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IoT approach towards smart water usage

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ABSTRACT

Monitoring indoor environments in buildings can be a useful tool in improving infrastructure efficiency. Water losses are an important parameter that can be assessed by monitoring water consumption. This paper presents the design and implementation of intelligent buildings for the monitoring of water consumption, which includes both the required hardware and the associated software. For implementation purposes, the paper focuses on technical descriptions of the steps required to successfully implement an IoT architecture, while describing the applications of smart water meters and providing data analysis. The main goal of such a system is to provide the user with transparent and easy-to-use data in real-time. By installing smart water meters and analyzing the collected data, it was possible to detect consumption patterns and to quantify and locate water losses. Looking at consumption overtime on different platforms is essential, as it can change habits and patterns of water consumption, reducing costs for users and the overall system. By increasing the distribution efficiency and maintaining resource sustainability, smart water distribution can be achieved.

1. Introduction

In recent years, the responsibility for water use has increased considerably, with the aim of ensuring sustainable water management in urban areas (Farah and Shahrour, 2017). To manage water consumption, loss control and demand meters are used to measure water consumption. Water meters are usually Manual Meter Reading (MMR) devices that require the end user to travel and read water consumption regularly, which makes reading water consumption quite expensive and complex (Depuru et al., 2011). However, recent advances in communication technologies have allowed the expansion of the IoT ecosystem, with many devices connected and exchanging sensor data (Zorzi et al., 2010). This enabled the development of Automated Meter Reading (AMRs), which allows real-time communication of recorded data (Anandhavalli et al., 2018; Slan ý et al., 2020a). These technologies include low-power large-scale networks, GSM-GPRS, Wi-Fi, Zigbee, 3G and 4G long-term evolution (LTE) (Benavente-Peces, 2019).

To improve building performance and forecast appropriate sustainability and improvement measures, it is critical to examine the consumption pattern of water, which is often unavailable due to a lack of measurements. The use of a smart water monitoring system can reveal a temporal pattern, or how water consumption varies over time due to numerous influencing factors, as well as information about the intensity of water consumption and peak demand (Almeida et al., 2021). This type of measurement technology enables the dissemination of knowledge about water consumption with the aim of reducing costs, raising awareness, and increasing transparency (Dahlstr ö m and S ö derberg, 2017). All recorded consumption data is sent to a computer platform that displays real-time usage statistics to consumers. In this way, they have insight into the quantities consumed at any time. In addition, the system enables the detection of losses in the distribution system, as well as possible interruptions that can be detected in the event of a sudden change in the amount of water. The use of such a system is beneficial to both the user and the water distributor. Just as consumers become more aware of their consumption through continuous monitoring, the distributor also has insight into the quantities and trend of consumption, allowing them to track the amount of water consumed with automatic meter reading without hiring additional staff (Yasin et al., 2021). The use of an automatic reader eliminates, among other things, the possibility of an incorrect reading of the scale or human error. All of this forms the basis for understanding water use patterns and quantities, and for identifying system problems and their solutions. Therefore, for long-term sustainability and better customer service, it is necessary to identify inadequacies and improve the distribution system by

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integrating new technologies such as smart water monitoring systems and infrastructure investments (Manoharan and Rathinasabapathy, 2018). The newest findings suggest that data collected from different types of water consumption events can give an insight into tap-water usage, ultimately giving information on population's adaptation of hygiene practices (Rahim et al., 2021). Involvement of building users is crucial in order to alter unfavorable consumption patterns, therefore implementation of smart meters should aim for long-term customer satisfaction step-change (Monks et al., 2021). To improve user awareness, the initial and periodic verification of the on-field reliability (Canale et al., 2019) of the system is necessary.

In this paper, three smart water meters were installed in a university building with a high daily change rate in the number of people. Each water meter measures the waterflow to a separate construction block, i.e. the first water meter measures the total waterflow, while the other 2 m measure the waterflow to two construction blocks (Blocks B and C in Fig. 1). These water meters are equipped with LoRaWAN radio technology transceivers that can transmit information from electromagnetically difficult environments (e.g., in a parking lot and under a metallic plate) to a central system. Information on water consumption, particularly in publicly available locations or available in an IoT wallet-like application, can lead to changes in water consumption habits and patterns, resulting in reduced overall operating cost of the system. The contributions are the following:

- A novel approach has been implemented to register consumption patterns and pinpoint locations of water losses, as well as quantify leakage by integrating signal processing of measured data,
- an IoT Wallet application was introduced that stores and previews data from an arbitrary sensor device, allows the users to set rules for alarms and has the capability to integrate an arbitrary sensor based on LoRaWAN radio technology,
- an analytics software has been introduced that can trigger alarms based on thresholds determined by the analysis of water consumption,
- an energy consumption analysis of available IoT radio technologies has been made and cross checked on-site with available infrastructures.

2. Materials and methods

2.1. IoT technology for smart buildings

To strengthen the concept of smart buildings, future IoT systems must include many sensor devices that measure environmental changes and inform the user and/or systems about these changes. From a smart building point of view, some of the most important elements of a smart building are smart water consumption management and the timely and rapid detection of pipe failures, water consumption control, and loss control in particular building segments. Traditional meters require users to regularly check and read the status of meters to obtain information about water consumption. In addition, in today's smart building era, water meters transmit data to a centralized system that stores water consumption data. This system can detect possibly broken pipes, send an alarm to the user or system about possible water leaks, apply machine learning algorithms to achieve savings, detect a decrease in consumption and/or consumption trends. To interpret the concept of intelligent buildings from the point of view of analysis of water consumption, water is collected that flows through the building pipes using water meters placed in three separate locations, as shown in Fig. 1(left). The investigated building is located on the University campus in Split in Croatia and over 1000 students and 150 employees use it every day. The average water consumption during the semester is 550 m^3/month. Turning this building into smart building started with the installation of smart water meters. The first device 1 (Fig. 1(right)) measures the entire water consumption of the building, while devices 2 and 3 measure the water consumption of the other two blocks (blocks B and C). Modern water meters use new methods to measure water flow, including electromagnetics (Boyle et al., 2013), fluids and ultrasonics (Li and Chong, 2019). Water-meter devices use ultrasonic technology as one of the most widely used methods to measure water data flow, ensuring high accuracy of measurement.[1] To transmit data collected from water measurement devices, the watermeter devices are equipped with LoRaWAN radio technology.

2.1.1. *Comparison of IoT technologies used in underground water-meters*

Water meters are located below the ground and usually a wireless interface should be used to transmit water flow data. Omnipresent wireless technologies, which are used for high (3G, WiFi, and LTE) or low throughput data (ZigBee, Bluetooth Low Energy (BLE)), are limited in coverage and do not adapt to such operations. Low-power-wide-area networks (LPWAs) enable battery devices to transmit data over long distances, enabling them to implement intelligent buildings. These technologies range from LoRa (Sain et al., 2017), Sigfox (Sanchez-Iborra and Cano, 2016), to NB-IoT [(Centenaro et al., 2016), (Mangalvedhe et al., 2016)]. In this section technical differences between Sigfox, LoRa and NB-IoT is provided.

2.1.1.1. Sigfox. Sigfox utilizes binary phase-shift keying (BPSK) modulation in an ultra-narrow band (100 Hz). It uses unlicensed ISM band, such as 868MHz in Europe, 915MHz in US, and 433*Mhz* in Asia. Due to ultra-narrow band, Sigfox technology results in low-cost antenna design, very low power consumption, and low noise level. The supported throughput for Sigfox communication is limited to 100bps. Although at first Sigfox was designed to support only uplink communication, it now supports both uplink and downlink. However, the maximum number of messages for the uplink communication is limited to 140 messages per day, with the limit of 12*bytes* for the payload size of each message. On the other hand, the maximum number of messages in downlink direction is limited to four messages per day, with the payload size limit of 8*bytes* per message. Sigfox communication does not support acknowledges. To ensure reliable communication, every device sends a single message multiple times over various frequency channels. Regarding channels in Europe Sigfox utilizes 400 channels with 100 Hz between 868.180MHz and 868.220MHz.

2.1.1.2. LoRa. LoRa, similarly as Sigfox, uses ISM bands, and operates on different frequencies, which depends on region. In EU region the frequency is 868MHz, in North America is 915MHz, while in Asia is 433MHz. Modulation for communication between end device and base station is chirp spread spectrum (CSS) that spreads a narrow-band signal over a wider channel bandwidth. As a result, the signal has low noise, with high resilience to interference and also resilience to jamming.

Data rate and range and can be tuned in LoRa with six different spreading factors (from SF7 to SF12). For example, high spreading factor gives longer range and low data rate. Data rate can be tuned between 300bps and 50bps which depends on used spreading factor and channel bandwidth. Also, base stations can receive massages if they are sent with different spreading factors. Maximum allowed payload is 243*bytes*. A standard that utilizes LoRa communication is LoRaWAN protocol. As a standard, LoRaWAN provides three classes of end devices to address multiple requirements for IoT applications. Class A devices have bidirectional communication links where one uplink transmission is followed by two downlink slots. Class B devices also have bidirectional communication, however, downlink transmission is scheduled at precise time. Finally, Class C devices always have open downlink communication channels and can receive messages from the base station at any

[1] https://www.axiomametering.com/en/products/water-metering-devices/ultrasonic/qalcosonic-f1-ip68-ultrasonic-flow-meter.

Fig. 1. Location of LoRaWAN-based watermeters placed at University building with a high-rate daily-based change in the number of people.

time.

2.1.1.3. NB-IoT. NB-IoT technology is based on LTE protocol standard. In uplink NB-IoT uses frequency division multiple access (FDMA) and orthogonal FDMA (OFDMA) in the downlink, and employs the quadrature phase-shift keying modulation (QPSK). In downlink data rate can go up to 200*kbps* and 20*kbps* in the uplink. Maximum available payload size is 1600*Bytes* for every message. NB-IoT operates in licensed frequency bands such as 700MHz, 800MHz and 900MHz, while the frequency band width is 200KHz.

Next, a comparison between Sigfox, LoRa and NB-IoT technologies regarding Quality of Service, Battery life and Latency, scalability, as well as Network coverage and Range is provided.

2.1.1.4. Quality of Service. Both Sigfox and LoRa operate in an unlicensed frequency spectrum which may impact interference, multipath, and fading. However, NB-IoT operates in licensed spectrum and is an LTE-based synchronous protocol.

2.1.1.5. Battery life & latency. All LPWAN-based devices, Sigfox, LoRa and NB-IoT are created to be held in sleep mode most of the time during their lifetime. However, NB-IoT devices consume energy due to synchronous communication. Class A LoRaWAN devices and Sigfox utilize low consumption during inactive period in between communication. However, NB-IoT and Class C LoRaWAN devices have low latency at the expense of increased energy consumption. Hence, for applications that require low latency NB-IoT and Class C LoRaWAN are a better option, otherwise, for applications that are not sensitive to latency and low power consumption, it is better to utilize Sigfox and Class A LoRaWAN.

2.1.1.6. Scalability & payload length. NB-IoT allows 100 *K* end devices per cell compared to 50 *K* devices for Sigfox and LoRa. In addition, NB-IoT has a maximum available payload length of up to 1600*B*. LoRa has 243*B* for the uplink message, while Sigfox allows only 12*B* for the uplink.

2.1.1.7. Network coverage. Sigfox has a very wide coverage with a range larger than 40 km. LoRa has a lower range that can go up to 20 km, while NB-IoT has the lowest range and coverage capabilities. Also, NB-IoT has limitations; in that sense, it is limited to LTE base stations, which does not make it suitable for rural and suburban regions that are not usually covered with LTE technology.

2.1.2. Selecting appropriate IoT radio technology for underground water-meters

As can be seen in Fig. 4, a water meter device is placed under the ground in the parking lot below a metallic hydrant cap. Before selecting the appropriate radio technology for the transmission of water-meter data, three different state-of-the-art IoT radio technologies were considered: Sigfox, LoRaWAN, and NB-IoT, each of them having its own pros and cons in terms of coverage, battery life, cost-efficiency, etc., as described in the previous section.

2.1.2.1. Testing the consumption of IoT radio technology. To measure the consumption of every IoT radio technology, we used Arduino-based boards that implement LoRa, Sigfox, and NB-IoT radio modules, as shown in Fig. 2. As can be seen, the Current ranger is connected to each board for current consumption measures, while each board is powered from the external power supply of 3.4V. In addition, a Current Ranger output is connected to an oscilloscope to capture detailed information regarding current consumption. During the measurement period, each board was set to deep sleep using the ArduinoLowPower library, after waking up, a message was sent. Fig. 3 shows the current consumption of each board during the active period, between two sleep periods. For the LoRa module, a transmission period depends on the used parameters of Spreading factor and bandwidth window, for which SF9BW125 was used in our scenario. The total air time was around 206 ms, while consumption during the transmission period was 35 mA. For the Sigfox module, it can be seen in Fig. 3 that during the active period, the radio module sends a message three times over the radio channel, which is determined by the Sigfox specification, while the consumption during this period is 45 mA and the duration is around 15 seconds. In the end, for the NB-IoT module, consumption is around 20 mA on average during the period of 5–10 seconds, with spikes around 65 mA during the transmission period. These measurement results clearly indicate that LoRa as IoT radio technology presents an appropriate solution for the Underground water-meter scenarios.

2.1.2.2. Testing the availability of IoT radio technology in underground water-meter scenarios. As the implementation of the IoT communication infrastructure in Croatia is still early, it is necessary to check the availability of LPWA technologies at particular positions, moreover at underground positions where smart water meters should be installed. It is important to note that the given locations are harsh in terms of radio signal propagation, that is, wireless communications, and need to be tested on sight before installation. The test procedure starts with establishing the setup of data acquisition from different IoT radios and on-sight performance measurements. To test the availability of the three IoT radios, an initial testing setup was established, both on the software and hardware side. The hardware setup comprises three Arduinos equipped with three different IoT radios (NB-IoT, LoRa, Sigfox), as shown in Fig. 5. To check if certain radios are transmitting, the Software Defined Radio (SDR) tool was used to listen to the radio channel between the Arduino radio and a particular receiver. The testing architecture is shown in Fig. 5 while the test setup is shown in Fig. 4(down).

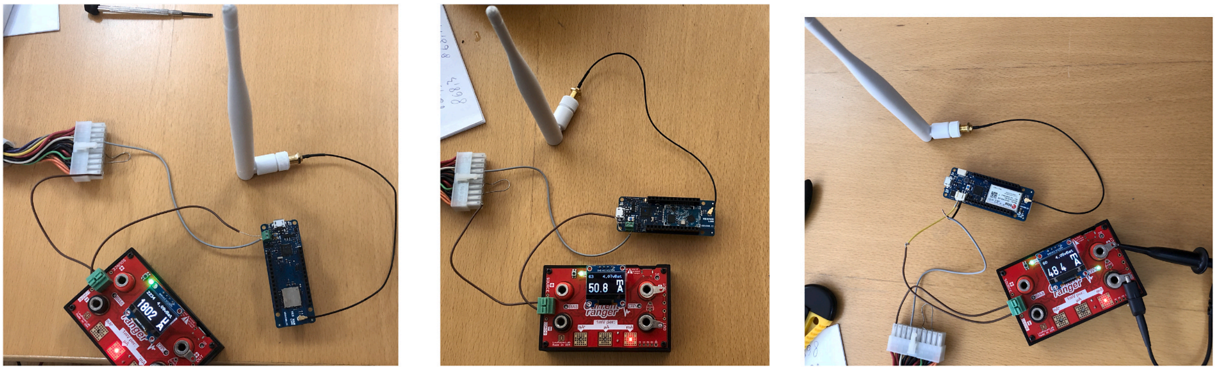

Fig. 2. LPWA development boards connected to external power supply and Current Ranger to measure consumption in active and inactive mode: (left) MKR WAN 1300 - LoRa module, (center) MKR FOX 1200 - Sigfox (right) MKR NB 1500 - NB-IoT.

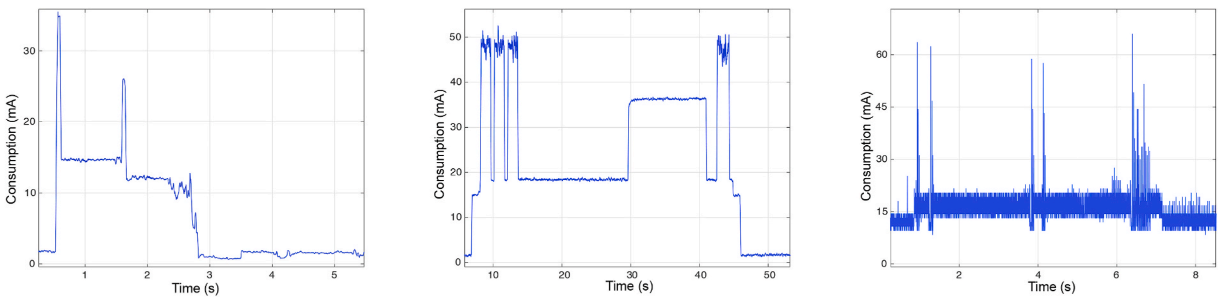

Fig. 3. Consumption of LPWA development boards based on (left) LoRaWAN (center) Sigfox and (right) NB-IoT technology.

Fig. 4. (up) Test procedure comprising LPWA devices that use LoRaWAN, Sigfox and NB-IoT technology and (down) installation phase that comprises watermeters with LoRaWAN transcievers.

The same system can be used to determine the attenuation of the signal strength at a particular location with the cover being closed and open, providing better information on the real-world performance of given radios and physical limiting factors.

The software architecture used to retrieve Arduino data is presented in Fig. 5, with each having its retrieval procedure considered in the

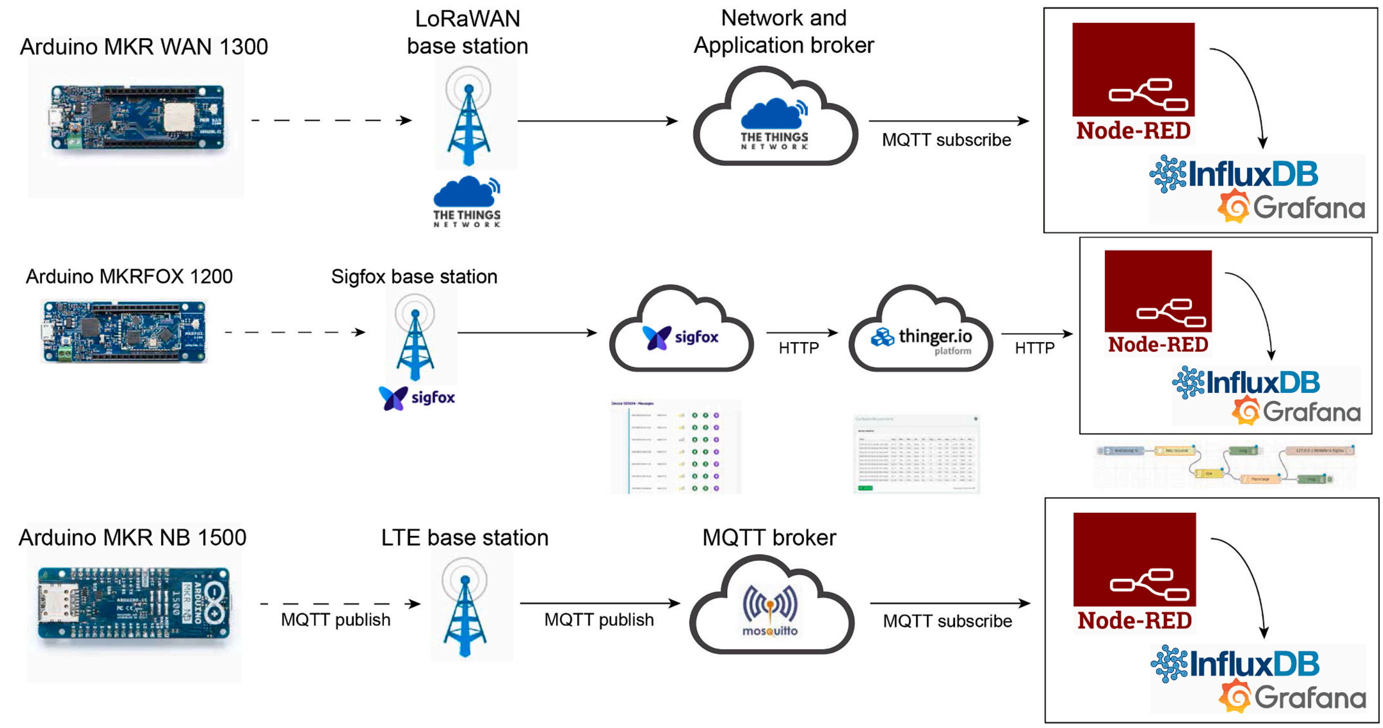

Fig. 5. Network architecture of (up) LoRaWAN, (center) Sigfox and (down) NB-IoT implementation used during the test procedure phase.

given experiment. The results of the experiments with related visualization are presented in Fig. 6. For testing purposes, the LoRaWAN gateway was placed in the university building, while Sigfox and NB-IoT clients depend on commercial infrastructure providers. The left part of Fig. 6 shows that Sigfox and NB-IoT can lead to a drop in performance (which can be noticed by missing counts in data retrieval), while position 2 (location C) is not covered by the service provider infrastructure. This means that the only reasonable technological approach among the tested is LoRa, i.e. LoRaWAN, since the coverage is reliable enough. The right part of Fig. 6 shows the influence of the surrounding in Location A

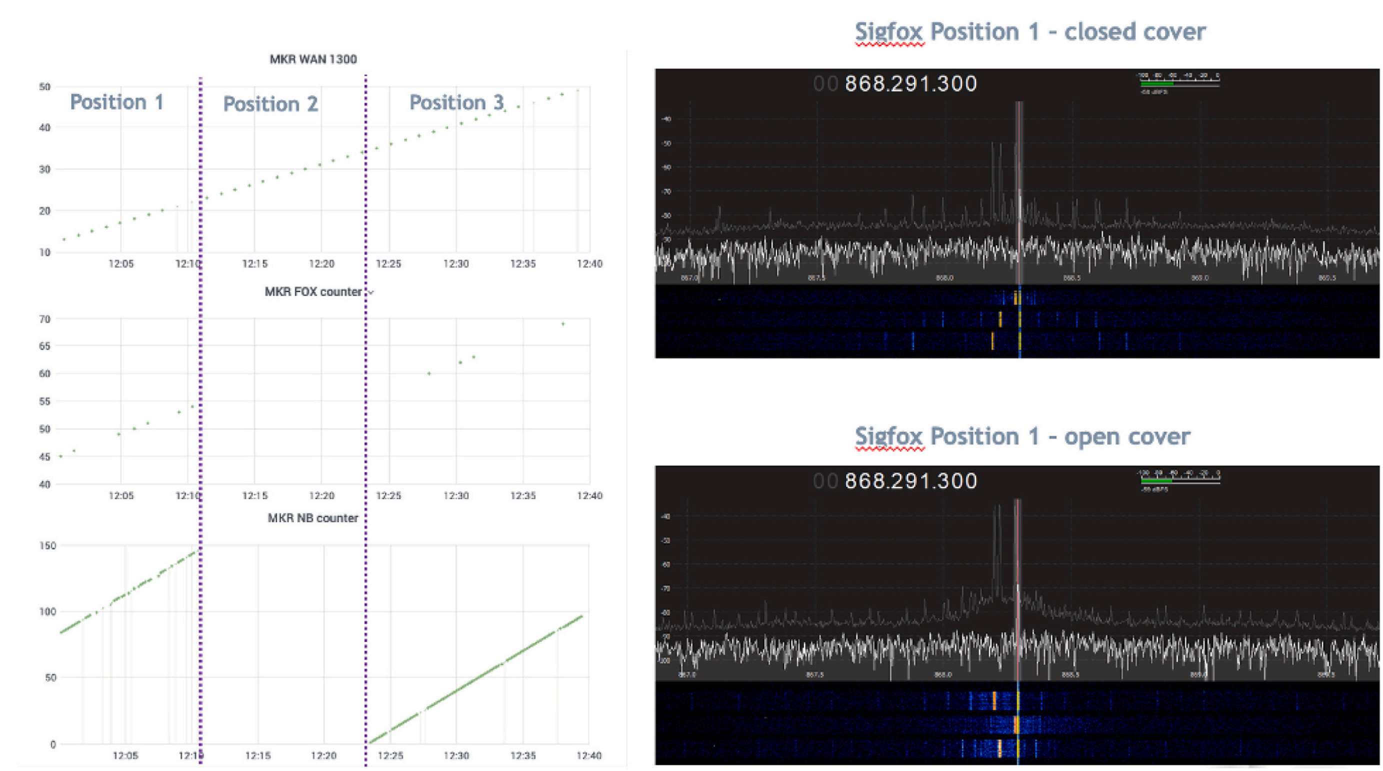

Fig. 6. (left) Testing different IoT radio technologies results; Missing dots, i.e. counts on the left side shows that reception of particular transmission between Arduino node and receiver failed; LoRaWAN gateway was located In pilot location building. (right) Influence of the closed and opened metallic cover of the manhole – 10 dB of difference.

– as the IoT radio is underground, the signal reception depends on whether the metal cover of the manhole is closed or open. As shown, a 10 dB drop in signal can be expected if the metallic cover is closed. This greatly reflects the distance the receiver can be located to ensure reliable data transmission.

Furthermore, to show the quality of LoRaWAN signals from publicly available gateways, a TTN mapper[2] tool was used to map the signal quality of LoRaWAN devices near the university building where water-meters are being installed. TTN mapper is an open source application developed by the TTN user community to better address coverage. The basic functionality of the TTN mapper is to combine information about the location of the transmitter and the strength of the signal that the transmitter sends to a single publicly available heat map on a global scale. From this map, rough conclusions can be drawn about where more gateways need to be introduced and where the coverage is already good enough to implement a sensor network. All measurements were made over a two-day period with MKRWAN 1300 Arduino device. Measurements were carried out between 12 noon and 6 p.m., which included the most dynamic period of the day in terms of the flow of people, vehicles and other disturbances. Since the omnidirectional antenna and automatic SF settings were used, a worst-case scenario was covered. The antenna was carried 1.2 m from the ground according to the instructions on the TTN mapper page, and the message was sent to the gateway every 35 seconds, taking care that at the time of transmission the person carrying the antenna was not between the antenna and the gateway. Measurements show the signal quality surrounding three TTN gateways that are publicly available at the University of Split. As can be seen, the signal quality at the university building where LoRaWAN water-meters where installed is very good, indicating that LoRaWAN technology can be employed to transmit sensor data from a sensor device to a cloud system using publicly available gateways.

2.1.3. LoRaWAN network architecture

The LoRaWAN network architecture is a typical star-of-star topology, as shown in Fig. 7. In this topology, the end devices communicate sensor data to one or more gateway devices. The gateway transmits all incoming communication to the network server to filter out duplicate and redundant messages. After security checks are performed, the network server sends information to the application server. LoRaWAN allows battery-operated devices to communicate information without the need to replace batteries. This is accomplished simply by shutting off the transceivers during the inactive transmission period, which results in significant power savings. The end devices are divided into three classes depending on their functionalities (LoRa Alliance Technical Committee). In Class A mode, battery-operated devices transmit only when intended, allowing transmission from the gateway in two slots after the communication with the gateway. Class B and Class C devices are intended for devices that have an external power source that allows for more frequent transmission.

Long-range communication of LoRaWAN communication relies on chirp spread spectrum (CSS) (Berni and Gregg, 1973) modulation technique with sub-1GHz frequency band. To achieve communication over large distances to the gateway, LoRaWAN allows communication with a specific spreading factor, which determines the number of bits encoded in a symbol in the range from 0 to 2^{SF-1}. By increasing the spreading factor, the total transmission time is increased, which results in a larger energy consumption. In Europe, a frequency range from 863 to 870 MHz is planned for LoRaWAN transmissions with max 16 non-interfering frequency channels within that band. Also, parameters such as Spreading Factor (SF) and Bandwidth (BW) are also defined for both uplink and downlink communication. For example, The Things Network provider defines the following frequency plan for uplink messages:

- 868.1 - SF7BW125 to SF12BW125
- 868.3 - SF7BW125 to SF12BW125 and SF7BW250
- 868.5 - SF7BW125 to SF12BW125
- 867.1 - SF7BW125 to SF12BW125
- 867.3 - SF7BW125 to SF12BW125
- 867.5 - SF7BW125 to SF12BW125
- 867.7 - SF7BW125 to SF12BW125
- 867.9 - SF7BW125 to SF12BW125

In addition, each device is limited by duty cycle as a percentage of active time a single device can occupy a particular channel. Using a duty cycle, along with channel, SF and BW selection, the chances of collision for LoRaWAN class A devices can be reduced. For example, TTN utilizes the so-called Fair access policy, where every device is allowed max. 30 sec/day time on air, allowing implementation of a large-scale network with more than 1000 devices per a single gateway (Adelantado et al., 2017). To reduce collisions, it is suggested to increase the number of gateway devices in a dense area.

2.2. Implementation phase

To transmit data collected from water measurement devices, the watermeter devices are equipped with LoRaWAN radio technology, as described below. As shown in Fig. 4 water meter is under the ground at the parking lot below the metallic hydrant cap. Installed water-meters are class 2 devices where, according to ISO4064-1,[3] maximum permissible errors (MPE) for class 2 water meters is ±5% between minimum and transitional flow rates, and ±2% for flow rates between transitional and overload flow rates for temperatures between 0.1 C and 30 C, while MPE is ±3% for temperatures higher than 30 C. Water-meters are equipped with LoRaWAN radio module that periodically sends sensor data to the gateway. Since the watermeter device is a battery-operated device, the radio module transmits messages every 6 hours to save energy and increase battery life. The payload snippet is shown below:

Listing 1. Decoded Payload


```
{
"date": "2020-12-31T14:00:00.000Z",
    "deltaVolumes": [0, 0, 0.013, 0.069, 0.066, 0.042, 0.036, 0.033, 0.034, 0.034, 0.034,
        0.031, 0.063, 0.079, 0.046],
    "logDate": "2020-12-30T23:00:12.000Z",
    "state": 0,
    "stateMessages": [ "OK" ],
    "volume": 0.58
}
```


[2] https://ttnmapper.org/heatmap/.

[3] https://www.iso.org/standard/55371.html.

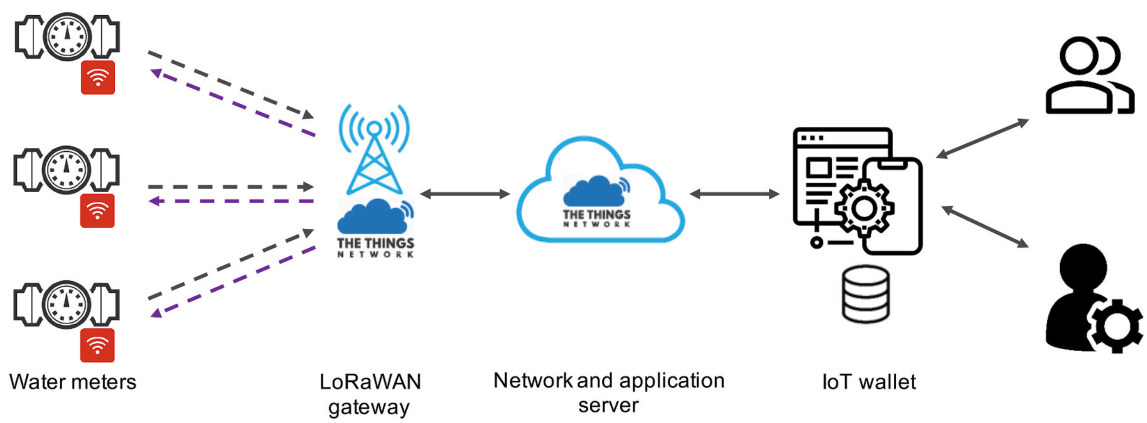

Fig. 7. High level overview of architecture of the proposed solution.

As can be seen, a single LoRaWAN data packet contains information about the timestamp of the packet received from the water-meter by a gateway device, delta volumes from last 15 hours (logged on an hour basis), a log date, possible error messages, and water-meter volume. Furthermore, the LoRaWAN device was programmed to periodically send a message every 6 hours to the gateway device. This way, if one packet does not reach the gateway, the following packet received after 6 hours (i.e. 12 hours after the last successful message reception) will contain log delta volumes from the last 15 hours. Note that duty cycle can be modified, since water-meter can be programmed to receive up-link commands from the gateway. In our application, water-meter was programmed to send a LoRaWAN packet every 6 hours, although, under harsh conditions, the duty cycle can even be reduced, affecting the battery lifetime.

In addition, the payload contains information on the status code such as low battery, dryness, backflow, burst, water leakage, low temperature, etc. As a LoRaWAN gateway, the Sentrius RG191 gateway concentrator was used to forward messages from watermeter sensor devices to the cloud infrastructure of the Things Network (TTN). The gateway is an indoor concentrator built on the Semtech SX1301/1257 LoRaWAN technology and equipped with a 2.0 dBi gain RP-SMA antenna that is vertically polarized and omnidirectional.

2.3. Software to use data - IoT wallet architecture

When the gateway receives the message from a water measurement device, it is transmitted to a cloud TTN infrastructure equipped with a network and an application server. TTN cloud infrastructure has many integrations, such as MQTT and webhooks, that allow message forwarding to a dedicated server for further processing, storage, and visualization. Fig. 8 shows an overview of the total water volume and the daily delta volume using a water meter, modeled by the IoT wallet application. This information can be interesting, as it can trigger alarm warnings when a pipe fracture occurs or send information about possible slow water leaks.

Wallet is organized into a set of microservices. Fig. 9 shows how the services interact with each other and with the databases, and also the most relevant technologies used in each service. All services are written in JavaScript and TypeScript.

The job of the ttn-microservice is to receive TTN data and store it in the Influx database. It is also responsible for querying/retrieving the stored data. The service subscribes to a set of TTN applications defined in the configuration file. Data are stored in the Influx database as they are received. Each time a data point is stored in Influx, an event is raised and the data point is also published to the server. Therefore, the ttn-microservice is a hub between the TTN, the influx database, and the server via the mqtt-broker. The mqtt-broker service runs an Hivemq MQTT server and allows message passing between the ttn-microservice and the server. It is an intermediary that allows the ttn-microservice and the server to publish events and receive data. Depending on which API endpoint is triggered, the server either needs to query the MySQL database or publish events via mqtt-broker. The MySQL database contains the data for all entities relevant to the server logic (users, sensors, sensor types, and payload fields). Whenever the server needs to retrieve or manage these entities, it queries the MySQL database. Given the number of users, devices, and the purpose of the database, any relational database could have been used, such as Postgre. In the future, if the number of users and/or sensors largely increases and we notice a degradation in performance, we might consider switching to another database or increasing the number of replicas. The server also communicates with openweathermap.org to retrieve the weather around the sensor location. Whenever the server needs some sensor data, it publishes an event. Events published from the server are forwarded to the ttn-microservice via the mqtt broker. The ttn-microservice queries the influx database for the requested sensor data and returns it to the server. The server then forwards the data back to the client via HTTP response.

The client is a web application that provides a responsive graphical interface for users and an admin panel for administrators. The dashboard allows users to view the data on two charts, one showing the rate of consumption per hour and one the cumulative volume spent. These charts can also be used to display other data relevant to the user. The dashboard also shows the location of the sensor on a map and the

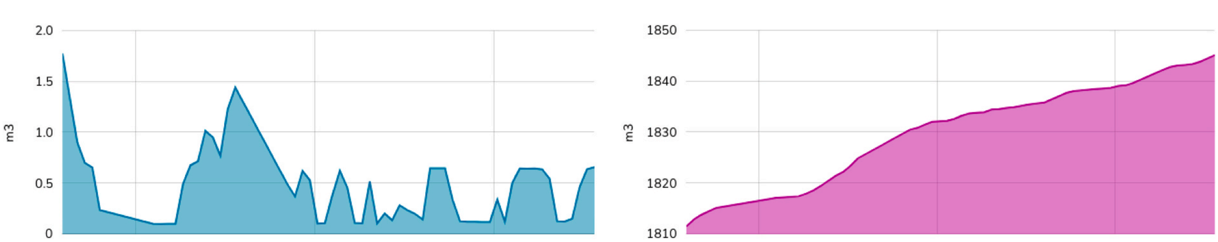

Fig. 8. Water consumption measurements collected by water meter device placed at one location - location A. Blue graph depicts delta volumes on an hour basis, while purple denotes overall water consumption.

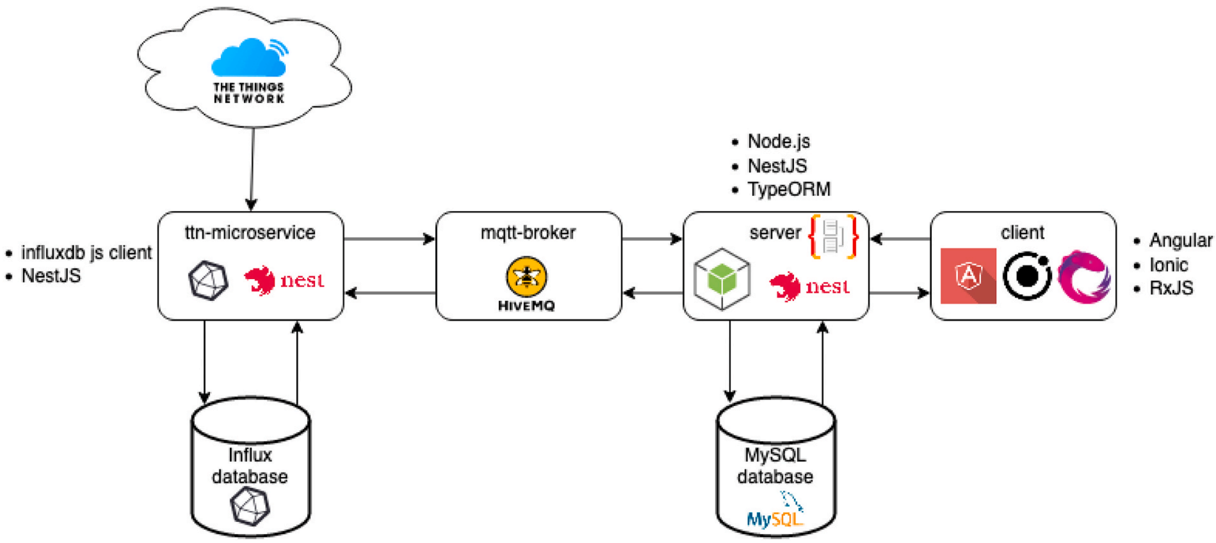

Fig. 9. Wallet's microservices and databases.

weather around that location. Users can also download the data collected by the sensors, set up alerts and add sub-users. Users can also edit their details and preferred language. Sub-users have access to the dashboard and sensor data. The dashboard is shown on user login. Administrators have the permission to manage sensors, sensor types and payload fields of interest. They can also add new users and delete or ban existing ones. The client is built using Ionic framework, which enables us to also compile it into an Android app. Whenever the client requires any kind of data, it communicates with the server by sending an HTTP request. Each HTTP request triggers some API endpoint on the server, depending on what data is requested. The server was discussed in the previous paragraph and an overview of the architecture is shown in Fig. 9.

Organizing applications as such microservices enables us to extend wallet functionality in a modular way. For example, if we would like to make predictions using machine learning, one approach would be to create a separate machine learning service which trains and stores models.

3. Results and discussion

3.1. Analysis of water consumption pattern

Water consumption was analyzed using data collected hourly at the three measurement points: the main valve and building blocks B and C. From the temporal distribution of the collected data (Fig. 10), large fluctuations in water consumption can be seen as a function of several key parameters. As with water consumption in residential buildings, where consumption depends primarily on the number of residents and their activities, water consumption in university buildings depends on the number of students, staff and their activities (Mohd Daud and Abdullah, 2020). It is clear that the population structure in residential buildings, where daily activities are consistent, is quite different from the structure in university buildings. The number of people in the university building changes from day to day due to the presence of students, employees, external associates, and other visitors. In addition to classrooms and offices, the university building also includes laboratories for scientific experiments, a library, and a mess hall in block A. Consistent with the above, a temporal distribution of water consumption was expected over the observed time.

The distribution of the data is also presented using boxplots that indicate the interquartile range (IQR) and whisker. The interquartile range, defined in the boxplot as the width of the box, thus assumes that the values are clustered around the central value (median), and the edges of the box, bottom, and top, are defined as the 25th (first quartile) and 75th (third quartile) percentiles. Respectively, the IQR indicates how much the "middle" values are spread out. The whiskers extend to the most extreme data points, minimum and maximum. Values that lie outside the interquartile range and whiskers are considered outliners. According to hourly water consumption, the values are normally distributed in the period from 7 a.m. to 4 p.m., in contrast to the rest of the period, where a larger number of outliers were recorded (Fig. 11). This can be explained by an unusual event that led to higher water consumption, such as a leak in the distribution system. Daily water consumption shows the expected pattern of water consumption with lower consumption on weekends. The presence of outliners on Sunday

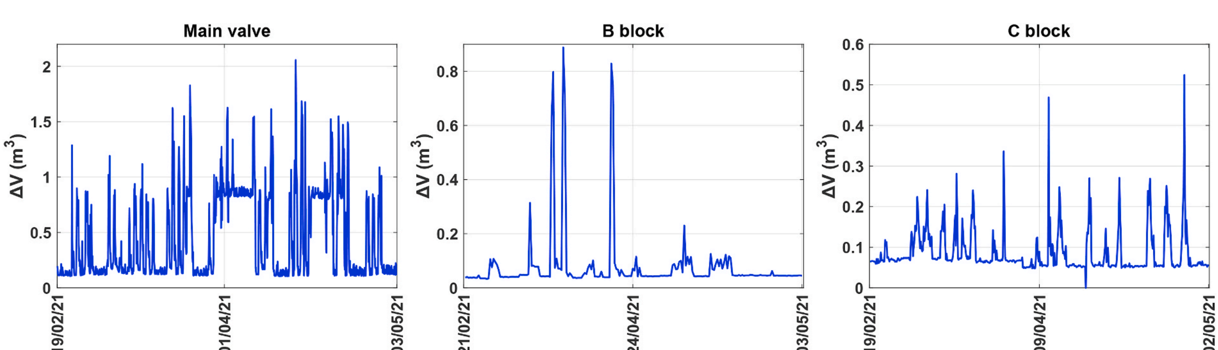

Fig. 10. Water consumption trends at the main valve, as well as in blocks B and C.

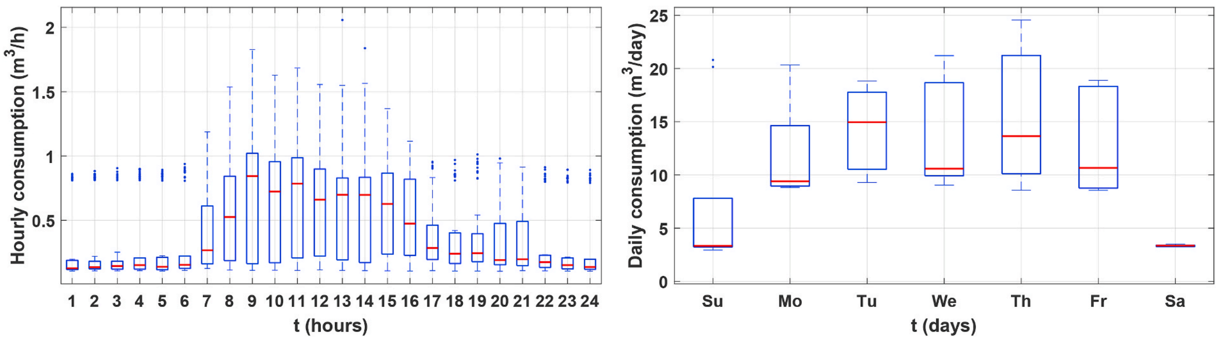

Fig. 11. Boxplot of hourly and daily water consumption.

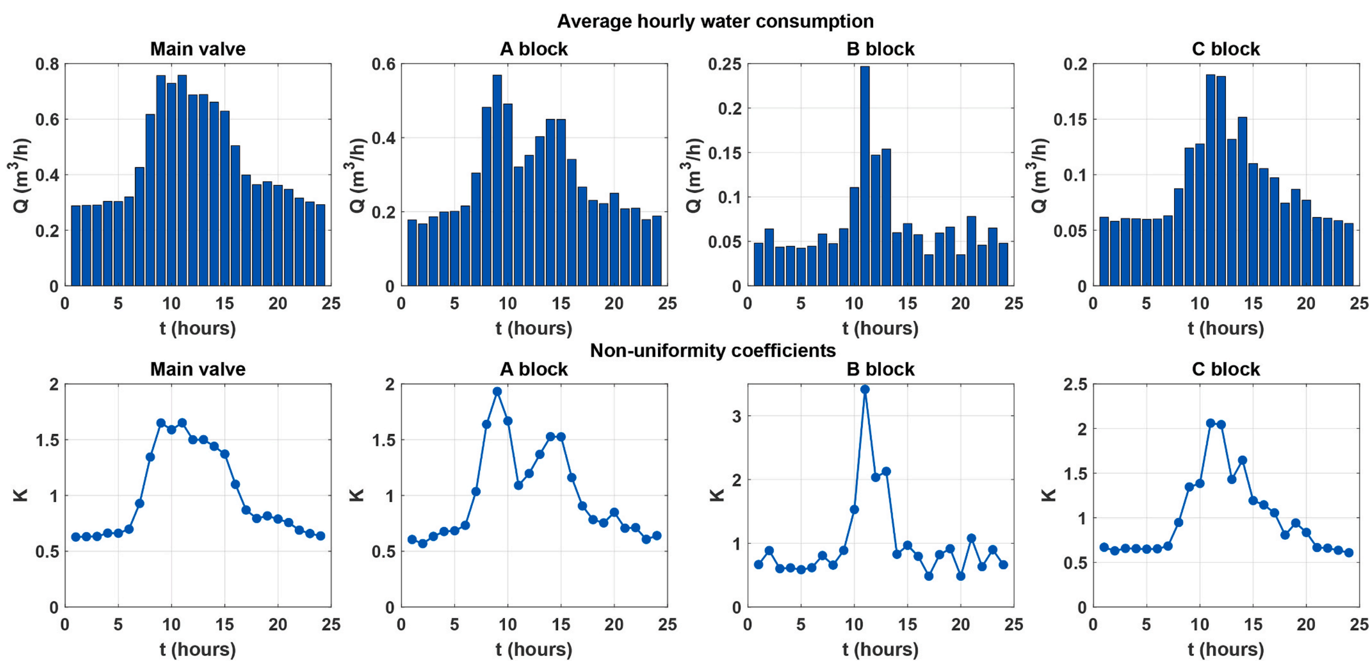

Fig. 12. Average hourly water consumption and corresponding non-uniformity coefficients for the main valve and three blocks.

can be explained by the project to improve the infrastructure of the scientific research area in the university building, which also occurred on Sunday due to the lower number of staff and students.

Averaging the available measurement data yielded the average hourly water consumption quantities for the entire building and blocks A, B, and C. Since there are water meters in blocks B and C, the average water consumption in block A is equal to the difference between the total consumption and the consumption in two other blocks. The calculated data reveal the unevenness of water consumption throughout the day (Fig. 12). Thus, consumption peaks occur in different time periods. Throughout the building, the maximum consumption is between 9 and 11 a.m., in block A at 9 a.m., in block B at 1 a.m., and in block C between 11 a.m. and 12 p.m. Because each block serves a different purpose, for example, classrooms and a restaurant in block A, offices and a laboratory in block B, and classrooms in block C, different consumption patterns were expected throughout the day. The uniformity of water consumption is between 7 a.m. and 4, 5 p.m., or during the working hours of most employees. The coefficient of non-uniformity, defined as the deviation from the mean, is used to describe the unevenness of daily water consumption (Fig. 12). The highest value of the coefficient of non-uniformity was computed in block B. The analysis of the hourly water consumption contributed to the detection of losses in the distribution system. Detection of unexpected water consumption can be identified as loss in the system in the form of possible leaks or failures in the system. Thus, a constant loss value of 0.3 m^3/h is registered in the main valve, 0.2 m^3/h in block A, and between 0.05 and 0.06 m^3/h in blocks B and C. The lower values of losses in blocks B and C compared to building A can be explained by the newer buildings and the resulting newer distribution system with new pipes and fittings.

3.2. Frequency distribution and analysis in frequency domain

The frequency distribution of a continuous numerical variable is shown in a histogram. The histograms in Fig. 13 represent the frequency of occurrence of consumption of a specific value. The main valve, for example, records a maximum consumption between 0.27 and 0.37 m3/h, block A between 0.16 and 0.25 m3/h, block B between 0.1 and 0.1 m3/h, and block C between 0.04 and 0.07 m3/h. The highest duration, that is, the cumulative frequency of consumption of the highest occurrences, is captured by the duration curves. As histograms, the duration curves indicate the presence of losses in the distribution system, the magnitudes of which lead to a higher frequency of consumption corresponding to the magnitude of the losses.

Analysis in the frequency domain includes the analysis of signals and their properties with respect to frequency, rather than time. Signals are converted from the time domain to the frequency domain by the Fourier transform. The function used in this article for frequency analysis is the spectral density function. The spectral density function S(f) used to

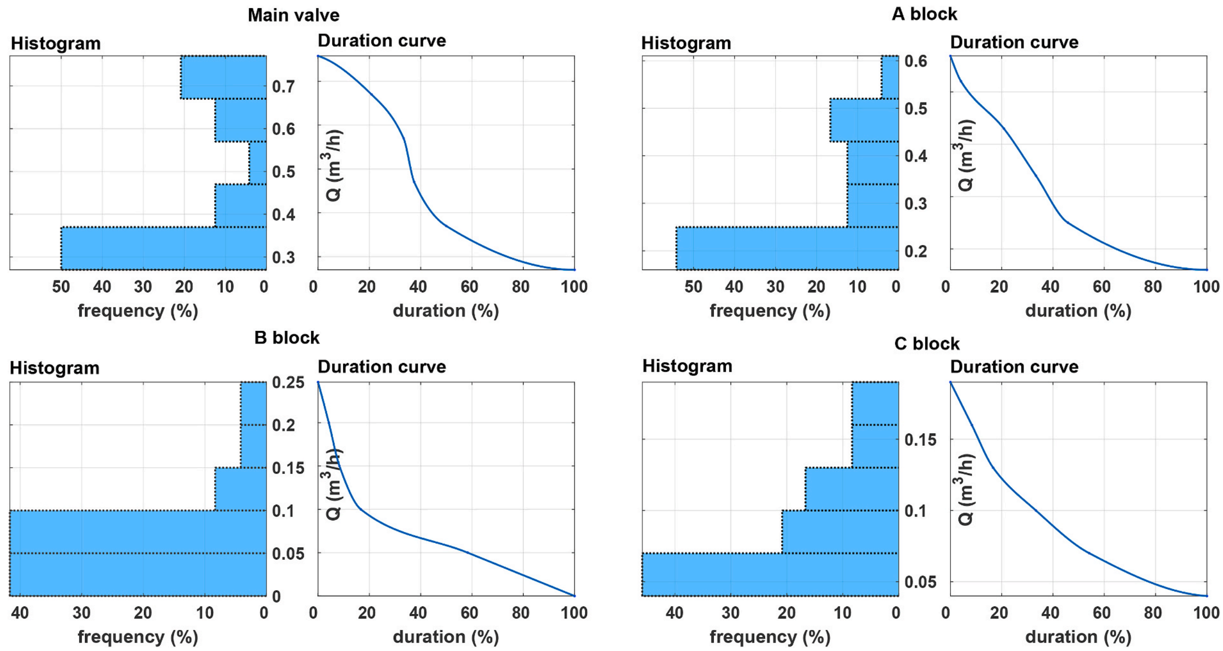

Fig. 13. Histograms and duration curves of data set for the main valve, block A, B, and C.

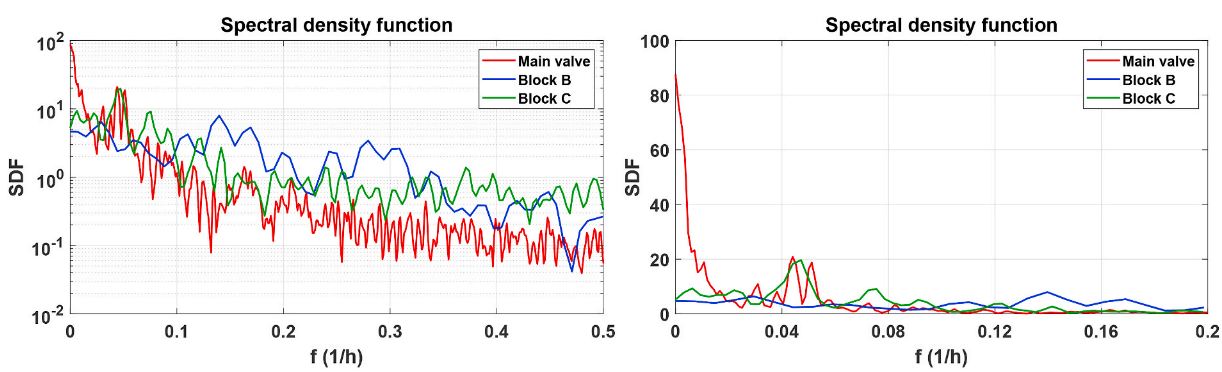

Fig. 14. Spectral density function of data set at main valve, block B and C.

detect the periodicity of the analyzed signal is defined as follows (Deni ć -Juki ć et al., 2020; Larocque et al., 1998):

$$s(f) = 2\left[1 + 2\sum_{k=1}^{m} D(k)r(k)\cos(2\pi fk)\right] \tag{1}$$

$$D(k) = \frac{1}{2}\left(1 + \cos\frac{\pi k}{m}\right) \tag{2}$$

for frequencies $f = l/2m$, $l = 0, 1, 2, \ldots, m$, where m is the truncation point and $r(k)$ is the autocorrelation function. The spectral density function was determined for the main valve, block B, and block C according to the positions of the water meters (Fig. 14). Thus, for the main valve and block C, peaks occur with a frequency corresponding to a period of 24 hours in the time domain. Periodicity is more difficult to discern in block B due to the smaller data set and lower water consumption. Taking into account the highest losses at the main valve that occur in each hour of observation, the spectral density function of the main valve has the highest value at frequency 0.

Both the frequency distribution and the analysis in the frequency domain by the spectral density function confirm the pattern of water consumption and the assumption of the existence of losses in the system according to the boxplot and the analysis of hourly consumption from the previous subtitle. One of the main benefits of smart water monitoring is the ability to quickly detect leaks. This helps to speed up troubleshooting, save time and money, and avoid excessive water consumption. Smart metering systems in water distribution systems can be used to improve management by analyzing and forecasting data obtained through various modeling approaches.

4. Discussion

As we live in times where the concept of sensing the environment using IoT became omnipresent and expected. By introducing the possibility for end users to access real-time information from smart water consumption devices, it can have multiple aspects of greener and positive behavior not only for an individual, or a householder, but also for company owners and water companies.

End users can detect possible water leaks by receiving an alarm message, which can result in real-time reaction and reduced financial loss. Having access to more detailed data that include current water consumption, analyzes, and statistics can motivate users to reduce water consumption in their home. In most cases, especially older buildings, water meters are installed in all homes, which requires water companies to enter homes and read information about consumption. Smart meters enabled with radio communication allow remote connection and reading of information without disrupting the privacy of end users.

For water companies, remote reading of water consumption reduces the requirement for their staff to read the consumption manually, which not only reduces staff but also gas consumption. Some smart water meters are equipped with hubs that collect information from surrounding water meters using WiFi radio communication, but since they are not connected online, water companies must send their staff to collect information from them. On the contrary, the use of radio technologies based on LPWAN radio communication enables the communication of information over large distances, allowing remote collection of information. In addition, building owners with smart water meters have access to detailed information about consumption which allows them to detect possible failures in installation process, of possible water leaks, which are especially visible in older buildings with deteriorated pipes. Furthermore, timely information about leaks with more advanced devices can prevent the building from additional leaks. Additionally, for companies, collecting information about water consumption will allow them to build savings strategies. Combining the collected data with more advanced machine learning-based solutions allows detection of water leaks (Slan ý et al., 2020b). Combining knowledge gathered from these buildings in buildings with similar structure and behavior pattern (such as a university building with students and staff), multiple machine learning models can be trained on data gathered from one building and applied on other, leading to transfer learning models.

5. Conclusions

This paper describes the steps required to successfully implement the intelligent IoT architecture of smart water meters and provides case studies to use the implementation of smart water meters and data analysis. Motivation for the implementation of such a system is related to cost reduction while providing user transparency and real-time data at the same time, allowing for more efficient spending. In the university building, three LoRaWAN-based smart water meters have been installed to track water consumption in three building blocks. Preliminary analysis showed peak water consumption hours and leakage in all building blocks. Blocks B and C have a lower loss due to the new and better quality pipes installed. Based on the preliminary analysis of the recorded data, peak water consumption hours and leakage in all building blocks were identified. Frequency analysis gives a clear insight into usage patterns, while data analysis in the time domain shows leakage rates specifically for each location. Hence, the peak hour recorded at the main valve occurs from 9 to 11 a.m. with losses of an average of 0.3 m^3/h. Significantly lower losses are detected in blocks B and C due to newly installed pipes and lower water consumption. Bins with highest frequency in histogram and the high duration in the duration curve correspond to the loss zones. The spectral density function validates the 24-h signal's periodicity and the presence of losses at the main valve in each hour of consumption. In future work, it is possible to apply machine learning technology to broaden perceptions of consumption trends and forecast future consumption and planned maintenance to avoid costly repairs or downtime in the system later. With the help of available data, savings concepts can be developed and sustainable measures implemented.

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