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Evolution and future of manufacturing systems

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The evolution of manufacturing systems, influenced by changes along four axes - products, technology, business strategies and production paradigms - is presented. Adoption of human-centric decision making in meshed collaboration with intelligent systems is examined. Implications and preparedness for the shift towards more responsive, intelligent adaptive systems are reviewed. Research and industrial use cases are presented. A vision for the new future Adaptive Cognitive Manufacturing System (ACMS) paradigm and its characteristics, drivers and enablers are articulated highlighting the digital and cognitive transformations. Perspectives and insights are offered for future research, education, and work to realize the evolution of manufacturing systems.

1. Introduction

Manufacturing systems continue to evolve in design, configuration, operation, and control in an eco-system characterized by new drivers, more advanced enablers and disruptive technologies and business models. Socio-technical developments and business strategies will shape their future.

1.1. Challenges and motivation

This section sets the stage with brief discussion of: importance of manufacturing, various challenges (technical, economic, social, strategic, business), drivers (cost, quality, variety, efficiency, value, sustainability), transformative innovations, complexity, responsiveness, knowledge-based and data-intensive manufacturing, digitalization, connectivity and communication, demographic changes, human capital development and future work. Tracking and analysing effects of industrial revolutions on changes in manufacturing systems and enabling axes of evolution is a good predictor of what is to come, and what industry and experts are saying about needed developments. The paper scope is illustrated in Fig. 1.

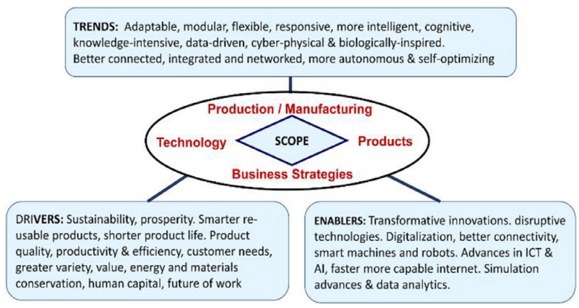

Fig. 1. Manufacturing systems evolution trends and scope.

1.2. Scope and objectives

Manufacturing systems changes over many decades are driven by advances in production and other technologies, introduction of new materials and complex products requiring new processing techniques, organizational strategies seeking to minimize cost, increase quality and reliability, maximize profit and concerns about societal and sustainability goals as well as humans' interaction with systems elements and the future of work.

The focus of this keynote paper is about the evolution and future of manufacturing systems for discrete parts/products production as well as the characteristics, enablers, and drivers of manufacturing systems paradigms.

Manufacturing systems encompass both the physical and logical aspects of production. Their physical configuration consists of

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machines, workstations, robots, and other equipment arranged in various layouts and integrated or connected physically by material handling equipment and logically via computer control and software applications. People are an integral part of manufacturing systems and play an important role in their design, planning, operation, and control. Computers have played a significant role in the operation and control of manufacturing systems and their modules including software applications for computer-aided design and computer-aided manufacturing (CAD/CAM), computerized numerical control (CNC), product life cycle management (PLM), process planning, production planning and scheduling, inspection, quality control, maintenance, inventory, and supply chain management. Hence, manufacturing systems are found physically on shop floors with logical support systems within and beyond the factory.

The objectives of this keynote paper are manifold including: a) reviewing the evolution of manufacturing systems to date by surveying the most relevant and important literature and identifying the major milestones along their evolution path and their defining features and characteristics, b) reviewing recent advances, trends and disruptors, relevant to the four axes of manufacturing systems evolution, and discussing their expected/anticipated effects on future manufacturing systems, c) reviewing the evolution of manufacturing systems, their future, and related concepts and paradigms, d) reviewing and assessing the readiness and state-of-implementation of the "new technologies and business strategies" in manufacturing systems, obstacles and challenges, and discussing illustrating use cases in industry and academia, e) articulating a vision for a new adaptive cognitive manufacturing systems paradigm, its drivers, characteristics, and enablers, work force requirements, and societal expectations and responsibilities, and f) offering future perspectives and establishing a map for research needs and challenges towards achieving smarter, more adaptive, more sustainable and human-centred manufacturing systems.

1.3. Terminology

"Production" and "manufacturing" have been used interchangeably over the years in the literature. While manufacturing and production have similar fundamentals, they are distinct with many key differences. This keynote paper focuses on manufacturing systems, which are broader and encompass production systems. The difference between "manufacturing" and "manufacturing systems" is emphasized particularly with regard to the paradigms names that have been introduced, mostly by CIRP, and generally agreed to in the literature to-date, up to the ongoing fourth industrial revolution. In addition, Cyber-Physical Production Systems (CPPS), Industrie 4.0 or Industry 4.0, and Smart Manufacturing Systems (SMS) share many similar features and characteristics. They are used interchangeably in the literature and in this keynote paper. Cognitive manufacturing leverages Industry 4.0 technologies, including big data analytics and artificial intelligence and generates actionable insights and interactions between humans and machines. This is discussed in greater detail later in this keynote paper. Most of the used terminology is consistent with, and often explicitly defined in, the CIRP Dictionary and the CIRP Encyclopedia [97] .

1.4. Publications trends and bibliometric analysis

Extensive literature survey was conducted from a variety of perspectives and sources. Various search approaches and keywords were used, with a focus on manufacturing systems documents published to date. It was noted that the frequency of publication related to earlier manufacturing paradigms, such as flexible manufacturing systems (FMS), reconfigurable manufacturing systems (RMS), and changeable manufacturing systems (CMS) had peaked in 2010, whilst papers relating to smart and cyber-physical manufacturing systems are on a steep rise. Fig. 2 illustrates the results of a Scopus search for the selected keywords in documents published annually since the year 2010. As illustrated, the number of publications relating to adaptive manufacturing systems and smart manufacturing systems, during this period, is steadily increasing.

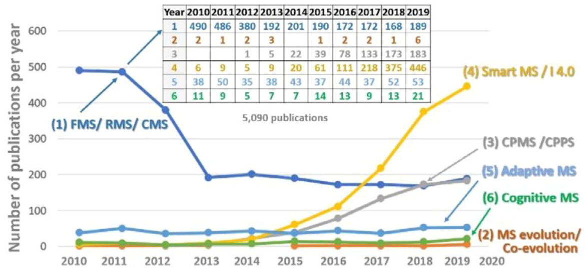

Fig. 2. Keywords for manufacturing systems literature survey.

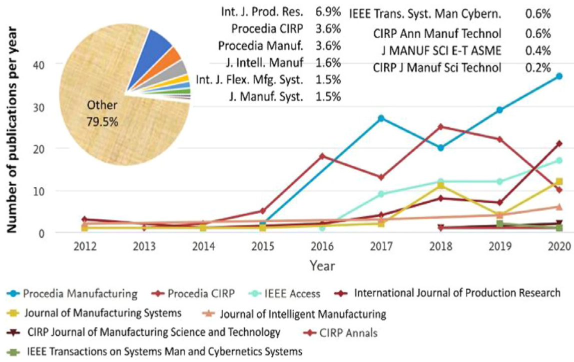

Fig. 3. Publications sources for manufacturing systems literature.

Fig. 3 shows the sources of these publications contributed to 10 high impact journals and conferences.

1.5. Keynote paper organization

The new trends and anticipated changes in the manufacturing landscape, strategies, and manufacturing systems paradigms provided the motivation for this keynote paper and shaped its scope. The following outlines the structure of the paper. Section 1 paints a picture of the eco-system in which manufacturing systems exist, change directions and expectations, and outlines the keynote paper motivation, objectives, and scope. Section 2 includes a survey of relevant literature, definitions, and innovations, introduces four axes of evolution of manufacturing systems and illustrates their co-evolution. It presents major manufacturing systems paradigms, nature-inspired products/manufacturing systems co-evolution, biologicalisation in manufacturing systems, and manufacturing systems life cycle and sustainability. Section 3 reviews the advances in cyber-physical systems (CPS) and smart manufacturing systems including smart manufacturing drivers and enablers such as internet of production (IoP) or industrial internet of things (IIoT), big-data analytics, communication, connectivity, smart data-driven manufacturing systems design and control, and bio-inspired methodologies for manufacturing systems design and operation and their co-development In the context of the on-going smart manufacturing (Industry 4.0) evolution, Section 4 focuses on smart systems industrial implementations and applications of digital manufacturing systems in car assembly, auto-parts tooling and communication, and illustrates the use of IoT, IoP and digital shadows. It discusses industry readiness and Industry 4.0 maturity models and indices. It includes joint research-industry use cases of many aspects of smart manufacturing systems examples of human-machine interaction and learning. Section 5 introduces a vision for the new adaptive cognitive manufacturing systems (ACMS) paradigm, its characteristics, drivers, and enablers and explains why it represents a paradigm shift. It discusses bio-intelligent manufacturing and human-centric adaptive manufacturing. The multiple facets of systems adaptation are presented in a new classification including cognitive adaptation which is at the core of the new paradigm. The ability of current manufacturing systems to respond and adapt under the impact of extreme disruption, such as those caused by the COVID-19 pandemic, are analysed. Human-centric cognitive manufacturing systems and evolution of cognitive digital twins (CDT) are discussed. Finally, Section 6 presents insights, reflections, and conclusions on how manufacturing systems are being re-imagined. It offers an outlook and perspectives on current challenges and future research.

2. Evolution of manufacturing systems and enablers

Manufacturing systems have evolved over many decades driven by advances in production technology, machine tools, information technology, materials, and products, as well as the evolution of organizational strategies seeking to minimize cost, increase quality and reliability, maximize productivity and profits, and promote sustainability. The proliferation of products variety and desire to increase competitiveness through differentiation had a significant impact on the evolution of manufacturing systems and motivated the development of several manufacturing systems paradigms.

2.1. Four axes of evolution

Earlier evolution of manufacturing systems, from dedicated to flexible and reconfigurable, was motivated by the need to manage changes in production volumes and products variety. The next waves of manufacturing systems evolution towards smart, cognitive and more adaptable systems are influenced by disruptive advances along four axes depicted in Fig. 4, which shows: a) products evolution, b) technological evolution, c) business strategies evolution and d) production/manufacturing evolution manifested in the industrial revolutions to date which collectively gave rise to the development of new manufacturing systems paradigms. The four axes of evolutions are highlighted in the coming sub-sections.

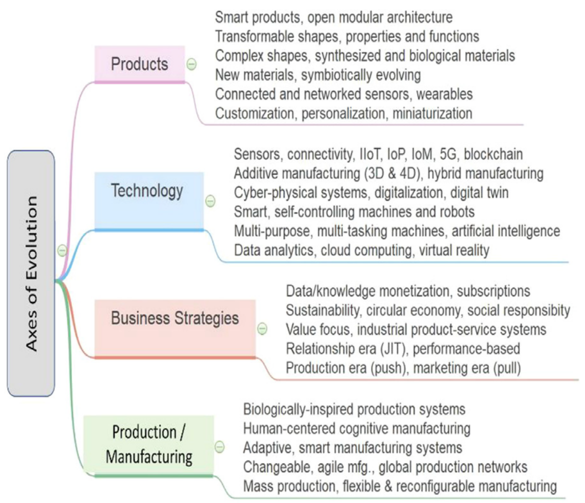

Fig. 4. Four axes of manufacturing and systems evolution.

2.1.1. Products evolution

In the early days of mass production, products had simple shapes and features due to limitations of technology, used materials and manufacturing processes. Products with intricate shapes, complex features, composite materials, and smart functionalities continued to emerge giving rise to associated design, modelling, machines, and manufacturing and services innovations and technologies to meet the new challenges.

Advances in computer science and technology along with introduction of several design theories and methodologies have directly contributed to the design of products and their manufacturing systems. Parts/products coding, classification and group technology lead to the efficient formation of product families and machine cells, and improved the efficiency of numerical control (NC)/CNC programming, fixtures and tooling design and process planning [17]. Modular product design lends itself to flexible, reconfigurable and changeable manufacturing systems and led to many methodologies for design for ease of manufacture (DFM) and ease of assembly (DFA) which directly improved manufacturing systems design, and rationalization and standardization of processes. Modularity is the degree to which a complex system (product, process plan, manufacturing system, etc.) can be divided into sub-units (modules) which can be reconfigured as needed [170]. Product modularity is enabled by design clustering and granularity methods, and reflected in the used manufacturing technologies, processes, machines clusters, and manufacturing cells, and is mirrored by organizational units and clusters of suppliers. Modularity reduces complexity and cost of design, manufacture, and repair, increases reliability, improves maintainability, and prolongs products life by facilitating selective updating of modules. Manufacturing systems are products that also require use of design methodologies, collaboration and complexity management [49,50,159,161], and quality prediction [51].

The products platforms design concept, where clustering is used to form a core of common components or modules that can later be customized to generate product variants belonging to the family, were developed as well as methods to optimize the design of the product platform. It is an important enabler of product mass customization by designing manufacturing systems where products differentiation is delayed, allowing manufacturing the product platform in large quantities, i.e. mass production with push business model, then individual product variants are produced in smaller volumes per variant, following a pull business model [70]. The effects of increased variety on products design, manufacturing systems design and strategies, industrial enterprises and supply chains, as well as management strategies on all levels were discussed extensively [47].

Design methods for products reconfiguration, such as open architecture products (OAP) [67,92] were introduced for added adaptation by allowing modules to be added/removed/swapped to change product features and functionality. Research followed to identify the optimal design of OAP and assess their assembly and disassembly complexity [210]. Open architecture products coupled with modularity, scalability and standard interfaces between product modules enabled, and increased the efficiency of corresponding reconfigurable manufacturing systems. These approaches apply to products made by reconfigurable machine tools, reconfigurable robots, universal/reconfigurable end-effectors, reconfigurable molds and fixtures, and universal tooling used in FMS and RMS. The discussed product design methodologies have evolved along with flexible, reconfigurable systems and the hybrid additive/subtractive technologies to satisfy the increasing need for products customization and personalization.

The use of new materials in consumer products continued to increase partly because of customer's demand for products with specific characteristics and performance. Light weight materials (aluminum, polymers, and composites) were introduced to automanufacturing to reduce vehicles weight and fuel consumption, which triggered related manufacturing technologies, processes, and machines. Environmental concerns motivated the design and development of new car engines and power trains using alternate fuels as well as electric mobility led to major disruption in the automotive powertrain production, which significantly impacted their manufacturing systems design, configuration and operation [80]. The manufacturing systems of mobility vehicles have witnessed significant disruption in design, configuration, size, location, and production volume not only due to these technological advances but also the changing business strategies such as ride sharing and integrated product-service models. This is not a unique example of the intertwined nature of the four axes of manufacturing systems evolution. More examples can be seen in many large and small consumer products in various sectors. The innovation helix best represents that intertwined nature of products, technology, and business innovations; and manufacturing systems evolution which mark the competitiveness frontier. Examples include smart materials capable of responding to external stimuli with shape change, self-actuation, self-sensing, self-diagnosing and self-healing behaviours [20]. Advances in 3D printing of products influenced products design. Additive manufacturing use in printing organs and tissues, and responsive materials for 4D printing [62] led to the development of special product design methods and additive manufacturing machines. In the textile industry, smart materials for wearables that can adapt to temperature and moisture to improve comfort are developed. All these applications call for commensurate manufacturing systems capabilities.

The demand for smart products which are intelligent, connected and highly responsive is increasing [188]. Smart products contain cyber-physical mechatronic components which have distinct differentiating features and capabilities including sensing with integrated or imbedded sensors, connectedness, and communication via internet (IoT), networking with other smart products, interaction with users, processing data and intelligence. Smart products are complex multi-domain/multi-disciplinary in nature. Manufacturing their individual components represents challenges for embedding sensors, assembly and testing and increases complexity as they have highly integrated hardware and software [114].

2.1.2. Technological evolution

Many technological advances have emerged in the manufacturing field. Important developments and disruptive trends, which influence manufacturing systems evolution are discussed in this section.

Automation and digitalization. Production systems have been evolving from standalone machinery with proprietary controllers to flexible and reconfigurable manufacturing systems with added modularity, mobility, and more open and smarter control architecture. The automation technologies developed since the 1st and 2nd industrial revolutions, such as computer-controlled programmable machines (NC, CNC) made it possible to move from hard-wired logic controls, punched cards and hard automation machines and production lines to digital programmable machines/ workstations and programmable, reconfigurable and smart logic control. Advances in communication control layers and systems from mobile application protocols (MAP) to supervisory control and data acquisition (SCADA) made it possible to control large and complex manufacturing systems in hierarchical and distributed manner with two-way communication and feedback. These are the backbone technologies the evolution of which paralleled that of manufacturing systems. Versatile multi-axis, multi-tasking flexible machines along with advances in laser triangulation and global positioning systems (GPS), bar code readers and proximity sensors used in automated and self-guided vehicles, made alternate part-machine assignment possible and enabled alternate routing flexibility.

Sensors, RFIDs (Radio-frequency identification), IoT and IIoT, and 4G and 5G internet communication protocols are essential elements of digitalization and evolution of advanced manufacturing systems. Sensors collect digital and analogue data from manufacturing systems and smart products for use in monitoring equipment conditions, operations execution, and feedback. Large number of sensors with different sizes and functionalities are required in any advanced manufacturing systems implementation. Hence, both capacity and speed of wireless networks and communication infrastructure as well as techniques for sensor data integration and fusion to utilize and interpret the measured data are crucial to the success of IIoT and IoP [162] in digital manufacturing systems implementation.

Additive manufacturing (AM) is an example of disruptive manufacturing technologies as parts are manufactured by adding material in successive layers instead of removing it. It can produce intricate shapes of many different materials with simple setup and minor post processing. This technology evolved from rapid prototyping of products using plastics in the 1980s to applications beyond prototyping such as producing automotive parts, aerospace products and medical instruments where end products can be manufactured in economical quantities [19,185]. Hybrid additive-subtractive manufacturing supports production of new products with better functionality more cost effectively. A macro-process planning methodology for optimally selecting the type and sequence of hybrid additive-subtractive processes was developed [46,125]. Multi-tasking machine tools for both additive and subtractive processes are now available. These advances in AM facilitate the design of systems for personalized manufacturing [92]. Advanced digital AM machines with imbedded sensors are easily integrated with computer-controlled manufacturing systems to be part of connected and data intensive CPSs, Industry 4.0 and digital manufacturing systems.

Artificial Intelligence (AI) plays an important role in smart machines and intelligent manufacturing systems by enabling the application of essential features of natural intelligence such as sensing, perception, learning, reasoning and decision making in areas such as operating and controlling manufacturing systems, process planning and production planning, and in planning robot-human collaboration and deep learning-based human motion trajectory recognition [39,142,200]. Throughout the life of products and manufacturing systems, large amounts of data are collected. The role of data analytics in supporting smart manufacturing systems, machines, products, and related technologies and business strategies has been discussed [61,101].

Cyber-physical systems (CPS) which integrates cyber components such as embedded sensors with the physical resources in the production system are important enablers for implementing smart systems [119]. Achieving realtime data acquisition, processing and decision making, development of computational dynamic systems theory for modelling and analysis, standardization of communication protocols, and data security are fundamental for the success of CPS applications.

Cloud manufacturing refers to decentralized and networked manufacturing resources that can be accessed by manufacturers as needed enabled by cloud computing, IoT and service-oriented architecture. Cloud manufacturing differs from computer integrated manufacturing (CIM) and CPS in that the connection between the physical and cyber domains proceeds through services [150]. Optimal allocation and scheduling of physical and computational resources is required for efficient use of cloud manufacturing. Cloud manufacturing models and protocols for cloud-based usage are not suitable for all manufacturing. Cost benefit analysis and validation are needed to assess their performance, effectiveness and technical and financial feasibility [124].

Digital transformation leverages information technology to disrupt traditional industry models and business practices to deliver exceptional customer and business value and create sustainable competitive advantage. Artificial intelligence and machine learning, big data, predictive analytics, and business process automation are important rapidly emerging digital transformation enablers which are being incorporated into the organization and modernization strategies of manufacturing systems such as self-awareness, self-learning, self-healing, and cognitive adaptation characteristics which are discussed in Sections 4 and 5.

2.1.3. Business models evolution

Business models followed by companies for creating value and profit have changed over time to satisfy consumers demands and requirements. This section overviews and classifies the evolution of classical and emerging business models as they affect manufacturing systems. In craft manufacturing, a product was designed and made for one customer following a pull model. In mass production, products were designed and made for customers a priori and offered in large quantities following a push business model. To satisfy more customer requirements, yet keep manufacturing cost manageable, flexible, reconfigurable, and changeable manufacturing and mass customization were introduced. Customers configure their products based on pre-designed and grouped features (packages) offered by the manufacturer. Therefore, the customer is satisfied by ordering the chosen product configuration, which is not unique, while the manufacturer is able to group similar orders to increase efficiency and reduce cost. Mass customization follows a hybrid push-pull business model where the product family platform is mass produced (push model) then customized according to customers configurations (pull model). Personalized manufacturing drives customization further where customers become closely involved in the design of many features of the product. The followed business model clearly drives the design, configuration and control of manufacturing systems and the utilized manufacturing processes and technologies to achieve the desired outcome. Personalized products cost more than mass customized ones. Bespoke personalized products would cost even more, where the production system is akin to craft manufacturing, albeit using more advanced machines and technologies.

Value creation within industrial enterprises has been gradually shifting from manufacturing products to providing services or a combination of both [178].

The production era - push model: Mass production follows the *push model* of Make-to-Forecast and the material resource planning (MRP) principle of Make-to-Stock, where products are produced in large quantities based on volume forecasts regardless of customer orders [56] and production planning and control flows from upper levels to the shop floor adding value through manufacturing processes.

The marketing era - pull model: Manufacturing companies adopted Make-To-Order strategy in which parts are ordered from suppliers based on actual customer demand. In this strategy, firms used economic ordering quantity principle, work-in-process, Kanban and base stock strategies for inventory management and control. A hybrid approach utilizes the benefits of push and pull business models where a portion of the manufacturing system is dedicated to producing common components shared among a product family, i.e. product platform, using a push model and Make-to-Stock strategies. Differentiating product components are manufactured based on customer orders, following the pull business model / Make-to-Order strategies, hence, delaying the differentiation point in manufacturing and maximizing efficiency and profit.

The relationship era - JIT model: In the seventies, production waste reduction started gaining momentum to reduce costs, and Just-In-Time (JIT) philosophy gained traction. It aims at supplying the right components, in the right place, at the right time, with the correct and exact quantity and order [208] and uses the Kanban system to control the material flow.

Industrial product-service systems - IPSS model: Industrial product-service systems business models can be either product-oriented where suppliers provide customers with a product and associated service, or use-oriented where suppliers provide the product's service to customers through rental or leasing, and/or result-oriented with agreed outcome [167]. IPSS business models also apply to manufacturing systems where focussed flexibility can be achieved by a) reconfiguration guarantee business model, in which the supplier provides an initial manufacturing system with pre-designed flexibility modules to be added as needed, and b) capacity guarantee business model, with built-in ability to change capacity if needed. These business models require close cooperation between the supplier and customer throughout the life of the manufacturing system [33,34].

Circular economy – sustainability model: It is a business model that supports sustainability throughout products life cycle by re-using, re-pairing, re-manufacturing, and re-cycling technologies and impacts manufacturing systems design and operation. Linear economy is characterized by a make-use-dispose business model [207]. Circular economy aims at "*a manufacturing system in which there is no waste, where the products of today are also the raw materials of tomorrow*". This business model has been actively researched and several prototypes and implementations have been reported [31,32].

Challenges exist in applying and monetizing the sustainable circular economy business model due to the complexity of products, multiplicity of materials, short life cycle of products and widely variable conditions of returned products. The use of Industry 4.0, IoT and design for sustainability can extend the product's life cycle and enhance value creation towards a more innovative, resilient, and sustainable economy.

It is evident that manufacturing systems business models have evolved from providing more affordable products through mass production (push) to more value through flexible, reconfigurable and changeable manufacturing systems (pull) and continue to maximize value by reducing waste (JIT and circular economy) and maximizing value to customers through customized and personalized products (pull) while enhancing the economic viability of manufacturing systems and companies.

2.1.4. Manufacturing and manufacturing systems paradigms

Craft Manufacturing or job shops feature general-purpose machines, low-volume, high-variety production, and significant human involvement. Upon receiving an order, single or few products are made to specification and tailored to the customer requirements. The work is carried out manually and/or using standalone versatile machines with varying degrees of automation and sophistication. This type of manufacturing still exists to satisfy the need for special customized products.

Several "variety-oriented" manufacturing systems have evolved over time influenced by changes in products, production technology and processes, production volume and varying degrees of automation, intelligence and adaptation as depicted in Fig. 5.

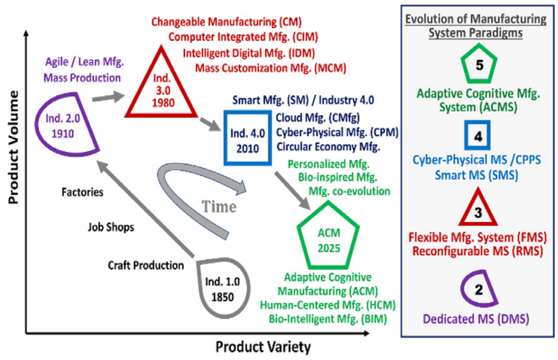

Fig. 5. Manufacturing paradigms & manufacturing systems paradigms [Intelligent Manufacturing Systems (IMS) Centre, U. Windsor].

Dedicated manufacturing systems (DMS). This significant change in production strategy goes back to 1908 when Henry Ford introduced affordable mobility by mass producing the Model–T sedan car with only 2 variants, then rationalized limited product variety in mid-1980s. The moving assembly lines signalled the shift from craft manufacturing to standardization, interchangeability, automated material handling systems (MHS), and Taylor's production principles. Dedicated manufacturing lines (DML) and systems are designed and optimized to mass produce single or very limited product variants following the "Economy of Scale" strategy to maximize efficiency and minimize cost. Factory automation and robotization are actively promoted by companies such as Fanuc's Oshino-mura factory, to achieve long hours of continuous unmanned machining [59].

Flexible manufacturing systems (FMS) consist of one or more integrated group of machines (NC, CNC, distributed numerical control (DNC)) and material handling equipment under central computer control for the automatic processing of palletized parts with flexible routing.

The concept of flexible manufacturing was developed by J. Lemelson, an American industrial engineer and inventor in the early 1950s. His 1956 automation patents included a "machine vision" and a robot-based system that could weld, rivet, convey, and inspect manufactured goods. Bar code scanning technology was developed around the world and installed everywhere from supermarkets to automobile assembly lines. Systems based on Lemelson's FMS inventions debuted on factory floors in the U.S. and Europe in the late 1960s and proliferated in the 1970s.

Flexible manufacturing systems continued to be used in discrete manufacturing in response to the need for products customization and greater responsiveness to changes in products, production technology and market demands. They are suitable for mid-volume, mid-variety production of pre-planned parts/product families with similarities in design features and/or production processes. They capitalize on the commonalities and grouping methods to produce the desired variety while achieving the efficiencies of high-volume manufacturing. FMSs are designed a priori with built-in flexibility features, for anticipated variety within the product/part family, including programmability, universal-adjustable fixtures, streamlined tools, changeable tool magazines, limited local buffers and central automated retrieval system (ASRS). The product family-oriented design, and use of group technology, and clustering in parts design, system layout, and process and tool planning are pre-requisites for their success. FMSs are applied in different discrete manufacturing for fabrication and assembly.

Flexibility can take many forms including machine, process, product, product mix, routing, material handling, production volume, labor, and expansion flexibility. The main objective is adaptation to changes in production volume and product variants, within a pre-planned family, without interruptions in production for changeovers between models or penalty in time and cost. The concept of "focused flexibility" [183] refers to building flexibility into a limited section within an otherwise dedicated manufacturing line (DML) or system, which features flexible and programable automated machines and MHS where limited variations in the product is allowed while not incurring the capital investment needed for a completely flexible system.

The enablers of FMS are programmability for quick changeover between different part/product variants; computer integrated control and operation of system modules and production schedules for more agility and responsiveness to change; parts pre-palletization, adjustable adaptable and universal fixtures and tooling to reduce time waste during the production cycle; flexible routing to reduce down-time and increase machine utilization; built-in sensors, realtime control and decision making for ease of fault detection and recovery; and adaptable process plans and production schedules. The key features of FMS are adaptability, responsiveness, agility, waste reduction and lean manufacturing. Flexible manufacturing systems follow a pull business model. They are robust but have high initial capital cost and their flexibility features are sometimes under-utilized.

Reconfigurable manufacturing systems (RMS). The reconfigurable manufacturing concept has emerged in the nineteen nineties [91] to achieve changeable functionality and scalable capacity. In RMS, machine components, machines, cells, and/or material handling units can be added, removed, modified, or interchanged to respond to changing market requirements or technologies. RMSs provide "customized flexibility on demand" for a part/product family. They can be improved, upgraded, reconfigured, and extended rather than replaced.

Reconfigurable manufacturing systems have distinguishing characteristics and enablers which affect the ease and cost of re-configuration. These include: a) modularity of physical and logical modules, b) integrability of system modules through standardized hardware and software interfaces, c) customization of system capability to match the variants within a planned product family, d) convertibility to allow quick change-over between product family variants and adaptation for future product changes, e) diagnosability to identify quickly the sources of quality and reliability problems requiring repair or maintenance and f) scalability to alter production capacity and capability by adding/removing system components.

The "plug and produce" reconfiguration may be physical or logical and can take place at three levels: system level (machines, buffers, MHS, parallel lines) [109], and machine level (machine modules/axes, tool magazine, modular robots, entire machines) [4,123,146] and controls level (open-architecture control modules, reconfigurable control systems, CNC programs) [146]. Hardware reconfiguration also requires major changes in the software used to control individual machines, complete cells, and systems as well as to plan and control individual processes and production; but it can potentially increase the life and utility of a manufacturing system.

A reconfigurable manufacturing system (RMS) architecture was proposed [67] to produce personalized products by including parallel subtractive and additive machine stages and allowing flow back-tracking, which can lead to less efficiency due to the complex flow, more movement times, imbalanced production and complicated scheduling. Examples of RMS research include design and configuration [13,22,82], optimal reconfiguration strategies [209], readiness of manufacturing firms for implementation [14], product family design [3,90,116], performance [66,93], and production planning and control [68,126]. FMS and RMS were compared regarding pre-requisites, scope, features, intelligence, benefits, limitations, cost and life [42]. Manufacturing paradigms evolved from mass production to mass customization and personalization [81].

Changeable manufacturing (CM). Changeability is key to dynamic adaptation of industrial production including FMS, RMS and beyond. It applies from machines/workstations level to cells, systems, segments, factories, and production networks. It includes characteristics to accomplish early, foresighted and economic adjustments of the structures and processes on all levels in response to change drivers [204]. Manufacturing changeability is an umbrella which embodies changeover-ability, flexibility, reconfigurability, transformability and agility according to the level within the manufacturing organization [158,204].

Some definitions would be helpful to put these types of changeability in perspective. Changeover ability is the operative ability of a single machine or workstation to switch between work pieces at any time with minimal effort and delay. Flexibility is the operative ability of a manufacturing or assembly system to switch with minimal effort and delay between parts/products within a pre-defined family of products through soft/logical changes (programs, plans) and the addition or removal of minor functional elements without changing the system physical structure. Reconfigurability is the tactical ability of an entire manufacturing and logistics system to switch with reasonable effort to new, albeit similar families of products by changing the manufacturing processes, machines, material flows and logistical functions as well as their structure, both physically and logically.

Changeability has additional characteristics beyond FMS and RMS including transformability and agility. Transformability is the tactical ability of an entire factory structure to switch to another product mix including production and logistics systems, facilities and buildings, organization structure and process, and personnel. Enablers of transformability include universality, modularity, scalability, mobility, and compatibility. Global production networks (GPNs) design, operation, and their transformation into changeable GPNs have been reviewed [96]. Agility is the strategic ability of an entire company to open new markets, to develop the requisite products and services, to respond to change, and to build necessary manufacturing capacity within and beyond the walls of the factory. Agility, therefore, is an enabler of dynamic adaptation of an organization [204].

Manufacturing changeability, design, operation, enablers such as reconfigurable process plans (RPP) and adaptive production planning and control (APPC), applications, performance indicators, cost and economic justification, industrial adoption, benefits, and challenges have been researched. A comprehensive framework of physical (hard) and logical (soft) capacity and capability adaptation in manufacturing systems is illustrated in Figure 6.

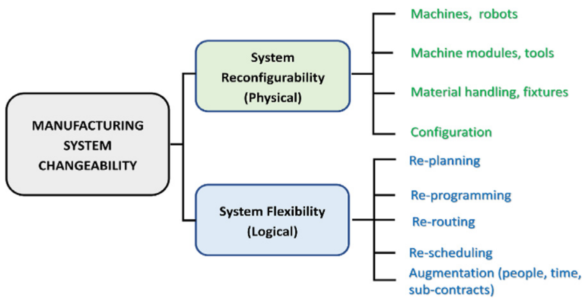

Fig. 6. Manufacturing systems changeability includes flexibility and re-configuration (modified from [42]).

2.2. Co-development of products and manufacturing systems

The co-platforming and biologically inspired co-evolution of products and manufacturing systems are two important developments in formalizing their bi-lateral association and co-development.

Products platforms methodologies are useful in managing products variety and coping with dynamic and uncertain market demands [170] due to the significant efficiencies in design, process and production planning and manufacturing of families of parts/products by capitalizing on the commonality between members of the same product family. Modules are added/removed from the platform to generate product variants. Product platforms are effective in achieving economy of scope by mass customizing products in high production volumes while achieving economy of scale as demonstrated in [60].

A methodology to develop manufacturing systems platforms was introduced [44]. The manufacturing system platform consists of the core machines, workstations, manufacturing processes required to produce the core characteristics of the product family platform. Additional machines capabilities or machines needed for certain product variants can be added through system re-configuration while the core platform remains unchanged.

2.2.1. Co-platforming of products and manufacturing systems

A novel methodology for designing manufacturing systems by co-platforming them with product families was introduced [44]. It used matrix-based mapping for machining and assembly and was validated using automobile cylinder engine blocks families of 4, 5 and 6-cylinder engines machined using the same system [1,2].

Other methods for integrating products and manufacturing systems development include: conceptual design [111], product architecture commonality [89], simultaneous assembly and disassembly for customizing products platforms [18], product platform optimal configuration and co-planning, and relationships between products and systems, knowledge discovery using Bayesian networks [71], matching product components with specific process capabilities [24], as well as a cladistics model to determine the relationship between product features and the associated machining capabilities [11]. The developed co-platforming concept and methodology were also used to develop a methodology that integrates the product platform synthesis with the selection of suppliers to form a suppliers platform [132].

2.2.2. Co-evolution of products and manufacturing systems

Engineers have been fascinated with the powerful biological transformations and their mechanisms and biological mimicry has long inspired products designs, algorithms and optimization techniques for planning, controlling, and scheduling of manufacturing systems [169]. A framework for the coordinated evolution (co−evolution) of products, processes, and production systems (Species) was elaborated [187].

Holonic systems, bionic systems and fractal manufacturing systems, multi-agent systems applied to manufacturing systems have been investigated [99]. Intelligent adaptations which possess self-properties, such as self-configuration, self-organization, self-optimization, and self-healing, are useful to apply to ensure robustness, scalability, flexibility and re-configurability, and support developing adaptive systems. These are discussed further in section 3.

This section focuses on the important phenomenon of symbiotic co-evolution observed among species in nature and its use to model co-evolution of products and manufacturing systems. The concepts of dynamic evolving families of parts and products inspired by evolution in nature, and co-evolving products and manufacturing systems were introduced [9]. Biologically inspired symbiosis, in the world of artefacts, between products and their manufacturing systems using cladistics models was introduced and further exploited as a powerful classification method to suggest future trends in the design of products and their manufacturing systems [45]. This powerful co-evolution model was applied to the co-evolution of milling and turning machine tools and products using data from Morei-Seiki as shown in Figure 7. An extended multi-domain evolution and cladogram model was later introduced and demonstrated for 3 domains [10].

A new biologically inspired co-evolution model of products design and manufacturing systems capabilities was introduced [9] using parsimony analysis of cladograms. The model is validated using several case studies including assembly of automotive engine accessories. Bio-inspired phylogenetics for designing product platforms and delayed differentiation utilizing hybrid additive/subtractive manufacturing was developed [46].

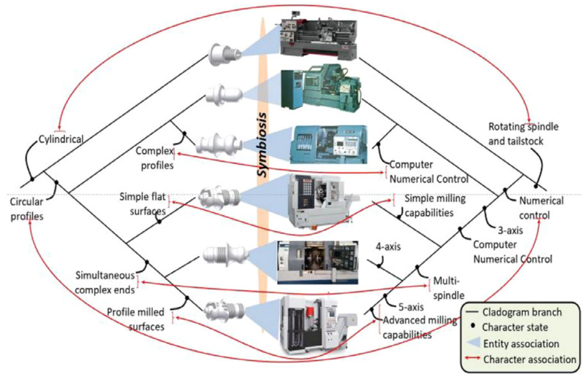

Fig. 7. Co-evolution model for products and manufacturing system [9].

2.3. Biologicalisation in manufacturing systems

A new emerging frontier in the evolution of the digitalization and the 4th industrial revolution is named *biologicalization in manufacturing* which is defined as "The use and integration of biological and bio-inspired principles, materials, functions, structures and resources for intelligent and sustainable manufacturing technologies and systems with the aim of achieving their full potential" [27].

The underlying concept of biologicalization in manufacturing cannot be considered as new. What is novel, however, is the acceleration of its realization, which builds on the capabilities available today and prospectively in the future through the Industry 4.0 developments. Although not exactly under this name, the principles of biologically inspired manufacturing systems have a remarkable history [26]. The concept of *biological manufacturing systems (BMS)* was introduced in [189] with the aim to deal with the dynamic changes in the external and internal environments in the whole product life cycle from planning to disposal, relying on biologically-inspired ideas such as self-growth, self-organization, adaptation and evolution [190,191,193]. Cyber-physical manufacturing is evaluated in the light of Professor Kanji Ueda's legacy in [195].

The cyber-physical era [119], i.e. the unprecedented integration of the physical and the cyber spheres in industry, creates opportunities to realize biology inspired solutions in practice, including production systems and organizations.

Fig. 8 maps the various manufacturing topics with similar biological elements (including botany) including "top-down" procedures, or problem-driven, or manufacturing-driven, or technology pull, and "bottom-up" approaches, i.e. from biology to manufacturing.

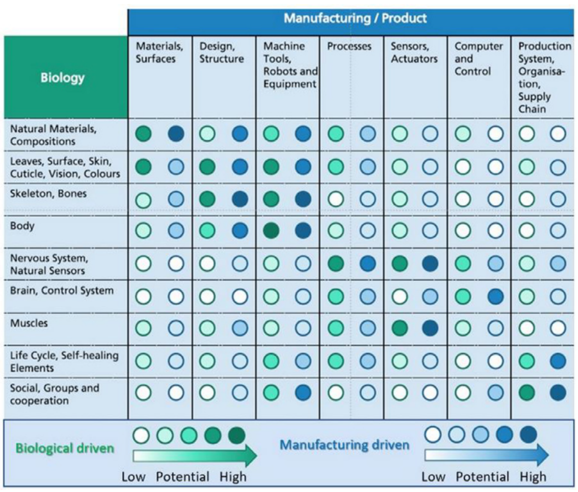

Fig. 8. Potential applications of biological transformation in manufacturing [27].

2.4. Manufacturing systems life cycle and sustainability

Sustainability has three pillars; environmental, social, and economic all of which affect manufacturing systems. Environmental sustainability emphasizes environmentally conscious manufacturing processes, and practices, and reduction of energy usage, resources consumption and harmful emissions [73]. Social sustainability is concerned with the wellbeing of the humans who work in these systems and the quality of their work as they are increasingly called upon to interact and share tasks with technology, machines, and robots. The present I4.0 industrial revolution has the capabilities required to focus on the use of technology to support humans and improve their quality of life and their jobs including within manufacturing systems [177].

Economic sustainability implies a good balance between the cost of manufacturing and profits to ensure business continuity. This in turn drives efficiency, waste reduction and productivity affecting the design and operation of manufacturing systems and the whole enterprise [203]. Important strategies for achieving economic sustainability of manufacturing systems are highlighted next.

Co-evolution and co-platforming of products and manufacturing systems proved to have a significant effect on the life and economic sustainability of manufacturing systems. Having an optimal stable core and non-core of machines capable of producing all product family variants as the product and manufacturing system evolve prolongs the life and utility of a manufacturing system beyond one product generation. They minimize the cost and need for factories re-tooling or re-building manufacturing systems every time a substantially new product is introduced, reduce repeated ramp-up cost, and improve quality. Co-evolution and co-platforming enhance manufacturing systems economic sustainability and prolongs their useful life.

The various stages of a manufacturing system life from its design, modelling, planning, construction, operation, reconfiguration, and redesign when needed are illustrated in Fig. 9 including end of life end of life reusing, recycling, and retiring.

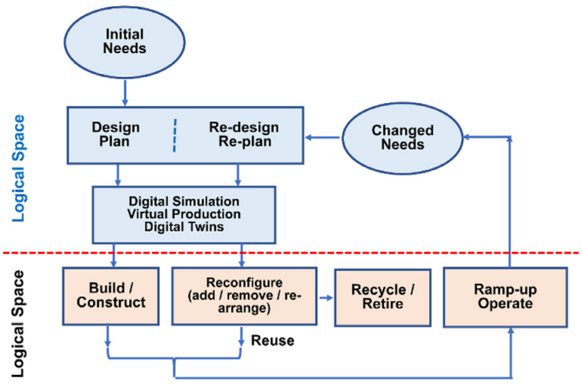

Fig. 9. Manufacturing systems life cycle for sustainability (modified from [43]).

A manufacturing systems classification code was developed [41] for characterizing the components of manufacturing systems including machines, robots, material handling equipment in great details. This classification system represents the characteristics of all system components in strings akin to genetics codes, much the same as OPITZ parts classification system. This novel classification and coding system was demonstrated and applied to machining and assembly systems [48] including industrial applications [172]. The developed manufacturing systems coding system is used during the design phase in identifying similarities, grouping of system components, streamlining the acquisition of machinery, and assessing the system design and operation complexity with a view to re-designing it to reduce complexity and hence cost.

Example of de- and re-manufacturing systems

A laboratory scale "De- and Remanufacturing" pilot plant is installed at CNR-STIIMA, Milan, Italy to integrate and validate multi-disciplinary methodologies, tools, and technologies for the smart de- and re-manufacturing systems of the future, with specific focus on mechatronic products. Research supporting this system is pursued at three levels; single process/technologies innovations, integrated process chain, and sustainable circular economy business models [31]. The pilot plant includes technologies to support products disassembly, remanufacturing and recycling of materials, including mechanical pre-treatments, and implementing the most valuable End-of-Life (EoL) strategy for the various parts [25]. Model predictive control (MPC), knowledge-based modules for adaptive distributed control systems, and a generic evolutionary control knowledge-based module (GECKO) multi-agent distributed control approach were developed. Online part routing problem (OPRP) where the reconfigurable transportation systems (RTSs) mechatronic modules transport parts according to their destinations efficiently and collision-free was implemented. A hyper spectral imaging (HSI) system for in-line recognition and classification of shredded products mixture composition (i.e. percentage of metal and non-metal fractions, shape, and dimensional distribution) enables application of smart waste classification. A virtual system model (Digital Twin) connected to the real plant was developed for implementing concepts of the digital de-manufacturing factory. In addition, the plant supports technology services to companies for assessing new integrated technological solutions for circular economy, mainly in the automotive, white goods, and telecommunication sectors. It is also used for training and education as a learning factory [186].

3. Smart manufacturing systems (SMS) paradigm

Smart manufacturing is defined as "fully-integrated, collaborative manufacturing systems that respond in realtime to meet changing demands and conditions in the factory, in the supply network, and in customer needs" [128]. There are a few similar paradigms which rely on previous and foreseeable further developments of computer science, information, and communication technologies, as well as manufacturing science and technology, and promise higher, sustainable performance of manufacturing systems.

The *cooperative and responsive manufacturing enterprises (CORME)* concept emphasizes abilities for cooperation and responsiveness of future manufacturing enterprises, which are vital in competitive, sustainable manufacturing. The compelling challenges due to generic conflicts between cooperation versus competition, local autonomy and emergence versus global behavior, adaptiveness and robustness versus optimization, plethora of information versus responsiveness are also discussed [196].

Cyber-physical production systems (CPPS) consist of autonomous and cooperative elements and sub-systems that, based on the context, are connected within and across all levels of production, from processes through machines up to production and logistics networks [118,119]. Three main characteristics of CPPS are underlined:

- Intelligence (smartness) where elements can acquire information from their surroundings and act autonomously.
- Connectedness, such as the ability to set up and use connections to the other system elements, including human beings, for cooperation and collaboration, and to the knowledge and services available on the Internet.
- Responsiveness towards internal and external changes.

Cyber-physical production systems (CPPS) enable the 4th Industrial Revolution (Industry 4.0) [6,8,16,88,154,173,184]. "Smart manufacturing integrates manufacturing assets of today and tomorrow with sensors, computing platforms, communication technology, data intensive modelling, control, simulation and predictive engineering. Smart manufacturing utilizes the concepts of CPS, Internet of Things (IoT) (and everything), cloud computing, service-oriented computing, artificial intelligence, and data science. Once implemented, these overlapping concepts and technologies will make manufacturing the hallmark of the next industrial revolution." [95].

3.1. Smart communication and connectivity

Throughout the development towards Smart Manufacturing, important key issues include IIoT, cloud computing, edge computing and fog computing, digital twins [181,198], digital shadows [174], and service-oriented technologies. The 5th generation mobile network (5G) promises high transmission rate, low latency and high security [29]. A critical review of standards applicable to smart automation is found in [103]. Architecture of intelligent perception, IoT, cloud manufacturing is discussed in [182] and [179] respectively.

3.2. Smart products

Industrial product-service systems (IPS2) [110] and hybrid products [88] consider the dynamic interdependencies of products and services throughout the entire product life cycle. Smart products using CPS represent the new generation of intelligent, agile, flexible and networked products [5,166,168]. *Smart products* are considered CPSs which integrate internet-based services [188].

3.3. Augmented reality for smart manufacturing systems design

Augmented reality (AR) has matured and proven to be an effective and innovative solutions in design and manufacturing [129]. It is related to the more general concept of *mixed reality (MR)* that merges real and virtual (digital) information into the user's view [105]. Products and manufacturing processes can be simulated, assisted, and improved using AR before implementation. Augmented reality enhanced human-machine interfaces are enabling users to manipulate components realistically using hand gestures and receive tactile feedback (forces and torques) for more realistic interaction [201].

3.4. Smart manufacturing systems control

Some earlier concepts, often considered revolutionary, can now find real industrial applications by utilizing the latest developments of information and communications technologies.

One such concept is the *holonic (or agent-based) manufacturing systems (HMSs)* which consist of autonomous, intelligent, flexible, distributed, cooperative agents or holons [21,107,122,192,193,194]. One of the most promising features of HMSs is that they represent a transition between fully hierarchical and heterarchical systems [72].

Digital twins represent a way for realizing these earlier concepts as they provide two-way interaction between the real and virtual worlds of manufacturing. "A Digital Twin is the digital representation of a unique asset (product, machine, service, product-service system or other intangible asset) that compromises its properties, condition and behavior by means of models, information and data" [174]. In the literature, digital twins and digital shadows are usually distinguished. Both incorporate data and information collected during the usage / operation phases of the product or production system. With the use of digital twins and digital shadows, together with predictive engineering [95] anticipatory rather than reactive enterprises can be realized. With the construction of high-fidelity models (digital representations) of the phenomena of interest, future spaces can be explored and appropriate decisions made [181].

3.5. Data-driven smart manufacturing

The volume of data collected is rapidly increasing due to the digitalization of manufacturing and growing number of sensors and different IoT devices. Cloud computing enables networked data storage, management and off-site analysis [180]. Data-driven strategies are important for companies to remain competitive. In manufacturing systems, multi-source, heterogeneous data are generated throughout the product life cycle. They can be characterized by 5Vs: high volume, variety, velocity veracity and value [28] as data is generated and collected [180]. *Machine learning* approaches can be used for processing and analyzing big manufacturing data [120]. Algorithms such *deep learning* are increasingly being used. They represent extremely powerful techniques for many applications such as pattern recognition, however, their applicability to a specific problem, availability of appropriate training patterns, and whether incremental learning is important should be assessed. A comprehensive survey of commonly used deep learning algorithms is presented and their applications towards making manufacturing smart are discussed [198].

4. Smart manufacturing systems implementations

Smart manufacturing systems offer competitive advantages for companies when technical progress is transferred to industry. Assessment of the gap between the state of research compared to actual industrial practice is accomplished using maturity models as indicators of progress. Ongoing innovation implementation is evaluated by examining various maturity models and analyzing the state of industrial practice based on latest research trends regarding SMS. The transformation path of different countries, and governments initiatives are described.

4.1. Maturity models and benchmarks for manufacturing systems

Maturity model is a tool to assist manufacturing companies in comparing their status quo with a defined target state and develop an implementation roadmap [155,163]. Comparing relevant maturity models for manufacturing systems regarding CPS, Industry 4.0 and sustainability provides an overview of their purpose and scope [156].

The capability maturity model integration (CMMI) and the process and enterprise maturity model (PEMM) are universally applicable as a basis for production-specific maturity models [69,197]. The smart manufacturing system readiness assessment model (SMSRL) examines four dimensions: organizational, IT, performance management and information connectivity maturity. The measurement categories are processes, personnel, software systems, output data format, key performance indicators (KPI) and KPI relationship [87].

The smart manufacturing maturity model for small and medium-sized enterprises (SMEs) (SM3E) developed in the USA and Mexico contains five categories: finance, people, strategy, process and product and evaluates smart manufacturing and the organizational structure [115]. PEMM, "Leitfaden Industrie 4.0" and the "Reifegrad für Industrie 4.0" examine an organization's maturity level by analyzing methodological competence and corporate culture [84,165]. They focus on information flow and use of data in production such as information generation and processing, networking, interaction of CPS and intelligent and self-controlling processes [84,152]. The "Leitfaden Industrie 4.0" and the "IMPULS" maturity models focus on technical assistance systems and production networks [12,102] for SMEs and classifies the company competencies in production data processing, machine-to-machine communication, company-wide networking, ICT infrastructure, human-machine-interfaces and efficiency for small batch sizes. Other models such as the Industry 4.0 / digital operations self-assessment are cross-industry self-assessments with subsequent recommendations for action to achieve a higher degree of maturity and add perspectives on market and customer access, compliance, legal, risk, security and taxes [144]. The SIMMI 4.0 measures maturity in information flow along the supply chain and across all hierarchical levels, cross-sectional technologies and digital product development [100].

Another important aspect of maturity models with focus on CPS is customer orientation. For example, the "Digitalisierungs" index assesses the digital maturity regarding customer relationship, productivity, digital offers and IT-security [38]. The Industry 4.0 "Reifegrad Test" assesses the maturity regarding research and development, production, logistics and warehouse management and administration as well as sales and customer service. Both the Leitfaden Industrie 4.0 and the Brazilian instrument to measure lean manufacturing maturity include customer orientation and supplier integration. The instrument to measure lean manufacturing maturity evaluates information flows, corporate culture, suppliers and customers regarding quality of data source, problem solving, processes and tools, strategic planning, continuous improvement, supplier integration and customer orientation [153]. The Korean assessment framework analyzes the maturity level of intelligent manufacturing regarding the integration of data analytics in production as well as finances. The smartness assessment framework for smart factories uses analytic network process and focuses on leadership and performance. It is the only maturity model that explicitly considers performance factors such as productivity, finance, quality and lead time as evaluation criteria as well as leadership, processes, and system and automation [98].

Most German and the Korean maturity models generally focus on technology, automation and production and many German models specifically cater to SMEs. The American and international models often focus on connectivity, corporate culture and finance or the company indicating the current technological mid-term outlook.

The Singapore smart industry readiness index (SIRI) assesses Industry 4.0 based on processes, technology, and organization criteria. The integration of operations, supply chain and product lifecycle are evaluated. Criteria for assessing technology readiness are the degree of automation, connectivity, and intelligence. In addition, the organization and employees' readiness for Industry 4.0 are evaluated [171].

Benchmarking studies assess the state of industrial practice, readiness and implementation and underlying success factors. A recent benchmarking of Industry 4.0 identified successful and proven approaches for German and European small, medium, and large companies. Manufacturing companies that specifically address smart data and digital assistance of Industry 4.0 in addition to culture and methods tend to be ahead with their systematic implementation of modern manufacturing systems (Fig. 10).

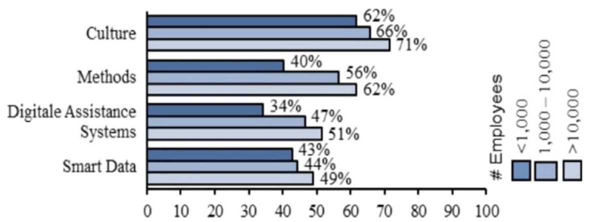

Fig. 10. Results of benchmarking Production Systems 4.0 [160].

Successful companies consistently apply lean methods in Industry 4.0 to increase agility and productivity, develop strategically important assistance systems and integrate users [171].

Smart data including effective analytics applications, consistent semantics along the entire order processing chain, a middleware connecting data of different domains as well as cooperation of data scientists and production employees are important success factors for increasing productivity.

4.2. Modern manufacturing in the global context

It is important to understand the economic and social impact of ongoing digital transition on the entire manufacturing economic sector in different countries, the role of manufacturing within an economy and the measures taken to secure or strengthen their relevance in global markets.

Some countries are selected based on rankings like the global competitiveness index (GCI) and the global manufacturing competitive index (GMCI) which reveal their economic and scientific relevance [37,58] to examine their efforts and spending related to GDP, Industry 4.0, regulations, tax policies, energy, transportation, health cost, workforce quality, infrastructure and innovation of different countries [58,130,131,202,205,206]. Fig. 11 summarizes the results [130,131,175,184,205,206]. Many countries introduced initiatives to support the digital transition of small, medium, and large manufacturers. Some examples include the USA smart manufacturing programs and clusters of excellence in IoT, advanced manufacturing, new materials and software [7,74]. Germany introduced the Industry 4.0 initiative and funded related academic and industrial research and development programs. Canada established an advanced manufacturing program through the national research council of Canada (NRC), next generation manufacturing supercluster (NGen), a network of super research clusters, and collaborative international

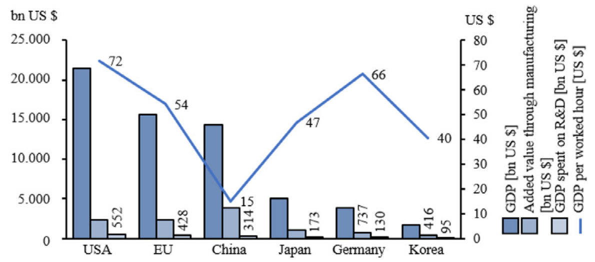

Fig. 11. Comparison of USA, EU, China, Japan, Germany and Korea.

research programs (e.g. with UK and Germany) to support small and medium size innovation and manufacturing enterprises and technology transfer of academic research in smart manufacturing. The Chinese government has initiated plans to develop artificial intelligence, robotics, better handling of big data and above all their initiative of "Made in China 2025" [138].

The Japanese government supports initiatives regarding robotics, new IT, IoT, industrial value chains or connected industries to build up new industries and strengthen existing ones and enhance data exchange, use of AI in SMEs and cloud services [64]. Besides manufacturing benefits, they focus on problems like the aging society with their Society 5.0 initiative to achieve high acceptance of human-machine-interaction including in manufacturing. In Korea, the term fourth industrial revolution is more used than smart manufacturing systems. Government initiatives include Manufacturing Industry Innovation 3.0 Strategy as part of the Creative Economy Initiative or the Connected Smart Factory, along with company collaborations regarding smart factories, intelligent manufacturing or smart engineering [7]. Korea is making huge efforts to support their companies through other initiatives from different ministries ranging from Science and ICT to interior and safety [176]. The European community supported many multi-national collaborative programs and projects focused on Industry 4.0 and its enabling technologies. Europe is heterogenous regarding programs, funding, and challenges. For example, Scandinavian countries, the Netherlands and the UK are dominating the digital economy and society index (DESI), which tracks digital performance and competitiveness in Europe, whilst Malta has the highest percentage of companies analyzing big data [57]. Regarding Industry 4.0, less than 35% of European companies have implemented two or more key technologies, which are social media, big data & data analytics, cloud technologies, IoT, mobile services, robots and automated machinery, cyber-security solutions, 3D printing, and artificial intelligence, while only 25% is using big data analytics countries have their own initiatives for implementing Industry 4.0 combined with the digitalizing European Industry initiative in 2016 [147]. In Germany, more than 20 Industry 4.0 competence centers are developed, and German companies are investing €40 bn annually in Industry 4.0 technologies until 2020 [145]. The government supports initiatives to strengthen Germany's position including Industry 4.0, smart service world, high-tech-strategy, and collaborations with companies and research organizations on digital factories and Internet of Things [87,163]. Together with research related to sustainability and efficiency [151], it is expected to achieve an overall efficiency (productivity, energy and resource utilization) gain of 18% in five years [145].

The gap between companies is mainly seen in Asia where some corporations are huge and innovative while followers are usually small without advanced manufacturing systems. While governments support companies significantly in achieving Industry 4.0 standards, they often face obstacles such as changes in regulations which hinder commercialization of innovative solutions [137].

In addition to governments supportive initiatives, it is up to the sector's ingenuity to invent and innovate new concepts, ecosystems and solutions and implement them successfully in practice, for example in *smart factories*. To apply CPS to manufacturing, the concept of the smart factory as a hyper-connected network-based integrated manufacturing system has been developed. It uses IoT to connect the real shop floor equipment such as machines and assembly lines by a

CPPS Platform that monitors, plans and controls manufacturing steps by MES which are supported by a cyber model of the real production - digital twin. Based on this model, discrete event simulation and data analytics methods help improve the factory performance [15]. This vertical integration of sensors, MES and ERP helps the smart factory to achieve product life cycle integration and a horizontal integration of several smart factories into a smart supply chain. The product life cycle integration allows an early integration of the optimal production structure for upcoming new and changing products and their manufacturing requirements in the factory development planning. PLM software is used to link R&D data with production and user-data. The connection of several smart factories in an inter-company value chain finally creates a hyper-connected network that allows new forms of cooperation and business models [141].

Smart manufacturing (Industry 4.0) industrial adoption

The smart manufacturing (Industry 4.0) adoption report [85] analyses the status in the manufacturing industry with regard to Industry 4.0. Overall, less than 30% of manufacturing companies use Industry 4.0 technologies to a great extent. In the regional comparison, North American companies have the highest adoption of Industry 4.0. The adoption of technologies and use cases varies between different industry sectors, with companies in the automotive sector using Industry 4.0 most extensively. For this also, the average return on investment and the likelihood to increase budget for Industry 4.0 technologies is highest in the automotive sector.

4.3. Industrial applications of smart manufacturing systems

The different smart manufacturing paradigms have already been springing to life in industry in the past years with many different solutions. Examples of implemented smart manufacturing systems and technologies, advantages and challenges are presented.

4.3.1. Smart digital manufacturing and assembly systems

The e.GO Life is an electric car designed and manufactured in Aachen, Germany by the e.GO Mobile AG. This example is an excellent demonstration of successful transfer of technical knowledge from academia to industrial application as well as commercial products and demonstration of several Industry 4.0 enablers.

Long time to market and low agility limit existing manufacturing systems in automotive industry. At the e.GO Mobile AG, the time to market for new products is drastically decreased by using a highly iterative product development approach. Horizontal integration of the manufacturing system is essential to enable industrialization while the product being developed is constantly changing without defined design freezes. Hence, company-wide agility, including handling of change requests, is required. A change request is a process which initiates a change of the product after releasing it for further development or manufacturing. It can be categorized into internal, such as due to construction mistakes, and external, e.g. induced by changes in customer needs and requests. These changes have a wide range of effects on the company as they influence employees, products, processes, and cost. Establishing an effective change request process ranges from increasing the customer surplus and integrating technological innovations to shortening the time needed for a development process in an agile environment. These two main goals are contradictory for most manufacturing processes. Certain steps are needed to reduce the conflict, by initiating a combination of organizational actions and other manual actions regarding the information and communication technology infrastructure.

Other key enablers of efficient change requests are filtering relevant data, transparency and flexibility of data distribution, defined data structures and high-quality data. The main challenge in realizing these key enablers is insufficient working infrastructure, which can effectively be overcome by implementing the IoP framework which combines the use of apps and smart data with integrated data management acting between raw and smart data, hence, enabling efficient change processes and highly iterative product development [23].

The idea of the IoP is pursued within Industry 4.0. Linkage heterogeneously available data from different IT systems and sensors (as done in IoT); the IoP generates a digital representation of the manufacturing system at different levels of aggregation, called digital shadow. Application-specific apps with detailed production engineering models can be created based on the digital shadow as shown in Fig. 12. They aim to enable production managers to react faster to problems and gain new insights to increase productivity. Therefore, the IoP is an extension of the IoT but with specific production technology models and associated data structures [162].

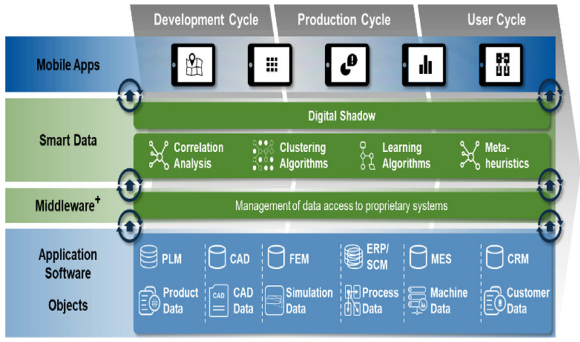

Fig. 12. Digital shadow and its use in different manufacturing cycles.

The e.GO Life electric car is produced in an Industry 4.0 plant where technologies like sensors, connected material handling equipment, automated guided vehicles (AGVs) and robots are used. The data collected in production is transmitted via 5G network, which guarantees high data transfer rates and reliable low latencies supporting realtime communication. Production and other data from IT systems are integrated to enable cross-domain collaboration. The change request procedures (Fig. 13) are used. Data is selected and aggregated on an application-specific basis to support daily work and decision-making.

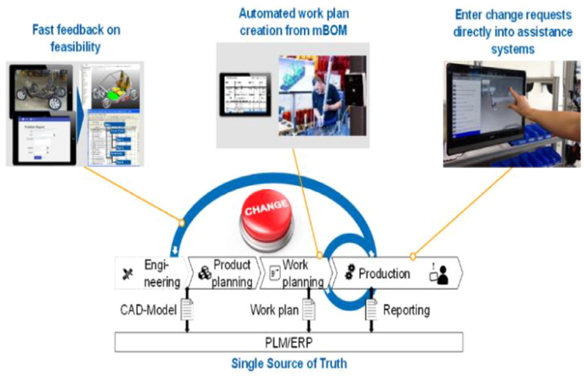

Fig. 13. Change request system at the e.Go LIFE electric car factory.

One example of implemented connected systems is the end of line control. The employee uses an augmented reality app to report errors. When entering a light tunnel, the vehicle is automatically recognized via RFID. The product life cycle management system provides information about the vehicle configuration and necessary checks. Cameras scan the vehicle and the image data is processed using artificial intelligence (AI) application trained to detect errors. Quality inspectors check the errors and manually enter errors in the app. All errors are documented in a manufacturing execution system (MES) which provides necessary data for rework. After rework, all information is added to a digital vehicle file. This example shows how different IT systems, sensors, AI, and augmented reality are connected in one system to simplify and improve the quality inspection. All necessary information is provided by an app, hence, reducing information search and increasing process stability. All data for a vehicle is immediately stored in the vehicle file creating continuous documentation and transparency where all assembled parts and performed work steps are traceable. In addition, the pre-evaluation of errors using AI enables a focused and faster inspection and improves quality. As a result, the time to market is decreased compared to traditional OEMs.

The e.Go electric cars, now in serial production (Fig. 14), are available in different configurations/variants e.g. size and wheels material, and depending on the model can feature infotainment system, seat heating, parking sensors and LED headlights.

Fig. 14. e.GO LIFE electric car production line in Aachen, Germany [e.GO Mobile AG].

4.3.2. Internet of things (IoT) platform at Hirotec

Hirotec is a US$1.6 billion automotive part and tooling manufacturer with 23 locations around the world. To improve quality, reduce downtime and optimize production planning, Hirotec implemented PTC's ThingWorx IoT Platform and Kepware's IoT Gateway in its Detroit, Michigan factory.

The company recognized early on that access to operating data from their machines had an enormous impact on planning, avoiding reactive maintenance, and missed opportunities. Today, production management can use realtime data from the factory linked to the ERP system for planning and optimizing CNC modules, systematic analysis and decision making. To support the long-term IoT vision, Hirotec developed an IoT framework with short six-week agile sprints. While a full IoT implementation would have taken several years for the first results to emerge, the Scrum model delivered early visible and quantifiable progress. In six weeks, the company went from no realtime visibility in its operations to full visibility of the operational states at any time, with data analytics capabilities for trend forecasts of uptime and efficiency.

Hirotec expects that the IoT measures will affect every aspect of the company, from operating the business and IT to financial forecasts, customer relations and sales. As the sprint projects progress, Hirotec will obtain various contextual data to develop new improvement case [104,148,149].

4.3.3. Smart factory by Ericsson

Ericsson, a global distributor, provider and manufacturer of communication technologies goods and services in Sweden, invested in a smart factory in the Jiangsu province, China. It is located in Nanjing and focuses on the manufacture of 5G and 4G radio technology products. With an investment of about US$50 million, smart manufacturing capabilities were enabled and automated streamlined production systems were implemented. The new technologies include a modular automatic assembly line for 5G radios as well as an upgraded automatic packing line for higher speed and efficiency. Modernized 5G testing equipment allow more efficient processes and higher flexibility in reacting to changes. Data analytics capabilities were implemented for components and objects recognition in production using AI and machine learning. IoT-technologies enabled an automated alert system for critical issues and faults. The decreased latency of error in production to initiate counter measures allows accelerated production and increased efficiency. Reduced cost of material and manual machine maintenance due to reduced human errors and production system downtime, amounted to annual savings of up to US $10,000. This smart factory project resulted in a 50% ROI, with a breakeven duration of about two years [54,55].

4.4. Research use cases

Extensive research in academia and industry is being devoted to developing enablers of smart manufacturing systems including human-machine collaboration. The following are but a few examples of ongoing joint academic-industrial research projects.

4.1.1. Autonomous, mobile, and ad-hoc cooperating robot teams

High integration costs and complex programming often limit the use of industrial robots to identical repetitive tasks behind protective fences and separate from workers. Advanced sensors and increasing miniaturization of control systems allow mobile industrial robots to navigate autonomously through the factory while using end effectors to perform a variety of tasks with sensory feedback. This was demonstrated by the Technical University of Munich (TUM) with three industrial partners as part of the FORobotics research network for utilizing autonomous mobile robot platforms in smart production. This use case features modular software architecture for flexible tasks execution through reconfiguration of robot tasks, and interaction between humans and robots. It includes interpretation of human gestures and 6 degrees of freedom pose estimation for assembly and heavy objects bin picking, a world model representing multi-user capability, combined consideration of geometric, topological, and hierarchical environment information, and integration of predicted and planned object dynamics. It enables motion and task planning in unstructured environments. For Human-Robot cooperation, the robot uses cameras to enable detection of human hand, eye, or speech gestures. A projector displays information on the floor about the motion direction and target for the human to understand the robot's activities. Various psychological and ergonomic aspects such as trust in automation, stress, safety perception or workers' attitudes and their experience were studied in this user-centred application using field observations, laboratory experiments with participants, employees' surveys, and interviews to use in further development. This combination of human and robot capabilities resulted in new forms of ad-hoc robot human cooperation in a smart manufacturing system (Fig. 15) [76,77].

Fig. 15. Human−robot collaboration autonomous production control [Fraunhofer IGCV/Institute for Machine Tools and Industrial Management] [76, 77].

4.4.2. Flexible reconfigurable allocation of work tasks

This use case conducted at iwb, TUM introduces flexible reconfigurable work tasks allocation using "jumpers" or "auxiliary workers". It is implemented on a balanced mixed-model assembly line at a brakes and transmission systems manufacturer, which is characterized by a one-piece flow of three product variants, running through the same assembly process and is fed by three pre-assembly stations. Hybrid combination of automated and manual processes at the same station is conducted with proportionately higher manual activities. Initially, the workstations were equipped with touch screens for digitally displaying work instructions. To avoid interruptions in production caused by bottlenecks, knowledge deficits or imbalanced distribution of the workers tasks; smart watches (wearables) were used by workers to initiate requests for "jumpers" and coordinate their deployment (Fig. 16). The smart watch app provides three jumper request options; namely replacement, assistance or coach jumper [40]. The use of smart watches and apps to coordinate replacement workers (jumpers) increased production by 15% by

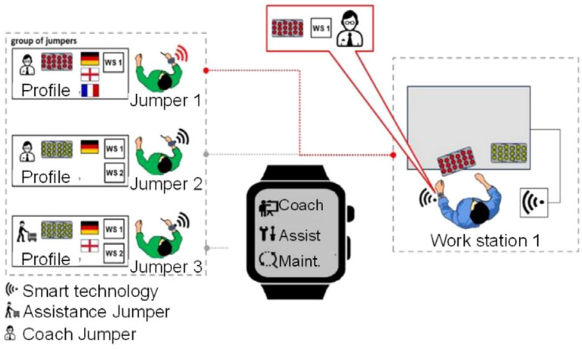

Fig. 16. Work tasks assignment with an App for jumpers' allocation [40].

maximizing the operation efficiency and capacity utilization of the assembly line, and reduced reaction time for handling interruptions by 20%. Insufficient internet speed, which caused the calls for jumpers to be interrupted frequently, presented a challenge. This confirms the importance of fast, high capacity integrated IT-infrastructure as a prerequisite for successfully implementing smart technologies in factories. The overall feedback from workers was very positive, as they could receive support promptly as needed. One downside for some jumpers was the uncertainty caused by not knowing the next assignment.

4.4.3. Autonomous matrix production control

Agile production system for remanufacturing using artificial intelligence (AgiPROBOT project 2019-2024) is carried out by nine research institutes at the Karlsruhe Institute of Technology (KIT) and funded by Carl-Zeiss-Stiftung. Integrated semi-automated demonstrator factory for remanufacturing capable of autonomously disassembling automotive electric drives manufactured by Bosch after their usage phase characterized by a high degree of variety and uncertainty regarding their condition and specification is used. This agile system is structured with a matrix layout to enable highly flexible and adaptable material flows (Fig. 17). It features several autonomous capsuled stations and a variable material flow using independent AGVs and robots for inspection and disassembly in collaboration with humans.

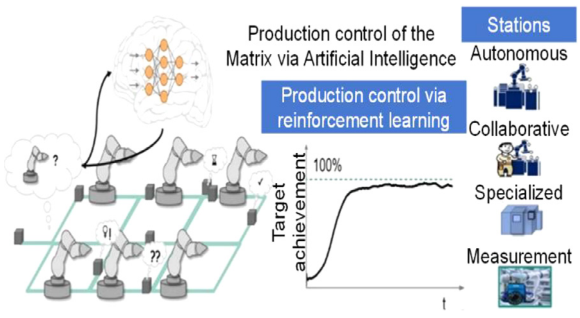

Fig. 17. Autonomous adaptable matrix production control [Karlsruhe Institute of Technology. KIT].

The system performance is enhanced using reinforced machine learning for adaptive dispatching, co-learning with humans in disassembly operations, and decentralized hierarchical intelligent control via autonomous agents to utilize the potential of the modular matrix or grid manufacturing systems [78]. This use case demonstrates a “plug-and-work” functionality of manufacturing systems designed with flexible matrix layout and intelligent production control all of which enable adaptable remanufacturing of electric drives with uncertain product specifications using adjustable automation.

4.4.4. Reconfigurable intelligent robotic assembly system

Dynamic reconfiguration of a factory by employing cooperating mobile robot platforms (MRPs) and mobile product platforms (MPPs) is researched at the laboratory for manufacturing systems and automation (LMS) at University of Patras, Greece. An assembly line inspired by assembly of the front axle of a passenger vehicle where dampers are assembled on the disks with 480 parts for three axle variants/models in 8-h shifts. Mobile dual-arm robot workers can autonomously navigate on the shop floor and perform multiple operations such as screwing, handling, and drilling while acting as assistants to human operators. Human operators' behavior is estimated using multiple sensors data to enable human robot interaction, task planning and robot behavior adaptation to surroundings. Robot perception libraries allow MRPs to avoid collisions, dock at different workstations accurately and detect parts orientation for assembly [112,140].

Application of the new system reduced weight lifted by operators; increased assembled variants from 3 to 6 models and operator utilization; reduced number of operators from 3 to 1 as well as part flow time.; improved quality and productivity by automating repetitive strenuous tasks, and reduced set-up time for changing models through robot mobility. The return on investment (ROI) was 12 months.

Some limitations of robot perception accuracy due to lighting conditions, realtime continuous object detection, and networking issues were encountered when multiple sensing devices were encountered and required human participation and support. This shows that the future of AI in robotics requires combined AI applications and creative human operators.

Summary of observations on industrial and academic use cases

Different applications and use-cases were presented which exemplified various aspects of smart manufacturing systems such as flexible operation and production control using intelligent mobile robots, connectivity and integration using advanced IT systems, use of smart automation and control technologies, and adjustable flow and adaptive intelligent control of equipment and systems to improve performance and increase responsiveness.

Digitalization which is an important foundation for smart manufacturing systems and the important role of humans in future manufacturing systems and facilitating their cooperation with machines is abundantly clear. These are only few of the numerous examples of smart manufacturing research carried out in academia and industry around the world. They illustrate the necessity of investing in research and development as well as effective technology transfer and implementations.

Increased attention is being paid to making the concepts and implementation of augmented human machine interaction in smart factories more accessible and clearer to industry and academia. Research centres and laboratories provide opportunities to explore innovations regarding the digital transformation, impact of Industry 4.0 on manufacturing, and making digitalization and automation solutions tangible to interested stakeholders. In different demonstrators the human-robot collaboration, use of AI and mobile apps in manufacturing and autonomous production as part of SMS have been illustrated.

5. Adaptive cognitive manufacturing systems paradigm

As many innovations and disruptors along the axes of evolution continue to appear, it is important to carefully consider, and be cognizant of, those changes that would truly lead to paradigm shift(s) in manufacturing systems causing them to be designed, operated, controlled and/or used differently. Disruptive innovation, a term used in business and technology, is one that helps create a new market and value network, and eventually disrupts existing ones and displaces an earlier technology [30,80].

Paradigm shift, a concept identified and coined by the American physicist and philosopher Thomas Kuhn [94], indicates a change in the basic assumptions within the ruling theory and represents a fundamental change in the basic concepts and experimental practices of a scientific discipline. In manufacturing systems this means fundamental change in the ways products are made. This paradigm shift criteria have been used in evaluating manufacturing systems evolution trends in this keynote paper and in identifying future new manufacturing systems paradigms.

5.1. Towards bio-intelligent manufacturing

In the long term, transition is expected from the old “lifeless manufacturing systems” to the manufacturing systems being alive: self-learning, cognitive, communicative, self-healing, and self-assembling towards a “living manufacturing system”. Future manufacturing systems are expected to incorporate components, features, and capabilities that enable the convergence towards living systems as hypothesized in [27] and further elaborated in [121]. It is observed that the ongoing Industry 4.0/Smart Manufacturing is increasingly bringing together the physical, virtual, and biological worlds. Next phase of the evolution is envisioned to be the emergence of what can be labeled “human-centric” “bio-intelligent” manufacturing [113] integrating automation, information, bio-production, smart products, and materials technologies.

5.2. Human-centric adaptive manufacturing

The manufacturing industry continues its evolution towards pervasive automation, while human-machine collaboration is advancing by placing human operators in the center of attention. Even with the advances towards more intelligent automation, the trend is an increased attention to the central role played by human workers and their well-being both physically and psychologically as well as considering the environmental issues. This socio-technical approach to the evolution of the manufacturing system, where automation is human-centric, cognitive, intelligent and environmentally friendly has led an IEEE technical committee to call this “bio-automation”, others have claimed that these are characteristics of the fifth industrial revolution (Industry 5.0), however, these terminologies and associated implementations have not yet been widely adopted.

The idea of self–optimizing machining systems (SOMS) in the context of Industry 4.0 was investigated [117]. Enabling technologies, principles, and methods are described that would potentially allow for the implementation of machining systems which are capable of adapting their parameters and settings autonomously, in order to optimize for productivity, quality, and efficiency and concluded that “last but not least, the higher complexity of SOMS requires new solutions for human–machine interaction”.

Industry 4.0 brought a great change in the interaction between workers and machines; the latter includes every kind of dynamic technical systems such as automation, robots, decision support, equipment, and software [127]. Industry 4.0 allows communication between humans and machines throughout a highly networked environment, using automation technologies like CPS, IoT and cloud computing and the various levels of the supervision and control systems. Furthermore, human–machine interaction deeply changed over the years, and reached a new level of innovation in Industry 4.0 due to some additional pillars including big data analytics; robot-assisted production; self-driving logistics vehicles; and augmented reality. It is possible to think of the resulting systems as the new ‘internet-of-people-and-things’ in which the cyber-human system (CHS) complements the activities deemed to be difficult for the CPS and vice-versa, with the CHS having the supervisory control to naturally leverage the needed cognitive, adaptive, and corrective actions. In the Industry 4.0 era, companies are required to use a socio-technical strategy. In addition to investing in technological infrastructures, it is essential to value the human factor and workers well-being before technology, and drive and anticipate change. The ability to solve complex problems and use critical thinking to help organizations adapt quickly to changes in perspective is critical. Database analysis must turn data into knowledge and strategic business suggestions [127].

The HumAn-CEntred (ACE) factories [83] cluster, shared in a key white paper, the understanding of future human-centered factories and provided recommendations on how to bring this vision into industrial practice. The vision and recommendations are based on the work of the five EU funded H2020 research projects (2016–2020): A4BLUE, Factory2Fit, INCLUSIVE, HUMAN and MANUWORK. The ACE Factories cluster has identified several lessons learned and recommendations for successful technology and best practices adoption including: a) augmented reality (AR) and virtual reality (VR) are efficient tools for on the job training, which increase productivity and enhance the workers’ well-being; b) making operators’ tacit knowledge, such as best work practices and problem solving, visible and accessible with social media-based tools can be a very effective complement for workers support and training; c) the usage of wearable apparatus like exoskeleton devices has shown their potential to reduce operator’s physical fatigue and increase their overall safety and productivity; d) ACE pilot cases have shown that human-centered factory solutions have positive impacts both on the productivity and well-being of the operators; e) the know-how of industrial workers must be protected from unauthorized use especially by data and analytics companies; f) the human-centered paradigm shift will only be successful if work processes are reshaped and new training approaches are introduced to support continuous development of skills taking into account personal capabilities, skills and situational preferences of individual operators; g) new technical solutions for the realtime measurement of the operator’s capacities, mental strain and adaptation to automated processes can be used to improve productivity and workers’ well-being and increase the value of humans role; h) providing factory workers with ways to influence and improve their work will increase work motivation and productivity; e) changing work roles should be implemented with consideration of the needs of elderly workers such that no one is left behind; j) criteria related to enhancing trust in the collaboration between automation and advanced technological applications such as human-machine and human-robot collaboration (HRC) should be considered; and k) small and medium enterprises (SMEs) should be supported in adopting human-centered factory solutions.

For adaptive factory automation and management solutions integrating the man in the loop, a methodology was proposed [35], validated in two industrial cases, to integrate cognitive workload into the design of workplaces to match the human safety and well-being necessities and the tasks cognitive requirements. The proposed approach allows for the human-in-the-loop within factory automation through seamless human and automation collaborative decision-making, while monitoring production performances and workers well-being indicators.

The symbiotic human-robot collaborative assembly issues were discussed [199] Human-robot collaboration (HRC) in a manufacturing context has been researched in the last few years, with a view to facilitating multimodal communication, dynamic assembly planning and tasks assignment assisted by deep learning. Insights on programming-free adaptive robot control through algorithm embedding and brainwave-driven methods; and different techniques for mobile worker assistance were discussed. Challenges and twelve future research directions were identified for further advancement in the years to come. It envisioned that “with the support of the latest technologies of sensing, communication, AI, AR and robot control, HRC will find its way to practical applications on shop floors in factories of the future”.

Human-centric bi-directional interaction between hardware and software components in the system and the people associated with its functioning will benefit from an effective blend and symbiotic relationship between the principles and drivers of Industry 4.0 and Society 5.0 to maximize the effectiveness and contributions of the humans in future manufacturing systems and enhance their well-being.

5.3. The multiple facets of adaptability

Three important related mechanisms of effecting changeability are resilience, robustness, and adaptability. Resilience is the capacity to recover quickly from disruptions and spring back into the original designed system state or normal operation. Robustness is fault-tolerance, i.e. the ability to withstand disruptions without the need for adaptation. Adaptability, however, is the ability to adjust to new conditions and to be modified for a new goal, use or purpose. It is the most relevant characteristic of evolving manufacturing systems and a core foundation for any new system paradigm.

System adaptability has been utilized in earlier paradigms such as flexible and reconfigurable manufacturing systems. A new classification is presented next. The four classes of adaptability are informative in differentiating the new adaptive cognitive manufacturing system (ACMS) paradigm.

5.3.1. Static adaptability

The static adaptability refers to built-in *pre-planned flexibility by design* (Section 2.1.4) enabled by the design of the system components, modules, machines, configuration, and operating rules. It allows flexible, resilient, and robust behavior within the pre-defined parameters and boundaries such as pre-planned product family and well-defined range of production capabilities (scope) and capacity (scale). This type of adaptability relies on universality and programmability features of machines, robots, fixtures, and manufacturing system, to cope with anticipated ranges of change in products and in production volume.

5.3.2. Dynamic adaptability

This class of adaptability is labeled dynamic because it involves action-oriented *changes that affect the manufacturing system and its constituents* and involves external efforts by the technical specialists such as engineers, technicians, and workers to implement and realize the intended adaptation. It *involves both physical hardware adaptation, and logical soft adaptation* by reprograming devices, changing controls of machines and/or system, and revising operating and sequencing rules as discussed in Section 2.1.4. It relies on built-in flexibility and reconfigurability enablers, such as modularity, standard interfaces, mobility, integrability, diagnosability, and programmability to allow agile changes in function (scope) and capacity (scale) between anticipated flexibility corridors within manageable variations above initially designed boundaries such as extending products family, and production scope and scale.

5.3.3. Cognitive adaptability

Cognitive adaptability is built on top of, but is differentiated from, static and dynamic adaptability in that the *adaptive responses are triggered and/or executed autonomously by important cognitive characteristics*. Human-centric adaptive cognition includes context- and self-aware as well as self-optimizing behavior in the two-way interactions between a) machines and other hardware components in the manufacturing system using sensors and IT, IoT and IoP capabilities, and b) human operators and intelligent technological applications. Therefore, cognitive adaptation utilizes built-in changeability enablers to allow agile and optimal changes in function (scope) and capacity (scale) beyond previously anticipated and planned total changeability ranges/corridors using the autonomously synthesized cognitive adaptation response. It is enabled by employing elements of artificial and hybrid human-machine intelligence such as sensing, perception, anticipation, prediction, planning, action, and autonomous decentralized decision making and control of machines and production. In addition to self-awareness and self-optimizing features, the cognitive adaptability includes self-planning, self-healing such as maintenance and repair, and generally knowledge and cognition-based adaptive responsiveness.

5.3.4. Extreme adaptability

Extreme adaptability relies on the manufacturing system resilience and capacity to recover (partially or fully) from major unexpected multi-dimensional extreme disruptions and return to the normal/near normal designed system state or operation with the least delay and losses. The key operative words in extreme adaptability are unanticipated, extreme disruptions, and least losses. The anticipation and prediction capabilities are therefore particularly important in forecasting impending disruptive changes and in timely planning and deciding optimal and economically feasible adaptation responses and action.

Manufacturing systems response to the unprecedented disruption during 2020 Pandemic brought to the fore the importance of this class of extreme adaptability.

"The COVID-19 pandemic is challenging politics, society and the economy to an unprecedented extent. Its effects are so drastic that it requires companies and industries not only to manage the crisis in the short term, but also to develop strategic options for the future" [143]. Indeed, this multi-domain disruption which occurred in 2020 significantly afflicted countries around the world. Drastic changes in production volume (increase and decrease depending on the product) often resulted in shutdowns for extended periods. Increased demands for essential products such as medical supplies and protective personal equipment depleted existing stock in very short order and outstripped any planned production scope and capacity/volume. Supply chains were crippled or broke down completely by travel and transportation restrictions as well as national protectionism. Companies which produce pharmaceuticals, medical gowns, face shields and masks were asked to double, triple, and quadruple their production; others like auto-parts manufacturers and OEMs were called upon to produce the essential products that are far from their normal products which presented many challenges. Other companies faced drastically reduced demands and were forced to consider producing significantly different products to stay afloat. Furthermore, the supply chains of just about all goods and materials came to a near standstill. In summary, the pre-planned defensive strategies of flexibility, reconfigurability, agility, changeability, resilience, and robustness of manufacturing systems were all put to the test compounded by the immediacy of the required responses. As discussed in Section 4, the degree of preparedness and implementation of flexibility, reconfigurability, agility, changeability and smart manufacturing paradigms varies among companies which affected their ability to respond to these extreme changes and in a timely manner.

Response to extreme disruption

Some manufacturing systems were able to make changes quickly to keep the business running and protect jobs. Wineries, liquor and perfumes makers and drinks bottlers were able to produce new product variants in an expanded product family. For example, wineries already using alcoholic liquids were able to switch to making disinfectants and hand sanitizers by changing the fluids formulation, the bottles, and labels, and reprogramming the material handling systems while using the same processes. Parts manufacturers and tool and die makers which produced small and medium size batches of custom orders using versatile multi-purpose and programmable flexible machines switched easily with minor changes to producing face shields and masks in large size lots. Use of advanced digital design and 3D printing technologies made rapid switching to new products feasible. Other urgent virus-related products include clips to attach to paediatric face masks, sheet metal components for automated COVID-19 lab test equipment, and different moulds for ventilators production. A vacuum-maker switched to making ventilators by switching from making suction machines to ones that blow air. Even Mints, known for making money bills and coins, tuned their focus to helping protect people against COVID-19 by making valuable plastic visors for healthcare staff. Major electronics manufacturers adapted existing clean-room production facilities for LCD display panels to make surgical masks in large quantities. Several automotive OEMs began producing face masks using medical-grade textiles previously used for car seats and interior details. Setting up new or re-configured production lines by adding/removing and reconfiguring portions of the manufacturing equipment and systems also worked for some other manufacturers. Many companies used time flexibility to increase the number of worked shifts as needed. Companies re-purposed their production lines for different reasons, such as government incentives or invoking certain laws, but the majority switched production willingly to maintain some output and revenues when regular orders dried up. Such drastic production changes are not without their hurdles, such as securing new materials at a time of scarcity and developing new/modified product designs and quickly getting regulatory approvals. Sharing design information and intellectual property across business sectors are other issues. Digitalization, communication, connectivity, and availability of open-source tools allowed effective sharing of knowledge and resources. The urgency and scale of disruption due to the pandemic could change the way collaboration is done in the future. The business paradigm may also change from "just-in-time" to "just-in-case", and the manufacturing system and supply chains may be designed for emergence and to accommodate black swan events. This need was addressed [143].

Observations

The above examples demonstrate successful static and dynamic adaptability. Manufacturers with reasonably diversified and robust supply chains fared better in securing the materials and parts needed for their operations. However, in dire situations such as the 2020 pandemic, increased nationalisms, and a continued gradual move away from globalization were clearly observed and affected the economic recovery efforts. Built-in passive and dynamic adaptability enablers in manufacturing systems and the extent of implementing supportive advanced technologies played an important role in the ability of manufacturing systems to cope with the drastic challenges posed by the pandemic and the required immediacy of response, but both are effective only within boundaries of anticipated changes and limited by the design of the systems and their components. Defensive passive responsiveness and adaptability proved insufficient in situations of extreme disruptions in manufacturing scope and/or scale. Offense strategies are required to ensure cognitive adaptation beyond the planned scenarios in short order. *Just-in-Case supply chains scenarios* not only Just-in-Time are essential [133,134,135,136]. A conceptualization of a decision-making environment of integrated supply chain (ISN) viability formation through a dynamic game-theoretic modeling of a biological system that resembles the intertwined supply network was proposed [86].

Lessons learned

Effective human-machine collaboration in all aspects of manufacturing is needed as workers proved pivotal and most flexible in making the transition to new manufacturing systems and operation strategies during this time of extreme changes. There is a need for a combination of proactive and reactive manufacturing systems adaptation, however, it is the cognitive adaptation that will play a crucial role in anticipating extreme changes and planning optimal adaptation plans and implementation strategies. These new norms are significantly influencing future manufacturing systems.

The pandemic experience will prove to be a turning point with significant impact for manufacturing and manufacturing systems. For instance, many of the artificial barriers to moving more of the manufacturing activities online will be removed. Not everything can be virtual, of course, but in many areas remote work will become not only feasible but also necessary. Once companies sort out related technicalities, it will be harder and more expensive to deny employees those options. Indeed, a great deal of design, planning, support functions and management meetings can be effectively done virtually and remotely saving travel, reducing pollution, and allowing more flexible work environment so workers can better support their families. It is anticipated that remote will become permanent with more people working from a distance. All these new modes of work in the future will make manufacturing and systems more environmentally, socially, and economically sustainable and more human-centered. Re-thinking the value of work and workers as most important and flexible assets is already on-going but workerless manufacturing systems are not part of the future manufacturing systems paradigms.

The experienced products shortages during the 2020 pandemic emphasized the importance of supporting local manufacturing, research and development, and promoting self-sufficiency that will slowly lead to de-globalization. It will intensify countries investment in innovation in product design and manufacturing technologies to maximize locally owned intellectual property (IP). Supply chains will be re-designed for the unexpected with optional scenarios that embrace uncertainty to increase their adaptability, robustness, and resilience.

5.4. ACMS paradigm characteristics, drivers, and enablers

The evolution of manufacturing systems and future trends towards smart cognitive manufacturing is discussed in this section within the context of the evolution of manufacturing throughout the industrial revolutions from craft production to the current smart manufacturing (Industry 4.0) era and into a future bio-intelligent manufacturing era, in which the augmented human abilities will play a central role in enhanced decision making.

The human cognition capabilities can receive visual cues from the environment and combine them with other sensory information such as sounds, smell and tactile feedback to create perceptual experiences. Perceptual processes depend on the perceiver's expectations and previous knowledge as well as the information available in the stimulus itself. Processing all this information in a lapse of milliseconds makes the humans a very powerful "cognition machine". Furthermore, humans are very adaptable to the environmental stresses, changes, and complexities. In this context, the cognitive system has emerged to meet human capabilities and has been defined as "a system that can modify its behavior on the basis of experience" [79]. In general, it can be said that the term "cognitive system" has been used to define a new solution, software or hardware that mimic in some ways human intelligence.

Manufacturing systems are continuing to evolve in response to may disruptive products, processes and market drivers, and the need to adapt to these changes. The evolution and co-evolution trends of products, technologies, business models, and production paradigms; the accelerated rate of adaptation to change; and research and development of new and disruptive game changing technologies all point to a fundamental change in the ways products are made.

It is envisioned that the next manufacturing systems paradigm will be an adaptive cognitive manufacturing system, coined as ACMS, and characterized by its cognitive adaptability. It differs from static and dynamic adaptability in the manner in which the need to adapt, e.g. due to different products/variants, change in production volume, supply shortages, technological advances, and online changes is recognized and response is triggered, as well as how adaptation gets implemented; will all be enabled and supported by AI modules, smart sensors, extensive information and data analytics, and the automated, cognitive and hybrid human-machine adaptation actions and execution methods and human experience and wisdom. It is a new paradigm where the power of the 4^{th} industrial revolution and beyond is deployed to achieve a more responsive as well as a more *humane* and *human-centric* manufacturing systems driven by economic and environmental sustainability and social responsibility.

Such new ACMS paradigm will be enabled and made possible by predictive analytics, AI enhanced decision making and cognitive behavior such perception, planning, and smart actions as well as effective connectivity and seamless integration. Features of the ACMS will include ability to anticipate changes by continuously analyzing wide range of data collected at all levels internally within the system and externally from other sites, partners, markets, and global trends; and planning and constructing sound strategies for the most appropriate type of adaptability to be implemented and the right timing supported by scenarios for just-in-case disruptions and commensurate physical, logical and strategic mitigation responses. The ACMS will ultimately also be characterized by context and self-awareness, self-diagnosing, self-healing and repairing behavior as well as self-optimizing control and operation strategies. These characteristics will be designed to make it possible to support a healthy symbiotic relationship between human workers and smart automation in an integrated collaborative workspace environment which utilizes essential humans' input to critical tactic and strategic decision making at all levels while also making the nature of work not only safer and more ergonomic but also more fulfilling and rewarding to maximize the satisfaction of the people in the system.

It should be emphasized that the time frame for when ACMS with all its features and capabilities will be developed and implemented in factories was intentionally left out as many of its enabling technologies are still being developed and evolving.

5.4.1. Cognitive digital twin (CDT) transformation

The digital twin (DT) of manufacturing systems has evolved greatly, since the term was first coined in 2002 [65]. In the first stage of digital transformation, DT transitioned from standalone simulation model to a more detailed digital mock-up. The next stage of digital transformation till present saw the introduction of IoT, IoP, sensors and data analytics allowing the digital simulation to become more representative of the physical system and more connected in realtime to its operation. This expanded its use from off-line decision support tool during the design and planning of a manufacturing system to an integrated multi-physics, multi-scale simulation system that uses the most appropriate model, data history and sensor updates to mirror the operation of its corresponding physical system throughout its life from design to implementation and actual operation. This is when it was labeled a digital twin. It is worth mentioning that even in real life human twins are not always identical, hence, the level of granularity and accuracy of a digital twin in model representation, analysis and simulation is a matter of trade-off between the desire for a high fidelity and need for realtime interaction performance depending on the application. Digital shadow is a term used to refer to reduced but sufficient level of detailed representation in favor of delivering time sensitive feedback for realtime adaptive machine and system control.

Introduction of smart sensors, artificial intelligence, and simple machine learning technologies such as pattern recognition to a DT saw the beginning of its cognitive transformation to stage 3 of its evolution. This is supported by the increased application of CPS, which is at the core of smart manufacturing systems (Industry 4.0), that resulted in digitally and adaptively controlled machines with embedded sensors and software, and high connectivity within, and between, machines in the system to collect and analyze pertinent data and control various functions. Digital twins are evolving and growing in sophistication and abilities mirroring the evolution of manufacturing systems as illustrated in Fig. 18.

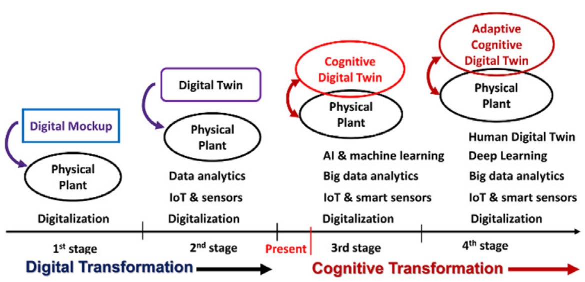

Fig. 18. Digital transformation towards the adaptive cognitive digital twin [Intelligent Manufacturing Systems (IMS) Centre, U. Windsor].

The future cognitive digital twin (CDT) will become not only an accurate digital representation but also an augmentation and intelligent companion of the physical system, including sub-systems, throughout its life cycle and evolution. In the fourth stage of transformation, CDTs will become highly interconnected, distributed cognitive adaptive systems evolving as their physical counterpart grows in complexity and smartness [63]. The adaptive cognitive digital twin will also have built-in models of human operators in the system not only physically but also behaviourally to capture their actions and guide their interaction with increasingly smart, adaptive, and cognitive collaborating robots and machines.

5.4.2. Prognostics predictive maintenance using CDT

Digital twins offer a great amount of business potential by predicting the future instead of just analyzing the past of the manufacturing process. General Electric (GE) currently operates more than 500,000 alive cognitive digital twins [63]. They are used to eliminate guesswork for service and to prevent catastrophic failures because they continuously learn and update themselves from multiple sources representing their near realtime status, working conditions or environmental factors. This learning system learns from itself, via artificial intelligence and/or machine learning algorithms using a trove of data from sensors that convey various aspects of its operating conditions, and from human operators making functional decisions and other human specialists with deep and relevant industry domain knowledge. A cognitive digital twin also integrates historical data from past usage to compare deviation from a baseline.

5.5. Future manufacturing systems perspectives

Highlights of expected features of future manufacturing systems considering the four axes of evolution include:

Products: will be more intelligent, more complex, and more environmentally friendly, include embedded systems and embedded intelligence, and use bio-degradable smart and self-healing materials.

Technology: will witness accelerated progress in exponential technologies including computing, information technology, communication, artificial intelligence applications, machine learning, and deep learning methodologies; advances in transformative manufacturing technologies; development of resilient, communicating, cognitive, and more autonomous machines; and deployment of biologically inspired technologies.

Business Models: will employ digital business strategies and more diversity in operating models; augment "just-in-time" model with scenarios for "just-in-case"; utilize new strategic collaboration and partnership networks; implement pay-per-use business models, such as leasing and subscription that will likely disrupt manufacturing systems with incremental payments for performance and guarantee of usage level a priori. They will ensure more effective scalability of systems capacity and capability by sharing distributed resources among many customers; derive increased value from digital services; use more resilient supply chains and value networks enabled by AI will contribute significantly to competitiveness and offer more support for local manufacturing and local innovation [164].

Manufacturing Systems: will feature maximum flexibility, physical and logical scalability, and agility; and utilize more static, dynamic, and cognitive adaptability enablers to improve productivity and emphasize all three facets of sustainability; increase shared human-machine collaboration and decision making, replace implicit interactions with explicit tasks sharing, and enjoy greater visibility throughout. Future manufacturing systems will use hybrid augmented natural and artificial intelligence in systems operation and control. The use of autonomous machines, robots, production planning and control, enhanced diagnostics, predictive maintenance, and quality verification will be extensive. Using intelligent management and business functions; expanded data and knowledge sharing with cyber-security measures in place will be commonplace.

Digital and physical twins will become inseparable for more efficient and optimum operation, but humans will continue to be an essential part of interactive decision-making on the operational, tactical, and strategic levels.

People are the most adaptable and valuable assets in manufacturing systems. Integrating human experience and insights with machine learning visibility and cyber-physical digital and cognitive transformation requires new skills and upgraded multi-disciplinary education. More versatile and flexible work and workers will be essential. Remote work will increase enabled by enhanced digital operation transparency. The nature of work in manufacturing systems will change, and different jobs will appear to support the new technologies.

The evolving adaptive cognitive manufacturing systems (ACMS) paradigm will become more predictive, adaptive, human-centric, and transparent and will enjoy increased industrial adoption.

6. Conclusions and future research

6.1. Insights and reflections

Manufacturing has witnessed many major changes throughout the first, second and third industrial revolutions. The fourth industrial revolution is characterized by more distributed, collaborative, connected, networked and global manufacturing. Sophisticated and powerful sensors and sensing techniques are introduced allowing better communication between manufacturing entities on the shop floor and throughout the enterprise and beyond. The ever-increasing computing power, speed and storage capacity and novel communication techniques created a very fast wide band information highway making it possible to more effectively utilize IoT, IIoT and IoP and enabled better knowledge-based decisions in realtime. This in turn led to generating huge amount of data (big data) about all aspects of manufacturing and products. Powerful data analytics, application of artificial intelligence, expert systems and machine learning methods made intelligent knowledge-based decision making in realtime feasible. New products with embedded intelligence and the design and control of more intelligent manufacturing systems allow autonomous planning, operation, and execution. Advances in intelligent automation and robotics and their use in manufacturing, along with human workers, presents novel ways of human-machine collaboration.

Advanced software applications and increased computing capabilities are enabling high fidelity simulation and digitalization of all manufacturing aspects including products design, making, use and recycling/re-use throughout their life cycle, as well as systems design, implementation, control/operation and redesign/recycle, and realistic useful mathematical and simulation models (DT, CDT, and ACDT). Smart products and systems which are increasingly multi-disciplinary coupled with increased variety add new layers of complexities and present challenges in managing such complexity while ensuring products and systems robustness and resilience [52,53].

There have been successes and failures along the evolution of manufacturing systems path, which have been used to inform future evolutions. For instance, the early enthusiasm for computer integrated manufacturing (CIM), artificial intelligence and machine learning did not achieve their intended purpose in the past, are now realized with the advent of the Industry 4.0 transformational technologies. The early vision of a fully automated unmanned factory is now being realized in autonomous systems and in human–machine symbiosis. Undoubtedly, the significant advances in manufacturing, information technologies and industrial revolutions will bring transformational change to all aspects of manufacturing and manufacturing systems, and the impact on society and humanity will be profound.

The following sections review how manufacturing systems are being re-imagined, highlight important conclusions, and indicate some directions of future research in the field.

6.2. Manufacturing systems re-imagined

Future manufacturing systems are being re-imagined in many aspects as categorized and summarized in Fig. 19.

Design	Resilient; Robust; Reusable; Adaptable; Co-platforming; Co-evolution; Digital Cognitive Twins; Manufacturing Systems as a Service
Configuration	Reconfigurable (Machines, layout and material flow); Modular; Mobile; De-coupled; Scalable; Changeable
Control/Operation	Semi-autonomous; de-centralized; Adaptive; Reconfigurable; Agile; Responsive; AI enabled; Knowledge driven; Cognitive
Human Capital	Multi-skills; Augmented work; AI support; Human-machines collaboration; Digital physical and behavioral human models; Responsible automation
Scale	Multiscale; Full scale; Smaller niche systems; Mini-system; Desktop/personalized
Location	De-globalization; Urban/suburban; Close to home; Mobile; Networked; Distributed; Connected; Resilient; Adaptive supply/value chains

Fig. 19. Aspects of re-imagined manufacturing systems.

The system *design* will include features to enable static, dynamic, and cognitive adaptability. It will continue to evolve and co-evolve with the four axes of evolution and benefit from biologically inspired designs, tools, and materials. The system design will also be influenced by emerging business models such as considering manufacturing systems as providers of valuable service by producing certain goods as needed. This subscription and pay-per-output model will lead to re-thinking the relationship between customers and manufacturers and affect how manufacturing systems are designed, operated, sized, located, and owned.

The system *configuration* is all the physical modules that make-up the system, their arrangement, and physical and logical relationships between them which define the parts flow. Increased adaptability requires more modularity at the machines, stations and system levels, and sufficient decoupling of function between modules to allow freedom of mobility, reconfiguration, and scalability of the equipment. This level of modular functionality leads to significantly streamlined production scheduling, flow control, changeability, and better cost.

The system *control and operation* will become more de-centralized, reconfigurable, agile, responsive, and adaptive. It will be data-, knowledge-, and AI-driven with many cognitive features such as self-awareness, self- repairing, self-organizing [36,157] and self-optimizing behavior. The control and operation will likely be semi-autonomous or autonomous.

The *human capital* and workers in the system will remain in the loop as important elements of future manufacturing systems but they will have to become multi-skilled through re-skilling and up-skilling for maximum versatility and adaptability in a smarter environment; their work will be AI supported and augmented by collaborating robots and machines to increase efficiency and reduce errors. Digital twins with imbedded cognitive abilities will include physical, behavioral, and cognitive models of human workers abilities which can be used for planning and training. Many work categories will become possible to perform remotely, and work weeks will be shorter. Automation applications in manufacturing systems will be more socially responsible with humans' safety and security at the fore front.

Multiple *scales* of manufacturing systems will exist with a wide range of sizes to suit the needs. Full scale large manufacturing systems will continue for certain types of manufacturing but with added agility, adaptability, and smart cognitive features. In addition, smaller highly agile niche or boutique manufacturing systems will increasingly be used for smaller production of specialty products. Demand will increase for mini-manufacturing systems with full and versatile capabilities and better ability to adapt and reconfigure as needed. Small, mini- and desk-top systems will surge in response to increased demand for more products variety, customization, and personalization, and remote manufacturing enabled by advances in additive 3D manufacturing for producing relatively simpler and smaller size products, will become more common place.

The *location* of future manufacturing systems also will vary from being in industrial sites as usual to more distributed yet well connected and integrated networks of manufacturing systems nationally and internationally. The location and relocation of manufacturing systems will be influenced by the need for more urban, sub-urban, close to home or at home manufacturing [75]; more diversified, resilient and adaptive supply/value chains closer to home base will increase; and increased tendency for de-globalization and protectionism will become evident.

6.3. Challenges and future research

The impact of manufacturing throughout the industrial revolutions up to the ongoing Industry 4.0 is well recognized and documented. The contributions of CIRP researchers and others to the development of manufacturing systems paradigms, drivers, and enablers from changeability (flexible and reconfigurable manufacturing systems (FMS/RMS)) to cyber-physical systems (CPS) and smart manufacturing systems (SMS) are extensively discussed in the literature. Manufacturing systems have been transformed from isolated optimized cells to fully integrated data and product flows within a factory and between distributed locations, with vertical and horizontal communication along the entire value chain. The objective of the earlier computer integrated manufacturing (CIM) is finally becoming realizable with the technological enablers and pillars of smart manufacturing (Industry 4.0). There is still a myriad of related research topics in which manufacturing researchers are actively engaged, and industry (large, medium, and small) continue to develop and implement to achieve the business objectives.

Nevertheless, the future productivity and growth in the manufacturing industries require careful long-term strategic planning of future research directions to reap the desired benefits from their industrial implementation and increase sustainability and competitiveness into the future.

It is recognized that each stage of the evolution makes full use of the results of and experience gained from earlier stages. Therefore, this section focuses on the research targets and topics that are motivated by the new adaptive cognitive manufacturing system (ACMS) paradigm, while recognizing that the earlier research agendas will naturally continue, probably at an accelerated pace. It is also known that the implementation in practice normally lags research results to various degrees depending on the industry sector and company size.

6.3.1. ACMS top strategic technology trends and challenges

Hyper-automation, blockchain, AI security, and autonomy drive disruption and create opportunities in strategic technology areas [139]. ACMS includes many of the Gartner 2020 technology trends such as: a) *Hyper-automation* which deals with the application of advanced technologies, including artificial intelligence (AI) and machine learning (ML) to increasingly automate processes and augment humans; b) *Multi-experience* that aims at replacing technology-literate people with people-literate technology, c) *Human augmentation* which uses technology to enhance a person's cognitive and physical experiences, for example by using smart wearables; d) *The empowered edge* which explores how increasing smart devices are forming the foundations for smart spaces, and moving key applications and services closer to the people and devices that use them; and e) *Autonomous technology* which operates on a spectrum of intelligence ranging from semi-autonomous to fully autonomous, and from stand-alone to collaborative swarms. Additional trends include democratization of technology, transparency, and traceability.

6.3.2. Adaptive cognitive manufacturing systems research

As manufacturing systems evolve to the next stage of adaptive cognitive manufacturing systems (ACMS), there are basic technological challenges ahead while incorporating concepts, enablers and technologies developed in earlier paradigms. New research directions are needed to support the evolution of future manufacturing systems through its digital and cognitive transformations including manufacturing systems physical, sensorial, and cognitive support; static, dynamic, cognitive and extreme adaptation methodologies; modularity, flexibility, reconfigurability, changeability, and responsiveness; more intelligent, cognitive, knowledge-intensive, data-driven cyber-physical and biologically inspired manufacturing systems; and better connected, integrated, and networked autonomous systems.

Smart adaptive automation systems design and operation

An imminent change to a future where fully integrated and inherently intelligent systems, subsystems, and components shall define the next generation of intelligent machines, systems, and enterprises. A great more research is needed to bring this closer to practical applications. Related research topics include: new production system concepts through the study of adaptability, emergence, self–organization, and cooperation; autonomous production systems; bio–inspired manufacturing; human–centric dynamic adaptation; manufacturing as a service; manufacturing on demand; and subscription models for production facilities.

Adaptive cognitive digital twin (ACDT)

Future research includes robust multi-scale mathematical models to increase the accuracy and fidelity of digital twins of machines and manufacturing systems; engineering CPS and IT powerful architectures to increase efficiency and reliability of digital twins and shorten their development cycle; and development of the new cognitive digital twins, and adaptive cognitive digital twins of humans for use in planning of human-centric manufacturing systems and in workers training.

Data processing, perception, and knowledge discovery

A main challenge is to develop systems capable of processing all the needed information and data from various sensors, devices and machines and any other contextual information available to characterize settings in analysis, and retrieve knowledge and past physical, virtual, or human experiences for creating perceptions and augmenting the human experience and expertise and knowledge. There is also need for implementing a human-centric decision making in meshed collaboration with intelligent systems. Therefore, knowledge representations capable of building a multi-modal space composed of information from different sources, in the form of experiential knowledge, would be a very useful tool to facilitate this process.

New smart strategies for vertical and horizontal integration

Physical and logical enablers need to be researched and enhanced to implement further collaboration between the hard and soft enablers, the physical and virtual domains, and the humans in the system. Connecting existing machines and systems, attaching sensors, and collecting large volumes of data are insufficient to make manufacturing systems cognitive. New concepts, theories and practices regarding engineering and design of future systems should be fully researched and developed.

Smart manufacturing systems prognostic maintenance

Prognostics in maintenance intended to predict failure before it happens is an enhanced predictive maintainability strategy which should be further researched and developed as well as AI-based algorithms and supportive cognitive and adaptive cognitive digital twins of systems, equipment and subsystems.

Complexity and trust management

Methodologies for ACMS complexity management, transparency, and traceability; blockchain and AI security with emphasis on ensuring human-centric decision making; and collaboration and mutual trust need further investigation. Careful attention should be paid to the ethical issues arising from use of smart machines, hybrid human-machine collaboration and intelligence. Specific topics include: cyber-security mechanisms and governing regulations and standards as the pervasive use of smart sensors, and data collection with 5G communication networks increase; better built-in protections and safeguards, and developing appropriate guidelines and legislations for operators in the new work environment under smart digitalized operating schemes; legislations for protection of data collected on human performance with digital supports, and regarding human-machine interaction; and socio-technical research regarding implementing socially responsible manufacturing and artificial intelligence.

Supply chain design and operation for the unexpected

Proactive and reactive strategies should be developed for ACMS to plan for inevitable disruptions in a multi-echelon supply chain, since unexpected or black swan events can highly deteriorate supply chains performance. The drastic effects of the COVID-19 pandemic highlighted the need for developing more effective methods and models not only to manage crises in the short term, but also to develop strategic options for future more resilient and robust supply chains.

Innovative dynamic cost models

Companies can achieve competitive advantage by reducing operating cost while investing in automated cognitive manufacturing systems. One of the important factors affecting the adoption and implementation of next generation manufacturing systems is cost. Better business and cost estimation models and comprehensive methods for justification of investments in ACMS and related advanced technologies are needed to accelerate the introduction and implementation of smart manufacturing systems.

Wireless power transfer for improved equipment mobility

The introduction and application of wireless power transfer systems in manufacturing can bring about not only convenience but also improvement in safety and reliability as well as cost savings due to the automatic recharging of AGVs, mobile robots, mobile inspection stations and other manufacturing equipment. In automated production systems and warehouses, AGVs are heavily used in material handling and transportation of material and goods. Optimally placed power transmission pods throughout the factory would help AGVs become self-charging while moving or when they are idle while goods are loaded/unloaded. A battery with a substantially reduced capacity can be used and recharged, thus considerably saving the operation and maintenance costs. New methods, hardware solutions and software tools to encourage using this emerging technology in manufacturing systems need further research. This technology can also facilitate the mobility of mini factories between several locations.

Smart reverse logistics and circular economy

The prospect of nearly 9 billion people on the planet by 2030 is driving leaders to retool their business models to enable their long-term growth and prosperity. Sustainability mega forces continue to change the operating conditions in which companies can succeed and thrive. Smart cognitive systems and ambitious long-term sustainability strategies can help guide manufacturers to contribute to a prosperous future for themselves and the society. New models and justification methods should be developed for making smart reverse logistics and circular economy not only more economically feasible but also to reap the full benefits of the adaptive cognitive principles.

Future manufacturing jobs, learning and training for ACMSs

The next phase of the evolution of manufacturing systems, discussed in detail in this paper, is a cognitive transformation that aims to develop smarter more sustainable factories and business processes. Therefore, the future of manufacturing jobs and the continual learning and training of the workforce is of paramount importance.

Several publications [106,108,198] have noted that AI is introducing asymmetries that are transforming the job market and creating misalignments with the effective technical readiness levels, which is typically the case with any new technology. It is understood that AI will affect some aspects of all jobs to various degrees. Existing literature project a loss in traditional manufacturing jobs, with the possibility that new jobs will be created. Research suggests that organizations adopting smart manufacturing technologies will need a workforce with increased variety of technical skills, autonomy, and interdependence, as well as increased cognitive, creative, technical, and social skills. While automation and AI will likely displace some manual work and entry level jobs, the engineering, planning, and managing tasks as well as all operation activities will remain human-centric, albeit with augmented machine intelligence capabilities, for the foreseeable future due to their relative complexity.

It should be noted, however, that the future is not inevitable. While the existence of the necessary technologies is a precondition for automation, it does not necessarily mean that all manufacturing activities will be automated, because automation depends on several other factors including a) cost of automation; b) cost and relative scarcity of trained labor and required skills; c) benefits of automation and return on investment; d) social acceptance, and e) regulatory issues.

Nevertheless, everyone must embrace change and develop a mindset of continuous evolution, and workers will require continuous retraining in advanced technological skills such as intelligent automation technologies, programming and big data analytics which will grow rapidly. Furthermore, it should be noted that the adaptive cognitive transition will favor social, emotional, and higher cognitive skills, such as creativity, critical thinking, and teamwork all of which machines find hard to replicate. Additional pressure on the already existing workforce skills challenge includes the need for new credentials and certification systems for training people to do the jobs that cannot be replaced by robotics and smart automation.

Finally, it agreed that AI is doing a lot of good in many fields and will continue to provide several benefits for manufacturing while allowing people to enhance their human contributions. However, along with the good, there will inevitably be some negative consequences. That is why humans should remain in control and develop and introduce the appropriate level of automation and intelligence to maintain the overall good. With careful planning, the worst fear by some about "superintelligence" - the point at which computers become more intelligent than humans - can be avoided as humans maintain control of their competitive creations, including adaptive cognitive manufacturing systems (ACMS).

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

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