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Article

A Primer on the Factories of the Future

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Abstract: In a dynamic and rapidly changing world, customers' often conflicting demands plus fluid economic requirements, often driven by geo-politics, have continued to evolve, out-striping the capability of existing production systems. With its inherent shortcomings, the traditional factory has proven to be incapable of addressing these modern-day manufacturing challenges. Recent advancements in Industry 4.0 have catalyzed the development of new manufacturing paradigms (or smart factory visions) under different monikers (e.g., Smart factory, Intelligent factory, Digital factory, Cloud-based factory etc.) would help fix these challenges. Due to a lack of consensus on a general nomenclature for these manufacturing paradigms, the term Future Factory (or Factory of the Future) is here used as a collective euphemism, without prejudice. The Future Factory constitutes a creative convergence of multiple technologies, techniques and capabilities that represent a significant change in current production capabilities, models, and practices. It is a data-driven manufacturing approach and system that harnesses intelligence from multiple information streams i.e., assets (including people), processes, and subsystems to help create new forms of production efficiency and flexibility. Serving both as a review monograph and reference companion, this paper details the meanings, characteristics, and technological underpinnings of the Future Factory. It also elucidates on the architectural models that guide the structured deployment of these modern factories with particular emphasis on three advanced communication technologies capable of speeding up advancements in the field. It not only highlights the relevance of communication between assets but also lays out mechanisms to achieve these interactions using the Administration shell. Finally, the paper also discusses the key enabling technologies that are typically embedded into bare bone factories to help improve their visibility, resilience, intelligence, and capacity, in addition to how these technologies are being deployed and to what effect. At the onset of the study, we were interested in developing a monograph which would serve as a comprehensive but concise review of general principles, fundamental concepts, major characteristics, key building blocks and implementation guidelines for the Future Factory within the overall context of the manufacturing ecosystem, in the age of Industry 4.0. Our hope is that this paper would enrich the extant literature on advanced manufacturing, help shape policy and research, and provide insights on how some of the identified pathways can be diffused into industry.

Keywords: smart factory; advanced manufacturing; intelligent manufacturing; Cyber Manufacturing; Cyber Physical Systems; Internet of Things; Industry 4.0; Artificial Intelligence; data driven manufacturing

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1. Introduction

There is a burgeoning commitment by governments, industry, and academia to the digital transformation of industry with a view to attaining the Future Factory. Though it is still in its infancy, the future factory is one of the key constructs of Industry 4.0. In this paper, it is envisioned as a highly connected, very intelligent and broadly digitized production facility. It represents the future state of a well-instrumented and fully connected manufacturing entity sitting atop a cyber-physical framework. It is assumed to be highly flexible and extremely adaptable to production processes that rapidly accommodate product customization. The competitive edge of the factory of the future is that it reaches beyond the bounds of a traditional factory which focuses on the rudimentary production of physical products and extends its reach into such far-flung functions like production planning, production scheduling, inventory management, supply chain logistics, and even product design and development, all with limited human intervention. It is imperative to understand past and present research trends to be able to fully understand and anticipate the future of factories. And thus, support the formulation of strategies for the diffusion of research findings and knowledge about future factories.

Section (1) lays a historical background for the evolution of manufacturing beginning with the first industrial revolution when manpower was the state-of-art. It proceeds with a System Maturity Model (i.e., Levels of System Sovereignty) that discriminates between the different levels of factory autonomy. It wraps up with a synopsis on the concept of Industry 4.0 and ends with an association between Industry 4.0 and the *Future Factory*. *Section* (2) oultlines the research methodology while *Section* (3) delves deeper into articulating the concept of a Future Factory and its characteristics in the context of the Manufacturing Ecosystem (MeS). *Section* (4) discusses the conceptual framework and the reference architectures which provide, in one model, vetted and recommended nomenclature, structures, and integrations of various aspects (IT, OT, Business etc.) of an enterprise that are necessary for the development or upgrade of a *Future Factory*. Practical techniques and technologies necessary for the integration of various assets to enable intra and inter-factor communication are discussed in *Section* (5) while *Section* (6) is dedicated to the key enabling technologies that make the *Future Factory* possible. The paper is concluded with a summary & conclusion in *Section* (8)

1.1. The Industrial Revolutions

Historical observers have reported a series of Industrial revolutions. These "Industrial revolutions" are frames-of-reference for the intersection of events and emergent technologies that often led to marked shifts in productivity, industry, and society. Each of the past revolutions were driven by the emergence of new technologies and systematically resulted in wholesale disruptions and concurrent transformations in industrial processes, manufacturing methodologies, business models and the organization of capital and labor. These shifts have not only resulted in global re-organization of the means of production but also in remarkable changes to the socio-political, cultural, and economic fortunes of nations. We are currently in the dawn of the fourth industrial revolution, and they are discussed as follows: (a) The *First Industrial Revolution* (1760 to 1840, circa): This was the advent of mechanized production using coal which resulted in the transition from muscle power to mechanical power. It was triggered by the invention of the stream engine, and hydropower. It led to the emergence of the railroad construction industry. The major contribution of this era was improved efficiency. (b) The *Second Industrial Revolution* (Late 19th [1870 circa] to early 20th century): This emerged in part due to the arrival of electric power and the advent of the assembly line. It enabled mass production and kick-started the era of automation. (c) The *Third Industrial Revolution* (Mid [1969, circa] to Late Twentieth Century): The third Industrial revolution is otherwise known as the computer or digital revolution. Electronics and information technology were key technologies of this era. The era heralded the rise of computer networks, the emergence of the Internet and the arrival of robots. Automated production was also a product of this era, mostly facilitated by the growth of machine control and robots. (d) The *Fourth Industrial Revolution:* This era was marked by the ubiquity of physical object representation in highly interactive virtual information networks [3,4], leading up to the blurring of the boundaries between the physical and virtual worlds. This era characterized a shift in reliance on the client-server model to the adoption of ubiquitous mobility that has come to catalyze the growth of smart things. Other remarkable elements of this era include the growth of exponential technologies like Artificial Intelligence (AI), Blockchain, Big Data and Analytics, augmented and Virtual Reality (AR, VR), Robotics etc. Industry 4.0 is a construct of the fourth industrial revolution. It seeks to bring together the various conceptual elements capable of framing the eminent transformation expected from the collision of these technologies and the events they would likely trigger. The

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Future Factory is one of many outcomes of this construct. Though industry watchers have identified and focused on the four (4) industrial revolutions referenced above, there are early contemplations about a *fifth industrial revolution*. There is currently a lack of consensus on a definition for this emerging revolution. However, current information suggests that the main distinction between the fourth and fifth industrial revolutions could surround the role of humans and the extent of their intervention in manufacturing. There are concerns that the full realization of the fourth Industrial revolution could alienate humans. There is therefore a strong debate being had around the idea of redefining the role of humans in the factory. This could mean bringing humans back as the central feature of the factory through a deliberate emphasis on strong human-machine interaction.

1.2. Levels of System Sovereignty (L2S): A System Maturity Model

To evaluate the degrees of sovereignty of systems, machines, or other industrial components within the period of the four (4) industrial periods, we have proposed a system maturity model referred to as "Levels of System Sovereignty (L2IS). It is a measure, state, or degree of a system's self-governance. The model divvies up the different stages of industrial (manufacturing) development based on the degree to which tasks, system control and authority are split between humans and machines (more broadly, technology).

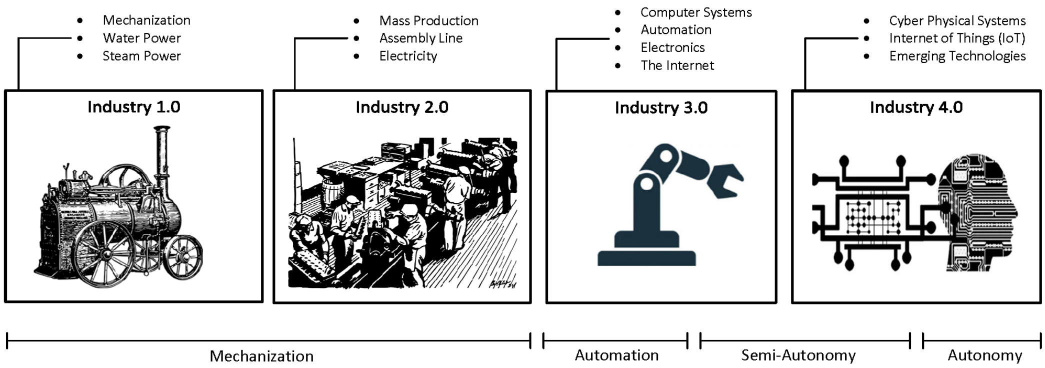

Figure 1. Diagram depicting the four industrial revolutions and degrees of system sovereignty

The sharing of control or authority between human and machines, has always been mutually complimentary. What has varied is the degree of autonomy (control, authority, or sovereignty) maintained by either party. Based on this model, a factory (or any other qualifying Industrial system) can be said to be at one of four (4) sovereignty levels: Mechanization, Automation, Semi-Autonomy and Autonomy (or Full Autonomy). Given this classification, the higher the autonomy of a system, the lower the demand for human-level intelligence or manual intervention. The model is further discussed using Figure 1.

1.2.1. **Mechanization:**

At this stage of industrialization machines (often heavy industrial machinery) were used to partially or completely do the work that was previously done using manual labor. Manual labor here refers to work performed by humans without any tools or support. Mechanization was a distinct feature of the first and second industrial revolutions. Though machines became the work horses of the industry, they lacked control of their actions. Humans had total control of the machines and provided all the direction, instruction, and information.

1.2.2. **Automation:**

Automation enables a reduction in human intervention in the production process. This is achieved through the predetermination of decision criteria, the development of subprocess relationships, and related actions and the embodiment of those pre-determinations in machines [5]. The integration of electronics, computers, control, and sensing elements

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into mechanized systems at the onset of the third Industrial revolution made it possible for machines to accept and execute instructions, this giving them the ability to self-think, self-dictate or more accurately, self-move. Automation is derived from two Greek words “autos” and “matos” meaning “self” and “thinking”, respectively. Notwithstanding, the etymology of the word, automated systems have no initiative. They still operate within rule-based boundaries. They primarily execute pre-defined tasks assigned to them by humans-they just happen to execute them faster and more efficiently. The automation category is also dominated by Industrial machines and processes that are managed by hierarchical, centralized, and rigid control systems. While they can be optimized for increased efficiency, they are very difficult to re-purpose and very poor at responding to change. The consequence is that they are unable to correctly respond when faced with unfamiliar situations especially within dynamic environments, often necessitating the inevitable intervention of humans. Notwithstanding the advantage of automation is that it reduced the demand for human (manual) intervention.

1.2.3. **Semi-Autonomy:**

Most advanced factories today are at the “semi-autonomy” level. Semi-autonomous systems feature programmable devices and machines. Unlike systems from the prior generation, they are smarter. They can better sense and understand their environment. Through the Internet of Things (IoT), they can interact with other entities, share data/information, and make some decisions within a volatile production environment leveraging Machine/Deep Learning (ML/DL) based technologies. The factors that helped facilitate this level of autonomy include the advent of the Internet, the maturation of computer networking technologies, the growth of the Internet of things (IoT), and the rise of Cyber-Physical Systems (CPS). Other factors would include the cross-domain integration of modern Operational Technologies (OT) and Info-Tech/Communication systems and the broader integration of Advanced Control Devices (PLCs, PCs, PACs, etc.) into Industrial systems.

1.2.4. **Autonomy:**

Autonomy is the highest level of system control by non-human actors within the Industrial and manufacturing process. It is the expected future state of the factory of the future. A state where very limited human intervention would be required for the full functioning of a factory. The factory of the future would be managed by intelligent heterarchical (i.e., non-hierarchical, or unranked) control mechanisms which would make it possible for the factory to respond well to volatility, unpredictable disturbances, or sudden change within a dynamic environment. While we are still years away from that day, there is the hope (think autonomous cars), that one day a fully autonomous factory would be technologically feasible. A factory at this level of autonomy would have the ability to execute work, predict failure, grow smarter, self-correct and if necessary, recover or compensate for failure with little or no explicit intervention or instructions from a human. The attainment of this state would require the maturation of autonomic systems which would involve the embedding of advanced cognitive and deep learning capabilities within multiple sub-systems within a factory. Currently, human involvement in autonomic systems is significant. As earlier hinted, the goal of achieving manufacturing systems autonomy is still far off. Many more years of significant technological advancements would be required. Until then, the factory of the future will continue to exist within the wide chasm between automation and autonomy (i.e., Semi-autonomy). Full autonomy is a future goal that would require significant embedding of smart technologies within the manufacturing mainstream.

1.3. Industry 4.0 and the Future Factory

The term "Industry 4.0" has its origins in Germany [6]. It has been a subject of great intellectual and economic discussion within academia, industry, and government both locally and internationally [7]. It has also been a subject of multiple work in the open

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literature[8,9]. Discussions around it first emerged in literature sometime in November 2011 following a national strategic initiative, by the German government aimed at the digitization, integration, transformation, and standardization of manufacturing. The US equivalent of this term is Smart Manufacturing [10,11]. Industrie 4.0 is a construct (idea or theory) of the fourth industrial revolution that promotes the digitization of manufacturing. It seeks to improve upon the advances achieved in the third industrial revolution which includes the adoption of computers and industrial automation. It is a step higher forward that includes the integration of interconnected systems of intuitive, self-regulating, smart, and autonomous entities that seamlessly exchange data, perform tasks, and work collaboratively. With the goal of the upgrade being the improvement in productivity, flexibility, efficiency, and agility.

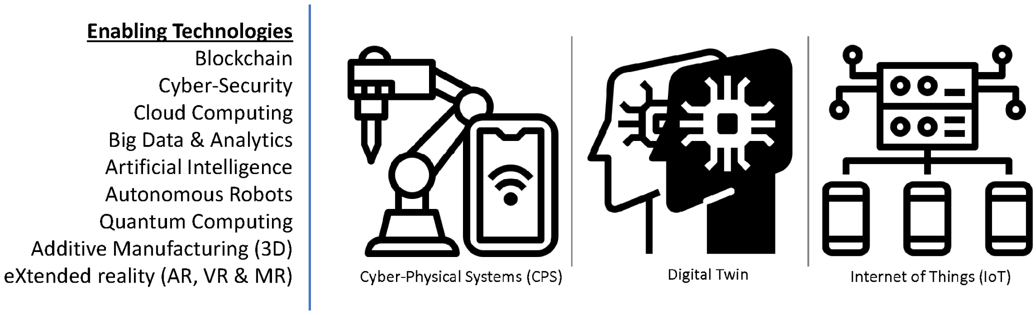

Figure 2. Emerging Technologies enabling the Development of the Future Factory

CPS [12] and IoT are the core technologies that make Industry 4.0 possible. In the final report of the Industrie 4.0 working group entitled, "Recommendations for implementing the strategic initiative INDUSTRIE 4.0" commissioned by the German Federal Ministry of Education and Research (BMBF) and aimed at securing the future of German manufacturing industry, Industrie 4.0 was defined as, "... networks of manufacturing resources (manufacturing machinery, robots, conveyor and warehousing systems and production facilities) that are autonomous, capable of controlling themselves in response to different situations, self-configuring, knowledge-based, sensor-equipped and spatially dispersed and that also incorporate the relevant planning and management systems" [13]. Industry 4.0 encompasses a plurality of methodologies, technologies, and emergent trends [2]. At the very minimum, it is based on the technological concepts of Cyber Physical Systems (CPS) and Internet of Things (IoT)[14]. It is expected that Industry 4.0 would result in the exponential growth of data, improvement in operational effectiveness and a radical transformation of the landscape within several industry segments that would result in the development of new but nimble business models, build-out of highly customized products and the creation of very customer-centric services [13,15,16]. Interoperability, Information transparency, technical assistance and decentralized decision-making were identified as the four pillars of Industrie 4.0 necessary for the development of the smart factories [17]. Industry 4.0 as a concept is evolving. It is embracing newer paradigms, technologies and distinct arrangements and organization of these assets. Beyond representing a technological transition from embedded systems to cyber-physical systems, it now refers to the networking, organization and marshaling of Intelligent objects (people, machines, and processes) leveraging information, services, and communication technologies to help achieve machine & system autonomy, decentralized intelligence, and production optimization. Interoperability is about the ability of machines and other assets to seamlessly connect and communicate with one another (i.e., share data and information). Information transparency relates to the ability to access and acquire data and information and using same to build virtual models of the physical device or system. Technical Assistance speaks to systems non-human assets (robots, devices, and systems) working together to assist humans in solving problems. And decentralized decision-making refers to the transfer of some resources and control to enable decision-making at distributed locations within the network without a need for consent from a central control hub [17].

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2. Research Methodology

The qualitative study of Future Factory as a concept is a daunting task due to its multi-dimensional and cross-disciplinary scope. It must therefore be understood that a meaningful review of literature would require the interrogation of multiple research streams, spread across a variety of domains and disciplines. For this reason, the reliance on traditional review methodologies for data collection, research trends tracking, knowledge syntheses and objective viewpoint critique, across such broad scope can be challenging at a minimum but more likely problematic. Therefore, a more compelling method for the execution of the study was thought to be the semi-systematic (narrative) review approach caters to our need to implement multi-disciplinary and multiple domain-based reviews of literature, in parallel this is compared to the traditional systematic review approach, which is often primarily focused on appraisal, and synthesize of primary sources information on one specific issue or topic. While a large portion of this review focuses on peer reviewed literature, it also draws upon findings from the grey literature (including Industry Reports, Policy documents, white papers etc.). The results later discussed in the paper are based on keyword search that relied on such digital sources like Google Scholar, Web of Science and Science Direct. The search was focused on qualitative studies with abstracts or titles containing terms related to important elements of the subject matter (factories) and the key enabling technologies that are driving the changes. On the one hand, terms like "smart factory", "intelligent factory", "digital factory", "industry 4.0", "advanced manufacturing" etc. were used to aggregate content to understand various aspects of the factories of tomorrow (Future Factories). On the other hand, terms that target articles related to enabling technologies were used like "artificial intelligence", "cloud computing", "block chain in manufacturing", "mixed reality", "augmented reality", "virtual reality", etc. The goal was to aggregate enough materials to understand these technologies and disciplines with particular focus on foundational principles, underlying concepts, and application. Using key articles on our primary subject, we were able tracked down related articles of relevance that did not show up in our prior searches (i.e., snowballing search methodology).

3. Understanding the Future Factory

As the traditional factory becomes increasingly unable to address the manufacturing challenges of the 21st century, there is a need to to rethink the design of today's manufacturing system. This would requires the development of factories with capabilities which radically improve the predictability, reliability, efficiency and security of manufacturing processes. This section explores the meaning and characteristics of a factory of this sort, otherwise referred to as the *Future Factory* or the *Factory of the Future*.

3.1. The Future Factory in the context of the Manufacturing Ecosystem (ME-S)

Accenture *Global Strategy or Management Consultants)* defined ***Manufacturing Ecosystem*** as, "*. . . a network of industry players who work together to define, build, and execute market-creating customer and consumer solutions; defined by the depth and breadth of potential collaboration among a set of players. The power of an ecosystem is that no single player owns or operate all components of the solution, and the value the ecosystem generates is larger than the combined value each of the players could contribute individually.*" [18]

In the past, production literally happened "under one roof". But as products became more sophisticated, and users demanded more affordable, yet higher quality products, it no longer makes sense to think of manufacturing as a one "factory-only" activity. Often no single entity owns or operates all elements of a manufacturing solution. Now more than ever, every product that rolls off the conveyor relies on some form of third-party service or technology. It is the case that producing high quality and cost-efficient products and services is dependent on partnering with other providers and cooperating with different entities within the larger ecosystem which incidentally is the key to efficiency. Because of the technological changes that have occurred in the past three decades, technology now has the power to reshape the production process by tightly connecting all relevant entities (humans, machines, and applications) to enable the seamless flow of the data required to provide the intelligence needed to drive efficiency. The goals of these networks are to exchange information, provide support and explore meaningful ways to achieve shared objectives. These networks, loosely referred to Manufacturing Eco-Systems (ME-S) often include partners, factory workers, suppliers, vendors, contractors, and even customers. Like a docking station, the Manufacturing Eco-Systems (MES) is a hub on which the Future Factory sits, enabling it to connect to an interdependent group of interrelated entities and systems with which it routinely communicates and on which it depends for the supply of information and resources. Because the Future Factory (FF) relies on the concepts of information and feedback, the seamless flow of information from and to entities within the Manufacturing Eco-Systems (MES) is critical for its optimal performance. At an abstract level, each of the entities within a Manufacturing Eco-Systems (MES) can be represented as objects which can be connected to one another and to various machines, devices, and sensors to help extract valuable information. Entities participating in a manufacturing ecosystem have the rare distinction of being able to access the decision-making knowledge they need, when they need it because of the power of technology. Entities in a manufacturing ecosystem collectively facilitate the transfer and eventual transformation of raw materials into finished products. It is difficult to fully understand the Future Factory (FF) in isolation of all other entities within the Future Manufacturing Eco-Systems (ME-S). In many manufacturing contexts, it is difficult to separate manufacturing operations, for example from the supply chains that support them, setting up the need to look at manufacturing through the prism of an ecosystem. Ultimately, the resilience of the smart factories and the third-party systems that supports them would depend on reliable interaction between the two. Ultimately, the future factory would be the result of the total reorganization, connection, and efficient utilization of the means of production including assets, processes, and people. It is less about the automation and digitization of individual elements or parts of the production process but more about the connectivity or tie-back between a broad range of internal and external components and processes to enable real-time data sharing, information exchange and intelligent feedback and response between all nodes within the manufacturing ecosystem. The goal being to enable the achievement of smarter, quicker, and more efficient solutions. This would require seamless connection, efficient data sharing and reliable transfer of information, in real-time between different asset categories including between Machine-to-Machine (M2M), Machine-to-Device (M2D), Human-to-Device (H2D), Machine-to Virtual Twin (M2VT), Factory-to-Factory (F2F), Factory-to-Product (F2P), Factory-to-Human (F2H) and Factory-to-Supply Chain (F2SC) within the manufacturing ecosystem. Each asset on the networked ecosystem is assigned an identity and connected to other assets in the network using Industrial Internet of Things (IoT) protocols and technologies.

3.2. Describing the Factory of the Future

The emergence of the factory of the future has been necessitated by sweeping globalization and unprecedented technological changes which have resulted in a very competitive and dynamic global marketplace. The resultant volatility has given rise to short product lifecycles, a "big ask" for on-demand production and increasing price pressures [19]. As a result, traditional manufacturing with all its advanced enhancements is fundamentally ill-equipped to meet the demand-pressures of the current environment. A state of play that has necessitated rethinking current manufacturing paradigms. In a bid to benefit from the on-going technology advancements in the manufacturing space, multiple actors (the state, industry, and academia) are actively involved in trying to shape the future of manufacturing, hence the various national strategies, paradigms (Smart factory, Intelligent factory, Factory of the future etc.)., frameworks, and nomenclature proposals.

Incremental changes to traditional manufacturing paradigms are fundamentally incapable of fully addressing modern manufacturing needs. As a result, manufacturing as a concept needs to be fundamentally re-imagined. As a craft, it needs to be radically

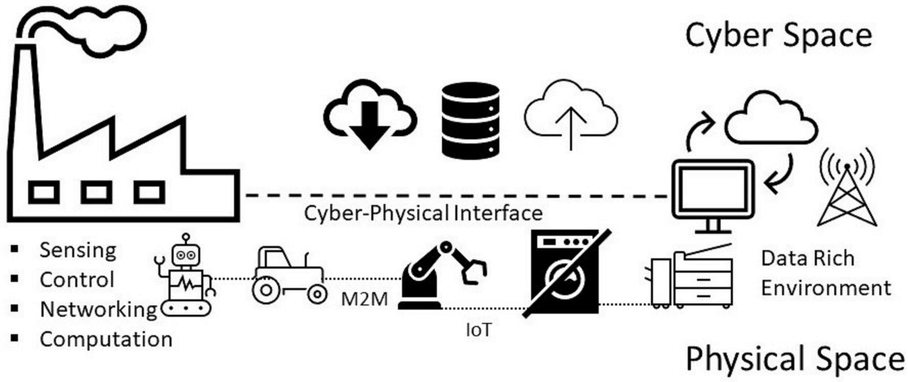

Figure 3. Cyber Manufacturing Systems (CMS)

re-engineered. Notwithstanding the obvious need and urgency to transform manufacturing as we know it, there is no consensus around a fitting nomenclature for a factory that can serve as a replacement for the traditional factory. Terms like Smart factory, Intelligent factory [1,2], Digital Factory etc. represent emergent paradigms that seek to fulfill this need. However, none has seemed adequate enough to capture the approval of a plurality of stakeholders within the manufacturing community. This paper does not propose a unified nomenclature but instead uses a generic term (i.e., *Future Factory* or the *Factory of the Future*) to help crystallize the general principles advocated by the most common advanced manufacturing paradigms. Also, note that the *Factory of the Future* and *Future Factory* have been used interchangeably in this text and represent the future state of the factory during and beyond the Fourth Industrial Revolution (4IR). Given that the end goals articulated by many of these paradigms are similar, we would be drawing insights and inspiration from them to help characterize the Factory of the Future.

The concept of the Future Factory upends the factors and elements of traditional manufacturing systems. The biggest challenge is being able to clearly define what the Future Factory is and to then transition those concepts effectively from theory to practice. For a start, the Future Factory is the nucleus of Industry 4.0 [20]. A proper articulation of the meaning of the Future Factory is heavily reliant on the contextual and comprehensive understanding of Industry 4.0 concepts which is the reason why sub-section (1.3) of this paper was dedicated to elaborating on Industry 4.0. The technical foundation on which it stands is the selective and strategic integration and exploitation of the unique advantages of a collection of emerging technologies like Cyber-Physical Production systems (CPPS)/Cyber Manufacturing Systems (CMS), the Industrial Internet of Things (IIoT), Internet of Systems (IoS), Artificial Intelligence (AI), Smart Robotics, Cloud computing, Cyber-security, Big Data analytics etc. making the factory of the future a System-of-Systems (SoS) that is designed to delivery key advantages that can potentially address the challenges confronting traditional manufacturing in the age of speed, volatility and uncertainty [21]. While all the above referenced technologies bring with them unique capabilities, the structural underpinning or technical framework that supports the Factory of the Future are Cyber-Physical Production Systems (CPPS). The future of manufacturing necessitates increased flexibility in product customization, process monitoring, product quality/process control and service delivery. Hence, collaborative networks and cyber-physical production systems (CPPS) have been identified as the future of industry [22] where administrated interactions and information flow among machine, people, organizations, and societies have been pursued as an ongoing research topic [23–25].

Definition 1: *Thus, a barebone definition of the Factory of the Future would be a dynamic, and highly integrated network of Cyber-Physical Production Systems (CPPS) that communicate or interact with each other using the Industrial Internet of Things (IIoT) and the Internet of Services (IoS). From an enterprise perspective, the Future*

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Factory is a vertically and horizontally integrated production system with an efficient connection between itself and the supply chain that supports it.

Definition 2: *Aptly named, the Future Factory is not an "end state", but a constantly evolving solution that continuously but strategically integrates new technologies and systems with the goal of creating a resilient, stable and efficient System-of-Systems (SoS) which can adapt to rapidly changing manufacturing requirements, fulfill dynamic customer demands (in a timely and cost-effective fashion), support customized mass production involving high variability (high product variety) with options for small lot sizes, adapt to disturbances and rapidly respond to change or otherwise recover from failure autonomously while eliminating the need for expensive post-process inspection.*

The Factory of The Future would be a key driver of manufacturing competitiveness across the globe because of expectations of higher efficiency, lower production costs, mass customization, adaptability, and flexibility. Its true essence is the incremental improvement in how we design, manufacture, distribute, and service products.

3.3. *The Characteristics of the Future Factory:*

In its mature state, the Future Factory (FF) is envisioned as a production ecosystem that operates autonomously (i.e., requiring little or no human intervention) in different manufacturing operations including production, logistics, prognostics, diagnostics etc. From a technical point, all of these are made possible by a technological framework built using CPS and IoT, with the intelligent decision support system reliant on advanced analytics and knowledge learning methodologies [26].

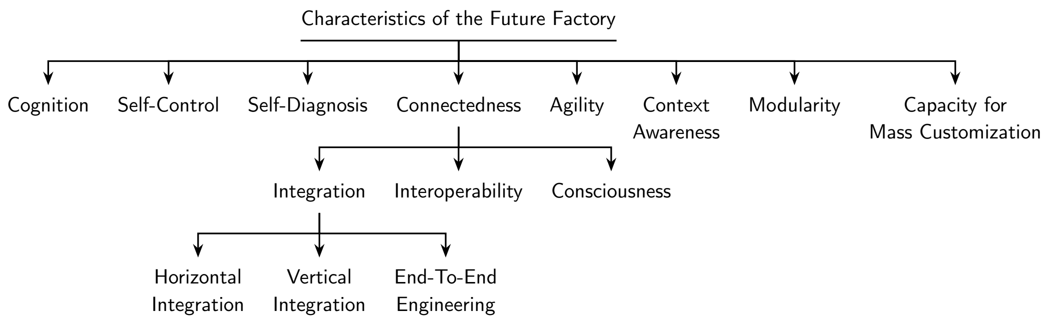

Figure 4. Characteristics of the Future Factory

3.3.1. **Cognition:**

The massive generation, analysis, and fusion of data (Big Data Analytics) into manufacturing operation means that agents or entities of the factory possess cognitive capabilities and can learn, plan, and interact, all while acting autonomously and in concert with other entities.

3.3.2. **Self-Control:**

The future factory would be able to respond to changing business demands and conditions in real-time [27]. It would have decision making and self-controlling abilities, leveraging the factory's ability to extract and analysis large amounts of customer and machine data (cloud computing) and subsequently transmit useful information and actionable intelligence on a need-to-know basis to the various entities within the network. The ability of the production facility to have access to real-time information about changes to the business environments can help the factory to adjust operations accordingly and help reduce business uncertainties and meet customer demands. The ability of the factory to self-control would be possible because of its decentralized architecture that allows for the distributed storage and flow of information. Data and information would flow through (to and from) a decentralized hierarchy that includes multiples localized systems, hubs, machines, and related nodes within the network (including the products themselves).

3.3.3. **Self-Diagnosis (Machine Health):**

They also self-diagnose, and repair identified malfunctions without halting production or switching to a downtime mode.

3.3.4. **Connectedness:**

Inter (and intra) connection, automation, and networking of asset within and between various activity layers including factory, supply chain and community (IoT, Blockchain). This characteristic is further discussed in sub-section (3.4).

3.3.5. **Agility:**

The factory of the future (Smart factories) is flexible and has adaptable production processes [28].

3.3.6. **Context Awareness:**

The Future factory is context aware. Context awareness in this instance refers to a system's ability to self-sense, respond, adapt its behavior, and communicate based on information transmitted from its environment or gleaned from sensors embedded in several nodes or entities within the system. Sensors which have become affordable and ubiquitous across factories and entire manufacturing ecosystems [29]. Key components of the system can negotiate with each other to both request and profile functions [30]. With technologies like Blockchain, Radio Frequency Identification (RFID) and Quick Response code (QR Code) the smart factory can systematically identify and track assets, products, and people, both spatially and temporally making it possible for the factory to have real time knowledge of its current state.

3.3.7. **Modularity:**

Ability to decentralize production (Cloud computing and Additive manufacturing)

3.3.8. **Capacity for Mass Customization:**

Mass customization involves the efficient, cost-effective, and speedy customization of products and services at scale leveraging customer preferences (Big Data). This would be facilitated by real-time communication between products and the production lines. Traditional automatic identification and transmission technologies like Radio Frequency Identification (RFID) and Quick Response code (QR Code) can play a role in enabling products and production lines to communicate in real-time. The information transmitted can be used, for example to address bespoke customer requests (product customization) or to control the path of products as they navigate through different manufacturing lines or stages.

3.4. Enabling Connectedness: Integration, Interoperability & Consciousness

Of the eight (8) characteristics of the *Factory of the Future* discussed in sub-section (3.3), connectedness is perhaps the most fundamental. For this reason, we would be expounding on the subject to help characterize the Future Factory. Unlike traditional factories, the Future Factory is very robust, fully connected, and agile. It can synchronously learn and adapt to changing conditions using information acquired from a constant flow of process and machine health data amassed from a variety of interconnected assets, processes, and systems. All of these are made possible because of the system's "connectedness". The connectedness of a factory is dependent on the degree of integration, interoperability, and consciousness of the system. Several researchers [8,31–33] have suggested that these elements constitute key success factors for Industry 4.0 in general, and the Future Factory (FF), in particular. Integration speaks to the tight combination, amalgamation, or homogeniza-

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tion of the entire manufacturing network, while Interoperability refers to the ability of these tightly integrated systems and components to communicate or talk to each other seamlessly and in real-time. Integration is central to interoperability. On the other hand, consciousness speaks to the ability to be aware (or cognizant) and responsive to one's environment. Below we would further discuss the three main functions elements of consciousness: Integration, Interoperability, and Consciousness

3.4.1. Integration:

Integration involves the tight linking of independent factories, processes, and product lifecycles into a core network that can communicate with one another, and share data as needed while supporting distinct or shared technological and businesses objectives. The goal of integration is to enable structural cohesion, seamless flow of data, and the ability of independent entities to access actionable information (technical or enterprise-related) from an integrated network. The three (3) different types of Integration identified in the Final report [12] of the Industrie 4.0 Working Group include (a) Horizontal integration through value networks, (b) End-to-end digital integration of engineering across the entire value chain and (c) Vertical integration and networked manufacturing systems. By integrating all systems, the most up-to-date process and product data is available at any time and can be shared with all entities (men, devices, and machines) on a need-to-know basis to help facilitate planning, production, maintenance, logistics, supply chain management and customer service. Proper integration can result in a factory that is innovative, proactive, and agile. Such a factory would be able to adapt to market changes quickly, respond flexibly and rapidly to changing customer demands and achieve/maintain competitive advantage over peers even in the most unpredictable business environment. One of the main features of the Future Factory is the data-integrated core capable of supporting truly automated value chains [34,35]. Currently, the degree of asset and system integration within most factories is very limited. Though some have achieved the full integration of the shop floor (field level), loopholes still exist as you through the integration layers up to the management level[36,37]. The goal of the Future factory is to connect all entities (machines, devices, people, systems etc.) using standard communication protocols and therefore enable seamless interaction between all parties.

a) *Vertical Integration:* Vertical Integration is the integration of all hierarchical physical and informational subsystems within a factory to achieve a flexible, self-managing (autonomous), self-organized and reconfigurable manufacturing system that can respond to production uncertainties quickly, flexibly, and effectively.
For example, if a client requests specific product customizations, the business development unit should not be on a call to engineering all day. All the information requested by the engineering department would already have been logged in the ERP system-essentially everyone has access to the same information (albeit different versions on a need-to-know basis). With this this level of transparency and the seamless flow of information, a vertically integrated system can be easily reconfigured to produce the customized product or manufacture small-lot sizes, at short notice without a significant technical or fiscal penalty. The integration typically cuts across different hierarchical stages beginning from the field (Factory Floor) right up to the enterprise resource planning (ERP) level. The joint implementation of all three integration options can result in a fully integrated factory comprising digitally connected entities (machines, people, products, and services). The overall goal being the integration of all digitized physical assets into an ecosystem that includes all elements of a local factory and all other entities or partners within their value chain. The ecosystems resulting from these integrations enable increased autonomy for system elements, decentralized control, improved efficiency, and transparency given the seamless transmission of data and information between all entities.
b) *Horizontal Integration:* Horizontal Integration involves the digital connection of a factory to other external entities and processes across its value chain. This arrangement

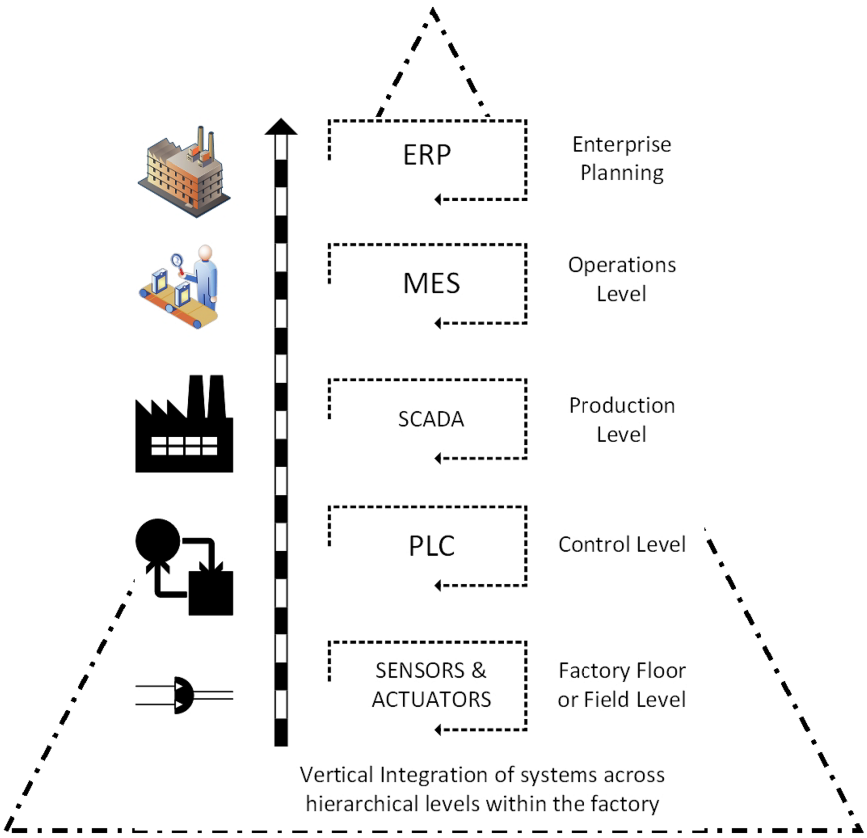

Figure 5. Automation Pyramid

would include a digitally developed network of warehousing systems, transportation assets, production facilities that feature ICT-based integration of everything from inbound logistics to production, marketing, outbound logistics, and services [26]. The connectedness makes it possible for real time data to be obtained, analyzed, and shared in real-time to facilitate rapid and accurate decision making. All nodes on the network can have access (on a need-to-know basis) to information about production status, inventory levels, available resources, and other critical information necessary for streamlined production. A factory so connected is said to be horizontally integrated. Horizontal integration can take place at different scales and at several levels. Optimal value can be created by a factory that can harness value from data gleaned from activities and processes, both internal and external to the factory. As part of the horizontal integration of a factory, suppliers, contractors, and even other factories, whether located in the same or different geographical locations can be connected into an efficient ecosystem where there is seamless transmission of data and information. The efficiency gained by this arrangement can be mutually shared by all parties. For example, a factory can have regulated remote access to a resource (machine, device, software etc.) within a company in another location. These outcomes can result in efficiency of scale, improvements in turn-around time and higher productivity levels. Other advantages include transparency, better knowledge sharing and improved communication.

c) *End-To-End Digital Integration of Engineering Across the Entire Value Chain:* Though many factories have successfully digitized different aspects of their business, some have also ended up with segmented or siloed organizations where the systems of various units are unable to talk to one another. Though most manufacturing processes are supported by ICT, much of the systems and technologies that underwrite them remain static and inflexible [12]. The result is that information flow is inhibited,

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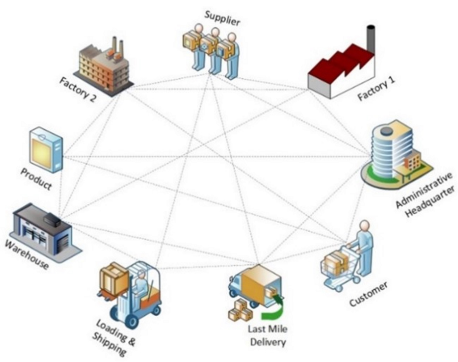

Figure 6. Horizontal Integration

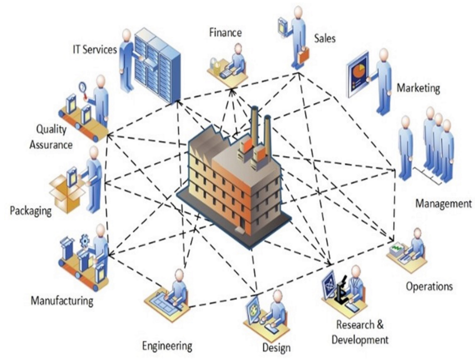

Figure 7. End-to-End Integration

throwing manual transmission of data across the individual aspects back into the discussion. Digitally connecting these different systems and technologies can be referred to as End-to-End Engineering Integration. More broadly, it involves the digital integration of all aspects of the value chain (Sourcing, Product development, Production, Logistics, Operations, marketing/Sales and After-Sale Services etc.) to enable the seamless flow of data across the network for the purpose of delivering real-time information about production status to all stakeholders, enabling the development of new efficiency, supporting product customization [38], streamlining of processes and a reduction in the unnecessary expenditure on manual activities.

3.4.2. Interoperability:

Interoperability is a very critical characteristic of the Future Factory, primarily because it involves the ability of different entities (machines, devices, applications etc.) to exchange, process and use data/information. Multiple definitions of interoperability exist [39–45] in literature but they all distil down to the ability of two or more entities to receive, process and exchange content (data, information, or services) for their mutual interest, in a timely manner, without distortions or any form of semantic inhibition. The goal of the data, information or service so exchanged is to help all parties to operate more effectively together [39]. Abe Zeid et al. (2019)[46] outlined three other types of interoperability i.e., Syntactic, Semantic and Cloud-Manufacturing Interoperability. (a) *Syntactic Interoperability* relates to data formats. The use of standardized data formats can support interoperability. (b) *Semantic Interoperability (human interpretation of content)*. The commonly used standards for semantic interoperability are XML and the Resource Definition Framework (RDF). (c) *Factory Interoperability (Vertical Integration)*: The ability of physical and informational subsystems within a factory to seamlessly communicate with each other. (d) *Cloud-Manufacturing Interoperability (Horizontal Integration)*: Cloud-Manufacturing Interoperability is defined as a form of horizontal interoperability where virtual elements of the production process can communicate with one another. This is broken down into three types: (1) *Transport interoperability* (related to the interoperability of data transfer/exchange using different protocols i.e., REpresentational State Transfer (REST) over HyperText Transfer Protocol (HTTP), and Message Queuing Telemetry Transport (MQTT)[47]. (2) *Behavioral interoperability* refers to system response when faced with multiple requests and (3) *Policy Interoperability* ensures cloud systems element comply and conform to standard of stated regulations and policies. A huge cost penalty (upwards of $1Bn) was identified in the U.S. automotive industry due to the lack of interoperability across its supply network [48]. Interoperability is required to make complete integration possible.

Challenges associated with interoperability remain the main constraint to the full realization of Industry 4.0 within the manufacturing industry. For example, enterprise interoperability is major hurdle for many businesses that currently own expensive legacy equipment. Some of these organizations are reluctant to replace these equipment with newer assets because of the additional replacement costs though they are open to getting

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the benefits of Industry 4.0 if it is possible to retain their existing assets [34] . Achieving interoperability in this case would require retrofitting these assets so that they can seamlessly communicate (or talk) to other assets (machines and devices). The ability of these assets to communicate with related assets within an industrial network is enterprise interoperability.

3.4.3. Consciousness:

Consciousness is the state of being aware of oneself and one's environment. In the context of the Factory of the Future, consciousness speak to the ability of a the factory and/or its respective elements (i.e., machines, robots,sensors, actuators, conveyors, products etc.) to be able to connect and exchange information automatically with other components or systems within their ecosystem. It also includes the ability to predict the behavior of connected systems, react appropriately and to optimize the processes that take place within and around them. To make all of these feasible, conscious factories (including all related systems, machines, and products) need to be equipped with the capacity to monitor, detect, and control events. A factory that is conscious would be able to (for example) sense machine component degradation autonomously. It would also be able to predict (without prompting) a machine's remaining useful life. Such a system would be self-aware and can self-predict, self-configure, self-maintain, and self-organize.

3.5. From the Automation Pyramid to a Decentralized & Distributed Network

The automation pyramid is a representation of the different layers or levels of automation in a factory. It helps graphically capture the integration of different technologies and the inter and intra-level communication pathways between them. In classical automation pyramid has a five-level control layers that includes the data, services, and functionalities which are hierarchical and relatively rigid.

Given the advent of Industry 4.0 and all the recent technological changes, the rigid, hierarchical model would not be adequate to represent the facts on the ground. Current manufacturing trends reflects a complete shift in paradigm from the previous era. Smart devices are ubiquitous within the manufacturing space making embedded intelligence available at the extremities. The connectedness of assets is also unprecedented with the advent of networking via open and global information networks like the Industrial Internet of Things (IIoT) and the Internet making IT/OT convergence easier.

This level of networking was unavailable in previous automation technologies. With different variety of devices and machines connected either in a mesh, laterally, horizontally, or vertically it is difficult to tell in advance what device, process or subsystem would interact with another and in what manner. More so, the existence of predictive analytics at the edges now makes responsive control possible without the need for clearance from monitors or assets domiciled in layers "higher up" in the automation pyramid. Cloud technology and virtual twinning also enable visualization of control. With such a preponderance technologies easy adaptability of individual assets and an unprecedented increase in the overall intelligence of the system is easily realizable.

The classical automation pyramid is insufficient to represent these new realities and it must be stressed that this hierarchical model is all but outdated. The attainment of the vision and goals of Industry 4.0 require more flexibility in the interconnectedness and communication between assets of different categories irrespective of the control layer to which they are currently assigned. It is for these reasons and more that there has been a growing interest by scholars and practitioners for a gradual dissolution of the classical pyramid and the introduction of a more decentralized and distributed framework that would serve as an update or outright retirement of the classical automation pyramid [49]. Figure (8) shows one of such models, laid side-by-side with the classical automation pyramid. The need for the realization of the full potentials of Industry 4.0 requires these changes. Traditionally, IT based enterprise systems (like the ERP, CRM) and Operational technologies (MES &

Table 1. Standards aligned to ISA95 Model

ISA95 Model Levels	Tools	Standards
Enterprise Level	ERP	ISO 15704 Enterprise Architecture Requirements ISO 20140 Automation Systems & Integration ISO 19439 Enterprise Integration ISO 19440 Enterprise Integration OAGIS BPMN, DMN, PMML B2MML
MOM Level	MOM	IEC 62541, IEC 62837 IEC 62264 (ISA 95) ISO 22400 OAGIS PMML DMIS, QIF
SCADA Level	HMI/DCS	IEC 62541 (OPC UA) IEC 61512 (ISA 88) Modbus BatchML, PACKML IEC 62541 (OPC UA)
Device Level	Field Device	MT Connect IEC 61158 (EtherCAT, PROFINET) IEC 61784 Modbus/Profibus PROFIenergy IEC 62591/HART IEC 62541(FDI)

SCADA) lived on different islands (i.e., different layers on the automation pyramid) with a firewall separating them.

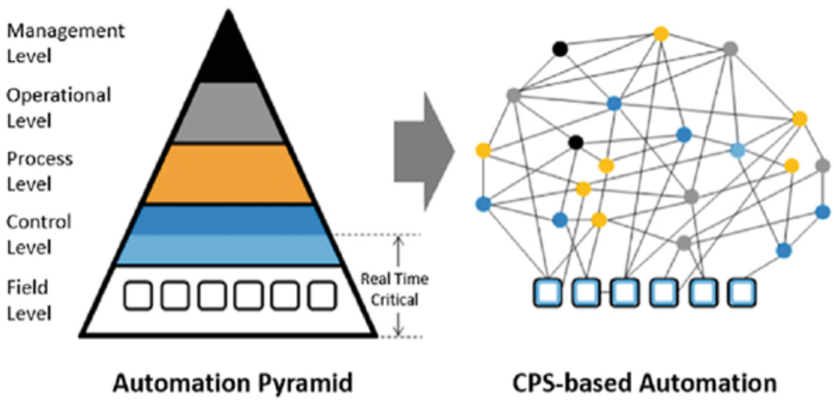

Figure 8. Classical Automation Pyramid laid side-by-side a CPS-based Automation Model *Source:* VDI/VDE-Gesellschaft Mess und Automatisierungstechnik (GMA)/VDE ([50])

While this model has worked well so far, it underutilized the potential value that integrating the two layers (and having them talk to each other) would have created. For example, data on customer complaints or preferences, maintenance data or user behavior typically captured with Customer Relationship Management (CRM) applications could

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potentially be useful product redesign or improvement information for product designers if they could have ready access to those through the Enterprise Resource Planning (ERP) applications.

4. Conceptual Frameworks and Reference Architectures

A reference architecture is a toolbox with recommended structures, relations and integration designed to guide practitioners towards solution approaches that meet accepted industry best practices. Reference architectures typically minimize complexity since they anticipate and addresses salient questions that would otherwise arise thereby enabling practitioners to accelerate model development and deployment. They are usually defined at different levels of abstraction. They provide a common lingo or vocabulary that serves as the basis of shared communication during implementation helping emphases commonality amongst users. Typically reference architectures also provide templates, reusable designs, and industry best practices that serve as scaffolds and building blocks (i.e., LEGO pieces) for new solutions. They also provide the interface (or APIs) and serve as a framework for interacting with outside elements or functions that are related but outside the scope of the architecture. There are several reference architectures. Most were developed by industry groups or stakeholders working in various countries helping advance national priorities. Two of the most cited reference architectures are the Industrial Internet Reference Architecture (IIRA) developed by the Industrial Internet Consortium (IIC) and the Reference Architectural Model for Industry 4.0 (RAMI 4.0) developed by the "Plattform Industrie 4.0" (Germany). Note that the Industrial Internet Consortium (IIC) is now Industry IoT Consortium as of August 2021. Discuss the similarities between IIRA and RAMI 4.0 and outline the reason for using RAMI 4.0. While these two architectures are every similar as can be seem in different studies in the open literature (REFERENCE HERE), we would be focusing on RAMI 4.0 because it is so popular that it is believed that it was the basis for the development of most other Reference Architectures.

4.1. The reference architectural model industrie 4.0 (RAMI 4.0)

RAMI 4.0 [51,52]is a reference designation system that describes the Industry 4.0's space using a cubic layer model. So quite simply, RAMI 4.0 is an architecture model of different elements of Industry 4.0 (i.e., Information Technology (IT), Manufacturing, and Product Life Cycle) integrated into a 3D layered model. The model makes it possible for the multiple elements and different internal connections within the Industry 4.0 ecosystem to be broken up as smaller subsystems and clearly represented in 3D [53,54].

Developed as part of the Platform Industrie 4.0 [55] working group standardization efforts for Industry 4.0 , RAMI 4.0 is a three-dimensional (3D) map that integrates several elements and concepts of Industry 4.0 and how they relate to one another [56]. Different components of the model are abstracted and linked to established automation standards like IEC 62264, IEC 62890, and IEC 61512/ISA95. The model provides insight on how to approach the deployment of Industry 4.0 in a structured manner. It can be used to illustrate the different elements within the Factory of the Future including classification, categorization, and logical groupings that provide insight on connections and potential data and information routes. As a communication tool, it provides stakeholders a framework for a common understanding and the exchange of ideas about the design and development of Industry 4.0 based systems. The RAMI 4.0 model cube shown in Fig. (9) provides three main axes for the dimensions of: (a) Product Life Cycle and Value Stream [Horizontal Axis-Left] (b) Hierarchy Levels [Horizontal Axis-Right]; and (c) Interoperability Layer [Vertical Axis].

4.1.1. Horizontal Axis (Right):

The horizontal axis is orthogonal to the Life Cycle & Value Stream axis and represents a hierarchy model of Cyber-Physical Systems (CPS) management based on functional considerations on a layer-by-layer basis. It stems from the international standard/s IEC

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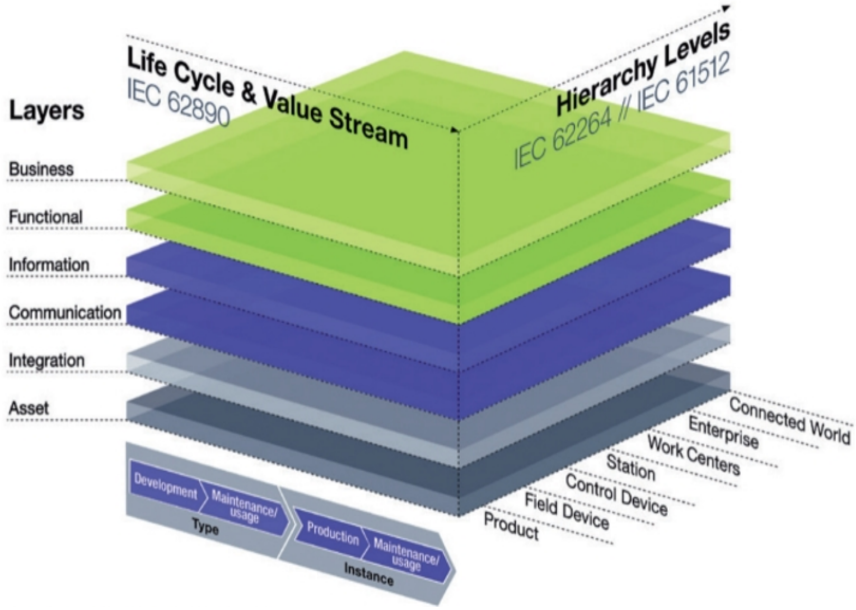

Figure 9. Reference Architectural Model Industrie 4.0 (RAMI 4.0)
Source: Plattform Industrie 4.0

62264/IEC 61512. The hierarchical layers were adopted from the classical automation pyramid with enhancements that introduced the Product and Connected World categories at the beginning and end if the layer stack, respectively. Level 0 represents intelligent products. Level 1 and 2 are associated with the control and automation of the factory floor; Level 3 is related to the management of manufacturing operations; Level 4 corresponds to business planning and logistics; Level 5 is decision-making systems at an enterprise level while Level 6 is related to connections to the cloud and interaction with (external) entities and associated stakeholders. The individual elements are further described as follows:

a) **Level 0** *(Products):* Refers to intelligent (communicating) products. They can interact with users and makers with or without embedded sensors, labels, or tags. Data pulled from these products enable product enhancement, maintenance, and future design improvements. Conversely, data can also be pushed to the products (example updates).
b) **Level 1** *(Field Device):* Functional level comprising intelligent devices that enable smart and intelligent control of machines and systems. Includes sensors, actuators and all other devices required to protect, control, and monitor manufacturing systems and processes. Process and machine health data can be pulled from these assets. Actionable information can also be pushed to some (e.g., actuators).

c) **Level 2** *(Control Device):* Represents industrial control systems that are responsible for the logical control of field devices. Examples include Distributed Control Systems (DCS) and Programmable Devices, prominent among which are the Programmable logic controllers (PLCs).

d) **Level 3** *((Work Unit OR Station):* A lower-level element in the manufacturing architecture where production planning and scheduling (including supervision of machines) based on events and processes are performed. This is usually done using supervisory control tools like Supervisory Control and Data Acquisition (SCADA).

e) **Level 4** *(Work Centers):* Work centers are the highest-level manufacturing elements that perform and manage end-to-end manufacturing processes and functions includ-

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ing planning, scheduling and production activities. They typically include Process cells, Production Units, Production lines & Storage zones. Management Execution Systems (MES) and Manufacturing Operations Management (MOM) applications are used to build a traceable record of the manufacturing process, build supply chain visibility, and keep track of information of everything from labor, materials, machine health, product shipment, job orders etc.

f) **Level 5** *(Enterprise):* Strategic business decisions are made at this level. Enterprise Resource Planning (ERP) tool are commonly used. The enterprise is a collection of business functions operating together to set and implement and manage the realization of strategic business imperatives.

g) **Level 6** *(Connected World:)* This level is one of two enhancements to the traditional automation pyramid. It is the level that enables connection to super-ordinate cloud services, the Internet of Things (IoT), the Internet of Services (IoS) helping link assets in one organization to the assets in external organizations. Flow of data from the shop floor, plant operating systems (MES), business systems (Enterprise Resource Planning, ERP) and the external world (e.g., other smart factories or external elements of the value chain or supply chain).

4.1.2. Horizontal Axis (Left):

This axis represents Life Cycle & Value Stream and is based on IEC 62890 (i.e., Lifecycle management for systems and products), used in the industrial-process measurement, control, and automation domain. It is focused on Product Life Cycle and Value Stream. The product life cycle captures the various stages a product undergoes beginning from its development to when it is decommissioned or removed from the market while value stream encompasses all the actions or activities that culminate in the addition of value to a customer beginning from the initial request to value realization. This axis emphases the extraction, processing, and utilization of product life cycle information in addition to data capture and utilization from all activities that culminate in value creation. This information be captured through digital representations of objects (products) using administrative shell (more on the administrative shell in section xYX), an Industry 4.0 component. The axis divides the product development and the usage process into a TYPE and an INSTANCE phase. One of the design premises for TYPE and an INSTANCE phase are the data type that can be captured during each phase. When an asset (e.g., Product) is in the development phase (i.e., idea, research, design, development, testing, analysis etc.) it is in the TYPE phase. As soon as it is production (physically produced) or service, it becomes an identifiable entity of the type and is transitioned to the INSTANCE phase. Once it transitions into production or service, it is then in the INSTANCE phase. The point of the delineation of the phases is that different data types would need to be collected in different phases. For example, the necessary data required during the research and development of a product (say a car) would be different from those that need to be collected during its production or operation (i.e., while in use or in service).

An asset can be said to be in its TYPE phase during its design (Research & Development).

Throughout the life of the asset, it is important that the relationship between the type and its instances is maintained (i.e., an INSTANCE of the asset might be required to mirror its TYPE). Different data would need to be collected from the product at different phases in its existence. Software products are a particular example where updates on the type is often transmitted to the instance.

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4.1.3. Vertical Axis:

The vertical axis represents the six (6) Interoperability layers [53,54]. The interoperability of the two horizontal components (left and right horizontal axes) can be considered in the context of these six (6) Interoperability layers. As an Information and Communication Technology (ICT) based representation system, it establishes a model for facilitating and implementing new features and choreographing the flow of data between different layers. The first three layers (Business, Functional and Information) are related to functionality, while the lower three layers (Asset, Integration and Communication) are associated with technical implementation. The interoperability layers are described as follows:

a) **Asset Layer:** The aggregation of all physical instances of assets and components required to provide functionality to the system. This would include physical objects like sensors, actuators, devices etc. It will also include humans, products, plans, documents, applications etc.

b) **Integration Layer:** This layer manages the digital representation of physical assets and is responsible for the transitions from the physical to the digital world. It contains asset documentation, applications, and assets (i.e., HMI devices, QR-code readers, Sensors, Control Systems etc.) that manage the transitions, that generate events from assets (e.g., equipment and machinery) and provide computer aided control of technical processes, system drivers and other collaterals.

c) **Communication Layer:** Responsible for data integration and standardization of communication between the Integration and the Information layers. This layer includes standards, communication protocols, and services that support interoperability and integration.

d) **Information Layer:** This level manages and stores data in an organized fashion. It is associated with data services and standards that regulate the flow and exchange of information between components, services, and their functions. It also ensures consistency in the integration of different data formats and interoperability between components and services.

e) **Functional Layer:** This layer is responsible for production rules, decision-making logic and the provisioning and management of the run time and modeling environment for services that support business processes. It also hosts the description of functions and supports remote access serving as a platform for the horizontal integration of various components and functions.

f) **Business Layer:** This level maps out the business model, links the various business processes and hosts the business rules that the system must follow. The said rules are based on information drawn from the value stream, the supply chain, the regulatory regime and subsisting laws. It also orchestrates (or arranges) services in the functional layer and receives events that help track the progress of business processes.

4.2. Communication Standards & Technologies of the future

The Communication Layer & the ISO/OSI Layers: The communication layer is only one of six (6) layers in the vertical axis of the reference architectural model industrie 4.0 (RAMI 4.0)[51,52]. Further treatment of this layer is being provided because of its relevance. It can be considered a crucial aspect of the factory because it provides the protocols, and mechanisms necessary for the standardization of communication between different networked elements.

The goal of this layer is to arrive at a unified data format that ensure interoperability and to provide interfaces that can support data access. An outcome that solves a protracted

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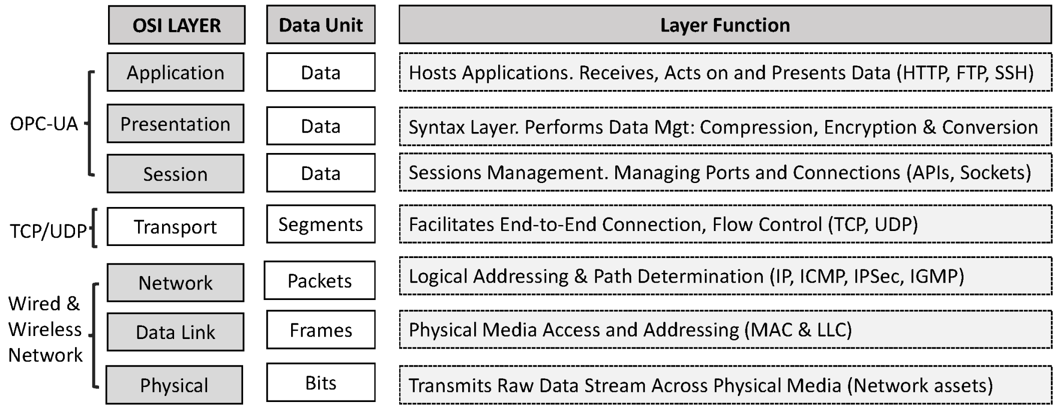

Figure 10. The Seven OSI Layers

bottleneck that has stymied Industry 4.0 adoption. Because the communication layer is heavily IT focused, it is complemented by the seven-layer International organization of Standardization/Open System Interconnection (ISO/OSI) model. The ISO/OSI model is a popular IT reference model that defines the seven (7) levels in a complete communication system.

To enable multi-vendor interoperability and integration, has adopted or recommended certain open communication technologies or standards for each layer (refer to Fig. YYY). Below we would be focusing on only three that we think would have the most significant impact on the Future Factory. These include (a) *The Open Platform Communication Unified Architecture (OPC-UA)*, (b) *Time-Sensitive Networking (TSN)* and (c) *5th Generation Mobile Network (5G)*.

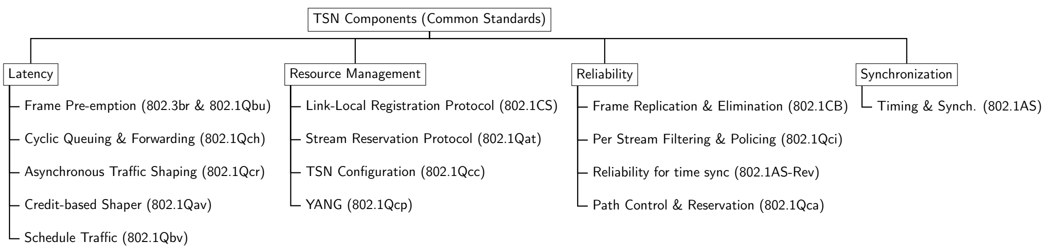

Figure 11. TSN Components

4.2.1. **Open Platform Communication-Unified Architecture (OPC-UA):**

Though not explicitly mandated, the Open Platform Communication Unified Architecture (OPC-UA [IEC 62541]) protocol [57] is RAMI 4.0's recommended approach for implementing this layer due to its stability, scalability, and superior performance. The recommendation beyond being very practical has also received numerous endorsements [58–62] from stakeholders. As the standardized interface for communication between numerous data sources, the OPC-UA has become the de facto communication technology standard for many applications (both in industry and academia) and the focus of on-going research [63,64]. So great characteristics of OPC-UA are that it is technology-independent, implements standard network protocols and allows for easy integration into pre-existing IT networks. It also satisfies standard communication security requirements supporting secure communication over VPN and across firewalls through which it can establish seamless client-to-server connectivity.

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4.2.2. **Time-Sensitive Networking (TSN):**

The OT systems used in many factories require specialized networks and protocols. Conversely, IT systems are typically general-purpose technology that rely on Ethernet networks. The unpredictable traffic patterns of the ethernet-based "best effort" approach is unsuitable for handling time-critical data. The real-time transmission of critical data (e.g., process data) that is necessary for real-time control within the industrial domain requires latency guarantees that are not always available from Ethernet networks. The cycle-time for transmission of time-critical data can be very minute, sometimes as small as one (1) second.

This disparity in standards and protocols often creates complications that significantly impact IT/OT integration efforts. There is also the problem of data volume and velocity. With the ubiquity of devices and sensors today, the amount of data running through some factories daily is enormous, sometimes overwhelming networks and storage systems. Though several real-time communication methods (like Profinet IRT, EtherCAT, and SERCOS III), have been applied to address some of these problems, Time Sensitive Networking (TSN) is clearly a better alternative. Not only does it close the technical gaps between IT & OT, but it also addresses most other underlying challenges that have bedeviled the industry for a long time. TSN is an adaptation of the Ethernet IEEE 802.1 standard. It was designed to support time sensitive networking that enables real-time, deterministic communication between networked assets. The four main components or characteristics of TSN are (1) Resource Management, (2) Synchronization, (3) Reliability and (4) Latency. These characteristics deliver several benefits, some of which include (a) Support for time synchronization i.e., all networked resources have a shared time reference. It is well-suited for the real-time control and the synchronization of high-performance machines plus it offers solutions for efficiently managing network infrastructure with high bandwidth requirements. (b) Support for traffic scheduling (i.e., all networked resources observe the same rules for processing and forwarding packets within specifically reserved time slots. With this arrangement different data traffic streams can be transmitted from a single standard open Ethernet network without any delays. (c) The possibility to merge multiple industrial networks, including TCP/IP traffic, into one single physical wire. (d) Availability of mechanisms to temporarily interrupt the transmission of regular Ethernet-based traffic (i.e., based on the best-effort approach) to offer priority to critical-data necessary gaining time-sensitive insight into processes and assets (e) The ability to maps across both the physical and data link layers, thus reducing complexity and making implementation/management easier, (f) Compatibility with general purpose IT standards. TSN is a special type of Ethernet, and it is compatible with most IT systems. Its functionalities can be integrated into one, standard open Ethernet network capable of supporting devices from different vendors thereby ensuring interoperability and integration.

4.2.3. **5th Generation Mobile Network**

The growing data traffic and bandwidth demand that is currently outstripping the ability of 4G (LTE) to cope because of the proliferation of smart devices, IoT devices and sensor etc. is creating the need for ultra-low, end-to-end latency in a variety of industries including automotive and industrial automation [65]. The ability of 5G to deliver on these metrics is putting 5G in play within the industrial environment. 5G provides end-to-end ultra-reliable and ultra-low latency connection [66,67], something that can help improve network efficiency in these settings. Several reviews [68–78] of the 5G technology exist in the open literature. The convergence of 5G, AI, and IoT will result in major transformations in industrial control and factory monitoring (i.e., condition monitoring and failure prediction). With fast, efficient cloud native 5G connections factories can strategically redistribute computational power to allow for fast collection and processing of data with rapid AI inference at the edges. On the other hand, networked devices and applications can easily and reliably tap into edge resources without needing to access the core network.

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The analysis of industrial processes can also be performed at high degrees of precision allowing for swift decision-making whenever necessary. Given 5Gs promise of extremely low latency (no jitters) and high data rates for video transmissions, there is an expectation of significantly growth in innovation around the development of Immersive and integrated media applications (e.g., Mixed Reality (MR)/Augmented Reality (AR)/Virtual Reality (VR) applications which are becoming ubiquitous on the shop floor and beyond.

The 3rd Generation Partnership Project (3GPPTM) is a joint project that bring together several national Standards Development Organizations (SDOs) with the goal of developing technical specifications for third generation (3G) mobile systems. The three main service categories for 5G New Radio (NR) as defined by the 3GPPTM are as follows: (a) Enhanced Mobile Broadband [eMBB], (b) Ultra-Reliable Low Latency Communications [URLLC] and Massive Machine-Type Communications [mMTC].

a) *Enhanced Mobile Broadband (eMBB)* services are geared towards applications that require high data rates across a wide coverage area. Compared to 4G it is capable for large payloads and stable over an extended time interval. Complimentary deployment of Enhanced Mobile Broadband (eMBB) alongside existing 4G broadband service can enable substantial improvements in traffic and the efficiency of the Industrial network at core network level.
b) *Ultra-Reliable Low Latency Communications [URLLC]* is almost deterministic in time bounds on packet delivery. It is ideal for applications that require end-to-end security and where reliability and speed are critical though bandwidth might not be as much. Mission critical applications that require quick reaction times would make this category. Because 5G URLLC delivers ultra-low latency and guarantees against triggering undesirable safety stops in production lines, it has been employed in automating factory processes and related power systems. For example, it has been used to run industry technical standards like PROFINET. Industrial robots have become ubiquitous on manufacturing floors. The transmission of time-critical communication messages to them using ultra-reliable low-latency communication (URLLC) might be necessary to accommodate for instances where decision time for responding to an incident or accident is almost non-existent. Combining 5G and MEC results in significant reduction in network latency which can improve the performance of previously tethered-only AR/VR, haptic and tactile based applications.
c) *Massive Machine-Type Communications (mMTC):* is a service that provides mainly wireless connections to massive numbers (tens of billions) of network-enabled devices that intermittently transmit payload sizes (small data packets) at low traffic [79]. While low transmission latency is not a requirement, it is low latency, secure, reliable, and scalable. Because mMTC transmits small payload sizes at low transmission rates and frequency, they require lower energy consumption making them well suited for battery powered, low maintenance, end devices (i.e., low-cost sensors, smart meters, wearables, trackers, and diverse monitoring devices, etc.). NB-IoT (narrowband IoT) and Cat-M1 (operated at 1.4 MHz bandwidth) are two 3GPP standardized technologies that supports these network-enabled devices. NB-IoT supports ultra-low complexity devices with very narrow bandwidth and data rate peaks of approximately, around 200 kHz and 250 kbs per second, respectively. Conversely, Cat-M1 supports relatively more complex devices and operates at a bandwidth of 1.4 MHz, with lower latency and better location and asset tracking capabilities. Both can also sleep for extended periods and maintain excellent power-saving mode (PSM) abilities and extended discontinuous reception [80].

5G can also be integrated with other communication standards for improved effects. For example, to exact optimal impact on industrial IoT services and wireless industrial networking, 5G is best integrated into the Ethernet based industrial network with TSN. While dedicated to the control of data communication (synchronization & data stream

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prioritization) TSN can also help forward critical process data ensuring that they arrive in time at different end points within the network. On the other hand, 5G can be dedicated to the transmission of non-real-time-capable data (i.e., monitoring, predictive maintenance, energy optimization etc. type data).

5. Realizing the promise of Industry 4.0 through the Digitization of Physical Assets

It is the case that there are often differences in device/equipment types (make, models, age e.g., legacy equipment), communication protocols employed and interactions between hardware, communication technologies, networking devices and applications within factories. Because of these differences, making all entities (equipment, devices, applications etc.) seamlessly talk to each other can be prohibitively difficult. Relying on a vast array of sensing devices, communication facilities, and services [81], these disparate systems generate and use large amounts of diverse and sometimes complex data types to perform varying functions. Building systems that effectively store, manage, and analyze these data and ensure valuable use can be daunting. Two main hurdles need to be crossed to make this happen. First, all assets need to be physically connected. That feat has been achieved using technologies like OPC-UA [82] (further discussed in section YYY) and related technologies like Profibus/Profinet [83]. The second challenge is making all devices, irrespective of the "language" they speak to both communicate and understand one another. As has been acknowledged in earlier sections of this paper, one of the key goals of the industry 4.0 era is the digitization of industrial systems and processes with a view to harnessing intelligence from them to help improve operational efficiency, productivity, and value. However, the digitization of manufacturing systems requires the efficient connection of all assets within the production network and the seamless exchange of data between assets. It also requires the development of information models that can accurately describe all assets and information sources to enable semantic integration and interoperable exchange of data between all assets [84]. The development of robust data/information models is critical to realizing some of the more creative goals of the factory of the future like plug-and-play automation of production modules, easy reconfigurability of production systems to cater to small batch production of customized products, self-organization of the production line etc. The Factory of the Future as a highly dynamic environment features a fluctuation in the number and variety of nodes (assets). With the right technologies in place, adding, removing, rearranging, retrofitting, or upgrading a network of assets would not be a hassle [85].

The practical significance of AAS is large as it can be used to transform a factory into an easily Re-configurable Manufacturing System (also known as Plug & Produce)[86,87] that is flexible [88] and is capable of dynamically orchestrating and allocating resources [89]. It can also have significant implications for Preventive Maintenance [90], Product customization, and the design and development of upgradable production lines and order-controlled production. Implementing the AAS paradigm within a factory can make integration faster. It can also mean faster ramp-down and ramp-up of production lines and maximization of production efficiency and throughout the life cycle of a plant [91].

Though the promise of the digitization of production (Future Factory) is very compelling, there is still concern about how to implement these ideas in concrete terms using available technologies, techniques, and standards. It is instructive that whatever techniques and standards are adopted must be flexible enough to accommodate different device categories (age, variety & types), application domains, use cases and must be able to transcend organizational boundaries [92]. RAMI 4.0 and Industry 4.0 Components are two important and complementary constructs of Industry 4.0. They are both described in the Reference Architecture Model Industrie 4.0 (DIN SPEC 91345) [93] . Sub-section (4.1) provides more details about RAMI 4.0. Industry 4.0 components, on the other hand, is made up of two main parts: (1) Asset and (2) Asset Administration Shell (AAS). This is further discussed in Sub-section (5.1)

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5.1. *Industry 4.0 Components: Assets and Asset Administration Shell (AAS)*

I4.0 components (and especially Asset Administration Shell (AAS)) is Industry 4.0's recommendation for tackling the afore-referenced implementation challenges. The entire idea of the I4.0 components is to encompass every asset within an administration shell.

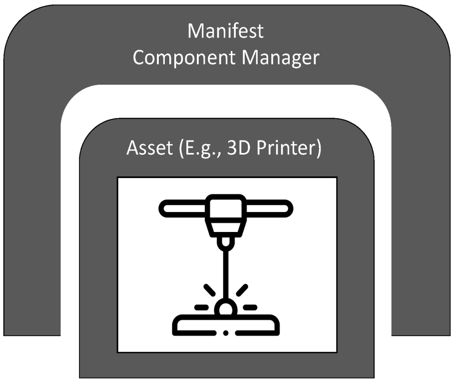

Figure 12. AAS showing an asset (3D Printer)

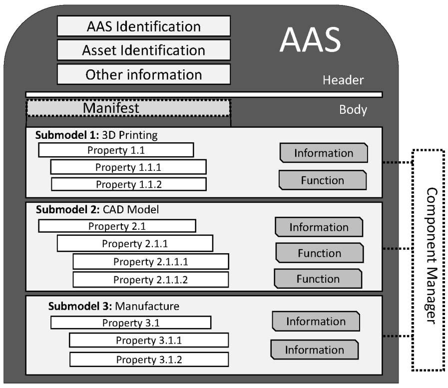

Figure 13. AAS Metamodel for 3D Printer

5.1.1. Key elements of Industry 4.0 Components:

Some of the key concepts or elements of Industry 4.0 components are outlined below:

a) **Asset** An Asset is anything (physical or non-physical) within the production system that requires a connection to another asset or an Industry 4.0 solution e.g., simple devices, components, machines, assembly lines or even entire production systems. Other examples of assets include automation components, services, and even applications/software platforms. Each asset within the production system must be identifiable to the system (in the first instance), and to all other assets (including devices, systems, and services). To be considered compatible, each asset must have a set of defined properties and must be able to collect and share all relevant data to similarly networked entities (other assets, stakeholders e.g., companies participating both in the value and supply chains.) throughout its lifecycle. This means they each need to read, interpret, and understand all asset data including identity (asset type, model numbers etc.), operational, status and all other asset-related data.

b) **Asset Administration Shell(AAS):** Industrie 4.0 recommends Asset Administration Shell (AAS) as an important building block of the Factory of the Future [12,94–96]. Multiple articles in literature provide reviews on Asset Administration Shell (AAS) [97,98]. The administration shell (AAS) is a mechanism for digitally representing physical assets and other abstract entities. In practice, it helps provide a description of the properties and capabilities of an asset and serves as a platform for interaction between the asset and other assets.
As an Industrial application of Digital Twin (DT), it helps transform an asset to its digital equivalent serving as a bridge between a tangible asset and the virtual or IoT world. A typical AAS holds identifying, operational, status and technical information about the asset it represents, over its lifetime. It contains the communication methods and stores all asset related data [34]. Some of the information the AAS stores are related to the configuration of the asset, its maintenance record, or data related to its connectivity with other devices. Diagrammatically an Asset is enclosed within an Asset Administration Shell (AAS) as shown in Figure (12).
Each asset in the production system has its own administration shell. Two or more assets can be grouped into a unit [99]. The unit (much like an individual asset) can map to its own administration shell. Refer to Figure (YYY). A common administration shell can also be used to manage the communication of multiple Asset Administration Shells (AAS) at a higher hierarchical level.

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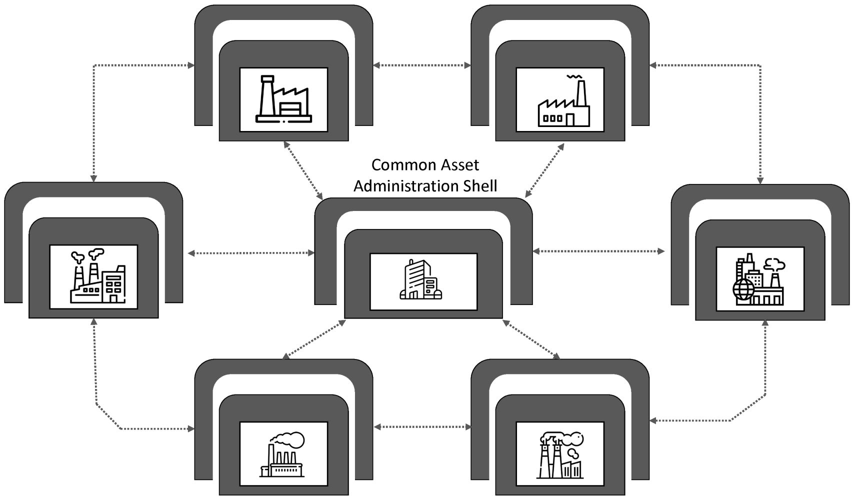

Figure 14. Inter-Factory (Factory-to-Factory) Common Asset Administration Shell

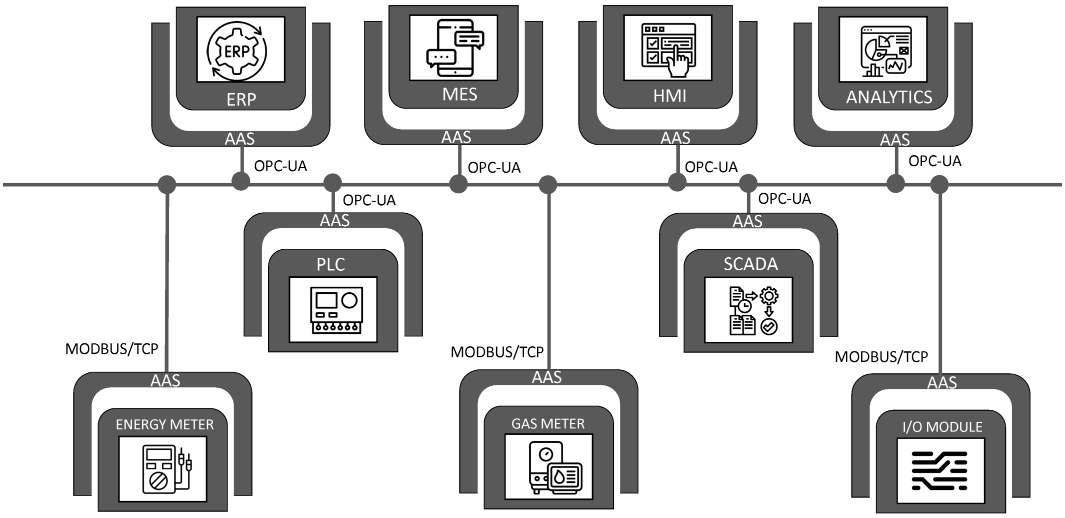

Figure 15. A network of assets wrapped in their respective AAS

Beyond acting as a store for important asset data, the AAS also serves as a reliable and consistent mechanism for managing data and related functions and services. The functions

5.1.2. The Anatomy of an Asset Administration Shell (AAS):

The Asset Administration Shell (AAS) is composed of a body and a header. The ***header*** contains identifying information that precisely describe the asset administration shell and the represented assets plus related asset utilization information. High-level asset-related information stored in the header would include the asset description, serial numbers, manufacturers identification etc. Other information could include information about the usage of the asset, its sub-components, and other high-level details about the administration shell. The ***body***, on the other hand contains information about the assets. It has two parts: a Manifest and Component Manager. The Manifest serves as a directory that lists different sub-models. Sub-models (or partial models) are important features of

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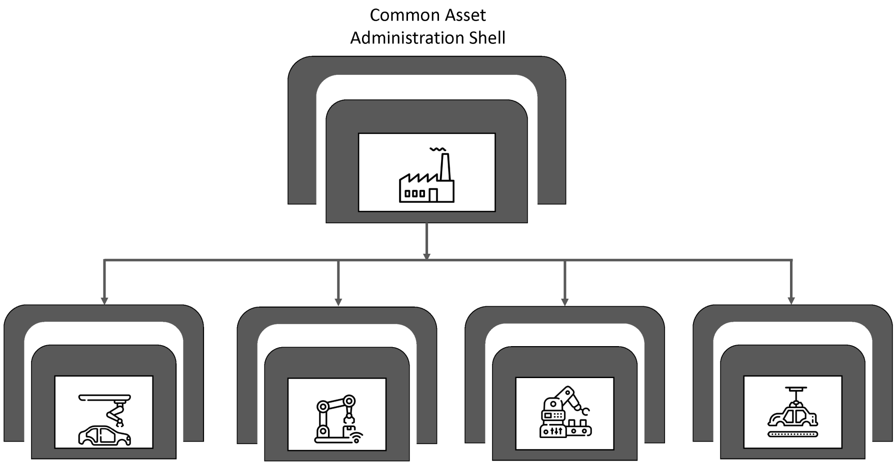

Figure 16. Intra-Factory Common Asset Administration Shell

the Administration Shell that represent different aspects of the asset they represent with each sub-model standardized for each aspect of the asset e.g., a description or capability of the asset. Each sub-model contains a structured quantity of hierarchically organized properties that refer to the asset's data and functions (or capabilities). The properties have a standardized format based on IEC 61360. On the other hand, the Component Manager (or resource manager) administers the sub-models and help link the information coming from the Asset Administration Shell (AAS) to the larger asset network through the Industrial Internet of Things (IIoT).

5.2. Seamless Transfer of Data: OPC-UA, AAS & Companion Specifications

Data exchange between entities in an industrial network is a critical feature of the Future Factory. The Open Platform Communications Unified Architecture (OPC UA) is an important technology for machine-to-machine communication. It defines data transport protocols and standardizes information modeling, however, OPC UA communication alone is not sufficient for seamless data exchange. Before OPC UA communication can effectively occur, the content of the data to be exchanged must be clearly defined. To make communication feasible and seamless, companion models need to be mapped onto OPC UA. OPC UA does not define data content but only serves as a framework for the description of the meta model. Though OPC UA defines a base information model, the actual definition of the data content for different domains is achieved using companion specifications or meta model, of which there are several (40+). Companion specifications make the definition of standardized exchanges possible within the framework of specific business functions. These domain-specific models make it easier to achieve interoperability between equipment and devices from different vendors. Companion information models follow standard syntax described in XSD file (XML Schema Definition) and therefore present data in a form that can be read by a computer program.

One such companion specification is AutomationML which focuses on the engineering of automation systems. So, an implementation for a I4.0 components and its asset administration shell could potentially involve a technology combination involving the OPC UA (IEC 62541) and AutomationML (IEC 62714).

Within a typical manufacturing environment, there are different kinds of equipment from a diverse range of manufacturers creating a situation where multiple communication protocols are in play within the asset pool. This creates communication problems for enterprises if the goal is IIOT integration (i.e., networking the assets and having them "talk" to one another) because until recently different companies relied on different communication protocols and applications which were not interoperable. OPC-UA was created to solve this problem and adoption rate by industry has been impressive. It provides the additional benefit of secure communication (encryption and authentication) and a standardized interface. OPC-UA solves the Operational Technology (OT) communication conundrum.

The Future Factory integrates previously independent and discrete systems transforming them into a complex whole. It is literally the convergence of Operational Technology (OT) and Information Technology (IT). There must be a way to connect OT to IT. However, the IT and OT domains have significant differences and there are unresolved integration and knowledge transfer challenges that need to be resolved. That's where Asset Administration Shell (AAS) comes in. It is the software/firmware component that transforms the physical assets into digital (or Industry 4.0 assets). That data content stored in the AAS is developed using the companion specification (i.e., AutomationML). The combination of OPC-UA and the AAS helps eliminate the discontinuity between the layers (OT & IT) enabling the seamless flow of data/information. Refer to Figure XYZ02 below.

5.3. Data Exchange: The Administration Shell & the Semantic Web

The AAS provides a consistent way of storing and managing all asset data, functions, and services so that they are readily available for manipulation, publication, and exchange between all network participants as required. Once connected, the AAS serves as a standardized and secure communication interface for sharing data and information about the asset's identity, operations, and status with the production system's network. Using a standard like AutomationML, the AAS can be mapped to OPC UA, MQTT, or other formats [100]. Because of its standardized design, AAS can integrate the knowledge and semantics of multiple domains together, to help achieve component and cross-company interoperability across the entire value stream.

Though the current data exchange process for many manufacturing applications has greatly improved due to the use of predefined structures and keys, real-world implementation is still dependent on laborious manual work. It requires a robust understanding of the AAS model, an appreciation of multiple terms/values and time-consuming/laborious data mapping [101]. To alleviate the burden, some scholars [102] have recommended building a connection between current manufacturing-based data provisioning models (like AAS) and the Semantic Web. Great reasons to consider this option is that Sematic Web representation formalisms such as RDF, RDF Schema and OWL are more matured, have more advanced data integration and formalization capabilities and have the capacity to introduce logical reasoning to Asset Administration Shell (AAS). For these reasons, information models developed using these frameworks would be useful additions to information exchange systems [101] like AAS. RDF and Linked Data principles have been successfully used to integrate different data types [103–105]. They are the basis for the development of semantic solutions or information models that have proved effective for seamlessly linking I4.0 components with generated data [106], hence helping improve the interoperability of production assets. To promote data exchange and enable semantic interoperability RDF-based information models are aligned to important industry standards, such as RAMI [56] and IEC 62264[107]. Because Resource Description Framework (RDF), a standard model for data interchange on the Web makes the generation and transmission of data across networks easy. An additional benefit of RDF is that it makes data readily available on a standard interface using SPARQL3 (an RDF query language). A group of researchers [102] proposed adding a semantic layer to the Administrative Shell. As part of the proposal the RDF would be included as a middle layer that can be deployed to support interoperability between the data generated from both I4.0 components and legacy systems. The researchers envision the establishment of RDF as a common communication language (lingua franca) between assets within Industry 4.0. Figure (17) shows the architecture of their proposed Information model or Semantic I4.0 Component that incorporates the vocabularies and RDF representations of relevant standards for representing information different assets.

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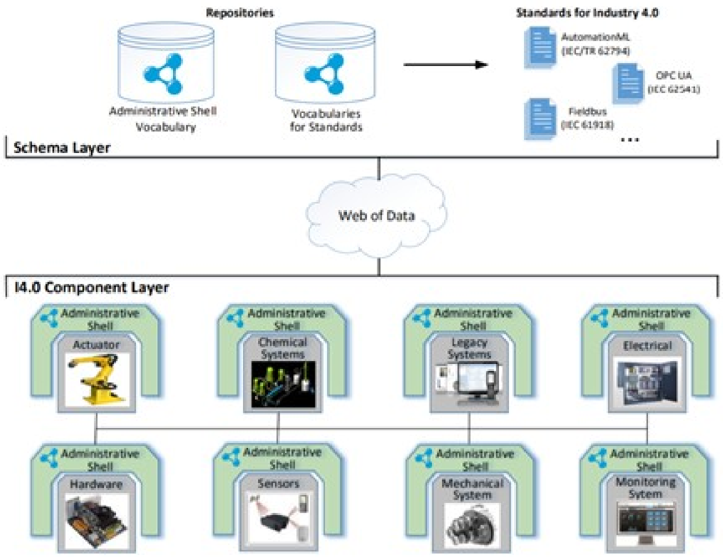

Figure 17. Semantic I4.0 component Architecture: Information Representation for Diverse Assets[102]

6. Key Building Blocks | Technology Enablers | Innovation Accelerators

Though many organizations now aspire to upgrade their manufacturing and business operations into full-scale factories of the future, knowing where to start or even what makes for an industry 4.0 compliant factory is not always clear-cut. The fact remains that applications or instances of the future factory would be process specific and therefore, might vary from one industry to another. However, these are certain elementary units or common building blocks that have emerged as the foundations of basic configurations of future factories. The number and variety of building blocks that constitute a specific future factory configuration will depend on the industry and the unique process applications a company seeks to improve or optimize. Understanding these key elements can help in understanding future factories and smoothing the transition for industrial adopters.

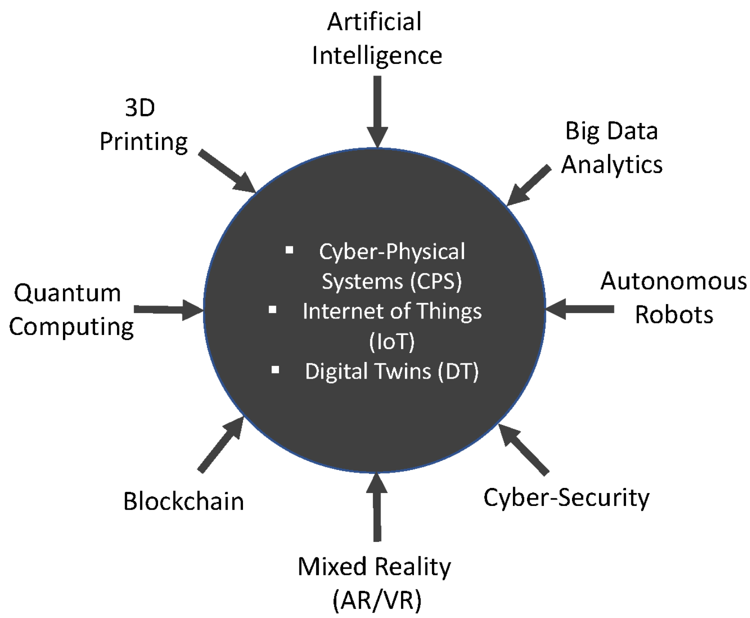

Figure 18. Building Block

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6.1. The Core Elements of the Factory of the Future

In the opinion of the authors, the trio: Cyber-physical system, the Industrial Internet of Things (IIoT) and the Digital Twin constitute the barebone elements of any Factory of the Future. As would be seen later, several other technologies (including Cloud, Artificial Intelligence, AR/VR, Blockchain etc.) can be wrapped around these to extend the functionality, resilience, and integrity of the system. Cyber-physical systems (CPS) and the Internet of Things (IoT) both enable end-to-end connectivity and support the transmission, transformation, and storage of data/information across different levels of the factory. The similarities and differences between CPS and IoT have been the subject of many debates within the research community. NIST [108] performed an extensive review of these debates based on several references in the open literature[109–114]. On the other hand, Digital twinning enables the virtualization of the system to enable data and information cloning and seamless transmission and manipulation. Based on our analysis, the three (3) foundational elements of the factory of the future are: (a) Cyber-Physical Systems (CPS), (b)Industrial Internet of Things (IIoT), and (c) Digital Twins. These elements are further discussed below:

a) **Cyber-Physical Systems (CPS):** Baring the development of some more complicated system, complex Cyber-physical systems (CPS) would be central features of factories of the future. The Factory of the Future is essentially a network of Cyber-Physical Systems (CPS). These systems integrate sensing, control, networking and computation into physical objects and related infrastructure [115]. The uses and roles to which they can be applied are virtually endless. A CPS is a system that bridges the cyber and physical worlds seamlessly. In CPS, computational and physical systems are intertwined with the interaction between the duo being a convergence of computation, communication, and control. Though things can get very complex, very quickly, multiple CPS can be combined into a super CPS or what can be referred to as a System of Systems (SoS). CPS has been variously defined as the integration of computation with physical processes where embedded computers and networks monitor and control the physical processes [115] and the behavior of the system is defined by both computational and physical components [116]. Rajkumar et al. refer to them as physical and engineered systems whose operations are monitored, coordinated, controlled, and integrated by a computing and communication core. They have also been referred to as hybrid systems that are simultaneously computational and physical[117]. Though there are different interpretations of what constitutes a Cyber-Physical System (CPS), there is nonetheless an agreement that they are the result of the integration of a computing nucleus and physical systems, where the computing core like a central intelligence entity orchestrates (monitors, coordinates, and controls) the operations of all elements nodes and entities within the physical or engineered system. In recent times, Cyber-physical systems have permeated several elements of modern life.
   There are multiple applications of CPS in a wide variety of industries. Some of these applications can be seen in self-driving cars, smart grids, robotics systems, unmanned aerials vehicles, advanced industrial control systems and automatic pilot avionics [118]. In the case of the self-driving car, also known as the Autonomous Vehicle (AV) or Driverless car, a computational core and the physical elements of the system are seamlessly incorporated to achieve the effective monitoring, coordination, and control of the vehicle. As a complex CPS, the vehicle combines a wide variety of physical nodes or sensors (like GPS, radar, sonar, odometer etc.) to perceive its environment. The sensory data collected from these physical assets are then analyzed and interpreted by Advanced control systems to help identify suitable navigation paths and avoid collisions autonomously. Some autonomous control systems have even been able to make control decision through knowledge acquired from steering patterns of human drivers acquired from video feeds from mounted-cameras and basic GPS-like maps. The seamless interaction of diverse

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components of the self-driving car to create value with little or no human intervention is a model for what is possible in the Future Factory (FF). Another relatable example is the smart phone, a mobile cyber-physical system which is a sub-class of cyber-physical systems. The smart phone is a composition of independently interacting physical components and a computing and communication core. The operations of the smart phone are monitored, coordinated, controlled, and integrated by the computing and communication core. The computational resources include a robust processing capacity with local storage facility. Plus, the mobile operating system and smart phone applications. The physical components would include several sensory input and output devices like cameras, GPS chips, touch screens, speakers, microphones, light sensors, and proximity sensors. The sensors gather distributed intelligence about the environment including monitoring physical and cyber-indicators like touch (touchscreen), sound (microphone) or presence of nearby objects (proximity sensors). The computing elements communicate, gather, and analyze data from the sensors developing actionable intelligence useful for carrying out more accurate actions and tasks or controlling or modifying the physical and cyber-environments. A communication highway between the smart phone and other CPS on the one hand and network connectivity that link the smart phone and various servers and the cloud environment are enabled by communication technologies like WiFi, 4G, EDGE etc. It is also important to note that there are structural similarities between CPS and the Internet of Things (IoT) like sharing similar architecture, however a major distinction between the duo is that there is a higher level of co-ordination between the computational and physical elements in CPS [119].

b) **Industrial Internet of Things (IIoT):**Generally, a device is considered an object, device (or "Thing") if it can use sensors and Application Programming Interfaces (APIs) to connect, transmit and exchange data over the Internet. Other acceptable characteristics of IoT devices include excellent power management, ability to self-diagnose and the capacity for configuration upgrade at low internet bandwidths and within domains with poor network connectivity. Hence the Internet of Things (IoT) is simply a growing network of billions of physical objects (or "Things") that are connected to the Internet or to other devices that can be connected to the internet themselves for the express purpose of data exchange or transmission. Almost every field of human endeavor can domain benefit in some way from IoT integration. Fields as diverse as agriculture, consumer electronics and home appliance industries have already experienced varying levels of adoption. Though the IoT evolved from the IIoT, the "Industrial Internet", also known as "Machine-to-Machine (M2M)" or Industrial Internet of Things (IIoT), is a much narrower or limited version of the Internet of Things (IoT).
It has been successfully applied to Manufacturing and other high stakes industries like aerospace, healthcare, defense, and energy. The "Industrial Internet" as a term was originally coined by General Electric (GE) in 2012. It refers to a system of connected, albeit uniquely identified devices alongside intelligent analytics able to transfer data over a network without requiring human-to-human or human-to-computer interaction. The connected devices are interrelated objects including sensors, actuators, instruments, and other networked assets like computing devices, digital and mechanical machines. While IIoT supports sophisticated devices with advanced analytics and automation usually with high-risk impact, the high-volume general IoT, uses simple applications and focuses of value creation in the low-risk impact consumer experience space. So important is the "Industrial Internet" that several organizations including Bosch, DellEMC, General Electric (GE), Huawei, Microsoft, and Purdue University (College of Engineering) came together in 2014 to form the Industrial Internet Consortium to help accelerate the growth of the Indus-

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trial Internet.

c) **Digital Twins:** The digital twin technology is a key enabler for the digital transformation of the traditional factory. One of the earliest references to "Digital Twin" as a concept date to 2003 when it was first introduced as a virtual, digital equivalent to a physical product by Dr. Michael Grieves in his University of Michigan Executive Course on Product Lifecycle Management (PLM)[120]. Other such early mentions can also be attributed to Främling et al. (2003)[121], Shafto et al. (2012) [122]. The Digital Twin has been variously defined as a sensor-enabled digital model[123] or digital replica of a physical entity [124] that "mirrors the life of its corresponding [flying] twin" (Shafto et al., 2012)[122] ; uses the best available physical models, sensor updates, fleet history, etc., and can simulate the health condition of the physical twin, by continuously recording and track its condition during the utilization stage (Lee et al, 2013). The digital twin is also defined by its ability to perform real-time optimization [125] and monitor and control its physical twin while being constantly updated, itself using data received from the physical twin. (Schroeder et al., 2016) [126]. The synchronous existence of a physical asset and its digital twin means that the boundaries between the physical and the virtual worlds are effectively blurred ensuring that data is transmitted seamlessly between both entities (2018)[124]. Though a relatively nascent technology, the Digital twin technology represents the next step in the development of intelligent products and a key enabler in the digital transformation of traditional manufacturing. It makes it possible for physical assets to take on virtual identities and interact with other machines and people across diminished virtual and physical boundaries. A digital twin (aka "living" simulation) mirrors the current state of its corresponding physical asset and maintains its characteristic as the assets exact virtual representation by constantly learning, refreshing, and updating itself through inputs from human experts, machine-to-machine interaction, and continuous exchange of data with key elements of the physical asset like sensors, actuators, and the like. The value of accurately capturing the current state of the asset is that critical outputs from the emergent model can be fed back to help optimize the performance of the asset and serve as a critical input into the simulation and prediction of the future state of the physical twin. Digital twins can be used to performance system optimization. They can also serve as sandboxes for testing new ideas or making informed production decisions. In such scenarios, they can be used as simulators where the possible outcomes of multiple production scenarios can be gamed, contemplated, or investigated before implementation to eliminate the cost of actual production testing or avoid the impact on or disruption of on-doing production. It can also be used to evaluate the impact of modifying manufacturing parameters or using a combination of system parameters in a manufacturing scenario. Think of this as a typical of what-if analysis. The best performing options determined within the digital twin can easily be deployed to the physical twin through embedded PLCs and/or microprocessors for immediate implementation, saving time and cost.
The digital twin is also gradually maturing into a technology that can ultimately revolutionize structural health monitoring, anomaly detection and the remote launch of maintenance services that allow products self-heal. On an even broader scale, digital twins of different factories and those of their suppliers, contractors etc. can be linked to establish virtual supply chain networks. The main benefit of the digital twin is its ability to integrate previously disparate models into an integrated set of interoperating sub-models that are able to communicate and transfer information with each other while simultaneously drawing on multiple data sources including historical data, comparable data and current (up-to-the-second data) to accurately mirror the state of the physical twin, determine failure trends, estimate projection to failure, and correctly interpolate results that help predict its likely future states. The continuous monitoring of the system means that multiple sensors (including

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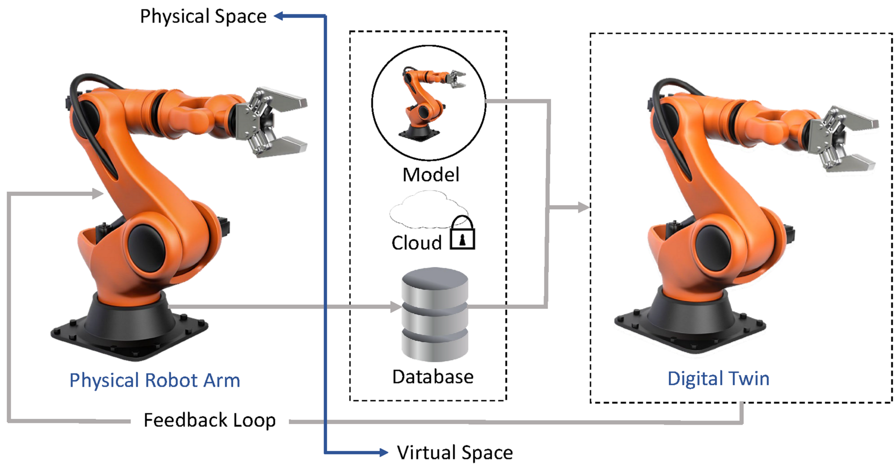

Figure 19. An implementation of a digital twin

smart sensors) positioned around the physical twin can constantly feedback data that would contribute to maturing the models and improving their accuracy and reliability. One of the challenges of the factory of the future is that it would be comprised of hundreds (and in some cases, thousands) of machines and devices at the edge. Updating the firmware, configuration, or software across these assets (machines and devices) within multiple platforms would be very challenging without some form of automation. The digital twins of these physical assets [machines, devices, systems, or system-of-systems (SoS)[127] can serve as remote centralized hubs or connection boundaries for their wireless updates without physical human intervention. Another value of digital twins is that they can be used for the remote co-ordination and operation of machines, devices, and systems. Other possible uses are process monitoring, and product tracking, not to mention that they can provide reliable alert and notification system functionality both for the manufacturing floor and supervisory and managerial teams. They can also be used to support the provision of remote technical assistance, equipment maintenance and repair and other technical support activities in combination with augmented and virtual reality technologies.

6.2. Peripheral Elements of the Factory of the Future

Key Enabling Technologies (KETs) are emerging, high-tech technologies and solutions that have been permeating the traditional manufacturing industry leading to industry wide transformations[128]. Using case studies from Germany, Michael Rüßmann et al (2015)[129] were able to identify the top nine technologies that constitute the building blocks of Industry 4.0. Several other authors have also identified similar technologies as major enablers driving the technological revolution. In this work, we would be focusing on some of these. The technologies and solutions that would be the basis of our discussion include Cyber-Physical Systems, Industrial Internet of Things (IIoT), Cybersecurity, Digital Twins, Cloud computing, Artificial & Cognitive Intelligence, Big Data & Analytics, Blockchain, Augmented Reality, 3D Printing (Additive Manufacturing) and Autonomous Robots.

The Industrial Internet of Things (IIoT) would emerge as an important feature of the factory of the future. Currently, many Industrial facilities are increasingly reliant on the Industrial Internet of Things (IIoT). The connection and exchange of data between sensors, software, and other technologies that it makes possibly helps in the streamlining of operations, performance optimization, predictive maintenance, remote process monitoring and online progress tracking. While the growth of the IIOT within the manufacturing

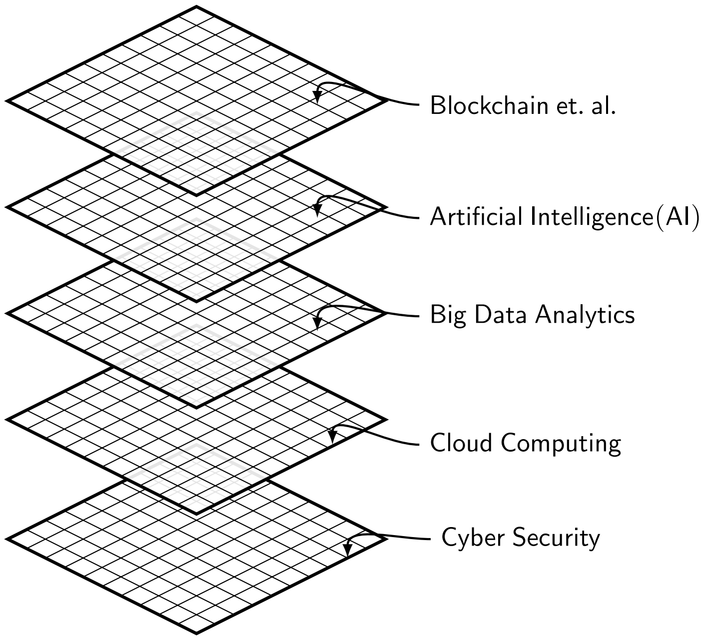

Figure 20. Layers of transformative technologies shaping the Future Factory

industry will enable manufacturers to operate at unmatched performance and revenue levels, it would also create unprecedented susceptibility to cyberattacks on industrial systems and networks. The main reason being that connectedness can create vulnerabilities since it opens more doors, exploitable touch points or attack vectors or surfaces for not only cybercriminals but also other bad actors including individuals, groups and nation states who might have ulterior motives or an axe to grind. The higher the number of devices and sensors connected through networking and internet protocol (IP) addressing, the more the access gateways. Potential security breaches by malicious actors, or even insider threats can portend grave technical and business risks if not adequately addressed. These vulnerabilities have been exploited in the IoT domain in the past. For example, hundreds of thousands of unsecured IoT devices were pulled into a botnet (codenamed Mirai) which aggregated their processing power to carry out large-scale cyberattacks that momentarily crippled major websites like PayPal, Netflix, and Spotify. These cyber-security challenges are even more complicated in the Industrial Internet of Things (IIoT) because both Information Technology (IT) and Operational Technology (OT) systems are being pulled into the Industrial Internet of Things (IIoT) even though Operational Technology (OP) systems were predominantly closed systems until recently. Furthermore, Information Technology systems have established cyber-security protocols which do not work well with Operational technology (OT) systems [130].Note that Information Technology systems as defined in this paper would include computer, computer networks, electronics, semiconductors and telecommunication systems while Operational technology (OT) systems include all software and hardware systems focused on the physical aspect of industrial production including the monitoring and control of physical devices and machines. More so, Operational technology (OT) systems are more likely to include outdated hardware components and legacy applications that have not been updated for years. There is also the challenge with very vulnerable communication protocols (i.e., Modbus and Profinet) that are used to control many sensors, controllers, and actuators. A March 2019 report by Ponemon Institute shows that 90% of organizations dependent on Operational Technology (OT) experienced at least one major cyberattack within the previous two years [131]. Since it is unlikely that companies would immediately upgrade their decades old equipment that are still functional, there is a need for more cybersecurity research and a paradigm shift to address most of these security challenges.

6.2.1. Cloud Computing:

The cloud has made it possible for data to be stored and accessed differently than was the case prior. The emergence of the cloud is one of the main factors driving the development of smart technologies. The cloud has forced a shift in the geography of data storage and computation. When "cloud" is combined with "computing" it takes on an even more consequential meaning. Many scholars have attempted to provide some insight into the meaning and consequence of cloud computing to technological change. Armbrust et al. described cloud computing as, "...both the applications delivered as services over the Internet and the hardware and system software in the data centers that provide those services". Cloud computing has also been described as a unique computing paradigm that involves the provision of flexible, dynamically scalable, and often virtualized resources over the Internet [132] . Because Cloud computing is based on an on-demand service delivery model it was referred to as a utility by a 2009 Berkeley Report, a reference that is not entirely surprising given that Cloud computing has been previously referred to as Utility Computing. Cloud computing is premised on the idea that IT services (computational power, storage, platform, and software) can be provided as a utility or service much like electricity or water. It features ubiquitous, on-demand and scalable access to resources. Under this arrangement, these resources are provisioned from a shared pool, obligating users to ONLY pay for resources consumed (pay-per-use model). It eliminates the need for users to individually build and maintain complex infrastructure. The accessibility (location) to cloud infrastructure and how they are deployed or controlled (proprietorship) and by whom, vary from one cloud system to another. The four most common deployment models include public, private, community, and hybrid. The suitability of each model would depend on the specific needs of an organization. The cloud services are packaged in three main service models viz. (a)*Infrastructure as a Service (IaaS)*, (b) *Platform as a Service (PaaS)*, and (c)*Software as a Service (SaaS)*, respectively. Quality of Service (QoS) requirements between providers and users ensure that high quality services are provided at competitive cost. Since the cloud is architected as a network of virtual services, deliverable over the internet, organizations can access and deploy applications easily from any location. End-user (or last-mile consumers) can also seamlessly access information or personal data, remotely. Because of its almost unlimited digital storage capacity, the cloud would be critical for the monitoring, tracking, management, and storage of an almost endless stream of data flowing from different nodes within the industrial internet of things (IIoT). Pairing the cloud and the Industrial Internet of things (IIOT) with a Future Factory enables the full integration of all key elements of the digital manufacturing ecosystem that which can then result in data and information sharing which can ultimately lead to gaining better understanding of how to improve productivity and ramp up efficiency.

In the context of manufacturing, data acquisition or capture primarily occurs at the nodal level. It typically involves the autonomous capture of data from production equipment, machines, devices, or systems using embedded or connected sensors, and related hardware. Large amounts and often expensive network bandwidth are required to transfer massive amounts of data captured from devices to the central cloud for deep learning (DL) model training and inference. Some results of inadequate network capacity when confronted with massive amount of transferable data are low throughput, delayed transmission (i.e., high latency), and poor network performance. Latency which is the round-trip time required for data to be transferred to and from the cloud needs to be as low as possible for systems to function optimally within the manufacturing network.

The long-established trend of capturing and transferring data from the factory floor to the cloud is increasingly becoming untenable due to the high latency and low bandwidth issues associated with the massive amounts of data captured daily by the ever-growing number of IoT devices now available within manufacturing ecosystems. Furthermore, many time-sensitive operations within the factory have strict delay requirements (in some cases, few milliseconds) [133] that cannot be met by reliance on the centralized cloud.

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Against this backdrop, it is instructive to look at the three levels at which storage and computing can occur:

a) *"Cloud-only" Computing:* Cloud services make it possible for businesses to increase storage and computing capacities on-demand and on the fly without the need to invest in new infrastructure, application, or IT personnel. Eliminating concerns about the availability of IT resources enables companies to focus on innovation and creating business value while simultaneously cutting down on maintenance and administrative costs associated with managing their own IT infrastructure.

b) *Fog Computing:* Another compute paradigm that has since emerged is fog computing. Hierarchically, it stands mid-way between the cloud and the edge and lives on the LAN. Programmable fog nodes serve as traffic hubs where decisions about the routing of data and inter-node Peer-to-Peer (P2P) communication and services orchestration are performed. They facilitate the decentralization of control and facilitate increased reliability, efficiency, and flexibility [134]. While fog computing and edge computing have been treated in some texts as interchangeable terms or overlapping terminology, it is important to clarify that they are indeed interrelated but also different in many ways. The OpenFog Consortium Architecture Working Group (now part of the Industrial Internet Consortium): an academia-industry group dedicated to the acceleration of the growth of the industrial internet called attention to some of the differences in a report entitled "OpenFog Reference Architecture for Fog Computing" [135]. While both computing paradigms bring processing power and intelligence closer to the data source, the major difference between them comes down to where data processing is performed. In the case of edge computing, data it occurs directly on the devices on which the sensors are embedded or attached or on some gateway device within proximity. In the case of fog computing, processing is performed by processors connected to the LAN (i.e., a micro-data center) or within a LAN hardware. In either Fog configurations, processing occurs further away from the sensors and actuators than in edge computing. Further to this, most edge devices only process data collected at one touch point while fog computing is about processing data aggregated from multiple devices. So, the fundamental construct of the fog architecture is the aggregation and high-level processing of data and the almost instantaneous real-time, return transmission of the acquired intelligence.

c) *Edge Computing:* Edge computing have since emerged as a viable alternative to the "cloud-only" or central cloud computing standard or architecture [136]. This distributed computing paradigm involves the transfer of compute power, networking, application services and data storage capabilities to where they are most needed, which are at multiple decision points that are usually as close as possible to the data sources [137,138]. They also enable dynamic monitoring and control of manufacturing processes [139]. By building in flexibility around where computation can be performed and extending cloud computing standards to the far reaches of the edges of the network, it helps address many of the latency, bandwidth, and data throughput issues [140] that have bedeviled cloud computing. The proliferation of edge computing as a concept has been facilitated by the growing adoption of faster networking technologies, such as 5G wireless and the integration of edge devices into manufacturing IT and OT networks and the tie-back of all these using IIoT. Under this arrangement, algorithms can now run locally on edge servers or gateways and data can be processed at a high level with some form of analytics reported so that insights are provided in real time and human and machine queries are responded to in seconds. Some of this intelligence can be used to actuate other connected devices or systems where necessary and actionable results can be instantly made available to workers on the factory floor and executives in offices. This is reminiscence of the autonomous vehicle, whose systems require instant feedback to make travel decisions even while the vehicle is in motion, and in some cases even at high speed. Edge devices (nodes) enable edge computing by providing entry points

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into manufacturing core networks. They are usually mobile or fixed assets, often embedded or connected to machines or equipment. They are typically distributed throughout the factory floor and other remote locations like nodes across a wide network or stars strewn across a dark sky. Large IIoT operations like a manufacturing facility would typically host hundreds (or even thousands) of edge devices (nodes) which together form a network of edge devices that recognize and communicate with each other. The edge devices continuously and autonomously collect, process and broadcast data which provide significant visibility and awareness about events across the network. Some edge devices serve a dual purpose as sensing devices for capturing sensory information as well as actuators that can trigger or control other devices or systems. Some common examples of sensors and actuators in edge devices within manufacturing facilities would include: (a) Sensors: Pressure, Temperature, Real Time Location System (RTLS), Cameras, Near-field communication (NFC), Light, Proximity, Motion, Acoustics, Radio-Frequency Identification (RFID), Ultrasonics, Flow Meter and Fluid. (b) Actuators: Hydraulic, Pneumatic, Switch, Relays, Programmable Logic Controllers (PLCs), Motors, Light, Acoustics. Under the edge computing arrangement, data is processed, and analysis results distributed by the same device used to acquire it or by a nearby server instead of a centralized cloud. The result of implementing edge architecture include the ability to process and store data faster, improved application performance, low latency, and significant reductions in bandwidth cost. Notwithstanding, it is important to note that edge computing does not eliminate the need for deeper data analytics, large data storage and extended archival capabilities, all functions that the cloud is better suited for. The main advantage of Edge computing is its capacity to reduce the compute requirements and data volume that must be transferred to data centers or cloud-based locations within short notice. In the *Future Factory* it is expected that more complex data processing would be performed at the edge as new system modules that incorporate advanced artificial intelligence functionalities are built into them. Edge computing has also helped in the management of many security and privacy related concerns within the industry.

Pending the development of better technologies and more advanced architectures, the cloud computing/data analytics needs of the *Future Factory* can be met using a hybrid architecture that relies on or one or more of the computing paradigms discussed above. Examples of such hybrid architecture are discussed include:

(i) *"Cloud-only" model:* In the Cloud-only model, no intermediate processing of data occurs. All data captured by multiple sensors are transmitted to the cloud where 100% of the processing occurs before the results are pushed down to all the sources that require the intelligence.

(ii) *The Cloud-Fog Computing model:* In this model, data from multiple sensors and devices are transmitted to the fog gateways. Depending on the urgency of the request, some high-level processing of data occurs at the fog layer and intelligence pushed back to the various nodes (machines and humans) in real-time. Non-time-sensitive data and some pre-processed data that require further (deep learning) processing are transmitted to the cloud.

(iii) *Cloud-Fog-Edge Computing Model:* This is a massive, distributed computing infrastructure that consists of three (3) inter-connected computing tiers [Cloud, Fog and Edge].

All data acquisition occurs at the logical extremes of the network using edge devices. Some instant, high-level processing of data occurs at this tier (the edge) to provide time-sensitive, real-time response from entities (man and machine) at different nodes. In this configuration, the Fog layer not only serves as a distribution hub for resources and services between the edge and the cloud but also stores and performs high-level data analysis of

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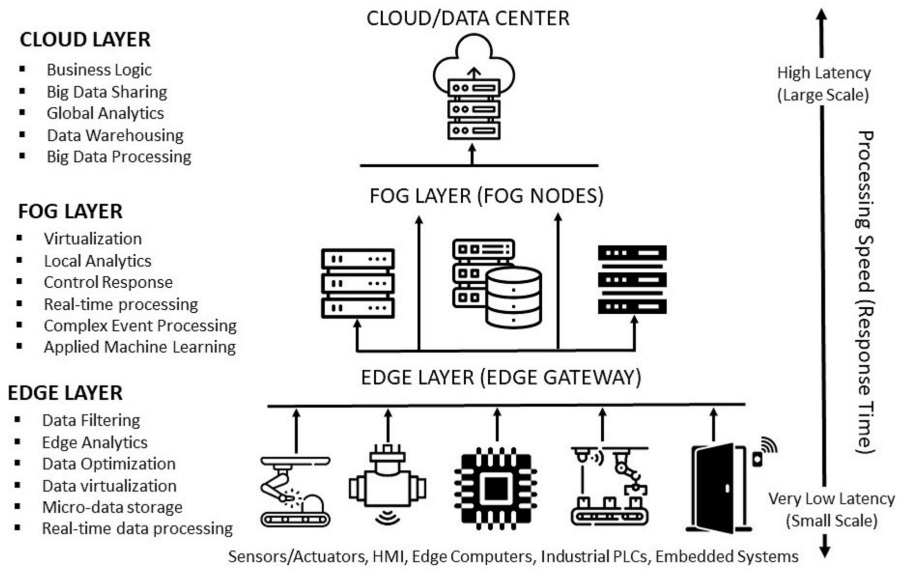

Figure 21. Cloud-Fog-Edge Layer architecture

data from multiple sensors at different edge location while providing low-latency network connection for the transmission to data and responses back and forth, the edge and the cloud. Unlike, the edge, the fog layer is best suited for analytic operations that require real-time analysis of data from multiple data sources (e.g., several edge devices). The Cloud tier is where the most robust, deep learning processing operation occurs. It is the tier where all non-time sensitive and pre-processed data arrives for thorough, deep, and final analysis. The cloud also has massive and scalable data storage and archival capabilities.

6.2.2. Big Data Analytics:

Data is the fuel that drives digitally transformed factories and is fast becoming the most consequential asset in manufacturing as the factory of the future begins to take shape. As part of this digital transformation process, some manufacturing organizations have been able to successfully connect their numerous fully automated manufacturing facilities (alongside all their production equipment) located in different global sites into a central cloud resulting in manufacturing architectures that are IoT-native, fully digital-capable, and broadly cloud-based. These architectures, which can qualify as benchmarks for Industry 4.0 enable seamless data sharing, collection and exchange across enterprise resource planning, manufacturing operations management and production life-cycle management processes, therefore enabling coherent feedback systems that leverage data analysis outputs for the optimization of manufacturing operations. These factories will plausibly grow ever more intelligent due to the exponential amounts of sensed data that will flow into servers and data reservoirs because of the continued digitization of industrial assets. However, no actual benefit would accrue from the possession of these vast amounts of data if they were not properly analyzed and the accruing intelligence distributed to all necessary end-users and connected systems in formats that make sense as value-add to help improve processes, productivity, and competitive advantage. Ultimately, deriving critical intelligence that can help make correct inferences and consequently acquire optimal value from data would require advanced analytics and the ability to effectively present results in formats that are easily ingestible by appropriate systems or visualization formats that are meaningful and can be effortlessly comprehended by end-users, both executive in the offices and technical personnel (engineers, technicians, fitters etc.) on the shop and manufacturing floor. Terms like data warehouse, data lake, edge, modeling, and optimization are all examples of words

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associated with data analytics.

6.2.3. Artificial & Cognitive Intelligence:

The Future Factory is a highly dynamic system that is comprised of several interconnected and sometimes co-dependent sub-systems that are subject to a wide variety of nonlinear and stochastic activities [141,142]. These assets also generate huge amounts of data which potentially contain useful operational and strategic business insights. Unfortunately, only a fraction of these data is currently analyzed by various traditional factories due to operational and technical constraints. With the increasing complexity of today's factory, many traditional methods often used to address a lot of common production issues (like process variability, root cause analysis, early detection of quality defects, degradation monitoring, process control etc.) are becoming increasingly inadequate. Because of its many successes in a variety of industries, Artificial intelligence is increasingly looking like a credible alternative for addressing a variety of manufacturing challenges because of its robust portfolio of solutions and its incredible ability to process vast amounts of manufacturing data making it possible for companies to transition from reactive to highly accurate proactive (and even predictive) decision-making. Several research-based concepts, mock-ups, test-bed prototypes, and even factory-ready artificial intelligence solutions have been developed or built-in recent years.

But what exactly is Artificial Intelligence (AI)? Artificial Intelligence (AI) is as an interdisciplinary discipline [143], a set of practices and a variety of systems or tools that model and/or exhibit intelligent behavior like perception, reasoning, decision-making, the ability to predict, and even understand context. The mimicry of human cognitive functions is at the core of Artificial intelligence (AI). The ability to reason, interact and learn are the three key attributes of a typical artificial intelligence system. Because of the implied similarities in intellect, comprehension and abilities, Artificial Intelligence (AI) is said to possess a certain kind of machine intelligence [144] that would parallel and possibly outmatch human intelligence [145] in certain respects. AI can either replace or augment human ability. While there are several sub-fields within Artificial Intelligence (AI), (e.g. Machine Learning, Deep Learning, Natural Language Processing, Computer vision, Expert Systems, Cognitive Computing etc) it is not easy to make clear distinctions between them because of clear overlaps in their relationships. To better understand AI we would be focusing on the two main sub-fields i.e., *Machine Learning (ML)* and *Deep Learning (DL)*, that drive performance in all the other sub-fields.

ML has been dubbed the workhorse of Artificial Intelligence (AI) and its applications are ubiquitous across multiple industries where it has been particularly useful as an effective tool for evidence-based decision-making [146]. Traditional ML involves a process of training a system by exposing it to examples of desired input-output behavior instead of explicitly programming it. ML is used to build assets or systems that can automatically improve through experience. The way it does this is by learning from data. Learning from data means being able to extract information accurately and quickly from raw data and to be able to make reasonable inferences. To do this Machine Learning (ML) relies on different purpose or task-specific algorithms. Figure (22) shows different types of traditional ML algorithms. There are no one-size-fits-all algorithms that can solve all ML problems. ML algorithms exploits meaningful relationships within data set to solve complex production problems. In his 1959 paper [147], Arthur Lee Samuel (1901-1990); an American pioneer in the field of computer gaming and artificial intelligence, noted that, "...a computer can be programmed so that it will learn to play a better game of checkers than can be played by the person who wrote the program". This statement underscores the power of Machine Learning (ML) i.e., its ability to learn what to, to do it automatically once the lesson is learned, and to in fact, improve its performance and accuracy over time. Applied ML solutions do not only learn from data but become more accurate and usefulness over time by leveraging knowledge acquired from new data in the cause of the use of the solution [148]. Vast

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amounts of data are generated in manufacturing. A great advantage of machine learning is that it can analyze large amounts of complex manufacturing data and quickly make meaning of it. There are numerous reviews of Machine learning (ML) and Deep learning (DL) techniques/applications in manufacturing [149–151]. The emergence of low-cost computation, next generation computing architecture, (particularly Graphics Processing Unit [GPU]), availability of data and the development of sophisticated algorithms are at the root of the rapid advancements in Machine Learning (ML)[152].

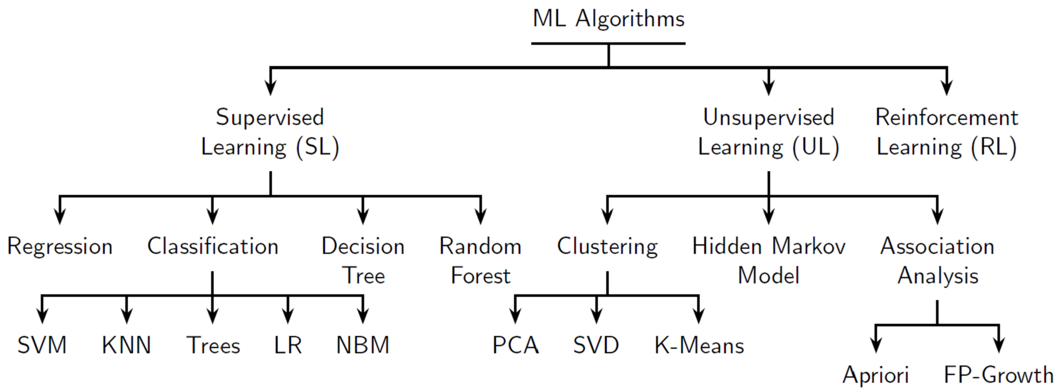

Figure 22. Machine Learning (ML) Algorithms
Acronyms: Support-Vector Machines (SVM), K-Nearest Neighbors (KNN), Logistic Regression (LR), Naïve Bayes Multinomial (NBM), Principle Component Analysis (PCA), Singular Value Decomposition (SVD), Frequent Pattern-Growth (FP-Growth)

Deep Learning is a special type of Machine Learning (ML) that is based on Artificial Neural Networks (ANN) [153]. The adjective "Deep" in "Deep Learning" refers to the multiple network layers common in DL. DL Algorithms use neural networks with multiple processing layers (often more than three layers) [154] that learn data representation at multiple abstraction levels [155] by optimizing some unsupervised criteria [156]. Beginning from the input layer, every subsequent layer within the network produces a distinct representation of the observed patterns based on inputs received from the previous layer . Ultimately, the algorithm achieves its results by progressively extracting high-level features from one representational layer to another. This intuitive stepwise feature extraction process results in slightly more abstract representation of the input data, the deeper into the neural network the data flows. Various Deep Learning (DL) approaches have been reviewed in the open literature [153,156–159]. Deep Learning (DL) is very scalable, with performance improving remarkedly as more data becomes available. Some common Deep Learning (DL) application areas include Computer Vision [160,161], Natural Language Processing (NLP) [162,163], Speech Recognition , Machine Translation etc. Of these, computer vision is perhaps one of the areas where DL has had the most impact. Computer vision application areas like Image Classification, Object Detection, Action Recognition [164,165], Motion/Visual tracking[166,167], Semantic Segmentation [168,169], Human Pose Estimation [170,171], are now common on many factory floors, in the value chain and supply chains of a many industries. The increase in popularity of DL-based solutions is in part because of the astounding human level results they have delivered [155]. One of the major differences between traditional Machine Learning (ML) and Deep Learning (DL) is in how representations are learned from the raw data. Unlike traditional ML, DL can perform automatic feature extraction (i.e., feature learning) intuitively. While important features are manually extracted in traditional Machine Learning (ML), Deep Learning (DL) achieves relatively higher accuracy classifications using general-purpose learning procedures that rely on automatic extraction of high-level, non-linear features from raw data, all with little or no human intervention. This is particularly helpful considering that 80-90% of available data today are unstructured in nature.

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Applications of Artificial Intelligence (AI) in Manufacturing: The typical manufacturing system integrates several elements including machinery (including machines, robots, conveyors, tools, fixtures, and related hardware), material handling systems, information handling systems (computers systems) and human workers. All these systems, the technologies that drive them, the processes they support and the strands that connect them can all potentially be infused with AI solutions to increase efficiency and ensure the "optimal control" of material flow, efficient use of energy and ultimately the cost-effective creation of value. Amongst many benefits, Artificial intelligence (AI) eliminates or replaces time-consuming and sometimes risky traditional practices, facilitates access to data, and enables effective execution of manufacturing tasks.

Artificial Intelligence (AI) has domain independent characteristics and has permeated many industries. AI based solutions have been implemented across all manufacturing processes (design, production, maintenance, assembly etc.) and the associated supply chain [172,173]. It has the potential for game-changing impact on Manufacturing in the long term.

AI technologies provide opportunities to maximize the value locked up in the vast troves of data generated daily within factories [174]. It facilitates autonomous and intelligent analysis of real-time and historical data, enabling smart and informed decision making [175]. This allows the factory, and its sub-systems to respond in real-time to changing demands and dynamic conditions streaming through the PLM systems [176,177].

The two aspects of Manufacturing that have experienced the most infusion of Artificial Intelligence (AI) solutions are Machinery Maintenance and Quality with the most focus directed towards advancements in overall equipment efficiency (OEE), growth in production yield, increases in uptime, and improvements in quality and consistency.

AI based solutions enable automatic evaluation, monitoring, and real-time insight into equipment condition to help minimize unplanned equipment downtime and expensive maintenance costs. They are also able to forecast (when) operational equipment is likely to fail to help guide maintenance scheduling. Artificial intelligence (AI) also provide visibility across manufacturing cells, lines, and the supply chain.

It has been used for inspections [178–180], diagnosis [181], anomaly detection and predictive maintenance [182,183]. To improve product quality, Artificial intelligence (AI) solutions have been used to automate defect detection processes by automatically verifying product quality and providing insight into quality issues, hence reducing waste, and enabling production improvements. Many ML-based fault/defect detection [184–189] and quality monitoring approaches [187] have been proposed in the literature. Several examples of fault diagnostics [186,190–200] are also available in literature. Bayesian approaches that enable root cause analysis of quality issues' [201,202] have also been proposed. It has also been used for robotics [203,204] robot-inspired path planning [205] and managing network traffic in computer networks [206]. Different Artificial intelligence (AI) strategies have also been infused into manufacturing-based technologies like Cyber-Security (Malware detection) [207,208], Augmented Reality (AR) systems [209,210] to enable them to operate more autonomously and intelligently.

Another area where AI has played a useful role in the factory is in the Prognostics and Health Management (PHM) of machinery [211]. The ability to detect deviations in the normal operating conditions of industrial components is helpful for the timely prediction, detection and isolation of faults and the prevention of costly and unplanned failure. Real-time visibility about the health status of individual machines and the entire production system provides immediate and long-term value to the production process. While the combination of data availability and the adoption of traditional ML techniques in recent years provided a lot of insight into component defects, root cause analysis, machine degradation and remaining useful life (RUL), the complexity of the manufacturing systems has prompted a pivot to deep learning (DL) solutions which are better able to better handle the complexity of input data provide hierarchical representation [212].

AI has also supported intelligent control of manufacturing systems. The growing complexity of controlled systems now means that no single control paradigm addresses the issues prompting the use of hybrid control systems that sometimes include both discrete event systems and continuous systems. To be effective, these hybrid control systems require intelligent control methodologies [213–217] to be embedded within them.

Optimal system configurations, performance evaluation, material flow modeling, throughput etc. are all within the purview of AI. Most factories contain highly integrated systems comprising manufacturing cells, workstations, assembly lines, material handling systems and a network of multiple machines, robot and conveyors that support the flow of materials and their processing/refinement. These arrangements typically have finite buffer capacity. These finite buffers and period system failures like unreliable machines, create uncertainties and inter-dependencies that make factory operations nonlinear, stochastic [218,219] making the determination of optimal system configurations, performance evaluation, material flow modeling etc., very challenging. A lot of work has been devoted to the analysis of the dynamics and performance of manufacturing systems [219–223]. Some of these, like the queuing theory and Markov Chains-based analytical modeling methods have known limitations [220,223–225]. AI based ML techniques appear to be compensating for these shortcomings [219,223,226–229].

AI solutions have also been used in job scheduling. To meet mass customization requirements, Flexible manufacturing systems (FMS) are designed to easily adapt to changes in the type and quantity of products. A particular challenge that then arises during implementation is the job dispatching problem where several product orders could be awaiting processing within the same time window. Exact approaches (best for small-scale job dispatching problems) and heuristic-based methods (not very adaptive in highly dynamic environments) have been traditionally used to address these issues. Because if their limitations, ML based methods have been used to compensate for these deficiencies .

6.2.4. Blockchain

This is a type of shareable ledger that runs atop a permissioned network [230]. It can also be described as a distributed network of nodes, typically running on multiple servers that feature a system of perpetually growing list of trusted or verified asset transaction. Depending on the way the system is set up, trust is distributed across nodes within the network. These nodes are responsible for the verification, authentication, and integrity of block data before the ultimate inclusion of the new block into the growing chain. These continuously growing chain link of blocks are aptly referred to as blockchain. Each block stores data associated with an asset (i.e., person, place, or thing). The relationship between the blocks is maintained through a mechanism that enables each block in the chain to inherit an immutable hash of the prior block that it is connected to. Transaction within a blockchain is usually processed and stored without consultation with, approval or even need for a central trust authority [231]. One of the main reasons blockchain is an important building block of a typical future factory is the fact that data stored on it (e.g., transaction details) are immutable or remain unchanged, unaltered, and indelible which means that the full history and data trail of all data, communication or transactions are preserved, thus establishing data provenance. A typical blockchain system includes a network of nodes that serve as a decentralized and trustless system that ensures data provenance and the efficient sharing of manufacturing (products & processes) information. Can be set up as a decentralized and connected network of manufacturing assets and computing nodes. This system will provide transparency, and audit trail of assets and a third-party verification system around an organization's manufacturing capacity, creating a mechanism for operationalizing "smart contracts" between different parties or entities. Essential for product customization and tracking of assets within a supply chain. Various factories and their value chains might need to be connected in the factory of the future in what could be termed networked organizations and machines. In a typical network of the sort suggested, multiple third-party entities might be involved in various aspects of the production of a product

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including supplies (materials & spares), service provisioning, product design, fabrication, and production. Other aspects might include product testing (validation/verification), regulatory control and shipment. Trustworthiness among the disparate parties (factories, distributors, suppliers, regulators, and other stakeholders) within such a network would be critical if all participants are to be at ease. Basic implementations of blockchain abound in the literature. Examples include in healthcare [232], Intellectual Property Protection of 3D Print Supply Chain [233], machine-to-machine (M2M) interactions in the Chemical Industry where Industrial plants trade electricity with each other over a blockchain. In a certain instance, a central server which typically manages information exchange and data authentication in an IoT system was replaced by blockchain (BC) technology, hence eliminating risks of device spoofing, false authentication and several other security and privacy concerns [234]. Atin Angrish et al. (2018)[235] provide some great insight into Blockchains with a bias to manufacturing.

6.2.5. Mixed Reality:

Mixed reality is a class of technologies that attempt to blend the physical and digital worlds. Mixed reality operates on a spectrum with Virtual Reality (VR) and Augmented Reality (AR)being the most prominent types. In this paper we would be focusing our attention on Augmented Reality (AR) mainly because it likely have the greatest potential to proliferate in the factory of the future. Augmented Reality (AR) systems project context-sensitive [236] digital information in 2D or 3D forms (i.e., texts, stats, maps, videos, images, animations, characters etc.) unto real-life objects (the physical world) for the express purpose of providing additional information, context, instructions, or guidance about the said object or a process that the object is undergoing. They enable users to interact with real and synthetic elements of the real and virtual worlds, simultaneously [237]. As a human-computer interaction tool, users (technicians, maintenance crew etc.) can directly interact with the "extended" information to make informed decisions. Augmented Reality (AR) systems complement (or augment) human abilities, providing users the guidance and support needed to complete tasks correctly in a consistent and efficient manner. Leading to higher productivity, greater accuracy and marked reduction in expensive rework by ensuring tasks are performed accurately, the first time. User-friendly and intuitive human interfaces alongside rich, appropriate, and context-aware content are factors critical for a great AR experience [238].

a) **Types of Augmented Reality (AR) Systems:** There are several types of Augmented Reality (AR) Systems depending on their application, functionality, or design. Of these, four (4) main types stand out: [a] Marker-Based AR: This class of AR systems display content (video, text, animation, 3D figures etc.) on surfaces contingent on the detection of a predefined marker embedded on a static image (trigger photo) or QR code often using AR devices like mobile devices [b] Markerless AR: Unlike Marker-based AR systems, they do not require physical markers for the overlay information to be triggered. They merely scan their environment to get their bearing and are generally guided by localization or positioning systems like GPS, accelerometers, digital compass etc., [c] Projection-Based AR works just like your typical projectors. They utilize image or video-based projection (with audio prompts, in some cases) to guide the pace, direction and "every step" of a process. They enable operators or factory workers through manual processes, enabling them to complete tasks quickly, efficiently, and consistently without recourse to hard copy manuals and instructions. [d] Superimposition-Based AR relies on the object recognition technique to first identify an object and then replacing its entire view or a portion thereof with an equivalent augmented image. An often-cited application of superimposition-based AR is in the medical field where doctors sometimes superimpose live feeds (x-ray images) of a patient's body part directly from an X-ray machine unto the patient's actual body to better understand the internal condition of the body part.

i) *Hardware Devices:* Hardware devices are a necessary and integral part of Augmented Reality (AR) systems. There are several types of AR devices in common use, some of these include Handheld Devices [HHD] [239–241] Holographic Displays, Head-Mounted Displays [HMD], Smart Glasses/lenses & Virtual retinal displays (VRDs), Mobile Phones (including Smart Phones) [241] , Wearable data-gloves [242], Haptic devices [243], tablets, iPads, computers etc.

ii) *Software Systems:* Software (or applications) also form an important of AR systems. Of particular interest are (a) Tracking & Registration Algorithms and (b) Development platforms (or content-creation applications). The primary function of the Tracking and Registration Algorithms is the alignment of the two (real and virtual) environments or object categories. On the other hand, development platforms are the applications used for the creation of AR content. They include anything from low-level programming libraries to the more complex AR applications that integrate features for sensor data acquisition & integration, image, and audio rendering, and in some cases even application engines.

b) **Industrial Applications of Augmented Reality:** Over the years, AR technology has continued to mature. Its ability to simulate processes, augment tasks, provide remote assistance, enhance communication between teammates and provide elaborate guidance to users have helped in demonstrating its relevance to manufacturing amidst the on-going re-imagination of the sector. There have been proposals [244], proof of concepts and actual applications [245], in a wide array of industries [246,247] . Its successful application at various manufacturing stages (Planning, Design [248,249], Assembly [245,250], Maintenance etc.) is particularly notable. It has also found application in different manufacturing processes and functions. A few of these are discussed below:

i) *Interact with Process Information:* They have been used to digitally access and interact with procedural and process information, including IIOT related data [251] acquired in real-time, rather than relying on physical manuals and paper documents. Some have been used to display augmented 3D images making it possible to view system components in multiple configurations including exploded, cross-sectional, and internal views. For example, internal views come highly recommended for providing insight into the internal sections of opaque structures or systems were accessibility or worker safety is an issue [252].

ii) *Quality Control:* AR systems is already playing a huge role in automated real-time, in-production quality control. The mobile nature of most AR systems supports the relocation of the quality control function away from static (fixed) input locations to mobile terminals, permitting intermediate inspections, and facilitating the flexible and cost-effective use of software license seats. The online, real-time, and decentralized characteristics of the AR systems provide the added advantage of instant access to and flexible flow of information to various manufacturing points where they are most needed. It also enables fast variance inspection, continuous, real-time error reporting & documentation. Finally, the instant generation of enhanced quality assurance reports [253] immediately after the completion of each instance of an inspection routine [254] is not a possibility.

iii) *Process Support, Training & Simulation:* AR technology has also been used to assist technicians and operators working on mechanical or technical tasks like welding [255], machinery repair, assembly operations and even to control robots [256,257]. Some AR Inspection systems incorporate features that provide graphic step-by-step instructions that can be used for process training. The step-wise design of these routines ensure that processes are performed in a consistent, accurate and reliable manner. They can also be used as simulators for practice runs to help user develop and perfect their skills ensuring that manufacturing tasks and processes are carried out right the first time. In the long-term, this helps in limiting errors and eliminating the need for rework. This level of expertise and dedication is useful for high-stress tasks where precision is critical.

iv) *Repair & Maintenance:* The repair and maintenance of complex machinery will be one of most consequential areas of AR application in manufacturing. Next generation AR-Inspired Maintenance systems are becoming important elements of the Factory of the future [258]. They are now more often the product of the intersection of AI, IIoT, Big Data, and associated technologies and capabilities. Excellent condition monitoring combined with dynamic predictive modeling make for a successful predictive maintenance program. In the factory of the future, technicians going about in the normal course of their daily duty can be prompted by their wearable IAR device (like smart glasses or mobile devices) about "just-beginning" maintenance problems, way in advance of actual system or component failure. These AR systems not only detect and warn operators and technicians about these anomalies but also offer on-the-spot visual analysis of the problem, display the service histories of the machineries, and deliver step-wise service instruction to aid in their resolution. For off-site maintenance, the AR systems can serve as remote collaboration tools where a technician can contact, collaborate with colleagues in resolving tough problems or be remotely guided by a more experienced supervisor [259].

v) **Collaborative Product Design & Prototyping:** Almost all aspects of product design, for early to late stages, can now be collaboratively performed (end-to-end), streamlined, sped-up and optimized using AR. These stages would include ideation, conceptual design (encompassing generic functionality management [260]), preliminary design, the interactive generation of models or virtual product prototyping [250,259,261], design review and evaluation [262]. Free form surface generation features in some AR applications have been used to support easy creation of design alternatives and to enable parameter adjustments [260]. In automotive design, for example, AR based Design tools have been used to evaluate multiple interior design options by simply overlaying different photo-realistic 3D car interior mock-ups over real cars[261] eliminating the need for physical prototypes. AR based design tools often generate sharable high quality, 1:1 scale, photo-realistic 3D visualization of augmented design models that can be converted into AR compatible format and transmittable to stakeholder's devices for easy and enhanced viewing. Availability and real-time remote access to these models make collaboration easy. They are enabling stakeholders (both designers and other collaborators, downstream in the product pipeline), to inspect and interact with the design models, and provide timely and objective feedback for design improvements, in advance of design approval and production [16]. The early detection of flaws facilitates design improvements and eliminates expensive post-production redesign costs. Several user-friendly AR computer-aided design environment like ARCADE are now available [263].

c) **The Challenge with current AR Systems:** Though there is a growing interest in the use of Augmented Reality (AR) as a support tool across industry [264,265] . One drawback of most AR-based maintenance systems is that most application are currently passive and static in nature. They merely push information and provide no feedback mechanism capable of ingesting, analyzing, and looping back explicit and implicit user and environmental responses. A feedback system of this sort can enable the output of targeted information to users, continuous process refinement,

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and better tailored solutions. Examples of responses (data points) that can be routed back to through the feedback system would include such data points as effectiveness of prior guidance, the experience of users or even the user actions or inactions that could help preempt user intent. There is a need for more adaptive AR, with creative feedback loops that can actively engage users and help them to solve problems more creatively. Attempts have been made in literature to spotlight this challenge and suggesting creative ways of solving this problem [266].

6.2.6. 3D Printing (Additive Manufacturing:)

3D Printing (also referred to as Additive Manufacturing [AM]) has been variously referred to as one of the major enabling technologies of the 4th Industrial revolution [267] because of its potential for massive disruption of the status quo across many Industrial sectors [268]. Alongside other disruptive technologies like IoT, Cloud, Big Data/Analytics, AI etc. it is expected that AM would create the necessary conditions for expedited processing, rapid prototyping, customized production, and agile manufacturing. Additive manufacturing has various definitions, but one of most descriptive is the one captured in the ISO/ASTM 52900 standard [269] which defines it as the "...process of joining materials to make parts from 3D model data, usually layer by layer, as opposed to subtractive manufacturing and formative manufacturing methodologies". Irrespective of what definition is accepted, the general principle upon which this technology rests are the creation of 3D geometries through the precise addition of basic building blocks such as grains of powder or polymer filaments laid out as a series of cross sections, often layer by layer. This occurs with minimal material waste and a nominal or limited need for post-processing [270] . The creation of these 3D geometries is driven by digital instructions (geometric information) typically sent from a computer (CAD model) to a printing head, nozzle, or related printing technology. The instructions which are processed as points, lines, or areas help guide the direction and rate of material deposition [271]. Over time, the technology has continuously matured getting to a point where it is now feasible to work with all sorts of materials including ABS plastic, photo-polymers, stereo-lithography materials (epoxy resins), metals (e.g., steel, titanium), wax, and even biological materials. The seven (7) categories of Additive Manufacturing (AM) [272]. Each category includes several techniques, some of which are well known within the AM community. The processes involved in either of the techniques differ depending on the materials used and the mechanism employed. They include (a) VAT Photo-polymerization, (b) Material Jetting [e.g., Continuous on Demand (CoD) and Drop on Demand (DoD)], (c) Binder Jetting, (d) Material Extrusion [Fuse deposition modeling (FDM)], (e) Powder Bed Fusion [e.g., Direct metal laser sintering (DMLS), Electron beam melting (EBM), Selective heat sintering (SHS), Selective laser melting (SLM) and Selective laser sintering (SLS)], (f) Sheet Lamination [ultrasonic additive manufacturing (UAM) and laminated object manufacturing (LOM)] and (g) Directed Energy Deposition [e.g., Laser engineered net shaping, directed light fabrication, direct metal deposition, 3D laser cladding].

Traditional manufacturing is generally expensive due to high labor cost and complicated set-up (machinery and process) requirements. Re-purposing and switching product lines can take weeks or even months. This contrasts with Additive manufacturing that lends itself to quicker process adjustments and easier adaptation within a larger production line. Furthermore, changing production speed or switching between products can be easy and fast and relatively fewer operational staff are often required to achieve equivalent work outputs. Additive Manufacturing [AM] has the potential to democratize manufacturing on a global scale. It is cheaper and best suited for high-value, low-volume, small and short-run parts production. AM is well positioned to benefit the growing demand for product personalization and mass customization. They are also very useful for creation of parts and structures with complex geometries and require flexible designs. Examples can be seen in machine parts, dental work (precise crowns & dentures), artwork, customizable gifts etc. In the Live sciences, layers of living cells have been printed over one another to create human skin. Some of these can potentially be surgically implanted into other living materials to fix complications on the body of burn victims. They are also being evaluated for skin products testing, to help reduce the controversial use of live animals for biological tests. There is also an emerging consensus amongst researchers that at some future time in the future, it would be possible to print human organs and increase options for people on organ waiting lists.

In manufacturing the fabrication of tools necessary for producing parts or components is important. Agile tooling, a specific tooling approach which involves the efficient and cost-effective design and fabrication of tools like molds, patterns, dies, jigs, fixtures etc. is an important aspect of manufacturing-related tooling. The most popular agile tooling techniques include die-casting, die-stamping, hydroforming, and thermoforming. Some of these tooling has been produced at great turn-around times and at a fraction of regular cost, thanks to Additive Manufacturing (3D printing) processes. For example, tooling typically created with the vacuum forming process can now be produced faster, more efficiently and at lower cost using Fused Filament Fabrication (FFM), an Additive manufacturing process. The ability to produce these tooling faster would mean quicker prototyping and shorter time-to-market. With the adoption of additive manufacturing (AM), a Future Factory (central hub) can potentially fill a demand for a replacement part initiated by a customer, from a thousand mile away, in record time, without any shipping requirements. An example of how this can play out is that a virtual 3D model of the requested part, released by the Future Factory to a cloud location, becomes immediately accessible to an authorized, out-sourced third-party 3D print location, closer to the customer. Following a few clicks, the 3D model is printed and becomes available for immediate customer pick-up. This arrangement would reduce wait-times, accelerate production rates, and eliminate shipping cost. It will also reduce time-to-market, making the creation of products cheaper and more accessible.

Opportunities to combine evolutionary or genetic algorithms with 3D-printing to speed up design and determine parts with the best configuration for specific industrial service, is very high. Researchers from NYU [273] used genetic algorithms alongside 3D-printing to determine the ideal wing shape for a fast-flapping flight. Mitra Asadi-Eydivand et al. [274] also used 3D and evolutionary algorithms to determine the optimal design of a scaffold. One of the biggest challenges that pervasive 3D-printing would face within the Industrial space is the issues of the ownership and control of Intellectual property. For example, how will the owner of a design or electronic product spec be compensated once the files end up in the hands of a client. How can the distribution of those files, once out of the owner's control be monitored? Some proponents have suggested online marketplaces, brokers or clearing houses that would serve the dual purpose of regulating access to electronic specs and managing compensations and payments to intellectual property owners.

6.2.7. Autonomous Robotics:

The factory of the future would have two employees: humans and robots. Of the two, robots are expected to play a prominent role because of a high likelihood of a disproportionate reliance on machines for industrial tasks as compared to humans. The word "robot" is a Czech word that is literally interpreted "forced labor". They are very useful for tasks that require high levels of accuracy or are dangerous or repetitive. They bring to tasks such benefits as improved effectiveness, higher efficiency, and reliability. They can perform tasks that humans cannot or should not (e.g., demeaning, or dangerous tasks). Aside from augmenting human efforts, they also create the flexibility for under-utilized labor to be replaced or re-assigned. Long term, they are relatively more cost effective and facilitate higher productivity. There are different classification of robots including commercial robots, industrial robots, and service robots. The focus of this section would be the industrial robots. *Industrial Robots:* ISO 8373:2012 defines an industrial robot as "an automatically controlled, reprogrammable, multipurpose manipulator, programmable in

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three or more axes, which can be either fixed or mobile for use in industrial automation application." The ability of Industrial robots to perform high-precision work, accurately, repeatably and quickly is helping factories deliver high quality products and driving plant efficiency and profitability. Industrial robots would become ubiquitous across most manufacturing environments. As these already highly productive robots become AI enabled (AI Robots) and get fully integrated into the data-rich manufacturing ecosystems, both sharing and receiving data/information with other subsystems, it is easy to see why they would eventually become the workhorse of the factory of the future. Over time, it is expected that AI enhanced would morph into more intelligent systems with rare cognitive abilities. Robots are used for a variety of tasks within the manufacturing space. Some of these include mechanical cutting, grinding, deburring, polishing, welding (i.e., Arc welding, Spot welding etc.) and painting. Other common robot tasks include picking, packing, and palletizing, material handling, assembly, firefighting, and patrolling of warehouses and storage areas.

Based on one classification; three (3) main types of robots operate within industrial environments. These include: (a) Traditional robots, (b) Collaborative robots (cobots) and (c) Mobile robots.

a) *Traditional Robots:* The technologies underpinning traditional robots are generally more mature. They generally have high payload, have longer reach and are able to achieve very high efficiency levels even at high production speeds.
b) *Collaborative Robots (Cobots):* ISO 10218-2 defined cobots as robot designed for direct interaction with a human within a defined collaborative workspace. Where workspace refers to the safeguarded space where the robot and a human can perform tasks simultaneously during production operation. Generally, they are relatively easier to program, enable more efficient production adjustments, and can more flexibly adapt to new requirements than traditional robots. For implementation, they require minimal changes to existing production layout and can be easily redeployed for different tasks, as necessary. A defining characteristic of these robots is that they work collaboratively with human workers, without concerns for worker safety. They possess several integrated safety features including collision detection technologies, minimized pinch points, safety-rated monitored stops and well controlled force and speed. Human workers can focus on tasks that require high cognitive abilities while the robots are assigned repetitive tasks and other activities that require precision or heavy lifting. Robots that work alongside humans are referred to as co-bots.
c) *Mobile Robots:* Mobile robots have a general awareness of their environment and the ability to effectively navigate through it in the process of accomplishing assigned tasks. While traditional robots are usually stationed at fixed locations and are mostly assigned tasks that do not require a lot of flexibility, Mobile robots, on the other hand, are usually ambulatory and they are best suited for constantly changing factory environments. Using their navigation systems, they transverse entire factory floors autonomously, seamlessly integrating themselves into the manufacturing ecosystem. They can stop, move, slow down, or navigate away from obstacles using sensory information obtained from a wide array of localization and navigation sensors embedded within their bodies or attached to their surfaces. Two main classes of robot sensors exist i.e., exteroceptive and proprioceptive sensors. Exteroceptive sensors help the robots discern and understand their environment. Examples of exteroceptive sensors would include stereo cameras, pan/tilt/zoom cameras, laser, 3D Lidar, projection-based systems, audio/ video feedback systems, touch sensors (whiskers or bump sensors), GPS, proximity, and certified safety sensors. Then there are proprioceptive sensors, which are sensors that gather information about the robot itself. Examples of proprioceptive sensors include accelerometers, gyroscope, magnetometer and compass, wheel encoders and temperature sensors). These sensors alongside accompanying algorithms enable the mobile robots to both understand and safely navigate their environment. For this reason, they are very safe to deploy alongside

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human workers with whom they sometimes work collaboratively transforming them from mere machines to fellow workers. The basic idea of the mobile robot is essentially moving the robot to the work instead of moving the work to the robot. Mobile robots would best benefit such tasks as automated assembly, inspection, painting, or welding of huge industrial components like airplane frames, large engines, and giant offshore or space structures. Because of their large sizes, working on such components with two or three stationary robots can be inadequate because of the limitations on the reach of such robots. Alternative courses of action could be to either add more robots (a costly option) or employ mobile robots which are not limited by reach due to their ability to move around the entire structure. Compared to traditional robots, mobile robots are more flexible and adaptable. Their ability to maneuver through space and structure helps shorten throughput times, improving efficiency and cutting down on production time. Mobile robots have a variety of locomotion mechanisms [275,276], e.g., flying (Drones) [277], rolling, walking (legged), swimming or water-based (Underwater vehicle manipulator system) [278], crawling, tracks, propellers etc. Automated guided vehicles or automatic guided vehicles (AGVs) are amongst the most common mobile robots within the manufacturing industry today. And they are poised to become even more ubiquitous as adoption continues to grow. They are currently used for moving materials, supplies and products around manufacturing facilities. Unmanned aerial vehicles (like the drone) are the next set of robots that would grow in relevance within manufacturing. They would be especially useful for picking and dropping, product and quality inspections especially the inspection of equipment or machinery at hard-to-reach locations (e.g., high elevation or dangerous locations) using thermal and video cameras.

7. The neXt Future Factory:

Smart manufacturing has great promise. However, realizing this promise would require deliberate and committed work at various levels and by different stakeholders (Industry Academia & Government) within each jurisdiction.

7.1. The focus of the Lab:

Our lab is part of the global value chain dedicated to advancing smart manufacturing. As a research and development concern, the neXt Lab located within the McNair Aerospace Center is the center of gravity for Advanced Manufacturing at the University of South Carolina (UofSC). The lab has a two-pronged approach that focuses first on Research & Development (R&D) and secondly on Industry engagement. On the R&D vertical, the lab is focused on determining the most optimal approaches for connecting different manufacturing modules and enabling them to exchange information efficiently, reliably, and quickly (Interoperability). Another issue of interest is to figure out efficient ways of connecting these modules securely and reliably to the Internet (Connectivity & Cyber-Security). A third issue is how to effectively collect, manage, and analyze disparate manufacturing data sets so that business intelligence can be gleaned from them in real-time. This is important because we believe that data hold the necessary intelligence that can influence technology innovation, competitiveness, and productivity growth in the manufacturing business. On the Industry engagement vertical, our lab provides Industry a secure, and advanced platform to investigate solutions, build proof of concepts and MVPs alongside our researchers and students, thereby de-risking their digital transformation projects and improving product and process efficiency.

7.2. The neXt Test Bed:

The lab contains a manufacturing test-bed (or functional mini-factory) designed to support the study, exploration, maturation and exploitation of manufacturing control elements, communication protocols and a variety of emerging technologies with a view to advancing smart manufacturing (and related) objectives. The test bed is technology agnostic and relies

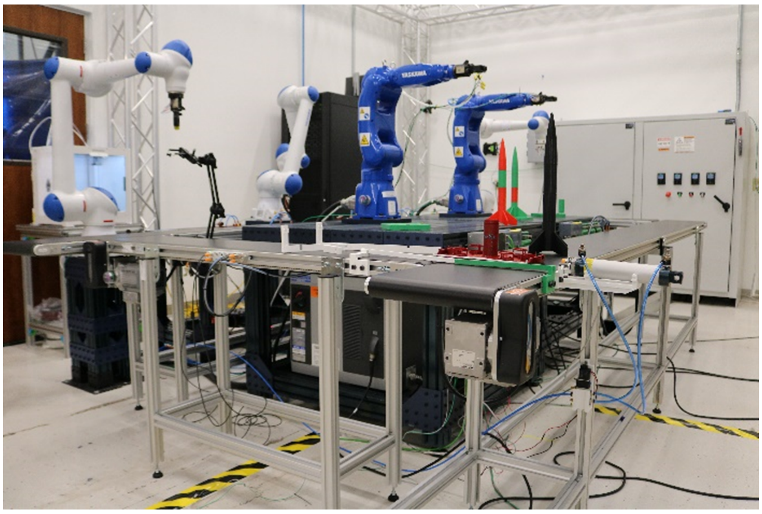

Figure 23. The neXt Future Factory Test Bed at University of South Carolina

on open standards for all its communication and data modeling requirements. It also has a flexible implementation architecture that makes it possible for new technology to be easily integrated and tested. This is to support the testing and maturation of new technologies and data strategies through industry use cases. It also supports the rapid creation of different iterations of product layouts to cater to the needs of diverse industrial products. The test-bed consists of several Yaskawa robotic arms, conveyor belt systems, and an array of multi-vendor and multi- platform equipment and devices including Programmable Logic Controllers (PLCs), Edge devices, Human-Machine Interfaces (HMIs), Cameras (FLIR, Infrared, Thermal), Sensors (wired & wireless), Variable Frequency Drives (VFDs), Actuators etc. The various modules of the test bed are connected to the Internet using the 4LTE and 5G networks. Data transfer between automation devices within the test bed, and between the test bed and some sister sites as part of our Factory-to-Factory project is made possible through IEC 62541 standard OPC UA. The platform also has access to a multi-vendor array of software applications that enable the real-time collection, ingestion, and visualization of data, the implementation of advanced process simulations solutions, path planning, offline robot arm programming, the development of visual inspection, AR/VR, and digital twin solutions etc. In the future, we hope to be able to able to use the test-bed as a DevOps platform for streamlining all development and operational processes including coding, analytics, modeling, deployment, updates etc.

7.3. Collaborations:

The lab has multiple academic and governmental agency partners that work together to advance various educational and policy goals. Beside providing our researchers a forum to investigate different IT/OT phenomena, and affording our students practical training opportunities, the facility also showcases the opportunities inherent in digitizing manufacturing to help drive productivity, reduce defects, cut cost, and accelerate time-to-market. We also work closely with some of the most innovative companies and consultancies in the country, each bringing in their best minds and an interesting amalgam of advanced technologies offerings (hardware and applications) to help address some of the most challenging problems in the advanced manufacturing space. The test-bed provides these industrial partners the platform to create different technology configurations, deploy them in real-time and explore their efficiencies without the possibility of disrupting production, this helps them essentially de-risk the development of novel digital solutions. Beside being a showcase for the technologies of partner companies, the lab also performs applied research and development for industry. All of these activities have created interest within industry and driven different forms of business value, including enabling strong customer engagement in addition to interest in our scholarship and our students (for employment), who are active participants in most of the R&D work.

8. Summary & Conclusion:

An Industry 4.0-enabled manufacturing environment that is flexible, adaptive, and transparent is the expected successor to the current traditional manufacturing system. This transformation of the manufacturing industry into a an ultra-high-tech industry using innovative smart technologies is poised to improve production processes, reduce cost, encourage mass customization, and enable the prediction of potential problems even before they occur using predictive maintenance/analytics solutions. It will also support the efficiently tracking of assets at each stage of the supply chain to improve asset visibility, control, and insight, enabling advances in inventory management and supporting improvements in logistics. The paradigm shift is clearly about making the manufacturing infrastructure and its supporting ecosystems smarter, quicker, and nimbler using data as a critical asset for self-optimization, self-adaptation, and competitive intelligence. The ability to ensure that assets are connected and that they "talk to and learn from each other" seamlessly is a defining feature of the Factory of the Future and is made possible through the deployment of machinery, components and technologies in a manner that ensures their interoperability and connectivity. Even though significant advances have already occurred in recent years, the goal of a fully digitized and highly networked manufacturing sector remains aspirational. Many solutions are still in their early stages of development (aspirational, conceptual, pilot, testbed etc.). It is however noteworthy that a lot of progress is being made both at the policy, research & development (R&D), and implementation levels. As new technologies and systems come available, it is critical for researchers and practitioners to continue to push the technological envelopes to ensure the full transformation of significant parts of the manufacturing ecosystem. There is also the urgent need for all stakeholders including the governments and the organized private sector to help in scaling some of the proved solutions and ensure rapid industrial diffusion beyond the walls of research facilities, test-beds, and well-funded factories.

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List of Acronyms

4IR Fourth Industrial Revolution

AAS Asset Administration Shell

AI Artificial Intelligence

B2MML Business to Manufacturing Markup Language

BatchML Batch Markup Language

BMBF German Federal Ministry of Education and Research

BPMN Specification-Business Process Model and Notation

CMS Cyber Manufacturing Systems

CPS Cyber-Physical Systems

CPPS Cyber-Physical Production systems

CRM Customer Relationship Management

DCS Distributed Control System

DMIS Dimensional Measuring Interface Standard

DMN Decision Model & Notation

ERP Enterprise Resource Planning

EtherCAT Ethernet for Control Automation Technology

F2H Factory-to-Human

F2P Factory-to-Product

F2SC Factory-to-Supply Chain

FDI Field Device Integration

FF Future Factory

FoF The Factory of the Future

FP-Growth Frequent Pattern-Growth

GPU Graphical Processing Units

H2D Human-to-Device

HART Highway Addressable Remote Transducer

HMI	Human-Machine Interface
HTTP	HyperText Transfer Protocol
ICT	Information and communications technology
IEC	International Electro-technical Commission
IoT	Internet of Things
IIoT	Industrial Internet of Things
IoS	Internet of Services
ISO	International Organization for Standardization
IT/OT	Information Technology/Operational Technology
KNN	K-Nearest Neighbors
L2S	Levels of System Sovereignty
LR	Logistical Regression
M2D	Machine-to-Device
M2VT	Machine-to Virtual Twin
M2M	Machine-to-Machine
MDPI	Multidisciplinary Digital Publishing Institute
ME-S	Manufacturing Ecosystem
MES	Manufacturing Execution Systems
ML/DL	Machine Learning/Deep Learning
MOM	Manufacturing Operation Management
MQTT	Message Queuing Telemetry Transport
NBM	Naïve Bayes Multinomial
OAGIS	Open Applications Group Integration Specification
OPC-UA	Open Platform Communications-Unified Architecture
PAC	Programmable Automation Controller
PACKML	Packaging Machine Language
PC	Personal Computer
PCA	Principle Component Analysis
PLC	Programmable Logic Controller
PMML	Predictive Model Markup Language
QIF	Quality Information Framework
QR	Quick Response
REST	REpresentational State Transfer
RFID	Radio Frequency Identification
RL	Reinforcement Learning
SCADA	Supervisory Control and Data Acquisition
SL	Supervised Learning
SVD	Singular Value Decomposition
SVM	Support Vector Machines
ISA	International Society of Automation
UL	Unsupervised Learning

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