Interference Suppression Methods with Adaptive Threshold in Internet of Things (IoT) Systems

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***Abstract*—The explosive growth in home, wearable, and wireless devices has not been matched by the growth in radio spectrum bands to accommodate them. The inter-networking of all of these devices known as "the internet of things (IoT)" is expected to have tens of billions of devices, mostly wireless, definitely incurring a coexistence or interference problem. The ubiquitous industrial, scientific and medical (ISM) radio band at 2.4GHz, in particular, one of the candidate band for IoT is heavily oversubscribed due to its unlicensed nature and could become all but unusable for priority systems in a densely populated area in the future at the present rate of growth of 2.4GHz transmitters and networks. In our study, the communications of the "last 100 meters" of an IoT network, i.e., from devices to an access point (AP) are considered. The interference suppression algorithms using the probability of false alarm P_{FA} based methods, i.e., the Neyman-Pearson (NP) criterion and the localization algorithm based on double-thresholding (LAD) are applied to enhance the transmission bit error rate (BER) performances in various scenarios. Besides the traditional fixed threshold approach, an adaptive threshold approaches are proposed to enhance the performances in frequency selective fading channels. The simulation results show that the proposed methods excellently work even in an IoT network, which contains a large number of devices.**

***Index Terms*—Interference suppression methods, Co-existing problem, Neyman-Pearson criterion, Adaptive threshold.**

I. Introduction

Internet of things (IoT) is an emerging technological concept including the various types of physical devices, vehicles, buildings, and other items embedded with electronics and defining how the things will be connected through the Internet and how those things communicate amongst other things or systems in order to expose their capabilities and functionalities. The IoT at large will foster the development of a number of applications that make use of the potentially enormous amount and variety of data generated [1].

In an IoT network system, each device has different requirements, such as data length or size, transmit power, and transmission rate. Collected data from multiple devices simultaneously is a challenging task. In a shared channel of fixed bandwidth, the transfer of the sensor data to the data processor must be made discrete in a suitable manner [2]. Today, the devices used in the "last 100 meters" are typically not connected. Various wireless technologies can compete in this short range communications including the international or domain-specific standards, and many proprietary technologies. There are also some applications, where the same IoT device or sensor is used for both mobile and fixed use cases [3,4]. The demand of wireless communications is gradually increased at present. However, there is no protection from all the other people using the same channels. Interferences could occur if overlapping channels are used, causing packet collisions and performance degradation [5].

To effectively enhance the wireless transmission, different interference mitigation methods have been proposed in the literatures. However, the algorithm does not apply for large-scale and dense wireless sensor networks (WSNs) since the 2.4 GHz ISM spectrum can be easily exhausted using three WLAN nodes operating on three different channels [6]. The narrowband IS has been studied for spread spectrum systems lately and several corresponding approaches have been proposed and mainly classified into time domain and transform domain techniques [7]. The time domain technique can theoretically inhibit the narrowband interference, but it requires large convergence time to reach the steady state [8], and it cannot effectively suppress time-varying narrowband interference [9]. The transform domain technique has the advantages, for instance, fast convergence, effective suppression of time-varying narrowband interference. In practice, the frequency domain method has been proved to especially useful for multi-tone narrowband IS [10]. In the frequency domain algorithm, the threshold setting is the most crucial task. The mean of the amplitude is used to obtain the threshold, it is simple method but not robust [11]. To improve the robustness, a median value has been replaced the the mean value, but the calculation of the median value is cumbersome [12]. A N-sigma algorithm is used to calculate the threshold, but N needs to be adjusted according to the channel condition [13]. The consecutive mean excision (CME) algorithm and its forward version, i.e., the forward CME (FCME), are introduced in [14] and [15], respectively. Both of them provide better performance than that of the median value based strategy. However, their study considered only single narrowband interference which is not the case occurred in an IoT network.

To suppress the impact of this coexistence or interference in an IoT network, in particular, the "last 100 meters," i.e., from

IoT devices to an AP, we study the probability of false alarm based algorithms, namely the Neyman-Pearson (NP) criterion and the localization algorithm based on double-thresholding (LAD). In addition to the traditional fixed threshold approach, an adaptive threshold approaches are proposed to enhance the performances in frequency selective fading channels. It can be seen that both methods are appropriate to be implemented in practical IoT networks since the knowledge of a waveform type is not required, for the NP method only noise power is needed as known as a semi-blind technique and for the LAD method even noise is not needed, i.e., completely blind. They can effectively detect the location of interference signals and suppress them, thereby significantly improving the overall system performance. To the extent of our knowledge, this is the first work that shows the interference suppression methods using the adaptive thresholds in IoT systems.

II. System Model

In this section, the system model is described as follows. We focus on the "last 100 meters" of an IoT network, which contains three components [16]. The first component is "Things" which is the physical objects around us, e.g., home appliances, monitoring devices in factories, personal electronic devices, and many others. The second component is "Access point (AP)" which is devices functioning as a local network coordinator and gateway. An IoT AP not only supports Internet access for mobile devices, but also connects to IoT objects. Finally, "Internet" is the basic components of an IoT network.

Both main signal and interference signals are assumed to be modulated by the binary phase shift keying (BPSK) scheme with non return to zero (NRZ) signaling in our study. The IoT network is modeled with M different types of devices. They all, in total N devices, are uniformly and independently deployed in a two-dimensional (2D) circular plane with the area $A = \pi R^2$, where R is the radius of the plane. Such a random deployment results in a 2D Poisson point distribution of devices. All devices are assumed to be static once the network has been deployed. The density, which is the number of devices per area in square meter and the number of each type of devices are represented as λ_i and N_i, respectively, where $i \in \{1, 2, \ldots, M\}$ denotes type of devices. The probability of occurring each type of devices at any particular time follows the Poisson distribution expressed as

$$\Pr(K = N_i) = \frac{\mu(A)^{N_i} e^{-\mu(A)}}{N_i!}, \tag{1}$$

where $\mu(A) = \lambda_i \pi R^2$. The distribution of a device around the circular plane is considered to be uniform. Hence, the distribution of the distance of a device to the AP, which is assumed to locate at the origin, r is given by

$$f_R(r) = \begin{cases} \frac{2r}{R^2}, \text{for } 0 < r < R, \\ 0, \text{otherwise.} \end{cases}$$

Like any other wirelesss systems, the wireless IoT system is contaminated by the channel quality, the interference, and the additive white Gaussian noise (AWGN) caused by the thermal noise in the receiver circuitry. The large scale fading of the channel, i.e., the log-distance path loss including the shadowing effect is considered, the corresponding model is expressed as

$$L_{\text{p}}(r)\text{dB} = L_{\text{FS}}(r_0)\text{dB} + 10\gamma log_{10}(\frac{r}{r_0}) - X_\sigma, \tag{2}$$

where r_0 is the reference distance, typically equal to 1m for indoor environment, γ is the path loss exponent, typically equal to 6 for obstructed indoor environments, and X_σ is a Gaussian random variable with zero mean ($\mu = 0$) and standard deviation σ as it is log-normal random variable in the linear scale. The worst case (non LoS or NLoS) of the small scale fading, i.e., Rayleigh multipath fading is considered in the narrowband or flat fading scenario as it is called Rayleigh flat fading channel. Thus, the channel gain is written by

$$H\text{dB} = -L_{\text{p}}(d)\text{dB} + 10\log_{10} Y, \tag{3}$$

where Y denotes an exponential random variable with mean a, which is the random power gain due to the Rayleigh flat fading. If the system bandwidth is much wider than the coherennce bandwidth of the channel, then the channel is not flat and is consider as the frequency selective fading channel consisting of multiple Rayleigh taps. The received complex baseband equivalent signal is expressed as

$$r(t) = x(t) * h(\tau, t) + i(t) + z(t), \tag{4}$$

where $x(t)$ is the transmitted signal and is assumed to be an independent and identically distributed (i.i.d.) Gaussian process with zero mean and variance σ_x^2, $h(\tau, t)$ is the channel impulse response, is assumed to be time-invariant, i.e., $h(\tau, t) = h(\tau)$, and is modeled as the zero mean unit variance complex Gaussian random variable $\mathcal{CN}(0, 1)$ representing Rayleigh multipath fading with the propagation delays τ, $i(t)$ is the overall interference signal caused by other devices after the channels, and $z(t)$ is the complex AWGN. It is also assumed that the signal $x(t)$, the interference $i(t)$, and the noise $z(t)$ are uncorrelated.

As previously mentioned, the most IoT-related applications are supposed to be operating at 2.4 GHz. Since a variety of wireless communication technologies, i.e., Bluetooth, Wi-Fi, ZigBee, and microwave devices also operate in this frequency range the interference problem is indispensable. The signal type of the interference is assumed to be exactly identical to the one of the main signal. Although Gaussian distribution might not exactly fit the statistics of interferences, we approximate them as Gaussian distributed random variable due to its simplicity and mathematical tractability.

III. Interference Suppression (IS) Techniques

Due to the advantage of frequency domain IS methods, the time-domain signal is first transformed to the frequency domain signal. We apply two probability of false alarm based IS Techniques, namely the Neyman-Pearson (NP) criterion and the localization algorithm based on double-thresholding (LAD) method. Both methods are appropriate to be implemented in practical IoT devices since the knowledge of a waveform type is not required, for the NP method only noise power is needed as known as a semi-blind technique and for the LAD method noise is not even needed to know, i.e., a completely blind technique. Besides the traditional fixed threshold approach, an adaptive threshold approaches are proposed to enhance the performances in frequency selective fading channels. Computer-intensive simulations are carried out to evaluate the performance of the IoT network and the effectiveness of the proposed algorithm. The simulation results show that the algorithms are able effectively detect the location of interferences and suppress them, thereby significantly improving the overall system performances.

A. Neyman-Pearson (NP) Criterion Method

The NP criterion method applies a decision rule that maximizes the probability of detection P_d subject to the constraint that the probability of false alarm P_fa. The NP criterion is known to provide the uniform most powerful (UMP) test [17]. The NP criterion is applicable only when both H_0 and H_1 are simple hypotheses. This is the case when both the noise level σ_W^2 and the channel H_k are a priori known. We assume that all frequency bins employ the equal threshold. For simplicity, X_kH_k is assumed to have Gaussian distribution. According to the NP criterion, the probability of false alarm is used to calculate the decision threshold t as

$$t_\text{NP} = \sqrt{-2(\sigma_S^2 + \sigma_Z^2)\ln(P_\text{fa})}, \tag{5}$$

where σ_S^2 and σ_Z^2 are the variances of X_kH_k and Z_k, respectively. Consequently, the interference signals are what locate above the threshold, whereas the signals, which are below the threshold, consist of the transmitted signal and the noise.

B. Forward Consecutive Mean Excision (FCME) Method

Similar to the NP criterion, the FCME method is an automated method for setting a threshold in order to separate the samples into two sets, i.e., the one below and the one above the threshold. However, the threshold of the FCME method is calculated iteratively. The FCME algorithm starts by rearranging the samples in the ascending order according to their energies [15,17]. The n smallest terms in the sorted set are selected to belong to the initial set assumed to be free of interference, i.e., the "clean set". The size of the initial set is typically about 10% of the size of the data set. This is defined as the set Q. The average sample envelope

$$\bar{R} = \frac{1}{Q}\sum_{i=1}^{Q}|R_i|. \tag{6}$$

The FCME method adds the samples R_i, $Q+1, \dots, N$ to the set Q if

$$|R_i| < t_\text{h} = \bar{R}t_\text{CME}, \tag{7}$$

where t_CME is given by

$$t_\text{CME} = \sqrt{\frac{4}{\pi}}\sqrt{-\ln(P_\text{fa})}, \tag{8}$$

This is done with the Gaussian assumption meaning that the concentrated signal is a Rayleigh distributed. The algorithm updates the set Q and calculates new $\bar{R}$ and t_h. The FCME algorithm is operated in a forward manner, i.e., the threshold increases in every iteration. The algorithm continues until there are no new samples below the threshold. The set is usually small enough to be free of interference, and large enough to ensure that the algorithm converges. Therefore, the threshold is calculated as

$$t_\text{h} = \sqrt{2\hat{\delta}^2} = \overline{|x|}\sqrt{\frac{4}{\pi}}\sqrt{-\ln(P_\text{fa})} = \overline{|x|}t_\text{CME}, \tag{9}$$

with

$$\hat{\delta} = \overline{|x|}\sqrt{\frac{2}{\pi}}. \tag{10}$$

For example, the t_CME are 2.97 and 2.42 corresponding to P_fa = 10^{-2} = 1% and P_fa = 10^{-3} = 0.1%, respectively.

C. Localization Algorithm based on Double-thresholding (LAD) Method

The LAD method is improved from the FCME method. As the name indicates, the LAD finds and localizes narrowband signals, where the use of two thresholds can provide clear signal separation and good localization accuracy. Preventing the falsely separated and detected signals problem, which is usually found in the FCME method are the aim of the LAD. With the mentioned two thresholds, the LAD method computes twice of the FCME yielding the upper (t_u) and lower (t_l) thresholds. After the threshold computation, a cluster is created to separate the sample which are above t_l . If the largest data in a cluster are above t_u, it is a concentrated signal. If the largest data is not exceed t_u, it is the noise.

The traditional fixed threshold setting is suitable when channels are assumed to be narrowband. In such cases, it happens when the coherence bandwidth of the channel is larger than the bandwidth of the signal, we then face just the flat fading caused by multipath propagations. However, when the coherence bandwidth of the channel is smaller than the bandwidth of the signal. Different frequency components of the signal therefore experience uncorrelated fading. In such cases, an adaptive threshold setting is more appropriate. The entire frequency band is divided into several sub-bands. A separate threshold is then computed for each sub-band.

IV. Simulation Results

As previously described, the "last 100 meters" of an IoT network is considered. Therefore, the IoT network is generated as shown in Fig. 1. The locations of the devices are created by 2D Poisson point model within circular plane with the radius of 100 meters. λ denotes the density of IoT devices on coverage area (number of devices/m^2). There are one access point (AP) located at the center of the area and four types of IoT devices located uniformly over the area. We investigate when the system operates under different environments, i.e., the AWGN channel, the Rayleigh flat fading channel, and the frequency selective fading channel. The path loss exponent

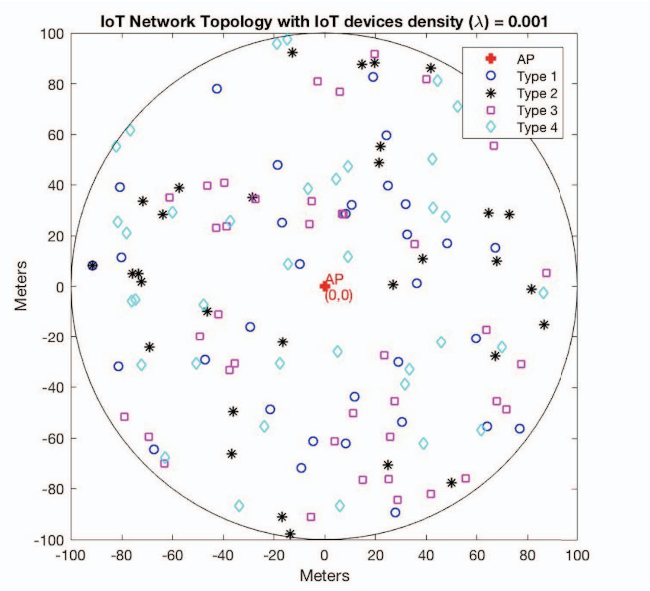

Fig. 1. The "last 100 meters" of an IoT network with one access point and four different types of IoT devices with the density of the IoT devices (λ) equal to 0.001

for each communication link is assumed to be equal to 4 for a typical obstructed indoor environment. The simulations are compared between the performances for the fixed and the adaptive thresholds under these channels. The signal to noise ratio (SNR) and interference to signal ratio (ISR) are computed. Four different types of IoT devices considered in our study have distinct transmit powers as follows:

- Type 1 has transmit power of 10 mw,
- Type 2 has transmit power of 30 mw,
- Type 3 has transmit power of 50 mw, and
- Type 4 has transmit power of 100 mw.

For simulations, the P_{fa} for the NP method is set to 0.01. The LAD thresholds use P_{fa} parameters are 0.05 as the lower threshold and 0.001 as the upper threshold.

Figs. 2-4 illustrate the distribution function or the cumulative distribution function (CDF) of bit error rate (BER) in the case of AWGN channel, Rayleigh flat fading channel, and frequency selective fading channel, respectively. Four tap delay line model is used for the frequency selective fading channel. The path delay follows the exponential decay. The performances of the NP and the LAD algorithms are shown in these figures with fixed and adaptive thresholds. In the adaptive threshold, the signal is divided into several sub-bands. The density of the IoT devices λ in the network is set to 0.001 number of devices/m^2. All IoT devices in the network are assumed to be in the active status in order to investigate the extreme case.

It can be observed that the LAD outperforms the NP algorithm in all scenarios, i.e., all different channel types. In the AWGN and the Rayleigh flat fading channels, the traditional fixed threshold is able to improve the BER performances.

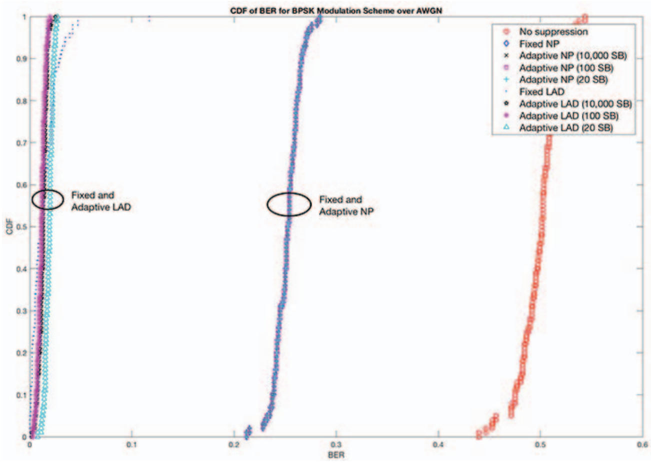

Fig. 2. CDF of BER in the AWGN channel in the IoT network (λ = 0.001) with all active devices

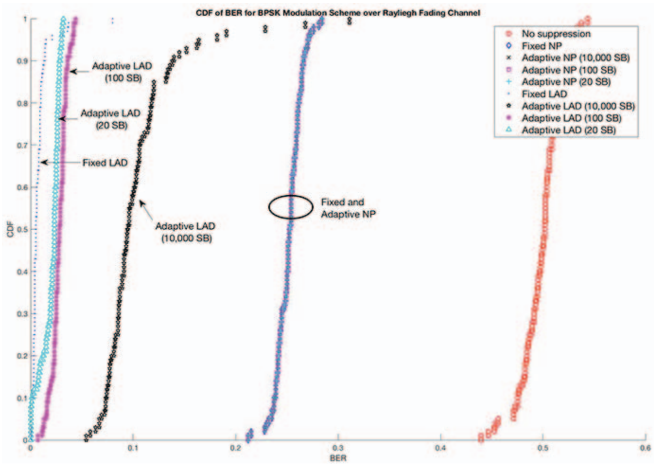

Fig. 3. CDF of BER in the Rayleigh flat fading channel in IoT network (λ = 0.001) with all active devices

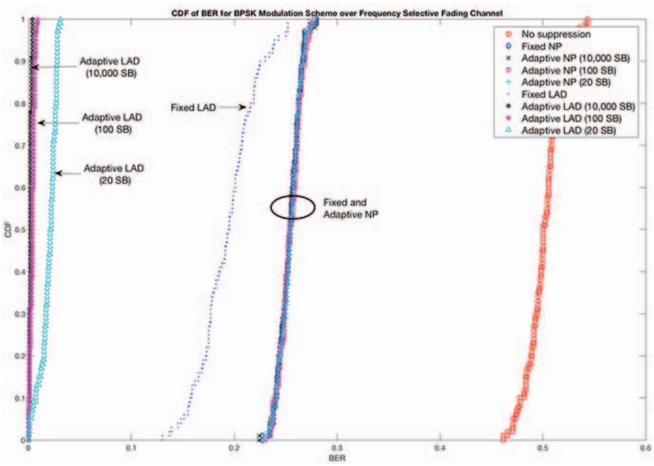

Fig. 4. CDF of BER in the frequency selective fading channel in the IoT network (λ = 0.001) with all active devices

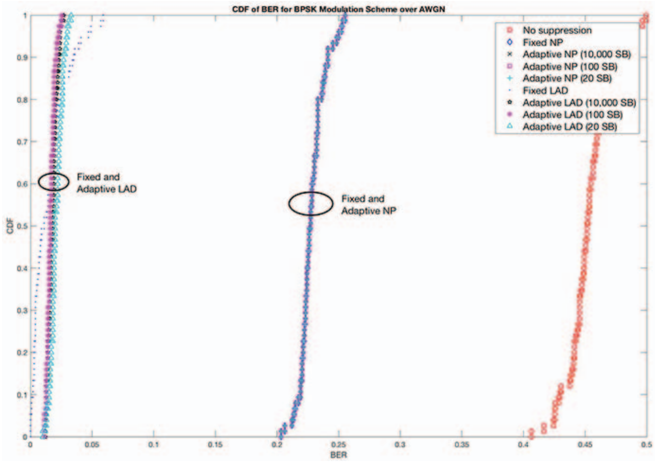

Fig. 5. CDF of BER in the AWGN channel in the IoT network with active and inactive devices

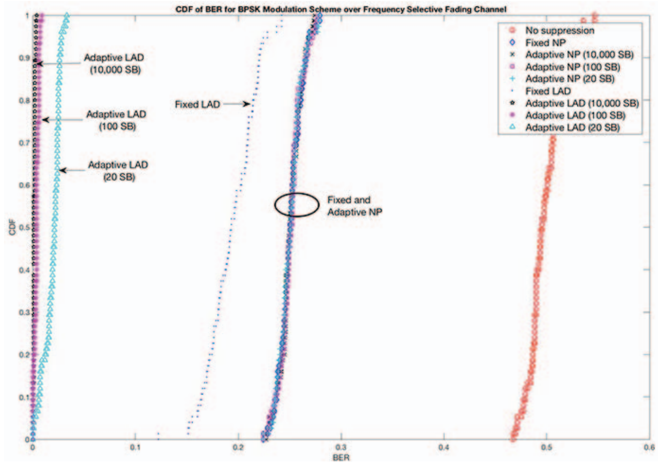

Fig. 7. CDF of BER in the frequency selective fading channel in the IoT network with active and inactive devices

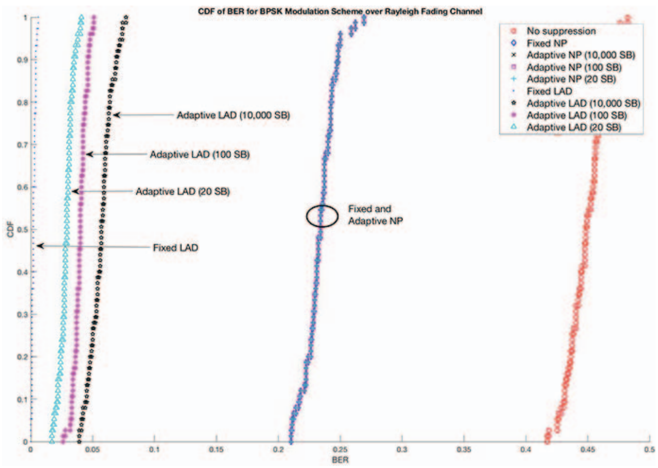

Fig. 6. CDF of BER in the Rayleigh flat fading channel in the IoT network with active and inactive devices

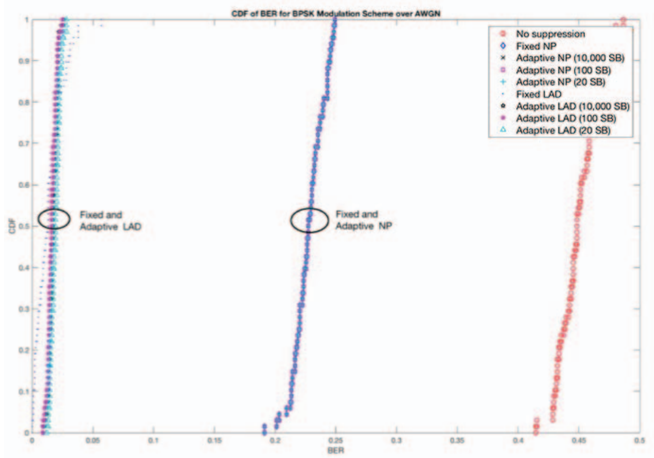

Fig. 8. CDF of BER in the AWGN channel in the IoT network with active and inactive devices and different λ

The benefit of the adaptive threshold is effectively gained in the frequency selective fading channel, while not giving any benefits to those flat frequency channels. The smaller sub-band provides high resolution of the adaptive technique and therefore outperforms the larger sub-band. Figs. 5-7 show the BER performance for the case that the status of the IoT devices are randomly set to be active and inactive (idle). As expected it shows that the overall BER performances in the case of randomly mixing the device statuses are better than the case of having all of active IoT devices. This is because the number of interfering devices in the mixing case is in average less than the case of all active devices. In the frequency selective fading channel scenario, the performances are almost the same as the ones shown in Fig. 4 because the effect of the frequency selective fading channel has more impact than the number of interfering devices in the system.

Next, the scenario with mixing randomly devices' status and different λ is investigated. Each type of IoT devices are generated with different values of λ as follows:

- Type 1 has λ_1 of 0.001 number of devices/m^2 (1% of total devices in the topology),
- Type 2 has λ_2 of 0.05 number of devices/m^2 (31% of total devices in the topology),
- Type 3 has λ_3 of 0.01 number of devices/m^2 (6% of total devices in the topology), and
- Type 4 has λ_4 of 0.1 number of devices/m^2 (62% of total devices in the topology).

In Figs. 8-9, it can be seen that the adaptive threshold does not gain the benefit due to the constant channel frequency responses of the AWGN and the flat fading channels. However, in the frequency selective fading channel in Fig. 10 we can see the benefit from using the adaptive threshold. Especially, when the sub-band is smaller, the performances become better. The performances of the system which has different values of λ in the AWGN and the Rayleigh flat fading are worse than the system which has the same λ and inactive/active devices

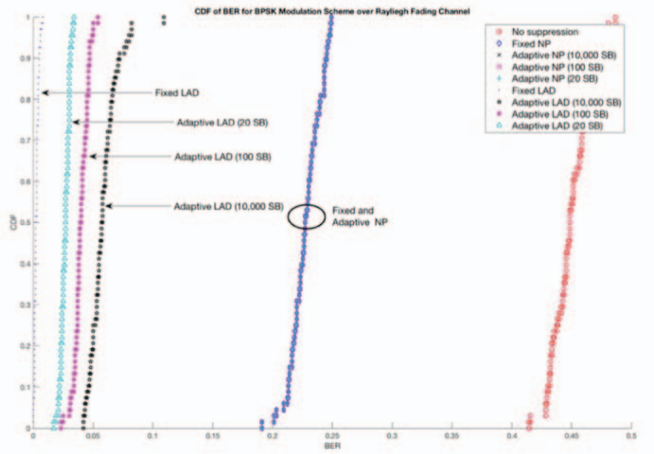

Fig. 9. CDF of BER in the Rayleigh flat fading channel in the IoT network with active and inactive devices and different λ

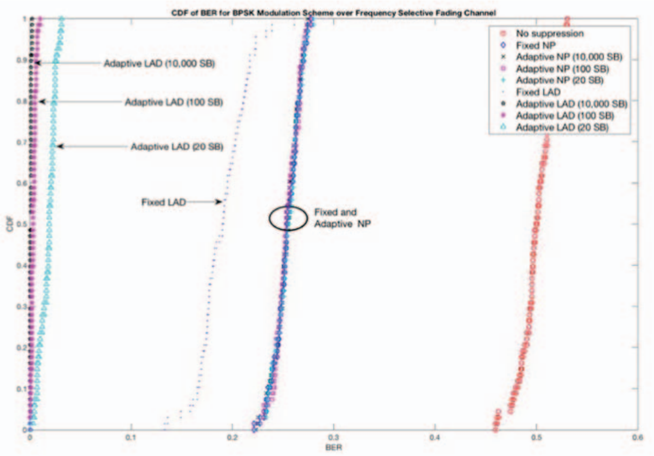

Fig. 10. CDF of BER in the frequensy selective fading channel in the IoT network with active and inactive devices and different λ

because the number of IoT devices are smaller in the mixing case in the same coverage area.

While the LAD method has advantages, i.e., a completely blind algorithm, clear signal separation and good localization accuracy, there are also some weak points. The LAD cannot always separate the adjacent when the system has to localize weak signals. Moreover, high sidelobes cause problems when estimating the bandwidth of a signal.

V. Conclusion

In this paper, the Neyman-Pearson (NP) Criterion method and the localization algorithm based on the double-thresholding (LAD) method were studied in the "last 100 meters" of an IoT network. The LAD method uses two threshold levels of the forward consecutive mean excision (FCME) algorithm. These two thresholds are for separating the concentrated signal and the interference signal. The results showed that the LAD method is able to detect and to suppress the interference better than the NP method in all cases. We also proposed the adaptive threshold setting, which could perform effectively under the frequency selective fading channel. Increasing the IoT nodes in the network is a significant factor yielding high BER because the number of devices made the high level of interference in the system.

References

[1] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of things for smart cities," *IEEE Internet of Things Journal*, vol.1, no. 1, pp. 22-32, 2014

[2] M. Weiser, "The computer for the 21st century,"' *Scientific American*, no. 265, pp. 94-104, 1991

[3] ITU Internet Reports, "The internet of things," International Telecommunication Union, Tech. Rep., 2005

[4] L. Atzori, A, Iera, G. Morabito, "The internet of things: a survey," *Computer Networks (Elsevier) Journal*, no. 54, pp. 2787-2805, 2010

[5] A. Sikora, V. F. Groza, "Coexistence of IEEE802. 15.4 with other Systems in the 2.4 GHz-ISM-Band," in Proc. *IEEE in Instrumentation and Measurement Technology Conference (IMTC)*, pp. 1786-1791, 2005

[6] W. Zhipeng, D. Tianyu, T. Yong, D. Makrakis, H. T. Mouftah, "ACK with interference detection technique for ZigBee network under Wi-Fi interference," in Proc. *Eighth International Conference on Broadband and Wireless Computing, Communication and Applications (BWCCA)*, pp. 128-135, 2013

[7] F. Inoue, M. Morikura, T. Nishio, K. Yamamoto, F. Nuno, T. Sugiyama, "Novel coexistence scheme between wireless sensor network and wireless LAN for HEMS," in Proc *IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 271-276, 2013

[8] Y. Lee, D. H. Kang, H. Park, W. Oh, "Tone-interference cancellation algorithm for direct sequence spread-spectrum systems," in Proc *3rd International Conference on Anti-Counterfeiting, Security, and Identification in Communication*, pp. 25-28, 2009

[9] T. T. Zhao, H. Zhao, Y. P. Zhao, X. Cheng, B. Ai, "A frequency-domain estimation scheme for single-tone interference in OFDM systems," in Proc *3rd International Conference on Communications and Mobile Computing*, pp. 409-412, 2011

[10] G. Iliev, V. Poulkov, M. Ovtcharov, "Performance comparison of NBI suppression methods for MIMO OSTBC-OFDM systems," in Proc *7th IEEE International Workshop on Performance and Management of Wireless and Mobile Networks*, pp. 630-633, 2011

[11] A. Pouttu, J. Juntti, T. Kumpumäki, "Adaptive transform domain interference suppression in a hybrid DS/FH-system," in Proc *IEEE International Symposium on Spread Spectrum Techniques and Applications*, pp. 351-355, 1998

[12] S. Wang, J. P. An, A. H. Wang, A. H., X. Y. Bu, "A minimum value based threshold setting strategy for frequency domain interference excision," *IEEE Signal Processing Letters*, no. 17, vol. 5, pp. 501-504, 2010

[13] P. Henttu, S. Aromaa, "Consecutive mean excision algorithm," in Proc *IEEE International Symposium on Spread Spectrum Techniques and Applications*, no. 2, vol. 3, pp. 450-454, 2002

[14] H. Saarnisaari, "Consecutive mean excision algorithms in narrowband or short time interference mitigation," in Proc *Position location and navigation symposium*, vol. 1, pp. 447-454, 2004

[15] J. Vartiainen, J. J. Lehtomäki, S. Aromaa, H. Saarnisaari, "Localization of multiple narrowband signals based on the FCME algorithm," in Proc. *The Nordic Radio Symposium (NRS)*, Aug. 2004

[16] H. Chong, M. J. Josep, F. Etimad, F. A. Ian, "A cross-layer communication module for the Internet of Things," *Computer Networks*, vol. 57, pp. 622-633, 2013

[17] J. Neyman, E. Pearson, "On the problem of the most efficient tests of statistical hypotheses," *Philosophical Transactions of the Royal Society of London*, Series A, vol. 231, pp. 289-337, 1933