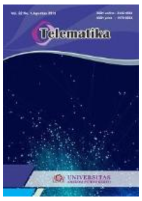

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Development of a Multi-point IoT Based Ship Draft Monitoring System for Barge Mounted Power Plants

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ABSTRACT

Continuous monitoring of ship draft is essential for maintaining vessel stability, operational safetakay, and fuel distribution efficiency, particularly in Barge Mounted Power Plants (BMPP), where load variations directly influence the vessel's balance. At the PLTMG BMPP Nusantara-1, draft measurements are currently performed through manual visual inspection of draft marks, making the process susceptible to human error and unsuitable for continuous real time monitoring. This study proposes the development of a multipoint Internet of Things (IoT) based ship draft monitoring system employing six waterproof JSN-SR04T ultrasonic sensors integrated with an Arduino Mega, ESP32 communication module, RTC DS3231, and Arduino IoT Cloud platform. The proposed system continuously measures draft values at the port and starboard sides along the bow, midship, and stern, enabling comprehensive monitoring of vessel trim and heel conditions. Measurement data are transmitted in real time to a cloud dashboard and automatically stored in Google Sheets for historical data logging. Ten latency trials produced a mean end to end response time of 30.00 s. In addition, the system incorporates an automatic warning mechanism that detects overdraft, minimum draft, and vessel imbalance conditions based on predefined operational thresholds. Experimental evaluation using a laboratory scale prototype of the BMPP Nusantara-1 demonstrates that the proposed system successfully performs continuous draft monitoring, provides real time visualization with an observed 30 s response interval, records historical measurement data, and generates timely warning notifications under various operating scenarios, including overdraft, heel, and minimum draft conditions. The developed system offers a practical IoT based solution for improving operational safety and supporting digital monitoring of floating power plants.

1. INTRODUCTION

Continuous monitoring of ship draft is essential for maintaining vessel stability, operational safety, and efficient load management (Briguglio & Crupi, 2024; Setiawan et al., 2024). Ship draft, defined as the vertical distance between the waterline and the keel, is a key indicator of a vessel's loading condition. Variations in draft influence hydrostatic characteristics, maneuverability, structural loading, and fuel efficiency under changing marine conditions. Maintaining an appropriate draft helps ensure operation within safe loading limits and reduces risks associated with excessive loading or imbalance. Recent reviews also emphasize the growing role of sensors, data processing, and connected monitoring in safe maritime applications (Briguglio & Crupi, 2024).

The Barge Mounted Power Plant (BMPP) Nusantara-1 is a domestically constructed floating power plant supplying electricity to the Ambon power system. Unlike conventional transport vessels, the BMPP permanently carries generating equipment, auxiliary systems, and fuel-storage tanks. Fuel is consumed from tanks on the port and starboard sides, producing gradual changes in weight distribution that may alter draft, trim, and heel. Continuous multipoint observation is therefore required to support timely operational decisions. At present, draft measurements are performed manually through visual observation of marks painted on the hull. This method depends on waves, lighting, viewing angle, and operator experience and does not inherently provide continuous records or automatic warnings (Zhang et al., 2024).

Based on the operational practice at BMPP Nusantara-1, manual draft readings are scheduled once every three hours. Consequently, a change in draft caused by wave conditions or changes in vessel weight may occur between two scheduled observations and may not be recorded when it occurs, producing a potential monitoring gap of up to three hours. No manual reading errors have been formally documented during the current operation. However, delayed or missed readings have occurred because the inspection schedule can overlap with the operator's other duties. Therefore, the main quantified operational limitation identified in this study is the three hour sampling interval, together with the risk of additional data gaps when scheduled observations are not performed. These conditions strengthen the need for automatic and continuous monitoring as an operational aid.

Recent advances in the Internet of Things (IoT) enable real time acquisition, remote access, automated decision support, and historical data storage in monitoring applications (Gerakoudi et al., 2024; Lanfranchi et al., 2025). Studies published in Telematika have demonstrated IoT based energy monitoring and control (Artono, 2023) and multi sensor acquisition using Arduino Mega, a WiFi controller, and a real time cloud database (Kusuma, 2023). Ultrasonic sensors are widely adopted because they provide non contact distance measurements with relatively low cost and simple implementation. IoT and ultrasonic sensing have been applied to water level monitoring in tanks and infrastructure (Azhar et al., 2024), oil volume monitoring in diesel power plant storage tanks (Prayetno et al., 2021), and ship mounted wave observation (Ølberg et al., 2024). Distributed marine sensor platforms have also demonstrated cloud connected environmental acquisition using wireless communication (Majumder et al., 2024).

Previous ultrasonic IoT studies have mainly focused on single-point liquid-level monitoring in stationary containers. Prayetno et al (2021) employed one HC-SR04 and ESP8266 to monitor a PLTD engine oil tank and provide Android/email information with relay control, while Azhar et al. (2024) implemented one HC-SR04 and NodeMCU ESP8266 for WiFi based water capacity monitoring and pump control. Although these systems demonstrate effective remote level observation, their single sensing points cannot represent longitudinal bow stern variation or transverse port starboard differences on a floating structure. In contrast, Zhang et al. (2024) applied multispectral imaging and dual flow deep learning to recognize hull draft marks, but this image-based method does not constitute an onboard distributed ultrasonic network for continuous spatial draft monitoring. The present study addresses this gap by integrating six JSN-SR04T sensors with an Arduino Mega, ESP32, RTC, Arduino IoT Cloud, and Google Sheets to measure draft at the bow, midship, and stern on both port and starboard sides, calculate trim and heel indicators, log data every five seconds, and generate configurable threshold alarms. Nevertheless, the proposed system remains a laboratory prototype and requires full scale marine validation.

Recent ship studies have examined the effects of draft and trim on resistance, course keeping, fuel consumption, and hydrostatic performance (Campbell et al., 2022; Himaya & Sano, 2023; Musulin et al., 2024; Zhu et al., 2025), while automated draft-reading research has primarily used image based waterline localization (Zhang et al., 2024; Zhu et al., 2025). These contributions establish the operational importance of draft information but do not provide a low cost six point ultrasonic arrangement that simultaneously represents longitudinal and transverse draft distribution on a BMPP. This unresolved measurement and implementation gap motivates the proposed system.

The novelty of this study is therefore not merely the use of ultrasonic sensing or cloud connectivity, but their integration in a six-point spatial configuration for a Barge Mounted Power Plant. Paired sensors at the bow, midship, and stern on the port and starboard sides enable separate longitudinal trim and transverse heel indicators, while the Arduino Mega ESP32 architecture provides five second historical logging and configurable warnings for maximum draft, minimum draft, and draft imbalance. The contribution is demonstrated on a laboratory prototype and is presented as a functional basis for full scale BMPP development rather than as a field validated replacement for approved vessel stability instruments.

2. RESEARCH METHODS

This section describes the research materials, instruments, design, procedures, assumptions, and evaluation methods used to construct and assess the prototype, thereby providing the information required to reproduce the laboratory experiment.

2.1. Research Framework

The research followed six stages: problem identification, system design, hardware and software development, system integration, experimental testing, and performance evaluation. Manual draft observation at BMPP Nusantara-1 was first examined to identify requirements for continuous acquisition, remote visualization, historical logging, and automatic warnings. The proposed components were then assembled and programmed, integrated on a laboratory prototype, and evaluated under controlled draft conditions. The study employed a laboratory scale engineering prototype with repeated measures functional testing. The imposed water level and load configurations were the independent experimental conditions, whereas the six equivalent draft outputs, trim and heel indicators, warning states, timestamps, and communication latency were the observed responses. The tests assumed fixed and vertically aligned sensors, a stable reference height, a nominally horizontal water surface except during the wave disturbance scenario, and the prototype scaling factor defined below. Hardware type, sensor positions, conversion equations, sampling interval, thresholds, calibration reference, repetitions, and evaluation metrics are specified in the following subsections to support reproducibility.

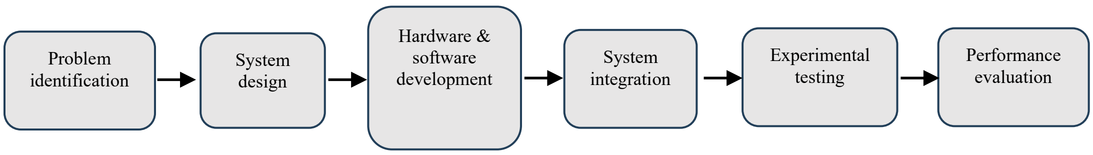


Figure 1. Research framework of the proposed multi point draft monitoring system.

2.2. System architecture

The architecture comprises sensing, processing, communication, and application layers (Figure 2). Six waterproof JSN SR04T sensors form the sensing layer. The Arduino Mega 2560 and DS3231 RTC constitute the processing layer. The communication layer uses an ESP32 and WiFi, while the application layer comprises Arduino IoT Cloud for visualization and warnings and Google Apps Script Google Sheets for historical records. This division separates measurement, calculation, transmission, and user facing functions.

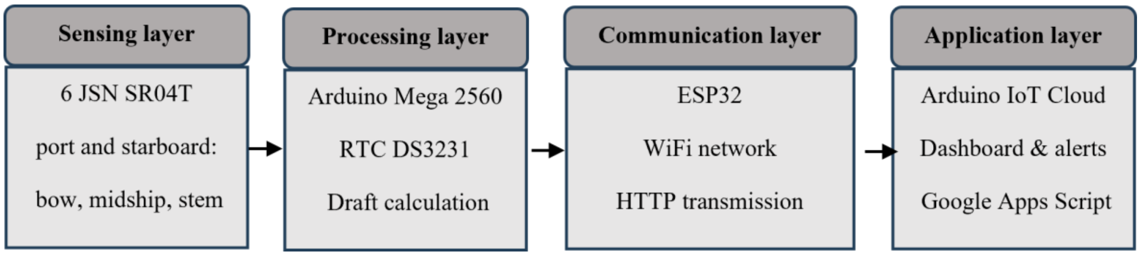


Figure 2. Overall architecture of the proposed IoT based monitoring system.

2.3. System operating principle

Each sensor measures the distance from its fixed installation position to the water surface. Draft is calculated in Equation (1).

$$D_i = H_i - d_i \tag{1}$$

D_i is draft; H_i is the fixed sensor to keel reference height, and d_i is the distance. Prototype measurements are converted to equivalent vessel values using Equation (2) with prototype distance in centimeters and equivalent draft in meters.

$$D_{actual} = 0.2D_{prototype} \tag{2}$$

The Arduino sequentially reads the six sensors and appends RTC time information before transferring the data to the ESP32. The implemented program calculates the minimum, maximum, and mean values of the six measurements. The imbalance warning is activated when the maximum minimum draft spread exceeds 0.40 m; the maximum draft warning is activated when the six point mean draft exceeds 4.20 m; and the minimum-draft warning is activated when the mean draft is below 3.60 m. The comparison operators are strict, a value exactly equal to a boundary does not activate the corresponding warning.

3. BASIS FOR SETTING THE EXPERIMENTAL THRESHOLDS

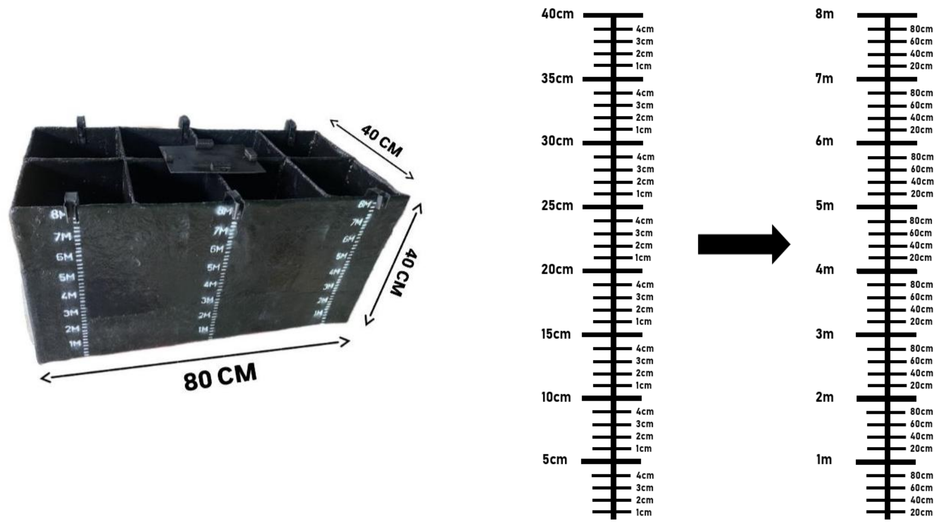
The thresholds used in this study were engineering setpoints for functional testing of the laboratory prototype, rather than statutory operating limits or values obtained from a complete stability calculation for BMPP Nusantara-1. The equivalent draft of 4.20 m was used as the reference boundary for the normal to high draft transition. Consequently, a mean value above 4.20 m activates the maximum draft warning, and the imposed 4.40 m condition demonstrates overdraft detection. The lower boundary of 3.60 m was selected to represent a distinct low draft condition, 0.60 m below the 4.20 m reference.

The imbalance threshold of 0.40 m corresponds to a 2 cm transverse or longitudinal difference on the prototype under the adopted vertical conversion of 1 cm = 0.20 m. This setpoint was selected to demonstrate that the six-point system can detect a meaningful spatial difference before the imposed heel test reaches 0.80 m. Accordingly, the three values are configurable experimental triggers used to verify alarm logic and should not be interpreted as certified safe operating limits.

For installation on an actual BMPP, the maximum permissible draft must be established from the assigned load line and freeboard requirements, while minimum draft and trim/heel alarm limits must be determined from the approved stability information, loading manual, operating condition, and requirements of the competent maritime authority or classification society. The International Convention on Load Lines links permissible loading to freeboard, reserve buoyancy, stability, and structural safety, whereas the 2008 IS Code requires stability to be assessed for relevant loading conditions (International Maritime Organization [IMO], 1966; IMO, 2008). Full scale commissioning should therefore replace the experimental setpoints with vessel-specific limits validated by the operator and the relevant approval authority.

3.1. Prototype development

A functional laboratory prototype was constructed with dimensions of 80 × 40 × 40 cm and a maximum measurable prototype draft of 40 cm. The vertical conversion factor was defined as 1 cm on the prototype to 0.2 m on the actual vessel, so 40 cm represents 8 m. The factor applies only to vertical draft conversion and does not imply complete geometric similarity. Sensors were installed at the port bow, port midship, port stern, starboard bow, starboard midship, and starboard stern. The prototype dimensions and the adopted vertical draft conversion are illustrated in Figure 3.



(a) (b)

Figure 3. Laboratory prototype: (a) overall dimensions and (b) vertical draft conversion.

3.2. Derivation of the vertical conversion factor

The vertical conversion factor was derived by linearly mapping the maximum measurable prototype draft of 40 cm to the selected maximum equivalent BMPP draft of 8 m. Let S_v denote the vertical conversion factor, D_e max, the maximum equivalent BMPP draft, and $D_p$max, the maximum prototype draft. The conversion factor is therefore:

$$S_v = \frac{D_e max}{D_p max} = \frac{8m}{40cm} = 0.2m/cm \tag{3}$$

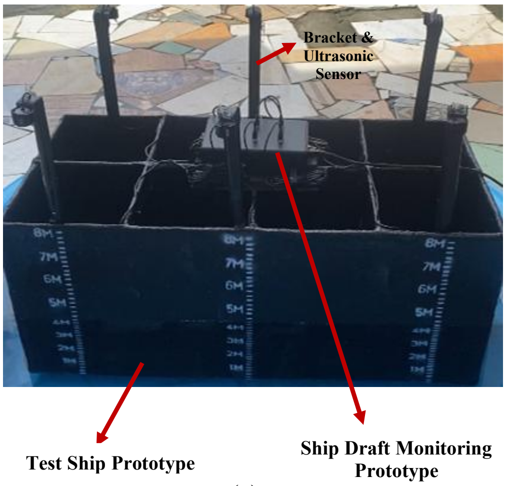
For any prototype draft D_p expressed in centimetres, the equivalent BMPP draft is calculated as:

$$D_e = S_v D_p = 0.2\, D_p \tag{4}$$

Consequently, 1 cm of prototype draft corresponds to 0.2 m of equivalent BMPP draft. This factor is a linear vertical mapping used for functional testing only; it does not represent complete geometric or dynamic similarity between the laboratory prototype and the actual BMPP.

3.3. Experimental setup

The prototype was placed in a controlled water filled test environment. Draft values were read automatically and compared with the graduated scale on the prototype. Four operating states were considered: normal, overdraft, heel, and minimum draft; an additional disturbance test introduced surface waves. Heel was created by adding transverse load to the port side, causing the prototype to incline while the water surface remained horizontal. All measurements, warning states, dashboard output, and stored records were observed during testing.



(a)

(b)

Figure 4. Prototype Implementation of the Proposed IoT Based Ship Draft Monitoring System: (a) Overall prototype installed on the test ship, and (b) Waterproof ultrasonic sensor mounted on the supporting bracket.

As illustrated in Figure 4, the prototype integrates six waterproof ultrasonic sensors installed at the bow, midship, and stern on both the port and starboard sides. This sensor configuration enables simultaneous draft measurements at multiple locations, allowing the system to evaluate draft distribution and identify vessel imbalance conditions such as trim and heel.

Table 1. Experimental configuration and evaluated scenarios

No.	Item	Specification
1	Prototype	80 × 40 × 40 cm functional model
2	Vertical conversion	1 cm prototype = 0.2 m equivalent draft
3	Measurement points	Port and starboard bow, midship, and stern
4	Reference	Graduated draft scale on the prototype
5	Data transmission	ESP32, WiFi, Arduino IoT Cloud, HTTP query string
6	Logging interval	5 s through Google Apps Script to Google Sheets
7	Overdraft demonstration	Mean draft approximately 4.40 m
8	Heel demonstration	PS = 4.60 m; SB = 3.80 m; difference = 0.80 m
9	Minimum-draft demonstration	Approximately 3.60 m; wave disturbance 3.60–3.80 m

3.4. Data processing

Processing followed acquisition, conversion, classification, transmission, and storage. The Arduino converted each sensor distance into draft and sent six timestamped values to the ESP32. The ESP32 updated Arduino IoT Cloud and, every five seconds, formatted the data as an HTTP query string for a Google Apps Script web application. The script inserted each record into Google Sheets. Functional performance was assessed by verifying agreement between the imposed scenario and dashboard values, warning activation and reset, and successful historical recording. Sensor measurement performance was additionally evaluated through a ruler based laboratory calibration after correction of the conversion code.

3.5. Sensor calibration and accuracy evaluation

The six JSN-SR04T sensors were evaluated using a ruler as the laboratory reference. Initial tests at distances of 10 and 15 cm produced zero output because these distances were below the minimum operating range of the sensors and were therefore excluded from the accuracy analysis. In the first trial at the valid reference distances, all sensor channels displayed 8 m because of an error in the draft-conversion code. After the code was corrected, four valid repetitions were conducted at reference distances of 20, 25, 30, and 35 cm. Thus, 16 valid observations were obtained for each sensor, resulting in 96 observations across all six sensors. The ruler based reference distances were converted into equivalent BMPP draft values using a conversion factor of 0.2 m/cm. Measurement accuracy was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE and RMSE quantify the error magnitude in metres, whereas MAPE expresses the relative error as a percentage (Hosamo & Mazzetto, 2025).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{7}$$

y_i is the equivalent BMPP draft derived from the ruler reference, $\hat{y}_i$ represents the equivalent draft measured by the sensor and displayed on Arduino IoT Cloud, and n represents the number of valid post correction observations. Accordingly, n = 16 for the evaluation of each sensor and n = 96 for the combined evaluation of all six sensors.

3.6. Justification of the six point configuration and trim heel formulation

The six point arrangement was selected as the minimum functional configuration capable of representing draft variation in both longitudinal and transverse directions. Three longitudinal stations bow, midship, and stern capture the spatial distribution of draft along the prototype, while paired port and starboard measurements at each station capture transverse differences. A single point system cannot distinguish these spatial variations. The configuration is an engineering choice for the laboratory prototype and is not presented as a sensor quantity prescribed by a maritime standard. Final sensor quantity and placement on an actual BMPP must be determined from vessel geometry, installation access, operational requirements, and applicable marine safety approval (Maritime Organization, 2009).

The operational relevance of monitoring longitudinal trim in a converted ship power plant has been demonstrated by (Setiawan et al., 2024). However, because the present system employs six spatially distributed sensors, this study defines separate longitudinal trim and transverse heel indicators based on the measured draft differences. These formulations are intended for prototype monitoring and do not replace a complete naval architecture stability assessment. In this study, the mean drafts at the bow and stern are calculated from the paired port and starboard measurements as follows:

$$\bar{D}_{bow} = \left(D_{port\ bow} + D_{starboard\ bow}\right)/_{2} \quad (8)$$

$$\bar{D}_{stern} = \left(D_{port\ stern} + D_{starboard\ stern}\right)/_{2} \quad (9)$$

The longitudinal trim indicator developed for the prototype is defined as the difference between the mean stern draft and the mean bow draft:

$$\Delta\, D_{trim} = \bar{D}_{stern} - \bar{D}_{bow} \quad (10)$$

A positive $\Delta\, Dtrim$ indicates a greater stern draft, a negative value indicates a greater bow draft, and a zero value indicates equal mean bow and stern drafts. To represent the transverse draft distribution, the mean drafts on the port and starboard sides are calculated from the bow, midship, and stern measurements as follows:

$$\bar{D}_{port} = D_{port\ bow} + D_{port\ mid} + D_{port\ stern})/_{3}$$
$$\bar{D}_{starboard} = D_{staboard\ bow} + D_{staboard\ mid} + D_{staboard\ mid})/_{3} \quad (11)$$

The transverse heel indicator developed for the prototype is then defined as the difference between the mean port and starboard drafts:

$$\Delta\, D_{heel} = \bar{D}_{port} - \bar{D}_{starboard} \quad (12)$$

A positive $\Delta\, D_{heel}$ indicates a greater port side draft, a negative value indicates a greater starboard side draft, and a zero value indicates equal mean drafts on both sides. Equations (6)-(10) provide separate draft difference indicators for longitudinal trim and transverse heel in metres. These equations were developed in this study based on the spatial arrangement of the six sensors and do not independently calculate angular inclination or complete ship-stability parameters. Determining angular inclination would additionally require the longitudinal and transverse distances between the measurement points, while a complete stability assessment would require vessel specific hydrostatic and stability data in accordance with the applicable maritime stability criteria (Maritime Organization, 2009).

3.7. Communication latency evaluation

Communication and response latency was evaluated through ten repeated trials. Four event timestamps were recorded in each trial: t_0 denotes the time at which a draft change was imposed, t_1 denotes the time of local alarm activation, t_2 denotes the time at which the updated draft value appeared on Arduino IoT Cloud, and t_3 denotes the time at which the corresponding record was inserted into Google Sheets. Based on these recorded events, this study defines local alarm latency, additional cloud synchronization delay, additional storage delay, and end to end response latency as follows:

$$L_{\mathrm{local}} = t_1 - t_0 \quad (13)$$

$$L_{\mathrm{sync}} = t_2 - t_1 \quad (14)$$

$$L_{\mathrm{storage}} = t_3 - t_2 \quad (15)$$

$$L_{\mathrm{end\ to\ end}} = t_3 - t_0 \quad (16)$$

In these equations, L_{local} represents the response time from the imposed draft change to local alarm activation, L_{sync} represents the additional delay from local alarm activation to the appearance of the updated value on Arduino IoT Cloud, L_{storage} represents the additional delay from the cloud update to insertion into

Google Sheets, and $L_{\text{end to end}}$ represents the total response time from the imposed draft change to data insertion into Google Sheets. For each latency metric, the mean, minimum, maximum, and sample standard deviation were calculated across the ten trials. All timestamps were recorded to the nearest second. Therefore, delays shorter than the timestamp resolution could not be distinguished.

4. RESULTS AND DISCUSSION

This section presents the research results obtained through a series of tests and analyses of the developed system.

4.1. System integration and cloud monitoring

The integrated prototype continuously displayed the six measurement points on Arduino IoT Cloud. RTC timestamps accompanied the sensor records, while Google Sheets retained the historical series. The system therefore addressed three limitations of manual observation: discontinuous readings, absence of centralized historical records, and lack of automatic notification. The separation between Arduino-based acquisition and ESP32-based communication also allowed multiple sensors to be processed while maintaining cloud connectivity.

4.2. Sensor calibration results

After correction of the conversion code, reference distances of 20, 25, 30, and 35 cm produced equivalent draft outputs of 4, 5, 6, and 7 m, respectively, across all six sensors in four valid post-correction repetitions. Each sensor contributed 16 observations, resulting in 96 observations for the combined dataset. The accuracy metrics calculated using Equations (3)-(5) are summarized in Table 2.

Table 2. Summary of post-correction calibration results

Scope	n	MAE (m)	RMSE (m)	MAPE (%)
All six sensors	96	0.00	0.00	0.00

The zero valued error metrics indicate agreement at the resolution of the cloud output, rather than perfect metrological accuracy. Because the stored values had already been converted and displayed in whole metres, small variations below the display resolution could not be recovered. The calibration therefore validates the implemented reading and conversion functions within the tested range, while certified calibration and uncertainty analysis remain necessary before operational deployment.

4.3. Operational scenario testing

The system response under the three principal abnormal conditions is summarized in Table 3. In the overdraft test, port and starboard averages reached approximately 4.40 m, exceeding the programmed maximum threshold and activating the maximum warning. When the draft returned to approximately 4.20 m, the warning reset. This demonstrated both activation and recovery behavior.

For the heel test, transverse loading produced a mean port-side draft of 4.60 m and a mean starboard-side draft of 3.80 m. The imbalance warning activated because the resulting transverse draft difference exceeded the programmed 0.40 m trigger. The maximum warning could also activate concurrently because a port side value exceeded the upper limit. A prototype inclination of approximately 2° was visually observed during the test; however, this angle was not calculated using Equations (9) and (10). After load redistribution, the mean drafts on both sides returned to approximately 4.20 m and the imbalance warning cleared.

Application of Equations (9) and (10) produced a transverse heel indicator of +0.80 m during transverse loading and 0.00 m after load redistribution, confirming the detection and recovery of the port–starboard draft imbalance. These values represent draft differences rather than heel angles or complete stability parameters. Because no separate longitudinal loading test was conducted, the trim indicator defined in Equations (6)-(8) remains an analytical capability that has not been experimentally validated.

The minimum draft scenario was established around 3.60 m. During the wave disturbance test, readings fluctuated between approximately 3.60 and 3.80 m. Warning status consequently changed when instantaneous or mean values crossed the programmed lower boundary. This behavior confirms sensitivity to changing water surfaces but also shows that a single threshold without persistence or hysteresis can cause repeated alarm switching near the boundary.

Table 3. Summary of functional scenario results

No.	Scenario	Imposed condition	Observed system response
1	Normal	PS and SB approximately 4.20 m	Normal display; alarms reset
2	Overdraft	PS and SB approximately 4.40 m	Maximum warning activated
3	Heel	PS 4.60 m; SB 3.80 m	Imbalance warning; maximum warning may coexist
4	Minimum draft	Approximately 3.60 m	Minimum warning near/below lower boundary
5	Wave disturbance	Fluctuation approximately 3.60 -3.80 m	Real time fluctuation recorded; warning switched at boundary

4.4. Historical data logging and comparison with manual monitoring

Google Apps Script successfully received the HTTP query parameters and inserted the six draft measurements and RTC timestamp into Google Sheets at five-second intervals. Successful record insertion was verified during the functional and latency tests. Historical logging allows operators to review trends rather than relying only on the current observation. Compared with direct visual reading, the prototype provides remote access, automatic recording, and configurable warnings. Nevertheless, dependence on WiFi and electrical power introduces failure modes that are absent from a purely visual draft mark.

Compared with recent image-based draft-reading systems, which localize a visible waterline from camera data (Zhang et al., 2024, 2025), the present prototype measures the water surface directly at six fixed hull locations and therefore produces spatial inputs for both longitudinal trim and transverse heel indicators. Studies by Campbell et al. (2022), Himaya and Sano (2023), Musulin et al. (2024), and Zhu et al. (Zhu et al., 2025) demonstrate why draft and trim conditions must be distinguished in hydrodynamic or hydrostatic analysis. The present contribution translates that distinction into a low cost multipoint monitoring architecture rather than a ship performance simulation. Maritime and distributed IoT studies also show the value of multimodal sensing, remote monitoring, confirmed messaging, edge processing, and scalable historical data platforms (Barron et al., 2022; Cil et al., 2022; Luo et al., 2022; Tusa et al., 2024; Zhong & Nie, 2024). In contrast, this study integrates those functions for the specific BMPP draft monitoring problem, although its laboratory scope prevents direct claims of full scale marine accuracy or communication robustness.

4.5. Communication latency results

Across ten trials, the local alarm, Arduino IoT Cloud display, and Google Sheets record were observed 30 s after the imposed draft change. Consequently, the mean local, cloud display, and end to end latencies were all 30.00 s, with minimum and maximum values of 30.00 s and a sample standard deviation of 0.00 s. Because t1, t2, and t3 had the same recorded timestamp in every trial, the additional cloud synchronization and storage delays were 0.00 s at the available timestamp resolution. This does not prove zero physical transmission delay. It indicates that any incremental delay was not resolved by the measurement method. In this study, real time monitoring is used in the application level soft real time sense. Measurements and warnings are updated automatically within an observed 30 s response interval, which is substantially shorter than the three hour manual inspection interval. This interpretation is consistent with recent IIoT studies that evaluate soft real time communication through latency and jitter rather than assuming deterministic hard deadlines (De Barrena Sarasola et al., 2024). The term therefore does not imply a hard-real-time guarantee, deterministic deadline compliance, or sub-second response for safety-critical control. The statistical summary of the communication latency results is presented in Table 4.

Table 4. Summary of communication latency results (n = 10)

Latency metric	*Mean (s)*	*Minimum (s)*	*Maximum (s)*	*Standard Deviation (s)*
Local alarm: t1 − t0	30.00	30.00	30.00	0.00
Cloud display: t2 − t0	30.00	30.00	30.00	0.00
Additional cloud synchronization: t2 − t1	0.00	0.00	0.00	0.00
Additional Google Sheets storage: t3 − t2	0.00	0.00	0.00	0.00
End-to-end: t3 − t0	30.00	30.00	30.00	0.00

4.6. Storage scalability and long term data management

At a five second logging interval, the eight field record structure generates approximately 17,280 rows per day, 518,400 rows per 30 day month, and 6,307,200 rows or 50,457,600 cells per year. This volume indicates that Google Sheets is suitable only for prototype demonstration and short term review, whereas long term deployment requires monthly file rotation, compressed archival storage or a dedicated time series database, and a defined data retention policy (Cai et al., 2021). Adaptive sampling and local buffering are also recommended to reduce storage demand and retain records during network interruptions.

4.7. Hardware and communication verification

Before scenario testing, supply voltages were checked to verify that the processing and communication components operated within the implemented prototype configuration. The measured values were 12.21 VDC at the main power supply, 4.616 VDC at the Arduino Mega output, 4.492 VDC at the RTC input, and 4.602 VDC at the ESP32 input. The modules remained operational during acquisition, serial transfer, WiFi communication, cloud updating, and five second spreadsheet logging. The Arduino Mega acquired six sensor channels and attached DS3231 time data. The ESP32 parsed the serial data, updated cloud properties, evaluated the configured warning logic, and transmitted an HTTP query string to Google Apps Script. Separating acquisition from network communication reduced the processing burden on the sensing controller and allowed the dashboard and historical recorder to operate concurrently.

Table 5. Electrical verification of principal hardware components

No	Components	Measurement point	Measured value
1	Main power supply	Output	12.21 VDC
2	Arduino Mega 2560	Output	4.616 VDC
3	DS3231 RTC	Input	4.492 VDC
4	ESP32	Input	4.602 VDC

4.8. Warning history and disturbance response

The dashboard retained a history of warning transitions, allowing operators to distinguish the occurrence and clearance of maximum, minimum, and imbalance conditions. During wave disturbance, draft values varied between approximately 3.60 and 3.80 m. The minimum warning changed state when the processed value crossed the configured lower boundary. The response confirms that short term surface variation is captured, but it also indicates the need for filtering, persistence time, or hysteresis before deployment in a real marine environment.

The warning behavior should therefore be interpreted as a functional early warning demonstration. It does not calculate intact stability parameters such as metacentric height or righting arm curves. Likewise, the maximum minimum spread identifies abnormal spatial variation but does not independently classify whether the variation originates from heel, trim, local wave action, or sensor noise. Future full scale validation should include systematic preprocessing, quality control, and calibration against an independent draft reference, as recommended in recent ship performance data processing and dynamic draft studies (Alexiou et al., 2023; Gupta et al., 2023; Kim et al., 2025). In addition to the stable minimum draft condition, a wave disturbance was introduced into the test pool to evaluate the system response under an unstable water surface. The laboratory prototype during this test is shown in Figure 5.

Figure 5. Laboratory prototype during the wave-disturbance test.

During the wave disturbance test, the measured draft values fluctuated between approximately 3.60 and 3.80 m. The warning status changed when the processed draft crossed the predefined minimum draft threshold. The results indicate that the system was able to record variations in the water surface; however, repeated alarm switching near the threshold demonstrates the need for signal filtering, persistence time, or hysteresis in future implementation.

4.9. Comparison with conventional monitoring

Conventional draft observation is simple and remains available without network communication, but it requires physical access to hull marks and periodic manual recording. The proposed system adds continuous six point acquisition, centralized display, timestamped historical records, and configurable alerts. These functions improve accessibility and situational awareness but introduce dependence on sensor calibration, electrical power, WiFi availability, and cloud services.

The functional advantages demonstrated in the laboratory support continued development, not immediate replacement of statutory or operational draft-reading procedures. A full scale system should retain visual draft marks as an independent reference, provide local storage during network outages, and undergo calibration and environmental qualification before operational use.

Table 6. Comparison of manual and proposed IoT based draft monitoring

o.	*Aspect*	*Manual observation*	*Proposed IoT system*
1	Acquisition	Periodic visual reading	Continuous six point sensing
2	Accessibility	Requires access to hull marks	Remote dashboard access
3	Historical record	Manual transcription	Automatic five second logging
4	Warning	Operator interpretation	Configurable cloud notification
5	Main limitation	Weather, lighting, observer judgment	Calibration, power, network, and cloud dependence

4.10. Sensor channel implementation and measurement mapping

The six sensor channels were assigned according to longitudinal and transverse location so that each measurement retained a clear physical meaning. The port channels represented bow, midship, and stern positions on the left side, while the starboard channels represented the corresponding positions on the right side. Sequential triggering was used to acquire each ultrasonic distance before the Arduino calculated the converted draft and prepared a framed serial message for the ESP32. This arrangement avoided treating the six values as an anonymous group and enabled the dashboard to display the spatial distribution of draft readings.

The DS3231 communicated with the Arduino through the I²C bus, whereas the ESP32 received processed measurements through a serial connection. Each value was registered as an Arduino IoT Cloud property and was also included in the Google Apps Script query string. The mapping shown in Table 7 was maintained from acquisition through visualization and storage, allowing a stored record to be traced to its original location on the prototype.

Table 7. Mapping of sensor channels to prototype locations and monitoring functions

N	**Channel**	**Location**	**Monitoring function**
1	PS-Bow	Port bow	Forward port draft
2	PS-Mid	Port midship	Midship port draft
3	PS-Stern	Port stern	Aft port draft
4	SB-Bow	Starboard bow	Forward starboard draft
5	SB-Mid	Starboard midship	Midship starboard draft
6	SB-Stern	Starboard stern	Aft starboard draft

4.11. Alarm activation and recovery sequences

Alarm performance was evaluated during both abnormal and recovery conditions. In the overdraft test, the mean draft increased from the normal value of approximately 4.20 m to approximately 4.40 m. Because the programmed maximum draft warning was activated when the mean draft exceeded 4.20 m, the warning became active at the imposed overdraft condition. When the mean draft returned to approximately 4.20 m, the maximum draft warning was automatically cleared.

In the heel test, an uneven transverse load caused the average port side draft to increase to 4.60 m, while the average starboard side draft decreased to 3.80 m. The resulting difference of 0.80 m exceeded the programmed draft imbalance threshold of 0.40 m and activated the imbalance warning. After the load was redistributed, both sides returned to approximately 4.20 m, and the imbalance warning was cleared.

In the minimum draft test, the measurements approached the programmed lower threshold of 3.60 m. When the processed mean draft fell below this threshold, the minimum draft warning became active. During the wave disturbance test, the measured draft fluctuated around 3.60 - 3.80 m, causing the warning status to change when the processed value crossed the lower threshold. The observed warning transitions are summarized in Table 8. Repeated switching near the minimum draft threshold indicates that signal filtering, a persistence time, or a hysteresis band should be incorporated in future development.

Table 8. Alarm activation and recovery during scenario testing

Scenario	Initial condition	Abnormal condition	Recovery condition
Overdraft	Mean draft ≈ 4.20 m; normal status	Mean draft ≈4.40 m; maximum draft warning active	Mean draft returned to ≈ 4.20 m; warning cleared
Heel	Port and starboard draft ≈ 4.20 m	Port=4.60 m and starboard=3.80 m; imbalance warning active	Load redistributed; both sides returned to ≈ 4.20 m
Minimum draft	Mean draft above 3.60 m	Mean draft below 3.60 m; minimum draft warning active	Mean draft increased above 3.60 m; warning cleared
Wave disturbance	Draft near the minimum operating condition	Draft fluctuated around 3.60 – 3.80 m; warning status changed near the threshold	Warning status followed subsequent threshold crossings

4.12. Limitations and practical implications

The present alarm tests were limited to predetermined threshold crossing scenarios. A sufficiently long dataset with independently labelled normal and abnormal conditions was not available; therefore, false-alarm and missed-detection rates were not quantified. Future validation should evaluate alarm decisions against synchronized reference observations under fluctuating environmental conditions.

Repeated alarm switching was observed when the draft fluctuated near the minimum threshold during the wave disturbance test. Moving average filtering and hysteresis are recommended to reduce short duration fluctuations and alarm chatter. However, their parameters and effects on detection delay have not been experimentally evaluated and should therefore be optimized in future testing.

Controlled WiFi interruption, packet loss, and reconnection tests were not conducted. Practical deployment should incorporate local data buffering and automatic resynchronization to prevent record loss during network interruptions. Because the experiments were conducted under controlled laboratory conditions, the effects of waves, currents, vibration, corrosion, and biofouling remain unverified. Full scale implementation requires marine-grade protection, periodic calibration and maintenance, and staged field validation on the actual BMPP. Economic feasibility should be evaluated using actual installation, maintenance, and operational cost data before full scale deployment.

5. CONCLUSIONS AND RECOMMENDATIONS

A six point IoT based draft monitoring prototype was developed for the BMPP Nusantara-1 application context. Laboratory testing demonstrated continuous multipoint visualization, five second historical logging, and automatic warnings during overdraft, transverse imbalance, minimum draft, and wave disturbance scenarios. Post correction ruler based calibration produced MAE and RMSE of 0.00 m and MAPE of 0.00% at the whole metre cloud display resolution; these results verify the implemented conversion within the tested range but do not constitute certified metrological accuracy. Ten latency trials produced a mean end to end response time of 30.00 s, supporting application level soft real time monitoring rather than hard real time or safety critical control.

The paired bow, midship, and stern measurements on the port and starboard sides enabled separate draft difference indicators for longitudinal trim and transverse heel. The transverse test identified a 0.80 m port starboard difference and its recovery to 0.00 m, whereas the longitudinal trim formulation was not independently validated. At a five-second logging interval, the estimated annual volume is approximately 6.31 million rows. Therefore, Google Sheets is suitable for prototype and short term use but not as the sole long term repository. The principal contribution is the integration of six spatially distributed measurements, separate trim heel indicators, quantitative calibration and latency evaluation, historical logging, and threshold based warnings in one BMPP oriented prototype.

The system remains a laboratory prototype rather than a certified draft survey or vessel stability instrument. False alarm and missed detection rates, filtering and hysteresis performance, communication recovery during network interruptions, and operation under actual marine conditions were not experimentally validated. Future work should therefore include higher resolution timing, filtering and hysteresis optimization, offline buffering, repeated calibration and uncertainty analysis, marine grade installation, full scale field validation, and an economic assessment based on actual installation, maintenance, and operational costs.

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