Learning-Driven Decision Mechanisms in Physical Layer: Facts, Challenges, and Remedies

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Abstract—Future communication systems must include extensive capabilities as they will embrace a vast diversity of devices and applications. Conventional physical layer decision mechanisms may not meet these requirements due to the frequent use of impracticable and oversimplifying assumptions that lead to a trade-off between complexity and efficiency. By utilizing past experiences, learning-driven designs are promising solutions to present a resilient decision mechanism and provide a quick response even under exceptional circumstances. The corresponding design solutions should evolve following the learning-driven paradigms that offer increased autonomy and robustness. This evolution must take place by considering the facts of real-world systems without restraining assumptions. This paper introduces the common assumptions in the physical layer to highlight their discrepancies with practical systems. As a solution, learning algorithms are examined by considering implementation steps and challenges. Additionally, these issues are discussed through algorithms are examined by considering implementation steps and challenges. Additionally, these issues are discussed through an analysis of deep-learning in 5G with challenges and applications. Differently, in this paper, we reveal an impending contradiction of learning solutions, as for classical counterparts, due to their fallacious system representations.

I. INTRODUCTION

TOWARDS the sixth-generation (6G) networks, flexible and ubiquitous connectivity is expected, even under extraordinary conditions that introduce strict physical layer (PHY) requirements. Various technologies are envisioned with these goals, and the heterogeneity of the application areas constitutes more characteristic deployments. These deployments require reassessments of solutions in each decision step at the transmitter and receiver, as summarized in Fig. 1.

The key point to obtain the optimal solution in PHY is structuring the problem in a linear model by assuming the system is minimum variated and unbiased. Simplifying assumptions – as listed in Table I – seem reasonable and effortless to examine the systems that are challenging to model theoretically. Analytical methods, such as maximum a posteriori (MAP) and maximum likelihood (ML), are employed by determining hypotheses and assuming prior probabilities. However, these hypotheses and the corresponding probability distributions may not accurately model realistic systems. For example, time variations or the channel correlations may not be accurately tracked, and the related assumptions become invalid. Moreover, the inconsistencies in practice make it difficult to detect proper decision thresholds for the likelihood-based hypothesis tests. These limitations arising from the assumptions can be overcome with solutions that are flexible and more compatible with the factual circumstances.

In the last decade, learning-driven approaches are considered as the leading candidates to provide the ambitious goals of next-generation communication systems. For example, providing competent systems capable of making joint decisions with instantly responsive designs by eliminating the need for human intervention or utilizing big data stacks in PHY motivate several studies. However, they neglect a major motivation. The learning algorithms can provide a solution based on real systems’ attributes without any simplifying assumptions, but some of these assumptions are invalid in real systems. Additionally, the learning algorithms in these studies are largely trained and tested via simulation-based datasets. All of these facts sidetrack presented learning solutions, as for classical counterparts, due to their fallacious system representations.

Yet, the following question needs to be answered: Why should we include learning algorithms in wireless communication systems? The studies [3–5] respond to the question by analyzing the deep-learning in 5G with challenges and applications. Differently, in this paper, we reveal an impending issue in PHY by proposing a changeover from the assumption-based to a learning-driven system. For this purpose, we clarify the principal methodology to determine the correct learning
### Table I: An overview of the simplifying assumptions and challenging facts in PHY.

| Technical Aspects | Issues                                                                 | Assumptions                                                                                                                                                                                                 | Facts                                                                                                                                 |
|-------------------|------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| **Synchronization** | *Initial Acquisition*                                                  | - Prior probabilities and pre-determined threshold are always valid for hypothesis tests.                                                                                                                   | - False alarm can occur when there is no reference signal.                                                                         |
|                   | *Carrier Phase*                                                        | - No ISI.                                                                                                                                                                                                    | - ISI can be realized in practice: ISI suppression should be added to approximate the assumption.                                   |
|                   | 
|                   | *Carrier Frequency Offset*                                              | - The carrier phase is constant or does not change significantly.                                                                                                                                           | - The carrier phase can change in time.                                                                                                                                                        |
|                   | *Timing Offset*                                                         | - No ISI.                                                                                                                                                                                                    | - ISI generally exists.                                                                                                                                                                       |
|                   | 
| **Channel Estimation Errors** | *Quantization Errors*                                                   | - The optimum threshold to quantize is known.                                                                                                                                                                 | - The threshold can change depending on the environmental conditions.                                                              |
|                   | *Interpolation Errors*                                                  | - Perfect knowledge of signal autocorrelation and noise variance is available (then Wiener interpolator is optimal).                                                                                      | - Quantization noise may have different statistical characteristics due to its time-varying nature.                                 |
| **Erroneous Feedback Information** | *Feedback Noise*                                                        | - Reverse (feedback) channel is noise-free.                                                                                                                                                                 | - Excellent knowledge about the signal and noise is not attainable.                                                               |
|                   | *Feedback Errors*                                                      | - Feedback channel is not bandwidth limited.                                                                                                                                                                 | - The equalizer may be unstable.                                                                                                                                                                |
|                   | 
| **RF Front-end Impairments** | *RI Imbalance*                                                          | - No imbalance between I and Q.                                                                                                                                                                           | - The channel coefficients can be correlated in time, frequency, and space.                                                       |
|                   | *Feedback Delays*                                                      | - There are no feedback delays.                                                                                                                                                                            | - The channel coefficients can be correlated in time, frequency, and space.                                                       |
|                   | *IQ Imbalance*                                                         | - IQ imbalance leads to performance degradation due to phase rotations and signal distortions.                                                                                                               |                                                                                                                                                                                                 |
|                   | *Phase Noise*                                                          | - No frequency deviation at the output of the RF oscillator.                                                                                                                                                 |                                                                                                                                                                                                 |
|                   | *Non-linearities*                                                      | - The electronic units work ideally.                                                                                                                                                                        |                                                                                                                                                                                                 |
| **Correlation**    | *Time Correlation*                                                     | - Information sources are statistically stationary, wide-sense stationary, ergodic, or cyclostationary random processes.                                                                                      | - The stationarity conditions can not always exist practically.                                                                    |
|                   | *Spatial Correlation*                                                  | - The position of the transmitter and the receiver do not change.                                                                                                                                           | - The channel characteristics can vary because of the external factors and mobility but show intrinsic relationships.             |
|                   | *Frequency Correlation*                                                | - The frequency correlation of the channel is related to the power delay profile.                                                                                                                             | - Each channel varies instantaneously.                                                                                                                                                          |
|                   |                                                                       | - The scattering is not always wide-sense stationary and uncorrelated.                                                                                                                                      | - User channels may not be statistically independent.                                                                                                                                          |
|                   |                                                                       | - The current scenarios include the high mobility and the ones will be in 3D.                                                                                                                               | - The current scenarios include the high mobility and the ones will be in 3D.                                                                                                                  |

Approach and challenges to implement learning methods in PHY. Our main contributions are listed below:

- We explain the fundamental assumptions of classical solutions that conflict with realistic scenarios (Section II).
- We address a remedy towards tight operational requirements of 6G by considering the PHY constraints and the competent algorithms’ requirements, besides their superiority (Section V).

#### II. Common Assumptions of Theoretical Implications

The system design assumptions benefit from the advantages of simplicity, such as effortlessness to achieve an understandable formulation, perceptibility, and interpretability. They allow us to discover the proposed system’s theoretical bounds and give rise to diversify sub-optimal methods by compromising on the inferior necessities. However, modeling mismatches due to these assumptions distract solutions from the intrinsic system. The current wireless communication systems are widely modeled under oversimplifying assumptions, listed in Table I as detailed below.

#### A. Synchronization

Synchronization is necessary to perform accurate transmission by unifying the transmitter and receiver processes. Various studies assume that the transmitter and receiver are perfectly synchronized during communications. However, a residual synchronization error may remain in time and frequency due to the factual circumstances. Contrary to idealized systems, the real-world systems must include more qualifications due to the radio frequency (RF) front-end impairments, mobility, variety of channel conditions, and delays. They can include several processes to reach a better synchronization, such as initial time synchronization between the transmitter and receiver, a robust lock mechanism, the estimation of carrier frequency offset (CFO) and timing offset (TO), algorithms for adaptable redundancy insert, and synchronization recovery.

Estimation plays a critical role in reaching tenable synchronization. Theoretically optimal data-assisted methods are presented, including the hypothesis test for the initial acquisition, ML-based estimation algorithms for CFO, TO, and phase offset. Furthermore, the majority of sub-optimal methods comprise moderately or based on the availability of the ideal channel state information (CSI) [6]. Additionally,
practice, propagation delay is generally unknown, intersymbol interference (ISI) or interchannel interference (ICI) may occur, and RF impairments may exist. Learning algorithms must be integrated to meet all synchronization requirements, not individually for CFO, TO, or ISI estimation.

B. Estimation Errors

Accurate channel estimation is critical to realize signal processing steps in PHY. The channel can be identified by correlation, ML, MAP, or least-squares based estimators. These methods hinge on several assumptions, as listed in Table 1 that are not always feasible from practical aspects. The acquisition of ideal CSI is not always available contrary to the common conjecture. For example, conventional systems assume that ADCs have infinite resolution, and there is no quantization error. On the other hand, the channel conditions in future networks will change rapidly, and channel estimation errors must be eliminated for a superior performance. Therefore, real-world impairments must be considered, and the solutions should be evaluated in terms of versatility. Learning-driven solutions do not outperform the optimal solution when ideal CSI exists. However, they can provide solutions concomitantly to the environmental changes instead of impracticable assumptions. The study in [9] evinces this by comparing learning-driven algorithms with classical Euclidean distance-based methods with a real-time dataset, including channel imperfections.

C. Erroneous Feedback Information

Feedback information is the primary requirement to coordinate the transmitter and receiver. It increases the overall performance. However, it is mostly erroneous by virtue of over-optimistic assumptions, as summarized in Table 1. The feedback information obtained via the forward link may not ideally represent the reverse link since they are not available simultaneously. Conversely, it must include all variations to ideally adjust the processes, such as antenna selection or beamforming. Consequently, the erroneous and delayed feedback information leads to a decrease in overall system performance. Learning algorithms can be applied to tolerate the performance loss.

D. RF Front-end Impairments

RF front-end impairments are apparent differences between real-world systems and simulated systems, and they are inevitable. Cost constraints and the fact that RF incompatibilities are hardware-based make them difficult to handle. Learning-driven evasion or check mechanisms can be developed by utilizing the learning ability from hybrid data sources. Here, we addressed three main issues with respect to the assumptions in Table 1 that significantly affect overall system performance.

1) In-phase/quadrature-phase (IQ) Imbalance: IQ imbalance is the mismatch of the amplitude and/or phase between in-phase (I) and quadrature-phase (Q) components. It stems from low-cost devices and causes a performance degradation; therefore, it must be considered in real systems. IQ imbalance restraints the systems by sensitizing towards other impairments such as CFO. Estimation algorithms to compensate IQ imbalance based on least mean squares, ML, expectation-maximization, or iterations exist, but they introduce extra computation.

2) Phase Noise: The phase noise in the oscillator results from the active circuit elements and makes frequency adjustments difficult. These fluctuations result in common phase error (CPE) and ICI. The real systems have to include a suppression process for ICI and an estimation algorithm for CPE mitigation.

3) Non-linearities: Non-linearities are realized by ADC/DAC, mixers, and amplifiers (the power amplifier in the transmitter and the low-noise amplifier in the receiver). The main part of the non-linearities in PHY is caused by power amplifiers. They are mostly ignored due to the difficulties of theoretically modeling.

E. Correlation

Formulation of correlation is not straightforward due to its uncertainty. Making assumptions may cause a fallacious representation of the correlation properties, leading to an inaccurate model. Furthermore, describing correlation can require continuous pattern tracing in time, frequency, or spatial domains, which introduces additional processes and increases complexity. For example, auto-correlation of information sequence in time and frequency domains or cross-correlations between different channels introduce the requirement of new computational blocks in the transmitter and receiver. Despite these drawbacks, correlation is essential to achieve the next generation’s target qualifications: capability for quick actions, reliability, and spectral efficiency; because the possible solutions of these requirements should not make the systems elaborate and unmanageable. Heuristic learning ability of the learning algorithms can provide simplicity by tracking the correlation, as demonstrated via measurements results in [9].

III. BEYOND SIMPLIFYING ASSUMPTIONS

Wireless communication environments dynamically change. These variations have stochastic patterns that make the system suitable for learning-driven solutions. Until today, the analytical methods are mostly preferred. They utilize the stochastic models to define a pattern by generalizing the statistical features. In the presence of correct and sufficient apriori information, stochastic models match real systems. Under this idealized scenario, optimal methods provide the best performance. On the other hand, this knowledge is not always available or may not be accurate. Therefore, they are mostly based on assumptions, as mentioned in Section 1. PHY decision mechanisms need for the reassessment towards the future to get advantages of learning-driven solutions. All changes – as demonstrated in Fig 2 – corroborate the idea that employing learning algorithms for PHY problems can overcome these limitations. This section points out the main milestones and challenges to get the inference about learning-driven solutions.
A. A Roadmap for Learning-Driven Solutions

Learning algorithms from shallow to deep architectures have been advancing to comprehend the system facts. However, it is unclear how an algorithm should be sifted out from several algorithms for a solution and which steps should be considered primarily. The following roadmap, as visualized in Fig. 2, can be used to develop solutions for next-generation systems.

1) Examine the data source and know your data: Learning algorithms do not magically provide answers to any system; they must be fed with suitable data to acquire the desired output. It can be accomplished by understanding the problem and its source. The input/output data ranges should also be carefully observed, and their relations should be considered. In communication systems, the input data may typify the received signal, whereas the output data may refer to the transmitted signal. If only data based on transmitted and received signals are provided, the performance may not be sufficiently high. The reason for that the output data is formed with many factors during the transmission due to real-life impairments, as summarized in Fig. 2. Then, the input data should include more information to obtain the correct output.

2) Determine the main expectations of the proposed learning-driven model: This step has a direct impact on learning-driven solution design. Performance targets such as accuracy, interpretability, scalability, training and prediction duration are determined depending on the proposed system. Some learning models, mostly based on deep learning, are not obvious in terms of model transparency and functionality. However, interpretability and low-latency of the solution are indispensable, especially for mission-critical systems. Such learning models may not be suitable in PHY, despite their accuracy. Besides the interpretability, the scalability of the models is highly crucial because wireless communication devices and their capabilities diversify widely. On the other hand, transfer learning that means reusing a fitted model as a baseline for new model development is a powerful candidate to defeat system bottlenecks.

3) Be aware of the system bottlenecks: The system constraints are critical for selecting the proper machine learning algorithm. They affect the solution’s performance considerably by delimiting the training process, the model quality, in other words. System bottlenecks vary depending on the present system; computational complexity and hardware capability.

4) Detect the solution’s major requirements: This milestone refers to the quantity of data and the quality of the model. Wireless communication environments have various destructive effects on the actual data information, and this makes data acquisition vital. On the other hand, the desired amount of data can not be provided instantly, and the model might be underfitted. Additional steps, such as transfer learning, feature selection and extraction, can be added to improve the model
of new features can be realized with linear and non-linear transformation methods such as principal component analysis, linear discriminant analysis, and autoencoder.

3) Computational complexity: A learning process consists of two main stages: model training and prediction. Both bring a computational complexity to the system. The complexities of these processes vary due to several factors such as the selected learning algorithm and the parameter values for the model architecture’s tuning and design. In the recent years, deep learning techniques have shown tremendous successes in broad application areas, and the trade-off between choosing less complex algorithms and attaining a higher accuracy is observed. The training complexity is overcome by the transfer learning, and the prediction complexity can be reduced with computational offloading or collaborative techniques.

4) Hardware capabilities: Learning algorithms require hardware competence for data pre-processing, model training and testing. The utilization of advanced methods such as deep or ensemble learning techniques requires large quantities of the following resources: processing power, physical size, cost, and memory. The hardware should include sufficient memory to store variables, dataset, and the trained model besides computational power. At this point, the implementation of learning algorithms on computationally constrained devices becomes a complicated problem, especially in PHY. For example, many edge Internet of things devices in the industry are insufficient to realize the training process or store the data set. Cloud platforms are a possible solution to store data, build models, or control the devices remotely. However, cloud-based solutions entail sturdy communication between the user and the cloud. This introduces another load in communication systems.

IV. SOFTWARE-DEFINED RADIO BASED CASE STUDY

We aim to show the capabilities of learning algorithms on real systems without theoretical approaches’ common assumptions through a case study. Antenna selection problem is tackled for different ADC/DAC resolutions with a test-bed design. Measurements are taken from a 4x1 multiple-input-single-output (MISO) test-bed, which is constructed using SDR units. Antenna selection is performed at the transmitter with the goal of reducing the bit error rate (BER). This test-bed aims to highlight the following implementation challenges. Firstly, a real system must overcome the front-end impairments of RF transceivers to sustain the efficacy (such as IQ imbalance distortions or phase noise) [12]. Secondly, the increase in antennas’ number brings new difficulties [13]. For instance, obtaining perfect CSI is not possible at the transmitter. Thirdly, multiple antennas require an increased number of RF chains, ADC/DAC, and larger volatile memory. Fourthly, the rise in the number of converters leads to the emergence of enormous data stacks in IQ planes, and the management of this data is another challenge. They can be minimized by reducing the bit-resolution of the conversion, but then quantization errors must be considered. The trade-off between the converter resolution and quantization errors is the final challenge. The measurement-based performance results allow us to observe the composite impact of these challenges in the BER results.
The dataset is prepared via the test-bed demonstrated in Fig. 3(a). It is designed with five SDR units, USRP-2943Rs at the transmitter and receiver. Each one is used with two RF chains. To provide hardware synchronization: reference clock is generated and shared via all USRP-2943Rs by using CDA-2990 8 channel clock distribution accessory. The transmitter’s operating frequency and bandwidth are tuned as 2.45 GHz and 1 MHz. As a single-carrier modulation method, BPSK is used, with a root-raised cosine filter of roll-off factor 0.5. The distance between the transmitter and the receiver is set to 1.5 meters. 32 symbols are used for the acquisition, and the data/pilot rate is selected as 5/1 at an IQ rate of 125 ksample/s. CSI feedback is obtained via time-division duplex feedback.

The proposed issue is defined as a classification problem. Three machine learning and deep learning methods are chosen: DTREE, MLP, CNN. The selection of algorithms is realized by considering the system constraints and expectations from learning models. The DTREE’s depth, MLP’s hidden layer number, and neurons at one layer are set as 15, 2, 10, respectively. As a deep learning algorithm, 1D-CNN is chosen to present a fair comparison. The CNN architecture is designed with a one-dimensional convolution layer (256 filters) and two fully-connected layers (128 and 6 neurons, respectively). The batch size of CNN and MLP is selected as 1024. Training is performed by utilizing the categorical-cross entropy loss function and adaptive moment estimation function with the hyperparameter settings in [14].

The performances of DTREE, CNN, and MLP are compared with the conventional detector based on ML in terms of the BER measurements. Least-square-based channel estimation is performed in ML along with Moose’s algorithm adopted to a single carrier as described in [15]. A comparative illustration of their capabilities against the aforementioned practical challenges is shown in Fig. 3. The algorithms are trained with an offline learning mechanism by performing the same analysis for the different training data sizes. When the data size becomes larger, the learning algorithms achieve a higher performance than the conventional method because of two reasons. The first reason is that numerous data samples carry the pervasive pattern of the system and represent conceivably. The second reason is the ability of heuristic learning. Moreover, these results prove the importance of data quantity and the performance flexibility of learning algorithms. Even though the necessary increase in data amount is not remarkable to reach a higher performance in this study, note that the required data amount depending on the problem can change to provide a desired leap of performance.

We can see that CNN outperforms the other methods when the conventional method generally shows a lower performance for each signal-to-noise ratio (SNR) and converter resolution. MLP and DTREE provide moderate performance compared to CNN and the conventional method. However, if the computational limitations are considered, their performances are substantially preferable. Furthermore, DTREE, after rising steeply, surpasses CNN and MLP in the case of the 16-bit converter at a high SNR. Even if it offers a simpler structure, it does not provide the capability to capture non-linear relationships between data. Therefore, its performance is closer to ML detector than neural network based algorithms. The decrease in the converters’ resolution leads to an explicit increment in BER, as shown in Figs. 3(b) and 3(c). BER differences increase, especially in high SNR. Although 16-bit ADC/DAC utilization is reasonable to sustain the reliability, this means two times IQ data, memory space, and complexity according to the number of antennas. The enormous data stacks in the IQ plane can be reduced by including feature extraction. The results show that feature extraction is a favorable process to defeat the hardware constraints in PHY and take advantage of the reliability besides boosting the learning algorithms’ performance.

V. A GLIMPSE OF FUTURE REMEDIES: A LAYER-FREE VIEW

The presented SDR-based case study substantiates that the assumptions in Section II and the challenges in Section III will become more crucial depending on the utilization
platform of learning algorithms. One reason is that wireless communication systems include time-sensitive data, and some of them are vulnerable to latency. Another reason is privacy, so systems must be sturdy against security attacks. Therefore, the inference engine generation and the operating place are highly critical, depending on the position of data storage and processing. The platform of learning can be categorized into three groups hinge on the closeness to the user equipment: on-device learning, edge learning, cloud learning.

Massive and diverse data availability and a capability for dense computation based DNNs make cloud learning more desirable to increase learning algorithms’ decision performance. However, the vast data transmissions from the end-user to the cloud lead to backhaul and transmission delays, a high traffic, bandwidth occupation, and a significant overhead to avoid security attacks. These limitations impel learning at the center of the data source. On-device learning is more suitable for time and security sensitive data and a preferable option against disconnections. Although on-device learning allows the development of unique devices depending on the environment, it is not applicable for all systems due to power consumption, thermal issues, memory, and computational constraints. An interim remedy is the utilization of edge devices. Next-generation designs must simultaneously employ all of them to take advantage of machine learning through all layers of wireless communication systems. The edge or end-user devices’ learning models can be updated in short periods based on their special ambients, and they infer quick responses during instantaneous cases. By considering the absence of big data, these models must be harmonized with other models in the cloud. The consolidated cloud models should be transplanted in the long term for coherence with other systems.

VI. CONCLUSION

This article presents a comprehensive overview of the wireless communication systems’ prominent conjectures in PHY and how they may introduce modeling errors in real-world systems. From this aspect, learning algorithms are addressed with an elucidating guideline to defeat their classical counterparts and eliminate the need for oversimplifying and impractical assumptions. Additionally, the challenges to employ learning-driven solutions in PHY are presented for a holistic view. The listed considerations are supported by a real-time SDR-based case study. Finally, a collectively remedial perspective of the mentioned challenges and opportunities is suggested for future research.

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