Comparative Analysis of Energy Consumption in Simulated LoRa Water Meter Reconfiguration vs. Real-world Readings

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***Abstract*—Detecting water leaks in distribution networks is crucial for conserving resources and preventing infrastructure damage. However, one of the most basic and significant challenges before employing any leak detection method is collecting data from the water distribution network. The sensors used for data collection are usually battery-powered; thus, the energy consumption of these devices is an essential factor. In this paper, we analyze the battery consumption of real devices placed in an operational water distribution network, and based on the obtained data, we perform a series of complex simulations to validate the preliminary assumptions we plan to use in further research of leak detection methods.**

***Index Terms*—simulation, water distribution systems, energy consumption, leak detection**

I. Introduction

One of the crucial points in municipal water distribution systems is leaks, which contribute to water loss and increase the cost of network operation. When left unattended, the water leakage can lead to further infrastructure damage. Timely detection and location of leakages are essential due to resource conservation, operational efficiency, and community well-being implications. The most essential information for leakage detection is the measurements collected from a water distribution network. The more data we have available, the more precise the methods of leak detection we can use. Water utilities usually use sensors throughout the infrastructure, such as water usage meters at clients' premises, flow meters that provide information on the inflow and outflow of water from the network, or pressure sensors. By feeding the sensor readings to the digital model developed in tools like EPANET ([1]–[5]), the network operator can identify the malfunctions and points where some anomalies are located. Most of the sensors, especially the smart meters, are battery-operated and have limited readings that can be sent during their lifetime. By increasing the frequency of measurements in areas where leakage is suspected and keeping it low, the system can balance the sensor lifetime and the detection sensitivity.

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In this paper, we address the battery consumption issue by reconfiguring mobile sensors according to the assumptions of the leak detection method. Specifically, we examine a water distribution network equipped with LoRa smart meters, which transmit readings twice daily under normal conditions or at shorter intervals (e.g., every 60 minutes) during leak detection operations. The choice of twice-daily transmission frequency reflects the configuration of an operational system deployed in a real-world setting. The 60-minute interval compromises between maximizing the "freshness" of data collection and ensuring sustainable battery usage, mitigating the risk of depleting the measuring device's battery.

We aim to verify energy consumption predictions, i.e., compile the expected relative battery consumption compared to the actual consumption recorded on meters installed in the water network. Based on the recorded results of unit energy consumption (consumed for listening and packet transfer in devices used in the actual LoRa network), we developed a simulation model to simulate and record energy consumption in a LoRa network based on an actual topology. Statistical energy consumption in the simulated network is compared with the actual consumption obtained from measurements of battery usage for intensified flow parameter registration frequencies for 20 devices over six months. The main goal of the experiments was to archive:

- The hardware validation time for transmitting measurements at an increased frequency for 10,000 devices must not exceed 15 minutes,
- The error of the estimated cost (battery, transmission) must not exceed 20%.

This paper is organized as follows: it begins with the state-of-the-art leak detection and measurement transmission technologies II, followed by detailed discussions on measurements III made on devices registering water consumption in the water supply network. Subsequent sections introduce the OMNET++ environment utilized for simulation IV, leading to thorough presentations of experimental procedures V and results and concluding with a discussion VI and a summary of the outcomes and their implications VII.

II. State of the Art

Significant advancements in leak detection technologies have spurred innovations in water management. These developments tackle critical issues like reducing water loss and maintaining infrastructure integrity. A comprehensive overview of these technologies from various review articles provides insights ranging from conventional techniques to state-of-the-art IoT-based systems.

[6] discusses an integrated approach to water leak detection using machine learning, focusing on data collected from District Metered Areas (DMA). The approach involves creating a digital twin of existing infrastructure and analyzing it using machine learning methods and the EPANET hydraulic simulator [1]–[5]. The authors use the method of intensifying the data collection based on the findings researched in this paper.

Article [7] presents a state-of-the-art review, highlighting hydrophones as a prime example of hydroacoustic water leak detection. [8] delves into smart building contexts, examining state-of-the-art approaches and suggesting future research directions. [9] and [10] comprehensively compare various leak detection technologies, including Listening Sticks, Vibration Sensors, Ground Penetrating Radars, Infrared Cameras, Hydrophones, Noise Loggers, Flow Sensors, Pressure Sensors, and Optical Fiber, providing insights into their efficacy and applicability.

Transitioning to leak detection through water consumption monitoring, [11] proposes a smart IoT-based system for urban housing complexes, utilizing ultrasonic sensors and Arduino for real-time data transmission. [12] introduces a sophisticated smart water measurement system with integrated leak detection algorithms, enabling real-time anomaly detection. [13] presents a Long Range (LoRa) IoT system for real-time water system monitoring, while [14] explores LoRaWAN technology for water leakage detection in housing complexes. [15] proposes a flow meter-based method utilizing LoRa for data transmission and cloud servers for real-time data retrieval.

Given the prevalence of IoT communication, particularly LoRa, in leak detection systems, understanding the energy consumption of such devices is essential. [16] proposes an energy consumption model based on LoRa specifications, facilitating sensor node energy consumption estimation. [17] presents a calculation model for optimizing LoRa modem parameters for reduced power consumption during packet transmission. [18] contributes an energy consumption model for LoRa and LoRaWAN, offering insights into energy-efficient communication strategies.

In conclusion, combining these studies emphasizes the wide range of leak detection technologies, from hydroacoustic methods to IoT-based systems. All of the mentioned papers clearly show the the significance of tackling energy consumption issues in IoT devices to promote sustainable water management practices. This problem will be discussed and researched in this paper.

III. Energy usage measurements

We measured the energy required to transmit measurements at an increased frequency to conduct measurements on actual smart water meters used in the water supply network. The process of conducting measurements consists of three stages, as listed below:

- Performing accurate, detailed, and meticulous measurements of electrical energy consumption in two devices identical to those used in the water supply network operation. Figure 1 presents an example of a single measurement. These measurements allow determining the energy charges consumed for transmitting an X-byte frame (Table I; $X \in \{60, 64\}$).
- Determining the deviations of the recorded energy consumption measurements based on 7279 samples (Figure 3) to determine the distribution and cumulative distribution function of the discrepancies in energy consumption values (Figures 3 and 4).
- Recording the number/quantity of transmitted frames separately for 20 available devices over six months to determine the actual energy consumption for each device (Figure 5).

More detailed descriptions of the presented graphs and results of the conducted measurements are provided in this paper's subsection V-A.

IV. Simulation model

We have implemented a model of measurement transmission in OMNeT++ by extending our previous model

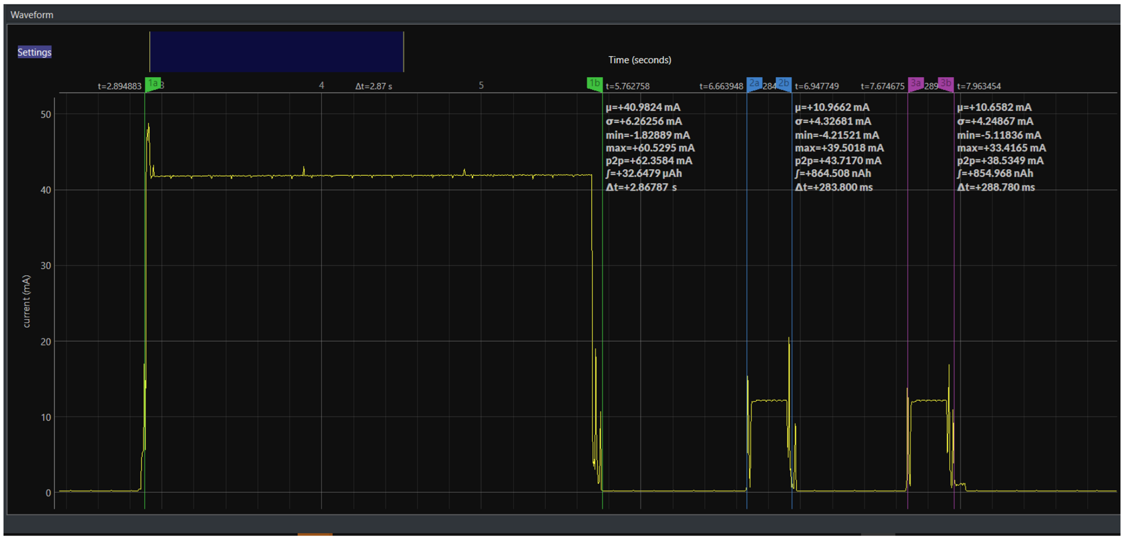

Fig. 1. An example of a registered individual measurement of energy consumption on one of the devices.

[19]. The model simulates the operation of a network consisting of selected locations of gateways and LoRaWAN devices deployed according to the real topology of the network provided by the water distribution network operator. The model simulates:

- Packet collisions between base stations and LoRa devices representing water meters (Figure 2). The topology of the real LoRa network was duplicated to obtain a network of 12,950 devices for simulation purposes,
- Packet delivery probability and energy utilization, including the Spreading Factor (SF) selection, based on transmission range and device sensitivity, based on statistics of packet delivery probability in the physical environment where the network operates,
- Reconfiguration of LoRa devices, enabling transmission of both regular and intensified frequencies for registering water consumption measurements,
- Energy consumption by battery-powered LoRa devices.

The formulas to calculate energy consumption are taken from [20] and were cited by many works, among others [16]–[18], [21]).

V. Experiments

The scenario involved the crucial task of conducting battery consumption measurements for intensified registration frequencies. This was carried out on a significant number of devices over a substantial period of time. Specifically, measurements were recorded from 20 devices over a span of 6 months, with each device representing a different frequency. The real architecture was used to model the test scenario, adding to the authenticity of the results. The comprehensive findings of these measurements, including auxiliary measurements, are detailed in subsection V-A.

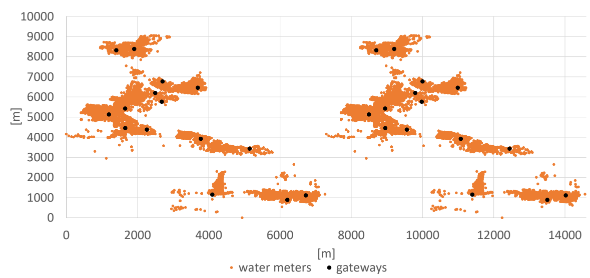

Fig. 2. The distribution of water meters.

The hardware validation of transmitting measurements at an increased frequency was performed precisely. This was done for the available topology containing 12,950 devices (Figure 2). In the initial approach, the execution time of a 6-month simulation was validated on a computer with the following specifications: AMD Ryzen 7 2700X Eight-Core 3.70 GHz processor, Installed RAM - 32.0 GB, 64-bit operating system. The execution times of 10 repetitions of this validation over a simulated period of 6 months (182 days) are within the range [34 minutes 49.17 seconds; 34 minutes 57.79 seconds], with an average value of 34 minutes 53.29 seconds. The following procedure was developed since achieving the experiment goals requires a hardware validation time of less than 15 minutes.

Hardware validation involves simulating energy consumption over one month, and the resulting energy consumption is multiplied by the number of 6 months corresponding to the measurements performed on real devices. This multiplication is done according to equation (2), which assumes introducing a random deviation in monthly energy consumption due to environmental factors. The execution times of 10 repetitions of this validation over a simulated period of 1 month (30 days) are within the range [5 minutes 43.33 seconds; 5 minutes 48.75 seconds], with an average value of 5 minutes 46.11 seconds. A comparison of the results: real measurements (V-A), 6-month simulation (V-B), and monthly extrapolated to six months (V-C); is concluded with a comparison presented in Figure 7.

A. Energy consumption recorded on real devices

In laboratory conditions, energy consumption measurements were conducted on two radio devices transmitting recorded water consumption measurements. Battery consumption measurements were performed for intensified registration frequencies using the APULSE-W radio extension modules [22], [23].

The total energy used as the payload required to send a frame, including the listen-after-talk functionality implemented after frame transmission to the recipient, was also recorded. The measurements are presented in the Table I:

TABLE I
THE REGISTERED ENERGY CONSUMPTION CONSISTS OF THE LOAD REQUIRED TO TRANSMIT ONE FRAME TO THE RECEIVING ANTENNA.

Spreading Factor	Load consumed for transmission and listening of 60 Bytes frame [mAs]	Load consumed for transmission and listening of 64 Bytes frame [mAs]
SF=12	123.18	130.85
SF=11	71.02	75.37
SF=10	34.37	36.35
SF=9	21.74	22.86
SF=8	14.43	15.08
SF=7	10.27	10.65

Another aspect considered during the data collection is determining the deviation of recorded energy consumption measurements. The battery usage in each electrical device varies due to environmental conditions in which the device operates - factors such as manufacturing inaccuracies (differences in the resistance of components used to build individual units of devices), temperature fluctuations, and humidity. The conducted research enabled the determination of the distribution of these deviations and, ultimately, the cumulative distribution functions used in the created simulation model as a generator of energy consumption variability among devices.

In the final step, measurements of the number of transmitted frames were recorded for 20 available devices over six months. These devices are installed in a real LoRa network in one of the Polish cities, functioning and operating at SF=12 over the past few years. The devices' affiliation with the operational network prevented detailed energy consumption measurements. The battery

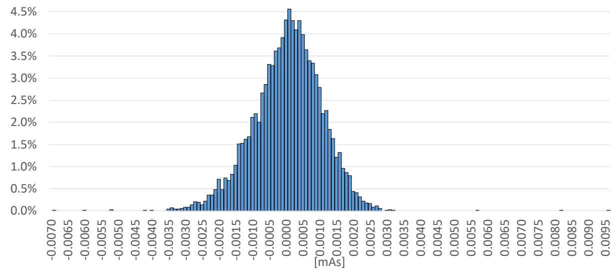

Fig. 3. The distribution of discrepancies in the registered electricity consumption values for 7279 samples

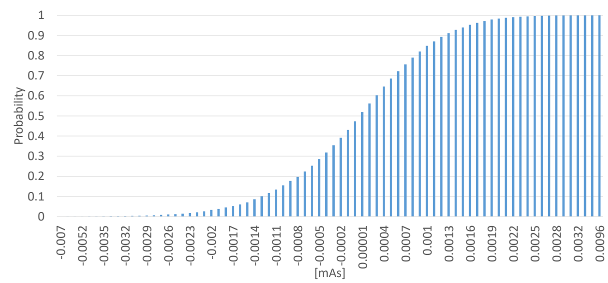

Fig. 4. The distribution function of discrepancies in electricity consumption values determined for 7279 samples.

status reported by the devices is in percentage form, posing another factor preventing the precise determination of energy consumption in terms of values expressed in mAs. Therefore, to conduct a comparative analysis, the energy consumption (BU-Battery Usage) in equation (1) was estimated individually for each of the 20 devices using the following formula:

$$BU = SP \times E64 + FP \times E60 \tag{1}$$

where:

- SP – the number of frames of regular size 64 B transmitted by the device over 6 months;
- FP=24 – the number of frames for intensified registration frequencies, with a size of 60 B, transmitted by the device every hour over 1 day during the conducted experiment;
- E64=130.85 – the energy consumed for transmitting one 64 B frame and subsequent listening after transmission;
- E60=123.18 – the energy consumed for transmitting one 60 B frame and subsequent listening after transmission.

Comparative analysis of energy consumption in the simulation model will be performed concerning the energy consumption calculations for the 20 devices using equation (1) and depicted in Figure 5, utilized for frame transmission and recorded for actual meters.

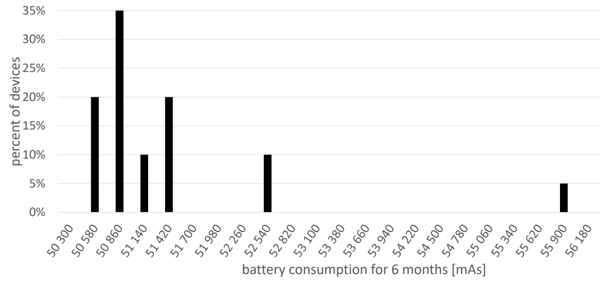

Fig. 5. Energy consumption histogram.

B. The energy consumption determined in the simulation model over a 6-month simulation period.

In the simulation, a test scenario was replicated for which statistics of energy consumption for real devices were previously obtained. Each of the end devices (marked on Figure 2 with an orange dot) sends a 64 B frame containing regular water consumption measurements twice a day over six months (182 days). Additionally, 24 frames of 60 B are sent containing the intensified frequency of registration measurements. For the comparative analysis of real results with simulated ones, all devices operating at SF=12 were selected on the simulation side, totalling 4463 out of 12950 devices. The comparison statistics are presented in Table II and Figure 6.

TABLE II
COMPARISON OF STATISTICS OBTAINED IN THE SIMULATION WITH STATISTICS GATHERED FROM MEASUREMENTS MADE ON REAL DEVICES.

Simulation	**min**	**max**	**avg**	**median**	**number of devices**
mAs	50590.78	53806.47	51176.2	51085.98	4463
Real data	**min**	**max**	**avg**	**median**	**number of devices**
mAs	50585.78	55950.64	51508.27	51109.18	20
Error percentage	0.01%	3.985%	0.649%	0.045%	

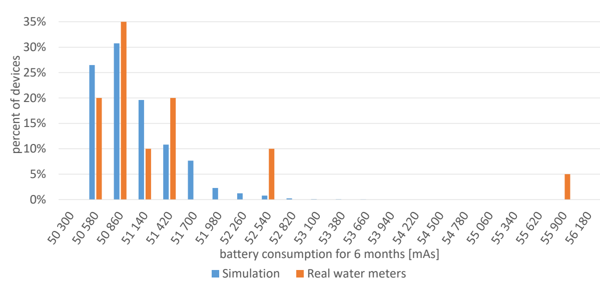

Fig. 6. Comparative histogram, juxtaposing the consumption recorded on real devices with the consumption determined in the simulation.

The obtained percentage errors of the mean and median calculated in the simulation of energy costs are relatively low, below one percent. Additionally, the maximum registered error, calculated between the maximum values, which is just under 4%, also does not exceed the experiment threshold set at 20%

C. The energy consumption determined in the simulation model conducted in a monthly simulation, multiplied by six, with deviations generated from a normal distribution taken into account.

In the simulation, a test scenario was replicated for which statistics of energy consumption for real devices were previously obtained. Each of the end devices (marked on Figure 2 with an orange dot) sends a 64 B frame containing regular water consumption measurements twice a day over 1 month (30 days). Additionally, 4 frames of 60 B are sent containing the intensified frequency of registration measurements. Then, the energy consumption collected for each device En[1m] in the monthly period [1m] was extended to 6 months [6m] using the following formula:

$$\mathrm{En}[6\mathrm{m}] = \sum_{i=1}^{6} \beta_i \cdot \mathrm{En}[1\mathrm{m}] \tag{2}$$

where β_i represents a random variable drawn from a normal distribution with a mean of 1 and a standard deviation of 0.01. For the comparative analysis of real results with simulated ones, all devices operating at SF=12 were selected on the simulation side, totalling 4463 out of 12950 devices. The comparison statistics are presented in Table III and Figure 7.

TABLE III
COMPARISON OF STATISTICS OBTAINED IN THE SIMULATION WITH STATISTICS GATHERED FROM MEASUREMENTS MADE ON REAL DEVICES.

Simulation 6 × 1 month	**min**	**max**	**avg**	**median**	**number of devices**
mAs	49408.63	55350.26	50650.86	50434.71	4463
Real data	**min**	**max**	**avg**	**median**	**number of devices**
mAs	50585.78	55950.64	51508.27	51109.18	20
Error percentage	2.38%	1.085%	1.693%	1.337%	

VI. DISCUSSION

The results obtained in experiments V-B and V-C and presented in figures 6, 7 and tables II and III prove that the assumed 20% error margin is more than satisfied with the result of 4% errors. The experiment V-C shows that the validation time for transmitting measurements not exceeding 15 minutes is also satisfied. A specific detail regarding the approximation of the length of the month is worth noting. We assumed that the month always has 30 days. However, in reality, and in the

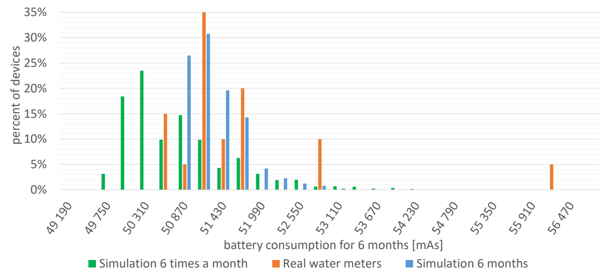

Fig. 7. Comparative histogram, juxtaposing the consumption recorded on real devices with the consumption determined in the 6-month simulation and discussed in the subsection V-C of the simulation of sixfold multiplied monthly consumption.

simulation, which covers six months, this period is 182 days. This relates to the measurement period, which occurred from December 26, 2022, to June 26, 2023. In our methodology, where six months equals six times a 30-day month, we obtain 180 days. As a result of this approximation, there is a discrepancy of 2 days, which affects some underestimation of energy consumption. This underestimation is visible both in Table III and Figure 7. However, it is so small that it does not hinder achieving the assumed results.

VII. Conclusions

The percentage errors obtained from the simulation of energy costs, conducted using the method of multiple replications of monthly consumption, turned out to be generally low—usually below two percent. Even the largest recorded error, which was slightly over 2.4%, still remains below the experiment threshold of 20%. The performed experiments and simulations prove that the assumed reconfiguration approach to leak detection is valid energetically and can be safely used in an operated environment without the risk of depleting the battery in the device.

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