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Review

NextG manufacturing – New extreme manufacturing paradigm from the temporal perspective

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ABSTRACT

This paper proposes a new paradigm of extreme manufacturing from the temporal perspective in contrast to the current extreme manufacturing paradigm based on length scales (e.g., from nanometer to close-to-atom). The advent of 5 G and future 6 G (NextG) wireless communication provides unique capabilities of ultra-low end-to-end (E2E) latency (~1 ms), high speed (up to 20 Gb/s), high reliability (>99.999 %), and high flexibility (wireless) to meet the stringent requirements of future manufacturing. The ultra-low E2E latency enables NextG Manufacturing - a new extreme manufacturing paradigm from the latency perspective. This positioning paper identifies the needs of NextG manufacturing, introduces the characteristics of NextG wireless communication networks, proposes a framework for NextG manufacturing, demonstrates use cases, summarizes current challenges, and provides an outlook for future research directions.

1. Introduction to NextG manufacturing

This decade sees a wave of dramatic changes [1–3] in the manufacturing landscape to shape future manufacturing. The fundamental change is referred to as "Industry 4.0" [4,5] which integrates IT and OT to forge a cyber-physical production system. A major enabler for Industry 4.0 is based on widespread and powerful connectivity and computing infrastructure, which interlinks machines, robots, sensors, devices, and people in a timely, flexible, consistent, and secure manner. In contrast to the conventional static sequential production paradigm, future manufacturers need machines and production lines that are flexible, versatile, scalable, modular, and plug-and-play [6–11]. However, there are several critical barriers to achieving such a future manufacturing paradigm:

Long End-to-End (E2E) latency: Latency, the time that it takes to transfer a given piece of information from a source to a destination, is critically important in real-time monitoring and control for future manufacturing [12]. Fig. 1 shows the definition of E2E latency and cycle time, which are commonly used in the field of communications [11].

Latency-critical manufacturing frequently needs ultra-low latency of 1–10 ms (ms) or even extreme-low latency of sub-1 ms for many vertical applications (Table 1) [10–15]. However, many current manufacturing processes cannot meet the latency requirement. Let's start with a use case to see how low E2E latency as a game-changer can be in reshaping future manufacturing processes, sensors, and products. The manufacturing of aircraft engine components is complex, time-consuming, and expensive. The whole manufacturing chain of a compressor component known as an integral blade rotor (IBR) [16] can cost up to US$250,000. Precision, accuracy, and cost are vital in IBR milling. Excessive vibration or "chatter" in milling is a very common problem that leads to surface defects and rework.

However, the critical challenge is that there is no effective approach to monitor vibration and tune the process in real-time while underway because the E2E latency of current sensing technology is too long, and the machined quality can only be known when the whole machining process is done. This can lead to surface defects, rework rate (~25 %), and thus high cost [17,18] in manufacturing high-value components such as IBRs which cannot be inspected until the lengthy milling process (> 24 hrs.) is over. To make the situation worse, the geometry of IBRs continue to evolve in the future; thinner blades with more complex geometry features make them more flexible and, therefore, prone to

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Nomenclature

3GPP	3rd Generation Partnership Project
5 G	Fifth Generation
5GPPP	5 g Infrastructure Public Private Partnership
5GSA	5 g Standalone
6 G	Sixth Generation
AGV	Automated Guided Vehicles
AI	Artificial Intelligence
AR	Augmented Reality
C2C	Control-To-Control
CAD	Computer Aid Design
E2E	End-To-End
eMBB	Enhanced Mobile Broadband
EWD	Education and Workforce Development
FPGAs	Field Programmable Gate Arrays
IBR	Integral Blade Rotor
ICT	Information and Communication Technology
IMT	International Mobile Telecommunications
IoT	Internet Of Things
IPT	Institute For Production Technology
IT	Information Technology
ITU	International Telecommunication Union
M2M	Machine-To-Machine
MIMO	Multiple Input Multiple Output
ML	Machine Learning
mMTC	Massive Machine Type Communications
mmWave	Millimeter Wave
MNOs	Mobile Network Operators
MPC	Model Predictive Control
NJAMI	New Jersey Advanced Manufacturing Initiative
NR	New Radio
OSCP	Open Spatial Computing Platform
OT	Operations Technology
PDEs	Partial Differential Equations
PDP	Physical-To-Digital-To-Physical (PDP)
PINN	Physics-Informed Neural Network
PLC	Programmable Logic Controller
SMS	Short Message/Messaging Services
TSN	Time-Sensitive Networking
UE	User Equipment
UKTIN	United Kingdom Telecoms Innovation Network
URLLC	Ultra-Reliable Low Latency Communication
VR	Virtual Reality
WSNs	Wireless Sensor Networks.

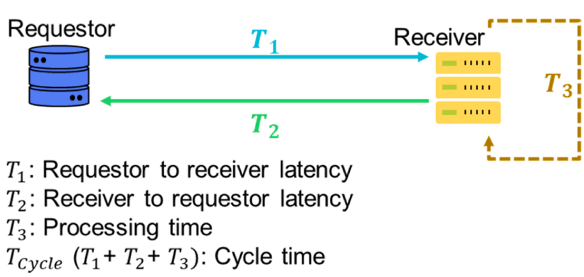

Fig. 1. Definition of latency and cycle time.

Table 1
Manufacturing performance requirements [10–15].

Applications	Latency	Pay-load	# of Device
Factory automation	1 –10 ms	Varies	10,000/Km^2
AGV	~1 ms	Kb ~ Mb	~50
VR/AR	< 1 ms	Kb ~ Mb	~50
Motion control	< 2 ms	~20 b	> 100
Mobile robots	< 10 ms	< 150 Kb	~100

chatter in machining, which will further increase the manufacturing challenge. However, in aerospace industries that require high process stability and strict compliance control, there is no room for error.

Reduced E2E latency has facilitated the development of many essential networked applications. For instance, the average E2E latency has consistently fallen below 300 ms since the early 2000s, and video conferencing over wide area networks has gained traction. Today, it is a staple of productivity – effectively connecting businesses and individuals in meaningful ways. In the manufacturing domain, wired Gigabit Ethernet networks do not supply low enough E2E latencies for these stringent manufacturing needs due to the accumulated latency caused by looping architectures and daisy-chaining devices. Future manufacturing needs an ultra-low E2E latency communication from the device level (sensor, actuator), to the Fieldbus (PLC, industrial PC), and from there up to the edge, cloud, and enterprise applications [4,5].

Limited flexibility: The communication among industrial machines is traditionally based on wired Ethernet systems. The key drawback is that it requires physical cabling between machines and moving parts, which significantly limits flexibility, mobility, and applicability [15]. Indeed, a wired sensor cannot be put on a fast-rotating part (e.g., blisk milling) [17]. The increasingly dynamic machines (e.g., AGVs and robots roaming or moving on tracks) make wired communication simply infeasible [15]. On the other hand, standard wireless protocols like Wi-Fi, Zigbee, and Bluetooth can't meet the stringent industrial requirements for consistency, latency, and scalability [14,15]. Future manufacturing needs flexibility in wireless connectivity and sensor placement.

Lack of computational intelligence: Many latency-critical applications such as real-time process monitoring and controlling are still conducted locally through machine-specific embedded sensors and controllers that only have limited computing power and limited access to the operation data from other machines [19]. This creates a critical barrier for leveraging the rich online data and modeling resources from multiple machines on the factory floor and taking advantage of the fast-developing AI and ML for future manufacturing.

The advent of fifth-generation (5 G) and future 6 G wireless communication (hereafter NextG) may reshape latency-critical manufacturing fundamentally because NextG holds the key to overcome these barriers due to its unique communication capabilities of ultra-low latency (1–10 ms), high speed (up to 20 Gb/s), high reliability (>99.999 %), and high flexibility (wireless) to meet the demanding requirements of latency-critical manufacturing [10,11,14,15].

In recent years, NextG has significantly reduced E2E latencies, enabling innovative applications such as real-time music/video streaming, multiplayer online gaming, and VR/AR. However, these applications are still in the early stages of adoption due to inconsistent latency performance. While NextG and other advanced wireless communication networks were expected to catalyze various low-latency dependent industries, their widespread implementation remains limited. This is partly because the current networks often fail to achieve latencies of a few ms. Data from 5 G Mobile Network Operators (MNOs) shows that the latency experienced by users typically stays within the range of tens of milliseconds. Sub-ms latencies might only be realistic in private 5 G networks with significant investment in radio resources.

Similarly, achieving less than 10 ms latencies in Wi-Fi 6 Wireless Local Area Networks (WLANs) is contingent on optimal conditions like low network traffic and high bandwidth. Furthermore, uplink latencies can be more than twice those of downlink, necessitating bidirectional E2E latency guarantees. For low-latency applications to thrive, factors such as Control Plane latency and service availability/reliability must also be addressed. Although Mobile Network Operators (MNOs) assert that 5 G Standalone (5 GSA) mode networks can achieve the required low-latency and reliability standards, their effectiveness under actual conditions still needs to be confirmed.

While current extreme manufacturing [20] has been dominantly focusing on extreme lengths from the nanometer scale [21] to the atomic scale [22], the generic and ubiquitous latency-critical manufacturing has represented a new paradigm of extreme manufacturing from the viewpoint of temporal scale to achieve extreme-low E2E latency in an integrated and networked manufacturing environment. NextG-enabled manufacturing (NextG manufacturing) may provide the degree of flexibility, mobility, versatility, and scalability that is required for the smart, sustainable, and resilient factory of the future. It is crucial to determine and confirm the specific latency guarantees needed for different vertical applications, and then to show how these standards, such as end-to-end latencies of a few milliseconds with high reliability, can be achieved in NextG networks. These demonstrations must also ensure that spectral efficiencies are maintained to preserve the profitability of deployments.

The methodology employed for this study is detailed in Fig. 2. Publications relevant to the scope of this review were selected based on publication date and keywords. The titles, abstracts, keywords, and citation count of these articles were examined to assess their relevance, scope, and quality. In addition to academic articles, government white papers and news articles were also included to enrich the discussion. This comprehensive analysis may help identify, summarize, and discuss key research hotspots, gaps, and challenges.

This positioning paper is organized as follows. The above Section 1 identifies the needs of extreme-low E2E latency for future manufacturing. Section 2 introduces the characteristics of the NextG wireless communication network. Section 3 proposes a framework for NextG manufacturing. Section 4 demonstrates the use cases of NextG manufacturing. Section 5 summarizes current challenges and the outlook.

2. NextG wireless communication network

2.1. NextG evolutions

While NextG refers to current 5 G and future 6 G and beyond, this paper will focus on 5 G due to its dominant role in future manufacturing. 5 G mobile network, representing the latest evolution in wireless communication systems, offers a dramatic leap in capabilities compared to its predecessors. The evolution of mobile networks from 1 G to 5 G can be seen as a continuous endeavor to improve wireless communication in various aspects, such as data rate, latency, and connectivity. Fig. 3 shows the evolution of mobile networks from 1 G to 5 G [23,24]. Each generation of mobile network technology aimed to enhance the existing standards significantly. 1 G, launched in the 1980s, laid the foundation for analog voice communication. The subsequent 2 G network, introduced in the 1990s, digitalized communication and brought forth services such as SMS. The 3 G network that emerged in 2001 provided mobile internet access and improved data services, which set the stage for the 4 G network in 2009, offering dramatically faster data speeds and enabling higher multimedia experiences. Current 5 G offers unprecedented speeds, low latency, mass connectivity, and many more. The use of the network standards and the number of connecting devices within the network is shown below the timeline. Around 80 billion devices are expected to be connected to the Internet by 2030 [23,25].

The 5 G standards are conceptualized and governed by the 3rd Generation Partnership Project (3GPP), a consortium of various telecommunications standards organizations. The foundational specifications for 5 G are delineated in the 3GPP's Release 15 and subsequent releases, which mark the advent of New Radio (NR) technology in 5 G networks. In June 2018, the 3GPP finalized the inaugural formal specifications for 5 G, encapsulated in Release 15 [26]. This event heralded a significant milestone in 5 G's evolution, laying the groundwork for subsequent technological advancements and deployments. The first commercial deployment of 5 G in the United States came to fruition in April 2019 [27] when Verizon rolled out its 5 G NR network in select regions of Chicago and Minneapolis.

5 G encompasses a broad set of improvements such as significantly higher data rates (potentially up to 10 Gbps), ultra-low latencies (as low as 1 ms), larger bandwidths per unit area, improved spectral efficiency, and the capability to connect a far greater number of devices concurrently. This monumental enhancement is facilitated using advanced technologies, including massive MIMO (Multiple Input Multiple Output), mmWave (millimeter wave) spectrum [28], beamforming, network slicing, and edge computing. Beyond providing faster individual connections, 5 G is designed to serve as the foundation for truly connected systems, driving innovations in various vertical domains, from smart cities and autonomous vehicles to telemedicine and Industry 4.0. As such, 5 G is more than just an upgrade; it is a critical infrastructure transformation that could reshape how we interact with technology in our daily lives.

2.2. 5 G unique characteristics

The advent of 5 G marks a pivotal moment in the evolution of mobile networks, primarily distinguished by its unparalleled capabilities and potential applications. Table 2 illustrates the comparative analysis of different wireless communication protocols and elucidates the advances in 5 G [29–37]. These attributes cement the role of 5 G as a revolutionary wireless communication technology capable of fulfilling the stringent demands of NextG manufacturing. The ensuing sections will delve deeper into the potentialities that NextG manufacturing could

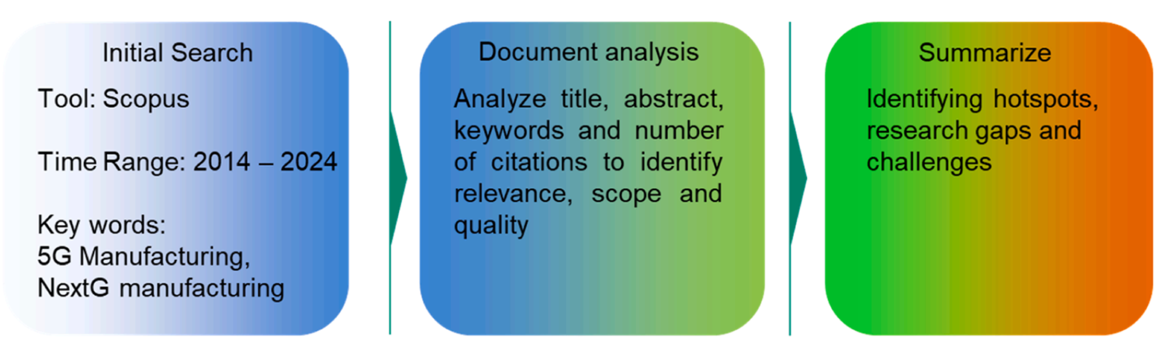

Fig. 2. Methodology used to conduct literature review.

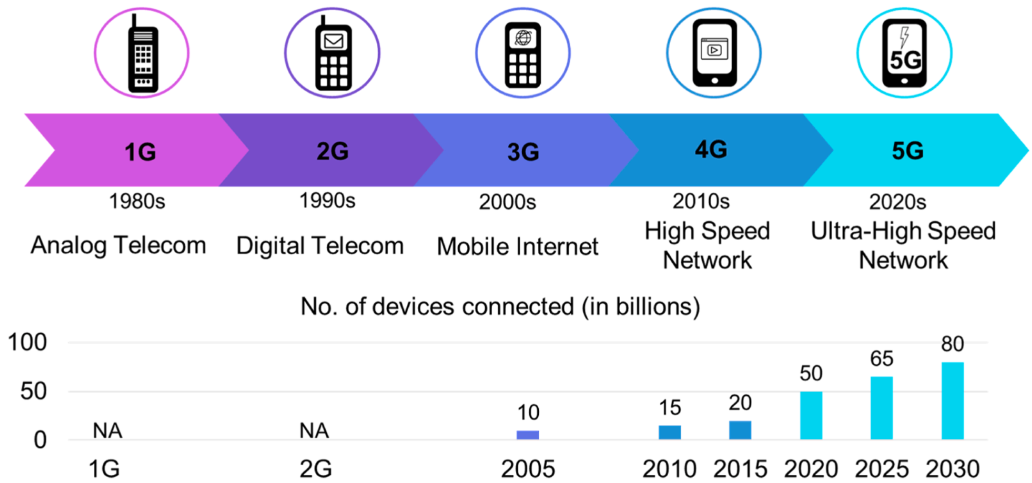

Fig. 3. Evolution from 1 G to 5 G.

Table 2
Comparative analysis of different wireless communication protocols.

Communication Protocol	Data Rate	Latency	Range	Frequency	Cell density (users/cell)
5 G*	~ 20 Gbps	< 10 ms	~ 200 m	24.25 GHz ~ 52.6 GHz 410 MHz ~ 6 GHz	20K-40K
4 G/LTE	~ 100 Mbps	20 - 50 ms	~ 10 Km	~ 3.8 GHz	200 –600
WLAN (Wi-Fi 6)	< 9.6 Gbps	< 50 ms	~ 10 Km	~ 5 GHz	~ 256
Bluetooth	~ 3 Mbps	100 ms ~ s	~ 100 m	~ 2.4 GHz	~ 7
Zigbee	~ 250 Kbps	A few ms ~ s	~ 15 m	~ 2.4 GHz	~ 64 K (theoretical) ~ 64 (typical)
LoRa/LoRAWAN	~ 21.9 Kbps	~ seconds	~ 10 Km	~ 928 MHz	1K-10K

*Note
- The data rate for 5 G is approximately 20 Gbps for downlink and 10 Gbps for uplink.
- The range of 200 m is specific to millimeter-wave (mmWave).
- The sub-6 GHz frequencies offer a significantly higher range.

unlock.

2.3. NextG-enabled smart manufacturing

The smart manufacturing domain is very diverse, which is manifested by distinct applications. This heterogeneous manufacturing environment requires very different communication requirements, including service quality, reliability, scalability, compatibility, cost-efficiency, maintainability, and cybersecurity (Fig. 4). For example, discrete manufacturing (i.e., making discrete parts) may differ substantially from others, such as continuous manufacturing (e.g., pharmaceutical manufacturing and oil refinery). The common view of these

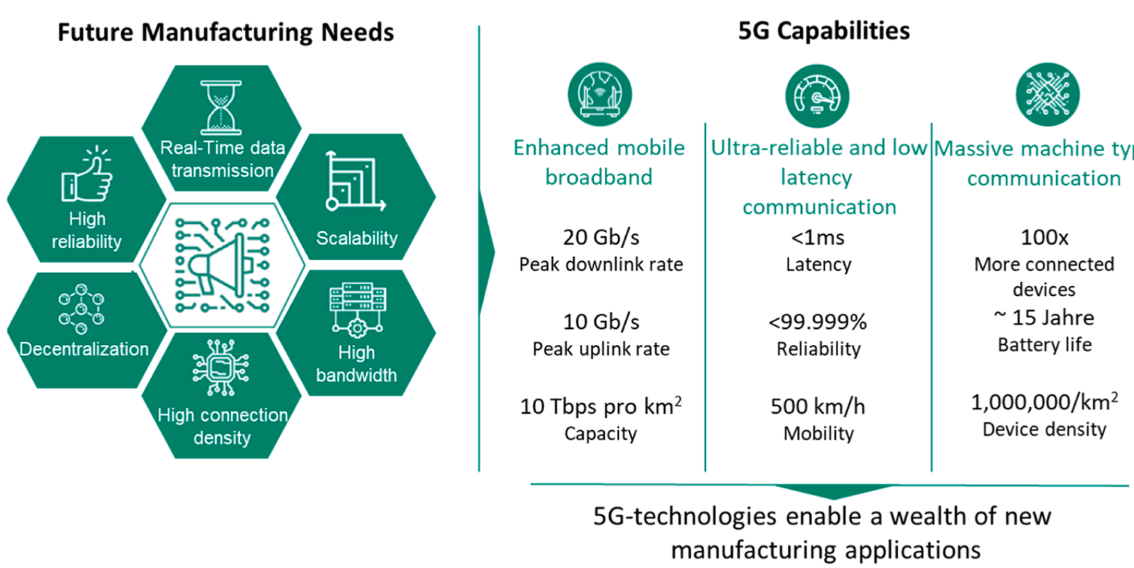

Fig. 4. Future manufacturing capabilities enabled by 5 G.

relevant manufacturing applications is that a new generation of digital connectivity may lead to significant manufacturing improvements and optimizations [38,39].

The major innovations enabled by 5 G have been defined in three broad application areas, including Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low Latency Communications (URLLC), and Massive Machine Type Communications (mMTC) as shown in Fig. 5 [40]. The area of eMBB is in continuous evolution from 4 G LTE with higher throughput, faster connections, and more capacity. URLLC is the key capability of 5 G that would enable uninterrupted, reliable, and ultra-low-latency services for mission-critical applications. mMTC refers to using the 5 G network to connect to a massive number of devices, providing internet access by collecting a huge volume of small data packets from large numbers of devices. By design, 5 G communication technology is being developed at a time when many industries are introducing connectivity and automation to their domains on an unprecedented scale using technologies such as the IoT, ML, and robotics. Smart manufacturing is part of this broader trend and incorporates different performance requirements. Private local-area networks deployed on the factory premises are usually required to meet URLLC performance targets of industrial automation consistently. The 5 G system architecture is designed to support such standalone operations without connections to external networks.

Digital connectivity is critical for smart manufacturing. Reliable and secure data transmission in real-time is the key requirement for an industrial communication system. Fig. 5 shows several representative examples of the benefits of 5 G in smart manufacturing, in which typical use cases are organized based on their primary communication needs according to the basic 5 G service types, i.e., eMBB, URLLC, and mMTC. It is clear that many industrial use cases, including motion control, have very strict demands in ultra-low latency, reliability, and determinism. On the other extreme scenario, augmented reality (AR) needs very high rates of data transmission of video streams from and to an AR device. Nevertheless, process automation lies between the two extreme scenarios and concentrates on monitoring and controlling mechanical, physical, biological, chemical, or other manufacturing processes within a facility. This involves using various sensors (e.g., for measuring flows, forces, speeds, and temperatures) and actuators (e.g. heaters or valves) to control the process. Whereas other cases, such as WSN often need more extensive mMTC-based services.

A comparison of the key performance of the current 5 G technology with the requirements of smart manufacturing shows clearly that some requirements have not been met in the current release of eMBB-focused 5 G technology [29]. However, these critical requirements are expected to be satisfied in future 5 G releases.

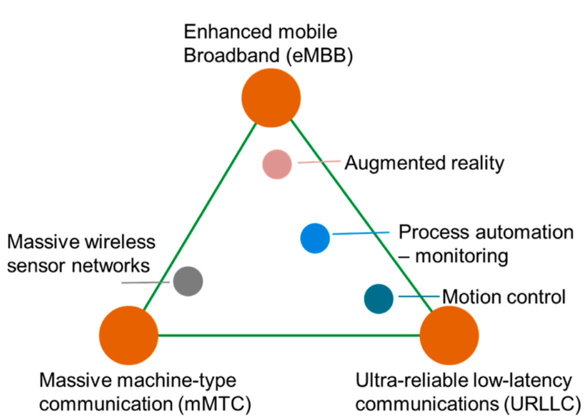

Fig. 5. Representative industrial use cases and their basic communication requirements (adapted ZVEI [40])

3. Framework of NextG manufacturing

3.1. Architecture of NextG manufacturing

In the pursuit of implementing Industry 4.0, Specification #22.804 has been outlined in the 3GPP (Release 16) [15]. The specification introduces a forward-looking vision for Factories of the Future, aiming at enhancing flexibility, versatility, resource and cost efficiency, worker support, and the quality of industrial production and logistics. The 3GPP Release delineates a series of 5 G industrial applications to realize these goals, detailing their specific requirements and challenges.

Building on this foundation, an innovative NextG manufacturing architecture is developed in this work to synthesize the key elements of the 3GPP Release into an integrated architectural blueprint. It aims to instigate a transformative shift in the industrial manufacturing sector by leveraging the inherent potential of 5 G. The NextG manufacturing framework presents an innovative paradigm designed to propel industrial manufacturing into an era of streamlined efficiency and unprecedented processing speeds. The NextG manufacturing framework explicitly highlights the E2E latency requirements and user equipment (UE) needs, which are defined and characterized across manufacturing levels - from machine, factory, to enterprise. These specifications address unique challenges in the context of NextG manufacturing, which have not previously been addressed [41].

The architecture envisions a tri-layered structure: machine level, factory level, and enterprise level. Each level reflects a distinct magnitude and complexity of components, as shown in Fig. 6. From the broad expanse of the enterprise level to the granular detail at the machine level, the structure exhibits a top-down hierarchical magnitude. Concurrently, the E2E latency and the quantity of user equipment (UE) requirements undergo a corresponding transition across these strata, mirroring their inherent breadth and complexity: The enterprise level, possessing the most extensive scale, tolerates the highest latency (1–2 s) and necessitates the largest number of UEs (~10,000). For the factory level in the middle, where most of the process automation is, the typical E2E latency gets smaller to ~50 ms (for process monitoring purposes), and the demand for UE connections is reduced to 10–100 units. At the machine level, machine tools require E2E latency of 1–10 ms and about 20 UEs. Ultimately, machine tools demand an E2E latency of 1–10 ms at the machine level and require around 20 UEs. For a given machine tool, especially in motion control applications, where communication primarily occurs between the controller, sensors, and actuators, the E2E latency may dip as low as 0.5 ms [14,15]. This gradation in latency and UE requirements across the structure's layers underscores their distinct roles and functionalities within the overarching architecture.

Enterprise level: The enterprise level is at the topmost tier of the architecture. It broadly encompasses multiple manufacturing factories and other facilities. Each of these units interfaces with the central Cloud server via the Internet [15,42]. This Cloud server, which can be physically distant from the manufacturing facilities, forges a connection with manufacturing factories through the 5 G Edge server.

The Cloud server possesses the capability to store non-time-sensitive data from factories, enabling its analysis for business management purposes. Equipped with the computing power of the Cloud, the management team can undertake computationally intensive tasks such as big data analysis [43]. The insights gleaned from these analyses, such as supply chain demand and planning decisions, are then channeled back to the manufacturing facilities to affect the necessary high-level adjustments. In essence, the enterprise level serves as the strategic command center, focusing on the business management objectives of manufacturing assets and supply chain management. This level is crucial in leveraging data and computational capacity for informed decision-making and operational optimization.

Factory level: The Factory level forms the intermediate tier in this architecture, representing the middle level of the system. Instead of treating factories as single, monolithic entities, this level breaks them

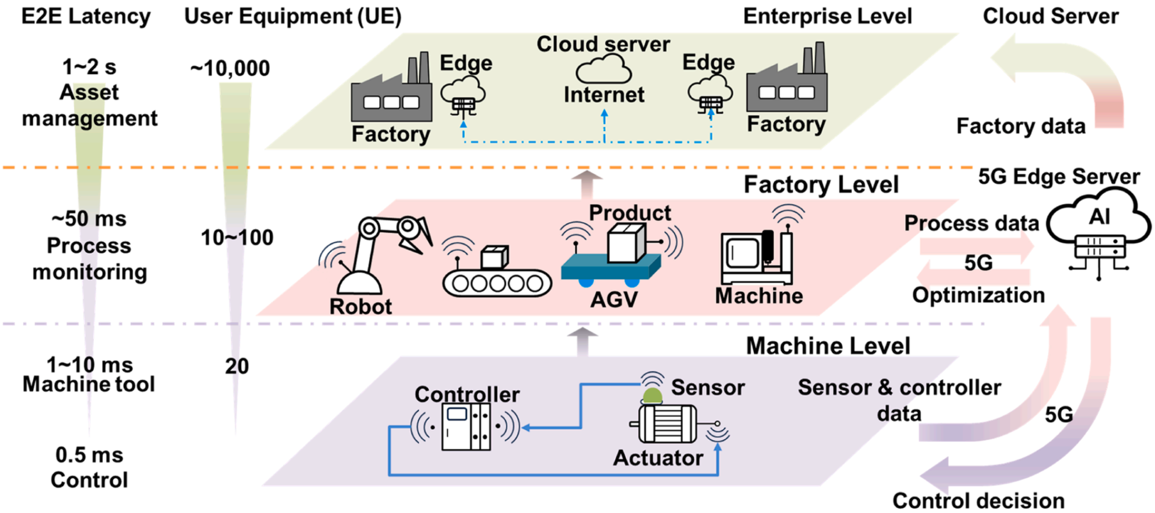

Fig. 6. NextG manufacturing architecture.

down into individual machines. Each machinery within a factory is connected to the overarching 5 G network, facilitating information sharing about machine status amongst various units - a communication form known as Control-to-Control (C2C). C2C communication, already prevalent in applications like large-scale machines (e.g., newspaper printing machines) and assembly lines, enables coordinated functioning and workpiece handover between individual units. Beyond sharing data within the factory, the machinery is also equipped to upload data to the 5 G edge server for process automation and optimization purposes. Despite its less powerful computing capacity compared to the enterprise Cloud server, the 5 G edge server serves a pivotal role as the gateway linking the factory network to the Internet. This server conducts real-time sensitive computations, returning results like optimized process decisions back to each machine. Additionally, it uploads machine status data to the enterprise cloud server via the Internet for managerial purposes. The machines' status is uploaded to the enterprise cloud server by the 5 G edge server through the Internet for management purposes.

In essence, the 5 G edge server functions as the distributed computational resource for real-time sensitive computations. This server can host AI/ML models such as pre-trained ML algorithms for accelerated decision-making. Through the 5 G network, these decisions are dispatched back to the machinery for automatic process optimization. Conversely, non-real-time data can be sent to the Cloud server for more comprehensive computational analysis and higher-tier asset management. This tier highlights the integral role of 5 G technology in ensuring robust and efficient inter-machine communication and data management.

Machine level: At the base of this system is the machine level, which spotlights the individual components of each machine. This level focuses on the fundamental elements that enable the functioning of machinery. These components are the smallest operational units of the overall architecture, but their performance significantly influences the efficiency of the machines and, consequently, the entire manufacturing facility.

This level is characterized by real-time sensitive data flow among sensors, controllers, and actuators. This high latency requirement is assured via 5 G networks, with as low as 1 ms latency for closed-loop control. The sensors, controllers, and actuators, all equipped with 5 G technology, are capable of intercommunication via the 5 G network while concurrently uploading data to the 5 G edge server. This allows the 5 G edge server to analyze real-time sensing data and dispatch updated control decisions to the controllers, helping to avoid product defects and wastage.

The NextG manufacturing architecture facilitates swift and seamless data transmission, high-speed data processing, and real-time control actions - three crucial elements for a successful implementation of NextG manufacturing. This structure illustrates how 5 G technology underpins every manufacturing level, offering unprecedented levels of efficiency, control, and precision.

3.2. Enabling technologies for NextG manufacturing

The foundation of NextG manufacturing is built upon a diverse array of enabling technologies/components, including 5G-enabled sensing and monitoring, data integration and computation, AI/ML models, and model-based real-time control. These components work in unison to enable NextG manufacturing that is not only smart and efficient but also capable of extreme-low E2E latencies crucial for real-time applications. To demonstrate the interrelationships among these components, Fig. 7 shows the data flow between these enabling components, which are summarized and detailed in Sections 3.3 – 3.6.

At the heart of NextG manufacturing is the 5 G network, acting as the communication backbone to link the enabling components, allowing ultra-low E2E latency and high-bandwidth data transmission critical for real-time operations. The 5 G capabilities are essential for facilitating the rapid exchange of data across the components, ensuring timely and synchronized operations across various manufacturing processes.

The 5G-enabled sensing and monitoring component is the primary data generator, capturing operational metrics such as speed,

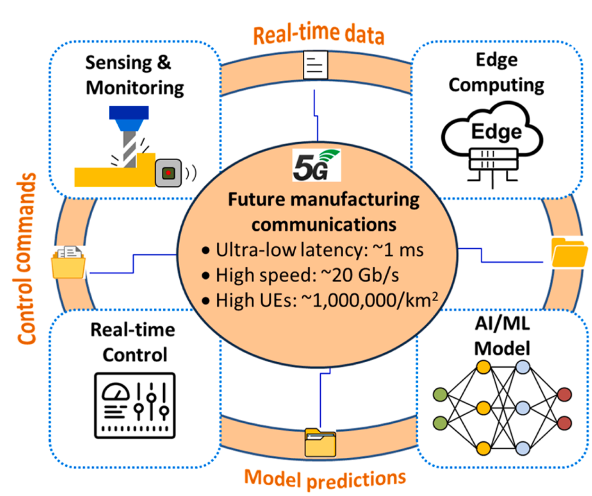

Fig. 7. Data flow of NextG manufacturing enabling components.

temperature, and other machine status. Integrated with 5 G, this component transmits monitoring data wirelessly and in real-time, ensuring immediate responsiveness to any operational changes or anomalies.

The edge computing component processes real-time monitoring data at a location close to the data source, which guarantees that instant data is processed at the earliest possible opportunity. The processed data is then standardized, facilitating utilization by AI/ML models.

AI/ML models can be developed to provide real-time insights at scale, detecting complex patterns, and accommodating to the needs of real-time applications. The model predictions are then translated into real-time control algorithms through the 5 G network, ensuring swift responses to dynamic manufacturing conditions.

Within the real-time control component, AI-driven decisions are promptly made, and appropriate control commands are issued to the actuators to adjust a manufacturing process as needed. The sensors monitor these adjustments and relay the information back into the system, sustaining the feedback loop essential for continuous process optimization.

3.3. NextG-enabled sensors and monitoring

Sensors are crucial components of NextG manufacturing for monitoring and optimizing manufacturing operations. Sensors can be categorized based on measured attributes, applications, and usage scenarios. For instance, depending on the attributes they measure, such as temperature [44], force [45], vibration [46,47], acoustic [48], pyrometry [49] and topography [50], sensors have distinct applications. A more comprehensive classification scheme and detailed discussion can be found in previous studies [51]. When classified by use, wireless sensors are witnessing significant growth [52]. The ongoing evolution of wireless communication technology has prompted an intensified focus on wireless sensors from users, sensor manufacturers, and the academic community.

NextG-enabled sensors offer several benefits, not only enabling technicians to gain useful information from hard-to-reach areas compared with wired sensors but also enabling ultra-low latency for data transmission. NextG-enabled sensor structure consists of four elements [53]: sensing elements, microcontroller, 5 G NR transceiver, and on-board power supply. Fig. 8 shows a NextG-enabled sensor architecture. The sensing element, the heart of the sensor, detects environmental changes. Depending on the sensor type, it can measure various parameters such as temperature, pressure, or motion. The microcontroller processes the data captured by the sensing element and directs the overall operations of the sensor. The on-board power supply ensures that the sensor can perform its sensing operations. The battery lifespan is critical, and consequently, energy efficiency is a significant focus in wireless sensor development [54,55]. The 5 G NR transceiver endows the sensor with wireless capabilities, facilitating the transmission and reception of data (uplink and downlink). The transceiver operates in four states - receive, transmit, idle, and sleep - each associated with different power consumption levels [51]. The 5 G NR transceiver enhances the sensor's capabilities by establishing direct communication with a 5 G edge server, ensuring rapid and reliable data transmission. This connection is essential for leveraging the full potential of real-time analytics in industrial applications.

In harmony, these components enable NextG sensing. These sensors do not require physical connections, so they can be deployed where space is limited, power is scarce, or wiring is impractical. They also enable data transmission to remote locations and offer the flexibility of repositioning sensors without rewiring. Consequently, wireless sensors are a pivotal trend in Industry 4.0, offering significant benefits and transforming numerous industries and applications.

Expanding on individual wireless sensors' capabilities, WSNs have emerged as a crucial technology underpinning smart manufacturing. A WSN is an ensemble of spatially distributed sensors designed to monitor specific environmental parameters, such as temperature fluctuations or movement. These sensors relay their collected data wirelessly, either to each other or to a central control point often referred to as the gateway. The configuration or layout of these sensor nodes within a WSN is known as the network's topology. The interaction between the sensor nodes and the gateway and the communication among the sensor nodes themselves primarily dictate the topology. The star, mesh, and hybrid topology represent the three primary types of topologies [15,51]. As shown in Fig. 9, a star topology, each sensor node communicates solely with the gateway, without any inter-node communication. This requires all nodes to be within the gateway's communication range. While energy efficient, this configuration is not suitable for larger networks due to its limited scalability.

On the contrary, a mesh topology allows sensor nodes to interact both with the gateway and other nodes, given they are within communication range. This configuration is ideal for larger networks due to its enhanced reliability but comes with higher energy consumption compared to a star topology. The hybrid topology incorporates elements of both the star and mesh models, creating a more adaptable network. Here, a sensor node with lower power reserves does not relay information from other nodes, promoting energy efficiency in the network. These topologies significantly influence the data routing from each sensor node to the gateway and the data management within each sensor node, making their selection a critical aspect of WSN design and operation.

Recently, 5G-enabled sensors have attracted great interest from researchers. The benefits of 5G-enabled sensors can be summarized in the following aspects: (1) Energy efficiency - 5 G has been designed to be more energy-efficient, an essential factor for battery-powered sensors in WSNs. Energy efficiency can lead to longer sensor battery life, reducing maintenance costs and time. (2) Low E2E latency - 5 G technology promises lower latency than previous generations of cellular technology (See Table 2). This means data is transmitted with minimal delay, which is crucial for time-sensitive vertical applications. (3) Support for massive IoT - 5 G supports massive IoT, meaning it's designed to efficiently connect with many devices in a small area [56]. This is particularly beneficial for applications like industrial automation, where many sensors must be interconnected. (4) Enhanced reliability - 5 G networks are

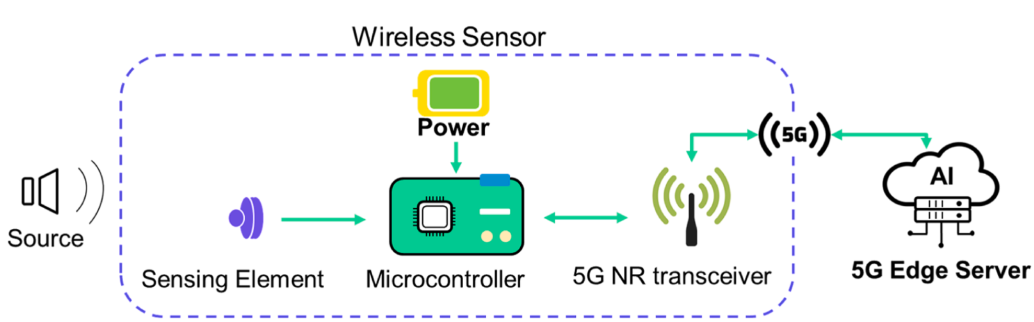

Fig. 8. NextG-enabled sensor architecture.

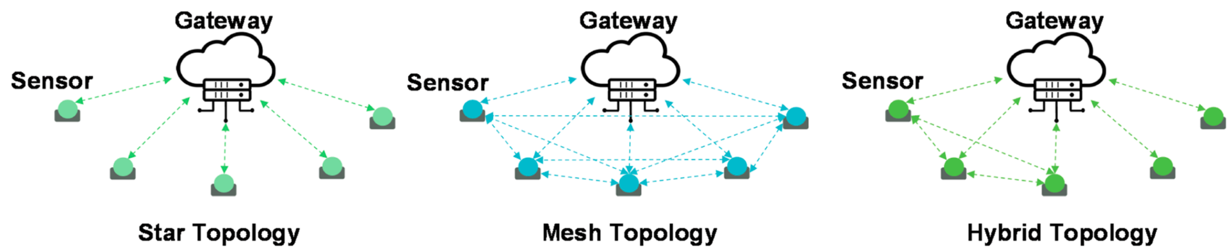

Fig. 9. Wireless sensor network topology.

designed to provide a more reliable connection, reducing the risk of dropped signals or lost data. This is critical in applications like industrial automation, where continuous monitoring is required.

In summary, the evolution of wireless sensors and 5 G technology has led to transformative advancements in smart manufacturing, underpinning the shift towards highly connected and efficient industrial processes. However, current 5G-enabled sensors are limited to lab-retrofitted environments, and industrial/commercial ones are still under development.

3.4. Edge-based data integration and computation

Data is the lifeblood of NextG manufacturing. The manufacturing data is not only heterogeneous (e.g. CAD data, sensor data, production data, model data) but also massive. However, simply putting all the data into the same repository would not make the data actionable. A holistic data architecture along with distributed algorithms is critical and highly needed to curate and integrate these multimodal data sets for subsequent analytics and actions. An information management system consisting of data placement, data discovery, data integration, and data standardization will overcome the inefficiencies caused by common data management shortcomings in current typical manufacturing operations. Toward this end, integrating edge computing and manufacturing operations provides unique opportunities with execution resources (compute and storage) and sufficient connectivity (networking) near the data sources on factory floors. In the context of NextG manufacturing, edge computing is the crucial nexus where data, computing power, and control coalesce to deliver real-time analytics and decision-making capabilities at the machine's edge. The core benefits of edge solutions are low E2E latency, high bandwidth, and trusted computing and storage, which are particularly important for latency-sensitive manufacturing automation.

Edge computing is a transformative approach to network architecture that processes data at the network's edge, as close as possible to the source where it is generated. While cloud computing offers significant computational power and data storage capacity [57,58], this centralized approach is marred by inherent latency issues, as the distance between data generation and processing centers impedes real-time data analysis. Moreover, constant data traffic to and from the Cloud may cause bandwidth congestion, which is particularly problematic in the realm of data-heavy manufacturing tasks. These constraints become critical obstacles when swift data processing and immediate decision-making are essential.

In response to these challenges, edge computing has emerged as a compelling alternative, decentralizing data processing by bringing it closer to where data is generated — at the edge of the network. This proximity markedly diminishes latency and mitigates bandwidth limitations. By enabling this paradigm shift, edge computing significantly amplifies the velocity and efficiency of processing operations while bolstering the system's dependability and agility in adapting to the exigencies of dynamic manufacturing environments.

In Fig. 6, the 5 G Edge Server, strategically positioned within the factory, connects to the manufacturing equipment via a 5 G network. This connection is crucial for achieving ultra-low latency communication. Real-time decision-making models, such as AI/ML analysis models, housed within the 5 G Edge Server enable on-site, in-situ process monitoring, optimization, and prediction. This arrangement accelerates data flow and integrates smoothly with real-time control systems.

With these advancements, the adoption of edge computing in NextG manufacturing signifies more than a mere technological upgrade; it represents a strategic overhaul of the manufacturing infrastructure. By distributing computational resources and harnessing the rapidity of 5 G networks, edge computing cultivates an ecosystem where precision, efficiency, and responsiveness are consistently realized in real-time.

3.5. AI/ML models

The federated data at a 5 G edge server may be utilized for forward prediction of manufacturing performance, inverse learning of unknown parameters of governing physical laws, making decisions under uncertain and time-varying conditions, and translating decisions from the digital domain into autonomous actions in the physical domain through real-time control. It is imperative to leverage the rich dataset to enable advances across the three horizons of (1) process/machine optimization to increase productivity via real-time control, (2) manufacturing system optimization to improve throughput, quality, and overall efficiency [59], and (3) new business models to leverage AI/ML and integrate solutions into manufacturing systems.

Data-driven models refer to approaches and techniques that derive insights, patterns, or knowledge directly from data when theoretical models are not feasible. Instead of relying on pre-defined models or theories, data-driven models adapt and evolve based on the online data they are exposed to. These techniques are particularly beneficial when there isn't a clear theoretical model to describe a phenomenon or when the volume of data is so vast that traditional or physics-driven methods become inefficient. ML is a subset of data-driven methods that allow computers to learn from data [60]. In essence, ML provides computers with the ability to automatically learn and forecast from the history data without being explicitly programmed for specific tasks. It involves algorithms that find patterns or regularities in data [61].

The advancement in communication and sensing technologies has significantly increased the availability of manufacturing data [62,63]. This surge in data accessibility has bolstered data-driven manufacturing, especially with the concurrent rise of AI/ML. Accounting for its multiple forms of AI, the McKinsey Global Institute report estimates that, by 2030, AI will increase the size of the global economy by $13 trillion [64]. Accenture estimates that AI will add $8.3 trillion to the U.S. economy alone [65] by 2035. Many manufacturing objectives are widely used to fulfill through different types of ML methods, such as supervised learning [66–68], unsupervised learning [69], reinforcement learning [70,71], and generative learning [72].

However, the "black-box" nature of data-driven AI/ML models is often criticized for lacking physics and uncertainty, limiting model interpretability, generalizability, applicability, and transferability in various conditions [73]. Incorporating ML into the vertical manufacturing domain also presents specific challenges, such as the need for vast datasets, time-consuming model training, expensive computing resources, and poor interpretability. While physics-based methods (e.g., multi-physics simulations) are based on real-world physical laws, data-driven ML models can sometimes provide physically inconsistent results or seem implausible though excellent at fitting observations. PINN provides a transformative approach to integrating manufacturing physics and sensor data to address such challenges [74]. Fig. 10 illustrates the three potential scenarios based on the availability of manufacturing data and knowledge of physics. The left scenario with a comprehensive understanding of the process physics but limited manufacturing data, making it conducive for traditional physics-based analysis. In the right scenario with abundant process data but minimal knowledge of its underlying physics, purely data-driven ML becomes the most appropriate choice. In the middle scenario, there is partial access to data, such as machine parameters and process conditions, but only partial knowledge of process physics. In such cases, PINN emerges as the natural choice due to the potential incompleteness of both data and physics. Currently, PINN is an emerging approach to solving dynamical manufacturing problems, often represented by PDEs, such as fluid dynamics [75–77], heat transfer [78,79], machining dynamics [80,81], and solid mechanics [82], etc.

The highly dynamic nature of manufacturing is manifested by non-linear effects, unknown dynamics, high dimensionality, stochasticity, and uncertainty, which are very difficult, even impossible, to be sufficiently taken into physics-based model development. The advances in AI/ML provide great opportunities to address this challenge in manufacturing by leveraging the rich data sets of measured data. However, AI/ML models cannot achieve absolute certainty inherently, as they operate on a limited scope of information. As ML models increasingly inform critical aspects of manufacturing, such as process optimization and quality control, the integration of uncertainty quantification becomes pivotal. This aspect of ML accounts for the variability and unpredictability inherent in real-world manufacturing processes. It enables models to predict outcomes and assess the confidence in these predictions, thereby facilitating more informed and resilient decision-making. The ultra-low latency of NextG enhances ML model capability, allowing for real-time adjustments in manufacturing operations based on predictions considering uncertainty factors. This approach is particularly crucial for scenarios where decisions must be made under incomplete information or where the consequences of incorrect decisions are significant. Advanced ML techniques, such as Bayesian Neural Networks, provide a framework for incorporating uncertainty directly into the learning process. This ensures that the ML models are not only fast and responsive but also robust and reliable, capable of guiding manufacturing systems through the complexities and variabilities of production environments.

Leveraging the capabilities of 5 G in NextG manufacturing, the resource-intensive training of ML models can be offloaded to Cloud Servers. These servers, equipped with substantial computational power, house vast data volumes aggregated from manufacturing facilities. Subsequently, once trained, sophisticated ML models like uncertainty-informed PINN models can be integrated into Field Programmable Gate Arrays (FPGAs) to expedite the inference process, thereby enabling real-time ML monitoring in on-field scenarios.

3.6. Learning-based NextG control

A survey by Deloitte [5] has highlighted the disconnects or paradoxes to fully harness each stage of the PDP loop in smart manufacturing. The survey has shown that while most studies have a sort of the first stage, i.e., establishing digital records, and some have the second (i.e., analytics and visualization), far fewer are yet able to harness the last, most important stage—the ability to leap from digital technologies to action in the physical world—that constitutes the essence of smart manufacturing. Model predictive control (MPC) [83, 84] is an advanced method to close the digital-physical loop.

Fig. 11 illustrates how NextG control advances MPC by integrating 5 G technology for enhanced data transmission and edge server capabilities. The 5 G edge server connects to the NextG sensor and actuator via the 5 G network. Within the edge server, an AI predictive model takes the current state of the measurement and predicts the future outputs over a certain horizon. This is based on potential control actions, considering disturbances. The AI model evaluates the difference between the predicted outputs (with disturbances) and the desired output. It computes control actions that minimize this difference, given the constraints. Then, the control action for the next time step is sent as the control input to the actuator. The actuator reacts to both the control input and the disturbances, resulting in a new output, which is measured and sent back to the 5 G edge server as the measured output. The process repeats at the next time step, with the 5 G edge server continually adjusting based on the latest measurements and disturbances.

Recent advancements in ML and the increasing availability of massive manufacturing data and high-performance computing resources have stimulated a rising interest in learning-based, data-driven control systems. Learning-based NextG control can be broadly segmented into two categories based on the learning objective [85]: understanding system dynamics and determining controller behavior. In many real-world manufacturing scenarios, the exact dynamics of a manufacturing system may remain elusive or evolve. Under such circumstances, comprehending system dynamics becomes paramount. Understanding manufacturing dynamics through a data-driven approach aims to bolster NextG control by integrating ML or adaptive methods, allowing for ongoing updates to a manufacturing dynamics model based on observed behaviors. Examples of this approach include applications in understanding the behavior of connected vehicles, such as in vehicle-to-vehicle communication for an intelligent transportation system [86], autonomous vehicles [87], and robots [88], and discerning the unfamiliar system dynamics of robots to boost their performance [89]. Conversely, the focus of learning controller behavior transcends merely understanding system dynamics. Instead, it zeroes in on the direct acquisition of control actions or policies. The goal here is to employ data-driven techniques to determine the optimal control actions considering a given system state and its anticipated future trajectory. Instances of this method include the extraction of controller parameters from amassed data [90,91]. Typically, this approach is performance-centric since it aims for the direct optimization of specific

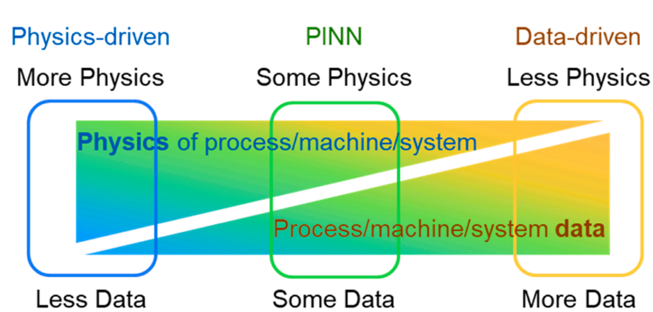

Fig. 10. Physics-based, PINN, and data-driven modeling scenarios.

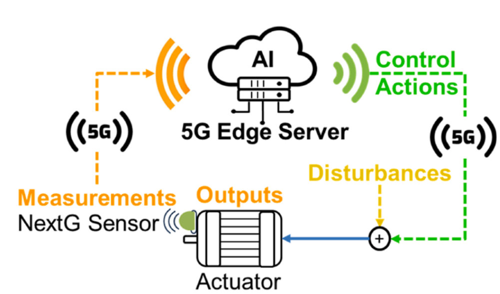

Fig. 11. Working principle of NextG Control.

performance metrics or reward functions [85,92].

In essence, learning-based NextG control amalgamates traditional control with ML, offering significant advantages. It's agile in adapting to manufacturing system alterations and is tailored for intricate scenarios that are challenging to model definitively. By incessantly fine-tuning its model, it champions performance and adeptly navigates uncertainties. Harnessing massive datasets, it curtails computational demands and adeptly manages non-linear scenarios, extending its relevance across a spectrum of manufacturing systems. Given these merits, learning-based NextG control, augmented by previously mentioned technologies like PINN and FPGA-enhanced ML, finds its niche in NextG manufacturing for real-time control applications, underscoring the promise of ultra-low latency and sterling performance.

4. Use cases of NextG manufacturing

The potential of NextG manufacturing is gradually materializing across the globe, with major industrialized countries embracing its transformative capabilities to redefine the manufacturing paradigm. From instantly responsive manufacturing operations to the inception of real-time future factories, the extreme-low E2E latency promised by NextG is enhancing manufacturing outcomes. This section delves into global trends highlighting NextG manufacturing initiatives and use cases, encapsulating its evolving influence.

4.1. Global trend of NextG manufacturing initiatives

Several initiatives around the world have been established to standardize 5G-enabled manufacturing. Table 3 shows the 5 G initiatives along with advanced manufacturing initiatives worldwide. Set by the International Telecommunication Union (ITU), the IMT-2020 represents the global standards for 5 G technologies. Notably, China has made significant efforts in its development and promotion, aligning the term "IMT-2020" with its vision for 5 G [93,94]. Europe's 5 G Infrastructure Public Private Partnership (5GPPP), a collaboration between the European Commission and the European ICT industry [95], spearheads the 5 G R&D in Europe and ensures regional leadership in the evolving telecommunication landscape. Concurrently, Germany introduced the "Industry 4.0" initiative, encapsulating the integration of contemporary digital technologies with conventional manufacturing. The 5 G Forum, established in 2013, acts as South Korea's beacon for 5 G advancement, comprising government, academia, and industry stakeholders [96]. Alongside this, the government launched the "Manufacturing Industry Innovation 3.0", focusing on holistic smart factory implementations to revolutionize manufacturing [97,98]. The United Kingdom's national innovation endeavor, UKTIN, propels its 5 G initiatives [99]. To complement this in the manufacturing domain, the "Made Smarter" program strives for manufacturing advancements. In the USA, "5 G Americas" [100] plays a pivotal role, primarily emphasizing 5 G's evolution and deployment. Concurrently, the "Smart Manufacturing" initiative emerges as the region's blueprint for information-integrated manufacturing, aiming to bolster productivity, efficiency, and adaptability [101,102].

The international endeavors and initiatives in 5 G, as elucidated in the preceding section, underscore the momentous shift in the global manufacturing landscape. These pioneering moves have concurrently catalyzed industrial and academic thrusts in the realm of NextG manufacturing. In the wake of globally resonating initiatives, key technological vendors have geared up to play seminal roles in materializing the NextG manufacturing vision. The key wireless vendors and their visions are summarized. Ericsson, for instance, envisions a world driven by massive M2M connectivity [103], widening technology applications across sectors. Huawei emphasizes the trinity of massive connectivity, ultra-low latency, and high reliability [104], looking to redefine manufacturing processes. Nokia champions the combination of scalable services with Gigabit bandwidths, making a case for ultra-low latency as a defining attribute [105]. Qualcomm foresees a connected society where the intelligent edge plays a pivotal role in streamlining operations and delivering efficiencies [106]. Not to be left behind, Samsung is betting big on multimedia services integrated with the IoT [107], envisaging a networked world where every device communicates and operates in harmony.

Table 3
Global NextG manufacturing initiatives.

Country/Regin	5 G Initiatives	Manufacturing Initiatives
Europe	5 GPPP	Industry 4.0
China	IMT 2020	Made in China 2025
South Korea	5 G Forum	Manufacturing Industry Innovation 3.0
United Kingdom	UKTIN	Made Smarter
USA	5 G Americas	Smart Manufacturing

4.2. Use cases

The proliferation of 5 G in manufacturing, backed by global initiatives and visions, opens the door to a multitude of advanced use cases, capitalizing on the promise of ultra-low E2E latency. These use cases are pivotal to realizing the full potential of NextG manufacturing, demonstrating how rapid communication can redefine the manufacturing realm.

5G-enabled smart sensor platforms refine traditional sensing technology by pairing it with 5 G networks for seamless, real-time data collection in manufacturing settings. Notably, the Fraunhofer Institute for Production Technology (IPT) in RWTH Aachen University, Germany has retrofitted multiple 5G-enabled sensors specifically for real-time monitoring of both machining processes and machine states [108,109] Each sensor in this sensing system is linked to a central motherboard equipped with data collection modules, a battery, and a 5 G communication unit. These wireless sensors can be affixed to moving components like spindles and rotary axes to capture precise, in-situ signals, which are then transmitted to 5 G servers for AI-based analysis. The NJAMI at Rutgers University in the USA, a smart milling testbed enabled by a 5G-enabled accelerometer and an ML model has been developed to monitor and predict chatter in milling engine blades in real-time. The Advanced Manufacturing Research Centre Northwest at the University of Sheffield in the UK has made similar efforts in innovating a 5G-enabled sensor to monitor auditory and vibrational signals in machinery [110].

AGVs are indispensable mobile robots in modern manufacturing [111], offering efficient and versatile material-handling solutions. A study by Nakimuli et al. [112] compared 4 G and 5G-enabled AGVs, focusing on guidance errors and energy consumption. Their findings reveal that 5G-powered AGVs demonstrate reduced latency, thereby enhancing control precision and conserving energy during course corrections. A use case of a 5G-enabled AGV was focused on the AGV guidance errors and current consumption compared to a 4G-enabled AGV. The results show that 5 G has a lower E2E latency connection, thus providing improved control of positioning and less power consumed on course corrections. Another study used edge-based ML models to predict and preemptively correct guidance errors, preventing potentially hazardous situations [113].

NextG manufacturing facilitates instantaneous, remote control of robotic systems in manufacturing units, offering substantial operational speed and reliability improvements. Specifically, Ericsson and Aachen University have developed a mobile robot platform controlled via 5 G edge computing [114,115]. This platform incorporates TSN into a 5 G framework, achieving communication latencies below 10 ms, thereby meeting the stringent requirements of real-time robotic control. NJAMI at Rutgers University has set up a 5G-enabled and computer vision-based robotic remanufacturing testbed to achieve a real-time sensing-learning-control loop with an E2E latency $<$ 10 ms.

In the manufacturing context, AR and VR primarily serve purposes such as design visualization, workforce training, and maintenance assistance. These technologies can significantly benefit from 5 G's ultra-low latency and high bandwidth. For example, a group of researchers recently introduced an open-source, 5G-enabled AR system that supports object visual positioning, content creation, and discovery. This system is built upon the OSCP and uses the COSMOS 5 G testbed, achieving the required latency of under 7 ms [116] for effective AR/VR applications [117].

In summary, NextG manufacturing opens a plethora of promising use cases that can demonstrate its significant business value in revolutionizing the manufacturing industry. As research and development in this area continue to progress, more advanced and diverse applications will likely emerge.

5. Summary, challenges, and outlook

5.1. Summary

As the developing wireless communication standard, 5 G is inherently designed to cater to the stringent demands of low E2E latency, flexibility, and reliability for highly time-sensitive and data-intensive vertical applications. The implications of NextG manufacturing, an extreme manufacturing paradigm from the temporal perspective, are substantial and transformative.

The advent of NextG augments the manufacturing landscape with unparalleled capabilities. Its hallmark extreme-low latency and high rate of data transmission make NextG a game-changer for Industry 4.0 use cases. The extreme-low latency facilitates immediate responses to sensor data, enabling swift real-time decision-making necessary in manufacturing automation. On the other hand, the impressive rate of data transmission makes NextG ideal for scenarios that demand instant processing of voluminous data in real-time, leading to an exponential rise in operational efficiency.

The 5 G's ability to simultaneously support a large number of devices, coupled with its network slicing capabilities, revolutionizes the fundamental infrastructure of manufacturing. It allows for each sensor, machine, and device on the factory floor to be interconnected, creating a unified, synchronized manufacturing ecosystem. Meanwhile, network slicing offers the ability to create customized virtual networks over a single physical network, optimizing resource allocation and enhancing overall efficiency in NextG manufacturing.

The transformative impact of NextG is further amplified when integrated with other technological developments inherent in Industry 4.0, such as AI/ML, digital twins [118,119], edge computing, and the IoT. These integrations enable more sophisticated, real-time data analytics, model development, decision-making, and operational control, all of which contribute to improving the seven levels of value creation in production [120]: quality, efficiency, lead time optimization, asset utilization, resource allocation, worker guidance, and production planning and control.

As a result, the advent of NextG catalyzes a new manufacturing paradigm. It is transforming how manufacturing operations are conceived, planned, and executed, elevating the global manufacturing industry to new heights. However, it is crucial to note that the journey to NextG manufacturing is complex and fraught with numerous challenges. The subsequent sections of this paper will delve deeper into these challenges, exploring potential solutions and future research directions.

5.2. Challenges and outlook

The advent of NextG wireless communication technologies will change the manufacturing landscape fundamentally. NextG holds the key to overcoming these barriers due to its unique communication capabilities of extreme-low E2E latency ($\sim$ 1 ms), high flexibility (wireless), high speed, and high reliability (>99.999 %) to meet the demanding requirements. Therefore, NextG manufacturing may meet the needs of a smart, sustainable, and resilient factory of the future. However, the challenges are very compelling.

NextG-enabled sensors. There is currently very limited capability to connect industrial equipment (e.g., machines, robots) to a NextG network. How to build NextG into a sensor to enable direct integration between NextG and industrial equipment is a pressing challenge. Building NextG into a sensor will enable direct integration between NextG and industrial equipment while eliminating the need to wire up using multiple devices. As current commercial sensors are not NextG-enabled, retrofitting industrial sensors (e.g., accelerometer) with NextG communication capability by adding a NextG module or chipset to these sensors would be very demanding. Future research could also focus on developing interntioanl standardized data transmission formats or protocols to ensure uniformity and ease of adaptation across different platforms. Additionally, miniaturizing NextG-enabled sensors is essential to enhance their applicability in space-constrained environments and improve adaptability in complex industrial settings. Addressing these areas will advance the integration of NextG technology in Industry 4.0, significantly expanding its potential applications.

Flexible NextG network architecture. For the flexible integration of the NextG network with the legacy sensors/machinery wire-bound Ethernet and industrial wireless (e.g., iWLAN) technologies for future manufacturing, a hybrid network architecture is required to use the industrial Ethernet-based solution (e.g., TTEthernet and TSN [121]) for stationary and legacy machines while robots, mobile control panels. To support diverse manufacturing applications, advanced network slicing is an important research direction because it allows for the dynamic allocation of network resources based on specific application needs, enhancing both performance and efficiency [122,123]. Energy efficiency and sustainability are also vital [124], as integrating energy-saving technologies and exploring renewable energy sources could significantly reduce the carbon footprint of manufacturing operations. Ultra-reliable low-latency communications are essential for supporting real-time applications, where enhancements in reliability and latency reduction can greatly improve automation and safety. Lastly, the incorporation of edge computing and distributed networks will address the need for processing large volumes of data near its source, thereby reducing latency and lessening the load on the core network.

Robust NextG network for complex and harsh manufacturing environments. Smart manufacturing environments pose the potential risk of interference caused by unintended electromagnetic emissions, the large number and types of devices using the same electromagnetic spectrum, and the disruption/jamming of humans and robots on the industrial floor. These potential disruptions point out the need for: a) constant spectrum monitoring and identification, b) deployment of multi-modal resilient communication techniques, and c) situational awareness that is also multimodal. Additionally, the relatively weak penetration capability of 5 G signals poses a significant challenge, especially in environments with dense or metallic obstructions. Research into how to enhance signal penetration or develop alternative strategies to overcome this limitation is crucial for an effective implementation of NextG technologies in industrial settings. Moreover, while security and privacy are general concerns for any networked manufacturing systems, which is not unique to NextG-enabled manufacturing and beyond the scope of this study. The ongoing evolution of network capabilities and integration levels highlights the importance of continual research in security and privacy. Such research may enhance the security of NextG manufacturing, ensuring that security measures evolve in tandem with technological advancements [125].

NextG edge-based controller. The development of an economic yet optimal NextG control algorithm with plug-and-play capability would constitute a compelling challenge. The certification of the robustness and stability of NextG edge-based control algorithms is also viewed as an emerging challenge. Further research directions include enhancing real-time data processing and decision-making to ensure that edge controllers can process and act on data instantaneously, which is crucial for dynamic industrial environments. Although NextG enables ultra-low latency data transmission, effectively processing and handling such massive amounts of data with similarly low latency remains a critical challenge. FPGAs or other specialized edge devices at the edge could be a promising direction to support the necessary processing speed and adaptability required for these complex tasks. Fault tolerance and reliability are also vital, as controllers must maintain operational efficacy despite system failures or external disruptions. This demands research into robust architectures and recovery protocols that ensure continuous operation under adverse conditions. Advancements in these areas will not only enhance the capabilities of NextG edge-based controllers but also facilitate their wider adoption and improve performance in real-world industrial settings.

Education and workforce development (EWD). The NextG revolution will create 4.6 million new jobs through 2034 [126]. Yet, 99 % of manufacturers cited that finding new skilled hires was the first and foremost challenge [127]. However, a diverse NextG-savvy workforce is scarce. Workforce development is a critical challenge for the successful implementation of NextG manufacturing.

CRediT authorship contribution statement

W. Guo: Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation. **J. Yi:** Writing – review & editing, Methodology, Investigation, Formal analysis. **Y. Chen:** Writing – review & editing, Methodology, Investigation, Conceptualization. **N. Mandayam:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis. **Y.B. Guo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **I. Seskar:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization. **L. Hu:** Writing – original draft, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

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

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