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Wireless Communication and Control Co-Design for Dynamic QoS Strategy in Industrial 4.0

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Abstract

Due to its technical characteristics, the 5G network is highly anticipated for its application in the industrial field, particularly in terms of ultra reliability and low latency (URLLC). 5G serves as a pivotal enabling technology that propels the robust development of the industrial Internet, while simultaneously benefiting from it. By leveraging the attributes of 5G URLLC, real-time control over factory automation equipment can be achieved, replacing traditional wired networks and reducing cable and wiring workload significantly. This not only saves valuable adjustment time on production lines but also enhances flexibility within factories. High-performance wireless networks seamlessly connect an array of sensors, robots, and information systems within factories, facilitating data analysis and decision-making processes that are fed back into operations. In the context of Industry 4.0, a multitude of wireless communication resources is required, thus minimizing communication resource consumption while ensuring efficient transmission has become a pressing challenge.

In order to implement dynamic Quality of Service (QoS) strategy in the context of Industry 4.0, this thesis initially provides an overview of the fundamental technologies, applications, and characteristics of 5G networks and Industry 4.0. Subsequently, it considers control and communication co-design problem in wireless network for achieving dynamic QoS strategy in Industry 4.0. In the industrial scenario, it will lead to a certain waste of resources if the task requirements at every moment are in accordance with the requirements of URLLC, while additional resources generated by a dynamic QoS strategy can be provided for other users since the communication and control systems are dynamic. This is especially true for the control system, whose requirements for tasks are changing almost all the time. The objective is thus to achieve maximum system capacity and minimum communication resource consumption. In this research, the proposed method is to use the dynamic QoS strategy based on communication and control co-design system by constructing a use case of a reconfigurable factory architecture for future Industry 4.0. Finally, based on dynamic QoS, three key and challenging research strategies are identified in terms of reducing communication resource consumption and optimizing system capacity.

The first research question and contribution focus on examining the relationship between user customization requirements and communication resource consumption within the context of Industry 4.0. Three mapping schemes are proposed to facilitate the implementation of a co-design control scheme, which encompasses mapping industrial demands to communication bandwidth resource consumption.

The second contribution explores the optimization of communication resource allocation. Implementation of dynamic QoS based on packet length design, the purpose is to minimize the bandwidth consumption of each robot arm. Simulation results show that the proposed solution can significantly reduce wireless resource consumption compared to other benchmarks while ensuring the required control system requirements.

The third contribution examines the impact of channel scheduling on enhancing the performance of dynamic QoS policies. In practical applications, due to varying locations of Automated Guided Vehicles (AGVs), the selection of frequency channels for AGV robot arms differs. The proposed scheme demonstrates that increasing transmit power can effectively increase system capacity.

The fourth contribution achieves the objective of average bandwidth resource consumption through task rescheduling with flexible delay. A task-oriented dynamic resource allocation model is proposed. Simulation results demonstrate that this strategy effectively reduces the peak of resource consumption by deferring low-priority tasks to subsequent idle periods, while maintaining total and average resource consumption unchanged.
Key words: Wireless control co-design, Dynamic QoS, Industry 4.0, URLLC.

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List of Acronyms

IIC	Industrial Internet Initiative
ASEAN	Association of Southeast Asian Nations
QoS	Quality of Service
URLLC	Ultra-Reliable and Low-Latency Communications
PPC	Packetized Predictive Control
M2M	Machine to Machine
TRDA	Task-based resource dynamic allocation
CPS	Cyber-physical systems
IOT	Internet of Things
5G	5th generation
ITU	International Telecommunication Union
OTT	One-way Transmission Time
RTT	Round Trip Time
4G	4th generation
eMBB	Enhanced Mobile Broadband
mMTC	Massive Machine Type of Communication
3GPP	3rd Generation Partnership Project
CIMT2015	The 14th China International Machine Tool Exhibition
BS	Base Station
BLER	Block Error Rate
AGV	Automated Guided Vehicle
AWGN	Additive White Gaussian Noise
SNR	signal-to-noise ratio
E2E	End-to-End
UPF	User Port Function
CDF	Cumulative Distribution Function
AP	Access Point
TBF	Transmit Block Size
PLC	Programmable Controller
PDF	probability density function
5GAA	5G Automotive Association

List of Acronyms

$\boldsymbol{x}_{m,n}$	The state vector of the plant
$\boldsymbol{u}_{m,n}$	The control input vector
$\boldsymbol{n}_{m,n}$	The disturbance modeled as ***additive white Gaussian noise***
$\boldsymbol{A}, \boldsymbol{B}$	The input matrix
s_n	The sample period
$\bar{s}_n$	The idle period
T_n	The communication time delay
ε_n	The packet loss rate
$1-\varepsilon_n$	The probability of successful packet transmission
α_n	The random variable
Q_n	The given positive definite matrix
ρ_n	The control convergency rate
ξ_n	The current plant states
N_n	The number of allocated bandwidths
T_n	The transmission duration
B_0	The bandwidth of each subcarrier
γ_n	The received signal-to-noise ratio
p_n	The allocated transmission power spectral density
N_0	The single-sided noise spectral density
C_n	the Shannon capacity
V_n	The channel dispersion
R	The transmission rate
$f_Q^{-1}(\cdot)$	The inverse of the Q-function
f_Q	Q-function
$g_{n_{[dB]}}$	The path-loss
d_n	The coverage distance of signal
h_n	The small-scale fading
T_b	The payload sizes
v	The robotic arm velocity
t_s	The control sample period

Δf	The subcarrier spacing
σ	The Rayleigh channel parameter
α	The path loss coefficient
p_s	The control outage probability
p_e	The packet loss probability
H	The bit for header
K	The prediction slots
λ	The total bits for a packet
$N_{m,n}$	The total available number of subcarriers
$T_{m,n}$	The time resource
$P_{m,n}$	The power consumption
$B_{max,n}$	The total maximum bandwidth
$P_{max,n}$	The total maximum power
$T_{m,n}$	The communication latency
θ	The time-frequency resource
C_t	The threshold of the communication capacity
R_i	The minimum transmission rate

List of Algorithms

1 Introduction

The proliferation of cyber-physical systems introduces the fourth stage of industrialization, commonly known as Industry 4.0 [1,2]. Also referred to as the Fourth Industrial Revolution, Industry 4.0 encompasses cutting-edge technologies such as artificial intelligence, the Internet of Things and big data analytics that are revolutionizing conventional industrial processes through Internet technologies. While the concept initially emerged in Germany, it quickly gained global recognition [3]. In response to this shared objective, the United States initiated the Industrial Internet Initiative (IIC), although it is worth noting that the term was coined much earlier [4].

The main technological foundation of Industry 4.0 lies in the integration of Internet technology into industrial processes. This technical underpinning is often intertwined with a corresponding futuristic vision, wherein the individual components within a facility is interconnected to enhance overall flexibility. Consequently, these components can autonomously decentralize or collaborate to customize product manufacturing according to diverse customer requirements. In comparison to traditional industrial assembly lines, this system offers greater adaptability, customization potential, and resource efficiency [5]. Therefore, it is imperative to equip workers with the skills and competencies necessary for analysing industrial requirements and developing tailored systems in Industry 4.0 [6].

Furthermore, analysing the demand for Industry 4.0 is crucial for a country's economic growth, and its rapid global development has exerted a significant impact on countries worldwide, compelling them to reassess and adapt their economic strategies to conserve resources [7]. Within the context of Industry 4.0, countries must develop novel strategies to ensure that their workforce can thrive in this new environment. Particularly, numerous Association of Southeast Asian Nations (ASEAN) countries are confronted with the challenge of poverty status. Historically, these nations have relied heavily on an assembly line labour force as a successful driver of economic growth. However, as Industry 4.0 advances, this model is becoming outdated and is not providing sufficient income for entry-level workers. This hinders GDP growth per capita as a large portion of the population is limited to low-skilled jobs. [8].

1.1 Context

The essence of Industry 4.0 lies in the seamless integration of production systems with underlying equipment, enabling comprehensive data collection on equipment operation. Through intelligent analysis by upper-level information systems, enterprises are empowered to optimize the performance of their underlying equipment and achieve unmanned control [9].

Thus, two core themes emerge: Smart Products and Smart Factories. Smart is a continuous and perfect fusion process between advanced information technology and industry within the realm of scientific and technological development, where constantly evolving information technology plays a decisive role [10].

Smart Products [10] not only enable real-time collection of all necessary information throughout the entire production chain but also possess the capability to make autonomous decisions and provide selective information based on production requirements. This revolutionary attribute of smart products will significantly transform industrial manufacturing. Smart Factories [10] are characterized by high energy efficiency, advanced technology, adaptability, and ergonomic production lines. Its objective is to seamlessly integrate customers and business partners while enabling customized product manufacturing and assembly. Furthermore, future smart factories will exhibit enhanced autonomy in decision-making about to production efficiency and safety [10].

To achieve customized production in the context of Industry 4.0, real-time wireless control loops need to be arranged flexibly according to the customized task demands, robot control capacities and communication resource constraints. Operators need to communicate with the robots with guidance details during the manufacturing process based on customized demands in a real-time fashion. The capacities, real-time status, and the parameters of each robot, e.g., machine type, and processing method, maximum processing size, manufacturing precision, processing roughness should be timely accessed by the entire system, which can be further used to better allocate suitable task to the robot schedule [11]. In addition, due to the limited wireless resources and the uncertainty of the wireless environment in the factory, it is necessary to have the correct wireless protocol to carry different kinds of communication packets in the system.

The reliability of automation and the efficient utilization of communication resources are indispensable in Industry 4.0, constituting a prominent challenge currently faced by this industrial revolution. Hence, it is imperative to address a pivotal research inquiry: **How can we optimize the utilization of wireless communication resources while ensuring the stability of the control system and the reliability of communication, to remotely manage an ever-growing number of plant equipment?**

The entire industrial system has currently been completed through the collaborative design of the communication and control systems, while also researching fundamental dynamic QoS schemes to achieve initial wireless resource savings. However, the overall control communication system has not yet considered the needs of the plant, and there is still room for further improvement in terms of communication resource savings. Therefore, constructing a dynamic mechanism mapping from the high-level task requirements to the low-level resource consumption, with robust resisting disturbance for all levels and developing novel strategies to minimize the communication resources consumption becomes a critical issue at this moment.

1.2 Contributions

This thesis primarily investigates the key challenges of reducing communication resource consumption and accommodating system equipment capacity in the context of Industry 4.0 through a joint design approach integrating communication and control systems following the requirements of the industry. The scope addressed in this study is discussed in the Latest Technologies section, encompassing areas such as 5G, URLLC, and QoS. In this rapidly evolving domain of Industry 4.0, this thesis aims to address the following fundamental inquiries derived from an extensive literature review while contributing novel strategies utilizing dynamic QoS to optimize communication resources and enhance industrial system capabilities.

This thesis aims to investigate strategies for minimizing the utilization of communication bandwidth resources throughout the entire industrial process. Therefore, the initial inquiry pertains to the common challenges encountered in joint communication control design. **How do the demands of industry affect the consumption of communication bandwidth resources**? This question can be explained by contributions 1 which is explained in detail in chapter 3. Specifically, this is done as follows:

Contribution 1: Mapping the customized accuracy demand to the communication resource consumption.

The requirements for customization are initially associated with control convergence rate. **This is the first implementation of a co-design control scheme mapping**

industry demands to communication bandwidth resource consumption in an industry 4.0 context. The concept of control convergence rate in control systems is introduced, which will be elaborated upon extensively in Chapter 2. According to Laplace's theorem, the control convergence rate is intricately linked to the temporal state of the robotic arms. The mapping relationship presented herein demonstrates that diverse tasks necessitate varying precision requirements, thereby directly impacting the speed at which convergence occurs. Then a real-time wireless control model is proposed to illustrate the control loop of each robotic arm. Based on this model, the relationship between communication and control is established by considering sampling period and packet loss. Subsequently, a communication model is proposed to investigate the mapping from communication reliability to consumption of wireless resources. Finally, the thesis discusses the relationship between communication reliability and wireless resource consumption.

The second question asks, **how can we effectively meet industrial demands while optimizing communication resource allocation to accommodate a larger number of plant equipment**?

Typically, to ensure reliable factory operations, high-reliability communication is employed to meet the requirements of URLLC. However, it should be noted that factory operations are inherently dynamic and certain tasks may not necessitate such a stringent level of communication reliability. Therefore, during these specific tasks, a portion of the communication resources can be allocated to other robotic arms to support a greater number of robotic arms. Consequently, employing a dynamic QoS strategy proves effective in addressing this issue. In this thesis, a novel dynamic QoS framework is proposed based on Contribution 1 to minimize bandwidth usage in the context of Industry 4.0. Furthermore, a comprehensive evaluation is conducted on the effect of three variations of our proposed dynamic QoS framework to enhance system gain and further reduce communication resource consumption in an Industry 4.0 context.

Contribution 2: Implementing dynamic QoS based on packet length design to minimize the consumed bandwidth for each robotic arm.

Packetized Predictive Control (PPC) offers an effective solution for robust control over unreliable wireless links, ensuring desired control system requirements while significantly minimizing wireless resource consumption [12]. Moreover, leveraging the wireless resource consumption and prediction length of PPC enables optimization of the total wireless resource consumption through optimized prediction lengths.

Contribution 3: Implementing dynamic QoS based on channel scheduling to improve the total bandwidth utilization rate.

The proposed solution from Contribution 1 involves establishing a mapping relationship between communication reliability and wireless resource consumption. This mapping is achieved by considering the frequency selection channel of each robotic arm. The impact of channel scheduling on enhancing the performance of dynamic QoS policies is therefore examined. In practice, considering that AGVs are placed in different locations, it is reasonable to assume that they are subject to different wireless channel environments, which contributes to different frequency selective channels for those robotic arms.

Contribution 4: Implementing task rescheduling with flexible delays to average the bandwidth resource consumption over time.

Resource allocation for delay at the task level in a wireless-control system is investigated and a task-based resource dynamic allocation (TRDA) profile is proposed to reduce the peak value for the total resource allocation consumption for each time slot. This profile considers the dynamic QoS characteristics, real-time resource requirements and the priorities for every task. Each task has a different priority, and then generated custom priority functions for them. The resource is allocated dynamically according to these functions.

Alternatively, the main content of the thesis is illustrated in Figure 1.

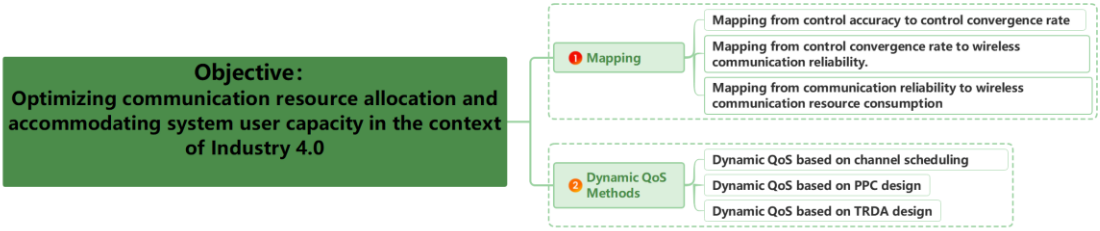


Figure 1. Report Outline

1.3 Thesis Structure

The remainder of this thesis is organised as follows:

Chapter 2 illustrates the technical background aspect of this project, which is primarily divided into four components: (1) The concept and developmental history of Industry 4.0; (2) The historical progression of 5G and its indispensability in the emerging Industry 4.0 scenario; (3) An introduction to URLLC; and (4) The concept of QoS design within the context of Industry 4.0.

Chapter 3 constitutes a comprehensive literature review, encompassing the latest advancements in this research domain. It effectively summarizes the notable accomplishments within this field and underscores the significance of this research endeavour.

Chapter 4 presents a specific customized Industry 4.0 scenario and the metrics of this design. The collaborative design theory of control communication systems is also introduced. Subsequently, by utilizing the theory of mapping the customized accuracy demand to the consumption of communication resources and dynamic QoS strategy, simulation results of the dynamic cross framework can be obtained.

Chapter 5 presents the proposed dynamic QoS, accompanied by simulation results based on the model described in Chapter 4. This chapter initially provides a comprehensive explanation of the distinctions between the baseline and dynamic QoS strategies, followed by an identification of the challenges within this design. Finally, an extensive discussion on the simulation of the proposed scheme is conducted.

Chapter 6 shows dynamic QoS based on packet length design. This chapter commences with an exposition of the package structure of PPC, followed by a presentation of the typical system model of packet predictive model and the multi-user PPC system model in a star topology scenario. Subsequently, PPC is applied to wireless communication models, wherein the problem formulation aims to attain optimal packet prediction length and subcarrier bandwidth allocation. The relevant parameters in this chapter affecting the gain are qualitatively analyzed and discussed, and the simulation results are obtained.

Chapter 7 shows dynamic QoS based on channel scheduling and simulation results. The chapter introduces the system model of channel scheduling, followed by the problem formulation in this design. Finally, the simulation results of the proposed scheme are discussed.

Chapter 8 shows dynamic QoS based on TRDA strategy and simulation results. The chapter introduces the concept of transmission scheduling, followed by an explanation of the TRDA algorithm and task scheduling method employed in this design. Finally, the simulation results of the proposed scheme are discussed.

Chapter 9, lastly, summarizes the conclusion of this thesis, and the development prospect of Industry 4.0 is prospected. It also covers the future works, which includes an introduction to the next steps for this project, experimental scenarios to consider, and open challenges.

2 Background

In this Chapter, the technical background of this thesis, the 5G background, the integration of 5G and URLLC in the context of Industry 4.0, Dynamic QoS considerations within Industry 4.0, and convergence rate in control concept will be introduced as support for the comprehension of the project.

This chapter initially elucidates the notion of Industry 4.0 and its historical progression, subsequently tracing the historical evolution of 5G and its indispensable role in the emerging industrial landscape. Furthermore, it introduces URLLC in industrial systems, followed by an in-depth examination of the concept of dynamic QoS design and control convergence rate.

2.1 Industry 4.0

Industry 4.0 refers to the fourth Industrial Revolution and is commonly understood as the application of cyber-physical systems (CPS) [13] to industrial production systems, known as cyber-physical production systems. In Germany, the term Industry 4.0 is currently widely used in relation to trade shows, conferences, and publicly funded projects within the industry sector. The term was initially introduced in North America at Hanover Fair 2011. General Electric proposed a similar concept under the name of the Industrial Internet [14]. While its technical foundation closely aligns with Industry 4.0, it encompasses a broader scope beyond industrial production and includes smart grids.

Figure 2 illustrates the progression of the four industrial revolutions, with the first three enduring for nearly two centuries [15]. The initial Industrial Revolution denotes the technological upheaval instigated by the United Kingdom in the 18th century, which constituted a monumental breakthrough in the annals of technological advancement and ushered in an era where manual labour was supplanted by machinery. This revolution commenced with the advent of mechanized production and was epitomized by widespread utilization of steam engines as power sources. The Second Industrial Revolution emerged during the mid-19th century, emphasizing mass production facilitated by electricity and establishing a novel paradigm for manufacturing goods on a large scale. In the 1870s, this second wave took flight, propelling humanity into an "electric age". The third industrial revolution commenced in the 1970s and endures to this day, characterized by extensive integration of electronics and information technology that has led to continuous automation within manufacturing processes. The fourth industrial revolution was officially embraced as part of Germany's national strategy in 2013, ultimately realizing intelligent factory production while directly aligning with consumer demand [15].

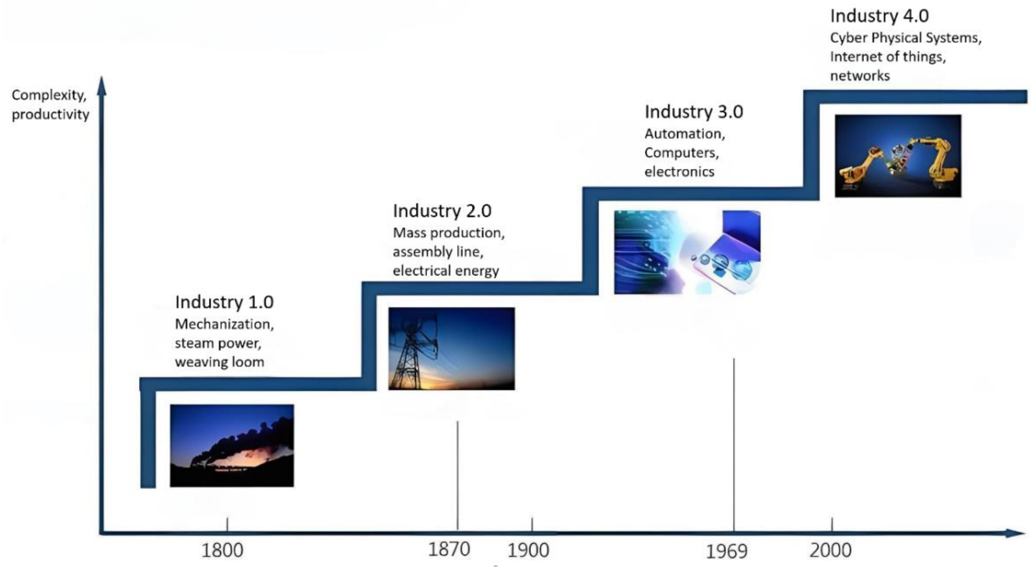


Figure 2. An overview of the four industrial revolutions.

The main technical foundation of Industry 4.0 lies in the integration of Internet technology into the industrial sector. It signifies the advent of a new era of industrial revolution, driving manufacturing towards intelligence and automation. Industry 4.0 encompasses not only technological advancements but also changes in production and business models. Throughout its development, five core characteristics have been identified: intelligence, networking, personalization, flexibility, and sustainability [16].

Firstly, intelligence stands as one of the fundamental features of Industry 4.0. In this era, machines and devices possess autonomous learning capabilities and decision-making abilities. By utilizing advanced sensors and artificial intelligence technology, machines can perceive and analyse various data during production processes to enable intelligent production management. Intelligent factories will be capable of automatically adjusting production lines to enhance efficiency and product quality [17]. Secondly, networking is another pivotal aspect of Industry 4.0's framework. Machines and devices are interconnected through the Internet in this era. This networked production model facilitates real-time collaboration and information sharing among devices, resulting in highly automated and flexible manufacturing processes. Through networking capabilities on a global scale, enterprises can achieve seamless integration between production systems and supply chains while enhancing their competitiveness [18]. Thirdly, personalization is a pivotal feature of Industry 4.0. In the era of Industry 4.0, production will transition from mass production to personalized manufacturing. Through the utilization of advanced digital technology, companies can tailor their production processes according to customer requirements, thereby catering to diverse customer needs. Personalized manufacturing will result in heightened customer satisfaction and product value addition while enhancing enterprise competitiveness [17]. Fourthly, flexibility is another key characteristic of Industry 4.0. Production will become more adaptable and adjustable. By employing advanced automation technology and flexible manufacturing systems, companies can swiftly modify their production lines to accommodate changes in market demand. The flexible mode of production will yield enhanced productivity and responsiveness while bolstering enterprise competitiveness [17]. Finally, sustainability is the last significant attribute of Industry 4.0. In the era of Industry 4.0, enterprises will place greater emphasis on sustainable development. By utilizing advanced environmental protection technologies and energy management systems, enterprises can reduce energy consumption and environmental pollution while achieving sustainable production and development [17]. A sustainable mode of production will produce a stronger sense of social responsibility and corporate image while improving enterprise competitiveness.

With the advent of cutting-edge technology in the manufacturing sector, the concepts of "Industry 4.0" and "future factory" have emerged. In the ongoing fourth Industrial Revolution, traditional production management systems will gradually phase out, enabling anyone to operate a production facility. Specifically, the transformation towards Industry 4.0 entails automation, robot deployment, and widespread utilization of real-time data. The promotion of Industry 4.0 signifies that human employees no longer need to dedicate significant time to manual labour but can instead channel their efforts into innovating industrial production models [19].

As manufacturers leverage the potential of technology to drive automation in factory processes, they often encounter various challenges when adopting an Industry 4.0 approach. For instance, the substantial cost associated with Industry 4.0 poses a significant hurdle for certain small and medium-sized enterprises seeking to invest in new equipment, sensors, and software solutions. Additionally, there is a lack of proficiency among workers in monitoring information pertaining to physical production systems, utilizing portable computing devices effectively, and adapting production processes based on software recommendations. Moreover, manufacturers may face difficulties in recruiting engineers, data scientists, and software developers due to their limited availability within the market. Furthermore, by implementing Industry 4.0 technologies within factories, potential vulnerability exists wherein factory equipment and networks could be susceptible to cyber-attacks leading to data breaches [19]. Industry 4.0 will therefore heavily rely on the telecommunication infrastructure that the 5th generation mobile communication promises to usher in a new era of connectivity.

2.2 5G

The 5G (5th-Generation) mobile communication standard, also known as the fifth generation of mobile communication technology, is an evolutionary extension of 4G. As defined by the IMT-2020 (5G) Promotion Group [20], 5G is characterized by key technologies and signature capability indicators. These include "Gbps user experience rate" as the signature capability indicator, along with a range of key technologies such as large-scale antenna arrays, ultra-dense networking, new multiple access methods, full spectrum access, and innovative network architectures. With its high speed, wide broadband coverage, exceptional reliability and low latency characteristics, 5G not only offers enhanced air interface technology with higher speeds and greater bandwidth capacity but also serves as an intelligent network for superior user experiences and business applications [20].

In the vision research phase of 5G in 2015, the International Telecommunication Union (ITU) pointed out that 5G will penetrate into all areas of the future society, so that information will break through the limitations of time and space, pull into the distance of all things, and eventually realize the intelligent interconnection of people and everything, thus ITU stipulated the key technical indicators of 5G, indicating that 5G will no longer pursue a single goal (peak rate) [20]. Instead, consider different business and application scenarios (such as IOT).

The 22nd meeting of ITU-RWP5D, organized by the ITU, identified three primary application scenarios for future 5G: eMBB (Enhanced Mobile Broadband), URLLC, and mMTC (Massive Machine Type of Communication) [21].Figure 3 shows the KPIs for 5G. The ITU has defined eight key performance indicators for 5G, including user experience rate, connection density, end-to-end latency, mobility, connection density, peak rate, spectrum efficiency and energy efficiency [21]. Mobility is a crucial metric in mobile communication systems throughout history that refers to the maximum relative moving speed of two communicating parties while maintaining certain system performance requirements. 5G mobile communication systems need to support ultra-high-speed scenarios such as aircrafts, highways, and urban subways as well as low-speed or stationary scenarios for data acquisition and industrial control purposes [22]. Delay can be measured using either OTT (One-way Transmission Time) or RTT (Round Trip Time). The former represents the time interval between sending and receiving data at the receiving end while the latter indicates the time interval between sending and confirming data at the sending end. In the era of 5G technology, business applications like vehicle communication, industrial control systems, and augmented reality demand higher delay requirements with a minimum air delay requirement reaching 1ms [23]. A user-centric mobile ecological information system will be established in the 5G era where user experienced data rate will serve as a network performance indicator for the first time [22]. Peak rate denotes the maximum service rate achievable by a user [22]. Connection density measures how many online devices can be supported per unit area and serves as an important metric to evaluate the capacity of 5G networks in supporting large-scale terminal devices [22]. Traffic density quantifies total traffic volume per unit area which reflects a mobile network's data transmission capability within a specific region [23]. Spectral efficiency is the optimized utilization of bandwidth or spectrum to minimize transmission errors and maximize data transmission [21]. Energy efficiency refers to how much data can be transmitted per unit of energy consumed in a mobile communication system [21].

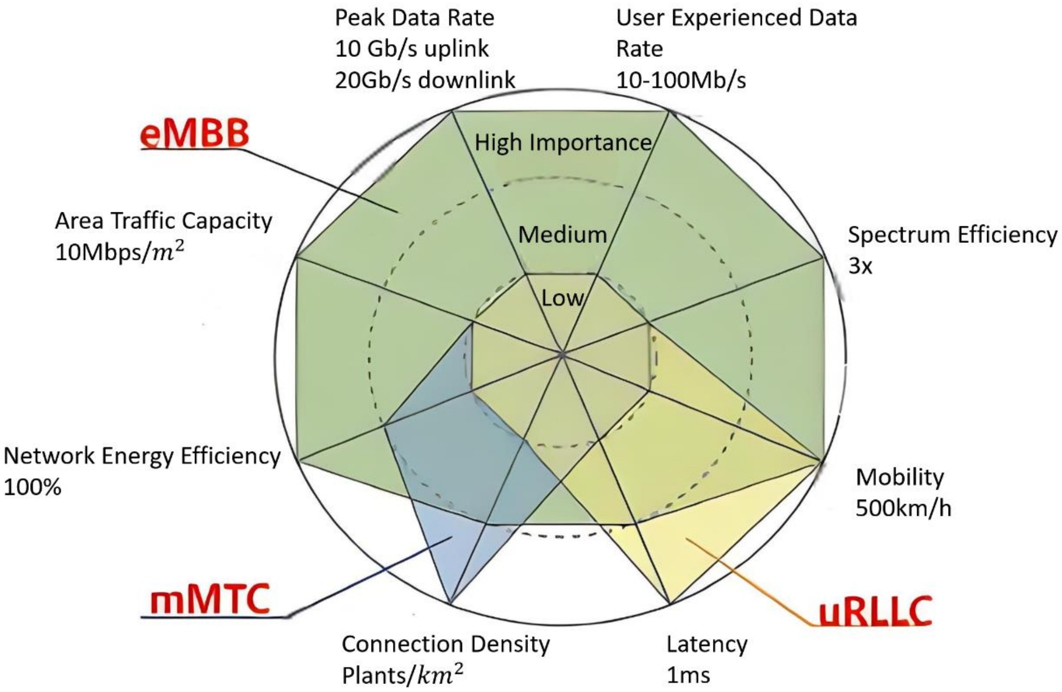


Figure 3. Key technical indicators for the main 5G use case scenarios.

The three main application scenarios of 5G in the future are shown in Figure 4 [24]. While eMBB primarily focuses on mobile communications, the latter two are specifically tailored for Internet of Things applications. eMBB represents the evolution of mobile broadband in the 4G era and holds paramount significance for operators. As the earliest commercial 5G application scenario, eMBB exhibits the most promising prospects for implementation, effectively catering to users' demands for high data rates and seamless mobility [24]. URLLC stands as a distinctive feature of 5G networks, setting it apart from its predecessors - 2G/3G/4G communication network upgrades [24]. URLLC serves as a pivotal breakthrough enabling mobile communication industry penetration into vertical industries, thereby driving multi-industry integration during this information revolution era. It finds extensive applications in intelligent connected vehicles, intelligent manufacturing, smart power systems, smart medical services, and other domains. mMTC among the three major 5G application scenarios, caters specifically to Internet of Things businesses with relatively relaxed real-time network perception requirements but significantly higher terminal density prerequisites [25].

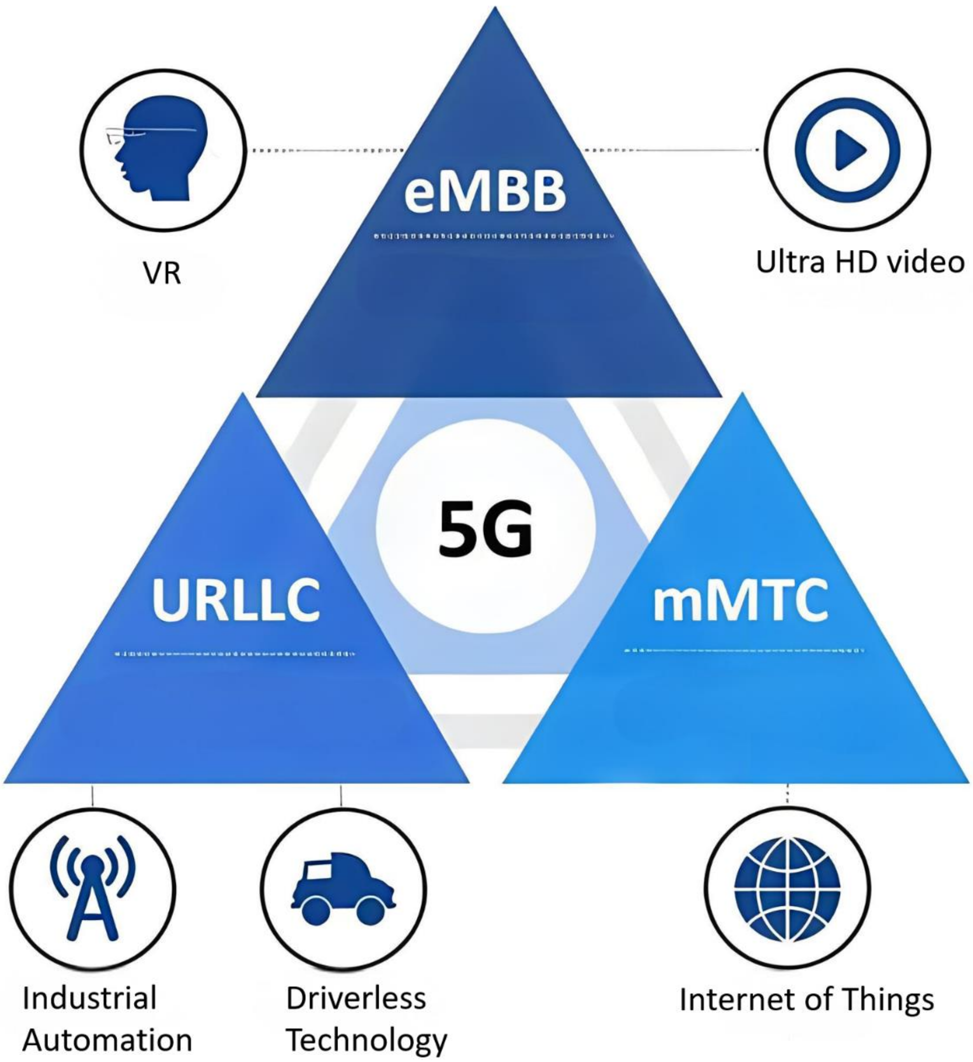


Figure 4. Application examples for 5G use case scenarios.

With the continuous advancement of technology and the rapid growth of the industry, 5G network, as an emerging generation of mobile communication infrastructure, has been swiftly adopted and extensively utilized across various sectors. In comparison to conventional 4G communication technology, 5G offers enhanced data transmission speed and superior signal quality. Additionally, it facilitates massive machine-to-machine communication while exhibiting remarkable reliability and minimal latency. The peak transmission rate of 5G networks can reach up to 10 Gigabits per second (Ggbit/s), achieving end-to-end delays in milliseconds [24]. Moreover, it enables a tenfold to hundredfold increase in connected device density, a thousandfold surge in data traffic density, and five to ten times higher spectrum efficiency [26]. The current application of 5G device data communication scenarios primarily rely on the inherent characteristics of 5G, such as its wide bandwidth and ability to connect numerous devices. This enables a reduction in latency and improved reliability, thereby replacing the existing Wi-Fi wireless communication scheme. One of the main limitations of Wi-Fi for device communication is its proximity to the 4G network frequency band, making it susceptible to interference and resulting in insufficient coverage and access capacity. In contrast, 5G offers several advantages over Wi-Fi including faster transmission rates, lower latency, support for simultaneous connections from multiple devices, and enhanced anti-interference capabilities [27]. Notably, compared to Wi-Fi technology, 5G significantly improves transmission speeds [27].

With the advancement of industrial Internet, an increasing number of workshop equipment, such as machine tools, robots, and AGV, have started connecting to the factory intranet. Particularly for mobile devices like AGV, wired networks struggle to meet their communication needs adequately due to limitations in flexibility and bandwidth requirements of the factory intranet. Traditional factory wired networks offer high reliability but lack flexibility; on the other hand, wireless networks provide high flexibility but exhibit shortcomings in terms of reliability, coverage, and access capacity. The emergence of 5G technology with its characteristics including flexibility, high bandwidth capability, and multi-terminal access has emerged as a promising solution for facilitating equipment access and communication within factories [28].

2.3 URLLC

The term URLLC denotes the combination of high reliability and low latency, which is crucial for various applications requiring ultra-reliable and low-latency communication. The 3rd Generation Partnership Project (3GPP) mandates a stringent requirement of 99.999% reliability and an impressive one-way latency of only 0.5 millisecond [29].

Ultra-reliability necessitates that the communication system can maintain stable transmission and communication services even in high interference, weak signal or challenging environments. The requirement for low latency is that the communication system can achieve extremely low delay, typically at the millisecond level, to meet application scenarios with high real-time demands, such as industrial automation and intelligent transportation. The URLLC is a specialized use case for cellular communications that encompasses a range of features tailored to low-latency and high-reliability applications, including mission-critical sectors such as industrial automation, autonomous vehicles, smart grids, intelligent transportation, and virtual reality or telemedicine or industrial processes [30].

The objective of URLLC is to facilitate the operation of its features and network functions at exceptionally high reliability standards, ensuring a one-way latency of less than 0.5 millisecond between critical infrastructure and computers [29]. With the forthcoming release of 3GPP version 16, a new variant of 5G will be introduced with a specific emphasis on reducing latency and enhancing network reliability [31]. Moreover, URLLC can also bring advantages to general-purpose data communication systems by minimizing propagation time between route and the data center, which is crucial for machine learning applications, while enabling faster responsive network automation capabilities [32].

In recent years, driven by the emphasis on Industry 4.0, industrial automation has emerged as a pivotal domain. The advent of industrial automation necessitates the integration of industrial communication and control to enable remote manipulation of machinery and equipment, thereby demanding utmost system reliability and minimal latency [33]. In particular, the accommodation of mission-critical services alongside eMBB services presents additional design constraints for ultra-reliable low-latency URLLC services, which demand exceptional levels of latency and reliability [34]. Industrial automation is a pivotal element of intelligent manufacturing in URLLC services, as recognized by 3GPP, necessitating an end-to-end delay of less than 1ms and a block error rate (BLER) target of 10^{-5} [34]. The adoption of wireless technology in lieu of traditional wired devices enables factories to enhance production efficiency, reduce costs, and streamline the automation process.

2.4 QoS

QoS indicates the quality of service. ITU defines QoS as a set of quality requirements specified for the collective behaviour of one or more objects [35]. Certain parameters related to quality of service, such as throughput, transmission delay, and error rate, serve to quantify the speed and reliability of data transfer [35]. QoS refers to a network's ability to utilize various fundamental technologies to enhance its service capabilities for specific network communications. It serves as both a security mechanism and a technology employed for addressing issues like network latency and congestion. Ensuring QoS is particularly crucial for networks with limited capacity, especially when it comes to streaming multimedia applications which often necessitate consistent transmission rates while being sensitive towards latency [36].

The justification for implementing QoS in the occurrence of four distinct issues during the transmission of data packets from sender to receiver [36]. Firstly, there is packet loss, which happens when a data packet encounters a router with a full buffer, resulting in transmission failure. Secondly, latency occurs when packets experience significant delays due to lengthy queues before reaching their destination. Thirdly, there can be errors in the transmission order as related packets are routed across the Internet and may choose different routers, leading to varying latency times for each packet. Consequently, the arrival order of final packets at the destination becomes inconsistent with their sending order from the sender. Lastly, errors can cause packets to follow incorrect paths or even become merged or destroyed during transportation [36].

A similar technique is network slicing, an on-demand networking approach that enables operators to partition a unified infrastructure into multiple virtual end-to-end networks [37]. The fundamental principle of network slicing design is to flexibly organize networks based on diverse service requirements and establish dedicated networks tailored for specific services, thereby achieving optimal alignment between networks and services [37]. The QoS mechanism efficiently allocates limited bandwidth resources to different services based on their demand, ensuring end-to-end service quality. For example, voice, video, and important data applications can be preferentially served on network devices by configuring QoS [36]. The technology in question involves the classification of services, allocation of diverse resources based on service priorities, and provision of varying levels of quality. It prioritizes services with high network requirements while also addressing issues such as network delay and congestion for lower priority services [36].

The concept of QoS is applicable in scenarios where it is crucial to ensure the delivery of critical service quality, particularly during instances of burst traffic on the network. If services fail to meet QoS requirements over an extended period (such as when service traffic consistently exceeds the bandwidth limit), it becomes necessary to expand the network infrastructure or employ dedicated devices that can control services based on upper-layer applications. In recent years, there has been a remarkable surge in video applications. Almost everyone now possesses a smartphone capable of capturing high-resolution videos at any time and from anywhere. Furthermore, with the advancement of wireless networks, an increasing number of users and enterprises are adopting wireless terminals that constantly change their location along with user movements, resulting in more unpredictable network traffic patterns [37]. Consequently, designing effective QoS schemes also encounters additional challenges.

QoS measures the factors that affect network quality, including the bandwidth of the transmission link, packet transmission delay and jitter, and packet loss rate [36]. Bandwidth, also known as throughput, is the maximum number of bits of data that can be transmitted from one end of a network to the other in a fixed period [38]. Delay refers to the delay time required for a packet or packet to travel from the sending end to the receiving end of the network [23]. Jitter is used to describe the degree of delay change, that is, the time difference between the maximum delay and the minimum delay [21]. The packet loss rate refers to the percentage of the lost packets in the network transmission process to the total number of transmitted packets [23].

In industrial production environments, time-sensitive control systems, sensors and actuators require efficient communication, which requires a reliable QoS mechanism. For example, for the control of industrial robots, immediate decision making, and execution are crucial, and the level of QoS directly affects the stability and accuracy of this process [39]. In automated production lines, QoS guarantees the real-time transmission of control signals, ensuring seamless collaboration among robots, sensors, and other devices. This not only enhances production efficiency but also minimizes errors in the manufacturing process. For distributed industrial systems, QoS ensures the stability of remote monitoring and maintenance operations. Engineers can monitor equipment status and troubleshoot faults in real time through the network, thereby improving equipment maintainability and manageability. With the increasing adoption of Industrial IoT, a multitude of devices and sensors require real-time data exchange. The implementation of QoS mechanisms enables these devices to communicate efficiently and orderly, ensuring uninterrupted operation across the entire IoT system [39].

In industrial networks, QoS refers to the network's ability to ensure reliable, real-time, and stable transmission of data. Many applications in industrial production have stringent real-time requirements, such as robot control and sensor data acquisition [40].

By implementing QoS mechanisms, industrial Ethernet switches can prioritize the transmission of time-sensitive data packets, ensuring their fast delivery and maintaining real-time performance. The reliability of data is paramount in industrial networks as any loss of a data packet can disrupt the production process and lead to system failure. QoS provides enhanced quality of service by reducing packet loss rate and ensuring dependable data transmission. QoS technology encompasses prioritizing and guaranteeing data transmission as well as managing network bandwidth allocation effectively. Industrial application scenarios often demand simultaneous real-time transmission for multiple types of data such as monitoring data, control instructions, process data etc., which imposes higher requirements on network bandwidth management and resource allocation. QoS technology facilitates proper distribution and scheduling of network bandwidth to ensure smooth transmission for different streams of data while avoiding delays or instability caused by network congestion or resource competition. This is crucial for maintaining stability and reliability in industrial networks since real-time data transmission is essential in industrial production processes. Therefore, applying QoS technology ensures that industrial networks can consistently deliver stable performance even during distributed data transmissions [40].

The implementation of Dynamic QoS represents one approach. The provision of URLLC entails significant utilization of wireless bandwidth resources. Moreover, it is not always imperative to achieve exceedingly high levels of communication quality for optimal control performance. In this paper, the concept of dynamic QoS pertains to a methodological approach that combines stringent QoS requirements with relatively lower ones to minimize energy consumption.

2.5 Control Convergence Rate

Control convergence represents the transmission performance of the system from the initial point to the target point, indicating a change in the state of the control system. [41]. The control convergence rate can be described as how fast the control system attains zero steady state error. The inverted pendulum system serves as an illustrative example in Figure 5, the goal of the control system is to keep the inverted pendulum upright, which is also means to achieve $\varphi_0 = 0$. Assuming the initial state is φ_1, the control convergence rate represents how quickly the control system stabilizes the inverted pendulum moves at φ_0.

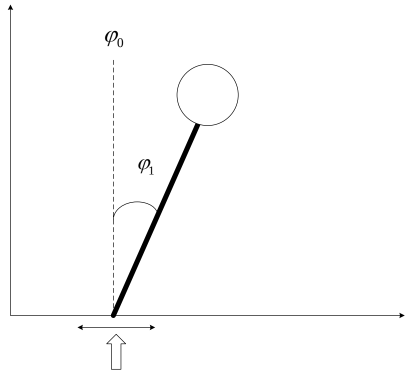


Figure 5. The inverted pendulum model.

Considering two sets of states plant 1 $\{\varphi_{11}, \varphi_{12}, \varphi_{13}, ..., \varphi_{1n}\}$ and plant 2 $\{\varphi_{21}, \varphi_{22}, \varphi_{23}, ..., \varphi_{2n}\}$ of two plants in the control process and formulation, if $\frac{\varphi_{12}}{\varphi_{11}} < \frac{\varphi_{22}}{\varphi_{21}}$, the control convergence rate of plant 1 is smaller than that of plant 2.

In this project, the control convergence rate is selected as the preferred metric to evaluate the performance of a control communication system. The primary control variables are the state sampling period and the control input gain, which collectively influence the control convergence rate. Subsequently, the control convergence rate further impacts various aspects of control performance, such as control cost or stability.

By imposing constraints on the rate of control convergence, limitations are imposed on both the state sampling period and the control input gain [41].

The convergence rate serves as an estimation of the performance of the robot motion control system and can also be utilized to represent the effectiveness of status updates in other control systems, such as temperature monitors [42]. This implies that the control convergence rate is a universal metric for measuring control performance. Furthermore, various indicators of control performance, including control cost, stability, and error, are closely intertwined with the speed at which control convergence occurs. The control cost associated with the control state and the command components, where the command is generated based on the state. Consequently, the control cost is determined by the control state. The update of control states exhibits a strong correlation with the control convergence rate. Subsequently, the cost incurred by controlling relies on the control convergence rate.

The control performance is evaluated by conducting a mathematical analysis [43] on the average cost control evaluation, aiming to achieve a low convergence rate for smooth state updates and consequently obtain a low average control cost. A high convergence rate leads to rough state updates and results in a higher average control cost [42]. Moreover, when the convergence rate is small, smooth state updates contribute to a lower average control cost over time, indicating that a smaller convergence rate exhibits better control performance compared to a larger one [42].

Based on the above discussion, we can conclude that the control convergence rate can be used to represent the control performance since it is related to almost all the other control performance criteria.

2.6 Conclusion

In the current context of Industry 4.0, there will be a significant growth in the application of wireless control technologies and concepts in automation. These technologies need to be thoroughly evaluated and further customized to cater to the specific needs of industrial automation. Similarly, for 5G, maintaining QoS and ensuring URLLC in an industrial setting pose similar challenges. The integration of end users representing vertical markets holds great promise. Managing complexity and heterogeneity will be one of the major challenges faced by future industrial communications. With both QoS and URLLC, technology can provide flexible network topologies along with their monitoring and management capabilities to meet the diverse requirements throughout the industrial cycle for end users. The fulfilment of customer customization requirements holds great significance within the framework of Industry 4.0, with such needs being closely intertwined with control convergence.

However, from a communication provider's perspective, there may still be a need for further optimization or even development of specific industrial technologies, especially when dealing with demanding application requirements that must be met. The next chapter will explore “how can we optimize the utilization of wireless communication resources while ensuring the stability of the control system and the reliability of communication, to remotely manage an ever-growing number of plant equipment?” through a literature review to determine what is the current state in the art.

3 Literature Review

Since the inception of the Industry 4.0 concept in 2011, researchers have conducted experiments across various domains to assess the indispensability of Industry 4.0 in today's societal context. Simultaneously, with the advent of the 5G era, communication reliability and latency have reached unprecedented heights compared to the previous generation (4G). Since 2015, there has been a surge in research on control-communication joint design, leading to diverse approaches aimed at minimizing resource overheads in communication and control. In summary, owing to the emergence of both the Industry 4.0 era and the 5G era, there is significant interest in reducing wireless communication resource costs within an Industry 4.0 framework. This chapter provides a comprehensive overview of relevant literature during this timeline while emphasizing optimization techniques for allocating communication resources that can accommodate additional plant equipment without compromising industry requirements. Furthermore, it highlights existing knowledge gaps where opportunities exist for contributing towards optimizing resource overheads within an Industry 4.0 context.

3.1 The indispensability of Industry 4.0

The initial two chapters delved into the technical underpinnings of Industry 4.0, thereby raising the question: What necessitates the adoption of Industry 4.0 in contemporary society?

Preliminary data indicate that successful integration of Fourth Industrial Revolution technologies holds potential for enhancing supply chain efficiency, optimizing utilization of working time, minimizing waste generation within plants, and yielding numerous other benefits for employees, stakeholders, and consumers [44].

Currently, enterprises manually exchange information to achieve machine-to-machine information transmission after receiving an order, which introduces numerous uncertainties. With the implementation of Industry 4.0, this process can be automated through machine-to-machine information transmission. This necessitates the establishment of a comprehensive information interaction system for coordination purposes.

At CIMT2015 (the 14th China International Machine Tool Exhibition) [45], Shenyang Machine Tool showcased a case of intelligent manufacturing within the context of Industry 4.0. Upon receiving an order, the system scans and decomposes its content in preparation for production tasks. For instance, it instructs the warehouse to prepare raw materials while AGVs transport them to machine trays where robots place them onto machines for processing according to programmed instructions sent by the system. Once completed, products are retrieved by robots, cleaned, inspected and handed over to AGVs responsible for transportation from production workshops to finished goods areas where robots handle packaging and palletizing tasks. At this stage, logistics is notified as part of the overall logistics process facilitated by Industry 4.0 in terms of automatic warehousing systems, AGVs, industrial robots, information exchange systems, machine tools with integrated automation capabilities such as automatic detection and packaging.

The case of the factory exemplifies the advantages of information exchange facilitated by Industry 4.0 in the context of factory assembly lines. However, the question remains **how to guarantee the reliability of information exchange in the context of Industry 4.0?** The next section answers this question by describing the impact of 5G's arrival on communications.

3.2 The initial research focuses on 5G

The deployment of 5G technology effectively addresses the challenges faced by industrial wired systems, such as limited mobility, rigid networking, and difficulties in laying infrastructure in specialized environments. It overcomes the limitations of existing industrial wireless technologies in terms of reliability, connection density, and transmission capacity. Consequently, it efficiently caters to the requirements of industrial production encompassing large-scale data acquisition and perception, precise control mechanisms, remote operations while continuously enhancing the fundamental capabilities of industrial Internet networks. This expansion further promotes integration and innovation within the realm of industrial Internet formats and serves as a potent driving force for its profound development [46].

One of the key features of 5G is its exceptional ultra-reliability and low latency. The advent of URLLC ensures the utmost dependability in information exchange within industrial assembly lines, with a delay that is merely one-tenth of that experienced in 4G networks. Several studies have explored the use cases of URLLC in factory automation. Reference [47] presents an analysis of a joint resource allocation and modulation coding scheme, considering both reliability and delay constraints. The simulation results demonstrate that the proposed resource allocation technique can achieve a significantly low error rate and enhanced reliability. The analysis, however, focuses on ensuring the high reliability of communication rather than addressing the issue of reducing the cost of communication resources. In [48], the authors evaluate system-level performance for industrial scenarios by investigating different waveforms. The findings demonstrate that by configuring 5G radio appropriately in industrial scenarios, it is possible to achieve the required high reliability and low latency for industrial applications. This further substantiates the feasibility of utilizing the 5G URLLC scenario in industrial contexts. Additionally, the study conducted in [49] demonstrates the challenges of implementing URLLC throughout an entire industrial process due to its demanding requirement for a substantial number of wireless communication bandwidth resources to maintain strict QoS. This article investigates the correlation between URLLC QoS and control performance, followed by a discussion on the impact of different communication QoS on control performance. The findings reveal that both stringent and low QoS levels in URLLC can be dynamically utilized across the entire control process, resulting in superior system performance. The feasibility of dynamic QoS design in the context of 5G URLLC is confirmed by this paper.

The traditional approach to industrial automation relies on assembly lines, whereas Industry 4.0 is centred around robotics, with real-time control of robots through network connectivity. Consequently, the construction of an exceptionally efficient robot control system necessitates a heightened demand for network latency. Therefore, URLLC plays a crucial role in the realm of industrial automation.

The aforementioned research demonstrates the feasibility of dynamic QoS design in the context of Industry 4.0 and communication 5G URLLC. However, due to the enormous communication resources required by URLLC, a current challenge is posed by the limited availability of communication bandwidth resources. Therefore, it is crucial to answer - **How to ensure reliable information exchange while minimizing the communication bandwidth resource consumption?** The subsequent section will delve into various approaches currently being implemented to tackle this issue.

3.3 The ongoing research focuses on communication resource consumption.

Since 5G was proposed, it is inevitable to consume a lot of communication resources to ensure its high reliability and low latency characteristics. The limited communication resources in wireless communication pose a challenge that necessitates the development of effective resource allocation and scheduling strategies.

To optimize communication bandwidth resource consumption, numerous studies have focused on resource allocation strategies. resource allocation refers to the process of assigning specific resources, such as bandwidth, power, and frequency, to users in wireless communication. This ensures equitable competition and efficient utilization of resources among users. A well-executed resource allocation strategy can enhance network capacity and efficiency, deliver superior network service quality, and minimize user communication delay and packet loss rate. The proposed resource allocation method in 2017 by Kim et al. [50] enhances the underlying V2X framework, effectively reducing power consumption in the communication system through leveraging the resource awareness of V2X terminals. In this scheme, the terminal monitors specific channels within the resource pool. After an initial selection of resources, UE reevaluates the remaining subchannels to avoid potential conflicts. In 2020, The resource allocation and power control algorithm proposed by Bo Wei et al. [51] is based on energy efficiency to optimize the sub-channel allocation and improve the energy consumption performance of the Internet of Things communication system. Firstly, the algorithm optimizes channel allocation and prioritizes sub-channels with high channel gain for terminals. Then, it allocates different power levels to sub-channels through power control to achieve minimum uplink energy consumption while maintaining fixed channel allocation. Finally, the algorithm adjusts the channel allocation coefficient to achieve global optimization of total energy consumption. Simulation results demonstrate that as the number of IoT terminals and average task load increase, this scheme effectively reduces average system energy consumption. In [52], PPC is an effective solution for robust control of unreliable wireless links in real-time cyber-physical systems. A communication control co-design method is proposed to optimize the predictive length of PPC, so that the system can achieve minimum wireless resource consumption.

Resource scheduling refers to the rational allocation of resources based on user requirements and network conditions, as well as the dynamic real-time allocation of resources in response to user demands. Effective resource scheduling plays a crucial role in enhancing network stability, preventing congestion, and mitigating faults. In [53], also in the context of the Internet of Things, a network resource scheduling and mapping mechanism scheme is proposed for multi-task scenarios. The experimental results demonstrate that the proposed scheme not only enhances resource utilization and load balancing but also reduces network energy consumption and task completion time. Jianpeng et al. [54] proposed a task scheduling algorithm of a heterogeneous real-time system based on deadline constraints according to the processing stage and urgency of the task. According to the idle time of the ready task and the estimated execution time of each node in the system, a classified scheduling policy is adopted to ensure the priority of the urgent task. Then, according to the task assigned on the processing node and the relative cut-off time of the execution task, different task-switching strategies are proposed. In addition to ensuring the success rate of the mission, the peak ratio of communication resources is reduced. In [55], a dynamic resource allocation method for cluster machine to machine (M2M) communication with QoS guarantee is proposed, which provides higher throughput, higher resource efficiency and lower access delay under the coexistence of delay-sensitive and delay-tolerant services.

To summarize, to minimize the communication resource consumption in the system, the adopted schemes are categorized into two groups: resource allocation and resource scheduling. In subsequent chapters, this paper will employ various resource allocation and resource scheduling algorithms based on dynamic QoS design to optimize the bandwidth resource consumption of the communication system.

However, in the current research context, with the emergence of Industry 4.0, factories have become more flexible and adaptable to customers' varying needs. To transmit these needs through communication systems, communication resources play a crucial role in factory assembly lines. Therefore, two research gaps need to be addressed under the backdrop of Industry 4.0 to achieve seamless operation across the entire industrial pipeline: firstly, **how to map customer requirements onto system communication resource costs**? Secondly, **how to minimize communication bandwidth resource consumption while ensuring reliability?** The answers to these two questions will be provided in the subsequent chapters.

3.4 Gaps

Table 1 considers the gaps of this research field from four aspects: theoretical gap, methodological gap, comparative gap and integrative gap, and how the research can fill these gaps.

Table 1. Gaps

Theoretical gap	[41]	The concept of controlling convergence rate is proposed. However, there is not enough theoretical support and research on the relationship between the user's demand and the control convergence rate. In the fourth chapter of this thesis, a mapping scheme is adopted to successfully map the user's demands to the convergence rate of the control
Methodological gap	[45]	The construction of Industry 4.0 scenarios has been successful. However, the current approach is insufficient to adequately support the widespread implementation of these scenarios due to resource, talent, and funding limitations. This thesis is dedicated to addressing the shortage of communication resources in the context of Industry 4.0
	[49]	The implementation of URLLC in industrial processes has been substantiated due to the necessity for a substantial allocation of wireless communication bandwidth resources to uphold stringent QoS requirements. Nevertheless, it does not offer a means to mitigate the utilization of wireless communication bandwidth resources within industrial scenarios.
Comparative gap	[52]	[52] aims to optimize the prediction length of PPC in order to minimize wireless resource consumption within the system. It demonstrates that the lowest wireless resource consumption occurs when the prediction length is optimized, however, it does not provide a comparison between the baseline of traditional methods and its algorithm.
	[48]	[48] affirms the viability of employing 5G URLLC scenarios in industrial settings. However, it lacks a comparative analysis to substantiate the superiority of 5G URLLC in such environments.
Integrative gap	[51]	[51] and [54] reduce the resource consumption from both aspects of subcarrier scheduling and task scheduling, but when it comes to the Industry 4.0 scenario, its optimization and gain are not enough to support more factory equipment. The enhancement of gain necessitates the development of more refined algorithms. In this thesis, dynamic QoS method is adopted, and scheduling and different resource optimization schemes are integrated to improve the gain of the system
	[54]	

3.5 Conclusion

This chapter explored the latest technologies for optimizing the allocation of communication resources to accommodate a greater number of plant equipment while effectively meeting industrial needs within the context of Industry 4.0. Each section identifies and summarizes previous works and experimental scenarios. The first section discusses the emergence and necessity of Industry 4.0, highlighting its advantages and emphasizing the importance of reliable information exchange through successful operational examples in this field. The subsequent section delves into research on 5G technology, which ensures high reliability in communication systems for Industry 4.0 due to its URLLC characteristics. However, achieving such reliability comes with resource overhead challenges, thus necessitating further research on optimizing communication resource allocation and scheduling strategies as outlined in the following section. Finally, this section highlights any limitations or shortcomings observed during experimentation under this background.

4 Simulation scenario and model

4.1 Simulation Scenario

In this section, a typical co-design system scenario is constructed Figure 6 illustrates a future Industry 4.0 architecture for customization-based reconfigurable manufacturing. Within such a system, flexible module-based facilities replace traditional production lines. The assembly tables for various customized products are allocated within the plant, with surrounding workpieces and tools stored based on table locations. Automated guided vehicles (AGVs) equipped with robotic arms provide flexible mobility. Depending on specific customization requirements, different AGVs select and retrieve appropriate workpieces and modular tools to assemble the customized products.

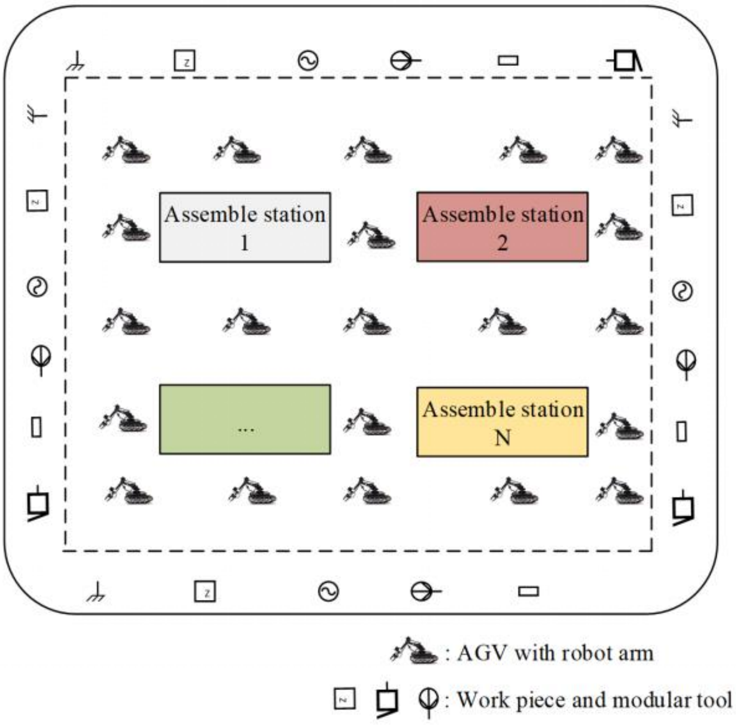


Figure 6. Customization-based reconfigurable manufacturing

4.2 Control Demand Model

In the reconfigurable manufacturing system, different customized tasks give rise to diverse manufacturing requirements, where each task can be universally described as a specific schedule of sequential actions performed by robot arms within a designated time frame. The superposition of tasks can be easily observed through the quantity of AGVs with robotic arms operated during a particular period. Hence, temporal accumulation is justifiable. The user demand for control encompasses multiple dimensions, including completion time, control accuracy, velocity, power consumption and energy efficiency. In this context, the level of task accuracy required to complete the task is concerned in this thesis. Control accuracy refers to the degree of conformity between the final control parameter value and the rated value in the control system. Control accuracy is quantified as a percentage, representing the deviation between the preset value and the actual value. A higher control accuracy indicates enhanced real-time response and adjustment capabilities of the control system, leading to superior control effectiveness.

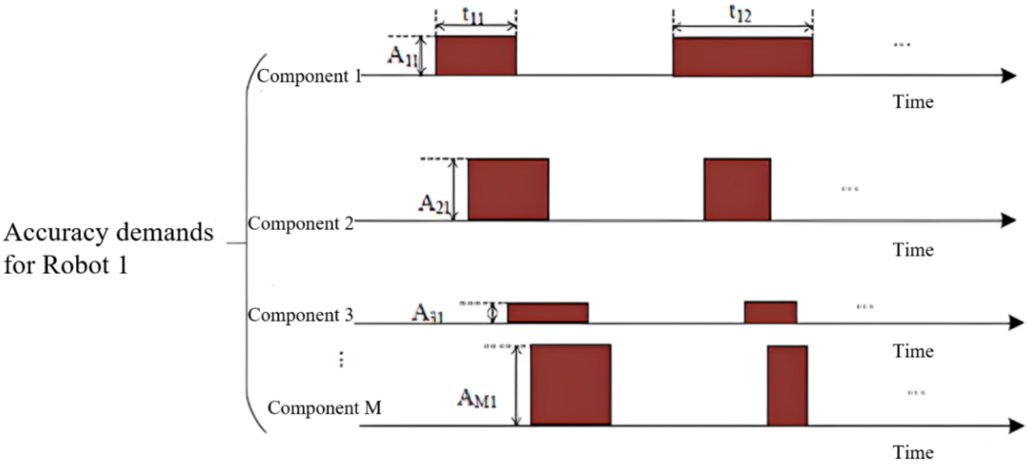
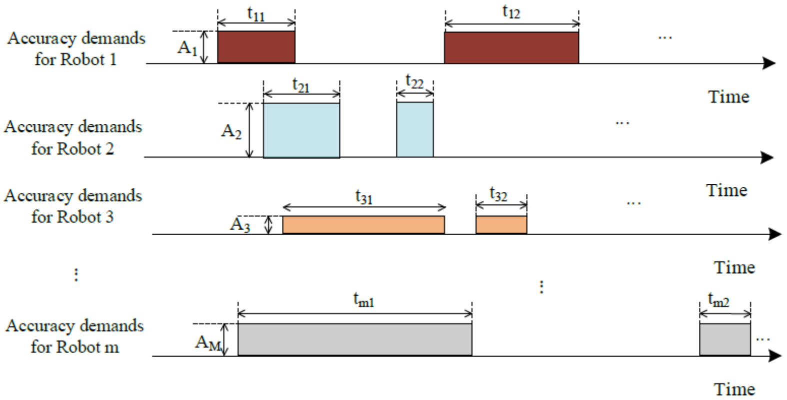


Figure 7. Accuracy demand profile for a specific robot at different time.

Figure 8. Illustration of accuracy demand profile of a robot with only one component.

The graph in Figure 7 illustrates the fluctuation of customization-based demands for a specific robot arm schedule, where the x-axis represents the time interval, and the vertical displacement indicates the accuracy demands of the arms. It is assumed that different components have varying accuracy requirements, with each demand following a Poisson process with rate λ. To simplify the discussion, only one component will be considered in subsequent analysis, as depicted in Figure 8.

Figure 9 demonstrates how customized accuracy demands vary across different robot arm schedules, where each arm has an identical accuracy demand and m robot arms are used for n customized productions within each time interval.



t_{mi}: Time interval spent of the m-th robot arm for the i-th task

A_m: Accuracy demand for the m-th robot arm

Figure 9. Accuracy demands for different robots at different times.

The assumption is made that each task involves N robot arms, where the schedule of each arm follows a Poisson process with a rate of λ_n. Additionally, it is further assumed that the time duration for each arm in completing a task follows an exponential distribution with a rate of u_n. Moreover, considering the actual demands in this design, the accuracy requirements for different robotics are uniformly distributed between 0 and A. The assumption is highly reasonable as one of the prevalent patterns in Industry 4.0 is the utilization of the Poisson distribution model, which effectively characterizes the temporal distribution of various real-world events [56]. Besides, in the design of this thesis, N robots are considered independent entities that do not interfere with each other during task completion, aligning with the characteristics of a Poisson distribution. The exponential distribution, being a continuous probability distribution, can effectively represent the time intervals between occurrences of independent random events. Hence, it is appropriate to model the time required for each robotic arm to complete a task using an exponential distribution. The accuracy requirements are considered to be uniformly distributed because the inherent properties of different robots and the accuracy requirements of each task are different.

Moving forward, we introduce a comprehensive wireless control model to illustrate the control loop for each robot arm. By utilizing this model, we can explore the correlation between control demand and communication reliability.

4.3 Wireless Control Model

In this subsection, we present a real-time wireless control model to illustrate the control loop for each robot arm. Based on the model, we can establish the relationship between communication and control by considering factors such as sampling period and packet loss. The discrete-time linear time-invariant state model can be mathematically described using a linear differential equation in [57].

$$\boldsymbol{x}_{m,n} = \boldsymbol{A}_m \boldsymbol{x}_{m,n} + \boldsymbol{B}_m \boldsymbol{u}_{m,n} + \boldsymbol{n}_{m,n}, \tag{1}$$

Where $\boldsymbol{x}_{m,n} \in \Re^{n_1}$ represents the state vector of the plant, $\boldsymbol{u}_{m,n} \in \Re^{n_2}$ denotes the control input vector, and $\boldsymbol{n}_{m,n} \in \Re^{n_1} \sim \mathcal{N}(0, \sigma^2)$ signifies the disturbance modeled as ***additive white Gaussian noise*** **(AWGN)**. The state transition matrix is denoted by $\boldsymbol{A} \in \Re^{n_1 \times n_1}$, while $\boldsymbol{B}_m \in \Re^{n_1 \times n_2}$ represents the input matrix. In consideration of the sample period of the m_{th} robot's plant at time index *n* in a reconfigurable manufacturing system can be obtained as:

$$s_{m,n} = \bar{s}_{m,n} + T_{m,n}, \tag{2}$$

where s_n represents the sample period, $\bar{s}_n$ denotes the idle period, and T_n signifies the communication time delay. The discrete time control model with delay can be expressed as follows.

$$\boldsymbol{x}_{m,n+1} = \Omega_{m,n}\boldsymbol{x}_{m,n} + \Phi_0^{m,n}\boldsymbol{u}_{m,n} + \Phi_1^{m,n}\boldsymbol{u}_{m,n-1} + \boldsymbol{n}_{m,n}, \tag{3}$$

Where $\Omega_{m,n} = e^{As_{m,n}}$, $\Phi_0^{m,n} = \left(\int_0^{\bar{s}_{m,n}} e^{Am,n^t}dt\right)\cdot \boldsymbol{B}_{m,n}$ and $\Phi_1^{m,n} = \left(\int_{\bar{s}_{m,n}}^{s_{m,n}} e^{A_{m,n}t}dt\right)\cdot \boldsymbol{B}_{m,n}$. The discrete time control model (3) can be further reformulated assuming that $\xi_n = (\boldsymbol{x}_n^T \quad \boldsymbol{u}_{n-1})^T$ represents the generalized state.

$$\xi_{m,n+1} = \Omega_{m,d}\xi_{m,n} + \Phi_{m,d}\boldsymbol{u}_{m,n} + \bar{\boldsymbol{n}}_{m,n}, \tag{4}$$

where $\bar{\boldsymbol{n}}_{m,n} = (\boldsymbol{n}_{n,m}^T \quad 0)^T$ and $\Phi_{m,d} = \begin{pmatrix}\Phi_0^{m,n}\\ \boldsymbol{I}\end{pmatrix}$. We assume $\Omega_{m,n} = \Omega_m$, then we have $\Omega\begin{pmatrix}\Omega_m & \Phi_1^{m,n}\\ 0 & 0\end{pmatrix}_{m,d}$. The probability of successful packet transmission in the open-loop controlled system can be modelled as $Pr\{\alpha_n = 1\} = 1 - \varepsilon_n$. Taking into account the presence of packet loss, the corresponding communication outage probability is denoted as $Pr\{\alpha_n = 0\} = \varepsilon_n$, where α_n represents the random variable describing whether the packet is successfully received and ε_n denotes the packet loss rate. Furthermore, assuming perfect state estimation, we employ a linear feedback control gain Θ such that $\boldsymbol{u}_n = \Theta\xi_n$. Consequently, the closed-loop system can be rewritten as:

$$\xi_{m,n+1} = \begin{cases} \left(\Omega_{m,d} + \Phi_{m,d}\theta_m\right)\xi_{m,n} + \overline{n_{m,n}}, & if\ \alpha_n = 1 \\ \Omega_{m,d}\xi_{m,n} + \overline{n_{m,n}}, & if\ \alpha_n = 0 \end{cases}, \tag{5}$$

which can be further derived as:

$$\xi_{m,n+1} = \begin{cases} \Omega_{e1}\xi_{m,n} + \overline{n_{m,n}}, & if\ \alpha_n = 1 \\ \Omega_{e0}\xi_{m,n} + \overline{n_{m,n}}, & if\ \alpha_n = 0 \end{cases}, \tag{6}$$

The control matrix of the system is represented by $\Omega_{e1} = \Omega_{m,d} + \Phi_{m,d}\Theta_m$ when the packet is successfully transmitted, and by $\Omega_{\mathrm{e0}} = \Omega_{m,d}$ when packet loss occurs. This relationship closely links the communication and control packet loss rates.

4.4 Mapping from Control Accuracy to Communication Resource Consumption

The reconfigurable manufacturing system requires different control accuracies for various robotics in order to assemble diverse customized productions. Additionally, specific robot arms are required to operate at different times according to the customized production being executed. Consequently, the control time and requirements necessary to achieve a desired control accuracy vary significantly among different robotics. Furthermore, it is crucial to note that the communication reliability has a direct impact on the control accuracy.

The study investigates three effective mappings, as illustrated in Figure 10, based on the procedure in customization-based reconfigurable manufacturing. These mappings include:

- Mapping from customized accuracy demands to control convergence rate.
- Mapping from control convergence rate to wireless communication reliability.
- Mapping from communication reliability to wireless communication resource consumption.

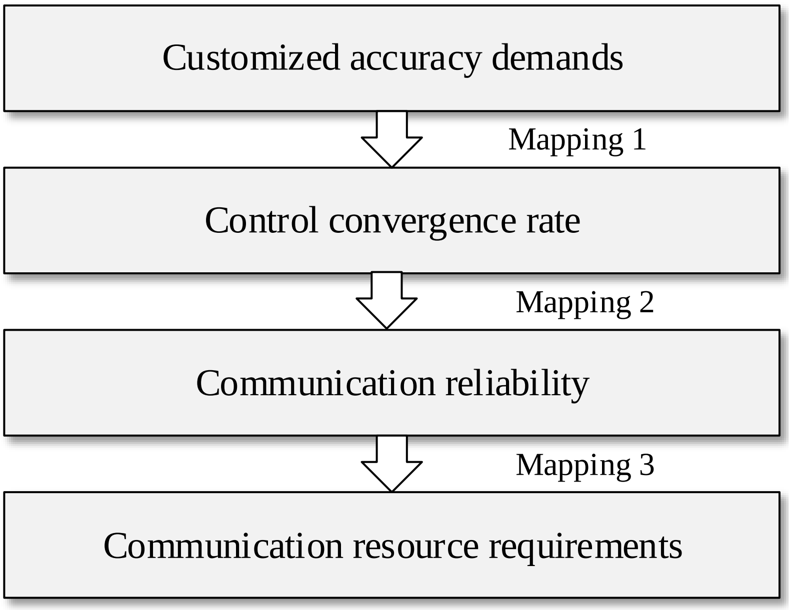


Figure 10. Mapping Control Accuracy to Wireless Communication resource consumption

Mapping 1: from customized accuracy demands to control convergence rate.

The mapping relationship between manufacturing accuracy demands and control convergence rate is examined in this section. Initially, the Lyapunov method [42] is employed to characterize the stability requirements for control. Subsequently, a mapping relationship is established between control accuracy and control convergence rate. The preliminary findings indicate that the different accuracy requirements of various tasks directly impact the control's convergence rate.

The Lyapunov-like function [42] can be formulated for each plant manipulated by different AGVs with robotic arms, ensuring the gradual decrease of the plant state to the pre-set point throughout the control process.

$$\mathit{\Delta}_n(\xi_n) = \xi_n^T Q_n \xi_n \tag{7}$$

The Lyapunov-like function is required to decrease at given rates $\rho_n < 1$ during the control process, where Q_n is a given positive definite matrix. However, due to the influence of control perturbation and stochastic communication coefficients, the Lyapunov-like function becomes random. Therefore, for any possible value of the current plant states ξ_n, it is necessary for the Lyapunov-like functions [42] to satisfy:

$$E(\mathit{\Delta}_{n+1}(\xi_{n+1})|\xi_n) \leq \rho_n \mathit{\Delta}_n(\xi_n) + \mathrm{Tr}(Q_n R'_n) \tag{8}$$

The expectation operator is represented by $E(\cdot)$, and the equation $R'_n = (R_n, 0)$ holds. The convergence of control is guaranteed with $\rho_n < 1$. From equation (8), we can deduce that the plant state ξ_n in (8) is determined by both the control parameters and packet transmission. Consequently, the expression $E(\mathit{\Delta}_{n+1}(\xi_{n+1})|\xi_n)$ relies on the probability of packet transmission.

Mapping 2: from control convergence rate to communication reliability.

The Lyapunov-like function can be also expressed based on equations (6) and (8)

$$E(\mathit{\Delta}_{n+1}(\xi_{n+1})|\xi_n) = Pr\{\alpha_n = 1\}\xi_n^T\mathit{\Omega}_{e1}^T Q_n \mathit{\Omega}_{e1}\xi_n + Pr\{\alpha_n = 0\}\xi_n^T\mathit{\Omega}_{e0}^T Q_n \mathit{\Omega}_{e0}\xi_n + \mathrm{Tr}(Q_n R'_n) \tag{9}$$

Which suggests that the direct impact of communication reliability on the control Lyapunov-like function is evident. Subsequently,

$$Pr\{\alpha_n = 1\} \geq \frac{\xi_n^T(\mathit{\Omega}_{e0}^T Q_n \mathit{\Omega}_{e0} - \rho_n Q_n)\xi_n}{\xi_n^T(\mathit{\Omega}_{e0}^T Q_n \mathit{\Omega}_{e0} - \mathit{\Omega}_{e1}^T Q_n \mathit{\Omega}_{e1})\xi_n} \tag{10}$$

The relationship functions between the control convergence rate ρ_n and communication reliability requirement $Pr\{\alpha_n = 1\}$can be derived from (10). In this context, the lower bound of communication reliability exhibits a monotonically decreasing trend with ρ_n . This observation is reasonable as a small value ρ_n of implies smooth plant state updates, resulting in superior control performance. To summarize, a smaller value ρ_n of indicates better control performance and necessitates higher communication reliability to sustain it. Conversely, a larger value ρ_n of signifies compromised control performance and does not require high communication reliability to maintain satisfactory results.

The different control requirements can be abstracted into distinct control needs, as indicated by (10). Achieving high control accuracy necessitates frequent updates of the control commands, resulting in frequent communication between the controller and the actuator. Consequently, the communication reliability becomes a crucial factor in meeting the control requirement.

Mapping 3: from communication reliability to wireless communication resource consumption

The mapping from communication reliability to communication consumption is investigated by introducing a communication model in the initial part of this subsection. Subsequently, the relationship between communication reliability and wireless resource consumption is discussed.

For the sake of discussion, we assume that the uplink experiences imperfections such as transmission time delay and packet loss, while the downlink is assumed to be perfect. Specifically, M plants are randomly distributed within the coverage area of a Base Station (BS) with a given radius R. Each plant is sampled by a corresponding robot allocated multiple subcarriers within a continuous bandwidth to avoid interference. The allocation ensures that each subcarrier can only be assigned to one robot without overlapping bandwidths for different robots. Additionally, we consider flat fading channels where channel gains over different subcarriers for one robot are approximately identical and perfectly known to it. The number of allocated bandwidth and transmission duration for the m_{th} robot at time slot n_{th} are assumed to be N_n and T_n respectively, with B_0 representing the bandwidth of each subcarrier. Subsequently, the received signal-to-noise ratio (SNR) at the BS for the m_{th} robot during time slot n_{th} is expressed as [58].

$$\gamma_n = \frac{|h_n|^2 g_n N_n B_0 p_n}{N_0 N_n B_0} = \frac{|h_n|^2 g_n p_n}{N_0}, \tag{11}$$

The allocated bandwidth for the m_{th} robot at time slot n_{th} can be expressed as $B_n = N_n B_0$, where h_n represents small-scale fading, g_n denotes path-loss, N_n is the number of allocated bandwidth, p_n stands for the allocated transmission power spectral density for the n_{th} robot, B_o indicates the separation among subcarriers, and N_0 represents the single-sided noise spectral density. Based on the received SNR, the Shannon capacity can be calculated.

$$C_n = log(1 + \gamma_n), \tag{12}$$

In the context of URLLC, where stringent requirements for reliability and latency exist, short block lengths and small packet sizes are employed. Moreover, control systems typically transmit payloads with small data sizes (e.g., around 100 bits), making them well-suited for URLLC scenarios. However, in such scenarios, decoding errors cannot be ignored. We assume that channel dispersion V_n is utilized to represent the capacity loss resulting from transmission errors, as described in [58].

$$V_n = (log\, e)^2(1 - \frac{1}{(1+\gamma_n^2)}), \tag{13}$$

where SNR is higher than $5dB$, the achievable rate with channel dispersion can be bounded by substituting $V_n = (log\, e)^2$ when $V_n \le (log\, e)^2$. Therefore, in the subsequent sections of this paper, we adopt:

$$V_n = (log\, e)^2 \tag{14}$$

The available uplink rate for robot m_{th} at time slot n_{th} , considering finite block length, refers to the capacity obtained after eliminating error bits introduced by channel dispersion. This expression is derived from [58].

$$R_n = C_n - \sqrt{\frac{V_n}{N_n B_0 T_n}} f_Q^{-1}(\varepsilon_n) + \frac{log(N_n B_0 T_n)}{2N_n B_0 T_n}, \tag{15}$$

where $\frac{log(N_n B_0 T_n)}{2N_n B_0 T_n}$ represents the approximation of the remainder terms of order $\frac{log(N_n B_0 T_n)}{N_n B_0 T_n}$ and $f_Q^{-1}(\cdot)$ denotes the inverse of the Q-function. The packet error probability can be expressed as follows.

$$\varepsilon_n = f_Q\left(\frac{N_n B_0 T_n C_n - N_n B_0 T_n R_n + log(N_n B_0 T_n)/2}{(log\, e)\cdot\sqrt{N_n B_0 T_n}}\right), \tag{16}$$

where $f_Q(\cdot)$ is the Q function.

The aforementioned channel model comprises of path-loss and small-scale fading, wherein the path-loss $g_{n_{[dB]}}$ can be mathematically represented as

$$g_{n_{[dB]}} = -128.1 - 37.6 log_{10}(d_n) \tag{17}$$

The distance d_n between the m_{th} robot at time slot n_{th} and the BS is greater than 0.035 km, measured in units of kilometres. The small-scale fading h_n follows a Rayleigh distribution with zero mean and variance $\sigma_0^2 = 1$. Furthermore, small-scale fading remains constant within coherence time, which exceeds the maximum end-to-end (E2E) delay time. Therefore, we consider a quasi-static fading channel that remains constant for each uplink subcarrier within a frame.

The assumption is made that the payload sizes for each robot are identical, denoted as λ_m. Consequently, we obtain:

$$\varepsilon_n = f_Q\left(\frac{N_n B_0 T_n C_n - \lambda + log(N_n B_0 T_n)/2}{(log\, e)\cdot\sqrt{N_n B_0 T_n}}\right) \tag{18}$$

By (18), we can derive the correlation between communication reliability and wireless resource consumption, which encompasses factors such as frequency and transmission power.

4.5 Dynamic Communication Resource Allocation in Time Sequence for Real-Time Wireless Control Systems in Industrial Scenarios

In this section, we explore the dynamic allocation of communication resources in a time sequence for real-time wireless control systems. The main industrial scenarios can be categorized into two industrial protocols, as illustrated in Figure 11. Here, the User Port

Function (UPF) is utilised to adapt specific user requirements to core functions and system administration functions.

- The first protocol is Profinet, an industrial communication protocol [59]. In the Profinet protocol, users are connected in a star structure network where each user communicates independently with the base station. Therefore, there is no data aggregation involved in this protocol.
- The second protocol is EtherCAT, another industrial communication protocol [59]. In the EtherCAT protocol, users are connected in a chain structure network. Multiple users are clustered together, and their data is aggregated at the head user before being transmitted between the head user and the base station.

The user clustering in EtherCAT poses a novel challenge compared to the Profinet protocol, as it necessitates optimal resource allocation for minimizing resource utilization.

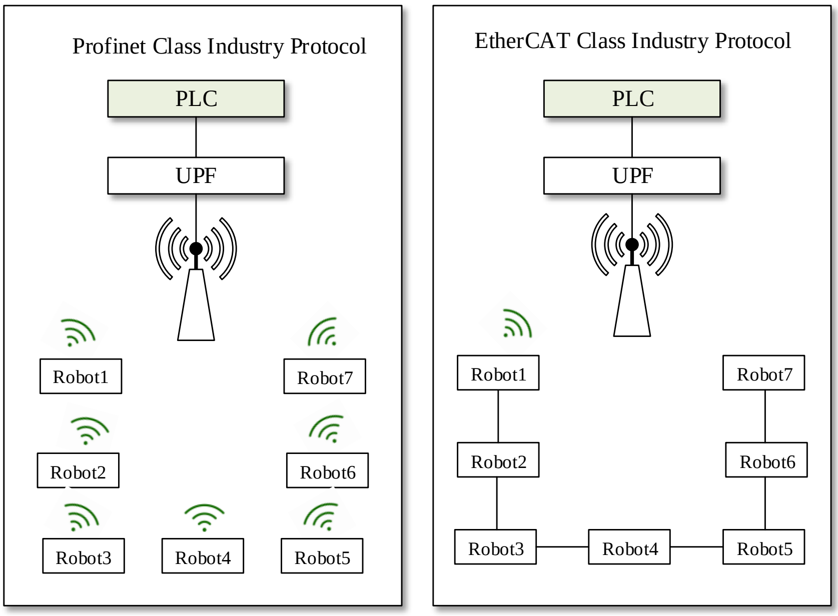


Figure 11. Two typical industrial protocols left) Profinet, right) EtherCAT.

We assume that there are α bits in each packet for each controller. Then, for each controller n , we have

$$\alpha = N_n B_0 T_n C_n - \sqrt{\frac{\mathrm{V}_n}{N_n B_0 T_n}} f_Q^{-1}\left(\varepsilon_n\right) + \frac{\log\left(N_n B_0 T_n\right)}{2 N_n B_0 T_n} \tag{19}$$

For Profinet protocol, we assume that all the users are triggered with the same sampling period with trigger probability which follows a Bernoulli distribution. On the other hand, for EtherCAT protocol, N users are clustered into a group, where the highest QoS is adopted to transmit data, which means that the data of all the users in a cluster is packaged and sent with the highest QoS requirement among all users in this cluster. Then, for EtherCAT protocol, we have

$$\alpha_N = N B_0 T C - \sqrt{\frac{\mathrm{V}}{N B_0 T}} f_Q^{-1}\left(\varepsilon\right) + \frac{\log\left(N B_0 T\right)}{2 N B_0 T} \tag{20}$$

Then, we intend to find optimal N users to maximize the capacity for EtherCAT protocol.

4.6 Simulation Setup

In this section, we have developed a real-time control system prototype to analyse the impact of implementing the proposed dynamic QoS strategy in typical industrial scenarios where commercial robotic arms are commonly used as manipulation tools.

The proposed prototype is illustrated in Figure 12, which is a typical structure adopted in industrial scenario. A cloud server or computer first receives data from various sensors and generates high-level control instructions. Then, the cloud computer transmits control instructions to the edge computer via network Link 1. After that, the edge computer receives the command and converts high-level instructions into low-level commands, e.g., angular velocity, torque, etc., that can be executed by the actuator, and sent via Link 2 to the entity consisting of the control cabinet and the manipulator.

By executing corresponding control orders sequentially, the robot arm will finally complete the expected tasks.

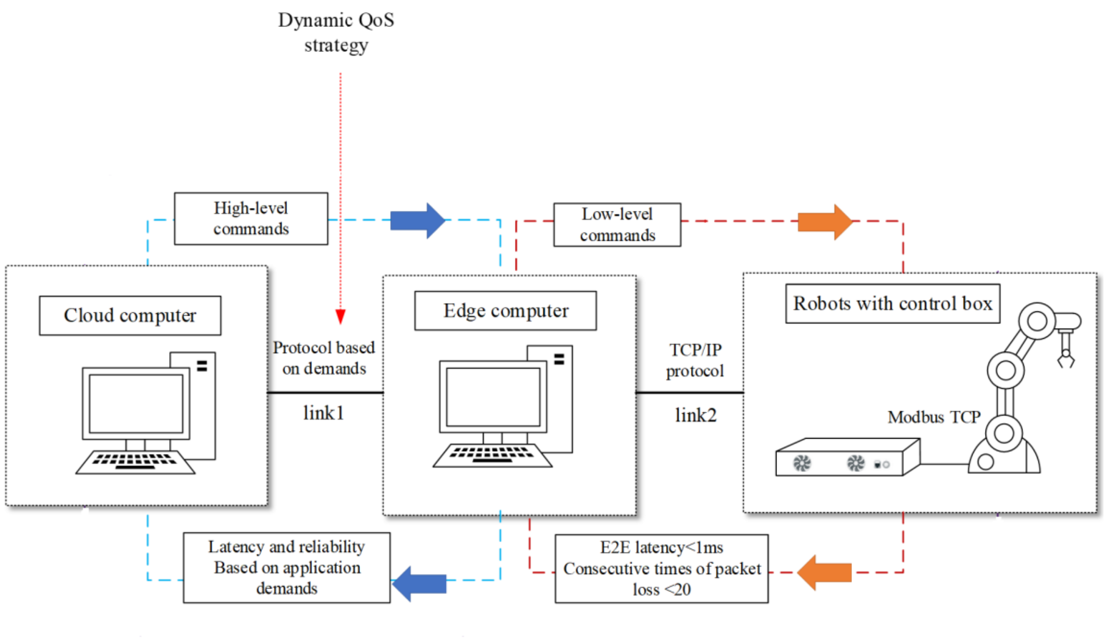


Figure 12. Prototype design of dynamic QoS strategy in communication and control co-design system

Consider that the two links depicted in Figure 12 possess distinct capabilities due to their focus on conveying different types of messages, which frequently results in varying communication strategies.

The first link, Link 1, is typically utilized for transmitting advanced commands generated by a central controller deployed by a cloud server or workstation, such as capture, dump, grab, target track, etc. These instructions need to be converted into speed, torque and other instructions on the edge device in order to be directly employed by the robot. Consequently, the configuration of Link 1 can be adjusted based on the system's performance requirements and actual design examples. With a constant Link 2 in place, the actuator can ultimately accomplish a satisfactory task that meets specific requirements. Due to its flexibility, we are able to implement the proposed dynamic QoS policy on Link 1.

Link 2 is typically utilized for transmitting low-level commands, such as angular speed and internal torque. This aspect is closely intertwined with the robot's characteristics, as each step of the robot arm relies directly on the packets transmitted through this link. Consequently, the properties of Link 2 are often constrained by those of commercial manipulators, which necessitate specific guarantees regarding delay bounds and packet loss rates. Therefore, the dynamic design of Link 1 must adhere to the limitations imposed by actuator attributes in Link 2. Taking the Panda robot as an example [60], it is imperative to ensure that the sum of the following time measurements does not exceed 1 ms

- RTT between the edge computer and robot control box
- Execution time of control loop (program execution time)
- Time needed by the robot to process your data and step the internal controller (Internal execution time of the manipulator)

In case this time limit is violated, packets will be discarded, ultimately leading to a halt in robotic operations.

The implementation of dynamic QoS policy on Link 1 necessitates ensuring the fulfilment of constraints imposed by the inherent attributes of the actuator in Link 2.

4.7 Conclusion

In this chapter, a future Industry 4.0 architecture based on customized reconfigurable manufacturing is first constructed to serve the simulation scenario of this design. Subsequently, the control demand model is described to link the user's demand with the control accuracy. Following that, a wireless control model is introduced to illustrate the control loop of each robot arm. By utilising this model, we can explore the relationship between control requirements and communication reliability. Three effective mappings are then investigated, and customization-based reconfigurable manufacturing processes successfully map custom accuracy requirements to communication bandwidth resources. Additionally, typical industrial protocols in industrial scenarios and the rationale behind using EtherCAT are examined. Finally, the effects of implementing the proposed dynamic QoS design in a typical industrial scenario and the experimental Settings used in the simulation are analysed.

The following chapter presents the simulation results of the design utilising dynamic QoS design and elucidates the system benefits that this approach can yield.

5 The proposed dynamic QoS strategy

In this Chapter 5, the system performance of proposed dynamic QoS strategy was evaluated based on the model of Chapter 4.

5.1 Simulation Evaluation

The proposed strategies are evaluated and compared to other baseline communication resource allocation methods:

- Baseline 1: URLLC services: The URLLC services are responsible for servicing all robots, ensuring the provision of communication services with the utmost reliability throughout the simulation. In essence, it is imperative that each robotic arm maintains a communication reliability level of 10^{-5} during every operational instance.
- Baseline 2: Communication resource allocation strategies for different robots involve assigning varying static communication resources to different arms based on their highest control accuracy requirements as indicated by their task profiles. This implies that one robotic arm will be assigned a communication reliability level of a certain value based on this task profile. This value remains constant for the simulation time. Besides, different robotic arms have different profiles based on their tasks.
- Strategy 1: Dynamic QoS strategy in time sequence: Robots are assigned different communication resources based real-time control demands of task profiles, which means communication service is provided with the different communication reliability and changed in different timeslot based on real-time demands throughout the entire simulation length.

Considering the diverse accuracy demands of individual tasks, the communication reliability and associated resource consumption vary accordingly. The thesis examines the scenario where the task necessitates communication reliability in line with 5G URLLC standards, resulting in the highest accuracy requirement and communication resource consumption.

Figure 13 shows the difference among baseline 1, baseline 2 and dynamic QoS strategy.

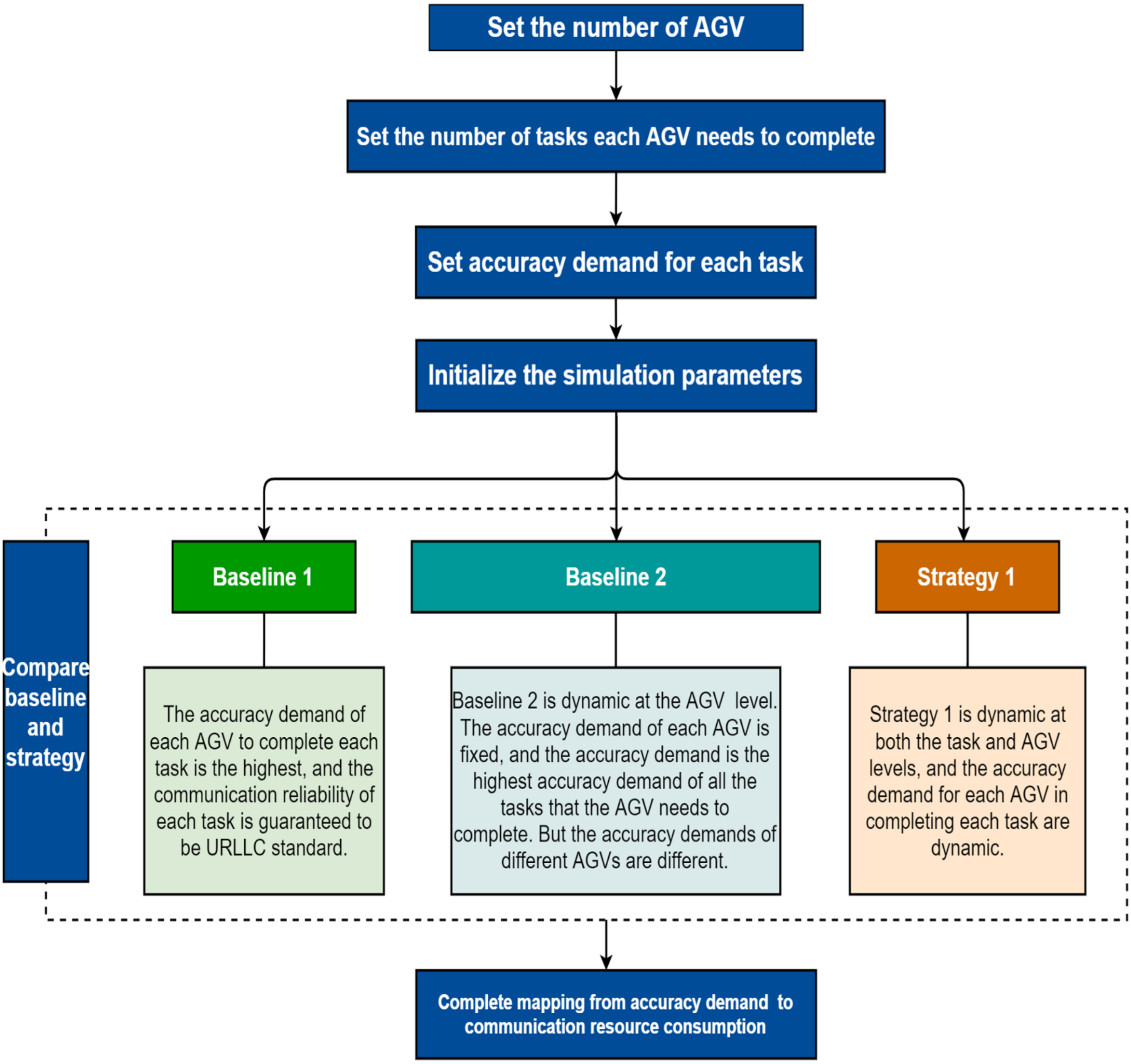


Figure 13. The flowchart of baseline and dynamic QoS strategy

5.2 Performance Metrics

To evaluate the performance of proposed strategies, different performance metrics are adopted. The metrics utilised for comparison are:

- Wireless bandwidth resource consumption.

Wireless bandwidth resource consumption can be calculated by formula (16), where B_0 is the wireless bandwidth resource consumption, and the unit of B_0 is Joule (J).

- The total average power consumption of the signal transmitted in the channel.

The total average power consumption can be found in formula (11), where p_0 is the total average power consumption, and the unit of p_0 is Watt (W).

- Performance gain in different scenarios.

The performance gain G is calculated by formula (32), which is used to compare the improvement of the research method in this thesis with the traditional baseline method.

5.3 Simulation Results

In this section, the system performance of proposed dynamic QoS strategy was evaluated. The system performance of the proposed strategy 1 (Dynamic QoS strategy in time sequence) was evaluated and compared the results with two baselines (baseline 1: URLLC services; baseline 2: Communication resource allocation strategy for different robots). For the baseline 1, the legacy URLLC services, we assume that all the maximum control convergence rate of robotic arm is supreme at, which suggests all the robotic arm require URLLC services to satisfy such high communication reliability with URLLC (10^{-5}). For baseline 2, we assume that the control convergence rate of the 300 robotic arms varied with uniform distribution which will and cannot change with time elapsing. Unless otherwise specified, the simulation parameters are based on Table 2.

Table 2. Simulation Configurations for dynamic QoS strategy.

Parameters	**Settings**
The number of robot arms M	300
On/Off probability	80%/20%
Robotic arm velocity $v(m/s)$	[1:0.02:3]
Communication reliability ϵ	10^{-3} ~10^{-5}
Control sample period $t_s(ms)$	0.5
Payload size T_b	300
Subcarrier spacing Δf(kHz)	15
Transmit power on each subcarrier(W)	0.02
Rayleigh channel parameter σ	0.5
Coverage distance $d(m)$	100
Path loss coefficient α	4

5.3.1 The Performance of Dynamic QoS Strategy in Time Sequence

In this section, we evaluate the system performance of the proposed strategy 1 (Dynamic QoS strategy in time sequence) and compared with two baselines (baseline 1: URLLC services; baseline 2: Communication resource allocation strategy for different robots). For the baseline 1, the legacy URLLC services, we assume that all the maximum control convergence rate of all robotic arms is within the limits of the machine, which indicates all the robotic arm require URLLC services to satisfy such high communication reliability with 10^{-5}. For baseline 2, we assume that the control convergence rate of the 100 robotic arms varies with uniform distribution which cannot change with time elapsing. Unless otherwise specified, the simulation parameters are based on Table 2.

Figure 14 shows that the average wireless power consumption of proposed strategy 1 Dynamic QoS strategy in time sequence. The straight line (A) (B) (C) in Figure 14 represent the average power consumption in different scenarios.

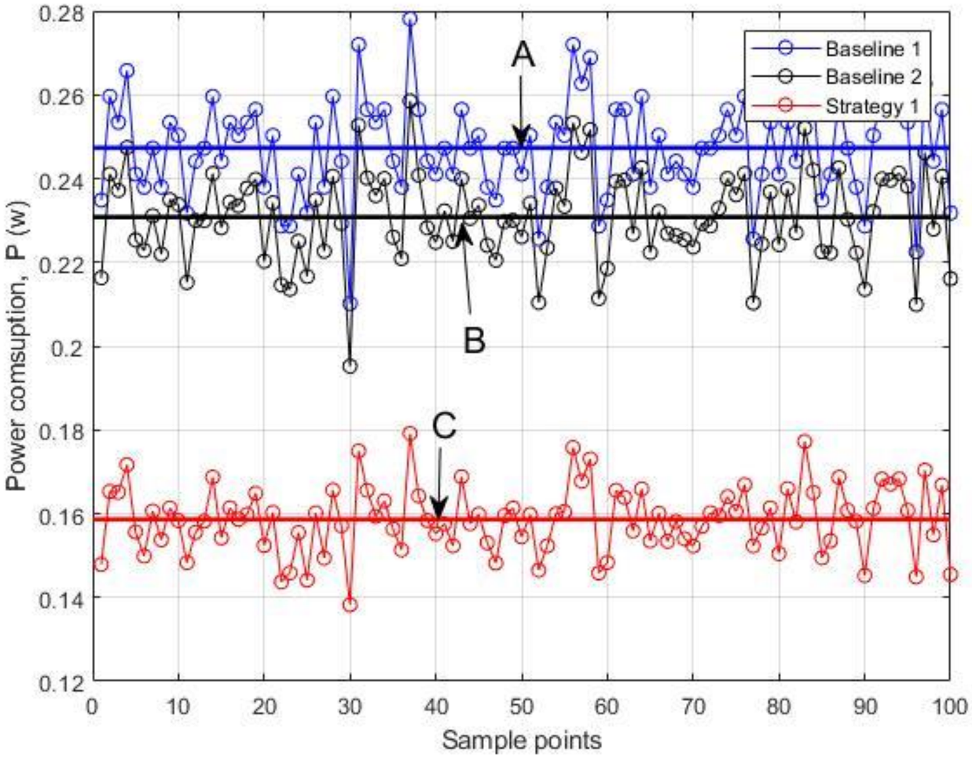


Figure 14. Total BS transmit power of proposed dynamic QoS strategy 1 versus legacy baseline scheme.

The results show that the average wireless power consumption of the proposed strategy when compared to URLLC services is reduced by 35.7% and when compared to baseline 2 communication resource allocation strategy for different robots, the average power consumption is reduced by 32.9%. For baseline 1, this is intuitively reasonable since not all control instructions transmitted need high URLLC services in terms of high reliability, which also indicates that when the allocated resource in traditional URLLC service is more than that is needed in guaranteeing the required control performance, the wireless resource waste is reflected in the transmitting power consumption. For baseline 2, it is reasonable since different arms are assigned to different static communication resources based on all their tasks profiles with highest control accuracy demands to satisfy all the potential task accuracy requirements. It is more likely to spend communication resources between the baseline1 and the proposed strategy 1. In summary, the higher control performance needs more communication resources and the proposed dynamic QoS strategy can reduce power consumption while maintaining performance.

Figure 15 shows the Cumulative Distribution Function (CDF) of three strategies. We define the Y label as being activated user's probability, which represents the percentage of total robots that work. From this graph, with the same number of users activated simultaneously, the proposed dynamic QoS strategy can significantly reduce transmit power consumption. For instance, at CDF =0.5, the average wireless power consumption of the proposed strategy when compared to URLLC services is reduced by 35.7% by solving $\frac{x_3 - x_1}{x_3} \times 100\%$ and when compared to baseline 2 communication resource allocation strategy for different robots, the average power consumption is reduced by 32.4% by solving $\frac{x_2 - x_1}{x_2} \times 100\%$. It is also evident that when the transmit power consumption is the same, the proposed dynamic QoS strategy is more likely to serve more users which can further explore the cell capacity.

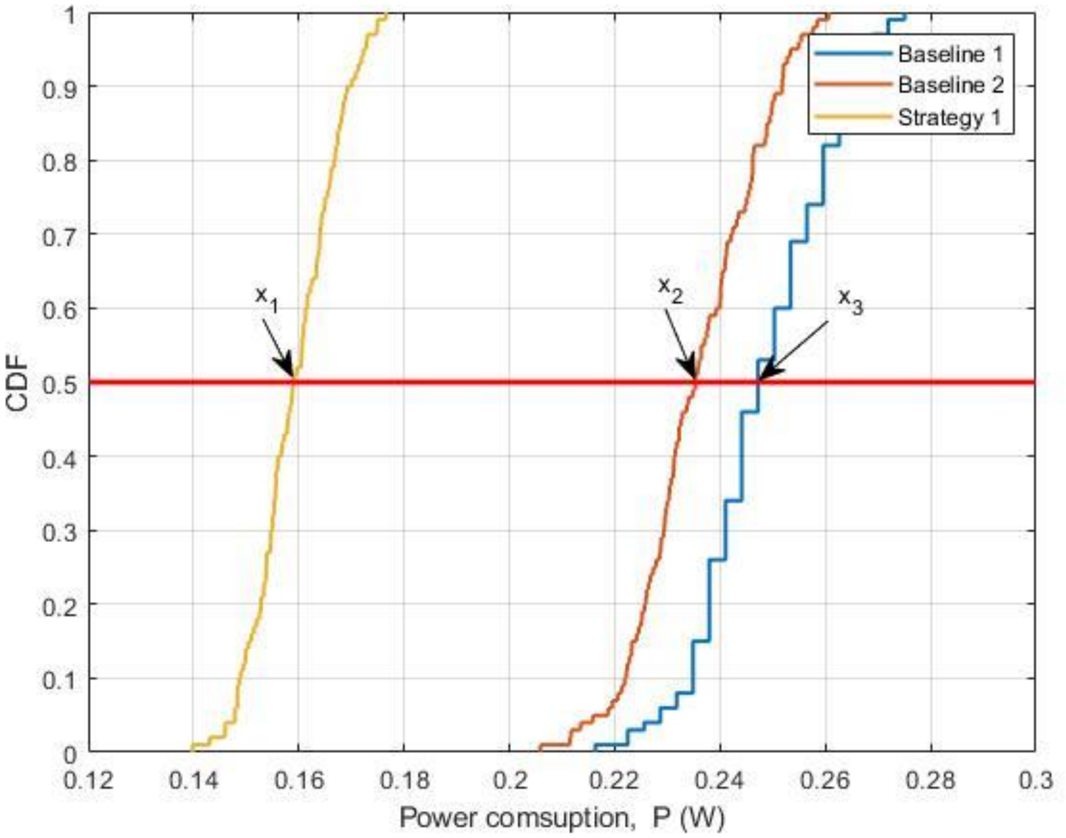


Figure 15. The CDF of total BS transmit power of proposed dynamic QoS strategy 1 versus legacy scheme.

In Figure 16， we present results that show the capacity (the total number of robots) that can be supported with a given amount of total power consumption. This is based on the statistical results of the number of robots supported on each time slot and the corresponding total power consumption. The working probability (duty cycle) is set to 50% and the simulation length is set to one million to get adequate robots working profiles. The generic trend of the results shows that, for a given power consumption value, the dynamic QoS strategy (strategy 1) has higher capacity to support more robots than URLLC (baseline 1). Due to different task profiles, the capacity provided by dynamic QoS policies has a certain range for a given power. An example of this, shown in Figure 16, is at a power consumption value of 0.101W, depending on the task profile, the capacity offered by the dynamic QoS strategy is between 25.3% and 35.7% higher than the URLLC. In the extreme case, when all the robotic arms are working at the point required by the highest communication reliability, there is no gain in strategy 1 compared with baseline 1. In other words, if the maximum performance for all robots working at the same time happens your strategy can still cope and is equal to baseline 1. This means the strategy is robust and is not crumbling if demand is sky rocketing. However, the probability of this event is extremely small which is equal to $\left(\frac{1}{200}\right)^{100}$ which can be ignored. Therefore, we focused more on the average performance gain, which is the number of users that can be increased on average.

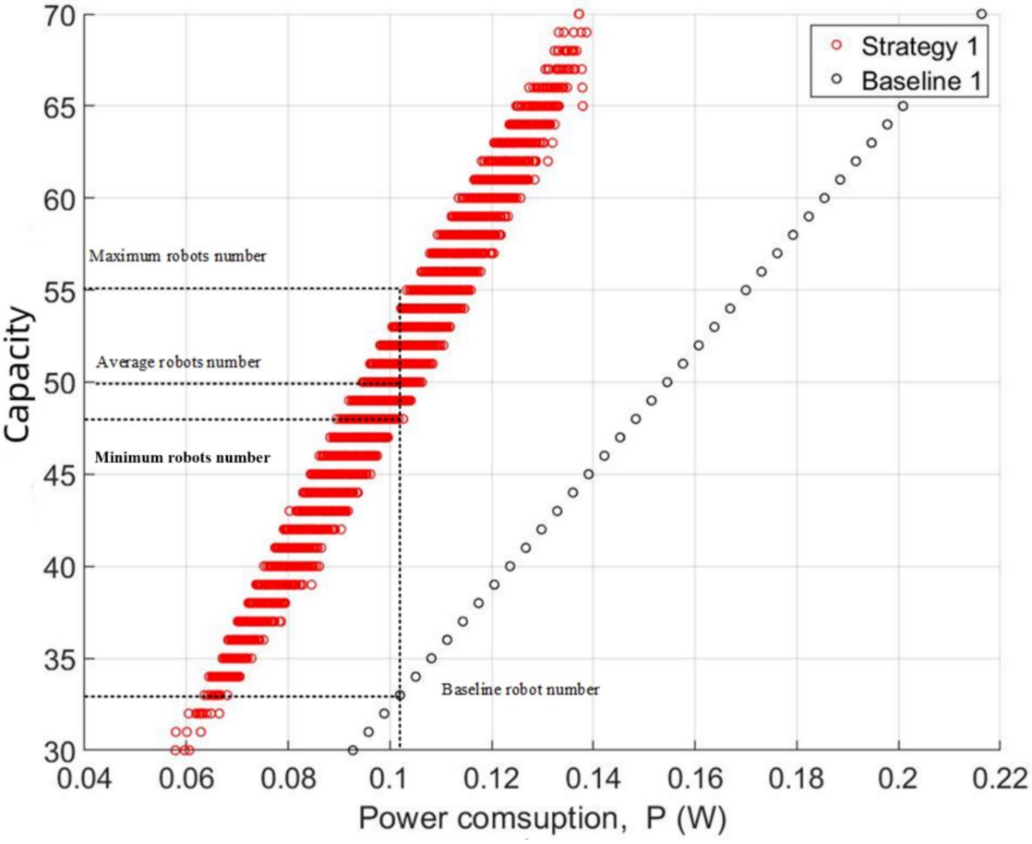


Figure 16. The capacity of dynamic QoS strategy (strategy 1) and URLLC service (baseline 1) versus total power consumption with working duty cycle 50%

We also compare the average capacity gain when altering different working profiles by changing different working probability of robots. Figure 17 illustrate the capacity of the system with working probability of 80%. The results also show that for a given power consumption value, the dynamic QoS strategy (strategy 1) has a higher capacity to support more robots than the URLLC (baseline 1) service. When the power consumption is taken as 0.182W, the capacity of the dynamic QoS strategy is between 29.2% and 38.7% higher than that of the URLLC service.

In Figure 18, we plot the average increase in capacity of the dynamic QoS strategy when compared with URLLC for increasing duty cycle (from 0.2 to 0.8). These values of duty cycle are also a representation of the working probability (from 20% to 80%). Statistically, the duty cycle refers to the percentage of the working time of the robot in the simulation time, as well as the working probability of the robot at each time slot. Over this range of duty cycle, the increase in capacity by the proposed system stays the same at an average value of about 35.75%. This is reasonable since the power consumption of URLLC service always increases linearly with the number of users. On the other hand, power consumption of the dynamic QoS strategy is only increased according to the actual control accuracy demands of robots which varies within the working probability range.

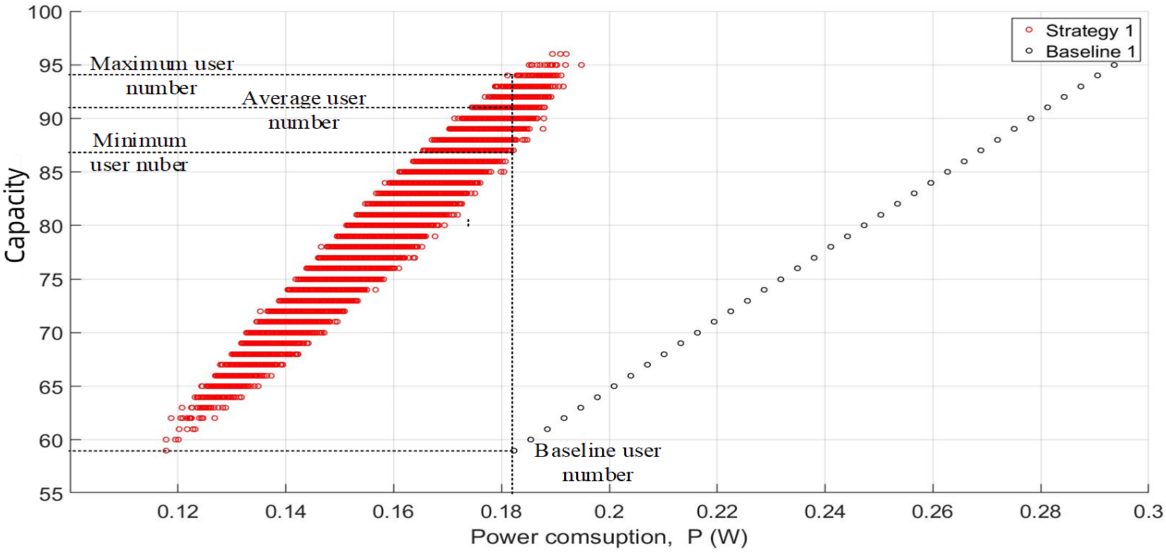


Figure 17. The capacity of proposed strategy 1 and baseline 1 (URLLC service) versus total power consumption with working duty cycle 80%

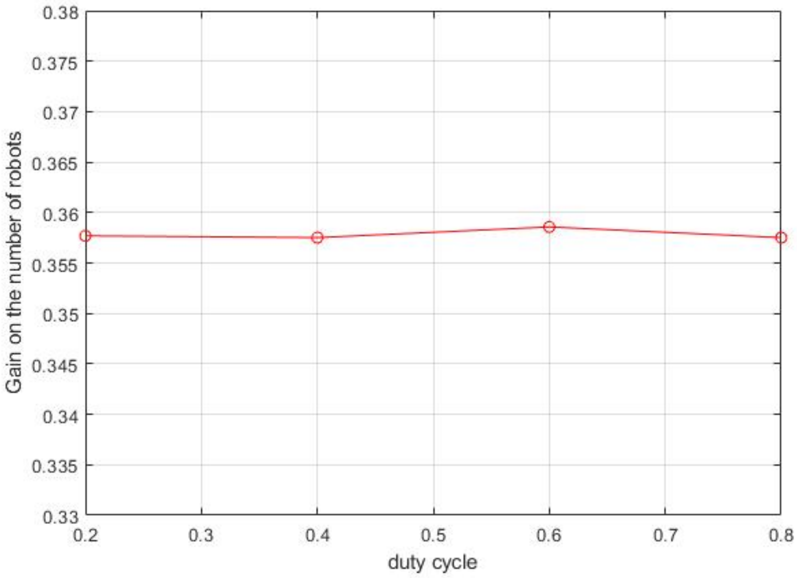


Figure 18. The capacity gain with different duty cycle

5.4 Conclusion

In this chapter, a dynamic QoS strategy is proposed to reduce the average power consumption, based on the model presented in Chapter 4. Firstly, two baseline and dynamic QoS strategies are introduced for comparison and results analysis. The performance metrics utilized in this chapter are also presented.

Subsequently, the simulation results are analyzed by describing the simulation parameters and evaluating the system performance of the proposed dynamic QoS strategy, as well as comparing it with the two baselines. The simulation results demonstrate that compared to baseline 1 (URLLC service), this strategy reduces average wireless power consumption by 35.7%. Furthermore, compared to baseline 2 (communication resource allocation strategy for different robots), it reduces average wireless power consumption by 32.9%. To provide more evident outcomes, CDF is employed next to analyze the capacity that can be supported for a given total power consumption (total number of robots). The findings reveal that the dynamic QoS strategy offers 25.3% to 35.7% more capacity than baseline 1 (URLLC service). Lastly, at different working probabilities of robots' operation profiles, an evaluation is conducted on their average capacity gain in comparison with URLLC service; when working probability reaches 80%, the capacity of dynamic QoS strategy surpasses URLLC service by approximately 29.2% to 38.7%. Within a range of operation probabilities from 20% to 80%, there remains a consistent increase in capacity provided by our proposed system averaging around 35.75%.

The subsequent chapter presents simulation results using packet length design for dynamic QoS and illustrates its potential benefits.

6 Packet Length Design for Dynamic QoS

In this Chapter 6, we consider PPC in the design system. PPC is an effective solution to conduct robust control over unreliable wireless links. By using PPC, wireless resource consumption can be significantly minimized while guaranteeing desired control system requirements (control convergence rate). In addition, by leveraging the wireless resource consumption and the prediction length of PPC, the optimized prediction length, which could be further used to optimize the total wireless resource consumption in the multi-user application scenario. A typical system model of packet predictive model is shown as Figure 19 and Figure 20.

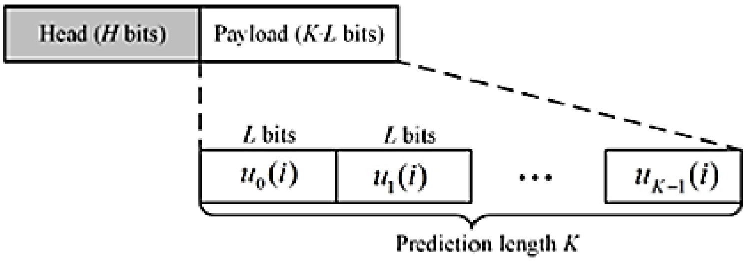


Figure 19. PPC packet structure

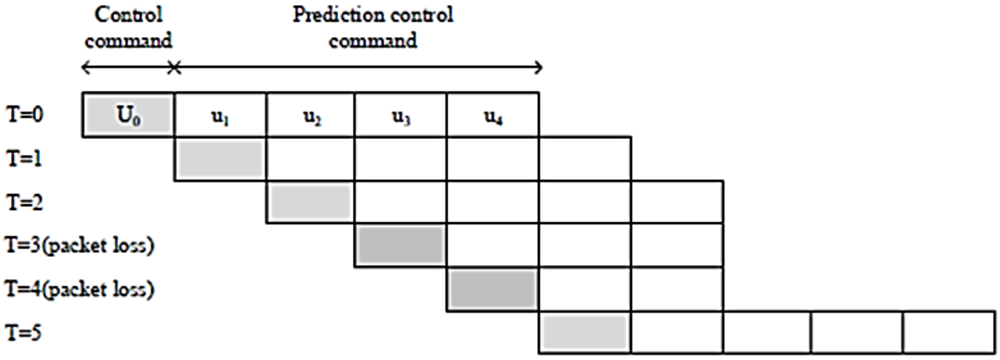


Figure 20. PPC packet structure

6.1 Single-User System model

A typical system model of packet predictive model is shown in Figure 20. In the wireless control loop, controllers generate current control commands $\mu_0(t)$ based on the current plant state $\chi_0(t)$ and generate a sequence of $K\text{-}1$ prediction control commands $[\mu_1(t), \mu_2(t), \mu_3(t), \ldots, \mu_{k\text{-}1}(t)]$ by estimating future plant state. Thus, packets for the payload in each packet not only contain the control commands for the current time slot, but also contain prediction control commands for the next few time slots. Then, the actuator will receive the packet transmitted by the controller in each slot and cache the entire packet information in a buffer. If communication fails, the executor will perform the prediction control command cached in a buffer, and if communication succeeds, the executor will perform the control information in the latest received packet and update the cache in the buffer.

Therefore, this system can increase the reliability of the control system in the aspect of increasing the tolerance of ‘control outage’, which is defined as the case of K consecutive packet drops and the buffer is empty. Here we define the control outage probability as p_s and packet loss probability as p_e. Then, the system needs to satisfy:

$$p_e \leq p_s^{\frac{1}{k}} \tag{21}$$

6.2 Multi-User System model

Figure 21 shows the multi-user PPC system model of the star topology scenario, m robots are connected to one Access Point (AP) by wireless communication. If the robot carries out different work tasks, their control convergence rates will be different. In addition, the requirements of control accuracy change dynamically in each time slot. Based on the previous deduction, the different control convergence rates can be mapped to different communication reliability, which further constrains the wireless resource consumption in the PPC application scenario. Without loss of generality, we assume that each robot will be on at a certain time slot with a certain probability, which will be receiving packets transmitted from the access point and updating the plant state. In each time slot, each controller will first find its optimized PPC length to minimize wireless resource consumption with guarantee the communication reliability requirements, and then transmit the packet to the corresponding actuator for actuation. In summary, for each time slot, the control plant dynamically updates its control convergence rate requirements based on specific tasks. Then, wireless resources are loaded according to this requirement with reduction by considering packetized predictive control.

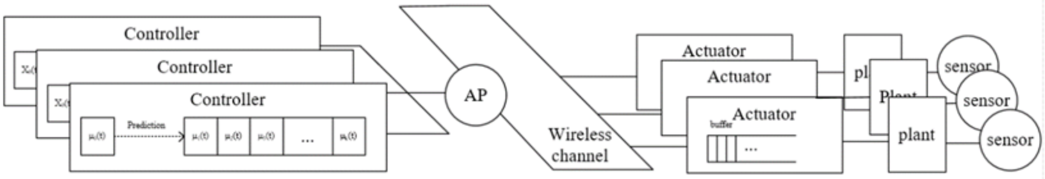


Figure 21. Star topology for Multi-user PPC system model

Since the system model is deployed in industrial control application scenarios, URLLC services is applied to the communication model. Here we assume short packet is used with H bit header for preamble, L bits for each control command in one time slot, and K for prediction slots. Thus, the total bits λ for a packet is:

$$\lambda = H + KL \tag{22}$$

We also assume that transmission time for each packet is less than the channel coherence time. Thus, an approximated archivable rate a quasi-static SIMO channel is provided by (23). Then, the total bits λ for a packet of robot m at time slot n can be formulized as:

$$\lambda_{m,n} = N_{m,n} T_{m,n} B_0 R_{m,n} \tag{23}$$

where $N_{m,n}$ is the total available number of subcarriers, $T_{m,n}$ is the time resource for the m_{th} robot at time slot n, B_0 is the bandwidth of each carrier.

6.3 Problem Formulation

Considering the scenario with limited communication resources, it is assumed that the robot m will consume $P_{m,n}$ power consumption and $N_{m,n}B_0$ subcarriers at times slot n. We also assume that the total maximum bandwidth and power that a centralized base station can provide at time-slot n are $B_{max,n}$ and $P_{max,n}$ respectively. where the constraints can be formulized as:

$$\sum_{m=1}^{M} N_{m,n}B_0 \leq B_{max,n} \tag{24}$$

$$\sum_{m=1}^{M} P_{m,n} \leq P_{max,n} \tag{25}$$

Then, the communication latency should also be bounded based on the task requirements, which can be expressed as:

$$T_{m,n} \leq T_{th} \tag{26}$$

Thus, $\theta = BT$ represents the time-frequency resource used for each packet which can be expressed as:

$$\theta = \frac{\lambda}{R} \leq \theta_{max} \tag{27}$$

Based on the previous deduction, for each user, communication reliability can affect the control Lyapunov-like function directly shown as:

$$Pr\{\, \alpha_n = 1\} \geq \frac{\xi_n^T(\Omega_{e0}^T Q_n \Omega_{e0} - \rho_n Q_n)\xi_n}{\xi_n^T(\Omega_{e0}^T Q_n \Omega_{e0} - \Omega_{e1}^T Q_n \Omega_{e1})\xi_n} \tag{28}$$

which indicates that the communication reliability can affect the control Lyapunov-like function directly. Then, we have:

$$\begin{aligned} 1 - \varepsilon_m &= c_m^* \\ &= \frac{\xi_{m,n}^T(\boldsymbol{\Omega}_{e_0}^T \boldsymbol{Q}_m \boldsymbol{\Omega}_{e_0} - \rho_m \boldsymbol{Q}_m)\xi_{m,n}}{\xi_{m,n}^T(\boldsymbol{\Omega}_{e_0}^T \boldsymbol{Q}_m \boldsymbol{\Omega}_{e_0} - \boldsymbol{\Omega}_{e_1}^T \boldsymbol{Q}_m \boldsymbol{\Omega}_{e_1})\xi_{m,n}} \end{aligned} \tag{29}$$

where small ρ_m means good control performance and needs high communication reliability to maintain the control performance. On the contrary, large ρ_m means the loss in control performance and does not need high communication reliability to maintain the control performance.

To maximize the capacity of the system by minimizing wireless resource consumption, we optimize the packetized prediction length K, and subcarrier bandwidth allocation. Considering all the constraints and relationship mentioned from (22)(23)(24)(25)(26)(27)(28)(29), the problem can be formulated as follows:

$$\min_{p_{m,n}} E = PBT = P \tag{30}$$

s.t.

$$\sum_{m=1}^{M} N_{m,n} B_0 \le B_{max,n} \tag{31b}$$

$$\sum_{m=1}^{M} P_{m,n} \le P_{max.n} \tag{31c}$$

$$T_{m,n} \le T_{th} \tag{31d}$$

$$\theta \le \theta_{max} \tag{31e}$$

$$\varepsilon_e \le \varepsilon_s^{\frac{1}{K}} \tag{31f}$$

$$\lambda = H + KL \tag{31g}$$

$$\lambda = N_{m,n} T_{m,n} B_0 R_{m,n} \tag{31h}$$

$$\varepsilon_s = f_Q\left(\frac{N_{m,n}T_{m,n}B_0C_{m,n} - N_{m,n}T_{m,n}B_0R_{m,n} + \frac{(log\, N_{m,n}T_{m,n}B_0)}{2}}{\sqrt{N_{m,n}T_{m,n}B_0V_{m,n}}}\right) \tag{31i}$$

$$\begin{aligned} 1 - \varepsilon_m &= c_m^* \\ &= \frac{\xi_{m,n}^T(\boldsymbol{\Omega}_{e_0}^T \boldsymbol{Q}_m \boldsymbol{\Omega}_{e_0} - \rho_m \boldsymbol{Q}_m)\xi_{m,n}}{\xi_{m,n}^T(\boldsymbol{\Omega}_{e_0}^T \boldsymbol{Q}_m \boldsymbol{\Omega}_{e_0} - \boldsymbol{\Omega}_{e_1}^T \boldsymbol{Q}_m \boldsymbol{\Omega}_{e_1})\xi_{m,n}} \end{aligned} \tag{31j}$$

6.4 Algorithm

```
Algorithm 1 PPC strategy based on dynamic QoS design
Input: $C$-Shannon Capacity; $H$-Head length; $t$-Working times
    $L$-Control command length;$R_0$-Amount of robot;
    $p$-working probability;$p_s$-Communication reliability;
Output: optimal $n^*$-Wireless resoutce consumption;
Randomly set $p_s$ 0.99 to 0.99999;
Combine $\gamma = (P_0G)/N$ and $C = log_2(1+\gamma)$, then $P_0 = (2^C - 1)N_0/G$;
Consider medium and high SNR regions in our simulation. then $(2^C - 1) \approx 2^C$, then $P_0 = (2^C - 1)N_0/G \approx 2^C N_0/G$;
To minimize the wireless resource consumption, we set $p_e = p_s^{1/k}$, then combine $p_e = p_s^{1/k}$ and $p_e = Q((nC - N + ((log)_2(n))/2)/\sqrt{nV})$, then $Q^{-1}(p_s^{1/k}) - ((nlog_2(1+\gamma) - N + (log_2(n))/2)/\sqrt{nV}) = 0$;
for $i$=1 to $R_0$ do
    Find the optimal prediction length $K$ for each communication reliability
end for
for $i$=1 to $R_0$ do
    for $j$=1 to $t$ do
        Using PPC strategy based on dynamic QoS, the predicted length $K$ is optimal for different communication reliability $p_s$
    end for
end for
Calculate the resource consumption $n^*$ per working time;
```

6.5 Simulation Results

To evaluate the proposed strategies, a simulation environment of proposed reconfigurable customized manufacturing system was designed in MATLAB. Table 3 shows the fundamental simulation parameters for the proposed scenario.

Considering a cluster workstation with R=100 AGVs, where a robotic arm with different accuracy parameters is deployed on each AGV to finish different customized tasks. For the task profiles, without loss of generality, we assume that the mechanism of consuming time-frequency resources conforms to the on / off model modelled as a standard Bernoulli process with on probability 80% and off probability 20%, which is also known as the duty cycle. For simplicity, we assume that each control cycle is completed in one time slot. So, in each time slot, control state is updated once. Therefore, we assume that the maximum control convergence rate is followed with uniform distribution, which suggests that the requirement of communication reliability is varied dynamically accordingly.

Table 3. Simulation Parameters for Dynamic QoS Strategy in PPC

Parameters	**Settings**
The number of robot arm R_0	100
On/Off probability	50%/50%
Time resources of the downlink for the m_{th} robot $T_{m,n}$ (ms)	0.5
Subcarrier bandwidth B_0 (kHz)	15
The range of communication packet loss rate ε_m^*	10^{-2} ~10^{-5}
Coverage radius of the base station d (m)	100
Path loss g (dB)	$-128.1 - 36.7lg(d_n)$

The proposed strategies are evaluated and compared to other base line communication resource allocation methods:

- Baseline 1: URLLC services: All the robots are served by URLLC services, which means that the communication service is provided with the highest possible communication reliability throughout the entire simulation length.
- Baseline 2: Communication resource allocation strategy for different robots: Different arms are assigned to different static communication resources based on all their tasks profiles with highest control accuracy demands, which means communication service is provided with the different communication reliability but cannot change over time throughout the entire simulation length.
- Strategy 1: Normal dynamic QoS strategy.
- Strategy 2: Dynamic QoS Strategy in packetized predictive control application: Based on the strategy of dynamic communication resource allocation in time sequence, packetized predictive strategy is adopted. In each time slot, the communication system loads tasks based on the optimal packet length.

6.5.1 The Performance of Dynamic QoS Strategy in Packetized Predictive Control

In this section, we first demonstrate the relationship between wireless resource consumption and prediction length. Then, based on the results, the prediction length K is optimized for each robot. Finally, the performance of dynamic QoS stretegy in packetized predictive control, as well as the maximum capacity of the system (minimum wireless resource consumption) is presented.

Figure 22 provides the relationship between wireless resource consumption E and the predication length K. Without loss of generality, we assume that the value of prediction length K will range from 1 to 11 and the maximum time-frequency resource block is set to n_{max}. Then, the corresponding wireless resource consumption E are obtained by optimizing power consumption by solving the problem formulation for a single robot.

Initially, transmitting a higher number of bits actually results in lower utilization of wireless resources. The increase of E is positively correlated with the increment of K when K exceeds a certain threshold value. The results show that for the given simulation parameters, the optimized predicted length of the robot m at time slot n is 3, which will result in the lowest wireless resource consumption. Choosing the best instead of the other lengths, such as 1, can yield about 24.36% performance gain. This trend is logical, as the primary objective of control and wireless systems is to accomplish control tasks rather than solely transmitting data. Hence, in order to attain specific control performance levels, reducing communication performance requirements may not necessarily result in a reduction of wireless resource consumption.

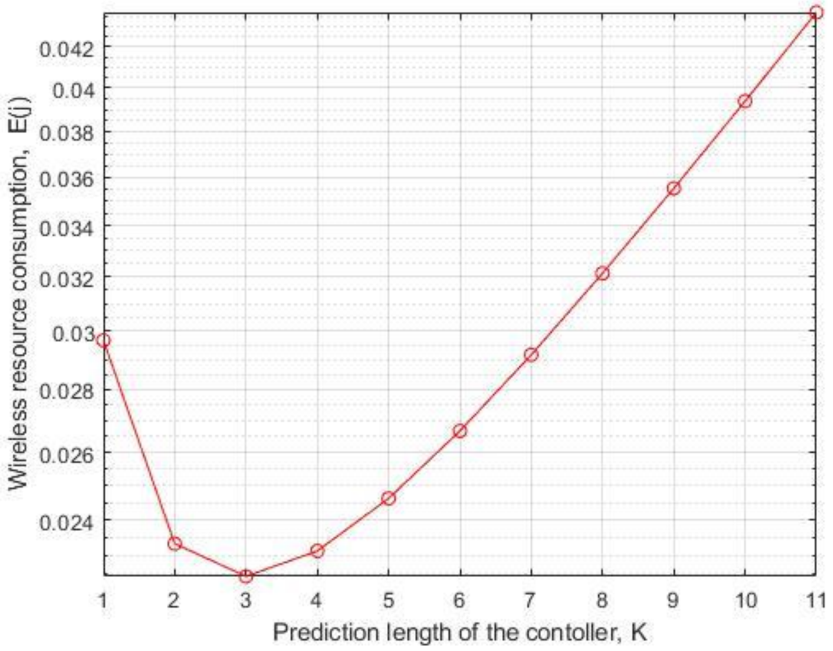


Figure 22. Wireless resource consumption E versus the prediction length K

The results also indicate that designing the control system that minimizes the control bits is not equivalent to minimizing the wireless resource consumption. The communication-control codesign is expected to choose the optimal value of K to minimize the wireless resource consumption while maintaining a certain control outage limit. This is mainly because the overall goal of control and wireless systems is to accomplish a control task rather than sending bitstreams. Therefore, in order to achieve a certain control performance, reducing communication performance requirements may not necessarily reduce the consumption of wireless resources.

6.5.2 The Performance of Dynamic QoS Strategy in Packetized Predictive Control

In this section, we use CDF to evaluate the system performance of the proposed PPC strategy based on dynamic QoS.

Figure 23 demonstrates the CDF of total wireless resource consumption for the proposed strategy 2: Dynamic QoS strategy in packetized predictive control by solving problem 2 and compared with strategy 1, baseline 1. In this figure, Baseline 1 and are overlapped since the simulation length is long enough for all robotic arms to complete the task with the highest accuracy. It can be observed that with the same number of users activated simultaneously, the proposed dynamic QoS strategy in packetized predictive control can further reduce wireless resource consumption compared with strategy 1 and significantly reduce wireless resource consumption compared with baseline1. At CDF =0.5, the results show that the average wireless resource consumption of the proposed strategy 2 when compared to URLLC services is reduced by 42.51% by solving $\frac{x_4 - x_1}{x_4} \times 100\%$ and when compared to strategy 1 (Dynamic QoS strategy in time sequence) , the average resource consumption is reduced by 14.16% by solving $\frac{x_3 - x_1}{x_3} \times 100\%$. For strategy 2, the predicted length of each robot in each time slot is optimized. It indicates that it is feasible to reduction in wireless resource overhead by adding the prediction length. The proposed dynamic QoS in packetized predictive control is more likely to serve more users based on the same wireless resource consumption.

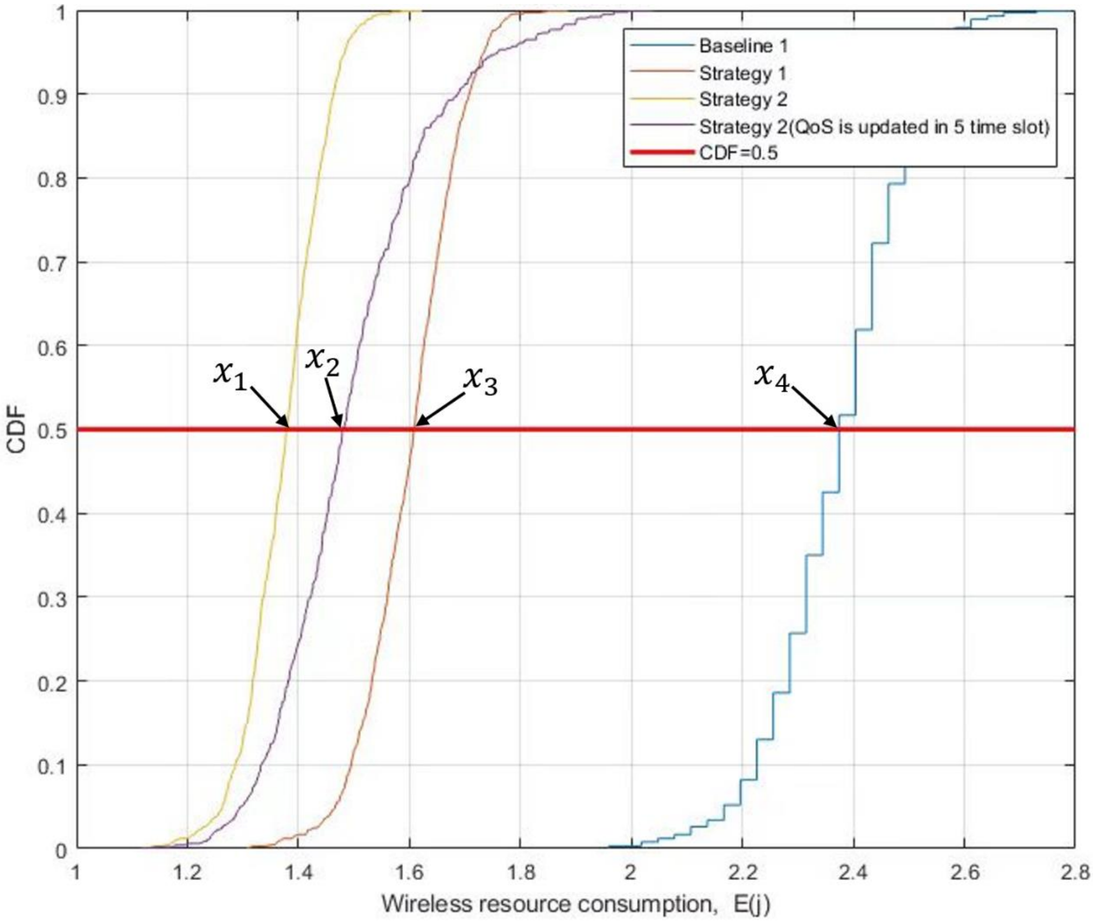


Figure 23. The CDF of total wireless resource consumption of proposed different schemes

Based on the proposed strategy 2: Dynamic QoS strategy in packetized predictive control, we then explore the effect of the update frequency of QoS on the wireless control system. Since in the real communication system, QoS often cannot be adjusted in time due to various real conditions. As shown in Figure 23, the curve of the Dynamic QoS strategy in packetized predictive control (QoS is updated in every 5 time slots) represents QoS reliability will change every 5 time slots for the proposed PPC strategy. The results show that when compared with the QoS updated in each time slot, there is a reduction of performance gain of 7.0% by solving $\frac{x_2 - x_1}{x_2} \times 100\%$ after combining multiple time slots into a set and using the same QoS group. The significance lies in the fact that when the resource consumption is substantial, if the QoS requirements cannot be promptly updated, the incremental benefit of incorporating a dynamic QoS strategy into PPC is inferior to that achieved by timely updates of the dynamic QoS strategy.

Figure 24 shows the capacity (the total number of robots) that can be supported with a given amount of total power consumption provided by PPC-based dynamic QoS (strategy 2). It can be observed that the dynamic QoS strategy in packetized predictive control can further increase the capacity (the number of robots supported) with the same total power consumption compared with strategy 1 and significantly increase compared with baseline1. If the power consumption is selected as 1W, the results show that the average capacity of the PPC-based dynamic QoS strategy (strategy 2) is increased by 42.12% when compared to URLLC services (baseline 1) and when compared to Dynamic QoS strategy in the time sequence (strategy 1), the average capacity however increased by 10.1%.

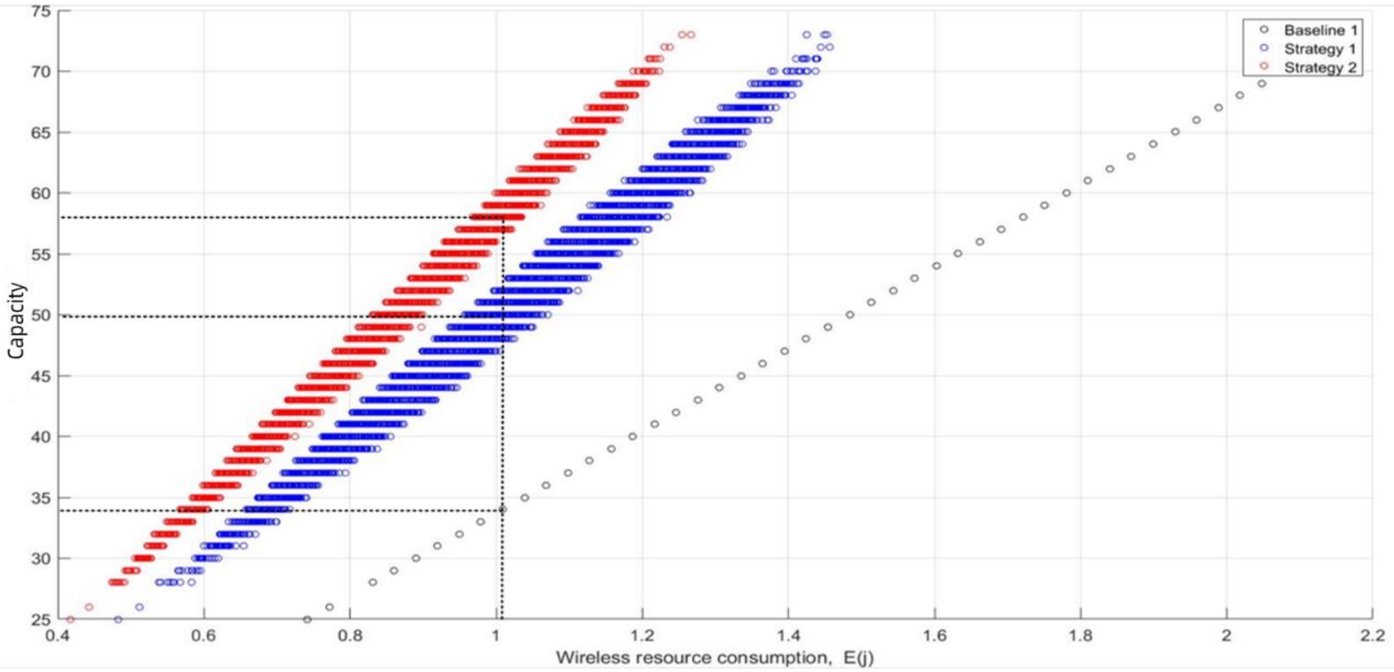


Figure 24. The capacity of proposed strategy 2, strategy1 and baseline 1 (URLLC service) versus total power consumption with working duty cycle 50%.

6.5.3 The Exploration of Parameters in Simulation

In this part, the relevant parameters that may affect gain are analyzed and explored qualitatively. We mainly consider the following parameters in this section: duty cycle, the number of robots, QoS update frequency, packet length (bits) and the range of communication reliability in this system. We can assume that E_1 represents the average value of wireless resource consumption E when applying proposed strategy 2: Dynamic QoS strategy in packetized predictive control and E_2 represents the average value of wireless resource consumption E when applying traditional baseline 1: URLLC service. Without loss of generality, the performance gain is defined as:

$$Gain = \frac{(E_2 - E_1)}{E_2} \tag{32}$$

Figure 25 and Figure 26 consider the effect of the number of users and the duty cycle of the robots on the performance gain respectively. The results in these two graphs show that with these parameters change, the gain is essentially stable around a fixed value. In other words, the gain is independent of these parameters. The reasonableness of this can be attributed to the fact that both the wireless resource consumption of URLLC services and dynamic QoS exhibit a linear increase in direct proportion to the number of users and total number of tasks. The observation is noteworthy that when the number of robots falls below 100 in Figure 25, there exists a minor fluctuation in the gain. This can be attributed to the limited sample size during this period, which exerts a weak influence on the resultant gain.

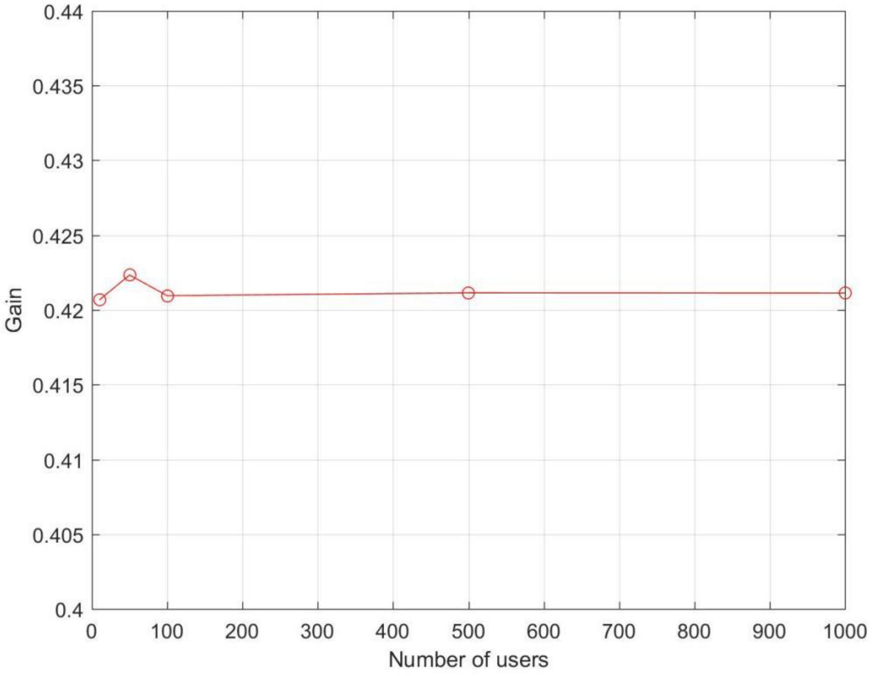


Figure 25. The relationship between the number of users and the gain.

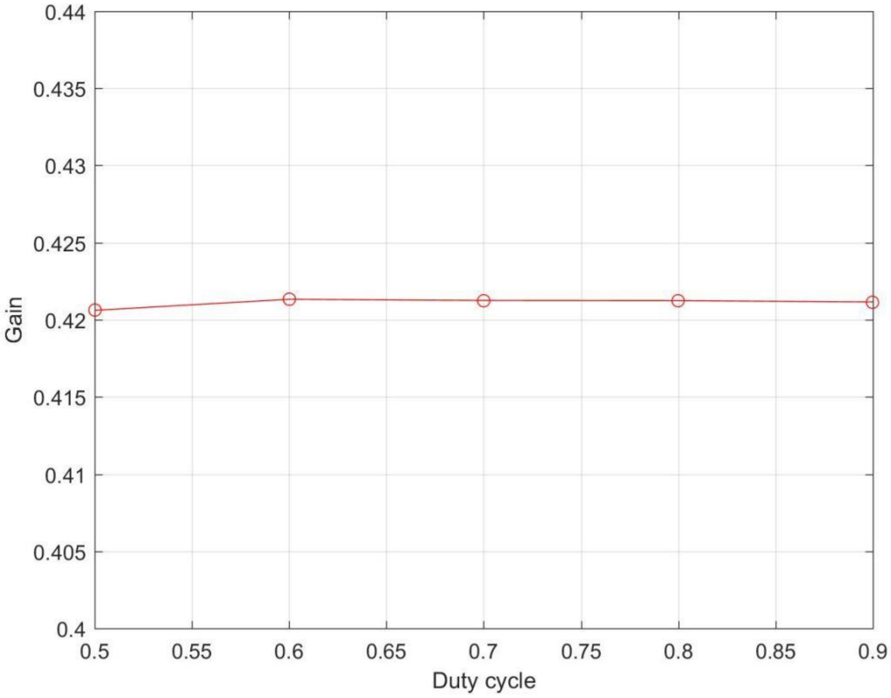


Figure 26. The relationship between the duty cycle and the gain.

The results shown in Figure 27 demonstrate that with the increment of the time slot length of the grouping, the performance reduction will further decrease. The reliability of each group is allocated according to the highest requirements. The starting point of this curve represents the dynamic allocation of QoS in each time slots, and the endpoint represents the situation when the group is 1000 which is equal to baseline 2, where the wireless resource consumption is not dynamically optimized. It can be observed from the change trend for the gain under different update frequencies. This result shows that the gain decreases monotonically as the update frequency increases. When QoS is updated once in 200 time slots, the performance gain will become 0.26. This indicates that in the proposed application scenario, the update frequency of communication QoS also affects the performance of reducing wireless communication consumption.

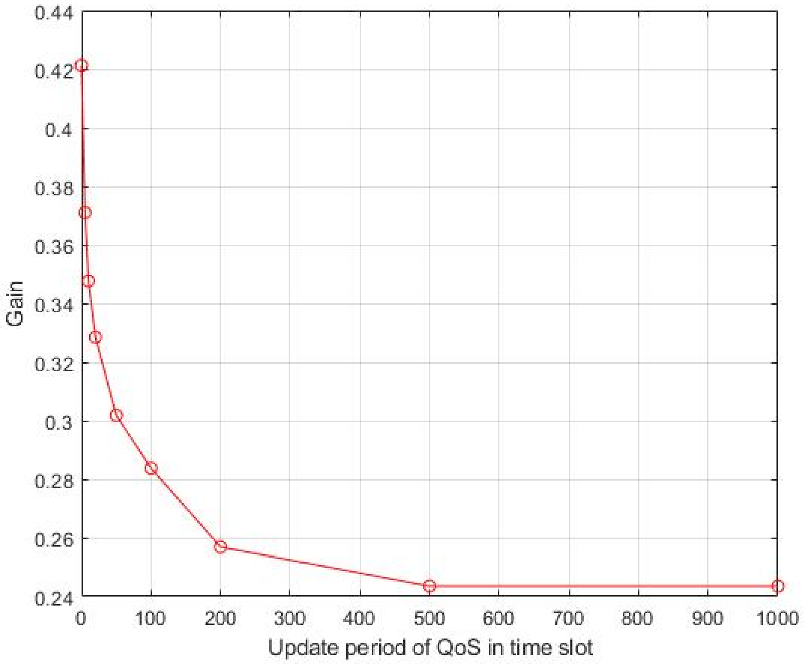


Figure 27. The relationship between QoS update frequency and gain.

Figure 28 and Figure 29 show the influence of the number of bits in one packet, the range of reliability on the gain respectively. The results indicate that these two parameters have significant effect on the gain. In Figure 28, assuming the number of head bits in one packet is 32 bits. Then we increase the payload bits continually by 4 bits until the total number of bits of one packet is 1000. As can be seen from Figure 28, within the short packet range, the gain shows a monotonically decreasing trend as the bits in one packet increases. After the bits in one packet is increased beyond 200 bits, the gain will become stable. At this point, it only has the gain from packetized predive control strategy. This observation explains the superiority of the dynamic QoS scheme in a short-packet environment. Figure 29 shows the relationship between the upper bound of reliability and the gain. The lower bound here is a fixed value 10^{-2}. This figure shows that the gain monotonically decreases as the reliability range increases. The implication is that under more stringent task requirements and communication environments, dynamic QoS strategy can yield greater benefits compared to traditional URLLC service.

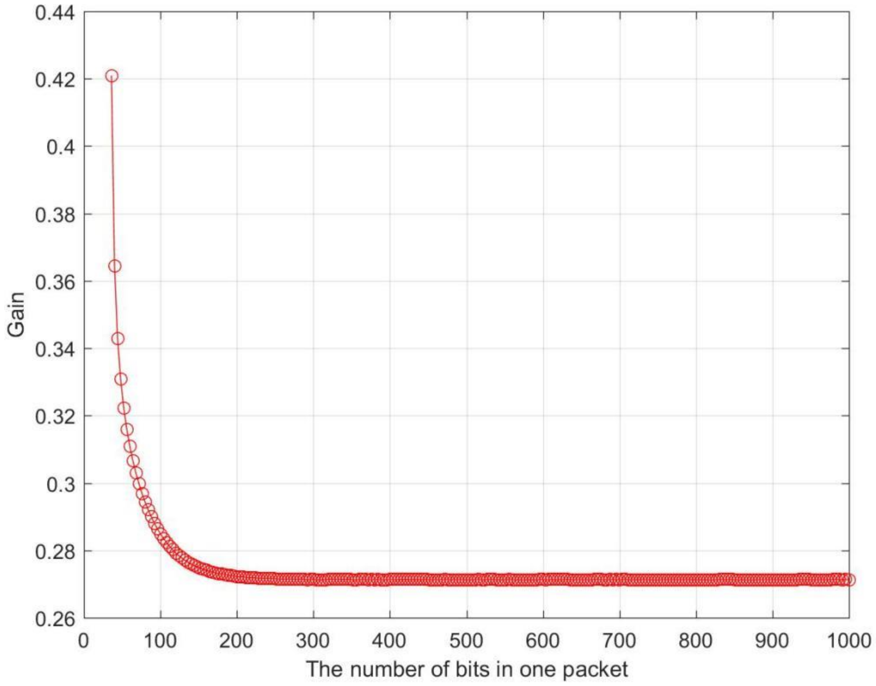


Figure 28. The relationship between the number of bits per packet and the gain.

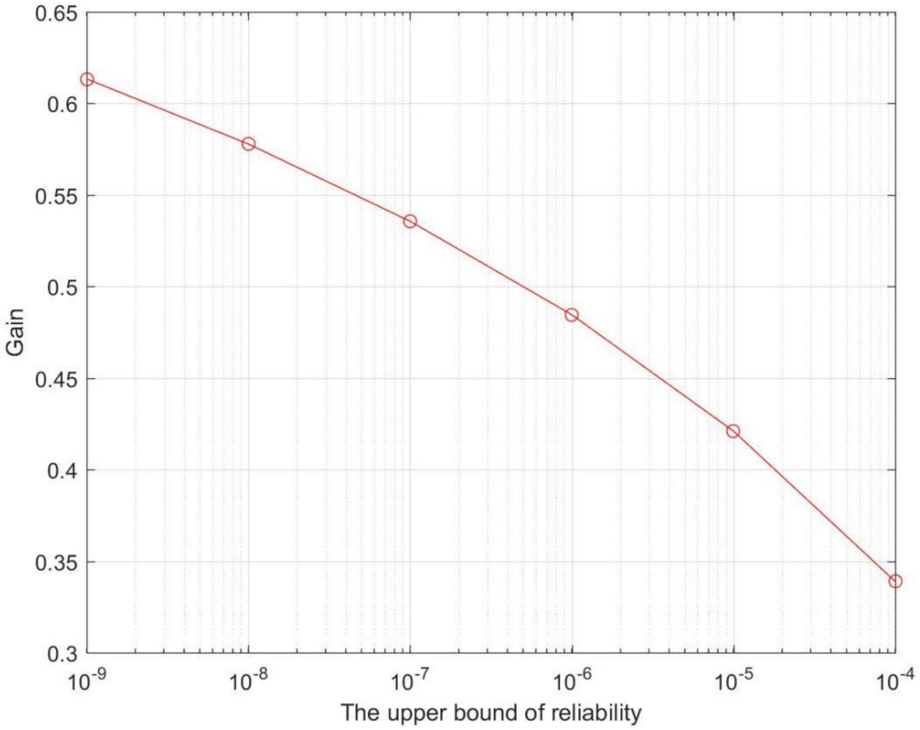


Figure 29. The gain of different reliability requirements

6.6 Conclusion

Chapter 6 introduces a packetized predictive control (PPC) into the design system, building upon the model presented in Chapter 4 and incorporating dynamic QoS from Chapter 5, with the aim of further minimizing wireless resource consumption.

Firstly, we introduce the typical System model prediction models of data packets, namely the Single-User System model and Multi-User system model. Subsequently, by formulating the problem, we optimize both the packet prediction length K and subcarrier bandwidth allocation in order to minimize wireless resource consumption. Additionally, we provide an algorithm to solve this problem. Moving on to the next section, we analyze the simulation results. Initially, we present the simulation parameters for this part and obtain the result of wireless resource consumption within a range of 1 to 11 for different prediction lengths. Consequently, it is observed that when the prediction length is set at 3, wireless resource consumption reaches its lowest point and thus represents an optimal value for this parameter. Furthermore, we present a CDF analysis of total wireless resource consumption for PPC strategy implementation. The obtained results demonstrate that after incorporating PPC strategy compared with dynamic QoS strategy discussed in Chapter 5, there is a significant system gain of 14.16%. Moreover, when comparing with URLLC service alone, our system achieves a remarkable improvement with a system gain as high as 42.51%. Finally, we calculate the system gain brought by PPC policy in terms of system capacity compared with URLLC service and dynamic QoS strategy implemented over time series data points. The simulation results reveal that average capacity under PPC-based dynamic QoS strategy (Strategy 2) increases by 42.12% compared to URLLC service (Baseline 1) and dynamic QoS strategy applied in time sequence (Strategy 1), while achieving an additional average capacity increase of 10.1%. In the final section, a qualitative analysis and discussion of relevant parameters affecting gain is presented. The following parameters are considered: QoS update frequency, duty cycle, number of robots, packet length (bits), and communication reliability range of the system. Results indicate that the first two parameters have minimal impact on the system while the last three significantly affect system gain.

The simulation results show that PPC is an effective solution to conduct robust control over unreliable wireless links. By using PPC, wireless resource consumption can be significantly minimized while guaranteeing desired control system requirements (control convergence rate). In addition, by leveraging the wireless resource consumption and the prediction length of PPC, the optimized prediction length, which is further used to optimize the total wireless resource consumption in the multi-user application scenario, is computed.

The next chapter presents simulation results of using Channel Scheduling to design dynamic QoS and illustrates the system benefits this approach can bring.

7 Channel Scheduling for Dynamic QoS

In chapter 4, a third mapping between communication reliability and wireless resource consumption is proposed. Such a mapping is achieved by considering a frequency-selective channel for each robot arm. In addition, a discussion on how channel scheduling affects the performance of the dynamic QoS strategy is provided.

7.1 System Model

In practice, considering that AGVs are placed in different locations, it is reasonable to assume that they are subject to different wireless channel environments (or delay spread), which contributes to different frequency selective channel for those users. By taking such an assumption into account, we first construct the channel model for all users in time *k*, as been illustrated in Figure 30, where $H_k = [h_{k,1}; h_{k,2}; \cdots ; h_{k,m}]$ is the channel response matrix. Vector $h_{k,i}$ contains the channel response for user *i* in time *k*, while each element $h_{k,i(j)}; i \in (1, M)$ denotes its channel gain on the *j*-th subcarrier.

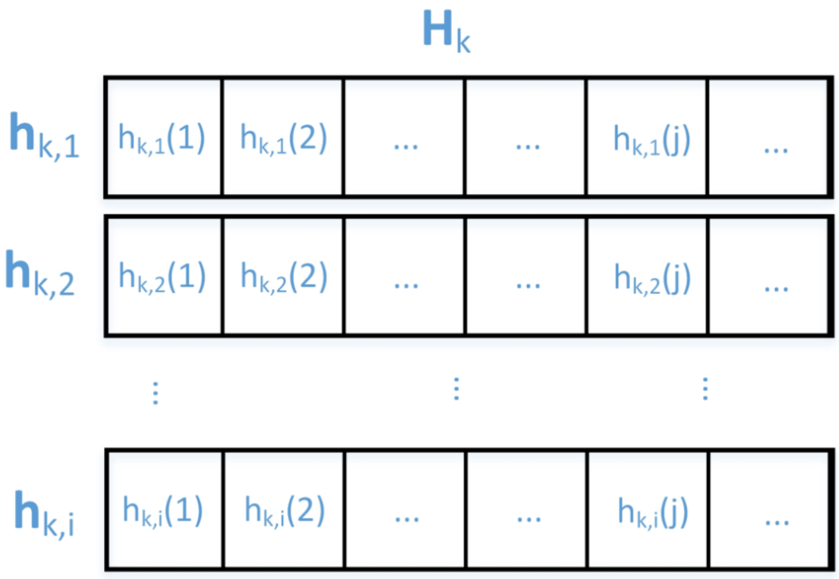


Figure 30. Channel model in time *k*.

With the channel matrix H_k and the Shannon capacity formula, we can calculate the transmission rate of each user *i* on subcarrier *j* as:

$$r_{k,i}(j) = log_2(1 + \frac{|h_{k,i}(j)|^2 P_0}{d^\alpha N_0}) \tag{33}$$

where P_0 and N_0 are the transmit power and noise power, respectively. d denotes the distance between AGVs and the BS, while α is the pathloss coefficient. In the same time, the corresponding channel capacity can be calculated as:

$$C_{k,i}(j) = r_{k,i}(j)\Delta f \tag{34}$$

where Δf is the subcarrier spacing.

7.2 Problem Formulation

Assume T_B as the transmit block size (TBS) for all AGVs, which should be propagated within one time slot (t_s = 0.5ms) to meet the latency requirement. Thus, a minimum required transmission capacity for each robot can be obtained:

$$C_0 = \frac{T_B}{t_s} \tag{35}$$

The communication reliability in terms of capacity loss probability could be derived based on a Rayleigh fading channel. Considering the real-time Shannon capacity, which is represented as:

$$C(t) = Blog_2(1 + \frac{\gamma(t)P_t}{d^\alpha N_0}) \tag{36}$$

where B is the bandwidth, P_t and N_0 are the transit and noise power, respectively. The distance between the transmitter and the receiver is d. In addition, denotes the path-loss factor. γ(t) is the envelope of the considered Rayleigh fading channel, whose probability density function (PDF) can be characterized as the following negative exponential distribution:

$$p_\gamma(x) = \frac{1}{2\sigma^2} e^{-\frac{x}{2\sigma^2}} \tag{37}$$

where σ is the Rayleigh distribution co-efficient. Assume C_t as the threshold of the communication capacity, hence, the channel will outage when

$$C(t) < C_t \tag{38}$$

Thus, the capacity outage probability can be written as

$$\Pr\{C(t) < C_t\} \tag{39}$$

which can be further derived as:

$$Pr\left\{\gamma(t) < \left(2^{\frac{C_t}{B}} - 1\right)\frac{d^\alpha N_0}{P_t}\right\}$$

$$= \int_0^{\left(e^{\frac{C_t}{B}}-1\right)\frac{d^\alpha N_0}{P_t}} \frac{1}{2\sigma^2} e^{-\frac{x}{2\sigma^2}} dx$$

$$= 1 - e^{-\frac{\left(e^{\frac{C_t}{B}}-1\right)\frac{d^\alpha N_0}{P_t}}{2\sigma^2}} \tag{40}$$

On the other hand, based on the capacity outage probability in (40), a minimum transmission rate requirement for robot i could be given as:

$$R_i = log_2(1 - \frac{2\sigma^2 P_t}{d^\alpha N_0} \ln\left(1 - \varepsilon_{k,i}\right)) \tag{41}$$

Where $\varepsilon_{k,i}$ is required communication reliability for robot i, and σ is the parameter of the corresponding Rayleigh fading channel.

7.3 Simulation Results

In this section, numerical results are provided to show how the fading channels could affect the performance of the dynamic QoS strategy. Specifically, by implementing the scheduling method, the performance of baseline strategy 1 (i.e., all AGVs are served by URLLC services, which means that the communication service is provided with the highest possible communication reliability throughout the entire simulation length.) and the dynamic QoS are compared in terms of the system capacity (i.e., number of supported robots) and the idle resource rate (i.e., the percentage of subcarriers that cannot be utilized). Moreover, simulations are performed based on different parameter configurations, as shown in Table 4, which could help us to reveal the relationships between dynamic QoS performance and system settings.

Table 4. Simulation Configurations for Dynamic QoS Strategy in Channel Scheduling

Parameters	**Settings**
The number of robot arms M	300
On/Off probability	80%/20%
Robotic arm velocity v (m/s)	[1:0.02:3]
Communication reliability ϵ	10^{-3} ~10^{-5}
Control sample period t_s (ms)	0.5
Payload size T_b	300
Subcarrier spacing Δf (kHz)	15k
Transmit power on each subcarrier (W)	0.02
Rayleigh channel parameter σ	0.5
Coverage distance d (m)	100
Path loss coefficient α	4

Considering that each robot is required to handle multiple tasks, the adoption of a greedy algorithm is essential to ensure local optimal solutions at each step, thereby achieving an overall optimal solution for the problem. It can be observed from Figure 31, the number of users of both baseline strategy and the dynamic QoS strategy gently increases with the rising transmit power. More specifically, when the transmit power increases from -25dB=Δf to -17dB=Δf, the number of supported users with baseline strategy and dynamic QoS strategy growths from 31 to 120, and 79 to 180, respectively. Accordingly, the capacity improvement with the dynamic QoS strategy shows a descending trend, i.e., a decrease from 175% to 50%. Therefore, although the capacity of the system can be boosted by using larger transmit power, it brings less gain by applying the dynamic QoS strategy. When the power increases to a certain extent, with only a fluctuation value of approximately 4 users, the number of users supported by dynamic QoS policy and URLLC service tends to stabilize.

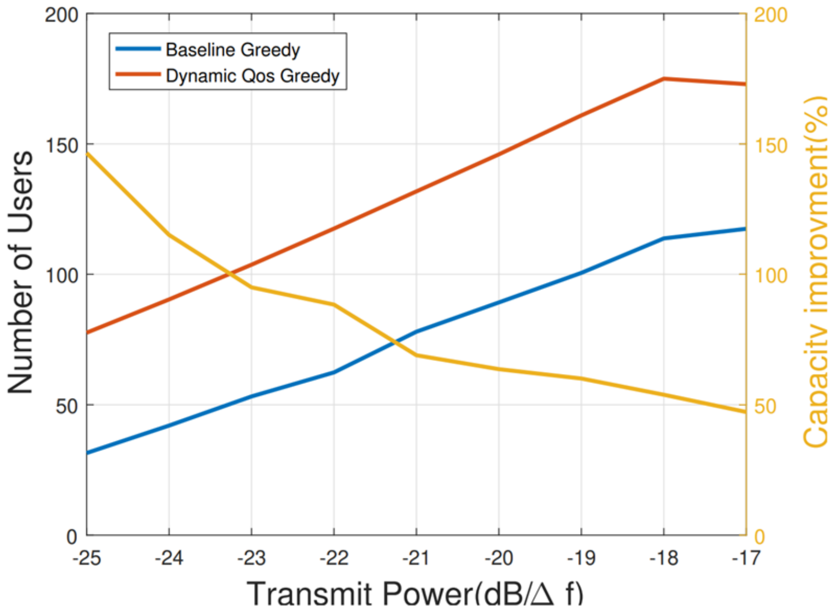


Figure 31. Transmit power versus number of supported users.

7.4 Conclusion

Chapter 7 is based on the third mapping model proposed in Chapter 4, which establishes a relationship between communication reliability and wireless resource consumption. This model takes into account the frequency selection channel of each robot arm to achieve its objectives. Furthermore, the impact of channel scheduling on dynamic QoS strategy' performance is also discussed with the aim of further reducing wireless resource consumption.

Firstly, the typical channel model in time dimension is introduced. Subsequently, a minimum transmission rate requirement for robot is obtained by formulating the problem in formulaic form. In the next section, we will analyze the simulation results and provide the simulation parameters for this part. Through the simulation results, it can be observed that when the transmit power increases from -25dB to -17dB, both baseline strategy and dynamic QoS strategy show an increase in supported users from 31 to 120 and 79 to 180 respectively. However, there is a downward trend in user capacity increase rate which decreases from 175% to 50%.

The simulation results demonstrate that although both baseline and dynamic QoS strategies show slow growth in terms of supported users with increasing transmit power, employing dynamic QoS policy brings less improvement despite enhancing system capacity.

The next chapter presents simulation results of using task scheduling to design dynamic QoS and illustrates the benefits this approach can bring to the system.

8 Task Rescheduling with Flexible Delays

In this Chapter 8, resource allocation for delay at the task level in wireless-control system is investigated and a TRDA profile is proposed to reduce the peak value for the total resource allocation consumption for each time slot. This profile considers the dynamic QoS characteristics, real-time resource requirements and the priorities for every task. Each task has a different priority, and then generated priority functions of them. The resource is allocated dynamically according to these functions. Simulation results indicate that TRDA works much better than traditional methods and achieves the target of reducing the peak to average ratio of total resource consumption and increasing the system capacity.

8.1 Method

8.1.1 Transmission Scheduling

Transmission scheduling is used to define the priority for every task. The tasks are categorized into different classes based on their roles. The high class provides vital messages of control, protection, and management. Those who carry meter readings or transmit delay-tolerant data, belong to the low class. This means that low-class tasks can be deferred in time whereas high-class tasks would have detrimental impact on the system's performance.

However, when some emergencies happen, such as the damage or regular hard check of devices, the tasks should have high priority for transmission to report the emergencies. Therefore, emergency priority of tasks should be beyond the normal tasks.

Besides, interruption during data transmission is more unexpected than being blocked occasionally on a new transmission. An interrupted task will have a higher priority to finish its interrupted transmission than a newly arrived task. Therefore, in the same class, the interrupted task should have higher priority than the newly arrived task. Similarly, the interrupted emergency tasks have higher priority than the newly arrived emergency tasks.

Therefore, there are four priority queues for transmission scheduling. Being sorted from high to low priority, they are primary tasks, interrupted emergency tasks, newly arrived emergency tasks, interrupted tasks, and newly arrived tasks. During transmission, tasks should queue according to their priorities. In each priority queue, tasks are sorted by their classes in decreasing order. When the resource consumption of a time slot is very high, the tasks with low-class move to the tail of the queue.

8.1.2 Task-based resource dynamic allocation

In this section, we consider QoS changes dynamically with time granularity and consider delay issues at the task level in industrial scenarios. Based on the actual situation, we make the following assumptions.

In terms of time delay, we assumed when the task is called, some tasks need to be executed immediately while some tasks can be deferred in the range of N samples. Based on the priority of the task, we defined tolerance degree of delay. It is assumed that different tasks have different tolerance degree of delay. Tolerance degree of delay is inversely proportional to the priority of the task. The lower the delay tolerance, the higher the task priority which will be executed first at each sampling point.

As shown in Figure 32, the first step is to define the priority function Y_n and assign a random priority index to each task. Then set a threshold U_{th} , if the resource consumption exceeds this value, then the task in this time slot needs to be delayed later.

Then define the value of the delay allowed for each task. The next step is to delay the task. If resource consumption U_i at a time slot is greater than the threshold $U_{t\hbar}$, we defer some tasks in the range of N samples. According to the priority function, we first defer the lower-priority tasks. Finally, the result is that the resource consumption at each time slot falls below the threshold.

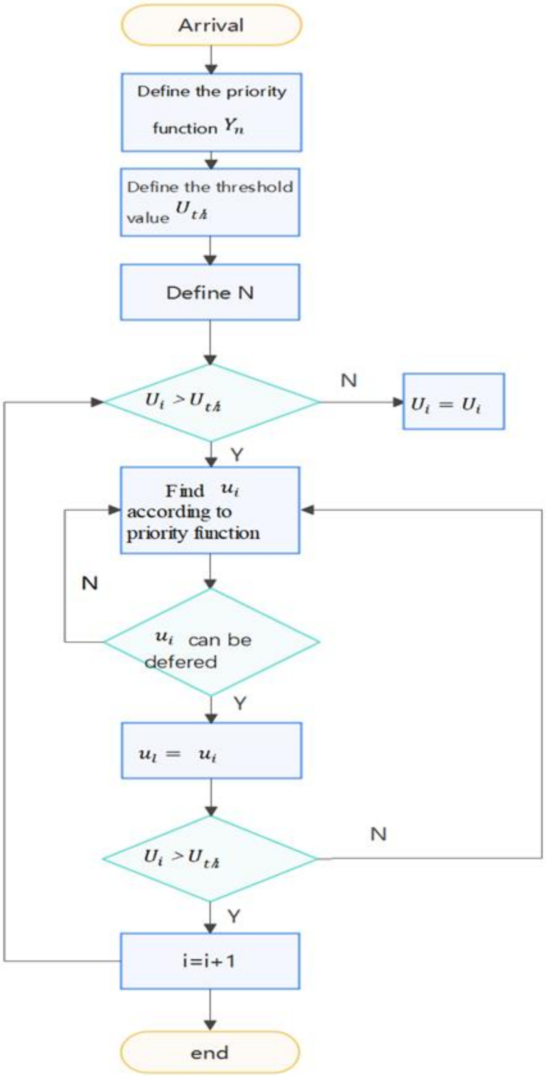


Figure 32. Task-based resource dynamic allocation

8.1.3 Algorithm

Algorithm 2 TRDA strategy based on dynamic QoS design

```
Input: $C_t$-Shannon Capacity; $P$-Transmit Power; $t$-Working times
    $\sigma$-Rayleigh channel parameter;$\alpha$-Path loss coefficient;
    $p$-working probability;$p_s$-Communication reliability;
    $T_B$-Payload size;$T_s$-Time slot duration;$N_0$-Noise power;
    $R_0$-Number of robots;$t$-working times;$X$-Maximum delay
Output: $B$-Bandwidth consumption;
Randomly set $p_s$ 0.99 to 0.99999
Calculate the bandwidth consumption accroding to different communication reliability by $B = C_t \div log_2(1 - ((2 * \alpha^2 * P * log(p_s))/((d^\sigma) * N_0)));$
for $i$=1 to $R_0$ do
    for $j$=1 to $t$ do
        Calculate bandwidth consumption $B$ per robot per working time based on dynamic QoS strategy;
    end for
end for
Calculate the sum of bandwidth consumption $B_{sum}$ per working time;
Calculate the peak value of the sum of bandwidth consumption $max_{Bsum}$;
Set the threshold value for the goal $B_{sum_{th}}$;
Generate different weight values for different tasks into 4 levels;
for $i$=1 to $R_0$ do                    ▷ Task Delay for the lowest priority robots
    if $B_{sum}(i) > B_{sum_{th}}$ then
        Defer the current task until the nearest idle period in the $X$ range;
        Set $B_{sum}(i)$ to zero
    else
        The current task cannot be defered
    end if
end for
Task Delay for the second lowest priority robots;
Task Delay for the third lowest priority robots;
Task Delay for the highest priority robots;
```

8.2 Simulation Results

To evaluate the proposed task-based resource dynamic allocation, a simulation environment was designed in MATLAB. Table 5 shows the fundamental simulation parameters for the proposed scenario. We consider one hexagonal cell is served for one customized production workstation, where a BS is deployed at the centre of the cell with the distance between the base station and the plants is 100m. We assume that the bandwidth of each subcarrier is $15kHz$. For URLLC, the maximum packet transmission error probability is "ε_{th} =10^{-5}, the maximum transmission time delay for the uplink is T_{th}= $0.5ms$.

For the task profiles, without loss of generality, we assume that the mechanism of consuming time-frequency resources conforms to the on / off model modelled as a standard Bernoulli process with an ‘on’ probability 80% and an ‘off’ probability 20%, which is also known as the duty cycle. For simplicity, we assume that each control cycle is completed in one time slot. Besides, we set the threshold at 8% of the original peak and each task could be delayed in the range of 5 time slots.

Table 5. Simulation Configurations for Dynamic QoS Strategy in TRDA

Parameters	**Settings**
The number of robot arms M	100
On/Off probability	80%/20%
The threshold value of target	$20\% \times U_{th}$
Tolerance of task delay N	5
Control sample period t_s (ms)	0.5
Subcarrier spacing Δf (kHz)	15
Rayleigh channel parameter σ	0.5
Coverage distance d (m)	100
Total bandwidth B (MHz)	20

Figure 33 shows that the wireless subcarrier consumption of proposed strategy TRDA and dynamic QoS strategy in time sequence. The straight line represents the average subcarrier consumption across different scenarios, which coincides with the average consumption of both strategies. This indicates that the peak value for wireless subcarrier consumption is reduced by 8% compared to the baseline. It is reasonable to observe this reduction in peak value for the proposed strategy as lower-priority tasks are deferred to later idle periods, without altering the total resource consumption or affecting the average resource consumption. In summary, while maintaining performance, the proposed TRDA strategy effectively reduces the peak-to-average ratio of wireless subcarrier consumption.

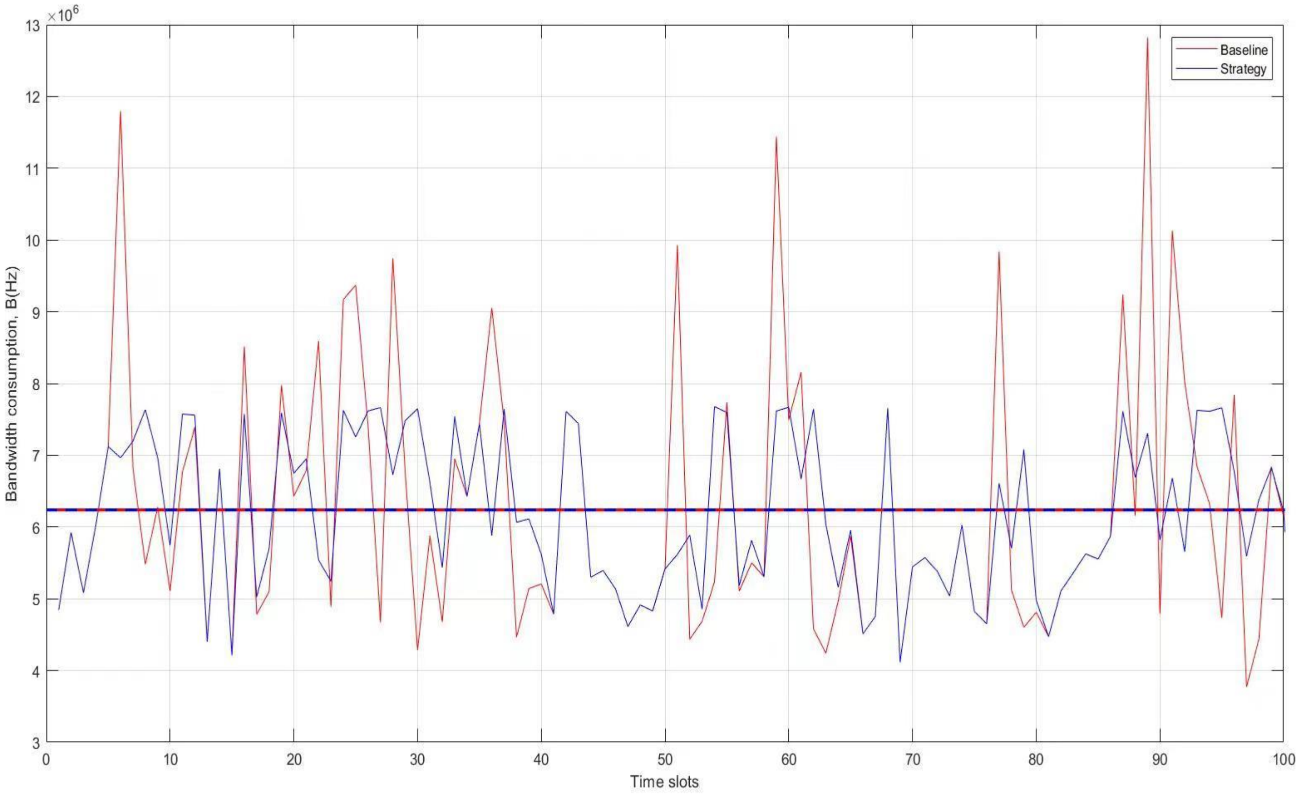


Figure 33. Total subcarrier consumption of proposed TRDA strategy 1 versus Baseline

Figure 34 shows the CDF of TRDA strategy and baseline. We define the Y label as being activated user's probability, which represents the percentage of total robots that work. From this graph, with the same number of users activated simultaneously, the proposed TRDA strategy can significantly increase the system's capacity. For instance, at CDF =0.5, the capacity of the proposed strategy when compared to the baseline is increased by 21.3%. It is also evident that the TRDA strategy is more likely to serve more users which can further explore the cell capacity.

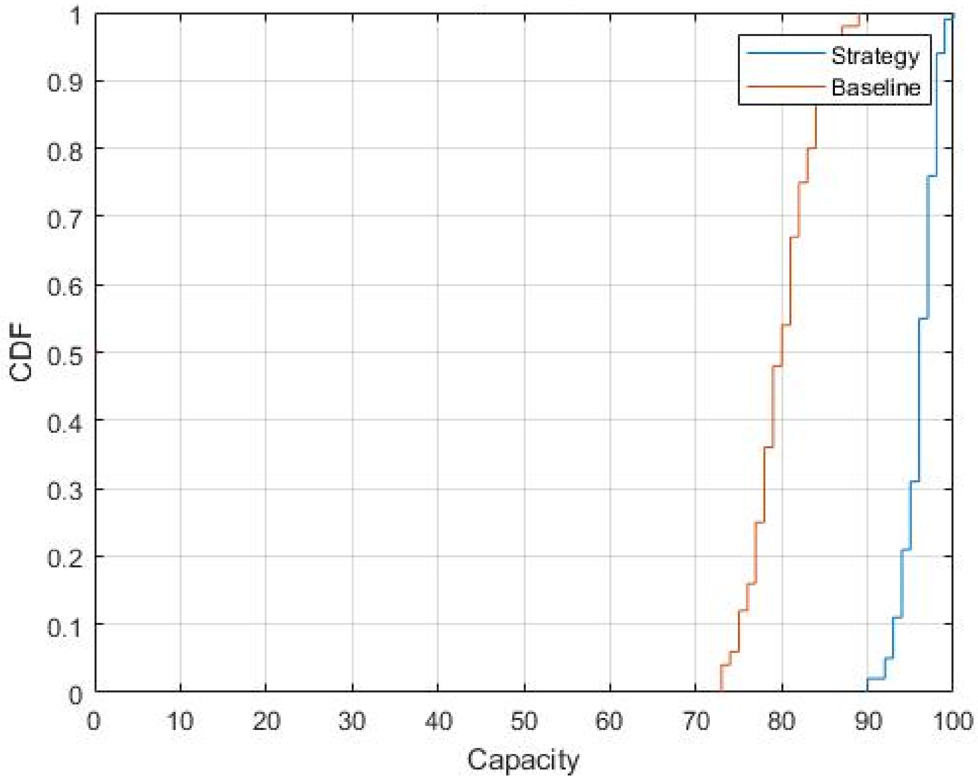


Figure 34. The CDF of total BS transmit power of proposed dynamic QoS strategy 1 versus legacy scheme.

8.3 Conclusion

Chapter 8 investigates the problem of task-level delayed resource allocation in wireless control systems, and a TRDA model is proposed to mitigate the peak consumption of total resource allocation per slot.

Firstly, the principle of task scheduling and the definition of transmission scheduling are introduced, along with specifying the prioritization of tasks. Subsequently, a factory profile is developed based on task priority, and task adjustments are made according to this profile and workflow.

In the simulation result section, we first present the simulation parameters pertaining to this component. Subsequently, we analyze the simulation outcomes of both the proposed TRDA strategy and the dynamic QoS strategy. The results indicate a consistent average subcarrier consumption between these two strategies. Upon incorporating the task scheduling strategy, there is an 8% reduction in peak wireless subcarrier consumption. Finally, we examine the impact of task scheduling strategy on system capacity by analyzing CDF data which reveals a 21.3% increase in capability for the TRDA strategy.

Simulation results demonstrate that the proposed strategy effectively reduces the peak by deferring low-priority tasks to subsequent idle periods, while maintaining total resource consumption and average resource consumption unchanged. In conclusion, the TRDA strategy demonstrates its capability to serve a larger number of users without compromising performance, thereby maximizing cell capacity.

9 Conclusion and Future Work

In recent years, extensive research has been conducted in the field of 5G communication. URLLC, as a prominent characteristic of 5G, has witnessed a significant surge in research topics focusing on the integrated design of URLLC and communication control, both in terms of breadth and number of scholarly papers. This remarkable trend reflects the growing interest in the field since its emergence into the spotlight around 2015. The advent of the Industry 4.0 enhances the optimization of manufacturing processes, making them more intelligent, customized, and service-oriented, thereby elevating the overall consumer experience. The high reliability and low latency feature inherent to 5G make it particularly suitable for applications within Industry 4.0 scenarios, aligning with the current market demand for advanced communication engineering solutions. The most prominent characteristic of Industry 4.0 is the real-time and customizable production, which necessitates the real-time processing and utilization of data to meet customers' customization needs. Leveraging its flexibility and URLLC features, 5G technology presents a promising solution for enhancing equipment access and communication within factories.

This thesis provides an overview of the historical background and distinctive features associated with both 5G technology and Industry 4.0 concept while elucidating why and how these two can be effectively combined within Industry 4.0 scenarios. Despite some existing relevant cases, today's society still grapples with a crucial issue: insufficient availability of communication resources. Therefore, it is imperative to minimize the utilization of such resources while ensuring feasibility within specific contexts to ultimately improve system capacity. In this digital era, from an individual standpoint, customizable services facilitated by Industry 4.0 cater to the diverse requirements while minimizing risks associated with machinery operations and processes; from a national perspective though automation may lead to workforce reduction at factories underpinning Industry 4.0 principles but simultaneously create numerous job vacancies elsewhere.

At the beginning of this study, several open research questions were identified in the literature, which have grown over the past few years with the development of state-of-the-art methods. The research described in this thesis contributes to addressing some of these issues, as described below.

9.1 Conclusion and contributions

The efficient utilization of communication resources is a critical aspect in industrial systems, as it not only enhances the overall system capacity but also mitigates constraints imposed by communication resource scarcity. Therefore, this thesis aims to **optimize wireless communication resource utilization while ensuring control system stability and reliability**.

Addressing **how industrial requirements impact communication bandwidth consumption** becomes the primary issue due to customizable user needs in the context of Industry 4.0. Since 2017, when the activities related to this thesis commenced, significant progress has been made in reducing the consumption of communication resources through various paper works. However, these studies have certain limitations, such as insufficient gains in some experimental designs and a lack of consideration for the characteristics of 5G and Industry 4.0 in algorithm design. Leveraging the features of Industry 4.0, A connection between user demands and communication consumption can be established to minimize resource consumption while meeting customer requirements and expanding support for Industry 4.0 scenarios. Notably, it is novelty that this thesis makes an original contribution by exploring how to link customer demand with communication resource consumption. In Chapter 4, a comprehensive framework for reconfigurable manufacturing systems was established at first, based on which a series of mappings were derived to form a real-time connection between customers' control requirements and the wireless communication reliability. Such mappings construct the foundation of the communication control co-design in this manuscript, and contribute to a dynamic QoS strategy, where the communication settings/scheduling methods could be dynamically configured according to the varying QoS requirements of users. This work aligns with the demands of the 5G era and advances in Industry 4.0 development.

After addressing the primary issue, the subsequent inquiry that required resolution was encountered: **How to effectively meet industrial requirements while optimizing the allocation of communication resources to accommodate a greater number of plant equipment**? The second issue concerns the limitation of system user capacity due to the constrained communication resources in the Industry 4.0 scenario. By employing the previously established approach, A dynamic QoS strategy designed to reduce the average communication resource consumption of the system was demonstrated. Through this scheme, the simulation work was carried out in the context of the Industry 4.0 scenario, and the simulation results in Chapter 5 indicate that the introduction of dynamic QoS strategy can effectively reduce the average power consumption of wireless resources and improve the system capacity. Compared to traditional URLLC service, this strategy can achieve a reduction of 35.7% in average wireless power consumption. Under various profiles, dynamic QoS strategy offer 25.3% to 35.7% more capacity than traditional URLLC services.

In the subsequent phase, to address the second issue and further enhance system capacity by reducing communication bandwidth consumption, three strategies were explored: packetized predictive control, channel scheduling, and task scheduling of industry in dynamic QoS design.

The simulation results in Chapter 6 have shown that after the introduction of PPC strategy, the consumption of wireless resources will be reduced to a certain extent. The PPC system exhibits significant advancements compared to traditional URLLC service, with a remarkable system gain of up to 42.51%. The average capacity under the PPC based on dynamic QoS strategy experiences a substantial improvement of 42.12% over URLLC service alone. Therefore, adding PPC strategy based on dynamic QoS can further reduce the consumption of wireless resources and bring higher system gain.

The simulation results in Chapter 7 have shown that after the introduction of channel scheduling, with the increase of power, for the increase of capacity, the channel scheduling strategy will be used, and it will have a higher proportion of gain increase. Within the channel scheduling scheme, as transmit power increases from -25dB to -17dB, both baseline policy and dynamic QoS policy witness an increase in supported users from 31 to 120 and from 79 to 180 respectively. Therefore, adding a channel allocation strategy based on dynamic QoS can further increase the system capacity and bring higher system gain.

The simulation results in Chapter 8 have shown that after the introduction of the proposed task-based resource dynamic allocation, the peak-to-average ratio for the consumption of wireless resources will be reduced to a certain extent. By implementing the TRDA strategy, wireless subcarrier peak consumption is reduced by 8%, resulting in a notable enhancement of system capacity by 21.3%. Therefore, adding a task-based resource dynamic-allocation strategy based on dynamic QoS can further increase the system capacity and bring higher system gain.

9.2 Impact

In this thesis, the challenges of communication resource consumption in the context of 5G and Industry 4.0 are discussed. The thesis achieves the mapping from customer's customized requirements to communication resources consumption through comprehensive analysis of results and data. Simultaneously, it ensures the smooth operation of the factory while reducing the communication resource consumption of the industrial system, thereby facilitating support for a larger user base.

The implementation of Industry 4.0 necessitates a highly dependable and low-latency communications infrastructure. Consequently, it becomes imperative to allocate a substantial number of communication resources in order to ensure the high reliability of this infrastructure. The findings presented in this paper enable the operation of intelligent factories while accommodating an increased number of users within the constraints of limited communication resources, thereby further enhancing production efficiency.

This research facilitated collaboration with Huawei, and through project development, successfully implemented various dynamic QoS-based schemes to demonstrate the feasibility of integrating 5G into the Industry 4.0 scenario. Ultimately, this research contributes to the field of 5G and Industry 4.0 by addressing existing literature gaps and proposing solutions for overcoming these challenges, thereby expanding human knowledge in this domain.

9.3 Limitations

The first limitation of this study is that it was designed based on a pre-existing profile, which may pose challenges if task design requires re-entry of instructions to meet customer requirements, thereby potentially diminishing production efficiency within the plant. Any alterations made to the plant's configuration would consequently disrupt its operations. However, in the context of Industry 4.0, particularly within warehousing and transportation environments, tasks tend to be diverse. If there is a high frequency of factory profile modifications, it can significantly impede task completion efficiency.

The second limitation of this research lies in the algorithm's processing time. In comparison to the conventional URLLC strategy, the dynamic QoS algorithm's complexity significantly prolongs its completion time when confronted with a substantial number of robots and tasks within the factory. The simulation in this thesis demonstrates that the traditional URLLC scheme only requires 1 to 2 minutes for execution when there are 100 robots, whereas the dynamic QoS algorithm takes approximately 6 minutes. When the number of robots was raised to 300, the runtime of the dynamic QoS algorithm increased to approximately 11 minutes. This implies that the algorithm exhibits computational intensity up to 11 times higher than conventional methods, rendering it impractical for average computers to efficiently handle such a substantial amount of computation within a limited timeframe. Consequently, when scaling up the number of tasks and robots in factory settings this necessitates increased expenditure on enhanced CPUs. Consequently, this delay adversely impacts the factory's production schedule.

The third limitation lies in the fact that the research remains at a simulation level and has not been implemented in an actual factory design. In real factory assembly lines, limitations arise from both accessory availability and the need to ensure overall industrial process safety. Consequently, these factors impose certain constraints on simulating industrial assembly lines.

For enterprises, although Industry 4.0 can offer numerous advantages to industrial production, from the perspective of future development, it has the potential to enhance production efficiency and reduce production costs. However, small and medium-sized enterprises face a primary challenge when it comes to industrial upgrading and transformation - the high cost of transformation. Automated production in Industry 4.0 demands substantial initial investments due to its requirements for intelligent manufacturing production lines or highly integrated industrial robots.

Furthermore, obtaining data from factories poses a challenge despite their primary purpose being beneficial for such systems; another common limitation and challenge pertains to dataset size and its applicability across different scenarios. In reality, various activities and confusions can occur within different factory assembly line situations. However, with increasing attention devoted to this field, these issues will gradually be resolved.

9.4 Future work

9.4.1 Extension of this thesis

For the short-term future work extending the research covered in this thesis, the Dynamic Energy Efficiency of Networked Control Systems over 5G for automatic guided vehicles in warehouse can be researched. The objective of this proposal is to minimize system energy consumption by implementing a dynamic energy efficiency system. In comparison to traditional schemes that meet fixed quality of service, this approach enables optimal spectrum allocation adjustment for maximizing control energy efficiency while maintaining actual control requirements. When the mobile robot moves in a straight line, the load can be reduced; however, when it navigates a curve, additional resources must be allocated to ensure adherence to its designated trajectory. The energy consumption of the system is reduced through the implementation of dynamic QoS design for AGV during straight line and curve driving.

During the previous years, mobile robots and autonomous vehicles have witnessed a remarkable evolution. These vehicles play an unquestionable role in the military, manufacturing and industrial fields [61]. They are also getting more and more included in other fields of study. Nonetheless, the batteries represent an important part of the cost of the equipment and its autonomy remains limited [61]. In fact, the use of the batteries as a source of nourishment in each electric vehicle raises several challenges such as the recharging period which is relatively long or the limited lifetime of the battery. The level of the used energy is straightly linked to the path planning. It is fundamental to take into consideration the energy standard in path planning.

One of the use cases studied in the project, in the context of the Industry 4.0 paradigm, is novel deployment strategies for AGVs in factories. These use cases will significantly benefit from 5G. AGVs allow important improvements in the temporal and spatial flexibility of the production lines by adjusting the distribution and cadence of the production flows.

Aligned with the essence of this thesis, the proposed future work topic is aimed at solving the problem of energy cost through a communication-control co-design, which considers the communication coefficient and the control coefficient jointly. In the original research, the goal is to dynamically reduce resource consumption while maintaining good control performance. Therefore, the goal here is to maximize the spectral efficiency and control energy efficiency by optimizing resource allocation while maintaining the control performance by considering a scenario where an AGV is running in a warehouse.

On this topic, many scholars have studied the energy consumption in the planning process. The optimized process of robot applications can contribute to energy conservation in reference [61]. A planning and control method considering the path energy consumption was proposed in reference [62]. Reference [63] improved the sampling-based path planning algorithm and designed a two-step algorithm to reduce energy consumption while in motion. Reference [64] proposed to apply the improved Newton algorithm to the motion planning of nonholonomic robots. The process of energy optimization was considered in the establishment of the motion matrix. Reference [65] achieved minimum energy by reducing the steering drive of the robot. Reference [66] smoothed the generated path during the trajectory planning process, thereby reducing unnecessary energy consumption in robot motion.

Figure 35 provides a real-world scenario demonstration with actual components [67]. This figure also shows the path trajectory, delimited by a magnetic band with a lemniscate-shaped (figure-eight) path. The AGV is placed on top of this path, and the main objective of this use case is that the AGV efficiently follows the path with minimal deviation (i.e., guide error) and energy consumption.

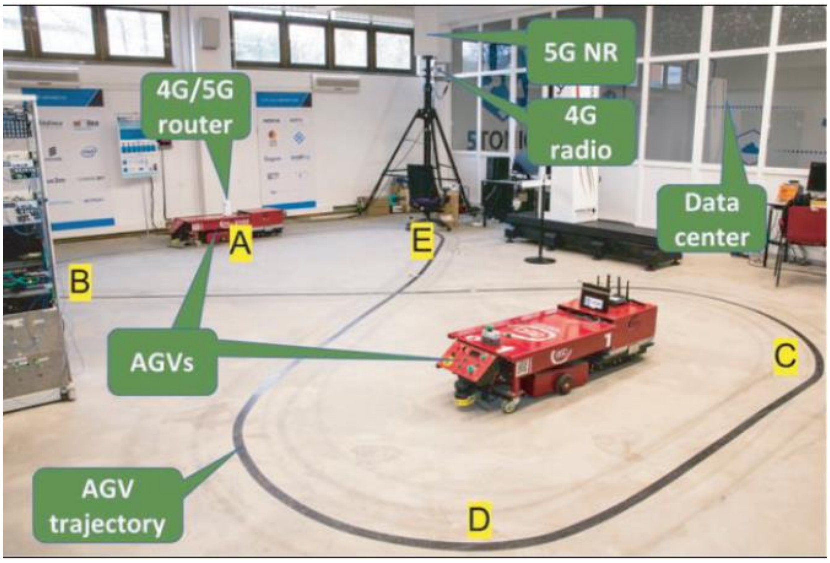


Figure 35. The main components of the use case [67].

This AGV is a mobile industrial platform equipped with

1. Sensors to measure critical variables such as the guide error, current consumption, battery status, and wheel velocity.
2. Actuators, which comprise the motors and the wheels, to perform the guided movement following the received instructions from the master PLC (Programmable Controller).
3. A slave PLC (sPLC) connected to one of the Ethernet ports of a 4G/5G router, responsible for transmitting this sensor information to the mPLC

9.4.2 Future research trend in 5G URLLC

With the fifth-generation mobile communication standardization, the vision of 5G is to realize the Internet of everything. Unlike previous generations that only focus on improving speed, the development of 5G emphasizes scenario-oriented adaptation. In order to achieve interoperability between the industrial control protocol and 5G URLLC, a set of standards for the industrial control field will need to be developed in the future. For example, 5GAA (5G Automotive Association) is currently being developed by relevant agencies [67]. Secondly, With the continuous expansion of 5G network coverage and application scenarios, the integration of industrial control protocols and 5G URLLC technology will no longer be limited to existing manufacturing operations, but will also involve more industries such as transportation, energy, and logistics [67]. Thirdly, it is necessary to further study and develop the compatibility and performance optimization of industrial control protocols and 5G URLLC, which will involve the research and development of key technologies such as network slicing and delay optimization [68].

In addition, under the guidance of the IMT-2020(5G) promotion group, a test on 5G enhancement technology for URLLC key technology was conducted to verify improvements in URLLC functionality and network performance metrics such as delay and transmission reliability [69]. However, the results indicate that the development of 5G applications still faces challenges including insufficient terminal and network supply capacity, as well as a lack of application standards. Therefore, it is necessary to further strengthen the supply of high-quality technological solutions in order to facilitate the integration of 5G across various industries. Key technologies such as 5G dedicated frame structure, uplink carrier aggregation can be employed to assist multiple types of networking in jointly enhancing uplink capability.

9.4.3 Future research trend in Industry 4.0

Beyond the research question studied in this thesis, in industry 4.0 application scenarios, intelligent assistance for complex services has emerged as a prominent topic of interest. AI holds significant potential in facilitating decision-making processes. The vast scale of traditional industries offers ample opportunities for the application of AI in decision support [70]. Numerous industrial intelligence projects exhibit substantial promise. As per Harris's data [71], the implementation of AI in manufacturing, resource, and other sectors has yielded considerable impact, particularly in predictive maintenance, product quality enhancement, product feature expansion, operational efficiency optimization, and various other domains.

In the future, Industry 4.0 will drive the automation and intelligent evolution of production processes, leading to wider adoption of robotics, autonomous driving systems, unmanned equipment, and automated warehousing systems in order to enhance the intelligence of production lines and improve production capacity. With the expansion of Industry 4.0 applications, data security and privacy protection will also become an important issue. Experts expect that in the development of Industry 4.0, more sophisticated data security and privacy protection strategies will emerge to ensure data security and compliance [72]. Besides, Industry 4.0 will further promote the development of human-machine collaboration, and people will work more closely with intelligent machines and robots.

9.4.4 Future research trend in communication resource consumption

The theory and technology of achieving higher information transmission with lower resource consumption are essential in the context of mobile communication and network, as they must meet the growing demand. Merely relying on advancements in wireless transmission technology and hardware implementation is insufficient to address this challenge.

It is imperative to investigate the mechanisms and methodologies for efficient resource utilization from a systemic and network perspective. The future trajectory can be broadly categorized into two directions: firstly, minimizing resource consumption by enabling base stations and edge servers to enter hibernation mode during periods of low business volume [73]. Secondly, achieving intelligent adaptation of energy flow and information flow through resource allocation, thereby significantly reducing communication system energy consumption [74]. Furthermore, the realization of green computing and artificial intelligence algorithms can be accomplished through network function virtualization, collaborative optimization of communication and computing resources for enhanced energy efficiency, as well as distributed computing and collaboration among mobile agents. Additionally, with the increasing demand for big data and cloud computing, data centres have become major energy consumers. In the future, energy-efficient servers can be employed to mitigate the energy consumption of these data centres.

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