly. This makes it effective for monitoring fluid levels in closed or confined environments. Gao *et al.* [17] confirmed its performance in fluids that are opaque or have reflective surfaces.

For wireless communication, a NodeMCU ESP8266 development board was added to the system. This board includes a wireless fidelity (Wi-Fi) interface, uses low power, and works directly with the Arduino integrated development environment (IDE), which helps with its integration into IoT infrastructures. The ESP8266 acts as a data bridge, transferring the measured fluid level to a remote server in real-time.

The prototype's physical structure, including the wiring of the Arduino, ultrasonic sensor, liquid crystal display (LCD), and wireless module, was designed with the Fritzing simulation platform, as shown in Figure 1. This modelling approach enabled a thorough check of the electronic connections before deployment and provided a clear visual guide during the hardware assembly process.

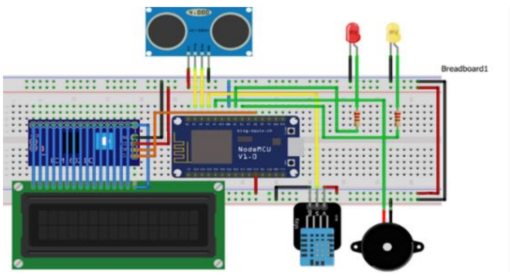


Figure 1. Prototype architecture: wiring diagram of the Arduino Uno, HC-SR04 sensor, ESP8266 Wi-Fi module and display and alarm modules

2.2. Sensor mounting, tank geometry and calibration

The ultrasonic sensor was mounted vertically above the liquid surface, with its acoustic axis oriented perpendicular to the liquid interface to ensure accurate distance measurements. To avoid any movement that could affect the readings, the sensor was securely fixed to an insulating wooden plate. The test tank has a total height $H = 200$. The fluid level L was computed using:

$$L = H - d \tag{1}$$

where d is the measured distance from the sensor to the fluid surface. This computation was handled directly by the Arduino Uno microcontroller, which then displayed the result on an LCD module for immediate user feedback. Figure 2 illustrates the HC-SR04 mounting configuration and the tank geometry used for calibration and validation ($H = 200$ cm).

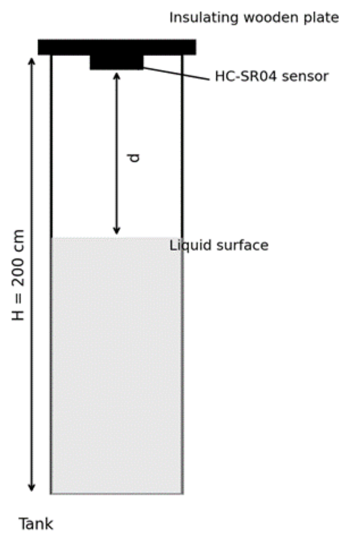


Figure 2. HC-SR04 sensor mounted on an insulating wooden plate at the top of the test tank ($H = 200$ cm)

Prior to data collection, the HC-SR04 sensor was calibrated in situ by comparing measured distances to known fluid heights within the 200 cm test tank, using a range of controlled fill levels. At each point, three consecutive measurements were recorded, and a median-of-three filter was applied to suppress isolated outliers and improve robustness against spurious echoes. A clear linear relationship was observed between the sensor's ToF readings and the actual fluid distances, indicating reliable behaviour under static conditions.

To contextualize environmental influences on ultrasonic propagation, a DHT11 sensor was integrated for real-time acquisition of ambient temperature. These values were used to dynamically correct the speed of sound in air, which directly impacts the accuracy of distance estimation. Although the DHT11 also provides relative humidity, only temperature was logged and used for compensation in this study; humidity-related effects are therefore considered a limitation and discussed in section 3.7. The correction was applied using the classical physical model:

$$v = 331 + 0.6 \times T(m/s) \tag{2}$$

where T is the measured ambient temperature in degrees Celsius, and v is the adjusted speed of sound. This corrected value of v was then used in the standard ToF distance calculation:

$$d = \frac{v * ToF}{2}$$

Such environmental compensation has been demonstrated to enhance the accuracy, stability, and repeatability of ultrasonic measurements. For example, Masoudimoghaddam *et al.* [13] showed that thermal correction helps reduce sensor drift in fluctuating conditions, while Kumar *et al.* [22] reported a reduction in the mean absolute deviation from 3.04 cm to 2.76 cm for the HC-SR04 when temperature data were applied during calibration.

Despite its practical advantages, the HC-SR04 is affected by intrinsic constraints, including near-field effects, finite operating range, and sensitivity to off-axis echoes due to its beam pattern, which can bias ToF estimates in confined geometries or under imperfect alignment [23]. These effects are most critical near extreme fill levels (very short or long sensor-to-surface distances), where echo stability may degrade and the returned signal becomes less reliable. In liquid-level monitoring, non-ideal interface conditions such as agitation or foaming (and, in practice, surface turbulence or condensation) may further reduce echo quality and increase measurement variance, particularly under dynamic regimes [14]. In this study, these effects were limited through rigid vertical mounting, in situ calibration, and repeated sampling with median-of-three filter, combined with temperature-based sound-speed compensation; humidity was not recorded and is addressed as a limitation in section 3.7.

2.3. Sampling procedure and data processing

Each measurement session consisted of a pair of readings: one using the ultrasonic system and one using a manual dipstick gauge. Pairs were collected every 2 h, yielding 32 paired measurements over 62 h. This two-hour interval was selected to replicate the typical stock-checking routine in small fuel stations while capturing day-night variations, thus making the dataset representative of real operating conditions. Between sessions the level was adjusted (removed fluid), and readings were taken only after surface settling; the dataset therefore consists of quasi-static snapshots rather than continuous dynamics. Raw distance readings were converted to fluid levels using (1) and corrected for temperature. At each sampling time, three consecutive ultrasonic readings were acquired, and a median-of-three filter was applied to suppress isolated outliers caused by spurious echoes. The resulting filtered estimates were compared with manual values, and discrepancies were analysed in terms of mean error and standard deviation.

2.4. Data transmission, storage, and power considerations

The Arduino Uno computed the fluid level from the HC-SR04 readings and appended a timestamp, then transmitted the record via serial to the NodeMCU ESP8266 for Wi-Fi connectivity. The ESP8266 uploaded the data to a remote server using an hypertext transfer protocol (HTTP) POST request over transmission control protocol / internet protocol (TCP/IP), synchronized with the measurement schedule (one upload every 2 h), and each transmission was validated by the server HTTP response (“200 OK”). The average upload cycle completed in about 5 s. From a power standpoint, the ESP8266 transmission current is on the order of 120 mA, corresponding to approximately 0.17 mAh per upload and about 2.0 mAh/day for 12 uploads/day when considering communication only. On the server side, a PHP script stored the records in a my structured query language (MySQL) database for subsequent analysis.

2.5. Statistical analysis

For each paired observation i, the error was defined as:

$$e_i(\text{cm}) = L_{proto,i} - L_{ref,i} \tag{3}$$

where $L_{proto,i}$ and $L_{ref,i}$ denote the prototype and reference measurements at time *i*, respectively. Accuracy was summarised using the following metrics computed over the *n=32* data pairs:

– Mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|L_{proto,i} - L_{ref,i}\right| \tag{4}$$

– Standard deviation (SD):

$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\left(L_{proto,i} - L_{ref,i}\right) - \bar{e}\right)^2} \tag{5}$$

With $\bar{e}$ calculated as:

$$\bar{e} = \frac{1}{n}\sum_{i=1}^{n}\left(L_{proto,i} - L_{ref,i}\right) \tag{6}$$

– Root means square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(L_{proto,i} - L_{ref,i}\right)^2} \quad (7)$$

A two-sided 95 % confidence interval (CI) for the mean error was obtained as:

$$CI_{95\%} = \bar{e} \pm t_{0.975,n-1}\frac{SD}{\sqrt{n}} \quad (8)$$

To assess association with the manual reference, we plotted prototype vs. manual against the line of equality $(y = x)$, computed Pearson's correlation coefficient r with two-sided 95 % CIs (Fisher z transform) and p-value, and fitted an ordinary-least-squares (OLS) regression:

$$Prototype = a + b \times Manual \quad (9)$$

We estimated the slope b, intercept a, and R^2, and formally test $b = 1$ (no proportional bias) and $a = 0$ (no constant bias). Model assumptions (normality, homoscedasticity of residuals) were checked visually. All tests were two-sided with $\alpha = 0.05$; analyses were performed in R (base stats, ggplot2).

3. RESULTS AND DISCUSSION

3.1. Prototype overview

The final prototype developed for fluid-level monitoring and illustrated in Figure 3, integrates multiple low-cost components into a compact and autonomous system. The core sensing unit consists of an HC-SR04 ultrasonic sensor mounted on a stable vertical support above a 200 cm test container, representing the fuel tank. The sensor captures the distance to the fluid surface using ToF principles. The Arduino Uno R3 serves as the central processing unit, handling sensor data acquisition and real-time computation of fluid level. To improve measurement precision, a DHT11 sensor continuously provides temperature values, enabling compensation for variations in the speed of sound. An LCD module displays the fluid level locally for on-site monitoring, while a NodeMCU ESP8266 ensures Wi-Fi communication by transmitting structured data to a remote server using HTTP POST requests. A buzzer module is also integrated to trigger local alerts when the fluid level falls below a predefined threshold.

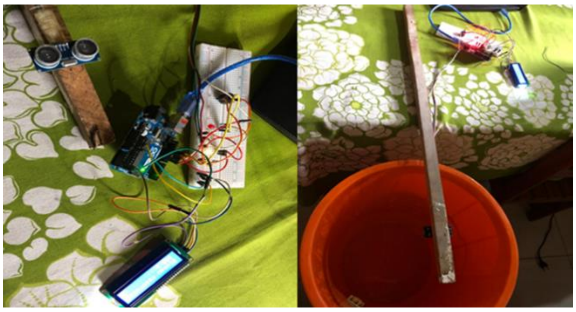


Figure 3. Prototype of the fuel monitoring system

3.2. Validation and accuracy

The validation of the prototype was conducted under controlled laboratory conditions over a period of 62 hours. The ultrasonic sensor was mounted at the top of a vertical test tank with a fixed height of 200 cm, simulating realistic fuel-storage scenarios. The system was powered continuously, and measurements were logged every two hours using both the automated sensor and a manual reference method.

Each validation cycle involved the following steps: i) the HC-SR04 sensor recorded the distance from the sensor to the fluid surface; ii) at each measurement interval, three consecutive distance readings were taken and filtered using a median-of-three operator to reduce random fluctuations; iii) the ambient temperature was measured using the DHT11 sensor, and the fluid level was computed after applying temperature-based correction to the speed of sound; iv) the computed value was displayed on the LCD module and simultaneously transmitted to the server; and v) a manual fluid-level reading was taken using a calibrated dipstick for ground-truth comparison.

A total of 32 paired measurements were collected over the 62-h test period and are reported in Table 1. Measurements were taken under quasi-static conditions after surface settling to minimize fluid-motion effects. Across the tested range (approximately 168–200 cm), the signed error remained stable, with deviations typically within ±2 cm and no clear trend with level. This suggests that the median-of-three estimate provided comparable accuracy at both ends of the investigated interval. These data form the basis for the accuracy analysis presented below; implications for dynamic operation and long-term drift are discussed in section 3.6.

Table 1. Paired measurements of fluid level during the 62-hour validation (n = 32)

Time (hour)	Prototype measurement (cm) $L_{proto,i}$	Manual measurement (Cm) $L_{ref,i}$	Temperature	Error (cm)
0	200	198	22	2
2	198	199	21	-1
4	197	196	20	1
6	195	197	23	-2
8	196	194	22	2
10	194	195	21	-1
12	193	192	20	1
14	192	193	22	-1
16	191	191	21	0
18	190	189	20	1
20	189	190	23	-1
22	188	188	22	0
24	187	186	21	1
26	186	187	20	-1
28	185	184	22	1
30	184	185	21	-1
32	183	182	20	1
34	182	183	22	-1
36	181	181	21	0
38	180	179	20	1
40	179	180	22	-1
42	178	178	21	0
44	177	176	20	1
46	176	177	22	-1
48	175	174	21	1
50	174	175	20	-1
52	173	172	22	1
54	172	173	21	-1
56	171	171	20	0
58	170	169	22	1
60	169	170	21	-1
62	168	168	20	0

The corresponding aggregate performance metrics derived from these paired observations are summarised in Table 2. Figure 4 illustrates the distribution of signed measurement errors ($L_{proto,i} - L_{ref,i}$), while agreement between the prototype and the manual reference is further assessed in Figures 5(a) and (b) using an equality plot ($y = x$) and an ordinary least-squares (OLS) regression analysis.

Table 2. Summary of performance metrics comparing ultrasonic measurements to manual measurements (n = 32)

Metric	Value
Mean error	0.03 cm
Mean absolute error (MAE)	0.91 cm
Standard deviation	1.06 cm
Root mean square error (RMSE)	1.05 cm
95% confidence interval of mean error	±0.37 cm
Pearson correlation (r)	0.994
95% CI for r	0.987–0.997
p-value (two-sided) for r	5.06×10^{-30}
OLS slope (b)	0.999
95% CI for slope	0.957–1.042
OLS intercept (a)	0.13 cm
95% CI for intercept	−7.62 to 7.89 cm
R^2 (OLS)	0.987

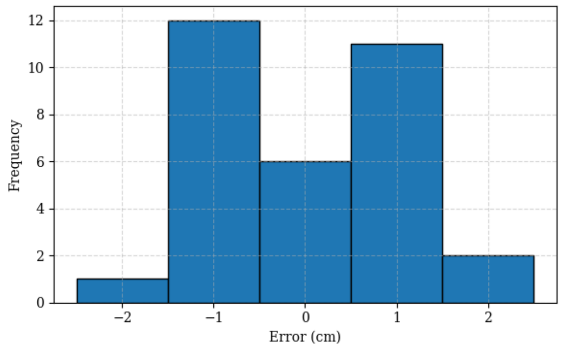
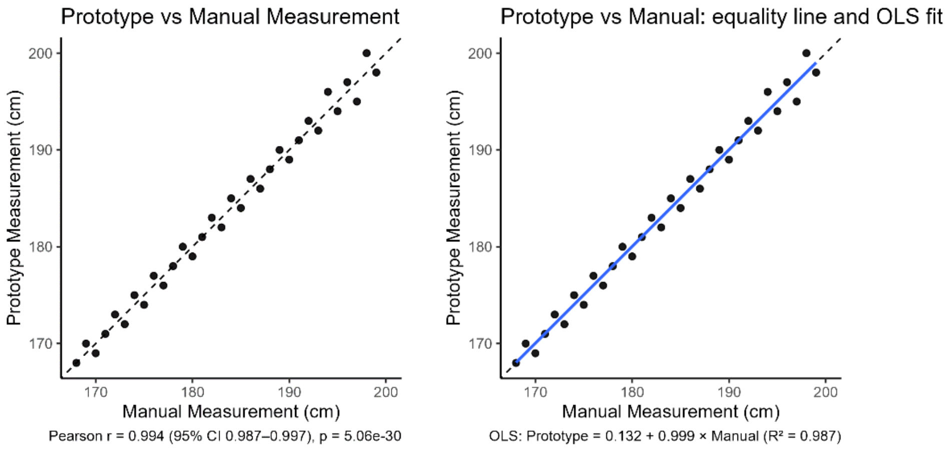


Figure 4. Histogram of ultrasonic measurement errors



(a) (b)

Figure 5. Correlation and regression analysis of prototype versus manual measurements; (a) scatter with equality line ($y = x$), showing near-perfect alignment and (b) equality line (dashed) and OLS regression

3.3. Comparison with previous studies and implications for static operation

The prototype developed here achieves centimetre-level accuracy at a cost of less than USD 55 for the bill of materials, placing it among the most economical non-contact fluid-level measurement solutions. When compared with manual dipstick readings, the error metrics remain within acceptable limits for fuel inventory management. The 2-h sampling interval and 32 paired measurements were sufficient to capture the small fluctuations observed in a static tank, and the strong linear correlation between the ultrasonic and manual readings confirms the validity of the calibration procedure. Under short-term static validation (62 h), the statistical agreement was quantified as follows: mean error 0.03 cm (95% CI ±0.37 cm), MAE 0.91 cm, SD 1.06 cm, RMSE 1.05 cm; Pearson's r = 0.994 (95% CI 0.987–0.997; p ≪ 0.001). An OLS fit ($Prototype = a + b \times Manual$) yielded b = 0.999 (95% CI 0.957–1.042), a = 0.13 cm (95% CI −7.62–7.89), and R^2 = 0.987, with b not different from 1 and a not different from 0, indicating no meaningful proportional or constant bias under these conditions. Taken together, these statistical results indicate centimetre-level accuracy under short-term static conditions, confirming the reliability of both the sensor calibration and the environmental compensation strategy. Agreement with the manual gauge was quantitatively strong, with high Pearson correlation and an OLS fit whose slope was near unity, intercept near zero, and high R^2, indicating no detectable proportional or constant bias. Moreover, the low variance of the paired errors and the narrow residual spread around the OLS fit reflect excellent repeatability, comparable to benchmarks reported by [16], [22].

By achieving centimetre-level accuracy in the static tank, it addresses the limitations of manual gauge readings and high-cost proprietary systems while maintaining operational safety and efficiency. This finding underscores the potential of low-cost open-source prototypes for resource-constrained fuel stations. Consistent with recent studies [13], [24], the presented system leverages a low-cost, modular Arduino architecture offering affordability, simplicity and autonomy. This aligns with the observations of [25], who confirmed that open-source IoT solutions can reduce costs by more than 75 % while maintaining measurement accuracy.

Additionally, Sunny *et al*. [26] reported high reliability and resilience for low-cost IoT sensor nodes deployed under challenging rural conditions, which strongly validates our approach and emphasises its practical value in resource-constrained settings. While the present study focused on static conditions, the methodology could be extended to other fluids or tank geometries after appropriate calibration. This is particularly relevant since prior studies employing float-based sensors have reported notable inaccuracies under turbulent or irregular tank conditions [27].

3.4. Influence of humidity and perspectives for compensation

Variations in the speed of sound due to humidity were not compensated for in this study. Humid air contains a greater proportion of water molecules; this tends to reduce air density and slightly accelerate sound, while the thermodynamic properties of water vapour induce a counteracting deceleration effect. Recent reviews have confirmed that, although this effect is much smaller than the influence of temperature, neglecting humidity can still introduce measurable biases in ultrasonic distance estimation [28]. In comparable experimental work, environmental factors including humidity have been shown to affect ultrasonic travel times and reduce rangefinder accuracy under realistic conditions [29].

A possible future enhancement would be to integrate a humidity sensor, which [30] found significantly influence ultrasonic signal propagation, and to use a more complete model $v\ (T,\ RH)$ to correct this bias and bring the accuracy closer to the millimetre-scale. Moreover, field evidence that misalignment or surface condensation can degrade ultrasonic performance further reinforces the importance of environmental compensation to ensure robust accuracy across variable conditions.

3.5. Comparison with recent literature

To situate our approach relative to recent work, Table 3 summarizes several fluid-level monitoring systems reported in the recent literature. Compared with these approaches, the system of [31] offered a wide measurement range (15–645 cm) but suffered from relatively high error (RMSE 1.5 cm) and lacked environmental compensation, limiting robustness. Galli *et al.* [32] improved accuracy (<6 % error) and added temperature correction, though at a higher unit cost (~50 €) and with dependence on local micro secure digital (microSD) storage. Lee and Jung [33] achieved outstanding sub-millimetre resolution (0.06 mm) and 0.9 % accuracy, but required a personal computer (PC)-based image processing setup with universal serial bus (USB) connectivity and dual compensation, which hinders field portability. In contrast, the present work achieves competitive accuracy (MAE 0.91 cm over 0–200 cm) while remaining low-cost (<55 USD), lightweight, and fully wireless through ESP8266 integration. Although its resolution is lower than that of image-based systems, the inclusion of temperature compensation and IoT connectivity provides a balanced and scalable solution for practical and remote monitoring applications, consistent with the benefits of IoT-enabled fluid management highlighted in recent studies [14], [34].

Table 3. Comparison of selected recent fluid-level monitoring systems

Work (year)	Sensor/principle	Measurement range	Typical error	Approximate cost	Connectivity	Environmental compensations
[31]	Ultrasonic (HC-SR04) + Arduino	15–645 cm	Accuracy 5 cm; RMSE 1.5 cm	≈ USD 100	Local (SD card)	None
[32]	Ultrasonic sensor (HC-SR04) + DS18B20 (ArduHydro)	2–450 cm	R^2 > 0.91; root-mean-square percentage error < 6 %	~50 € per sensor (32 € each device)	Local storage on microSD	Temperature
[33]	Image-based sensor with camera + processing algorithm	~0–30 cm (adjustable)	0.9% accuracy, 0.06 mm resolution	≈ USD 80	USB cable connection to PC	Temperature and pressure
Present work	HC-SR04 + DHT11	0–200 cm	MAE 0.91 cm	< USD 55	Wi-Fi (ESP8266)	Temperature

3.6. Deployment considerations: power consumption, connectivity and maintenance

In the context of low-cost, real-time fluid-level monitoring, Wi-Fi offers simplicity and easy integration with existing infrastructure but falls short in range, energy efficiency, and reliability under unstable connectivity. The ESP8266 module used in this study consumes approximately 70 mA during active Wi-Fi transmission, with transient peaks exceeding 170 mA, significantly restricting long-term battery autonomy [35]. A practical mitigation is duty-cycled operation which lowers average current [36]. For deployments demanding extended range and minimal maintenance, for example, fuel stations with poor coverage, long range

(LoRa) provides kilometer-scale communication with ultra-low energy consumption, while ZigBee supports resilient mesh networking in distributed setups [37]–[39].

From a maintenance standpoint, ultrasonic sensors can be subject to gradual performance degradation due to fuel vapours, dust accumulation, or thermal drift. Regular inspection and periodic recalibration are therefore essential to preserve measurement accuracy. These operational aspects, together with energy consumption and connectivity trade-offs, should be carefully considered when transitioning the prototype from laboratory validation to real deployment in fuel stations.

3.7. Limitations and future work

This study presents a promising low-cost ultrasonic prototype, but several limitations must be acknowledged. The experimental protocol was restricted to a static tank over 62 h, with levels stabilised between successive readings; no filling or draining was performed during acquisition. While the HC-SR04 sensor and the Arduino introduce only millisecond-scale latency (i.e., negligible intrinsic delay), the 2-hour sampling interval is not suited to capturing rapid level changes during transfer operations. For real-time monitoring of fuel transfers, we recommend shortening the acquisition interval to seconds–minutes and applying on-device filtering to attenuate noise while tracking level dynamics. Liu *et al.* [40] demonstrated that applying embedded filtering algorithms, such as the Kalman filter, improve precision by reducing noise and rejecting anomalies more effectively than the median-of-three filtering employed in this study. A dedicated dynamic test campaign is therefore required to quantify tracking error and RMSE under turbulence, sloshing and vibration, and to verify stability across typical operating scenarios. Although the centimetre-level accuracy obtained in this study is adequate for fuel inventory management, recent laboratory work has shown that ultrasonic detection can reach sub-centimetre accuracy, with errors below 3 mm under controlled conditions [7]. This contrast highlights opportunities for further refinement and motivates future efforts to reduce error margins.

Second, while temperature compensation was implemented, humidity effects were not addressed. Previous studies have shown that humidity can alter the speed of sound and slightly bias ultrasonic measurements [30]. Incorporating a humidity sensor and adopting a complete $v\ (T,\ RH)$ model could improve robustness.

Third, the current design relies on Wi-Fi connectivity, which is energy-intensive and less reliable under unstable network conditions [35]. Alternative IoT technologies such as LoRa and Zigbee offer promising solutions for large-scale deployment [37].

Finally, long-term field trials are needed to evaluate sensor durability, the impact of dust and fuel vapours on transducer performance, and maintenance requirements such as cleaning and recalibration. In such deployments, the use of industrial-grade ultrasonic transducers certified for explosive atmospheres, as demonstrated in intrinsically safe circuit designs for ultrasonic ranging [41] and more recently in ultrasonic gas detection systems integrating IoT and artificial intelligence (AI) for hazardous environments [42], would be required to ensure compliance with safety standards while preserving the low-cost and open-source design principles demonstrated in this prototype. These aspects are crucial for confirming the scalability and sustainability of the proposed system in operational environments.

Future research will therefore include extended dynamic tests, environmental compensation (temperature and humidity), and long-term pilot deployments. Recent works in IEEE Sensors, Measurement, and Instrumentation [13], [22], [24], [32], [33] will provide methodological guidance and benchmarks for strengthening the validation and positioning the system relative to state-of-the-art solutions.

4. CONCLUSION

This study demonstrates that an open-source low-cost prototype combining an HC-SR04 ultrasonic sensor, an Arduino Uno microcontroller, an ESP8266 Wi-Fi module and a DHT11 temperature sensor can monitor fuel level with centimetre-level accuracy (MAE < 1 cm) over a range of 0–200 cm under short-term static conditions. Temperature compensation effectively reduces systematic bias and ensures centimetre-level accuracy. Strong agreement with the manual gauge was confirmed (high r; OLS $b \approx 1$, $a \approx 0$; high R^2) with no detectable proportional or constant bias. The discussion showed that the effect of humidity on the speed of sound is negligible for most applications, but future improvements could integrate a full $v\ (T,\ RH)$ compensation and advanced filtering algorithms to adapt to dynamic conditions. The experimental validation, however, was limited to static conditions and short-term testing (62 h in a single tank) with a 2-h sampling interval, which constrains the generalisation of the findings. Dynamic filling and draining scenarios, as well as long-term deployments, remain to be addressed in order to confirm robustness and scalability. Although the results are promising for resource-limited fuel stations, extended field trials under operational conditions, together with considerations of energy consumption and maintenance strategies, are necessary to validate large-scale deployment. With these improvements, open-source ultrasonic systems can constitute a viable alternative to costly proprietary gauges for autonomous fuel-stock management and for enabling remote logging and supervision.

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Stéphane Birindwa Birhashwirwa	✓		✓			✓	✓	✓	✓		✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
The authors declare that they have no conflict of interest.

DATA AVAILABILITY
The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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