



(RESEARCH ARTICLE)



EXPERIMENTAL CHARACTERIZATION OF MEASUREMENT CONSISTENCY AND TEMPORAL VARIATION IN AN ESP32 BASED IOT SYSTEM FOR BRIDGE MONITORING

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ABSTRACT

Structural health monitoring (SHM) relies on the systematic acquisition and temporal analysis of data that reflect structural behavior. Internet of Things (IoT) architectures offer considerable potential for developing distributed, connected, and low-cost monitoring systems [1–6]. Before these systems can support anomaly detection or structural condition assessment, however, the quality, consistency, and temporal variability of the acquired data must be evaluated [7–11]. This study reports the experimental deployment of an ESP32-based IoT prototype for multiparameter monitoring of a bridge. The prototype integrates DHT22 and DS18B20 sensors for temperature measurement and an MPU-6050 module comprising a triaxial accelerometer and gyroscope for inertial measurements. Three measurement campaigns were conducted at different locations on the bridge. Temperature measurements from the DHT22 and DS18B20 sensors exhibited closely correlated temporal trends, with correlation coefficients of 0.97, 0.90, and 0.83 for the three campaigns, respectively. Nevertheless, differences in measured temperature levels and fluctuation ranges suggest sensitivity to local environmental conditions and sensor placement. The indicators derived from the MPU-6050 measurements also differed in magnitude and variability across the experimental configurations. These findings provide a preliminary characterization of the temporal patterns captured by the prototype and identify similarities and differences among measurement locations. Further validation is required to establish measurement accuracy and determine the suitability of the system for structural condition assessment.

Keywords: Structural health monitoring; Internet of Things; ESP32; MPU-6050; DHT22; DS18B20; Measurement consistency; Temporal variation; Remote monitoring.

1 INTRODUCTION

Structural health monitoring (SHM) enables the observation of changes in infrastructure behavior throughout its service life. It complements periodic inspections by providing measurements acquired directly from a structure and its

surrounding environment [10,11]. For bridges and other civil engineering structures, monitored quantities may include temperature, strain, displacement, acceleration, and dynamic parameters.

The value of a monitoring system extends beyond its capacity to collect large volumes of data. Reliable interpretation depends on measurement quality, continuity, and stability, together with an understanding of the variability induced by environmental and operational conditions [7–11]. Accordingly, deviations in measured responses should be assessed against an established baseline before they can be attributed to changes in structural condition.

This distinction is particularly relevant to structures subjected to temperature fluctuations. Thermal effects can substantially influence structural responses and dynamic parameters, potentially masking or mimicking changes associated with deterioration [11–15]. Long-term bridge monitoring studies have therefore emphasized the need to characterize temperature-dependent behavior when establishing baseline responses [12–15].

Advances in Internet of Things (IoT) technologies and low-cost sensors have enabled more accessible and distributed monitoring architectures [1–6]. Wireless sensor networks have been investigated for both continuous and periodic bridge monitoring [4–6]. Recent studies have also explored the use of ESP32 microcontrollers coupled with microelectromechanical systems (MEMS) sensors to acquire and transmit structural monitoring data [1–3].

Rehman et al. [1] developed an ESP32-based IoT architecture for vibration data acquisition and transmission. Lee et al. [2] introduced MANTIS-32, a dynamic monitoring system integrating ESP32 units and MPU-6050 sensors. Wang et al. [3] proposed a lightweight bridge monitoring architecture based on the ESP32-S3, combining data acquisition, storage, and onboard processing. Saravanan et al. [4] investigated a low-cost IoT system comprising an ESP8266 microcontroller and an MPU-6050 sensor and compared its measurements with those obtained using conventional accelerometers.

These studies illustrate the potential of IoT architectures for structural monitoring while underscoring the need to characterize the performance of low-cost sensors experimentally [4,16]. Komarizadehasl et al. [16], for example, evaluated low-cost accelerometers for bridge monitoring, identifying both their potential and practical considerations related to installation and measurement performance.

Against this background, the present study investigates the field data acquisition capabilities of an IoT monitoring system developed in Benin and deployed on a bridge. The analysis focuses on characterizing the acquired data, examining their consistency, and describing their temporal variability as an initial step toward assessing the system's suitability for structural monitoring applications.

2 MATERIAL AND METHODS

2.1 System architecture

The system adopts a distributed architecture organized into three functional layers: a sensing layer, a data acquisition and processing layer, and a data storage and access layer. Sensors installed on the bridge measure the physical quantities of interest. An ESP32 microcontroller acquires the sensor data, performs basic processing, and transmits the measurements wirelessly to a remote platform, where they are stored and made available for subsequent retrieval and analysis (figure 1).

The proposed architecture follows established principles of IoT-based structural monitoring, whereby measurement nodes integrate sensing, local processing, and wireless communication capabilities [1–6]. The ESP32 was selected as the central processing unit because it combines the computational and communication capabilities required for the prototype, consistent with architectures reported in recent structural monitoring studies [1–3]. Nevertheless, the operational functionality of the electronic unit alone does not establish the metrological performance of the complete measurement system. Data quality also depends on sensor characteristics, installation conditions, calibration procedures, sampling rate, and data processing methods [7,8,16].

2.2 Temperature instrumentation

Two sensors were used for temperature monitoring: a DHT22 sensor to measure local ambient temperature and a DS18B20 sensor to measure temperature at the selected installation point (figure 2).

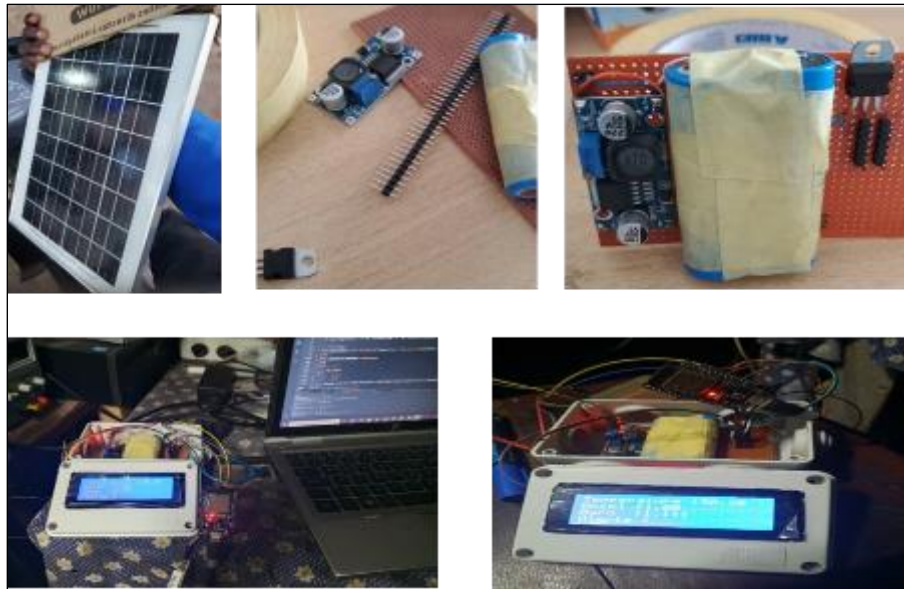


Figure 1: Architecture of the ESP32-based IoT system for bridge monitoring: sensing, data acquisition and processing, and remote data storage.



Figure 2: Temperature sensors used in the monitoring system: DHT22 and DS18B20.

The simultaneous use of two temperature sensors enables the assessment of consistency in their temporal trends and the identification of response differences potentially associated with exposure conditions. Interpretation of this comparison must account for sensor placement, as sensors exposed to different thermal environments may record different temperatures.

2.3 Inertial instrumentation

Inertial measurements were acquired using an MPU-6050 module integrating a triaxial accelerometer and a triaxial gyroscope. The use of MEMS inertial sensors in structural monitoring systems has been explored in previous studies [2,4,16]. Their compact size and compatibility with embedded platforms facilitate their integration into monitoring prototypes. In the present study, the acquired inertial signals are used primarily to characterize temporal variations in the measured acceleration and angular velocity at the instrumented location.

3 EXPERIMENTAL CAMPAIGNS

Three experimental campaigns were conducted.

3.1 First campaign

The temperature monitoring device was installed at the joint located at the end of the bridge, while the inertial sensor was mounted on the adjacent deck. This configuration was intended to capture temporal variations in the monitored quantities in an area subjected to traffic-induced loading as vehicles crossed the joint.

3.2 Second campaign

Temperature measurements were taken at the joint at the beginning of the bridge. The inertial sensor was installed beneath the deck. This configuration provided a second experimental setting for comparing the measured variations at another location on the bridge.

3.3 Third campaign

The sensors were positioned in the central part of the deck through the drainage scuppers. This configuration made it possible to observe temperature variations within the deck section and the inertial indicators associated with this location.

4 ANALYSIS METHODOLOGY

The analysis strategy deliberately focuses on data characterization. This approach is consistent with studies addressing sensor validation and SHM data quality [7,8]. Yi et al. [7] emphasize that sensor validation is an important step in preventing instrumental errors from being interpreted as changes in structural condition. Four levels of analysis were adopted.

4.1 Data continuity analysis

The first step consisted of checking:

- the number of records;
- the presence of missing data;
- the regularity of timestamps;
- any discontinuities in the time series;
- the stability of system operation during the campaigns.

This step characterizes the operational quality of the data acquisition chain.

4.2 Descriptive statistical analysis

For each time series, the following indicators were calculated:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad \text{equation (1)}$$

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{equation (2)}$$

along with the minimum and maximum values and the range:

$$A = x_{\max} - x_{\min} \quad \text{equation (3)}$$

These indicators characterize the mean level, dispersion, and magnitude of variation in the measurements.

4.3 Analysis of temporal variation

Time-series analysis is the central focus of this initial phase.

For each day, the time series were plotted against time to identify:

- overall trends;
- increasing phases;
- decreasing phases;
- periods of stability;
- isolated variations;
- differences between sensors;
- differences between configurations.

For temperature measurements, this analysis characterizes the daily thermal cycle and differences in response between the external environment and the installation location. For inertial indicators, it identifies periods of greater activity without attempting to reconstruct high-frequency dynamics.

4.4 Analysis of intersensor consistency

Consistency between the two temperature measurement chains was assessed using the Pearson correlation coefficient:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad \text{equation (4)}$$

The correlation coefficient, r , quantifies the strength and direction of the linear association between the two-time series. In this study, it is used to assess consistency in their temporal trends rather than absolute measurement accuracy or agreement. A high correlation can coexist with systematic differences between sensor readings. Accordingly, measurement validation requires additional assessment of errors, bias, drift, and potential sensor faults [7,8].

5 RESULTS

5.1 3D model of the printed circuit board



Figure 3: 3D model of the printed circuit board1

The 3D model of the system's printed circuit board shows all the components used, together with spare pins provided for future sensors as the system is further developed. The model was created using Proteus software (figure 3).

5.2 Electronic board wiring

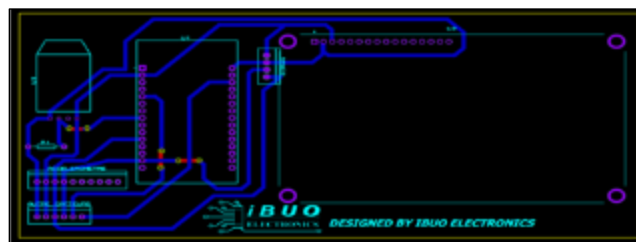


Figure 4: Electronic board wiring

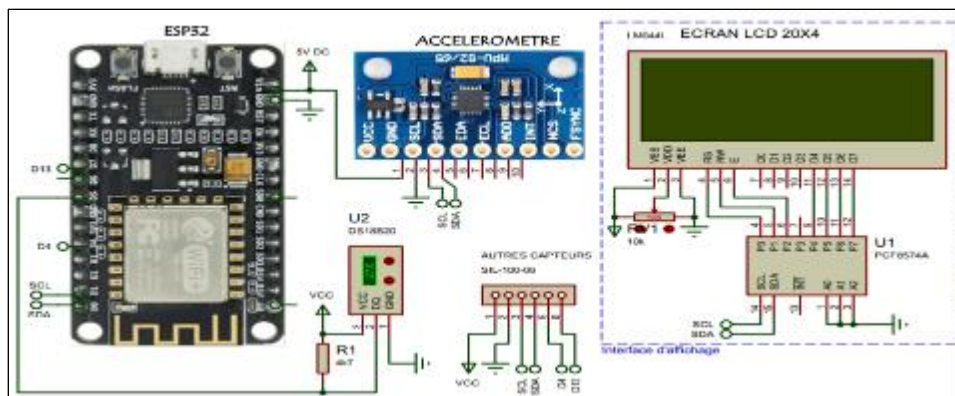


Figure 5: Circuit diagram of the data acquisition system

The circuit diagram above was obtained by modeling the system in Proteus software (figure 4 and 5).

5.3 Continuity of data acquisition

The available dataset comprises approximately 284–285 records distributed across the three experimental campaigns. The interval between the records used in the analysis is approximately five minutes.

This amount of data allows slow variations in the measured parameters to be examined over the periods covered by the campaigns.

The available time series therefore provides an initial dataset for assessing the system's temporal behavior under actual installation conditions.

5.4 Temporal variation in temperature

Temperature measurements exhibited distinct patterns across the three monitoring campaigns, as summarized in Table 1.

Table 1: Descriptive statistics of temperature measurements recorded during the three monitoring campaigns.

Date	DHT22 mean	DHT22 min-max	DS18B20 mean	DS18B20 min-max
04/09/2026	37.06 °C	25.6–48.4 °C	37.01 °C	29.4–42.6 °C
05/09/2026	41.01 °C	33.9–45.7 °C	43.36 °C	37.9–46.9 °C
07/09/2026	28.32 °C	27.3–29.9 °C	28.73 °C	27.8–29.9 °C

The campaign conducted on 4 September exhibited the widest temperature ranges, spanning 22.8 °C for the DHT22 and 13.2 °C for the DS18B20. Despite these differences, the mean temperatures were nearly identical, at 37.06 and 37.01 °C, respectively.

The highest mean temperatures occurred on 5 September, reaching 41.01 °C for the DHT22 and 43.36 °C for the DS18B20. The DS18B20 recorded its highest temperature during this campaign, at 46.9 °C, whereas the highest DHT22 reading across all campaigns was 48.4 °C on 4 September.

By contrast, temperature fluctuations were substantially smaller on 7 September. Measurements ranged from 27.3 to 29.9 °C for the DHT22 and from 27.8 to 29.9 °C for the DS18B20, with corresponding means of 28.32 and 28.73 °C.

These intercampaign differences may reflect changes in environmental exposure and sensor installation conditions. However, the available statistics alone do not establish the respective contributions of these factors. Previous bridge monitoring studies have emphasized the influence of temperature on structural responses and the need to characterize thermal variability when interpreting other monitoring parameters [12–15].

5.5 Consistency between the DHT22 and DS18B20 measurement chains

Comparison of the temperature time series yielded the following correlation coefficients (table 2):

Table 2: Comparison of the temperature time series yielded the following correlation coefficients

Campaign	Coefficient r
04/09/2026	≈ 0.97
05/09/2026	≈ 0.90
07/09/2026	≈ 0.83

All three coefficients are positive and relatively high. The two measurement chains therefore exhibit broadly consistent temporal trends.

The value of 0.97 obtained on 4 September indicates particularly close agreement between the trends in the two-time series during that campaign. The correlation remained high on 5 September, with $r \approx 0.90$, and then decreased to approximately 0.83 on 7 September.

This decrease should not be directly interpreted as a deterioration in sensor quality. The two sensors were not exposed to exactly the same thermal conditions. Differences in placement may affect both response time and the magnitude of variation.

The analysis thus reveals overall temporal consistency between the two measurement chains, while also demonstrating that this consistency depends on experimental conditions.

This approach is particularly useful during an initial characterization campaign: before investigating anomalies, the normal response of the measurement system and the differences that may arise from environmental conditions must be understood [7,12–15].

5.6 Analysis of inertial indicators

Acceleration values in the available dataset are close to 1.00.

- On 4 September, the mean was approximately 1.000, with a minimum of 0.99 and a maximum of 1.00.
- On 5 September, the value remained almost constant at approximately 1.00.
- On 7 September, the mean reached approximately 1.013, and the maximum was approximately 1.03.

The gyroscope indicator exhibited greater variability:

- a mean of approximately 0.105 on 4 September;
- approximately 0.293 on 5 September;
- approximately 0.407 on 7 September.

These differences show that the levels of the inertial indicators depend on the experimental configuration.

At this stage, the most robust approach is to examine:

- the mean level;
- dispersion;
- the range of variation;
- temporal variation;
- periods of substantial variation;
- signal stability across periods.

However, it would be premature to associate each variation directly with a specific structural phenomenon.

In particular, acceleration values close to 1.00 must be interpreted in light of the gravitational component and sensor orientation. The available data do not allow the static and dynamic components to be rigorously separated.

5.7 Temporal comparison of the three configurations

Comparison of the three campaigns shows that the measurements are sensitive to the location of the instrumented system.

Thermal behavior differs substantially between the joint locations and the central part of the deck. This observation is consistent with the dependence of local thermal conditions on exposure, the immediate surroundings, and position within the bridge cross-section.

The inertial response also exhibits different levels across configurations. However, this comparison should be regarded as a preliminary spatial characterization rather than a direct comparison of structural condition on three dates. Environmental conditions, sensor positions, and traffic loading were not identical. This distinction is essential in SHM. Environmental and operational variations must be distinguished from variations potentially associated with structural condition [11–15].

6 DISCUSSION OF THE SCIENTIFIC VALUE OF THE INITIAL PHASE

At this stage, the main contribution of the experiment is the establishment of an initial dataset for characterizing the temporal behavior of the instrumented system and assessing the consistency of the acquired information, rather than structural damage detection.

6.1 Establishing an initial baseline

A structural monitoring strategy requires an understanding of the normal behavior of both the structure and its measurement system. Yarnold and Moon [13] highlight the value of establishing a baseline response that is sensitive to structural changes while remaining relatively robust to normal variations in operating conditions.

The three campaigns conducted here are not yet sufficient to establish a comprehensive baseline. Nevertheless, they provide an initial or exploratory baseline for the measured parameters. This baseline can be expanded through longer campaigns covering different weather conditions and loading levels.

6.2 Characterization of thermal variability

The results clearly show substantial temperature differences between campaigns. This finding is fundamental to the subsequent experimental program because temperature variations can alter the measured behavior of a structure without necessarily indicating deterioration. Studies of instrumented bridges have demonstrated the importance of temperature in changes in structural responses and dynamic parameters [12–15]. Temperature monitoring therefore provides an essential environmental variable for the future interpretation of other measurements, beyond its role as a complementary measurement.

6.3 Assessing the consistency of the measurement chains

The temporal agreement between the DHT22 and DS18B20 provides an initial positive indication of the operation of the temperature measurement chain. However, this consistency should not be confused with metrological validation. Subsequent validation should compare the sensors against a known reference to determine their errors, bias, repeatability, and stability. This approach is consistent with studies on SHM sensor validation [7] and broader issues concerning monitoring data quality [8].

Future experimental work

This initial phase provides a basis for the following subsequent steps.

- Extending the monitoring period

The first improvement is to extend the monitoring duration to obtain a sufficiently long time series to characterize:

- daily cycles;
- weekly variations;
- weather effects;
- periods of high and low loading;
- seasonal variations.

Long-term monitoring would also enable a more representative baseline of system behavior to be established.

- *Improving inertial characterization*

A subsequent stage should enable the acquisition of raw inertial signals at a sufficiently high sampling rate to analyze their behavior in the time and frequency domains. The systems developed by Rehman et al. [1], Lee et al. [2], and Saravanan et al. [4] demonstrate different ways of using MEMS sensors and IoT platforms for dynamic data acquisition. However, this phase should be preceded by experimental validation of the sensor and the complete data acquisition chain.

7 CONCLUSION

This study presented the experimental deployment of an ESP32-based IoT system for multiparameter data acquisition on a bridge. Rather than immediately seeking to identify damage or modal parameters, the study deliberately focused on an initial fundamental question: do the data produced by the system exhibit sufficiently characterizable consistency and temporal variation to provide a basis for subsequent monitoring?

The three campaigns provided approximately 284–285 records across three different configurations. The temperature results show consistent temporal trends between the DHT22 and DS18B20 measurements, with correlation coefficients of 0.97, 0.90, and 0.83 across the campaigns. This consistency is an important initial finding for system characterization. It is complemented by the analysis of amplitudes, mean values, ranges of variation, and differences between

instrumented locations. The inertial data also exhibit variations across experimental configurations. At this stage, they allow the temporal variation and variability of the measured indicators to be characterized.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRedit authorship contribution statement

- **Valéry k. DOKO:** Writing – review & editing, Supervision, Resources, Methodology.
- **Afouda Aristide YAI:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.
- **Thède AGBELELE:** Writing – review & editing.
- **Mohamed Gibigaye :** Writing – review & editing.

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