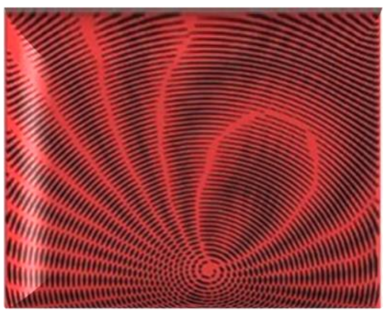
OPTCOM

A GN/EGN-MODEL REAL-TIME CLOSED-FORM FORMULA TESTED OVER 7,000 VIRTUAL LINKS



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context

- People have been talking about **physical-layer-aware** ***management-and-control*** of optical-networks, for quite some time

- Now people are also looking at **real-time** physical-layer-aware management and control
  - where "*real-time*" means assessing a whole network *in a fraction of a second*…
  - …to do on-the-fly network optimization, fault recovery, etc…

- **How do you achieve** *physical-layer-aware* *real-time* management and control ?

- You first need a non-linearity model…
- …and then **you make it fast**
  - you also need to get all the linear stuff right… *but that's a story for another day* !

the NLI models

- There are several non-linear interference (NLI) models, such as
  - time-domain
  - GN/EGN
  - pulse collision
  - logarithmic perturbation
  - ... many others

- However **NONE of them is real-time** in their ‘native form’, because they include ***integrals*** that need to be solved numerically

- *We need an approximate* ***CFM*** ***(Closed-Form Model)*** *that removes all the integrals*

accuracy ??

generality requirements

- On the WDM COMB: **the CFM must support** any mix of
  - channel symbol rates
  - frequency spacings
  - modulation-formats
  - launch powers
  - change of neighboring WDM channels at each node

- On the LINK: **the CFM must support**
  - any mix of fiber type and span lengths
  - dispersion and dispersion derivative
  - frequency dependent loss
  - different amplifier NF and frequency response
  - presence of equalizers (GFFs)
  - Inter-Channel Stimulated Raman Scattering, ISRS (for C+L-band)
  - Raman amplification

older and newer CFMs

- A few years ago, we derived a rather general CFM from the GN-model:
  - [2] P. Poggiolini, G. Bosco, A. Carena, V. Curri, Y. Jiang, F. Forghieri, 'The GN model of fiber non-linear propagation and its applications,' *J. of Lightw.Technol.*, vol. 32, no. 4, pp. 694-721, Feb. **2014**.
- However, not all the features on the previous slide were supported
- About a year ago, two papers started from [2] and filled in the missing requirements:
  - [3] D. Semrau, R. I. Killey, P. Bayvel, 'A Closed-Form Approximation of the Gaussian Noise Model in the Presence of Inter-Channel Stimulated Raman Scattering,' paper arXiv:1808.07940, Aug. 23rd 2018.
  - [4] P. Poggiolini, 'A generalized GN-model closed-form formula,' paper arXiv:1810.06545v2, Sept. 24th 2018.
- The two papers proposed similar formulas, though not identical, with similar capabilities
- This **CFM** [4] is general enough …
- but… *is it fast enough… ???*

… *is it accurate enough … ???* *[again, it is an approximation]*

the “CFM”

The version with ISRS in [4] is about **twice** as complex

$$\ldots_{\mathrm{T}}) = \sum_{n=1}^{N_{\mathrm{span}}} G_{\mathrm{NLI}}^{(n)}(f_{\mathrm{CUT}}) \prod_{k=n+1}^{N_{\mathrm{span}}} \Gamma^{(k)}(f_{\mathrm{CUT}}) \cdot e^{-2\alpha^{(k)}(f_{\mathrm{CUT}}) \cdot L_{\mathrm{span}}^{(k)}}$$

In this paper we focus on C-band and these formulas do not include ISRS

$$\Gamma^{(n)}(f_{\mathrm{CUT}}) \cdot e^{-2\alpha^{(n)}(f_{\mathrm{CUT}}) \cdot L_{\mathrm{span}}^{(n)}} \cdot \bar{G}_{\mathrm{CUT}}^{(n)} \cdot \left[\left(\bar{G}_{\mathrm{CUT}}^{(n)}\right)^2 I_{\mathrm{CUT}}^{(n)} + \sum_{n_{\mathrm{ch}}=1,\, n_{\mathrm{ch}} \neq n_{\mathrm{CUT}}^{(n)}}^{N_{\mathrm{ch}}^{(n)}} 2\left(\bar{G}_{n_{\mathrm{ch}}}^{(n)}\right)^2 I_{n_{\mathrm{ch}}}^{(n)} \right]$$

$$I_{n_{\mathrm{ch}}}^{(n)} = \frac{\operatorname{asinh}\left(\pi^2 \left| \frac{\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)} \right| \left[f_{n_{\mathrm{ch}}}^{(n)} - f_{\mathrm{CUT}} + \frac{B_{n_{\mathrm{ch}}}^{(n)}}{2} \right] B_{\mathrm{CUT}} \right) - \operatorname{asinh}\left(\pi^2 \left| \frac{\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)} \right| \left[f_{n_{\mathrm{ch}}}^{(n)} - f_{\mathrm{CUT}} - \frac{B_{n_{\mathrm{ch}}}^{(n)}}{2} \right] B_{\mathrm{CUT}} \right)}{4\pi \left| \bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)} \right| \cdot 2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}$$

$$I_{\mathrm{CUT}}^{(n)} = \frac{\operatorname{asinh}\left(\frac{\pi^2}{4} \left| \frac{\bar{\beta}_{2,\mathrm{CUT}}^{(n)}}{\alpha_n(f_{\mathrm{CUT}})} \right| B_{\mathrm{CUT}}^2 \right)}{2\pi \bar{\beta}_{2,\mathrm{CUT}}^{(n)} \cdot 2\alpha_n(f_{\mathrm{CUT}})}$$

$$\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)} = \beta_2^{(n)} + \pi\beta_3^{(n)} \left[f_{n_{\mathrm{ch}}}^{(n)} + f_{\mathrm{CUT}} - 2 f_c^{(n)} \right]$$

$$\bar{\beta}_{2,\mathrm{CUT}}^{(n)} = \beta_2^{(n)} + \pi\beta_3^{(n)} \left[2 f_{\mathrm{CUT}} - 2 f_c^{(n)} \right]$$

the "CFM"

$$G_{\mathrm{NLI}}^{\mathrm{Rx}}\left(f_{\mathrm{CUT}}\right)=\sum_{n=1}^{N_{\mathrm{span}}} G_{\mathrm{NLI}}^{(n)}\left(f_{\mathrm{CUT}}\right)\prod_{k=n+1}^{N_{\mathrm{span}}}\Gamma^{(k)}\left(f_{\mathrm{CUT}}\right)\cdot e^{-2\alpha^{(k)}\left(f_{\mathrm{CUT}}\right)\cdot L_{\mathrm{span}}^{(k)}}$$

$$G_{\mathrm{NLI}}^{(n)}\left(f_{\mathrm{CUT}}\right)=\frac{16}{27}\left(\gamma^{(n)}\right)^2\Gamma^{(n)}\left(f_{\mathrm{CUT}}\right)\cdot e^{-2\alpha^{(n)}\left(f_{\mathrm{CUT}}\right)\cdot L_{\mathrm{span}}^{(n)}}\cdot\bar{G}_{\mathrm{CUT}}^{(n)}\cdot\left[\left(\bar{G}_{\mathrm{CUT}}^{(n)}\right)^2 I_{\mathrm{CUT}}^{(n)}+\sum_{n_{\mathrm{ch}}=1,\, n_{\mathrm{ch}}\neq n_{\mathrm{CUT}}^{(n)}}^{N_{\mathrm{ch}}^{(n)}} 2\left(\bar{G}_{n_{\mathrm{ch}}}^{(n)}\right)^2 I_{n_{\mathrm{ch}}}^{(n)}\right]$$

$$I_{n_{\mathrm{ch}}}^{(n)}=\frac{\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}\right|\left[f_{n_{\mathrm{ch}}}^{(n)}-f_{\mathrm{CUT}}+\frac{B_{n_{\mathrm{ch}}}^{(n)}}{2}\right]B_{\mathrm{CUT}}\right)-\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}\right|\left[f_{n_{\mathrm{ch}}}^{(n)}-f_{\mathrm{CUT}}-\frac{B_{n_{\mathrm{ch}}}^{(n)}}{2}\right]B_{\mathrm{CUT}}\right)}{4\pi\left|\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}\right|\cdot 2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}$$

$$I_{\mathrm{CUT}}^{(n)}=\frac{\operatorname{asinh}\left(\frac{\pi^2}{4}\left|\frac{\bar{\beta}_{2,\mathrm{CUT}}^{(n)}}{\alpha_n\left(f_{\mathrm{CUT}}\right)}\right|B_{\mathrm{CUT}}^2\right)}{2\pi\bar{\beta}_{2,\mathrm{CUT}}^{(n)}\cdot 2\alpha_n\left(f_{\mathrm{CUT}}\right)}$$

$$\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[f_{n_{\mathrm{ch}}}^{(n)}+f_{\mathrm{CUT}}-2f_c^{(n)}\right]$$

$$\bar{\beta}_{2,\mathrm{CUT}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[2f_{\mathrm{CUT}}-2f_c^{(n)}\right]$$

complexity

- *the complex appearance is misleading*

- **this CFM requires only about 5 ms**
  - to evauate *all channels* of a C-band fully-populated system, at the link end…
  - **…using a laptop and interpreted Matlab**

- So, *it is real time*

- …but what about accuracy…?

what about accuracy ?

- To test the accuracy of the CFM, *we compared it with the EGN*-model…*
  - …and we did it over
    8500 highly diversified C-band system scenarios
    - 6250 systems with 100% load
    - 2250 systems with partial random load (average 50%)
- Why so many…?
- We thought *it was necessary* to *guarantee reliability* for practical use
- AFAWK, no such extensive and diversified validation has been attempted so far…
- But there is also another reason… (see later)

* the full-fledged, numerically-integrated EGN-model

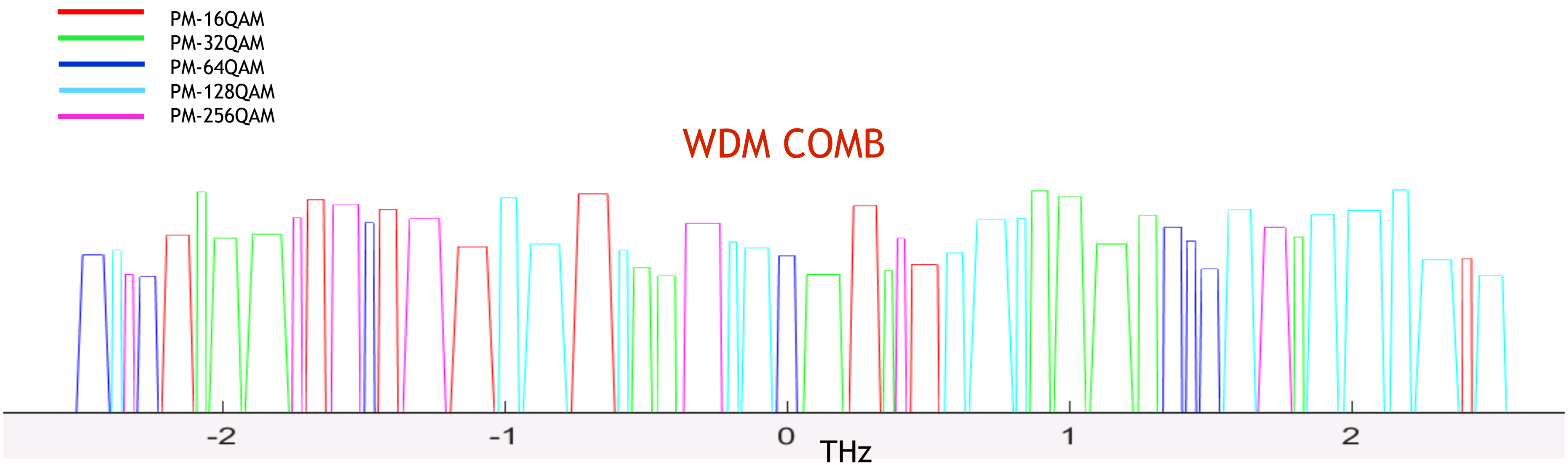
8500 systems random generation

- Each channel of the C-band WDM comb was chosen randomly as
  - format:
    - **PM-QAM** 4 / 8 / 16 / 32 / 64 / 128 / 256
    - **PM-Gaussian** with MI equivalent to any of the above QAM systems
  - symbol rate:
    - 32, 64, 96, 128 GBaud
    - with spectral slot 43.5, 87.5, 131.25, 175 GHz, respectively
    - roll-off: between 0.05 and 0.25
  - **6,250 systems 100% load, 2250 systems partial load** (average 50%)

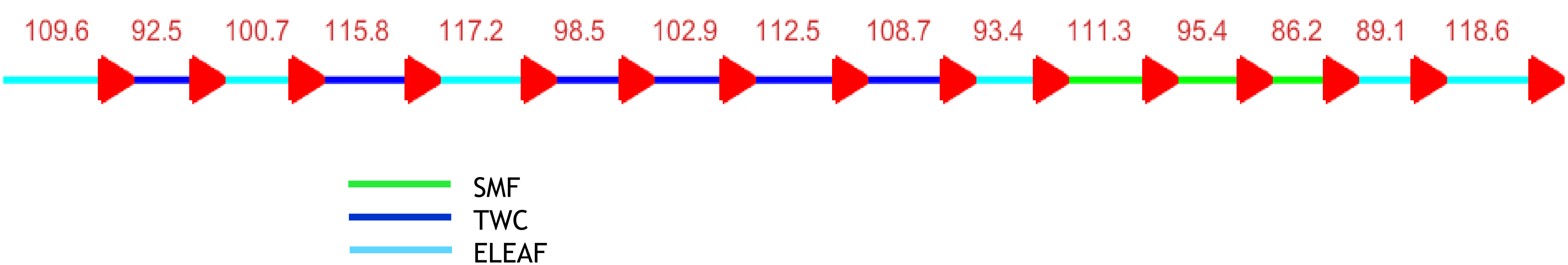
- Each span of the link has randomly chosen
  - fiber type: SMF, E-LEAF, TWC
  - length: uniform between 80 and 120 km
  - dispersion: *slope* was accounted for

- **Performance predictions testing** was performed on either the
  - *lowest frequency channel* (f_c - 2.5 THz)
  - *center channel* (f_c)
  - *highest frequency channel* (f_c + 2.5 THz)

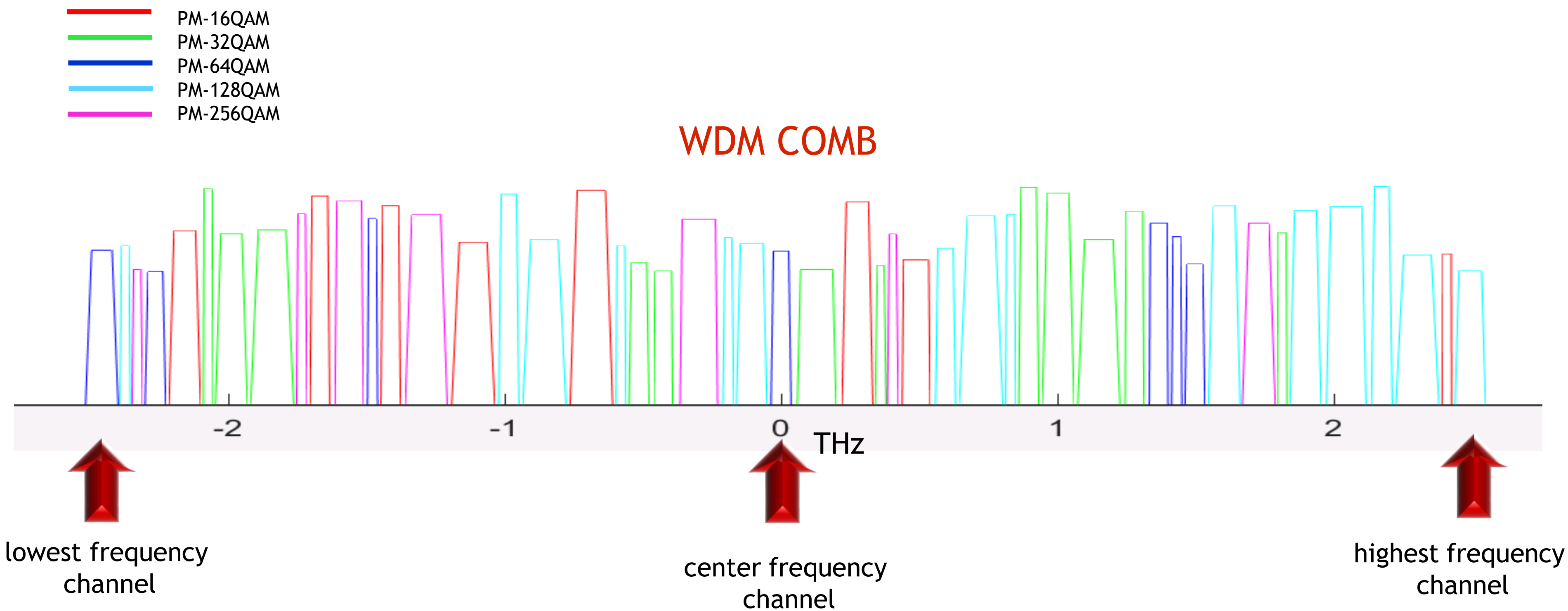
example of PM-QAM fully-loaded test system



LINK



example of PM-QAM fully-loaded test system



what performance indicator ?

- We use as *performance indicator* the system "non-linear" OSNR for the "channel under test" (CUT):

$$\mathrm{OSNR} = \frac{P_{\mathrm{CUT}}}{P_{\mathrm{ASE}} + P_{\mathrm{NLI}}}$$

- **We calculated it**
  - using the *CFM*
  - using the *numerically-integrated EGN-model*

  and compared the two results:

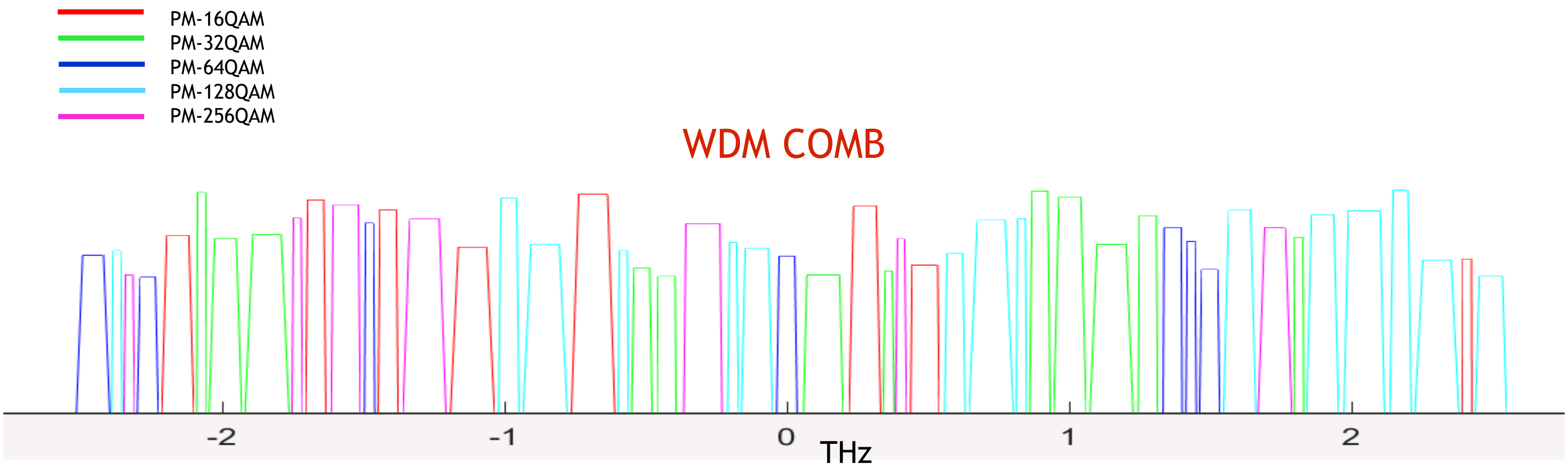
$$\mathrm{OSNR}_{\mathrm{CFM}}^{\mathrm{dB}} - \mathrm{OSNR}_{\mathrm{EGN}}^{\mathrm{dB}}$$

- The comparison was performed for each of the 8500 systems at *maximum reach*
  - found as where the normalized GMI of the CUT is down to 87% of entropy

- **Launch power was optimized for all channels** *into each span* but then…

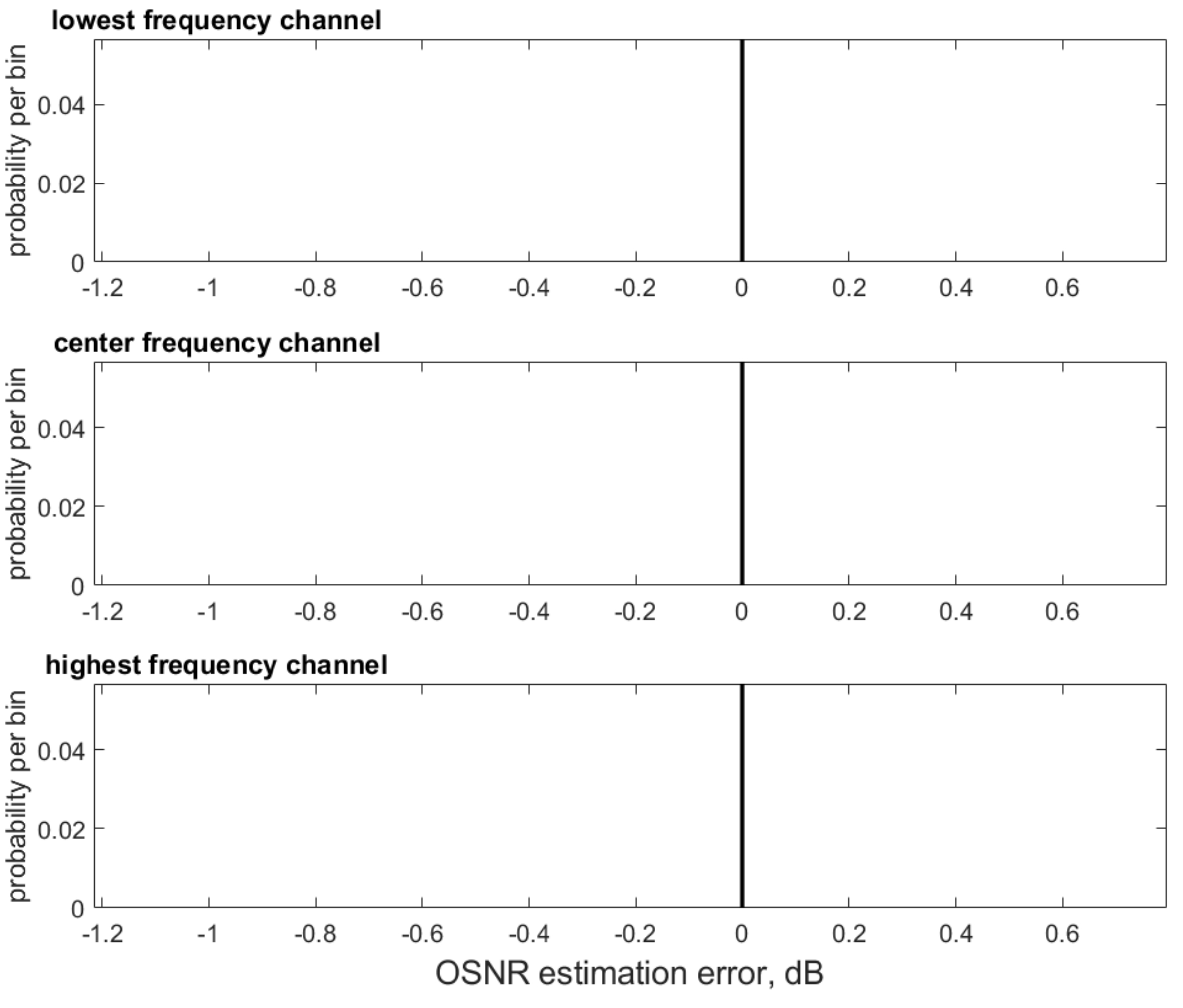
  …each channel's power was scrambled randomly *to within ±30% of optimum*

example of PM-QAM fully-loaded test system



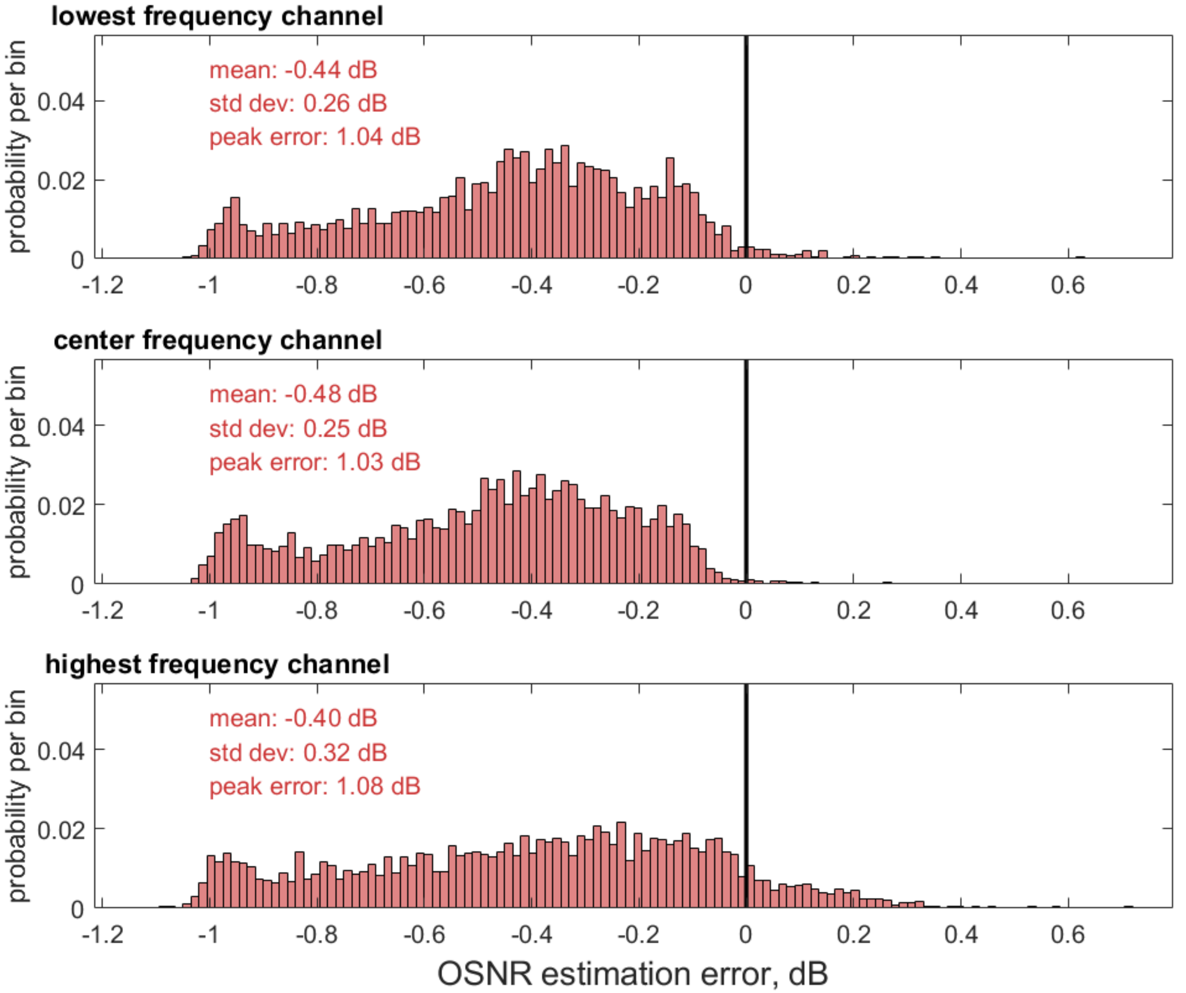
CFM error vs. EGN

$$\mathrm{OSNR}_{\mathrm{CFM}}^{\mathrm{dB}} - \mathrm{OSNR}_{\mathrm{EGN}}^{\mathrm{dB}}$$



CFM error vs. EGN

$$\mathrm{OSNR}^{\mathrm{dB}}_{\mathrm{CFM}} - \mathrm{OSNR}^{\mathrm{dB}}_{\mathrm{EGN}}$$



- The **mean error** is about -0.45 dB
- The **std dev** is not too large, about 0.3 dB
- The **peak error** is however rather large, over 1 dB
- The highest-frequency channel histogram seems more "spread out" → *more on this later*

Can we do better ?

- *Can we do better ?...*
- *... and how ???*
- We **leveraged the "big-data" test-set (the 8500 scenarios)** *to find a simple closed-form "machine-learning" correction*
- *This* is the other reason why the test set was generated so large...

the CFM

$$G_{\mathrm{NLI}}^{\mathrm{Rx}}\left(f_{\mathrm{CUT}}\right)=\sum_{n=1}^{N_{\mathrm{span}}} G_{\mathrm{NLI}}^{(n)}\left(f_{\mathrm{CUT}}\right)\prod_{k=n+1}^{N_{\mathrm{span}}}\Gamma^{(k)}\left(f_{\mathrm{CUT}}\right)\cdot e^{-2\alpha^{(k)}\left(f_{\mathrm{CUT}}\right)\cdot L_{\mathrm{span}}^{(k)}}$$

$$G_{\mathrm{NLI}}^{(n)}\left(f_{\mathrm{CUT}}\right)=\frac{16}{27}\left(\gamma^{(n)}\right)^2\Gamma^{(n)}\left(f_{\mathrm{CUT}}\right)\cdot e^{-2\alpha^{(n)}\left(f_{\mathrm{CUT}}\right)\cdot L_{\mathrm{span}}^{(n)}}\cdot \bar{G}_{\mathrm{CUT}}^{(n)}\cdot\left[\left(\bar{G}_{\mathrm{CUT}}^{(n)}\right)^2 I_{\mathrm{CUT}}^{(n)}+\sum_{n_{\mathrm{ch}}=1,\, n_{\mathrm{ch}}\neq n_{\mathrm{CUT}}^{(n)}}^{N_{\mathrm{ch}}^{(n)}} 2\left(\bar{G}_{n_{\mathrm{ch}}}^{(n)}\right)^2 I_{n_{\mathrm{ch}}}^{(n)}\right]$$

$$I_{n_{\mathrm{ch}}}^{(n)}=\frac{\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}\right|\left[f_{n_{\mathrm{ch}}}^{(n)}-f_{\mathrm{CUT}}+\frac{B_{n_{\mathrm{ch}}}^{(n)}}{2}\right]B_{\mathrm{CUT}}\right)-\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}\right|\left[f_{n_{\mathrm{ch}}}^{(n)}-f_{\mathrm{CUT}}-\frac{B_{n_{\mathrm{ch}}}^{(n)}}{2}\right]B_{\mathrm{CUT}}\right)}{4\pi\left|\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}\right|\cdot 2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}$$

$$I_{\mathrm{CUT}}^{(n)}=\frac{\operatorname{asinh}\left(\frac{\pi^2}{4}\left|\frac{\bar{\beta}_{2,\mathrm{CUT}}^{(n)}}{\alpha_n\left(f_{\mathrm{CUT}}\right)}\right|B_{\mathrm{CUT}}^2\right)}{2\pi\bar{\beta}_{2,\mathrm{CUT}}^{(n)}\cdot 2\alpha_n\left(f_{\mathrm{CUT}}\right)}$$

$$\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[f_{n_{\mathrm{ch}}}^{(n)}+f_{\mathrm{CUT}}-2f_c^{(n)}\right]$$

$$\bar{\beta}_{2,\mathrm{CUT}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[2f_{\mathrm{CUT}}-2f_c^{(n)}\right]$$

the CFM with ML

"machine learning" factors

$$G_{\rm NLI}^{\rm Rx}\left(f_{\rm CUT}\right)=\sum_{n=1}^{N_{\rm span}} G_{\rm NLI}^{(n)}\left(f_{\rm CUT}\right)\prod_{k=n+1}^{N_{\rm span}}\Gamma^{(k)}\left(f_{\rm CUT}\right)\cdot e^{-2\alpha^{(k)}\left(f_{\rm CUT}\right)\cdot L_{\rm span}^{(k)}}$$

$$G_{\rm NLI}^{(n)}\left(f_{\rm CUT}\right)=\frac{16}{27}\left(\gamma^{(n)}\right)^2\Gamma^{(n)}\left(f_{\rm CUT}\right)\cdot e^{-2\alpha^{(n)}\left(f_{\rm CUT}\right)\cdot L_{\rm span}^{(n)}}\cdot\bar{G}_{\rm CUT}^{(n)}\cdot\left[\rho_{\rm CUT}^{(n)}\cdot\left(\bar{G}_{\rm CUT}^{(n)}\right)^2 I_{\rm CUT}^{(n)}+\sum_{n_{\rm ch}=1,\, n_{\rm ch}\neq n_{\rm CUT}^{(n)}}^{N_{\rm ch}^{(n)}} 2\rho_{n_{\rm ch}}^{(n)}\cdot\left(\bar{G}_{n_{\rm ch}}^{(n)}\right)^2 I_{n_{\rm ch}}^{(n)}\right]$$

$$I_{n_{\rm ch}}^{(n)}=\frac{\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\rm ch}}^{(n)}}{2\alpha_n\left(f_{n_{\rm ch}}^{(n)}\right)}\right|\left[f_{n_{\rm ch}}^{(n)}-f_{\rm CUT}+\frac{B_{n_{\rm ch}}^{(n)}}{2}\right]B_{\rm CUT}\right)-\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\rm ch}}^{(n)}}{2\alpha_n\left(f_{n_{\rm ch}}^{(n)}\right)}\right|\left[f_{n_{\rm ch}}^{(n)}-f_{\rm CUT}-\frac{B_{n_{\rm ch}}^{(n)}}{2}\right]B_{\rm CUT}\right)}{4\pi\left|\bar{\beta}_{2,n_{\rm ch}}^{(n)}\right|\cdot 2\alpha_n\left(f_{n_{\rm ch}}^{(n)}\right)}$$

$$I_{\rm CUT}^{(n)}=\frac{\operatorname{asinh}\left(\frac{\pi^2}{4}\left|\frac{\bar{\beta}_{2,\rm CUT}^{(n)}}{\alpha_n\left(f_{\rm CUT}\right)}\right|B_{\rm CUT}^2\right)}{2\pi\bar{\beta}_{2,\rm CUT}^{(n)}\cdot 2\alpha_n\left(f_{\rm CUT}\right)}$$

$$\bar{\beta}_{2,n_{\rm ch}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[f_{n_{\rm ch}}^{(n)}+f_{\rm CUT}-2f_c^{(n)}\right]\qquad \bar{\beta}_{2,\rm CUT}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[2f_{\rm CUT}-2f_c^{(n)}\right]$$

the machine-learning factors

$$\rho_{n_{\text{ch}}}^{(n)} = a_1 + a_2 \cdot \Phi_{n_{\text{ch}}}^{a_3} + \left[1 + a_4 \left(\left|\bar{\beta}_{2,\text{acc}}\left(n, n_{\text{ch}}\right)\right| + a_5\right)^{a_6}\right] \cdot a_7 \cdot \Phi_{n_{\text{ch}}}^{a_8}$$

$$\rho_{\text{CUT}}^{(n)} = a_9 + a_{10} \Phi_{\text{CUT}}^{a_{11}} + \left[1 + a_{12} R_{\text{CUT}}^{a_{13}} + a_{14} \left(\left|\bar{\beta}_{2,\text{acc}}\left(n, n_{\text{CUT}}\right)\right| + a_{15}\right)^{a_{16}}\right] a_{17} \Phi_{\text{CUT}}^{a_{18}}$$

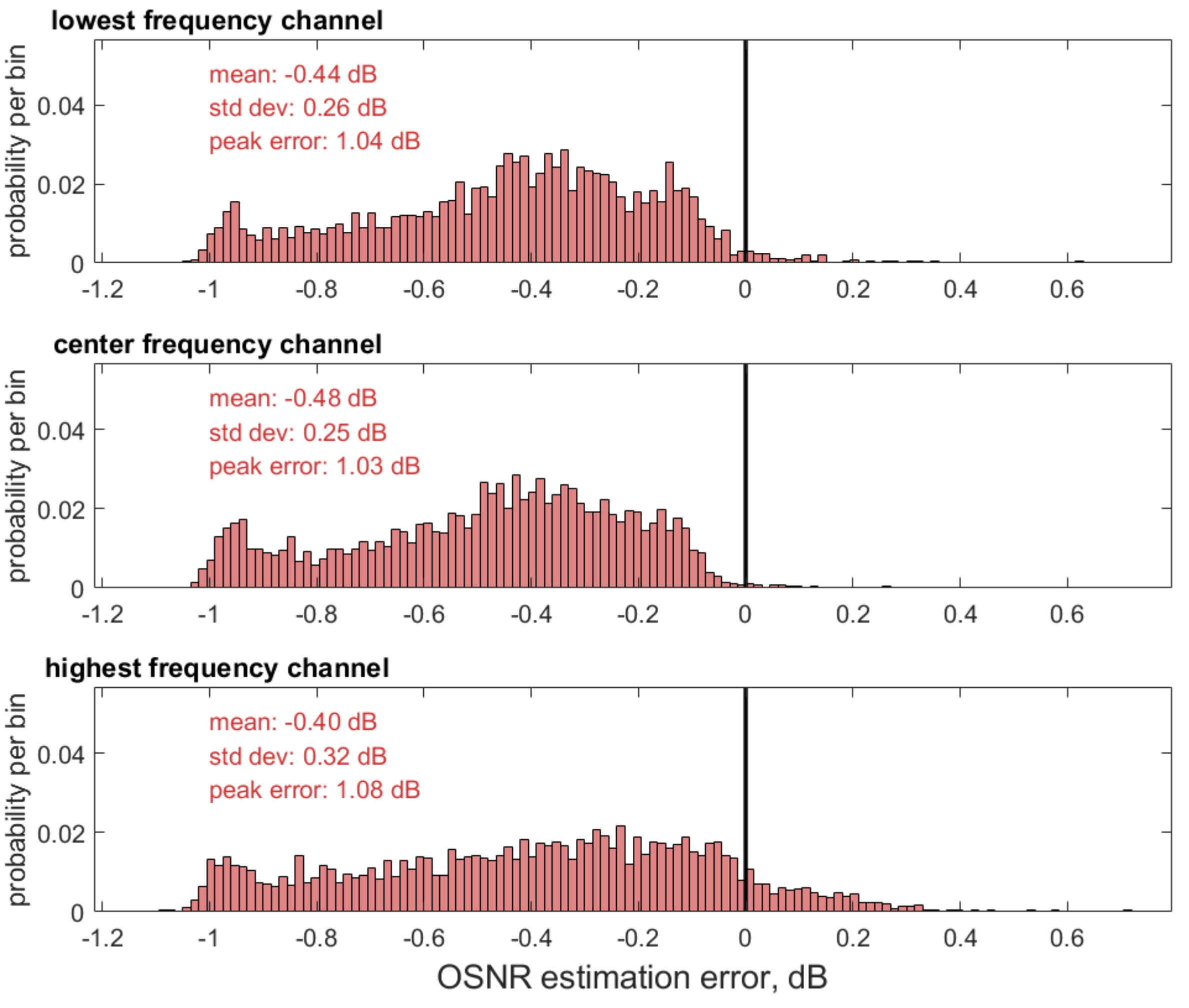
- These machine-learning factors hinge on a few system parameters:
  - <u>*the CUT symbol rate*</u> R_{CUT}
  - <u>*the channel format EGN-model constant*</u> Φ
  - <u>*the accumulated dispersion*</u> for each channel at the start of each span

$$\bar{\beta}_{2,\text{acc}}\left(n, n_{\text{ch}}\right) = \sum_{k=1}^{n-1} \bar{\beta}_{2,n_{\text{ch}}}^{(k)} \cdot L_{\text{span}}^{(k)}$$

  - It then requires “machine-learning” 18 coefficients $a_1 \ldots a_{18}$
  - A standard MSE minimization algorithm was used

CFM vs. EGN

$$\mathrm{OSNR}_{\mathrm{CFM}}^{\mathrm{dB}} - \mathrm{OSNR}_{\mathrm{EGN}}^{\mathrm{dB}}$$



CFM vs. EGN

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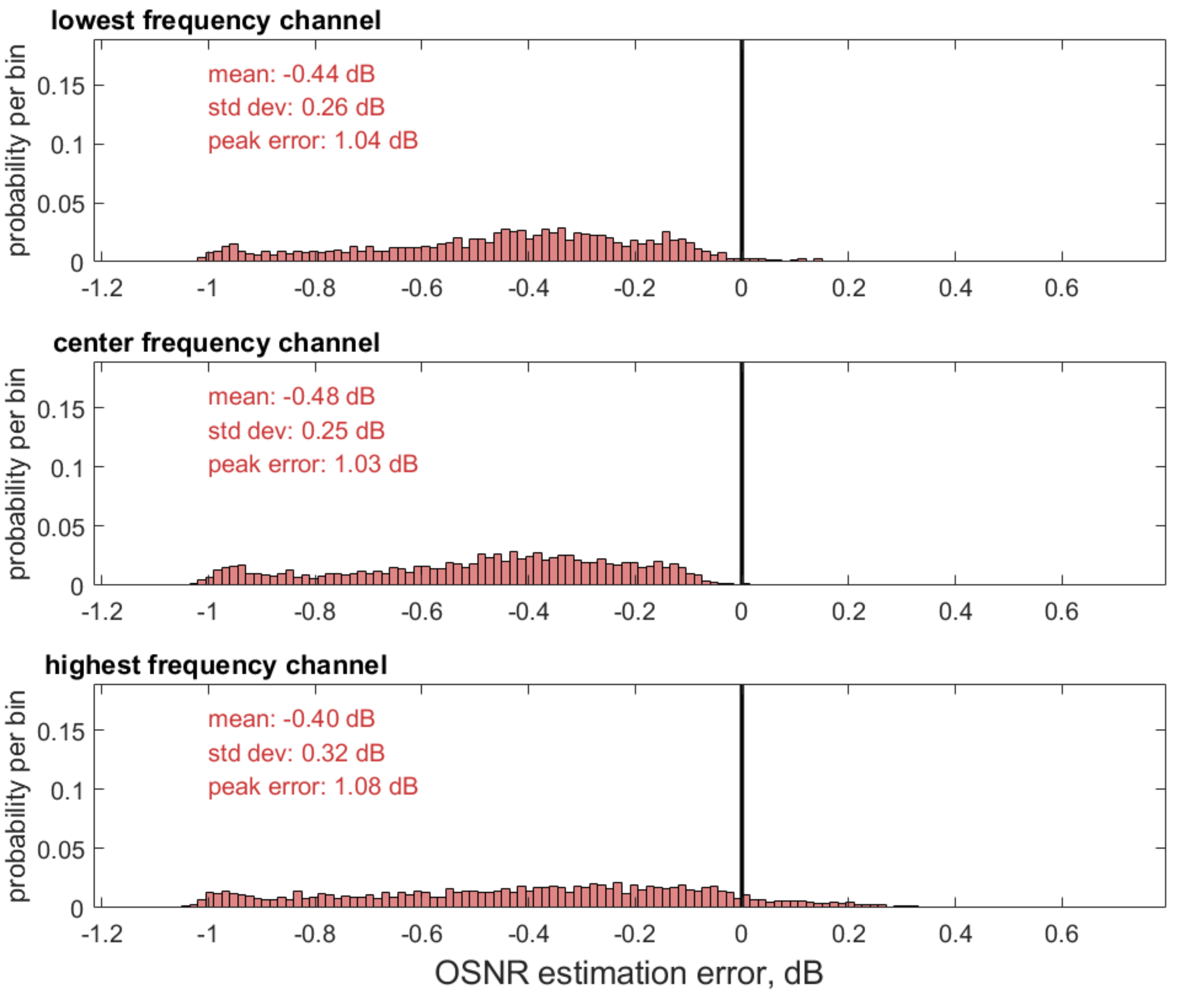
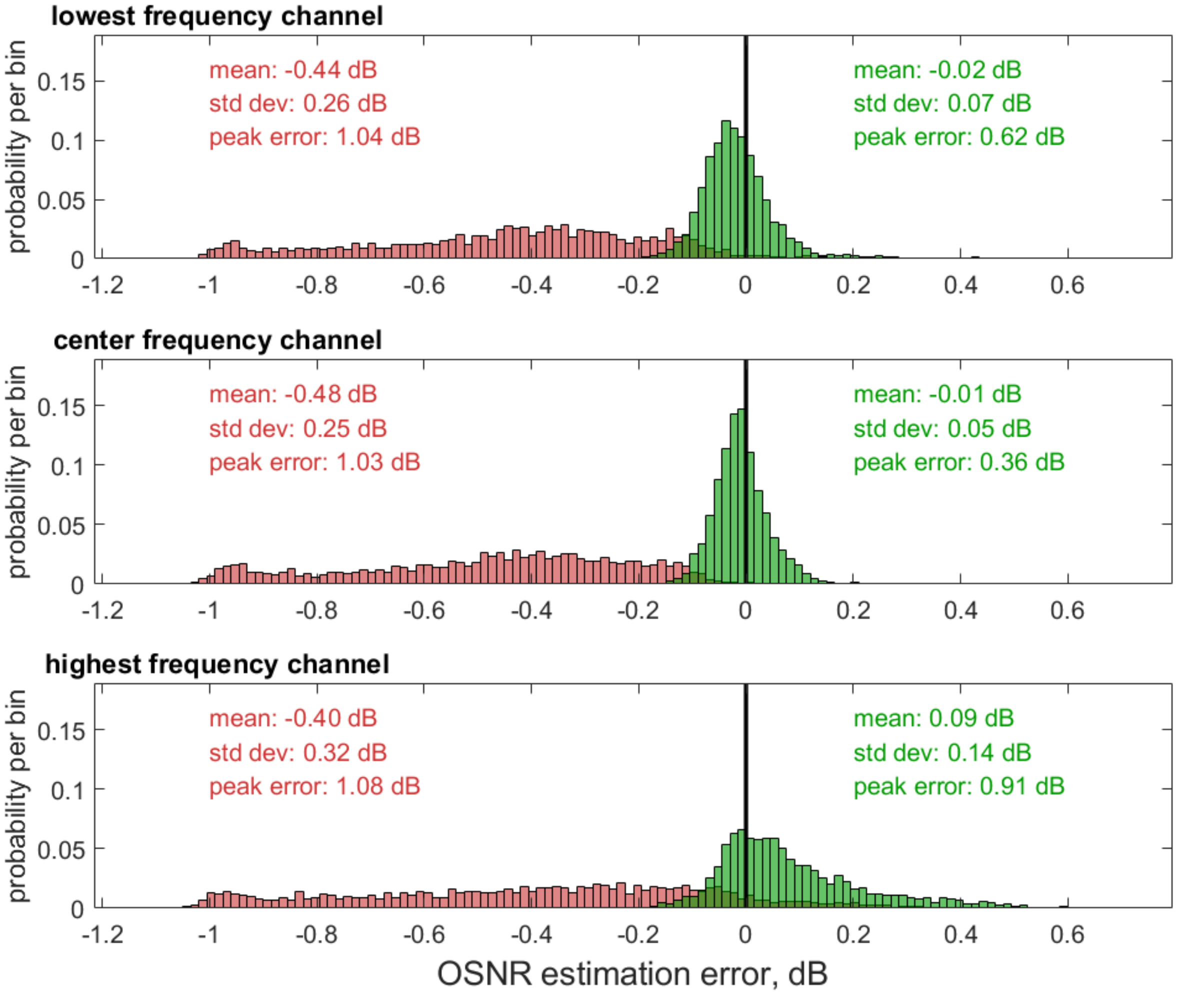


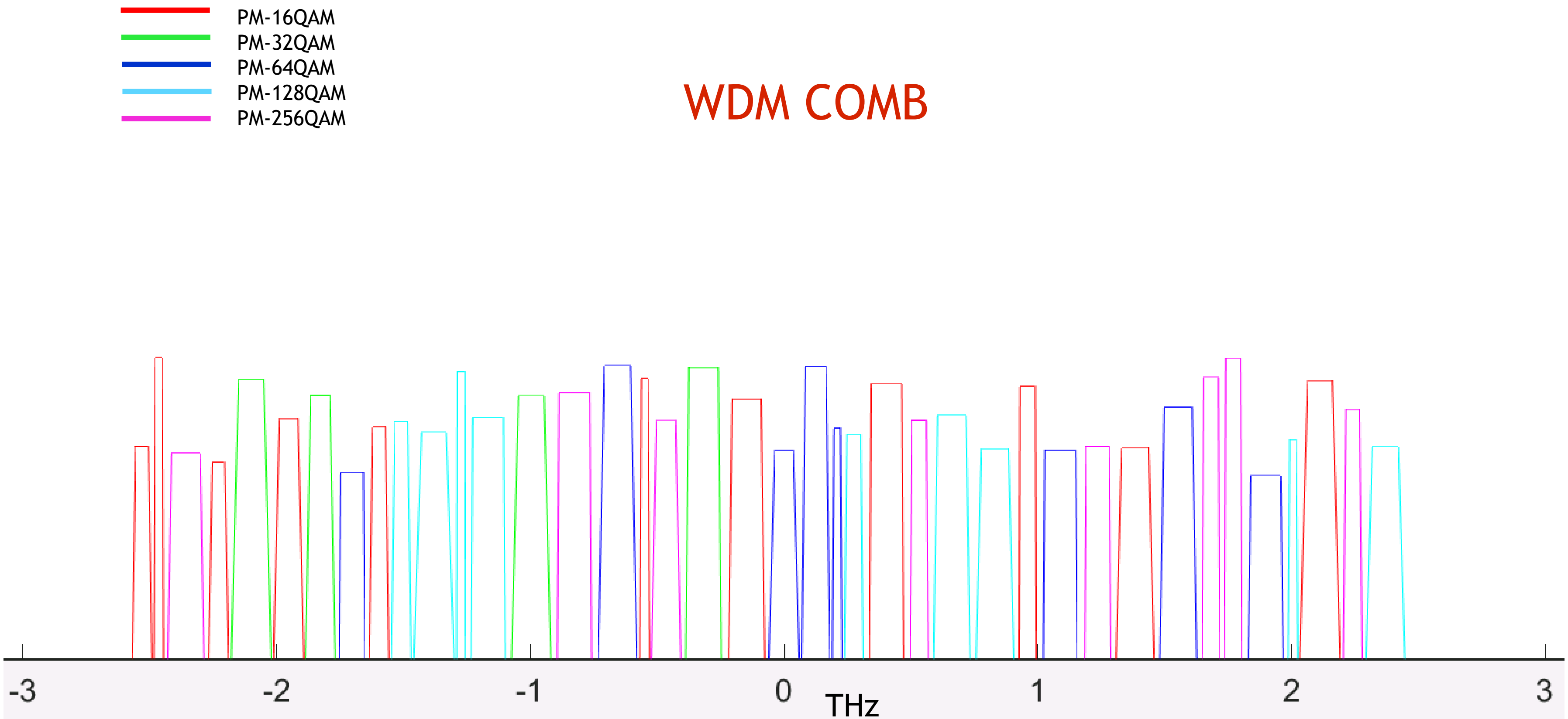
CFM with ML vs. EGN

$$\mathrm{OSNR}_{\mathrm{CFM}}^{\mathrm{dB}} - \mathrm{OSNR}_{\mathrm{EGN}}^{\mathrm{dB}}$$



- Looking at the **lowest and center frequency channels:**
  - the **mean error** goes to almost to zero
  - the **std dev** is very small 0.05-0.07 dB
  - the **peak error** is non-negligible: there are outliers
- The high-frequency channel appears to be more critical in all respects
- **Why?**

dispersion at high frequency



dispersion at high frequency

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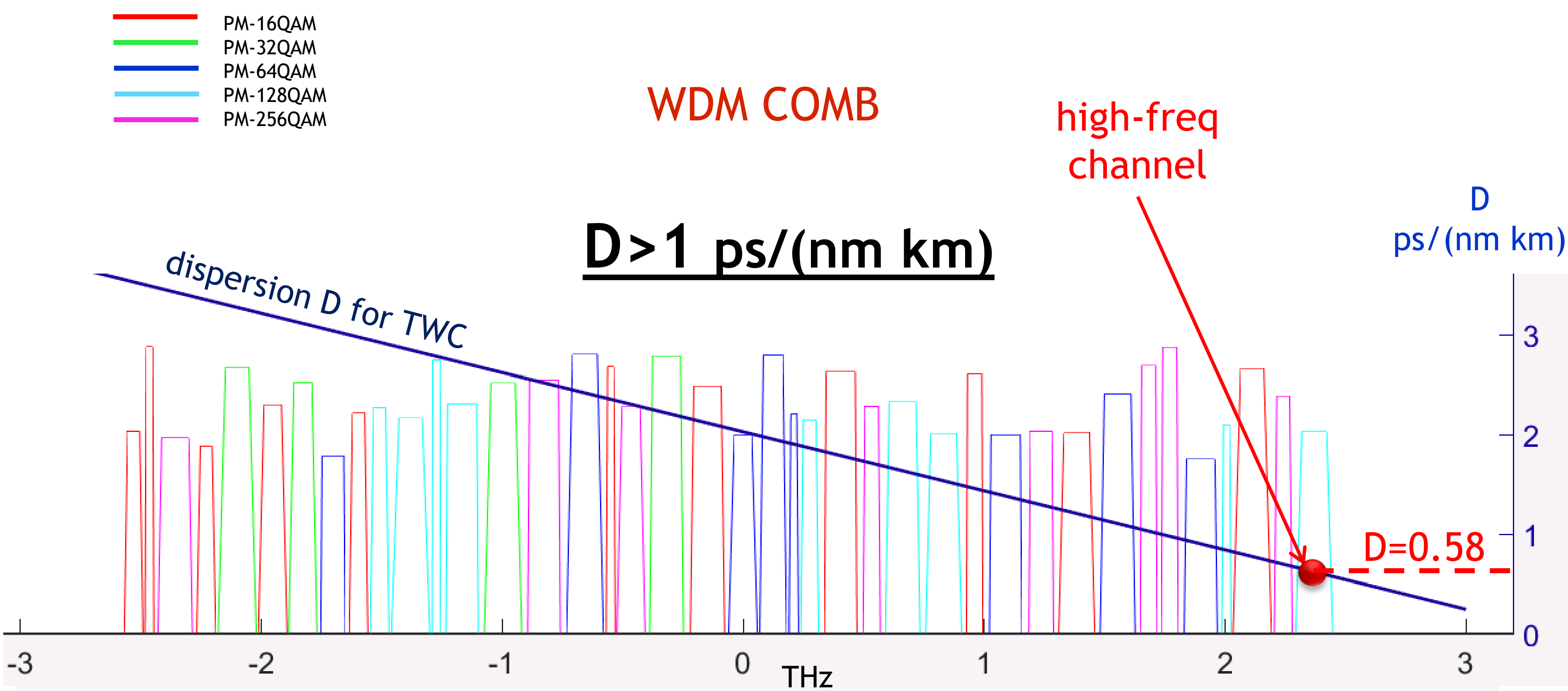
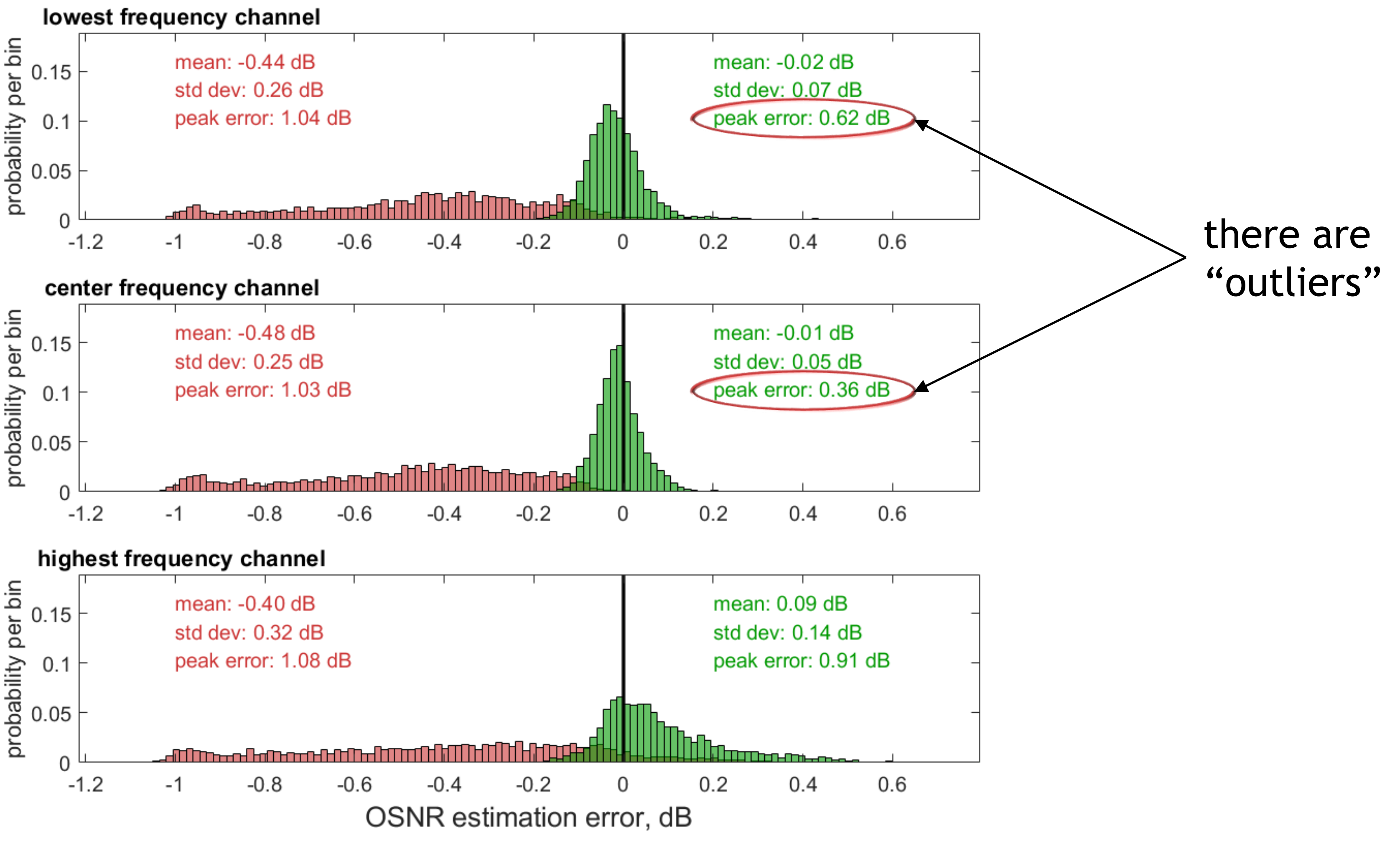


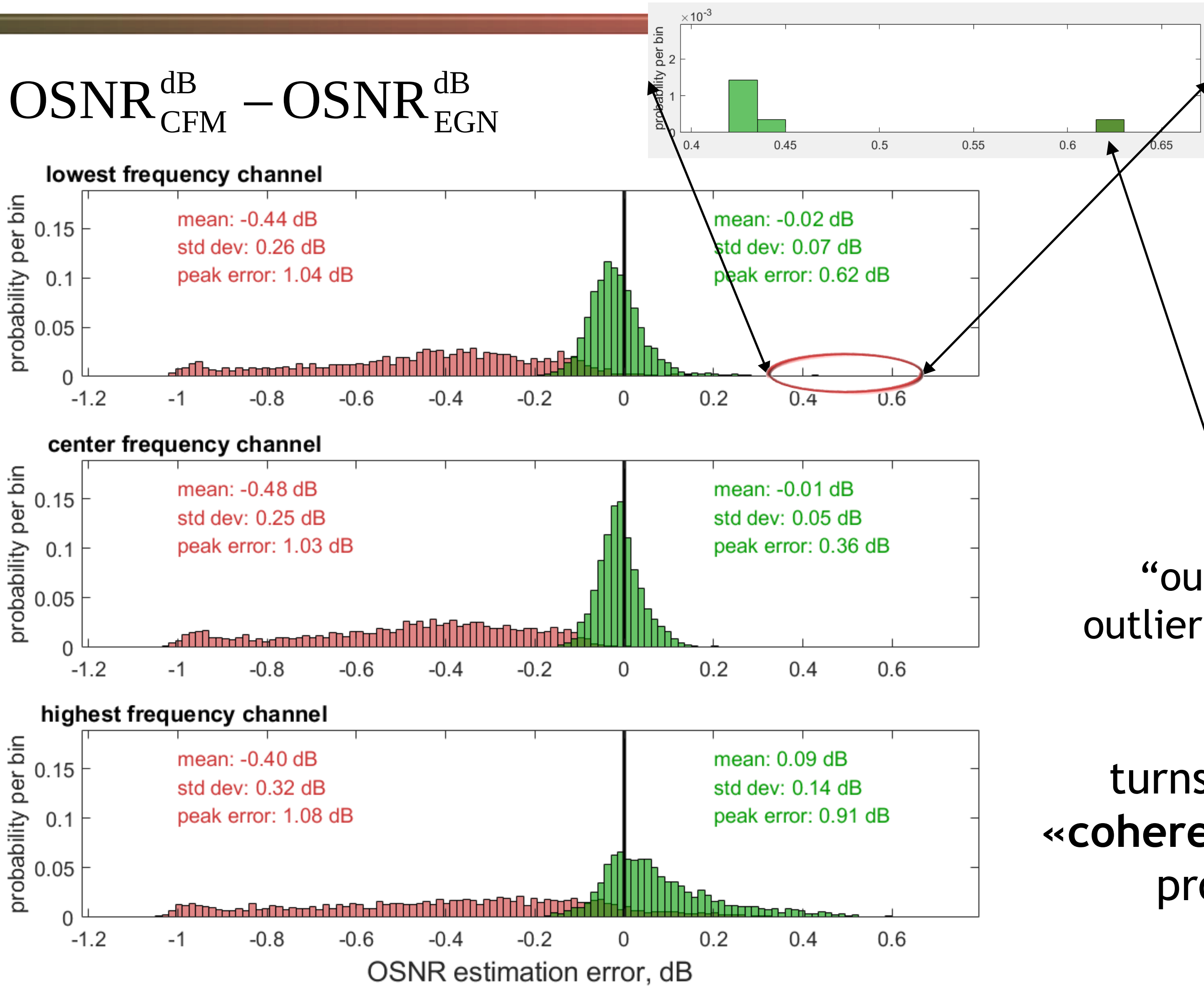
CFM with ML vs. EGN

$$\mathrm{OSNR}_{\mathrm{CFM}}^{\mathrm{dB}} - \mathrm{OSNR}_{\mathrm{EGN}}^{\mathrm{dB}}$$



CFM with ML vs. EGN

$$\mathrm{OSNR}_{\mathrm{CFM}}^{\mathrm{dB}} - \mathrm{OSNR}_{\mathrm{EGN}}^{\mathrm{dB}}$$



"outermost" outlier at +0.62 dB

turns out **NLI «coherence»** is the problem

CFM with ML

"machine learning" factors

$$G_{\mathrm{NLI}}^{\mathrm{Rx}}\left(f_{\mathrm{CUT}}\right)=\sum_{n=1}^{N_{\mathrm{span}}} G_{\mathrm{NLI}}^{(n)}\left(f_{\mathrm{CUT}}\right)\prod_{k=n+1}^{N_{\mathrm{span}}}\Gamma^{(k)}\left(f_{\mathrm{CUT}}\right)\cdot e^{-2\alpha^{(k)}\left(f_{\mathrm{CUT}}\right)\cdot L_{\mathrm{span}}^{(k)}}$$

$$G_{\mathrm{NLI}}^{(n)}\left(f_{\mathrm{CUT}}\right)=\frac{16}{27}\left(\gamma^{(n)}\right)^2\Gamma^{(n)}\left(f_{\mathrm{CUT}}\right)\cdot e^{-2\alpha^{(n)}\left(f_{\mathrm{CUT}}\right)\cdot L_{\mathrm{span}}^{(n)}}\cdot\bar{G}_{\mathrm{CUT}}^{(n)}\cdot\left[\rho_{\mathrm{CUT}}^{(n)}\cdot\left(\bar{G}_{\mathrm{CUT}}^{(n)}\right)^2 I_{\mathrm{CUT}}^{(n)}+\sum_{n_{\mathrm{ch}}=1,\,n_{\mathrm{ch}}\neq n_{\mathrm{CUT}}^{(n)}}^{N_{\mathrm{ch}}^{(n)}}2\rho_{n_{\mathrm{ch}}}^{(n)}\cdot\left(\bar{G}_{n_{\mathrm{ch}}}^{(n)}\right)^2 I_{n_{\mathrm{ch}}}^{(n)}\right]$$

$$I_{n_{\mathrm{ch}}}^{(n)}=\frac{\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}\right|\left[f_{n_{\mathrm{ch}}}^{(n)}-f_{\mathrm{CUT}}+\frac{B_{n_{\mathrm{ch}}}^{(n)}}{2}\right]B_{\mathrm{CUT}}\right)-\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}\right|\left[f_{n_{\mathrm{ch}}}^{(n)}-f_{\mathrm{CUT}}-\frac{B_{n_{\mathrm{ch}}}^{(n)}}{2}\right]B_{\mathrm{CUT}}\right)}{4\pi\left|\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}\right|\cdot 2\alpha_n\left(f_{n_{\mathrm{ch}}}^{(n)}\right)}$$

$$I_{\mathrm{CUT}}^{(n)}=\frac{\operatorname{asinh}\left(\frac{\pi^2}{4}\left|\frac{\bar{\beta}_{2,\mathrm{CUT}}^{(n)}}{\alpha_n\left(f_{\mathrm{CUT}}\right)}\right|B_{\mathrm{CUT}}^2\right)}{2\pi\bar{\beta}_{2,\mathrm{CUT}}^{(n)}\cdot 2\alpha_n\left(f_{\mathrm{CUT}}\right)}$$

$$\bar{\beta}_{2,n_{\mathrm{ch}}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[f_{n_{\mathrm{ch}}}^{(n)}+f_{\mathrm{CUT}}-2f_c^{(n)}\right]\qquad \bar{\beta}_{2,\mathrm{CUT}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[2f_{\mathrm{CUT}}-2f_c^{(n)}\right]$$

CFM with ML and CC

"NLI coherence correction" term

"machine learning" factors

$$G_{\text{NLI}}^{\text{Rx}}\left(f_{\text{CUT}}\right)=\sum_{n=1}^{N_{\text{span}}} G_{\text{NLI}}^{(n)}\left(f_{\text{CUT}}\right)\prod_{k=n+1}^{N_{\text{span}}}\Gamma^{(k)}\left(f_{\text{CUT}}\right)\cdot e^{-2\alpha^{(k)}\left(f_{\text{CUT}}\right)\cdot L_{\text{span}}^{(k)}}$$

$$G_{\text{NLI}}^{(n)}\left(f_{\text{CUT}}\right)=\frac{16}{27}\left(\gamma^{(n)}\right)^2\Gamma^{(n)}\left(f_{\text{CUT}}\right)\cdot e^{-2\alpha^{(n)}\left(f_{\text{CUT}}\right)\cdot L_{\text{span}}^{(n)}}\cdot\bar{G}_{\text{CUT}}^{(n)}\cdot\left[\rho_{\text{CUT}}^{(n)}\cdot\left(\bar{G}_{\text{CUT}}^{(n)}\right)^2 I_{\text{CUT}}^{(n)}+\sum_{n_{\text{ch}}=1,\, n_{\text{ch}}\neq n_{\text{CUT}}^{(n)}}^{N_{\text{ch}}^{(n)}} 2\rho_{n_{\text{ch}}}^{(n)}\cdot\left(\bar{G}_{n_{\text{ch}}}^{(n)}\right)^2 I_{n_{\text{ch}}}^{(n)}\right]$$

$$I_{n_{\text{ch}}}^{(n)}=\frac{\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\text{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\text{ch}}}^{(n)}\right)}\right|\left[f_{n_{\text{ch}}}^{(n)}-f_{\text{CUT}}+\frac{B_{n_{\text{ch}}}^{(n)}}{2}\right]B_{\text{CUT}}\right)-\operatorname{asinh}\left(\pi^2\left|\frac{\bar{\beta}_{2,n_{\text{ch}}}^{(n)}}{2\alpha_n\left(f_{n_{\text{ch}}}^{(n)}\right)}\right|\left[f_{n_{\text{ch}}}^{(n)}-f_{\text{CUT}}-\frac{B_{n_{\text{ch}}}^{(n)}}{2}\right]B_{\text{CUT}}\right)}{4\pi\left|\bar{\beta}_{2,n_{\text{ch}}}^{(n)}\right|\cdot 2\alpha_n\left(f_{n_{\text{ch}}}^{(n)}\right)}$$

$$I_{\text{CUT}}^{(n)}=\frac{\operatorname{asinh}\left(\frac{\pi^2}{4}\left|\frac{\bar{\beta}_{2,\text{CUT}}^{(n)}}{\alpha_n\left(f_{\text{CUT}}\right)}\right|B_{\text{CUT}}^2\right)+2\frac{\operatorname{Si}\left(\pi^2\bar{\beta}_{2,\text{CUT}}^{(n)}L_{\text{span}}^{(n)}B_{\text{CUT}}^2\right)}{\pi\alpha_n\left(f_{\text{CUT}}\right)L_{\text{span}}^{(n)}}\left[\operatorname{HN}\left(N_{\text{span}}-1\right)+\frac{1-N_{\text{span}}}{N_{\text{span}}}\right]}{2\pi\bar{\beta}_{2,\text{CUT}}^{(n)}\cdot 2\alpha_n\left(f_{\text{CUT}}\right)}$$

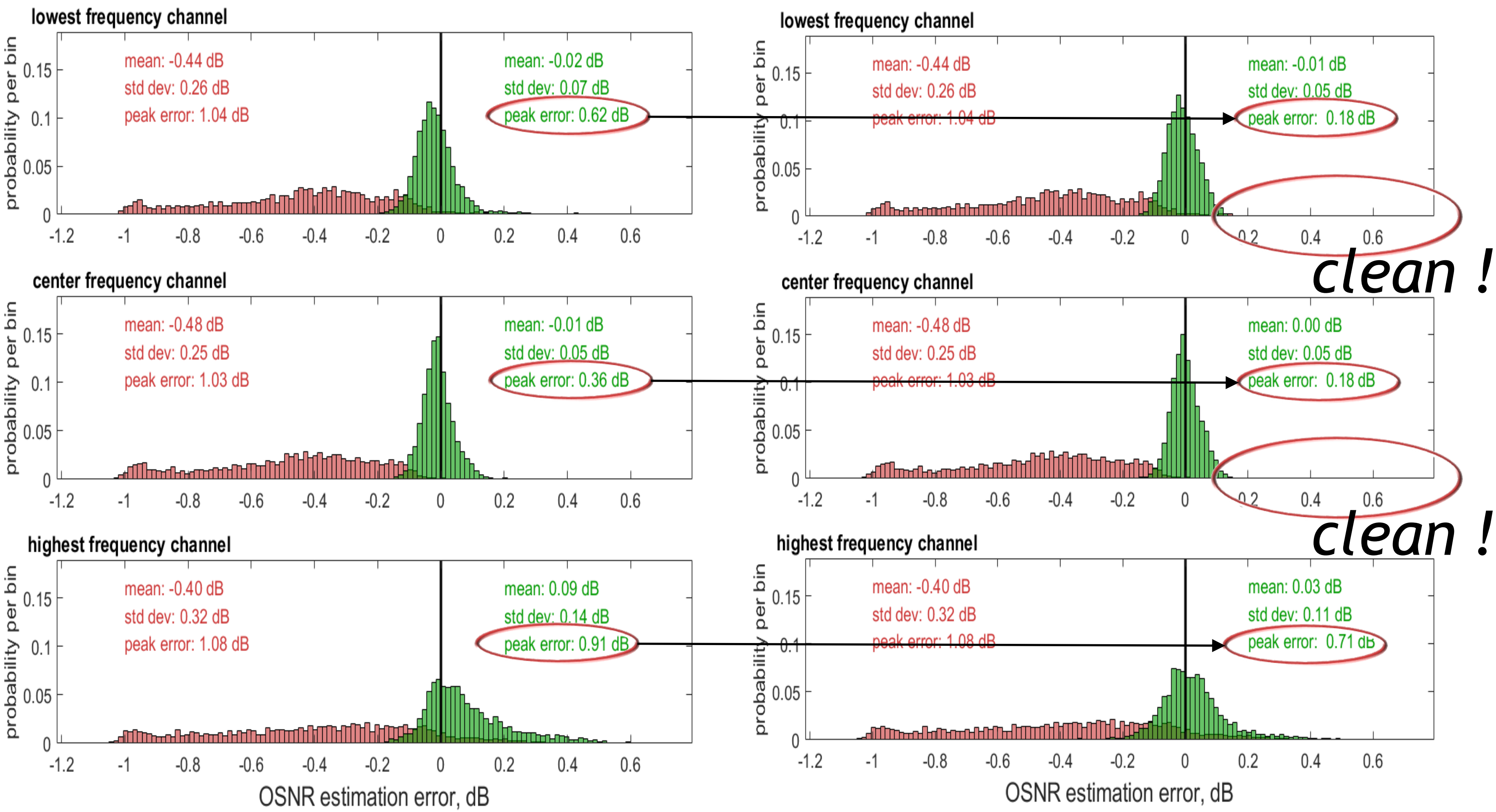
[7] P. Poggiolini, "A Closed-Form GN-Model Non-Linear Interference Coherence Term," arXiv:1906.03883, June 10th 2019.

$$\bar{\beta}_{2,n_{\text{ch}}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[f_{n_{\text{ch}}}^{(n)}+f_{\text{CUT}}-2f_c^{(n)}\right]$$

$$\bar{\beta}_{2,\text{CUT}}^{(n)}=\beta_2^{(n)}+\pi\beta_3^{(n)}\left[2f_{\text{CUT}}-2f_c^{(n)}\right]$$

CC vs. no CC

no coher. term — *with coher. term*

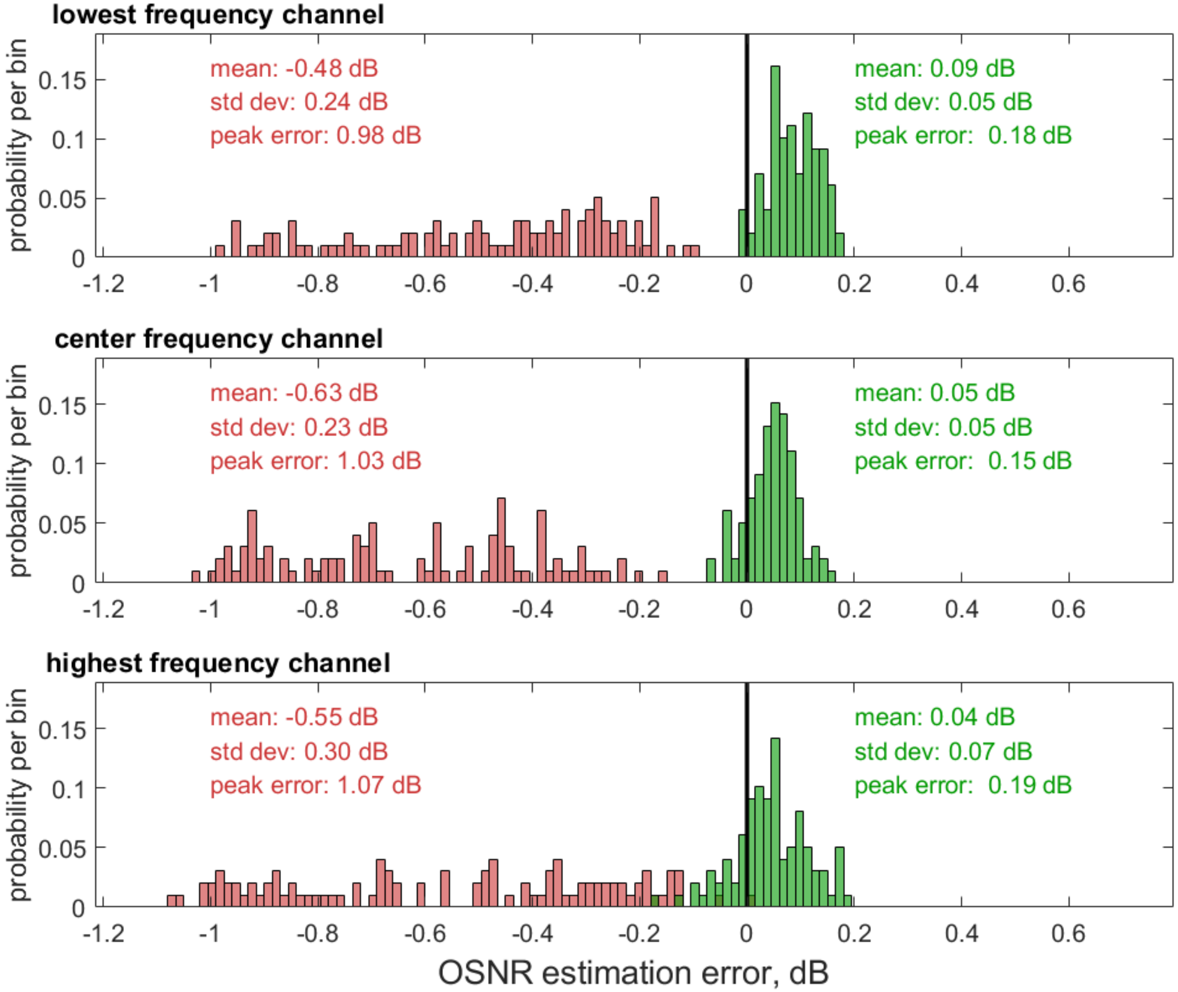


split-step simulation test

- This far, the CFM was compared to EGN
- As a critical double-check, we decided to compare it with **full C-band split-step simulations**
- We used **300** out of the 8500 test cases
  - *(full C-band split-step simulations take substantial CPU time!)*

best CFM vs. split-step

$$\mathrm{OSNR}_{\mathrm{CFM}}^{\mathrm{dB}} - \mathrm{OSNR}_{\mathrm{SIM}}^{\mathrm{dB}}$$



- The results are very similar to those vs. EGN
- **The effectiveness of the CFM is therefore confirmed by simulations as well !**

conclusion

OPTCOM

- We aimed at providing a fully closed-form NLI model (CFM) that could:
  - handle *very <u>general</u> system scenarios*
  - allow <u>*real-time*</u> full-system computation (<< 1s)
  - be as <u>accurate</u> as the *EGN-model*

thank you !

- We generalized some previously available GN-model closed-form approximations
- We then leveraged a very large test-set of 8,500 system scenarios to perform "machine-learning" improvements

- The validation over the large test-set shows that **our CFM is very accurate and reliable and closely matches the EGN model** (as long as D>1)
- We also performed a **successful test of the CFM vs. full C-band simulations**

- The CFM allows **all-channel performance estimation in <5ms**

- We therefore believe <u>***this could be an effective tool***</u> for real-time physical-layer-awareness in the management and control of optical networks

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