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Vision Article

Wireless control: Retrospective and open vistas

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ABSTRACT

The convergence of wireless networks and control engineering has been a technological driver since the beginning of this century. It has significantly contributed to a wide set of emerging applications, such as smart homes, robot swarms, connected autonomous vehicles, and wireless process automation. Envisioning further integration and developments in wireless control, in this paper we provide an overview of past results and present some perspective on the future of the area. Rather than extensively reviewing existing results, we provide a handbook for practitioners who want to tackle and contribute to wireless control. First, we introduce the key types of wireless networks for control applications pointing out their main strengths and their main bottlenecks. Then, we introduce the main technical approaches for the analysis and the design of wireless control showing both their basic ideas and their applicability. Finally, we provide a vision for the future of wireless control and we try to outline the main directions and research questions of the next decade.

Contents

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1. Introduction

The wireless revolution of the last decades has impacted everyday life far beyond the mere way of communicating. The pervasive connection guaranteed by wireless networks has enabled the connected world where we live in, where both people and devices are constantly linked in a networked fashion. For control applications, wireless is particularly attractive because wiring can be drastically reduced, reconfigurability and interoperability can be enhanced, troubleshooting can be simplified, fewer computational capabilities can be allocated to the plant, and more complex control algorithms can be implemented. Wireless networks can effectively bridge the gap between the surrounding dynamical physical systems that we want to control and interact with and the countless algorithms that we can envisage and implement in a cyber support. The so-called cyber–physical systems enabled by wireless connectivity and control theory is expected to be one the most impactful technologies of the new century (Annaswamy, Johansson, & Pappas, 2024; Lamnabhi-Lagarrigue et al., 2017).

The main challenge slowing down the diffusion of wireless control is the contraposition between the time requirements of control and the communication timing provided by wireless. Since physical systems evolve dynamically and are affected by unknown disturbances, control needs up-to-date information and prompt actions, while, since the network evolves dynamically and is affected by disturbances as well, wireless communications might occur not on time. Indeed, wireless communications are affected by packet losses and delays which negatively affect the control. The faster the dynamical system is, and the more safety-critical the application is, the more important timing communications are and the more challenging control with imperfect communications is. For this reason, wireless has different penetration in different control applications depending on their time-criticality.

Today, wireless is widely employed to connect sets of spatially distributed sensors. This setup is usually referred to as Wireless Sensor Network (WSN). WSNs have been applied for monitoring in a wide range of scenarios spanning from the industrial environment (the interested reader is referred to the seminal successful application at Cherry Point refinery in 2006 (Emerson, 2008)), civil infrastructures like bridges and skyscrapers, (a curious early implementation was in the Golden Gate Bridge in San Francisco bay (Kim et al., 2007)), and in the medical area (an interesting pilot application has been implemented at Johns Hopkins Hospital Emergency Department (Ko et al., 2010)). Looking forward, environmental monitoring is expected to exploit WSNs to achieve future sustainability and ecological goals (Malaver, Motta, Corke, & Gonzalez, 2015). Since monitoring does not have hard real-time requirements, these kinds of applications well tolerate wireless communications and WSNs are nowadays routinely used.

WSNs usually include only sensing devices and, consequently, allow only to observe the underlying process. By including actuators in the network it is possible to go beyond simple monitoring applications and actively act on the system. This more powerful setup, where sensor, controller, and actuator are connected over a communication network, is referred to as Networked Control System (NCS) and, more specifically, as wireless NCS when links are wireless.

The NCS architecture can be found in home automation applications such as light control and temperature control. In fact, a home can be seen as a dynamical system with several outputs, e.g. the temperature and the room light, and inputs, e.g. heating, ventilation, air conditioning (HVAC) and light switches. NCSs have found big room for applications also in agriculture, e.g. for irrigation (see the remarkable results of the automated irrigation systems for sage, thyme, origanum, and basil, installed in Mexico (Gutiérrez, Villa-Medina, Nieto-Garibay, & Porta-Gándara, 2013)). Note that such applications are not safety critical, transmission rates are generally low (generally speaking, less than 1 transmission per second) and timing flaws are negligible. For these reasons, they can operate over wireless without safety concerns.

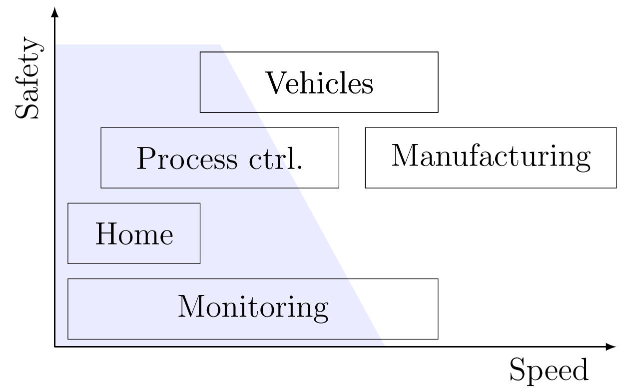

Fig. 1. Rough representation of some control applications and their requirements. The blue area represents the requirements that are met by wireless. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Wireless is fundamental for control applications involving multiple autonomous plants. For instance, swarms of drones use wireless to efficiently coordinate with each other and reach the desired formation. Similarly, wireless is a fundamental feature in the next-future connected and autonomous cars. In this application, vehicles communicate with the surrounding infrastructure, in order to collect information on the traffic or the environment, and with each other, to effectively share the road. Here, communication timing plays a critical role from the control point of view. For instance, at road intersections, a car might need to quickly retrieve information from other vehicles about their positions, velocities, and intentions in order to properly compute its own trajectory. As additional challenges, this kind of system is safety-critical since humans are involved and requires fast communications to deliver possibly large amounts of data. Indeed, such wireless vehicular networks are still under study and suitable controllers are not ready yet.

Another gap in wireless control is regarding its use on the factory floor. While wireless sensing for monitoring in the industrial environment is consolidated, control with actuators connected by wireless links is much less developed. In fact, industrial applications are safety-critical since small errors can lead to hazardous events and, for this reason, the actors are extremely reluctant to adopt wireless. The shift to wireless for process control, which is mostly characterized by low communication rates, is still in its infancy (see the seminal wireless control system implemented for a starch cooker process at the Iggesund paper mill in Sweden (Ahlén et al., 2019)). Manufacturing, which is characterized by higher communication rates, is growing and no solid solutions or implementations exist. In particular, robotic manipulation is firmly tied to wired cables. Future smart factories, as long advocated by Industry 4.0, need to pervasively use wireless to connect all the sensors, controllers, and actuators in a systematic and harmonious way, taking into account many devices in large industrial plants and small sampling periods for wireless robotics. These applications require safety guarantees and high communication rates that are still not available over wireless today.

Fig. 1 shows where we stand along the path of adopting wireless control from the application point of view. In this paper, we try to show this in a more rigorous and critical way. We introduce the main wireless options for control and point out their main strengths and their main limitations. We then introduce the main control approaches showing their applicability and their limitations. This work aims to provide a handbook for practitioners dealing with wireless control and an overview of the current research trends. Building on top of this, we provide a vision of the future of wireless control.

Table 1
Overview of wireless network standards that can be used for control. Note that the values of the communication range and number of connected devices may vary in practice due to the specific hardware employed. For WLAN, the maximum data rate is retrieved for the case of 20 Mhz bandwidth and 20 μs guard interval.

	Low Rate WPAN				WLAN		LPWAN		Cellular	
	ZigBee	ISA100	W-HART	WIA-PA	WiFi 5	WiFi 6	SigFox	LoRa	4G	5G
Max data rate	250 kbit/s	250 kbit/s	250 kbit/s	250 kbit/s	624 Mbit/s	1G bit/s	100 bps	50 kbit/s	1G bit/s	20 Gbit/s
Comm. range	10–100 m	10–250 m	10–250 m	10–250 m	10–120 m	10–120 m	10–40 km	10–20 km	10 km	10–20 km
Channel access	CSMA/CD	TDMA	TDMA	TDMA	CSMA/CD	OFDMA	ALOHA	ALOHA	OFDMA	OFDMA
max no. of devices	100	250	250	250	250	250	≥1000	≥1000	≥1000	≥1000
topology	star, tree, mesh	star, mesh, star-mesh	star, mesh	star-mesh	star	star	star	star	star	star

Table 2
Typical performances of wireless networks under typical conditions. We consider Low-Rate Personal Area Networks (LRWPAN), Wireless Local Area Networks (WLAN), Low-Power Wide-Area Networks (LPWAN), and cellular networks. For each kind of network, we chose a representative standard. Comparisons are ideally considered under similar typical conditions. Due to the complex PHY and the stochastic MAC layer of modern WLAN and cellular networks, only qualitative values are possible for some metrics. The cycle time is defined as the period between two following transmissions from the same device. For WirelessHart, the cycle time is computed assuming that N different systems with 1 sensor and 1 actuator are served by the network. For Wi-Fi 6 and 5G, the ideal cycle times are given. For LoRa, the cycle time is computed considering a transmission of 1ms and taking into account the ISM regulation.

	Low-Rate WPAN (WirelessHart)	WLAN (Wi-Fi) 6	LPWAN (LoRa)	Cellular (5G)
Control apps	healthcare smart home proc. monitoring proc. automation	management	smart building smart city agriculture	smart city V2X
Cycle time	2N × 10 ms	≤ 1 ms	100 × 1 ms	≤ 1 ms
Packet rate	100 Hz	≥ 1 kHz	10 Hz	≥ 1 kHz
Packet loss	rare	potentially high	potentially high	potentially high
Delay	deterministic	potentially high	potentially high	potentially high
Energy	moderate	high	low	high
Cost	moderate	moderate	low	high
Max data rate	250 kbit/s	1G bit/s	50 kbit/s	20 Gbit/s
Comm. range	50 m	30 m	20 km	20 km
Channel access	TDMA	OFDMA	ALOHA	OFDMA
Max no. of devices	250	250	≥ 1000	≥ 1000

2. Wireless networks

In this section, we provide an up-to-date overview of the existing wireless networks of interest for control. We explicitly focus on the features that have the main impact on control applications. The objective is to explain what happens between the control algorithm and the physical plant in order to guide the choice of the most suitable wireless standard and its best setup for the desired application. Hopefully, this also gives rise to possible insight for future research in the design of wireless networks for control.

We dedicate 4 different subsections for the 4 different main types of wireless networks, namely the Low-Rate Wireless Personal Area Networks, the Wireless Local Area Networks, the cellular networks, and the Low Powered Wide Area Networks. We start each subsection with the practical need for which each network has been designed and the main uses for which it is employed today. Each subsection contains a description of the physical layer (PHY) and the medium access layer (MAC) of the different wireless standards since they play the most critical role in the reliability and timeliness of the communication. A general overview is reported in Tables 1 and 2.

2.1. Low rate WPAN

When wireless connectivity is needed for control applications, the most common choice for control engineers are Low-Rate Wireless Personal Area Networks (LRWPAN) which include IEEE 802.15.4, ZigBee, WirelessHART, ISA100.11a, WIA-PA, and others. Such standards have been specifically designed to substitute wired connections in factories at the lower levels of the automation pyramid with the aim of easily connecting sensors, actuators, and controllers (Petersen & Carlsen, 2011). Today LRWPANs are the norm for process monitoring (Emerson, 2008). They are also used for process automation and some attempts have been made for slow factory automation (Seibert & Blevins, 2011). They are widely used for smart home applications (Gill, Yang, Yao, & Lu, 2009).

Since natively designed for control applications, the main objective of LRWPAN is reliability. Small delays and extremely rare packet losses are targeted in order for the overall system to be virtually identical to the wired counterpart. This is achieved through robust transmission schemes at the PHY layer and deterministic channel access methods at the MAC layer.

Virtually all the LRWPAN standards adopt the PHY layer originally proposed by IEEE 802.15.4 standard (Wang & Jiang, 2016). The standard adopts Direct Sequence Spectrum Spread (DSSS), which is particularly robust to interference (Ergen, 2004), together with low-order modulation and coding schemes to reduce the effect of noise (Ergen, 2004). Due to these choices, although high reliability is achieved, communication speed is largely compromised and the data rate is limited at 250 kbit/s (Ergen, 2004; Petersen & Carlsen, 2011).

LRWPAN standards adopt different features at the MAC layer. Originally, IEEE 802.15.4 standard defines two medium access schemes, i.e. an unslotted channel access using CSMA/CA and a slotted channel access using both CSMA/CA and TDMA (Park, Ergen, Fischione, Lu, & Johansson, 2017). While ZigBee employs the MAC layer of IEEE 802.15.4 standard, WirelessHART, ISA100.11a, and WIA-PA have defined their own MAC layers. Although they have different features, they adopt a superframe structure consisting of multiple time slots (Park et al., 2017). Typically, along the line of TDMA, each time slot is allocated to a device and includes data transmission followed by the acknowledgment (Wang & Jiang, 2016). However, some time slots can be allocated also to other purposes, e.g. intra-cell and inter-cell communications, sleeping, or transmissions with access contention (Wang & Jiang, 2016). Since time slots are reserved, each device is guaranteed to transmit within a known interval, collisions are excluded and consequent retransmissions are avoided. It follows that the cycle time is strongly preserved and low transmission delays are guaranteed.

On the other hand, a delay before transmission is possible if the packet generation instant does not coincide with the assigned transmission instant. Moreover, communication resources are partially wasted if a transmission is accomplished in less than a time slot.

At the LLC layer, LRWPAN standards usually adopt channel hopping strategies to increase the robustness against frequency selective noise (Petersen & Carlsen, 2011). At NET layer, LRWPANs propose ad-hoc routing strategies to effectively route packets from the source node to the destination node in multi-hop setups (Park et al., 2017).

Based on the experience gathered from WirelessHART, ISA100.11.a, and WIA-PA, a new amendment of IEEE 802.15.4, referred to as IEEE 802.15.4e, has been recently standardized. Other LRWPAN standards are 6LoWPAN and 6TiSCH which integrate IPv6. Further details can be found in Park et al. (2017).

The design choices of most widespread LRWPANs succeed in achieving the reliability and the determinism advocated by control systems. However, precisely the same choices result in the bottleneck which limits the scope of application of LRWPANs. In fact, since each time slot has to accommodate the transmissions of a packet of maximum size and of an acknowledgment, the duration of the time slot is largely limited by the robust but low data rate. The resulting slot duration of 10 ms prevents sampling periods below 20 ms even with a single plant and, due to TDMA and the superframe structure, it scales linearly with the number of systems. Plants with small sampling periods or with many systems (even if characterized by modest sampling periods) cannot be effectively implemented on current LRWPANs.

2.2. WLAN

Control engineers can decide to choose Wireless Local Area Networks (WLAN), which essentially coincide with the family of standards IEEE 802.11, commonly referred to as Wi-Fi. WLANs have been specifically designed to provide high-speed communications among computers in a limited area and high-speed connections to the internet without relying on wired links. Although this is still the most common use, WLANs are today employed in factories at the higher levels of the automation pyramid to collect large data from the whole plant for management purposes. Currently, WLANs are under evaluation also for process control and manufacturing (Luvisotto, Pang, & Dzung, 2019; Tramarin, Mok, & Han, 2019). Along this line, they have been used to control robotic systems in some case studies (Branz et al., 2021).

Since the original scope of WLAN is to connect computers for general data exchange, the main focus is on the transmission speed despite the reliability. The key metric is the overall network throughput which quantifies the total amount of data transmitted in the time unit. In contrast with LRWPAN, high throughputs can be achieved by sophisticated transmission schemes at the PHY layer and efficient stochastic channel access methods at the MAC layer.

At the PHY layer, Wi-Fi (since IEEE 802.11a/g in 2003) adopts Orthogonal Frequency-Division Multiplexing (OFDM) (Tramarin et al., 2019). Roughly speaking, the stream of data is divided into several sub-streams which are transmitted simultaneously, in parallel, over orthogonal subcarriers with narrow bandwidth and overlapping bands (Proakis, 2008). OFDM largely increases the spectrum efficiency compared to DSSS but suffers from Peak-To-Average Power Ratio, which may result in off-band interference and higher bit error probability (Jiang & Wu, 2008). Wi-Fi (since IEEE 802.11a/g in 2009) supports multi-antenna systems that enable MIMO technologies (Tramarin et al., 2019). Multi-antenna systems are extremely flexible and they can be used to decrease the packet loss probability by transmitting multiple copies of the same packet (Transmit Diversity), to increase the throughput by transmitting several data-streams in parallel (Spatial Multiplexing, both on the downlink and on uplink, both in single-user and multi-user configurations), or to increase SNR (Beamforming) (Tramarin et al., 2019). MIMO techniques are powerful for WLAN though fragile, since they require accurate knowledge of the channel matrix. Timeliness is also compromised by the overhead due to synchronization and channel matrix estimation. Wi-Fi standard offers a wide range of Modulation and Coding Schemes, ranging from BPSK with 1/2 code-rate to 1024-QAM with 5/6 code-rate. Such sophisticated solutions allow us to achieve extremely high data rates. In the single-antenna configuration, the maximum data rate is equal to 143.4 Mbit/s but in the multiple-antenna configurations data rates approaching 1 Gbit/s are possible (see https://mcsindex.com/).

Historically, the MAC layer of Wi-Fi relies on the well-known CSMA/CD. Roughly speaking, when a device needs to transmit, it senses the channel and checks if there are ongoing communications. If the channel is free, the device (waits for a random period of time and eventually) transmits while, if the channel is busy, the device waits for a random period of time and eventually senses again the channel (Proakis, 2008). Wi-Fi defines two variations of the classic CSMA/CD, namely the Distributed Coordination Function (and its enhanced version called Enhanced Distributed Channel Access) and the Point Coordination Function (and its enhanced version called Hybrid Coordination Function) (Tramarin et al., 2019). Essentially, the former includes RTS/CTS, user prioritization, and dedicated transmission windows, while the latter consists of the alternation of contention and contention-free periods (Tramarin et al., 2019). Such channel access has resulted to be effective in increasing the asymptotic throughput but it presents limitations for short packets due to large overheads.

From the last release (IEEE 802.11ax in 2019), WiFi adds Orthogonal Frequency Division Multiple Access (OFDMA) on top of the existing channel access (Tramarin et al., 2019). Informally, OFDMA can be seen as a multi-user version of OFDM where subcarriers are allocated to multiple users. In Wi-Fi, OFDMA is used for transmissions both from the access point to multiple users and from multiple users to the access point (Khorov, Kiryanov, Lyakhov, & Bianchi, 2018). While the former is easier to implement since the transmitter is unique, the latter requires sophisticated coordination governed by the access point through special trigger frames. Essentially, the access point has to allocate the subcarriers to the different users and select their modulation, coding rate, transmission power, and MIMO configuration (Khorov et al., 2018). Interestingly, transmissions from the access point, including the trigger frames initializing OFDMA exchanges, follow the underlying random channel access based on CSMA/CD. Through prioritization, however, it is possible to almost exclude classic data transmission not governed by OFDMA (Khorov et al., 2018).

Along the path of increasing the overall throughput, Wi-Fi has favored the overall average asymptotic communication performances over a pointwise-in-time minimal service. Consequently, the communications are prone to packet losses and delays, possibly with transient communication blackouts, which are not suitable for control applications. For these reasons, Wi-Fi is still not used in practice for real-time control purposes.

2.3. Cellular networks

Cellular networks have been conceived to provide wireless connection between users ideally spread all over the world. Starting from the pure voice communications of the first standards, nowadays modern cellular networks allow a tremendous variety of services mainly enabled by the support of fast internet connection. In the area of control systems, since cellular networks natively connect many mobile users spread over wide areas, they have been studied for Smart Grids (Kalalas, Thrybom, & Alonso-Zarate, 2016) and Smart Cities (Marabissi et al., 2018). Moreover, backed by its capillary penetration, the latest standards have included services devised for Vehicle-to-Everything (V2X) and more general Machine-to-Machine communications (Araniti, Campolo, Condoluci, Iera, & Molinaro, 2013; Shah, Ahmed, Imran, & Zeadally, 2018).

From the historical perspective, the pioneering first generation of cellular networks (including NTT, NMT, AMPS) appeared no more than 40 years ago. It encompassed many different standards developed all over the world and it merely employed analog transmissions, thus provided only voice communications (Khan, 2009; Lin & Lee, 2021). The second generation of cellular networks (including GSM, GPRS, EDGE standardized by 3GPP, and CDMA2000 standardized by 3GPP2) appeared around 30 years ago and decisively adopted digital communications, allowing also short text exchange (Lin & Lee, 2021). The second generation achieved a great capillary diffusion but it is the third generation of cellular networks (including UMTS, HSDPA, HSPA+ standardized by 3GPP, and HRPD standardized by 3GPP2), appeared around 20 years ago, that has enabled the connected world where we live in thanks to its support to internet connection (Khan, 2009; Lin & Lee, 2021). In a few years, anyway, this milestone has been overstepped and novel transmission schemes were advocated to accommodate more devices, more traffic, and more application cases. Here, the fourth generation (including LTE and LTE Advance) and the fifth generation of cellular networks (including NR) come into play.

LTE and NR adopt similar transmission schemes. At the PHY layer, OFDM is used. Visually, the channel looks like a time–frequency grid. In the frequency domain, subcarrier spacing is fixed and equal to 15 kHz in LTE (Astély et al., 2009), while it is flexible and ranges between 15,30,60,120,240 kHz in NR (Parkvall, Dahlman, Furuskar, & Frenne, 2017). In the time domain, frames of 10 ms are divided into 10 subframes of 1 ms. On top of the time and frequency domains, also a spatial domain is enabled thanks to MIMO technologies. Similarly to Wi-Fi, multiple antennas at the transmitter and at the receiver can be exploited to achieve Transmit Diversity, Spatial Multiplexing, and Beamforming. Massive MIMO is also a possibility (Parkvall et al., 2017).

At the MAC layer, both LTE and NR adopt OFDMA with scheduling governed at the base station (Astély et al., 2009; Parkvall et al., 2017). Control channels are used to communicate time–frequency-space allocation. Physical Downlink Control Channels, typically allocated in the first symbols of a slot, communicate the transmission allocation and the other scheduling information (such as modulation, coding rate, and MIMO configuration) to the interested devices (Parkvall et al., 2017). Physical Uplink Control Channels, allocated in dedicated slot or, possibly, in the last symbols of a slot in NR (self-contained slot), are used for hybrid-ARQ acknowledgments and other channel state information (Parkvall et al., 2017). Both dynamic and semi-persistent scheduling are possible. Dynamic scheduling on a slot basis is particularly flexible, while semi-persistent scheduling allows to avoid scheduling requests by reserving periodic resources to a device (Parkvall et al., 2017). The interested reader is referred to Dahlman, Parkvall, and Skold (2020) for a more detailed description.

The latest releases of LTE and NR include specific features that are attractive for control purposes. LTE has introduced Narrowband Internet of Thing (NB-IOT) technology and support for V2X communication, together with additional features to reduce latency such as the short transmission time interval (Dahlman et al., 2020). NR has been natively designed to serve three different classes of use cases: Enhanced Mobile Broadband (eMBB), Massive Machine-type Communication (mMTC), and Ultra-Reliable Low-Latency Communication (URLLC) (Dahlman et al., 2020). While eMBB is devoted to high-throughput communications, mMTC and URLLC have been designed to serve IoT applications and safety-critical systems, respectively. As such, mMTC provides low data rates but wide area coverage and low power consumption, while URLLC targets small latencies. This wide spectrum of services comes with the possibility of splitting a network into different slices characterized by different classes of use cases (Zhang, 2019), making NR an extremely flexible solution able to accommodate different applications within the same infrastructure.

URLLC is particularly interesting for industrial control applications (Sachs, Wikstrom, Dudda, Baldemair, & Kittichokechai, 2018). Features outlined above such as larger frequency spacing, self-contained slots, and semi-persistent scheduling, have been precisely proposed with the aim of providing low latencies. Along the line of short transmission time interval in LTE, NR standard also defines the possibility of non-slot-based transmissions, referred to as minislots, that can be shorter than a slot (so that decoding can start sooner and information can be ready sooner) and can start later in the slot (so that a packet generated during a slot can be transmitted without waiting the next slot) (Parkvall et al., 2017; Sachs et al., 2018). The standard also allows high-priority packets to preempt an ongoing communication (Parkvall et al., 2017; Sachs et al., 2018).

2.4. LPWAN

In order to connect devices spread over wide areas with strong energy requirements, Low Powered Wide Area Networks (LPWAN) such as LoRaWAN and SigFox can be effectively employed. Such networks are convenient when the devices cannot be easily changed or recharged because of their locations (either because they are far, in harsh environments, or not easily accessible) but also to lighten maintenance procedures. For this reason, the original applications of LPWAN are building and environmental monitoring but they have been used also in agriculture and in factory applications (Fedullo et al., 2022).

In order to extend the battery life as much as possible, standards have been explicitly designed to minimize the energy consumption for communication at the cost of minimal communication performances. This is achieved through robust solutions at the PHY layer and a minimal channel access at the MAC layer.

LoRaWAN adopts the proprietary PHY layer of LoRa standard, developed by Simtech, using Chirp Spread Spectrum. Intuitively, the transmitted waveform is a sinusoidal signal with frequency varying linearly with time (Haxhibeqiri, De Poorter, Moerman, & Hoebeke, 2018). The frequency profile of a chirp starts at a given initial frequency, increases until the upper limits of the band, jumps to the lower limit of the band, and keeps increasing until returning to the initial frequency (Reynders, Meert, & Pollin, 2017). It follows that the whole band is swapped during each symbol and the information is encoded in the value of the initial frequency (Liando, Gamage, Tengourtius, & Li, 2019; Reynders et al., 2017). The resulting data-rate can reach values up to 27 Kbit/s (Liando et al., 2019) and up to 50 Kbit/s with channel aggregation (Augustin, Yi, Clausen, & Townsley, 2016). This solution proves to be extremely robust to frequency offset, possibly allowing to save costs of sophisticated hardware (Augustin et al., 2016). Similarly to DSSS, since the entire spectrum is used, transmissions are robust to external noise. The low bitrate is beneficial to increase the communication range.

At the MAC layer transmissions follow the traditional ALOHA algorithm (with varying packet length) where a user attempts to transmit as soon as data is generated (Augustin et al., 2016). This strategy is beneficial to save energy since listening and waiting periods are avoided. However, since no carrier sense procedure is employed, collisions are possible (Augustin et al., 2016). An evaluation of the packet losses due to collisions for different channel loads has been done by Augustin et al. (2016). The allocation of downlink transmissions depends on the receiver setup. Depending on the device, downlink transmissions are scheduled either in two windows following an uplink transmission from the same device, in specific windows communicated in advance, or in any time instants. The three configurations have different energy consumption due to the different amounts of time the device is required to be awake and to listen to the channel. It must be noted that a device cannot directly communicate with another device (Augustin et al., 2016).

LoRaWAN operates at the license-free ISM band. According to the current regulation, devices have to follow a duty cycle of 1%, which strongly reduces the possible packet rate (Augustin et al., 2016).

An alternative solution is the proprietary standard SigFox. At the PHY layer, it adopts Ultra-Narrow Band modulation type which guarantees a good SNR even with low transmitted power or long distances

(Lavric, Petrariu, & Popa, 2019). Of course, this comes with really small data rates, typically less than 100bps. Similarly to LoRaWAN, the MAC layer employs the simple ALOHA protocol, and downlink transmissions are allowed only in specific slots after uplink transmissions. Notably, communications between a device and the user application pass through the remote proprietary SigFox cloud. Due to the duty-cycle regulations of the ISM band where SigFox operates and the extremely low data rate, a device can transmit at most 140 packets of 12 bytes per day (Lavric et al., 2019).

Interestingly, in the last years, also cellular standards have defined interfaces for LPWAN. LTE standard has included NB-IoT and eMTC in later releases, while NR has included since the beginning the aforementioned mMCT technology. Essentially, they consist of simplified versions of the communication protocols (PHY and MAC layers) aiming to reduce power consumption while providing low packet rates and low data rates.

3. Wireless control

In this section, we dive into the control aspects of wireless control. Following the typical pipeline of control design, we first start with the modeling of the wireless network (Section 3.1) and we then outline the control techniques (Section 3.2, Section 3.3, Section 3.4). As wireless control has been a highly active research theme for already 20 years now, a comprehensive review of the main results would take several pages and it is out of the scope of the paper. We prefer to provide the main ideas and the mathematical formulations of some relevant approaches. The objective is to provide a handbook for practitioners so that they can readily (recover and) implement the controller that better fits their applications and the available network performances. At the same time, by describing the solutions devised in the past few years, we make visible the main current limitations and we envision the main future challenges of the field.

3.1. Modeling a wireless network for control

As in Fig. 2, a communication network can be represented as a dynamical system that takes as input the time sequence of data to transmit and provides as output the time sequence of received data, with disturbance given by the external noise and the interference affecting the data transmission. In analogy with dynamical systems, the function relating the input and the output depends on the parameters characterizing the network, the most important of which were mentioned in Section 2.

In this representation, the input signal is affected by the sampling policy, while the output signal is affected by packet losses and delays. Modulation, coding scheme, transmission power, channel access, and so on are parameters of the network. As the output signal is the transformed version of the input signal through the system, packet losses and delays appearing in the output are determined by the network and depend on the features of the input such as the sampling policy and on the parameters of the network. For instance, a smaller sampling period results in a higher network load and possibly more packet loss. A higher-order modulation ideally results in a smaller interval between the start and the end of the transmission but, for the same level of external noise, the average loss probability is higher. Similarly, the channel access scheme affects the delay.

This general representation can be used to model any network standard and any network configuration. However, when wireless networks come to control applications, an effective model of the network is needed. A high-fidelity model taking into account all the features of the network is in general difficult to derive and is too complex to accommodate control design. For this reason, several simpler models have been proposed. Each model usually focuses on a specific imperfection that characterizes the communication. In the following, we summarize some relevant models that have been largely considered in the literature.

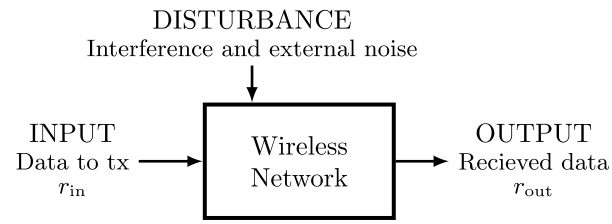

Fig. 2. Wireless network can be seen as a *system* with inputs, outputs, disturbances, and characterized by system parameters.

Limited bitrate

Digital communications cannot deliver information at an arbitrarily high rate with an arbitrarily high reliability. In information theory, this limit is formalized by the channel capacity. According to the Shannon theorem on channel coding, information rates below the channel capacity can be achieved with an arbitrarily high reliability. Building upon this fundamental feature, a wireless network can be modeled as a reliable link with limited data rate. More formally, symbols from a finite set are transmitted with a fixed periodicity and received without errors with negligible delay. Mathematically, this can be formalized as

$$r_{\text{out}}(k) = r_{\text{in}}(k) = s_{i_k}, \quad s_{i_k} \in \mathcal{S} = \{s_i \;:\; i = 1, \dots, M\} \tag{1}$$

where r_{out} is the received signal, r_{in} is the transmitted signal, and the number of symbols M is determined by the data rate. A small data rate entails a small number of symbols.

As transmission power, fading, and noise all affect the channel capacity and consequently the data rate, this model can be adapted to consider these aspects. Also, signal quantization can be readily included.

Varying transmission intervals

The limited data rate model captures the physical limitation of a single wireless link but neglects that multiple links are served within a wireless network. In fact, because data transmission is not instantaneous and the network is shared by multiple devices, wireless networks cannot ensure ideal transmission timing. A transmission cannot start at any arbitrary instant but each device has to wait and to gather access to the network before to transmit data. Moreover, transmission instants can depend on scheduling or event-triggered mechanisms. In order to capture the resulting behavior, the network can be modeled by considering varying transmission intervals. Depending on the case, transmission intervals can be deterministic or randomly distributed.

Mathematically, let $\{t_i\}$ be the sequence of transmission instants. Then, the network can be modeled as

$$r_{\text{out}}(t) = r_{\text{in}}(t_i) \quad t \in [t_i, t_{i+1}) \tag{2}$$

namely, the information delivered by the network is updated only at the transmission instants.

Communication delay

Besides varying transmission intervals due to the network access protocol, propagation, computation, and retransmissions result into delays in the end-to-end communications. In the case of multihop networks, the delay also accumulates over multiple links. Overall, at the control layer, the wireless network can be modeled as a delay block. Depending on the setup, it is possible to distinguish between real-valued delays and integer-valued delays, where it is a multiple of the sampling period. In general, a random variable can be used to mathematically model the length of the delay period.

Let $\{t_i\}$ be the sequence of transmission instants and let $d_i \geq 0$ be the delay of the packet transmitted at time t_i. Under the assumption that the delay is shorter than the transmission interval, namely $d_i < t_{i+1} - t_i$, the network can be mathematically modeled as

Table 3
Different wireless models have been addressed with different approaches.

Wireless model		Representative solutions	Main approach
Limited bitrate		Hespanha, Ortega, and Vasudevan (2002), Tatikonda and Mitter (2004), Nair and Evans (2004), Nair and Evans (2004), Tatikonda, Sahai, and Mitter (2004), Nair, Fagnani, Zampieri, and Evans (2007),	control with limited bitrate
Varying transmission intervals		Walsh, Ye, and Bushnell (2002), Nešić and Teel (2004), Tabbara, Nesic, and Teel (2007), Tabbara and Nesic (2008) Carnevale, Teel, and Nešić (2007), Tabbara et al. (2007), Seuret and Gouaisbaut (2013), Liu, Fridman, Johansson, Henrik (2015), Heijmans, Postoyan, Nešić, and Heemels (2020), Tabuada (2007), Heemels, Sandee, and Van Den Bosch (2008), Postoyan, Tabuada, Nešić, and Anta (2014), Donkers and Heemels (2011), Heemels, Donkers, and Teel (2012), Heemels and Donkers (2013), Anta and Tabuada (2010)	emulation-based and event-triggered
Delay	real-valued	Cloosterman, Van de Wouw, Heemels, and Nijmeijer (2009), Heemels, Teel, Van de Wouw, and Nešić (2010), Garcia and Antsaklis (2012), Dolk, Borgers, and Heemels (2016)	emulation-based and event-triggered
	integer-valued	Schenato (2008), Pin and Parisini (2010), Seuret, Gouaisbaut, and Fridman (2015), Seuret and Gouaisbaut (2013)	
Lossy links	i.i.d.	Sinopoli et al. (2004), Imer, Yüksel, and Başar (2006), Gupta, Hassibi, and Murray (2007), Schenato, Sinopoli, Franceschetti, Poolla, and Sastry (2007), Garone, Sinopoli, Goldsmith, and Casavola (2011)	model-based
	Gilbert-Elliot	Huang and Dey (2007), Sun, Xie, Xiao, and Soh (2008), You, Fu, and Xie (2011), Mo, Garone, and Sinopoli (2013), Wu, Shi, Anderson, and Johansson (2017)	model-based
	Markovian	Quevedo, Ahlen, and Johansson (2012), Liu, Quevedo, Li, Johansson, and Vucetic (2021)	model-based
	Bounded seq	Quevedo, Silva, and Goodwin (2007), Quevedo and Nešić (2010), Li and Shi (2013)	PPC
	Dependent on network params	Park, Di Marco, Fischione, and Johansson (2012), Gatsis, Ribeiro, and Pappas (2014), Gatsis, Ribeiro, and Pappas (2018), Pezzutto, Tramarin, Dey, and Schenato (2020)	model-based

$$r_{\text{out}}(t) = r_{\text{in}}(t_i) \quad t \in [t_i + d_i, t_{i+1} + d_{i+1}) \tag{3}$$

namely, the information delivered by the network is updated a certain period after the transmission instant. In the more general case where delays are arbitrary and possibly longer than the transmission interval, received packets can be out-of-order. In that case, a more involved function is needed to model the network.

Lossy link

External noise and interference might corrupt the transmitted packet in such a way it cannot be decoded. If retransmissions are not present, dropped, or outdated, the control packet is regarded as lost. In order to capture this phenomenon, from the control point of view, the wireless network can be modeled as a lossy link. Intuitively, a lossy link can be represented as a switch: a successful communication is represented as a closed switch, and a lost packet can be represented as an open switch since it is equivalent to cut the communication link.

Packet loss can be mathematically represented as a binary random variable.

$$\theta_k = \begin{cases} 1 \text{ if packet } r_{\text{in}}(k) \text{ has arrived} \\ 0 \text{ otherwise} \end{cases} \tag{4}$$

Then the network can be mathematically expressed as

$$r_{\text{out}}(k) = \theta_k r_{\text{in}}(k) \tag{5}$$

so that no information is actually delivered when the packet has not arrived.

As successful wireless transmissions depend on many network parameters, such as transmission power, fading, modulation, and coding, this model can be extended to let the packet loss process depend on these parameters.

3.2. Closing the feedback loop over a wireless network

In this section we focus on the case where the wireless network is used to close the feedback loop. Fig. 3 depicts the wireless counterpart of the basic control architecture studied in any control course. The standard feedback loop is modified by substituting the ideal links between the plant and the controller with wireless communications. This architecture can be specialized or generalized to encompass many other interesting setups. For instance, the link from the controller to the actuator can be considered as ideal to represent the case where they are co-located. Similarly, the link from the sensor to the controller can be considered as ideal when they are co-located. Actuators and sensors provided with computational capabilities, usually referred to as smart actuators and smart sensors, respectively, are also considered. More general setups with multiple actuators and multiple sensors or with multiple plants and agents (in this case, the setup is closely related to the centralized control approach) can be immediately obtained as an extension of the fundamental scheme above. We remark that,

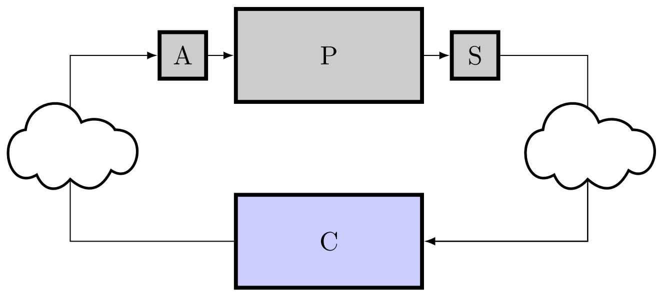

Fig. 3. Wireless is used to close the feedback loop. This architecture can be generalized to consider multiple sensors and actuators or multiple systems.

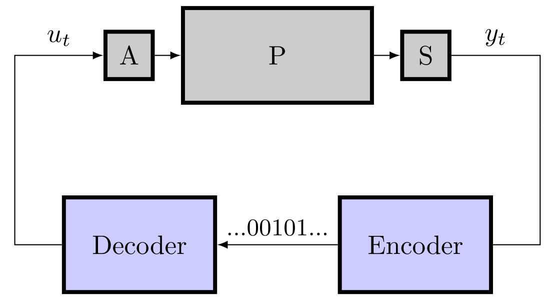

Fig. 4. Typical setup in control with limited bitrate. The network is modeled as a binary channel with limited data rate.

even in the cases where a single system is considered, the network is implicitly used to connect multiple devices. Limiting the analysis to a single system and representing the overall network behavoiur through a specific model are typically needed to make the problem tractable.

Some relevant works on the case where the wireless network is used to close the feedback loop are reported in Table 3. Different network models have resulted into different control approaches. In the following, Without being exhaustive, we provide a rough description of the typical approaches used in the literature. The aim is to rearrange the main existing frameworks and orient the practitioners toward the solutions that can better meet their needs. Interested readers can find more references in targeted surveys such as Baillieul and Antsaklis (2007), Hespanha, Naghshtabrizi, and Xu (2007), Hetel et al. (2017), Liu, Selivanov, and Fridman (2019), Nair et al. (2007), Park et al. (2017), Zhang, Gao, and Kaynak (2012), Zhang et al. (2019).

Control with limited bitrate

Since the bitrate of a wireless link is limited, it is fundamental to quantify the information rate needed to stabilize the system. This is the main objective of control with limited bitrate. For clarity of exposition, let the plant be modeled as a discrete-time linear system

$$x_{t+1} = Ax_t + Bu_t + w_t \tag{6}$$

$$y_t = Cx_t + \mathrm{v}_t \tag{7}$$

where $x_t \in \mathbb{R}^n$ is the state, $u_t \in \mathbb{R}^m$ is the input, $y_t \in \mathbb{R}^p$ is the output, $w_t \in \mathbb{R}^n$ is the process noise, and $\mathrm{v}_t \in \mathbb{R}^p$ is the measurement noise.

The network is modeled as a digital link where a symbol from a finite set is transmitted and received without errors at every sampling period. The data rate of the communication is limited and computed as $R = \log_2(M)$, where M is the number of symbols in the set. The data rate is assumed to be small and, consequently, the number of symbols is low. It follows that scalar values cannot be communicated with high precision and large intervals are mapped to the same symbol.

In the classic setup, represented in Fig. 4, an encoder is present at the sensor and a decoder is present at the actuator. At each time instant $t \in \mathbb{N}$, the encoder maps the past measurements and the past symbols into a new symbol

$$s_t = \mathcal{E}(y_t, y_{t-1}, \dots, y_0, s_{t-1}, \dots, s_0) \tag{8}$$

which is transmitted to the actuator. The decoder, which plays the role of the controller, maps the received symbols into a control input

$$u_t = \mathcal{D}(s_t, s_{t-1}, \dots, s_0) \tag{9}$$

and it is applied.

If the full state is measured and no process noise is present, the data rate theorem (Nair & Evans, 2004) states that a system can be stabilized if

$$R \geq \log_2\left(\prod_i |\lambda_i^u|\right) \tag{10}$$

where λ_i^u are the unstable eigenvalues of A. This fundamental result shows that there exists a minimum data rate needed to stabilize a given dynamical system. This approach has been used to study the stability and state boundedness for systems with unknown bounded disturbances (Hespanha et al., 2002; Tatikonda & Mitter, 2004) and mean-square stability for random disturbances with unbounded support (Nair & Evans, 2004; Tatikonda et al., 2004). Performance bounds achieved with different data rates and the optimal encoder have been also studied (Nair et al., 2007). More general systems are considered e.g. in Liberzon (2014), Liberzon and Hespanha (2005). The setup has also been generalized e.g. to jointly study limited bitrate and packet losses (Minero, Franceschetti, Dey, & Nair, 2009; You & Xie, 2010). Designs oriented to the control performance given the limited data rate are e.g. Dey, Chiuso, and Schenato (2017), Tanaka, Esfahani, and Mitter (2017).

Emulation-based control

In automatic control history, when digital microprocessors were introduced, control engineers kept using standard continuous-time control design techniques although the new support was intrinsically at discrete-time. Typically, first, the continuous-time controller was obtained, and then it was sampled and implemented. This approach, referred to as design by emulation, has proved to be effective and is actually still used nowadays. It is following the same idea that, with the advent of communication networks, researchers proposed to first design the controller as if the links were ideal, namely neglecting the network effects, and then to check the stability when the network is present. The focus is thus not on control design but on system analysis and, typically, bounds on the network performances are derived such that closed-loop stability is preserved.

In the typical setup, the plant is modeled as a continuous-time nonlinear system

$$\dot{x}_p = f_p(x_p, \hat{u}, w) \tag{11}$$

$$y = g_p(x_p) \tag{12}$$

and a stabilizing continuous-time nonlinear controller is defined as

$$\dot{x}_c = f_c(x_c, \hat{y}, w) \tag{13}$$

$$u = g_c(x_c) \tag{14}$$

where $x_p \in \mathbb{R}^n$ and $x_c \in \mathbb{R}^q$ are the plant and controller state, respectively, $u \in \mathbb{R}^m$ is the desired control input, $\hat{u} \in \mathbb{R}^m$ is the applied control input, $y \in \mathbb{R}^p$ is the system output, $\hat{y} \in \mathbb{R}^p$ is the last received system output, and $w \in \mathbb{R}^d$ is the process noise. In general, the plant can consist of several subsystems and the overall controller can consist of several decoupled control units. Multiple spatially distributed sensors and actuators are present.

Let $\{t_i\}$ be the sequence of transmission instants with $t_{i+1} > t_i$ for any $i \in \mathbb{N}$. Between two following transmission instants, the applied input and the last received output are not updated but kept constant.

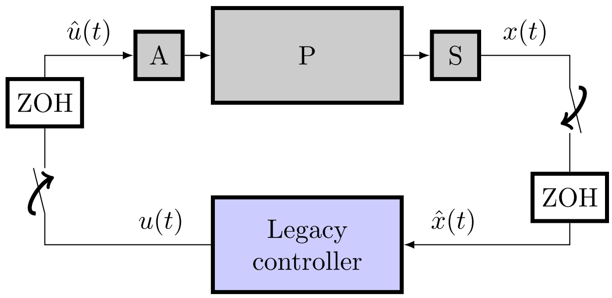

Fig. 5. Typical setup in emulation-based control. Due to the network, system input and controller input are not continuously updated but sampled values are held. Stability of the networked system with a legacy controller is studied.

In this interval, the network behaves as a Zero-Order Hold. At each transmission instant, since the network is shared, only one device can transmit. It follows that only some components of the desired input or of plant output are transmitted. Assuming that transmission time is negligible, the resulting behavior can be formalized as

$$\hat{y}(t_i^+) = y(t_i) + h_y(i, \hat{y} - y(t_i)) \tag{15}$$

$$\hat{u}(t_i^+) = u(t_i) + h_u(i, \hat{u} - u(t_i)) \tag{16}$$

where $z(t^+) = \lim_{s \to t, s>t} z(t)$. The maps h_y and h_u are opportunely defined to set to zero the components of either $\hat{y} - y$ or $\hat{u} - u$ corresponding to the device that transmits, while leaving unchanged the other components. This setup is represented in Fig. 5.

Let $e \in \mathbb{R}^{p+m}$ be the error induced by the network

$$e = \begin{bmatrix} e_y \\ e_u \end{bmatrix} = \begin{bmatrix} \hat{y} - y \\ \hat{u} - u \end{bmatrix} \tag{17}$$

With some manipulations, the system can be written as

$$\dot{x} = f(x, e, w) \quad t \in [t_i, t_{i+1}] \tag{18}$$

$$\dot{e} = g(x, e, w) \tag{19}$$

$$e(t_i^+) = h(i, e(t_i)) \tag{20}$$

that is a dynamical system with jumps. The period $t_{i+1} - t_i$ captures the interval occurring between two following transmissions on the network due to the physical limitations of wireless links. The map h can be regarded as the communication protocol. It models the channel access method and the scheduling.

General descriptions of the most common communication protocols have been proposed. A wide class is the set of Uniformly Globally Exponentially Stable (UGES) protocols (Nešić & Teel, 2004). A protocol h is UGES with gain ρ if there exists a Lyapunov function W such that

$$a_1|e| \le W(i, e) \le a_2|e| \tag{21}$$

$$W(i, h(i, e)) \le \rho W(i, e) \tag{22}$$

It has been shown that Round Robin (RR) and Try-Once-Discard (TOD) protocols are UGES. Other classes of protocols are persistently exciting protocols (Tabbara et al., 2007), which can model general CSMA, stochastic protocols (Tabbara & Nesic, 2008), which can model CSMA with waiting times and slotted p-persistent CSMA, almost surely UGES (Tabbara & Nesic, 2008), which can effectively model RR and TOD with packet losses.

The general model (18) is used to analyze the stability of the closed-loop system for different communication protocols following a small-gain approach. Assume that the protocol h is UGES with gain ρ and satisfies

$$\langle \frac{\partial W(i, e)}{\partial e}, g(x, e, w) \rangle \le L W(i, e) + |H(x) + w| \tag{23}$$

for some L and a desired function H. Assume that the original system $\dot{x} = f(x, e, w)$ with e and w exogenous inputs is $\mathcal{L}_p$ stable from (e, w) to $H(x)$ with gain γ. Assume that $\epsilon < t_{i+1} - t_i < \tau_{MATI}$ where $\epsilon > 0$ and

$$\tau_{MATI} = \frac{1}{L} \ln \left(\frac{L + \gamma}{\rho L + \gamma} \right) \tag{24}$$

where τ_{MATI} is called the Maximum Allowable Transmission Interval (MATI). Then, the overall NCS is $\mathcal{L}_p$ stable from w to $H(x)$ (Nešić & Teel, 2004).

Other bounds have been derived in Carnevale et al. (2007), Heijmans, Postoyan, Nešić, and Heemels (2017), Liu, Fridman, et al. (2015). More loose conditions on the MATI can be derived by requiring a condition on the average transmission interval (Heijmans et al., 2020).

The representation of the network behavior through the network-induced error is particularly convenient to generalize the approach. In fact, in the view of Fig. 2, while the network behavior is described by the relation between r_{in} and r_{out}, the network-induced error roughly represents $r_{\text{in}} - r_{\text{out}}$. Consequently, the dynamics of the error can be adapted to take into account other network effects, such as limited bitrate, quantization, and packet loss. In particular, such modifications to consider also transmission delays (Cloosterman et al., 2009; Heemels et al., 2010; Maass & Nešić, 2019) and packet disordering (Yu & Chen, 2024) have been investigated. Using a slightly different formulation, varying transmission intervals and communication delays have been also addressed with tools from time-delay systems (Gao, Chen, & Lam, 2008; Liu, Fridman, & Hetel, 2012; Seuret & Gouaisbaut, 2013; Seuret et al., 2015).

Model-based control

Instead of following the emulation-based approach and neglecting the network effects in the control design, the opposite philosophy can be pursuit and the communication flaws can be explicitly compensated through the controller. While emulation-based control takes inspiration from the design by emulation, this alternative approach follows in the footsteps of classic stochastic control. It turns out that missing information can be optimally compensated using the model of the system. For this reason, this approach is sometimes referred to as model-based control in the context of networked control systems.

Let the plant be modeled as a discrete-time linear system

$$x_{t+1} = A x_t + B u_t + w_t \tag{25}$$

$$y_t = C x_t + \mathrm{v}_t \tag{26}$$

where $x_t \in \mathbb{R}^n$ is the state, $u_t \in \mathbb{R}^m$ is the input, $y_t \in \mathbb{R}^p$ is the output, $w_t \in \mathbb{R}^n$ is the process noise, and $\mathrm{v}_t \in \mathbb{R}^p$ is the measurement noise. We assume that $x_0 \sim \mathcal{N}(\hat{x}_0, P_0)$, $w_t \sim \mathcal{N}(0, Q)$, and $v_t \sim \mathcal{N}(0, R)$ and they are independent.

At time instant $t \in \mathbb{N}$, the sensor samples and sends the measurement y_t to the controller, while the controller computes and transmits the control input v_t to the actuator.

In the original setup, represented in Fig. 6, the wireless network is modeled as a lossy link where the transmitted packet is either arrived immediately or lost. The network behavior is described by the two binary variables $\gamma_t, \theta_t \in \{0, 1\}$ defined as

$$\gamma_t = \begin{cases} 1 \text{ if } y_t \text{ has arrived at the controller} \\ 0 \text{ otherwise} \end{cases} \tag{27}$$

$$\theta_t = \begin{cases} 1 \text{ if } v_t \text{ has arrived at the actuator} \\ 0 \text{ otherwise} \end{cases} \tag{28}$$

The network can be provided with an ACK mechanism to inform the controller if the control packet has arrived or not. If ACK is present, the network is called UDP-like, while, if it is not, the network is called TCP-like. The information sets available at the controller are

$$\mathcal{I}_t^{UDP} = \bigcup_{k=0}^{t} \{\theta_k, \gamma_k, \gamma_k y_k\} \quad \mathcal{I}_t^{TCP} = \bigcup_{k=0}^{t} \{\gamma_k, \gamma_k y_k\} \tag{29}$$

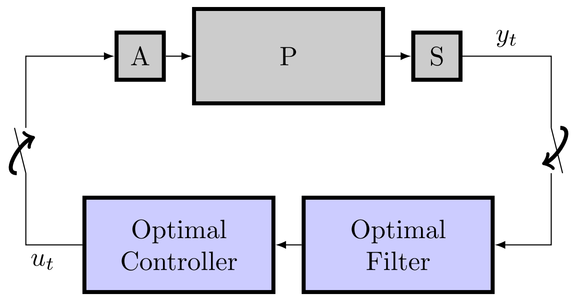

Fig. 6. Typical setup in model-based control. The model is exploited in the optimal filter and in the optimal controller to compensate network flaws.

respectively. The two information sets differ for the knowledge of the past realizations of the random variable θ_k.

The actuator updates the applied input according to the simple law

$$u_t = \theta_t v_t \tag{30}$$

namely, when the control packet is lost, the input is set to 0.

Building upon this setup, a natural question is to find what is the optimal estimator, that is

$$\hat{x}_{t|t} = \mathbb{E}\left[x_t|\mathcal{I}_t\right] \tag{31}$$

where $\mathcal{I}_t$ is the information set available at the controller at time t, and the optimal controller, that is the solution of the following optimal control problem

$$\min_{\{v_k\}} J(v_0,\dots,v_{N-1},\hat{x}_0,P_0) \tag{32}$$

with $v_t = g_t(\mathcal{I}_t)$ where $g_t(\cdot)$ is an arbitrary function and $J(\cdot)$ is the control cost defined as

$$J(v_0,\dots,v_{N-1},\hat{x}_0,P_0) = \mathbb{E}\left[\frac{1}{N}\sum_{k=0}^{N-1} x_k' W x_k + u_k' U u_k + x_N' S x_N \middle| v_0,\dots,v_{N-1},\hat{x}_0,P_0\right] \tag{33}$$

for $W \geq 0$, $U \geq 0$, $S \geq 0$.

With TCP-like networks ($\mathcal{I}_t = \mathcal{I}_t^{TCP}$) or for autonomous systems ($u_t = 0$), the optimal estimator derived in Sinopoli et al. (2004) is

$$\hat{x}_{t|t} = A\hat{x}_{t-1|t-1} + Bu_{t-1} + \gamma_t K_t\left(Cy_t - A\hat{x}_{t-1|t-1}\right) \tag{34}$$

$$K_t = AP_{t-1}C'(CP_{t-1}C' + R)^{-1} \tag{35}$$

$$P_t = AP_{t-1}A' + Q - \gamma_t AP_{t-1}C'(CP_{t-1}C' + R)^{-1}CP_{t-1}A' \tag{36}$$

Interestingly, the optimal estimator is a modified time-varying Kalman filter, where the optimal estimate is obtained by applying a closed-loop update of the standard Kalman filter if the packet is arrived and applying an open-loop update using only the model if the packet is lost. Due to the dependence on the arrival process, the error covariance does not converge and the optimal gain is time-varying. It has been shown that there exists a critical threshold γ_c on the arrival probability $\gamma = \mathbb{E}[\gamma_t]$ below which the expected error covariance diverges (Sinopoli et al., 2004). The asymptotic behavior of the estimator and the critical threshold has been widely studied. For i.i.d. channels, upper and lower bounds have been provided in Schenato et al. (2007) while analytical characterization has been studied in Mo and Sinopoli (2008, 2011), Plarre and Bullo (2009), Rohr, Marelli, and Fu (2014). Properties of the stationary distribution of the error covariance of the optimal estimator have been studied in Censi (2010), Kar, Sinopoli, and Moura (2011), Mo and Sinopoli (2011), Pezzutto, Schenato, and Dey (2019). Stability with Gilber-Elliot model has ben studied in Huang and Dey (2007), Sun et al. (2008), Wu et al. (2017), You et al. (2011) and for general Markovian channel in Liu et al. (2021), Quevedo et al. (2012). The optimal estimator with multiple sensors, which is indeed the original motivation to study wireless control, has been studied in Garone et al. (2011), Liu and Goldsmith (2004). The problem of sensor selection to minimize the expected error covariance has also been widely studied, see Leong, Dey, and Quevedo (2016), Mo, Garone, Casavola, and Sinopoli (2011), Shi, Cheng, and Chen (2011).

With TCP-like networks (Gupta et al., 2007; Imer et al., 2006; Schenato et al., 2007) shows that the separation principle holds and the optimal control is

$$v_t = L_t\hat{x}_{t|t} \tag{37}$$

$$L_t = (B'S_{t+1}B + U)^{-1}B'S_{t+1}A \tag{38}$$

$$S_t = AS_{t+1}A' + Q - \theta AS_{t+1}B(B'S_{t+1}B + R)^{-1}B'S_{t+1}A' \tag{39}$$

with $S_N = S$ and $\theta = \mathbb{E}[\theta_t]$ in the i.i.d. case. The asymptotic behavior has been studied and, similarly to the optimal filter, it has been shown that there exists a critical threshold θ_c on the arrival probability θ below which the cost diverges (Schenato et al., 2007). Generalization to the case of multiple sensors and actuators has been studied in Garone et al. (2011), while the case with Gilber-Elliot model has been studied in Mo, Garone, and Sinopoli (2013). The case where optimal control when the previous applied input is kept is studied in Schenato (2009), while more elaborated laws are studied in Gupta and Martins (2009), Henriksson, Sandberg, and Johansson (2009). The setup has been considered for more general problems, e.g. disordered packets (Liu, Zhang, Yu, Liu, Chen, Michael ZQ, 2015) or time-varying transmission rates (Pezzutto et al., 2020), and to derive suboptimal compensation strategies (Kögel, Blind, Allgöwer, & Findeisen, 2011; Maass, Vargas, & Silva, 2016; Silva & Solis, 2013; Zhang, Song, & Shi, 2012).

With UDP-like network it has been shown that the separation principle does not hold (Schenato et al., 2007). The optimal control is a nonlinear function of the optimal estimate and the optimal estimate is a nonlinear function of the optimal control. It has been shown that the same is true even if the ACK is present but it can be randomly lost (Garone, Sinopoli, & Casavola, 2010). Since the optimal controller cannot be derived in closed form and cannot be implemented in practice, suboptimal solutions have been studied (Epstein, Shi, & Murray, 2007; Lin, Su, Shi, Lu, & Wu, 2016; Lin, Su, Shu, Wu, & Xu, 2015; Sinopoli, Schenato, Franceschetti, Poolla, & Sastry, 2008).

In a similar setup but following a different approach, instead of optimizing the average performance, control can be designed to take into account the worst-case scenario. This approach is particularly useful when the delay and the number of consecutive packet losses are bounded. Moreover, it is interesting for safety-critical applications since stability can be enforced by design up to certain system uncertainty or network conditions. This approach has been widely studied in the literature. Wireless control in presence of bounded system uncertainty has been studied in Wang, Yang, Ho, and Liu (2005, 2007), Zhang, Shi, Wang, and Chen (2018), the case of bounded delays has been considered in Gao and Chen (2007b), Gao, Meng, and Chen (2008), and bounded packet losses in Wang, Wang, and Wang (2013), Xiong and Lam (2007), while their combinations have been considered in Gao and Chen (2007a), Li and Gao (2011), Qiu, Shi, Pan, and Xu (2016), Qiu, Shi, Yao, Xu, and Xu (2014).

Packetized predictive control

Following the usual approach of classic control theory, in the approaches presented so far, only the current input is computed by the controller and forwarded to the actuator. Indeed, no other strategies are meaningful when links are ideal, since it is always possible to forward a new input at the next time instant. However, this might not be the case with wireless links, since the next input might not arrive at the actuator. In these cases, it is convenient to transmit a sequence of future control inputs that the actuator can use if future packets are lost. This is the intuitive idea behind Packetized Predictive Control and other algorithms based on MPC.

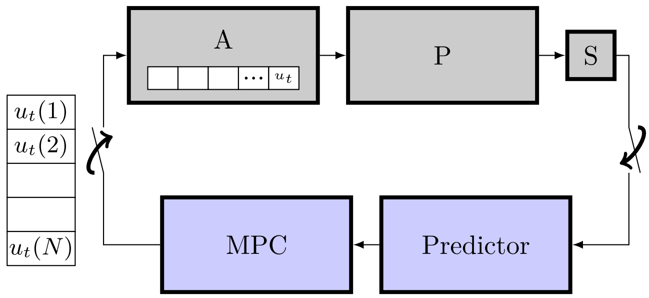

Fig. 7. Typical setup of packetized predictive control. A control input sequence is transmitted and a buffer is used by the actuator to store the most recent received control packet.

In the related literature, the plant is usually modeled as a nonlinear discrete-time system

$$x_{t+1} = f(x_t, u_t, w_t) \tag{40}$$

where $x_t \in \mathbb{R}^n$ is the state, $u_t \in \mathbb{R}^m$ is the input, and $w_t \in \mathbb{R}^d$ is the process noise. The full state is assumed to be measured. The system is possibly subject to constraints

$$x_t \in \mathbb{X}, \quad u_t \in \mathbb{U} \tag{41}$$

where $\mathbb{X} \subseteq \mathbb{R}^n$ and $\mathbb{U} \subseteq \mathbb{R}^m$ are sets. The network behavior is described by the binary sequences θ_t and γ_t described above.

Similarly to classical MPC, the key ingredient is the finite-horizon optimization problem $\mathcal{P}(x)$ defined as

$$\min_{\{u(k)\}} \sum_{k=0}^{N-1} L(x(k), u(k)) + F(X(N)) \tag{42}$$

$$x(k+1) = f(x(k), u(k), 0) \quad x(0) = x \tag{43}$$

$$x(k) \in \mathbb{X}_k, u(k) \in \mathbb{U}_k, \ k = 0, \dots, N-1 \tag{44}$$

$$x(N) \in \mathbb{X}_N \tag{45}$$

which is solved in a receding horizon fashion. At each time instant $t \in \mathbb{N}$, the optimization problem $\mathcal{P}(x)$ is solved for a suitable initial point x. The optimal control sequence, denoted as $u_t(0), \dots, u_t(N-1)$, is then suitably packetized in the control packet U_t and transmitted to the actuator. A buffer in the actuator is used to store the last admissible control sequence received. In general, the buffer is updated as

$$B_t = \theta_t U_t + (1-\theta_t)\Delta B_{t-1} \tag{46}$$

where

$$\Delta = \begin{bmatrix} 0 & I_m & 0 & \cdots & 0 \\ 0 & 0 & I_m & \cdots & 0 \\ & & & & \\ 0 & 0 & \cdots & 0 & I_m \\ 0 & 0 & \cdots & 0 & 0 \end{bmatrix} \tag{47}$$

The first element of the buffer is extracted

$$u_t = [I_m \ 0 \ \dots \ 0] B_t \tag{48}$$

and applied. This setup is represented in Fig. 7.

Due to packet losses, the current state might be not available and it has to be estimated based on the past received measurements and the past computed inputs. In the unconstrained case, the main focus is on the design of the estimator and the characterization of the overall stability conditions (Mishra, Chatterjee, & Quevedo, 2017, 2020; Quevedo & Nešić, 2012). In the constrained case, however, an additional issue arises. In fact, if the past inputs used in the estimation process and past inputs applied at the plant are not coincident due to packet losses, the computed control sequence based on the state estimate is not necessarily admissible from the actual state and the system might violate the constraints. This problem is referred to as input consistency in the literature and it has stimulated different solutions.

In the case where the communication from the sensor to the controller is ideal, i.e. $\gamma_t = 1 \ \forall t \geq 0$, it is always possible to set $\hat{x}_t = x_t$ and input consistency is guaranteed (Quevedo et al., 2012, 2007). Under technical assumptions on the cost and the terminal set, stability is guaranteed if the number of consecutive packet losses is always smaller than the control horizon N. In the case with reliable acknowledgment (Bahraini, Zanon, Falcone, & Colombo, 2021; Li & Shi, 2013), state estimate can be obtained as $\hat{x}_t = \gamma_t x_t + (1-\gamma_t)\hat{x}_{t|t-1}$ with $\hat{x}_{t|t-1} = A\hat{x}_t + Bu_t$ and input consistency is preserved. If acknowledgment is not present, it is possible to guess a possible past input sequence and then to check at the actuator if it coincides with the actual applied input sequence (Pezzutto, Farina, Carli, & Schenato, 2021). A possible choice is $\hat{x}_t = \gamma_t x_t + (1-\gamma_t)\hat{x}_{t|t-1}$ with $\hat{x}_{t|t-1} = A\hat{x}_t + Bu_t(0)$. In this case, input consistency is not automatically guaranteed but a received control packet has to be discarded if it is computed based on a wrong state estimate. Formally, this can be achieved using the modified buffer update rule $B_t = \Theta_t U_t + (1-\Theta_t)\Delta B_{t-1}$ with $\Theta_t = \prod_{i=0,\dots,a_t} \theta_{t-i}$ where a_t is the age of the last received packet at the controller at time t. On one hand, in ideal channel conditions, the solution is as prompt as the wired counterpart. On the other, the performance loss in bad channel conditions is made more evident because discarded packets are added to lost packets.

Another approach proposed in the literature consists of introducing a fictitious delays in the control loop (Findeisen & Varutti, 2009; Pin, Fenu, Casagrande, Zorzenon, & Parisini, 2020; Pin & Parisini, 2009, 2010). More specifically, at time instant t, the optimization problem $\mathcal{P}(\hat{x}_{t+\tau|t})$ is solved with $\hat{x}_{t+i+1|t} = A\hat{x}_{t+i|t} + Bu_{t+i-\tau}(0)$ starting from $\hat{x}_t$ The control packet is constructed as

$$U_t = (u_{t-\tau}(0), u_{t-\tau+1}(0), \dots, u_t(0), u_t(1), \dots u_t(N-1)) \tag{49}$$

namely, the first τ elements are kept from the previous control packet. In this case, input consistency and stability are guaranteed if the number of consecutive packet losses is always smaller than the fictitious delay τ. With this approach, however, the applied control input is always computed τ steps in advance, degrading the performance even in ideal channel conditions.

Solutions with a smaller fictitious delay τ and a suitable discard policy in case the number of consecutive losses is longer than τ can be an effective trade-off between the system promptness and the number of discarded packets (Bemporad, 1998; Grüne, Pannek, & Worthmann, 2009). With this approach, a re-synchronization procedure is usually needed to re-align the state prediction $\hat{x}_{t+\tau|t}$ to the future system state by properly choosing the inputs to use in the predictor at time t.

The main focus of the solutions mentioned above is to stabilize a system while enforcing constraints. From the theoretical point of view, as we have seen, stability is guaranteed up to a certain delay or number of consecutive packet losses. From a more practical point of view, however, even if stability is guaranteed, long open-loop evolutions of unstable systems tend to be unsatisfactory. Motivated by this observation, along the original idea of Bemporad (1998), Casavola, Mosca, and Papini (2006), some recent works (Li, Geng, Kolmanovsky & Girard, 2022; Pezzutto et al., 2021; Pezzutto, Garone, & Schenato, 2019) consider a multi-loop control system where the inner control loop at the plant side makes use of a simple controller and the outer control loop closed over wireless adopts a constrained controller. The remote controller, possibly designed along the lines of Packetized Predictive Control, is used to enforce constraints while tracking reference signals. According to this approach, rather than stabilizing an unstable remote system, the main objective of wireless control is enforcing safety, expressed by the constraints, which cannot be guaranteed with the simple hardware at the plant side.

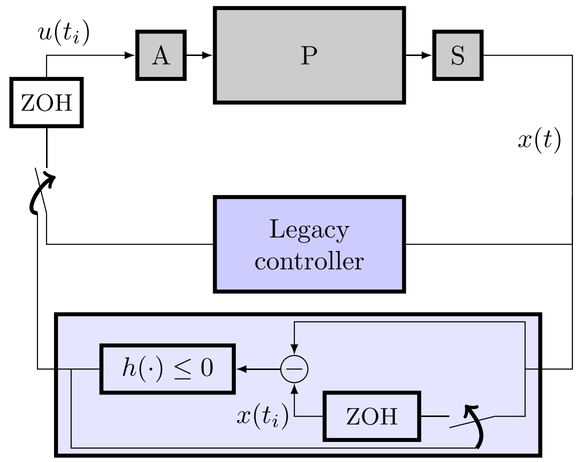

Fig. 8. Typical setup in event-triggered control. A legacy controller is used together with a trigger that, based on the error between the current and the last used state, decides when to transmit the new input.

Event-triggered control

The control approaches presented above investigate how the network affects the control performances. However, also control influences the network. If the network is shared by many control systems that require frequent transmissions, delays and packet losses are increased because of the higher channel occupancy and collision probability. In contrast, delays and packet losses can be minimized if communications are not scheduled at each sampling time but only when necessary. Interestingly enough, decreasing the number of transmissions is also beneficial for reducing energy consumption and computational burden. These advantages motivate an alternative setup consisting of two components, a control law and a transmission trigger based on the current measurement. The critical point of this approach, called event-triggered or event-driven control, is deciding when to transmit or not so as to reduce the network load while not compromising performance and stability.

In the typical setup, the plant is modeled as a continuous-time nonlinear system

$$\dot{x} = f(x, u, w) \qquad u = k(x) \tag{50}$$

where $x \in \mathbb{R}^n$ is the state, $u \in \mathbb{R}^m$ is the input, $w \in \mathbb{R}^d$ is the process noise, and $k(\cdot)$ is a stabilizing state feedback law.

Instead of classical periodic sampling, in order to decrease the network load, the control input is updated and transmitted only when performances are not satisfactory. Such an event can be formalized through a suitable condition referred to as trigger condition.

Let $\{t_i\}$ be the sequence of triggering instants. Between two following triggering instants, the applied input is kept constant

$$u(t) = u(t_i) = k(x(t_i)) \quad t \in [t_i, t_{i+1}) \tag{51}$$

Let $e \in \mathbb{R}^n$ be the error defined as

$$e(t) = x(t_i) - x(t) \quad t \in [t_i, t_{i+1}] \tag{52}$$

Arbitrary event trigger condition can be formalized as

$$h(t, x, e) = 0 \tag{53}$$

Triggering instants can be formalized as

$$t_{i+1} = \inf\{t : t > t_i \text{ and } h(t, x, e) = 0\} \tag{54}$$

This setup is depicted in Fig. 8. In the case without noise, a typical procedure to design the trigger condition (Heemels, Johansson, & Tabuada, 2012; Tabuada, 2007) consists in obtaining a Lyapunov function V satisfying

$$\alpha_1(|x|) \leq V(x) \leq \alpha_2(|x|) \tag{55}$$

$$\frac{\partial V(x)}{\partial x} f(x, k(x+e)) \leq -\alpha(|x|)+\gamma(|e|) \tag{56}$$

where α_1, α_2, α, and γ are $\mathcal{K}_\infty$ functions. With this approach, the trigger condition

$$\gamma(|e|) = \sigma\alpha(|x|) \tag{57}$$

with $\sigma < 1$ guarantees that

$$\frac{dV(x)}{dt} = \frac{\partial V(x)}{\partial x} f(x, k(x+e)) \leq (\sigma - 1)\alpha(|x|) \leq 0 \tag{58}$$

between any two following triggering instants, namely the cost is decreasing along the system trajectory and asymptotic stability is guaranteed. This simple yet effective idea has been extended to include disturbances (Borgers & Heemels, 2014; Lunze & Lehmann, 2010) and constraints (Brunner, Heemels, & Allgöwer, 2017), as well as to consider more general input law (Garcia & Antsaklis, 2012) and dynamic trigger conditions (Girard, 2014; Wang, Zheng, & Zhang, 2017). Reformulations based on hybrid systems have been also introduced (Postoyan et al., 2014) particularly effective in dealing with output feedback (Dolk et al., 2016; Donkers & Heemels, 2011). Event-triggered control for discrete-time systems, usually referred to as Periodic Event-triggered control, has been considered (Heemels & Donkers, 2013; Heemels, Donkers, & Teel, 2012; Heemels et al., 2008; Wang, Postoyan, Nešić, & Heemels, 2019). The approach has been adapted to consider transmission delays (Dolk et al., 2016; Garcia & Antsaklis, 2012; Tabbara et al., 2007), packet losses (Dolk & Heemels, 2017), and the coupling with the communication protocol (Kartakis, Fu, Mazo, & McCann, 2017).

To further reduce the network load and energy consumption, continuous sensing can be avoided by triggering the output sampling together with input computation. In that case, the controller is provided with a suitable law determining the next instant when the output has to be sampled and the input has to be updated. The resulting scheme is referred to as self-triggered control (Anta & Tabuada, 2010; Gao, Yu, Dimarogonas, Johansson, & Xie, 2019; Heemels, Johansson, & Tabuada, 2012; Henriksson, Quevedo, Peters, Sandberg, & Johansson, 2015; Li, Yan, & Shi, 2018; Mazo, Anta, & Tabuada, 2010).

3.3. Connecting multiple systems over wireless

The previous subsection, and references therein, focus on the case where there is a single control unit. Although a single dynamical system with a single sensor and a single actuator is typically considered, the case with multiple sensors and multiple actuators has been addressed too with very similar approaches, simply at the cost of more involved derivations. Backed on the multi-sensor multi-actuator case, multiple agents can be treated with no additional effort as a single system model can be extended to wrap the models of arbitrarily many possibly coupled sub-systems. With this approach, an agent is treated as a mere pair of a sensor and an actuator governed by a remote centralized controller. Alternatively, it is possible to use multiple control units collocated on the agents, spreading the computational power in the system, quitting centralized control in favor of distributed control. Fig. 9 depicts the setup consisting of a set of different, possibly heterogeneous, systems connected over wireless. The setup consists of multiple controllers that make local decisions based only on local information.

More formally, the overall system consists of a set of N subsystems, or agents. The overall system structure is mathematically modeled through the graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$ where $\mathcal{N} = \{1, 2, \dots, N\}$ is the set of nodes, representing the agents, and $\mathcal{E} \subset \mathcal{N} \times \mathcal{N}$ is the set of edges, representing the connections between agents. In general, agent i and agent j are neighbors if $(i, j) \in \mathcal{E}$ and $\mathcal{N}_i$ denotes the set of neighbors of agent i. The overall system dynamics is modeled through the dynamics

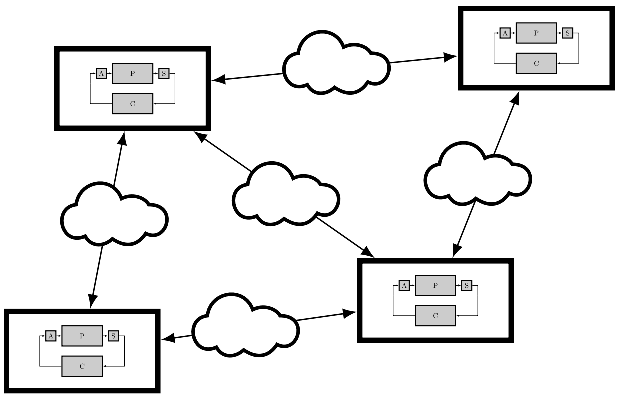

Fig. 9. Wireless is used to connect multiple dynamical systems.

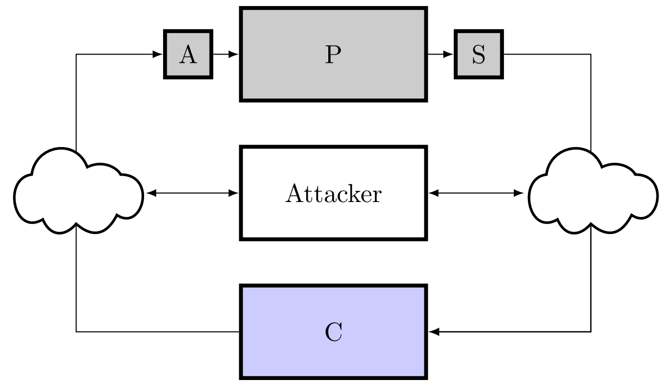

Fig. 10. Wireless exposes the control loop to attacks.

of the subsystems. In general, agent i is modeled as a continuous-time linear system

$$\dot{x}_i(t) = A_i x_i(t) + B_i u_i(t) + \sum_{j\in\mathcal{N}_i} A_{ij} x_j(t) \tag{59}$$

where $x_i \in \mathbb{R}^{n_i}$ is the state of agent i and $u_i \in \mathbb{R}^{m_i}$ is the input of agent i, typically computed as

$$u_i(t) = K_i x_i(t) + \sum_{j\in\mathcal{N}_i} K_{ij} x_j(t) \tag{60}$$

In this formulation, the set of neighbors $\mathcal{N}_i$ captures both the case where the dynamics of agent i are coupled with the dynamics of agent j and the case where agent i has information on the state of agent j, either because it can be measured directly by agent i or because it is communicated by agent j.

The core tool to address this kind of problem is consensus (Fax & Murray, 2004; Olfati-Saber & Murray, 2004). Roughly speaking, in a consensus problem, a set of agents agree upon specific quantities of interest. In the original formulation, the dynamics are simplified as simple integrator without coupling

$$\dot{x}_i(t) = u_i(t) \tag{61}$$

and the goal for the agents is to reach the same state. In mobile robotics, this corresponds to the well-known problem where a set of simple agents has to meet in a point in the space (rendez vous). The same framework is used to consider the relevant problem where the goal is to reach the desired distances between the agents. In mobile robotics, this corresponds to the problem where agents, instead of agreeing on the value of the state, need to reach a desired formation (formation control). Consensus has been generalized to more complex agent dynamics (Ma & Zhang, 2010; Ren & Beard, 2008). More general distributed control problems including coupled dynamics and arbitrary objectives have been considered (Carli, Chiuso, Schenato, & Zampieri, 2008; Casavola, Garone, & Tedesco, 2014; Farina & Scattolini, 2012; Rawlings & Stewart, 2008).

Technically speaking, in this kind of problem, an agent requires the measurements of the states of the neighbors, which, in line of principle, can be directly measured from on-board sensors (e.g. cameras). When the state is not directly accessible through remote sensing, wireless communication needs to be used. Through wireless, also more elaborated information can be transmitted, e.g. the current and the intended future inputs. When information is transmitted over wireless, since communications are not continuous, the input updates at discrete-time instants. This has required deriving and studying the discrete-time counterpart of the problem above. A large body of literature has considered the case of wireless modeled as an ideal link with discrete-time transmissions, e.g. Moreau (2005), Ren and Beard (2005). More accurate models have been lately addressed following similar approaches to the previous section. In particular, consensus has been studied in the presence of delays (Hadjicostis & Charalambous, 2013; Xiao & Wang, 2008), with lossy links (Fagnani & Zampieri, 2009; Zhang & Tian, 2010), and in the event-triggered framework (Dimarogonas, Frazzoli, & Johansson, 2011; Garcia, Cao, & Casbeer, 2014; Seyboth, Dimarogonas, & Johansson, 2013; Yi, Liu, Dimarogonas, & Johansson, 2018; Zhu, Jiang, & Feng, 2014). More general distributed event-triggered control problems have been studied (Wang & Lemmon, 2009, 2010). The interested reader is referred to Nowzari, Garcia, and Cortés (2019) for more references.

3.4. Securing wireless control

The broadcast nature of communications has been both a driving factor and a critical drawback for wireless control as it exposes the control loop to eavesdropping and attacks from external malicious agents. This situation is represented in Fig. 10.

When wireless links are used to close the feedback loop as in Section 3.2, there are three main classes of attacks. Denial-of-Service (DoS) attacks consist of overwhelming the network in order to disable the communications causing the system to evolve in open loop (Amin, Cárdenas, & Sastry, 2009). False Data Injection (FDI) attacks consist of transmitting corrupted packets to the controller or to the plant (Mo, Garone, Casavola, & Sinopoli, 2010). Replay attacks implement eavesdropping on communication to later provide false measurements for the controller that mimic the regular plant behavior while manipulating the inputs for the actuator (Mo & Sinopoli, 2009). In a simpler version, the wireless control systems can simply be subject to eavesdropping (sometimes referred to as passive attack) to obtain crucial system parameter information by rogue agents. Ensuring security against these attacks is a fundamental requirement for wireless control systems.

Complementary to the traditional cryptography-based encryption and authentication-based defense mechanisms, these attacks can also be addressed within the design of the control system itself. In the presence of a DoS attack, some of the wireless control strategies introduced in Section 3.2 can be implemented to limit the effects of the malicious agent on the system. In this regard, with the aim of understanding the fragility of the system, optimal DoS attack strategies and corresponding defense mechanisms have been studied in Li, Quevedo, Dey, and Shi (2016), Li, Shi, Cheng, Chen, and Quevedo (2015), Zhang, Cheng, Shi, and Chen (2015). To further increase the robustness, the controller can be effectively equipped with a detector to detect the attack (Pasqualetti, Dörfler, & Bullo, 2013). From a theoretical point of view, significant attention has been paid to the detectability of FDI attacks. In particular, it has been shown that attacks might be undetectable or stealthy (Bai, Gupta, & Pasqualetti, 2017; Bai et al., 2017) also when the adversary has resource constraints (Teixeira, Shames, Sandberg, & Johansson, 2015). Detection of reply attacks is more complex because false measurements are based on real past measurements. In particular, at the steady state, it is enough to replicate the previous outputs $y(k-d)$ in order to preserve the statistics of $y(k) - C\hat{x}(k|k)$, since it is an i.i.d. Gaussian vector (Mo, Chabukswar, & Sinopoli, 2013). To overcome this issue, a typical solution consists of adding to the ideal (possibly optimal) control input an additional noise term. This is usually referred to as a watermarking signal (Mo, Weerakkody, & Sinopoli, 2015). If the variation due to the additional term is not present in the received measurement, the attack can be detected, at the price of additional control costs (Mo, Chabukswar, & Sinopoli, 2013). The design of dynamic watermarking signals in various setups has been studied in Satchidanandan and Kumar (2016). Alternatively, how to limit the information revealed at the eavesdroppers, while maintaining a satisfactory control performance, is studied in Leong, Quevedo, Dolz, and Dey (2018).

When wireless links are used to connect multiple systems or agents as in Section 3.2, another class of attacks can be constructed by misbehaving agents. In this case, the behavior of the malicious agents may not comply with the communication and algorithmic protocol designed to achieve the prescribed control task. Due to the coupled evolution of the agents, the misbehaving agents affect the behavior of their neighbors and, through cascading, the overall behavior of the system. Resilience to the misbehaving agents is a fundamental requirement. As a fundamental element of multi-agent control, consensus has been studied to be robust to misbehaving agents (LeBlanc, Zhang, Koutsoukos, & Sundaram, 2013). More general problems have also been studied (Ballotta, Como, Shamma, & Schenato, 2023; Dibaji & Ishii, 2015; Usevitch & Panagou, 2019). The interested reader is referred to Ishii, Wang, and Feng (2022) for a comprehensive overview.

4. Open vistas on wireless control

While previous sections have sketched the past and the present of the field, in this section, we try to guess the future evolution of wireless control. Rather than listing any possible future developments, we try to identify some of the most promising directions. Among the possible future developments, we pick up four different topics that, we believe, can have a huge impact both from the practical and theoretical point of view in the next decade. In particular, in Section 4.1 we outline the open questions in the definition of a wireless standard that ideally supports control applications. In Section 4.2 we focus on the possibilities and the challenges related to the expected tremendous number of connected devices and the resulting massive networked control systems. In Section 4.3 we introduce the new communication-computation platforms, sometimes referred to as IoT–Edge–Cloud Continuum, which might support many future control applications. Finally, in Section 4.4, we outline the great possibilities enabled by data-driven wireless control.

4.1. New wireless networks for control

If no big changes are envisioned for LRWPANs and LPWANs in the next future, the newest versions of WLAN and cellular networks are rapidly progressing. Wi-Fi 7, whose final amendment is expected in 2024, is an evolution of the currently available Wi-Fi 6 (Garcia-Rodriguez, López-Pérez, Galati-Giordano, & Geraci, 2021; Khorov, Levitsky, & Akyildiz, 2020). Introducing multi-link operations and adopting extreme modulation schemes, large bandwidth, and high numbers of MIMO spatial streams, WiFi 7 promises extremely high throughput and time-sensitive networking capabilities. Conversely to the imminent Wi-Fi, 6G standardization is still at its infancy and the final version is envisioned for 2030 but the hype around it is noticeable (Bhat & Alqahtani, 2021). Following the direction started with 5G, 6G will likely consider control applications natively. This emerges from the

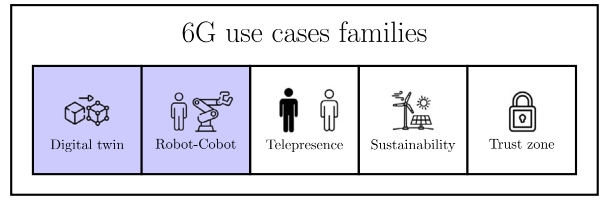

Fig. 11. 6G use cases families according to Uusitalo et al. (2022) Two out of five are explicitly targeting monitoring and control of dynamical systems.

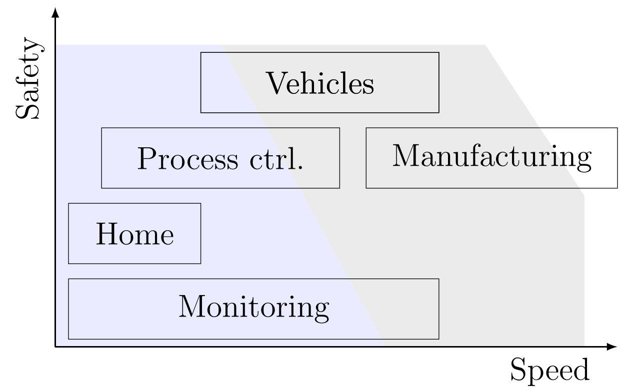

Fig. 12. Control applications and their requirements. The blue area represents the requirements that are met by wireless nowadays, the gray area represents the desired next future advances. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

European 6G Flagship Project Hexa-X which has selected as use case families, reported in Fig. 11, massive digital twining of physical systems and robots. As pointed out in Uusitalo et al. (2022), there is agreement among many stakeholders that cyber–physical systems, and consequently control, are the key target of future 6G.

Cyber–physical systems span a range of applications and have a range of requirements. Indeed, as outlined in Fig. 12, many control applications (e.g., monitoring in the industrial environment) are already feasible over wireless but systems characterized by both high packet rates and high safety requirements (e.g., manufacturing) are still not covered. To extend the scope of wireless to include also such applications, new wireless standards need to be developed to provide systematically low latency communications, supporting both frequent packet transmissions and instantaneous successful receptions.

To achieve low latency, a sufficiently high data rate is needed in order for the packet transmission to be completed as soon as possible and to occupy the network as few as possible. Latest WLAN and cellular networks achieve terrific data rates by adopting, as prescribed by information-theoretic arguments, large packets. Indeed, when communication is characterized by few and large packets, the length of the preamble is negligible compared to the amount of data and the effect of channel access is limited. However, in many control applications, packets are small, usually consisting of only a few bytes representing a few real numbers. In this case, the critical network load is not due to occasional large amounts of data, e.g. when downloading high-definition video, but when data is generated more frequently, e.g. with smaller sampling periods and a higher number of connected systems. For this reason, further increasing the data rate would give only a marginal improvement and a different network design paradigm is needed. Novel research works have to characterize the theoretical principles that govern the transmission of short packets (Durisi, Koch, & Popovski, 2016). From a more practical point of view, solutions such as shortening the preamble as much as possible can be effective (Luvisotto et al., 2019). Research in short packet communication for control applications is underway (Gatsis, Hassani, & Pappas, 2020; Liu et al., 2020) as well as research in higher network layers (Soleymani, Baras, & Johansson, 2019).

To achieve low latency in a consistent way, efficient channel access is needed. Standardization organizations and vendors are actively trying to develop new wireless standards that enforce determinism in communication by adopting TDMA-like protocols. This is the case e.g. of WIA/Fi and Flexware. Indeed, TDMA and more elaborate OFDMA schemes guarantee a known communication schedule and known reception deadlines. On the other hand, they require centralized schedulers and complex scheduling algorithms, especially to handle many devices with wide ranges of sampling periods and to adapt dynamically when new devices join the network. The design of an efficient TDMA access protocol poses novel research problems. Alternatively, CSMA can be a possible solution. CSMA cannot in general guarantee a deterministic reception deadline but allows immediate channel access on average and does not require a scheduling process. Strategies to suitably tune CSMA parameters need to be studied. Guaranteeing upper-bounded latencies with CSMA is also an open problem at the moment.

High reliability is a necessary condition for always small latencies. In this sense, future wireless standards for control applications should be able to provide acceptable performances in any condition. Since interference will be inevitably present as the number of wireless devices increases, new solutions should be devised able to adapt to the channel conditions. This can stimulate novel cross-layer design approaches where the network parameters are set based on the specific control application.

Future wireless standards should meet the variety of requirements of different wireless control applications. To this end, it is fundamental to identify the needs of different applications in terms of transmission rate, packet size, maximum latency, maximum packet losses, and other features. Potentially, different wireless standards can be devised to target different control applications or, alternatively, a standard should allow different adjustments to accommodate different applications.

4.2. Massive networked control systems

As IoT has caught on, a large number of connected devices able to sense and act has started to be present in the most diverse places, ranging from home deployment to the factory and the city level. By 2030 the number of IoT devices is expected to double (Statista, 2024) and IoT technologies will become even more pervasive. As the number of connected devices continues to grow, future cyber–physical systems will include a growing number of sensors and actuators, possibly deployed over wide areas and several interconnected processes, leading to Massive Networked Control Systems.

Examples of Massive NCSs are the future connected factory and the future smart city. Also, autonomous connected systems will be ideally supported by the resulting hyper-sensed environment. For instance, autonomous cars and mobile robots can exploit information from the surrounding connected infrastructure for better localization and reconstruction of the environment. Broadly, the resulting systems consist of multiple inter-dependent sub-systems evolving in a complex environment with multiple heterogeneous sensors and actuators.

Differently from physical systems of interest for typical control applications, the system has high dimensions and spans multiple levels. For instance, in traffic control for smart cities, the number of variables is (approximately) equal to the number of intersections. Control of such interconnected high-dimensional systems is a challenging task that calls for a suitable theoretical framework, whose first steps have been made in the last years in the area of complex networks (Liu, Slotine, & Barabási, 2011). However, differently from traditional approaches in the area, the increase of the number of sensors will allow to collect large amounts of data, paving the way for the identification of complex networks and, possibly, for data-driven control (Baggio, Bassett, & Pasqualetti, 2021).

Compared to traditional control systems, sensing and actuation can be located at several distinct points. For instance, autonomous cars can collect data from on-board sensors, from other cars, and from the infrastructure. Similarly, in smart grids and smart cities, the same effects on the system can be obtained by acting on different components. It follows that sensor and actuator selection is not straightforward but it needs to be carefully studied. When possibly redundant sensors and actuators are present (e.g. for traffic control in a smart city), the most effective way to gather data and take actions has to be selected. Robustness to devices leaving the network, possibly due to faults, is a relevant problem that has to be studied.

Applications involving massive number of connected devices impose strong requirements on the communication protocol. This problem is widely recognized in the ICT community and has motivated a large body of literature (Sotenga, Djouani, & Kurien, 2020). Unfortunately, these works do not take into account the underlying control applications. In fact, it has been shown in Kaul, Yates, and Gruteser (2012) that timely updating, as needed in control, is not the same as maximizing network utilization or minimizing packet delay, as advocated for general-purpose communication systems. In order to guarantee the specific needs of control in terms of timeliness, it is fundamental to devise communication protocols and transmission scheduling that focus on how old is the most fresh received packet. This metric is known as Age of Information and has been largely studied for scheduling in cyber–physical systems (Yates, Sun, Brown, Kaul, Modiano, & Ulukus, 2021). Solutions targeting specifically control metrics have been studied also, however, they usually consider simpler setups with only sensor transmissions and static configurations (Leong et al., 2016). Future Massive NCSs require the consideration of more general architectures that include both heterogeneous sensors and actuators (e.g. in a smart factory) and with devices that can dynamically join and leave the network (e.g. autonomous cars in intersections).

When many devices coexist in the same environment as in the case of Massive NCSs, interference is a major issue. When devices are connected to different networks with overlapping bands, network coexistence needs to be studied. In particular, transmission power needs to be selected to guarantee stability and desired control performances by finding the suitable trade-off between the received power at the receiver and the interference caused on other networks. Recent works have studied transmission power allocation problems and have proposed policies tailored for specific settings (Eisen & Ribeiro, 2020; Knorn & Dey, 2017; Ren, Wu, Johansson, Shi, & Shi, 2017). Generalizing these results to the case with an high number of connected systems is a relevant future direction. When devices are connected to the same network, interference can be actively removed by properly coordinating the communications through the channel access mechanism. As the number of devices increases, however, this might be no longer possible or it might come at the cost of high latencies. Alternatively, since simultaneous transmissions and successful receptions on the same time–frequency resources are possible in wireless communications, interference can be explicitly admitted by allowing multiple devices to communicate. In such cases, Signal-to-Interference-and-Noise-Ratio, which critically depends on the transmission powers, is the key metric that determines the correct reception of the multiple signals. Designing an effective transmission power selection algorithm to enable simultaneous communications, possibly prioritizing packets carrying relevant control information, can be a relevant problem. Although some steps have been made, existing solutions consider a small number of systems (Forootani, Iervolino, Tipaldi, & Dey, 2022; Pezzutto, Schenato, & Dey, 2022) and more advanced techniques able to scale with an increasing number of devices are needed.

As systems become massive in terms of number of devices, they might become massive in terms of data traffic generation and covered area. The case of massive data is not common for typical control applications but might be the case of machine learning. In the same way, the span of typical control systems is limited to hundreds of square meters (see e.g. factory plants) but some emerging applications can cover areas in the range of thousands of square meters (see e.g. smart cities). This massive condition of future NCSs will require novel communication solutions that are tailored for control. Moreover, the massive number of devices entails higher chance of malicious attacks that advocates for rethinking existing secure control solutions, in particular in terms of scalability.

4.3. The IoT–edge–cloud continuum

Traditional control systems have always consisted of a physical plant and a co-located or possibly wired control unit. However, seamless wireless connectivity has greatly enlarged the spectrum of possible architectures, including both decentralized and supervisory control and a hybrid of the two. Even more, in the last years, the evolution of the flexible edge–cloud computing architecture has made possible information processing and computation to be distributed across multiple layers. The current trend in the ICT community has conceptualized a hierarchical three-layered platform consisting of end devices (any IoT device with sensing, computing, and/or actuating capabilities) at the bottom level, the middle level comprising edge devices (communication gateways with possibly high computational capabilities), and cloud systems (servers with high data storage and high computation resources) at the top level (Cao, Liu, Meng, & Sun, 2020). Next-generation wireless networks (5G or even 6G) are expected to provide connectivity among these various layers. This setup is visually represented in Fig. 13. In this architecture, also sometimes called the IoT–Edge–Cloud continuum, the control system is no longer implemented in a single location but it spreads over different computational units at different layers and can interact with other control systems over wireless links.

In the single-agent case, the cloud can be used to store complex models and proprietary control algorithms, the edge can implement a sophisticated constrained controller while the end device can run simpler control algorithms. In applications such as safety-constrained control of autonomous systems, the cloud can implement complex learning-based controllers to effectively deal with unmodeled uncertainties and nonlinearities, while the edge-based controllers (being naturally closer to the end devices) can use partial model knowledge to implement safety certification or a safe backup control law, especially when the access to the cloud server can be lost intermittently or the learning-based control results in unsafe strategies.

In the multi-agent case, computational resources at the edge and at the cloud can be used to improve coordination and cooperation. Distributed control algorithms implemented at the end device layer can be combined with centralized strategies at the edge or at the cloud. The resulting hybrid scheme, naturally supported by the new computation communication platform, can outperform typical fully distributed or fully centralized approaches. In an even more general setup, multiple dynamical systems with multiple dedicated edge resources can be connected to organically gather and share information on the physical environment. In this way, more refined models can be obtained, while decision-making and resource allocation on the large scale can be effectively optimized.

This new communication-computing architecture and the emerging networked control applications pose new fundamental theoretical questions. For the single-agent case, it is interesting to study the optimal allocation of the control computation. This problem is strictly intertwined with the design of an effective hierarchical controller that takes into account the different computational capabilities and the different communication limitations while achieving guaranteed safety and high control performances. This requires handling scenarios where access to the cloud is lost or interrupted, or delays are incurred in obtaining control information from the cloud. Some preliminary solutions are Li, Zhang, Li, Srivastava and and Yin (2022), Skarin, Tärneberg, Årzen, and Kihl (2018) but several aspects remained unexplored. From a

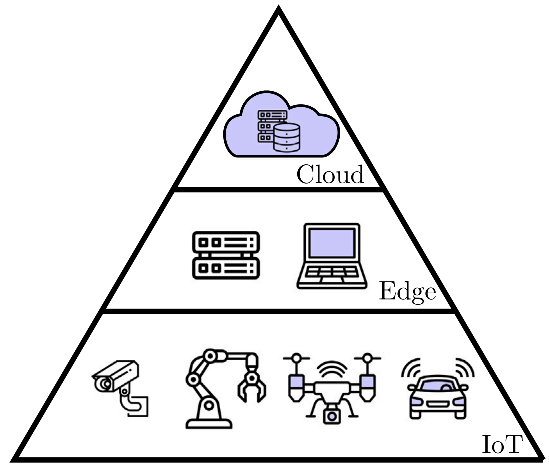

Fig. 13. IoT–Edge–Cloud continuum.

technological point of view, computation offloading between edge and cloud requires an effective selection of the relevant information to transmit and a suitable communication scheduling procedure to optimize the use of the communication resources and energy. Moreover, new vulnerabilities across the IoT–Edge–Cloud Continuum need to be suitably addressed. Specialized attacks and detectors have to be studied and, as different control units might be attacked simultaneously, the overall effect of multiple attacks has to be characterized.

For the multi-agent case, the optimal coordination with different information sets available at different controllers is a well-known challenging problem. A critical aspect is to determine the role to assign to the centralized controller. For larger-scale applications, distributed optimization and learning need to be investigated taking into account the communication limitations and also privacy requirements for proprietary data (Shi, Yang, Jiang, Zhang, & Letaief, 2020). In particular, the architecture can support federated reinforcement learning procedures (Gatsis, 2022; Wang, Mitra, Hassani, Pappas & Anderson, 2023; Wang, Toso, & Felipe and Anderson, 2023) where collaborative learning of the unknown environment or dynamics can be achieved by small-scale local learning at the edge servers based on local data sets, with communication of local feature vectors (e.g. policy gradients) to the cloud where these are merged to learn a global model, which is then shared with the agents for control policy updating. Typical to any networked control system design task, various implementation aspects of communication and computational resource allocation also need to be investigated given the specific aspects of the control architecture, connectivity constraints, and privacy requirements.

4.4. Data-driven wireless control

The machine learning advances over the last decade in tasks such as image classification, generative models, and game playing, are already influencing the control system community — see for example the new venues arising such as the Learning for Dynamics and Control (L4DC) conference. Equally, there has been significant interest in the wireless communications community in exploiting machine learning techniques to design and optimize communication systems (Gündüz et al., 2019). It is natural to expect that machine learning is going to be a fundamental tool in the service of wireless control as well.

Here we would like to point out two distinct opportunities for employing machine learning tools. First, machine learning tools can be used to derive a data-driven model of the communication network behavior (O'Shea, Roy, & West, 2019). This is useful when we seek to expand the deployment of wireless control systems in complex environments, where it is likely that a complete characterization of the communication network, in terms of, for example, the channel fading distributions, the latency distributions, or the packet success rate along multiple links, is not a priori known or such characteristics are varying over time. Instead, these characteristics could be approximated from collected data before operation or online. Indeed the control community has been investigating data-driven approaches for modeling the communication characteristics along these directions (Eisen, Gatsis, Pappas, & Ribeiro, 2018; Farjam, Wymeersch, & Charalambous, 2021, 2023; Leong, Quevedo, & Liu, 2023; Wu, Ren, Jia, Johansson, & Shi, 2019). These data-driven approaches can be used to approximate the communication model as in Section 3.1 and subsequently the existing control approaches of Section 3.2 can be used. However, a key challenge is that there is a mismatch between the true underlying communication network and the data-driven approximation, often due to limited data for training, and as a result these approximation errors require revisiting the analysis as well as the control design methods of Section 3.2. For example, recent literature utilizes techniques from statistical learning theory (Gatsis & Pappas, 2021; Schuurmans, Sopasakis, & Patrinos, 2019) or investigates regret bounds (Du et al., 2022; Leong et al., 2023).

The second problem where machine learning tools could be useful is the co-design of control and communication policies. This is a great opportunity to take advantage of the expressive power of machine learning models, including deep neural networks, to approximate arbitrarily complex functions used in wireless control systems, for example, resource allocation functions that map dynamical system states and communication states to resources, or controllers mapping system states to control inputs. Indeed, as discussed in the existing control approaches of Section 3.2 optimal solutions can be explicitly computed only in specific cases. Learning becomes even more promising in the context of co-design of control and wireless communication policies, as optimal and computationally practical co-design in the literature is scarce. Initial approaches, for example, target learning sensor scheduling over networks (Chen et al., 2023; Demirel, Ramaswamy, Quevedo, & Karl, 2018; Leong, Ramaswamy, Quevedo, Karl, & Shi, 2020; Pang, Liu, Li, & Vucetic, 2022; Vasconcelos & Mitra, 2021). It is worth emphasizing that training such policies is often based on reinforcement learning algorithms, which requires iteratively generating trajectories of system inputs and responses. The prospect of employing multi-agent reinforcement learning is a promising avenue for jointly learning communication and control policies (Funk, Baumann, Berenz, & Trimpe, 2021; Lima, Eisen, Gatsis, & Ribeiro, 2022). Unfortunately, learned policies such as those based on deep neural networks lack theoretical guarantees, in contrast to standard wireless control approaches in Section 3.2 that facilitate stability or performance verification. Furthermore, deep neural networks are notorious for their lack of robustness, which can pose security concerns for wireless control systems. Finally, future research will focus on machine learning solutions that can offer scalability to enable Massive NCSs, where, for example, large state and action spaces need to be considered (Pang et al., 2022). In addition, selection of appropriate parameterization of the machine learning models (Kalogerias, Eisen, Pappas, & Ribeiro, 2020) needs to be investigated, which remains an open challenge.

5. Conclusion

Wireless control has been an active technological area for years and will likely have an even larger impact in the future. By revising existing solutions, both in terms of network choice and control design, we aimed to provide a practical toolkit for the practitioner. However, wireless control will keep evolving, driven by the technological advances of networks and novel leading applications. Based on the current trends, we envisioned as future relevant topics the design of novel wireless networks for control, the convergence of wireless, control, and learning, the massive spread of IoT, and the advent of novel communication-computation infrastructure based on the edge–cloud continuum. We also foresee, however, that wireless control will find new applications beyond those identified in this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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