Spectrum usage models for the analysis, design and simulation of cognitive radio networks

PhD Thesis

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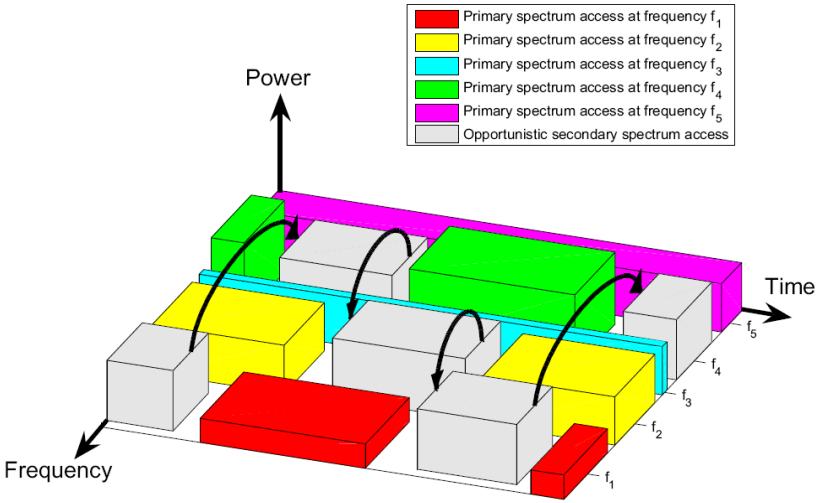
Outline

- Introduction
- Low time-resolution measurements
- High time-resolution measurements
- Spectrum usage models
- Conclusions and future work

Introduction

- Spectrum demand growth since early days of radio communication:
  - Technology has been evolving accordingly.
  - Rather static spectrum management policies:
    - Spectrum bands allocated over large geographical areas, long term basis, and exclusive use.
    - "Depletion" of bands with commercially attractive radio propagation characteristics.
    - Effective control of interference, but non-uniform (inefficient) spectrum usage.
    - The owned spectrum allocation policy is outdated: new paradigms are required.
- Dynamic Spectrum Access (DSA) / Cognitive Radio (CR):
  - Promising solution to the existing conflicts between:
    - Spectrum demand growth.
    - Spectrum underutilization.
  - Basic underlying idea:
    - Opportunistic and non-interfering "secondary" access to temporarily unoccupied "primary" licensed bands.



Introduction

- Opportunistic nature of the DSA/CR paradigm.
- Importance of realistic and accurate models of spectrum usage.
- Applications:
  - Analytical studies.
  - Design and dimensioning of DSA/CR networks.
  - Development of innovative simulation tools.
  - Development of new and more efficient techniques.
- Existing spectrum models:
  - Early models date from the late 1970s: only for HF bands.
  - More recent models:
    - Limited in scope and based on assumptions/oversimplifications not validated with spectrum data.
  - Spectrum usage modeling: rather unexplored area in the context of DSA/CR.

- Thesis objective:

To contribute a holistic set of realistic models capable to accurately capture and reproduce relevant statistical properties of spectrum usage in real radio communication systems, in the time, frequency and space dimensions, for its application to the development and improvement of the future DSA/CR technology.

Introduction

- Distinguishing feature of proposed models: REALISM.
  - Development of realistic models requires validation with empirical spectrum data.
  - Empirical spectrum data requires field measurements.

- Two sophisticated measurement equipments:

  - Spectrum analyzer-based platform:
    - High dynamic range, high sensitivity, and high bandwidth capabilities (wideband measurements).
    - Poor time resolution (secs).

    → **PART I**

  - USRP/GNU radio-based platform:
    - Lower dynamic range, lower sensitivity, and lower bandwidth capabilities (narrowband measurements).
    - Very high time resolutions (μsecs/msecs).

    → **PART II**

PART I

Low time-resolution measurements

Methodology: Motivation

- Previous spectrum measurement campaigns:
  - Based on similar approaches, but
  - Lack of common and appropriate evaluation methodology.
    - Spectrum analyzer measurements may considerably differ depending on the selected configuration and data analysis procedures.
  - Unified methodological framework desirable to:
    - Avoid inaccurate/non-reliable results.
    - Enable comparison of results from different sources.

- Motivation of this study:
  - Comprehensive and in-depth analysis of several important methodological aspects that need to be carefully accounted for when evaluating spectrum occupancy in the context of DSA/CR.

Methodology: Procedure

- The methodological measurement and analysis procedures to be followed were carefully analyzed and studied.

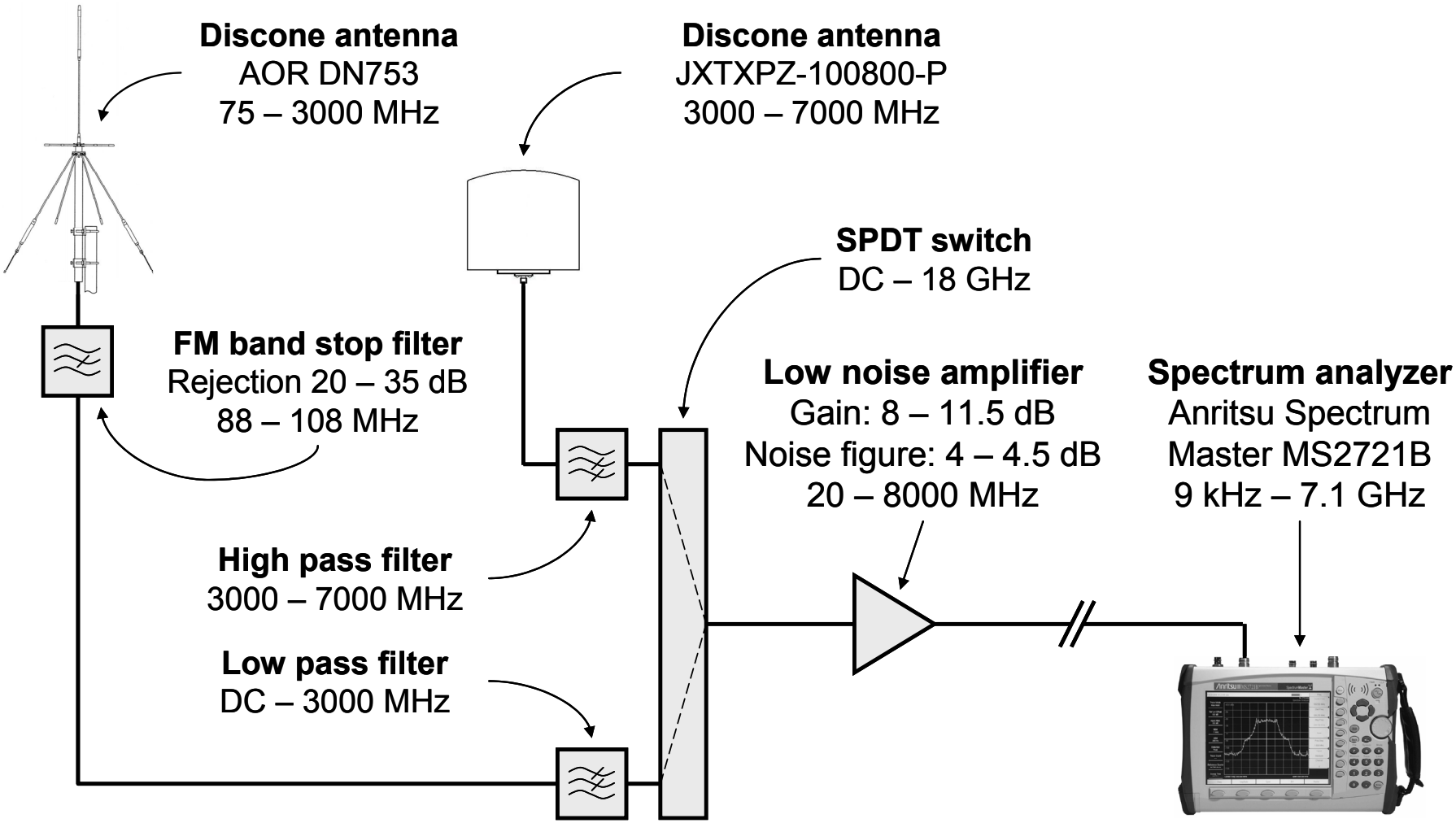
- Every single hardware component, configuration parameter, and data post-processing procedure, was isolated and its impact on the obtained occupancy statistics was analyzed and quantified.

- Based on the obtained results, an adequate methodological framework was defined by selecting the optimum configurations and procedures that guarantee reliable and accurate results.

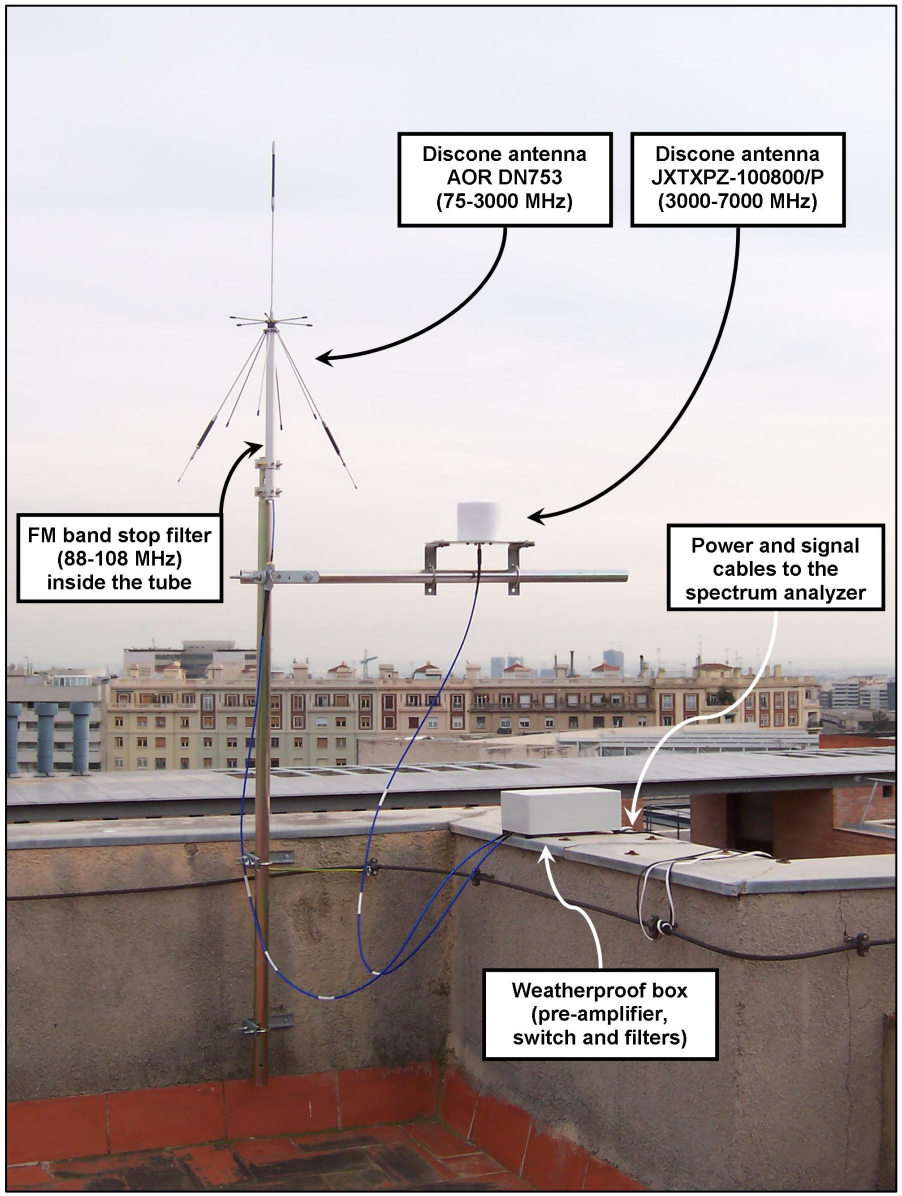
Methodology: Analyzed aspects

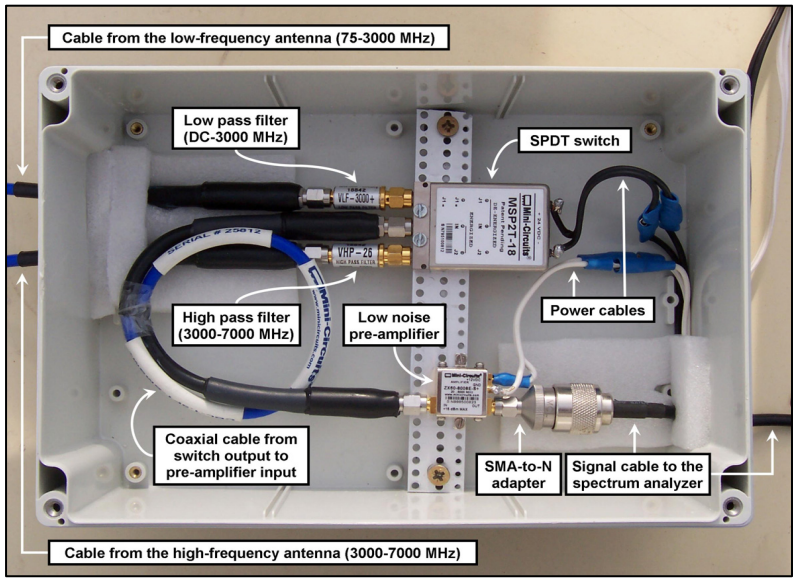
- Measurement setup.
  - Selection of antennas:
    - Narrow-band vs. broad-band.
    - Vertical vs. horizontal polarization.
    - Omni-directional vs. directive/arrays/beam-forming.
  - Selection of amplifiers:
    - High/medium/low gain: Tradeoff between sensitivity and dynamic range (SFDR).
    - Appropriate amplification configuration.
    - Impact of sensitivity on obtained results (up to 29% error).
- Frequency aspects:
  - Division of frequency range to be measured: wide vs. narrow bands.
  - Impact of frequency resolution (bin) on detected activity.
  - Impact of resolution bandwidth (RBW) on obtained results.
- Time dimension:
  - Sampling rate and measurement period.
  - Long-term vs. short-term measurements.
- Data post-processing:
  - Energy detection and selection of the energy decision threshold.
  - Trade-off between false alarm (occupancy overestimation) and miss detection (underestimation).

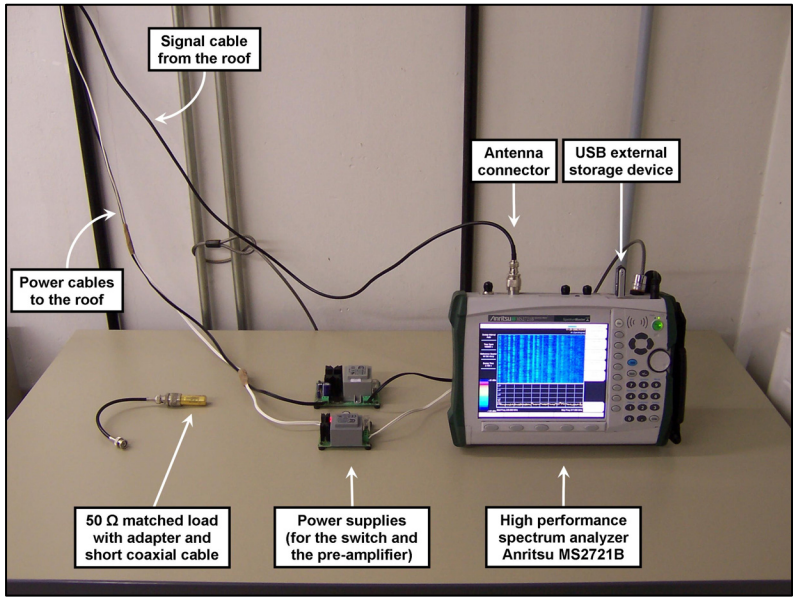
Measurement setup



Measurement setup







Measurements: Purpose

- Extensive broadband spectrum measurement campaign, embracing selected spectrum bands between 75 MHz and 7 GHz in different specific scenarios and environments in the metropolitan area of Barcelona (from 2008 to 2010).

- Need for empirical spectrum data:

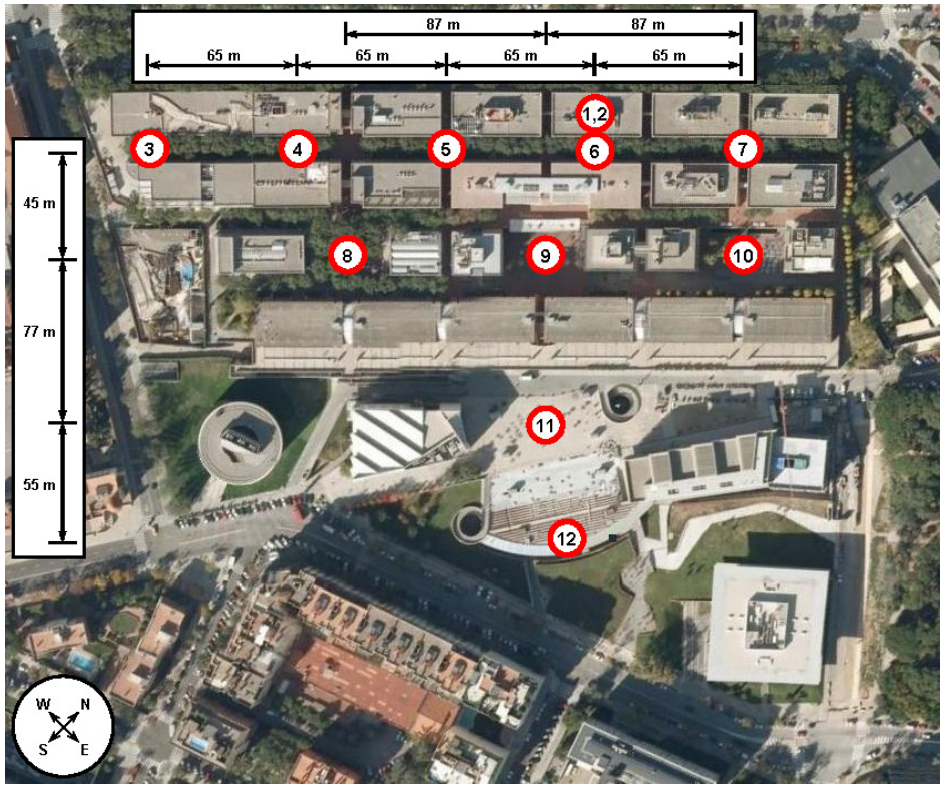
  - Provide a "big picture" and better understanding of how real wireless systems make use of the allocated spectrum bands.

  - *Which bands are worth studying and modeling?*
    → Identification of potential bands of interest for DSA/CR applications.

  - *Which are the general features of such bands?*
    → Development of realistic models based on:
    - Empirical models obtained from empirical data:
      - Identified spectrum usage patterns.
      - Observed statistical properties.
    - Theoretical models corroborated/validated with empirical data.

Measurements: Scenarios

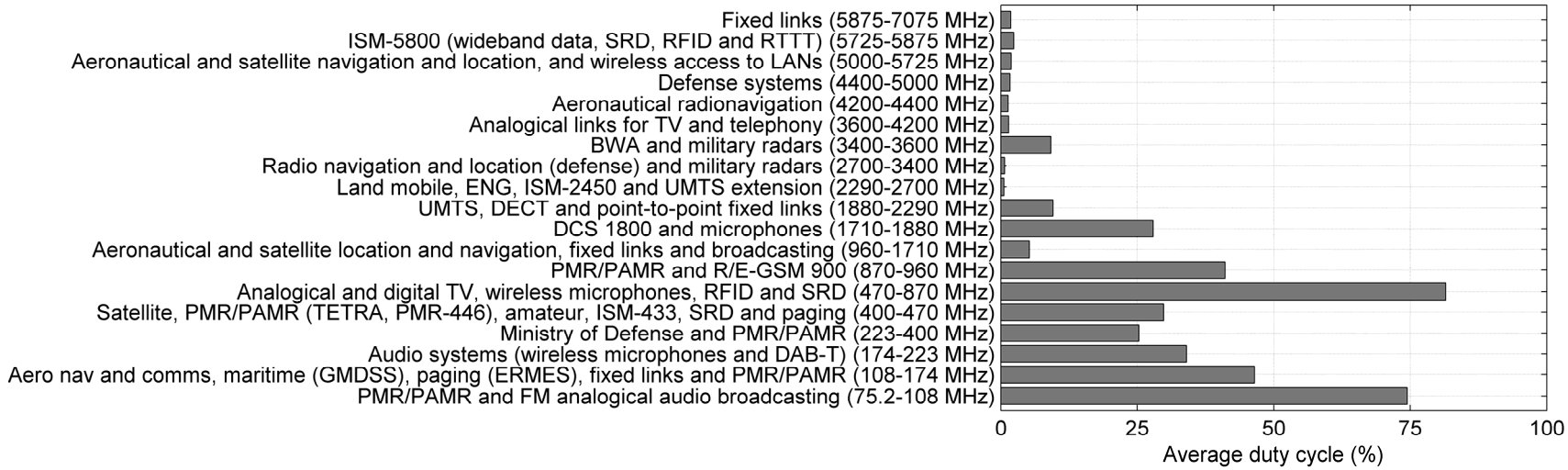
- Urban (UPC's Campus Nord):
  - Outdoor:
    - High points: Roof of Department's building – LOS conditions (1).
    - Narrow streets (3–7).
    - Between buildings (8–10).
    - Open areas (11, 12).
  - Indoor: Inside building D4 (2).
- Sub-urban (UPC's Campus Castelldefels):
  - Outdoor high point (building rooftop).



Measurement point	Environment
1	Outdoor high point (building roof)
2	Indoor (building room)
3 – 7	Outdoor at ground level in narrow streets
8 – 10	Outdoor at ground level between buildings
11 – 12	Outdoor at ground level in open areas

Measurements: Results

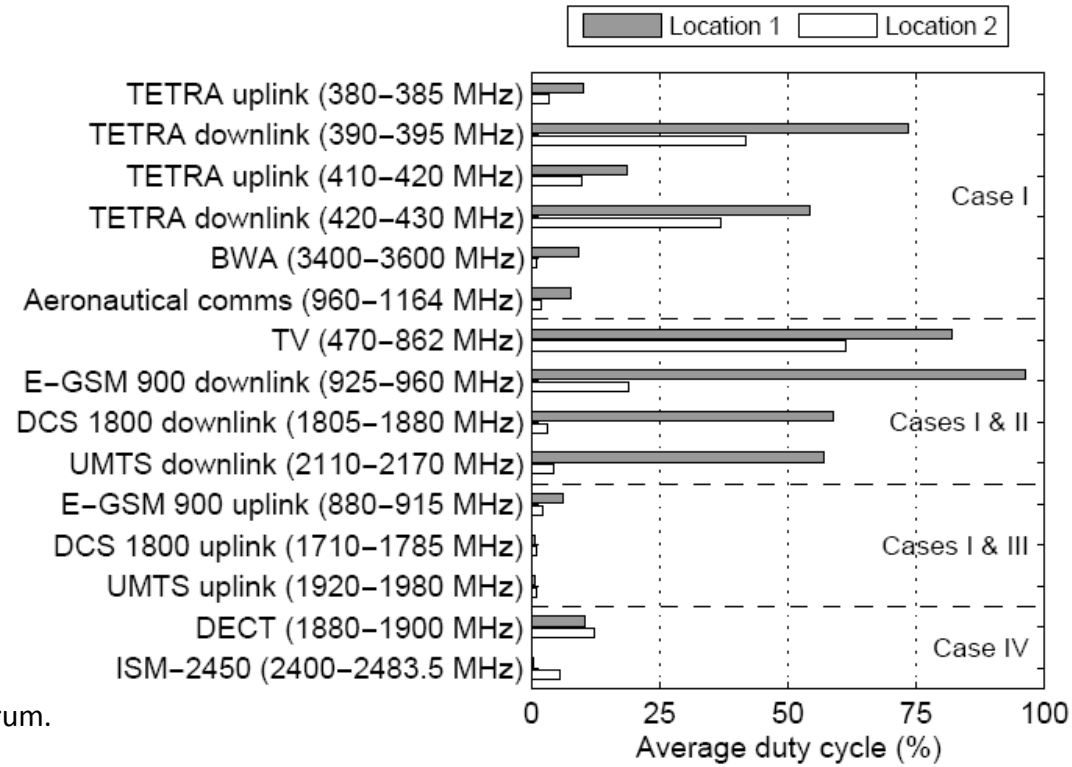
- Location 1: Urban outdoor high points.



- Average duty cycle 75–7075 MHz = **17.78%** (most of spectrum is available for DSA/CR).
  - 0–1 GHz → Relatively moderate usage (42.00%).
  - 1–2 GHz → Low usage (13.30%).
  - 2–7 GHz → Mostly underutilized (2.75%) with a few particular exceptions: UMTS, ISM.
- Usage depends on the considered bands:
  - Highest occupancy rates: Broadcast (TV & digitial/analogical audio).
  - Followed by digital cellular services: PMR/PAMR, paging and mobile communications (E-GSM 900, DCS 1800, UMTS).
  - Other services depend on the band: aeronautical radio navigation/location & defense systems.
- **Most of spectrum offers opportunities for secondary DSA/CR usage:**
  - **Even those bands with the highest observed duty cycles (e.g., ≈80 MHz free in TV band).**

- Location 2: Urban indoor locations.

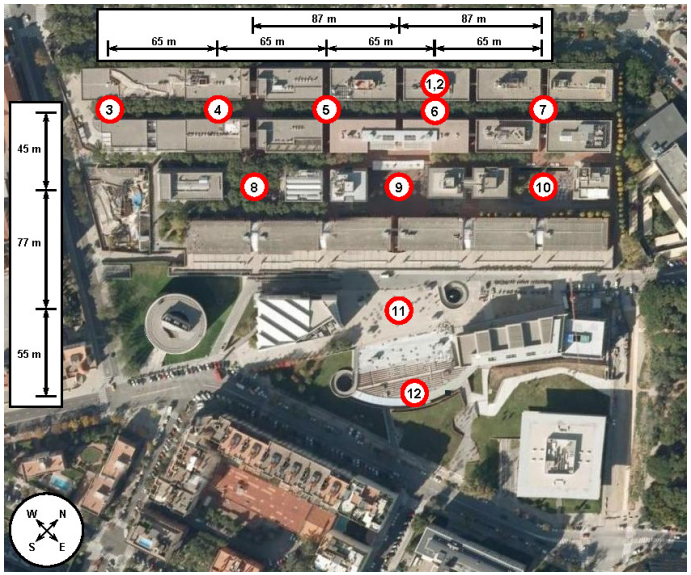
Case	Transmitter location	Receiver location
I	Outdoor	Outdoor
II	Outdoor	Indoor
III	Indoor	Outdoor
IV	Indoor	Indoor

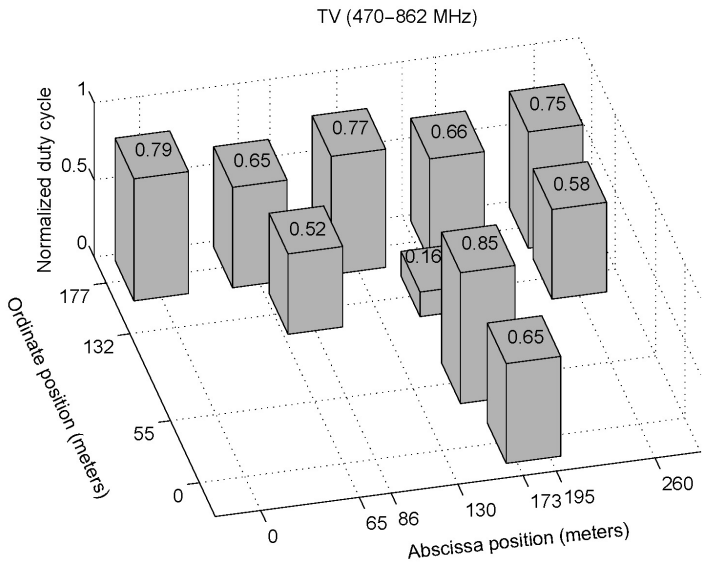


- For bands with outdoor transmitters (I/II):
  - Indoor DC is, in general, lower.
  - When outdoor receivers (I) → More free spectrum.
  - When indoor receivers (II) → Not necessarily.
- For bands with indoor transmitters (III/IV):
  - Indoor DC is, in general, higher.
  - When indoor receivers (IV) → Less free spectrum.
  - When outdoor receivers (III) → Not necessarily.
- The particular circumstances of individual bands need to be taken into account → Adequate modeling.

Measurements: Results

- Locations 3–12: Urban narrow streets and open areas.



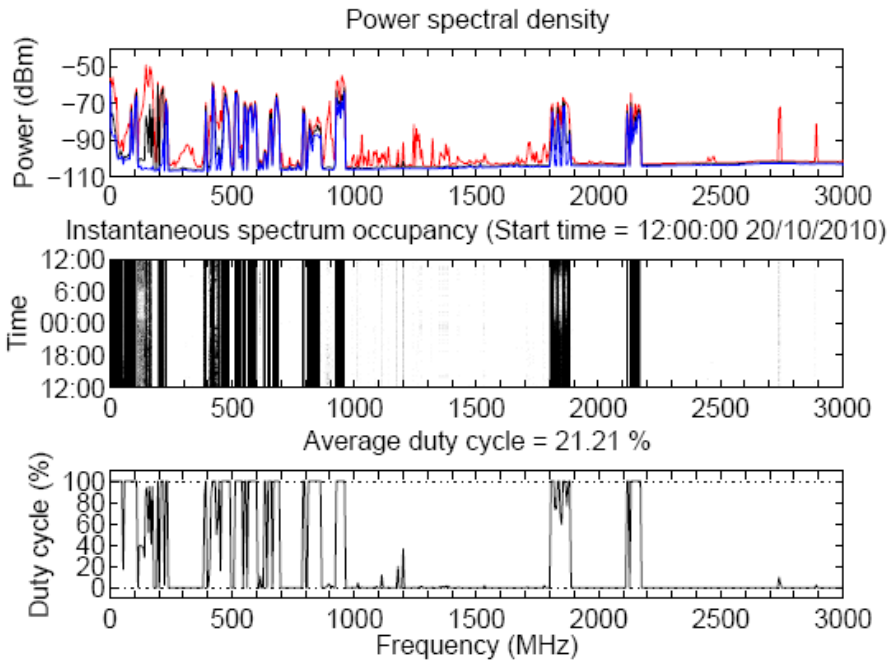


- The spectral activity perceived by a DSA/CR user strongly depends on the user location (even in reduced areas):
  - Occupancy patterns observed at high points are not representative of observations at other locations.
- The perceived occupancy level can be associated to the level of radio propagation blocking:
  - The higher the propagation blocking, the lower the perceived spectrum occupancy.
- All these aspects need to be taken into account in spectrum occupancy modeling.

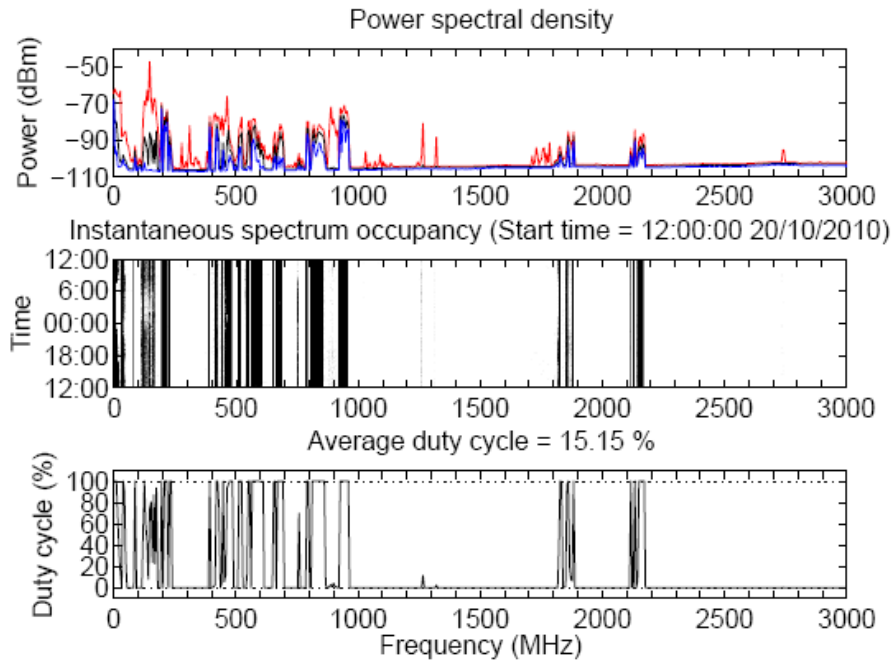
Measurements: Results

- Suburban environments.

Urban environment



Sub-urban environment



- Spectrum occupancy is lower in sub-urban (15.15%) than in urban (21.21%) environments.
  - Especially for bands with occupancy levels dependent of the number of users (e.g., DCS and UMTS).
  - Not a significant difference for bands with independent occupancy levels (e.g., TV and DAB-T).

Part I: Conclusions

- Actual utilization of spectrum is not uniform:
  - Some bands are subject to intensive or moderate usage levels.
  - Some other bands are sparsely used, or not used at all.
- Overall spectrum occupancy is very low.
  - Large amount of spectrum opportunities, even in those bands with the highest observed occupancy levels.
  - Observed spectrum occupancy is related to the surrounding radio propagation environment and, thus, depends on DSA/CR user location.
  - These aspects need to be accounted for in spectrum modeling.
    - And will be considered in detail in subsequent quantitative analyses.

Part I: Contributions

- Design and implementation of an advanced radio spectrum measurement platform, specifically envisaged for the evaluation of spectrum occupancy in the context of DSA/CR.

- Development of unified methodological framework for spectrum occupancy evaluation in the context of DSA/CR.

- Evaluation of spectrum occupancy and identification of potential bands for the deployment of DSA/CR systems.
  - (To the best of the author's knowledge:) The first study of these characteristics under the scope of the Spanish spectrum regulation, and one of the earliest studies in Europe.

PART II

High time-resolution measurements

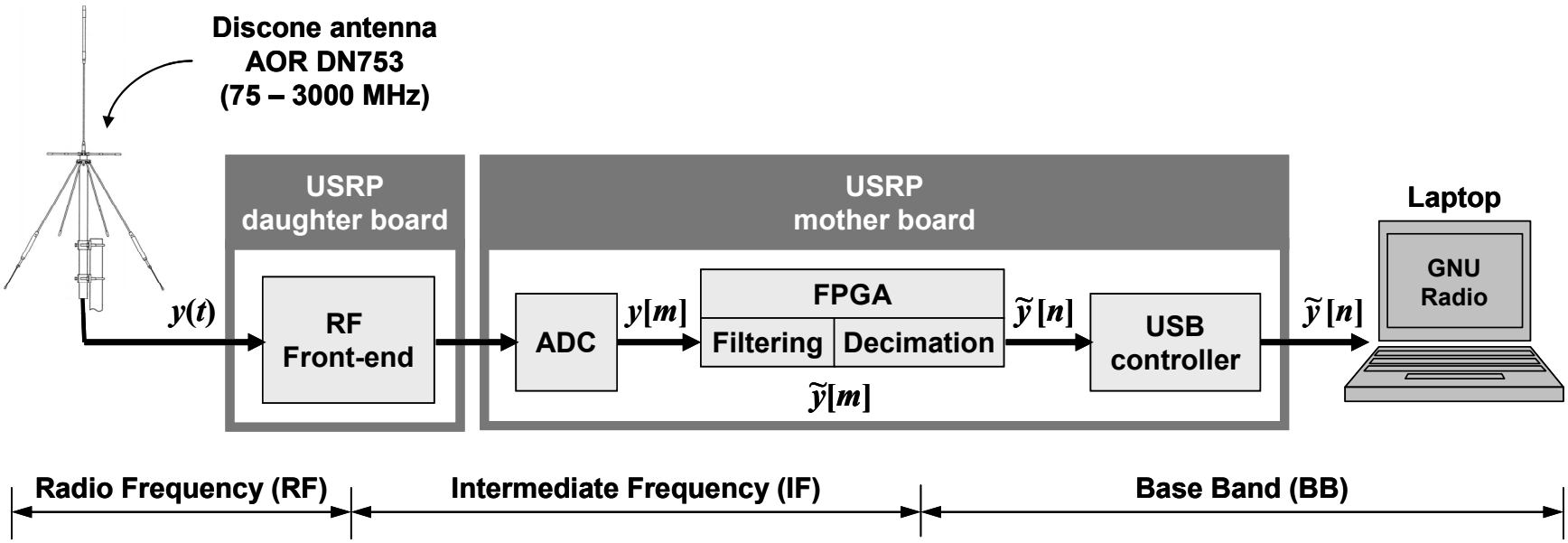
ED performance: Motivation

- Processing high time-resolution signals ≈ spectrum sensing in DSA/CR.
- Spectrum sensing determines presence/absence of primary signals based on captured samples.
- Many spectrum sensing algorithms.
  - Different tradeoffs between:
    - Required sensing time.
    - Complexity.
    - Detection capabilities.
  - Applicability depends on available information:
    - Energy Detection (ED) does not require any prior information.
      - ED is the most widely employed spectrum sensing technique.

ED performance: Motivation

- ED compares received energy with a decision threshold:
  - Received energy > threshold → Channel is busy.
  - Received energy < threshold → Channel is idle.
- Operating principle is simple and general (does not depend on the primary signal to be detected).
  - Is its performance independent of the primary signal?
- This study evaluates the performance of ED based on field measurements of various real-world signals.
  - Relevant question in the context of this work.

ED performance: Measurement setup



TVRX daughter board (50 - 860 MHz)

DBSRX daughter board (800-2400 MHz)

High-speed 12-bit ADC at 64 MS/s.

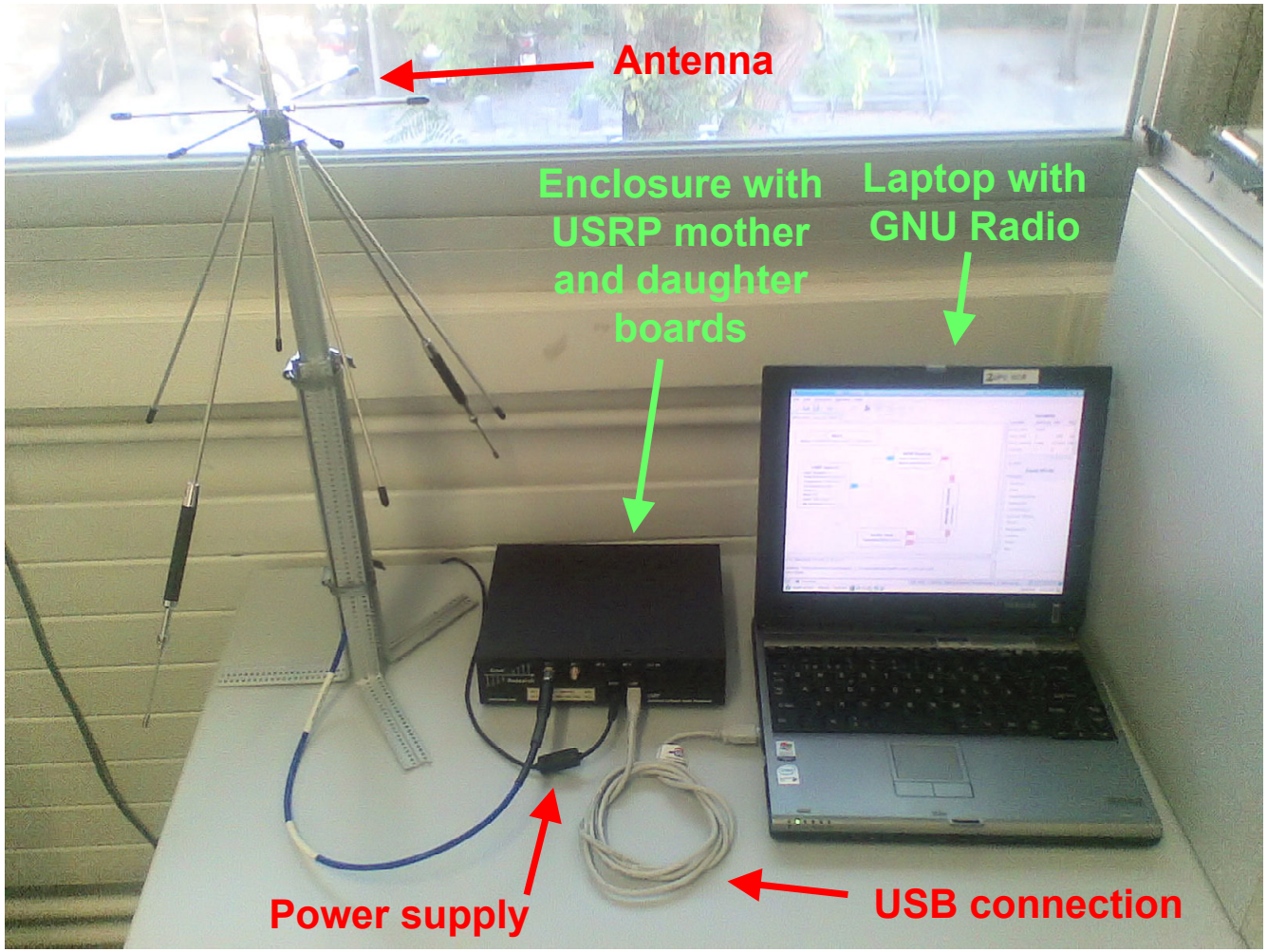
Decimates the signal to adapt data rate to the USB 2.0 and PCs' computing capability.

USB controller sends base band samples in 16-bit I / 16-bit Q complex data format.

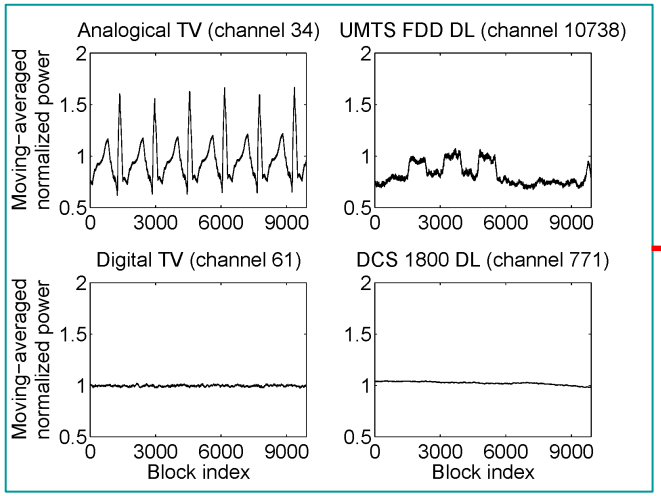
GNU Radio is free & open-source

Used to collect samples and save them to a file.

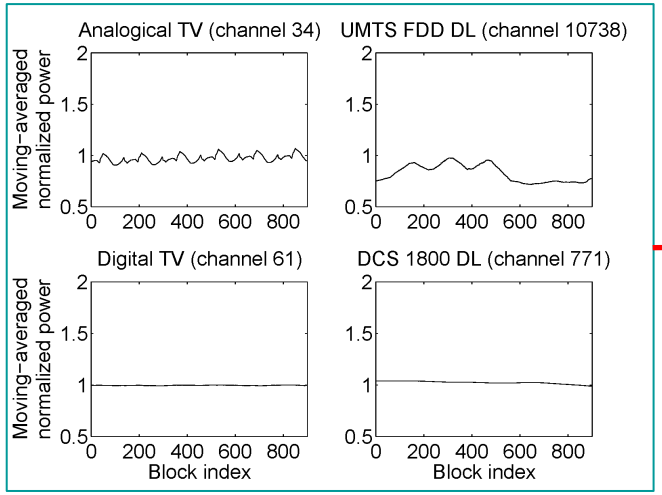
ED performance: Measurement setup



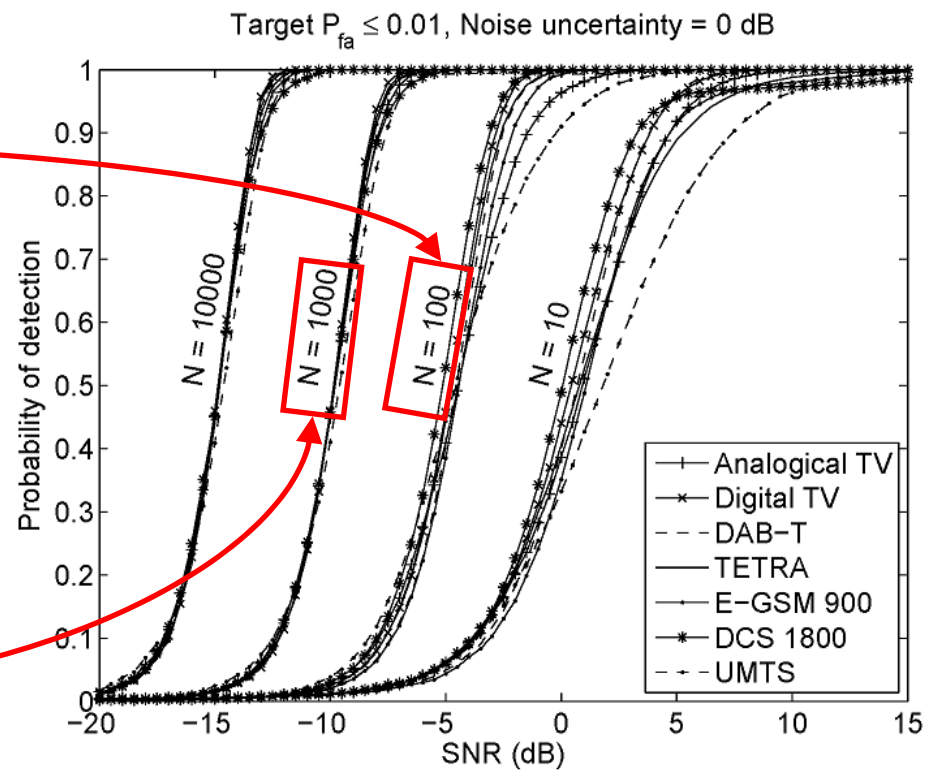
ED performance: Results



N = 100



N = 1000



ED performance: Conclusions

- ED performance depends on the primary radio technology:
  - Short sensing period (*N*):
    - High signal variability → Poorer detection performance.
    - Low signal variability → Better detection performance.
  - Increasing sensing period (*N*):
    - Detection performance converges.
    - But there is some loss in time resolution.

- Important practical consequences:
  - The classical theoretical results for ED cannot predict the impact of signal variability on detection performance.
    - **Need for a more accurate and realistic model of ED performance.**
  - For fixed operating parameters, detection performance might (NOT) be enough to reliably detect some primary signals → Impact on the estimation of the ON/OFF periods and therefore on the accuracy of the spectrum model.
    - **Need for an improved ED scheme that overcomes this drawback.**

ED performance model: Introduction

- Classical theoretical result for ED performance:

$$P_d(\gamma) = Q\left(\frac{Q^{-1}(P_{fa})\sqrt{2N} - N\gamma}{\sqrt{2N}(1+\gamma)}\right)$$

(without noise uncertainty)

$$P_d(\gamma) = Q\left(\frac{\alpha Q^{-1}(P_{fa})\sqrt{2N} - N(\gamma+1-\alpha)}{\sqrt{2N}(1+\gamma)}\right) \qquad \begin{array}{l}\hat{\sigma}^2_{\tilde{w}} \in [\sigma^2_{\tilde{w}}, \alpha\sigma^2_{\tilde{w}}] \\ \hat{\sigma}^2_{\tilde{w}} = \alpha\sigma^2_{\tilde{w}}\end{array}$$

(with noise uncertainty)

  - For a given set of conditions, P_d is unique (theoretical prediction).
  - In practice P_d varies and depends on the primary signal variability.
  - New closed-form expression for P_d that accounts for the variability of the primary signal.

- The variability of the primary signal results in a variation of the instantaneous SNR at the receiver.
- The average P_d for an average SNR is:

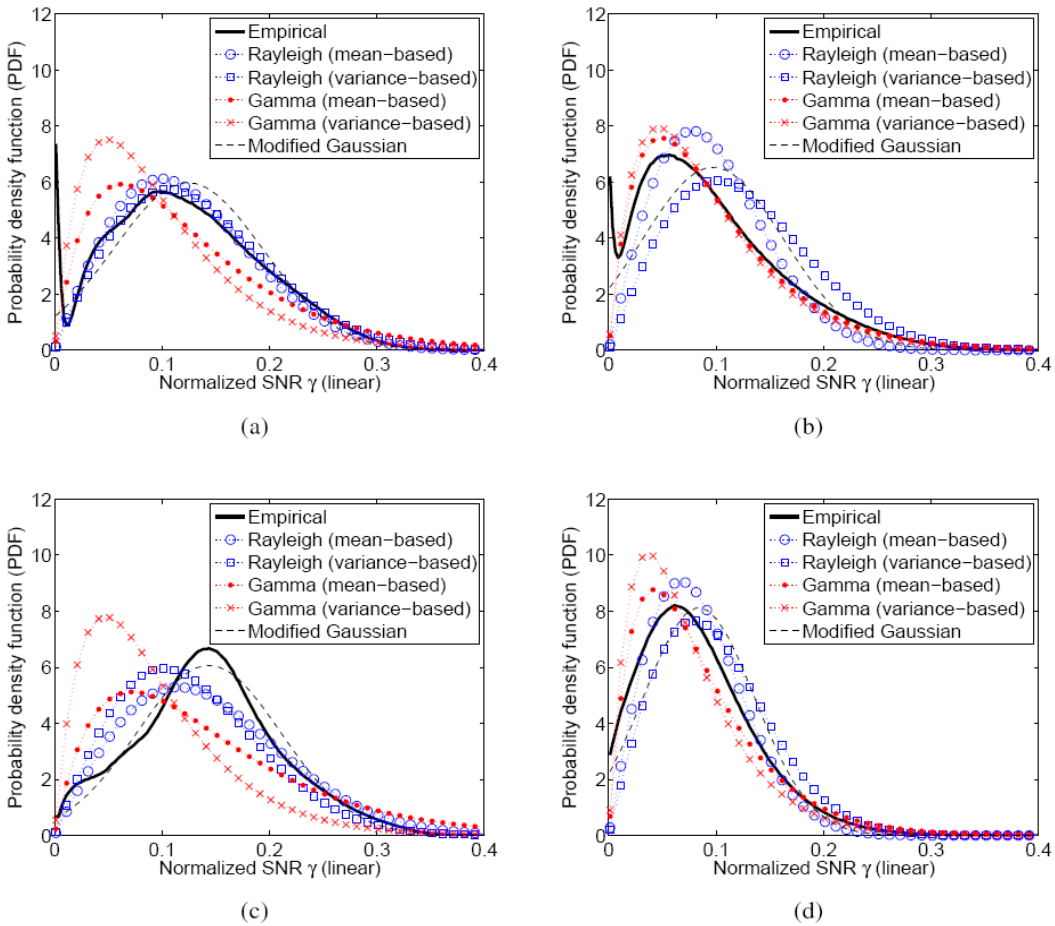
$$\overline{P}_d(\gamma_0) = \mathbb{E}[P_d(\gamma)] = \int_\gamma P_d(\gamma) f_\gamma(\gamma) d\gamma \longrightarrow \text{statistics of } f_\gamma(\gamma)\text{ ?}$$

ED performance model: SNR statistics

Rayleigh distribution:

$$f_\gamma^R(\gamma) = \frac{\gamma}{s^2}\exp\left(-\frac{\gamma^2}{2s^2}\right), \quad \gamma \geq 0$$

$$\sigma_\gamma^2 = (4/\pi - 1)\gamma_0^2 \approx 0.27\gamma_0^2$$



Gamma distribution:

$$f_\gamma^G(\gamma) = \frac{\gamma^{k-1}}{\theta^k\Gamma(k)}\exp\left(-\frac{\gamma}{\theta}\right), \quad \gamma \geq 0$$

$$\sigma_\gamma^2 = 0.5\gamma_0^2$$

Modified Gaussian distribution:

$$f_\gamma^{MG}(\gamma) \approx \frac{\kappa}{\sqrt{2\pi}\sigma_\gamma}e^{-\frac{1}{2}\left(\frac{\gamma-\gamma_0}{\sigma_\gamma}\right)^2}, \quad \gamma \geq 0 \xrightarrow{\int_0^\infty f_\gamma(\gamma)d\gamma = 1} \kappa = \frac{2}{1+\mathrm{erf}\left(\frac{\gamma_0}{\sqrt{2}\sigma_\gamma}\right)} \qquad \sigma_\gamma^2 = \beta\gamma_0^2$$

ED performance model: P_d approximation

- Approximation for Pd:

$$P_d(\gamma) = Q\left(\frac{\alpha Q^{-1}(P_{fa})\sqrt{2N} - N(\gamma + 1 - \alpha)}{\sqrt{2N}(1+\gamma)}\right)$$

$$P_d(\gamma) = Q(\zeta(\gamma)) \longleftarrow \quad \zeta(\gamma) = \frac{\alpha Q^{-1}(P_{fa})\sqrt{2N} - N(\gamma + 1 - \alpha)}{\sqrt{2N}(1+\gamma)}$$

- Development of an approximation for the Gaussian *Q*-function:

$$Q(x) \approx e^{-(ax^2+bx+c)}, \quad x \geq 0$$

where (*a*,*b*,*c*) are determined by minimizing:
  - Sum of Square Errors (SSE).
  - Maximum Absolute Relative Error (MARE).

- This approximation, along with the modified Gaussian model for $f_\gamma(\gamma)$, allows solving the integral, thus yielding a closed-form expression for P_d that accounts for the variability of the primary signal.

ED performance model: Expressions

$$\overline{P}_d^{MG}(\gamma_0) \approx \frac{\kappa}{2}\,\mathrm{erfc}\left(\frac{\xi-\gamma_0}{\sqrt{2}\sigma_\gamma}\right) = \frac{\mathrm{erfc}\left(\frac{\xi-\gamma_0}{\sqrt{2}\sigma_\gamma}\right)}{1+\mathrm{erf}\left(\frac{\gamma_0}{\sqrt{2}\sigma_\gamma}\right)}$$

$$\overline{P}_d^{R}(\gamma_0) \approx \exp\left(-\frac{\pi}{4}\left(\frac{\xi}{\gamma_0}\right)^2\right)$$

$$\overline{P}_d^{G}(\gamma_0) \approx \left(1+\frac{2\xi}{\gamma_0}\right)\exp\left(-\frac{2\xi}{\gamma_0}\right)$$

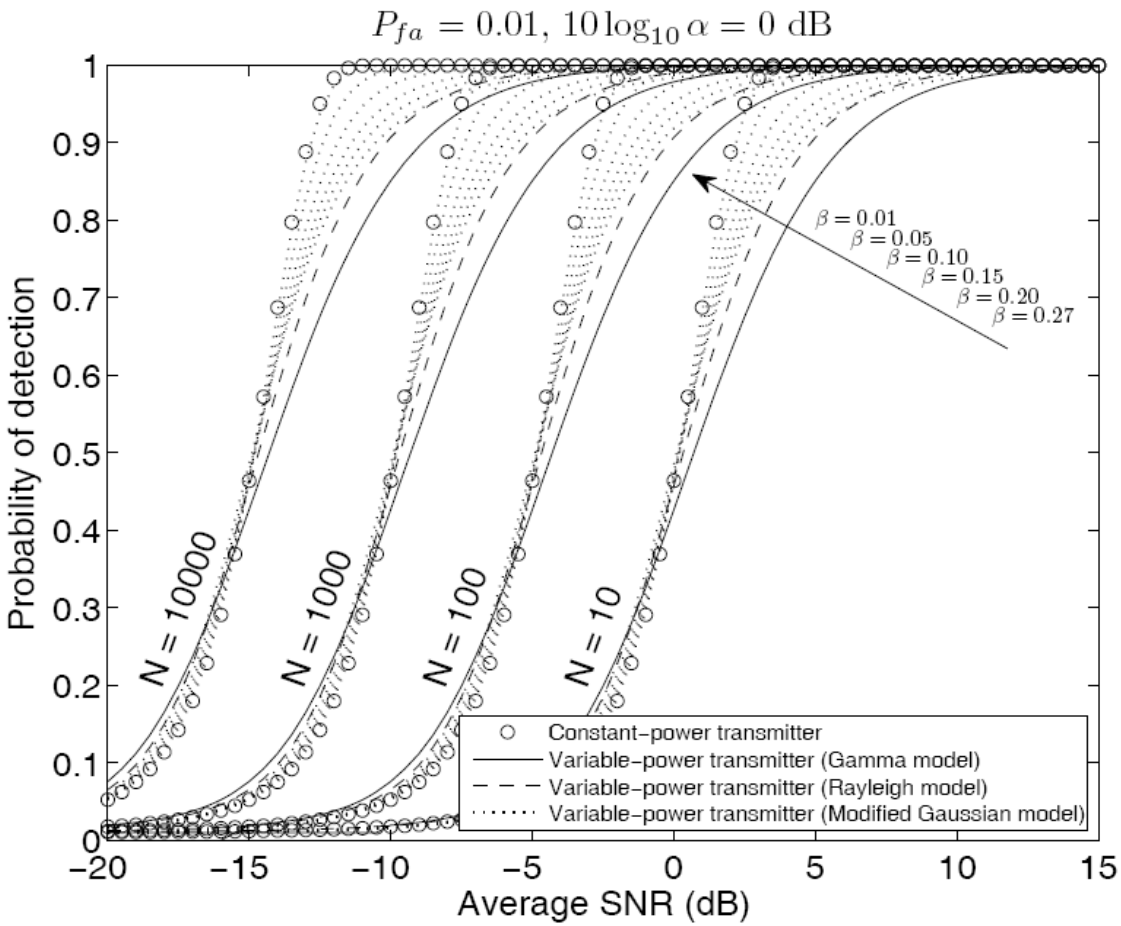
- Impact of signal variability $\beta \geq 0$ is clearly reproduced.
- Convergence as *N* increases can be modeled as:

$$\sigma_\gamma^2 = \beta\,\tau(N)\,\gamma_0^2$$

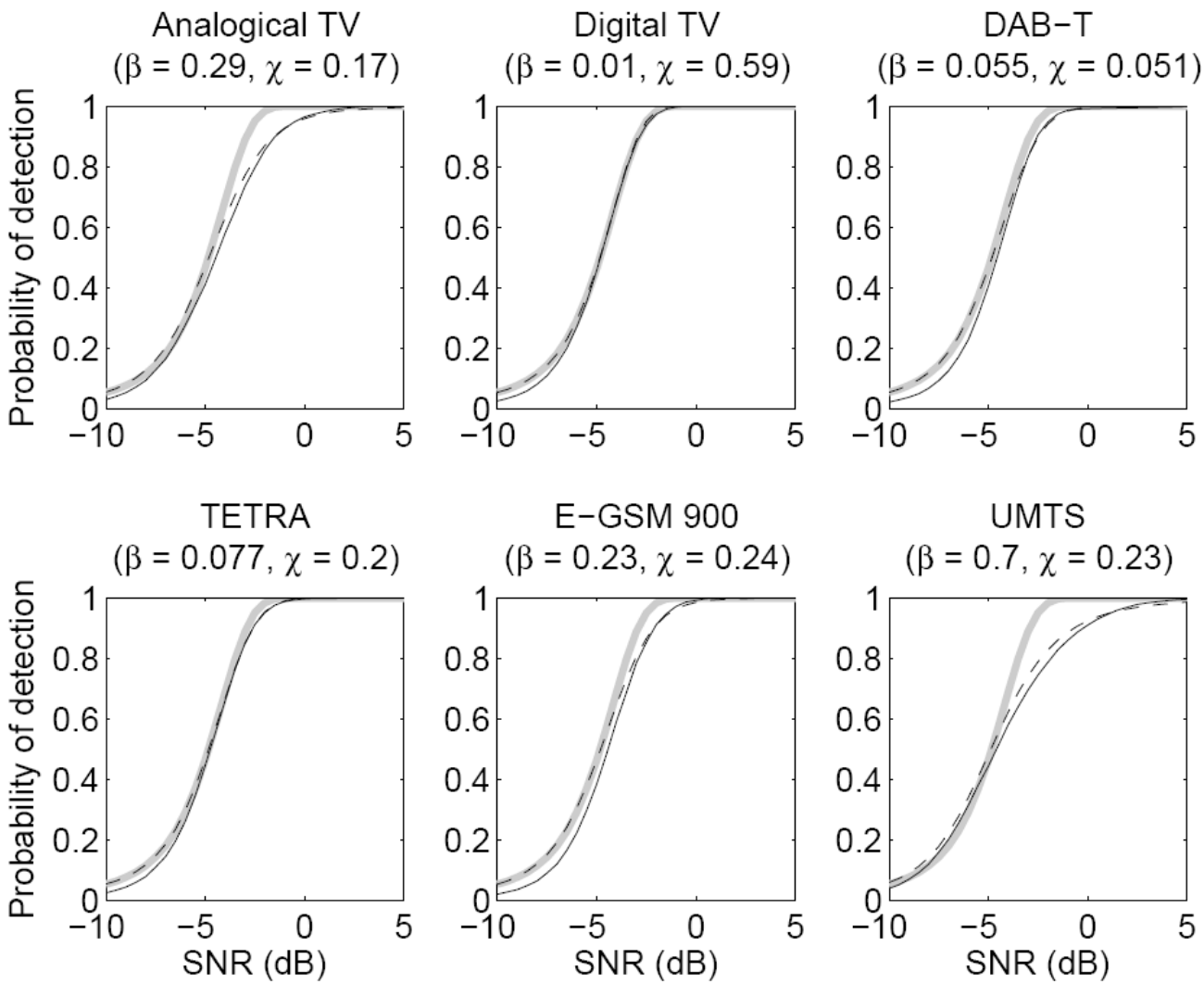
where $\tau(N) \in (0,1]$ is a monotically decreasing function of *N* given by:

$$\tau(N) \approx N^{-\chi}$$

where $\chi \in [0,1]$ is the convergence rate.



ED performance model: Validation



Improved ED scheme: Introduction & CED

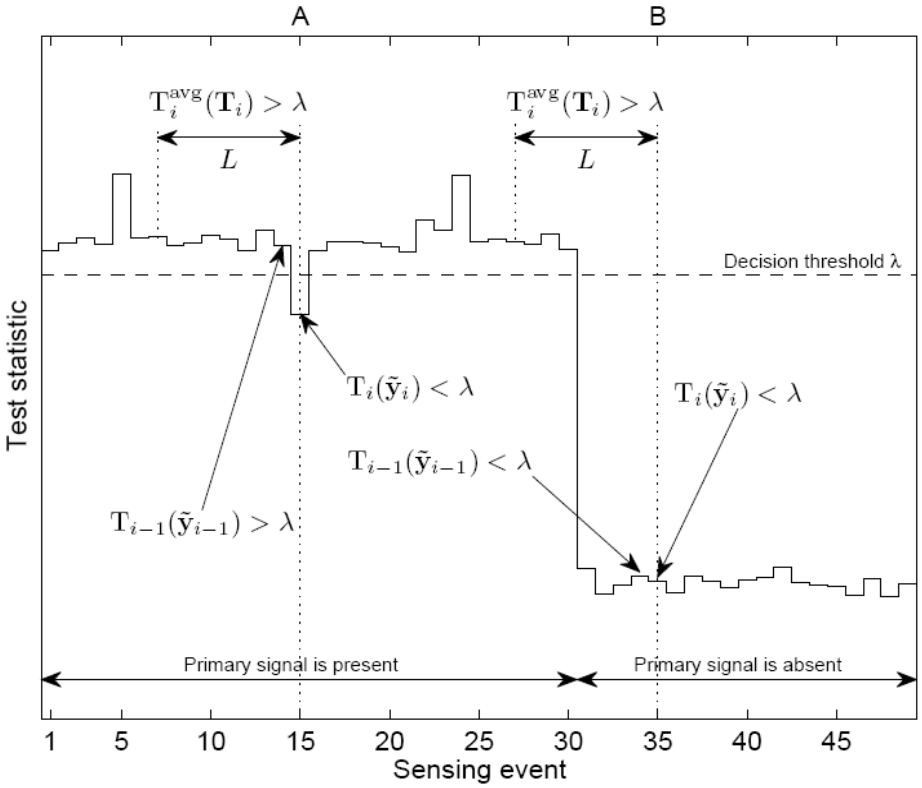
- ED performance depends on primary signal:
  - Detection probability may be lower for highly variable signals.
  - Can be improved with alternative (more complex) algorithms.
  - Objective: Improve performance with similar complexity and costs.

Classical Energy Detection (CED) scheme

Input: $\lambda \in \mathbb{R}^+, N \in \mathbb{N}$
Output: $S_i \in \{\mathcal{H}_0, \mathcal{H}_1\}$

```
for each sensing event i do
    T_i(ỹ_i) ← Energy of N samples
    if T_i(ỹ_i) > λ then
        S_i ← H_1
    else
        S_i ← H_0
    end if
end for
```

$$\mathbb{T}_i(\tilde{\mathbf{y}}_i) = \sum_{n=1}^{N} |\tilde{y}_i[n]|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda$$

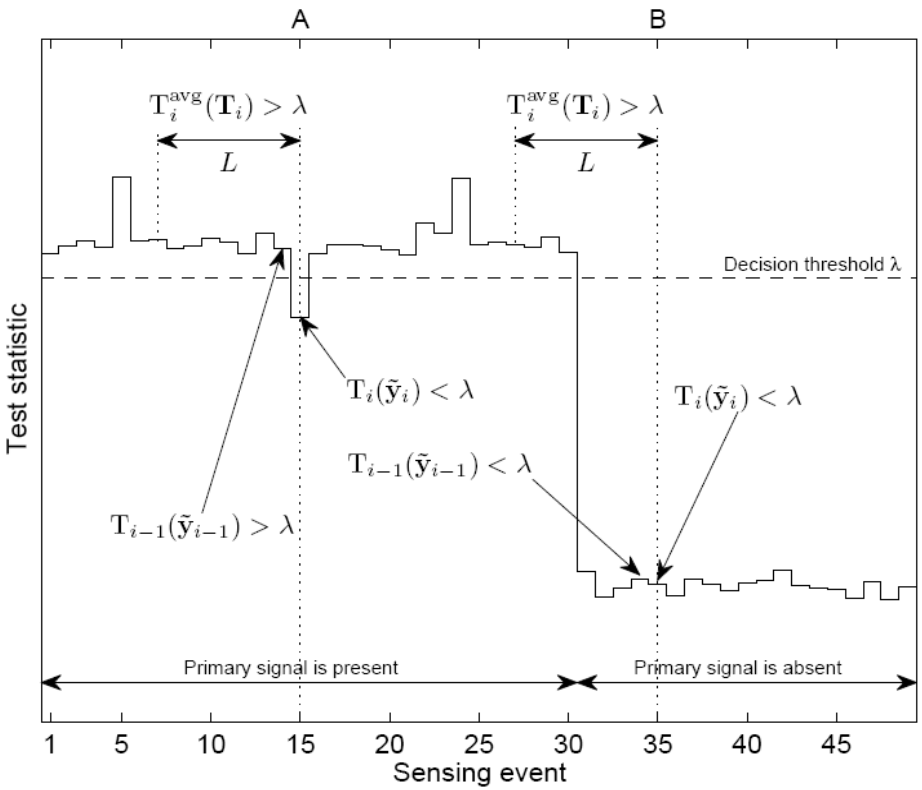


Improved ED scheme: MED

Modified Energy Detection (MED) scheme

Input: $\lambda \in \mathbb{R}^+, N \in \mathbb{N}, L \in \mathbb{N}$
Output: $S_i \in \{\mathcal{H}_0, \mathcal{H}_1\}$

```
for each sensing event i do
    T_i(ỹ_i) ← Energy of N samples
    T_i^avg(T_i) ← Mean of {T_{i-L+1}(ỹ_{i-L+1}), ..., T_{i-1}(ỹ_{i-1}), T_i(ỹ_i)}
    if T_i(ỹ_i) > λ then
        S_i ← H_1
    else
        if T_i^avg(T_i) > λ then
            S_i ← H_1
        else
            S_i ← H_0
        end if
    end if
end for
```



- Consequences:
  - P_d increases, but
  - P_{fa} also increases.
- Overall, MED is worse than CED.

$$P_d^{\text{MED}} \approx P_d^{\text{CED}} + \left(1 - P_d^{\text{CED}}\right) Q\left(\frac{\lambda - \mu_{\text{avg}}}{\sigma_{\text{avg}}}\right)$$

$$P_{fa}^{\text{MED}} \approx P_{fa}^{\text{CED}} + \left(1 - P_{fa}^{\text{CED}}\right) Q\left(\frac{\lambda - \mu_{\text{avg}}}{\sigma_{\text{avg}}}\right)$$

$\rightarrow$

$$P_d^{\text{CED}} \leq P_d^{\text{MED}} \leq 1$$

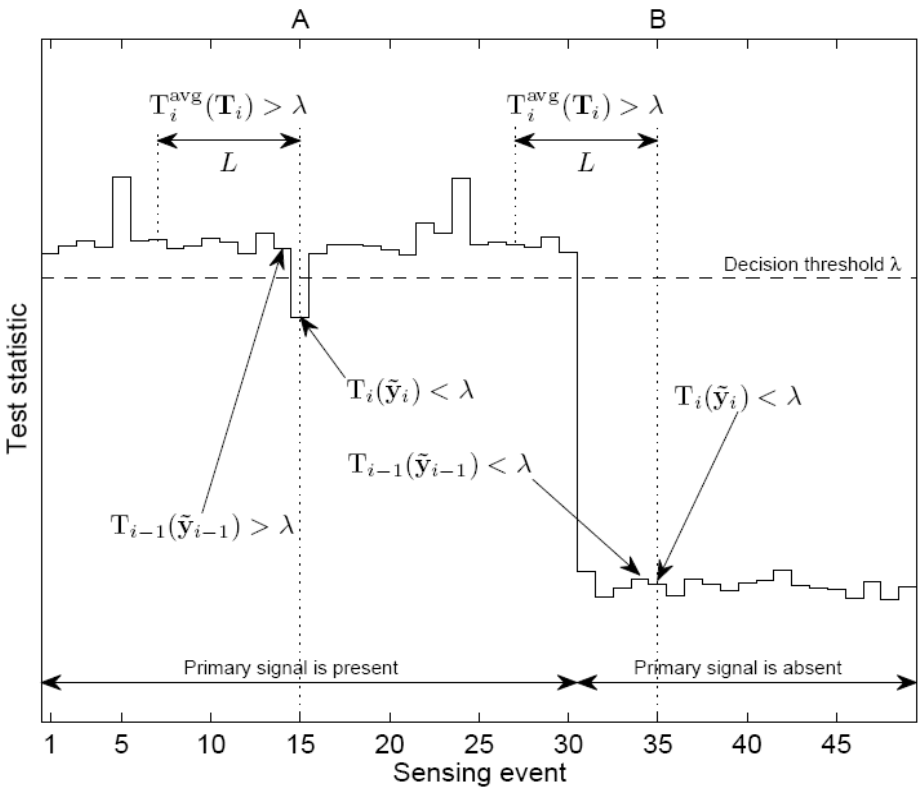
$$P_{fa}^{\text{CED}} \leq P_{fa}^{\text{MED}} \leq 1$$

Improved ED scheme: IED

Improved Energy Detection (IED) scheme

Input: $\lambda \in \mathbb{R}^+, N \in \mathbb{N}, L \in \mathbb{N}$
Output: $S_i \in \{\mathcal{H}_0, \mathcal{H}_1\}$

```
for each sensing event i do
    T_i(ỹ_i) ← Energy of N samples
    T_i^avg(T_i) ← Mean of {T_{i-L+1}(ỹ_{i-L+1}), ..., T_{i-1}(ỹ_{i-1}), T_i(ỹ_i)}
    if T_i(ỹ_i) > λ then
        S_i ← H_1
    else
        if T_i^avg(T_i) > λ then
            if T_{i-1}(ỹ_{i-1}) > λ then
                S_i ← H_1
            else
                S_i ← H_0
            end if
        else
            S_i ← H_0
        end if
    end if
end for
```



$$P_d^{\mathrm{IED}} \approx P_d^{\mathrm{CED}} + P_d^{\mathrm{CED}}\left(1 - P_d^{\mathrm{CED}}\right) Q\left(\frac{\lambda - \mu_{\mathrm{avg}}}{\sigma_{\mathrm{avg}}}\right)$$

$$P_{fa}^{\mathrm{IED}} \approx P_{fa}^{\mathrm{CED}} + P_{fa}^{\mathrm{CED}}\left(1 - P_{fa}^{\mathrm{CED}}\right) Q\left(\frac{\lambda - \mu_{\mathrm{avg}}}{\sigma_{\mathrm{avg}}}\right)$$

$$\rightarrow \quad P_d^{\mathrm{CED}} \le P_d^{\mathrm{IED}} \le 2P_d^{\mathrm{CED}} - \left(P_d^{\mathrm{CED}}\right)^2$$

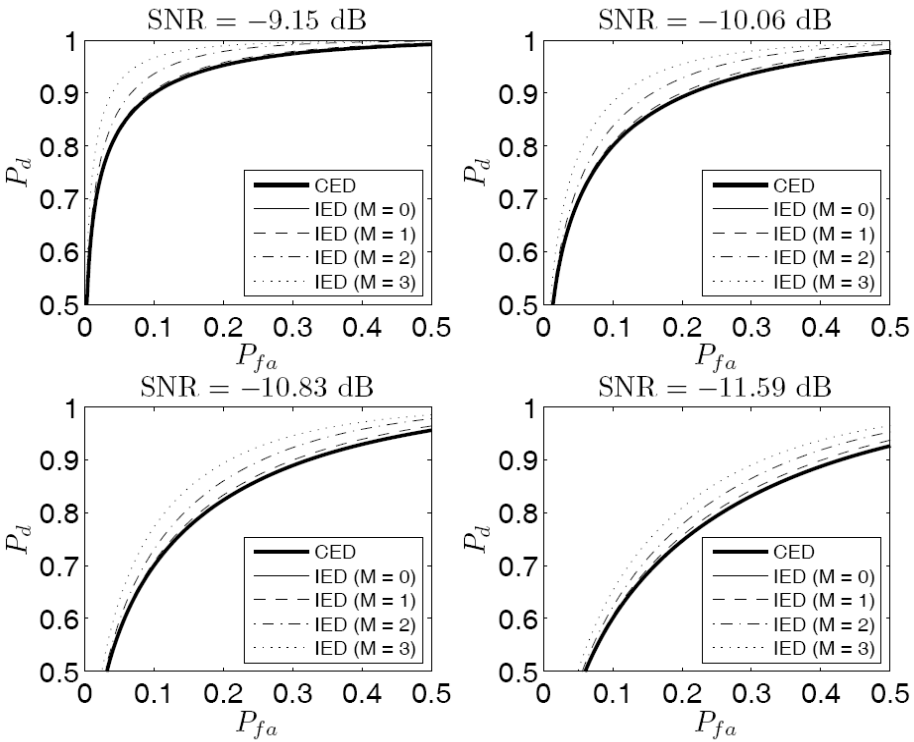
$$P_{fa}^{\mathrm{CED}} \le P_{fa}^{\mathrm{IED}} \le 2P_{fa}^{\mathrm{CED}} - \left(P_{fa}^{\mathrm{CED}}\right)^2$$

- Overall, IED is better than CED.

Improved ED scheme: Validation

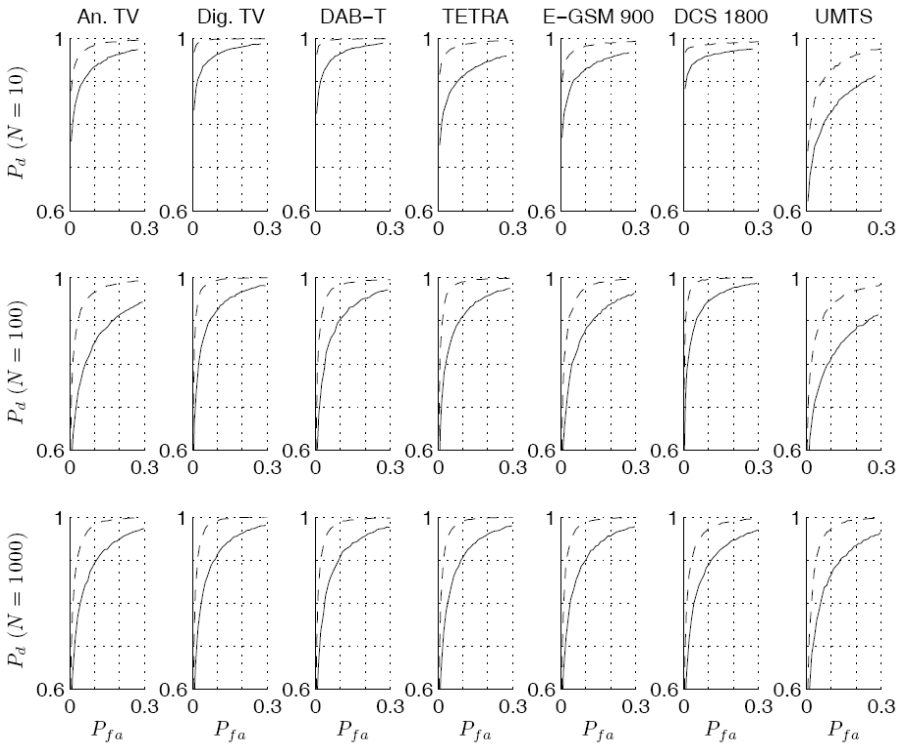
Theoretical performance

IED vs. CED



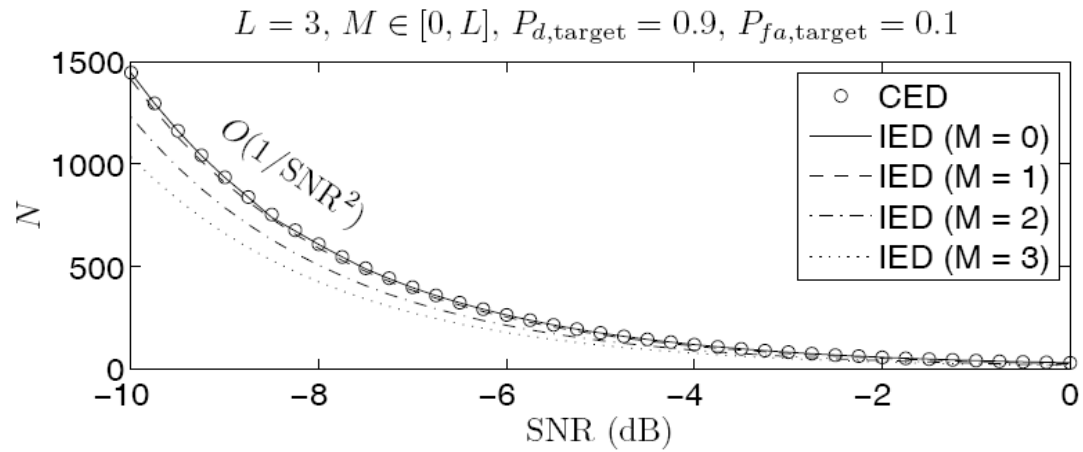
Experimental performance

IED vs. CED

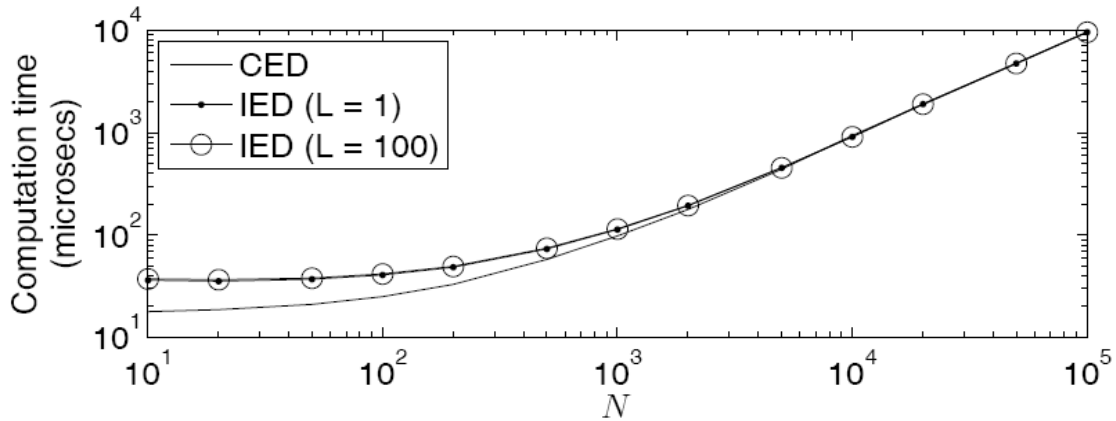


Improved ED scheme: Complexity

Sample complexity



Computational complexity



- Sample and computational complexities of IED are equivalent to CED.
- IED outperforms CED with simple approach and similar generality and complexity.
  - IED will be employed to extract ON/OFF periods from empirical data to develop the models.

Part II: Conclusions

- ED performance depends on the primary radio technology:
  - Short sensing period (*N*):
    - High signal variability → Poorer detection performance.
    - Low signal variability → Better detection performance.
  - Increasing sensing period (*N*):
    - Detection performance converges.
    - But there is some loss in time resolution.

- Important practical consequences:
  - The classical theoretical results for ED cannot predict the impact of signal variability on detection performance.
    - A more accurate and realistic model of ED performance has been developed.
  - Detection probability may be lower for highly variable signals.
    - An improved ED scheme that overcomes this drawback has been developed.
      - The proposed IED scheme is a general algorithm, as CED (does not depend on primary signal).
      - IED outperforms CED in terms of P_d/P_{fa} with similar sample and computational complexities.
    - IED scheme will enable more accurate estimation of ON/OFF statistics from field measurements.

Part II: Contributions

- Assessment of ED performance based on field measurements of various radio technologies.

- Development of a more realistic and accurate model for ED performance that accounts for primary signal variability.

- Design and evaluation of an improved ED (IED) scheme:
  - Range of applicability similar to classical ED (CED).
  - Similar sample and computational complexities.
  - Significant detection performance improvements.

- Development of a versatile, accurate and analytically tractable approximation for the Gaussian *Q*-function.

PART III

Spectrum usage models

Models: Motivation

- Importance of realistic and accurate models of spectrum usage.
  - Opportunistic nature of the DSA/CR paradigm.

- Existing models:
  - Limited in scope and based on assumptions/oversimplifications not validated with spectrum data.

- Spectrum usage models:
  - Time dimension.
  - Frequency dimension.
  - Space dimension.

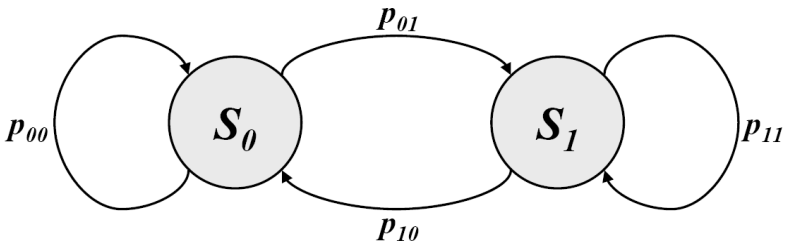
Models: Time dimension

- Statistical properties of spectrum usage in time domain:
  - 1) Average channel occupancy level → Duty Cycle (DC).
  - 2) Distribution of busy and idle periods.
  - 3) Time-correlation properties (ON/OFF, ON/ON, OFF/OFF).

- Model commonly used:
  - Markov chain model.
    - Discrete-time.
    - Continuous-time.

Models: Time dimension (DTMC)

- Two-state Discrete-Time Markov Chain (DTMC):



  - Stationary / time-homogeneous DTMC:

$$\mathbf{P} = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}$$

- Which properties of spectrum usage can be described with DTMC model?
  - 1) Duty Cycle (DC):
    - Probability or fraction/percentage of time that a channel is busy.
    - For a DTMC, the DC is given by:

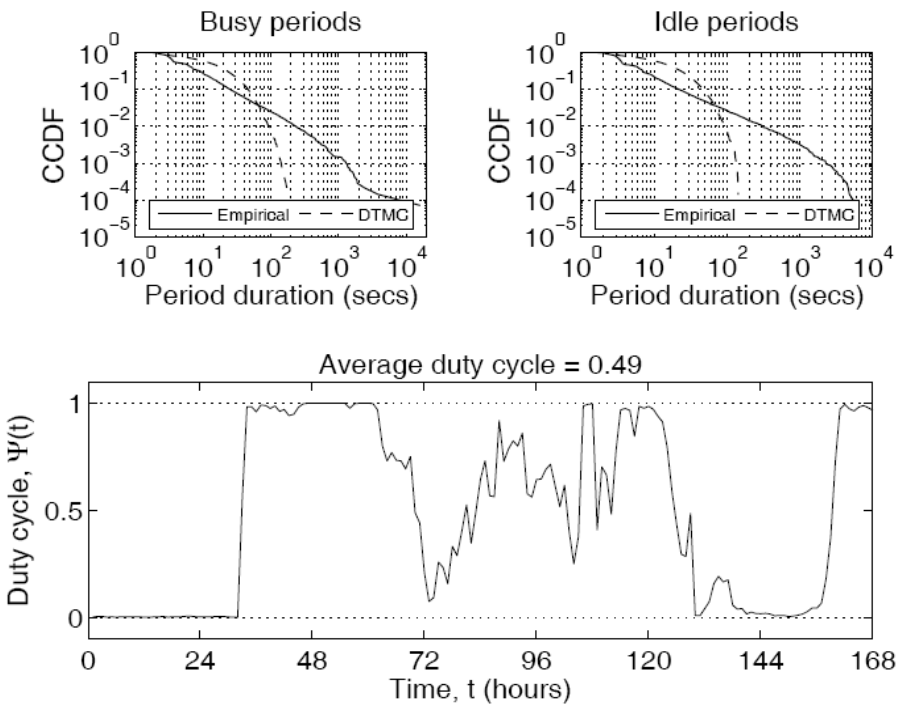
$$\pi_1 = \frac{p_{01}}{p_{01} + p_{10}} \longrightarrow \mathbf{P} = \begin{bmatrix} 1-\Psi & \Psi \\ 1-\Psi & \Psi \end{bmatrix}$$

    - The DTMC model can be configured to reproduce any DC.

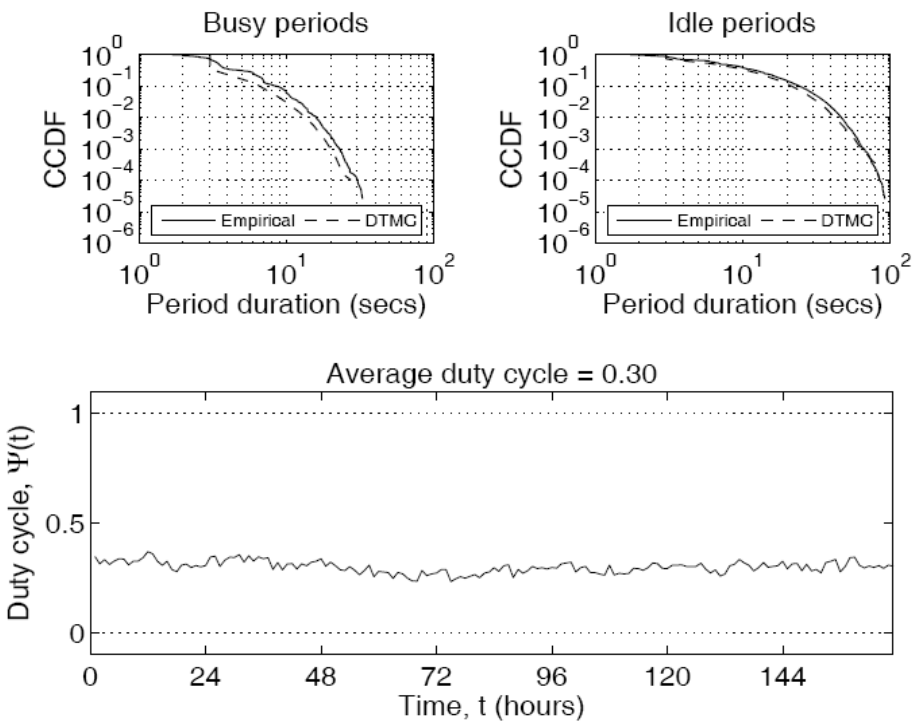
Models: Time dimension (DTMC)

- Which properties of spectrum usage can be described with DTMC model?
  - 2) Length of busy/idle periods (distributions).
    - This aspect is not explicitly modeled by the DTMC model.
    - It is not expected to reproduce busy/idle period lengths.
    - Empirical verification:

Channel with varying load pattern



Channel with constant load pattern



Models: Time dimension (DTMC)

- The probabilities of the transition matrix depend on the DC.
  - If the DC is constant with time → Stationary DTMC is valid.
  - If the DC is NOT constant → Stationary DTMC is NOT valid.

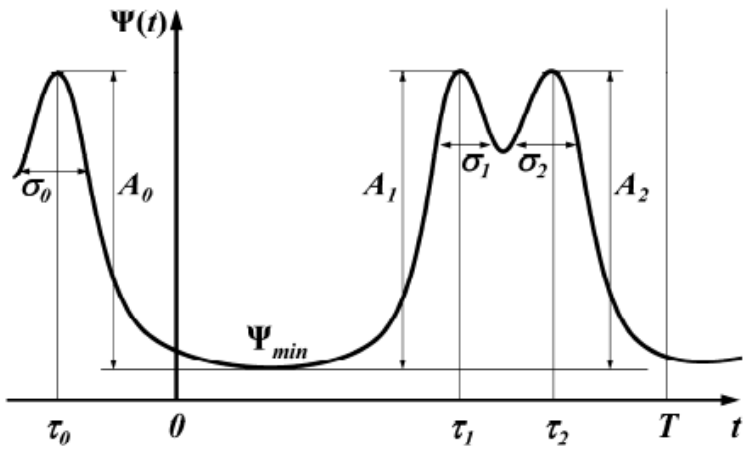
$$\mathbf{P} = \begin{bmatrix} 1-\Psi & \Psi \\ 1-\Psi & \Psi \end{bmatrix} \longrightarrow \mathbf{P}(t) = \begin{bmatrix} 1-\Psi(t) & \Psi(t) \\ 1-\Psi(t) & \Psi(t) \end{bmatrix}$$

- Duty Cycle (DC):
  - Stationary case: constant parameter Ψ.
  - Non-stationary case: time-dependent function Ψ(t).
  - DC Ψ(t) needs to be characterized → DC models.
  - Two different DC patterns:
    - Deterministic pattern.
    - Stochastic pattern.

Models: Time dimension (DTMC)

- Channel load is in general random: Incoming/outgoing users, RRM policies, etc.
- In some cases, strong deterministic component: Social behavior, common habits, etc.
  - Good example: cellular mobile communication systems.

Low/medium average loads

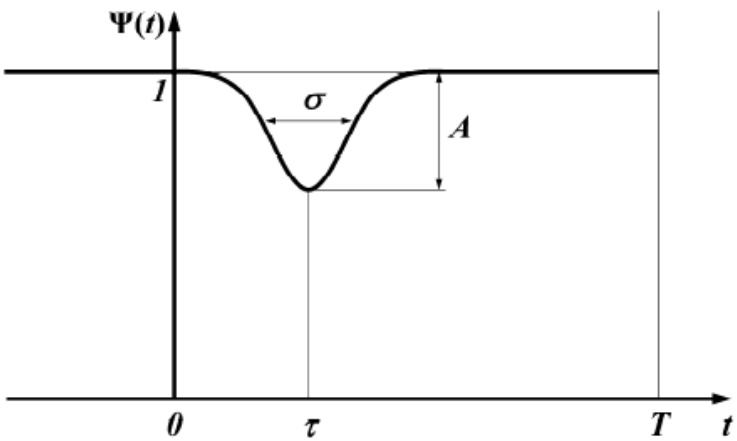


$$\Psi(t) \approx \Psi_{min} + \frac{2T\left(\overline{\Psi} - \Psi_{min}\right)}{\sigma\sqrt{\pi}} \cdot \frac{f_{\exp}^{l/m}(t, \tau_m, \sigma)}{f_{\mathrm{erf}}^{l/m}(T, \tau_m, \sigma)}$$

$$f_{\exp}^{l/m}(t, \tau_m, \sigma) = \sum_{m=0}^{M-1} e^{-\left(\frac{t-\tau_m}{\sigma}\right)^2}$$

$$f_{\mathrm{erf}}^{l/m}(T, \tau_m, \sigma) = \sum_{m=0}^{M-1} \left[\mathrm{erf}\left(\frac{\tau_m}{\sigma}\right) + \mathrm{erf}\left(\frac{T-\tau_m}{\sigma}\right)\right]$$

Medium/high average loads



$$\Psi(t) \approx 1 - \frac{2T\left(1 - \overline{\Psi}\right)}{\sigma\sqrt{\pi}} \cdot \frac{f_{\exp}^{m/h}(t, \tau, \sigma)}{f_{\mathrm{erf}}^{m/h}(T, \tau, \sigma)}$$

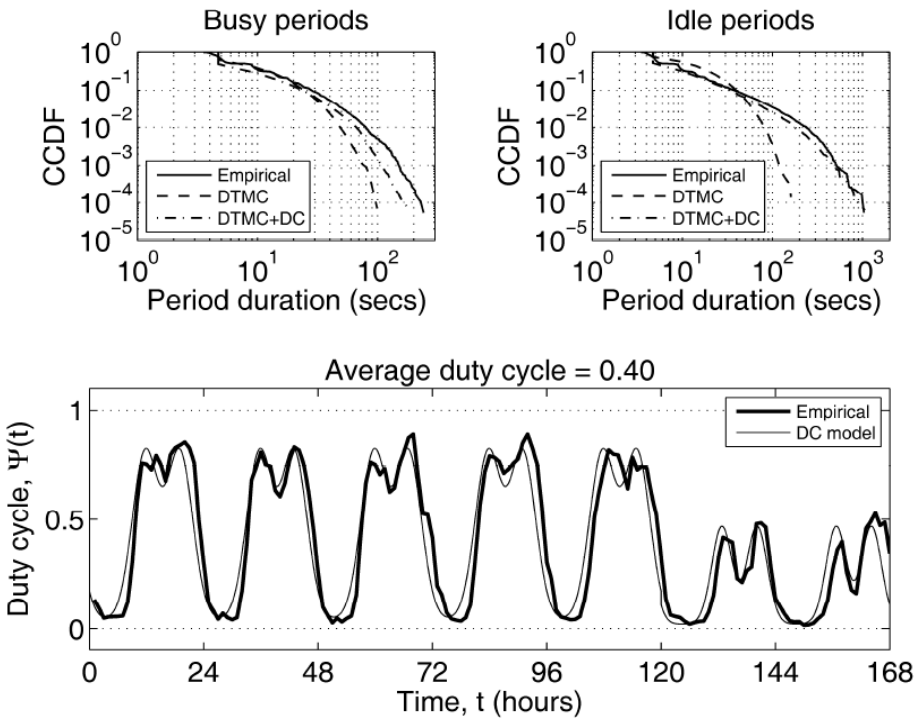
$$f_{\exp}^{m/h}(t, \tau, \sigma) = e^{-\left(\frac{t-\tau}{\sigma}\right)^2}$$

$$f_{\mathrm{erf}}^{m/h}(T, \tau, \sigma) = \mathrm{erf}\left(\frac{\tau}{\sigma}\right) + \mathrm{erf}\left(\frac{T-\tau}{\sigma}\right)$$

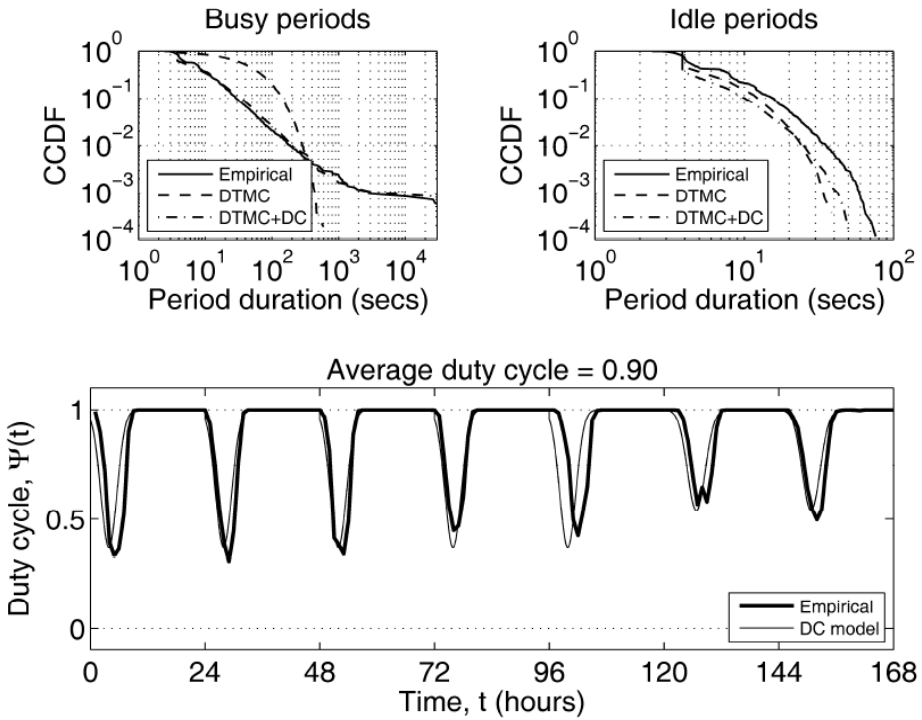
Models: Time dimension (DTMC)

- Validation of deterministic DC models.

Low/medium average loads



Medium/high average loads



Models: Time dimension (DTMC)

- Channel load pattern cannot be considered to be deterministic in some cases:
  - Channel load itself is in general random: Incoming/outgoing users, RRM policies, etc.
  - Even in deterministic cases, channel load may vary randomly over short time periods.
- Stochastic modeling approach is needed:
  - DC can be considered as a stochastic process whose values are drawn from:
    - Beta distribution:

$$f_x^B(x;\alpha,\beta) = \frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1}, \quad x \in (0,1) \qquad B(\alpha,\beta) = \int_0^1 z^{\alpha-1}(1-z)^{\beta-1} dz$$

    - Kumaraswamy distribution:

$$f_x^K(x;a,b) = abx^{a-1}(1-x^a)^{b-1}, \quad x \in (0,1)$$

  - Any arbitrary mean channel DC can be obtained by configuring as:

$$\bar{\Psi} = \begin{cases} \dfrac{\alpha}{\alpha+\beta} & \text{for beta distribution} \\ bB\left(1+\dfrac{1}{a}, b\right) & \text{for Kumaraswamy distribution} \end{cases}$$

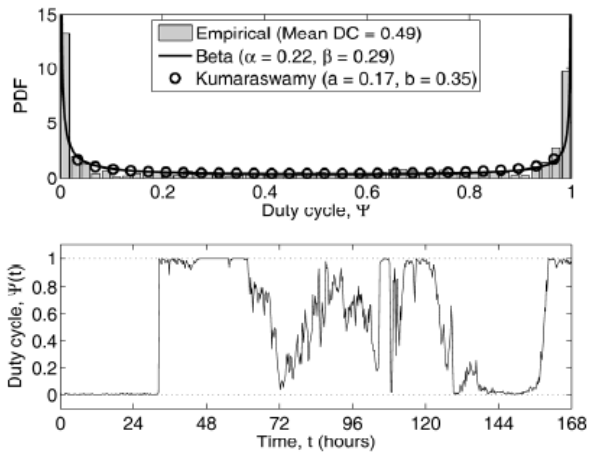
Models: Time dimension (DTMC)

- Distribution parameters have a direct impact on resulting DC pattern in time-domain.
- Definition of 6 archetypes based on:
  - Load level → L: low / M: medium / H: high
  - Load pattern → type I: very bursty / type II: moderately bursty, but not constant

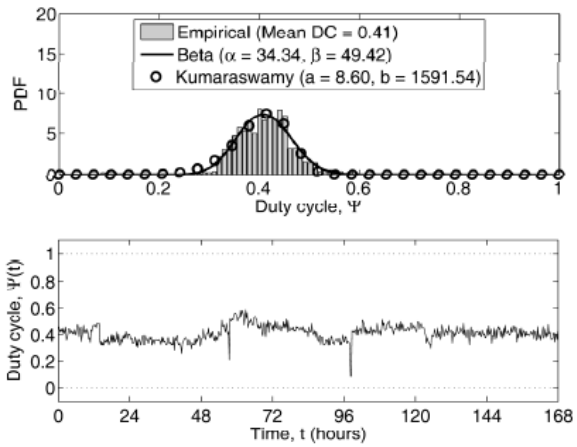
Also for Kumaraswamy for type I cases.
Difficult to control in type-II cases.

	Low (L)	Medium (M)	High (H)
Type I	$\alpha<1, \beta\geq1$	$\alpha<1, \beta<1$	$\alpha\geq1, \beta<1$
Type II	$1<\alpha<\beta$	$\alpha>1, \beta>1, \alpha\sim\beta$	$\alpha>\beta>1$

M.I

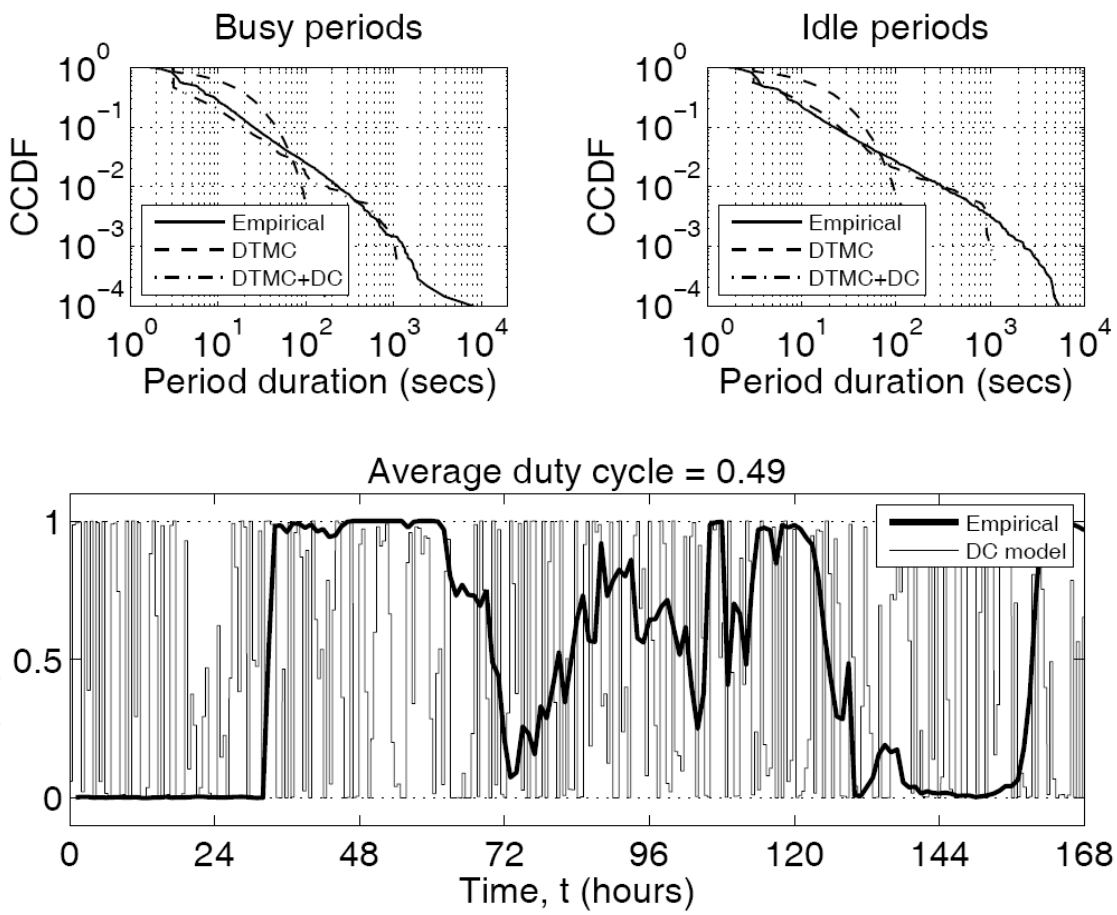


M.II



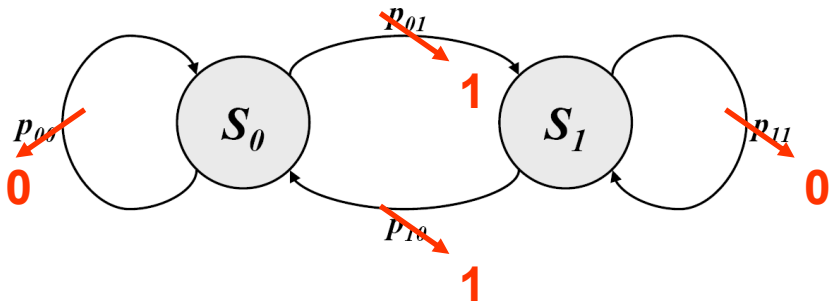
Models: Time dimension (DTMC)

- Validation of stochastic DC model.



Models: Time dimension (CTMC/CTSMC)

- Two-state Continuous-Time Markov Chain (CTMC):



  - The model is characterized by ON/OFF distributions → Exponential.
  - Exponential distribution of state holding times is NOT valid in reality (unrealistic)
    - Works by Geirhofer, Stabellini and Wellens.
  - Other distributions have been shown to be more appropriate.
    - Continuous-Time Semi-Markov Chain (CTSMC) model is more adequate (w).
  - The model reproduces:
    - Statistical distribution of busy/idle periods (EXPLICITLY).
    - Average channel occupancy / duty cycle (IMPLICITLY).

$$\Psi = \frac{\mathbb{E}\{T_1\}}{\mathbb{E}\{T_0\} + \mathbb{E}\{T_1\}}$$

Models: Time dimension (CTMC/CTSMC)

- Objective: Find probability distributions that best fit busy/idle durations:
  - Based on empirical measurements :
    - Low time-resolution measurements.
    - High time-resolution measurements.
  - Analyzed radio technologies/services:
    - Amateur, paging, TETRA UL/DL, E-GSM 900 UL/DL, DCS 1800 UL/DL, DECT and ISM.
  - Considered distributions:
    - Exponential (E), generalized exponential (GE), Pareto (P), generalized Pareto (GP), log-normal (LN), gamma (G) and Weibull (W).
  - Parameter fitting/inference methods:
    - Maximum Likelihood Estimation (MLE).
    - Method Of Moments (MOM).
  - Goodness-of-fit metrics:
    - Kolmogorov-Smirnov (D_{KS}) distance.
    - Symmetric Kullback-Leibler (D_{KL}^{sym}) divergence.
    - Bhattacharyya distance (D_B).

Models: Time dimension (CTMC/CTSMC)

- Results from low time-resolution measurements:
  - Generalized Pareto (GP) is an adequate model for both busy and idle periods and for all the radio technologies considered in this study.

			E	GE	P	GP	LN	G	W
Busy periods	D_{KS}	MOM	0.20	0.23	0.35	0.18	0.21	0.22	0.19
		MLE	0.20	0.19	0.23	**0.16**	0.20	0.19	0.43
	D_{KL}^{sym}	MOM	2.00	2.32	2.55	1.96	**1.88**	2.29	2.11
		MLE	2.00	1.89	2.22	1.93	1.94	1.91	2.63
	D_B	MOM	0.25	0.30	0.32	0.24	0.32	0.30	0.27
		MLE	0.25	**0.23**	0.29	0.24	0.28	0.24	0.34
Idle periods	D_{KS}	MOM	0.23	0.26	0.39	0.17	0.19	0.25	0.16
		MLE	0.23	0.15	0.20	**0.11**	0.14	0.15	0.26
	D_{KL}^{sym}	MOM	1.59	1.88	2.41	1.39	1.34	1.82	1.46
		MLE	1.59	1.38	1.64	**1.29**	1.32	1.38	1.70
	D_B	MOM	0.19	0.28	0.31	0.17	0.23	0.27	0.19
		MLE	0.19	0.18	0.23	**0.16**	0.20	0.18	0.22

Models: Time dimension (CTMC/CTSMC)

- Results from high time-resolution measurements:
  - The best fitting distribution depends on the considered radio technology.

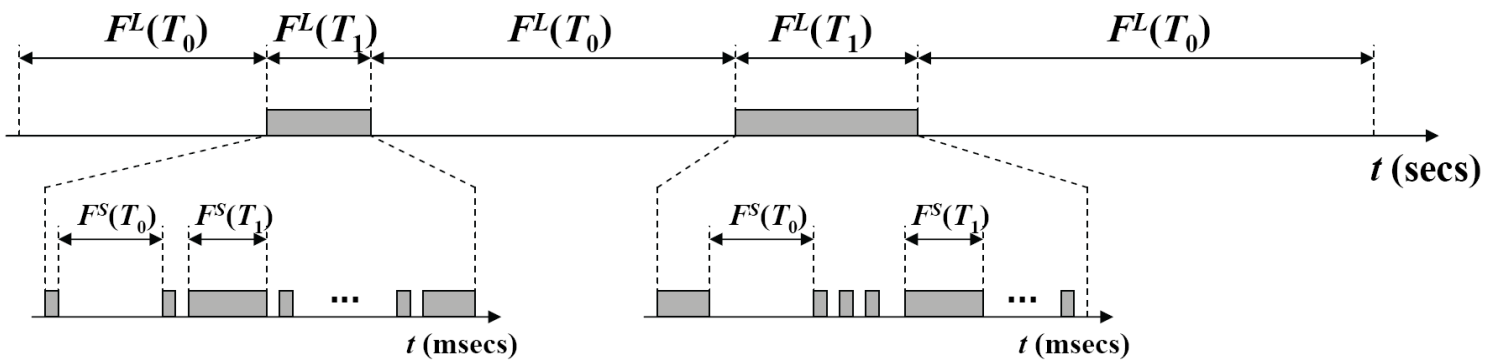
Primary radio technology/band	Idle periods	Busy periods
Amateur	GP, W, GE, G	GP
Paging	P	W, GE, G
TETRA	W or GP, P	GP, P or W
GSM/DCS	GE, G	GP

  - For time-slotted systems, alternative (discrete-time) modeling based on the distribution of the number of slots per busy/idle period:
    - For example, for GSM/DCS → Negative binomial distribution.

Models: Time dimension (CTMC/CTSMC)

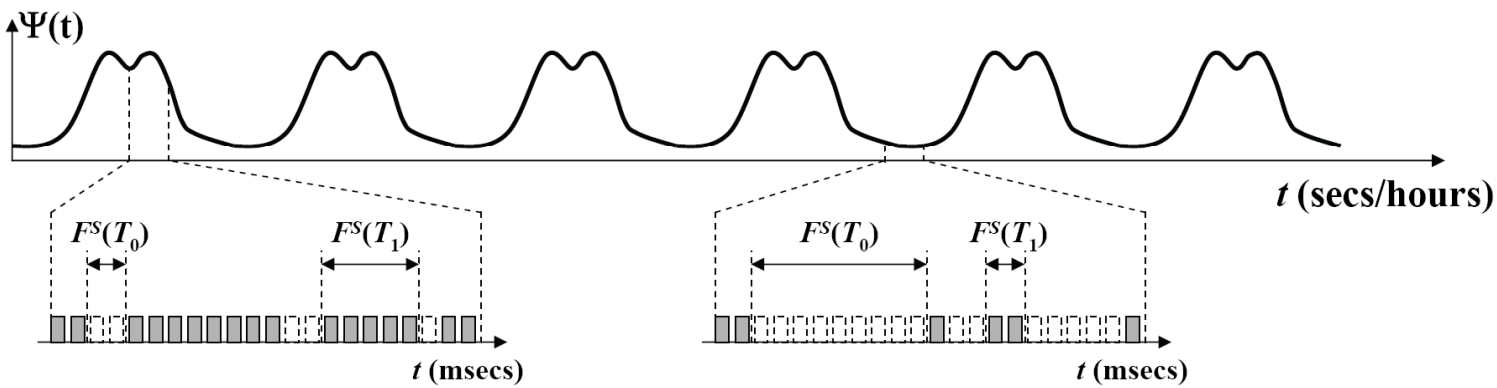
- Combined low/high-time resolution modeling approaches:

Amateur, paging, PMR/PAMR and cordless phones.



(a)

GSM/DCS systems.

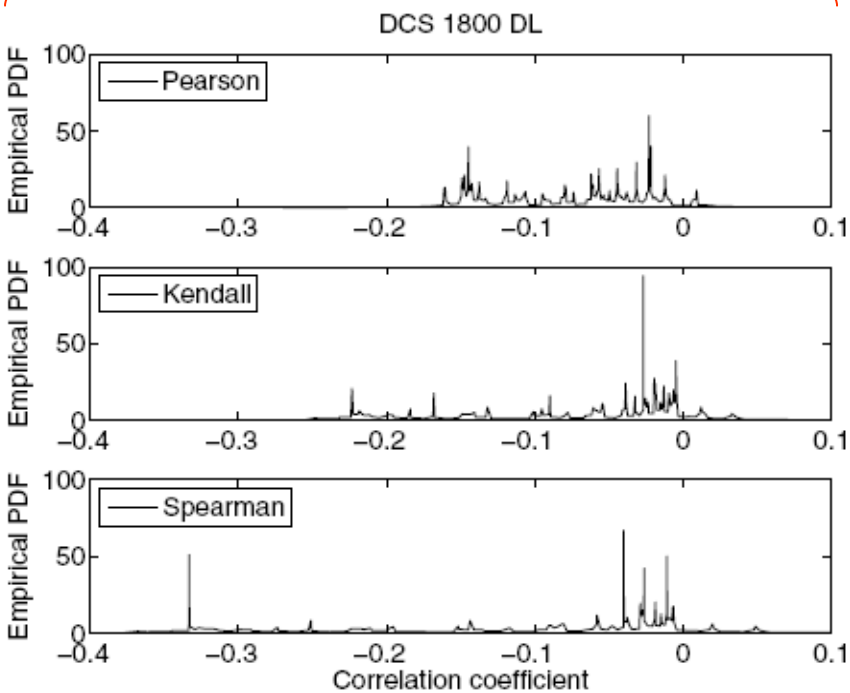


(b)

Models: Time dimension (Correlations)

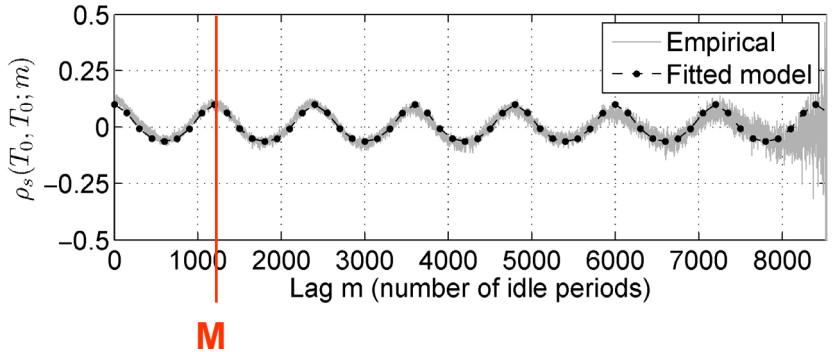
- 3) Time-correlation properties:
  - The length of busy and idle periods can be correlated in real systems.
  - DTMC / CTMC / CTSMC models cannot reproduce this property.
  - Specific models for ON/OFF, ON/ON and OFF/OFF correlations.
  - Correlation between busy / idle periods:
    - Tends to be negative in general.
    - Correlation levels are not very high (close to zero, but NON-zero).
    - In some cases there are significant correlation levels, up to –0.64.
  - Correlation between periods of the same type (autocorrelation):
    - Periodic behavior.
    - Non-periodic behavior.

Representative example for other radio technologies, not only DCS 1800



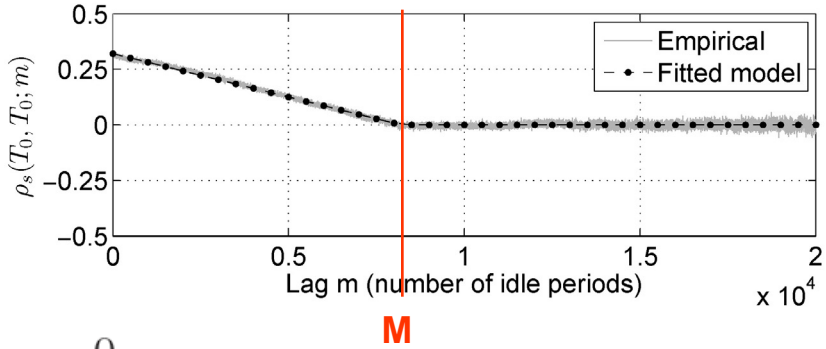
Models: Time dimension (Correlations)

Periodic autocorrelation



$$\rho_s(T_i, T_i; m) = \begin{cases} 1, & m = 0 \\ \rho_s^{min} + Ae^{-\left(\frac{m-1}{\sigma}\right)^2} + Ae^{-\left(\frac{m-M-1}{\sigma}\right)^2}, & 1 \leq m \leq M \end{cases}$$

Non-periodic autocorrelation



$$\rho_s(T_i, T_i; m) = \begin{cases} 1, & m = 0 \\ \rho_s^{max}\left(\frac{M-m}{M-1}\right), & 1 \leq m \leq M \\ 0, & m > M \end{cases}$$

Models: Time dimension (Correlations)

- Simulation of time-correlation properties:

Algorithm 1 Proposed simulation method

Input: $F_0(\cdot)$, $F_1(\cdot)$, $\tau(T_0, T_1)$ or $\rho_s(T_0, T_1)$, $\tau(T_0, T_0; m)$ or $\rho_s(T_0, T_0; m)$

Output: T_0, T_1

$\rho(T_0, T_1) \leftarrow f\left(\{\tau(T_0, T_1) \,|\, \rho_s(T_0, T_1)\}\right)$

$\rho(T_0, T_0; m) \leftarrow f\left(\{\tau(T_0, T_0; m) \,|\, \rho_s(T_0, T_0; m)\}\right)$

for every block of M values **do**

  Generate $\vartheta = \vartheta_1, \vartheta_2, \ldots, \vartheta_M \sim \mathcal{CN}(0, 1)$

  $\xi_0 \leftarrow \mathrm{Re}\left\{\mathcal{F}^{-1}\{\vartheta \odot \sqrt{|\mathcal{F}\{\rho(T_0, T_0; m)\}|}\}\right\}$

  Generate $\chi = \chi_1, \chi_2, \ldots, \chi_M \sim \mathcal{N}(0, 1)$

  $\xi_1 \leftarrow \rho(T_0, T_1) \cdot \xi_0 + \sqrt{1 - [\rho(T_0, T_1)]^2} \cdot \chi$

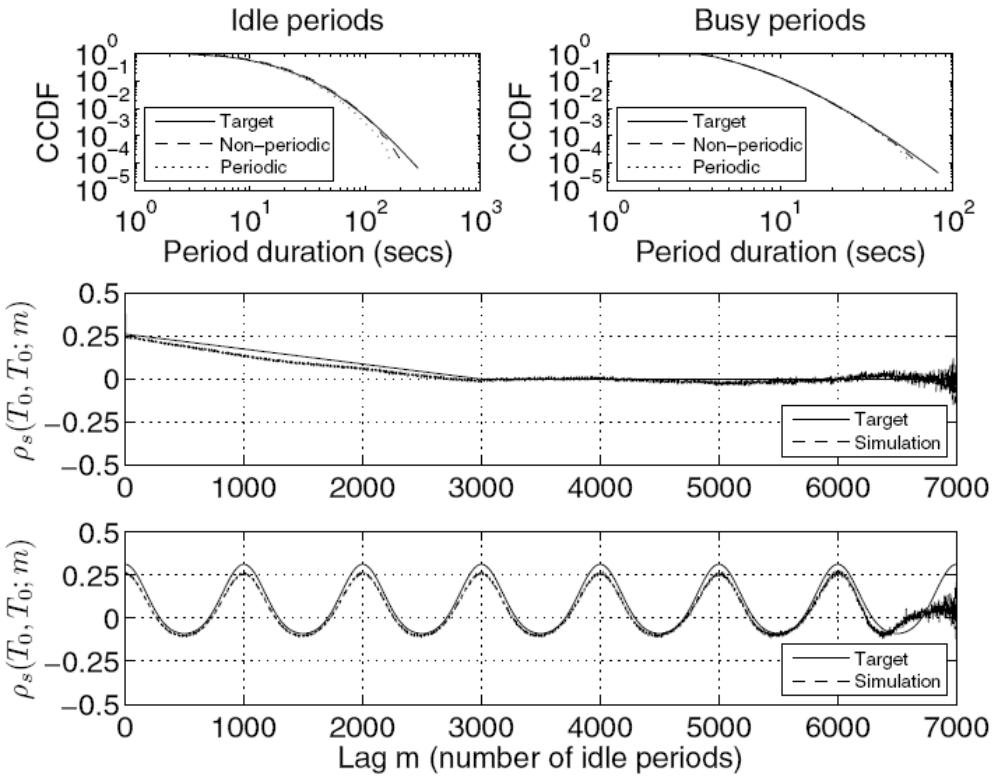
  $T_0 \leftarrow F_0^{-1}\left(\Phi\left(\xi_0\right)\right)$

  $T_1 \leftarrow F_1^{-1}\left(\Phi\left(\xi_1\right)\right)$

end for

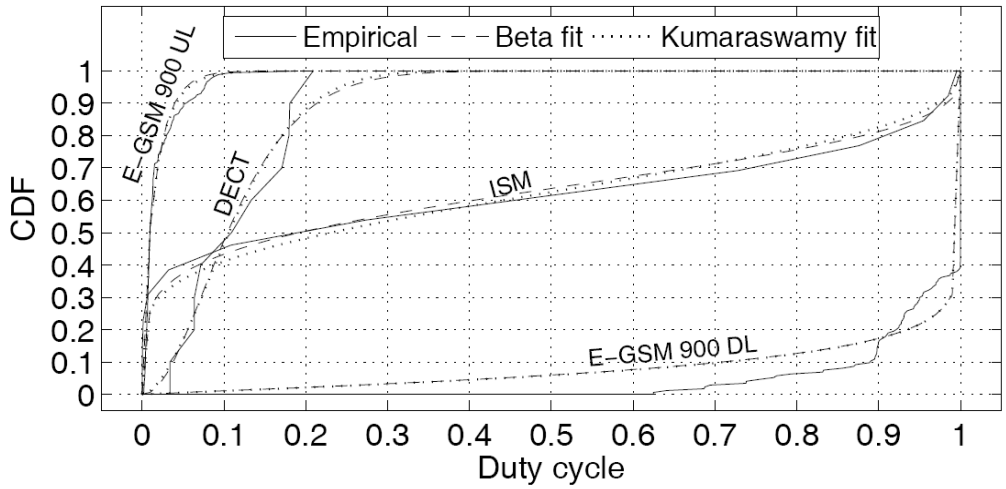
Models: Time dimension (Correlations)

- Simulation of time-correlation properties:
  - Selected parameters:
    - $F_0(\cdot)$ and $F_1(\cdot)$ are generalized Pareto distributions configured according to measurements.
    - Desired correlation busy/idle = –0.3
    - Autocorrelation function of idle periods:
      - Periodic: min = –0.1, A = 0.4, M = 1000, σ = 250.
      - Non-periodic: smax = –0.25, M = 3000.
  - The proposed simulation method reproduces any:
    - Distribution busy & idle periods.
    - Correlation busy/idle periods.
    - Autocorr. (busy) idle periods.



Models: Frequency dimension

- Two Important properties in the frequency domain:
  - <u>1) Duty cycle distribution over frequency (channels in the same band).</u>
    - Beta and Kumaraswamy distributions are adequate.

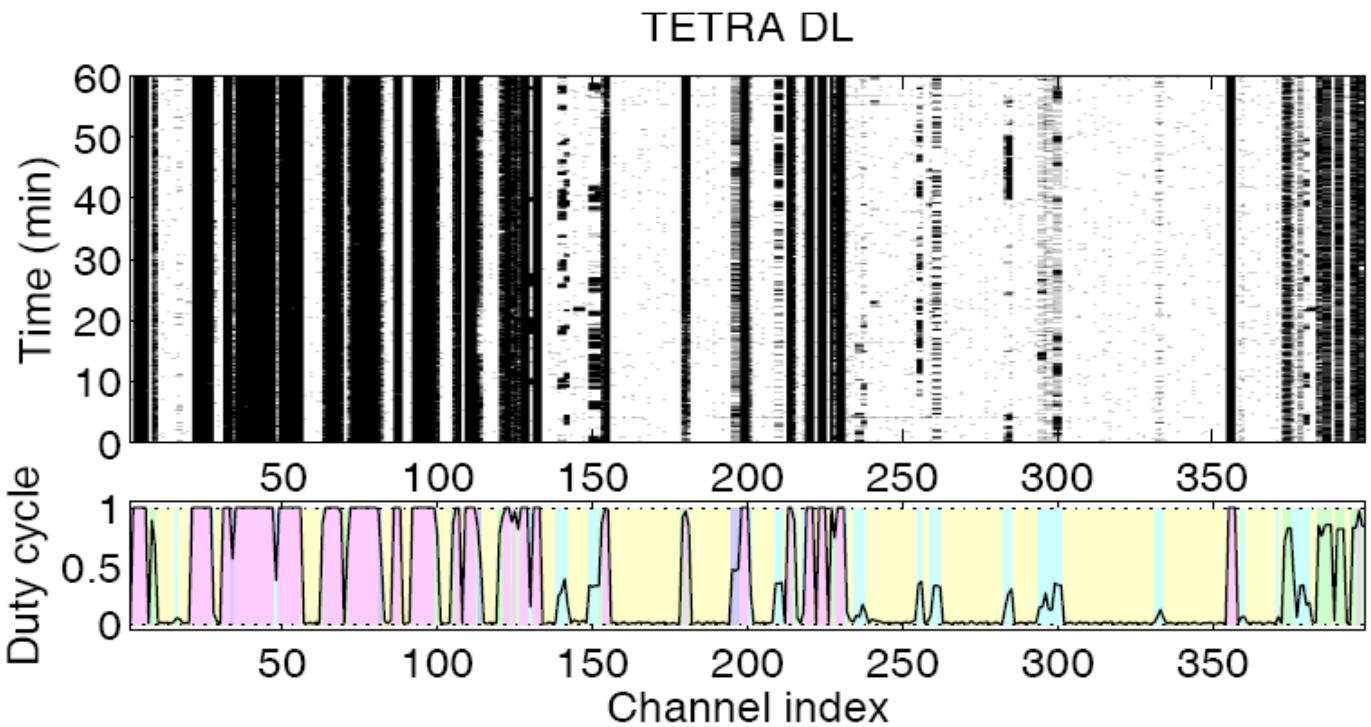


- Beta vs. Kumaraswamy expressions.

$$\left.\begin{aligned} f_x^B(x;\alpha,\beta) &= \frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1}, \quad x \in (0,1) \\ f_x^K(x;a,b) &= abx^{a-1}(1-x^a)^{b-1}, \quad x \in (0,1) \end{aligned}\right\} \quad \overline{\Psi} = \frac{\alpha}{\alpha+\beta} = bB\left(1+\frac{1}{a}, b\right)$$

Models: Frequency dimension

- Two Important properties in the frequency domain:
  - <u>2) Duty cycle clustering.</u>
    - Duty cycle is clustered over frequency.
    - Number of channels per cluster ~ Geometric distribution.



Models: Frequency dimension

- Simulation method for generating artificial time-frequency data:
  - <u>Phase 1: Generation of DC values</u>
    - Generation of DC values based on beta/Kumaraswamy distribution.
  - <u>Phase 2: Assign DC values to channels</u>
    - Define DC archetypes and then compute probability of occurrence of each archetype.
    - Classify the generated DC values into subsets, one per DC archetype.
    - Iterative method:
      - Select DC archetype for the next cluster based on probabilities of each archetype.
      - Select cluster size χ as a geometric random number (adjust if necessary).
      - Select χ DC values from the corresponding DC archetype and allocate them.
      - Repeat until all channels are assigned a DC value.
  - <u>Phase 3: Generation of time-domain occupancy sequences</u>
    - Select distributions for busy/idle periods.
    - For each channel, configure distribution parameters so that the assigned DC is met.
    - For each channel, generate busy/idle periods based on proposed time dimension models.

Models: Space dimension

- Particularity of space-dimension models:
  - Time / frequency models reproduce properties of **primary transmission patterns** in the time / frequency domains.
  - Space models characterize the local occupancy **perception of secondary users** at various locations.

- Proposed models
  - Models for average spectrum occupancy perception
  - Models for concurrent snapshots observations

Models: Space dimension (average DC)

- Spectrum occupancy is described in terms of DC:
  - Summarizes spectrum occupancy in time/frequency range within single numerical value.
  - Quantify / compare spectrum occupancy among various bands, locations and operating conditions.

- Activity Factor (AF) ≠ Duty Cycle (DC):
  - Transmitter's AF is unique.
  - DSA/CR's perceived DC may change among locations.

- Model → Spatial DC distribution:
  - As a function of propagation conditions.
  - As a mean to characterize spectrum occupancy perceived at various locations.

- Assuming energy detection:

$$P_R = \frac{1}{2T}\int_{-T}^{+T} P_R(t)\,dt \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda$$

Decision threshold

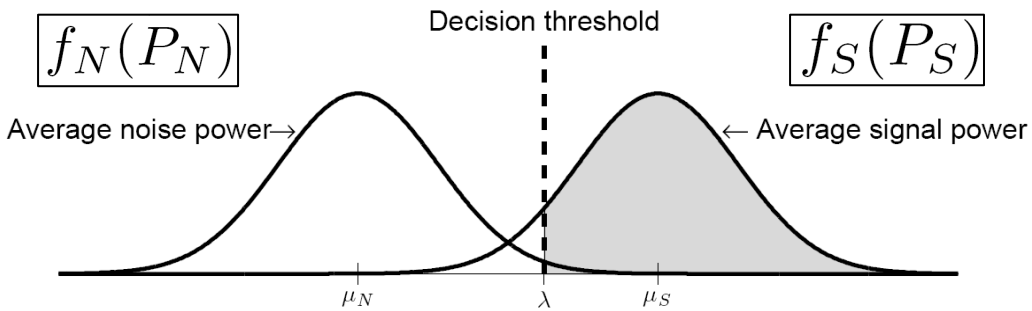
Average received power

Sensing period

Instantaneous received power

Models: Space dimension (average DC)

- Constant-power continuous transmitter:



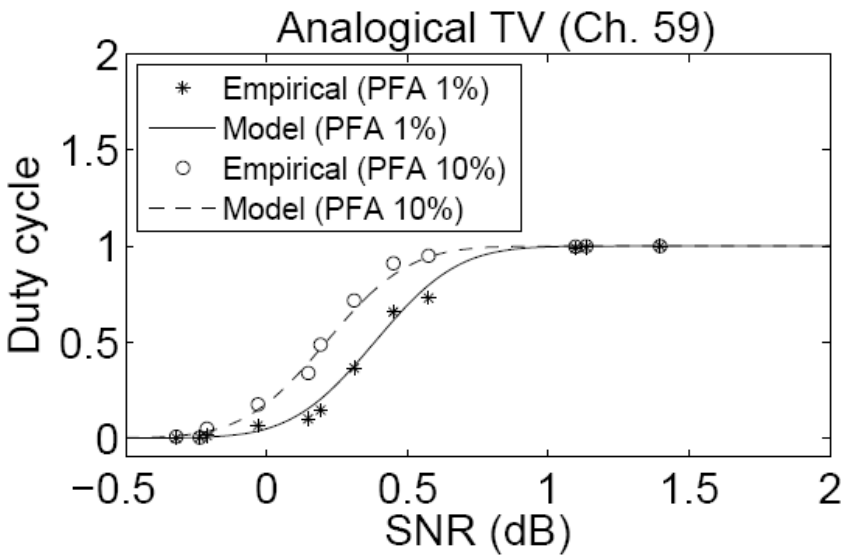
$$\Psi = \int_{\lambda}^{\infty} f_R(P_R)dP_R = \frac{1}{\sqrt{2\pi}\sigma_S}\int_{\lambda}^{\infty} e^{-\frac{1}{2}\left(\frac{P_S-\mu_S}{\sigma_S}\right)^2} dP_S = Q\left(\frac{\lambda-\mu_S}{\sigma_S}\right)$$

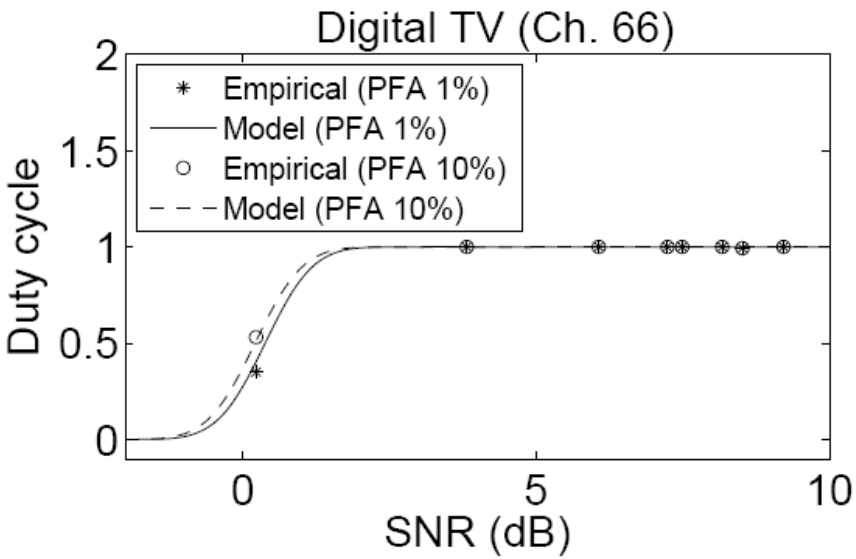
$$P_{fa} = \frac{1}{\sqrt{2\pi}\sigma_N}\int_{\lambda}^{\infty} e^{-\frac{1}{2}\left(\frac{P_N-\mu_N}{\sigma_N}\right)^2} dP_N = Q\left(\frac{\lambda-\mu_N}{\sigma_N}\right) \longrightarrow \lambda = Q^{-1}(P_{fa})\,\sigma_N + \mu_N$$

$$\boxed{\Psi = Q\left(\frac{Q^{-1}(P_{fa})\,\sigma_N - \gamma}{\sigma_S}\right)} \qquad \boxed{\gamma = \mu_S - \mu_N}$$

Models: Space dimension (average DC)

- Constant-power continuous transmitter:



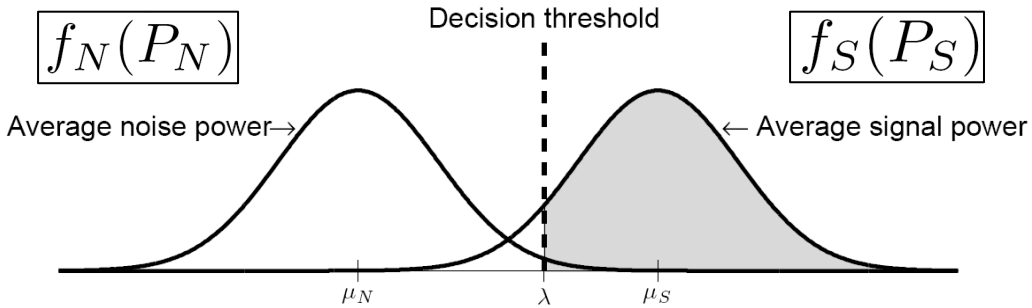


$$\Psi = Q\left(\frac{Q^{-1}(P_{fa})\,\sigma_N - \gamma}{\sigma_S}\right)$$

$$\gamma = \mu_S - \mu_N$$

Models: Space dimension (average DC)

- Constant-power discontinuous transmitter:



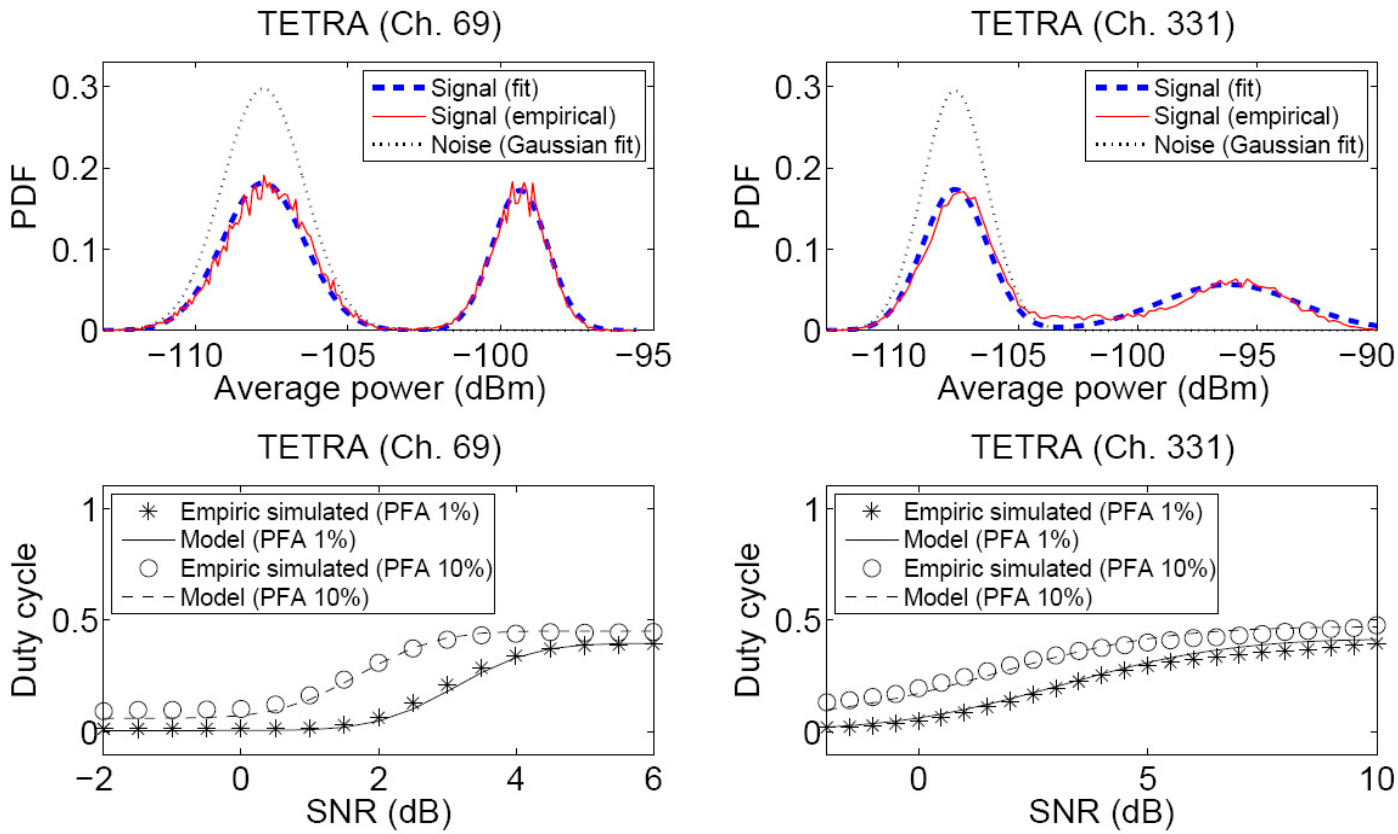
$$0 < \alpha < 1 \longrightarrow f_R(P_R) = (1-\alpha)\, f_N(P_N) + \alpha\, f_S(P_S)$$

$$\begin{aligned}
\Psi &= \int_\lambda^\infty f_R(P_R) dP_R \\
&= (1-\alpha) \int_\lambda^\infty f_N(P_N) dP_N + \alpha \int_\lambda^\infty f_S(P_S) dP_S \\
&= \frac{1-\alpha}{\sqrt{2\pi}\sigma_N} \int_\lambda^\infty e^{-\frac{1}{2}\left(\frac{P_N-\mu_N}{\sigma_N}\right)^2} dP_N + \\
&+ \frac{\alpha}{\sqrt{2\pi}\sigma_S} \int_\lambda^\infty e^{-\frac{1}{2}\left(\frac{P_S-\mu_S}{\sigma_S}\right)^2} dP_S \longrightarrow
\end{aligned}$$

$$\boxed{\Psi = (1-\alpha) P_{fa} + \alpha\, Q\left(\frac{Q^{-1}(P_{fa})\, \sigma_N - \gamma}{\sigma_S}\right)}$$

Models: Space dimension (average DC)

- Constant-power discontinuous transmitter:



$$\Psi = (1-\alpha)P_{fa} + \alpha\, Q\left(\frac{Q^{-1}(P_{fa})\,\sigma_N - \gamma}{\sigma_S}\right)$$

Models: Space dimension (average DC)

- Variable-power discontinuous transmitter:
  - We assume discrete set of *K* average power levels:
    - A variable-power transmitter whose PDF can be describe by *K* discrete values.
    - *K* constant-power transmitters time-sharing the channel.
    - A combination thereof.

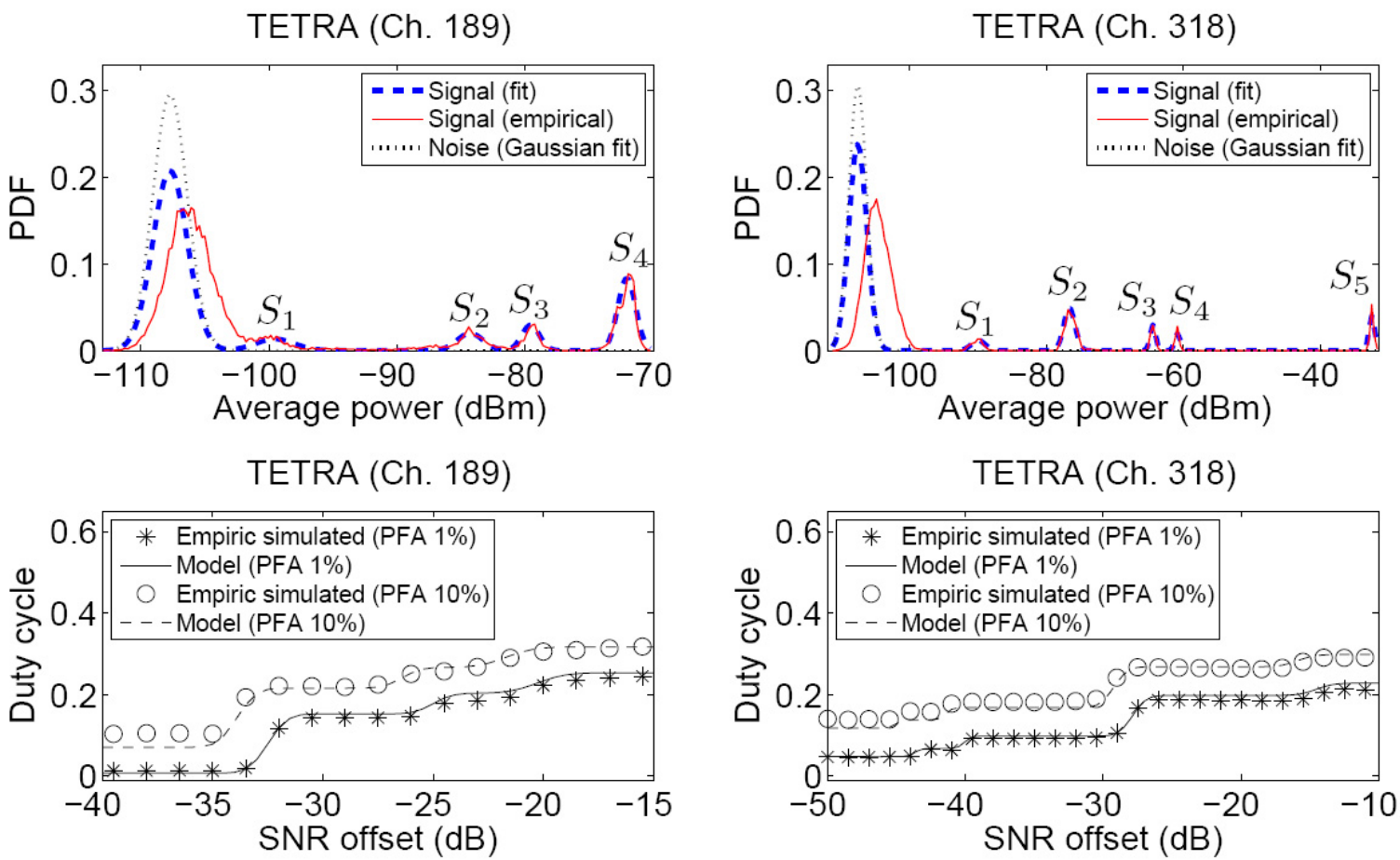
$$\sum_{k=1}^{K} \alpha_k \leq 1 \longrightarrow f_R(P_R) = \left(1 - \sum_{k=1}^{K} \alpha_k\right) f_N(P_N) + \sum_{k=1}^{K} \alpha_k \, f_{S_k}(P_{S_k})$$

$$\begin{aligned} \Psi &= \int_{\lambda}^{\infty} f_R(P_R) dP_R = \left(1 - \sum_{k=1}^{K} \alpha_k\right) P_{fa} + \\ &+ \sum_{k=1}^{K} \alpha_k \, Q\left(\frac{Q^{-1}(P_{fa}) \, \sigma_N - \gamma_k}{\sigma_{S_k}}\right) \end{aligned}$$

$$\gamma_k = \mu_{S_k} - \mu_N$$

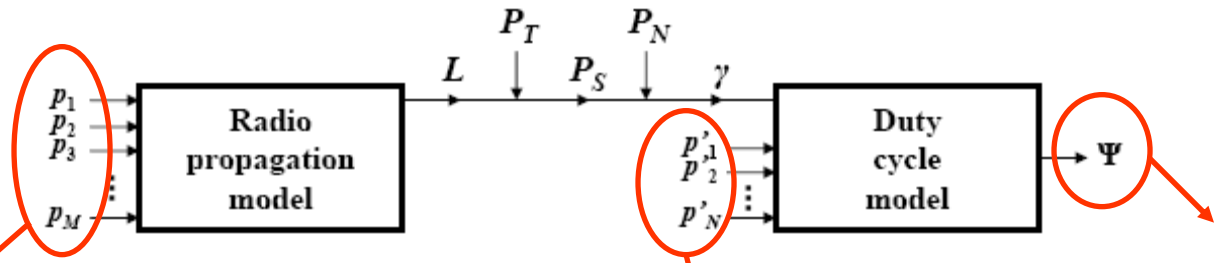
Models: Space dimension (average DC)

- Variable-power discontinuous transmitter:



Models: Space dimension (average DC)

- Proposed modeling approach:



Duty cycle = probability that the channel is busy

Operating frequency, distance, path loss exponent, scenario aspects, other environmental conditions, etc.

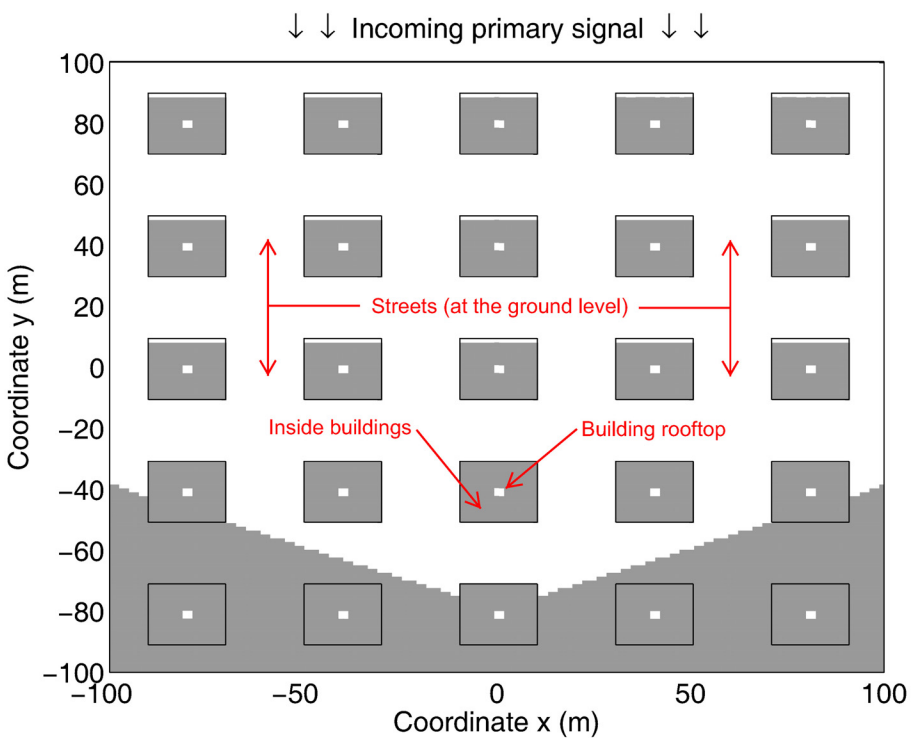
These parameters are model-specific. Model is not constrained.

$$\Psi = \left(1 - \sum_{k=1}^{K} \alpha_k\right) P_{fa} + \sum_{k=1}^{K} \alpha_k \, Q\left(\frac{Q^{-1}(P_{fa})\,\sigma_N - \gamma_k}{\sigma_{S_k}}\right)$$

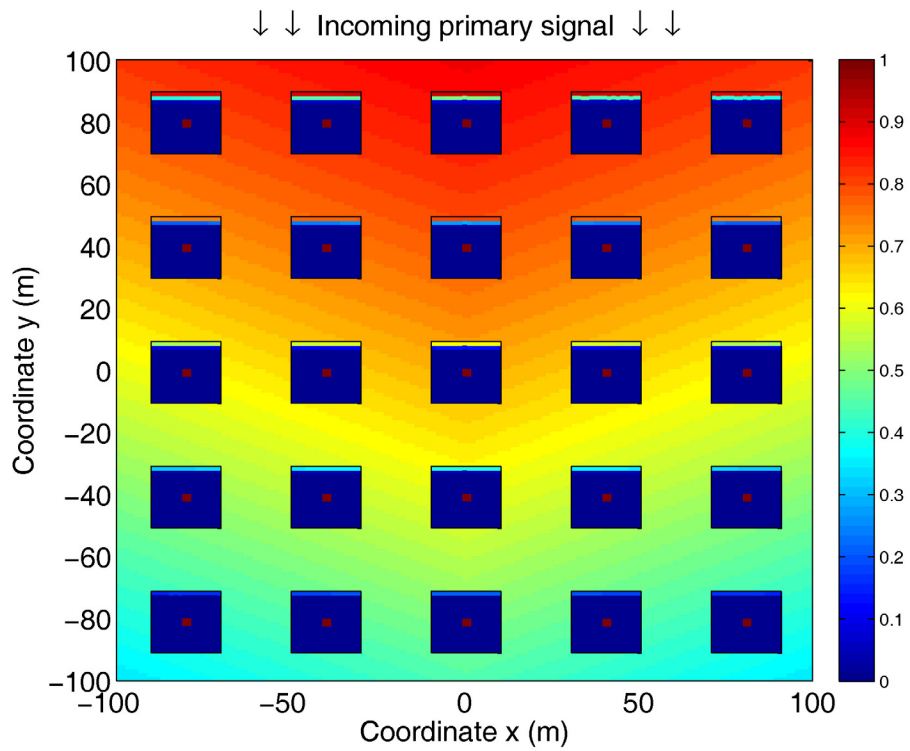
Spatial duty cycle model

Models: Space dimension (average DC)

Binary modeling approach



Probabilistic modeling approach



Models: Space dimension (snapshots)

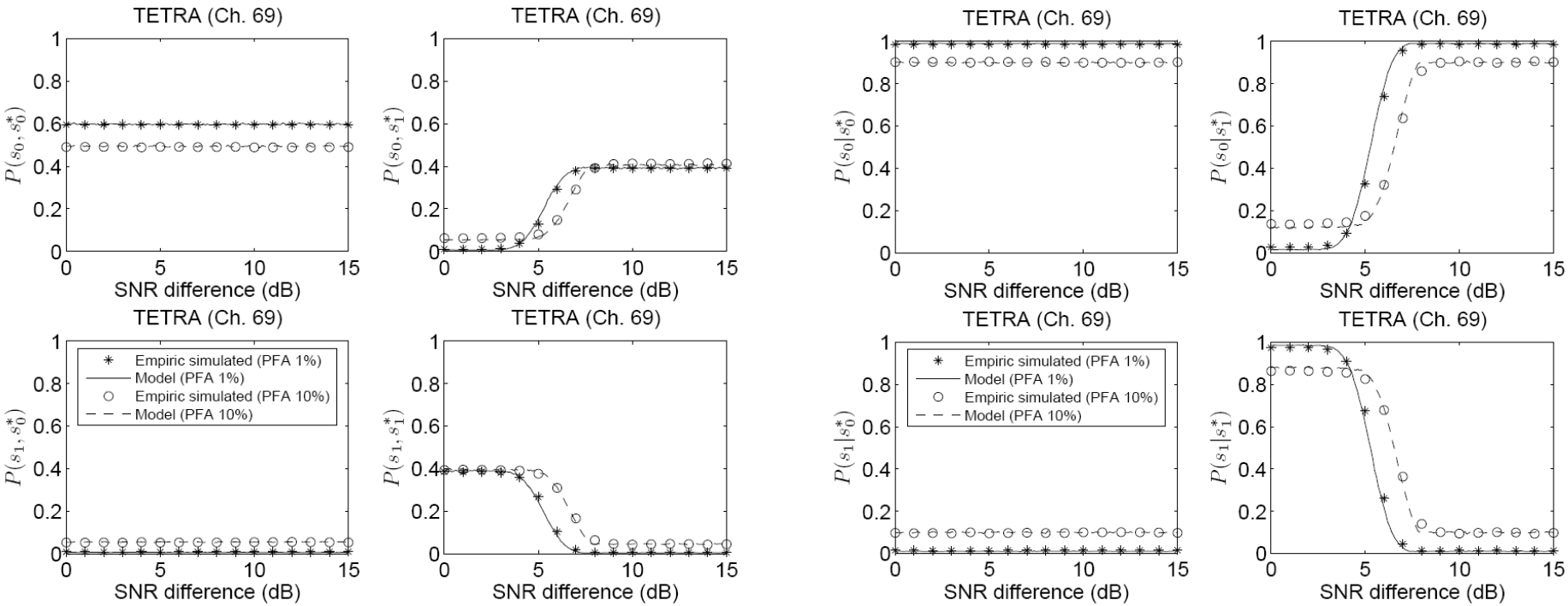
- Average DC perception may not be enough in some cases.
  - Simultaneous observations may be important (e.g., cooperative sensing).
- Concurrent snapshot observations can be modeled in terms of:
  - Joint probabilities $P(s_i,s_j^*)$.
  - Conditional probabilities $P(s_i|s_j^*)$.

s_i	s_j^*	$P(s_i, s_j^*)$	$P(s_i \mid s_j^*)$
s_0	s_0^*	$(1-P_{fa})(1-\Psi^*)$	$1-P_{fa}$
s_1	s_0^*	$P_{fa}(1-\Psi^*)$	P_{fa}
s_0	s_1^*	$1-\Psi-(1-P_{fa})(1-\Psi^*)$	$\frac{1-\Psi-(1-P_{fa})(1-\Psi^*)}{\Psi^*}$
s_1	s_1^*	$\Psi-P_{fa}(1-\Psi^*)$	$\frac{\Psi-P_{fa}(1-\Psi^*)}{\Psi^*}$

Models: Space dimension (snapshots)

Joint probabilities

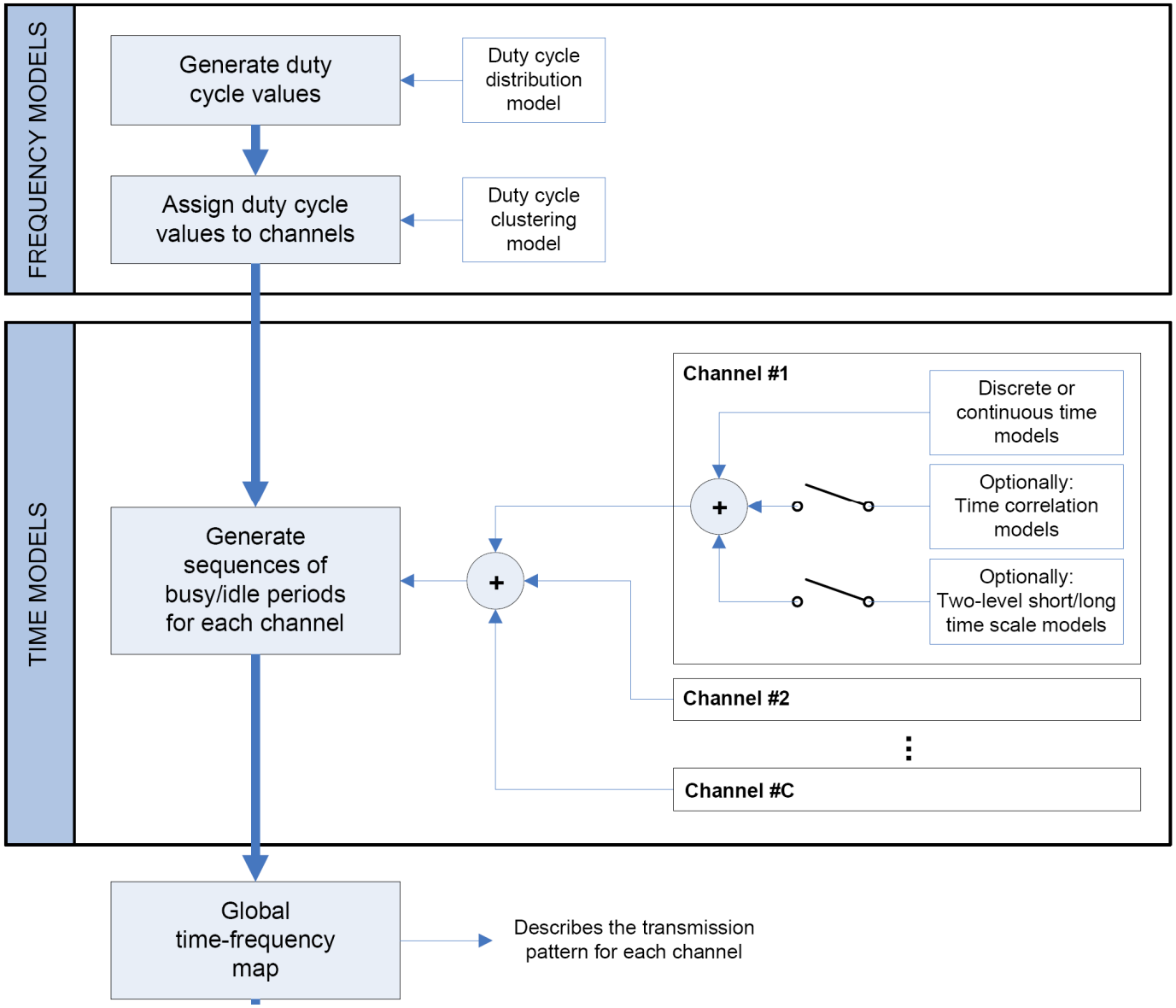
Conditional probabilities



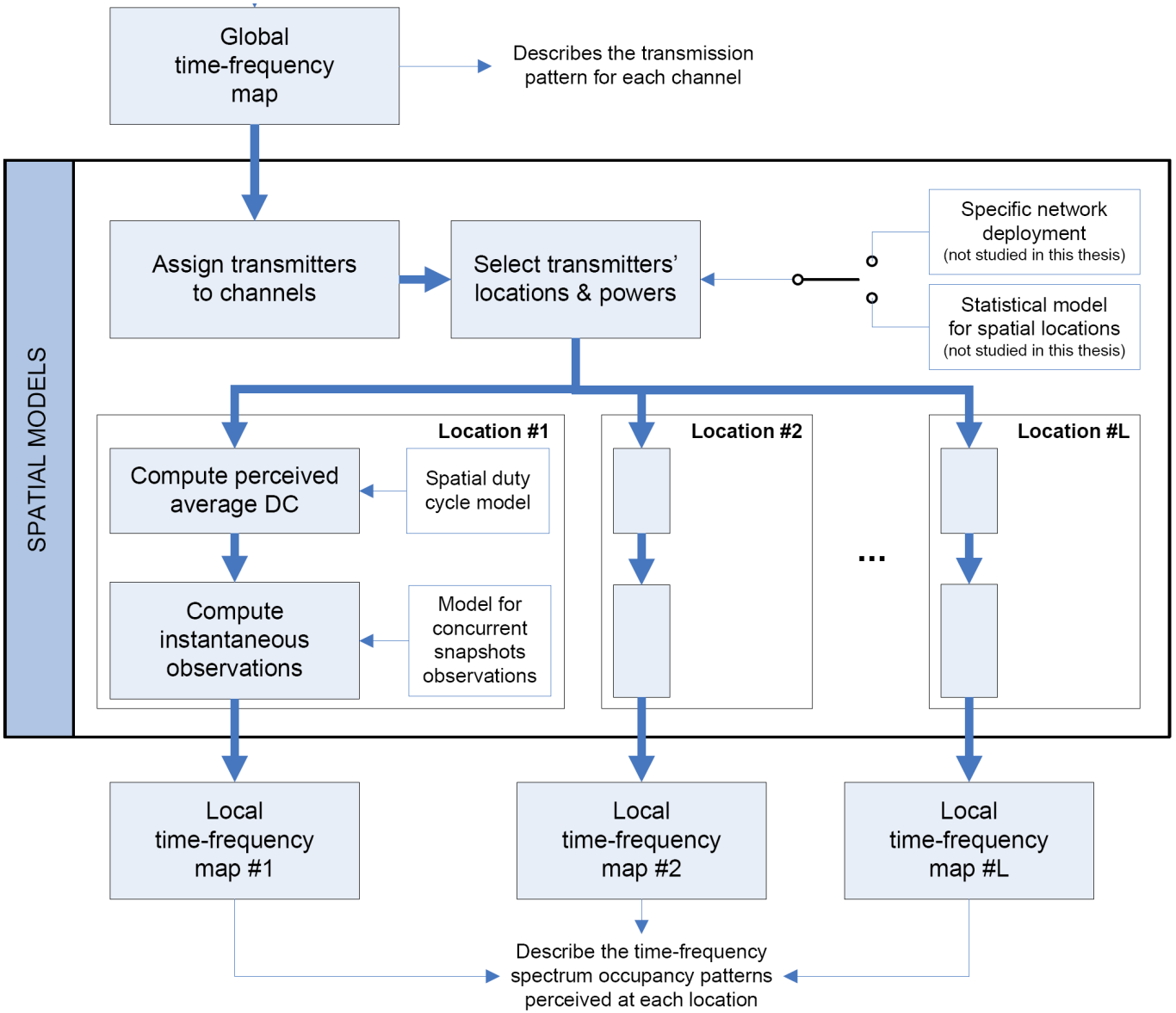
Models: Unified approach

- Proposed models have analyzed independently:
  - Time dimension.
  - Frequency dimension.
  - Space dimension.
- But they can be integrated into a unified approach.
  - Theoretical study:
    - Models provide closed-form expressions that can be combined (problem-specific aspect).
  - Simulation study:
    - Models and simulation methods can be gathered into a complete simulation approach.

Models: Unified approach



Models: Unified approach



Part III: Conclusions

- Opportunistic nature of the Dynamic Spectrum Access / Cognitive Radio (DSA/CR) paradigm.
  - Importance of realistic and accurate models of spectrum usage.
- Time-dimension models:
  - Important characteristics:
    - (1) Average channel occupancy level (duty cycle).
    - (2) Statistical distribution of the length of busy / idle periods.
    - (3) Time-correlation structures.
  - Discrete-Time Markov Chain (DTMC) model:
    - Stationary DTMC → Only (1).
    - Non-stationary DTMC + DC models → (1) + (2)
  - Continuous-Time Semi-Markov Chain (CTSMC) model:
    - Reproduce (1) implicitly and (2) explicitly.
  - Time-correlation properties require specific approaches and algorithms:
    - Correlation between periods of different types → Tends to be negative.
    - Autocorrelation between periods of the same type → Periodic and non-periodic behaviors.

Part III: Conclusions

- Frequency-dimension models:
  - Important characteristics:
    - (1) Duty cycle distribution over frequency → Beta or Kumaraswamy distributions.
    - (2) Duty cycle clustering → No. of channels per cluster ~ Geometric distribution.

- Space-dimension models:
  - Modeling approaches:
    - Binary perception busy/idle by comparing average power vs. decision threshold.
      - Simple but unrealistic.
    - Probabilistic approach based on propagation models + spatial duty cycle model.
      - Slightly more complex but more realistic and accurate.

Part III: Contributions

- Development of realistic and accurate discrete-time models with deterministic and stochastic DC models.
- Development of realistic and accurate continuous-time models, at both short and long time scales, along with a combined modeling approach.
- Development of realistic and accurate time correlation models.
- Development of realistic and accurate time-frequency models.
- Development of realistic and accurate spatial models.

General conclusions

- Development of holistic set of spectrum occupancy models for its application in the study of DSA/CR systems.
  - Realistic models derived from, or validated with, empirical measurements.
- Low time-resolution measurements:
  - Methodological study of important aspects for spectrum occupancy evaluation in DSA/CR.
    - Measurement setup (antennas, amplifiers, filters, etc.), time-dimension aspects, frequency-dimension aspects and data post-processing aspects.
  - Evaluation of spectrum occupancy in real systems.
    - Broadband study (75-7075 MHz) in urban/sub-urban and outdoor/indoor environments.
- High time-resolution measurements:
  - Performance evaluation of ED with field measurements of various radio technologies.
  - Development of a more realistic and accurate ED performance model.
  - Development of an improved ED scheme with enhanced detection capabilities but similar levels of complexity, computational costs and range of applicability.
- Spectrum usage models:
  - Time (discrete and continuous), frequency and space dimensions + Unified modeling approach.

Future work

- Impact of time resolution of measurements on the observed spectrum occupancy.
  - Tradeoff between accuracy/time-resolution and amount of data.
  - Two-level modeling approach proposed in this thesis is based on separate measurements with different time resolutions.
  - Desirable: long-term measurements at high time resolution.
    - Drawback: Huge amount of spectrum data and huge computational costs.
- New spectrum sensing methods.
  - Occupancy statistics extracted from field data based on spectrum sensing techniques.
  - Advanced techniques are complex, computationally costly and of limited applicability.
  - New spectrum sensing techniques aimed at:
    - Not only improving detection performance, but
    - Bearing in mind the need to preserve field of application and reasonable computational costs.
- Technology-specific models.
  - Models developed in this thesis, based on generic approaches, applicable to wide range of radio technologies by changing models' parameters.
  - New technology-specific models based on particular aspects of physical and higher layers.
- Application of models to novel emerging concepts.
  - Prediction of primary spectrum occupancy patterns to anticipate the behavior of the primary network.
  - Key element of the Radio Environment Map (REM) concept in order to optimize utilization of radio resources.

List of publications

- Book chapter

[1] **M. López-Benítez**, F. Casadevall, "Spectrum usage models for the analysis, design and simulation of cognitive radio networks," to appear in "*Cognitive radio for wireless and cellular networks,*" to be published by Springer.

- Journals (published/in press)

[1] **M. López-Benítez**, F. Casadevall, "Methodological aspects of spectrum occupancy evaluation in the context of cognitive radio," EUROPEAN TRANSACTIONS ON TELECOMMUNICATIONS, Special Issue on Selected Papers from the European Wireless 2009 Conference, vol. 21, no. 8, pp. 680-693, December 2010.

[2] **M. López-Benítez**, F. Casadevall, "Spectrum occupancy in realistic scenarios and duty cycle model for cognitive radio," ADVANCES IN ELECTRONICS AND TELECOMMUNICATIONS, Special Issue on Radio Communication Series: Recent Advances and Future Trends in Wireless Communication, vol. 1, no. 1, pp. 26-34, April 2010.

[3] J. Pérez-Romero, D. Noguet, **M. López-Benítez**, F. Casadevall, "Towards a more efficient spectrum usage: Spectrum sensing and cognitive radio techniques," URSI RADIO SCIENCE BULLETIN, no. 336, pp. 59-74, March 2011.

[4] **M. López-Benítez**, F. Casadevall, "Improved energy detection spectrum sensing for cognitive radio," To appear in IET COMMUNICATIONS, Special Issue on Cognitive Communications (in press).

[5] **M. López-Benítez**, F. Casadevall, "Versatile, accurate and analytically tractable approximation for the Gaussian Q-function," IEEE TRANSACTIONS ON COMMUNICATIONS, vol. 59, no. 4, pp. 917-922, April 2011.

[6] **M. López-Benítez**, F. Casadevall, "Empirical time-dimension model of spectrum use based on discrete-time Markov chain with deterministic and stochastic duty cycle models," To appear in IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY (in press).

List of publications

- Journals (submitted)

[7] **M. López-Benítez**, F. Casadevall, "Signal uncertainty in spectrum sensing for cognitive radio," submitted for consideration of publication, October 2010 (undergoing second round of review).

- Journals (in preparation)

[8] **M. López-Benítez**, F. Casadevall, "Time-dimension models of spectrum usage for the analysis, design and simulation of cognitive radio networks".

[9] **M. López-Benítez**, F. Casadevall, "Space-dimension models of spectrum usage for the analysis, design and simulation of cognitive radio networks".

[10] **M. López-Benítez**, F. Casadevall, "Spectrum usage in cognitive radio networks: From field measurements to empirical models".

- International conferences

  - 14 international conference papers (13 papers as the first author, 2 invited papers).
  - General conferences on wireless communications: ICC, PIMRC, VTC, …
  - Specific conferences on DSA/CR: DySPAN, CrownCom, …

- Other publications

  - 2 Spanish conferences, 1 technical report, 4 exhibitions/demonstrations, 5 deliverables (European projects).

Thank you for your attention