Energy-efficient Mobile Sensor Data Offloading via WiFi using LoRa-based Connectivity Estimations

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Abstract: Animal monitoring in natural habitats provides significant insights into the animals' behavior, interactions, health, or external influences. However, the sizes of monitoring devices attachable to animals strongly depends on the animals' sizes, and thus the range of possible sensors including batteries is severely limited. Gathered data can be offloaded from monitoring devices to data sinks in a wireless sensor network using available radio access technologies, but this process also needs to be as energy-efficient as possible. This paper presents an approach to combine the benefits of high-throughput WiFi and robust low-power LoRa communication for energy-efficient data offloading. WiFi is only used when connectivity between mobile devices and data sinks is available, which is determined by LoRa-based distance estimations without the need for additional GPS sensors. A prototypical implementation on low-end commodity-off-the-shelf hardware is used to evaluate the proposed approach in a German mixed forest using a simple path loss model for distance estimation. The system provides an offloading success rate of 87%, which is similar to that of a GPS-based approach, but with around 37% less power consumption.

Keywords: LoRa; Distance Estimation; Multi-RAT Wireless Sensor Networks; Data Offloading

1 Introduction

The monitoring of animals in their natural habitats provides valuable scientific insights for researchers. This includes animal health, territorial behavior, interactions with other animals or other species, and external influences like humans and human-made infrastructure [Xu16, Wy18, As19, KA20]. Monitoring can be performed using a range of sensors and technologies attached to animals, but these are typically strictly limited by weight and size, depending on the monitored animals. This is especially true for the battery size, which stands in contrast to a desired long-term performance of the monitoring sensors, and may also prohibit the use of GPS sensors [Go19].

Transmitting the monitored data from sensor nodes to data sinks is similarly demanding, and a considerate amount of the available battery power is usually consumed for the transmission [SIB12]. With limited storage size, data must be collected before it is overwrit-

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ten and lost. However, different *Radio Access Technologies* (RAT) or data collection approaches have various advantages and drawbacks. Cellular services can be used, but may not be available within the animal habitat and are usually too expensive in terms of hardware, provider costs, power consumption, and weight. Long-range low-power communications for *Low-Power Wide Area Networks* (LPWANs) like LoRa require significantly less power, weight, and have long transmission ranges, but can only send very small datasets due to their limited bandwidth.

Furthermore, data collection using Unmanned Aerial Vehicles (UAVs) is a recent and promising approach, but this would require the sensor node to be available at any time, which also increases power consumption [Xu16]. In addition, motorized UAVs yield severe audible disturbances in the animal habitat, negatively and artificially influencing animal behavior [Rü16]. A common approach is to integrate mobile nodes into a larger *Wireless Sensor Network* (WSN). If several communication technologies are available, they are also referred to as *multi-RAT WSNs*. Whenever a mobile node, e.g., attached to an animal, moves within the communication range of a static data sink, the mobile node attempts to offload its data. Such opportunistic offloading approaches are usually performed over high-throughput RATs like WiFi or Bluetooth. Nevertheless, regularly probing for the availability of a data sink increases power consumption, e.g., approximately $180\,\mu\mathrm{Ah}$ for a single scan for available WiFi networks [Hu15].

In this paper, we overcome these challenges by combining the benefits of high-throughput WiFi and robust low-power LoRa communication in a multi-RAT WSN. Our approach predicts the WiFi connectivity between mobile sensor nodes and static data sinks based on LoRa distance estimations, without the need for additional GPS sensors on mobile nodes or time synchronization within the network. WiFi is only activated when a node determines a possible connection to a data sink, to further increase the node's energy efficiency. The approach is implemented in a prototype system based on widely available low-cost low-end hardware, and evaluated in a German mixed forest. We achieve an offloading success rate of 87%, which is similar to that of a GPS-based system, but with up to 37% lower power consumption for the communication and data offloading process.

To summarize, this paper makes the following contributions:

- We provide a design for a lightweight data offloading approach based on LoRa and WiFi communication that is independent of power-hungry GPS-based localization on mobile nodes and time synchronization in the WSN.
- We present the implementation of our prototype system using commodity-off-the-shelf low-end hardware and a simple path loss model for LoRa-based connectivity estimations.
- In a proof-of-concept evaluation, we highlight the applicability and benefits of our approach for data offloading in mobile multi-RAT WSNs.

The rest of this paper is structured as follows. Section 2 discusses related work for data offloading as well as localization and distance estimation in WSNs. Our protocol design is presented in Section 3, followed by the prototypical system implementation in Section 4. This prototype is then evaluated in a forest environment in Section 5 and compared to a GPS-based approach. Section 6 concludes the paper and gives an outlook on future work.

2 Related Work

Within multi-RAT applications, data offloading describes the general approach of redirecting traffic flows over a more suitable communication medium, i.e., a medium that provides higher throughput, increased reliability, reduced energy consumption, or better cost-efficiency. Typically, data offloading is studied in the field of cellular networks. Here, the common idea is to relieve the usually more expensive and more occupied cellular medium (e.g., LTE or 5G) by using other available networks such as an available *Wireless Local Area Network* (WLAN) provided by public WiFi hotspots [Hu15, Zh18], WiFi or Bluetooth using ad hoc communication for localized communication exchange [Ri14], or even access points of power line carriers [Wu17]. For WSN or IoT applications with small and infrequent data generation, offloading is also possible using long-range low-power communication technologies for LPWANs like SigFox and LoRa [Le19].

A typical research problem in the field of multi-RAT applications is the definition of conditions, which trigger the switch between communication technologies. This switch may be initiated by the user or the mobile device, which provides an individual choice of the used technology. However, this decision may be not optimal due to the lack of global knowledge on that device. In contrast, if the operator or a base station decides to switch based on a broader knowledge, the decision is often better for the overall network, but not necessarily for the individual user [Yu17]. Similar to handover procedures in cellular networks, the decision for switching between RATs can be based simply on the availability of another network, measured or estimated signal properties like *Received Signal Strength Indicator* (RSSI) and *Signal-to-Noise Ratio* (SNR), the throughput of the networks, or the distance between a mobile device and the access point [Wu17, Zh18, Le19].

In energy-constrained applications like mobile WSNs, constantly probing or listening for available network access points is not feasible due to the significant power consumption [Hu15, SIB12]. Mobile nodes can match their position to determine if they are in range of access points. Similarly, localization of mobile sensor nodes by *global navigation satellite systems* (GNSS) like GPS or Galileo may also be unavailable due to high energy consumption and comparably expensive hardware. Therefore, a considerable amount of research is conducted in GNSS-less localization of mobile nodes in WSNs. Triangulation is one of the most widespread approaches, where multiple base stations with known locations use incoming signals of a mobile node to estimate its position. By comparing differences in metrics like time of arrival, time of flight, RSSI, or SNR between base stations, this method achieves good results. However, triangulation requires a highly accurate

time synchronization within the WSN and several—i.e., three or better more– base stations to function properly and , which may be infeasible in certain scenarios [LCL18, DPT19]. Another well-known approach is fingerprinting the area of operation. Basically, a map of the area is created that contains important information like RSSI or SNR. Mobile nodes then compare their measurements of received signals with this map to obtain their location [AGM09, Ha19]. Obviously, this requires a detailed fingerprint map for accurate localization. The creation of such a map requires a tremendous effort — or even an impossible effort for large or inaccessible operation areas — before being able to deploy the WSN.

However, acquiring the exact position is often not necessary for data offloading, but estimating the distance to a base station is sufficient in many scenarios [Xu10]. Recent simulations have shown that localization over LoRa is possible using the time of flight or the RSSI values from received LoRa packets to estimate distances between base stations [LCL18, LSH19]. These distances themselves are obtained using a *path loss model* that matches RSSI values to a certain distance [J 17, KT17, Wi17, Li18, Wu20]. A commonly used model is the *Log-Distance Model* that uses a logarithmic decrease of the RSSI with the distance. More sophisticated variants, like the *Log-Normal Shadowing Model*, include non-deterministic characteristics of real-world signal propagation like occasional obstruction, reflection, or interference [Xu10, Wu20]. The drawback of such models is that model parameters are highly scenario-specific and may change over the course of a year [Wu20]. Thus, they are usually derived from empirical data within the corresponding environment for a certain model, for example, as performed for the *Log-Normal Shadowing Model* in a representative Central European mixed forest area by Palaios *et al.* [PLM14]. In this work, we use these acquired parameters in the *Log-Normal Shadowing Model* for the distance estimation and demonstrate how this model can be used on low-end hardware with restricted performance for energy-efficient data offloading.

3 Design

In this section, we present our design of a lightweight, energy-efficient data offloading approach that is executable on low-end hardware. We assume a heterogeneous, multi-RAT WSN with small, battery-powered mobile sensor nodes, which are mounted, for example, on deer. More powerful, static sensor nodes are sparsely located throughout the animal habitat and act as distributed data sinks. Nodes and data sinks provide both LoRa and WiFi as communication technologies, but due to the size of the habitat, data sinks do not cover the whole area. As a restriction, we neglect the data acquisition within this work, because it is highly dependent on the specific application with its used sensors, measurement intervals, and more. We also assume that nodes and data sinks have no time synchronization.

Battery longevity is very important for animal monitoring, since it allows a long-term assessment without disturbing animals. However, it is also of high interest to acquire the collected monitoring data in a timely manner, which should be done energy-efficiently due to the first restriction. On the one hand, the obvious first choice of transmitting the data via

the long-range low-power technology LoRa is, however, infeasible. The limited bandwidth and the strict duty cycle restrictions in the used frequency bands do not allow transmitting large amounts of data. Additionally, best-effort transmissions of LoRa over long distances can possibly lead to lost messages and, thus, lost data. On the other hand, WiFi has very limited range and a large habitat cannot be fully covered by data sinks due to ecological and economical reasons. By utilizing the mobility of the observed animals, an opportunistic approach to upload data when the monitored animal moves in range of a data sink is possible. However, constantly using WiFi to probe for available data sinks would rapidly deplete the battery of a mobile node [Hu15]. In a similar fashion as presented in Section 2, using GPS sensors or RSSI fingerprinting is infeasible due to high power consumption and the vast size of animal habitats, respectively. Furthermore, the positions and the number of data sinks can change during long-term animal monitoring and, thus, rendering fingerprinting or location matching infeasible without replacing the information on the mobile nodes.

To overcome these problems, we propose an approach to combine the possibility for distance estimation over LoRa with the capability of WiFi for high-throughput data transmission on mobile nodes. The energy-efficient LoRa technology is used to opportunistically probe for available data sinks and estimate distances to them. Because LoRa is strictly limited by a duty cycle, due to the used frequency bands, and to minimize power consumption, LoRa messages should be as small as possible in general. If a monitored animal moves within the WiFi range of a data sink, a data offloading attempt is started. The activation of the energy-demanding WiFi connection is minimized and only used for a quick transmission. Our approach for combined distance estimation and data offloading is divided into three phases for mobile nodes. An overview of these phases is shown in Figure 1.

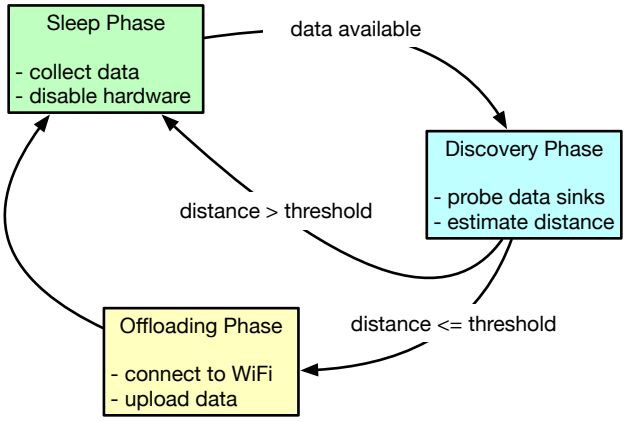


Fig. 1: Overview on the three-phased data offloading approach.

Sleep Phase The *sleep phase* is the basic condition of the mobile node, in which most components are turned off to save power. Within a predefined interval, the node comes out of hibernation to perform certain tasks, like collecting data or probing for data sinks. As stated beforehand, we do not incorporate a specified data collection phase into our communication protocol within the scope of this paper, since data acquisition is specific to the application and the used sensors. Similarly, the node should only proceed to the *discovery phase* if data is available for offloading.

Discovery Phase In the *discovery phase*, the mobile node opportunistically probes over LoRa for available data sinks using a beacon message. On reception at a data sink, the sink sends a response back that the mobile node will use to estimate the distance to the data sink with a path loss model and the RSSI of the response. The time of flight as additional metric to the RSSI cannot be used reliably without a highly accurate time synchronization between sender and receiver. Additionally, timestamps would significantly increase the size of LoRa packets. By using only the RSSI, our approach is independent of time synchronization. If the estimated distance based on the RSSI is less or equal to an offloading threshold, the mobile node switches to the next phase. However, if no response is received or the estimated distance exceeds the threshold, it goes back to the *sleep phase*.

Offloading Phase In the *offloading phase*, the node will activate its WiFi module and attempt to connect to the data sink's WiFi hotspot. When connected, available data is offloaded to the data sink. The node deactivates its WiFi directly afterwards to minimize WiFi usage. Then, the node switches back to the *sleep phase* to further save energy.

As an alternative, the distance estimation could also be performed on the data sink, for example if the mobile node hardware is not capable of calculating the path loss model. A response could then only be sent if the distance estimation on the sink is lower than the threshold. However, communication properties may not be bidirectionally balanced, e.g., due to more powerful hardware on the sink than on the node. It is, therefore, possible that the data sink will reach the node via WiFi, but not vice versa. A deeper analysis of this alternative approach is left open for future research. Using low-end commodity-off-the-shelf hardware, we realized this communication protocol in a prototypical implementation, as presented in the following section.

4 Prototypical Implementation

In this section, we present our prototype system for mobile sensor data offloading with LoRa-based connectivity estimations. First, we describe the realization of data sinks and mobile sensor nodes with a focus on the hardware components, followed by the communication protocol and interaction between them. The prototype is realized by using broadly available, inexpensive commodity-off-the-shelf hardware and open source libraries.

4.1 Data Sink

The foundation of the data sink is a single-board *Raspberry Pi 4B* computer. It provides a 64-bit quad-core 1.5 GHz ARM Cortex-A72 processor, 2 GB of RAM, and built-in WiFi capabilities. A standard installation of the Raspberry Pi OS[3] as provided by Raspberry Pi Foundation[4] is used. The prototype is powered over the Raspberry's USB-C port with a 99 Wh LiPo battery, but can also be powered for long-term use by a combination of a solar panel and a 12 V car battery as power source [Go19].

For the additional LoRa communication capabilities, we use a *Dragino PG1301 LoRa Concentrator*[5], which is connected directly to the GPIOs of the Raspberry Pi. The PG1301 uses one SX1301 and two SX1257 LoRa modules to allow receiving on up to 10 parallel LoRa channels and sending on one LoRa channel, respectively, using the manufacturer's standard library[6]. It is used by our *LoRaPi* service that processes incoming messages and can also send out replies, as detailed in Sections 4.3 and 4.4. Furthermore, the *LoRaPi* service can also interact with the WiFi management service to activate or deactivate the sink's WiFi access point.

The WiFi management service *hostapd*[7] runs in the background, managing the Raspberry's WiFi access point and IP addresses of mobile nodes. Each sink uses a standardized SSID which is extended by the specific sink's ID for a unique WiFi SSID. Additionally, a UDP service is running in parallel that monitors the connection of all mobile nodes and the progress of their data upload. The upload itself is performed over FTP, using the *proftpd*[8] library that collects the data on an FTP server in the background.

4.2 Mobile Nodes

Our prototype of a mobile sensor node is realized on a *Heltec ESP32 LoRa WiFi v2*[9] board. It has a 32-bit dual-core 240 MHz LX6 microcontroller and 529 kB internal SRAM with a weight of only 20 g. It provides Bluetooth, 2.4 GHz dual-mode WiFi, and LoRa using one SX1276 LoRa transceiver for communication. As a prototyping device, it also provides a 0.96 inch OLED display and can be powered either over a micro-USB port or a 1.25 mm JST LiPo battery interface.

[3] `https://www.raspberrypi.org/software/`
[4] `https://www.raspberrypi.org/`
[5] `https://www.dragino.com/products/lora/item/149-lora-gps-hat.html`
[6] `https://github.com/dragino/pi_gateway_fwd`
[7] `https://w1.fi/hostapd/`
[8] `http://www.proftpd.org/`
[9] `https://heltec.org/project/wifi-lora-32/`

For data storage, we use a standard SD card breakout board[10] connected via SPI. The SD card stores the used dummy sensor data and configuration files for the mobile node. The latter include a node's ID, LoRa settings, and configurations of the main program running on the node. Configuration files are stored in JSON format[11]. For evaluation purposes, the prototype can be equipped with an optional GPS device[12] connected via SPI.

The main program is written in the C-like Arduino language and uses the standard library of the Heltec ESP32[13] for LoRa communication. WiFi communication is provided by the standard Arduino library, the FTP transfer uses the ESP32 FTP Client[14] library.

The software running on a mobile node includes the lightweight communication protocol over LoRa and WiFi, further discussed in detail in the following sections. The crucial part of the main program is the distance estimation. For evaluation purposes, this includes the possibility to use GPS localization and matching with a predefined location of the data sink.

However, for the main procedure, distance estimation is performed by a path loss model estimation. The code of the estimation can be easily exchanged with different models, but for our prototype, we used the already discussed *Log-Normal Shadowing Model*. In addition to the logarithmic reduction of a signal's RSSI over distance, this model also includes non-deterministic influences from the environment for the path loss PL:

$$PL(d) = PL(d_0) + 10n\log_{10}(\frac{d}{d_0}) + X_\sigma \tag{1}$$

where n is the path loss exponent, d is the distance between sender and receiver, X_σ is a zero-mean Gaussian-distributed random variable with standard deviation σ, and a reference measurement PL_{d_0} at a distance d_0. The estimated distance d_E on a given RSSI is then calculated by

$$d_E(RSSI) = d_0 * 10^{(RSSI - PL(d_0) - X_\sigma)/(10n)}. \tag{2}$$

The fitted properties are $n = 4.96$, $\sigma = 6.13\,\mathrm{dB}$, and $PL(d_0) = 52.4\,\mathrm{dB}$ with $d_0 = 10\,\mathrm{m}$ as measured by Palaios *et al.* [PLM14] for a Central European mixed forest. Note that these measurements were conducted with a center frequency of 485 MHz, but our LoRa communication is performed in the 868 MHz EU SRD frequency band. However, we assume this to have only a minor influence, since possible external influences of different foliage or forestation in our work compared to the related work are expected to have a more significant influence.

[10] Code based on: `https://iotdesignpro.com/projects/logging-temperature-and-humidity-data-on-sd-card-using-esp32`
[11] `https://rapidjson.org/`
[12] `https://github.com/adafruit/Adafruit_GPS`
[13] `https://github.com/HelTecAutomation/Heltec_ESP32`
[14] `https://github.com/ldab/ESP32_FTPClient`

4.3 LoRa Communication in the Discovery Phase

Within the discovery phase, all communication is performed over LoRa. We use a customized LoRa approach with very small messages, to minimize medium occupancy and power consumption. Each message is only 2 bytes in size, consisting of a 1-byte ID of the sending device and a 1-byte field for message flags that identify the type of message that is sent. Such a packet has an airtime of approximately 166 ms with a robust standard setting of spreading factor 10, coding rate 4/5, and bandwidth of 125 kHz of LoRa. This setting is also used in our evaluation setup. As a theoretical upper limit, each node and data sink could, therefore, send more than 200 of such packets each hour with a duty cycle of 1% in the 868 MHz EU SRD frequency band.

In our current implementation, four message types are available: *Beacon*, *Reply*, *Offload Initialization*, and *Offload Acknowledge*. *Beacons* are sent by mobile nodes containing their ID. Within a single discovery phase, only a single beacon is sent. When no *Reply* is received, the mobile node goes back to the sleep phase. Every *Beacon* that is received by a data sink is answered with a *Reply* message containing the ID of that sink. The mobile node listens to incoming replies for a certain reception window, as multiple data sinks may possibly overhear and answer its message. Only the reply with the largest RSSI is used, all others are discarded. This reply message is then used for the distance estimation, as presented above. If this estimated distance is below the given threshold, the mobile node sends an *Offload Initialization* message to the data sink with the sink's ID.

On reception of an *Offload Initialization* message at a data sink, the ID is checked first to assure that the message is intended for that device. Then, the sink starts up the WiFi access point and acknowledges the availability with an *Offload Acknowledge* message. If the mobile node does not receive the ACK within its reception window, it again goes back to the sleep phase. Otherwise, when the offload ACK is received, the mobile node also turns on its WiFi module and switches to the *offloading* phase.

4.4 WiFi Communication in the Offloading Phase

In the offloading phase, the mobile node tries to access the wireless network provided by the data sink. The WiFi SSID of each sink is a standard identifier followed by the sink's ID, e.g., "SSID-A1" for the data sink with the (hexadecimal) ID *0xA1*. The mobile node directly connects to that specific access point by using the ID information provided in the previously received *Reply* message. If the WiFi cannot be found, e.g., if the distance estimation was wrong or other circumstances prevent the mobile node from accessing WiFi, the mobile node will go back to the sleep phase.

If it is connected, however, a short acknowledgement is sent to the UDP service running on the data sink. This service blocks the sink's WiFi from deactivating until the mobile node has transferred its data to the background FTP service. After offloading the data, the

mobile node again sends a small UDP packet to confirm the transfer. The UDP service then unblocks the WiFi again if there are no other devices currently connected. Furthermore, it also manages timeouts, in case that the WiFi connection is lost and the second UDP message is received. The mobile node, either after confirming the transfer or after losing connection, turns off its WiFi module and goes to the sleep phase.

4.5 Limitations of the Prototype

In its current state, the prototype does not generate any meaningful sensor data and does not incorporate a distinct data acquisition phase. Since the used sensors and the type and frequency of measurements are specific for animals, scenarios, and applications, respectively, we deliberately omit a specification of the data acquisition, but focus on the communication. However, our implementation provides the possibility to easily integrate such a phase in the prototype.

The ESP32's LoRa transceiver theoretically provides the full range of spreading factors from 7 to 12. However, a significant amount of messages is not received for spreading factors 11 and 12. As stated in the transceiver's datasheet[15], high spreading factors have a limited tolerance for frequency errors and require a reliable reference frequency, which we assume is not provided by the ESP32's XO. For higher spreading factors—or other LoRa settings with higher demands on the frequency stability, like low bandwidths—, an external TCXO is advised by the manufacturer. Within this work, we limit our prototype to a maximum spreading factor 10.

Another limitation of mobile nodes is the used FTP library for ESP32. It is only possible to reserve blocks of a maximum of 100 kB due to the construction of the ESP32's heap memory. Therefore, files that are transferred directly from the SD card to the FTP server can only have that same or a smaller size. An adaptation of the library to larger file sizes is out of the scope of this paper and, thus, left for future work.

5 Experimental Evaluation

The evaluation of the prototype was conducted as a field experiment in a forest near the city of Darmstadt, Germany[16]. As shown in Figure 2, the data sink was non-invasively attached to a tree at a height of approximately 1.80 m. The terrain around the chosen tree is slightly leveled without any artificial elements or forest aisles within 100 m, and mostly accessible with few bushes or shrubs within the direct vicinity. Since we measured in the winter months, there was no foliage.

[15] The current datasheet for LoRa transceivers is provided by Semtech Corporation, `www.semtech.com`

[16] Data Sink Coordinates: 49.857028 N 8.696744 E

(a) Data sink prototype. (b) Tape measurements.

Fig. 2: The data sink prototype was attached to a tree at around 1.80 m height. Distances were measured with a tape measure in a German mixed forest.

Parameter	Setting
TX Power	14 dB
Frequency	868 MHz
Spreading Factor	10
Bandwidth	125 kHz
Coding Rate	4/5
Preamble Length	8 symbols
CRC	disabled

Tab. 1: LoRa settings for the field experiments.

We used a mobile node including a GPS sensor for tracking the position of each measurement location in the experiment. LoRa communication was used on a robust standard setting, as summarized in Table 1. A total of 331 measurements were taken centered around the data sink tree over several days. Since the GPS localization has an inaccuracy of more than ±10 meters in the forest, we used a tape measure to determine the distance between mobile node and data sink and took measurements every five meters. Shrubs, bushes, and other trees, however, did not allow to measure in all directions and usually only up to 40 to 60 meters, depending on the direction. Furthermore, we also took measurements at the approximate limits of the WiFi range (approx. 40–100 m) in a circle around the data sink

tree. As a result, 174 of the 331 measurements are taken with a tape measure, from which 144 data points are in a measured distance of 50 meters or less.

For each measurement, the mobile station is started in the *discovery phase*. As expected for LoRa, it is possible to send and receive LoRa messages at all measurement locations within that comparably short range. In addition, the evaluation system is adapted, such that it switched to the *offloading phase* regardless of the measured distance. With that, we determine if a WiFi connection to the data sink is possible at that location and if the decision of the mobile node to switch to the *offloading phase* would be correct. We use the acquired data points to first assess the quality of the distance estimation.

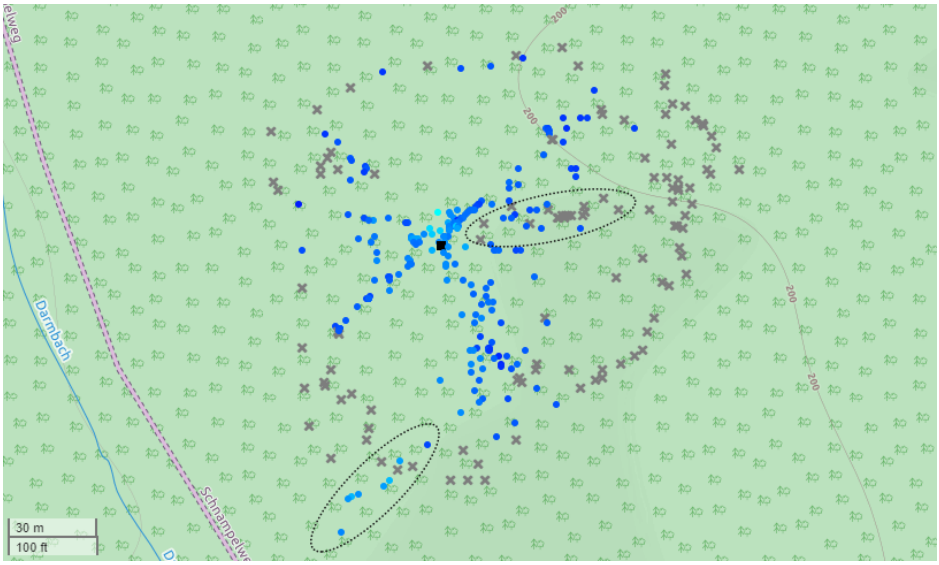


Fig. 3: Data points for 331 WiFi offloading attempts. The location of the data sink is denoted by the black square. Blue points denote positions with successful offloading, with lighter colors showing a higher LoRa RSSI, crosses where WiFi access is not possible.
(Maps ©Thunderforest, Data ©OpenStreetMap contributors)

5.1 Distance Estimation and Data Offloading

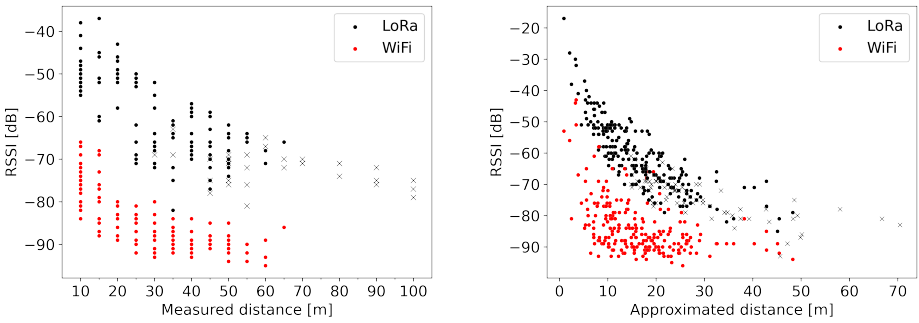
All data points are visualized in Figure 3, showing successful and unsuccessful WiFi offloading attempts, respectively. The location of the data sink is shown as a black square. Blue dots are locations where access to the sink's WiFi is possible, with lighter colors showing a stronger LoRa RSSI. Grey crosses denote where a WiFi connection is not possible. The measured area is approximately 200 m by 200 m in size.

As expected, a WiFi connection is typically possible within 50 meters, especially with line-of-sight to the data sink. To the east of the data sink, however, a large number of connection

attempts fails even at close distance, most probably due to the the obstruction by several larger trees. The LoRa RSSI degrades similarly in this area. In contrast, a relatively large isle to the south-west allows line-of-sight to the data sink, with WiFi connections to around 100 m and reasonably good RSSI values for the LoRa communication. Nevertheless, nearby locations that are even closer to the data sink but without line-of-sight do not succeed in establishing a WiFi connection at all. It is therefore clear that the surrounding environment has a more significant impact on the connectivity than the pure distance to the data sink. Furthermore, this impact is similarly perceivable on the RSSI measurements for LoRa and WiFi, respectively.

Figure 4 highlights this coherence between LoRa RSSI and WiFi RSSI for the tape-measured distances and the approximated distances by the used path loss model, respectively. The general trend of decreasing RSSI values at longer distances is evident for both wireless technologies. The measured RSSI values in Figure 4a also show a significant variance, comparable to the results of Palaios *et al.* [PLM14]. With increasing distance, the number of failed WiFi connections increases. The longest exactly measured distance for a successful upload is 65 meters, although two out of three connections are unsuccessful at that same location. However, as already stated, longer distances are possible but highly dependent on the surrounding environment.

More interestingly, no WiFi connection is possible in any case where the approximated distance by the path loss model exceeds 50 m, as shown in Figure 4b. For less than 15 m approximated distance, every WiFi connection is successful. Approximations between 15 and 30 meters result in circa 30% failed connections, similar to the obstructed locations to the west of the data sink (cf. Figure 3), and the ratio of failed connections further increases with distance. Nevertheless, the number of failed connections between 15 and 30 meters cannot entirely be described by these measurements. We, therefore, also compare the ap-

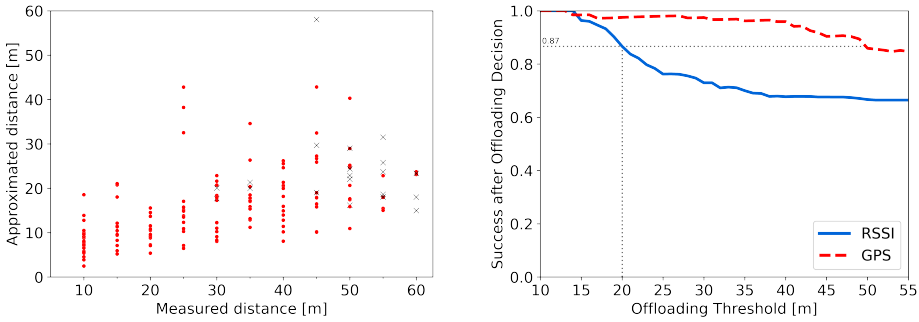


(a) RSSI for tape-measured distances.

(b) RSSI for PLM distance approximation.

Fig. 4: LoRa RSSI and WiFi RSSI values for tape-measured and approximated distances, respectively. Unsuccessful WiFi connections are marked by a cross.

proximated distance with all measured distances in Figure 5a. Clearly, the used path loss model with the respective parameter settings (cf. [PLM14]) underestimates the real distance on the average. This might be a result of the used LoRa technology: it is more robust and uses a different frequency band compared to the related work. Other possible influences are differences in the terrain, the forestation, or foliage at the respective evaluation site. Clearly, the parameter settings or the path loss model must be adapted specifically for the used evaluation environment for a more realistic distance estimation, or may even require an adaptive adjustment to cope with varying influences of a diverse environment.



(a) Approximated distance vs. measured distance.

(b) Success after an offloading decision of the prototype w.r.t. the offloading threshold.

Fig. 5: The comparison of the approximated distance with the real distance shows a significant underestimation. Nevertheless, the results can be used to make a correct decision for offloading on the mobile node. The RSSI-based LoRa approach with an offloading threshold of 20 m provides a similar success rate to a GPS-based approach with an offloading threshold of 50 m.

5.2 Offloading Threshold

Despite the underestimation in the distances between data sink and mobile node, it is possible to use the approximated distance to decide whether the mobile node should start the offloading process or not. For that, we compare different offloading thresholds on the evaluation data, as depicted in Figure 5b. The ordinate shows the success rate of the offloading phase for both the LoRa RSSI-based approach and the GPS-based approach based on a fixed threshold. Success is defined as a completed WiFi connection and data offloading phase, happening after the respective approach calculates the distance to the data sink to be less or equal to that threshold. In case of the RSSI approach, this distance is approximated by the path loss model. In case of GPS, this is the difference between the measured GPS location and the location of the data sink. With a threshold of 50 m, the GPS approach has a success rate of 0.86, i.e., 86% of all offloading attempts were successful for that threshold. A similar success rate of 0.87 is achieved by the RSSI approach at 20 m. This resembles a similar offset than that between measured and approximated distance (cf. Figure 5a). Thus, due to the divergence of the RSSI approach, using an offloading threshold of 20 m for the

decision based on LoRa RSSI measurements allows to offload data within 50 m in reality. As a result, both approaches result in a similar success rate with appropriately defined thresholds.

The eventual decision on an offloading threshold must be based on the specific application scenario and must include factors like the monitored animals and their mobility, the area coverage by data sinks, as well as available power resources and the amount of generated data on mobile nodes. In general, a smaller threshold will yield a higher probability for successful WiFi connections, on the one hand, but will equally decrease the actual chance for data offloading in the context of animal monitoring significantly. On the other hand, a larger threshold increases the chances for offloading attempts, but similarly also the number of unsuccessful attempts, leading to a lower energy efficiency.

5.3 Power Consumption of the Prototype

Finally, we measure the power consumption of our prototype's mobile node using a USB multimeter in three scenarios for 60 seconds with and without GPS, respectively, resulting in a total of six settings. For all settings using GPS, a GPS satellite lock is established before starting the test. Acquiring a lock takes up to 5 minutes and, therefore, would have significantly increased the power consumption for each test. By acquiring the lock beforehand, our results only incorporate the difference of GPS usage compared to no GPS usage within the evaluation frame. This allows us to specifically evaluate and compare the communication and distance estimation part, without external influences on the GPS. Similarly, we do not include further sensors, measure any sensor's power requirements, or perform a long-term measurement on the prototype, due to the scope of this paper and the prototype which focus on the offloading procedure and the communication. The three scenarios, on which me measured the power consumption of the prototype, are (1) an idle mode of the ESP32 without the use of LoRa or WiFi, but activated built-in OLED display, (2) a full procedure of LoRa communication between mobile node and data sink but without activating WiFi, and (3) the same procedure with a connection and upload to the data sink over WiFi.

The results of the comparison of the scenarios is depicted in Figure 6. We find that the full bidirectional LoRa communication between mobile node and data sink consumes 109–120 µAh, which is less than for scanning for a WiFi access point once [Hu15]. Accessing the data sinks WiFi and uploading a 100 kByte dummy file to the FTP server consumes an additional 226–253 µAh. But as expected, the most significant impact on the overall power consumption is the running GPS. The idle mobile node without GPS consumes around 467 µAh, but with active GPS consumes an additional 431–469 µAh within the same measurement frame. As already stated, this does not include additional power required for acquiring a satellite lock and a position in the first place. Furthermore, note that also the data sink's WiFi has to be constantly activated for a GPS-based system due to the lack of a second communication channel, further increasing the overall power demand.

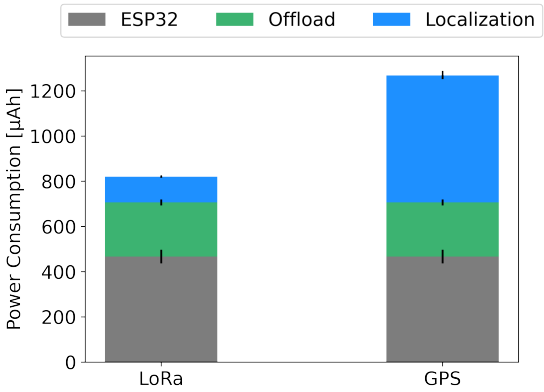


Fig. 6: Power consumption for the LoRa- and GPS-based localization, respectively, split for consumption of the ESP32 device, the WiFi offloading, and the localization approach. The LoRa-based approach requires only 63% of the power of the GPS-based approach.

It is evident that substituting the GPS-based approach with the RSSI-based approach has a significant impact on the overall power consumption, while maintaining a similar offloading success rate within 50 meters. Within the measurement setup, our approach only requires 63% of the power of the GPS approach. Even when omitting the power consumption of LoRa communication, which may not be required in a GPS approach, the power demand is still reduced to 70%. Additionally, our RSSI-based approach using LoRa communication is highly applicable for making the offloading decision with a sensibly chosen offloading threshold with a success rate of 87%.

6 Conclusion

In this paper, we presented an approach for energy-efficient data offloading via WiFi using LoRa-based connectivity estimations for mobile sensor nodes in multi-RAT WSNs. An experimental evaluation of our prototypical implementation demonstrated that our approach is capable of providing reasonable estimations whether data offloading via WiFi is possible or not, based on received LoRa messages and without further GPS capabilities. Our prototype uses available parameters for the log-normal shadowing path loss model [PLM14] for distance estimation, which has shown to underestimate real distances within our forestry evaluation setup. Nevertheless, it was possible to determine a reasonable offloading distance threshold in the evaluation results. In particular, we achieved an offloading success of 87%, which is similar to the performance of an GPS-based approach, while reducing the power consumption by up to 37%.

In our evaluation, we observed that the path loss model is highly dependent on its parametrization. Determining the environment-specific parameters is, therefore, of primary interest for future work to obtain realistic distance estimations. Furthermore, extended evaluations are required to determine if our rather static approach is also applicable in large-scale scenarios with very different terrain or types of forests in the same area, or for long-term monitoring under varying environmental conditions like rain and snow or the change of foliage over the year. Additionally, future work may encompass the influence of animal mobility, data sink distribution, area coverage, as well as adaptive offloading thresholds and more complex path loss models. Our next research goal is to compare sensor node-based, data sink-based, and cooperative distance estimation approaches and evaluate their influence on the offloading decision accuracy. Nevertheless, we have shown that wireless sensor networks with heterogeneous communication technologies are already capable of energy-efficient data offloading without the need for a GPS device and that a simple path loss model calculated on low-end commodity hardware yields valuable results.

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