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Machine learning for a 5G future

MULTIFRACTAL MODELING OF THE RADIO ELECTRIC SPECTRUM APPLIED IN COGNITIVE RADIO NETWORKS.

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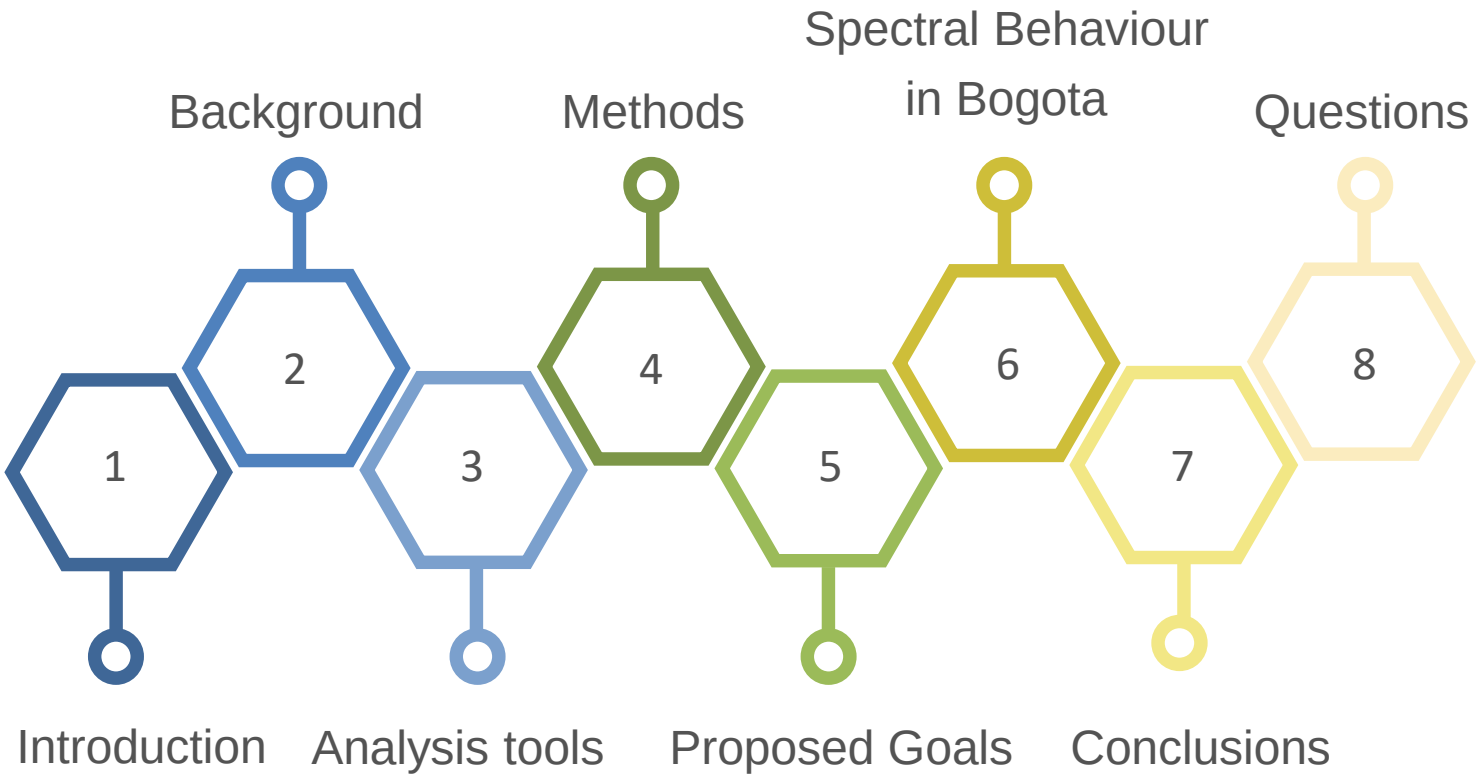
AGENDA


Background
Methods
Spectral Behaviour in Bogota
Questions
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Introduction
Analysis tools
Proposed Goals
Conclusions

INTRODUCTION

Initial Development

INITIATIVE

- Study the current state of the radio spectrum.
- Define methodologies to perform measurements in the radio spectrum of bogota
- Lead Campaigns in specific areas of the city.
- Analyse the acquired data.

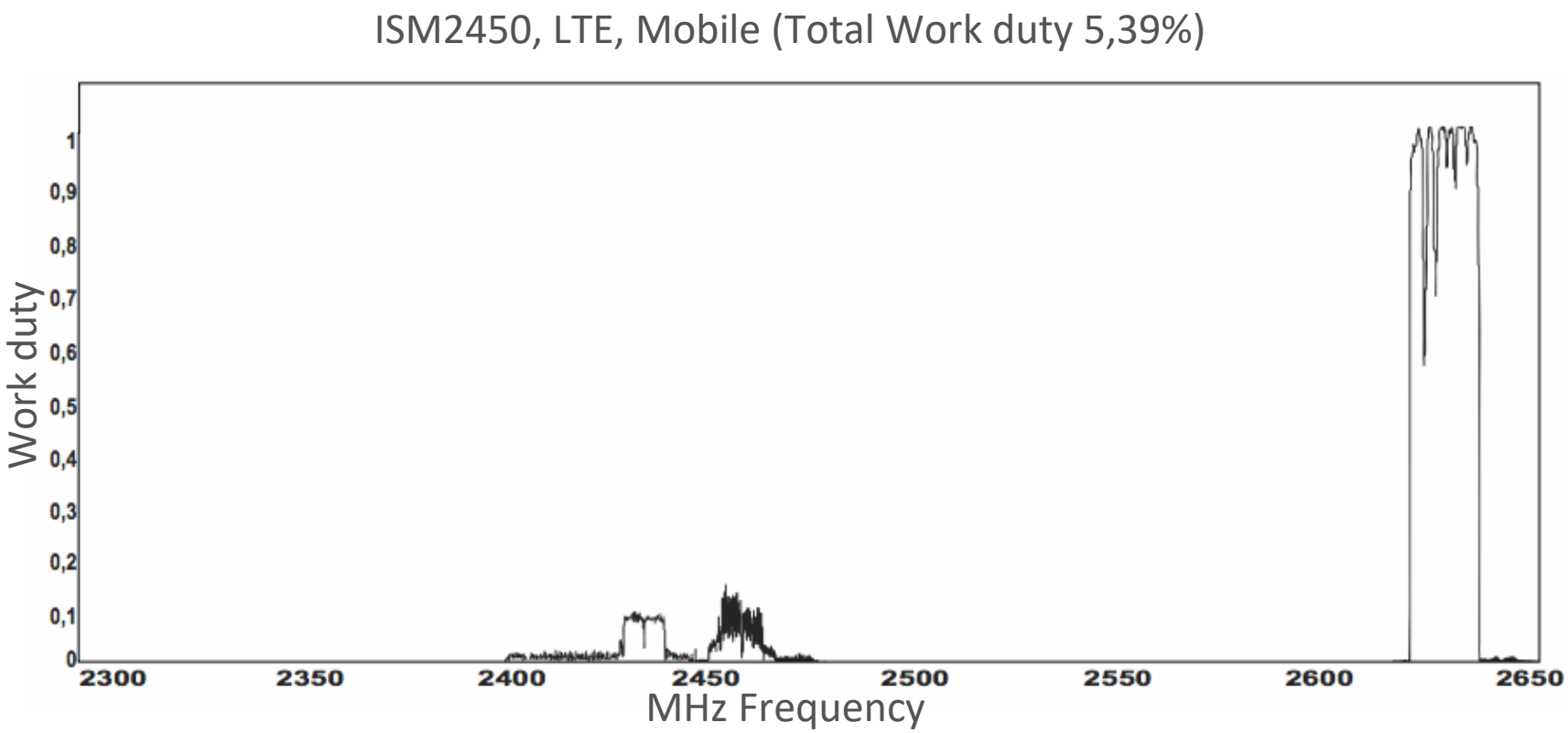
- L. F. Pedraza, Hernández, Galeano, Rodríguez-Colina, & Páez, 2016

DATA COLLECTION

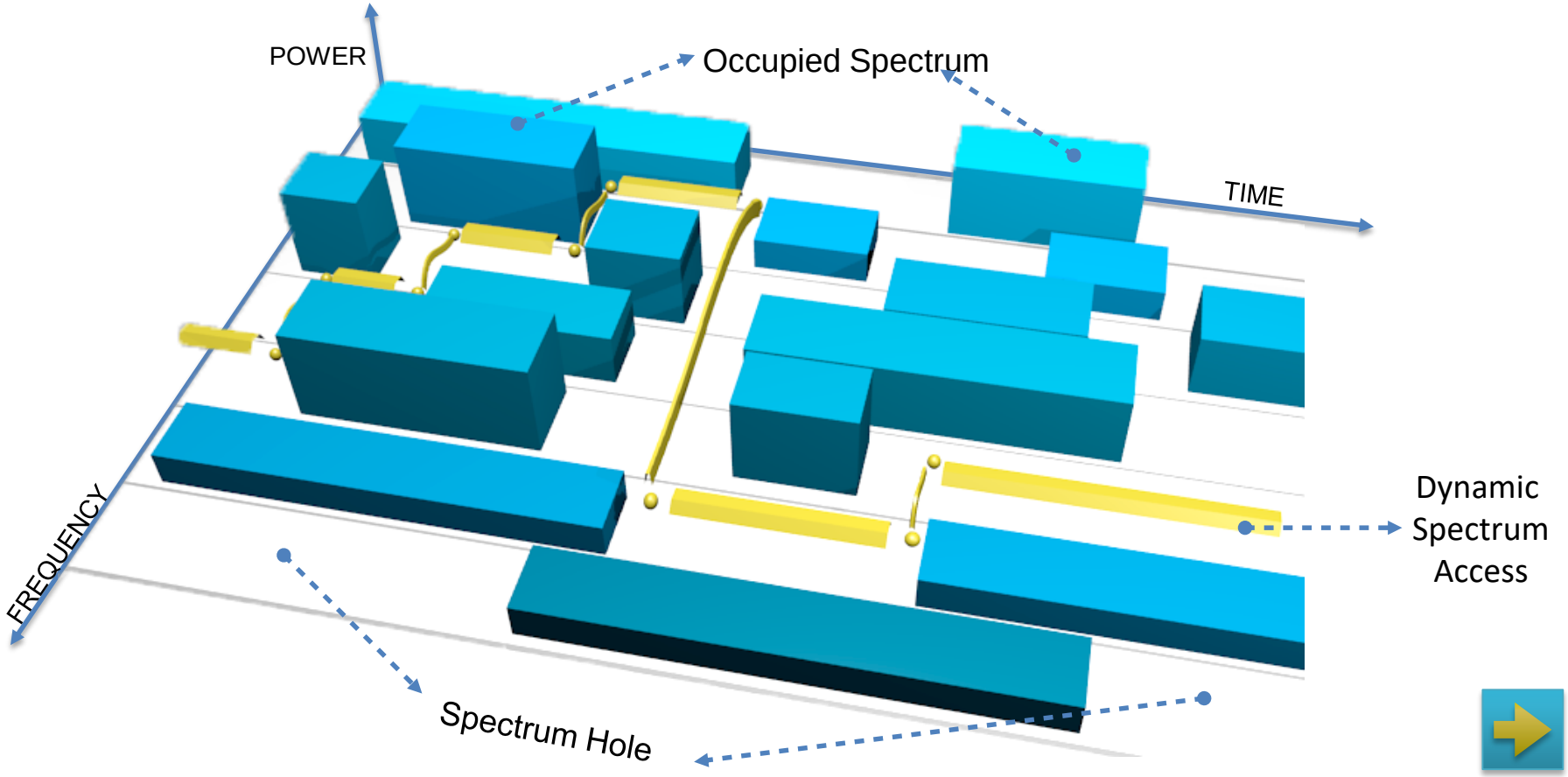
CUNDINAMARCA DEPARTMENT

- L. F. Pedraza, Hernández, Galeano, Rodríguez-Colina, & Páez, 2016

UNDERUSED SPECTRUM



COGNITIVE RADIO



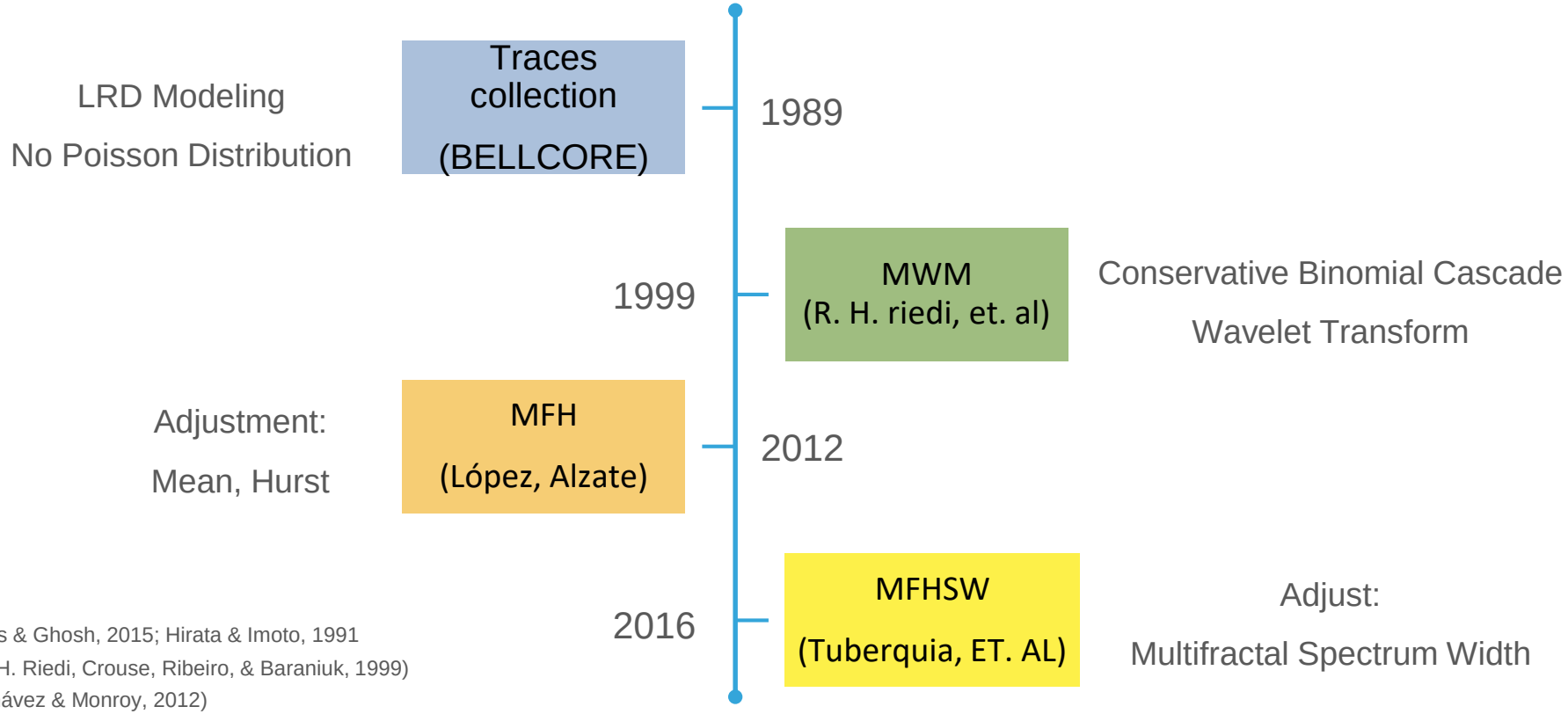
BACKGROUND

Related Work

PREDICTION IN COGNITIVE RADIOS

Linear Prediction	The output is used to improve sensing accuracy and reduce costs.	- Boyacı, Akı, & Yarkan, 2015; Kumar - Aishwarya, Srinivasan, & Raj, 2016 - Ozden, 2015; Z. Wang & Salous, 2008
Markov Models	Such models work well under the assumption of low memory, which is a property of an evolving spectrum.	- Ghosh, Cordeiro, Agrawal, & Rao, 2009 - Jiang et al., 2017 - Yarkan & Arslan, 2007
Bayesian Inference	Used to predict the probabilities of a signal such as energy.	- Sayrac, Galindo-Serrano, Jemaa, & Riihijärvi, 2013
Support Vector Machines	Applied in predictions where geospatial assumptions are made	- Iliya, Goodyer, Gow, Shell, & Gongora, 2015 - Y. Wang, Zhang, Ma, & Chen, 2014
Artificial Neural Networks	Suitable for correlated prediction scenarios, ANN offer superior prediction accuracy compared to other models.	- Fleifel, Soliman, Hamouda, & Badawi, 2017 - Iliya et al., 2015

TRAFFIC GENERATION

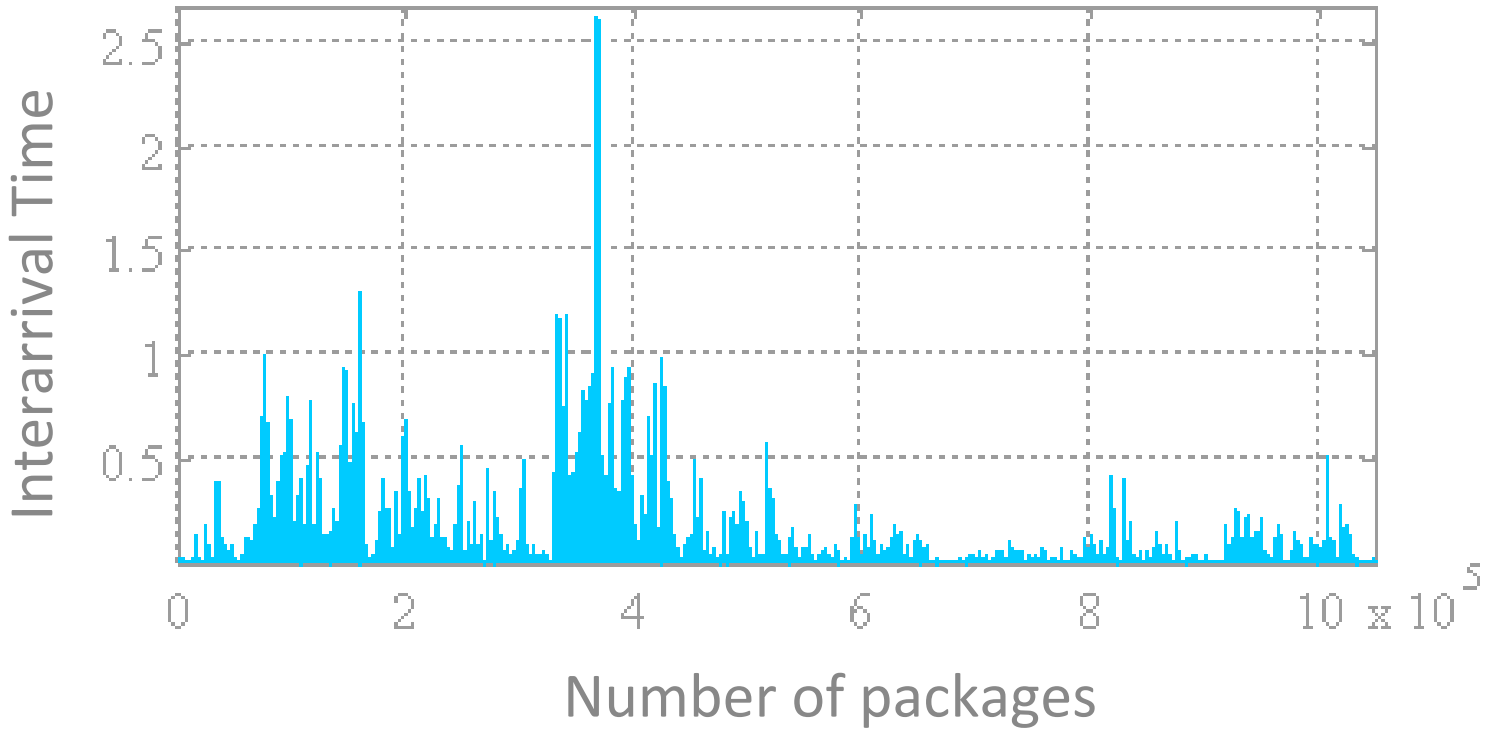


- Das & Ghosh, 2015; Hirata & Imoto, 1991
- (R.H. Riedi, Crouse, Ribeiro, & Baraniuk, 1999)
- (Chávez & Monroy, 2012)
- Tuberquia-David, Vela-Vargas, López-Chávez, & Hernández, 2016

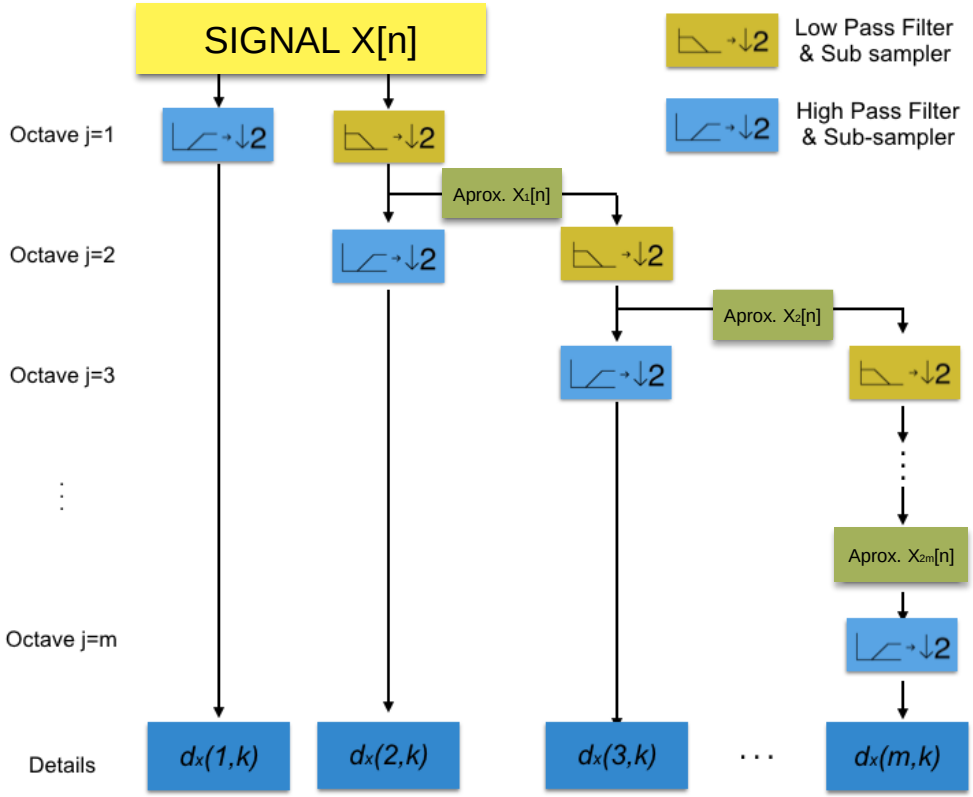
ANALYSIS TOOLS

Multifractal Dimension Estimation

TRACE


Interarrival Time
2.5
2
1.5
1
0.5
0
2
4
6
8
10 x 10^5
Number of packages

FAST CALCULATION OF THE DETAIL COEFFICIENTS



VARIANCE ESTIMATOR

EQ. 1

$$\mu_j = \frac{1}{n_j} \sum_{k=1}^{n_j} |d_x(j,k)|^2$$

(Flandrin, Gonçalves, & Abry, 2009)

EQ. 2

$$\mu_j \approx E[|d_X(j,\cdot)|2] \sim 2^{j(2H-1)} C$$

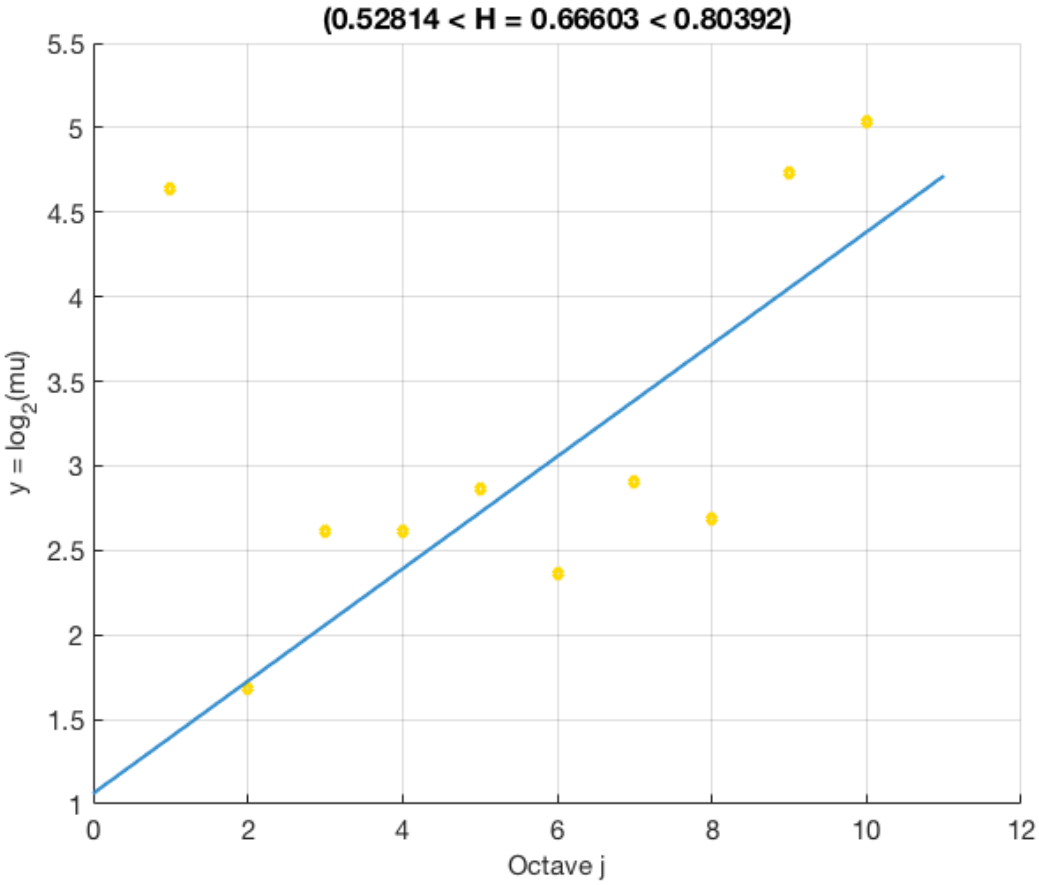
(Sheluhin, Smolskiy, & Osin, 2007)

EQ. 3

$$\log_2 \mu_j = (2H-1)j + \log_2 C$$

(López, 2012)

LOG SCALE DIAGRAM



LOG SCALE DIAGRAM

EQ. 4

$$\mu_j^q = \frac{1}{n_j} \sum_{k=1}^{n_j} |d_x(j,k)|^q$$

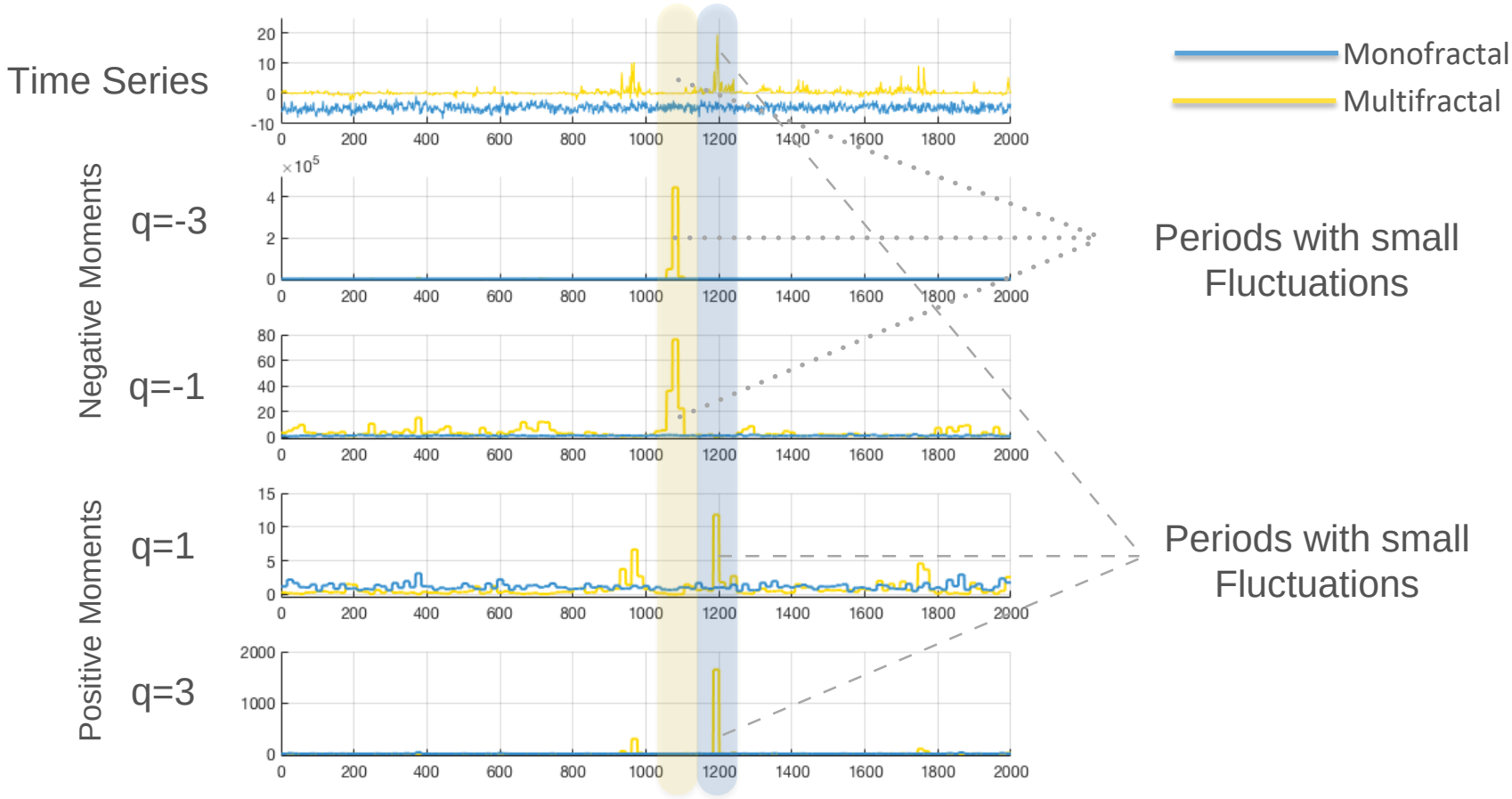
(P. Abry et al., 2000)

EQ. 5

$$H(q) = {}^{\alpha_q}/_{q} + {}^{1}/_{2}$$

(P. Abry et al., 2000)

STATISTICAL MOMENTS

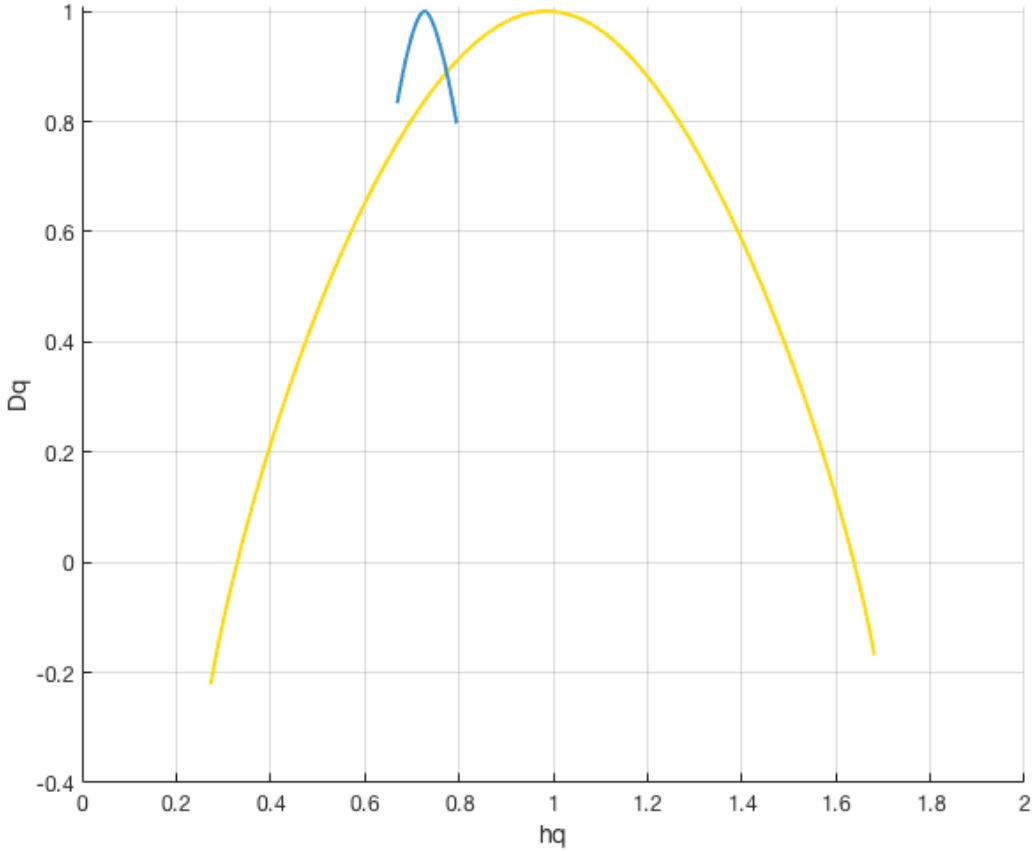


STATISTICAL MOMENTS

EQ. 6 $$T(q) = qH(q) - 1$$ (Meakin, 1998)

EQ. 7 $$D(q) \equiv \frac{T(q)}{q-1} = \frac{qH(q)-1}{q-1}$$ (Kantelhardt et al., 2002)

MULTIFRACTAL SPECTRUM



Monofractal

Multifractal

PROPOSED GOALS

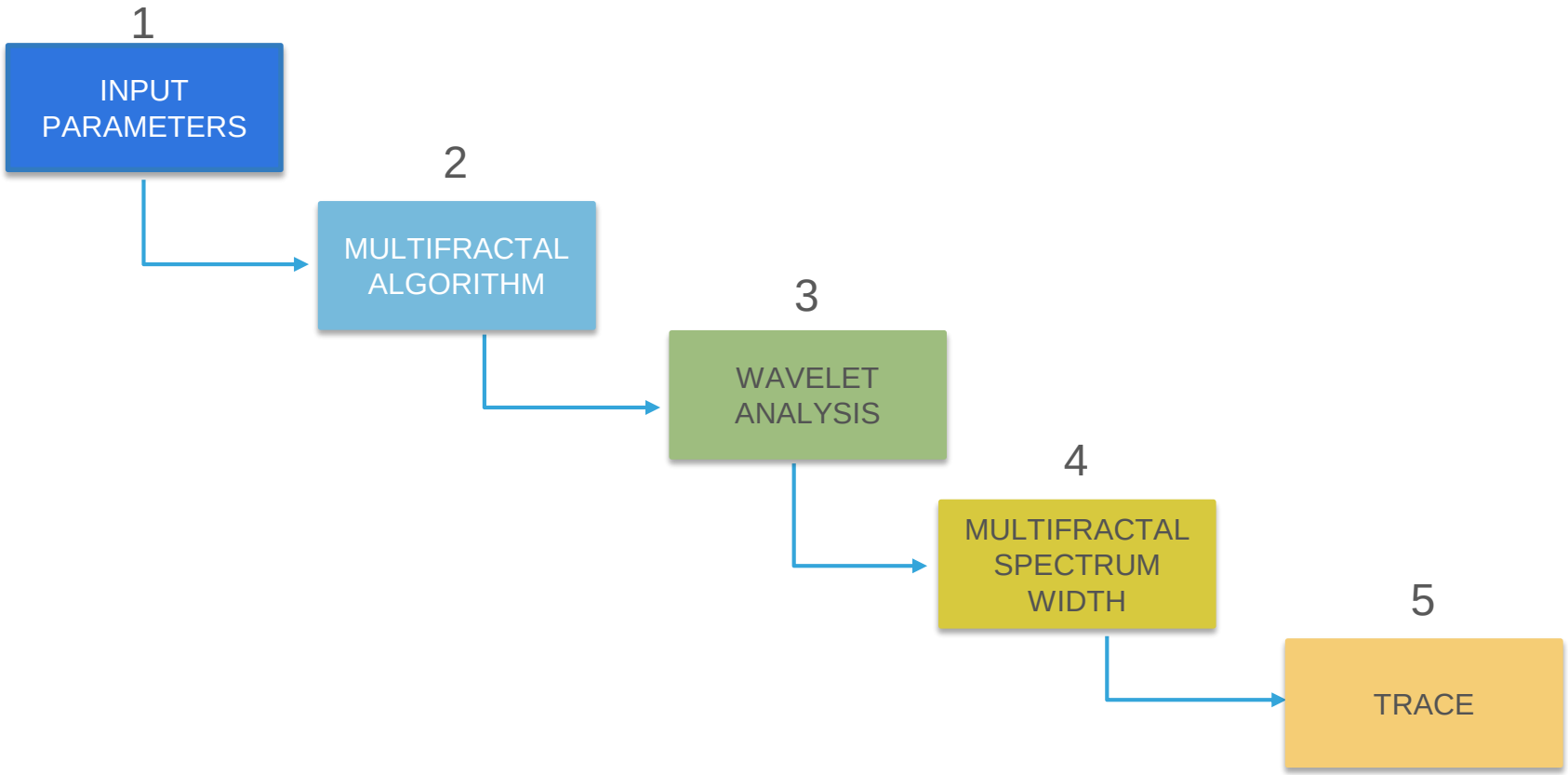
OBJECTIVE

- Establish a tool that can estimate traffic with similar characteristics to those found in the radio spectrum of Bogotá.

METHODS

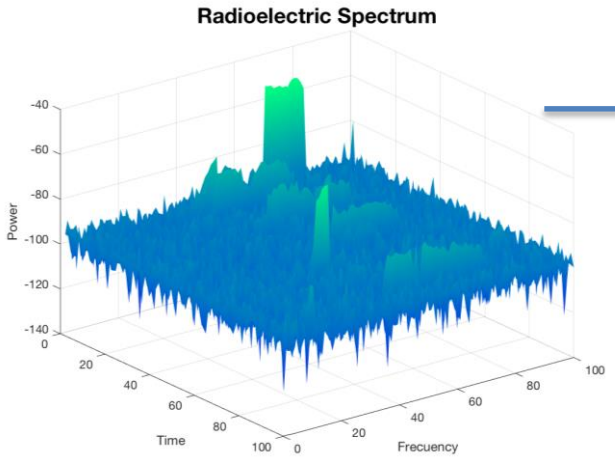
Adjusting Traffic as Multifractal Traces

MFHW


1
INPUT PARAMETERS
2
MULTIFRACTAL ALGORITHM
3
WAVELET ANALYSIS
4
MULTIFRACTAL SPECTRUM WIDTH
5
TRACE

STEP 1

INPUT PARAMETERS → MULTIFRACTAL ALGORITHM → WAVELET ANALYSIS → MULTIFRACTAL SPECTRUM WIDTH → TRACE



INPUT

Threshold

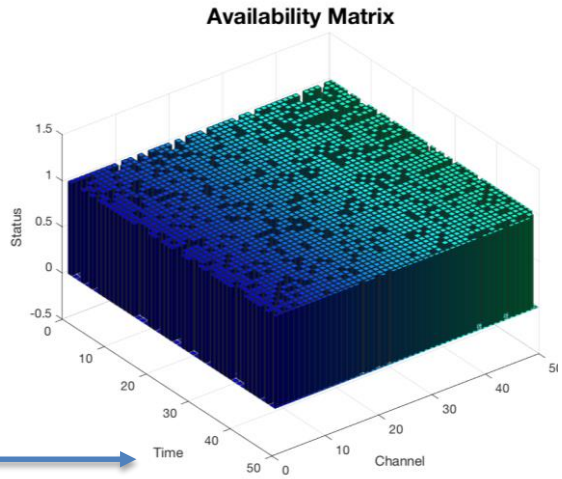
Noise Floor

Fixed BW

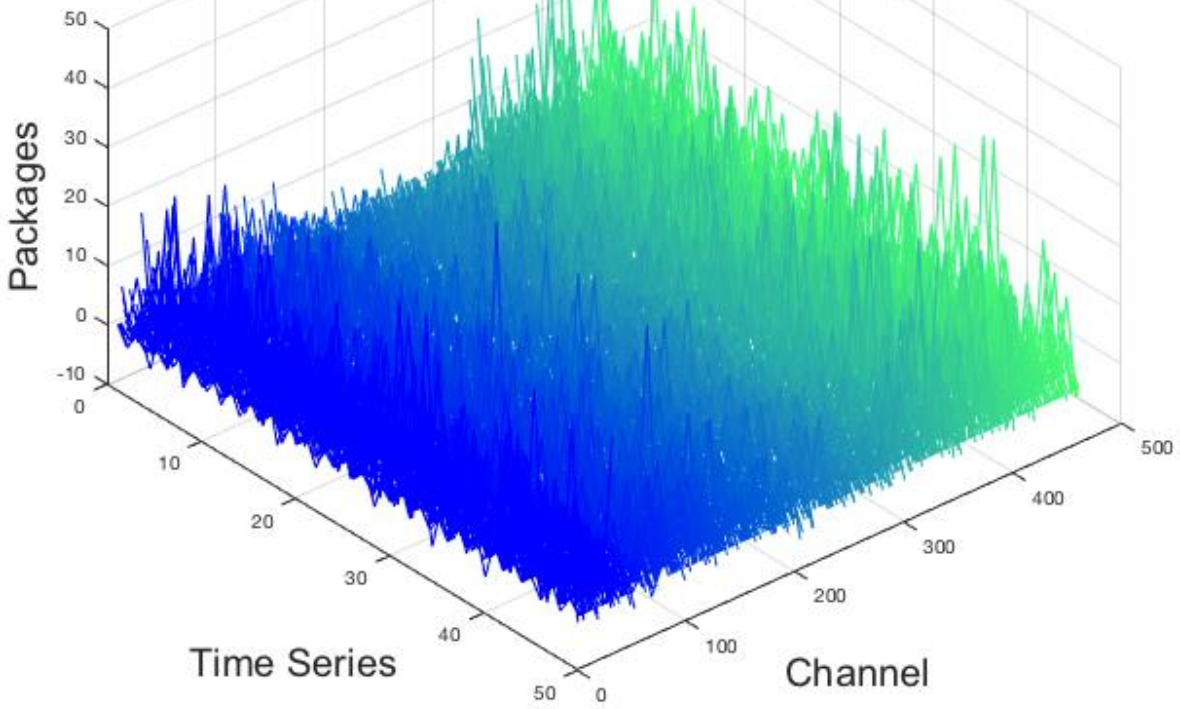
Multichannel

Decision-Making System

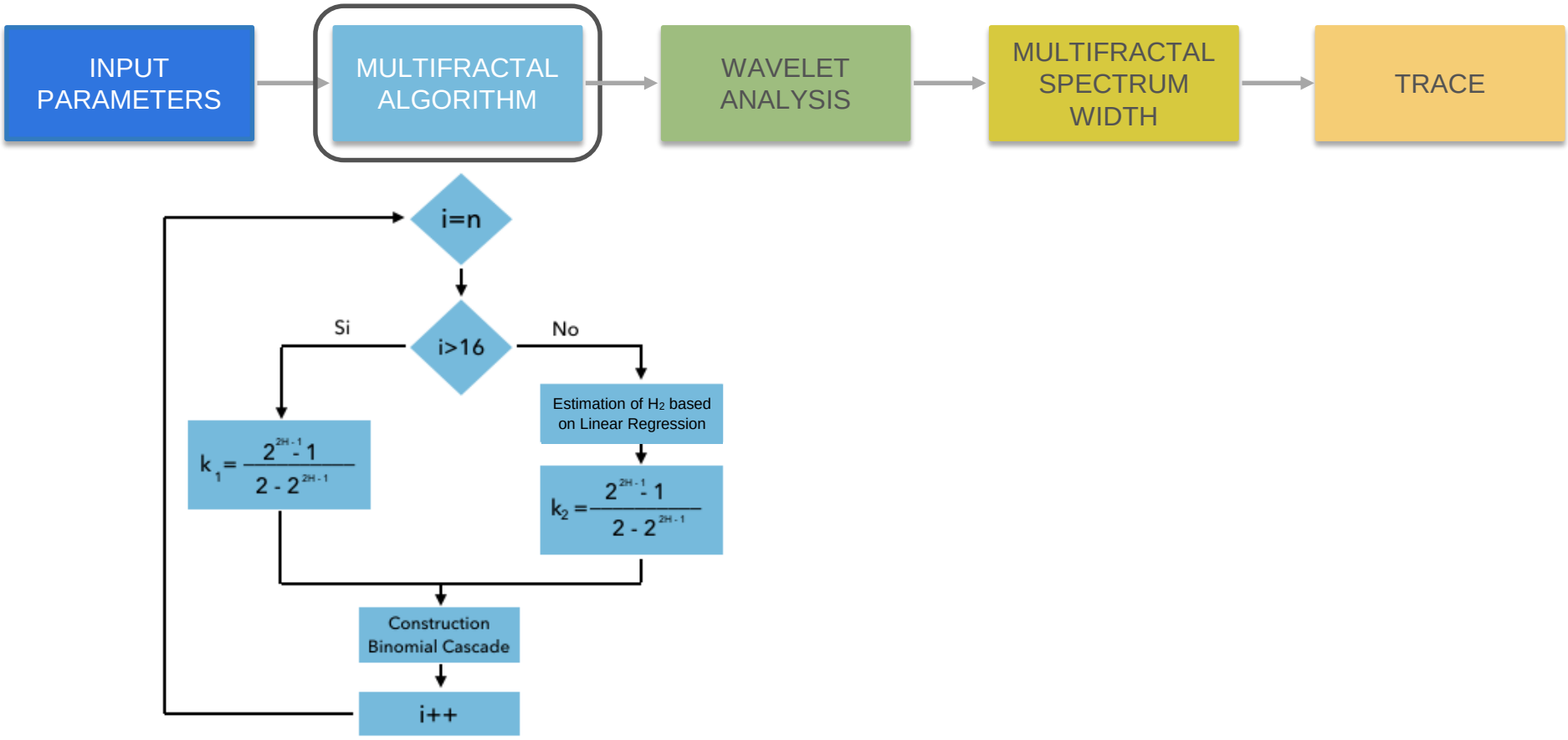
OUTPUT



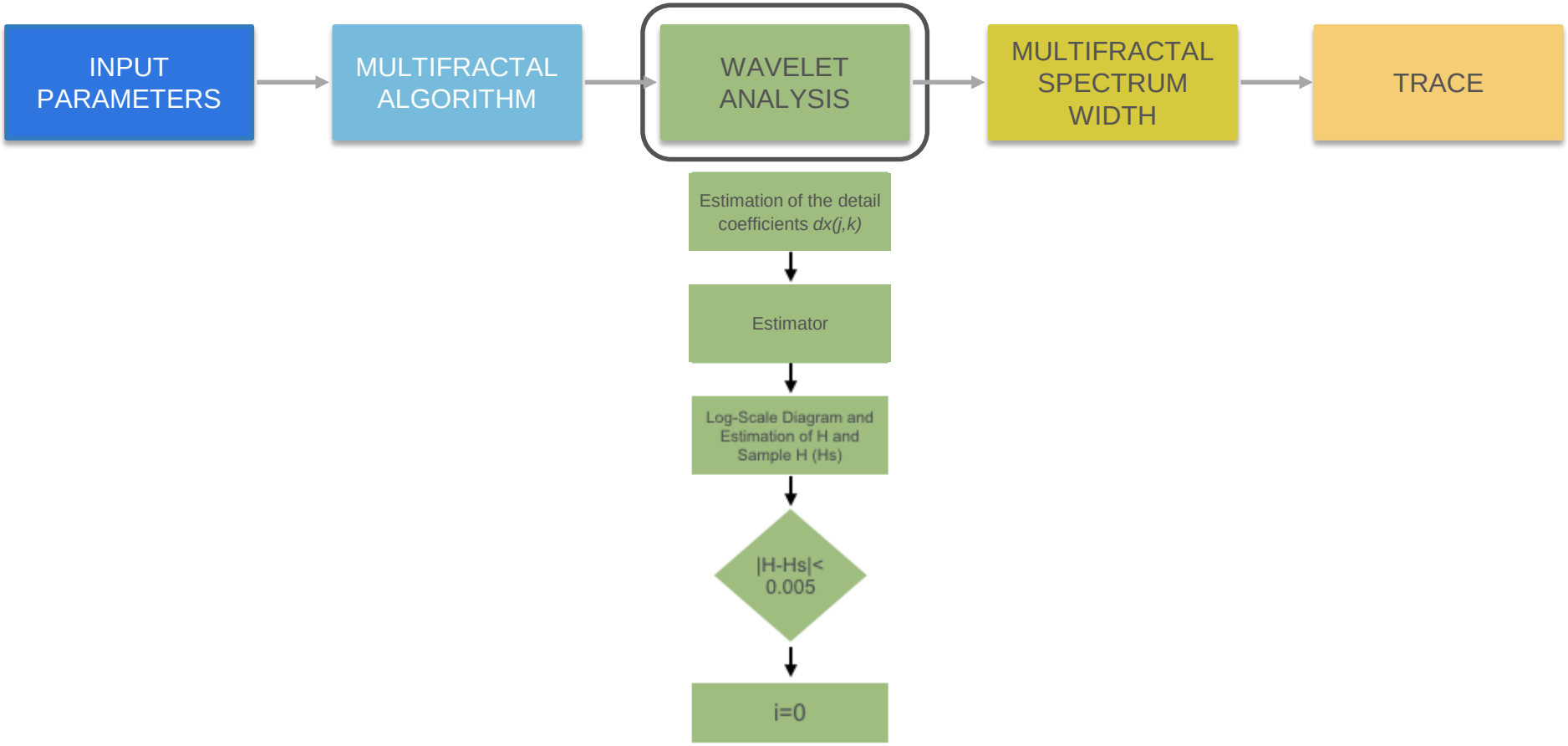
BEHAVIOUR OF THE RADIO ELECTRIC SPECTRUM AFTER COUNTING



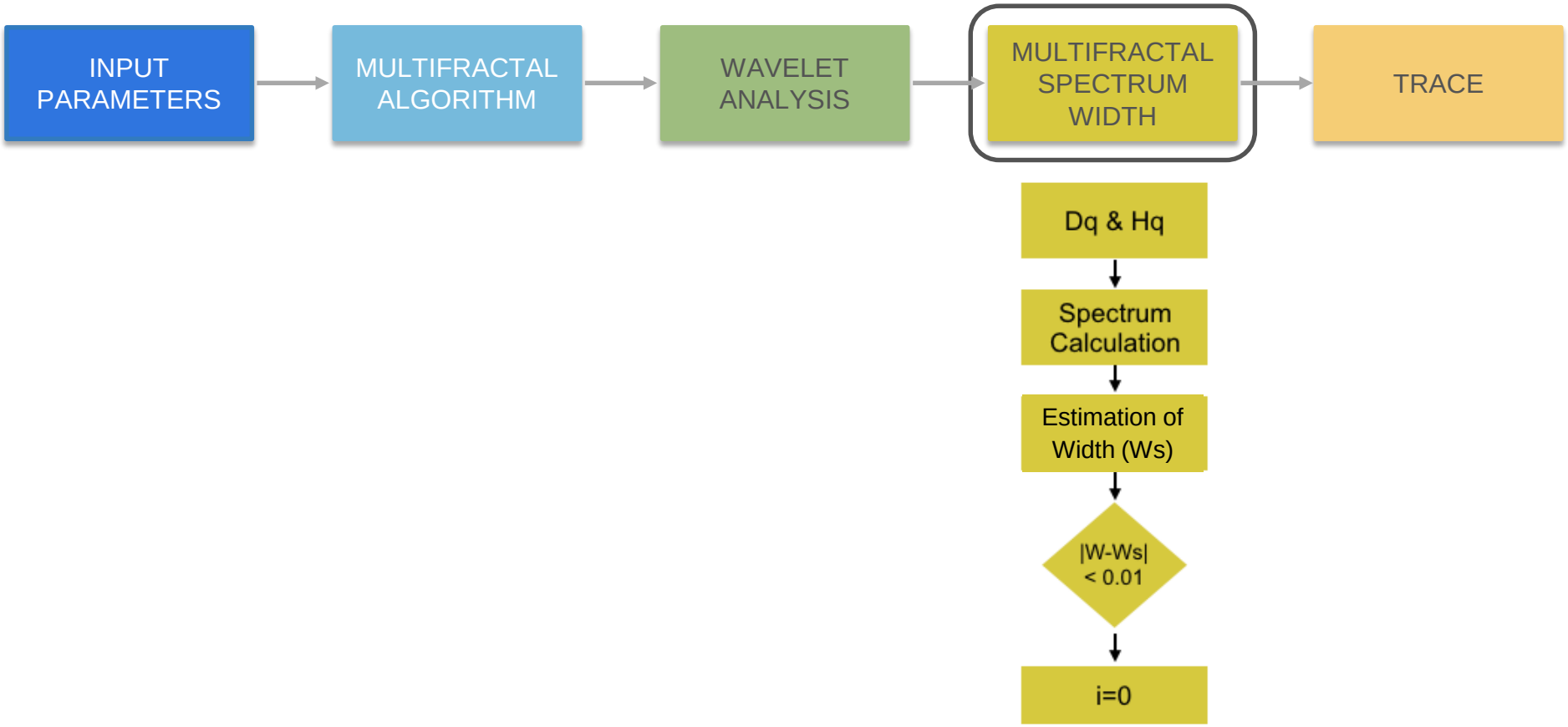
STEP 2


INPUT PARAMETERS
MULTIFRACTAL ALGORITHM
WAVELET ANALYSIS
MULTIFRACTAL SPECTRUM WIDTH
TRACE
i=n
i>16
Si
No
$k_1 = \frac{2^{2H-1} - 1}{2 - 2^{2H-1}}$
Estimation of H_2 based on Linear Regression
$k_2 = \frac{2^{2H-1} - 1}{2 - 2^{2H-1}}$
Construction Binomial Cascade
i++

STEP 3

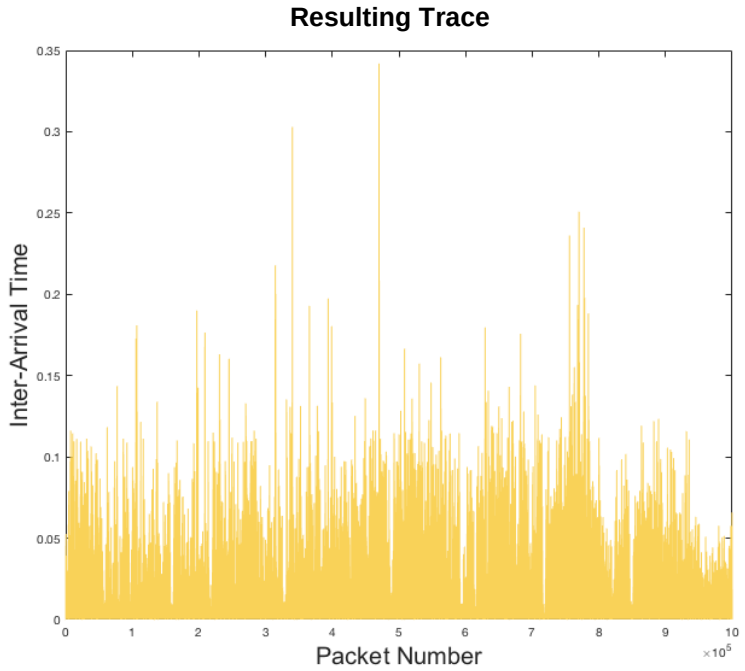

INPUT PARAMETERS
MULTIFRACTAL ALGORITHM
WAVELET ANALYSIS
MULTIFRACTAL SPECTRUM WIDTH
TRACE
Estimation of the detail coefficients dx(j,k)
Estimator
Log-Scale Diagram and Estimation of H and Sample H (Hs)
|H-Hs|< 0.005
i=0

STEP 4


INPUT PARAMETERS
MULTIFRACTAL ALGORITHM
WAVELET ANALYSIS
MULTIFRACTAL SPECTRUM WIDTH
TRACE
Dq & Hq
Spectrum Calculation
Estimation of Width (Ws)
|W-Ws| < 0.01
i=0

STEP 4

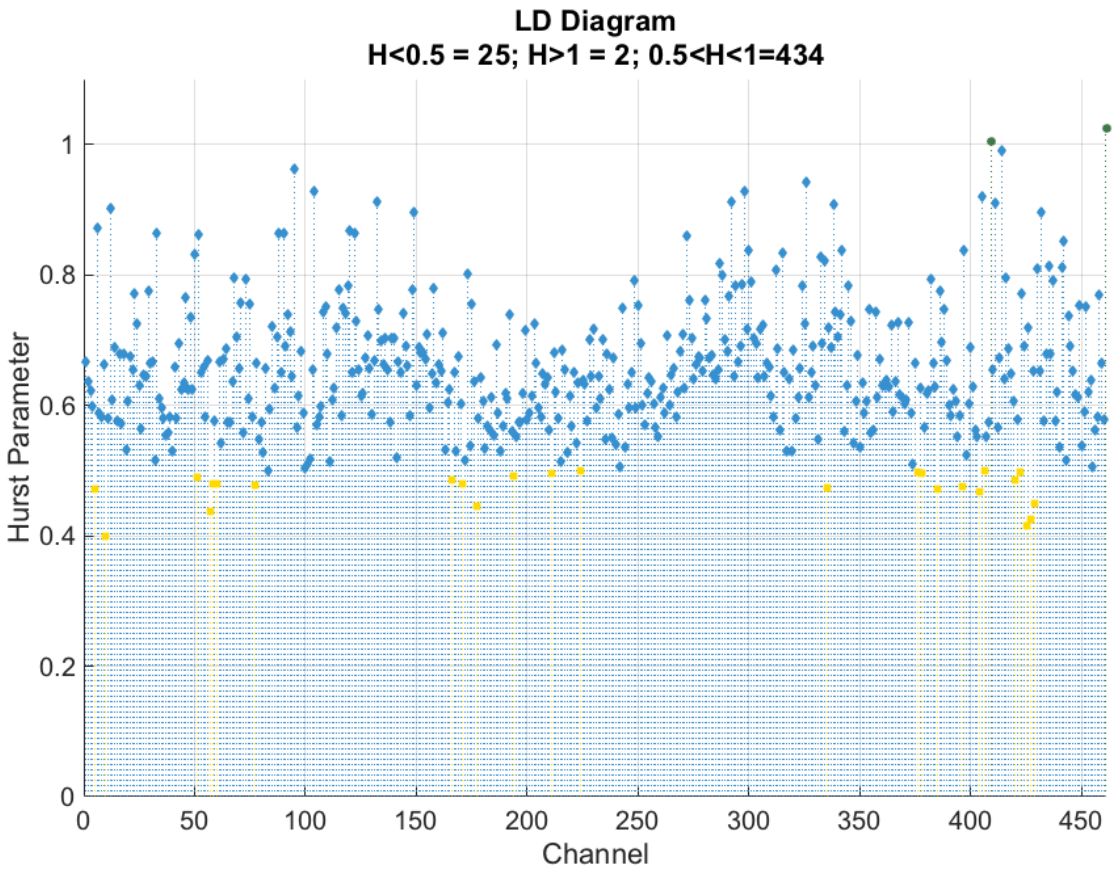
INPUT PARAMETERS → MULTIFRACTAL ALGORITHM → WAVELET ANALYSIS → MULTIFRACTAL SPECTRUM WIDTH → TRACE



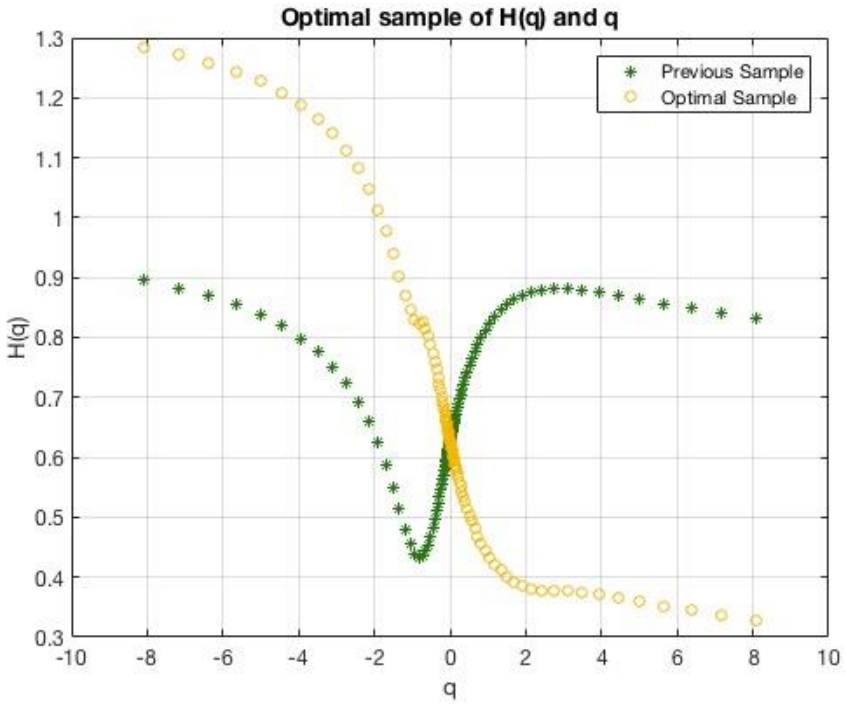
BEHAVIOR OF THE SPECTRUM IN BOGOTÁ

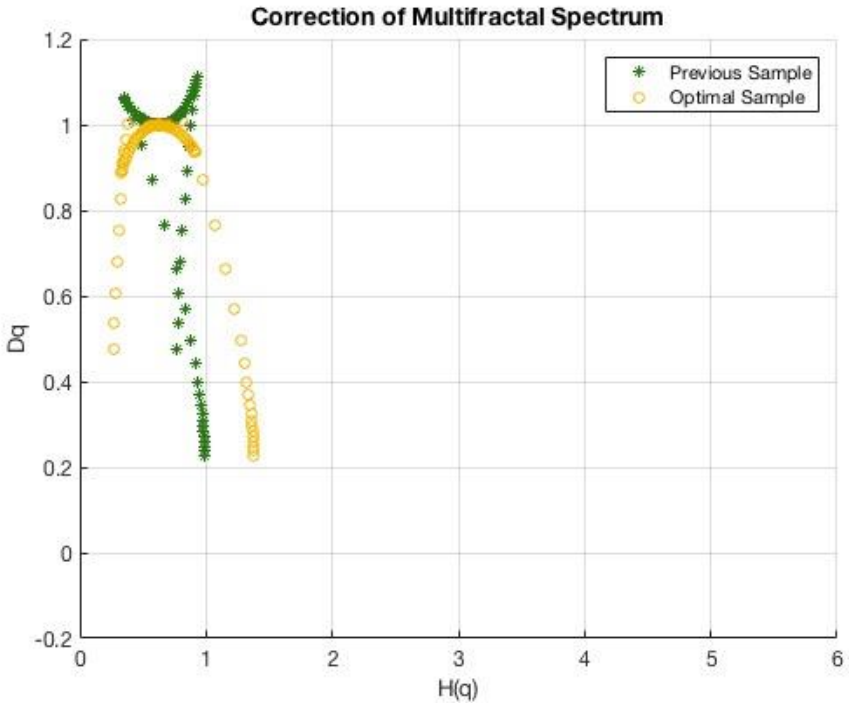
How the spectrum in Bogota works?

HURST PARAMETER OF THE RADIO SPECTRUM

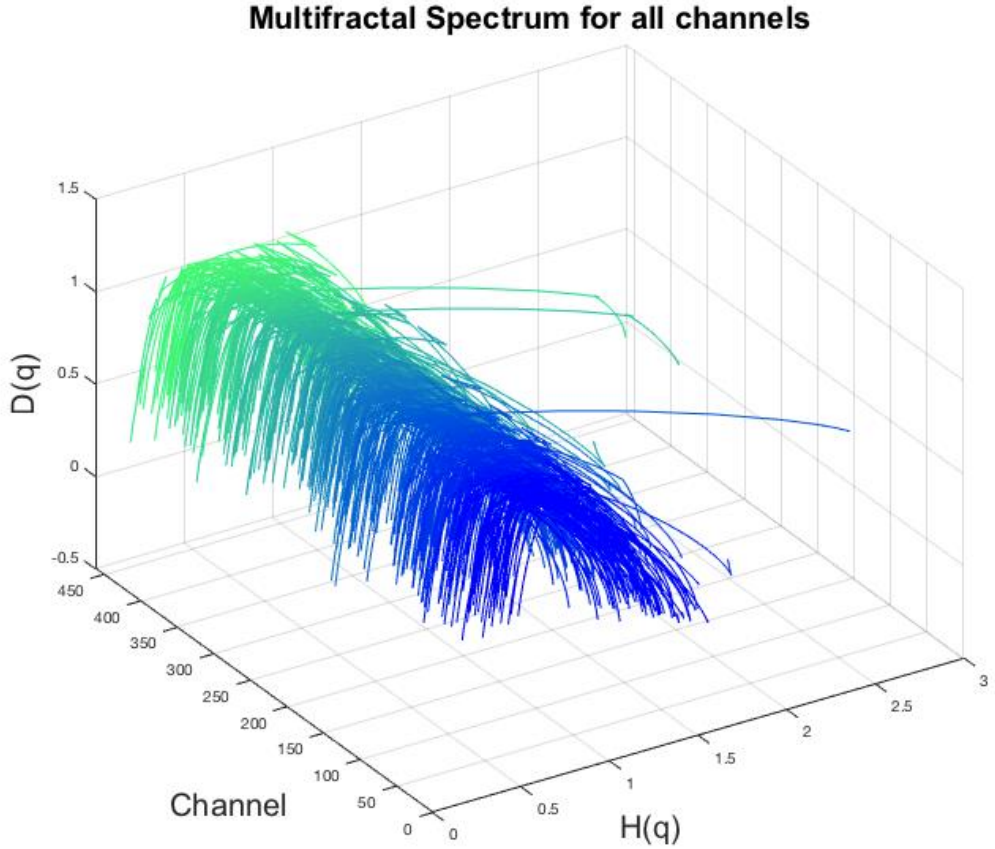


ADJUSTING THE SAMPLING PROCESS





SYNTHESIS OF THE 461 CHANNELS



CONCLUSIONS

CONCLUSIONS

- After comparing both algorithms exposed in this investigation, the MaF method delivered more significant results offering the best routes. When H is calculated for all channels, not all of them have $0.5 < H < 1$ which indicates that some channels have short range dependence while others do not. However, over 90% of the channels are in the [0.5; 1] range, indicating a long-range dependence in the traces found.

CONCLUSIONS

- In fact, the sampling correction of the MD and the realignment of the values of H(q) improves accuracy in the multifractal spectrum width of radio channels. Although the readjustment of the coefficients H(q) improves width response, there is no method for checking new samples.

- In conclusion, the data collected from the radio spectrum of Bogotá reveals that Wi-Fi traffic has a multifractal behavior.

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QUESTIONS

Thank you