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A Waveform Parameter Assignment Framework for 6G With the Role of Machine Learning

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ABSTRACT 5G enables a wide variety of wireless communications applications and use cases. There are different requirements associated with the applications, use cases, channel structure, network and user. To meet all of the requirements, several new configurable parameters are defined in 5G New Radio (NR). It is possible that 6G will have even higher number of configurable parameters based on new potential conditions. In line with this trend, configurable waveform parameters are also varied and this variation will increase in 6G considering the potential future necessities. In this paper, association of users and possible configurable waveform parameters in a cell is discussed for 6G communication systems. An assignment framework of configurable waveform parameters with different types of resource allocation optimization mechanisms is proposed. Most of all, the role and usage of machine learning (ML) in this framework is described. A case study with a simulation based dataset generation methodology is also presented.

INDEX TERMS 6G, beyond 5G, machine learning, multiple numerologies, OFDM, radio resource management, scheduling, waveform.

I. INTRODUCTION

The number of configurable parameters at a transmission point (TP) is increasing with every new generation of cellular communications. There are 500, 1000, and 1500 configurable parameters in 2G, 3G, and 4G TPs, respectively [1]. In line with this trend, it is evident that 5G and 6G nodes will have an even higher number of configurable parameters. The reason for this rise includes more use cases, diverse channel structures, complex and heterogeneous networks, different user-cell association capabilities, and the other possible requirements. A flexible structure is constituted with a rich set of parameter options to simultaneously meet different requirements in 5G New Radio (NR) [2]. Compared to 5G NR, 6G will need to meet more requirements [3]–[6] with a very large number of configurable parameters. There are three main use cases in 5G NR – enhanced mobile broadband (eMBB), ultra reliable low latency communications (uRLLC), and massive machine type communications (mMTC). For 6G, possible use cases are exemplified in Table 1. The necessity of new use cases shows

TABLE 1. Possible Use Cases for 6G

Work	Possible Use Cases
[3]	• eMBB Plus • Big communications (BigCom) • Secure uRLLC (SuRLLC) • Three-dimensional integrated communications (3D-InteCom) • Unconventional data communications (UCDC)
[4]	• Reliable eMBB • Mobile broadband RLLC (MBRLLC) • Massive URLLC (mURLLC) • Human-centric services (HCS) • Multi-purpose services (MPS)
[5]	• Further eMBB (FeMBB) • Extremely RLLC (ERLLC) • Ultra mMTC (umMTC) • Long-distance and high-mobility communications (LDHMC) • Extremely low-power communications (ELPC)
[6]	• Ubiquitous mobile ultrabroadband (uMUB) • Ultrahigh-speed-with-low-latency communications (uHSLLC) • Ultrahigh data density (uHDD)

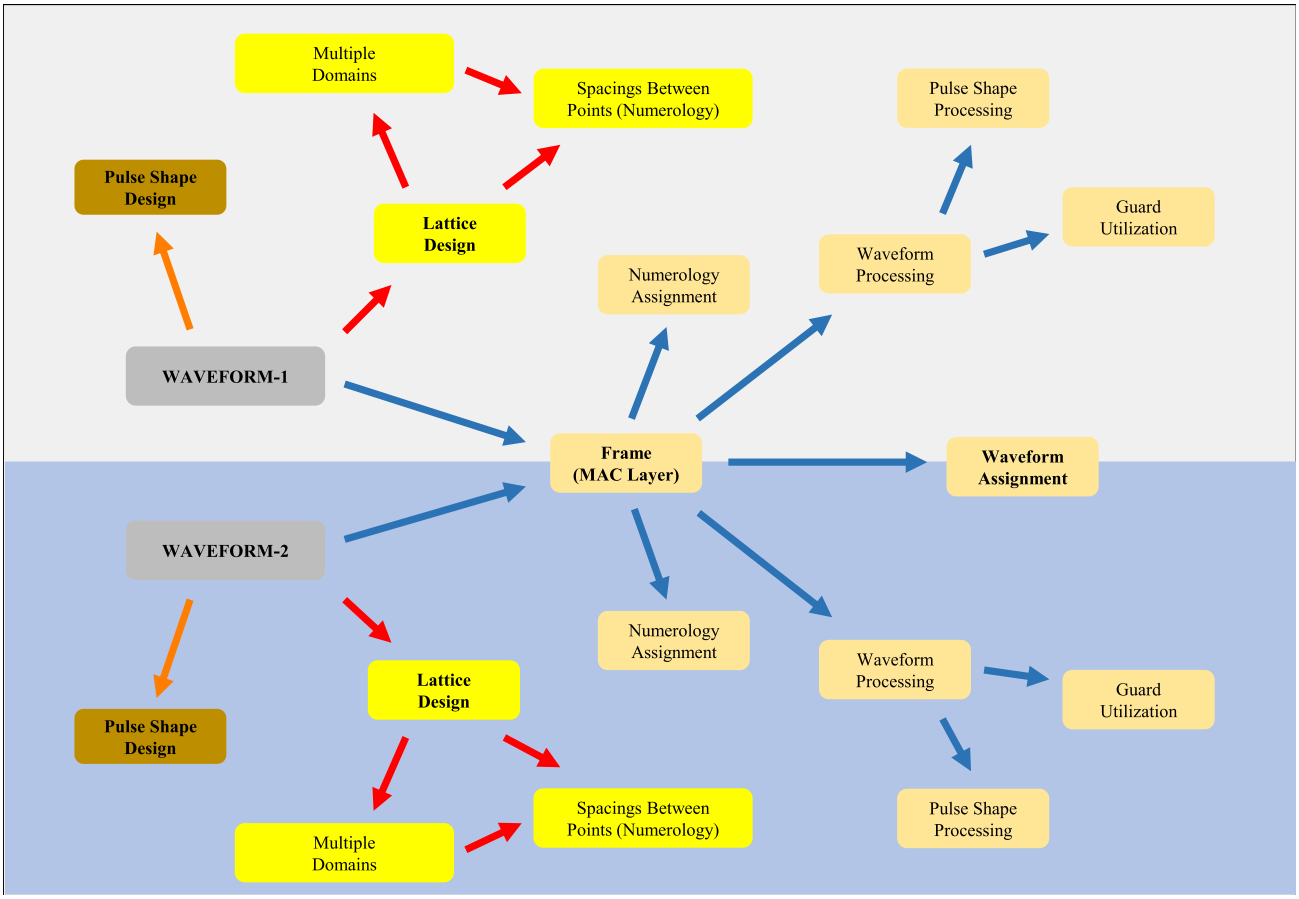


FIGURE 1. **The main parts of a waveform design. It is assumed that there can be more than one waveform in the same frame.**

that there will be new application requirements in 6G. Therefore, more parameter options should be utilized to meet the future application requirements of the next generation cellular communications systems.

For the future prediction of the number of configurable parameters, the co-existence of different standards such as Wi-Fi and 6G systems should also be taken into account [7]. Similarly, radar sensing and 6G communications may complement each other in the future [8]. Different standards constitute a very large set of requirements and configurable parameters together under the leadership of 6G.

Waveform is one of the core components of the physical layer (PHY) design. Generally, the waveform is designed considering the whole communications system. The other components are designed considering the chosen waveform in standards. Basically, waveform is a physical signal that contains information. Data bits are mapped to the physical signal through a proper waveform. Also, additional symbols (e.g., redundancy, preconditioning like precoding and guard utilization, noise, etc.) are the parts of the physical signal. These signals occupy physical resources (like bandwidth, time, space, code, power, etc.) in multi-dimensional hyperspace. Fig. 1 shows the main components of a waveform design including lattice structure, pulse shape and frame structure. Lattice structure is a multi-dimensional resource mapping and each point show a location of one resource element [9]. The possible spacings between lattice points are defined by numerology structures for a waveform. Pulse shape (also known as filter) gives the main characteristic to a waveform by deciding how to transmit the symbols on lattice points [9]. Frame structure can be defined as a packaging (formation) of multiple user information because waveform is the process of generating the collective pysical signal corresponding to multiple users (and/or multiple information data) that occupies the hyperspace. Waveform designs employ various parameters under these main components.

Numerology includes a set of parameters for a specific lattice structure of a waveform and 5G NR is standardized based on multiple numerologies of cyclic prefix orthogonal frequency division multiplexing (CP-OFDM) on the time-frequency plane. For 5G NR, subcarrier spacing, CP duration, inter-numerology guard band, roll-off factor, filter coefficients, slot duration, the number of symbols in one slot, the number of slots per subframe, and frame length can be given as waveform parameters. However, more parameters can be included if different types of waveform processing methods are employed.

Apparently, the number of configurable parameters and numerologies for a single waveform may increase with 6G [10]. There may be more parameter variety than the 5G

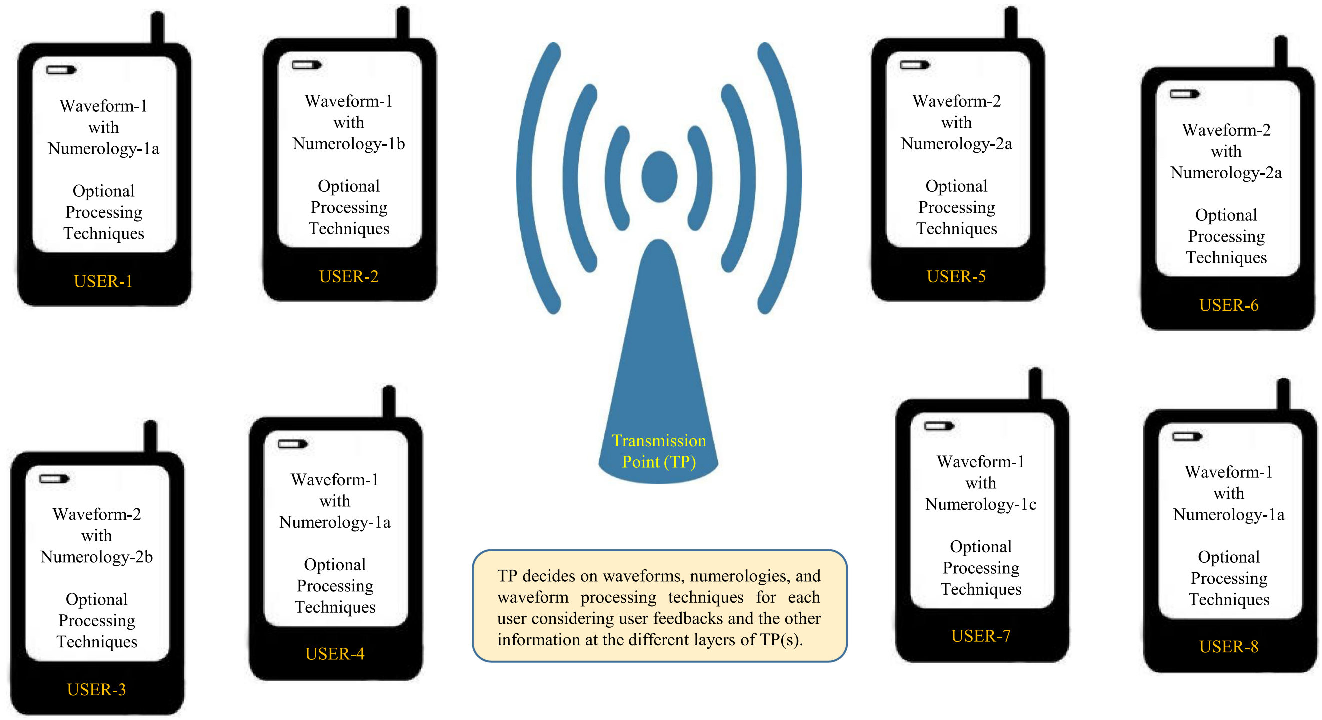


FIGURE 2. **Different parameter assignments for each user in the same coverage area. It is assumed that coexistence of multiple waveforms in the same frame is also possible with multiple numerologies and additional waveform processing techniques.**

numerologies (e.g., flexibility in subcarrier spacings) [11]. Different lattice domains can be exploited with or without time-frequency. These domains provide new types of numerology parameters (e.g., beamwidth parameter for space domain). Hence, variety of numerology parameters increases. In the future generations, also different types of CP structures can be employed along with multiple numerologies [12]. Moreover, CP parameter can take more values independent from the subcarrier spacing. There can be different waveform processing methods in 6G, so these methods can bring new parameter types. Parametrization of new techniques will increase the number of waveform parameters. Additionally, multiple waveforms may be utilized together in the same frame for the next generation of wireless communications standards [13]. For example, it is possible to use different waveforms together for beyond 52.6 GHz [14]. Coexistence of various standards may also trigger the designs of multiple waveforms in a frame. Different waveforms can have specific numerologies with several types of parameters. Therefore, there will be considerable amount of waveform parameters in 6G and options will exponentially increase with the number of waveform types. An example usage of multiple waveforms and numerologies with some processing techniques is illustrated in Fig. 2. There is a necessity of configurable parameter richness to meet the potential future requirements of 6G networks flexibly. All of the potential waveform parameters are important because they will define the flexibility in 6G.

The assignment of waveform parameters for each user is done at TP considering user feedbacks and the other information acquired in different layers. However, multiplexing waveforms with different parameterization may give rise to several penalties that include new forms of interferences, such as inter-numerology interference (INI) and inter-waveform interference (IWI), scheduling complexity, and signaling overhead [15]. As a consequence, various optimization mechanisms are developed in the literature to compensate or exploit the adverse effects (e.g., INI) of utilizing multiple waveform parameters in 5G and beyond. Example resource allocation optimization techniques are proposed in [11] and [16]. Waveform parameter assignment will be a more difficult task in 6G because of the increasing number of configurable parameters and requirements. From the optimization perspective, providing a flexible structure with a high number of controllable waveform parameters can not always be the best solution for users that have several requirements in a coverage area of one TP. A balance should exist between the constructive and destructive impacts of employing different types of waveform parameters together [11]. Furthermore, more difficult scenarios can be realized, such as waveform parameter assignment in coordinated multiple TPs with multiple users. Joint parameter assignment for all users in different cells is not an easy problem. Hence, next generation TPs require powerful waveform parameter assignment mechanisms with proper optimizations so that an efficient resource allocation is ensured in 6G cellular systems.

Waveform parameter assignment from a large number of parameter options for each user and the resource allocation optimization requirements considering all users (in a single

TP or multiple TPs) are two critical challenges. Different solutions can be provided for these problems with traditional methods or new technologies such as machine learning (ML). In ML, learning process is carried out by using data and the system does not need to be explicitly programmed. It provides promising results for different wireless communications research areas as exemplified in [17]–[20]. If there is a large number of parameter options, dilemma, or trade-off, ML based solutions can be helpful because ML can establish useful and unnoticeable relationships without heuristic engineering design and theoretical analysis. Designing a classical method sometimes is not an easy task in practice for a problem that requires to establish relationships considering a large number of parameter options. The importance of ML lies in the process of obtaining the classical model based solutions faster than before. It may be helpful to use ML and conventional methods together in complex scenarios with heterogeneous structures.

The motivation of this paper can be summarized as follows:

1) Requirement variety is increasing over the years and 6G will have more requirements than 5G NR [3]–[6].
2) More flexible structures are needed since the requirement variety is increasing. The number of configurable parameters also increase to bring more flexibility for the cellular communications.
3) Waveform parameter assignment is an important topic for 5G NR. However, it will be more important problem in 6G because there will be more optimization necessities with tremendous configurable parameters.
4) The role of ML cannot be ignored for the waveform parameter assignment topic, especially for 6G. ML can establish useful and unnoticeable relationships in this domain. Also it is possible to obtain fast significant solutions when ML methods are preferred.

The use of ML for 5G is discusses in several studies. For example, artificial neural networks are investigated in [20] to be employed for solving various problems with unmanned aerial vehicles (UAV)-based wireless networks, wireless virtual reality (VR), mobile edge caching and computing, coexistence of multiple radio access technologies (RAT), and Internet of Things (IoT). In [20], resource allocation and management problems are given for specific applications of UAV networks [21], [22], VR concept [23], [24] and multi-RAT systems [25]. Several ML-based scheduling mechanisms are utilized for resource allocation and management [26], interference management [27] and dynamic multichannel access [28]. However, existing 5G resource allocation and management works that employ ML are not focused on waveform parameter assignment and optimization.

A discussion on the ML-enabled methodologies for 6G networks and the possible new challenges of ML in 6G are presented in [29]. One of the new challenges is transformation of the "network softwarization" to "network intelligentization". Moreover, "intelligent PHY layer" for 6G will include self-learning and self-optimization capabilities [29]. 6G networks will employ ML to optimize and automate many operations [30]. ML will play a more important role during the standardization of 6G [3]. In 5G, ML can have a supporting role, however, it will be a leading role for ML in 6G. If 5G is called as "connected things," 6G can be called as "connected intelligence" [29]. A number of existing works has studied 6G and they are summarized in Section II. To the best of the authors' knowledge, this is the first study that focuses on the waveform parameter assignment and optimization for 6G.

In this paper, importance of waveform parameter assignment issue is emphasized and a general assignment framework with optimizations for this issue is proposed for 6G cellular communications. Moreover, the role and usage of ML based techniques are discussed in terms of waveform parameter assignment with proper optimizations. Possible 6G challenges are discussed. Then, a case study with ML is presented as an example system to show the role of ML.

Contributions of this paper can be itemized as:

1) Possible waveform parameters are investigated from the 6G perspective in comparison to 5G.
2) Several subproblems are defined related with the waveform parameter assignment and optimization.
3) A general framework is constituted for waveform parameter assignment problems.
4) The role of ML is defined under the proposed framework for waveform parameter assignment and optimization.
5) A case study with ML is provided for the optimal parameter subset decisions.
6) A simulation based dataset generation methodology is proposed together with the given case study.

The rest of the paper is organized as follows: Section II presents the previous works on the related topics. Section III provides the possible waveform parameter options for 6G. Discussions on waveform parameter assignment and resource allocation optimization are introduced in Section IV. The role of ML is explained in Section V and the case study is given in Section VI. Finally, conclusions are drawn in Section VII.

II. PREVIOUS WORKS

In the literature, generally numerology assignment is given as an assumption to make the optimizations for waveform parameters. Some of the studies present joint optimization with the numerology assignment like in [31]–[33]. In [31], ML methods are utilized to optimize the numerology assignment and guard band selection between different numerologies jointly. In [32], the authors assume that there is a direct mapping between numerologies and use cases. The paper optimizes the numerology configuration and the DL-UL duplexing ratio in a TDD. The focus of [33] is the joint optimization of bandwidth allocations and numerology assignments for four users. There are also pure numerology assignment optimization studies in the literature [11], [32], [34], [35]. In [11], optimal numerology assignment is done regarding the requirements and frame design considerations to find effective number of numerologies. In [34], the authors find the best single subcarrier spacing for all users. Adaptive numerology selection method is developed for V2X service in [35]. Adaptive guard band concept is analyzed in [36]–[38] for multiple numerologies. Putting guard band between different numerologies has important effect on INI but using large guard bands decrease spectral efficiency. Moreover, it is possible to use different amount of guard bands between different numerology pairs. Most of the multi-numerology scheduling studies are focused on the resource allocation [16], [33], [39]–[45]. The main aim of these studies is the optimization of bandwidth allocations rather than waveform parameter assignment. However, resource allocation and waveform parameter assignment should be handled together jointly.

There are three main types of ML schemes - supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL). SL requires class labels in the training stage. On the contrary, UL process does not use class labels but utilizes a clustering type of algorithms, e.g. specifing the class distinctions with learning more about the input data. RL employs feedback mechanisms to improve the ML system consistently. These schemes can be employed for different optimization aims in wireless communications. Additionally, there are several state-of-the-art concepts such as deep learning (DL) and edge computing. DL is a special case of ML and it consists of multi-layered neural network (NN) models. Edge computing is a distributed computing framework to process data on the device itself rather than a centralized data processing. It is possible to use main ML schemes for DL and edge computing algorithms. Furthermore, DL can be used for the edge computing. Besides, federated learning (FL) is one way of the edge learning across multiple decentralized devices.

Relationships between ML and the wireles networks are discussed comprehensively in several studies such as [17]–[20]. A set of network design and optimization schemes to make wireless networks intelligent regarding being self-aware, self-adaptive, proactive and prescriptive is introduced with big data concept in [46]. An overview of the emerging studies on DL-based solutions for different network layers are provided in [47]–[49]. Signal identification for emerging intelligent radios and end-to-end learning from spectrum data are investigated in several papers [50]–[53]. ML-aided channel estimation is studied from different perspectives such as OFDM, NOMA and MIMO in [54]–[56]. Beam management with ML for highly mobile mm-wave systems [57], beam selection with ML [58], beam allocation with ML in multi-user massive MIMO systems [59] and antenna selection with ML [60] are some other useful researches in the literature. ML for vehicular networks is discussed in [61] and [62]. A ML vision and an overview of ML architectures for network traffic control are introduced in [63] and [64]. For edge computing learning, mostly FL is used to schedule wireless networks. Scheduling policies for FL in wireless networks [65], FL-based multichannel random access [66], joint power and resource allocation with FL for vehicular communications [67] and FL for UAVs-enabled wireless networks [68] are several previous works on edge computing learning.

ML is also investigated with considering the potential technologies for 6G networks. Mobile edge computing and learning-based frameworks for 6G are studied in [69] and [70]. A survey on various ML techniques applied to communications, networking and security parts in vehicular networks from the 6G perspective is presented in [71]. Lastly, the usage of quantum ML is introduced in [72] for 6G communications. All of these studies are focused on the potential ML roles in upcoming technological trends.

Potential 6G requirements and use cases are discussed with promising technologies in [3]–[6], [30], [73]–[78]. New application scenarios and key potential features for 6G are investigated in these studies. Several radio access technologies such as NOMA, mm-wave and reconfigurable intelligent surfaces (RIS) are studied from the 6G perspective in [79]–[82]. Partially overlapping NOMA technique is introduced for 6G in [79]. Integration of NOMA in mm-wave communications for 6G is analyzed in [80]. Challenges and opportunities for wireless communications and sensing applications above 100 GHz are provided in [81]. RISs are studied with index modulation (IM) as a new MIMO paradigm in [82]. The usage of RISs to rethink the communication-theoretic models for 6G networks is discussed in [83]. Additionally, promising network structures with green communications and new backhaul systems are investigated for 6G in [84]–[88]. Novel frameworks and architectural changes associated with 6G networks for wireless power transfer are analyzed in [84] and [85]. An adaptive security specification method for 6G IoT networks with energy harvesting is proposed in [86]. Airplane-aided integrated networking with high-data-rate backbone links for 6G wireless is introduced in [87]. Lastly, a survey of technologies for providing connectivity to rural areas, access/fronthaul and backhaul techniques is presented in [88].

III. POSSIBLE WAVEFORM PARAMETER OPTIONS FOR 6G

Possible waveform parameter options are described for 6G in this section. A projection of 5G NR is combined with potential waveform structures to forecast the waveform parameters in 6G. It is shown that there will be numerous waveform parameter options in the future. TPs will use all of these waveform parameter options while assigning them to different users with the optimal resource allocation decisions.

Multi-numerology based CP-OFDM waveform is standardized in 5G NR. There are also optional waveform processing techniques like guard utilization, windowing and filtering in 5G NR as exemplified with Fig. 3. All of the optional waveform processing techniques have different type of parameters with various implementation structures. The number of numerologies and processing options will increase in 6G and the coexistence of multiple waveforms in the same frame may also be possible for 6G.

Possible differences between 5G and 6G waveform parameters are summarized in Table 2. New attempts to increase flexibility generally will increase the number of parameter types in 6G. Some possible challenges can be listed as follow:

Numerology Structures

Subcarrier Spacing (kHz)	CP Duration (us)	Slot Duration (ms)	Number of Symbols in One Slot
15	4.76	1	14
30	2.38	0.5	14
60	1.19 | 4.17	0.25	12 | 14
120	0.60	0.125	14

+

Optional Waveform Processing Techniques

- Different or same guard bands between numerologies.
- Windowing with different windowing functions for each user or numerology.
- Filtering with different filter length and coefficients for each user or numerology.

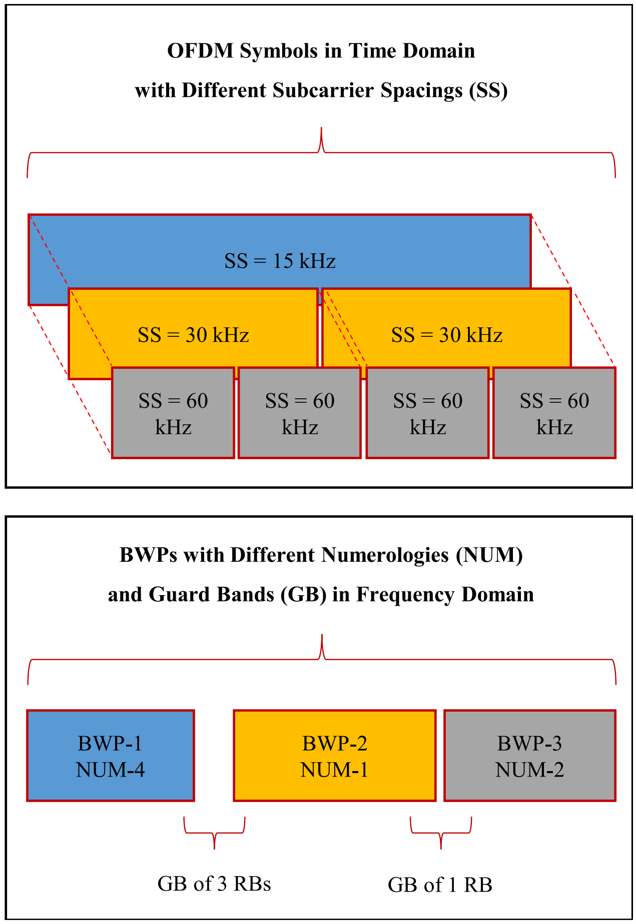


FIGURE 3. The list of numerology parameters and additional parameter types for CP-OFDM in 5G NR with example demonstrations.

TABLE 2. Possible Differences Between 5G and 6G Waveform Parameters

	5G Waveform Parameters	Possible 6G Waveform Parameters
Numerology Structures	• Time-frequency lattice domains. • Subcarrier spacings of 15 kHz, 30 kHz, 60 kHz and 120 kHz. • Fixed CP ratio but two options for 60 kHz subcarrier spacing.	• There may be different lattice domains with or without time-frequency. • Different domains provide new types of numerology parameters. • Common CP utilization [15] can be preferred to make CP ratio flexible. • CP parameter can take more values independent from the subcarrier spacing. • There may be more parameter variety than the 5G numerologies [11]. • For the case of multiple waveforms, each waveform may have separate numerology options on the same or different lattice structures.
Waveform Processing	• Inter-numerology guard bands. • Roll-off factors for windowing. • Filter coefficients for filtering. • Different types of parameters for the other processing techniques.	• Waveform processing methods need to be enhanced because of more INI effects. • For new lattice structures, new INI management techniques need to be developed. • New type of interferences if multiple waveforms are utilized in the same frame. • New waveform processing techniques to control, reduce and exploit IWI. • Parametrization of each new technique will increase the number of waveform parameters.

- There may be more numerology options in 6G but it will increase INI effects. Hence, waveform processing techniques need to be enhanced. This situation will give rise the increment for the number of possible new parameters.
- New types of CP utilization methods can be preferred in 6G, such as common CP [15]. It makes CP ratio more flexible but number of possible CP values increases compared to the numerology designs in 5G systems.
- If different lattice domains are used in 6G rather than the time-frequency, new types of waveform parameters will be included in the numerology sets. Therefore, the number of numerology options will increase. Additionally, the current INI management techniques will be useless for different lattice domains. Then, new waveform processing techniques and the related parameters need to be defined. This case will also increase the number of possible waveform parameters.

- Utilizing multiple waveforms in a single frame may be possible for 6G. Lattice structures can be different for each waveform as an important challenge. Besides, there may be different types of numerology parameters for multiple waveforms. Additionally, IWI needs to be controlled by new waveform processing techniqes and the related parameters. Waveform parameters will increase in all of these cases for 6G.

The next subsections give more details on the possible waveform parameters. These details are discussed under the topics of 1) multiple numerologies, 2) waveform processing techniques, and 3) multiple waveforms. 5G an 6G perspectives are given together.

A. MULTIPLE NUMEROLOGIES

In one of the first studies on multiple numerologies [89], channel-aware numerology assignments are done for multiple users with CP-OFDM. However, multi-numerology structure of 5G NR is flexible in order to consider different feedbacks including channel structures of users. Different frame parameters under four numerologies are provided for data transmission of 5G NR in Fig. 3 [15]. Numerologies can have various parameters that are dependent or independent of each other. In 5G NR, there is only one main adjustable parameter which is a subcarrier spacing. The other parameters are generally dependent on it because of the practicality.

6G systems probably will come with more numerology structures that provides more flexibility. If the number of waveform related adjustable parameters increase with 6G, then there will be more options for multiple numerologies [11]. For example, adjustable CP duration and utilization are important concepts for 6G [12]. Using one common CP for different numerologies may be one of the new concepts in 6G and it changes the number of numerology options noteworthily [15].

Furthermore, possible implementation structures for multi-numerology CP-OFDM vary with different bandwidth part (BWP) operations in 5G NR [90]. BWP defines a fixed band with the same numerology. It is a bridge between numerologies and 5G NR scheduling. BWP operations are flexible, e.g., users with the same numerologies can be located contiguously in the frequency domain rather than creating several non-adjacent BWPs with the same numerology. Similarly, there are many different BWP implementation options or radio access network (RAN) slicing methods in 5G and beyond systems. The number of scheduling-related implementations and methods will likely increase in 6G.

B. WAVEFORM PROCESSING TECHNIQUES

Windowing usage, filtering usage, and inter-numerology guard utilization are example waveform processing techniques for cellular communications systems [91]. More waveform processing techniques can be developed in 6G to address prospective requirements. Multiple numerologies and the other non-orthogonality sources increase the importance of waveform processing techniques [15]. These techniques require various adjustable parameters. For example, several prototype filters in the literature including rectangular, raised-cosine, Gaussian and so on, are provided in [9]. There is a flexibility to apply windowing with different or same roll-off factors on the subframes for each numerology or composite signal of multiple numerologies at the transmitter. Receiver windowing is the another option. Roll-off factor optimization is analyzed in [92]. Different filters, the related coefficients, and roll-off factors increase the number of options for waveform processing techniques. Coexistence of 6G and the other standards will have even more options, especially if there are multiple waveforms in the same frame.

C. MULTIPLE WAVEFORMS

In addition to multiple numerologies and waveform processing techniques, one of the future technologies is coexistence of multiple waveforms in the same frame together with multiple numerologies and processing techniques. In [93], frequency-domain non-orthogonal multiple access (NOMA) structure with two sets of orthogonal signal waveforms (CDMA and OFDMA) is presented. OFDM and OFDM-IM are used together as another NOMA scheme in [94] and [95]. Probably, there will be more studies on multi-waveform concept in 6G.

If there are multiple waveforms in the same coverage area [13], it means that there will be a tremendously high number of options for the waveform parameters. Thus, the number of parameter options will double many times, depending on the number and types of waveforms. In addition, there will be more types of numerology structures if 6G waveforms use different lattice domains. Decision mechanisms for the waveform parameter assignment units of the 6G systems will likely be more complex compared to 5G NR.

IV. WAVEFORM PARAMETER ASSIGNMENT AND RESOURCE ALLOCATION OPTIMIZATION

If there are many waveform parameter options in one coverage area, it provides a flexible structure considering the different requirements of users. However, the variety of waveform parameter options comes with a price like INI and similar impairment sources. Employing multiple waveforms in 6G may also cause additional interferences. Several performance indicators (or metrics) are affected while handling the different types of additional interferences. This situation brings difficult dilemma problems.

Performance metrics of reliability, latency, spectral efficiency and complexity are affected by multi-numerology implementations, directly or indirectly. For example, the number of numerologies that are assigned to the users change the amount of INI in a directly proportional way. Reliability decreases if there are INI effects. To compensate INI effects, re-transmission schemes can be used at the expense of additional delays, increasing latency. INI reduction techniques or waveform processing techniques can be utilized to decrease

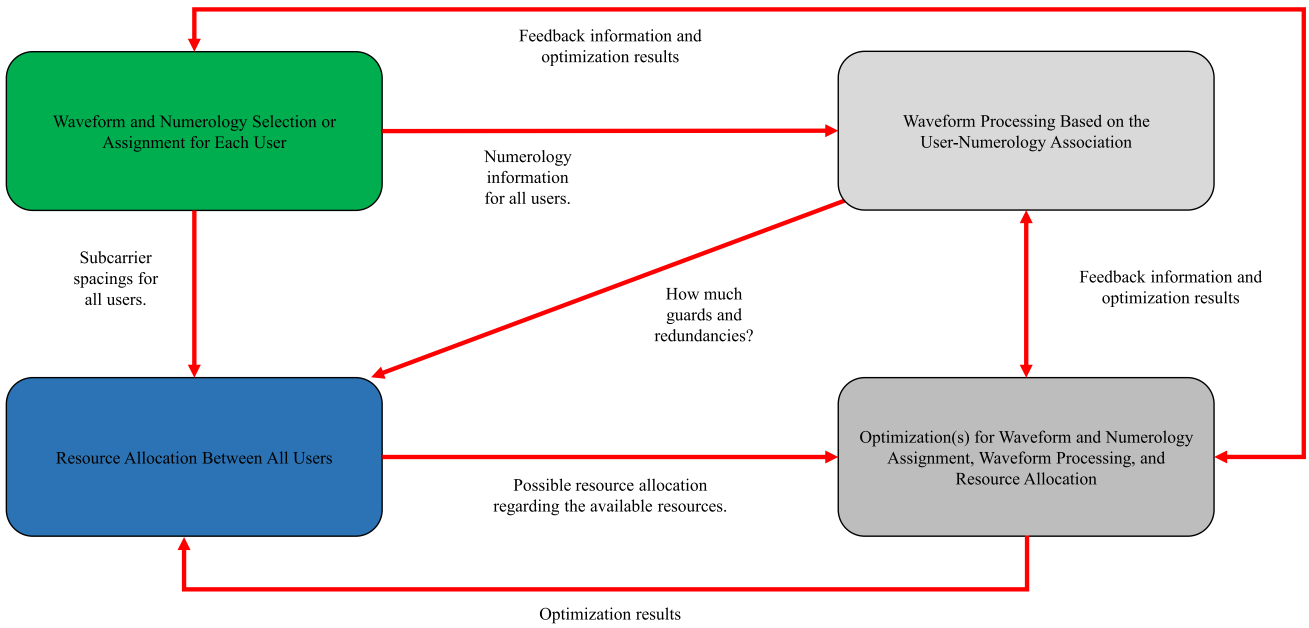


FIGURE 4. Illustrations of the several subproblems and their example relationships.

INI effects, however, these techniques generally reduce spectral efficiency. Indeed, some of the INI cancellation techniques can be used but they may increase complexity of the receiver units. As it can be seen from these examples, different trade-off situations need to be handled with proper resource allocation optimizations if multiple numerologies and waveform processing techniques are employed for different users. If there are multiple waveforms, the problem becomes more difficult.

All the users should be assumed to be in the same coverage area. Waveform parameter decisions cannot be given for a single user independently of the other users, as they are indirectly related with each other due to various constraints, like limited radio spectrum. Illustrations of the several subproblems and their example relationships are shown in Fig. 4. Waveform and numerology assignment for each user, waveform processing, resource allocation, and all related optimizations effect each other. Collaboration during the solutions of these problems is necessary and as stated before, the level of this collaboration will increase in 6G. The given subproblems can be solved with different waveform parameter assignment, optimization and supplementary methods. A general framework for these methods is presented in the next subsections.

A. WAVEFORM PARAMETER ASSIGNMENT

Waveform parameter assignment units should decide on the user parameters by considering the optimization restrictions to provide the possible maximum flexibility regarding different user requirements. Optimization restrictions are achieved at the optimization unit of the waveform parameters for all users. Optimization unit is discussed in the next subsection. The aim of waveform parameter assignment unit is to meet different requirements of all users separately as much as possible under the given optimization restrictions if there is any.

Waveform parameter assignment is repeated in every cycle, as shown in Fig. 5 with different structures. Assignment unit can be run as the first step or as the second step. If it is run as the second step, the first step should be a pre-optimization unit. However, the last step is always the determination of ultimate waveform parameters in all structures. The previous decisions of waveform parameter assignment units can be defined as provisional decisions.

All of the parameter assignment units can work with different flowcharts or with a same flowchart. For example, some of the waveform parameters can be decided in the first iteration and the other parameters can be determined in the next iterations with different flowcharts. Alternatively, all assignment units can work with the same flowchart and can decide on all of the waveform parameters in each iteration step. For the first alternative, options or class labels (for ML) need to be designed application-specific because each assignment unit can provide different types of class labels.

As a case study, a user-numerology association method in [11] can be given. In this study, user channels and use cases are associated with the most suitable numerology from different numerology sets. This step is shown with the first waveform parameter assignment unit in Fig. 5(b). After the first step, less assigned numerologies are detected and removed from the numerology set. It brings an optimization restriction and decreases INI effects by forbidding some of the numerologies. As a last step, user-numerology association step is repeated one more time to determine ultimate numerologies for users.

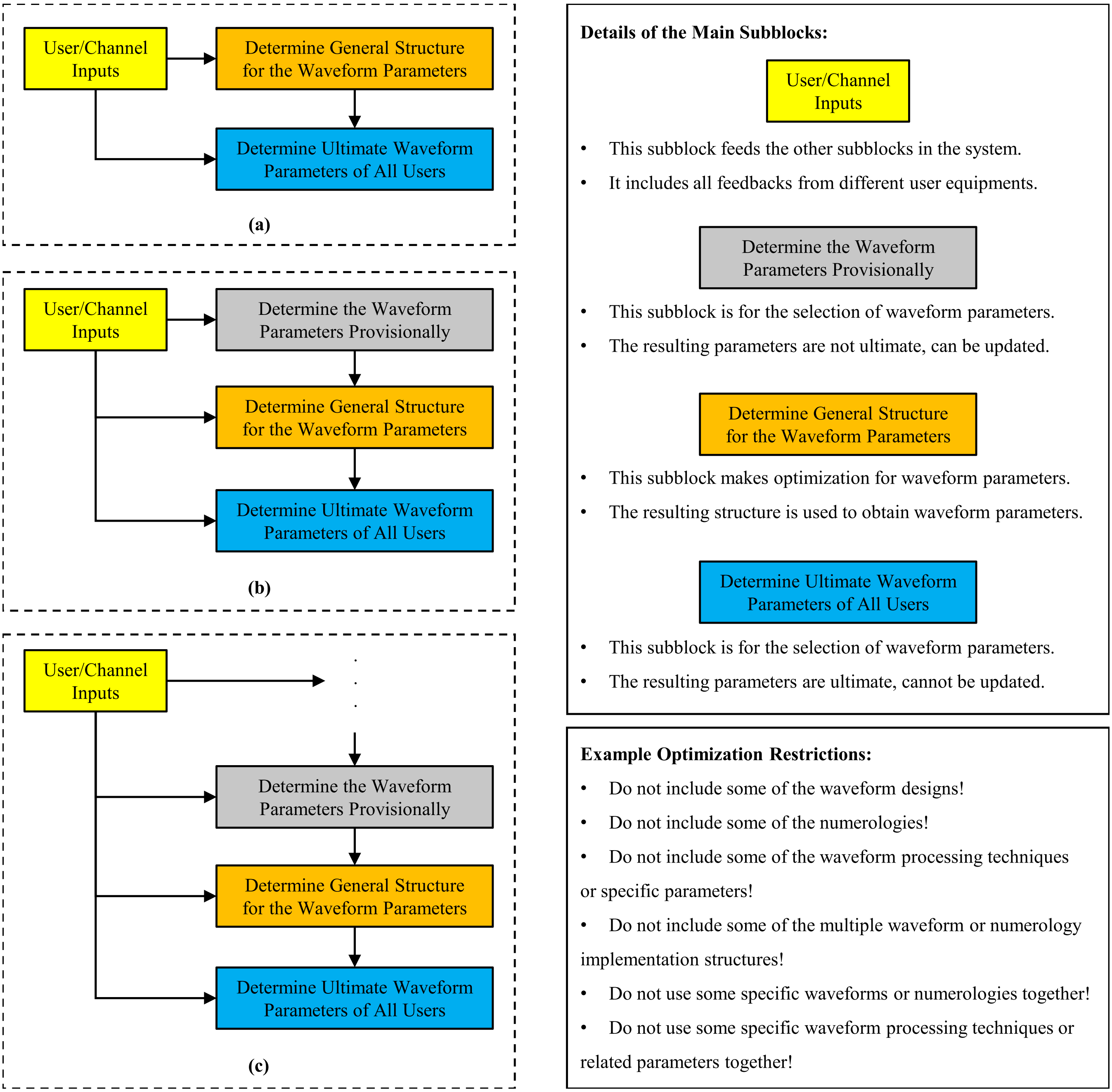


FIGURE 5. **General structures of the framework for waveform parameter assignment and resource allocation optimization mechanisms. These mechanisms can include (a) two iteration steps, (b) three iteration steps, and (c) more than three iteration steps.**

B. OPTIMIZATION FOR WAVEFORM PARAMETERS

We can assign the waveform parameters of different users directly but there are some constraints, as mentioned before. It will not be a practical and efficient solution without proper optimizations. The main objective of the optimization unit is to create a balance between several performance metrics and find optimum points regarding these metrics. This balance can be provided by meeting requirements of different users together with some sacrifices instead of meeting different requirements of all users separately without any sacrifices. Penalty functions need to be defined to increase the success of general performance for the cellular communications.

Similar to waveform parameter assignment units, optimization units in different steps can also be designed as one type or more. A designer needs to decide on the number of steps for different structures. As an example, a general structure for multiple numerologies can be determined by deciding on the number of numerologies as a first optimization unit like in [31] and as shown with Fig. 5(a). After one cycle of waveform parameter assignment unit, a general structure

TABLE 3. Differences of Three Mechanisms for the General Waveform Parameter Assignment and Optimization Framework

	Advantages and Disadvantages	Scenarios
Fig. 5(a)	• Low complexity in general considering the number of units. • High complexity in a single optimization unit. • Low performance regarding the meeting requirements if there are large number of waveform parameters.	• Reasonable if there are small number of waveform parameters. • It is also preferable when the requirement variety is low.
Fig. 5(b)	• Medium complexity in general considering the number of units. • Variable complexity in optimization units. • Medium performance regarding the meeting requirements if there are large number of waveform parameters.	• Reasonable if the number of waveform parameters is not high. • It is also preferable when the requirement variety is medium.
Fig. 5(c)	• High complexity in general considering the number of units. • Variable complexity in optimization units. • High performance regarding the meeting requirements if there are large number of waveform parameters.	• Reasonable if there are large number of waveform parameters. • It is also preferable when the requirement variety is high.

for waveform processing techniques can be obtained in the second optimization unit. Alternatively, different types of optimization units can be combined in one type of unit, and then the unit can be employed in each cycle of the optimization.

Only one cycle of optimization unit is preferred in [31]. Increasing the number of optimization steps provides a better general performance regarding all requirements of different users in a coverage area. However, it can also increase computational complexity of the related radio resource management (RRM) units. Hence, there should be a meaningful reason for increasing the steps of optimization units under different scenarios. An efficient work load distribution is needed between waveform parameter assignment units and optimization mechanisms to obtain ultimate optimal waveform parameters.

C. SUPPLEMENTARY METHODS

In addition to waveform parameter assignment and resource allocation optimization methods, different techniques, like INI cancellation [96] and resource allocation based scheduling [97], can play indirect roles to help and simplify the parameter assignment strategies by changing the results of various performance metrics. The work distribution for waveform parameter assignment units and optimization units is changed with these types of practical supplementary methods.

In [97], INI effects at the numerology edges are decreased and also ultra reliable low latency communication (uRLLC) users are scheduled at the inner subcarriers of different numerologies to move away from intensive INI effects at the numerology edges. This method enables providing to make waveform parameter assignment process more simple through proper optimizations. Hence, the number of steps for waveform parameter assignment strategies is reduced inherently.

The design criteria of decision strategies can change regarding different supplementary methods. INI modelling and trade-off analysis through different waveform processing techniques are some other example research topics that are helpful for waveform parameter assignment and corresponding resource allocation optimization methods. Moreover, it can be said that all of the RRM techniques are correlated with the waveform parameter assignment with proper optimizations in some way.

Three mechanisms of the proposed framework that are given as subfigures of Fig. 5 are compared in Table 3. For 6G, the last mechanism, Fig. 5(c), may be more suitable because there will be very large number of waveform parameters and 6G requirement variety will be high. As an important challenge, there will be many optimization necessities so that work load distribution between the optimization units should be balanced carefully. Hence, complexity per unit can be kept under control. Moreover, optimization unit redundancy should be prevented to limit the general complexity.

V. THE ROLE OF MACHINE LEARNING IN WAVEFORM PARAMETER ASSIGNMENT AND OPTIMIZATION

ML and conventional methods can be used while waveform parameter assignment units and resource allocation optimization units are run alternately to obtain ultimate optimal waveform parameters. Understanding the role of ML is useful to constitute efficient waveform parameter assignment systems in 6G communications. In general, the aim of ML usage for the waveform parameter assignment can be listed as follow:

- ML can establish useful and unnoticeable relationships in waveform parameter assignment domain.
- It is possible to obtain fast significant solutions when ML methods are preferred.

A. THE ROLE OF MACHINE LEARNING

Designing a classical method sometimes is not an easy task in practice for a problem that requires to establish relationships considering a large number of options. At this point, ML plays an important role to establish useful and unnoticeable relationships without heuristic engineering design and theoretical analysis. It does not mean that ML methods are superior to conventional methods. However, ML methods can make the design process easier compared to developing non-ML techniques. ML methods learns from data without requiring a specific design. If there are optimal classical methods for all stages of the design units, ML may not provide extra advantages but this scenario is not valid for our case. Therefore, it is more preferable to use ML and conventional methods together in a hybrid way.

TABLE 4. Analysis of ML Usage in the Proposed Framework

	ML Usage Scenarios
Parameter Assignment Roles	• If there are too many parameter options as class labels in parameter assignment steps, difficulty in training and low success rates. • The model needs to have more complex rules and the boundary samples have more influence for a large number of class labels. • A large number of class labels for one ML model introduces an imbalanced learning problem and degrades prediction accuracy. • The complexity for the learning process also increases for a large number of class labels. • ML can play a role in waveform parameter assignment for 5G systems because the number of waveform parameters is limited. • Parameter assignment with ML in 6G networks may not be feasible because of the tremendous number of potential class labels. • After the optimization steps, edge computing can be preferred to minimize the class labels for each user's parameter assignments.
Optimization Roles	• ML can be employed efficiently to decide on general structures during optimization steps for waveform parameter assignment. • For ML-based optimization steps, the work distribution should be adjusted to reduce the number of class labels in each step. • Some parts of the optimizations can be done using edge computing for a better work distribution between the other steps. • Trying to solve an optimization problem with only one ML model sometimes makes the problem more difficult. • ML plays an important role in optimization of waveform parameter assignments for 5G and 6G. • There will be more optimization necessities for 6G because of the possible high number of waveform parameters. • A high number of parameters makes ML more feasible for optimization steps but not for parameter assignment roles directly.

ML methods can be employed efficiently to decide on general structures during optimization steps for waveform parameter assignment. The other steps also can be designed with ML methods but there are too many parameter options as class labels in waveform parameter assignment steps. It causes a difficulty in training and reduces success rates. The number of waveform parameter options or class labels for one assignment/optimization unit should not be higher than a desired level if this unit is designed with ML model. The model needs to have more complex rules and the boundary samples have more influence for a large number of class labels. Using a large number of class labels for one ML model is not preferable as this introduces an imbalanced learning problem and degrades prediction accuracy. In imbalanced dataset has disproportional ratios of observations in the class labels. Because of this, a class with insufficient number of samples is hard to learn. Additionally, the complexity for the learning process also increases dramatically for a large number of class labels. Therefore, ML models should have less number of class labels and the work distribution needs to be designed considering this hypothesis. If ML methods are employed during optimization steps, most of the work load should not be shifted to the optimization units, as this increases the number of class labels in ML models. The number of optimization steps can also be adjusted to reduce the number of class labels in each step. The work distribution for parameter assignment units and optimization units should be adjusted considering the role of ML. Conventional methods need to be preferred if there is not an efficient work distribution between the units. Additionally, edge computing can be used for different steps of waveform parameter assignment and optimization. For example, edge computing can be preferred to minimize the class labels for each user's parameter assignments after the necessary optimization steps. Learning with the edge computing can enhance the practicability of employing ML in parameter assignment steps. Also, some parts of the optimizations can be done using edge computing for a better work distribution between the other steps.

Analysis of ML usage in the proposed framework is summarized in Table 4. ML plays an important role especially in optimization of waveform parameter assignments for 5G and 6G. There will be more optimization necessities for 6G because of the possible high number of waveform parameters. Hence, the role of ML in optimization of waveform parameter assignments for 6G will be more than 5G. This is one of the possible challenges in 6G from the ML perspective. The increasing number of waveform parameter options makes ML usage more feasible for optimization steps. Additionally, another ML challenge for 6G is the large number of class labels for direct waveform parameter assignment roles. Difficulty in ML training, more complex rules, imbalanced learning problem and high computational complexity are the potential 6G challenges for waveform parameter assignment steps.

B. DATASETS FOR MACHINE LEARNING

There are many issues for the use of ML techniques for wireless communications. However, one of the most important issues is the availability of datasets to make ML works. It is crucial to have large datasets while making ML systems functional [98]. In the literature, there are only limited datasets for many of the wireless communications research opportunities. ML systems need large datasets during the training and testing stages. Data-driven learning process cannot be possible without a dataset. Therefore, the role of datasets is given together with the ML role in this study.

In practice, it is not feasible to constitute a measurement based dataset that includes data for too many different scenarios. Simulation based dataset generation methodologies can be preferred as shown in Fig. 6. After forming the types of class labels in different units, functional datasets can be prepared with simulations and automatic class labeling methods to use these datasets in the training of ML based units. An example simulation based dataset generation methodology and an automatic class labeling method for the purpose of supervised learning is shown in Fig. 6. Details are given in the next section with a case study. At the end, obtained class labels are

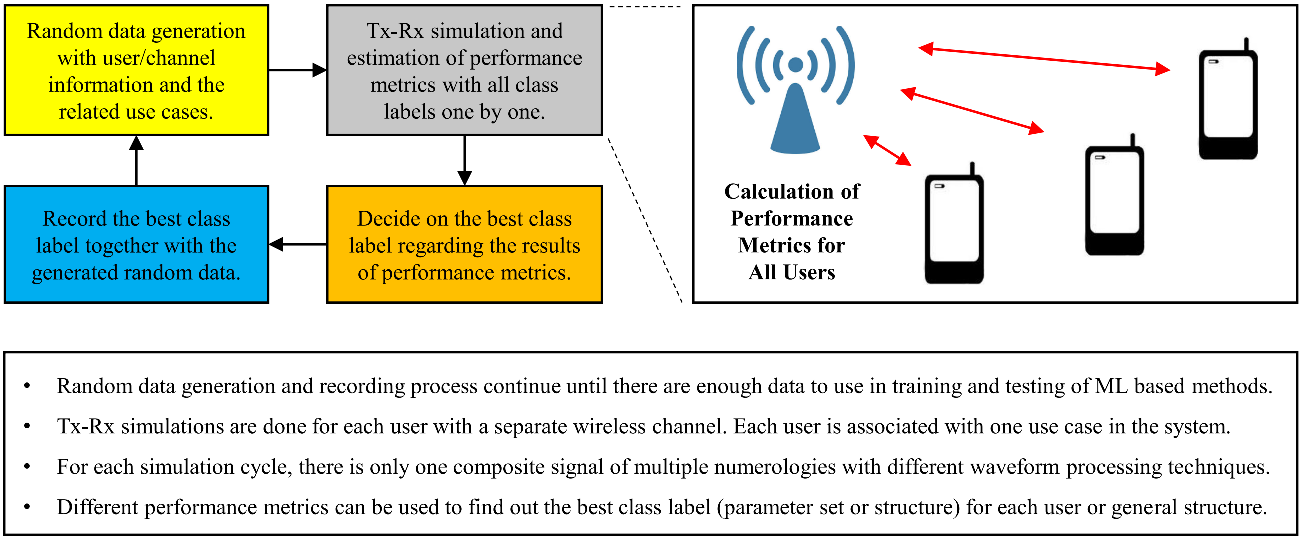


FIGURE 6. **Block diagram and basic explanations for the simulation based dataset generation methodology.**

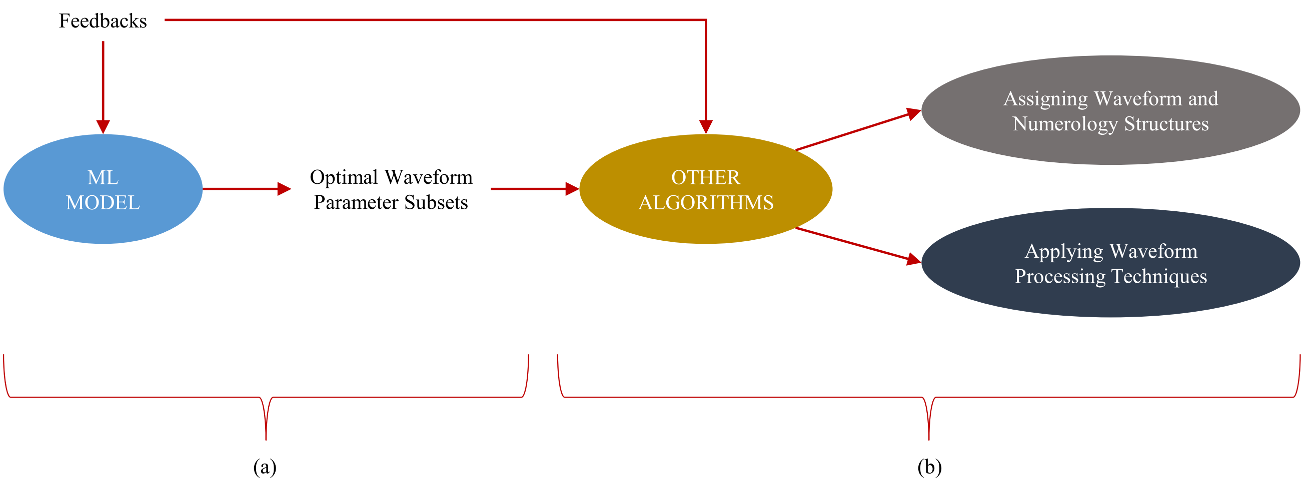


FIGURE 7. **Example demonstrations for (a) decision on general structure for the configurable waveform parameters and (b) assignments of user-based waveform parameters.**

recorded in a dataset along with the randomly generated data. This dataset can be used for ML purposes after the feature engineering processes that include data cleaning, preprocessing, feature extraction, feature selection and feature reduction if necessary. The simulation based datasets can also be used as an initialization point and a priori info for reinforcement learning models.

VI. CASE STUDY: ML-BASED DECISION OF OPTIMAL WAVEFORM PARAMETER SUBSETS

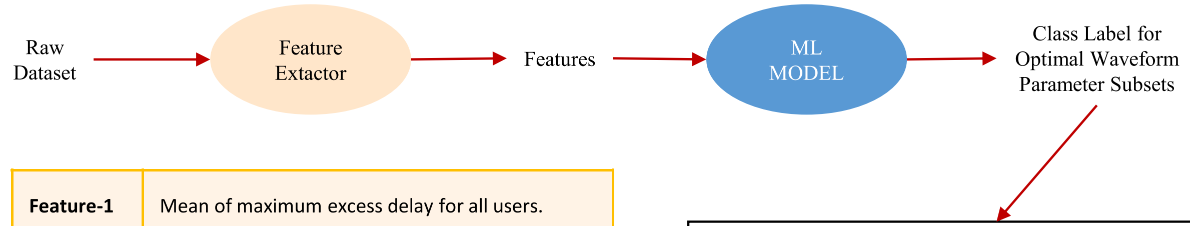
A supervised ML based method is developed with a case study example[1] to provide an optimal waveform parameter subsets before the assignment of waveform parameters for each user. For example, the proposed method decides on the efficient number of numerologies that can be assigned to users. However, it does not make a direct user-numerology association. In this case study, the main focus is on finding the optimal waveform parameter subsets by utilizing ML algorithms. A simple model is shown in Fig. 7(a)

A. CLASS LABELS FOR THE DATASET

It is assumed that each class label corresponds to one set of waveform parameters. Therefore, more than one thousand classes can be considered for 5G cellular systems with different numerology assignments and waveform processing parameters. The number of classes may increase exponentially for 6G especially if there are multiple waveforms. In this case, a multidimensional look-up table may be necessary.

The number of class labels changes the learning problem difficulty, affects the training complexity and requires a larger

[1]This case study is reproduction of the authors' another work in [33].



Feature-1	Mean of maximum excess delay for all users.
Feature-2	Variance of maximum excess delay for all users.
Feature-3	Mean of maximum Doppler effect for all users.
Feature-4	Variance of maximum Doppler effect for all users.
Feature-5	The number of users for eMBB service.
Feature-6	The number of users for uRLLC service.
Feature-7	The number of users for mMTC service.

(a)

Number of Numerologies	The Amount of Guard Band		
	Class-1 (4 numerologies, zero GB)	Class-2 (4 numerologies, small GB)	Class-3 (4 numerologies, large GB)
	Class-4 (3 numerologies, zero GB)	Class-5 (3 numerologies, small GB)	Class-6 (3 numerologies, large GB)
	Class-7 (2 numerologies, zero GB)	Class-8 (2 numerologies, small GB)	Class-9 (2 numerologies, large GB)
	Class-10 (1 numerology)		

(b)

FIGURE 8. **Details of the features and class labels that are included in the dataset. This figure is adapted from another work of the authors in [31].**

dataset. Also, a larger dataset is needed when there are more class labels. Due to these restrictions, only ten classes are taken in this case study for the sake of simplicity.

It is assumed that there are four numerology related options – using four numerologies, three numerologies, two numerologies, and only one numerology at a time. In other words, a subset is decided for the efficient number of numerologies in a frame. In addition, three guard band options are defined as the waveform processing techniques. Windowing and filtering options are not included. The class labels and short descriptions for the case study are provided in Fig. 8(b).

There are three and four type of numerologies in the first and second row classes in Fig. 8(b). If the number of distinct requirements in one coverage area is rich, these classes may suitable to meet the requirements under this scenario. Third and fourth row classes are more compatible for a scenario that the number of distinct requirements is limited. Classes in different columns vary with INI effects on the requirements.

B. FEATURE EXTRACTION

For all users, independent random data is generated under different scenarios (e.g. thousands of random scenarios) based on the channel information in [99] and use cases[2] that include eMBB, uRLLC and mMTC. Scenarios are defined with the parameters of random maximum excess delay, random maximum Doppler effect, and random service type (eMBB, uRLLC, or mMTC). Users can be associated with one of the use cases and different Rayleigh fading channel models are used for each user. Hence, the proposed ML system model can be assumed as channel-aware and service type-aware.

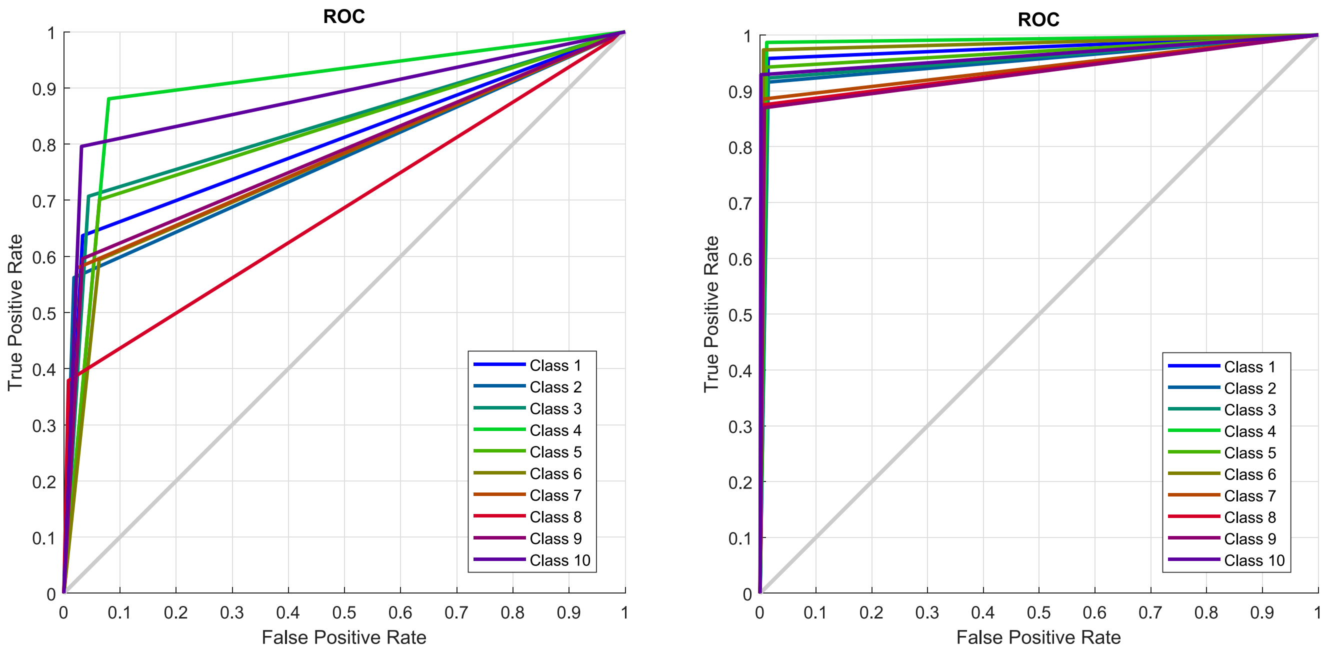
Short definitions of the extracted seven features include mean of maximum excess delay, variance of maximum excess delay, mean of maximum Doppler effect, variance of maximum Doppler effect, the number of users for eMBB, the number of users for uRLLC and the number of users for mMTC as shown in Fig. 8(a). The first four features give information about the channels of users in general. The remaining three features are obtained related with use case statistics. All of the features aim to describe requirement trends in one coverage area for a TP. ML model is trained considering these requirement trends and the available class labels.

In the future cellular systems, there will be more use cases. In addition, there will be more different types of new channel models for 6G, especially for millimeter wave systems. New models will increase the number of scenario parameters and then the feature characteristics.

C. SIMULATION BASED AUTOMATIC CLASS LABELLING

After the feature extraction process, a simulation based automatic class labelling is done before training ML models.

[2]Alternative usages can be given as service types or application groups.



(a) ROC curve for NN networks with 20 hidden neurons using Bayesian regularization backpropagation algorithm.

(b) ROC curve for NN networks with 20 hidden neurons using Bayesian regularization backpropagation algorithm. Neighbour class labels are grouped.

FIGURE 9. Example ROC curves for the simulation results in MATLAB platform. These results are adapted from another work of the authors in [31].

This process is realized using the calculation of several performance indicators that include signal to interference plus noise ratio (SINR), spectral efficiency, and flexibility. A multi-numerology waveform transceiver simulation is employed to obtain the calculation of these performance indicators. [100] is taken as a reference for multiple numerologies. It is assumed that MATLAB simulation gives perfect results. Additionally, flexibility is defined as a metric that changes directly proportional to the number of different numerologies.

For the automatic class labelling process, different waveform options (ten classes in this case study) are tested one by one in separate simulations for the same inputs and features. Three performance indicators are obtained for each simulation. A single performance value is calculated using three indicators with different priorities and weights. These priorities and weights change considering the service type majority. For example, the spectral efficiency metric has more priority for eMBB but the SINR metric has more priority for uRLLC. If there are a high number of users with all type of services, then the flexibility metric has also a priority because the overall system needs to meet with many different requirements together. At the end, performance values for each simulation are compared and the best one is decided. This decision gives the optimal class label that has specific waveform options.

D. SIMULATION RESULTS

While training and testing ML models, 114420 samples with seven features and one class label are used for each random scenario. The dataset is divided as training, validation, and testing with 60%, 20%, and 20% ratios, respectively.

MATLAB platform is employed in the simulations. For the ML traning and hyperparameter optimizations, 'fitcecoc' and 'patternnet' functions are preferred in MATLAB. Several classifiers are trained and tested during the simulations. Success rates change between 60% and 65% for ten classes. Additionally, if neighbour classes in Fig. 8(b) are grouped together, the success rates vary between 90% and 93% for the same classifier models. For example, if the decision for number of numerologies is three or four, it can be acceptable while neighbour classes are grouped. Receiver operating characteristic (ROC) curves in Fig. 9(a) and (b) shows the results without and with grouping neighbour classes, respectively. Success rates are not high but they are promising.

E. 6G PROJECTION OF THE PROPOSED CASE STUDY

In Sections IV and V, it is emphasized that the increasing number of waveform parameter options makes ML usage more feasible for optimization steps rather than the direct parameter assignment roles without optimizations. Hence, optimization units for waveform parameter assignment should be discussed more for ML roles. The proposed case study is a basic example for ML usage in pre-optimization of waveform parameter assignment problems of 5G and 6G.

As discussed in Section III, numerology options, CP utilization methods, lattice domains and waveform types may be diversified with the next generation cellular systems. If the number of class labels is increased tremendously in 6G, the solution of the parameter assignment problems will be more difficult. Under the assumption of large number of new parameter options in 6G, the following potential challenges may be listed for the adjustment of future waveform parameters:

1) There will be more interferences (INI and IWI) because of the increasing number of parameter options.
2) New processing techniques and the related parameters will be needed for the interference management.
3) The number of steps for parameter assignment and optimization in the proposed framework will increase.
4) There will be a need for better optimization algorithms in general.
5) A more efficient work distribution will be required between different steps in the proposed framework.
6) The role of ML will increase and more ML models will work together under an optimized work distribution.
7) The number of useful features should be improved to enhance the accuracy of ML models.
8) Feature selection and reduction methods can be applied after the extraction of features.
9) More powerful methods like DL and edge computing will be integrated to the ML role.
10) Edge computing algorithm structures can be designed to reduce the work load at TPs. For that purpose, FL-based edge computing solutions can be preferred.
11) There will be a need for better and larger datasets to make ML mechanisms more functional.
12) More user inputs as new feedbacks will be included for the datasets.
13) New mechanisms for the evaluation of user feedbacks will be designed.
14) Data cleaning and preprocessing algorithms may need to be used on the raw dataset.
15) 6G frames need to implemented to form useful datasets with simulation based automatic class labelling system.

VII. CONCLUSION

Assignment of waveform parameters in 6G will be an important and promising research topic. There is a great flexibility to be exploited. This paper constitutes a basis for all different types of waveform parameter assignment techniques that employ ML and conventional methods; alone or together. Probably, the future techniques for waveform parameter assignment will be compatible with the proposed inclusive framework.

Feasibility of ML based systems should be analyzed before applying them into cellular communications systems to see whether ML provides beneficial solutions together with the practical and effective conventional techniques. ML systems will play an important role when classical methods cannot be designed for different scenarios easily. Combination of ML and conventional methods may result with optimal solutions for the RAN technologies.

As a future work, the proposed dataset generation methodology can be used to develop large datasets for better ML models for 6G. Many different information can feed the feature extractor to obtain useful 6G datasets related with waveform parameters. New numerology options, CP utilization methods and different lattice domains may be integrated to waveform parameters considering the possible 6G requirements. Multiple waveforms can be implemented and then different work distributions in the proposed framework can be compared.

REFERENCES

[1] A. Imran, A. Zoha, and A. Abu-Dayya, “Challenges in 5G: How to empower SON with big data for enabling 5G,” *IEEE Netw.*, vol. 28, no. 6, pp. 27–33, Nov./Dec. 2014.

[2] A. Ijaz *et al.*, “Enabling massive IoT in 5G and beyond systems: PHY radio frame design considerations,” *IEEE Access*, vol. 4, pp. 3322–3339, 2016.

[3] S. Dang *et al.*, “What should 6G be,” *Nature Electron.*, vol. 3, pp. 20–29, Jan. 2020.

[4] W. Saad, M. Bennis, and M. Chen, “A vision of 6G wireless systems: Applications, trends, technologies, and open research problems,” *IEEE Netw.* to be published.

[5] Z. Zhang *et al.*, “6G wireless networks: Vision, requirements, architecture, and key technologies,” *IEEE Veh. Technol. Mag.*, vol. 14, no. 3, pp. 28–41, Sep. 2019.

[6] B. Zong, C. Fan, X. Wang, X. Duan, B. Wang, and J. Wang, “6G technologies: Key drivers, core requirements, system architectures, and enabling technologies,” *IEEE Veh. Technol. Mag.*, vol. 14, no. 3, pp. 18–27, Sep. 2019.

[7] D. Lopez-Perez, A. Garcia-Rodriguez, L. Galati-Giordano, M. Kasslin, and K. Doppler, “IEEE 802.11be extremely high throughput: The next-generation of Wi-Fi technology beyond 802.11ax,” *IEEE Commun. Mag.*, vol. 57, no. 9, pp. 113–119, Sep. 2019.

[8] C. B. Barneto *et al.*, “Full-duplex OFDM radar with LTE and 5G NR waveforms: Challenges, solutions, and measurements,” *IEEE Trans. Microw. Theory Technol.*, vol. 67, no. 10, pp. 4042–4054, Oct. 2019.

[9] A. Sahin, I. Guvenc, and H. Arslan, “A survey on multicarrier communications: Prototype filters, lattice structures, and implementation aspects,” *IEEE Commun. Surv. Tut.*, vol. 16, no. 3, pp. 1312–1338, Jul.-Sep. 2014.

[10] S. Han, C. I, G. Li, S. Wang, and Q. Sun, “Big data enabled mobile network design for 5G and beyond,” *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 150–157, Sep. 2017.

[11] A. Yazar and H. Arslan, “A flexibility metric and optimization methods for mixed numerologies in 5G and beyond,” *IEEE Access*, vol. 6, no. 1, pp. 3755–3764, Feb. 2018.

[12] A. B. Kihero, M. S. J. Solaija, and H. Arslan, “Inter-numerology interference for beyond 5G,” *IEEE Access*, vol. 7, pp. 146512–146523, 2019.

[13] C. I, S. Han, Z. Xu, S. Wang, Q. Sun, and Y. Chen, “New paradigm of 5G wireless internet,” *IEEE J. Sel. Areas Commun.*, vol. 34, no. 3, pp. 474–482, Mar. 2016.

[14] A. Ghosh, A. Maeder, M. Baker, and D. Chandramouli, “5G evolution: A view on 5G cellular technology beyond 3GPP release 15,” *IEEE Access*, vol. 7, pp. 127639–127651, 2019.

[15] A. Yazar and H. Arslan, “Flexible multi-numerology systems for 5G new radio,” *River Publishers J. Mobile Multimedia*, vol. 14, no. 4, pp. 367–394, Oct. 2018.

[16] L. You, Q. Liao, N. Pappas, and D. Yuan, “Resource optimization with flexible numerology and frame structure for heterogeneous services,” *IEEE Commun. Lett.*, vol. 22, no. 12, pp. 2579–2582, Dec. 2018.

[17] C. Jiang, H. Zhang, Y. Ren, Z. Han, K. Chen, and L. Hanzo, “Machine learning paradigms for next-generation wireless networks,” *IEEE Wireless Commun.*, vol. 24, no. 2, pp. 98–105, Apr. 2017.

[18] R. Li *et al.*, “Intelligent 5G: When cellular networks meet artificial intelligence,” *IEEE Wireless Commun.*, vol. 24, no. 5, pp. 175–183, Oct. 2017.

[19] O. Simeone, “A very brief introduction to machine learning with applications to communication systems,” *IEEE Trans. Cogn. Commun. Netw.*, vol. 4, no. 4, pp. 648–664, Dec. 2018.

[20] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," *IEEE Commun. Surv. Tut.*, vol. 21, no. 4, pp. 3039–3071, Oct.-Dec. 2019.

[21] M. Chen, M. Mozaffari, W. Saad, C. Yin, M. Debbah, and C. S. Hong, "Caching in the sky: Proactive deployment of cache-enabled unmanned aerial vehicles for optimized quality-of-experience," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 5, pp. 1046–1061, May 2017.

[22] X. Liu, M. Chen, and C. Yin, "Optimized trajectory design in UAV based cellular networks for 3D Users: A double Q-learning approach," *J. Commun. Inf. Netw.*, vol. 4, no. 1, pp. 24–32, Mar. 2019.

[23] M. Chen, W. Saad, and C. Yin, "Virtual reality over wireless networks: Quality-of-service model and learning-based resource management," *IEEE Trans. Commun.*, vol. 66, no. 11, pp. 5621–5635, Nov. 2018.

[24] M. Chen, O. Semiari, W. Saad, X. Liu, and C. Yin, "Federated echo state learning for minimizing breaks in presence in wireless virtual reality networks," *IEEE Trans. Wireless Commun.*, vol. 19, no. 1, pp. 177–191, Jan. 2020.

[25] H. He, C. Wen, S. Jin, and G. Y. Li, "Deep learning-based channel estimation for beamspace mmwave massive MIMO systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 5, pp. 852–855, Oct. 2018.

[26] U. Challita, L. Dong, and W. Saad, "Proactive resource management for LTE in unlicensed spectrum: A deep learning perspective," *IEEE Trans. Wireless Commun.*, vol. 17, no. 7, pp. 4674–4689, Jul. 2018.

[27] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, "Learning to optimize: Training deep neural networks for interference management," *IEEE Trans. Signal Process.*, vol. 66, no. 20, pp. 5438–5453, Oct. 2018.

[28] S. Wang, H. Liu, P. H. Gomes, and B. Krishnamachari, "Deep reinforcement learning for dynamic multichannel access in wireless networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 4, no. 2, pp. 257–265, Jun. 2018.

[29] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y. A. Zhang, "The roadmap to 6G: AI empowered wireless networks," *IEEE Commun. Mag.*, vol. 57, no. 8, pp. 84–90, Aug. 2019.

[30] I. Tomkos, D. Klonidis, E. Pikasis, and S. Theodoridis, "Toward the 6G network era: Opportunities and challenges," *IT Professional*, vol. 22, no. 1, pp. 34–38, Jan./Feb. 2020.

[31] A. Yazar and H. Arslan, "Selection of waveform parameters using machine learning for 5G and beyond," in *Proc. IEEE 30th Annu. Int. Symp. Pers., Indoor Mobile Radio Commun.*, 2019, pp. 1–6.

[32] S. Lagen, B. Bojovic, S. Goyal, L. Giupponi, and J. Mangues-Bafalluy, "Subband configuration optimization for multiplexing of numerologies in 5G TDD new radio," in *Proc. IEEE 29th Annu. Int. Symp. Pers., Indoor Mobile Radio Commun.*, 2018, pp. 1–7.

[33] L. Marijanovic, S. Schwarz, and M. Rupp, "A novel optimization method for resource allocation based on mixed numerology," in *Proc. IEEE Int. Conf. Commun.*, 2019, pp. 1–6.

[34] L. Marijanovic, S. Schwarz, and M. Rupp, "Optimal numerology in OFDM systems based on imperfect channel knowledge," in *Proc. IEEE 87th Veh. Technol. Conf.*, 2018, pp. 1–5.

[35] T. Soni, A. R. Ali, K. Ganesan, and M. Schellmann, "Adaptive numerology - A solution to address the demanding QoS in 5G-V2X," in *Proc. IEEE Wireless Commun. Netw. Conf.*, 2018, pp. 1–6.

[36] E. Memisoglu, A. B. Kihero, E. Basar, and H. Arslan, "Guard band reduction for 5G and beyond multiple numerologies," *IEEE Commun. Lett.*, vol. 24, no. 3, pp. 644–647, Mar. 2020.

[37] D. Demmer, R. Gerzaguet, J. Dore, and D. Le Ruyet, "Analytical study of 5G NR eMBB co-existence," in *Proc. 25th Int. Conf. Telecommun.*, 2018, pp. 186–190.

[38] A. F. Demir and H. Arslan, "The impact of adaptive guards for 5G and beyond," in *Proc. IEEE 28th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun.*, 2017, pp. 1–5.

[39] L. Marijanović, S. Schwarz, and M. Rupp, "Optimal resource allocation with flexible numerology," in *Proc. IEEE Int. Conf. Commun. Syst.*, 2018, pp. 136–141.

[40] L. Marijanovic, S. Schwarz, and M. Rupp, "Multi-user resource allocation for low latency communications based on mixed numerology," in *Proc. IEEE 90th Veh. Technol. Conf.*, 2019, pp. 1–7.

[41] A. Gonzalez, S. Kuhlmorgen, A. Festag, and G. Fettweis, "Resource allocation for block-based multi-carrier systems considering QoS requirements," in *Proc. IEEE Global Commun. Conf.*, 2017, pp. 1–7.

[42] J. Zhang, X. Xu, K. Zhang, B. Zhang, X. Tao, and P. Zhang, "Machine learning based flexible transmission time interval scheduling for eMBB and uRLLC coexistence scenario," *IEEE Access*, vol. 7, pp. 65811–65820, 2019.

[43] T. Bag, S. Garg, Z. Shaik, and A. M.-Thiel, "Multi-numerology based resource allocation for reducing average scheduling latencies for 5G NR wireless networks," in *Proc. Eur. Conf. Netw. Commun.*, 2019, pp. 597–602.

[44] W. Sui, X. Chen, S. Zhang, Z. Jiang, and S. Xu, "Energy-efficient resource allocation with flexible frame structure for heterogeneous services," in *Proc. Int. Conf. Internet Things IEEE Green Comput. Commun. IEEE Cyber, Phys. Soc. Comput. IEEE Smart Data*, 2019, pp. 749–755.

[45] B. Chang, L. Zhang, L. Li, G. Zhao, and Z. Chen, "Optimizing resource allocation in URLLC for real-time wireless control systems," *IEEE Trans. Veh. Technol.*, vol. 68, no. 9, pp. 8916–8927, Sep. 2019.

[46] M. G. Kibria, K. Nguyen, G. P. Villardi, O. Zhao, K. Ishizu, and F. Kojima, "Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks," *IEEE Access*, vol. 6, pp. 32328–32338, 2018.

[47] Q. Mao, F. Hu, and Q. Hao, "Deep learning for intelligent wireless networks: A comprehensive survey," *IEEE Commun. Surv. Tut.*, vol. 20, no. 4, pp. 2595–2621, Oct.-Dec. 2018.

[48] T. Wang, C. Wen, H. Wang, F. Gao, T. Jiang, and S. Jin, "Deep learning for wireless physical layer: Opportunities and challenges," *China Commun.*, vol. 14, no. 11, pp. 92–111, Nov. 2017.

[49] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Commun. Surv. Tut.*, vol. 21, no. 3, pp. 2224–2287, Jul.-Sep. 2019.

[50] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563–575, Dec. 2017.

[51] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-air deep learning based radio signal classification," *IEEE J. Sel. Topics Signal Process.*, vol. 12, no. 1, pp. 168–179, Feb. 2018.

[52] O. A. Dobre, "Signal identification for emerging intelligent radios: Classical problems and new challenges," *IEEE Instrum. Meas. Mag.*, vol. 18, no. 2, pp. 11–18, Apr. 2015.

[53] M. Kulin, T. Kazaz, I. Moerman, and E. De Poorter, "End-to-end learning from spectrum data: A deep learning approach for wireless signal identification in spectrum monitoring applications," *IEEE Access*, vol. 6, pp. 18484–18501, 2018.

[54] H. Ye, G. Y. Li, and B. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[55] G. Gui, H. Huang, Y. Song, and H. Sari, "Deep learning for an effective nonorthogonal multiple access scheme," *IEEE Trans. Veh. Technol.*, vol. 67, no. 9, pp. 8440–8450, Sep. 2018.

[56] H. Huang, J. Yang, H. Huang, Y. Song, and G. Gui, "Deep learning for super-resolution channel estimation and DOA estimation based massive MIMO system," *IEEE Trans. Veh. Technol.*, vol. 67, no. 9, pp. 8549–8560, Sep. 2018.

[57] A. Alkhateeb, S. Alex, P. Varkey, Y. Li, Q. Qu, and D. Tujkovic, "Deep learning coordinated beamforming for highly-mobile millimeter wave systems," *IEEE Access*, vol. 6, pp. 37328–37348, 2018.

[58] M. S. Sim, Y. Lim, S. H. Park, L. Dai, and C. Chae, "Deep learning-based mmWave beam selection for 5G NR/6G with sub-6 GHz channel information: Algorithms and prototype validation," *IEEE Access*, vol. 8, pp. 51634–51646, 2020.

[59] J. Wang *et al.*, "A machine learning framework for resource allocation assisted by cloud computing," *IEEE Netw.*, vol. 32, no. 2, pp. 144–151, Mar./Apr. 2018.

[60] J. Joung, "Machine learning-based antenna selection in wireless communications," *IEEE Commun. Lett.*, vol. 20, no. 11, pp. 2241–2244, Nov. 2016.

[61] H. Ye, L. Liang, G. Ye Li, J. Kim, L. Lu, and M. Wu, "Machine learning for vehicular networks: Recent advances and application examples," *IEEE Veh. Technol. Mag.*, vol. 13, no. 2, pp. 94–101, Jun. 2018.

[62] L. Liang, H. Ye, and G. Y. Li, "Toward intelligent vehicular networks: A machine learning framework," *IEEE Internet Things J.*, vol. 6, no. 1, pp. 124–135, Feb. 2019.

[63] Z. M. Fadlullah *et al.*, "State-of-the-art deep learning: Evolving machine intelligence toward tomorrow's intelligent network traffic control systems," *IEEE Commun. Surv. Tut.*, vol. 19, no. 4, pp. 2432–2455, Oct.-Dec. 2017.
[64] N. Kato *et al.*, "The deep learning vision for heterogeneous network traffic control: Proposal, challenges, and future perspective," *IEEE Wireless Commun.*, vol. 24, no. 3, pp. 146–153, Jun. 2017.
[65] H. H. Yang, Z. Liu, T. Q. S. Quek, and H. V. Poor, "Scheduling policies for federated learning in wireless networks," *IEEE Trans. Commun.*, vol. 68, no. 1, pp. 317–333, Jan. 2020.
[66] J. Choi and S. R. Pokhrel, "Federated learning with multichannel ALOHA," *IEEE Wireless Commun. Lett.*, to be published.
[67] S. Samarakoon, M. Bennis, W. Saad, and M. Debbah, "Distributed federated learning for ultra-reliable low-latency vehicular communications," *IEEE Trans. Commun.*, vol. 68, no. 2, pp. 1146–1159, Feb. 2020.
[68] B. Brik, A. Ksentini, and M. Bouaziz, "Federated learning for UAVs-enabled wireless networks: Use cases, challenges, and open problems," *IEEE Access*, vol. 8, pp. 53841–53849, 2020.
[69] T. Koketsu Rodrigues, K. Suto, and N. Kato, "Edge cloud server deployment with transmission power control through machine learning for 6G internet of things," *IEEE Trans. Emerg. Topics Comput.*, to be published.
[70] Y. Zhang, B. Di, P. Wang, J. Lin, and L. Song, "HetMEC: Heterogeneous multi-layer mobile edge computing in the 6G era," *IEEE Trans. Veh. Technol.*, vol. 69, no. 4, pp. 4388–4400, Apr. 2020.
[71] F. Tang, Y. Kawamoto, N. Kato, and J. Liu, "Future intelligent and secure vehicular network toward 6G: Machine-learning approaches," *Proc. IEEE*, vol. 108, no. 2, pp. 292–307, Feb. 2020.
[72] S. J. Nawaz, S. K. Sharma, S. Wyne, M. N. Patwary, and M. Asaduzzaman, "Quantum machine learning for 6G communication networks: State-of-the-art and vision for the future," *IEEE Access*, vol. 7, pp. 46317–46350, 2019.
[73] Q. Bi, "Ten trends in the cellular industry and an outlook on 6G," *IEEE Commun. Mag.*, vol. 57, no. 12, pp. 31–36, Dec. 2019.
[74] P. Yang, Y. Xiao, M. Xiao, and S. Li, "6G wireless communications: Vision and potential techniques," *IEEE Netw.*, vol. 33, no. 4, pp. 70–75, Jul./Aug. 2019.
[75] L. Zhang, Y. Liang, and D. Niyato, "6G visions: Mobile ultra-broadband, super internet-of-things, and artificial intelligence," *China Commun.*, vol. 16, no. 8, pp. 1–14, Aug. 2019.
[76] H. Viswanathan and P. E. Mogensen, "Communications in the 6G Era," *IEEE Access*, vol. 8, pp. 57063–57074, 2020.
[77] M. Giordani, M. Polese, M. Mezzavilla, S. Rangan, and M. Zorzi, "Toward 6G networks: Use cases and technologies," *IEEE Commun. Mag.*, vol. 58, no. 3, pp. 55–61, Mar. 2020.
[78] S. Zhang, C. Xiang, and S. Xu, "6G: Connecting everything by 1000 times price reduction," *IEEE Open J. Veh. Technol.*, to be published.
[79] Y. Al-Eryani and E. Hossain, "The D-OMA method for massive multiple access in 6G: Performance, security, and challenges," *IEEE Veh. Technol. Mag.*, vol. 14, no. 3, pp. 92–99, Sep. 2019.
[80] L. Zhu, Z. Xiao, X. Xia, and D. O. Wu, "Millimeter-wave communications with non-orthogonal multiple access for B5G/6G," *IEEE Access*, vol. 7, pp. 116123–116132, 2019.
[81] T. S. Rappaport *et al.*, "Wireless communications and applications above 100 GHz: Opportunities and challenges for 6G and beyond," *IEEE Access*, vol. 7, pp. 78729–78757, 2019.
[82] E. Basar, "Reconfigurable intelligent surface-based index modulation: A new beyond MIMO paradigm for 6G," *IEEE Trans. Commun.*, to be published.
[83] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M. Alouini, and R. Zhang, "Wireless communications through reconfigurable intelligent surfaces," *IEEE Access*, vol. 7, pp. 116753–116773, 2019.
[84] Q. Qi, X. Chen, C. Zhong, and Z. Zhang, "Integration of energy, computation and communication in 6G cellular internet of things," *IEEE Commun. Lett.*, to be published.
[85] T. Huang, W. Yang, J. Wu, J. Ma, X. Zhang, and D. Zhang, "A survey on green 6G Network: Architecture and technologies," *IEEE Access*, vol. 7, pp. 175758–175768, 2019.
[86] B. Mao, Y. Kawamoto, and N. Kato, "AI-based joint optimization of QoS and security for 6G energy harvesting internet of things," *IEEE Internet Things J.*, to be published.
[87] X. Huang, J. A. Zhang, R. P. Liu, Y. J. Guo, and L. Hanzo, "Airplane-aided integrated networking for 6G wireless: Will it work," *IEEE Veh. Technol. Mag.*, vol. 14, no. 3, pp. 84–91, Sep. 2019.
[88] E. Yaacoub and M. Alouini, "A key 6G challenge and opportunity–connecting the base of the pyramid: A survey on rural connectivity," *Proc. IEEE*, to be published.
[89] A. Sahin and H. Arslan, "Multi-user aware frame structure for OFDMA based system," in *Proc. IEEE Veh. Technol. Conf.*, 2012, pp. 1–5.
[90] J. Jeon, "NR wide bandwidth operations," *IEEE Commun. Mag.*, vol. 56, no. 3, pp. 42–46, Mar. 2018.
[91] T. Levanen, J. Pirskanen, K. Pajukoski, M. Renfors, and M. Valkama, "Transparent Tx and Rx waveform processing for 5G new radio mobile communications," *IEEE Wireless Commun.*, vol. 26, no. 1, pp. 128–136, Feb. 2019.
[92] A. Tusha, S. Dogan, and H. Arslan, "Performance analysis of frequency domain IM schemes under CFO and IQ imbalance," in *Proc. IEEE 30th Annu. Int. Symp. Pers., Indoor Mobile Radio Commun.*, 2019, pp. 1–5.
[93] A. Maatouk, E. Caliskan, M. Koca, M. Assaad, G. Gui, and H. Sari, "Frequency-domain NOMA with two sets of orthogonal signal waveforms," *IEEE Commun. Lett.*, vol. 22, no. 5, pp. 906–909, May 2018.
[94] S. Dogan, A. Tusha, and H. Arslan, "NOMA with index modulation for uplink URLLC through grant-free access," *IEEE J. Sel. Topics Signal Process.*, vol. 13, no. 6, pp. 1249–1257, Oct. 2019.
[95] A. Tusha, S. Dogan, and H. Arslan, "A hybrid downlink NOMA with OFDM and OFDM-IM for beyond 5G wireless networks," *IEEE Signal Process. Lett.*, vol. 27, pp. 491–495.
[96] X. Zhang, L. Zhang, P. Xiao, D. Ma, J. Wei, and Y. Xin, "Mixed numerologies interference analysis and inter-numerology interference cancellation for windowed OFDM systems," *IEEE Trans. Veh. Technol.*, vol. 67, no. 8, pp. 7047–7061, Aug. 2018.
[97] A. Yazar and H. Arslan, "Reliability enhancement in multi-numerology-based 5G new radio using INI-aware scheduling," *EURASIP J. Wireless Commun. Netw.*, vol. 2019, no. 110, pp. 1–14, May 2019.
[98] Y. Roh, G. Heo, and S. E. Whang, "A survey on data collection for machine learning: A big data - AI integration perspective," *IEEE Trans. Knowl. Data Eng.*, to be published.
[99] S. Yarkan and H. Arslan, "Exploiting location awareness toward improved wireless system design in cognitive radio," *IEEE Commun. Mag.*, vol. 46, no. 1, pp. 128–136, Jan. 2008.
[100] 3rd Generation Partnership Project (3GPP), "NR; Physical channels and modulation," Technical Specification 38.211, ver. 15.5.0, Mar. 2019.

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