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Low-cost internet of things system for water metering in smart campus

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ABSTRACT

Internet of things (IoT) technologies are transforming the monitoring of water distribution networks (WDN) and urban water infrastructure (UWI), as well as smart campus infrastructures, which has the same problems as an urban water network, such as leaks, inaccurate readings, and unnecessary expenses. Smart water meters (SWM) represent an economical IoT solution for remotely monitoring system parameters such as flow rate, pressure, and water quality to reduce losses. This paper introduces an IoT-based smart water metering solution employing message queuing telemetry transport (MQTT), long range (LoRa), a middleware for IoT, and low-cost sensors, implemented at the Federal Institute of Paraíba, Brazil, as an initial effort toward establishing a smart campus. The evaluation of the IoT device showed a measurement performance index (MPI) of 97.83%, with a flow sensor error margin (FS400A) below 2% for calibrated ranges. The quality of the wireless link yielded an average RSSI of -89 dBm and a packet error rate of 0.35%. The IoT system demonstrated potential as a feasible smart campus application.

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1. INTRODUCTION

The concern about rational utilization of water and the search for sustainable water management solutions has increased in recent decades, mainly due to population growth, over-exploitation of natural resources, climate change, and industrial activities [1]-[3]. More specifically, with the increase in demand for water resources on a university campus, the implementation of smart water measurement systems (SWMS) becomes relevant to promote waste reduction, early detection of leaks, and efficient monitoring of consumption. Furthermore, the application of these technologies contributes to raising awareness of the importance of water preservation and the adoption of sustainable practices [1], [4], [5].

In the context of smart applications, intelligent water measurement emerges as a promising internet of things (IoT) application to improve water resource management using intelligent water meters that remotely and autonomously monitor various parameters, such as pressure, flow rate and water quality [6]-[8], in key locations within water distribution systems [9]. Smart water meters (SWM) currently employ low power wide area network (LPWAN) technologies, such as narrowband IoT (NB-IoT), Sigfox, and long range (LoRa) [10].

LPWAN technologies have a set of interesting features, including low power consumption, strong resistance to electromagnetic interference, and LoRa [11], [12]. This facilitates the transmission of data to a processing center located on-premises or in the cloud. Consequently, this enables intelligent decision making by monitoring water usage, helping utility companies improve their services through data collected from meters. In addition, customers can make informed choices by reviewing their own water consumption [13], [14].

Despite the benefits mentioned, the implementation of these systems remains limited in educational institutions (such as university campuses). The main barriers to the adoption of smart meters in these settings are rooted in technological, environmental, and organizational issues [15]. In this context, this paper presents a smart water monitoring and measurement system based on LoRa® technology and an IoT middleware (the Dojot middleware). The system was implemented as a pilot project on a campus of the Federal Institute of Paraíba, in Brazil.

This research aims to evolve the campus into a smart campus. The proposed solution aims not only to decrease the usage of water on campus but also to increase awareness within the community about the importance of managing water resources. Additionally, it validates an IoT framework for water measurement on a smart campus, which can be applied to other comparable scenarios.

The focus of the presented solution is to enable low-cost and flexible IoT applications for smart campus scenarios. Thus, low-cost sensors were used and an edge infrastructure was used using Dojot middleware. This enables the development of innovative IoT applications for a smart campus, such as water usage pattern analysis and leak detection, by applying more instances of the proposed system in different parts of the campus. The use of a middleware employed at the edge also allows the development of applications that require low latency. Although low-cost components were used, a calibration was performed according to Brazilian standards, to achieve an accuracy close to the one obtained with high-cost meters.

2. RELATED WORK

In this section, some related works are described, providing an overview of the state-of-the-art, according to our literature review. Ye *et al.* [16] propose a smart water metering technique for smart cities, integrating LoRa® technology, the STM32 platform, and an induction sensor with a detection algorithm to monitor analog water meters. Their algorithm reduces reading errors in mechanical meters under high pressure or flow conditions. Experiments simulating household consumption revealed a 0.36% discrepancy between mechanical and electronic readings, although metrological validation remains necessary for real-world applications.

The study presented by Syrmos *et al.* [17] also used LoRa® to build a modular IoT system for water monitoring. The system facilitates both qualitative and quantitative analyses of water, making it applicable to use in both urban and rural settings to track water quality and usage patterns. In addition, it allows efficient profiling of consumers and reduces the initial implementation costs for suppliers, improves environmental management, and offers an effective response strategy during emergencies.

A system that uses NodeMCU and a YF-S201 sensor is proposed, powered by a solar panel, with data sent to ThingSpeak over Wi-Fi and using machine learning for flow pattern recognition; however, verification of measurement quality is lacking [18]. Similarly, Nadipalli *et al.* [19] proposes a smart system using YF-S201 and NodeMCU linked to the Thinger.io platform to monitor consumption goals, but it lacks sufficient data samples or statistical validation for accurate assessment.

García-Martín *et al.* [20] present a solution for water distribution networks (WDN) by combining different wireless network technologies. An existing IEEE 802.15.4 network was expanded using NB-IoT to provide communication to the devices. The proposed solution demonstrated that it is possible to design combined networks that allow the use of wireless networks using different technologies to solve the problem of wireless smart metering in the water sector and also increase overall battery life.

The work described in [21] proposes an IoT solution to capture images of conventional analog meter displays, locally process the images using a deep learning-based digit detection algorithm, and transmit them to the cloud for real-time analysis, enabling analysis of water supply behavior and usage patterns with greater accuracy and reliability. The proposal has been validated through prototypes deployed at the IIIT-Hyderabad university campus.

An IoT-based SWM system is proposed to accurately assess the water usage of each household and apartment in gated communities [22]. This method allows for precise volumetric pricing instead of equally splitting total water consumption. The data collected are transmitted to cloud platforms for monitoring and computational analysis. Similarly, the study presented in [23] explores the analysis of water usage patterns utilizing data acquired from SWM installed in 1,871 residences in the Chibata area of the city of Kosai, Japan. The IoT-equipped water meters provided insight into peak usage periods and enabled the detection of homes with lone residents, as well as classifying these domiciles as those inhabited by solitary employed persons and those lacking employed residents.

This article proposes a solution that distinguishes itself by focusing on the following elements:

a. A sensor calibration method rooted in metrological techniques conforming to Brazilian standards and the 2022 INMETRO Metrological Technical Regulation (RTM);
b. The use of the Dojot middleware, an open-source, cost-effective solution deployed at the edge to reduce communication latency, conserve network bandwidth, and enable real-time data visualization;
c. The creation of a modular SWM, which incorporates sensors for flow, pressure, temperature, atmospheric pressure, and humidity, along with a solenoid valve for remote flow management, a check valve, and a particle filter, to enhance water consumption accuracy;
d. Employment of the Heltec IoT Wi-Fi LoRa® 32 (V2) board, functioning at 917 MHz utilizing LoRa® physical layer communication.

Table 1 contains a quick comparison between the related works and this article regarding the monitored parameters, sensors used, IoT platform used, wireless technology, and middleware used.

Table 1. Characteristics of the related works

Publication	Monitored parameters	Sensors used	IoT platforms	Wireless technology	Use of cloud or edge platform
[16]	Flow rate	Not provided	STM32	LoRa®	Not provided
[17]	Flowmeter Hydrogenionic potencial water quality unit Oxidation-reduction potential eletric conductivity temperature	EC sensor ORP sensor pH sensor Temp. sensor	Arduino Mega 2560 Rev3	LoRaWAN	The things network IoT (TTN)
[18]	Flow rate	YF-S201	NodeMCU	Wi-Fi	ThingSpeak
[19]	Flow rate	YF-S202	NodeMCU	Wi-Fi	Thinger.io
[20]	Water quality	Advanced sensing unit (ASU), which collects 7 measurements from water quality sensors	Not provided	NB-IoT and IEEE 802.15.4 g	Not provided
[21]	Water consumption	PiCam Diodo LED	Raspberry Pi 3B+	Not provided	Not provided
[22]	Water flow	YS-F201	Arduino Uno	Not provided	Not provided
[23]	Water consumption	Not provided	Not provided	Not provided	Not provided
This paper	Flow rate Pressure Temperature	FS400A OEM 1,2 MPa BME280	Heltec Wi-Fi LoRa® 32	LoRa®	Dojot

3. KEY CONCEPTS

The following are definitions of some important concepts related to the development of smart water monitoring and measurement system (SWMMS). For more details, it is recommended to consult the provided references.

– Metrology: it is the science of measurements and their applications, encompassing all theoretical and practical elements of measurement, regardless of the uncertainty of the measurement or its field of application [24];
– LoRa®: is one of the most widely used LPWAN technologies in the IoT field. LoRa® allows for a reduction in the hardware and network complexity, and in the header size, enabling simple bidirectional communications with a simple infrastructure and with low energy consumption [25];
– Message queuing telemetry transport (MQTT): according to the current documentation (version 5.0) of the protocol specifications, prepared by OASIS [26], MQTT is an open-source communication protocol known for its simplicity and straightforward implementation. It follows a publish/subscribe architecture and is ideal for use in many situations, including restricted environments, such as for communication in machine-to-machine (M2M) and IoT contexts;
– Middleware: consists of a set of software components that operate at an intermediate layer between the operating system and the end-user application interface, and also provide a common software abstraction layer for distributed applications [27].

4. METHOD

To develop the proposed system, extensive laboratory experiments were carried out to fine-tune sensor calibration and test the communication protocols between the embedded system and the middleware. Subsequently, remote and automated field data acquisition was performed using the SWM deployed at the campus water inlet station. More specifically, the development and implementation of the system involved 8 phases, as follows:

1) Installation and configuration of the Dojot middleware;
2) Development of the embedded software;
3) Test of sensors and communication with Dojot;
4) Characterization of the campus water consumption profile;
5) Tests to calibrate the flow sensor;
6) Calculation of measurement uncertainty and meter performance index (MPI);
7) Assembly and installation of the prototype; and
8) Monitoring of the smart water measurement system.

In the first phase, Dojot middleware was installed using version 0.6.1 and the default Docker Compose configurations (Docker Engine version; Docker-Compose), in which the middleware was installed on a Debian Linux distribution (version 10.9.0) on a Lenovo server (ThinkSystem SR630 model) located at the Information Technology Coordination of the IFPB Campina Grande campus, in a virtualized environment (VMware ESXi hypervisor version 6.7) of a private network.

The second phase consisted in the development of the embedded software for the The WIFI LoRa® 32 platform, using the PlatformIO plugin. The C++ programming language was used with the Arduino framework. The main libraries used were:

FlowMeter.h, library used to calibrate the flow sensor; *DallasTemperature.h*: specific library for reading the temperature of the DS18B20 sensor; and the *Adafruit_BME280.h*: library for reading temperature, humidity and atmospheric pressure from the BME280 sensor. Figure 1 illustrates the high-level diagram of SWMMS, containing the types of sensors and their respective reference codes, as well as the interconnection between the system elements.

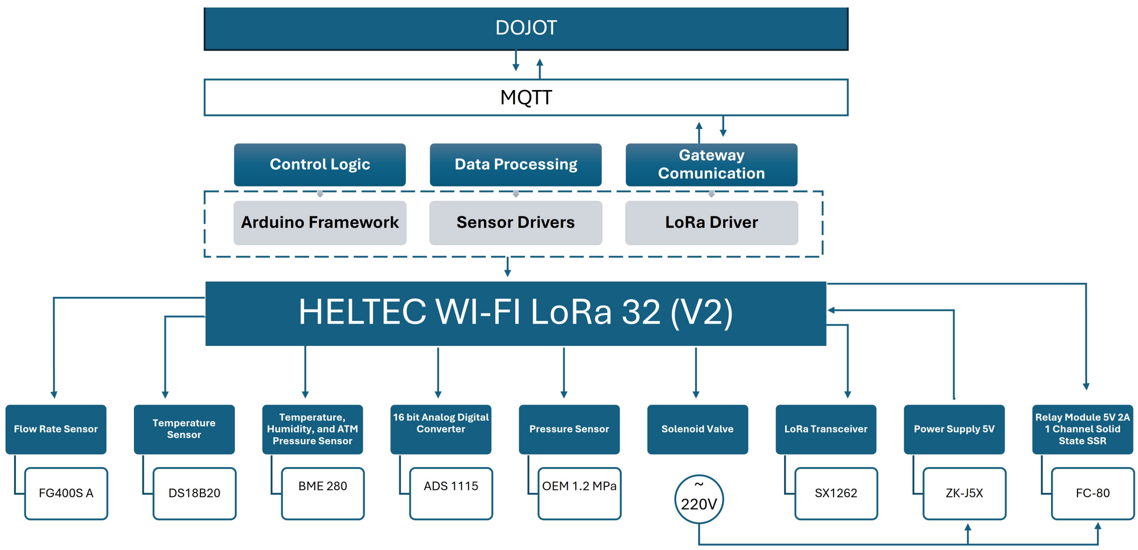


Figure 1. High-level diagram of SWMMS

In the third phase, basic tests were performed to verify the electronic components of the device, in which it was possible to verify the communication between the sensors and the WIFI LoRa® 32, Dojot platform and LoRa® gateway. The configuration parameters of the initial setup used for the communication of the physical layer of LoRa® are shown in Table 2.

Table 2. Initial setup of the LoRa® physical layer

Parameter	Configured value
Frequency	917 mHz
Transmission power	14 dBm
Spreading factor (SF)	7
Bandwidth	500 kHz
Code rate	4/5

Understanding the pattern of water usage (flow rate and total volume) and pressure is vital for accurately sizing a measurement sensor. Therefore, in the fourth phase the consumption profile from Annex C of the Brazilian Regulation NBR 15538:2014 was analyzed. Real-time monitoring over seven days at the campus water inlet used an FS400A G1 flow sensor and an OEM 1.2 MPa pressure sensor linked to WIFI LoRa® 32, transmitting data to the Dojot platform every 15 seconds for storage. Additionally, campus water consumption records from January to December 2022 were reviewed via the water supplier's WEB platform.

The fifth phase employed the static calibration method, deemed most appropriate for the adapted calibration bench model per NBR ISO 4185:2009 standards. Section 5 delves into the procedure and findings. This calibration assesses measurement uncertainty via statistical analysis over multiple observations and evaluates the MPI to gauge an equipment's ability to measure discharged volume according to a specific consumption pattern [28].

Although there are still no well-established methods in the literature for calculating measurement uncertainty (MI) and MPI specific to SWM, we sought to use tests established in Brazilian technical standards, such as the MPI test established in NBR 15538/2014, and the step-by-step procedure for calculating measurement uncertainty described in Annex A of NBR ISO 1568. In the sixth phase, only the Type A assessment of the uncertainty of the measurement was performed, which is calculated from a series of readings, using statistical methods.

The final assembly of the SWM developed in this work, which corresponds to the eighth phase, was based on the recommendations of the NBR 16043-4 (where applicable), which defines the following criteria downstream of the meter [29]:

a. An adjustable length device to facilitate installation and removal of the water meter. This device is especially recommended for meters with Q3 $\geq$ 16 m^3/h;
b. A device that includes a drain valve, which can be used for pressure monitoring, sterilization and water sampling;
c. A shut-off valve for meters with Q3 $>$ 4 m^3/h, which must be operated in the same direction as the upstream valve; and
d. A check valve, if necessary, except for the application of bidirectional flow.

Finally, in the ninth phase the prototype was installed and monitored remotely through the Dojot middleware. Periodic on-site inspections were also carried out to check for possible anomalies and leaks.

5. RESULT AND DISCUSSION

This section analyzes the results derived from the experimental procedures conducted throughout the development of the SWMMS prototype, as well as describes the scenario where the prototype was installed for better understanding.

5.1. Scenario description

The deployment scenario is illustrated in Figure 2, which presents an image from Google Maps with the location and estimated distance between the devices, a photo of the machine room where the SWM is installed and a photo of the front view of the SWM towards the coordination room. The distance between the SWM (H in the figure) and the gateway (G in the figure) is approximately 85 meters.

SWMMS collects data from the sensors (H in the figure) and sends the information via LoRa® wireless communication to the Dragino LG02 LoRa® gateway installed at the campus Information Technology Coordination (ITC) (G in the figure) every 1s, where the data is translated and retransmitted to the Dojot middleware via MQTT protocol. It is worth noting that the system's energy consumption remained practically constant at approximately 115 mA, with peaks of 120 mA to 125 mA when transmitting via LoRa®.

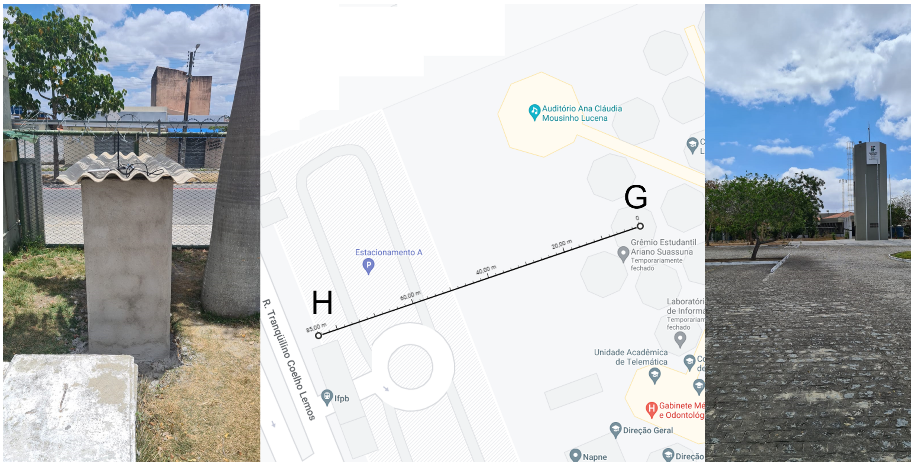


Figure 2. SWMMS deployment scenario

Opting for raw LoRa over LoRaWAN stems from its suitability for small, fixed topology, point-to-point, and low-traffic data collection tasks. While both share the LoRa physical layer, they diverge significantly above it. LoRaWAN excels in scalability and automatic network management, incorporating strong security with built-in encryption and authentication, but requires complex infrastructure and is less flexible due to strict protocol adherence. Conversely, raw LoRa offers simplicity and flexibility, lacking inherent security and scalability but providing developers complete protocol control, ideal for quick prototyping.

5.2. The smart water monitoring and measurement system prototype

The SWMMS is composed of an embedded system and a software executing at the edge (Dojot middleware), designed to remotely and autonomously monitor water consumption on campus. In addition, it measures the pressure of the water network at the entry point, as well as environmental temperature, humidity, and atmospheric pressure at the SWM installation site. The prototype developed is based on the standard LoRa®/LoRa®WAN™ network architecture presented by [30], as shown in Figure 3.

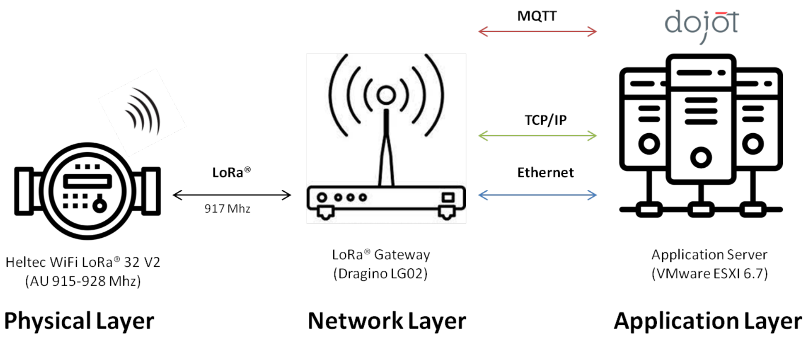
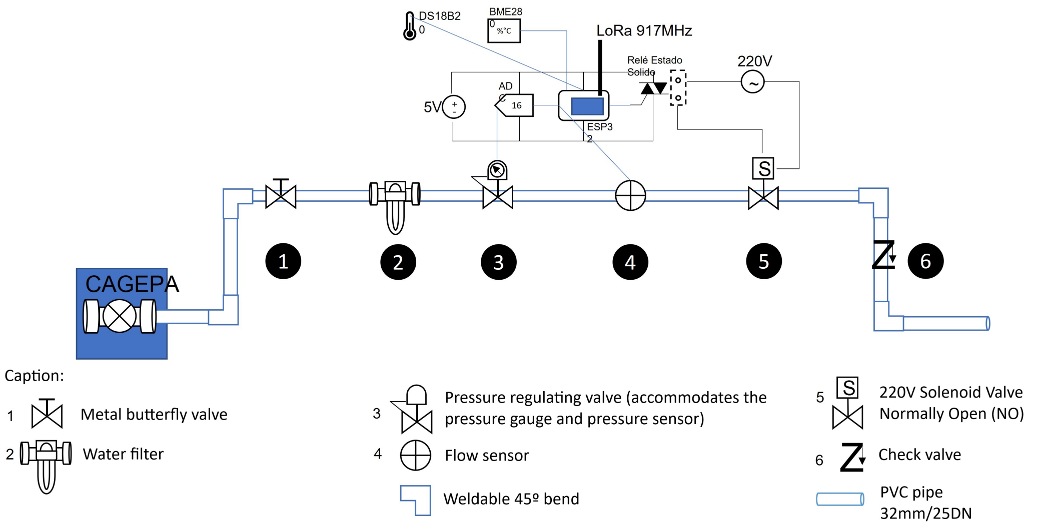
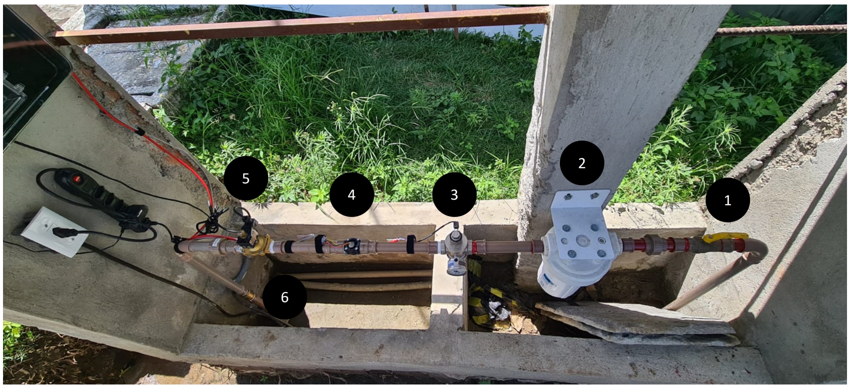


Figure 3. SWMMS network architecture

The physical layer, known as Layer 1, comprises LoRa® sensor nodes and endpoints, notably housing the system's water sensors and actuators, all linked to a microcontroller with a built-in LoRa® transceiver. Communication between these LoRa® endpoints and the LoRa® gateway is facilitated by the standard radio modulation techniques inherent to this physical layer. In this particular scenario, the LoRa®WAN™ protocol was not used, as communication using the LoRa® physical layer alone sufficed for the application requirements. A modular SWM was built, featuring a distinct separation between the "smart" components (comprising electronics and embedded software) and the water sensors, as depicted in Figure 4(a) (hydroelectric schematic) and Figure 4(b) illustrates the actual installation at the campus water intake. The components of the device on the campus water inlet trestle were positioned between two hydraulic couplings (referred to as weldable joints), which provided enhanced flexibility, simplified maintenance, and easier adjustments to the system.



(a)



(b)

Figure 4. Components of the smart metering system in the; (a) hydroelectric diagram and (b) on-site installation of the SWMMS (1-manual opening valve; 2-water filter; 3-pressure regulating valve with analog pressure gauge and electronic pressure sensor; 4-flow sensor; 5-solenoid valve; and 6-water check valve)

Layer 2, also referred to as the network layer, encompasses a LoRa® gateway, which serves the crucial function of converting messages and transmitting them to the application through the TCP/IP protocols (covering transport and network layers) and MQTT (pertaining to the application layer). The LoRa® gateway used in the network layer was the dual-channel LG02 model from the manufacturer Dragino. The device, which combines both hardware and software into a single ”box”, employs a customized Linux distribution to manage two distinct LoRa® modules with separate frequency operations (Sx1276 at 868/915 MHz and Sx1278 at 433 MHz). This configuration enables the device to operate in full duplex mode. The gateway was configured to operate in MQTT mode, sending LoRa® packets to middleware Dojot.

During data collection, the signal strength (RSSI) between the end device and the LG02 varied between -80 dBm and -100 dBm, with an average of -89.14 dBm. The Dragino LG02 transceiver’s sensitivity is less than -148 dBm, as specified by the manufacturer. In terms of packet loss, only 110 out of 30,729 packets were lost, resulting in a packet loss rate of 0.35%, indicating a communication performance of 99.65%.

Ultimately, Layer 3 encompasses an application server known as Dojot (version 0.6.1), which is responsible for processing, storing, and distributing the data transmitted by the LoRa® endpoints to various applications that have an interest in utilizing the data provided by the end nodes.

Dojot operates as a middleware offering a collection of sophisticated functionalities that facilitates the management of the IoT ecosystem, including features such as:

a. Open source APIs to enable external applications in accessing the resources of the platform;
b. End device life-cycle management (planning, configuration and monitoring, as well as remote endpoint firmware updates);
c. Visual interface to build data flows and data processing rules in real time;
d. Data persistence; and
e. Dashboard with an intuitive interface for accessing data in real time.

The Dojot middleware was installed on a Debian (GNU/Linux) virtual machine (VM), version 10.9 (64-bit), managed by the VMware vSphere ESXi hypervisor (version 6.7) on a Lenovo ThinkSystem SR630 host. The host was equipped with 32GB DDR4 RAM (2666 MHz), 4 x 1TB 7.2K SATA HDDs in RAID 5 (providing 2.79 TB of storage) and an Intel Xeon Gold 6134 CPU (8 cores @ 3.20 GHz). The VM was allocated 8 GB of RAM, 4 virtual processors, and 20GB of storage. During a 7-day monitoring period, data was collected every 15 seconds from the IoT device. The analysis revealed that the average consumption of RAM was 68% of the allocated resources, the average storage usage was 67%, and the SWM generated approximately 106 MB of data, with more than 1 million values recorded in MongoDB.

5.3. Characterization of the water consumption profile

The characterization of the water consumption profile at the IFPB Campina Grande included an in-depth analysis of the consumption and pressure patterns according to the Brazilian standard NBR 15784. This was achieved using the intelligent measurement system (SWMMS), which collected data every 15 seconds for 7 days, identifying the following characteristics:

a. The most common flow rates: intervals between 25-50 l/min (1500-3000 l/h) exhibited the highest operational frequency, indicating these are the main consumption ranges on campus;
b. Flow variation: the system demonstrated its capability to monitor a broad spectrum of water flow rates, with recorded values ranging from a minimum of 0.26 l/min to a maximum of 45 l/min;
c. Concerning the campus water inlet truss pressure characterization: the measured peak pressure reached 4.73 bar (48.23 mca), with an average around 3.90 bar (39.77 mca). This indicates that the current analog pressure gauge should be substituted with a more suitable gauge having a full scale of at least 5 bar;
d. Comparison with historical records: system measurements were evaluated against the historical data from the company responsible for supplying water to the campus (CAGEPA), verifying the accuracy of the collected data;
e. Disparity in measurements between SWMMS and SAGA water meters (hydrometer used by CAGEPA): during this period, SWMMS observed approximately a 7.00% reduction in total volume, attributed to the lack of calibration of the FS400A G1 sensor for flow rates greater than 35 l/min with the calibration setup used.

Table 3 presents this information in a concise way. It facilitates the analysis of water consumption behavior on campus, aiding in the detection of usage trends and potential improvements in water resource management, and evaluates whether the sensors function within their expected measurement range.

Table 3. Comparison between SAGA and SWMMS hydrometer

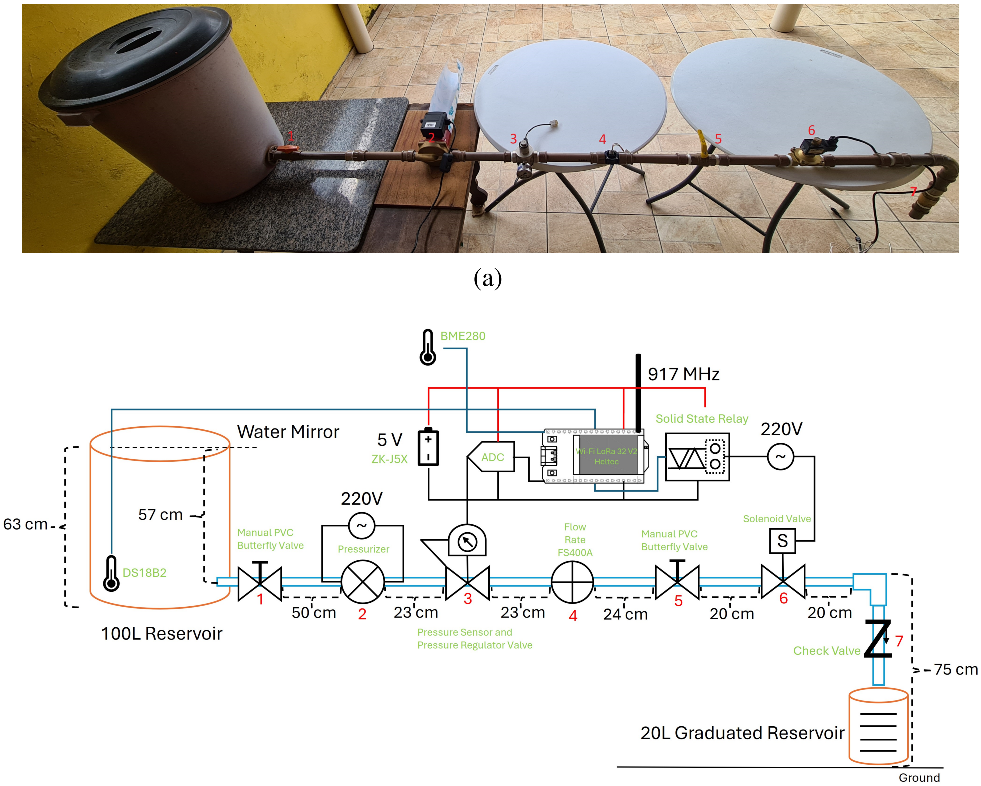
Day	SAGA (m³)	SWMMS (m³)	SAGA-SWMMS (m³)	Error (%)
01	0	0	0	0
02	24.85	23.05	1.80	7.24
03	34.50	32.16	2.34	6.77
04	45.20	42.99	2.21	4.90
05	53.28	49.67	3.61	6.77
06	57.50	52.44	5.06	8.79
07	73.82	68.16	5.66	7.67
	Average		3.45	7.02

5.4. Flow sensor calibration

An adaptation of the 1C model from ABNT NBR ISO 4185:2009 was performed due to the unavailability of a certified bench according to the technical standard. Locally accessible and cost-effective materials were utilized, facilitating the calibration of the flow sensor, the measurement uncertainty index, and the MPI.

A visualization of the adapted bench can be seen in Figure 5, which Figure 5(a) illustrates the real bench and Figure 5(b) the electrical and hydraulic interconnection diagram.

The setup includes a 100 L reservoir, a manual PVC butterfly valve (1), a water pressurizer (2), a regulator valve with an electronic pressure sensor and analog gauge (3), a flow sensor (4), another manual metal butterfly valve (5), a 220 V normally open solenoid valve (NO) (6), and a check valve. Pipes are 32 mm/25 DN PVC to match the campus water inlet. For weighing, the water mass was corrected by deducting the graduated reservoir's weight (≈ 695 g plus a 5 g error) and the mass of water between the flow sensor and check valve (≈ 700 g), giving a tare of about 1400 g. The visual weighing process was simplified by accounting for the trapped volume within the reservoir and directly entering the tare into the scale for auto-subtraction.



(a)

(b)

Figure 5. Adapted laboratory bench for calibration of the FS400A G1" flow sensor (static method, powered by direct pressurization) in; (a) adapted bench in a real scenario and (b) diagram of the bench adapted for calibration of the FS400A G1" flow sensor (static method, powered by direct pressurization)

Following the aforementioned procedure, 15 measurements were made for each calibration point, ranging from 250 l/h (4.167 l/min) to 1350 l/h (22.083 l/min). Figure 6 presents the indication error curve derived from the calibration of the FS400A sensor. It is possible to note the non-linearity in the FS400A sensor at flow rates below 11.667 l/min, achieving more linearity at higher flows, as described in the FlowMeter 14 calibration library. No measurement showed an indication error greater than 2%, underscoring its efficacy as a low-cost sensor.

5.5. Measurement performance index

The MPI is the approach for evaluating under-measurement in water meters as outlined in ABNT NBR 15.538 – drinking water meters – tests for efficiency assessment. This method determines the error curve for average flows associated with consumption profile ranges shown in Table 4. Measurement uncertainty quantifies the accuracy of a measurement, indicating the expected range of values for the flow or quantity with a certain confidence level (ABNT ISO 5168:2015). The FS400A sensor calculates flow rate using a hall effect sensor model, involving a square wave pulse. The flow rate, Q, in liters per minute (l/min), is calculated as

$Q = \sum(\frac{f}{KF}) \times MF$. Here, f is the vane's rotation frequency in Hz (pulses per unit volume), KF is the conversion factor (4.8 pulses/second equals 1 l/min at 1 l volume), and MF modifies the KF. The flow error, E_v, in liters, is determined by $V_s - V_r$, where E_v is the error, V_s is the sensor volume in liters, and V_r is the actual mass, subtracting the tare weight P_T from the combined weight of the reservoir P_r and the volume in the pipeline P_a.

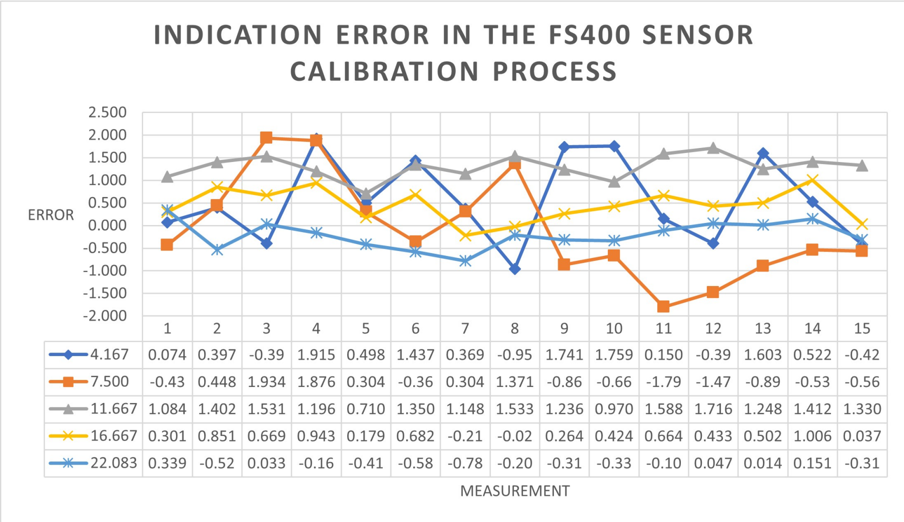


Figure 6. Indication error obtained in the calibration process

Table 4. Test flow ranges

Flow rate range (l/h)	Flow rates for error checking (l/h)	Flow rate range (l/min)	Flow rates for error checking (l/min)	Consumption profile %
0 a 5	2.5	0 a 0.083	0.042	4.56
5 a 15	10	0.083 a 0.25	0.167	6.99
15 a 30	22.5	0.25 a 0.5	0.375	6.83
30 a 50	40	0.5 a 0.83	0.667	7.34
50 a 150	100	0.83 a 2.5	1.667	23.21
150 a 350	250	2.5 a 5.83	4.167	23.92
350 a 550	450	5.83 a 9.16	7.500	12.27
550 a 850	700	9.16 a 14.16	11.667	7.29
850 a 1150	1000	14.16 a 19.16	16.667	5.86
1150 a 1500	1325	19.16 a 25	22.083	1.73

The percentage indication error is calculated as $Error(\%) = \frac{V_s - V_r}{V_r} \times 100$. According to [31], to calculate the MPI the following steps must be followed:

a. Compute the weighted error (WE) as a performance evaluation metric achieved by correlating the consumption profile with the relative error exhibited by the water meter within specified flow ranges, described by [31]: $WE(\%) = \frac{\sum[(error\ Q_x) \times (weight\ Q_x)]}{100}$, where $weight\ Q_x$ represents the volume used in each flow range divided by the total volume consumed.

b. Determine the MPI, a percentage reflecting the performance of a water meter under certain tests, calculated by [31]: $MPI = 100 + WE$.

Table 5 provides an example of the MPI calculation for the first measurement. Calculating the MPI based on the arithmetic mean of 15 measurements showed a 97.83% efficiency rate, indicating a mere -2. 17% (WE) in the unaccounted volume of the FS400A sensor (undermeasurement). This suggests potential for sensor usage if correctly calibrated and placed. However, a comprehensive MPI evaluation over a decade with an expanded sensor sample size, as per standards, is essential to ascertain its operational limits.

Table 5. Example of MPI calculation for the first measurement

Flow rate (l/min)	Error checking (l/min)	Average error (%)	Weight (%)	WE (%)	MPI (%)
0 a 0.083	0.042	-5.00	4.56	-2.38	97.62
0.083 a 0.25	0.167	-5.00	6.99		
0.25 a 0.5	0.375	-5.00	6.83		
0.5 a 0.83	0.667	-5.00	7.34		
0.83 a 2.5	1,667	-5.00	23.21		
2.5 a 5.83	4.167	0.07	23.92		
5.83 a 9.16	7.500	-0.43	12.27		
9.16 a 14.16	11.667	1.08	7.29		
14.16 a 19.16	16.667	0.30	5.86		
19.16 a 25	22.083	0.34	1.73		

5.6. Measurement uncertainty

Measurement uncertainty is a parameter that indicates the quality of a measurement in a quantitative way. The uncertainty characterizes the range of values within which the flow or measured quantity is expected to lie, with a specified level of confidence [32].

Figure 7 presents a summary table comparing the main measurement indicators between the gravimetric method and that recorded by the sensor: the indication error (%) of the measurement, the arithmetic mean ($\bar{X}$) of the sample, the standard deviation of the sample (S), the variance (S^2), the standard uncertainty (u_x) and the expanded uncertainty of the measurement (U_x) for 15 observations and 14 degrees of freedom (v), coverage factor $k = 2.2$, and confidence level of 95.45%, in accordance with Table C.1 of ABNT NBR ISO 5168:2015. The worst values obtained in the calibration tests of the FS400A sensor are highlighted in bold.

SENSOR MEASUREMENT (SM)					GAVIMETRIC MEASUREMENT (GM)					INDICATION ERROR (ERROR (%))		
FLOW RATE (l/min)	$\bar{X}$	S($\bar{X}$)	$U_{\bar{X}}$	Real Interval	FLOW RATE (l/min)	$\bar{X}$	S($\bar{X}$)	$U_{\bar{X}}$	Real Interval	FLOW RATE (l/min)	ERROR (%)	S($\bar{X}$)
4.167	4.055	0.036	0.021	[4.034 a 4.076]	4.167	4.032	0.026	0.0015	[4.017 a 4.047]	4.167	0.553	0.93
7.500	6.928	0.128	0.073	[6.855 a 7.001]	7.500	6.934	0.087	0.049	[6.885 a 6.983]	7.500	0.09	1.125
11.667	11.234	0.039	0.022	[11.212 a 11.256]	11.667	11.090	0.04	0.023	[11.067 a 11.113]	11.667	1.297	0.258
16.667	16.259	0.078	0.044	[16.215 a 16.303]	16.667	16.187	0.07	0.04	[16.147 a 16.227]	16.667	0.448	0.362
22.083	21.229	0.089	0.05	[21.179 a 21.279]	22.083	21.184	0.05	0.028	[21.156 a 21.212]	22.083	0.211	0.301

Figure 7. Measurement summary

The Grubbs test (statistical technique used to detect outliers in a data set) 15 was performed at a confidence level 95% with 15 observations on the indication error, which revealed that no outlier (>2.51). The complementary data with the measurement results, as well as the application source code and the customization of the docker-compose file of the Dojot middleware, can be viewed on the project's Github, available at: "https://github.com/atilasmedeiros/smmia".

6. CONCLUSION

The IoT has profoundly transformed sectors such as water resource management by enabling the measurement and monitoring of various parameters, such as monthly consumption and water quality, through SWM devices. Central to SWM are IoT devices, sensors, data protocols, and the internet, all critical for smart water meters (SWGN). Implementing these technologies offers an innovative and efficient means of managing water use in large areas, such as university campuses.

By collecting precise, real-time data, these systems can detect leaks, optimize use, and enhance environmental sustainability. This paper examines the methodology, architecture and findings of a SWM prototype installed at the IFPB, Campina Grande, Brazil. The SWGN architecture stands out for employing LoRa® technology and Dojot middleware at the network edge, with bidirectional communication via the Dragino LG02 gateway, and incorporates adjustments to Brazilian metrological standards for calibrating flow sensors, evaluating meter performance, and estimating measurement uncertainty.

This is one of the distinguishing features of this work, since these parameters are not adequately addressed in related articles, since the result of a measurement is an estimate of the real value, therefore, the presentation of the result is only complete when it is accompanied by a quantity that declares its uncertainty.

This paper demonstrates that real-time telemetry (monitoring) and remote control of a campus' water supply are feasible using low-cost IoT technologies, through LoRa® wireless communication technology. The ecosystem used in this pilot project can be replicated with a solution for IoT applications on a Smart Campus.

Regarding the limitations of the work, it is important to note that the methodological rigor of the standards was not fully followed, due to the lack of infrastructure and resources, making the control of variables of the test procedures (such as temperature, humidity, flow, and system pressure) impossible to be obtained with the precision established in the standard. However, the goal of the work is not the certification of sensors.

As recommendations for future work, we can list a series of improvements that can be made, both in terms of hardware and software, as well as in methodological testing procedures and equipment to be used, such as the adoption of a system of solar panels and/or turbine-type generators for the use of predictive AI models for detecting anomalies in water distribution systems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Átila de Souza Medeiros	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓			
Ruan Delgado Gomes	✓	✓					✓			✓		✓	✓	✓
Anderson F. B. F. da Costa	✓	✓								✓		✓		

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

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [initials: ASM].

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