Reliability Evaluation Framework for Centralized Agricultural Internet of Things (Agri-IoT)

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***Abstract*—This paper presents a holistic reliability evaluation framework for Agri-IoT based on real-world testbed and mathematical modeling of network failure prediction. A testbed has been designed, implemented, and deployed in the real-world in the experimental farm at Saint-Louis/Senegal as a representative area of Sahel conditions. Data collected has been used for real-world reliability analysis and to feed mathematical modeling of network reliability based on energy and environmental conditions data with Kaplan Meier and Nelson Aalen estimators. Key factors affecting the network's lifespan, such as network coverage and density, are explored, along with a comprehensive evaluation of energy consumption to understand node discharge rates impact. The survival analysis, employing Kaplan-Meier and Nelson-Aalen estimators, establishes network stability and the probability of node survival over time. The findings contribute to the understanding of Agri-IoT reliability in a real-world Sahel environment, offering practical insights for system optimization and environmental challenge mitigation in real-world deployments.**

Keywords*—*Energy; IoT; reliability; real-world testbed; optimization; Agri-IoT

I. Introduction

IoT is increasingly adopted in agriculture (Agri-IoT) to improve management methods, performance, and productivity of agricultural farms[1]. In particular, Agri-IoT provides tools for input management, automatic irrigation management, remote control of agricultural fields, yield forecasting, and input prediction.

Deployed Agri-IoT systems are very common in many European and American countries (North and South) and Asia [2], [3]. In developing countries, especially in Africa, more particularly in the Sahelian zone, the deployment of such systems is needed for food security purposes [4]. However, to reproduce the same results of Agri-IoT as elsewhere, reassessments of the reliability of IoT are needed in the specific environment of the Sahel.

Indeed, the Sahel has many white areas without a network, the sector power is not ensured in agricultural areas, and a dry, dusty environment is sometimes rainy which has an impact on the reliability of the electronic devices, the sensors, and the maintenance in the event of a fault is not always possible.

Limited power resources in the IoT network devices, can cause failures due to internal instability or external disturbances. Identifying vulnerabilities and using reliability analysis [5] and fault diagnosis techniques [6] can enhance system stability and resilience.

This reliability assessment is necessary for good network lifespan and data sensor reliability knowing food security issues if an Agri-IoT device fails. More importantly, most of the proposed research is theoretical or in lab tests.

The reliability of IoT systems can be assessed using different metrics such as power consumption and its impact on the network lifetime, network lifespan, sensors data trustworthiness (error rate), network availability, and environmental impact.

This paper aims to provide a holistic reliability analysis framework on a Sahel area based on real-world data collection from the experimental farm and mathematical modeling of network failure prediction.

The main contributions of this paper are: begin

- Design, implement, and deploy real-world Agri-IoT deployment in the experimental farm at Gaston Berger University in Saint-Louis (Senegal).
- Collect real data for reliability evaluation.
- Experiment with different environmental constraints in IoT operation.
- Modeling mathematically the network reliability based on energy and environmental conditions data with Kaplan Meier and Nelson Aalen estimators.

This paper is organized as follows: Section I gives a brief background on IoT and the problem statements. Section II presents a related work on IoT power evaluation and modelization strategies. Section III looked at reliability assessment tools, especially the mathematical techniques on lifetime evaluation. Section IV presents an experimentation of Agri-IoT system deployment and, in that same way, presents the results of our power evaluation and survival analysis for a centralized Agri-IoT Network in real-life deployment. Section V presents the evaluation, analysis, and discussion and Section VI, finally presents the Conclusion.

II. Related Work

Deploying Agri-IoT systems is challenging in terms of hardware, network architecture density (topology and density), type of power supply, and environment. Battery drain is a parameter of reliability related to network lifespan.

Regarding that, several research [7], [8], [9] evaluated power consumption in different LPWAN technologies. In [7], an analytical approach is proposed to assess individual sensor node power consumption, providing insights for optimizing sensor node design with a focus on energy autonomy. In [8], the authors presented an energy model for NB-IoT, considering power-saving modes and discontinuous reception mechanisms. In [9], the authors compared the power consumption impact of SF7 and SF12 and their respective applications in a LoRaWAN-based IoT system.

In [10], the authors evaluated the energy usage of LPWAN wireless technologies (LoRaWAN, DASH7, Sigfox, and NB-IoT) to determine battery lifetimes. They found that actual battery lives can differ from ideal scenarios and provide insights on selecting appropriate technologies and battery capacity to improve IoT applications.

Banti et al. [11] identified challenges in designing an energy-efficient LoRaWAN communication protocol. Their findings guide research toward a GreenLoRaWAN protocol that is robust, scalable, and energy efficient. The authors emphasized the need for independent power sources for IoT nodes, as studies often overlook network lifetime constraints by assuming gateways are connected to the grid.

In [12], the authors proposed a node lifetime estimation approach applicable to both static and dynamic loads, investigating the influence of parameters such as self-discharge, discharge rate, age, and temperature on Alkaline and Nickel-Metal-Hydride (NiMH) batteries.

Based on reviews, many energy models simplify analysis for manageability, potentially overlooking real-world complexities and leading to inaccuracies in predictions. Some studies assume grid power for gateways, but in the Sahel, where reliable power is rare, overlooking network lifetime constraints in IoT system design can affect practicality. Dynamic factors impacting energy consumption over time, like environmental conditions and hardware variations, may not align with assumed ideal conditions. In this study, battery consumption estimation relies on node voltage measurement and payload tests, using real-world testbed data under actual conditions in the Sahel. This approach is based on modeling mathematically of network reliability on Kaplan Meier and Nelson Aalen estimators.

III. Background Probabilistic IoT Reliability Prediction

In statistics, survival analysis [13], [14], [15] is for analyzing life expectation and lifetime based on an event occurring such as the death or failure of a mechanism in a system. This topic is also called reliability analysis.

Reliability analysis determines the probability of a population that survives past a specific time, the rate of the population that survived or died at any given time, or how an event impacts the population's lifetime. In the Agri-IoT context, it enables modeling network nodes' survival by predicting it.

In mechanical systems, determining the cause of death or failure of a component is required. In survival analysis, this is considered an "event" and involves time-to-event data. Time is defined as the beginning or end of an observation period. Censored observation focuses on an individual's survival time, even if the information is incomplete or imprecise.

In 1958, Kaplan and Meier introduced the Kaplan-Meier estimator [15], which has since become widely used for estimating and summarizing survival curves. This approach is the most common way to estimate and summarize survival curves for being a highly cited statistic paper. The survival function, $S(t)$, gives the probability that a device or a mechanism survives after a specific time t. The non-parametric estimator functions will be used to analyze the survival data from field experiments and to evaluate two related probability paradigms.

1) The survival probability using the Kaplan-Meier estimator (KME).
2) The Hazard rate denoted $H(t)$ using the Nelson-Aalon estimator(NAE) [16], [17].

The Kaplan-Meier distribution estimates the probability of the event of interest not happening at time t. At the same time, the NAE Hazard probability gives a visualization of the event occurring on the subject within an interval of time.

$S(t)$ is the probability that a given population member has a lifetime greater than t. For a sample of size N in this population, the time until each death of the members of population N is represented as follows:

$$t_1 \leq t_2 \leq t_3 \leq \cdots \leq t_N. \tag{1}$$

The KME function $S(t)$ is express as following :

$$\hat{S}(t) = \prod_{t_i < t} \frac{n_i - d_i}{n_i} \tag{2}$$

The NAE function $H(t)$ is expressed as following :

$$\hat{H}(t) = \sum_{t_i < t} \frac{d_i}{n_i} \tag{3}$$

where n_i is the number of subjects "at risk" just before time t_i, and d_i is the number of deaths at time t_i. The KME is not used to estimate the cumulative hazard, plus the NAE hazard function has a better small-sample performance than the KME [18] function. An empirical comparison of the two solutions has been broadly studied by Colosimo *et al.*[19].

The IoT systems are hardware and software deployed to monitor specific parameters. In some cases, human intervention can be a requirement for provisioning and maintenance reasons or as an oracle. Then, the reliability of IoT systems can be assessed in three ways:

- Hardware reliability;
- Software or operation reliability;
- External reliability.

Hardware reliability is the failure rate of the hardware component system. It has been assessed in many ways in the literature [20], [6], [21]. The software reliability involves protocols, logistic support, and the system's operationality. External reliability is correlated to the maintenance of the system or human intervention and the impact of outside parameters in the system. The system reliability can be expressed as follows:

$$R_{system} = \frac{R_{gateway}(\sum(R_{mn}) + R_{software} + R_{human}}{3}) \quad (4)$$

Where $R_{gateway}$ is the reliability of the gateway, which centralizes the network and all the system depends on. R_{mn} is the reliability of the network participant, the member nodes. $R_{software}$ is the software reliability of participants. R_{human} is the human reliability.

In this study, the $R_{software}$ is not considered, same for the R_{human} on the system reliability. Consequently, in this work, several evaluation and prediction results are achieved. This is based on an IoT system's energy consumption behavior during its operation with on-field collected data from the testbed: Node Lifespan; Network lifespan; Impact of activity level on the system; Network density, and participants' death over time for maintenance and human intervention time prediction.

The next section presents the simulation part and how the reliability analysis is executed and correlated to the on-field implemented system's observations.

IV. Contributions: Experimentations and Modeling

A. Context and Test Bed Architecture Design

The test bed site is located at Gaston Berger University's (UGB) experimental farm in northern Senegal, specifically in Saint-Louis (see Fig. 1).

This site has been set up for practical training and research activities focusing on animal and crop production techniques. It covers an area of 26 ha and is irrigated with a drip irrigation system and two submerged pumps in the Djeuss River, Senegal River, with flow rates of 160 and 196 m^3 $per\ hour$. It has a storage and recovery basin measuring 15 meters by 10 meters by 8 meters, a filtering station with sand tanks, multiple control heads, distribution ramps, and conduits supporting the drip emitters. This infrastructure enables a controlled water supply for agricultural experimentation on the farm.

The Agi-IoT test bed installation was done between August and September 2021. Meteorological conditions during this period are characterized by the rainy season, sunny days, and daytime temperatures ranging from 28°C to 33°C during the day and 24°C and 27°C during the night, while relative humidity levels consistently exceed 70% based on on-field measurements and from National Agency for Civil Aviation and Meteorology [22], [23].

The architecture of the test bed consists of one Gateway and four sensor nodes deployed into an okra exploitation. The system provides sensing and analyzing functions (Fig. 2). The aim is to monitor environmental parameters (temperature and soil humidity) and infer the need for irrigation actioning.

The sensing part consists of a digital temperature and humidity sensor, a controller, and an energy source from a finite battery. Moreover, the sensor used in this work incorporates an integrated temperature sensor to gauge the soil's temperature accurately. The collected data is transmitted to the gateway using BLE technology. Bluetooth Low Energy (BLE) technology is known for providing reliable communication over relatively short distances.

The IoT's Cisco Reference Model defines the gateway as a Level 3 and 4 component that acts as a hub for receiving all data collected from sensor nodes [24]. The gateway processes the packets to extract relevant information, generates customized irrigation plans for each sensor node, and transmits refined data to a database. This makes it accessible to various applications and services for the end-users.

B. Hardware Design, Implementation, and Deployment

The IoT Network test bed consists of a gateway and sensor nodes. These components encompass a controlling board, a communication module (integrated into the controller), sensors, and the power supply. The nodes, including gateway and sensor nodes, are implemented using the Raspberry Pi 3B+ as the main electronic board (Fig. 3). Nodes use BLE 4.2 for network, power bank, solar panels, soil sensors for data collection, UM25C Meter for energy monitoring, and an 8-inch display, keyboard, and mouse for RPIs.

The Cypress CYW43455 Bluetooth Chipset and BLE 4.2 are used for the Network Communication interface between the nodes. The BLE 4.2 module is built in the RPi 3B+ for communication among the Network's nodes. In this context, the Gateway is the master, and simple nodes are slaves.

A solar power bank with a battery capacity of $36,000mAh$ is connected to the nodes (gateway and simple node). The power bank has a USB output for the devices' power supply. A 24 by 6 cells poly-crystalline silicon solar panel is coupled to the gateway battery. The criteria for choosing the battery model were durability, robustness to the outdoor conditions, and water resistance in accordance with the deployment area conditions.

The UM25C Meter [25] is a device that measures electrical quantities, such as voltage, current, resistance, capacitance, and temperature. It has a large display screen and can be connected to a computer or smartphone via Bluetooth. It is connected to the RPI via USB 2.0. It is used to monitor our field ambient temperature and nodes' electrical metrics quantities.

A WiFi connection was also used to establish Internet connectivity for the gateway. However, this connection was deliberately not kept continuously active in order to reduce power consumption. Instead, the connection was established twice daily to transmit data to the database and was subsequently disconnected. The data acquired from the sensor node was stored using Google Sheets as the storage platform.

In the experimental farm, five(5) nodes have been deployed on the field in a star topology to collect data. The Gateway is in the center with a solar panel and enclosure at $1m$ up to the ground (Fig. 4). It coordinates communication and has two network interfaces: One with BLE to communicate with the sensor nodes in WI-FI to be connected to the Internet. The four(4) Sensor nodes are in the perimeter of a chosen area to collect temperature and humidity and send data to the gateway (Fig. 5).

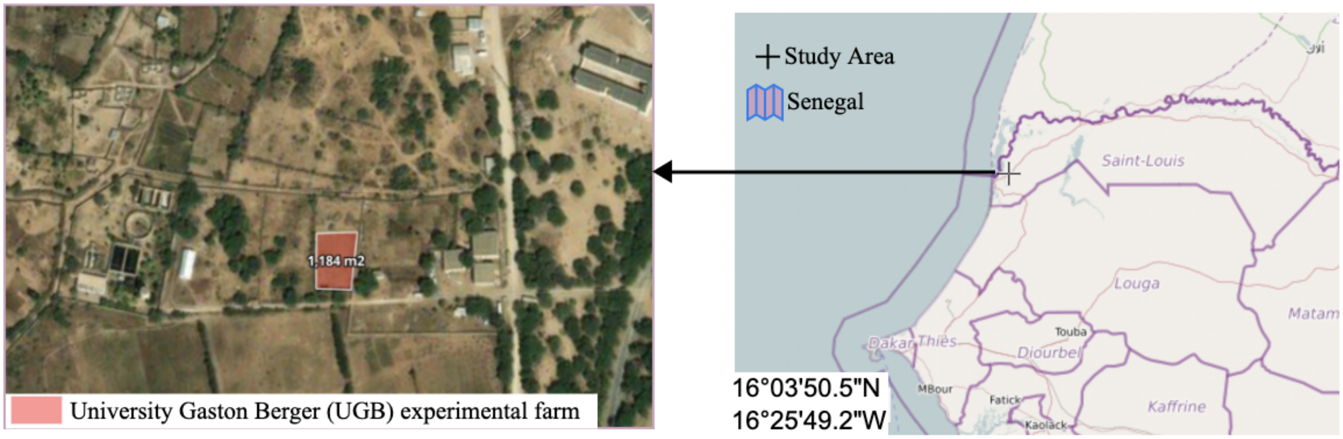

Fig. 1. Location of the outdoor experimental farm of UGB located at UGB, Saint-Louis, Senegal.

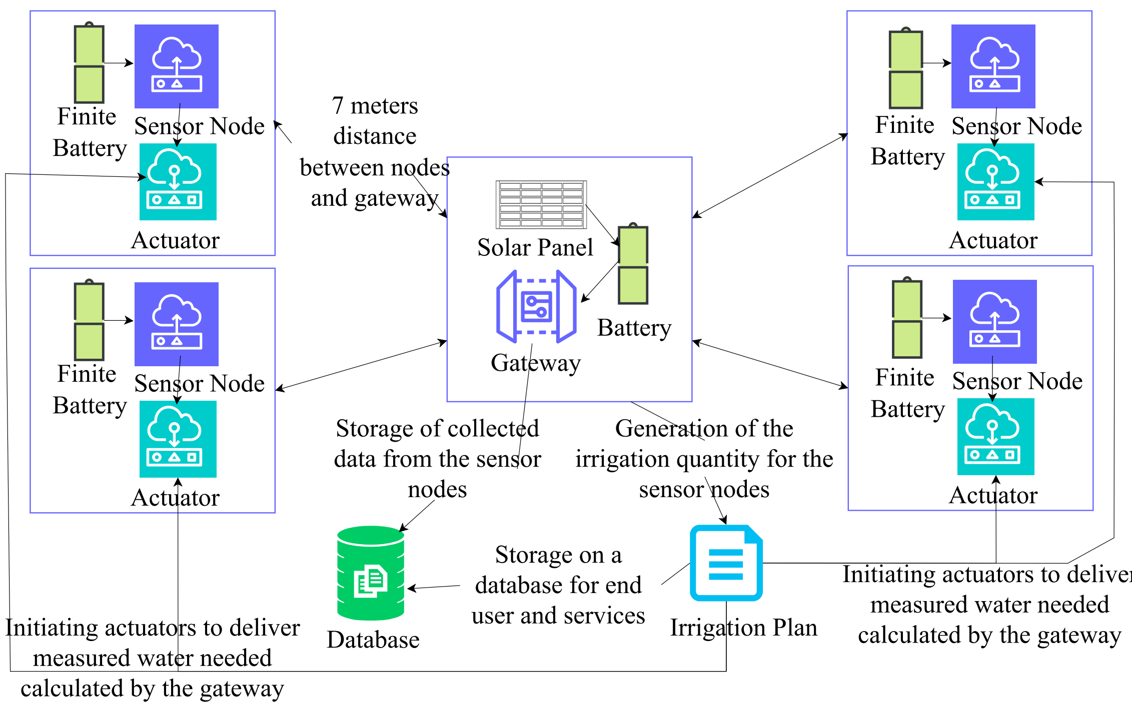

Fig. 2. Agri-IoT deployment architecture diagram.

V. Evaluation, Analysis, and Discussion

A. Reliability Evaluation Results

This section presents the main results and learned lessons from the testbed related to reliability. The on-field testbed deployment further highlights the importance of designing and simulating scenarios with detailed realism, ensuring accurate and representative results regarding the hostile Sahel environment.

Table I presents the status of various parameters that impact energy consumption in a node. The gateway plays the role of a server. Several experiments were realized to observe the system's activity level and running tasks. The running software is implemented in Python with the BLE communication protocol.

TABLE I. The Gateway Internal Activities

	Status
Server	Gateway
Platform RPI	3B+
Running Tasks	156
User	Python3.7
Memory	873.3/1000
Network	BLE
Display	None

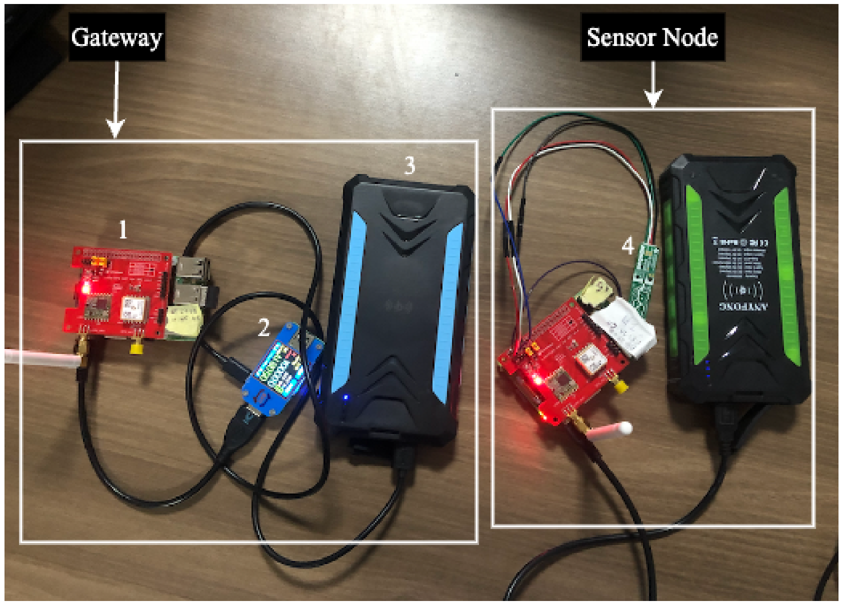

Fig. 3. Gateway and sensor basic components lab integration and testing. (1) Raspberry Pi 3B+ with built-in BLE 4.2, (2) UM25C Meter, (3) Battery power bank, (4) STEMMA soil moisture and temperature sensor.

Fig. 4. (1) Gateway's initial deployment: Solar power bank responsible for energy supply. This setup lacks protection against the sun, significantly impacting board operations due to enforced sleep mode during high temperatures within the enclosure. (2) Enclosed gateway setup featuring an RPI, a body with a fan, and a UM256C meter for energy behavior monitoring during node activities.

1) Network Coverage: Considering a node as dead once it stops operating. The operation time of the field experiment is 72 hours testing period. The maximum communication distance for the BLE connection was about 11 meters in line of sight. The BLE range of the Raspberry Pi is limited without an external antenna. For any distance beyond 7 to 10 meters or another use case that involves reasonable communication distance, adding an antenna might suit best.

2) Impact of Density in Network Lifespan: It is very important to have a global view of the impact of network density on the network to provide energy-saving and optimized operation. Fig. 6(2) shows how the network size impacts the network's longevity. The experiment was run five times and plotted the mean values of the network lifetime against the network size. Then, observations were made based on the activity and the node's role(sensor node or gateway) to obtain a concise evaluation of its lifespan. Node density was set to 5, 10, 15, 20, and 25 participant nodes with one gateway in a centralized architecture.

Two important facts were deducted from the evaluation of Network Density over Node Lifetime. The red curve represents the lifespan of 'at-risk' nodes over time, which are nodes that are more prone to failure. On the other hand, the blue curve illustrates the lifespan of 'died nodes' over time, which are

Fig. 5. Field deployment of the testbed IoT network, emphasizing a sensor node, its energy source.

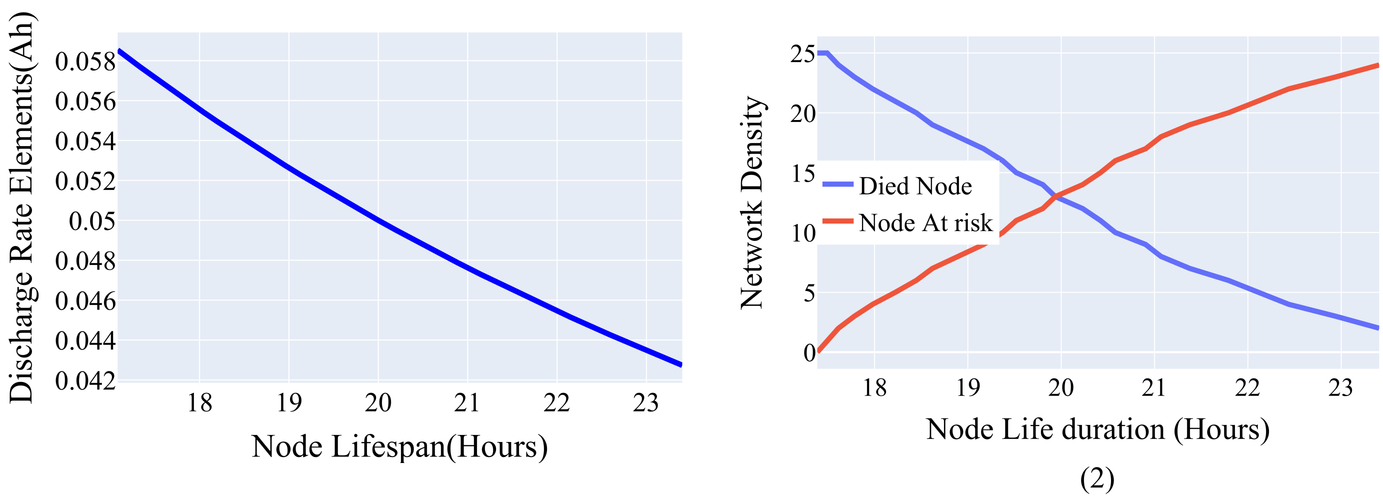

Fig. 6. (1) Node discharge rate effect on lifetime. (2) Influence of network density on node lifetime: The red curve represents the lifespan of 'at-risk' nodes over time, while the blue curve illustrates the lifespan of 'died nodes' over time.

the nodes that have experienced failure events. This analysis provides a valuable understanding of the network's stability, reliability, and overall performance.

3) Impact of energy in network lifespan and reliability : The reliability evaluation encompassed a comprehensive assessment of discharge rate impact and inclusion of factors such as transmission, reception, idling periods, duty cycling, data, and the node's designated tasks. This comprehensive evaluation allowed us to estimate the node's lifespan, as depicted in Fig. 6(1). Thus, the figure illustrates that with a discharge rate of up to $0.054Ah$, the projected node lifetime could extend beyond $25hours$. As demonstrated through indoor testing, this prolonged node lifespan translates to approximately $22hours$ of sustained gateway operation connected to a finite power source of $36000mA$. This is a way to predict network failure and anticipate self-healing methods to minimize network failures.

This observation highlights the critical role of gateway efficiency and longevity in overall network performance by deepening our understanding of the correlation between node discharge rates and lifespan.

The battery capacity can be expressed as a function of the time it takes to charge fully (see Eq. 5):

$$C_n = \frac{A(chargingordischarging)}{Capacity} \tag{5}$$

- Where C_n or C/n, expressed in ampere-hours (Ah), measures the speed of charging or discharging the battery, and the n stands for the number of hours the discharging takes.

- A is the electrical current.
- The capacity is the amount of current held in the battery; it is different from the power.

To find out this quantity of energy (which is expressed in Watt-hours - Wh), the capacity must be multiplied by the voltage of the battery:

$$Ah \times V = Wh \tag{6}$$

The current (A) can fluctuate depending on the charging style or type, and different parameters like heat, dust, wear-out, and activity load can affect battery charging and discharge speed. Hence, All battery parameters are affected by the battery charging and recharging cycle. The current can be expressed in Eq. 7.

$$A = \frac{capacity}{H} \tag{7}$$

From Eq. 5 and 7,the lifetime is deduce as follows:

$$H = \frac{1}{Cn} \tag{8}$$

4) Mitigating environmental-related issues:: Nodes went to sleep after sending measurements, making data collection impossible. The gateway received data only the next morning. No protection against the sun heat in Fig. 3 affected performance. High temperatures triggered sleep mode, posing a deployment challenge.

The temperature was 46°C in the field. High temperature triggers sleep mode and reduces charging efficiency. More energy is required for proper recharging. High temperatures slow down charging. Our batteries come with a less-efficient amorphous solar panel.

The power bank's operational temperature range spans from 0° to 45°, with a cautionary recommendation not to exceed 60°. During the deployment phase, high temperature consequently impacted the battery's performance. This explains the occurrence of node failures in the field due to the influence of heat.

Furthermore, an important observation concerning the new gateway's design. It featured a wider solar panel (refer to Fig. 4(1)) that served as a protection against sun heat, effectively preventing node overheating. The system's efficiency is improved by adjusting the battery supply and raising the solar panel. This created better airflow, resulting in a cooling effect. The change was needed because inconsistent data reception was experienced from the end nodes. Initially, attempts were made to enhance the gateway's power supply, but upon further investigation, it was determined to be unnecessary. As a result, the gateway functions optimally in cooler environments with average temperatures ranging from 25° to 30°.

B. Network Survival Analysis

A thorough survival analysis was performed to explore the correlation between network density and the lifespan of the network. This investigation enabled us to make accurate predictions about the network's behavior in response to a 10% increase or decrease in workload or network size. Fig. 7 is a visual representation of our findings. Network expansion impacts payload and data processing at the gateway. This data was analyzed using Python 3.7 and the Lifelines library, with the Kaplan Meier distribution fitter method - a widely accepted approach.

During the investigation, time-to-event data was analyzed using two non-parametric survival function estimator techniques: the Kaplan-Meier Estimator (KME) and the Nelson-Aalen Estimator (NAE) to consecutively estimate $S(t)$ and $H(t)$.

The KME was used to estimate the probability of nodes surviving over time. This estimator is represented as a step function, which shows discontinuities at the occurrence of events. Initially, the probability of a node's survival remains at 100%, indicating network stability during the first 18 hours, between the intervals of t_0 and t_{18}, as shown in Fig. 8(2). This interval represents a period of network stability. Additionally, the median survival time indicates that nodes can operate reliably for at least 22 hours, providing valuable information for proactive network maintenance planning.

Due to the limited amount of data, the Kaplan-Meier estimate was not applicable. Consequently, the Nelson-Aalen estimator, more accurate for a limited amount of data, was utilized to assess the cumulative hazard rate. This involves calculating the total number of node failures during specific time intervals to determine the cumulative count. Refer to Fig. 8(2) for the results.

Our analysis found no "early node mortality." Our metric for assessing node performance was battery depletion. Failures became more prevalent as the network aged, suggesting that nodes performed well initially but gradually became less reliable over time.

In the scope of the study, the metric related to battery depletion in the network component was closely monitored. It is important to note that no subjects were censored in this investigation. This can be visualized in Fig. 8(1) and 8(2).

VI. Conclusion

This paper evaluates the reliability of an Agri-IoT system deployed in the challenging Sahel environment. Accurately simulated on-field scenarios provided valuable insights. Monitoring the gateway's internal activities revealed critical data impacting node energy consumption. Network coverage and density emerged as key factors affecting the network's lifespan. The comprehensive evaluation of energy consumption provided crucial insights into node discharge rates and their correlation with lifespan, aiding in predicting and mitigating network failures.

The study addressed environmental challenges, highlighting the impact of high temperatures on node performance and the successful design adaptation of the gateway for improved efficiency in cooler environments.

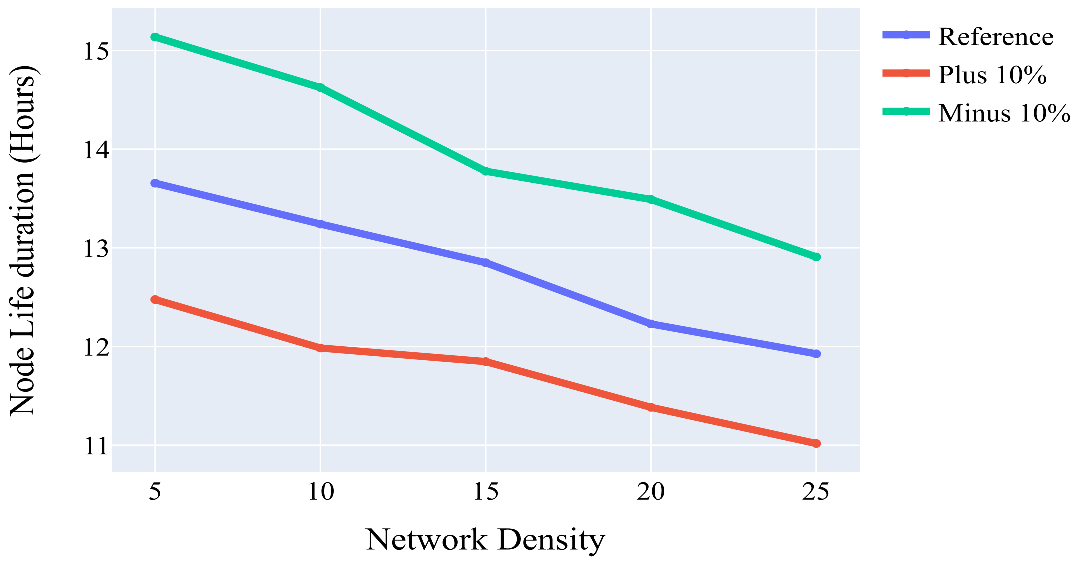

Fig. 7. Network density and duty-cycling impact on the network lifetime.

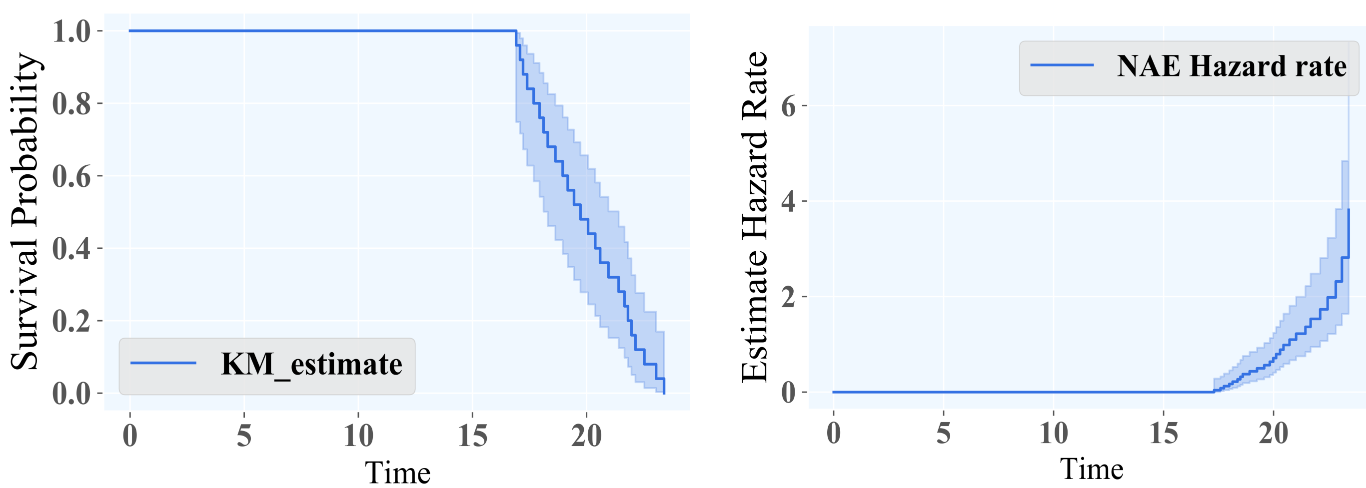

Fig. 8. (1) Kaplan Meier estimate survival function, $S(t)$ described in Eq. 2. It is the probability that a node survives from the time it is switched on to a specific future time t. (2) Nelson-Aalen Estimator cumulative hazard rate. It is denoted $H(t)$ described in Eq. 3. It represents the probability a node, in our case, who is under observation at a time t, has died at that time.

Survival analysis, utilizing Kaplan-Meier and Nelson-Aalen estimators, established network stability and the probability of node survival over time. The absence of ”early node mortality” indicated initial reliability, gradually decreasing over time.

These results enabled to better understanding of Agri-IoT reliability in typical Sahel Environment, providing practical insights for optimizing system performance and addressing environmental challenges in real-world deployments.

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