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Statistical Analysis of Indoor RSSI Read-outs for 433 MHz, 868 MHz, 2.4 GHz and 5 GHz ISM Bands

Łukasz Chruszczyk

***Abstract*—This paper presents statistical analysis of RSSI read-outs recorded in indoor environment. Many papers concerning indoor location, based on RSSI measurement, assume its normal probability density function (PDF). This is partially excused by relation to PDF of radio-receiver's noise and/or together with influence of AWGN (average white Gaussian noise) radio-channel – generally modelled by normal PDF. Unfortunately, commercial (usually unknown) methods of RSSI calculations, typically as "side-effect" function of receiver's AGC (automatic gain control), results in PDF being far different from Gaussian PDF. This paper presents results of RSSI measurements in selected ISM bands: 433/868 MHz and 2.4/5 GHz. The measurements have been recorded using low-cost integrated RF modules (at 433/868 MHz and 2.4 GHz) and 802.11 WLAN access points (at 2.4/5 GHz). Then estimated PDF of collected data is shown and compared to normal (Gaussian) PDF.**

***Keywords*—indoor location, RSSI measurement, RSSI statistical analysis, ISM bands, probability density function.**

I. INTRODUCTION

INDOOR positioning based on RSSI measurements has got great interest in areas related with indoor positioning. One of the reason is low price of easily available RF modules returning RSSI data. Therefore, there have been proposed many ideas for its practical utilization and accuracy improvements [1]–[24]. Unfortunately, many authors still blindly assume that error of RSSI read-out follows normal (Gaussian) probability distribution function (PDF). It is not impossible - however, many measurements prove that such distribution can be far from normal PDF.

There have been performed exemplary, indoor RSSI measurements for 4 ISM bands, by means of 5 RF modules. The environment has been static constant for all measurements: a standard university building from 70's: concrete ceilings and full-brick walls. Measurements in ISM 433 MHz and 868 MHz bands have been performed using RFM69W-433S2 and RFM69CW-868S2 RF modules respectively - both from HopeRF. There have been collected 4000 samples for each band, every 700 ms. The modules have been selected for their low cost, low power consumption and high dynamics of the RSSI read-out: 115 dB.

Measurements in WLAN ISM 2.4 GHz and 5 GHz band have been performed be means of TP-Link TL-WDR3500 v1.2, running OpenWRT v15.05 (*Chaos Calmer*). There have been collected 640 000 samples, every 3 s.

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Łukasz Chruszczyk is at Faculty of Automatic Control, Electronics and Computer Science, Institute of Electronics, Poland, 44-100 Gliwice, Akademicka 16 (e-mail: *lch@polsl.pl*).

Additionally, IoT module ESP8266 MOD-12E (from AI-Thinker) has been used for 2.4 GHz band. There have been collected 4000 samples, every 1 s. RSSI dynamics of the last three modules was approx. 90 dB.

Because of different levels of power transmission, antenna gains, receivers sensitivity and wave attenuation for each case (module and frequency), all RSSI measurements have been normalized. First, there has been calculated *quasi-mean value*:

$$RSSI_{mean} = \frac{1}{N}\sum_{n=1}^{N} RSSI_n \tag{1}$$

where:

- N – number of $RSSI$ samples (measurements),
- $RSSI_n$ – single n-th RSSI measurement [dBm],
- $RSSI_{mean}$ – "mean" value [dBm].

It should be strongly emphasized that abovementioned *quasi-mean value* equals *estimated value* only for case, when probability density function of RSSI data is symmetrical – which not always holds true. Asymmetrical PDFs will be presented in next chapters.

Then, *quasi-normalization* is performed:

$$\begin{gathered} RSSI_n^{norm} = RSSI_n - RSSI_{mean} \\ n = 1,2,\dots,N \end{gathered} \tag{2}$$

where $RSSI_n^{norm}$ is "normalized" value of n-th RSSI sample [dBm].

There have been used six typical probability density functions:

- Normal (Gaussian),
- Kernel (with *normal* kernel functions),
- Stable,
- *t*-Location Scale,
- Logistic,
- Extreme Value.

The main reasons for selection of the abovementioned density functions have been continuous support over entire real domain (-∞, +∞), "good support" for *heavy tails* and possible multimodality (Kernel). Normal density function has been used for reference. There have not been made any assumptions over probabilistic process from particular RSSI measurements – thus *a priori* selection of appropriate density function. The only criterion for *agreement* of a normalized histogram (in sense of probability density function) of normalized RSSI data has been *mean-squared error* (MSE) between histogram points and corresponding values of proposed density function (3). The histogram centres are discrete values of RSSI [dBm] from measured interval [min($RSSI_n$), max($RSSI_n$)]. The reason is discrete values of RSSI read-outs (with resolution of 1 dBm), returned by all used RF modules.

$$MSE = \frac{1}{K}\sum_{k=1}^{K}(H_k - E_k)^2$$
$$K = \frac{\max(RSSI) - \min(RSSI)}{1\ [dBm]} \tag{3}$$

where:

- *MSE* – mean-squared error between normalized histogram *H* and probability density function estimate *E*,
- *K* – number of histogram bins,
- *RSSI* – set of all RSSI samples for particular case.

Above definition of MSE makes it useful for comparison within particular case – not between different cases, which is not needed here. The smaller value of MSE – the greater similarity between data histogram and PDF estimate.

II. 433 MHz Band

Tab. I presents mean-squared errors for selected probability density functions. The results are sorted beginning from the best one – minimal value of MSE.

TABLE I.
MEAN-SQUARED ERRORS FOR 433 MHz BAND

Probability density function (PDF)	**Mean-squared error [dBm]**	**PDF parameters**
t-Location Scale	$1.58 \cdot 10^{-7}$	μ = -0.0680 σ = 0.918 ν = 3.39
Kernel	$1.83 \cdot 10^{-7}$	bandwidth = 0.43
Stable	$5.60 \cdot 10^{-7}$	α = 1.71 β = 0.0601 γ = 0.759 δ = -0.0686
Logistic	$9.38 \cdot 10^{-7}$	μ = -0.0699 σ = 0.704
Normal (Gaussian)	$5.91 \cdot 10^{-6}$	μ = -0.108 σ = 1.44
Extreme Value	$1.10 \cdot 10^{-5}$	μ = 0.546 σ = 1.35

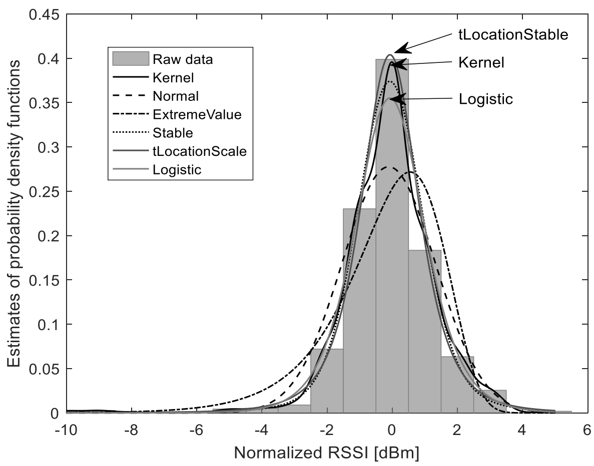

Fig. 1. PDF estimates for 433 MHz band.

It can be observed that normal (Gaussian) PDF estimate has been outperformed by four other functions: MSE has been reduced by order of magnitude. *t*-Location Scale and kernel PDF estimates give comparable (the smallest) values of the MSE. Fig. 1 compares selected PDFs with normalized histogram of raw RSSI samples. Fig. 2 presents dependence of MSE on value of kernel *bandwidth* (for kernel PDF estimate).

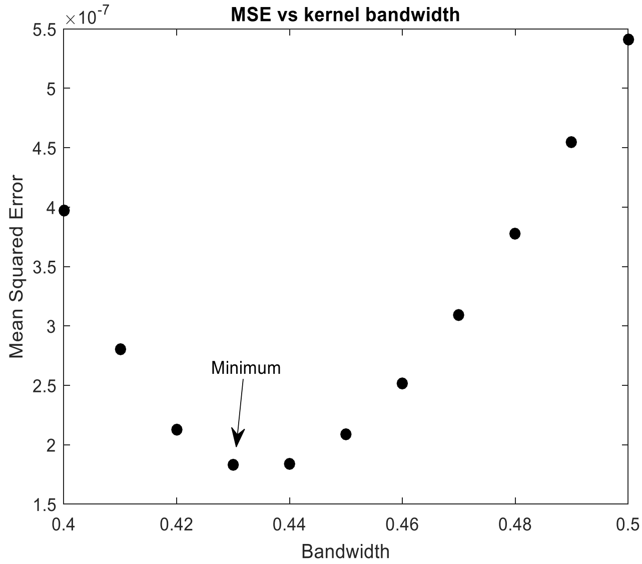

Fig. 2. MSE vs kernel bandwidth for 433 MHz.

III. 868 MHz Band

Tab. II presents mean-squared errors for selected probability density functions. The results are sorted beginning from the best one – minimal value of MSE.

It can be observed that normal (Gaussian) PDF estimate has got the worst (largest) value of MSE – greater by two orders of magnitude then the other PDF estimates. Fig. 3 compares selected PDFs with normalized histogram of raw RSSI samples. Fig. 4 presents dependence of MSE on value of kernel bandwidth (for kernel PDF estimate).

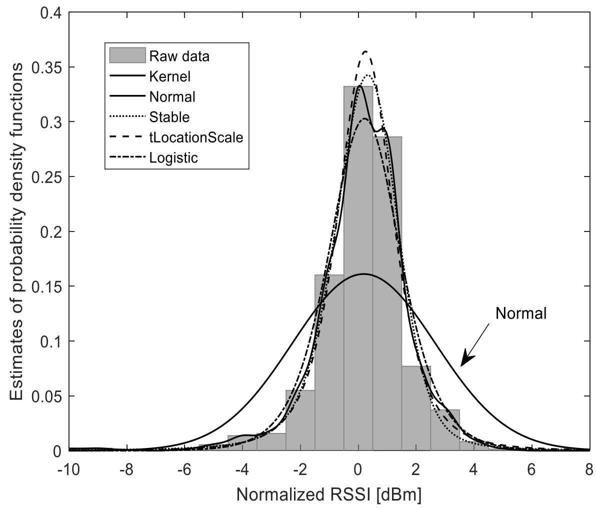

Fig. 3. PDF estimates for 868 MHz band.

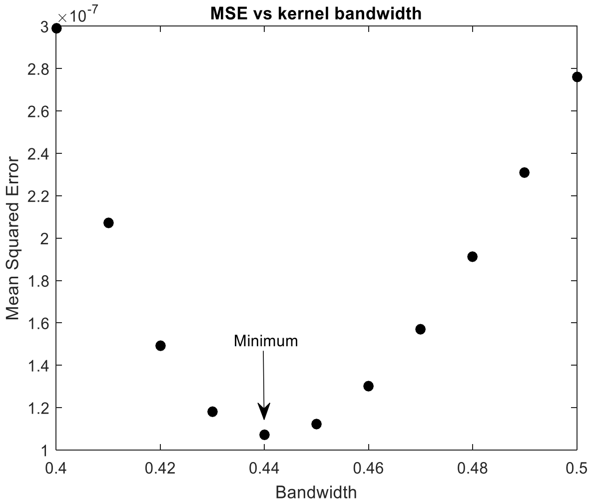

Fig. 4. MSE vs kernel bandwidth for 868 MHz.

TABLE II

MEAN-SQUARED ERRORS FOR 868 MHZ BAND

Probability density function (PDF)	**Mean-squared error [dBm]**	**PDF parameters**
Kernel	$1.07{\cdot}10^{-7}$	bandwidth = 0.44
Stable	$2.21{\cdot}10^{-7}$	α = 1.64 β = -0.289 γ = 0.830 δ = 0.299
t-Location Scale	$3.39{\cdot}10^{-7}$	μ = 0.247 σ = 1.01 ν = 3.10
Logistic	$1.31{\cdot}10^{-6}$	μ = 0.217 σ = 0.826
Normal (Gaussian)	$1.52{\cdot}10^{-5}$	μ = 0.188 σ = 2.48

IV. 2.4 GHZ BAND – ESP 8266 MODULE

Tab. III presents mean-squared errors for selected probability density functions. The results are sorted beginning from the best one – minimal value of MSE.

TABLE III

MEAN-SQUARED ERRORS FOR 2.4 GHZ BAND (ESP 8266)

Probability density function (PDF)	**Mean-squared error [dBm]**	**PDF parameters**
Kernel	$4.24{\cdot}10^{-8}$	bandwidth = 0.47
Stable	$1.13{\cdot}10^{-6}$	α = 1.99 β = -0.642 γ = 1.14 δ = -0.0842
Normal (Gaussian)	$1.41{\cdot}10^{-6}$	μ = -0.099 σ = 2.02
t-Location Scale	$1.59{\cdot}10^{-6}$	μ = -0.0864 σ = 1.54 ν = 11.7
Logistic	$1.90{\cdot}10^{-6}$	μ = -0.082 σ = 0.976

It can be observed that all unimodal PDFs perform similarly. Still, MSE of kernel PDF estimate is smaller by two orders of magnitude. Fig. 5 compares selected PDFs with normalized histogram of raw RSSI samples. Fig. 6 presents dependence of MSE on value of kernel bandwidth (for kernel PDF estimate).

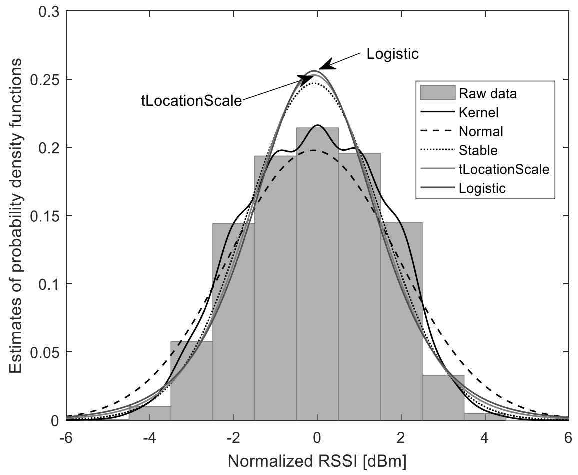

Fig. 5. PDF estimates for 2.4 GHz band (ESP 8266).

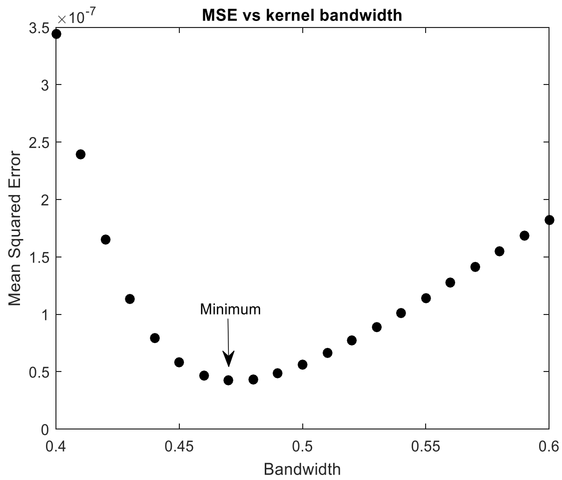

Fig. 6. MSE vs kernel bandwidth for 2.4 GHz.

V. 2.4 GHZ BAND – WLAN CHANNEL 2

Tab. IV presents mean-squared errors for selected probability density functions. The results are sorted beginning from the best one – minimal value of MSE.

TABLE IV

MEAN-SQUARED ERRORS FOR 2.4 GHZ BAND (WLAN CH. 2)

Probability density function (PDF)	**Mean-squared error [dBm]**	**PDF parameters**
Kernel	$1.45{\cdot}10^{-10}$	bandwidth = 0.46
t-Location Scale	$2.42{\cdot}10^{-8}$	μ = -1.64 σ = 3.91 ν = 1.65
Stable	$2.58{\cdot}10^{-8}$	α = 1.32 β = 0.538 γ = 3.55 δ = -2.32
Logistic	$3.35{\cdot}10^{-8}$	μ = -0.972 σ = 4.41
Normal (Gaussian)	$4.47{\cdot}10^{-8}$	μ = 0.263 σ = 8.90

RSSI measurement in the WLAN channel 2 has been strongly affected by other transmitters. This is not surprise, because this channel is very busy at the university building – and it has been selected intentionally. Strong and asymmetrical multimodality of the RSSI normalized histogram can be observed, thus only kernel PDF estimate is a reasonable choice here. The other PDF estimates have been shown for reference only. Fig. 7 compares selected PDFs with normalized histogram of raw RSSI samples. Fig. 8 presents dependence of MSE on value of kernel bandwidth (for kernel PDF estimate).

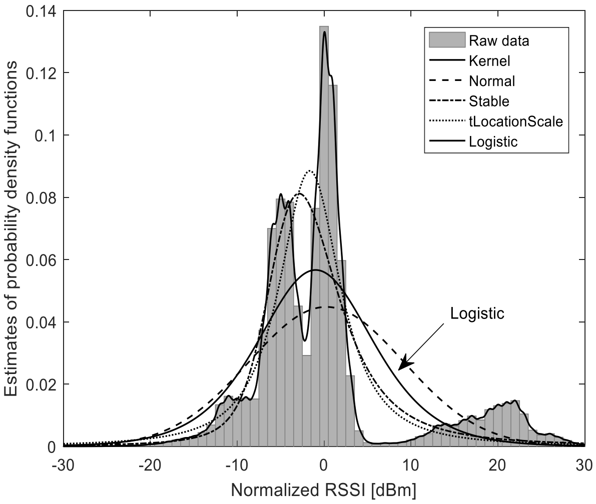

Fig. 7. PDF estimates for 2.4 GHz band (WLAN ch. 2).

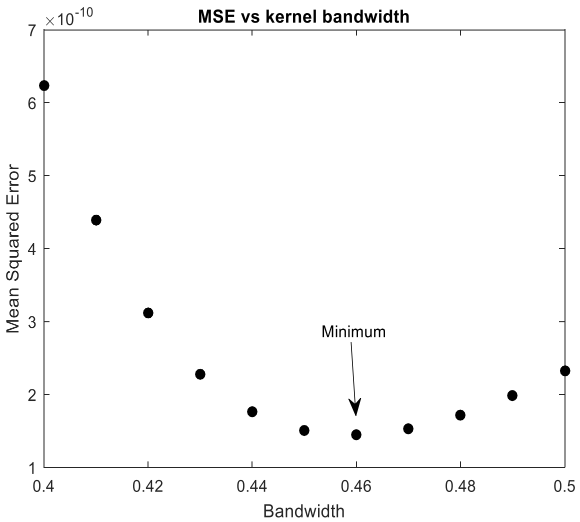

Fig. 8. MSE vs kernel bandwidth for 2.4 GHz.

VI. 2.4 GHz Band – WLAN Channel 14

WLAN channel 14 should be less affected by wireless traffic, because many Wi-Fi devices cannot (or are not configured by default) to use it. Therefore, "less spikes" should make RSSI histogram to more resemble unimodal PDF. Tab. V presents mean-squared errors for selected probability density functions. The results are sorted beginning from the best one – minimal value of MSE.

TABLE V

MEAN-SQUARED ERRORS FOR 2.4 GHZ BAND (WLAN CH. 14)

Probability density function (PDF)	**Mean-squared error [dBm]**	**PDF parameters**
Kernel	$3.50 \cdot 10^{-11}$	bandwidth = 0.50
t-Location Scale	$4.43 \cdot 10^{-9}$	$\mu = -3.85$ $\sigma = 4.97$ $\nu = 1.54$
Stable	$5.99 \cdot 10^{-9}$	$\alpha = 1.33$ $\beta = 0.871$ $\gamma = 4.74$ $\delta = -4.72$
Normal (Gaussian)	$2.20 \cdot 10^{-8}$	$\mu = -0.303$ $\sigma = 11.7$

Indeed, RSSI measurement partially confirms previous guess. Less busy channel 14 makes RSSI histogram to contain fewer modes than for channel 2. Still, however, it's strong second mode (around +20 dBm) and noticeable third (around -12 dBm) are problematic for typical, unimodal PDF estimates. Fig. 9 compares selected PDFs with normalized histogram of raw RSSI samples. Fig. 10 presents dependence of MSE on value of kernel bandwidth (for kernel PDF estimate).

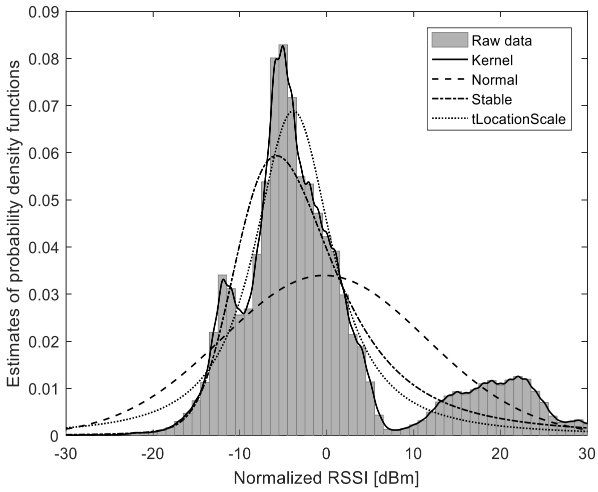

Fig. 9. PDF estimates for 2.4 GHz band (WLAN ch. 14).

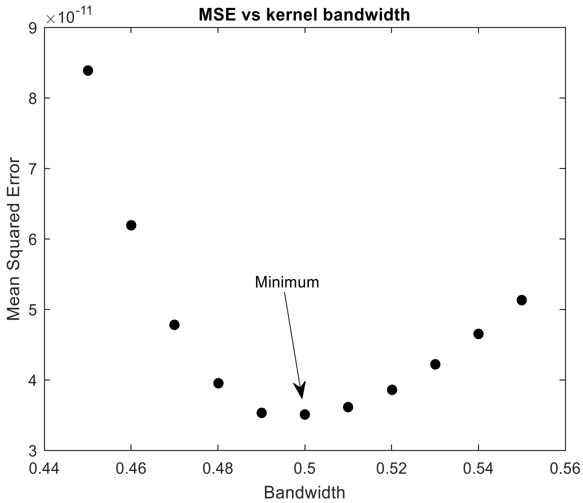

Fig. 10. MSE vs kernel bandwidth for 2.4 GHz.

VII. 5 GHz Band – WLAN Channel 40

Furthermore, WLAN channel 40 should be less affected by wireless traffic, because Wi-Fi devices operating in 5 GHz band are not yet so popular as their 2.4 GHz counterparts. Therefore, RSSI histogram is expected to resemble unimodal PDF. Tab. VI presents mean-squared errors for selected probability density functions. The results are sorted beginning from the best one – minimal value of MSE.

TABLE VI

MEAN-SQUARED ERRORS FOR 5 GHz BAND (WLAN CH. 40)

Probability density function (PDF)	Mean-squared error [dBm]	PDF parameters
Kernel	$9.18 \cdot 10^{-11}$	bandwidth = 0.49
t-Location Scale	$2.03 \cdot 10^{-10}$	μ = -0.423 σ = 1.80 ν = 6.58
Logistic	$2.10 \cdot 10^{-10}$	μ = -0.428 σ = 1.18
Normal (Gaussian)	$2.99 \cdot 10^{-9}$	μ = -0.471 σ = 2.19
Stable	$4.06 \cdot 10^{-9}$	α = 1.84 β = -0.836 γ = 1.39 δ = 0
Extreme Value	$1.96 \cdot 10^{-8}$	μ = 0.564 σ = 2.38

Indeed, RSSI measurements confirm previous guess. Less busy channel 40 makes RSSI histogram “almost unimodal”, therefore *t*-Location Scale and Logistic PDFs perform quite well. Unfortunately, normal PDF is still one magnitude “behind”. Fig. 11 compares selected PDFs with normalized histogram of raw RSSI samples. Fig. 12 presents dependence of MSE on value of kernel bandwidth (for kernel PDF estimate).

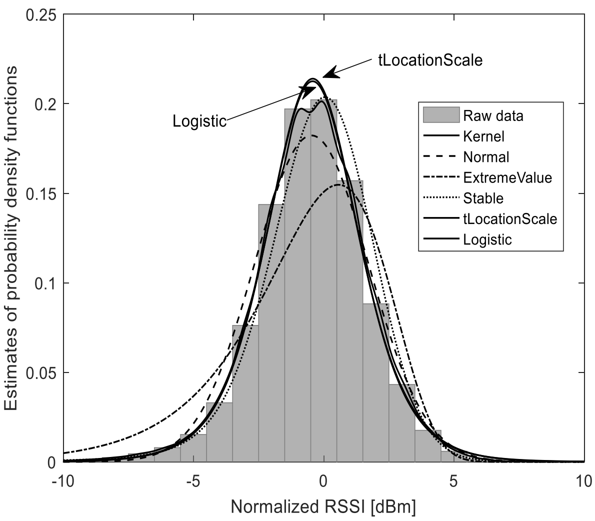

Fig. 11. PDF estimates for 5 GHz band (WLAN ch. 40).

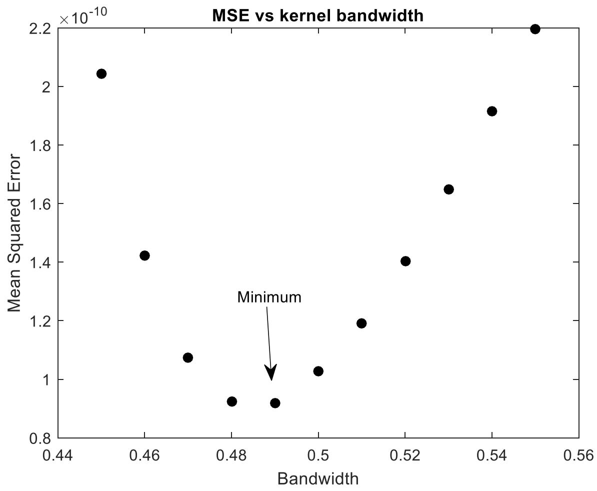

Fig. 12. MSE vs kernel bandwidth for 5 GHz.

VIII. 5 GHz Band – WLAN Channel 157

WLAN channel 157 is not affected by Wi-Fi traffic, because it is placed far beyond frequencies allowed for 5 GHz Wi-Fi devices in Europe. Therefore, it is expected to be “silent” and affected mainly by receiver’s noise – thus RSSI histogram should be unimodal. Tab. VII presents mean-squared errors for selected probability density functions. The results are sorted beginning from the best one – minimal value of MSE.

This time, guess about radio-channel silence was missed. Clear multimodality of RSSI histogram can be noticed in the fig. 1. Possible explanation can be interference with radio-links using proprietary frequencies or weather (cloud) radars operating in 5 GHz band. Again, kernel PDF estimate have been found the best one. Fig. 13 compares selected PDFs with normalized histogram of raw RSSI samples. Fig. 14 presents dependence of MSE on value of kernel bandwidth (for kernel PDF estimate).

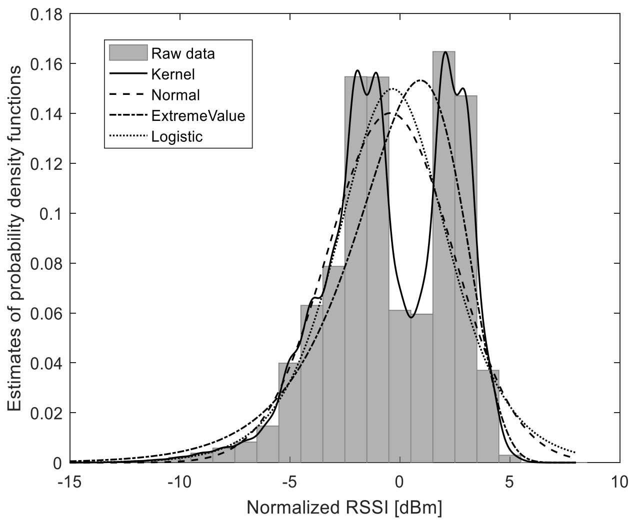

Fig. 13. PDF estimates for 5 GHz band (WLAN ch. 157).

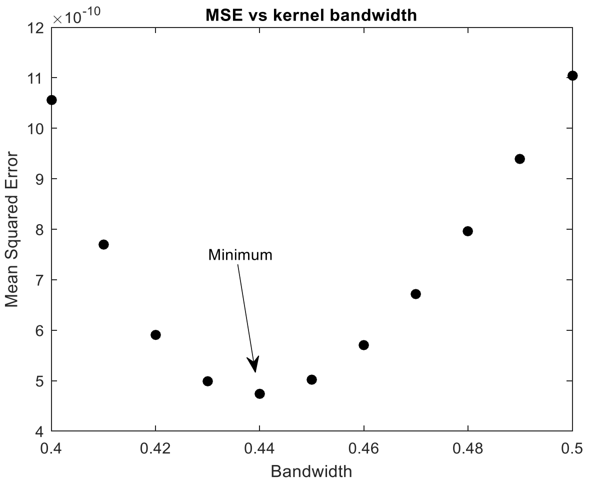

Fig. 14. MSE vs kernel bandwidth for 5 GHz.

TABLE VII
MEAN-SQUARED ERRORS FOR 5 GHZ BAND (WLAN CH. 157)

Probability density function (PDF)	Mean-squared error [dBm]	PDF parameters
Kernel	$4.74 \cdot 10^{-10}$	bandwidth = 0.44
Normal (Gaussian)	$3.62 \cdot 10^{-8}$	$\mu = -0.428$ $\sigma = 2.85$
Extreme Value	$3.94 \cdot 10^{-8}$	$\mu = 0.933$ $\sigma = 2.40$
Logistic	$4.14 \cdot 10^{-8}$	$\mu = -0.334$ $\sigma = 1.67$

CONCLUSIONS

Presented measurements and statistical analyses prove that estimates of probability density functions for RSSI measurements are far from normal (Gaussian) distribution. Strong multimodalities can be observed in 3 (of total 7) measurement cases. Two of them are strongly asymmetrical, thus definition of such a basic property like a *mean (expected) value* is not trivial and straightforward task. In these cases definitely, kernel PDF estimate is the only reasonable choice.

The remaining cases have histograms of raw measurement data more resemble to unimodal probability density function, however their asymmetry can easily be observed. Therefore, all analysed histograms are better estimated by other PDFs than normal one!

Therefore, the final conclusion is that, normal (Gaussian) probability density function is, in many cases, *not good candidate* for estimate of RSSI read-outs. Unfortunately, there has not been found a single good estimate. Reasons are not clear – definitely they depend on hardware/software implementation how RSSI is calculated for particular receiver. Therefore, for every "new" RF module, there should be performed statistical tests in order to find the closest PDF estimate. This can be important for proper modelling of synthetic RSSI data. On the other hand, using or assuming improper PDF estimate may e.g. reduce effectiveness of data filtering methods.

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