**5G physical and higher layer design techniques** **for massive ultra-reliable low latency communication (mURLLC) for UAS Application**

# **Research Abstract and Goals**

The ultra-reliable and low-latency communications (URLLC) has been considered as one of the new application scenarios in the fifth generation (5G) wireless communications [1]. It is necessary for enabling mission-critical unmanned aerial systems (UAS), internet of things (IoT), remote control in tactile internet, safety application in vehicular networks, and future healthcare systems [2]. Specifically, UAS applications have very strict quality-of-service (QoS) requirements due to their high mobility, long distance coverage, critical missions they carry out and their high cost of making and operation. Its main operational requirements focus on the end-to-end delay and reliability, as well as the network availability, which is defined as the probability that the QoS requirement of users can be satisfied in a wireless network (e.g., 99.999 %) [3]. Due to path loss, shadowing, and fast channel fading over wireless links, it is very challenging to satisfy the QoS requirement of URLLC in UAS applications. Therefore, to realize this application with flexibility and low-cost, future 5G wireless communication should achieve use-case-specific performance such as much higher reliability (e.g. < 10-6 block error rate @ 256 bytes), lower latency (e.g. < 1 ms @ round trip time), and massive connections (e.g. > 1 million nodes @ 1 km2), in comparison with existing technologies such as 4G cellular networks [4].

Currently technologies being investigated to address these issues include massive multiple-input multiple-output (MIMO) techniques to provide ultra reliable communication with an over-the-air latency of few milliseconds and extreme throughput [5]. Exploiting the huge degrees of freedom of massive MIMO is essential for achieving high spectral efficiency, high data rates, and highly spatial multiplexing of densely distributed users. In addition, large antenna array can be packed into highly directional beamforming, which makes massive MIMO practically feasible and much reliable [5].

Taking the above into consideration, in this project we intend to work on 5G physical and higher layer design algorithms and evaluate their performance for massive URLLC (mURLLC) for UAS application by using computer simulations and testbeds using massive MIMO at sub-6 GHz frequency bands.

# **Scope of the project**

The topics of interest of this project include:

• Definitions of target use cases and a description of their related problem(s) to be solved by the proposed solution(s),

• Designing physical and higher-layer protocols and corresponding mechanisms/algorithms, and

• Performance evaluations based on either computer simulations and/or test-bed.

# **Technical Challenges to be Overcome**

The technical challenges we plan to address are the following

1. Provision of scalable, ultra-reliable and secure Air-to-Ground (AG) command and control (C2) links in challenging and dynamic urban channel environments.
2. Estimate required capacity of UAS C2 links; identify and evaluate the use of potential frequency spectrum, and from this provide ranking of feasible existing and planned aviation and 5G cellular systems specifically its URLLC service type design efforts.
3. Feasibility study of emerging 5G systems for potential use in UAS communications. Consequent communication link recommendations.
4. New ultra-reliable, scalable, and secure physical layer and higher layer designs for UAS, evaluated by analysis, simulation, and laboratory experiment, validated by measurements, including at the NCAT State University test bed. This includes testing with large scale antenna arrays (up to 32 antenna arrays in several bands).

**Proposed Research Themes**

In addressing these technical challenges, the following three corresponding research themes are proposed.

## **Theme A: Latency sensitive scheduling and beamforming**

In contrast to the 4G LTE systems, latency, reliability, and throughput requirements should be jointly considered in 5G NR; hence, there should be a fundamental change in the physical layer architecture (packet, slot, and frame). Specifically, a flexible frame structure to support a dynamic change of the resource grid based on the latency requirement and latency-sensitive packet structure for a fast decoding process are needed. In addition, the URLLC packet should be transmitted instantly without delay when the URLLC service is initiated. To achieve this, a scheduling scheme minimizing the transmit latency of the URLLC packet should be introduced. For this at the initial stage of the scheduling process, a computationally less expensive algorithm will be employed. However, the full search will be utilized to acquire enough training data. Then, we will apply novel machine learning (ML) techniques to determine the model coefﬁcients to be used in the subsequent network operation.

Once the latency sensitive scheduling design is performed, the remaining task is to apply suitable beamforming technique to optimize the system performance. As stated, UAS applications require ultra-reliable, low-latency communications which have maximum transmission coverage without delay. Base stations (BSs) will employ beamforming technologies to steer their radiation pattern to the desired UAS, and in turn can be used to increase the reliability. To handle this, we will employ different techniques in subsequent beamforming design stages. One way can be by applying multiuser beamforming on different sub-channels. This might help to increase reliability as the information of one UAS will be transmitted over multiple sub-channels.

In general, UAS often tend to be dynamic in location and their physical characteristics such as CSI and position information cannot be learnt just by using simple mathematical models, however by utilizing appropriate learning techniques it can be learnt in a reasonable accuracy. In this aspect, we will use novel ML approach for beamforming and scheduling design. In a typical ML algorithm, the learning process requires appropriate training data set. However, this data set may not be available in the beginning when the model is trained in a new environment. In such a case, the design will use extremely low complex numerical suboptimal solutions to operate the network. Meanwhile, the optimal solution is computed offline so that the ML algorithms can use for testing phase. To reduce the overhead of the downlink training phase, we will use practical open-loop training frameworks in massive MIMO [12]. We assume that the BS and user share a common set of training signals in advance. In open-loop training, BSs transmit training signals in a round-robin manner, and user successively estimates the current channel using long term channel statistics such as temporal and spatial correlations and previous channel estimates. Once the training data is sufficient, the ML algorithm will use them to obtain optimal design coefficients. After this stage, the network is operated by employing the design coefficients obtained from the trained dataset. In this regard, the proposed design will use different simple ML techniques such as linear, polynomial and Kernel regressions as well as the well-known Autoencoder approach [10-11].

## **Theme B: Channel prediction algorithm design**

The other objective to be met will be selection of channel impulse response prediction. UAS communication has its own distinctive channel characteristics compared with widely used cellular and satellite systems. Thus, accurate channel characterization and prediction is crucial for the performance optimization and design of efficient UAS communication systems. However, several challenges exist in UAS channel modeling. For example, propagation characteristics of UAS channels are still less explored for spatial and temporal variations in non–stationary channels. Therefore, channel prediction algorithm design is an essential step to study the impact of fast spatial-temporal variations in the UAS channel and consequently to predict the performance of UAS communications. In addition, prediction will be used to reduce training overhead, which can also be used to create beams based on the predicted channel. Here, when the channel model is not known, we will use ML techniques to solve the problem.

## **Theme C: Cross Layer Design Techniques for reliability**

## We propose to exploit different higher layer techniques. This includes the utilization of situation aware packet queuing technique. We will also employ an intelligent technique to intelligently select traffics as per the delay/reliability requirement. In this regard, the proposed technique will target reducing the collision probability by exploiting more than one channels. More will comeout here

## **Theme D: Performance evaluations**

After the algorithms and designs have been developed, we will evaluate their performance by using computer simulation and/or at the NCAT State University test bed. For computer simulation, we will use NETSIM, QualNet, MATLAB 5G toolbox to configure, simulate, measure, and analyze our designs. On the other hand, we can also use the National Instrument test bed NI PXIe‑1085 to measure and analyze the performance of our system. The PXIe‑1085 features a high-bandwidth, all-hybrid backplane to meet a wide range of high-performance test and measurement application needs.

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