On the Feasibility of Location-based Discovery and Vertical Handover in IEEE 802.11ah

Serena Santi, Filip Lemic, Jeroen Famaey
Internet and Data Lab (IDLab), University of Antwerp - imec, Belgium
{serena.santi, filip.lemic, jeroen.famaey}@uantwerpen.be

***Abstract*—Multi-Radio Access Technology (RAT) IoT devices are able to combine the high coverage of Low-Power Wide-Area (LPWA) technologies with the higher data-rates of shorter range technologies such as IEEE 802.11ah. In such scenarios, a discovery procedure has to be used for detecting the availability of a IEEE 802.11ah network. Currently, these procedures consume substantial energy, as the discovery has to be periodically performed, even if the IEEE 802.11ah technology is not available, which is undesirable for low-power Internet of Things (IoT) devices. We propose using the device's location information for making more optimized discovery and handover decisions. We demonstrate the feasibility of this approach in performing energy efficient handovers between various LPWA technologies and IEEE 802.11ah based on estimated location. We carry out our evaluation in terms of the energy consumption of the procedure and the duration of the device's association to IEEE 802.11ah. We show 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.**

I. Introduction

Low-Power Wide-Area (LPWA) network technologies utilize sub-GHz frequencies for connecting Internet of Things (IoT) devices, providing long range and low-power connectivity. Some LPWA technologies offer connectivity over a range of tens of kilometers with throughputs of at most kilobits per second (e.g., NB-IoT, LoRa, Sigfox). In contrast, shorter range sub-GHz technologies, such as IEEE 802.11ah [1], provide megabits per second data-rates at shorter ranges of around 1 kilometer [2]. As such, IEEE 802.11ah is suitable for bandwidth-consuming tasks, such as firmware updates or data offloading.

Many IoT use-cases would benefit from almost full coverage of LPWA networks combined with higher throughput and energy efficiency of IEEE 802.11ah. To enable that, several multi-Radio Access Technology (RAT) devices have been proposed, such as the one presented in [3]. Since IEEE 802.11ah is not expected to be continuously available due to its relatively short range, these multi-RAT devices will have to utilize a discovery procedure for deciding if a vertical handover from LPWA to IEEE 802.11ah should be performed. Currently, these discovery procedures rely on the device listening for beacons transmitted by the nearby IEEE 802.11ah Access Point (AP). When a beacon is received, the device initiates the connection to IEEE 802.11ah. This procedure can consume high amounts of energy due to periodic idle listening when IEEE 802.11ah is not available, which is undesirable for IoT devices targeting low-power performance.

To mitigate these drawbacks, in our previous work we presented a mechanism that, based on the location information of the device, performs more efficient discovery and handover procedures between sub-GHz LPWA technologies [4]. 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.

As many use-cases require localization capability of the mobile IoT devices (e.g., track-and-trace of equipment in construction sites [5], [3]), these devices usually have means of localizing themselves. The Global Positioning System (GPS) is a widely used localization approach, providing high localization accuracy, but consuming relatively high amounts of energy in its operation. This is not always feasible for IoT devices targeting low-power performance. Hence, a number of alternative approaches have been suggested in the literature. Very promising candidates for low-power localization are sub-GHz technologies themselves [6], [7], [8], [9], [10]. However, their localization accuracy is at least one order of magnitude lower than the one provided by the GPS. Given that the localization errors in such scenarios can be substantial, our mechanism explicitly accounts for such errors, in addition to the location estimates per-se. In [4], the proposed mechanism has been validated in terms of percentage of correct decisions (i.e., when the mechanism correctly decided to connect to a given technology) and its feasibility has been demonstrated for Sigfox and LoRa.

In this work, we adapt the proposed mechanism to support discovery and vertical handover to IEEE 802.11ah. We evaluate the mechanism in terms of energy consumption and association time of the device to IEEE 802.11ah, which provides more accurate network performance insights than the plain number of correct decisions. Moreover, we evaluate the effects of different types of localization services and show the feasibility of the mechanism for IEEE 802.11ah even in case the location estimates feature relatively large localization errors of up to hundreds of meters. Finally, we demonstrate that the threshold that is used as an internal parameter in the mechanism can successfully serve its purpose of tuning the mechanism's performance to the use-case requirements.

II. Location-aware handover algorithm

An overview of the considered scenario is given in Figure 1. We assume a moving multi-RAT device implementing at least one LPWA technology, in addition to IEEE 802.11ah. If the

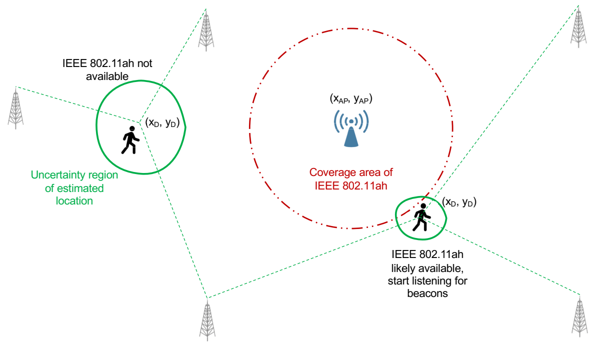

Fig. 1. The considered scenario where a device implementing multiple sub-GHz technologies can adapt the choice of technology based on its location.

Algorithm 1: Handover based on periodic beacon listening

```
for TB beacon intervals elapsed do
    Wake up to receive beacon for one beacon interval;
    if Beacon Received then
        Start Association Procedure;
    else
        Sleep;
```

IEEE 802.11ah technology is available, the device should perform a vertical handover from the LPWA to IEEE 802.11ah. In the following, we present two mechanisms that can be used for deciding if a vertical handover to IEEE 802.11ah should be initiated. The first one relies on periodic listening for beacons, while the other accounts for the location of the device in order to take the decision on when to start listening for beacons.

A. Periodic Beacon Listening

The first procedure is described by Algorithm 1. While the device is not associated to IEEE 802.11ah, it periodically wakes up to listen for beacons. When 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 a certain amount of beacons missed, the connection is dropped [1]. Once disconnected from IEEE 802.11ah, the device starts the discovery procedure again.

On the one hand, by waking up periodically, this mechanism allows the device to associate to IEEE 802.11ah whenever it is available. On the other hand, due to continuous idle listening even if IEEE 802.11ah is not available, the device consumes substantial amounts of energy. In order to reduce the energy consumption, the device can wake up less frequently (i.e., once every TB beacon intervals, where TB is a configurable parameter). However, this leads to higher delays in association.

B. Location-based Handover

In the location-based mechanism, the device uses its location estimates in order to decide if the listening for IEEE 802.11ah beacons should be initiated. The location estimates are provided by a localization service, which, as mentioned, features a certain level of localization error. This error ranges from tens (i.e., GPS) to hundreds (i.e., LPWA) of meters, which we assume to be characterized by a zero-mean Gaussian distribution. Moreover, the mechanism assumes the location of the IEEE 802.11ah AP to be perfectly accurate and known by the moving device, which is a realistic assumption, given the static position of the AP [11], [12].

The mechanism proposed in our previous work [4] accounts for this erroneous location information for calculating the estimated Signal-to-Noise Ratio (SNR) between the mobile device and the AP. Here we modify the mechanism to use IEEE 802.11ah as target technology. Specifically, we integrate into the mechanism the propagation loss model from [13], where the signal attenuation $L(d)$ in dB is given by:

$$L(d) = l_c + 10\gamma \log(d). \tag{1}$$

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

As mentioned before, we assume that the 2D coordinate of the location information of the device provided by GPS or the localization service of the LPWA technology features 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 [14], [15], [16]. The true location information of the device is then a Gaussian 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:

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

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

$$\lambda = \sqrt{(\mu_{x_D} - x_{AP})^2 + (\mu_{y_D} - y_{AP})^2} \tag{3}$$

According to [11], the estimated SNR calculated between the device and the AP can be then calculated as:

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

with P_{tx} being the transmit power of the AP in dBm and N being the noise floor. Moreover the parameter k for IEEE 802.11ah equals 0.5 and γ equals 3.76, while the function $g(.)$ is defined as follows:

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

Algorithm 2 shows how the device decides whether to start listening for beacons. The required SNR is the value needed by IEEE 802.11ah in order to be able to receive and decode signals (i.e., 0 dB). If the estimated SNR is over the required SNR increased by a certain *Threshold*, the device will start listening for beacons; otherwise the IEEE 802.11ah radio will

Algorithm 2: Location-based Handover

```
for Beacon interval elapsed 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;
        end
    else
        Sleep;
    end
end
```

remain in a power saving mode until a new location estimate is generated. *Threshold* is a parameter in the mechanism that can be configured during its deployment and based on a particular use-case. Specifically, if the focus is on energy efficiency, then the mechanism should be "conservative" in making handover decisions (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" (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 in the choice of the policy of the mechanism (i.e., "conservative" or "liberal").

III. Results and Discussion

A. Simulation Set Up and Methodology

In our evaluation, we simulate a device repeatedly moving away from the IEEE 802.11ah AP and then moving back towards it. We do that by utilizing the ns-3 event-based simulation framework for IEEE 802.11ah [17]. The goal of the evaluation is to compare the energy consumption and association time to IEEE 802.11ah of a moving device, using the two presented handover mechanisms (i.e., periodic beacon listening and location-based).

Going away from the coverage area and coming back to the starting point is defined as a "cycle" and in each of our experiments we execute 1000 cycles to achieve statistically meaningful performance metrics. We set the furthest distance of the device to the AP to 1000 meters, as the device loses the connection from IEEE 802.11ah at around 600 meters from the AP (using the modulation and coding scheme MCS10).

As a baseline for comparison, we use the periodic beacon listening algorithm. The device wakes up for every 1 (BL 1), 5 (BL 5), or 10 (BL 10) beacon intervals, to listen for an incoming beacon during one beacon interval period. The association time is calculated as the average association time during a single cycle. As we assume the device has a speed of 1 m/s (in line with various track-and-trace scenarios, e.g., [9]), the maximum time the device can be associated to IEEE 802.11ah is roughly 1200 s per cycle.

TABLE I
Default power consumption, PHY and MAC layer 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	Outdoor, macro [13]
Error Rate Model	YansErrorRate
Wi-Fi mode	MCS10, 1 MHz
Minimum Distance from AP	1 m
Maximal Distance from AP	1000 m
Beacon Interval	2.048 s
Speed	1 m/s
Power consumption (from [18])	**Value**
Receiving (P_{rx})	92 mW
Idle (P_{idle})	20 mW
Sleeping (P_{sleep})	99 nW

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 have a more "liberal" wake-up policy) to 2 dB (a more "conservative" policy). The discovery decision is made based on the current location of the device, that is generated every beacon interval. If the discovery decision made by the mechanism is positive, then the device wakes up and starts listening for beacons, otherwise it remains asleep. To isolate the effects of the handover mechanism and characterize its performance, we only consider the energy consumed by listening for beacons and not that of data transmission and localization. We calculate the energy consumption by multiplying the time spent in each radio state (i.e., Rx, Idle, Sleep) with the power consumption in that state. The power consumption values are obtained from the Atmel AT86RF215 radio [18] and given in Table I.

To account for background noise, as well as noise caused by surrounding devices communicating in the same frequencies, we add a certain amount of white background noise to the calculated SNR on a given communication link, drawn from a zero-mean Gaussian distribution with a standard deviation between 0 and 4 dB [19], [20]. Moreover, we evaluate the mechanism for different localization inaccuracies typical for the GPS (10 m), Sigfox/LoRa fingerprinting (400 m) [21], [22], and NB-IoT time-difference of arrival (100 m) [9], 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. In order to demonstrate the effects of localization errors on the performance of the mechanism, we also perform simulations assuming a non erroneous location. A comprehensive list of the simulation parameters is given in Table I.

B. Influence of SNR Threshold Parameter

In Figures 2 and 3 we show respectively the results for the association time and for the energy consumption (y-axis) for varying values of the *Threshold* parameter (x-axis). We do that for different location inaccuracies (i.e., GPS, NB-IoT, and Sigfox/LoRa), as well as for perfectly accurate location of the mobile device, while considering no background noise in the communication channel. We show three different baselines based on periodic beacon listening with different periods. As visible in the figure, as the device wakes up less frequently, its average association time is reduced, i.e., higher delays in association are incurred. Moreover, it can be derived from the figures that BL 5 is the best performing baseline algorithm, as it achieves a total association time very similar to BL 1, while simultaneously consuming 5 times less energy.

Figure 2 indicates that setting the *Threshold* parameter to values lower than 0 dB leads to longer association times of the location-based mechanism compared to the baseline. This is observed for all location inaccuracies and irrespective of the baseline. However, as shown in Figure 3, the energy consumption of the location-based mechanism is higher than the one observed for the BL 5 and BL 10 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.

However, for a relatively high localization error of 400 meters (e.g., when using localization based on Sigfox and LoRa fingerprinting) and for a *Threshold* higher than 0 dB, the location-based mechanism becomes too conservative and does not wake up the device to listen for beacons anymore. Therefore, the device does not associate to IEEE 802.11ah and its energy consumption equals zero. This is not the case for the *Threshold* higher than 0 dB and a GPS and NB-IoT-like location inaccuracies. Figure 3 shows a decrease in the energy consumption of the device compared to the baselines, while having comparable association time. For NB-IoT-like accuracy, the optimal *Threshold* is 1 dB and the energy consumption of the location-based mechanism is 100 times lower and the association time is slightly higher than the best performing baseline. A similar observation can be made for the *Threshold* of 0 dB and GPS-like accuracy, where the energy consumption of the location-based mechanism is more than 2 times lower than the best performing baseline (i.e., BL 5), however in this case the association time has a 2% decrease. For a large localization error of 400 meters, the location-based mechanism is not able to significantly outperform the baseline BL 5, as both energy consumption and association time are similar for the optimal SNR Threshold of 0 dB. When utilizing perfectly accurate location information, the mechanism manages to outperform the baselines by not listening to unnecessary beacons, thus having the lowest energy consumption and the best association time. However, we would like to note that in these experiments, the IEEE 802.11ah network is available approximately 60% of the time. If it would be available a smaller percentage of time, the energy consumed by the baseline algorithm would increase, as it would more frequently perform unnecessary beacon listening. As a result, our location-based algorithm would more easily outperform the baseline in such scenarios, even with high localization errors of 400 meters or more.

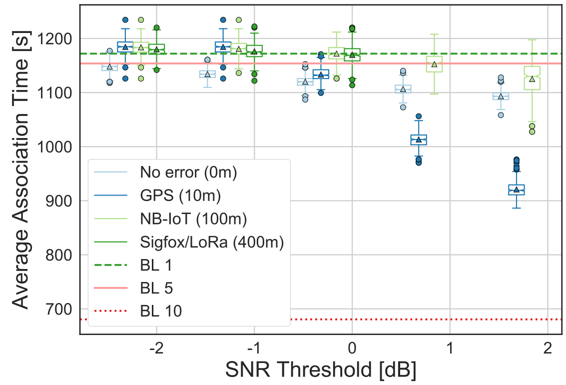

Fig. 2. Duration of association to IEEE 802.11ah in seconds, considering different location inaccuracies, without background noise.

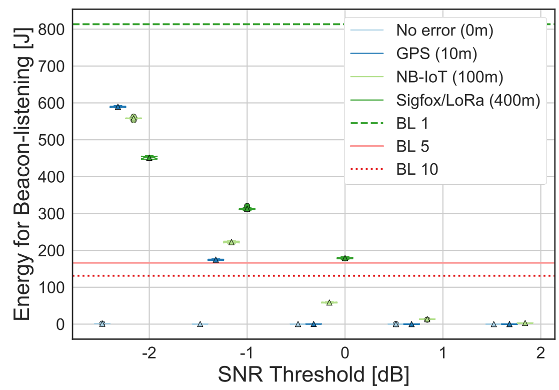

Fig. 3. Energy consumed while not associated, considering different location inaccuracies, without background noise.

Figures 4 and 5 depict the same insight as the previous ones, however taking into account a realistic amount of white noise with the standard deviation of 2 dB. The results are in this case very similar to the ones from the previous experiment, with the only difference being that the association time-related performance of the location-based mechanism degrades faster than without noise for the *Threshold* higher than 0 dB. Even so, they show the same improvements to the baseline as before.

The above-discussed results indicate that the optimal value of the *Threshold* parameter depends on the expected localization errors. If the expected localization errors are relatively high (e.g., 400 meters), the *Threshold* should be set in a liberal way, otherwise the mechanism will never yield positive discovery decisions. In contrast, when the localization error is 100 meters or less, the optimal value is between 0 and 1 dB.

C. Influence of Localization Error

Figures 6 and 7 show respectively the results of the average association time and the energy consumed for beacon listening (y-axis) considering different localization errors (x-axis) and

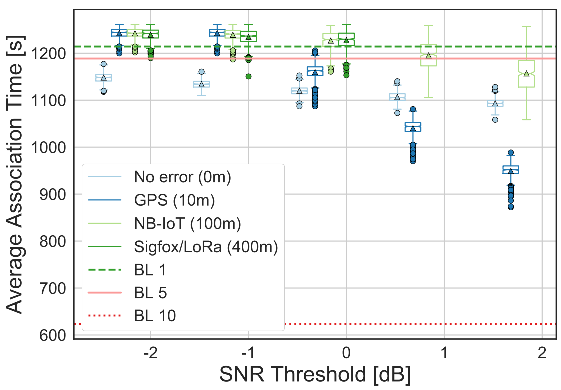

Fig. 4. Duration of association to IEEE 802.11ah in seconds, considering different location inaccuracies, with an average amount of noise of 2 dB.

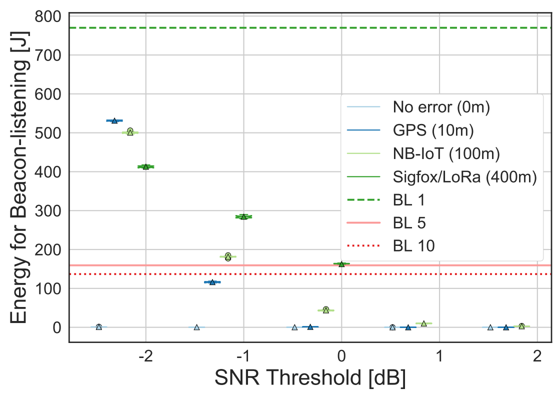

Fig. 5. Energy consumed while not associated, considering different location inaccuracies, with an average amount of noise of 2 dB.

different thresholds between -2 dB and 2 dB. These graphs show how GPS-like localization accuracy yields better energy consumption and association time when using a more liberal *Threshold* (i.e., lower than 0 dB). For localization errors of 200 meters and above, the trend is different. A conservative *Threshold* is more optimal in terms of energy consumption for smaller errors close to 200 meters, and a more liberal *Threshold* becomes better as the error increases further. This is due to the previously mentioned fact that conservative *Threshold* values no longer allow association to IEEE 802.11ah when the localization error becomes very high. Specifically, the *Threshold* of 2 dB is optimal for 200 meters error, 1.5 dB is optimal up to 400 meters, 0.5 dB is optimal up to 500 meters and -0.5 dB is optimal while having localization error over 500 meters. These results indicate that the location-based mechanism can achieve good performance even in case of very large localization errors. Hence, the mechanism can be operational even on highly energy-constrained IoT devices that cannot support the operation of the energy-hungry GPS.

D. Influence of White Background Noise

In Figures 8 and 9 we show respectively the results for the association time and for the energy consumption (y-axis), for different values of *Threshold* (x-axis) and white background

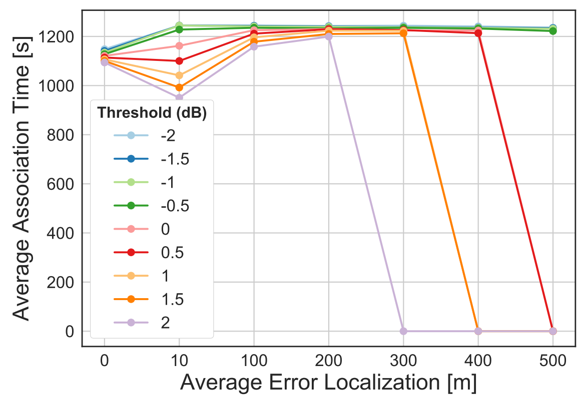

Fig. 6. Duration of association to IEEE 802.11ah in seconds with different thresholds and localization inaccuracies, with an average amount of noise of 2 dB.

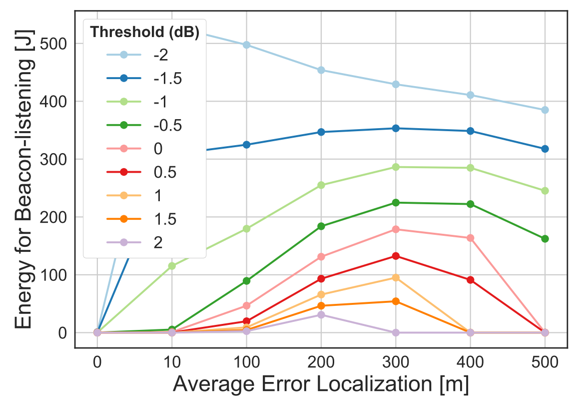

Fig. 7. Energy consumed while not associated with different thresholds and localization inaccuracies, with an average amount of noise of 2 dB.

noise (between 0 dB and 4 dB), with a localization inaccuracy of 10 m.

By including white noise in the communication channel, we emulate an environment densely populated with devices communicating in the sub-GHz frequency band. Figure 9 shows that when the *Threshold* is higher than -1 dB, the energy consumed while the device is not connected to IEEE 802.11ah is nearly 0 J, meaning that the mechanism always correctly decides to connect to IEEE 802.11ah. An interesting observation is that the increase in the background noise improves the association time and decreases the energy consumed while not being associated to IEEE 802.11ah. This is the effect of the noise being modeled as a Gaussian random variable. For that reason, the coverage area of the IEEE 802.11ah AP is effectively increased with an increase in the standard deviation of the noise value due to possible additive noise. This causes an increase in the association time and consequent decrease in the energy consumed while listening for beacons. The above-results show the capacity of the location-based mechanism to coexist with other communicating devices in densely populated environments.

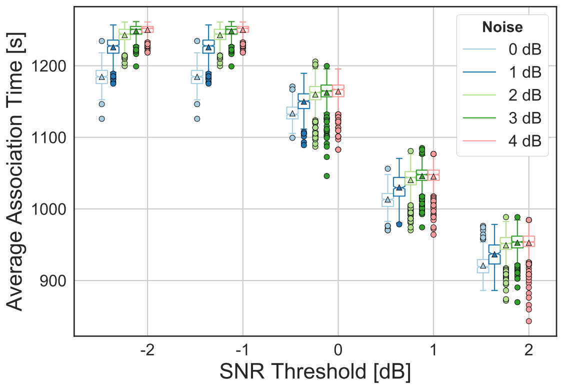

Fig. 8. Duration of association to IEEE 802.11ah with increasing levels of white noise, with a localization inaccuracy of 10 meters.

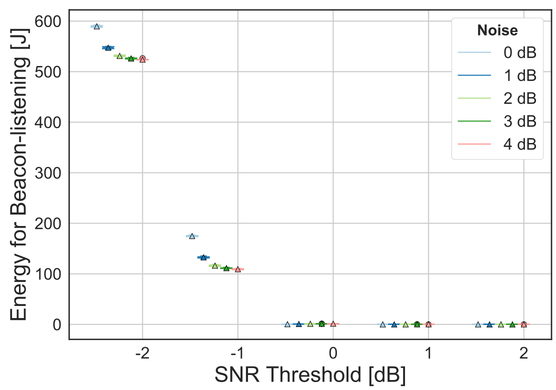

Fig. 9. Energy consumed while not associated with increasing levels of white noise, with a localization inaccuracy of 10 meters.

IV. Conclusion

We evaluated the association time and energy consumption of a location-based mechanism for initiating vertical handover from LPWA (e.g., NB-IoT, Sigfox, LoRa) to IEEE 802.11ah networks. Moreover, we compared the achieved results with a baseline approach, where the device wakes up periodically to listen for IEEE 802.11ah beacons. Our results show that the location-based mechanism substantially improves the energy consumption of the device by 100 times, while having similar association time compared to the best baseline approach.

Future work will be focused on studying the behavior of mobile devices at the edge of the IEEE 802.11ah coverage area toward reducing possible oscillations and optimising the edge perfomance. We will consider environment-specific (e.g., non-Gaussian) localization errors and signal attenuation in our evaluation framework. Finally, we will aim at validating the results experimentally in different testbed infrastructures.

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References

[1] "IEEE Local and metropolitan area networks–Specific requirements - Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications Amendment 2: Sub-1GHz License Exempt Operation," *IEEE Std 802.11ah-2016*, pp. 1–594, May 2017.

[2] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low power wide area networks: An overview," *IEEE Communications Surveys Tutorials*, vol. 19, no. 2, pp. 855–873, Secondquarter 2017.

[3] J. Famaey, R. Berkvens *et al.*, "Flexible multimodal sub-gigahertz communication for heterogeneous internet of things applications," *IEEE Communications Magazine*, vol. 56, no. 7, pp. 146–153, July 2018.

[4] F. Lemic, A. Behboodi, J. Famaey, and R. Mathar, "Location-based discovery and vertical handover in heterogeneous low-power wide-area networks," *IEEE Internet of Things Journal*, pp. 1–1, 2019.

[5] T. Janssen *et al.*, "Localization in low power wide area networks using wi-fi fingerprints," *Applied Sciences*, vol. 7, no. 9, 2017.

[6] G. G. L. Ribeiro *et al.*, "An outdoor localization system based on sigfox," in *IEEE Vehicular Technology (VTC Spring)*, June 2018, pp. 1–5.

[7] B. C. Fargas *et al.*, "Gps-free geolocation using lora in low-power wans," in *2017 global internet of things summit (Giots)*. IEEE, 2017, pp. 1–6.

[8] M. Aernouts *et al.*, "A comparison of signal strength localization methods with sigfox," in *Positioning, Navigation and Communications (WPNC)*. IEEE, 2018, pp. 1–6.

[9] X. Lin *et al.*, "Positioning for the internet of things: A 3gpp perspective," *IEEE Communications Magazine*, vol. 55, no. 12, pp. 179–185, 2017.

[10] X. Tian, X. Wu, H. Li, and X. Wang, "Rf fingerprints prediction for cellular network positioning: A subspace identification approach," *IEEE Transactions on Mobile Computing*, pp. 1–1, 2019.

[11] F. a. Lemic, "Location-based mechanism for positioning of a mobile relay," in *ACM Symposium on QoS and Security for Wireless and Mobile Networks*. ACM, 2017, pp. 73–80.

[12] A. Behboodi *et al.*, "Hypothesis testing based model for fingerprinting localization algorithms," in *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)*. IEEE, 2017, pp. 1–6.

[13] B. Bellekens *et al.*, "Outdoor IEEE 802.11ah range characterization using validated propagation models," in *IEEE Global Communications Conference (GLOBECOM)*, Singapore, Singapore, 2017.

[14] G. Caso *et al.*, "Vifi: Virtual fingerprinting wifi-based indoor positioning via multi-wall multi-floor propagation model," *IEEE Transactions on Mobile Computing*, 2019.

[15] F. Lemic *et al.*, "Localization as a feature of mmwave communication," in *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*. IEEE, 2016, pp. 1033–1038.

[16] 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.

[17] L. Tian, A. Sljivo, S. Santi, E. De Poorter, J. Hoebeke, and J. Famaey, "Extension of the IEEE 802.11ah ns-3 simulation module," in *Proceedings of the Workshop on ns-3*, 2018, pp. 53–60. [Online]. Available: http://doi.acm.org/10.1145/3199902.3199906

[18] Atmel Corporation, "Atmel AT86RF215 Device Family," http://ww1.microchip.com/downloads/en/devicedoc/atmel-42415-wireless-at86rf215_datasheet.pdf.

[19] A. Behboodi *et al.*, "Interference effect on localization solutions: Signal feature perspective," in *2015 IEEE 81st Vehicular Technology Conference (VTC Spring)*, May 2015, pp. 1–7.

[20] J. Luo and X. Zhan, "Characterization of smart phone received signal strength indication for wlan indoor positioning accuracy improvement," *Journal of Networks*, vol. 9, 03 2014.

[21] T. Janssen *et al.*, "Outdoor fingerprinting localization using Sigfox," in *2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Sep. 2018, pp. 1–6.

[22] F. Lemic, V. Handziski, and J. Famaey, "Toward regression-based estimation of localization errors in fingerprinting-based localization," in *IEEE Vehicular Technology (VTC2019-Spring)*, April 2019, pp. 1–5.