Location-based Discovery and Network Handover Management for Heterogeneous IEEE 802.11ah IoT Applications

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***Abstract*—Low-Power Wide-Area Network (LPWAN) multi-Radio Access Technology (RAT) devices combine features of different low-power network technologies to flexibly manage heterogeneous requirements stemming from various Internet of Things (IoT) applications. IEEE 802.11ah is a novel technology that is envisioned to provide a "bridge" between Wi-Fi and LPWANs, thus it has been often considered as one of the supporting technologies in multi-RAT devices. In such multi-RAT scenarios, network discovery and handover procedures need to be utilized for determining the availability of a given technology and managing if the connection to the technology should be initiated. However, traditional discovery and handover procedures, such as beacon listening, have to be performed periodically and, therefore, consume substantial amount of energy, making them unsuitable for battery-powered IoT devices. To address this issue, we present a mechanism that is able to make more optimal discovery and handover decisions by leveraging the physical location information of the multi-RAT devices. We demonstrate how this approach is feasible in performing energy efficient handovers between a LPWAN technology (NB-IoT) and IEEE 802.11ah based on estimated location. We do that by showing that the location-based procedure substantially reduces the energy consumption of the mobile device compared to the traditional discovery based on periodical listening for beacons, while maintaining comparable duration of the device's association to IEEE 802.11ah. Moreover, we evaluate the energy and delay overheads caused by the localization service, showing only slight effects on the performance of the mechanism.**

***Index Terms*—IEEE 802.11ah, low-power wide-area networks, network discovery, vertical handover, location-awareness.**

I. Introduction

In recent years, we are witnessing an increase in utilization of Low-Power Wide-Area Network (LPWAN) technologies in a variety of Internet of Things (IoT) contexts, such as in asset tracking, smart metering, and fleet management [1]. These technologies utilize sub-GHz frequencies and feature long communication ranges and low power performance. Some LPWAN technologies offer connectivity over a range of tens of kilometers with up to kilobit per second throughputs (e.g., NB-IoT, LoRa, Sigfox). In contrast, shorter range sub-GHz technologies, such as IEEE 802.11ah, provide hundreds of kilobits data rates at the range of around 1 kilometer [2], [3]. As such, IEEE 802.11ah is suitable for bandwidth-consuming tasks, such as firmware updates or data offloading. Its higher data-rate and shorter airtime make it highly energy efficient compared to the longer range LPWAN alternatives [3].

Many IoT applications would benefit from almost full coverage of long-range LPWANs combined with the higher throughput and energy efficiency of IEEE 802.11ah. To enable that, several multi-Radio Access Technology (RAT) devices have been proposed (e.g., [4]). On the one hand, LPWAN technologies, despite having lower throughput, can more easily provide omnipresent coverage. As IEEE 802.11ah is not expected to be continuously available, while LPWAN technologies can more easily provide omnipresent coverage, these multi-RAT devices will have to utilize a certain procedure for managing if a network discovery or handover to IEEE 802.11ah should be performed. Existing Wi-Fi discovery and handover procedures mostly rely on the device listening for beacons transmitted by the nearby IEEE 802.11ah Access Point (AP) [5]. When a beacon is received, the device initiates a connection to IEEE 802.11ah. This procedure consumes high amounts of energy due to periodic beacon listening even when IEEE 802.11ah is not available, which is undesirable for IoT applications targeting low power performance, such as those using battery-powered actuators or sensors.

A large number of IoT applications envision some type of localization or tracking of the mobile IEEE 802.11ah-enabled multi-RAT devices [4]. These use-cases might have heterogeneous requirements, such as maximizing battery life or association duration to a specific network, being deployed in environments with different characteristics (e.g., urban, sub-urban, rural) with different types of location services. Hence, as the physical location of the device is already tracked for application purposes, it can potentially be used "for free" for performing energy efficient discovery and network handover management. This argument has been outlined in different works in the literature, however usually aiming at more traditional Wi-Fi and LPWAN technologies (cf., Section II). Based on this intuition, in this paper we present a mechanism that, based on the location information of the multi-RAT device, can perform more efficient discovery and handover procedures between sub-GHz LPWAN technologies and IEEE 802.11ah than the traditional approach.Specifically, we envision multi-RAT devices that exhibit mobility across wide areas that can not be covered by a single IEEE 802.11ah network. Moreover, they will move across different environments. The mechanism reduces the need for continuous idle listening as the device is able to listen for beacons only if there is a high probability that a given technology will be available, with the result of being adaptable to different conditions (e.g., environments, localization services), supporting IoT use-cases with heterogeneous requirements.

We follow by exhaustively evaluating the presented mechanism accounting for location-dependent signal attenuation, localization errors of different types of underlying localization services, and overhead and latency of message exchange between the multi-RAT device and network management backend. Specifically, we chose NB-IoT as LPWAN technology. Finally, we demonstrate the flexibility of the presented mechanism and, therefore, its feasibility in supporting highly heterogeneous set of use-cases. In particular, we show that the mechanism consistently outperforms the baseline, it can be supported by different localization services, and can be adapted to different types of deployment environments, as well as to different use-case requirements.

The rest of this paper is structured as follows. The next section discusses the related literature. In Section III we outline the proposed mechanism for location-based discovery and handover in LPWAN networks with IEEE 802.11ah. In Section IV, we discuss the approach in evaluating the performance of the presented mechanism, as well as outline the obtained results. Finally, we conclude the paper and provide several directions for future efforts in Section V.

II. Related work

In this section, we provide an overview of the existing efforts aiming at enabling IoT applications using IEEE 802.11ah and supporting location-based discovery and handover in Wi-Fi and LPWAN networks.

A. IEEE 802.11ah in IoT

IEEE 802.11ah is a novel Wi-Fi-based communication standard, providing comparatively higher communication range, scalability, and energy efficiency than the other standards from the Wi-Fi umbrella [6]. As mentioned, IEEE 802.11ah is envisioned to serve as a "bridge" between traditional Wi-Fi targeting Local Area Network (LAN) deployments on the one hand and various LPWAN technologies on the other. As such, it is expected to be a suitable candidate for enabling a variety of use-cases in different industrial verticals, where these use-cases are expected to posit a highly heterogeneous set of requirements on the underlying IEEE 802.11ah-based networking infrastructures.

For example, IEEE 802.11ah is envisioned as an enabler of a variety of use-cases, ranging from smart sensors and meters for environmental monitoring to tracking devices for elderly care [6]. For optimizing the performance in such use-cases, the underlying IEEE 802.11ah-based network solutions should be highly energy efficient, while the other requirements such as the communication delay or data throughput are considered as less relevant. Similarly, IEEE 802.11ah is envisioned as an enabler of a variety of Machine to Machine (M2M) applications in a number of IoT contexts [7]. The requirements toward the underlying IEEE 802.11ah networks are expected to include supporting a large number of power-constrained stations over a long transmission range, where these messages are small and sent infrequently with a non-critical delay [7]. Adversely, IEEE 802.11ah is also envisioned as an enabler in the context of Smart Industries [8], primarily as a replacement of wired infrastructures. IEEE 802.11ah will in this context serve for supporting time-constrained control loops, which find their utilization in applications such as connected lighting or communication with mobile infrastructures such as drones, robots, cranes, etc. In such scenarios, the most stringent application requirement for IEEE 802.11ah is the short communication delay in the sub-second range [8]. Finally, IEEE 802.11ah is envisioned as an enabler in large IoT contexts, where it will serve as a "hotspot" for high data-rate communication tasks such as firmware updates or data offloading, while another technology with a longer range is expected to provide basic connectivity. Example applications in this context include monitoring of construction and other industrial equipment [4], and data offloading in Smart Agriculture [9] and emergency response scenarios [10].

From the discussion above, it is clear that IEEE 802.11ah will be used for enabling use-cases in a variety of industrial verticals. These use-cases are expected to feature a highly heterogeneous set of requirements and will be operational in different types on deployments environments. This implies that IEEE 802.11ah should be highly flexible and tuneable based on the requirements of the use-cases to be supported, providing the main motivation for this work. Finally, IEEE 802.11ah will often be utilized jointly with other communication technologies with differing features. As a result, multi-RAT devices, such as the one from [4], have been proposed for simultaneously benefiting from the features of different technologies.

B. Location-based Discovery and Handover

In multi-RAT setups there is a need for a mechanism for establishing if a multi-RAT device is in the communication range of a certain technology, typically known as a network discovery mechanism. Similarly, there is a need for switching between different network technologies supported by the device based on their availability and other features such as the supported data-rate. This process is usually supported through a network handover mechanism. This mechanism can be categorized into horizontal handover for switching between APs or gateways of the same network and vertical handover for switching between different network technologies. Traditional discovery and handover approaches are mostly based on beacon listening, but also on active probing or blind data transmissions. However, even though the latter is energy efficient, its communication reliability is rather low in scenarios without full coverage [11]. The traditional mechanisms based on beacon listening or active probing result in excessive energy consumption of the multi-RAT devices.

As an alternative, the decision on when to trigger network discovery and handovers can be based on physical locations of the networking devices. Specifically, our previous work [5] outline a mechanism that utilizes location-awareness for performing significantly more efficient discovery and handover procedures between sub-GHz LPWAN technologies in outdoor environments compared to the utilization of traditional mechanisms. In the presented approach, the decision on when to perform a discovery of or handover between LPWAN technologies is based on the physical locations of the device and the APs. By utilizing the locations and high-level knowledge about the environment of interest (i.e., average path loss in the environment), the system is able to determine the expected Signal-to-Noise Ratio (SNR) between the devices, which is then used for deciding if the handover should be initiated. The mechanism uses a log-distance propagation loss model with parameters that can be adapted to different scenarios. In our previous research, we have evaluated different propagation loss models ([12], [13]) and we chose AH Macro as log-distance propagation loss model used in the mechanism as it provided a good fit to the real data in an outdoor environment. Due to the design advantages of location-based vertical handover outlined in [14], different flavors of this mechanism have been evaluated for established LPWAN technologies such as Sigfox and LoRa [14], as well as for the combination of traditional Wi-Fi networks and IEEE 802.11ah [15].

These studies generally suggest highly promising performance of the location-based discovery and vertical handover, especially for LPWAN technologies for which energy efficiency is among the primary concerns. Based on these insights, in this paper we extend our work in [5] (a conference paper) by adapting the originally proposed mechanism for enhancing its flexibility in supporting IoT use-cases with heterogeneous requirements. Moreover, we consider a more realistic environment with signal attenuation due to obstacles, and the control overhead in latency and energy of the mechanism for different localization technologies. In contrast to our previous work [15] that focuses on the interplay between IEEE 802.11ah, which is per-se novel, and traditional Wi-Fi, we now focus on the combination of IEEE 802.11ah and NB-IoT, a representative of LPWAN technologies with substantial utilization in IoT contexts [16], [17].

III. Location-based Discovery and Network Handover in IEEE 802.11ah

In this section, we provide a high-level overview of the mechanism for location-based discovery and vertical handover in LPWAN networks with IEEE 802.11ah. We follow by discussing its applicability for supporting use-cases with heterogeneous requirements.

A. Location-based Discovery and Handover Mechanism

An overview of the considered scenario is given in Figure 1. We assume the location information of the IEEE 802.11ah AP in an environment of interest to be perfectly accurate and known by a mobile multi-RAT device, which is a realistic assumption given that such APs are usually statically deployed [18], [19]. Moreover, we assume that the multi-RAT device supports at least one LPWAN technology jointly with IEEE 802.11ah. Additionally, we assume that the 2-dimensional (2D) coordinates of the location information of the device can be estimated and the resulting location estimates feature a certain level of localization error. This error is modeled by a zero-mean Gaussian distribution characterized by its standard deviation σ. This type of modelling of localization errors has been established in the literature [20]–[22]. The true location information of the device is then a Gaussian

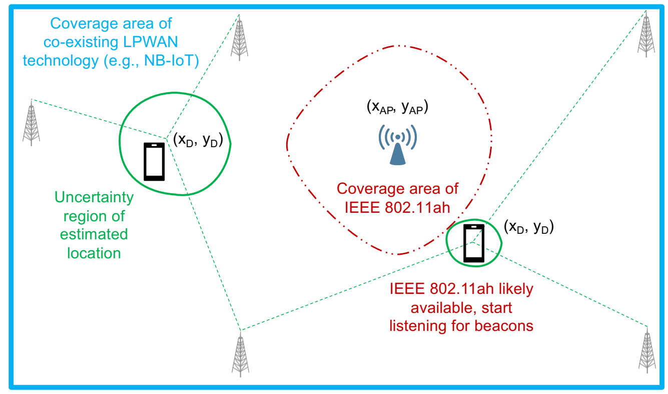


Figure 1: The considered scenario with a device implementing multiple sub-GHz technologies

distributed random variable pair (X_D, Y_D) given as follows, with (μ_{x_D}, μ_{y_D}) being the estimated location of the device:

$$X_D \sim \mathcal{N}(\mu_{x_D}, \sigma^2)\,, Y_D \sim \mathcal{N}(\mu_{y_D}, \sigma^2)\,. \tag{1}$$

As we assume the location of the AP to be known as (x_{AP}, y_{AP}), the Euclidean distance between the AP and the device can be estimated as:

$$\hat{\lambda} = \sqrt{(\mu_{x_D} - x_{AP})^2 + (\mu_{y_D} - y_{AP})^2} \tag{2}$$

The signal attenuation at a distance λ between the device and an AP is modelled using the log-distance path loss model, where the signal attenuation $L(\lambda)$ in dB is given by:

$$L(\lambda) = l_c + 10\gamma \log(\lambda). \tag{3}$$

l_c is a constant value related to the model fitting procedure. The attenuation $L(\lambda)$ is dependent on the distance λ from the transmitting or receiving device (i.e., AP) and on the path-loss coefficient γ of the environment.

According to [18], the estimated SNR between the device and the AP can then be calculated as:

$$\overline{SNR} = \ln \frac{P_{tx}}{N\kappa\sigma^{\gamma}} - \frac{\gamma}{2}\ln(\frac{\hat{\lambda}^2}{\sigma^2} g(\frac{\hat{\lambda}^2}{\sigma^2})), \tag{4}$$

with P_{tx} being the transmit power of the AP in dBm and N being the noise floor. Moreover, the parameter κ is given as $\kappa = 10^{l_c/10}$. Finally, the parameter γ is the path loss coefficient in the environment of interest, while $g(.)$ is a Marcum 1 function defined as follows:

$$g(\xi) = \exp(\int_{\xi/2}^{\infty} \frac{e^{-t}}{t} dt). \tag{5}$$

The procedural diagram of the proposed mechanism is given in Algorithm 1. The decision if a network discovery or handover should be initiated is based on the estimated SNR between the devices (cf., Equation (4)). In particular, the discovery or handover procedure are envisioned to be initiated if the estimated SNR from Equation (4) is higher than the sum of a predefined SNR required for initiating a discovery or handover and the *Threshold* parameter, otherwise the IEEE 802.11ah radio will remain in a power saving mode.

Algorithm 1: Location-based Handover

```
while Not associated do
    Calculate estimated SNR;
    if Estimated SNR ≥ required SNR + Threshold then
        Wake up to receive beacon for one beacon interval;
        if Beacon Received then
            Start Association Procedure;
        else
            Sleep until next location estimate available;
        end
    else
        Sleep until next location estimate available;
    end
end
```

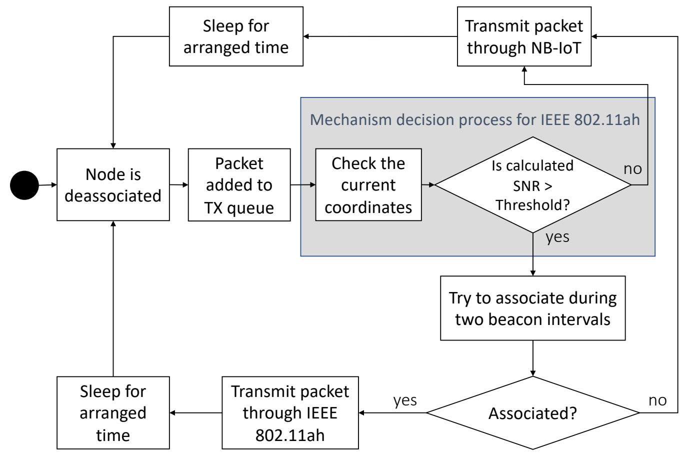


Figure 2: State diagram for IEEE 802.11ah for the retrieval of the current location using GPS

Note that in IEEE 802.11ah the required SNR for discovery equals 0 dBm, while for the handover different required SNRs can be defined based on the desired data-rates to be supported after the handover. The usual SNR values in this context are in the range between 0 and 20 dBm [14].

B. Threshold parameter

Threshold is a parameter in the mechanism that can be configured based on a particular use-case. Specifically, if the focus is on the energy efficiency, the mechanism should be "conservative" in making discovery and handover decisions, meaning that the device should be closer to the AP (i.e., the value of the *Threshold* should be higher than 0 dB). If the focus is more on faster association, the mechanism should be more "liberal" and aim at establishing the connection to IEEE 802.11ah when the device is further away from the AP (i.e., the *Threshold* should be lower than 0 dB). By utilizing the *Threshold* parameter, the resulting energy consumption and association time to IEEE 802.11ah of this procedure can be tuned based on the requirements of a particular use-case.

C. Localization Service

In the presented mechanism, the multi-RAT device utilizes the estimates of its physical location for deciding if the discovery or handover should be performed. The location estimates are provided by a localization service, which, as mentioned, features a certain level of localization error. Due to the fact that the mechanism explicitly accounts for different localization errors σ in making proactive discovery and handover decisions, it can support different types of localization services. This is important, as the errors in localization differ significantly for different types of localization sources. For example, this error ranges from tens of meters for Global Positioning System (GPS)-based localization to hundreds when using LPWAN services [11].

We envision estimating such errors characterized by σ utilizing two main approaches. A more traditional one is based on exhaustive experimental benchmarking of localization accuracy in the environment of interest [23]. A more suitable one is to base the estimation of localization errors on a per estimate basis (e.g., [24], [25]), which has been shown to feature higher accuracy than the traditional approaches.

In addition, obtaining the location information of the device incurs a certain delay, which differs for different types of localization services. Figure 2 shows a flowchart of the system with GPS-based localization, where the device has to have a GPS module installed. Periodicaly (e.g., when it has a packet to send) the device calculates its location through the GPS module and then it calculates the current SNR. As before, if the SNR is bigger than the sum of the desired SNR and *Threshold*, the device will start listening for IEEE 802.11ah beacons. If it manages to associate to IEEE 802.11ah, then the packet is sent through this technology, otherwise the alternative LPWAN technology is used. Getting the localization through GPS incurs certain delay, depending on whether the GPS module has to perform a hot, warm, or cold start. As in many cases the device can predict when it wants to send data, it can proactively start the GPS module to avoid a delay in obtaining the location estimate.

Figure 3 shows a flowchart of the system when using LPWAN signals for localizing the device. Different from before, the device first sends a message, of which the characteristics can subsequently be used to estimate the device's location (e.g., using fingerprinting, time-difference of arrival, or angle-of-arrival localization [26]). The data being sent by the application running on the device can be used as localization message, and it does not necessarily need to be an extra message. As before, the device then calculates the current SNR and depending on the comparison to the *Threshold*, it starts listening for IEEE 802.11ah beacons for a predefined time.

D. Environment Adaptation

The proposed algorithm is intrinsically able to adapt to different types of deployment environments expected in different use-cases. This can be done by adjusting the fitting parameters of the utilized log-distance path-loss model. For deriving the optimal parameters for the fitting of the model, we envision

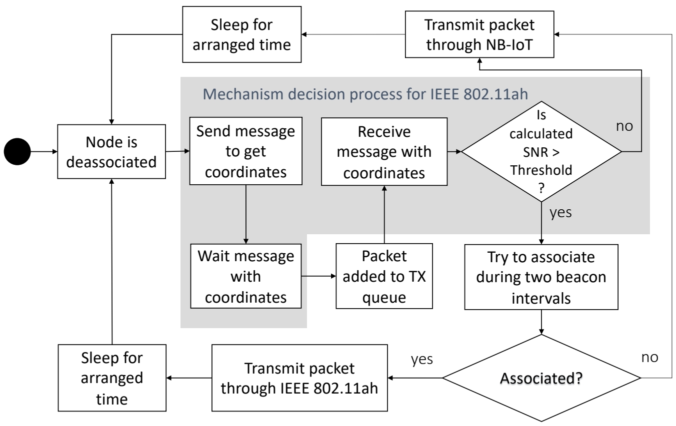


Figure 3: State diagram for IEEE 802.11ah for the retrieval of the current location using LPWAN-based localization

the usage of crowd-sourced measurements. Crowd-sourcing is a method for opportunistic collection of environmental measurements, which can be applied to reduce the efforts of generating coverage maps [27]. Through crowd-sourcing, one can obtain received signal powers at different locations in an environment of interest. This information can then serve as a basis for deriving l_c and γ in the Equation 3 (e.g., using least squares polynomial fitting).

IV. RESULTS

In this section, we present the evaluation methodology and the obtained performance results of the proposed mechanism in order to demonstrate its flexibility in meeting requirements stemming from different IoT use-cases.

A. Evaluation Setup

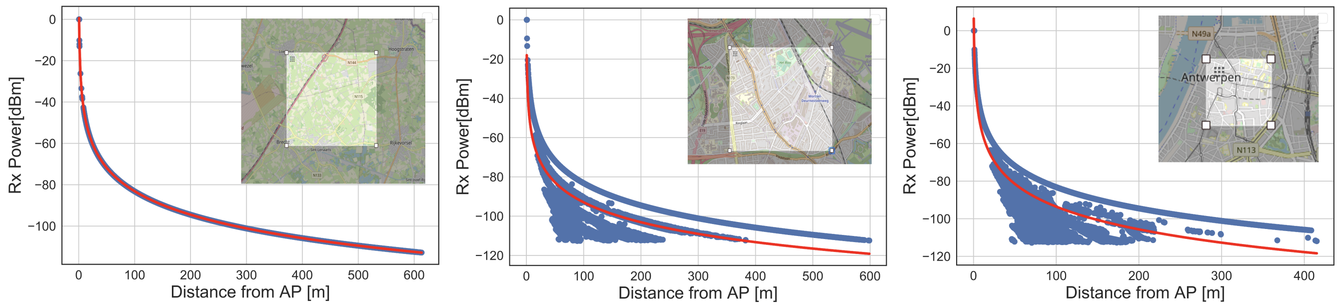
We derive the results using the ns-3 event-based simulation framework for IEEE 802.11ah [28]. The goal of the evaluation is to capture the energy consumption, total time the device is associated to IEEE 802.11ah, and delay in associating to IEEE 802.11ah. We do that for the presented mechanism, as well as for the baseline based on active beacon listening, which is among the most widely used procedures for performing discovery and handovers in Wi-Fi-based networks. In the baseline approach, we consider the scenarios in which the device periodically wakes up every 1 (BL 1), 5 (BL 5), 10 (BL 10), or 15 (BL 15) beacon intervals. If a beacon is received, the device starts the association to IEEE 802.11ah. If the device manages to associate to IEEE 802.11ah it remains associated until, after 7 beacons missed, the connection is dropped, representing a standard-compliant disassociation procedure [2].

We carry out the evaluation in three types of deployment environments: rural, suburban, and urban, as it is expected that different use-cases will be enabled in all of these main environmental types (cf., Section II). For simulating the IEEE 802.11ah signal attenuation in the different environments, we use a COST231 multi-wall model [29], as it has been extensively used in the existing literature due to its adaptability and simplicity [30]–[32]. Specifically, we model the received signal strength by accounting for the path loss between the transmitter and the receiver (3.76 dB/meter for signal propagation and 0.12 dB/meter of additional attenuation inside buildings [12]), as well as add an attenuation contribution of 3 dB for each wall in the direct path between the devices. The number of buildings/walls in the direct path between the devices has been captured using Open Street Map (OSM) in combination with SUMO for importing OSM specifications into ns-3 [33].

In addition, using the least square fitting procedure we fit the log-distance propagation loss model used by the proposed location-based mechanism with the propagation parameters of the three selected environments (cf., Equation 3). We do that by collecting crowd-sourced measurements from random locations, that were drawn according to a uniform distribution, in the three environments, based on ns-3 propagation modelling discussed in the previous paragraph. We assume a mobile RAT-device moving in a straight line from one location to a new random location, with a speed of 2.78m/s (i.e., 10km/h) and a sampling rate of 1 second, without taking into account any localization error. Specifically, we collect measurements at 63671, 22964, and 48860 locations in the rural, suburban, and urban environments, respectively. In these measurements the effect of mobile obstacles are not taken into account, as we collected a sufficient amount of data to average out such transient effects. The collected crowd-sourced measurements are depicted (in blue) in Figure 4 together with their fitted log-distance propagation loss models (in red). In the figure, it can be seen that the maximum distance where the packets could still be correctly received is 600 m for the rural and suburban environments, while for urban scenario the range is reduced to 400 m. This is an expected behaviour as there are significantly more buildings causing additional signal attenuation in the urban environment compared to its suburban and rural counterparts.

We simulate a device randomly moving inside and outside a rectangular area that is partially covered by IEEE 802.11ah ($25km^2$ for rural, $4km^2$ for suburban, and $1km^2$ for urban), while we assume the entire area is covered by NB-IoT. We have opted for NB-IoT as a representative LPWAN technology in contrast to other technologies with even higher communication ranges (e.g., LoRa, Sigfox) primarily due to its superior localization accuracy. In other words, NB-IoT offers comparatively higher communication ranges than IEEE 802.11ah, while simultaneously significantly outperforming the LPWAN alternatives in terms of localization accuracy, making it a desired candidate in the considered evaluation scenarios [34]. Additional simulation parameters are shown in Table I.

To isolate the effects of the discovery and handover mechanism and characterize its performance, in the first part of the evaluation we only consider the energy consumed by listening for beacons and not that of data transmission and localization. Moreover, we also do not consider other system aspects, like latency due to the localization. This is because data transmission and localization are required by the IoT applications and can therefore be used for free for making proactive discovery and handover decisions. We calculate the energy consumption by multiplying the time spent in each radio state (i.e., Rx, sleep, idle) with the power consumption



(a) Rural (b) Suburban (c) Urban

Figure 4: Fitted log-distance propagation loss models (in red) from the crowd-sourced collected data (in blue) and maps of the three environments

TABLE I: Parameters used in the evaluation

Parameter	**Value**
Transmission power	0 dBm
Transmission gain	0 dB
Reception gain	3 dB
Noise-floor	3 dB
Propagation loss model	LogDistance
Error rate model	YansErrorRate
Wi-Fi mode	MCS10, 1 MHz
Beacon interval	2.048 s
Speed	10 m/s
Inaccuracies in localization (std in m)	10, 100
Required SNR	0 dBm
$Threshold$ (in dBm)	-2, -1, 0, 1, 2
Power consumption (from [35])	**Value**
Receiving (P_{rx})	92 mW
Idle (P_{idle})	20 mW
Sleeping (P_{sleep})	99 nW

in that state. The power consumption values for IEEE 802.11ah are obtained from the Atmel AT86RF215 radio, as it partially supports IEEE 802.11ah modulations, are given in Table I [35].

As mentioned, the *Threshold* parameter is envisioned to be used in the location-based mechanism for tuning its performance to the use-case requirements (i.e., energy consumption minimization vs. associating time maximization). To evaluate if it serves its purpose, we vary the *Threshold* values from -2 to 2 dB. Moreover, we evaluate the mechanism for different localization inaccuracies typical for GPS (10 m) and NB-IoT time-difference of arrival (100 m) [36], by adding a value drawn from a zero-mean Gaussian distribution with standard deviation based on the localization inaccuracy to the current location of the device, which is a standard procedure in modelling of localization errors (e.g., [21]).

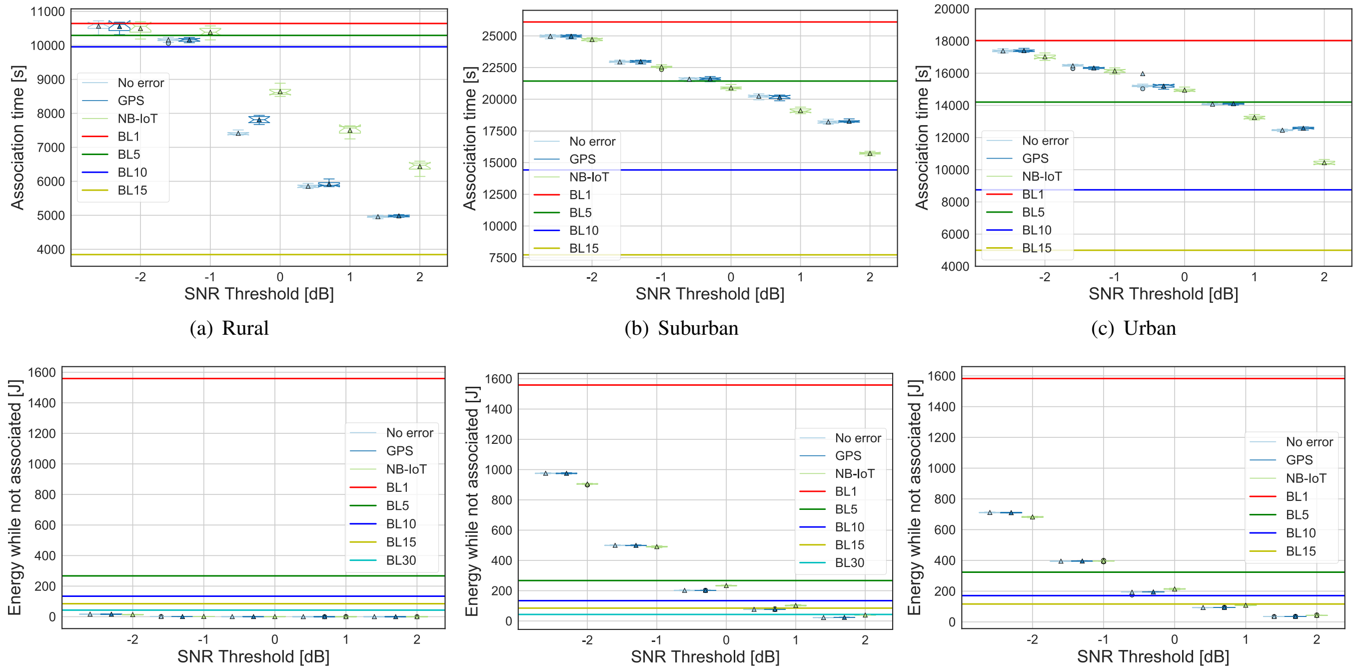
In the second part of the evaluation, we aim at accounting for the overhead caused by utilizing the location information from GPS and LPWAN by comparing the delay in associating to IEEE 802.11ah. In more general terms, we aim at demonstrating that the presented mechanism outperforms the baseline regardless of the underlying localization service and its location information provisioning features. Finally, we consider two different packet generation intervals. Specifically, we assume a packet being generated for transmission every 60 and 600 sec, as such intervals are to be expected in realistic IEEE 802.11ah use-cases (e.g., [6]). The simulation parameters are summarized in Table I.

B. Performance Analysis of the Location-based Mechanism for Network Discovery and Handover in IEEE 802.11ah

We evaluate the proposed location-based mechanism comparing it to the continuous beacon-listening approach. We do that by capturing the consumed energy due to unsuccessful handovers to IEEE 802.11ah, as well as the total time the device is associated with the IEEE 802.11ah network throughout the entire experiment (i.e., the association time). First, we show the effect of localization accuracy on the performance of the location-based mechanism. Then, we characterize the effect of different thresholds on the handover performance.

In Figure 5, we depict the association time and energy consumption for varying values of the *Threshold* parameter. We do that for different location inaccuracies (i.e., GPS and NB-IoT), as well as for perfectly accurate location of the mobile device. Moreover, we depict four beacon-listening baselines with different periods. As visible in the figure, as the device wakes up less frequently to listen to beacons, its average association time is reduced, i.e., higher delays in association are incurred. For all the graphs, it can be seen that lowering the *Threshold* parameter below 0 dB, makes the mechanism more aggressive and this allows achieving association times closer to BL1 (i.e., the baseline approach where the device is always listening for beacons). This is observed for all location inaccuracies and irrespective of the baseline. However, as can be clearly seen in Figure 5e, the energy consumption of the location-based mechanism is higher than the one observed for the BL5, BL10, and BL15 baselines for the liberal *Threshold* values lower than 0 dB. In conclusion, the *Threshold* parameter used for tuning the performance of the location-based mechanism can indeed serve its purpose of trading-off the association time and energy consumption.

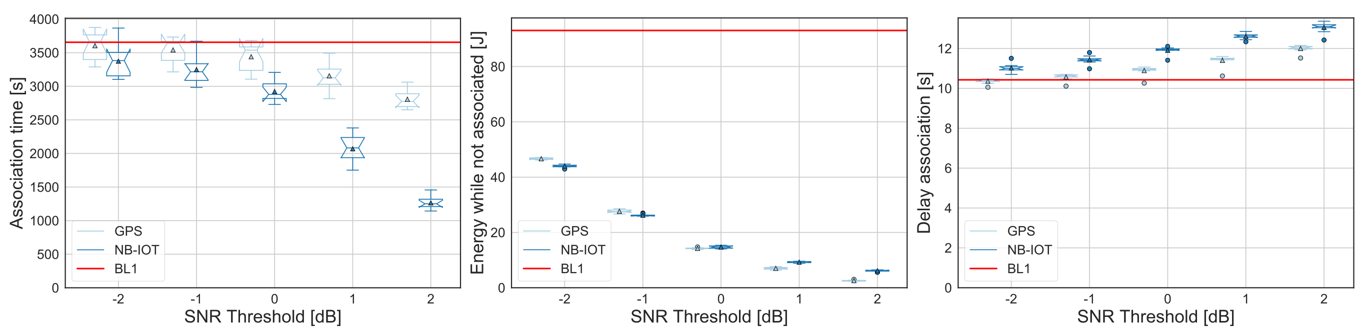
For different types of environments, the same localization technology can have different behaviours. For example, when using NB-IoT-like accuracy in rural environments, the association time is up to 20% better than GPS-like accuracy, having similar energy consumption. On the other side, in urban environments, GPS-like accuracy performs better, yielding up to 25% higher association time than NB-IoT-like accuracy, with comparable energy consumption. This is due to the



(a) Rural (b) Suburban (c) Urban

(d) Rural (e) Suburban (f) Urban

Figure 5: Duration of association to IEEE 802.11ah and energy consumed while not associated, considering different environments



(a) Association time to IEEE 802.11ah (b) Energy consumed while not associated to IEEE 802.11ah (c) Delay in association to IEEE 802.11ah

Figure 6: Performance results considering the overhead caused by the localization service, with a packet generation interval of 60 s

fact that with a more liberal *Threshold*, GPS-like accuracy generally performs better. However, NB-IoT-like accuracy performs better in rural environments because the device tries to connect to IEEE 802.11ah even when the device is further away from the AP, as rural areas have higher coverage range for IEEE 802.11ah. Moreover, the algorithm will try to connect from further away with higher localization error, due to the uncertainty that causes. This is especially visible in Figure 5f, where the energy consumption of NB-IoT-like accuracy is always slightly higher then GPS-like, however the resulting duration of association is lower.

In the rural environment, a *Threshold* of -1 dB is overall very good for all the localization inaccuracies, as it shows similar association time to BL5 (and only 2% worse than BL1), but with 10 times lower energy consumption. In suburban environments, -2 and -1 dB achieve performance close to BL1, with the 68% lower energy consumption. On the other side, in suburban environments, 1 dB is within the 5-10% association of BL5, but at only half of the power consumption. In urban, 0 dB has better association time than BL5 (15% less than BL1), but with 50% lower energy consumption.These results show that the proposed mechanism is flexible, as it can be deployed in different types on environments and it can be supported by different types of localization services. Moreover, these results indicate that the location-based mechanism can achieve performance comparable to the baseline, with a dramatic reduction in the energy consumption.

C. Full System Analysis

Here we consider the energy and latency overhead caused by using a localization-service, specifically GPS and NB-IoT. Specifically, the latency is the delay in association of the device from the moment it can virtually connect to IEEE 802.11ah to the moment it actually connects. In Figure 6, we show respectively the results for the association time, energy consumption, and delay in associating for varying values of the *Threshold* parameter. We do that for different localization-services (i.e., GPS and NB-IoT). We depict our results for the urban environment due to the fact that the trends and conclusions are consistent in the other two environments. The baseline that we used here is based on periodic beacon listening with the device waking up for every beacon. We only show the results with packets being generated for transmission every 60 sec, as the results for the 600 s show the same trend.

In line with the previous results, in Figure 6 it can be seen that the *Threshold* parameter is able to tune the policy of the mechanism, showing differences up to 250% between -2 and 2 dB in the association time for NB-IoT localization in Figure 6. As it is shown by Figures 6a and 6b, with the increase of the *Threshold* parameter the association time and the energy consumption diminish. However, in both cases there is an increase in latency, as the device will try to connect only when in proximity of the AP. With *Threshold* smaller than 0 dB, the graphs show that the association time and the delay of association are similar to the baseline, however the energy consumption is 65 times lower. However, as it can be seen in Figure 6, despite accounting for the overhead due to the localization service, the proposed location-based mechanism consistently outperforms the baseline in terms of energy consumption.

V. Conclusion

In this paper, we have presented a mechanism for optimizing network discovery and handover management in IEEE 802.11ah-supporting multi-RAT devices by utilizing physical location information of the devices. By explicitly accounting for the expected errors in localization, the mechanism can be supported by different localization services (i.e., NB-IoT, GPS), usually with differing localization accuracy and location information provisioning delays. The mechanism can also account for signal propagation differences in different types of environments and is, therefore, suitable for supporting heterogeneous IoT applications.

We have evaluated the association time and energy consumption of a location-based mechanism for initiating the discovery and the handover from LPWAN to IEEE 802.11ah networks.We have compared the achieved results with a baseline based on periodic beacon listening, showing that the location-based mechanism substantially improves the energy consumption of the device, while having association times comparable to the optimal baseline. In addition, we have shown that the proposed mechanism is intrinsically able to adjust its performance to the requirements of the use-case to be be supported. Specifically, we have observed that, especially in urban and suburban environments, a more liberal *Threshold* of -2dB yields higher association time (up to 66%), with much higher energy consumption (up to 1900%) compared to a more conservative *Threshold* of 2dB, due to its being aggressive in trying to connect more. However, in rural environments the choice of the *Threshold* policy highly affects the association time, with decreases up to 52%, without affecting much the energy consumed, due to the fact that rural environments have less obstacles. Through the utilization of flexible propagation modelling based on crowd-sourcing, the proposed approach can be adapted to different types of the deployment environments by having more accurate path-loss coefficients, again making a case for its flexibility in supporting different use-case requirements. Finally, we studied the overhead caused by the adopted localization service, showing that the proposed mechanism can be supported by localization services with varying accuracy and outperforms the optimal baseline even when considering the localization service overhead. As future work, we will consider alternative methods than log-distance propagation loss model using Machine Learning techniques.

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References

[1] T. Janssen *et al.*, “Localization in Low Power Wide Area Networks Using Wi-Fi Fingerprints,” *Applied Sciences*, vol. 7, no. 9, 2017.

[2] “IEEE Local and metropolitan area networks–Specific requirements,” *IEEE Std 802.11ah-2016*, pp. 1–594, 2017.

[3] U. Raza *et al.*, “Low Power Wide Area Networks: An Overview,” *IEEE Communications Surveys Tutorials*, vol. 19, no. 2, pp. 855–873, 2017.

[4] J. Famaey *et al.*, “Flexible Multimodal Sub-Gigahertz Communication for Heterogeneous Internet of Things Applications,” *IEEE Communications Magazine*, vol. 56, no. 7, pp. 146–153, 2018.

[5] S. Santi *et al.*, “On the Feasibility of Location-based Discovery and Vertical Handover in IEEE 802.11ah,” in *2020 IEEE Wireless Communications and Networking Conference (WCNC)*, 2020, pp. 1–6.

[6] E. Khorov *et al.*, “A Survey on IEEE 802.11ah: An Enabling Networking Technology for Smart Cities,” *Computer Communications*, vol. 58, pp. 53–69, 2015.

[7] T. Adame *et al.*, “IEEE 802.11ah: the WiFi approach for M2M communications,” *IEEE Wireless Communications*, vol. 21, no. 6, pp. 144–152, 2014.

[8] A. Seferagić *et al.*, “Enabling Wireless Closed Loop Communication: Optimal Scheduling Over IEEE 802.11 ah Networks,” *IEEE Access*, vol. 9, pp. 9084–9100, 2021.

[9] M. Bacco *et al.*, “Smart farming: Opportunities, challenges and technology enablers,” in *2018 IoT Vertical and Topical Summit on Agriculture-Tuscany (IOT Tuscany)*. IEEE, 2018, pp. 1–6.

[10] A. Abdallah *et al.*, “Efficient Security Scheme for Disaster Surveillance UAV Communication Networks,” *Information*, vol. 10, no. 2, p. 43, 2019.

[11] F. Lemic, V. Handziski, and J. Famaey, “Toward Regression-Based Estimation of Localization Errors in Fingerprinting-Based Localization,” in *IEEE Vehicular Technology (VTC2019-Spring)*, 2019, pp. 1–5.

[12] B. Bellekens *et al.*, “Outdoor IEEE 802.11ah range characterization using validated propagation models,” in *IEEE Global Comms.*, 2017.

[13] T. De Koninck *et al.*, “Experimental validation of ieee 802.11ah propagation models in heterogeneous smarty city environments,” in *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, 2020, pp. 1–6.

[14] F. Lemic *et al.*, “Location-based Discovery and Vertical Handover in Heterogeneous Low-Power Wide-Area Networks,” *IEEE Internet of Things Journal*, pp. 1–1, 2019.

[15] S. Santi *et al.*, “Location-Based Vertical Handovers in Wi-Fi Networks With IEEE 802.11ah,” *IEEE Access*, vol. 9, pp. 54 389–54 400, 2021.

[16] A. Brdulak, “Characteristics of Narrowband IoT (NB-IoT) technology that supports smart city management, based on the chosen use cases from the environment area,” *Journal of Decision Systems*, pp. 1–8, 2020.

[17] M. Ballerini *et al.*, “NB-IoT Versus LoRaWAN: An Experimental Evaluation for Industrial Applications,” *IEEE Transactions on Industrial Informatics*, vol. 16, no. 12, pp. 7802–7811, 2020.

[18] F. Lemic *et al.*, “Location-based Mechanism for Positioning of a Mobile Relay,” in *QoS and Security for Wireless Networks*, 2017, pp. 73–80.

[19] A. Behboodi *et al.*, “Hypothesis Testing Based Model for Fingerprinting Localization Algorithms,” in *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)*, 2017, pp. 1–6.
[20] G. Caso *et al.*, “ViFi: Virtual Fingerprinting WiFi-Based Indoor Positioning via Multi-Wall Multi-Floor Propagation Model,” *IEEE Mobile Computing*, vol. 19, no. 6, pp. 1478–1491, 2020.
[21] F. Lemic *et al.*, “Localization as a feature of mmWave communication,” in *Wireless Communications and Mobile Computing (IWCMC)*. IEEE, 2016, pp. 1033–1038.
[22] N. Moayeri *et al.*, “Perfloc: An extensive data repository for development and a web-based capability for performance evaluation of smartphone indoor localization apps,” in *IEEE Personal, Indoor and Mobile Radio Communications*, 2016, pp. 4–7.
[23] T. V. Haute *et al.*, “Comparability of RF-based indoor localisation solutions in heterogeneous environments: an experimental study,” *Ad Hoc and Ubiquitous Computing*, vol. 23, no. 1-2, pp. 92–114, 2016.
[24] F. Lemic *et al.*, “Regression-Based Estimation of Individual Errors in Fingerprinting Localization,” *IEEE Access*, vol. 7, pp. 33 652–33 664, 2019.
[25] F. Lemic and J. Famaey, “Artificial Neural Network-based Estimation of Individual Localization Errors in Fingerprinting,” in *Consumer Communications & Networking (CCNC)*. IEEE, 2020, pp. 1–6.
[26] N. Bnilam *et al.*, “AoA-Based Localization System Using a Single IoT Gateway: An Application for Smart Pedestrian Crossing,” *IEEE Access*, vol. 9, pp. 13 532–13 541, 2021.
[27] Q. Jiang *et al.*, “A Probabilistic Radio Map Construction Scheme for Crowdsourcing-Based Fingerprinting Localization,” *IEEE Sensors Journal*, vol. 16, no. 10, pp. 3764–3774, 2016.
[28] L. Tian *et al.*, “Extension of the IEEE 802.11ah ns-3 Simulation Module,” in *Proceedings of the Workshop on ns-3*, 2018, pp. 53–60.
[29] C. Sommer *et al.*, “A computationally inexpensive empirical model of IEEE 802.11p radio shadowing in urban environments,” in *Wireless on-demand network systems and services*. IEEE, 2011, pp. 84–90.
[30] C. B. Andrade and R. P. F. Hoefel, “Ieee 802.11 wlans: A comparison on indoor coverage models,” in *CCECE 2010*, 2010, pp. 1–6.
[31] Y. F. Solahuddin and R. Mardeni, “Indoor empirical path loss prediction model for 2.4 ghz 802.11n network,” in *2011 IEEE International Conference on Control System, Computing and Engineering*, 2011, pp. 12–17.
[32] S. Lavdas *et al.*, “The effect of temperature and humidity on indoor lora propagation model,” in *2021 17th International Conference on Distributed Computing in Sensor Systems (DCOSS)*, 2021, pp. 374–379.
[33] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wiessner, “Microscopic Traffic Simulation using SUMO,” in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018.
[34] T. Janssen *et al.*, “Rss-based localization and mobility evaluation using a single nb-iot cell,” *Sensors*, vol. 20, no. 21, 2020.
[35] Atmel Corporation, “Atmel AT86RF215 Device Family,” http://ww1.microchip.com/downloads/en/devicedoc/atmel-42415-wireless-at86rf215_datasheet.pdf.
[36] X. Lin *et al.*, “Positioning for the Internet of Things: A 3GPP Perspective,” *IEEE Communications Magazine*, vol. 55, no. 12, pp. 179–185, 2017.

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