Abstract—Notwithstanding the significant traction gained by ultra-reliable and low-latency communication (URLLC) in both academia and 3GPP standardization, fundamentals of URLLC remain elusive. Meanwhile, new immersive and high-stake control applications with much stricter reliability, latency and scalability requirements are posing unprecedented challenges in terms of system design and algorithmic solutions. This article aspires at providing a fresh and in-depth look into URLLC by first examining the limitations of 5G URLLC, and putting forward key research directions for the next generation of URLLC, coined eXtreme ultra-reliable and low-latency communication (xURLLC). xURLLC is underpinned by three core concepts: (1) it leverages recent advances in machine learning (ML) for faster and reliable data-driven predictions; (2) it fuses both radio frequency (RF) and non-RF modalities for modeling and combating rare events without sacrificing spectral efficiency; and (3) it underscores the much needed joint communication and control co-design, as opposed to the communication-centric 5G URLLC. The intent of this article is to spearhead beyond-5G/6G mission-critical applications by laying out a holistic vision of xURLLC, its research challenges and enabling technologies, while providing key insights grounded in selected use cases.

1 INTRODUCTION

The overarching goal of ultra-reliable and low-latency communication (URLLC) lies in satisfying the stringent reliability and latency requirements of mission and safety-critical applications. Achieving this is tantamount to characterizing statistics of extreme and rare events (e.g., taming the tail of latency distribution), in contrast to the average-based system design [1], [2]. To remedy to this, 3GPP has been using a brute-force approach centered on system-level simulations to meet the 99.999% (5-nine) reliability and 1 ms latency targets, using a plethora of techniques (short packet transmission, grant-free mechanisms, leveraging spatial, frequency, and temporal diversity techniques [1], [3], [4]). While advances have been made in sparse, stationary and controlled environments with traditional model-based approaches, we still lack a deep understanding of wireless channel dynamics, estimation, stability of control-loop systems, robustness to unmodeled phenomena, to mention a few. These challenges are further exacerbated in light of the following recent trends.

On one hand, the emergence of new applications necessitates much stricter reliability and latency requirements than those set in 5G URLLC. In particular, high-precision robot control and autonomous vehicles cannot afford 5-nine reliability and millisecond latency [4]. Factory automation over wireless links should guarantee 7-nine reliability and sub-1 ms latency, similar to those of the Ethernet-based time sensitive networking (TSN) and isochronous real time (IRT) system standards [5]. Meanwhile, the next generation (6G) wireless systems is advocating 9-nine reliability with 0.1 ms latency for supporting intelligent systems built upon various perceptual modalities (or Internet of senses) and real-time human-machine interactions [3], [6], [7].

On the other hand, URLLC has become conflated with both massive machine-type communication (mMTC) and enhanced mobile broadband (eMBB) [8]. Unlike the rigid 5G URLLC design focusing on sparse deployments and short packet transmissions, some applications must simultaneously support massive connections and high data rates, i.e., scalability. For instance, an autonomous drone swarm in a rescue mission requires not only URLLC but also a massive number of wireless control loops for inter-drone collision avoidance. In precision agriculture, vision-based monitoring and remotely controlling sowing robots call for both URLLC and high-speed data rates. In short, the eMBB-URLLC-mMTC compound is no longer a zero-sum game, mandating novel solutions to enable scalable support for high data rate mission critical applications.

As we shall examine, this article discusses the limitations of 5G URLLC, and puts forward a new research agenda for the next generation of URLLC, coined eXtreme URLLC (xURLLC), rooted in three key concepts.
1. Predictive URLLC. 5G URLLC is reactive in nature, and is built upon the availability of known, stationary channel and traffic models, questioning the adequacy of the definition of reliability, as noted in [9]. In contrast, xURLLC is essentially predictive, leveraging the recent advancement in machine learning (ML) to enable highly accurate predictions of channels, traffic, states, and other key performance indicators [8]. A fundamental research question addressed by predictive URLLC is summarized as follows.

Q1. Can wireless environments (channels, interference, services, etc.) be reliably predicted based on past data samples? and under what future horizon?

The challenges raised by Q1 and associated research agenda (R1-3) are discussed in Sect. 2, followed by selected use cases.

2. Non-radio frequency (RF) Aided URLLC. By design 5G URLLC is RF-based and requires investing wireless resources for channel probing and estimation. By contrast, xURLLC exploits non-RF modalities, such as color and depth (RGB-D) images for channel prediction [10]. This data provides rich features for predicting extreme and sudden events (e.g., blockages), which cannot be done with current RF-based solutions, due to lack of statistical relevance and/or expensive acquisition under limited radio resources. By extension, one can utilize reconfigurable intelligent surfaces (RISs) and metasurfaces [7] to tune channel randomness by manipulating surface reflections, while inducing higher energy efficiency (EE). Enjoying these benefits hinges on addressing the following question.

Q2. How to transfer and fuse non-RF and RF modalities with minimum overhead to enable xURLLC?

Sect. 3 addresses the challenges and opportunities (R4-6) raised by Q2 through the lens of exemplary use cases.

3. Control Co-Designed URLLC. In 3GPP parlance, communication reliability is calculated by counting erroneous packets divided by the total transmitted packets during an observed time period [4]. In contrast, xURLLC cares about whether consecutive packet errors or losses disrupt the control operation. Understanding control dynamics provides a natural (yet untapped) opportunity to relax the very stringent latency and reliability requirements, making communication and control co-design (CoCoCo) a core concept in xURLLC. To reach this goal, one should take into account wireless channel dynamics in control systems, through which the received state observations and actuating commands may be outdated and distorted. Moreover, relaxing communication latency and reliability requirements, while guaranteeing control stability and safety against external perturbations, internal state fluctuations, and inter-agent collision is of paramount importance, raising the following question.

Q3. Can URLLC requirements be relaxed by taking into account control dynamics, while ensuring control stability?

In Sect. 4, R7-R9 discuss the challenges and opportunities raised in Q3 through selected case studies, followed by conclusions in Sect. 5.

2 Predictive URLLC

5G URLLC focuses on characterizing extreme events at the cost of spectral efficiency, limiting its scalability. In doing so, 5G URLLC presumes a static channel model that fails to capture non-stationary channel dynamics and exogenous uncertainties (e.g., out-of-distribution or other under-modeled rare events), which are common in uncontrolled environments. In contrast, xURLLC aims at proactive decision making powered by ML, in which proactiveness offers available resources to satisfy 9-nine reliability within 0.1 ms latency, which is on par with Ethernet-based TSN and IRT [5]. Furthermore, in contrast to the static and model-based paradigm, xURLLC allows to communicate by learning from data samples even under non-stationary and unpredictable environments. Examples include latency estimation, age-of-information (AoI) [11], and traffic demand prediction [12] based on users’ visuo-haptic perceptions.

2.1 Challenges and Opportunities

The adoption of ML entails novel challenges and research opportunities in xURLLC, as we shall examine.

R1. Sample Complexity. Making predictions using an ML model, i.e., inference, should be preceded by model training. A trained model is valid so long as the training data distribution is unchanged; otherwise, the outdated model must be re-trained. The interval of this continual learning, i.e., training convergence time, should be sufficiently small compared to the temporal channel evolution dynamics. Training convergence analysis quantifies the required number of training samples to achieve a target accuracy, i.e., sample complexity [8]. Due to the lack of samples at a single location, taming sample complexity requires communication. Federated learning (FL) addresses this problem by periodically exchanging locally trained model parameters, rather than instantly exchanging raw samples [8], thereby reducing the cost of predictive URLLC.

R2. Reliable Prediction. Predictive URLLC improves communication reliability, as long as the ML prediction is reliable. Although traditional deep neural network (NN) models can achieve high prediction accuracy, they do not report the reliability of their prediction. To measure reliability against unseen training samples, one needs to quantify the generalization error, defined as the difference between the expected loss across the entire dataset and the empirical training loss [8]. Another solution is to leverage Bayesian learning methods such as Gaussian process regression (GPR) that provide the prediction confidence via the variance of the posterior distribution [11]. Last but not least, adversarial training improves reliability against non-stationary data distributions due to time-varying channels, malfunctions and attacks, by training with synthetic adversarial data samples.

R3. Perception-Aware Prediction. Look-ahead forecasting offers more available resources, at the expense of accuracy. Prediction horizon should therefore be minimized by utilizing perceptual characteristics. For driving scenarios, the prediction horizon can be determined by the driver’s perception-reaction time (PRT) that is around 2.5 s for human drivers and several milliseconds for driverless cars. When human-driving and driverless cars coexist, the PRT of both driving
agents may increase if they do not understand the other agents’ reasoning. The human-robot interaction (HRI) should therefore be closely investigated. In high-precision control applications involving multiple perceptual modalities (e.g., vision, touch, Lidar, etc.), the perceptual relationships and their integrated resolutions measured using the just noticeable difference (JND) ought to be considered [12].

The following subsections discuss some of the issues raised in R1-R3 in vehicle-to-vehicle (V2V) and virtual reality (VR)/augmented reality (AR) scenarios.

2.2 Use Cases

2.2.1 Predictive AoI for Ultra-Reliable V2V Communication

Ensuring the freshness of safety messages is crucial in V2V communication, which is measured using the notion of AoI. AoI is defined as the time duration from the message generation to reception [11]. Estimating future AoI is however difficult due to the varying V2V channel, every transmitter locally determines its transmission power and resource block (RB) selection, such that the receiver’s AoI is bounded by a predefined threshold with a target reliability. To overcome this difficulty, GPR can be utilized as follows.

**Scenario.** There are 20 transmitting-receiving vehicle pairs driving in a Manhattan grid scenario. Under this time-varying V2V channel, every transmitter locally determines its transmission power and resource block (RB) selection, such that the receiver’s AoI is bounded by a predefined threshold with a target reliability. To this end, each transmitter runs GPR by feeding its past AoI and RB selections, yielding the next transmission power and RB selection.

**Results.** Fig. 2 plots the tail distribution of the error between the true and estimated AoI for a given power and RB decision. The more samples are used, the sharper the tail distribution is (see R1). Furthermore, the prediction reliability is fully characterized by the posterior distribution’s variance, which decreases with more samples (see R3).

2.2.2 VR/AR Perception-Aware Proactive Network Slicing

Supporting multimodal perceptions at a single device is becoming increasingly important in 5G and beyond. Indeed, a mobile VR user may simultaneously look at and touch a virtual object. Such concurrent visual and haptic perceptions should be synchronously received at the user as experienced in real life, so as to avoid cybersickness while increasing immersion in virtual spaces. Since these visual and haptic modalities have distinct rate and latency requirements, they should be supported through separate eMBB and URLLC links, while mitigating their inter-modal interference. By utilizing their perceptual relationship eMBB-URLLC links can be proactively sliced as follows.

**Scenario.** Using eMBB-URLLC links, a base station (BS) serves a downlink VR user watching a visuo-haptic interactive movie, while ensuring a target perceptual resolution (see R3). JND quantifies the perceptual resolution (e.g., 3 mm minimum detectable object size), which is given by the harmonic mean of the individual links’ packet error rates [12]. Unfortunately, satisfying the multimodal perception requirement consumes huge wireless resources. To resolve this problem, we utilize the fact that haptic experiences are limited by touchable objects within the visual field-of-view (FoV). Consequently, using a recurrent NN and feeding past FoVs, the BS deactivates the URLLC link, if there exists no touchable object within the future FoV.

**Results.** Fig. 3 shows that proactive URLLC deactivation improves the eMBB data rate under both orthogonal and
non-orthogonal slicing methods, particularly for a high URLLC target data rate, i.e., supporting high-resolution haptic experiences. The prediction horizon of FoV was 5 frames ahead, corresponding to 41.7 ms under 120 Hz frame rate.

3 Non-RF Aided URLLC

Spurred by recent advances in ML and computer vision, leveraging non-RF modalities (e.g., RGB-D and cameras, Lidar, etc.) is crucial for confronting the extreme event prediction problem, without sacrificing spectral efficiency. Compelling non-RF aided URLLC use cases include vision-based channel prediction and mobility management, vision-aided coordination and control of robotic swarms. To overcome the issue of occlusion, transferring visual modalities into RF expedites channel blockage predictions without pilot signaling [10], allows high-precision location prediction and tracking [13], to mention a few. Not only that, for enabling scalable xURLLC, non-RF modalities provide yet another source of diversity-enhancements, free from RF resource constraints and negligible signaling overhead.

3.1 Challenges and Opportunities

Smartly incorporating non-RF modalities is crucial for enabling xURLLC with negligible overhead. This rests on addressing the following challenges and research opportunities.

R4. Multimodal Fusion. Different types of data have distinct spatio-temporal resolutions (e.g., image sizes, frame rates, and sensing/sampling rates) and their appropriate processing methods (e.g., convolutional NN for vision). Efficiently fusing multiple modalities while balancing their useful features is a critical challenge. Split learning (SL) is a powerful framework, in which an NN consists of a shared upper segment connected to multiple lower segments fed by different types of data. SL can effectively fuse multiple modalities by applying different data-specific architectures to the lower segment, while balancing the aggregating weights at the upper segment [10].

R5. Beyond Visual Modality. Besides vision, there exist other non-RF modalities to enable xURLLC. Accelerometer information is one possible candidate, from which mobility patterns can be extracted, thereby estimating blockage duration. Another possibility is RIS-endowed walls based on the idea of manipulating signal amplitude, phase, reflection angle, and polarization via RIS such that the desired signals and interference can be engineered. To effectively fuse these non-RF modalities, their pros and cons should be carefully examined vis-a-vis RF-based URLLC.

R6. Non-RF Overhead. Utilizing non-RF data does not come for free, and its extra energy cost for acquisition, processing, and control cannot be neglected. Indeed, to enable vision-aided channel estimation, training images need to be collected from multiple cameras to overcome each camera’s limited FoV, consuming communication energy. Extracting hidden useful features via principal component analysis (PCA) or convolutional NN entails processing energy. Balancing vision and RF modalities in the fusion operations requires an optimization procedure that consumes additional computing energy. These energy footprints may negate the effectiveness of non-RF modalities, notably compared to advanced digital beamforming in 6G [6], [7]. Therefore, EE, defined as the ratio of the performance gain to the total energy consumption, should be carefully examined.

The following subsections tackle R4-R6 focusing on RGB-D image based millimeter wave (mmWave) channel prediction and ML based energy-efficient RIS use cases.

3.2 Use Cases

3.2.1 RGB-D Aided mmWave Received Power Prediction

RF signals do not always have sufficient features for high-accuracy prediction. Predicting future mmWave channels is one example, in which predictions using past RF signals fail to detect sudden transitions between line-of-sight (LoS) and non-LoS (NLoS) conditions due to pedestrian blockages [10]. This is where visual modalities come to the rescue, namely where a sequence of camera images containing sufficient features to predict channel blockages complements to the RF modality, as detailed next.

Scenario. Consider an RGB-D camera with 30 Hz frame rate observing a 60 GHz mmWave channel that is randomly blocked by two moving pedestrians. Our goal is to predict 120 ms ahead the received power using past camera images and received powers observed at the same time. To this end, a split NN is considered (see R4), comprising: 1) two convolutional layers that extract features from images; 2) another single-layer NN whose output dimension is the same as the output dimension of 1); and 3) a recurrent NN layer that concatenates the outputs of 1) and 2) into a sequence as its input, thereby performing a time-series prediction of the future mmWave received power.

Results. Fig. 4 shows that the received power prediction using both images and RF signals (RF+Img) achieves the
highest accuracy while precisely detecting the LoS/NLoS transitions. By contrast, the baseline predictions using either RF signals (RF) or images (Img) fail to accurately predict the transitions or short-term channel fluctuations for a given LoS or NLoS condition. While RF+Img is effective in minimizing the mean prediction error, the tail probability shows that extremely large error occurrences are minimized under Img, calling for further optimizing the multimodal fusion using a tail-risk minimization framework [1].

3.2.2 ML Based Energy-Efficient RIS

Ensuring reliable connectivity with extremely low energy consumption is instrumental in realizing scalable xURLLC. Towards achieving this goal, RIS is a promising enabler, in which a large number of low-cost reflectors within a planar array passively shift the phases of incident RF signals (see R5). This begs the question of how to design a low-complexity RIS controller with minimal signaling overhead, while achieving high EE.

Scenario. An RIS with 64 elements serves a single user, by reflecting the signals transmitted from a single BS. The entire elements are equally divided and controlled by $K$ controllers, each of which is a fully-connected 3-layer NN with $N$ neurons per layer. By feeding in the user location, the NN outputs either 0 or $\pi$ phase shift per element. The NN is trained via supervised learning using 650 samples, by minimizing the signal-to-noise ratio (SNR) difference between the proposed method and the ground truth found via exhaustive search. Subsequently, for a given new user’s location, the RIS phase shift is inferred using the trained NN model.

Results. Fig. 5 shows that the proposed method achieves higher EE (see R6), defined as spectral efficiency per total energy consumption (excluding the BS transmission power), than a random phase shifting baseline. Compared to exhaustive search, the proposed method yields almost the same spectral efficiency without dissipating energy as done in exhaustive search, resulting in higher EE. To further improve EE, increasing the BS transmission power is shown to be effective up to a certain inflection point after which the bottleneck stems from the binary phase shifting, calling for the controller’s design and optimization. Compared to a single large NN controller (Goliath), $K$ small NN controllers (Davids) consume less energy that is proportional to the number of weights ($2N^2/K$). On the contrary, too many Davids incur much fewer weights, reducing the NN model capacity. Under this energy consumption and model capacity trade-off, EE is maximized at $K = 2$.

4 CONTROL CO-DESIGNED URLLC

Real-time control over wireless links is a cornerstone application in URLLC, requiring the strictest reliability and latency targets [1], [7], [14]. Conversely, control is a domain where relaxing the URLLC requirements can be maximized, thereby enabling scalability. This hinges on identifying the importance of each transmission packet in control operations subject to, for example, the maximum allowable transfer interval (MATI), the maximally allowable delay (MAD), and AoI [11]. This system design is at odds with 5G URLLC focusing solely on over-the-air and one-way transmission errors with equal importance for all packets. Not only that, a key requirement overlooked in 5G URLLC is stability, which makes CoCoCo of utmost importance for guaranteeing physical stability [15]. Indeed, once a device drifts away from controllable states, further communication becomes useless and wasteful. xURLLC should therefore play a pivotal role in, for instance, avoiding collisions of autonomous vehicles and guaranteeing to reach a target destination.

4.1 Challenges and Opportunities

Reaping the benefits of CoCoCo requires confronting several challenges, while opening novel research opportunities.

R7. Controller Connectivity. A control system comprises sensors measuring states, controllers calculating commands based on the states, and actuators executing control commands. These three intertwined components are not always physically co-located, but connected over wireless links, resulting in missing and/or distorted state and command receptions. To alleviate this problem, by accounting for the sequential control operations, the controller’s transmission power can be ramped up if the preceding sensor’s transmission delay is too long. By utilizing previous states and commands, future states and commands can also be inferred via predictive URLLC (see R3). If future channel conditions are predicted to be poor, relocating the controller’s functionality to its actuator allows to switch remote control to autonomous control.

8. Stable Control. When only communication reliability is considered, its associated control stability may be underestimated (e.g., useless communication attempts after collision)
or overestimated (e.g., guaranteeing 9-nine communication reliability for achieving only 90% stability). To correct this problem, control stability should first be clearly formalized. For a single agent control, when the output state is proportional to the input control, i.e., linear system, system stability is determined by ensuring bounded output for any bounded input, i.e., bounded-input, bounded-output (BIBO) stability. In non-linear systems, stability can be examined through the lens of Lyapunov stability that is ensured when the temporal derivative of the Lyapunov function decreases. For multiple-agent control, inter-agent collision avoidance can be described using swarm stability that is satisfied when all agents’ relative velocities converge to zero. For a chain of agents (e.g., vehicle platooning), alleviating chain fluctuations can be measured via string stability that holds if any inter-agent spacing is bounded for a finite disturbance. Reconciling control stability constraints with communication reliability requirements under R7 is a major challenge.

R9. Scalable Control. In high-precision control applications, both control input and output dimensions are large incurring huge computing overhead. Moreover, in reality state dynamics are often unknown due to non-stationarity and external uncertainties, making traditional model-based control unfit for URLLC applications. ML based control resolves both problems, in which an ML model outputs an optimal control by directly feeding a state input. Another challenge comes from multiple interacting agents whose states are intertwined. Control decisions should thus be preceded by exchanging states, which may hinder scalability. Mean-field (MF) game framework elegantly detours this issue, in which each agent interacts only with the population’s distribution that can be locally estimated. Lastly, human intervention may interrupt machine operations due to their different perceptual characteristics (see R3), limiting scalability. In this respect, transferring human knowledge to machines via demonstrations or human-machine FL is an emerging research direction.

4.2 Use Cases

4.2.1 ML-Aided Single UAV Remote Control

Remote UAV control is an important use case highlighting the importance of CoCoCo. In order to control a remote UAV under random wind perturbations, the controller should download its state and upload the control decision to the UAV within a short time deadline. To meet this end-to-end control latency requirement, the effectiveness of uplink transmission power control and opportunistic controller relocation is studied as follows.

Scenario. A single UAV is controlled by a ground BS so as to reach a target destination. For each control cycle, the BS downloads (DLs) the UAV state $s(t)$ (velocity and remaining distance) at time $t$, and runs an NN (see R9) to compute its optimal action (acceleration) that is then uploaded to the UAV, until a time deadline, i.e., MAD. To meet the MAD, if the DL latency is high, the upload (UL) transmission power is ramped up. To cope with persistent remote control failures, when leaving a certain range, the UL information

![Fig. 6. NN-based single UAV control with its Lyapunov stability (destination arrival guarantee, left) and massive autonomous UAV control with their swarm stability (bounded maximum relative velocity guarantee, right).](image-url)
is switched to the latest NN model from its output control actions, enabling autonomous UAV control (see R7). Finally, in order not to pass by the destination, the NN loss function is penalized when the Lyapunov stability $s(t)ds(t)/dt < 0$ is violated (see R8).

**Results.** Action UL payload sizes are smaller than model sizes. Hence, always uploading actions (action UL) has faster control cycles with more state observations, yielding its better trained NN model compared to always uploading NN models (model UL). However, even with maximum UL transmission power, action UL looses control of a faraway UAV that can be autonomously controlled under model UL. This trade-off is observed in Fig. 6(a). In comparison to these two baselines, by switching from action UL to model UL, the proposed control method (switch UL) ensures Lyapunov stability more frequently during the entire travel, while achieving shorter travel time.

### 4.2.2 ML Aided Massive Autonomous UAV Control

UAV swarms are critical in search and rescue missions, whereby forming a flock of UAVs can avoid inter-UAV collision, at the expense of exchanging instantaneous UAV states, hampering real-time control. MF game theoretic control alleviates the swarming communication overhead, enabling real-time control while avoiding collision. This is done by recasting the inter-UAV interactions as the interplay between a UAV and the population state distribution [8], as exemplified next.

**Scenario.** There are 25 UAVs dispatched to a destination. Each UAV is autonomously controlled by locally running a pair of two NNs (see R9), computing optimal control actions (action NN) and population state distributions (MF NN), respectively. To avoid collision, the action NN’s loss function is penalized, when the maximum relative velocity is larger than a threshold, i.e., violating swarm stability $|v_{\text{max}} - v_{\text{min}}| > \varepsilon$ (see R8).

**Results.** The convergence of the proposed control method (action+MF) is guaranteed, as long as the initial UAV states are exchanged. Therefore, even with small transmission power (see R7), action+MF incurs no collision by achieving swarming faster than a benchmark scheme (action) running only action NN after exchanging instantaneous states, as observed by Fig. 6(b).

5 **Conclusions**

This article outlined a detailed vision for the next generation of URLLC, coined xURLLC. Breaking away from the reactive, RF based, and communication centric 5G URLLC, xURLLC is predictive, non-RF aided, and weaves in communication and control. This vision overcomes several key limitations of URLLC, namely extreme/rate event prediction, scalability, while building in new diversity enhancements with minimal overhead, and relaxing latency and reliability requirements based on the value of information. The intent of the xURLLC vision is to spearhead beyond-5G/6G mission-critical applications (e.g., vision-based control, visuo-haptic VR, autonomous/remote-controlled drone swarms, and other cyber-physical control applications). Going forward, xURLLC can no longer be designed in a vacuum, but instead must leverage and build upon other domains and knowledge such as ML, non-RF, and control, while factoring in the cost of these domains, notably with the era of data-driven decision-making and predictions.