

Joint Estimation of Multiple RF Impairments Using Deep Multi-Task Learning

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Abstract—Radio-frequency (RF) front-end forms a critical part of any radio system, defining its cost as well as communication performance. However, these components frequently exhibit non-ideal behavior, referred to as impairments, due to the imperfections in the manufacturing/design process. Most of the designers rely on simplified closed-form models to estimate these impairments. On the other hand, these models do not holistically or accurately capture the effects of real-world RF front-end components. Recently, machine learning-based algorithms have been proposed to estimate these impairments. However, these algorithms are not capable of estimating multiple RF impairments jointly, which leads to limited estimation accuracy. In this paper, the joint estimation of multiple RF impairments by exploiting the relationship between them is proposed. To do this, a deep multi-task learning-based algorithm is designed. Extensive simulation results reveal that the performance of the proposed joint RF impairments estimation algorithm is superior to the conventional individual estimations in terms of mean-square error. Moreover, the proposed algorithm removes the need of training multiple models for estimating the different impairments.

Index Terms—Deep learning, joint estimation, multi-task learning, multiple RF impairments.

I. INTRODUCTION

The sixth-generation (6G) of mobile communication envisages even more diversity of applications compared to the previous generations. This will result in its application in various domains such as education, entertainment, banking, retails, healthcare, etc. [1]. This necessitates new enablers including higher carrier frequencies, the accompanying larger bandwidths, higher modulation orders, massive multiple-input multiple-output (MIMO) technology, etc. However, these new enablers make the wireless communication systems more sensitive to radio-frequency (RF) impairments [2]. Communication system engineers and researchers should take into consideration the effect of these impairments while designing the next generation wireless systems.

The RF impairments can be studied from various perspectives in wireless systems. For instance, [3]–[5] look at the impairments from a decoding aspect, while [6]–[8] try to utilize the impairments for predistortion, hardware problem identification, and authentication aspect, respectively. In the case of [3]–[5], since the target is to remove the effect of these impairments at the receiver, there is no need to estimate

the individual impairments. This is because the transmitted symbols can be decoded successfully as long as the sum of multiplicative and additive impairments (joint effect of multiple impairments) are estimated and compensated. However, in the latter case where the objective is to use these impairments for predistortion, hardware problem identification, or authentication perspectives, impairments should be estimated individually to have better granularity.

In the literature, many algorithms use the statistical properties of the signals to estimate the RF impairments individually. Some of these model-based algorithms are explained in [9]. Recent literature shows that some of these impairments have non-stationary characteristics. Hence, the aforementioned algorithms may not always be capable of addressing this issue. This effect becomes more pronounced with the aforementioned enablers, such as higher modulation orders and frequencies, envisaged in 6G and beyond communication systems [10]. In view of these challenges, machine learning (ML) and deep learning (DL)-based algorithms have been proposed for more sophisticated RF impairment estimation.

Several algorithms are developed to estimate RF impairments with ML-based algorithms [11]–[16]. Bayesian filtering is used to estimate phase noise [11]. Convolutional neural networks are used to estimate the transmitter in-phase (I) and quadrature (Q) path gain imbalance using raw I/Q data as an input [12], [13]. A reinforcement learning-based algorithm is proposed to estimate the same in [14]. Frequency offset estimation is addressed in [15], [16] where the former provides a neural-network-based solution for MIMO systems, while the latter proposes a DL algorithm for estimating the same in millimeter-wave and terahertz frequencies systems. However, these algorithms estimate the impairments individually and do not utilize the existing relationship between the impairments, which may limit the estimation accuracy if impairments have similar effects on the received signals.

The joint estimation of multiple RF impairments is especially suitable for cases where the different impairments have a joint (additive and/or multiplicative) effect on the signal. However, joint estimation is a complex problem, and it is difficult to have an accurate estimation performance. It is intuitively sound to think of using a DL algorithm to solve complex problems

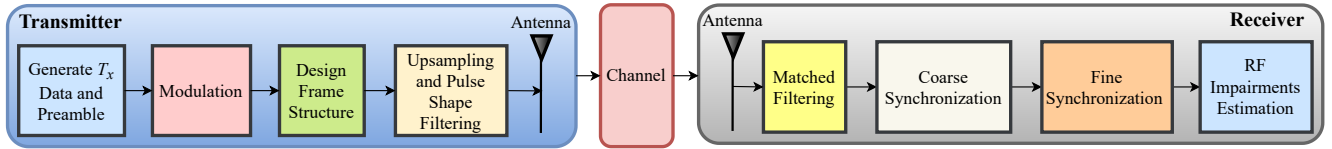


Fig. 1. A block diagram of data transmission in a wireless communication system.

[17]. Especially, DL-based multi-task learning algorithms [18] are capable of addressing complex joint estimation problems since they can utilize the relationship between related tasks through their hidden layers. Along with this line, different from the existing literature, this paper proposes to estimate multiple RF impairments jointly for improving their estimation accuracy by using relationships between different impairments. For this purpose, a DL-based multi-task learning algorithm is designed. Extensive simulation results show a performance improvement achieved by the proposed algorithm compared to DL-based single RF impairment estimation in terms of mean square error (MSE). Furthermore, instead of training a DL model for each impairment, a single DL model is used in the proposed algorithm.

II. SYSTEM MODEL AND PRELIMINARIES

A. System Model

In this paper, single-carrier modulation is considered as in [19]. The system model can be divided into three blocks; transmitter, channel, and receiver. These blocks are illustrated in Fig. 1. In the transmitter, transmitted data T_x and the preambles with M -sequence length are generated. Then, the modulated symbols are designed as the frame structure in Fig. 2. Here note that the cyclic prefix (CP) is used to avoid inter-symbol interference and provide circular convolution. Afterward, the signal is upsampled and filtered, and send through the channel. In the channel, the frequency selective channel with additive white Gaussian noise (AWGN) distorts the transmitted signal. In the receiver, the matched filter is used to maximize the signal-to-noise ratio (SNR) and the coarse synchronization is performed to find the starting point of the frame. Then, fine synchronization is performed and RF impairments are estimated.

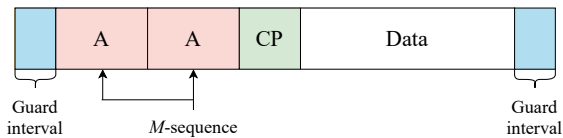


Fig. 2. Illustration of the designed frame.

B. The RF Impairments

Communication systems suffer from a wide variety of impairments. Some of these impairments (their parameters); I/Q gain imbalance (I_g/Q_g), quadrature offset (ψ), phase noise (ϕ), and I/Q offset (I_o/Q_o); are estimated in this paper. These impairments are briefly explained below, and their effects

are illustrated in Fig. 3 with their components [20], [21]. In this figure, parameters of the RF impairments are selected as follows; $I_g = 1.3$, $Q_g = 0.8$, $\psi = 0.9$, $\phi = \pi/3$, $I_o = 0.21$, and $Q_o = -0.15$.

1) *I/Q gain imbalance*: It causes the in-phase component of the signal (I) to be smaller than the quadrature component of the signal (Q), or vice versa. This results in an imbalanced change in the original constellation. The imbalance of I/Q gain can be measured as $(I_g/Q_g - 1) \times 100$ in percent.

2) *Quadrature offset*: It causes due to the phase offset in the sine and cosine signal generation. This distorts the orthogonality between I/Q branches so that the degree between the branches is not 90° . The signal with quadrature offset is modeled as

$$x_{qo}(t) = \cos(2\pi f_c t) I_g \Re\{x(n)\} + \sin(2\pi f_c t + \psi) Q_g \Im\{x(n)\}, \quad (1)$$

where f_c and $x(t)$ denote the carrier frequency and modulated time-domain signal after DAC and band-pass filter processes, respectively. \Re and \Im represent real and imaginary part of the data, respectively. Also, t and n represent the time and sample, respectively.

3) *Phase noise*: It is caused by the spectrum spread at the desired spectrum of a practical local oscillator. It is assumed that the phase noise is constant over the data so that the effect of the phase noise is only the phase rotation of the symbols. This can be described as

$$x_{pn}(t) = x_{qo}(t) e^{j\phi}, \quad (2)$$

where ϕ denotes the phase rotation.

4) *I/Q offset*: It is essentially caused by the mixers and direct current signals. The effect is a shift in the constellation. The signal with I/Q offset is modeled as

$$x_{iqo}(t) = x_{pn}(t) + I_o + jQ_o, \quad (3)$$

where I_o and Q_o denote the offsets for the I and Q components.

When all of the aforementioned impairments are added to the transmitted signal, the modulated symbols are seen as the constellation plot in Fig. 3. As seen from this figure, when the effect of impairments is mixed, the constellation diagram becomes more distorted, which makes the estimation problem complex and difficult.

After the signal with all these impairments passes through the wireless channel, the baseband received time-domain signal can be defined as

$$r(n) = \kappa(n)x(n) + \zeta(n) + w(n), \quad (4)$$

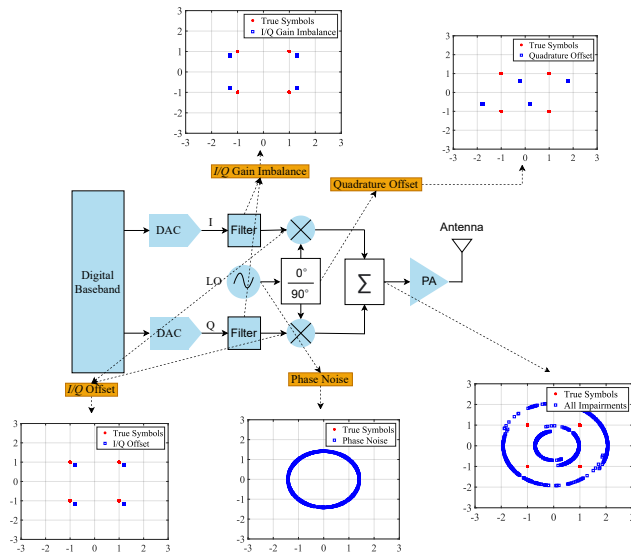


Fig. 3. Typical transceiver chain with various sources of RF impairments.

where $\kappa(n)$, $\zeta(n)$, and $w(n)$ denote the multiplicative impairments, the additive impairments, respectively and the complex Gaussian sample with the distribution of $\mathcal{CN}(0, \sigma_N^2)$. Here, the channel is considered as frequency selective, and the maximum excess delay is smaller than the CP duration.

C. Deep Learning

There is a wide variety of successful ML algorithms applications in diverse areas ranging from image and speech processing to pattern recognition. This success motivated their applicability to the area of wireless communication [22]. These algorithms are expected to become an indispensable part of 6G and beyond wireless communication systems.

Amongst ML algorithms, DL-based algorithms have become popular since the usage of multiple hidden layers of DL algorithms enables to magnify the intrinsic distinctive data features while suppressing the irrelevant information at each layer [23]. This is especially the case for complex problems where multiple problems are tried to estimate jointly and the system becomes a black box [24]. Therefore, these algorithms are suitable candidates for complex problems. Also, in these algorithms, raw data can be used without specific feature engineering/crafting thanks to the aforementioned added benefits of the deep architectures.

III. JOINT RF IMPAIRMENTS ESTIMATION

A. The Proposed Algorithm

The RF front-end components cause multiplicative and additive impairments in the communication systems, as described in (4). In this model, if only one RF impairment is considered in the system, the estimation with the classical algorithms can be performed optimally. However, multiple RF impairments are considered as a practical scenario in the system model, as shown in Fig. 3. Therefore, the accurate estimation of the impairments caused by the individual components becomes a challenging problem with classical estimation algorithms. For

instance, let's assume that the phase noise and I/Q offset exist in (4), then the received signal considering the AWGN channel can be written as

$$r(n) = x(n)e^{j\phi} + I_o + jQ_o + w(n). \quad (5)$$

This equation shows that when the estimation of the phase offset is made from $r(n)$, the accuracy of the estimation does not only depend on the noise but both noise and I/Q impairment. Moreover, when the number of RF components causing an impairment increases, the problem becomes kind of a black box, and accurate estimation of individual impairment becomes unfeasible with the classical algorithms.

DL-based algorithms are highly preferred in black box problems. Still, in DL, optimization is made based on a certain metric, whether this is a score on a particular benchmark or a business key performance indicator. For this optimization, a single model or an ensemble of models are generally trained to perform the desired task. While an acceptable performance is generally achieved in this way, by being laser-focused on a single task, trying to find optimum solutions simultaneously for different tasks may increase the performance of the original task. In other words, our model can estimate the original problem better, by sharing representations between related tasks.

Multi-task learning is well-suited to estimate multiple impairments since it can leverage useful information contained in multiple related tasks to improve the individual estimates [25]. This is especially the case where it is used with several hidden layers (DL-based multi-task learning algorithm). In view of these discussions, the usage of a DL-based multi-task learning algorithm is proposed in this paper to estimate multiple RF impairments jointly.

The proposed algorithm based on DL-based multi-task learning operates in two stages. First, the proposed algorithm is performed in the training stage, where the dataset is generated, and a DL algorithm is configured and trained. Afterward, it is performed in the testing stage where multiple RF impairments are estimated simultaneously.

In the training stage, T_x signals are transmitted via a wireless communication channel. Then, R_x is captured at the receiver based on the system model explained in Section II. Afterward, various impairments, such as I/Q gain imbalance, quadrature offset, phase noise, and I/Q offset or their parameters are estimated by conventional algorithms (model or ML-based algorithms). Then, these estimated values are stored as output in vector format. Note that the training output dataset can be also obtained by a computer or test equipment. Correspondingly, the received signals, where these values are obtained, are stored as the input. These processes are repeated until enough amount of dataset is generated. The size of the dataset is determined according to the system requirements as it is optimum in terms of system performance, complexity, and memory. Then, the DL algorithm is trained with the created dataset. Note that all hyperparameters of the DL algorithm are tuned empirically by considering the performance and generalization capability of the proposed algorithm. These

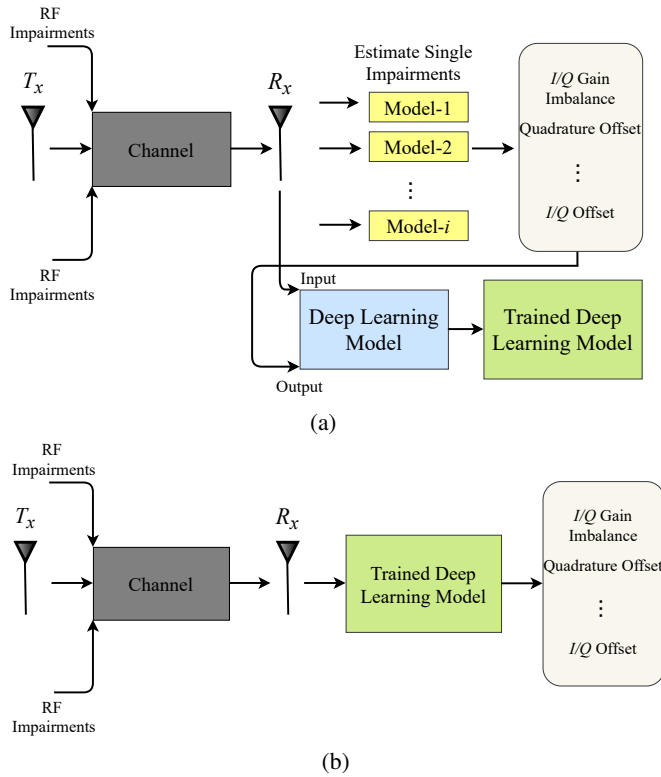


Fig. 4. The proposed algorithm for RF impairments estimation; (a) training and (b) testing stages.

processes are illustrated in Fig. 4 (a). Also, an example of the DL-based multi task learning algorithm is illustrated in Fig. 5. Once the training and validation loss convergence is done in the training stage, the testing stage starts, which characterizes the run-time operation of the algorithm.

In the testing stage, a signal, which is distorted by the wireless channel and RF impairments, is captured in the receiver. Then, this distorted signal is fed to the trained DL algorithm. Afterward, the trained DL algorithm estimates the multiple RF impairments. These processes are illustrated in

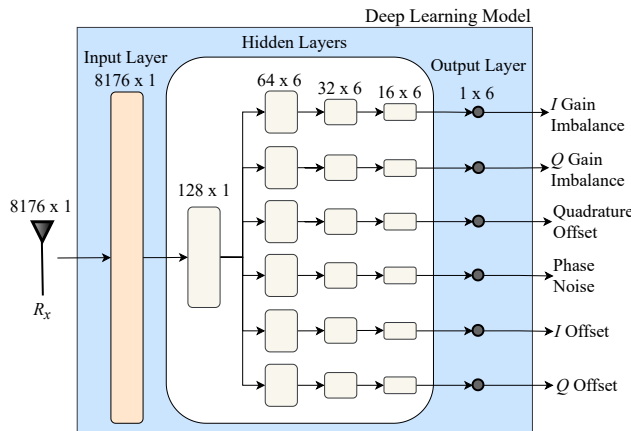


Fig. 5. A DL-based multi-task learning algorithm for joint RF impairments estimation.

Algorithm 1 Estimating multiple impairments with a single model.

Input: S number of training received signals (R_{xtrain}), N number of validating received signals ($R_{xvalidation}$), initial hyperparameters, conventional algorithms to estimate single-RF impairments, and testing received signals (R_{xtest}).

Output: Estimated RF impairments (E_{test}).

Training Stage:

- 1: **for** $s = 1$ **to** S **do**
- 2: Receive R_{xtrain} .
- 3: Conventional algorithms estimate each RF impairments (E_{train}).
- 4: A new data point R_{xtrain} and E_{train} is added to the training dataset (D).
- 5: **end for**
- 6: Train the DL algorithm using D .
- 7: **while** the training and validation loss graphs are converged **do**
- 8: Change the hyperparameters of the DL algorithm.
- 9: Train the DL algorithm using D .
- 10: **end while**

Testing Stage:

- 11: Receive R_{xtest} .
- 12: Estimate multiple RF impairments E_{test} using R_{xtest} and trained DL algorithm.

Fig. 4 (b). Overall processes of the proposed algorithm can be found in Algorithm 1.

B. A Note on Computational Complexity

Training and testing stages determine the computational complexity of the proposed algorithm. The complexity of the training stage is based on both the model-based estimations and the DL algorithm, while the testing stage complexity solely depends on the DL algorithm.

A DL-based multi-task learning algorithm is used in this work with an input layer, four hidden layers, and an output layer. This algorithm has a units in the input layer, where a represents the size of the input vector. Also, it has b hidden units for joint learning. Besides that it has c , d , and e hidden units and f output units for each impairment. Therefore, the overall training computational complexity of this algorithm is $\mathcal{O}(ml \times (ab + 6(bc) + 6(cd) + 6(de) + 6(ef)))$, where m and l represents number of epochs and training examples, respectively. Also, the computational complexity of the validation and the number of trials to select optimum hyperparameters of the DL algorithm can be added to the training complexity. Note that, number of trials and validation data depends on the complexity and reliability requirements of the application. The per-sample computational complexity of testing is around half that of the training stage since the testing stage does not need back-propagation [26].

IV. SIMULATION RESULTS

A. Parameter Settings

Dataset is generated by MATLAB simulation environment depending on the setup explained in Section II. In this setup, all transmitter parameters such as modulation type, roll of factor of root-raised-cosine (RRC) filter, data length, etc., are assumed to be known by the receiver. Detailed specifications of the simulation parameters are listed in Table I. In these simulations, only I/Q gain imbalance, quadrature offset, phase noise, and I/Q offset impairments are estimated. The values of these parameters and other imperfections added to the system are given in Table II. These parameters are randomly selected between the given values for each sample. Here note that it is possible to estimate any kind of impairment in the system, without changing the architecture, by training the network according to newly added impairment.

The dataset is split into three sets; training, validation, and testing. In the training stage, 30000 samples are used. Here note that, in the training stage, SNR is varied from 0 to 20 with a step size of 5. In other words, 6000 samples are used for each SNR value. Also, it is assumed that the true values of the impairments are known by the receiver in the training stage for the sake of simplicity. In the validation and testing stages, 10000 samples are used for each SNR value.

The conventional and the proposed DL algorithms for RF impairments estimation are implemented by Keras [27], an open-source ML library under the Python environment. All of the algorithms were trained and tested on an MSI computer with an Intel® Core™ i7-7700HQ central processing unit (CPU) @ 2.80 GHz CPU, GeForce GTX 1050 Ti graphics processing unit (GPU), 16 GB RAM, and Windows 10 operating system.

B. Hyperparameters of the Deep Learning Algorithms

An input layer, four hidden layers (fully connected layers), and an output layer are used in the proposed algorithm. Particularly, 8176 units are used in the input layer. Then, joint learning of the impairments is made in the first hidden layer with 128 units to learn the relationship between the impairments. Afterward, three hidden layers are used to learn characteristics of each impairments. In these layers, 64, 32, and 16 units are used, respectively. Lastly, all of the impairments are estimated in the output layer with a unit per impairment. In all of these layers, the rectified linear unit is used as an activation function. In total, 1090214 parameters are used in the proposed DL algorithm and the DL algorithm is trained with a batch size of 16 and 40 epochs. ADAM [28] is used for adaptive learning rate optimization and the optimum learning rate in this algorithm was found at 0.00001.

For the conventional algorithm, six different DL algorithms are implemented. In these algorithms, an input layer, four hidden layers, and an output layer are used. In the input layer 8176 units, in the hidden layers, 128, 64, 32, and 16 hidden units are used, while a unit is used in the output layer. In total, 1057537 parameters are used for each impairment estimation

TABLE I
SIMULATION PARAMETERS.

Parameter	Value
Number of symbol blocks	10
Number of symbols in each block	64
Cyclic prefix ratio compared to block size	1/4
Oversampling rate	4
Sampling frequency (sample/second)	4×10^6
M -sequence length	$2^9 - 1$
Modulation order	QPSK
Guard interval	245
Filter type	RRC
Roll of Factor	0.3

TABLE II
RF IMPAIRMENTS PARAMETERS.

Impairment	Range
Channel model	Rayleigh channel
Noise	AWGN
I/Q gain imbalance	0 to 1.5
Quadrature offset	-1 to 1
Phase noise	0 to $\pi/2$
I/Q offset	-0.5 to 0.5

(each DL algorithm). Other all hyperparameters are the same as the proposed algorithm.

C. Performance Evaluation

The performance of the conventional algorithm (*Single Estimation*), where each DL algorithm estimates one impairment at a time, and the proposed algorithm (*Joint Estimation*), where the DL algorithm estimates all impairments jointly, is compared in Fig. 6. These analyses are made by comparing the MSE of the estimations. Here note that for the sake of simplicity, estimation of the corresponding parameters of each impairment is compared to evaluate the performance of the algorithms. Fig. 6 demonstrates that

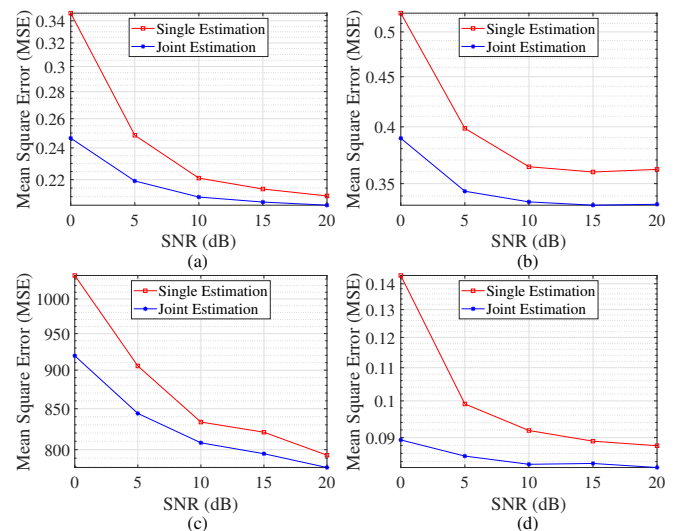


Fig. 6. MSE results for (a) I/Q gain imbalance estimation, (b) quadrature offset estimation, (c) phase noise estimation, and (d) I/Q offset estimation.

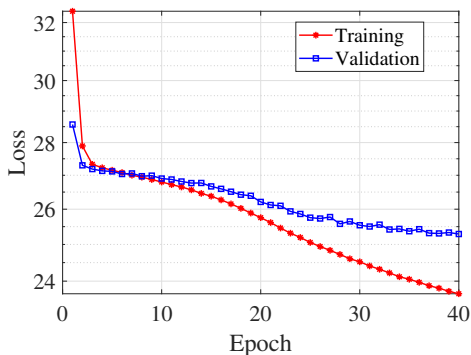


Fig. 7. The loss graph of the DL algorithm.

the performance of the proposed algorithm is superior to the conventional algorithm. This is consistently true for all impairments (I/Q gain imbalance, I/Q offset, quadrature offset, and phase noise) and SNR values.

As the proposed algorithm is based on DL, it is crucial to ensure that the developed algorithm is generalized well [29], i.e., the inputs are not memorized during the training stage. In order to observe this, the training and validation losses versus epochs for joint RF impairments estimation problem is presented in Fig. 7. This figure demonstrates that the training sets converges to the validation set. This means there is no overfitting during the training which demonstrates the ability to work with unforeseen data for the proposed algorithm.

V. CONCLUSIONS

This paper proposed the joint estimation of multiple RF impairments to exploit the relationship between them. For this purpose, a DL-based multi-task learning algorithm was designed. This algorithm estimated the RF impairments of I/Q gain imbalance, I/Q offset, quadrature offset, and phase noise with a single model. Thus, there was no need to train multiple models to estimate different impairments. Simulation results were shown that estimating multiple-RF impairments jointly improves the estimation accuracy, as tested over a realistic scenario. As future work, the DL-based joint RF impairments estimation will be investigated from the perspectives of predistortion, hardware problem identification, and physical layer authentication. Also, the performance of the proposed algorithm will be evaluated in the real-world environment.

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REFERENCES

- [1] C. De Alwis et al., "Survey on 6G frontiers: Trends, applications, requirements, technologies and future research," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 836–886, 2021.
- [2] M. Valkama, "RF impairment compensation for future radio systems," *Multi-Mode/Multi-Band RF Transceivers Wireless Commun.: Advanced Tech. Arch. Trends*, p. 453, 2011.
- [3] E. A. Fernández et al., "Machine learning techniques to mitigate nonlinear phase noise in moderate baud rate optical communication systems," in *Intelligent Syst. Comput.* IntechOpen, 2019.
- [4] O. Hilburn and T. R. B. Tim, "DeepSig: Deep learning for wireless communications," *Nvidia Blog*, 2018.
- [5] S. Sygletos, A. Redyuk, and O. Sidelnikov, "Nonlinearity compensation techniques using machine learning," in *Signal Process. Photon. Commun.* Optical Society of America, 2019, pp. SpT2E–2.
- [6] P. Jaraut, M. Rawat, and F. M. Ghannouchi, "Composite neural network digital predistortion model for joint mitigation of crosstalk, I/Q imbalance, nonlinearity in MIMO transmitters," *IEEE Trans. Microw. Theory Techn.*, vol. 66, no. 11, pp. 5011–5020, 2018.
- [7] G. C. Tripathi and M. Rawat, "Characterization of hardware impairments in software defined radio," in *Proc. Int. Conf. Electrical, Electronics Comput. Eng. (UPCON)*. IEEE, 2019, pp. 1–4.
- [8] L. Y. Paul, J. S. Baras, and B. M. Sadler, "Physical-layer authentication," *IEEE Trans. Inf. Forensics Sec.*, vol. 3, no. 1, pp. 38–51, 2008.
- [9] A. Mohammadian and C. Tellambura, "RF impairments in wireless transceivers: Phase noise, CFO, and IQ imbalance-A survey," *IEEE Access*, vol. 9, pp. 111 718–111 791, 2021.
- [10] M. Giordani et al., "Toward 6G networks: Use cases and technologies," *IEEE Commun. Mag.*, vol. 58, no. 3, pp. 55–61, 2020.
- [11] D. Zibar et al., "Application of machine learning techniques for amplitude and phase noise characterization," *J. Lightw. Technol.*, vol. 33, no. 7, pp. 1333–1343, 2015.
- [12] L. J. Wong, W. C. Headley, and A. J. Michaels, "Estimation of transmitter I/Q imbalance using convolutional neural networks," in *Proc. IEEE 8th Annual Comput. Commun. Wksh. Conf. (CCWC)*. IEEE, 2018, pp. 948–955.
- [13] —, "Specific emitter identification using convolutional neural network-based IQ imbalance estimators," *IEEE Access*, vol. 7, pp. 33 544–33 555, 2019.
- [14] H. Park, J. Jee, and G. Kwon, "I/Q method and system for estimating I/Q imbalance parameter of transceiver based on reinforcement learning," Jul. 2019, Korean Patent, KR102027674B1.
- [15] M. Zhou, X. Huang, Z. Feng, and Y. Liu, "Coarse frequency offset estimation in MIMO systems using neural networks: A solution with higher compatibility," *IEEE Access*, vol. 7, pp. 121 565–121 573, 2019.
- [16] R. M. Dreifuerst et al., "Deep learning-based carrier frequency offset estimation with one-bit ADCs," in *Proc. IEEE 21st Int. Wksh. Signal Process. Advances Wireless Commun. (SPAWC)*. IEEE, 2020, pp. 1–5.
- [17] M. M. Najafabadi et al., "Deep learning applications and challenges in big data analytics," *J. Big Data*, vol. 2, no. 1, pp. 1–21, 2015.
- [18] R. Caruana, "Multitask learning," *Machine learning*, vol. 28, no. 1, pp. 41–75, 1997.
- [19] F. Pancaldi et al., "Single-carrier frequency domain equalization," *IEEE Signal Process. Mag.*, vol. 25, no. 5, pp. 37–56, 2008.
- [20] H. Arslan, "RF impairments," *Wireless Communication Signals: A Laboratory-based Approach*, 2021.
- [21] —, "Analysis of single-carrier communication systems," *Wireless Communication Signals: A Laboratory-based Approach*, 2021.
- [22] C. Jiang et al., "Machine learning paradigms for next-generation wireless networks," *IEEE Wireless Commun.*, vol. 24, no. 2, pp. 98–105, 2016.
- [23] Y. Le Cun et al., "Handwritten digit recognition with a back-propagation network," in *Proc. Advances in Neural Information Process. Systems (NIPS)*, 1990, pp. 396–404.
- [24] M. A. Aygül, A. Naeem, and H. Arslan, "Blind signal analysis," *Wireless Communication Signals: A Laboratory-based Approach*, pp. 355–381, 2021.
- [25] Y. Zhang and Q. Yang, "A survey on multi-task learning," *arXiv preprint arXiv:1707.08114*, 2017.
- [26] K. He and J. Sun, "Convolutional neural networks at constrained time cost," in *Proc. IEEE Conf. Comput. Vision Pattern Recognition (CVPR)*, 2015, pp. 5353–5360.
- [27] F. Chollet, "Keras," <https://keras.io>, accessed: 2021-09-10.
- [28] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.
- [29] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, <http://www.deeplearningbook.org>.