



HAL
open science

An Experimental Demonstration of Joint Linear Impairments Compensation in Coherent Optical Systems Using a Parametric Network

Alexandru Frunza, Vincent V. Choqueuse, Pascal Morel, Alexandru Serbanescu, Stéphane Azou

► **To cite this version:**

Alexandru Frunza, Vincent V. Choqueuse, Pascal Morel, Alexandru Serbanescu, Stéphane Azou. An Experimental Demonstration of Joint Linear Impairments Compensation in Coherent Optical Systems Using a Parametric Network. *Journal of Military Technology*, 2022, 5 (2), 10.32754/JMT.2022.2.03 . hal-04145533

HAL Id: hal-04145533

<https://hal.science/hal-04145533>

Submitted on 29 Jun 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

An Experimental Demonstration of Joint Linear Impairments Compensation in Coherent Optical Systems Using a Parametric Network

Alexandru FRUNZĂ, Vincent CHOQUEUSE, Pascal MOREL, Alexandru ȘERBĂNESCU and Stéphane AZOU

Abstract— This paper proposes a parametric network that benefits from the system knowledge and jointly compensates for the transmitter in-phase/quadrature imbalance, carrier frequency offset, and laser phase noise in coherent optical systems. The approach uses an original training technique that increases its experimentally validated effectiveness. For the considered setup, the performance of the network reaches the 3rd Generation Partnership Project threshold of 17.5% Error Vector Magnitude for 4-QAM communications.

Index Terms— Joint compensation, parametric network, coherent optical systems, experimental demonstration.

I. INTRODUCTION

Coherent optical communications are essential in meeting the requirements for high data rate applications [1]. At these data rates, device imperfections and channel effects are key challenges that need to be faced in order to maintain desirable system performance. Different digital signal processing techniques have been proposed to compensate for these imperfections and effects as they have good performances and are more flexible than analog ones [2,3]. These approaches generally benefit from a model knowledge and can provide optimal performances in particular scenarios. Unfortunately, they are sensible of model mismatches and are difficult to adapt to new scenarios. Recently, machine learning and deep learning approaches have proved near-optimal performance in different engineering tasks [4,5]. These techniques are known as data-driven methods that acquire knowledge from the data, with minimal prior assumption about it. However, these techniques require large amount of data to achieve good performance and, in addition,

This work was supported by the Embassy of France in Romania (Institut Français de Roumanie) and the Romanian Ministry of National Defense.

A. FRUNZA is with the Military Technical Academy “Ferdinand I”, C.E.C.T.I. 050141 Bucharest, Romania, and Lab-STICC, UMR CNRS 6285, ENIB, Technopole Brest-Iroise, CS 73862, 29238 Brest Cedex 3, France (e-mail: alexandru.frunza@mta.ro, frunza@enib.fr)

V. CHOQUEUSE is with Lab-STICC, UMR CNRS 6285, ENIB, Technopole Brest-Iroise, CS 73862, 29238 Brest Cedex 3, France (e-mail: vincent.choqueuse@enib.fr).

P. MOREL is with Lab-STICC, UMR CNRS 6285, ENIB, Technopole Brest-Iroise, CS 73862, 29238 Brest Cedex 3, France (e-mail: pascal.morel@enib.fr).

A. ȘERBĂNESCU is with the Military Technical Academy “Ferdinand I”, Department of Communications and Information Technology, 050141 Bucharest, Romania (e-mail: alexandru.serbanescu@mta.ro)

S. AZOU is with Lab-STICC, UMR CNRS 6285, ENIB, Technopole Brest-Iroise, CS 73862, 29238 Brest Cedex 3, France (e-mail: azou@enib.fr).

have difficulties to operate in the presence of time-variant effects. In [6-9], both concepts are combined by inserting the domain knowledge into the network model. By this, the cited works benefit from the advantages of both approaches, while minimizing their drawbacks. In our recent work [10], we proposed a parametric network for global compensation of linear impairments in coherent optical systems. This network benefits from the system knowledge by using some compensation parameters related to the parametric model of the impairments.

In this paper, an experimental demonstration of the parametric network effectiveness is presented. The proposed approach is experimentally validated in a simplified back-to-back optical setup, where a joint compensation of transmitter in-phase/quadrature (IQ) imbalance, carrier frequency offset (CFO), and laser phase noise (PN) is performed.

The paper is organized as follows. First, in section II, the signal model is introduced. Then, in section III, the network architecture is presented. Finally, in section IV, the results are analyzed.

II. SYSTEM MODEL

This work considers a single-polarization coherent optical system like the one depicted in Figure 1. The transmitted signal is upsampled with an upsampling ratio of 4 and pulse shaping filtered using a Root-Raised-Cosine (RRC) filter. Then, the signal undergoes multiple imperfections occurring over the global communication chain. On the receiver side, the signal is once again filtered by an RRC filter, which has also the role of matched filtering and downsampled. Finally, the imperfections impact is compensated for using the proposed parametric network and the data is recovered. The transmitted signal \mathbf{x} is impaired by transmitter IQ imbalance, CFO, laser PN, and noise. Mathematically, the system can be described by a linear equation with respect to real and imaginary parts of the original data:

$$\tilde{\mathbf{y}} = \mathbf{F}(\boldsymbol{\alpha})\tilde{\mathbf{x}} \quad (1)$$

where the tilde denotes the real augmented values of the original data, \mathbf{y} is the received signal before compensation, and $\mathbf{F}(\boldsymbol{\alpha})$ is a real-valued transfer matrix that depends on the unknown vector of parameters $\boldsymbol{\alpha} = [\mu, \nu, f_0, \delta f]$ related to the imperfections. The impact of each imperfection is modeled in the following.

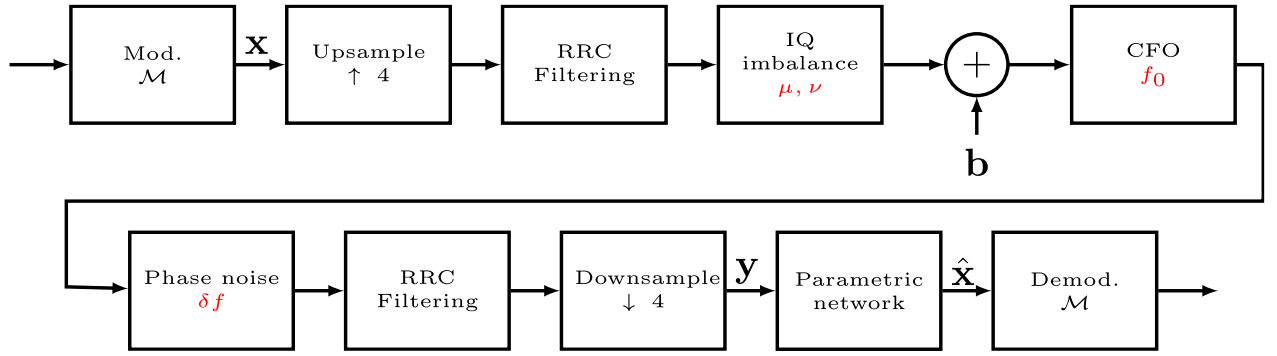


Figure 1- Block diagram of the communication chain

A. Impairments model

Each block corresponding to an impairment from Figure 1 can be modeled by using the generic expression $\mathbf{x}_{\text{out}} = f(\mathbf{x}_{\text{in}})$, where \mathbf{x}_{in} represents the signal at the input of the block, and \mathbf{x}_{out} the impaired signal at the output of it. The function $f(\cdot)$ is a generic function that describes the impairment impact on the input signal.

1) Transmitter IQ Imbalance

Transmitter IQ imbalance is a critical impairment that can degrade communications performance. It can occur on the electrical or optical side of the transmitter because of amplifiers gain differences, unequal split and/or combining ratios of the couplers, phase control shift, or diverse manufacturing problems. Regarding its time-evolution, it can be considered as a quasi-static imperfection. It is characterized by an amplitude imbalance and a phase deviation from the ideal 90° . Its impact can be modeled in an analytical more convenient manner by using the complex parameters μ and ν as follows [11]:

$$x_{\text{out}}[n] = \mu x_{\text{in}}[n] + \nu x_{\text{in}}^*[n]. \quad (2)$$

2) CFO

The CFO is another important impairment that impacts coherent optical communications. It appears because of the frequency difference between the transmitter and receiver lasers and can be assumed quasi-static during a transmission. Its impact can be modeled as follows [12]:

$$x_{\text{out}}[n] = x_{\text{in}}[n]e^{j2\pi n f_0 T_s}, \quad (3)$$

where f_0 is the frequency offset, and T_s the symbol period.

3) Laser PN

Finally, the laser PN is yet another significant impairment that occurs in coherent optical communications. It appears because of the frequency fluctuation of the lasers and is described by the laser linewidth δf . It is a time-variant impairment that can be modeled as Wiener process as follows [13]:

$$\varphi[n] = \sum_{l=-\infty}^n f[l], \quad (4)$$

where $f[l]$ are independent and identically distributed random Gaussian variables with zero mean and variance $\sigma_f^2 = 2\pi\delta f T_s$. The impact of laser PN on a transmitted signal can be expressed as:

$$x_{\text{out}}[n] = x_{\text{in}}[n]e^{j\varphi[n]}. \quad (5)$$

III. PROPOSED NETWORK ARCHITECTURE

A parametric network that exploits the knowledge of impairments parametric model is considered in order to compensate for the impact of imperfections. The network compensates for the impairments by applying the following linear transformation:

$$\hat{\mathbf{x}} = \mathbf{B}(\boldsymbol{\beta})\tilde{\mathbf{y}}, \quad (6)$$

where $\mathbf{B}(\boldsymbol{\beta})$ is the transfer matrix of the parametric network depending on the $\boldsymbol{\beta} = [\beta_1, \beta_2, \beta_3, \beta_4]$ vector parameter that is learned during the training.

A. Compensation Layers

The network architecture is depicted in Figure 2. It can be seen that it is composed of three layers. Similarly, to the impairments' models, each layer corresponds to a compensation operation that can be modeled by using the generic expression $\mathbf{x}_{\text{out}} = r(\mathbf{x}_{\text{in}})$, where \mathbf{x}_{in} represents the signal at the input of the layer, and \mathbf{x}_{out} the compensated signal at the output of it. The function $r(\cdot)$ is a generic function that describes the compensation operation. It is important to note that the order of the compensation layer is reversed compared to the one of the impairments.

1) Laser PN compensation layer

The impact of the laser PN can be mitigated using the real-valued compensation vector parameter β_1 . It can be checked that by setting $\beta_1[n] = -\varphi[n]$, the network can compensate for the impact of the laser PN. Generally, the laser phase has a slower evolution compared to the signal phase, and we can assume it to be constant over K consecutive symbols [14]. Using this assumption, the compensated signal at the output of this layer can be expressed as:

$$x_{\text{out}}[n] = x_{\text{in}}[n]e^{j\beta_1 \lfloor n/K \rfloor}, \quad (7)$$

where $\lfloor \cdot \rfloor$ denotes the integer part. This layer has a single learnable real-valued vector parameter represented by β_1 .

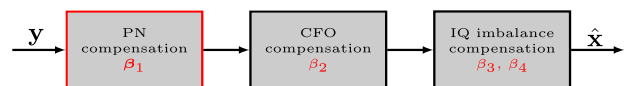


Figure 2 - Parametric network architecture

2) CFO compensation layer

The impact of the CFO can be mitigated using the scalar real-valued parameter β_2 . By setting $\beta_2 = -f_0$ the impact of CFO is completely compensated for. The compensated signal at the output of this layer can be expressed as:

$$x_{out}[n] = x_{in}[n]e^{j2\pi n\beta_2 T_s}, \quad (8)$$

This layer has a single learnable real-valued scalar parameter represented by β_2 .

3) IQ imbalance compensation layer

The IQ imbalance impact can be compensated for by using the complex parameters β_3 and β_4 . The compensated signal at the output of the layer can be expressed as:

$$x_{out}[n] = \beta_3 x_{in}[n] + \beta_4 x_{in}^*[n]. \quad (9)$$

It can be checked that by setting:

$$\beta_3 = \frac{\mu^*}{|\mu|^2 - |\nu|^2}, \quad (10)$$

$$\beta_4 = \frac{-\nu}{|\mu|^2 - |\nu|^2}, \quad (11)$$

the IQ imbalance impact can be fully compensated for. This compensation layer has four learnable real-valued scalar parameters: $\text{Re}\{\beta_3\}$, $\text{Im}\{\beta_3\}$, $\text{Re}\{\beta_4\}$, $\text{Im}\{\beta_4\}$.

B. Network Training and Validation

During the training the network objective is to estimate the unknown parameters β . This is generally done by minimizing the cost between some target data and the output of the network:

$$\hat{\beta} = \underset{\beta}{\text{argmin}} \|\mathbf{x}_{target} - \mathbf{x}_{out}\|^2. \quad (12)$$

To be able to do that we consider a particular target data allocation as can be seen in Figure 3. The frame structure consists of a preamble and multiple pilot symbols inserted periodically into the data blocks. The preamble and pilot symbols are known on the receiver side. Based on this, the training is divided into three steps: a preamble-based training, a pilot-based training, and a self-labeling training that make use of the modulation knowledge.

1) Preamble-based training

This training is performed only once, and during it all the parameters of β are estimated. The target data is represented by transmitted preamble symbols $\tilde{\mathbf{x}}_{target} = \tilde{\mathbf{x}}_0$, while the output of the network is represented by $\tilde{\mathbf{x}}_{out} = \mathbf{B}(\beta)\tilde{\mathbf{y}}$. After this training, the quasi-static parameters related to IQ imbalance and CFO are fixed during the following training stages and testing.

2) Pilot-based training

The pilot-based training is performed for each data block and has the role to estimate the compensation parameters related to the time-variant laser PN. Specifically, during this stage, the network re-updates the β_1 vector parameter. The target data is represented by the transmitted pilot symbols $\tilde{\mathbf{x}}_{target} = \tilde{\mathbf{x}}_1$, while the output of the network is represented by the compensated received pilot symbols $\tilde{\mathbf{x}}_{out} = \mathbf{PB}(\beta)\tilde{\mathbf{y}}$,

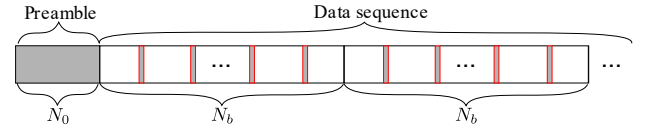


Figure 3 - Data frame structure consisting of preamble and pilot symbols

where \mathbf{P} is an allocation matrix that extracts the pilot symbols on the receiver side.

3) Self-labeling-based training

The final step of the training is also performed for each data block and has the role to perform a finer estimation of the time-variant β_1 parameter. It can be seen as a decision-directed step, where the detected data after the pilot-based training is used as a target $\tilde{\mathbf{x}}_{target} = \tilde{\mathbf{x}}_2$. The output is as in the case of the preamble-based training $\tilde{\mathbf{x}}_{out} = \mathbf{B}(\beta)\tilde{\mathbf{y}}$.

4) Validation

As in our previous work [10], to avoid overfitting during the pilot-based training, the received data is periodically projected on the constellation and the cost function from (11) is computed using $\tilde{\mathbf{x}}_{target} = \tilde{\mathbf{x}}_2$, and $\tilde{\mathbf{x}}_{out} = \mathbf{B}(\beta)\tilde{\mathbf{y}}$. If the values of the cost function stop decreasing with the number of iterations, the training is stopped.

IV. EXPERIMENTAL RESULTS

The experimental setup used is the one depicted in Figure 4 [15]. The setup consists of an Keysight M8195A Arbitrary Waveform Generator that operates at 32 GSa/s and has Digital-to-Analog Converters with 8 bits resolution. To convert the signal into the optical domain the MXIQER-LN-30 optical modulator that has a V_π of 5.4 V and the Keysight N4391A Optical Modulation Analyzer (OMA) local oscillator operating at 1540 nm with a laser linewidth of 100 kHz are used. On the receiver side, the conversion from the optical to the electrical domain is performed using the OMA with the 40 GSa/s analog-to-digital converters at a resolution of 8 bits. An 8 GHz bandwidth signal is transmitted over the back-to-back chain, then is sent to the computer, where it goes through synchronization, compensation, and demodulation. The results are obtained by using 3900 4-QAM symbols. The preamble and data blocks contain 300 symbols. Each data block contains pilots inserted at an interval of 30 symbols. The laser phase noise corresponds to a 100 kHz linewidth, and we consider software IQ imbalance and CFO of (1 dB, 20°) and 200 MHz, respectively. We initialize the IQ imbalance parameters search with the values related to the absence of this impairment ($\beta_3 = 1, \beta_4 = 0$), CFO compensation parameter (β_2) with a random value related to a CFO interval of [187.5, 212.5] MHz, and laser phase compensation parameter (β_1) with 0s for preamble. To be able to track the evolution of the laser phase over the data blocks, we initialize it with the last estimated phase value of the previous block. During the training, we use approximately 3000 iterations for the preamble-based, 400

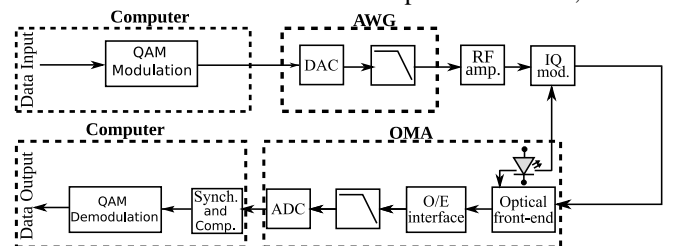


Figure 4 - QAM coherent optical experimental setup. AWG: Arbitrary Waveform Generator, OMA: Optical Modulation Analyzer

for supervised pilots-based, and 100 for self-labeling training. Throughout the self-labeling step, we investigate the influence of the number K of consecutive symbols with an assumed constant phase. A low value of K leads to a better reproduction of the laser phase dynamic, but is more prone to overfitting, and more computationally demanding. In Figure 5, the Error Vector Magnitude (EVM) evolution for different values of K during the self-labeling step can be observed. As we reduce the values of K , the EVM decreases. For the case where $K=2$, the EVM value is 17.5%, reaching the imposed performance by 3rd Generation Partnership Project [16]. However, reducing K increases the computational complexity since it requires estimating more parameters. In Figure 6 (a), the highly impacted constellation after synchronization can be seen. In Figure 6 (b), (c), (d), the symbol constellations for the pilots-based tracking, and self-labeling tracking with $K=300$ and $K=2$ can be seen. The EVM decreases from 21.98% for the pilot-based tracking to 20.34%, and 17.5% for the self-labeling tracking with $K=300$, and $K=2$, respectively. In addition, the EVM penalty introduced by the IQ imbalance and CFO is less than 2% for $K=2$.

V. CONCLUSION

The joint compensation of transmitter IQ imbalance, CFO, and laser phase noise was experimentally demonstrated by

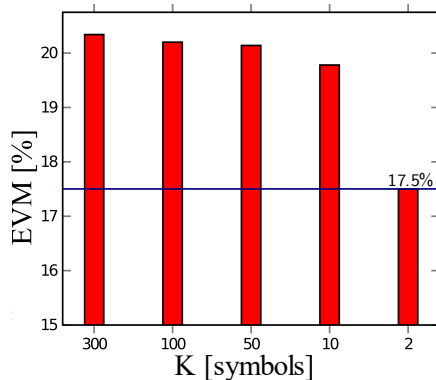


Figure 5 - EVM for the self-labeling tracking for different values of K

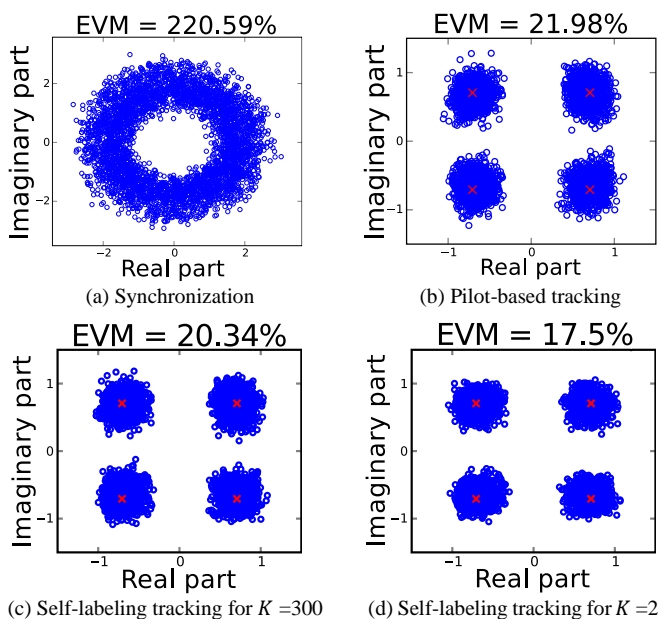


Figure 6 - (a) Constellation after synchronization, (b) Constellation after pilot-based tracking, (c) Constellation after self-labeling tracking for $K=300$, (d) Constellation for self-labeling tracking for $K=2$

using a parametric network. The proposed approach uses a reduced database for training and relies on an original technique to avoid overfitting. The approach proves to be flexible by being able to switch between improved performance and reduced computational complexity. In future work, we propose to extend the experimental research for more complex scenario.

ACKNOWLEDGEMENT

This work would not have been possible without the help of Jacqueline E. Sime, who provided us with the experimental signals for which we are very grateful.

REFERENCES

- [1] E. Agrell, M. Karlsson, A. R. Chraplyvy, D. J. Richardson, P. M. Krummrich, P. Winzer, K. Roberts, J. K. Fischer, S. J. Savory, B. J. Eggleton and others, "Roadmap of optical communications," *Journal of Optics*, vol. 18, p. 063002, 2016.
- [2] E. Ip, A. P. T. Lau, D. J. F. Barros and J. M. Kahn, "Coherent detection in optical fiber systems," *Optics express*, vol. 16, p. 753–791, 2008.
- [3] M. S. Faruk and S. J. Savory, "Digital signal processing for coherent transceivers employing multilevel formats," *Journal of Lightwave Technology*, vol. 35, p. 1125–1141, February 2017.
- [4] F. N. Khan, Q. Fan, C. Lu and A. P. T. Lau, "An optical communication's perspective on machine learning and its applications," *Journal of Lightwave Technology*, vol. 37, p. 493–516, 2019.
- [5] P. J. Freire, V. Neskornuik, and others, "Complex-valued neural network design for mitigation of signal distortions in optical links," *Journal of Lightwave Technology*, vol. 39, p. 1696–1705, 2020.
- [6] N. Shlezinger, J. Whang, Y. C. Eldar and A. G. Dimakis, "Model-based deep learning," *arXiv preprint arXiv:2012.08405*, 2020.
- [7] V. Choqueuse, A. Frunza, S. Azou and P. Morel, "PhyCOM: A Multi-Layer Parametric Network for Joint Linear Impairments Compensation and Symbol Detection," *arXiv preprint arXiv:2203.00266*, 2022.
- [8] G. Revach, N. Shlezinger, T. Locher, X. Ni, R. J. G. van Sloun and Y. C. Eldar, "Unsupervised Learned Kalman Filtering," *30th European Signal Processing Conference (EUSIPCO 2022)*, 2022.
- [9] V. Choqueuse, A. Frunza, A. Belouchrani, S. Azou and P. Morel, "ParamNet: A Multi-Layer Parametric Network for Joint Channel Estimation and Symbol Detection," *30th European Signal Processing Conference (EUSIPCO 2022)*, 2022.
- [10] Frunza, A. V. Choqueuse, P. Morel and S. Azou, "A Parametric Network for the Global Compensation of Physical Layer Linear Impairments in Coherent Optical Communications," *IEEE Open Journal of the Communications Society*, pp. 1-1, 2022.
- [11] A. Tarighat, R. Bagheri and A. H. Sayed, "Compensation schemes and performance analysis of IQ imbalances in OFDM receivers," *IEEE Transactions on Signal Processing*, vol. 53, p. 3257–3268, July 2005.
- [12] C. Xie and G. Raybon, "Digital PLL based frequency offset compensation and carrier phase estimation for 16-QAM coherent optical communication systems," in *European conference and exhibition on optical communication*, 2012.
- [13] Y. Gao, A. P. T. Lau and C. Lu, "Modulation-format-independent carrier phase estimation for square M-QAM systems," *IEEE Photonics Technology Letters*, vol. 25, p. 1073–1076, 2013.
- [14] D. Huang, T.-H. Cheng and C. Yu, "Decision-aided carrier phase estimation with selective averaging for low-cost optical coherent communication," in *2013 9th International Conference on Information, Communications & Signal Processing*, 2013.
- [15] A. Frunzã, J. E. Sime, V. Choqueuse, P. Morel and S. Azou, "Joint Estimation and Compensation of Transmitter IQ Imbalance and Laser Phase Noise in Coherent Optical Systems," in *2021 IEEE Photonics Conference (IPC)*, 2021.
- [16] 3. T. S. 36.104, "Base Station (BS) Radio Transmission and Reception (2018)," (*version 16.0.0*), 2018.