Journal of Manufacturing Systems 59 (2021) 481–506

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Review

Industry 4.0 smart reconfigurable manufacturing machines

Jeff Morgan [a,*,1], Mark Halton [b], Yuansong Qiao [c], John G. Breslin [a]

[a] CONFIRM SFI Research Centre for Smart Manufacturing, Data Science Institute, National University Ireland Galway, Ireland
[b] CONFIRM SFI Research Centre for Smart Manufacturing, University Limerick, Ireland
[c] CONFIRM SFI Research Centre for Smart Manufacturing, Athlone Institute of Technology, Ireland

A R T I C L E I N F O

Keywords:
Smart manufacturing
Reconfigurable manufacturing systems
Cyber physical systems
Industry 4.0

A B S T R A C T

This paper provides a fundamental research review of Reconfigurable Manufacturing Systems (RMS), which uniquely explores the state-of-the-art in distributed and decentralized machine control and machine intelligence. The aim of this review is to draw objective answers to two proposed research questions, relating to: (1) reconfigurable design and industry adoption; and (2) enabling present and future state technology. Key areas reviewed include: (a) RMS – fundamentals, design rational, economic benefits, needs and challenges; (b) Machine Control – modern operational technology, vertical and horizontal system integration, advanced distributed and decentralized control; (c) Machine Intelligence – distributed and decentralized paradigms, technology landscape, smart machine modelling, simulation, and smart reconfigurable synergy. Uniquely, this paper establishes a vision for next-generation Industry 4.0 manufacturing machines, which will exhibit extraordinary Smart and Reconfigurable (SR*) capabilities.

1. Introduction

1.1. Smarter and reconfigurable

Presently, the world has embarked from the year 2020, a decade promising new digital value [1] on what has been characterized as the 4th industrial revolution, [2]. Digital value has been identified in both increased manufacturing effectiveness and efficiency through technical agility [3], as engineers strive to harness the power of distributed and decentralized technology, from the factory floor to the enterprise Cloud [4]. Objectively, these new digital capabilities and digital aptitude have been made possible by the convergence of high power computation, high speed communication over widespread networks, lower cost sensing, ubiquitous computing, Cloud services, open source tools and frameworks, and unprecedented global software programming literacy.

With this new wave of innovation comes both methods and motive to enable collaborative, agile, intelligent manufacturing paradigms proposed in the past and present [5–9]. In particular, the development of Reconfigurable Manufacturing System (RMS) [9] is expanding rapidly from both an industry and academic perspective [10], due to volatile global demand and emerging new markets [4,11,12]. Furthermore, the COVID-19 pandemic has unprecedently disrupted manufacturing operations and supply chains [13,14], with new demand for critical healthcare products [15], extreme ASAP delivery requirements, and under production and distribution restrictions [16]. Now more than ever, manufacturers are seeking machines which are both 'Smarter' and 'Reconfigurable' (SR*) to dynamically and rapidly meet the requirements of today, tomorrow, and across their product(s) lifecycle.

1.2. Industry demand

RMS support the rapid addition, removal, or modification of process controls, functions, and/or operations, through reconfigurable hardware and software, to scale production capability and capacity [17]. From an industry perspective, the world marketplace has increased the demand for product variety and customization, which has created a competitive need to rapidly provide and scale product types and production volumes [18]. This demand is felt across Small to Medium Enterprises (SME) and Large Manufacturing Enterprises (LME).

For LMEs, the demand represents a shift from mass production to mass customization, and mass individualization [11]. Historically, LMEs have been observed to be reluctant in adopting RMS, quoting high investment costs and lower throughput capabilities [19]. As a result, LMEs largely rely on rigid high yield Dedicated Manufacturing Lines (DML),

* Corresponding author.
E-mail address: jeff.morgan@nuigalway.ie (J. Morgan).

https://doi.org/10.1016/j.jmsy.2021.03.001
Received 24 November 2020; Received in revised form 28 February 2021; Accepted 2 March 2021
Available online 7 April 2021

and the variability provided by Flexible Manufacturing System (FMS) [19]. However, the emergence of "on-demand" customized or 'individualized' products has seen a shift in LME focus towards the research and development of RMS within geographically distributed "moveable factories" [20] or "fractal factories" [21], Cloud enabled product customization, ordering and scheduling [22], and autonomous co-operative industrial robotics [23] "Cobots" [24].

For SMEs, the challenge is far greater, as SMEs do not have resources equal to LMEs, and can be excluded from modern and advanced automation, due to the high technical learning curve associated with their design, integration, operation, and maintenance [25,26]. However, an SMEs agile capability is fundamental to their sustainability in transient markets with shorter product life cycles.

As such, manufacturing SMEs still widely adopt manual manufacturing processes to support the diversity of their products and small batch sizes [27]. This is a significant disadvantage to SMEs, as the capability to dynamically adjust, grow, and ultimately evolve product portfolios in-line with market demand is limited, or split between: 1. manual low volume / high variety batches, and 2. automated high volume / low variety medium to large batches; as depicted in Fig. 1.

Furthermore, the market response to the Covid-19 pandemic has shown volatile demand with limited supply due to broken supply chains and production restrictions [13]. Challenges that are inhibiting supply chains include [14]: inflexible global supply chains with limited transport/storage capability and capacity; shortage of manpower for labor intensive production, new governmental restrictions and risks to employee safety; inviable sustainability due to lack of resilience, adaptability, and slow market recovery. Early responses to some of these challenges, are recognized by manufacturers racing to adapt their production processes [15], exploring new 'service-oriented' supply chain possibilities [16], and a global roll out of the remote workforce.

For both SMEs and LMEs, RMSs have the potential to provide new agility, scaling beyond traditional design methodologies, and potentially provide adaptability and a resilience to future disruptive crises. While the benefits of RMS are well documented in literature [19,28,29], there are also barriers which limit industry adoption, such as higher costs, complexity and lower speeds. Furthermore, some academics state the greatest barrier toward the application of reconfigurable manufacturing is an enterprise's resistance to change [23]. As such, our first research question is proposed.

Research Question 1:

How can an RMS be designed to enable agile capability and capacity, with increased throughput, decreased cost, and be intuitively operable for multi-level enterprise adoption and user operation?

1.3. Academic developments

From an academic perspective, RMSs epitomize the next generation of manufacturing automation, as the technology landscape is evolving [30] from a traditional hierarchical 2D model, as depicted in the ISA-95 standard [31], to a semi-heterarchical 3D model, as depicted in the Reference Architecture Model Industry 4.0 (RAMI 4.0) [32]. RMS developments to-date span different research streams focusing on reconfigurable level assessment, analysis of features and performances, applied research and field applications, and the alignment with Industry 4.0 goals [23]. The recent emergence of tangible state-of-the-art RMS solutions demonstrates a maturity, or "golden age", of the research field, which is in line with the new "smart manufacturing" era.

Scholz et al. [33] proposed a SMARTLAM RMS for custom microsystem manufacturing. This solution identified a dynamic transitional tool chain for 3D printed parts, from design, to process chain selection, to manufacturing machine control and setup.

Adamietz et al. [34] developed a container-integrated RMS, in-line with the 'micro/movable/fractal' factory concept. Key design

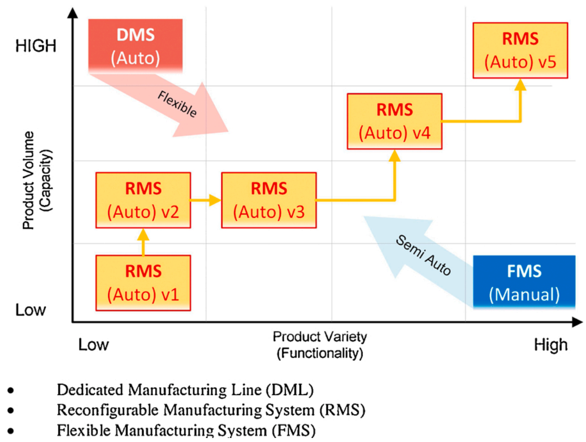


Fig. 1. Production Volume vs Variety, derived from [19].

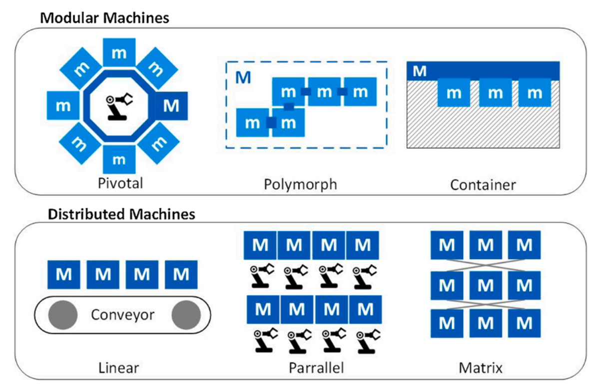


Fig. 2. Examples of Reconfigurable Manufacturing Systems in academic publications.

attributes can be seen in the encapsulation of the RMS in a mobile container, with a unified automaton platform, modular production units, and plug-and-produce control system.

Nikolakis et al. [35] discussed an end-to-end approach for RMS dynamic planning and control, in-line with Cyber-Physical Production System (CPPS) research. This work presents a containerized software framework for high-level planning and low-level execution. Specifically, the Docker software container environment, Python (high level) programming language, and IEC61499 industrial standard for function block (low level) programming of distributed field devices.

Kim et al. [36] explored the concept of a modular factory testbed, emphasizing transformability and modularity within a distributed shop-floor control architecture. This work demonstrates how modular production components, both automated and manual, can be reassembled to produce different product types.

Park et al. [37] outlined a convergence architecture for RMS, which pivoted around a central robot with modular stations positioned in an octagon formation, for personal production in a "micro factory" setting. This solution is a convergence framework of several technologies and research paradigms, including CPPS, Digital Twin (DT), and the P4R information model.

Liu et al. [38], proposed a large scale IoT-enabled Intelligent Assembly System for Mechanical Products (IIASMP), which is in line with the Internet of Things (IoT), and Agent-Based Design. The framework presented spans feature mapping, data modelling layers, vertical and horizontal technology interface levels, and optimization modelling and simulation capabilities.

He et al. [39] demonstrated a high automation RMS which consisted of sequential stages grouped into cells, each containing rail positioned robots and various machines. Core to this work was the exploration of line balancing algorithms to obtain optimal performance and reduce costs in a distributed production scheduling.

Objectively, these RMS represent Next Generation Manufacturing Systems (NGMS), with increased levels of flexibility, reconfigurability, and intelligence [23]. The manufacturing processes these RMSs have been applied to include: additive, subtractive, inspection/test, and robotic handling. In contrast, each solution is highly distinguishable in composition and application, e.g. technology, scale, orientation, etc. as depicted in Fig. 2. A separation in RMS design can be observed between ‘decentralized’ modular machine control, and wider ‘distributed’ control of collective machines, with supervisory control, scheduling, and management. The advancement of these systems are observably defined by: varying Artificial Intelligent (AI) manufacturing paradigms, which are characteristics of Industry 4.0 innovations, such as CPPS, DT, IoT, etc. Furthermore, the design of these systems incorporates varying modern information and operational technologies, and semi-bespoke architectures. For clarity, in literature it has been stated that reconfigurability towards Industry 4.0 has been less explored because of the novelty of the Industry 4.0 environment [23], yet the application of these technologies have the potential to bring new optimization potential [29]. As such, our second research question is proposed.

Research Question 2:

What is a state-of-the-art understanding of RMS from a machine control, intelligence, and technology stack perspective? And what is a ‘future-state’ model for these next-generation Industry 4.0 Smart Reconfigurable (SR*) machines?

1.4. Summary

In summary, a fundamental market and industry need for RMS has been presented. The literature to-date has identified several tangible RMS solutions which demonstrate reconfigurable capabilities in different manufacturing applications. Observably, next generation RMS are aligning with new Industry 4.0 technologies. As such, there is a research opportunity to explore ways to overcome barriers to RMS adoption by industry (Research Question 1); and further provide clarity on modern innovations with a comparative state-of-the-art review of RMS control, intelligence, and enabling technology (Research Question 2). Furthermore, in an effort to demystify and succinctly communicate the new AI capabilities of next generation RMS, the abbreviation is presented as Smart Reconfigurable (SR*) manufacturing machines.

2. Paper scope

This paper provides a fundamental research review of: Reconfigurable Manufacturing Systems - Section 3.1, Machine Control - Section 3.2, Machine Intelligence - Section 3.3. Each section is explored through modern theory, cutting-edge research, and state-of-the-art technology. A short summary is provided at the end of each section, drawing focus to key points and supporting a bridge to the next section. Unique comparatives provided in this paper include: distributed and decentralized control, smart machine modelling, and smart reconfigurable synergy. The schematic of the research topics explored in this paper is presented in Fig. 3. Key findings of the research review are presented in a short summary format in Section 4. A discussion is provided in Section 5, which outlines objective answers to the two previously defined research questions. Finally, a succinct conclusion to the paper is presented in Section 6, in which the authors further discuss the potential impact the technologies reviewed in this paper will have on the manufacturing

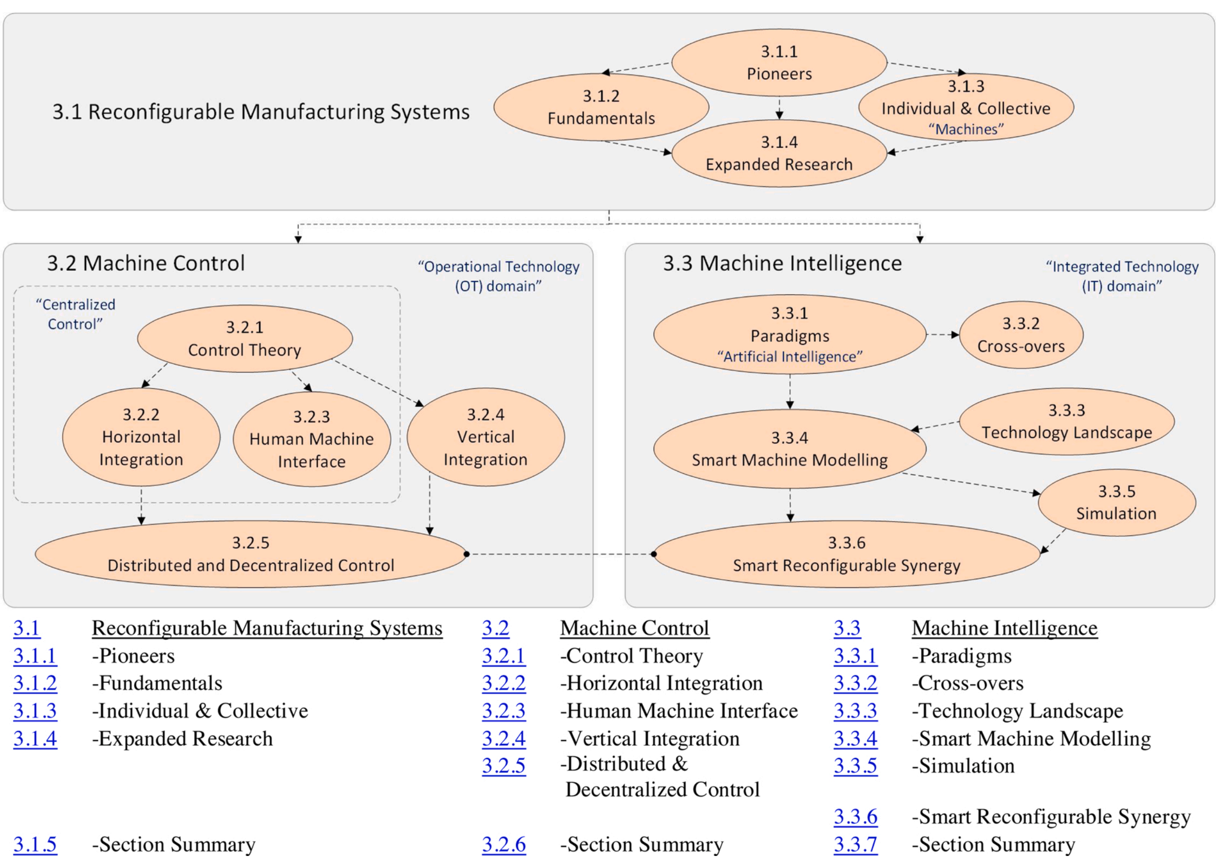


Fig. 3. Schematic of Section 3 - ‘Research Review’.

sector.

This paper utilized an investigative methodology, consisting of a cross university collaboration, which was supported by the Confirm SFI Research Centre. As such, the authors present relevant research articles to succinctly summarize a current state-of-the-art understanding on reconfigurable manufacturing systems, machine control, and machine intelligence; and aligns the subject matter to create a novel holistic perspective. In addition, collective references to research articles are provided periodically throughout the paper to support the reader in seeking in-depth knowledge in relation to certain subtopics. For example, this paper excludes a review of control and intelligence algorithms, as greater focus is placed on enabling cyber physical system frameworks. For these subtopics, collective references are provided.

In summary, this paper is an original contribution to the research community, as it:

- Draws objective answers to the proposed 'research questions', through a holistic perspective of RMS, machine control, and machine intelligence.
- Extends the understanding of RMS within future Industry 4.0 control and intelligence environments.
- Cross references and rationalizes leading research paradigms, with the aim of providing wider visibility and supporting a clearer universal understanding.
- Connects leading theories with state-of-the-art supporting technologies, to guide and promote new accelerated research development.
- Establishes a foundation for what is to be known as Smart Reconfigurable (SR*) manufacturing machines, through a progressive narrative ×, which explores present and future research potential ¤.

3. Research review

3.1. Reconfigurability manufacturing systems

3.1.1. Pioneers

In 1999, Koren et al. [9] introduced the RMS paradigm as a solution to the challenges of a high-paced unpredictable market, citing demand for increased frequency of new product types, changes in existing products, fluctuations in product volumes, changes in government regulations, and changes in production technology. Mehrabi, Ulsoy, and Koren [17] provide further historic context to RMS, by mapping out the chronological scientific, technology, and market factors, which lead to its emergence across the 20th century.

Koren has been a key pioneer in defining and expanding the RMS research field, For reference, key publications include [9,11,17,19,40,28]. Furthermore, three consolidated books on RMS have been published characterizing theory and developments, namely: "Reconfigurable Manufacturing Systems and Transformable Factories" in 2006 [41], "The Global Manufacturing Revolution: Product-Process-Business Integration and Reconfigurable Systems" in 2010 [42], and "Reconfigurable Manufacturing Systems: From Design to Implementation" in 2020 [43]. The following key research content is included from these references to provide context within this present review.

3.1.2. Fundamentals

The RMS definition is a "reconfigurable manufacturing system is designed for rapid adjustment of production capacity and functionality, in response to new circumstances, by rearrangement or change of its components." Changing components can include machines in a system, or modules and mechanisms in individual machines, such as tools, actuators and fixtures (hardware), functions, programs, services (software). New circumstances can include changing product demand (capacity), and new product family variety (capability).

For clarity, Dedicated Manufacturing Lines (DML) are typically designed to produce a single part at a high production rate, which is achieved by fixed simultaneously operations. Flexible manufacturing systems (FMSs) can produce a variety of products, with changeable volume and mix, on the same system. However, FMS typically utilize general purpose technology, which have a range of operational flexibility, but at lower throughput speeds due to sequential operations. This is a tradeoff between speed and flexibility, as depicted previously in Fig. 1. A typical example of an FMS is a CNC machine tool, which is capable of multi-axis dynamic motion, and custom part production. Throughout the literature key focus is given to the correct classification between RMSs and FMSs. For example, CNC machine tools are considered FMSs, but can exhibit reconfigurable behaviors with custom programs, and physically reconfigurable cutting tools. As such, emphasis is placed on the level of reconfigurability in the system, specifically in the control and structure composition of the system. »Koren outlines that 'True' RMSs need to incorporate changeable structures, simultaneous operations, and open control architectures.

Reconfigurable Manufacturing Systems (RMS) are considered "the best of both worlds" as they are designed for change, scaling functional capability and capacity as needed, while providing higher throughput speeds. While reconfigurable capability is highly desirable, it can also be considerably challenging when accounting for wide variability in product dimensions and machine design. A rational argument is made towards designing RMSs around specific part families, as such to narrow scope, and maintain higher automation speeds. This balance between capability and capacity is key to enabling RMSs. Future advancements in RMSs will seek to maximize both attributes.

»There are six original core characteristics of an RMS, which enable a manufacturer to increase their rapid response capabilities and reduce the costs associated with change.

C1. <u>Modularity</u> - agile modular software and hardware system components.
C2. <u>Integrability</u> - component designs for both present integration and future technology introduction.
C3. <u>Customization</u> - system capability and flexibility to meet product family varieties.
C4. <u>Convertibility</u> - changeover between existing products and adaptability for future products.
C5. <u>Scalability</u> - ability to expand overall system capacity, the counterpart to convertibility.
C6. <u>Diagnosability</u> - ability to identify sources of quality and reliability problems, and the tuning of readily configured systems.

Additional desirable characteristics of an RMS include:

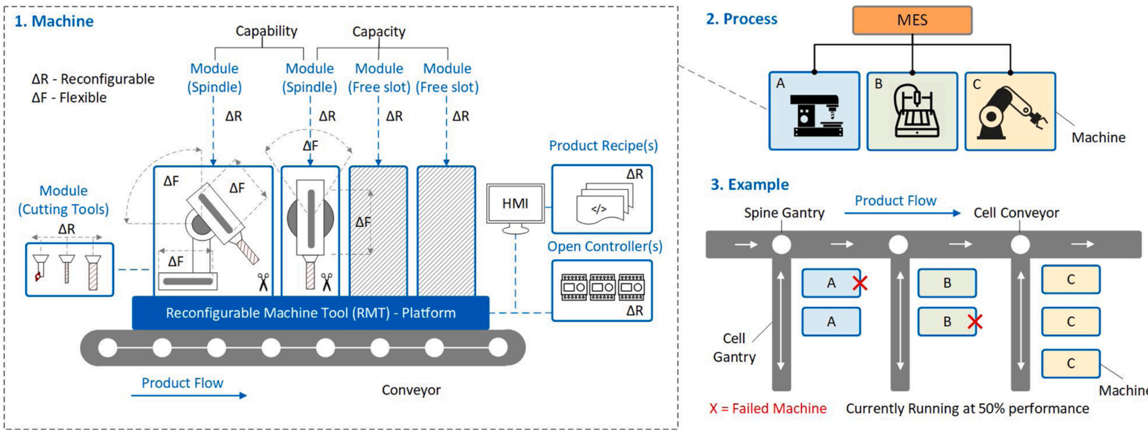
C7. <u>Mobility</u> - ability to move products through the system (transport mechanisms and resources).
C8. <u>Adaptability</u> - ability to be responsive to changes in production volume and product characteristics.

3.1.3. Individual & collective

×RMSs are considered holistically, from an individual machine/system perspective, to a collective of machines/systems.

Individual reconfigurable machine examples are provided with reference to: Reconfigurable Machine Tools (RMT), Reconfigurable Assembly Machines (RAM), and Reconfigurable Inspection Machines (RIM). An example of an RMT can be seen in Fig. 4-1. This example identifies the multilayered modular capability of a reconfigurable machine, including both flexibility ΔF "to bend as part of the body" [44], and reconfigurable ΔR "to change the shape or formation" [44]. The composition of this example adheres to the RMS definition and characteristics, for hardware, software, and control architecture.

When considering a collective of machines to form a cell or system of cells, the RMS definition and characteristics are maintained. However the composition of such systems can be heterogeneous in nature. Meaning, an RMS can consist of a mix of Dedicated, Flexible, and Reconfigurable machines. This higher level 'cell' or 'system' grouping in



1.Reconfigurable Machine Tool (RMT) Concept, derived from [42] [45]
2 & 3.Example multi-stage manufacturing, derived from [19]

Fig. 4. Reconfigurable Manufacturing Systems (RMS).

machining is standard in manufacturing factories, where parallel machines, cells, and systems produce a variety of product types and product volumes. From a production control perspective, it is typically considered in terms of Supervisory Control And Data Acquisition (SCADA), and Manufacturing Execution Systems (MES). From a manufacturing processing perspective, it can be described in terms of manufacturing 'streams' or 'multi-stages'.

Multi-stage manufacturing systems can allow for several operational configurations, depending on how the machines/stages are arranged, and depending on how the machines are connected via the material handling system. A configuration classification model is presented in Fig. 3-2 and -3, which is derived from [19,42,45]. The importance of parallel operating machines of the same type and asynchronous transport mechanisms, such as conveyors, robots, and Automated Guided Vehicles (AGV); is emphasized, to enable a resilience to failure in the system.

For example, if one machine fails, the machine must not be a "bottleneck", and product flow through the transport system must be possible. This is illustrated in the RMS model depicted in Fig. 4-3, in which the machines with X's have failed, yet the system will continue to operate at 50 % performance, due to the parallel operation of identical machine types, and the asynchronous transport mechanism. This resilience is a key economic efficiency of the RMS paradigm.

Further economic values of RMSs are considered in regards to the responsiveness of a manufacturing enterprise to deliver the desired product, in the correct quantity, at the correct time, and at the right place. When analyzing cost vs capacity, RMS are observed to exhibit high initial cost/investment, with low incremental scaling cost when compared to DMLs, and higher maximum capacity when compared to FMSs. Economic value is also observed in RMSs with faster time to market for new product types associated with established product families. Furthermore, RMSs exhibit higher productivity as the systems are systematically designed to change, with rapid "changeover" speeds between part types.

3.1.4. *Expanded research*

The characterization and expanse of RMSs have been well documented in literature over the past 20 years, with multiple review papers [18,23,46–48], and more recent publications providing supportive design methods [10,49,50], optimization analysis [51–53], overcoming challenges [29,54,55]. As such, the following key research contributions from these review papers, and a collection of original contribution papers; are provided for context within this present review.

In 2007 Wiendahl et al. [56] reviewed 'changeable' manufacturing systems, taking a holistic view of the enterprise. In this work, changeability is recognized with scaling production and product levels, from changeover-ability, reconfigurability, flexibility, transformability, and agility. The authors attribute the acute economic benefits of 'changeability' in manufacturing when considering the life-cycle of the system. Changeable systems have a reduction in changeable costs and time to market, for product variation and volume. Therefore, the high investment costs of changeable systems will have a Return On Investment (ROI) breakeven point with traditional systems, which is dependent on the number and extent of necessary changes to the system in the future. Furthermore, changeable systems allow for agile production of different products, whose volumes taken separately would not justify the adoption of a specific production system, but together they can justify the adoption of a single system capable of producing all of them.

In 2008, Bi et al. provided a state of the art review on RMSs [47], identifying RMS as a means to reduce lead-time, increase product variants, handle fluctuating volume, and reduce cost. Key to this capability is the reduction of direct and/or indirect activities, associated with change, e.g. time and burden. The authors made reference to the ability of an RMS to be generalized to consider all levels of a manufacturing enterprise, and focus their work on systems on the "shop-floor". As such, the author identified three design issues with RMSs, spanning: Architecture (mechatronics), Configuration (variables and parameters), and Control (software). Fundamental to this is the design stage in which the process requirements need to be considered in regard to RMS characteristics.

Marco Bortolini et al. [23] provided a comprehensive literature review of RMS up to 2018, which characterized the research into streams, such as: level assessment, analysis of features, analysis of performance, applied research, and Industry 4.0 alignment. The major findings of this study recognize a need for the adoption of more rigorous analytic metrics for assessing reconfigurability level, and the need for successful case studies and best practices to efficiently drive the transition of modern industrial companies toward reconfigurable manufacturing.

Amro Farid [57] established measures and characteristics of reconfigurability in intelligent manufacturing systems, in line with Levels 0–3 of the ISA-95 standard. The measures exampled include the identification of reconfigurable 'potential' and the understanding and establishment of reconfigurable 'ease'. Furthermore, the author identified four pieces of information required to describe reconfigurability: 1. Definition of system and its boundary; 2. Definition of system configuration; 3. Description and rationale for a desired set of reconfigurations; 4. Description of time/cost/effort of potential reconfigurations. The RMS characteristics examined span C1-C4 of the core characteristics of RMS [40]. »A key observations include: the consideration of C1 'modularity', the coupling and decoupling systems, which is not just physical mechanisms, but span multiple control levels, with modular physical, electrical, and information interfaces. This thought pattern is shared by Koren et al. [9] who visualizes an RMS in modular blocks, similar to which modern Object Orient Programming (OOP) methods.

Andersen et al. [10] examined the design methodology associated with RMSs, and proposed a generic design method. This method defines a flow from plan development, requirement specification, design concept, design specification, implementation and reconfiguration. Key to this work is defining the 'long term' view for the manufacturing system, from functionality and capacity; and understanding the degree, type, and level of reconfigurability needed. The authors conclude that there is a lack of RMS research on how to "actually solve design issues in practice", with current state tools providing advanced decision support, which has proven difficult to apply in commercial manufacturing.

Saliba et al. [58] deployed a field study to discuss various aspects of automation use and RMS capability with commercial manufacturers. The results of which indicated that "industry recognizes the benefits of reconfigurable manufacturing assembly systems and are employing systems of this type, however the potential of such systems may not yet be exploited to the full". Through this field study, and RMS research, the authors defined guidelines for manufacturing companies that are considering modularity and reconfigurability of equipment, to increase their competitiveness by improving their production systems. Some key guidelines include: recognizing the value of human investment and time investment for production improvements; seeking process improvements through simplification; and learning to recognize what 'not' to automate.

Gauss et al. [59] proposed a design method to support the planning, conceptual, and system-level design of modular machine families for RMS. The authors drew references from various areas including: Expectation Maximization (EM) clustering algorithms, decomposition/classification trees, planning flow charts, classification schemes, systematic selection charts, and design process hierarchies and matrices. The result is an intricate framework, which assists in the definition, classification and relationship visualization of: Design Parameters (DP), Functional Requirements (FR), Working Principles (WR), Design Modules (DM). This work identifies a top-down approach for "engineering-to-order" manufacturers who wish to understand their reconfigurable requirements for different product families.

Najid et al. [60] outlined an engineering based methodology to design RMS with the ISO/IEC/IEEE15288 standard. This standard outlines a common framework consisting of process descriptions for describing the life cycle of systems created by humans. The authors makes references to the Verification and Validation (V&V) process required for machines. For clarity:

- Verification - Objective evidence that a system, or system elements/modules, fulfil their specified requirements and characteristics
- Validation - Objective evidence that the system, when in use, fulfils its intended purpose, in its intended operational environment.

As such, each configuration of a RMS, from individual module to whole system, will need V&V, taking into account the perceived risks, safety and criticality of the unit. All changeable, or ΔR aspects of the RMS will need to be analyzed for present and future requirements. Uniquely, changes in the future will be streamlined for V&V, as the change to the system will either have already been considered and require no further or minor V&V; or the strategy and requirements for the change will already have been pre-defined. Furthermore, safety, ergonomics and human factors are considered by Bortolini et al. [61], for the individuals who need to interact with and reconfigure RMSs. All of which should be included in a V&V process.

Yelles-Chaouche et al. [29] surveyed RMS literature in order to characterize production optimization objectives, challenges, and solutions. In this work, the authors notably separate industry implementation objectives between the machine and system level, and further classified objectives in regards to cost, time, reconfigurable, and operational capacity. Furthermore, the authors examine RMS optimization problems relating to machine design, production planning and scheduling, layout, and line balancing. In the conclusion of this work, the authors suggest research directions for RMS optimization, including: material handling, product family modules, anticipation over reactivity, and online digital configuration design and planning systems.

3.1.5. *Summary*

In summary, the fundamentals of RMS have been reviewed, including: characteristics, comparatives with dedicated and flexible systems, and a discussion on individual reconfigurable machines and collective reconfigurable systems. The references that support this Section, range from pioneering research papers, wider review articles, and more recent papers in the RMS research field.

Key research content from this Section is summarized in Section 4 - 'Table 1', with focus placed on a fundamental understanding of RMS: design rational, economic impact, needs, and challenges. In the following Section 3.2 - 'Machine Control', the state-of-the-art in Operational Technology (OT), for controlling reconfigurable manufacturing machines, and reconfigurable manufacturing systems, is explored.

3.2. *Machine control*

3.2.1. *Control theory*

The fundamentals of modern machine control are represented in 'control theory', more specifically "closed-loop" systems [62]. ¤In such a system a controller is in operation of a target system, by measuring input signals, applying logic, and outputting control signals to influence or control the target system. Furthermore, the measured output of the target system is feedback, in a closed-loop; to the controller, which will compensate or adapt to dynamic disturbances and achieve the desired output. The number of control loops in operation in a single machine varies between applications, with advanced machines utilizing multiple feedback control units, for example axial robot positioning. ×In a manufacturing plant, these control loops are compounded when viewing the machine as a unit within a cell, a system, and a plant. ¤This represents the horizontal and vertical integration of sensing, actuating, control, management, and logistics systems. Often commercially referred to as the merger, or convergence, of the Operational Technology (OT) domain, and the wider Integrated Technology (IT) domain. Furthermore, this abstraction of control throughout layers of computational devices and networks is academically referred to as a Cyber Physical System (CPS) [63], which is explored further in the Section 3.3.1.

3.2.2. *Horizontal integration*

Typical OT control hardware for manufacturing machines are Programmable Logic Controllers (PLC) [64]. A PLC is an industrial computer that is standardized, e.g. IEC 61131; for the control of manufacturing processes which require high speeds, high reliability, robust hardware, easy of programming, and process fault diagnosis. Fundamentally, a PLC enables the programming of logic in connection with Inputs/Outputs (I/O) to control a process. This logic is programmed through industrial standardized languages, such as: textual languages, e.g. an instruction list, structured text; and graphical languages, e.g. ladder diagrams or function block diagrams [65]. The software modularity and execution is characterized by: configuration, resources, tasks, programs, functions & function blocks [66]. PLCs which incorporate higher level programming capabilities are commonly referred to as Production Automation Controllers (PACs). PLCs and PACs traditionally utilize proprietary Real-Time Operating Systems (RTOS) to enable their operations to be deterministic, and are utilized in safety control applications. However, modern programming techniques such as Object Oriented Programming (OOP), has been included in a revision of the IEC 6113 standard [67].

The capability, cost, and size of a PLC varies between Original

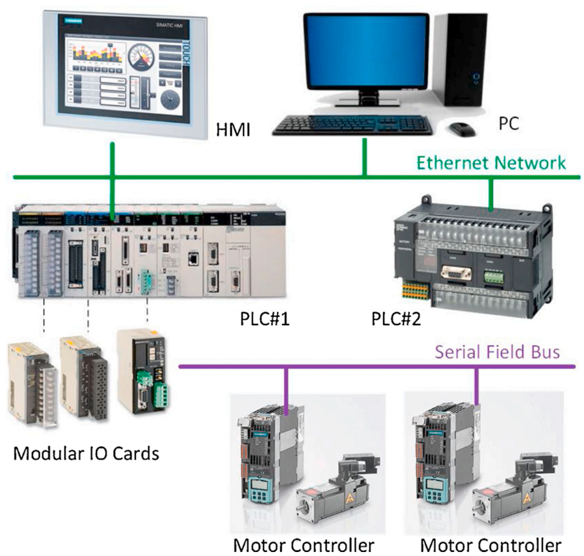


Fig. 5. Standard Automation Control Architecture, derived from [77].

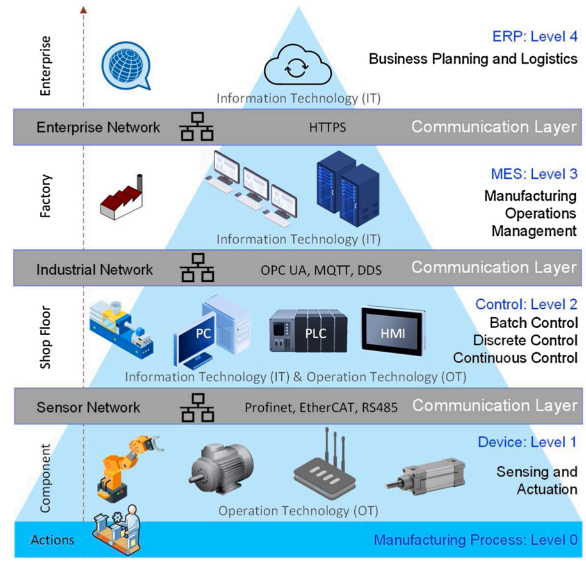


Fig. 6. Manufacturing Control Hierarchy, derived from [84,85].

Equipment Manufacturers (OEMs), e.g. OMRON, SIEMENS, ALLEN BRADLEY, WAGO. PLCs can be highly integrated solid state devices, or decentralized modular devices with expanding I/O and communication capabilities, as depicted in Fig. 5. PLCs are key to effective manufacturing automation, as their capabilities are used in proven production environments, their tools are standardized and tuned for engineers to utilize, and their design is reconfigurable to meet the requirements of nearly any application. Standardized serial and parallel communication mediums/protocols enable PLCs to be further interoperable/collaborative (horizontal integration), with other PLCs, computers, devices, and sensors. Examples include: RS232, RS485, DeviceNet, Modbus, Profibus, EtherCAT, etc. These communications protocols make use of various network topologies including: peer-to-peer, daisy chain, ring, star, tree, etc. [68]. To further support this horizontal integration, functional block programming for distributed systems is standardized in IEC 61499, which is an event-driven execution/triggering model [69]. Another example is the open source Distributed Control and Automation Framework (DCAF) for Labview graphical programming, and PLC and PAC integration [70].

A standard model for machine control is defined in the ISA-88 standard for 'batch machine control' [71]. This standard defines several hierarchical models to modularize machine control, such as the Process model (Process, Stage, Operation, Action), the Physical model (Enterprise, Site, Area, Process, Unit, Equipment, Control), and the Procedure module (Procedure, Unit, Operation, Phase). Concepts such as 'recipes' and standard operating 'states' are introduced. A Recipe provides a way to describe products and how those products are produced, with the minimum set of information. Machine states define the operating condition of the machine, such as: running, pausing, idle, stopped, aborted, etc. (state transitions are also structured). Furthermore, machine standardization can be identified in the PackML standard, for packaging machines [72]. The PackML standard is a consortium of standards, such as ISA-88; for more holistic machine standardization, and uniquely includes standard data, such as: PLC data tags, Overall Equipment Effectiveness (OEE) data, Root Cause Analysis (RCA) data.

3.2.3. Human machine interface

Human-Machine Interfaces (HMI) originated as buttons and switches before the introduction of the integrated computer chip, and at present incorporates digital displays, dashboards, and touch screens in modern control systems. A HMI represents a translation system between humans and machines, and their effectiveness is dependent on their designers and their human operators. The roles HMIs play in discrete control have been a focal point for academics, who recognize the sociological importance of human factors [73–75]. As such, HMIs have the power to introduce risk and inefficiencies into a system, with human error and complex controls. On the other hand, HMIs also have the power to reduce risk if designed and implemented correctly, with intuitive controls and insightful displays, to provide effective decision support and control.

In modern IT systems, the importance of HMI or Universal Interface (UI) and User Experience (UX) is paramount to the success of the application, and is a profession of its own [76]. In modern OT systems, the sophistication/complexity of HMI is defined by the designer, set by the discrete control capabilities of the controller, and the interpretability requirements of the user.

From a technology perspective, these systems can be separate units, e.g. computer-to-controller, or singular units, e.g. computer-integrated-controller [77]. The significance of collaboration is made even more evident when considering the flow of product design to production control, from Computer Aided Design (CAD) to Computer Aided Manufacturing (CAM) to Computer Numerical Control (CNC) [78]. As such, the intuitive capabilities of the HMI unlock the reconfigurable capabilities of complex machines. State-the-art HMI research has been carried out in areas including: wearable Augmented Reality (AR) devices [79], projection-based assembly AR [80], vision recognition in robotic safety and collaboration [75], and verbal recognition interfaces [81]. Modern AR vendors include: Re-Flekt, Vuforia, Teamviewer AR.

3.2.4. Vertical integration

A standard 2D model for machine control in manufacturing systems is defined in ISA-95 for the 'integration of enterprise and control systems', such as MES and ERP [82], as depicted in Fig. 6. For context, low-level control systems, as reviewed in Section 3.2.2 - 'Horizontal Integration'; are represented in Levels 1 & 2, from sensing, actuating, continuous control, discrete control, and batch control. Initial vertical control integrations are traditional recognized in Supervisory Control And Data Acquisition (SCADA) systems. SCADA systems can be localized at the machine level, or represent factory wide systems, providing live dashboards and remote process controls. MES and ERP are responsible for production scheduling, operations management, resource planning. For example, an MES creates validated records of production information, can govern recipe management, and track/trace a product throughout a factory. Typically an MES has central management, with transactions being service oriented, through direct network connections to a machine, and/or manual HMIs on the factory floor. MES examples include: SAP MES, SIEMENS SIMATIC IT, Critical Manufacturing,

From an IT and OT convergence perspective, the different layers of the manufacturing structure identify a need for different computation capabilities [83–85], as depicted in Fig. 6. For example, Low level systems/machines, in the OT domain; require robust real-time control systems. The separation in commercial compute technology and industrial compute is recognized in the requirements of industrial technology to be validated for industrial environments, such as extraordinary vibration, and for exceedingly long life spans, e.g. potentially 10–20 years. In contrast, high-level systems in the IT domain, such as MES, require their own form of resilient computation, such as data-center servers, with high connectivity, service load capacity, and redundancy. The integration of high and low level manufacturing systems, is typically achieved through ‘servers’, also referred to as ‘message-brokers’, ‘middleware’ or ‘Data Distribution Services (DDS)’; all of which are well documented, standardized, and reviewed [86–90]. For reference, some common communication protocols include: MQTT, AMQP, HTTP, OPC DA, etc. Modern examples of IT/OT middleware which unify IT/OT protocols and dynamically integrate enterprise applications, include: DeviceWise, Kepware, Ignition, Kafka, RTI DDS.

¤Presently, a new model has emerged to take into account the new connectivity, interoperability, and data centricity of Industry 4.0 technology, namely the Reference Architecture Model Industry 4.0 (RAMI 4.0) [32], as depicted in Fig. 7 [91]. This model is a Service Oriented Architecture (SOA), which depicts an open 3D connectivity landscape, referencing factory hierarchy levels, machine life cycle management and data (type/instance), and technology layers. One unique aspect of this model aims to encapsulate assets in an IT ‘administration shell’ to autonomously integrate the asset or object with new vertical and horizontal integration capabilities and resources [92]. The Administration Shell is composed of interconnecting standards, for data access, data security, data structuring, and safety [93]. An example of interconnecting ‘collaborative’ standards can be seen in OPC-UA and AutomationML engineering plant information representation [94], OPC-UA and IEC 61131−3 PLC data modelling for universal monitoring and control [95]. Furthermore, industrial technology providers are now embracing the connectivity requirements of the “smart” or “digital” factory, by providing unique connectivity and data access services natively in PLCs/PACs. Examples include: SIEMENS integrated OPC-UA servers [96], WAGO Cloud enabled MQTT communication [97] with the ‘sparkplug’ specification [98].

¤×Collectively, this new ‘digital factory’ horizontal and vertical connectivity and interoperability, identifies a shift away from strictly centralization hierarchical designs and towards more technically agile, distributed and decentralized designs [99–101], which is characteristically fundamental in RMSs, as outlined in Section 3.1.2. Comparably, the equivalent, or ‘mirroring’ of distributed and decentralized computing infrastructure (IT), is observed in distributed and decentralized machine/process control (OT). Both of which are enabled through a combination of Information and Communication Technology (ICT) systems, which is further explored in Section 3.3.3.

3.2.5. Distributed and decentralized control

Decentralization and distribution is not a new concept in machine control [102]. The decentralized modularity and interconnectivity of field-level control devices and sensors through fieldbus technology, is standard automation design [103], as seen in Fig. 5. The distributed connectivity of controllers, machines, and systems through ethernet networks for SCADA and MES, is a standardized industry hierarchy. However, the classification of decentralized and distributed control can commonly be interchanged in automation [104]. As such, within this present review paper, a clear separation is established.

In industrial automation design [105], distributed control systems are distributed both geographically and functionally across a plant, and these system communicate among themselves and other systems/terminals to carry out all necessary control functions for large plants/processes.

In academic control research, the author Lubomír Bakule [106] has defined an overview of decentralized control theory for large complex systems. In this work, the author classifies decentralization in parallel to decomposition. As such, decentralization enables completely independent implementations of control stations, and decomposition represents a simplified synthesis of tasks, which reduces computational complexity. Furthermore, the author identifies distributed control as decentralized control systems with non-strict hierarchical relationships, as seen in Fig. 8-A.

In distributed production control research, the author Damien Trentesaux [3] identifies decentralized control as a form of distribution, in which the decisional activities that are assigned can be seen as local control activities. Furthermore, distributed control was sometimes used in the context of distributed resources. Fundamentally, the author characterizes the centralized, decentralized, and distributed control patterns, by: hierarchical, semi-hierarchical, and heterarchical relationships, as seen in Fig. 8-B. Therefore, distributed control systems

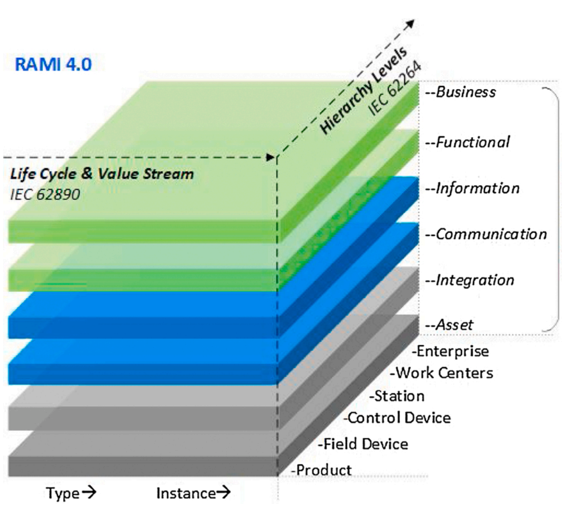
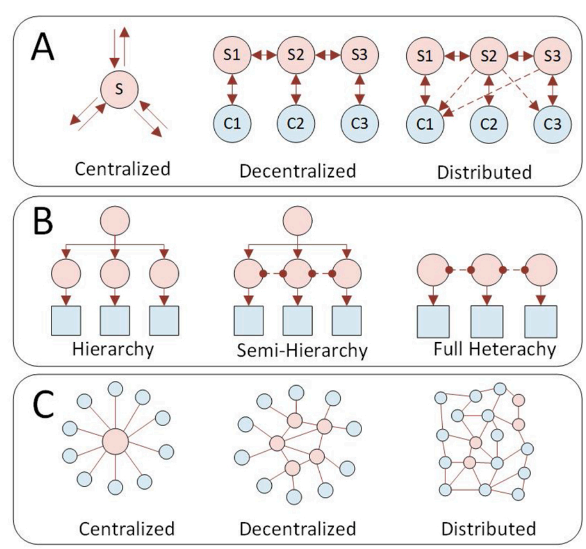


Fig. 7. Industry 4.0 Reference Architecture Model (RAMI-4.0), as presented in [91], CC Platform Industry 4.0.



A: Decentralised Control Systems, derived from [106]
B: Distributed Production Control, derived from [3]
C: Distributed Network Communication, derived from [108]

Fig. 8. Comparitive of Decentralized and Distributed system Theory.

are referred to in both semi-heterarchical (Class II) and fully-heterarchical structures (Class III).

In the area of decentralized modular control research, the authors M. S. Essers and T.H.J. Vaneker [107] identify centralized control in traditional hierarchical structures, and decentralized control in heterarchical structures. Key observations made with decentralized control systems are that they: have no centralized control unit; grow in size without growing in complexity; are resilient to single point of failure; utilize intelligent collaboration among components; and have problem solving capabilities.

In network communication [108], there can be observed a decentralized network consisting of a semi-hierarchical, collaborative core of nodes, with sub-connecting peripheral nodes. A distributed network consisting of unstructured meshed peer-to-peer interoperable nodes is seen in Fig. 8-C. A key differentiation is made when considering redundancy in communication, as a central system has no resilience, a decentralized system has some resilience, and a distributed system is highly resilient.

In distributed computing [109], the configuration of a distributed system is considered as 'decentralized' if none of the participants in the system are more important than the others, as such if one of the participants fails it is neither more nor less harmful to the system than any other participant failure in the system. Furthermore, decentralized systems are highly scalable as they can seamlessly 'add' or 'remove' the components or resource pool in order to accommodate varying workload. Key examples of distributed and decentralized technology include cloud platforms [110], and blockchain-based transaction management frameworks [111].

While there is some ambiguity between distributed and decentralized definitions, there are key traits for universal control classification. Therefore, manufacturing systems can be seen to exhibit a variety of centralized, decentralized, and distributed control relationships, with both 'vertical' and 'horizontal' integration. From a distinct machine control perspective, and for further reference within this paper, the following definitions will be used:

- Centralized Control (CC) - maintain a singular central control unit, which can control technology locally. Horizontal integration. Hierarchical structures.
- Distributed Control (DC) – multiple control units, which can control technology and systems locally and globally. Vertical and horizontal integration. Hierarchical to Heterarchical structures.
- Decentralized Control (DZC) - multiple control units, operating in parallel, which are of equal importance, enable a resilience to failure, and can have identical or different functions. Vertical and horizontal scaling. Hierarchical to Heterarchical structures. resilient

¤DC and DZC are extensible open architectures, and support RMSs both individually and collectively, as discussed in Section 3.1.3. It is important to note, that within this paradigm, control units are not defined by any specific hardware or software components. Additionally, the classification of control system is not ubiquitous or inherent. For example, a supervisory DC system can consist of multiple CC machines, or a DZC multi cell system can consist of CC, DC, and even DZC machines. For context, traditional manufacturing systems operate with CC systems and vertical hierarchies. Both DC and DZC represent an advanced state of control capability, which can take advantage of standardized Industry 4.0 connectivity and interoperability.

With new capabilities, comes new challenges. DC and DZC systems rely on network communication, and are subject to constraints on communication bandwidth, congestion, and contention for resources, delay, jitter, noise, fading, and the management of signal transmission power [112]. The real-time control demands need to be verified through the various feedback paths in the network, under various conditions. Further challenges in DC production systems are identified in [3,113,114]: Guarantee of optimal or satisfactory performance, such as real-time performance; Increased complexity of design methodology; Shared decisional control autonomy; Development and scalability costs; Human understanding and managerial trust in behavior. Key issues of DC and DZC applications within sensor networks are identified in [115], such as: location determination, time synchronization, reliable communication, cooperation and coordination, and security.

×Finally, when considering the classification of control systems holistically, it is important to take into account the system's control composition, horizontal and vertical relationships, and level of intelligent behavior. For example, a centralized hierarchical MES connected to a collection of identical parallel operating cells could be considered as a supervisory DZC system. As such, if one cell fails, the other cells will continue to operate. ¤This passive redundancy brings into perspective the fundamental of what modern control is, e.g. "to compensate or adapt, to dynamic disturbances and achieve the desired output". Therefore, the DZC system 'composition' would need to be resilient to a single point of failure. As such, it could be 'flexible' to continue operation within its current formation (passive), or potentially 'reconfigure' and rapidly adjust its formation or function (reactive). To achieve this an intelligent DZC would act, or 'behave', in some way to adapt and overcome the issue. A 'behavior' could be to divert product flow, activate redundant machines, or reschedule production shifts to meet production targets. While this horizontal and vertical, or "holonic" control could be considered convoluted. It is becoming more important as machine control and intelligence is becoming more distributed [116], decentralized, and resilient at all control levels, which is a fundamental vision of smarter manufacturing [117]. ×This Smart Reconfigurable (SR*) adaptive capability is supported by several distributed and decentralized machine intelligence paradigms, from interoperable IT, collaborative AI, to digital avatars.

3.2.6. Summary

In summary, the fundamentals of modern machine control have been reviewed, including: control theory, Human-Machine-Interfaces (HMI), horizontal and vertical integration. The state-of-the-art in Operational Technology (OT) is established with reference to appropriate research papers, wider review articles, and technology providers. A unique comparative is made between Centralized Control (CC), Distributed Control (DC) and Decentralized Control (DZC) systems. Objectively, DC and DZC architectures support modern RMS both individually and collectively. Some key opportunities for RMS innovation are recognized in: advanced machine controllers that are capable of higher programming capabilities to support reconfigurable tasks; intuitive HMI technology to support user design and operation of complex reconfigurable machines; the utilization of data acquisition and distribution services for collective RMS monitoring and control; and the adoption of new Industry 4.0 control and data standards to enable universal Service Oriented Architectures (SOA) for DC and DZC in digital factories.

Key research content from this Section has been summarized in Section 4 - 'Table 2', with focus placed on DC and DZC: classification, benefits, and challenges. In the following Section 3.3 - 'Machine Intelligence', distributed and decentralized systems will be further explored through enabling Artificial Intelligence (AI) paradigms, and the wider Integrated Technology (IT) environment is examined for enabling both smarter reconfigurable (SR*) manufacturing machines and SR* manufacturing systems.

3.3. Machine intelligence

3.3.1. Paradigms

Distributed and decentralized intelligence paradigms in manufacturing have been extensively explored by academics over the past half-century. These paradigms include: Agent-Based Design, Holonic Manufacturing, Service Oriented Architecture (SOA), Industrial Internet of Things (IIoT), Cyber Physical Systems (CPS), and the Digital Twin (DT). For detailed reference, there are multiple review papers at present detailing their origin, theory, and application [101,114, 118–122]. Furthermore, the incorporation of these paradigms within RMS has also been explored, and is continuing to be explored [35,37,38, 118,123,124]. However, a universal challenge across each paradigm is the ambiguity of each of their definitions, overlapping aspects, and hybrid connectivity. While any definition is not being disputed in this paper, the following key research content is provided for context in this present review.

Computational Agents emerged within the Distributed Artificial Intelligence (DAI) research domain [125]. An Agent is a computational system that is situated in a dynamic environment and is capable of exhibiting autonomous and intelligent behavior [126]. Agents operate in an environment by interacting with other agents through Information Communication Technology (ICT), and as such act as a 'whole' system [126]. Key properties of an Agent include autonomy, intelligence, adaptation and co-operation [114]. Collectives of Agents are called Multi-Agent Systems (MAS), which emphasize self-optimization capabilities and dynamic reconfiguration through collaboration [127].

Holonic systems were devised to explain the evolution of biological and social systems, where Holon's represent singular entities and form 'scalar chains' of holonic systems [128]. At each level of reference in a Holonic system, the Holons can be considered to consist as part of a higher-level system and to contain lower-level subsystems of their own. In manufacturing systems, a Holon is autonomous and cooperative building block, for transforming, transporting, storing, and/or validating information and physical objects [118]. Holons are designed with capabilities such as self-autonomy, cooperation, and are capable of forming hierarchies and heterarchies to achieve global goals.

Service Oriented Architecture (SOA) is a set of architecture tenets for building autonomous yet interoperable systems [129]. Autonomous refers to being created independently of each other, operating independently of their environment, providing self-contained functionality. Interoperability refers to the abstracting of the service via the interface the service exposes to its environment. Within the manufacturing domain, SOA has the potential to provide the necessary system-wide visibility and device interoperability for complex collaborative automation systems [119]. The Industry 4.0 standard RAMI 4.0 is referenced as a SOA, as outlined previously in Section 3.2.4.

The Internet of Things (IoT) explores the inter-connected world-wide network based on sensory, communication, networking, and information processing technologies, which was previously referred to generally as Information and Communication Technology (ICT) [120]. IoT defines a new technology landscape of "things" that are connected to an internet, provide their data or operations as services, and span small-to-large networks, locally and globally. IoT is extremely broad, having applications in industry, social systems, healthcare, security, and infrastructure. The application of IoT in manufacturing industrial automation applications, is often referred to the Industrial Internet of Things (IIoT) [88]. The design of IIoT systems typically exhibit capabilities such as extensibility, scalability, modularity, and interoperability among heterogeneous devices.

Cyber Physical Systems (CPS) are computational integration systems, which are abstracted across distributed functional 'cyber' layers, such as embedded computers and networked systems, to concurrently control 'physical' processes [130]. Additionally, CPS can be further defined by transformative technologies for managing interconnected systems between its physical assets and computational capabilities [7]. From a manufacturing application perspective, CPS are also referred to as Cyber Physical Production Systems (CPPS), consisting of autonomous and cooperative elements and sub-systems that are connected across all manufacturing enterprise levels [101]. CPPS characteristics can be defined by: flexibility and changeability, reliability, reconfigurability, adaptability, agility, and dependability [131]. CPS are a key pillar of Industry 4.0, and are seen to represent the shift in traditional hierarchical manufacturing structures to distributed or decentralized semi-heterarchical structures [30]. ¤Architecturally, CPS define the merging of the physical space and cyber space with scaling modular capability, across five levels:

1. Connection - data acquisition.
2. Conversion - data to information.
3. Cyber - analysis.
4. Cognition - decision support.
5. Configuration - automation of actions.

This 5C architecture [30] is cross referenced with a CPS maturity model in Fig. 9.

A Digital Twin (DT) acts as a mirror to a real world object, providing a means of simulating, predicting and optimizing physical manufacturing systems and processes [8]. DTs can consist of high-fidelity virtual models of physical objects in virtual space, which can simulate the behaviors of their physical process and provide feedback in real-time [132]. Characteristics of a DT includes: 1. Real time reflection of physical space in virtual space; 2. Interaction and convergence of system data and flow; and 3. Self-evolving virtual modelling through feedback of the physical space [133]. The DT is an advanced control paradigm, incorporating digital avatars, with "single source of truth" data flow, simulation, and potentially expanding the "4th dimension" of control, from hindsight to foresight, with predictive and prescriptive actions and behaviors.

3.3.2. Cross-over

The comparative and merger of both Agent-Based Design and Holonic Systems, has been well documented in [134–,135,136]. The aggregate of Agent-Based Design and Holonic Systems results in the visualization of a complex system through Holonic hierarchical and heterarchical structures and substructures, and the incorporation of interactive decentralized Agent elements whom accomplish local goals

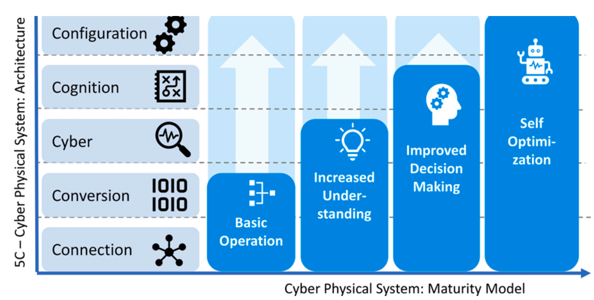


Fig. 9. Cyber Physical System Architecture and Maturity Model, derived from [30].

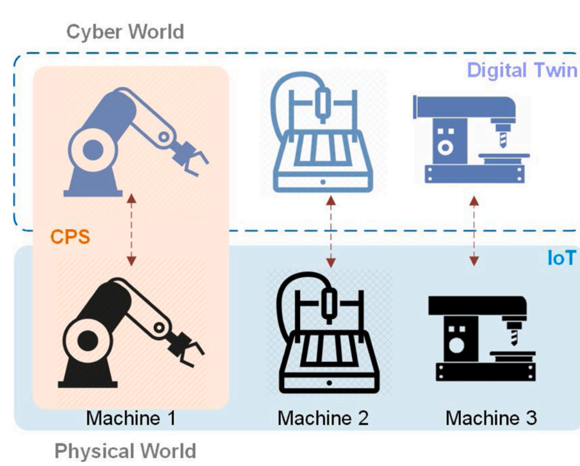


Fig. 10. Paradigm Cross Over, derived from [8,137].

and global goals through collaboration. The further encapsulation of Agents, Holons, and CPSs for production control is reviewed in [131, 137].

Fundamentally, SOA principles are inherent to IoT, and is well represent in [120,138,139]. As such, a SOA is 'method' to IoT's 'motive', providing structure in architecting IoT solutions. Furthermore, this observation can be extended to all other ideologies, which rely on interoperable communication [140].

CPS and IoT are noted as both key components, enablers, or characteristics of Industry 4.0 [12,140,141]. Sisinni et al. represent Industry 4.0 as the convergence zone between IoT and CPSs [88]. As such, IoT is a key 'physical' link within a CPS. Furthermore, SOA, Agent-Based Design, and Holonic Systems have been associated with CPS, forming in part the composition architecture [142].

The inclusion and correlation between the DT with CPS has been explored in [132,143] [144]. Both systems can be observed as potentially competing models. However the layered control aspect of CPS can consider the DT a high level of control intelligence, the 'cyber → cognition→ configuration' layers as defined in the 5C implementation model for CPSs [7] [30]. To provide context to this comparative, Lu et al. created visual as seen in Fig. 10 [8].

×While these paradigms can be considered inclusively or cross referenced to create hybrid models, a 'hypothesis' is that they are collectively exploring the cyber-physical, or metaphysical domain of decentralized and distributed control, with layered intelligence; where one paradigm is an enabler of another, and each paradigm represents, or supports an advancing intelligent control state for systems, such as: machines, systems, factories, and enterprises.

3.3.3. Technology landscape

¤×The state-of-the-art computational landscape, or 'technology stack', which supports vertical and horizontal integration and CPS intelligence; can be further encapsulated by three computational layers, namely: the Edge, the Fog, the Cloud. Philosophically this represents the 4th industrial (r)evolution of the centralized 'biological mind', transcending to the distributed cyber physical 'digital mind', as depicted in Fig. 11.

Edge computing [145–147] consists of physical computation devices, in and around machines, on the factory floor, at the 'edge' of the network. Edge computing is a fundamental pillar of manufacturing automation, as discussed previously in Section 3.3.2. The key purposes of these devices include: mission critical applications (Control & Safety); sensing and data acquisition (DAQ); signal processing; and human machine interfaces (HMI). Edge devices operate at the lowest latency speed, and their computation is dedicated to its application, with either deterministic (fixed) or un-deterministic (dynamic) operations. Furthermore, pushing computation to the Edge reduces the load on the communication network and Fog/Cloud services. State-of-the-art Edge technology is being enabled by different computer chips, such as: Centralized Processing Units (CPUs) with Real-Time Operating Systems (RTOS), Field Programmable Gate Arrays (FPGAs), Graphical Processing Units (GPUs), and Application Specific Integrated Circuits (ASICs). For context, ASICs include Visual Processing Units (VPUs), with machine learning being carried out on many of the above processors [148]. Examples of Edge technology providers include: NI cRIO, Intel Movidius Myriad, Nvidia Jetson. Academically, some novel reconfigurable Edge research is seen in the areas of: dynamically reconfigurable systems 'on-chip' for distributed control [149], modular smart controllers with dual partitioned OS and RTOS capabilities [150], real-time software containerized controllers [151], multi-core RTOS for open source robotic control [152], and machine learning on distributed IoT Edge devices [153,154].

Fog computing [155–158] is performed on middleware systems and services between a local resource, e.g. an Edge resource, and a Cloud service. In a traditional sense the Fog represents an on-premise data center. However, the Fog is considered an extension of the Cloud, a 'Cloudlet', acquiring data, processing data, providing services, etc. The Fog is distributed and decentralized geographically into nodes, which can be orchestrated remotely. The composition of nodes can vary depending upon the application and performance requirements, e.g. communication servers, databases, data processing engines, etc. Analytical Fog systems can process data into meaningful information, and reduce the complexity of big data systems through data filtering and structuring, which are challenges often encountered in Industry 4.0 solutions [159]. Furthermore, Fog systems are proven to have lower latency and improved quality of service compared to external Cloud

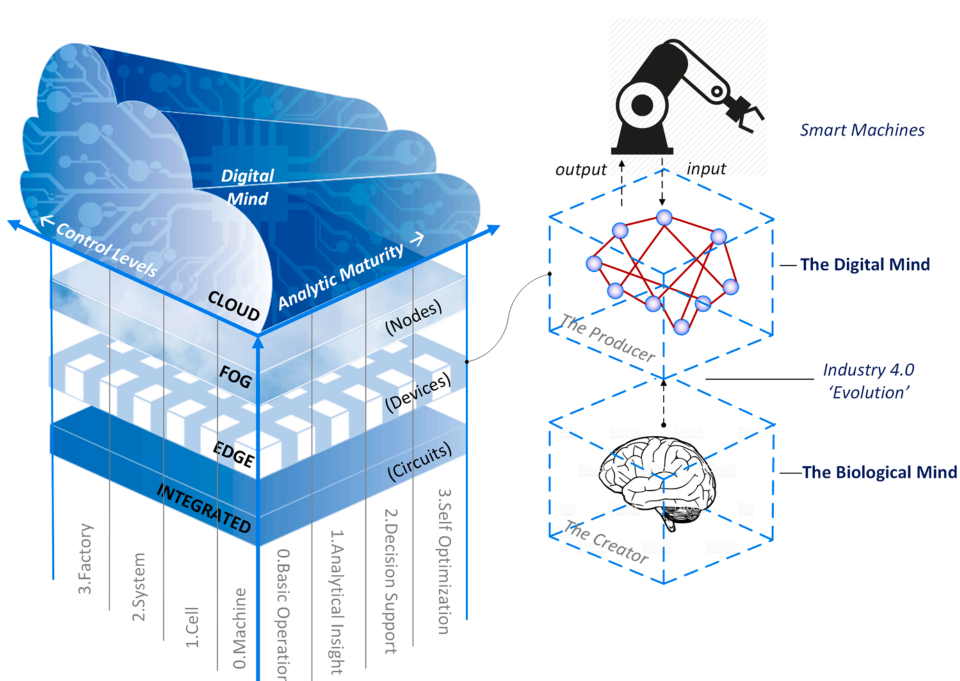


Fig. 11. The Digital Mind, inspired by [30,63,91,156].

platforms [160]. State-of-the-art Fog technology is recognized in multiple open-source tools, platforms and frameworks, for example: Docker: a distributed containerized environment for micro-services; Kubernetes: a system for automating the deployment, scaling, and management of containerized applications; and Hadoop: a framework that allows for the decentralized processing of large data sets across clusters of computers. Objectively, these dynamic and efficient distributed and decentralized environments form next-generation architectures for smart manufacturing [161,162].

Cloud computing [110,163–165] consists of on-demand computing services with high reliability, scalability and availability in a distributed and decentralized environment. Cloud "pay-as-you-go" service layers are defined by: Infrastructure as a Services (IaaS), Platform as a Service (PaaS), Software as a Services (SaaS). Cloud manufacturing depicts the distribution of manufacturing resources as services throughout a Cloud platform, e.g. sales, inventory, maintenance, management, intelligence, etc. Cloud manufacturing services can support a product throughout its lifecycle, from planning to disposal, with "data warehouses". Cloud users are recognized as Cloud providers, Cloud operators, and Cloud customers. Clouds are distributed, and incorporate internal enterprise Cloud and external commercial Clouds, which are modelled as private, community, public and hybrid. Cloud solutions scale throughout the evolving needs of the enterprise, and are resistant to failure with decentralized compute and storage. State-of-the-art Cloud technology is provided by a wide range of Cloud providers, e.g. Microsoft Azure, Amazon Web Services (AWS), Google Cloud, with vast amounts of SaaS instances to enable fast effective value to their customers. Academically, some novel pragmatic Cloud solutions can be seen in the areas of: human robot collaboration and energy consumption efficiency in industrial robots [166]; production performance monitoring and big data analytics [22]; and Augmented Reality (AR) remote maintenance [167].

It is important to note that 5G network communication, which offers higher data transfer rates; and blockchain technology, which offers next-generation transaction management; can be considered disruptive innovation technologies to the previously reviewed technology stack. For context:

5G is the fifth generation technology standard for wireless technology, offering more than "10 gigabits per second" data transfer speeds [168]. 5G has the potential to improve Quality of Service (QoS), lower latency, and increase data bandwidths [87]. However, it has been stated that "it is unlikely that 5G will be able to satisfy all stringent automation demands for real time and completely replace dedicated industrial automation networks" [87].

Blockchain is essentially a distributed database system that records transactional data [111]. Blockchain is secure, irreversible, transparent, and accurate, and maintained by distributed and decentralized nodes,

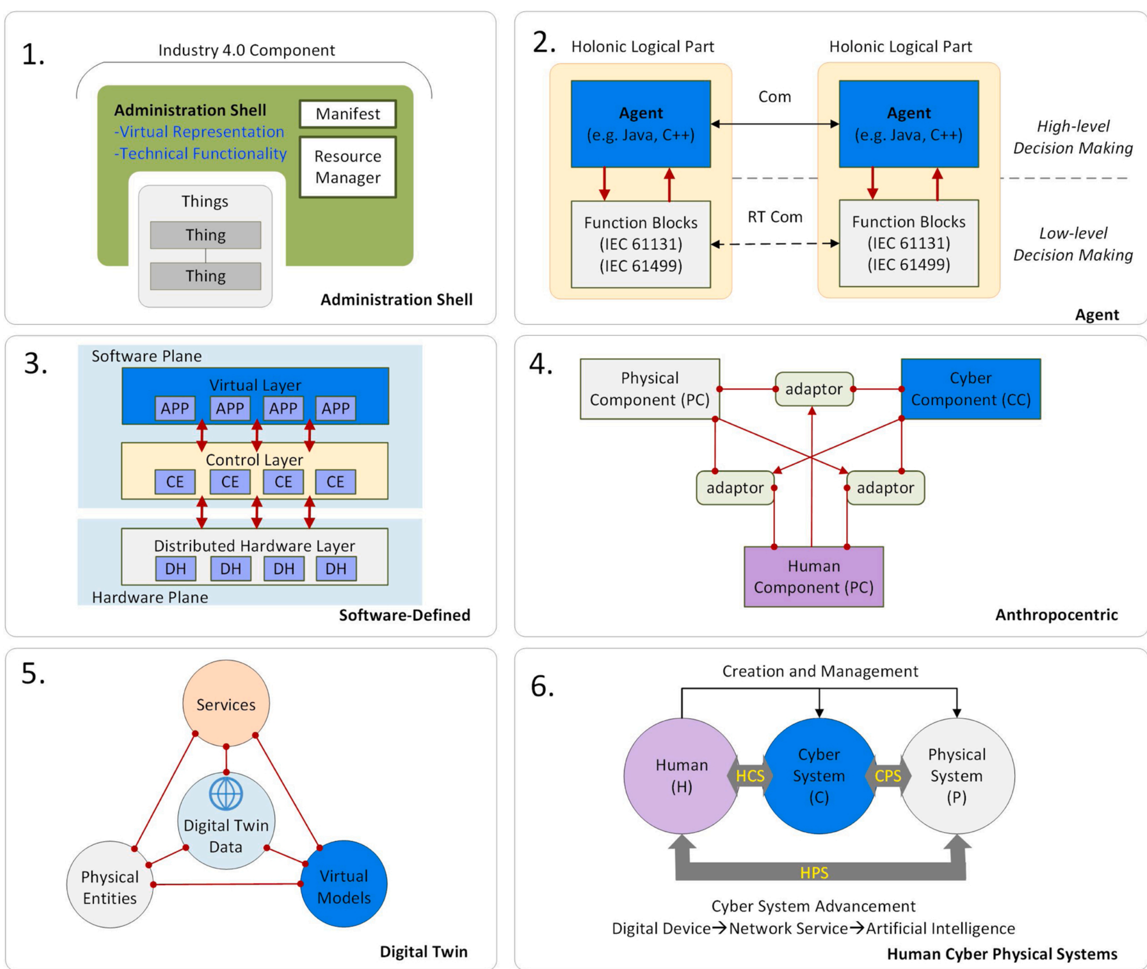


Fig. 12. Basic Smart Machine Modelling.
1. RAMI 4.0 – Administration Shell, as presented in [91,92], CC Platform Industry 4.0.
2. Agent and Holonic, derived from [113,114].
3. Software-Defined Cloud Manufacturing Architecture, derived from [180,183].
4. Anthropocentric, derived from [191].
5. Digital Twin, derived from [8,185,216].
6. Human Cyber Physical System (HCPS), derived from [192].

and uniquely without a central management agency. Blockchain offers a shift from centrally managed and vendor specific Cloud Manufacturing (CM), to Open Manufacturing (OM) which is based on a distributed knowledge and services exchange [111]. Examples include traceable product lifecycle management for sustainable manufacturing [169], anti-counterfeit crowd intelligence for mass personalization manufacturing [170], and horizontal and vertical factory control [171]. Furthermore, blockchain is being explored in collective decision making in robotics [172], manufacturing process control and monitoring by integrating open source technologies, such as OpenPLC and Hyperledger Sawtooth [173].

Both 5G and blockchain research and applications are expanding rapidly. Future research will identify their true distributive and beneficial impact.

3.3.4. Smart machine modelling

¤×The variation in advanced intelligence paradigms, and supporting Edge, Fog, Cloud technology, has led to the emergence of several "Smart Machine" architectures and models. These models act as convergence points in literature for applied research and technology development. Observably, there are similarities in their abstraction of the machine control, intelligence, virtualization, modularity, universal service integration, and collaborative communication; as seen in Fig. 12. Objectively, these models can form part of, or integrate with, the CPS 5C architecture and its maturity model, as represented in Fig. 9. CPS is hypothesized to be a holistic model for advancing intelligent control, as stated in Section 3.3.3. To assist with further imagination of these models, the depiction of the "digital mind" Fig. 10, and "digital avatar" Fig. 11, should be cross-referenced.

The following leading smart machine models are discussed and compared for context within this present review.

Fig. 12-1, depicts the Asset Administration Shell [92]. In this model, a 'thing' is a globally uniquely identifiable object, e.g. a machine or a station with a communication capability. Once the 'thing' is connected to, or conforms to, the administration shell requirements, it becomes a standard Industry 4.0 component within a wider information system. ¤As such, the component provides its data and functions to the collaborative 'Digital Ecosystem'. The component is now standardized for interoperability, and gains access to other resources and services. Furthermore, the component becomes a virtual resource, and in some cases a service for use by other components connect on the network. Marcos A. Pisching et al. [91] explored this model in line with RAMI 4.0 standards, e.g. OPC-UA, in a production line test environment, which exhibits the capabilities of a RMS. Additionally, the Fraunhofer Institute explored "Plug and Work" capabilities for modular services within automation hierarchies, and industrial standards including OPC-UA [30]. The benefits of which, are being estimated at 20 % reduction in machine startup time/cost and a 70 % reduction in vertical integration time/cost [174]. For reference, the OPC-UA standard is open access.

Fig. 12-2, depicts an Agent/Holonic model for machine control [113,114]. This model incorporates high and low, or bi-level, communication. The lower level real-time machine controls, or 'decision making', is standardized in PLC function block coding. The higher level decision making capabilities of the machine, are abstracted and elevated into an 'Agent', which is coded with standard IT programming languages. This Agent is capable of collaborating and interacting with other Agents across additional network communication. As such, the Agent and machine form a Holonic unit, which can further form part of a wider holonic network. In this model, real time direct control, communication and modular programming, is maintained at the machine level. The Agent at the higher level provides discrete control service integration and complex collaborative interactions with other Agents. Wang and Haghighi expanded on this model within Multi-Agent System (MAS) holarchies for CPPS control [137]. Leitao et al. [142] identified the use of the MAS model as a central CPS technology, in connection with SOA for interoperability, and wider Cloud service integration for advanced capability integration and scalable resourcing. Derigent et al. reviewed the development of Holonic Control Architectures (HCA) to enable Industry 4.0 manufacturing [175]. Expansive mapping of CPPS, MAS, and alignment of RAMI 4.0 standardization is presented by Salazar et al. [131]. Self-organization and decisional autonomy of MAS for smart factories is explored by Wang et al. [127]. Service integration in agent-based 'evolvable' assembly systems is introduced by Chaplin et al. [176]. A standardization of the Agent model is recognized in OPC-UA: Programs [177], Dorofeev & Zoitl [178] explored the application of which in combination with standardized PackML state-machines. For reference, a universal robot control architecture that is similar to the Agent model, is recognized in the open source Robot Operating System (ROS) [179].

Fig. 12-3 depicts a "basic" Software-defined Cloud manufacturing architecture, with two planes: 1. hardware and 2. software, and three layers: 1. hardware, 2. control, and 3. virtual [180]. Uniquely, this model explores the use of "virtualization", e.g. software-defined control environments/platforms, in which the 'control layer' is an abstracted universal 'software plane' from the 'hardware layer'. Software Control Elements (CE), e.g. control logic, scripts, programs, etc. are hosted in the 'Control Layer'. A CE orchestrates lower level elements in the hardware layers via a communication network, and seamlessly integrate higher level elements in the 'virtual layer', such as Cloud-based applications, services, and platforms. Similarly, Nayak and Rothermel [181] proposed a software-defined control environment for RMS, with high speed CPS control loops, which consist of monitoring, analysis, planning, and execution. Lopez et al. [182] introduced a software-defined control framework for smart manufacturing, which interfaces with a factory's MES and Enterprise databases. Software-defined technologies originated in the IoT research domain with Software-Defined Networking (SDN) [183]. SDN decouples control logic (control plane) from physical communication devices (data plane). In doing so, they create a universally connected, dynamically reprogrammable, centrally managed, decentralized network. SDN systems have been proven to overcome challenges in complex networking, avoid vendor "lock-in" problems, and reduce restrictions in change and innovation. The key to SDN is standardization, most notably through the OpenFlow protocol [184]. For reference, a resource which promotes SDN standardization is the Open Networking Foundation (ONF), which offers SDN open source software.

Fig. 12-5, depicts a Digital Twin (DT) Five-Dimension (5D) model [8,185]: D1. Physical Entities - consisting of a device or product, physical system, activities process, and even an whole organization; D2. Virtual Models - faithful replicas of physical entities, which reproduce the physical geometries, properties, behaviors, and rules; D3. Services - integration of distributed services, examples include: simulation, verification, monitoring, optimization, diagnosis and prognosis; D4. Data - multi-temporal data scale, dimension, source, and storage; D5. Connections - interconnects between the dimensional entities, to enable data and information exchange. The 5D model stays true to the DT's simulation and analytical origin, as discussed in Section 3.3.1. However, this model can be universal, as DTs become more central to cyber physical control. An example of this can be seen of the work of Xun Xu et al. [8,186,187]. Equivalently, a DT model has a physical entity, such as a machine tool, which communicates with a 'virtual' or 'cyber' or 'information' model, which has data processing modules. These DTs connect to Cloud services, utilize a shared knowledge base, and can potentially communicate and collaborate with other DTs. It is important to note that there is a wide expanse of potential DT compositions, e.g. technology stack and standardization, as reviewed in [121,122]. For context, Xun Xu et al. [8,188] defined a DT or 'Cyber Physical' architecture for machining, which utilizes a collection of industrial standards. The 'Digital Machine Tool' exposes its capability as a service, e.g. product design generation; and also integrates other services, such as metrology. Data is captured from the machine via industrial communication, and also captured from users via ubiquitous HMIs. Similarly, Y. Altintas et al.

outlined a 'Virtual Machine Tool', which is true to the DT origin, with coupled simulation components [189]. Leng et al. are exploring the synchronization between Digital Twin cyber physical components, with bi-level IIoT communication [124], and blockchain [171]. For reference, an emerging 'IT centric' open source platform for DT's is called Eclipse Ditto [190].

Fig. 12-4, depicts a Anthropocentric CPS (A-CPS) model [191], which recognizes humans as a key component in intelligent manufacturing systems. A similar model, is the Human-CPS (H-CPS) model [192], as seen in Fig. 12-6. Both models depict a "Human-in-the-Loop", yet each explore paradigm from different perspectives. Pirvu et al. [191] defined the A-CPS architecture through state-of-the-art HMI methods and technologies, such as Virtual Reality (VR) and Augmented Reality (AR). Ji et al. [192] explored the H-CPS model through advancing cyber intelligence states, from digital device, to networked service, and Artificial Intelligence (AI). Both models recognize the future state of HMIs, to be more than just CPS interactions, and better represented as an advanced symbiotic Human Machine Collaboration (HMC) [193]. As such, CPS can empower the workforce with AI decision support, and enhanced collaboration through state-of-the-art digital inception and virtual interfaces. For reference, to support ubiquitous HMI or HMC research, ARCore offers open source AR Development Kits (SDK).

3.3.5. Simulation

The cyber abstraction, or 'virtualization', depicted in the 'smart machine' models, offer new capabilities beyond traditional machines, including: intelligence, modularity, interoperability, etc. Furthermore, virtualization has the potential to define a new era for manufacturing simulation, with real cyber control models and real time data, e.g. "hardware in the loop". For context, simulation is a key characteristic of the 'Digital Twin' paradigm, as previously reviewed in Section 3.3.1. As such, Digital Twin high-fidelity modeling and simulation has the potential to revolutionize test and validation, and define new dimensions for optimized iterative design of RMS control and intelligence. All of which is a targeted research direction for future RMS optimization [29].

A key example of this can be seen in the collective work of Xin Chen et al. [124,144,194–196]. For context, Liu and Leng et al. demonstrated an intelligent Digital-twin "semi-physical" simulation system for the rapid designing and optimization of 'individualized flow-shop manufacturing' [194], and 'package/storage assignment in a large-scale automated high-rise warehouse' [195]. Liu et al. [196] expanded this Digital Twin research into an architecture for Configuration design, Motion planning, Control development, and Optimization decoupling, namely the CMCO. Uniquely, this Digital Twin solution, provided synchronization between asset monitoring (SCADA), production execution (MES), and simulation systems. Leng et al. [124,144] further expanded the reconfigurable capabilities of the Digital Twin system by proposing an Open Architecture for Machine Tools (OAMT).

Uniquely, this end-to-end control alignment would enable rapid alterations and faster system integrations for RMS. The Digital Twin simulations would generate, test, optimize, and deploy the new configurations directly to vertically integrated systems, e.g. Machine/SCADA/MES. For reference, a key technology which supports the reviewed Digital Twin system is the Unity3D platform, which has open-source repositories. Further advances in Digital Twin simulation, explore the use of machine learning techniques to optimize controls, and increase the accuracy of Digital Twins simulations [197–199].

3.3.6. Smart reconfigurable synergy

×In the present research review, machine control and machine intelligence (AI) have been explored through distributed and decentralized theory, layered computation technology, future-state 'smart machine' models, and simulation. All of these support and form part of CPS architectures, which enable the dynamic integration and aligning of various algorithms, to unlock "smarter" machine capabilities. While these algorithms are not under review in this present research paper, some other key papers for reference include:

- Machine/Process Insights - [200–202].
- Production Scheduling - [203–205].
- Machining Learning (ML) - [206–208].
- Transfer Learning (TL) - [209,210].

¤For context, analytical capability levels can be simply characterized by:

- Descriptive- Knowing what is happening.
- Diagnostic- Knowing why is it happening.
- Predictive - Knowing when it will happen.
- Prescriptive - Knowing what action to take.

Furthermore, analytical capabilities are enabled through 'advanced monitoring systems', which have been proven to improve production performance, extend machine longevity, and increase resource efficiency. ¤Advanced monitoring systems operate with both autonomous-loops, and with "humans-in-the-loop", via:

- Sensing - measuring phenomena.
- Data Acquisition - acquiring raw data.
- Signal Processing - extracting features.
- Decision Support - cognitive insight.
- Control - adaptive controls +/-.

×This sequence of analytical capability and closed-loop control is mirrored in the CPS 5C architecture, from: connection, conversion, cyber analytics, cognition, to (re)configuration. Uniquely, this convergence of 'Smart' analytics and 'Reconfigurable' control capabilities, has the potential to produce unique synergies in Smart Reconfigurable (SR*) machines.

For context, an SR* machine has the capability to autonomously change, and the intelligence to know when and what to change. As such, an SR* machine combines CPS intelligence with RMS composition and control, to unlock new adaptive reconfigurable behavior.

SR* Scaling Capability - Uniquely, SR* synergy has the potential to increase the effectiveness and efficiency of a machine in scalable ways. For example, the complexity of SR* machines is defined by its designer (s). Therefore, basic capabilities may not need to be initially predictive, they can be reactive, e.g. triggered via an HMI, RFID, or other sensor. This basic AI can however be scaled, or 'advanced'; throughout the SR* machines lifecycle, within the boundaries of its enabling CPS framework. Drivers for advancing intelligence include: new algorithms, new technology, iterative simulation optimization and machine learning calibration. Furthermore, an SR* machine can be manually 'thought' over time, connecting cause and effect, initiating real-time adaptive controls, with reconfigurable actuations. This represents an advancing CPS maturity, from basic operation, to analytical insight, decision support, and ultimately self-optimization. All of which should be aligned to the RMS characteristics, as defined in Section 3.1.2, and can be further aligned with Industry 4.0 standards, as discussed in Section 3.2.4.

There are two further key examples in literature that demonstrates this unique SR* synergy through extraordinary behaviors, for the individual machine (self-healing), and a collective of machines (orchestration).

SR* Self-healing - The idea of self-maintenance, self-repair, or a "artificial immune system", is characterized within Prognostic and Health Monitoring (PHM) [185,202,211,212]. With such systems, a machine can perform repair or maintenance tasks autonomously, and potentially protect itself from damage or attack. This adaptive capability identifies an extraordinary resilience to failure. From an SR* perspective, this is the artificial intelligence to understand what is happening, diagnose and/or predict issues, and prescribe solutions. These prescribed solutions would be defined by the flexibility and reconfigurability of the machine's operational capability. Therefore, maintenance tasks could be programmed into the machine, enabling the machine to reconfigure and solve problems. Furthermore, machine design considerations could be taken into account for how to autonomously overcome issues, e.g. backup valves, isolating relays, reset switches, etc. A reconfigurable hardware/software composition would ensure new maintenance tasks could be added throughout a machine's lifecycle. The identification and exposure of key problem-solving reconfigurable machine activities aims to 'close-the-loop' in the CPS architecture, in safely Verified and Validated (V&V) ways, as depicted in Fig. 13. However, the severity of the failure is a key factor, as a machine could implement simple preventative maintenance tasks to avoid a sever failure. If a severe failure was to occur, it might not have the autonomous capability or high level intelligence to identify or solve the problem. Therefore, if the failure is outside the capability of the machine to fix, the operator or engineer on duty could be notified of the problem and potentially prescribed the solution, as such maintaining a 'human-in-the-loop' and reducing downtime. This SR* capability aligns with the RMS objective for time and cost oriented manufacturing optimization [29], and has the potential to scale the capability towards predictive analytical to enable "anticipation over reactivity".

SR* Orchestration – Orchestration is a common component of decentralized systems and Cloud services [213,214]. Orchestrator node (s) coordinate data and control flow among clients and services. In modern containerized environments, such as Docker and Kubernetes [215] "Orchestrators are tools which manage, scale, and maintain containerized applications". These technologies were previously referenced in Section 3.3.3 'Technology Landscape – Fog Systems'. Similarly, in industrial automation SOA research, an Orchestration 'engine' and/or a 'Orchestrator', maintains a hierarchical relationship with the connected devices, controls workflow and facilitates the interoperability between devices [123,142]. In contrast, heterarchical control relationships, interactions and negotiations, sometimes called "choreography" behavior, are a fundamental part of AI among Multi Agent Systems (MAS) [113]. Some MAS robotic frameworks have exhibited orchestration through use of 'Master' nodes [179]. This combination of both hierarchical and heterarchical relationships, is classified as a Distributed Control (DC) "class II – semi-heterarchical system" [3], which was previously reviewed in Section 3.2.5. Semi-heterarchical systems have the potential to provide extraordinary agile capabilities, such as: enabling improved management, shorter reaction delays, extensibility, and resilience to failure.

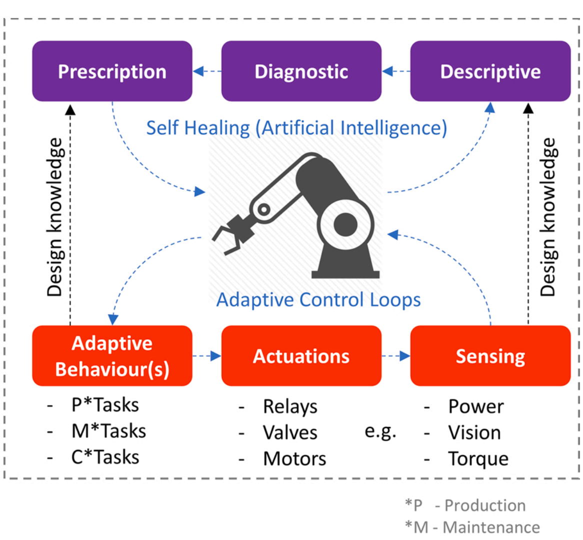


Fig. 13. Extraordinary SR* Capabilities: Self-Healing.

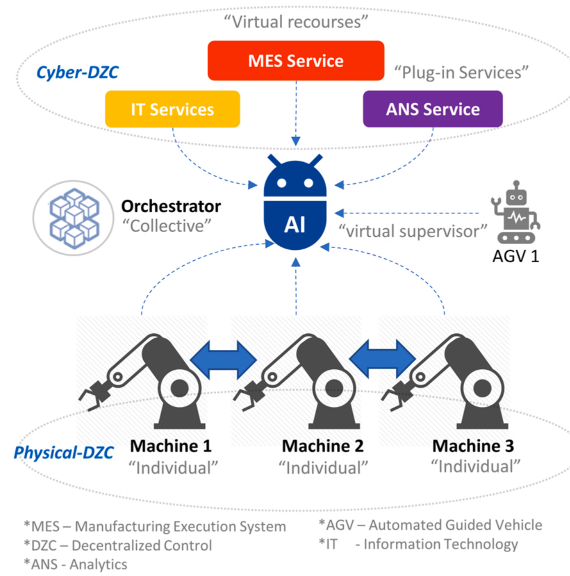


Fig. 14. Extraordinary SR* Capabilities: Orchestration.

From an SR* perspective, the intelligence of the collective is elevated from the individual and managed by an Orchestrator. The Orchestrator is responsible for the system as a whole, 'the collective'. The Machine is responsible for its task, 'the individual'. Universally, Orchestrators represent collectives and act as central contact points in decentralized cyber-physical environments, for configuration, co-ordination, and/or adaptive behavior, as depicted in Fig. 14.

For example, an Orchestrator could control what product type to produce, and broadcast it to the machines within its collective. The machines can individually re-'configure' to carry out the production batch request. The Orchestrator then 'co-ordinates' the efficient flow of product between machines. While the production management and scheduling is typically maintained by the MES, the Orchestrator would work within its boundaries, and/or potentially negotiating with the MES. Furthermore, as machines, or their Digital Twins; are responsible for individual failure with potentially "self-healing", the collective resilience to failure is achieved through the intelligence of the Orchestrator. The goal of this adaptive behavior is to autonomous maximize the potential production output.

For example, an Orchestrator could reroute product flow with adaptive conveyor control or with Automated Guided Vehicle (AGV) control, potentially rescheduling production shifts, activate redundant machines, or start producing different product types with the available machines to fill different orders. This SR* capability aligns with the RMS objective of line balancing [29] to minimize production lead time, reducing machine idle time and maximizing production capacity [39]. An example of which could be seen in the orchestration of complex manufacturing systems, for custom and individualized manufacturing [11], such as processes which utilize 3D printing [33].

Holistically and 'holonically', there is further opportunity to group orchestrators together, with enabling collaborative AI, and/or further virtually abstracting control to 'Supervisory' Orchestrators. Therefore defining the hierarchal control priority, with local and global goals, across machines/cells/process/factories. An example can be envisaged for optimizing production scheduling in local factories, and across interlinked global factories. As such, local and global delays in supply chains, or disruptions in transport, new priority orders, or increased order volumes; can be adapted autonomously, achieving an optimal scheduling balance. This autonomous RMS future state is a common vision in the "factory of the future" [23]. Objectively however, the scope and scale of reconfigurable autonomy has the potential to reach new heights of internal and external system integration. An example of which could be seen in the global orchestration of distributed Fractal factories [20,21,34].

Furthermore, it has been stated that the emergence of intelligent orchestration platforms will coincide with the application of 5G network technology [87], which was previously characterized as a distributive innovation technology in Section 3.3.3.

3.3.7. Summary

In summary, the framework which characterizes the state-of-the-art in 'machine intelligence' has been progressively reviewed from intelligence paradigms, to layered technology environments, with reference to appropriate research papers, wider review articles, and technology providers. Furthermore, references were provided to open-access resources to promote new accelerated research development. The convergence of theory and technology was recognized with a comparative review of several 'smart machine models', which uniquely depict an abstraction of machine control and intelligence through a virtual layer. Key insight established in this Section identifies Cyber Physical Systems (CPS) and the 5C architecture, as a holistic model for advancing intelligent control. Finally, the combined impact of distributed and decentralized 'Smart' analytics and 'Reconfigurable' control capabilities, namely SR* synergy, was discussed in relation to extraordinary scaling capabilities, self-healing, and orchestration. The key research content from this Section has been summarized in Section 4 - 'Table 3'.

4. Key review findings

Key research findings established in this research review are presented in:

- Table 1. Reconfigurable Manufacturing Systems
- Table 2. Machine Control
- Table 3. Machine Intelligence

These tables provide succinct insights into the three explored research sections, in an effort to support ease of cross reference, and draw objective answers to the Research Questions proposed in Section 1, relating to reconfigurable design and industry adoption - Section 1.2; and enabling present and future state technology - Section 1.3.

Throughout the review there has been a progressive narrative which has lead to the definition of SR* machines, as marked with symbol (×); is collectively summarized in Table 4. Additionally, key conceptual alignment reference points made throughout this review that support a vision for next generation Industry 4.0 SR* machines, as marked with symbol (¤); is collectively summarized in Table 5.

In an effort to depict the conceptual convergence of the three reviewed research sections, Fig. 15 is presented. This figure identifies a fundamental RMS foundation, consisting of:

- Coupling and decoupling: Hardware, Software, Information, Communication
- Changeable structures, Simultaneous operations, and Open control architectures.
- Characteristics: Modularity, Integrability, Customization, Convertibility, Scalability, Diagnosability, Mobility, Adaptability

These reconfigurable fundamentals are represented in both the state-of-the-art domains of Operational Technology (OT) for machine control, and Integrated Technology (IT) for machine Intelligence; as distributed and decentralized environments, which are horizontally and vertically integrated. The convergence of these domains is represented with a intermedium virtual layer, which is enabled by industrial communication and data standardization, virtual models, and collective orchestrators. As such, Fig. 15 depicts closing the loop in distributed and decentralized control and intelligence systems, which has the potential to enable extraordinary Smart Reconfigurable (SR*) capabilities in next generation Industry 4.0 SR* manufacturing machines and systems.

5. Discussion

Research Question 1: How can an RMS be designed to enable agile capability and capacity, with increased throughput, decreased cost, and be intuitively operable for multi-level enterprise adoption and user operation?

Objective Answer: An RMS is fundamentally designed to enable agile capability and capacity through incorporating RMS design characteristics, and potentially incorporate distributed and decentralized control and intelligence designs. Specific reconfigurable application design considerations and rational should be assessed within the machine(s) design phase, and take into account the full life-cycle of the machine and

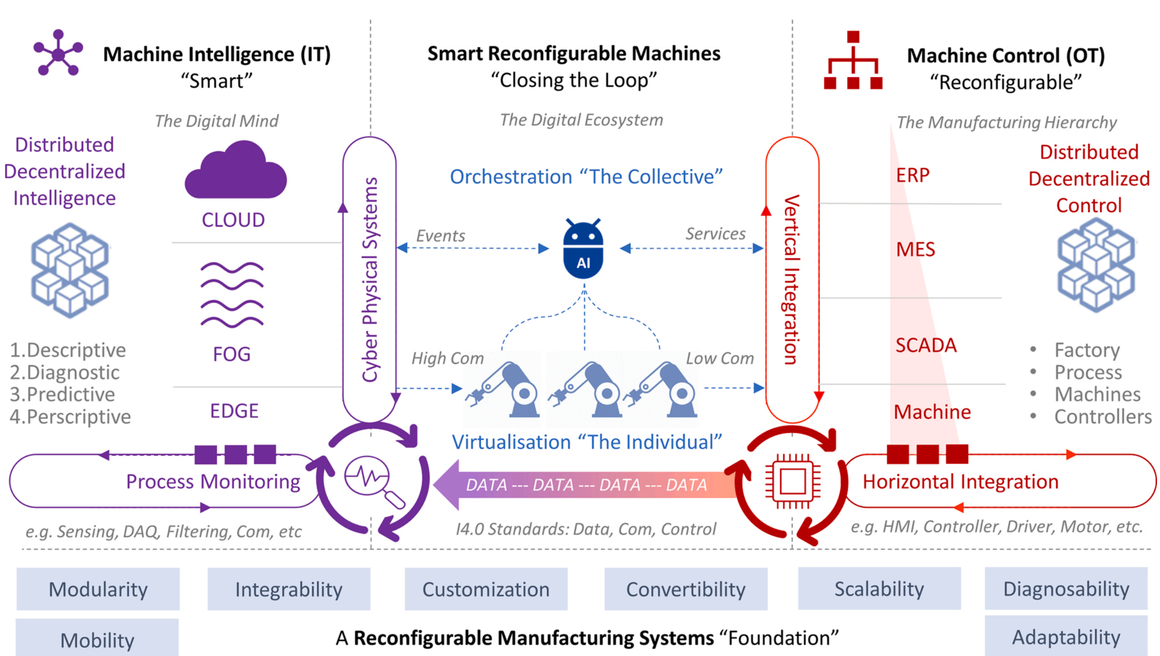


Fig. 15. SR* Machine Convergence.

Table 1
Key review findings – Section 3.1. Reconfigurable Manufacturing Systems.

3.1.2. Definition
"A reconfigurable manufacturing system is designed for rapid adjustment of production capacity and functionality, in response to new circumstances, by rearrangement or change of its components"

3.1.2. Capability & Capacity
- DML: low variety high speeds
- FML: high variety low speeds
- RMS: wider variety (DML) increased speeds (FML)

Examples: changing product demand (capacity), and new product family variety (capability).
Changing components: tools, actuators and fixtures (hardware), functions, programs, services (software).

3.1.2. Characteristics
Modularity, Integrability, Customization, Convertibility, Scalability, Diagnosability, Mobility, Adaptability

3.1.3. Individual (machine/system)
- Flexibility ΔF "to bend as part of the body"
- Reconfigurable ΔR "to change the shape or formation"

3.1.3. Collective (machines/ systems)
- Heterogeneous – mix of dedicated, flexible, and reconfigurable machines
- Asynchronous transport – conveyors, robots, automated guided vehicles

3.1.1-4. Design & rational
- Narrow the scope of RMS to increase speed (balance capability and capacity)
- A "true" RMS has changeable structures, simultaneous operations, and incorporate open control architectures
- Process requirements for RMS characteristics across its potential life-cycle need to be considered in the 'design stage'
- Identify reconfigurable 'potential' and reconfigurable 'ease'
- Object Oriented Modularity: control, hardware, software, information
- Reconfigurability description: System and its boundary, System configuration(s), Rationale for a desired set of reconfigurations, Time/cost/effort of potential reconfigurations
- Recognizing the value of human investment and time investment for production improvements
- Seek process improvements through simplification
- Learning to recognize what not to automate
- Definition / Classification / Relationship Visualization of Design Parameters (DP), Functional Requirements (FR), Working Principles (WR), Design Modules (DM)
- Design methodology ISO/IEC/IEEE15288 describing the life cycle of systems, Verification and Validation (V&V) of each RMS configuration, considering safety ergonomics and human factors, streamline future V&V change requirements

3.1.3-4. Economic Impact
- Resilience to failure, Increased Market Responsiveness, Low cost scaling, Faster time to market, High productivity rates, Rapid changeover speeds between product types
- ROI dependent on number/extent of changes to system across life-cycle
- Reduced time and burden across system life-cycle
- Industry implementation objectives: cost, time, reconfigurable capability, operational capacity

3.1.4. Needs
- Adoption of more rigorous analytic metrics to assessing reconfigurability level
- Successful case studies and best practices to drive industrial companies toward RMS
- Lack of RMS research on how to 'actually solve design issues in practice'
- Current state tools providing advanced decision support, which has proven difficult to apply in commercial manufacturing
- Methods to increase automation speeds
- Optimization: material handling, product family, anticipation over reactivity, online digital configuration and design planning

3.1.1-4. Challenges
- Higher initial investment cost
- Higher 'perceived' complexity, more requirements earlier
- Lower production speeds to traditional dedicated manufacturing lines
- Optimization: system design, production planning and scheduling, layout design, and line balancing and rebalancing

its potential product range, as summarized in Table 1.

A key feature of an RMS when compared to an FMS, is its increased speed and throughput potential. New methods and mechanisms to maximize automation speed and production throughput are paramount to RMS adoption. Some recommendations include narrowing the scope of production variation, and utilizing: parallel processing (actuations, services, stations, machines), asynchronous transport systems, smart adaptive control algorithms, real-time control technology, and the adoption/development of optimized DC and DZC architectures.

RMSs exhibit higher initial costs, due to the extra material, development time, sophistication, and technical skillset required to enable the machine to become reconfigurable. However, this initial high cost unlocks a lower scaling cost, an increased productivity rate from rapid product changeover speeds, and an ability to bring faster product variations to market. Furthermore, these systems can be connected to analytical and AI systems, to enable extraordinary adaptive behaviors for increased resilience to failure, and an increased use-full life expectancy. Therefore, RMSs have break-even cost points with traditional machines, which is dependent on the number and extent of the necessary changes made to the system in the future. Some opportunities for RMS cost reductions include: leveraging open-source tools; aligning with standards for interoperable connectivity; the development of a reusable framework for current and future machine requirements; and availing of research grants with academic innovation partnerships to develop future-state SR* solutions.

RMS design rational includes considerations for intuitive end user operations, which should make use of the state-of-the-art in HMI design methods, technologies, and potentially anthropocentric solution modelling. It has been identified that intuitive and computerized HMIs unlock the reconfigurable capabilities of complex machines. As such,

Table 2
Key review findings – Section 3.2. Machine Control.

3.2.1. Control Theory
- Direct Control, Adaptive Control (Closed loops)
- Control loops are compounded when viewing the machine as a unit within a cell, a system, and a plant (Vertical & Horizontal Integration, IT and OT Convergence, Cyber Physical Systems)

3.2.2. Programmable Logic Controllers (PLC)
- Standardized, high speed, high reliability, deterministic, easy of programming, fault diagnosis
- Key to effective manufacturing automation, as their capability is proven in production environments, it's a standardized tool and tuned for engineers to utilize, and their design is reconfigurable to meet the requirements of nearly any application
- IEC 61131 - Software modularity: configuration, resources, tasks, programs, functions & function blocks
- Next gen Production Automation Controllers (PACs) incorporate higher level programming capabilities and cloud connectivity

3.2.3. Human Machine Interface (HMI)
- Discrete Control, Translation system (design, control, collaboration)
- Reduce risk with intuitive controls and insightful displays, and to provide effective decision support and control
- Universal Interface (UI) and User Experience (UX) is paramount to the success of an IT application
- Intuitive HMI unlock the reconfigurable capabilities of complex machines, effectively and efficiently (e.g. CAD,CAM,CNC)
- Examples of state-the-art HMI research: Wearable AR devices, Projection based assembly AR, Vision recognition in robotic safety and collaboration, verbal recognition interfaces.

3.2.2. Horizontal Integration (OT)
- PLC Modular IO
- Communication e.g. DeviceNet, Modubus, Profibus
- Network Topologies: p-to-p, daisy chain, ring, star, tree
- Distributed event programing IEC 61499
- ISA 88 – Models (Process, Physical, Procedure), Recipes(product production information), States(operating condition)
- PackML –data standards (Tags, OEE, RCA)

3.2.4. Vertical Integration (IT)
- SCADA, ISA-95 (MES, ERP)
- High and low level integration through 'servers', middleware', 'Data Distribution Services (DDS)
- Com protocols (e.g. MQTT, AMQP, HTTP, OPC DA)
- RAMI 4.0 standards (e.g. OPC UA, Automation ML)
- Administration Shell: autonomously integrate an asset or object with new vertical and horizontal integration capabilities
- Modern interoperability with cloud enabled controller data access

3.2.5. Distributed and Decentralized Control - Classification
- Centralized Control (CC) - maintain a singular central control unit, which can control technology locally. Horizontal integration. Hierarchical structures.
- Distributed Control (DC) – singular or multiple control units, which can control technology and systems locally and globally. Vertical and horizontal integration. Hierarchical to Heterarchical structures.
- Decentralized Control (DZC) - multiple control units, operating in parallel, are of equal importance, enable a resilience to failure, and can have identical or different functions. Vertical and horizontal scaling. Hierarchical to Heterarchical structures.

Note: The classification of control system is not ubiquitous or inherent.
Control units are not defined by any specific hardware or software components

3.2.5. Distributed and Decentralized Control - Benefits
- Independent parallel control operations
- Decomposition enables a simplified synthesis of tasks, which reduces computational complexity
- Resilience to failure, such as a reduction in single point of failures
- Highly scalable, seamlessly add or remove the components in order to accommodate varying workload
- Possible to exhibit intelligence through collective collaboration and problem solving capabilities

3.2.5. Distributed and Decentralized Control - Challenges
- Constraints on communication network (bandwidth, congestion, resource contention, delay, jitter, noise, transmission power)
- Guaranteed near-optimal or satisfactory performances
- Design methodology and engineering in distributed control system
- Interoperability and deployment norms
- Development, scalability and costs
- Human factors, manager trust and speculative investment returns
- Sensor Networks (location, time synchronization, reliable communication, cooperation / coordination, and security)

3.2.5. Closing Statement
Machine control and intelligence is becoming more distributed, decentralized, and resilient, at all control levels, which is fundamental to smarter manufacturing, with Smart Reconfigurable (SR*) capabilities.

accessible RMS interfaces and ubiquitous modular plugin designs are imperative for successful enterprise adoption. Further adoption benefits are summarized in Tables 1–3.

Observably, the complexity of RMS development and operation can be considered a barrier for Small-Medium Enterprise (SME) and Large Manufacturing Enterprise (LMS) adoption. Rationally, the skill and knowledge needed to create SR* capabilities, requires a multi-disciplinary development team, e.g. automation engineers, software engineers, data scientists. Furthermore, machine intelligence paradigms can be perceived as convoluted, with some proof-of-concepts consisting of complex and bespoke heavily integrated software. Emerging solutions aimed at reducing RMS complexity and development time, include: DC & DZC task decomposition; the utilization of open-source technology; a focus towards industrial standard alignment; modular service-oriented capability designs; the elevation of complex machine behaviors through virtualization and software-defined environments; and utilizing simulation technology to optimize designs and semi-automate changes. Collectively these solutions, in connection with the state-of-the-art technology landscape; has the potential to form CPS framework(s) which offer "turn-key" advanced control and intelligence capabilities, to ultimately unlock value with SR* manufacturing.

Research Question 2: What is a state-of-the-art understanding of RMS from a machine control, intelligence, and technology stack perspective? And what is a 'future-state' model for these next-generation Industry 4.0 Smart Reconfigurable (SR*) machines?

Objective Answer: A fundamental RMS understanding is summarized in Table 1 'definition, capability and capacity, and characteristics'. Comparatively, the majority of manufacturing automation control

Table 3
Key review findings – Section 3.3. Machine Intelligence.

3.3.1 Paradigms

<u>Agent based design</u> Distributed Artificial Intelligence (DAI) research domain. An Agent is a computational system that is situated in a dynamic environment and is capable of exhibiting autonomous, intelligent, adaptation, and co-operation behavior.	<u>Holonic Manufacturing</u> Evolution of biological and social systems. A manufacturing Holon is an autonomous and cooperative building block, which together form 'scalar chains', both vertically and horizontally, called holonic systems.
<u>Service Oriented Architecture (SOA)</u> A set of architecture tenets for building autonomous yet interoperable systems. Potential to provide the necessary system-wide visibility and device interoperability for complex collaborative manufacturing automation systems.	<u>Internet of Things (IoT)</u> IoT explores the inter-connected world-wide network based on sensory, communication, networking, and information processing technologies. Exhibit capabilities such as extensibility, scalability, modularity, and interoperability among heterogeneous manufacturing devices.
<u>Cyber Physical Systems (CPS)</u> CPS are integrations of computation systems with physical processes, which are abstracted across functional control layers. CPS define the merging of the physical space and cyber space with scaling modular capability. CPS 5C Architecture: 1. Connection - data acquisition 2. Conversion - data to information 3. Cyber - data analysis 4. Cognition - decision making / support 5. Configuration - automation of actions.	<u>Digital Twin (DT)</u> A DT act as a mirrors of real world objects, providing a means of simulating, predicting and optimizing physical manufacturing systems and processes. Characteristics include; 1. Real time reflection of physical space in virtual space 2. Interaction and convergence of system data and flow, 3. Self-evolving virtual modelling through feedback of the physical space.

3.3.3. Technology Landscape – "distributed and decentralized compute"

<u>The Edge</u>
- Edge computing are physical computation devices, in and around machines, on the factory floor, at the 'Edge' of the network
- Mission critical applications, lowest latency speeds, compute is dedicated to its application
- State-of-the-art: CPU, FPGA, ASIC:VPU

<u>The Fog</u>
- Fog computing middleware systems and services between a local resource, e.g. an 'Edge' resource, and a 'Cloud' service.
- Distributed geographically (nodes), to reduce the complexity of big data systems, low latency and improved quality of service
- State-of-the-art: distributed and decentralized environments and open source tools

<u>The Cloud</u>
- Cloud computing, on-demand computing services with high-reliability, scalability and availability in distributed environments
- "Pay-as-you-go" service layers (IaaS, PaaS, SaaS), Cloud users (Operators, Providers, Customers),
- State-of-the-art: multiple vendors, multiple SaaS, end-to-end applications (maintenance, performance, resource efficiency)

Note: identified disruptive innovation technologies include 5G and Blockchain.

3.3.4. Smart machine "Virtualization" models • RAMI 4.0 Administration Shell – Plug & Produce • Agent and Holonic – Collective Decision Making • Software-defined control – Universal integration • Digital Twin – Collective Data and/or Simulation • Anthropocentric & Human Cyber Physical Systems – 'Human in the loop', symbiotic Human Machine Collaboration (HMC)	3.3.6. Smart machine – "analytical capability levels" • Descriptive - Knowing what is happening • Diagnostic - Knowing why is it happening • Predictive - Knowing what will happen next • Prescriptive - Knowing what action to take

3.3.6. Smart Reconfigurable (SR*) Synergy
- SR* machine capability to autonomously change, and the intelligence to know when and what to change
- Combines CPS intelligence with RMS composition and control, to unlock adaptive reconfigurable behavior
- SR*synergy has the potential to increase the effectiveness and efficiency of a machine in scalable ways
- Can be 'thought' over time, connecting cause and effect, initiating real-time adaptive controls, with reconfigurable actuations
- Exhibit extraordinary (adaptive control) behaviors: Self-Maintenance (the individual), Orchestration (the collective)
- The scope and scale of reconfigurable autonomy is reaching new heights of internal and external system integration and AI

technology is fundamentally designed to be modular and reconfigurable. Machine builders utilize standardized industrial computation devices, communication protocols and data servers, to horizontally and vertically integrate technology and create effective manufacturing equipment. As such, RMS leverage this foundation of dynamic OT composition, yet seek to further advance its capability and capacity in relation to: speed (rapid adjustment), cost reduction (labor, burden, material), and provider (external, internal, automated); as depicted in Fig. 16. Furthermore, reconfigurable designs seek to predefine and standardize the method of change, becoming proactive in a less critical timeframes (design phase), rather than being reactive in a highly critical timeframe (production phase). Key enabling and distinguishing reconfigurable aspects includes: the reconfigurable automation of both hardware, software and information; reconfigurable Distributed Control (DC) and Decentralized Control (DZC) machines/systems; and the incorporation of reconfigurable intelligent behaviors for individual and collectives of machines/systems.

A state-of-the-art technology stack that supports and enables modern RMS, is represented in the parallel, horizontal/vertically integrated domains of IT and OT, as depicted in Fig. 15. Both domains exhibit distributed and decentralized computing control, and intelligence paradigms, to enable increased scalability, technical agility and failure resilience. Presently, the convergence of these domains is being further enabled through the alignment of end-to-end machine control, data, and communication standards, as exhibited in the RAMI 4.0 reference architecture. Objectively, the ability to orchestrate and reconfigure machines is reaching new levels of possibility and autonomy, by 'closing-the-loop' in distributed CPS intelligence and hierarchical manufacturing control systems. Uniquely, this convergence, or alignment; has the potential to produce Smart Reconfigurable (SR*) synergies, as summarized in Table 3. Further key conceptual alignment references points are summarized in Tables 4 and 5. All of which, objectively defines a new generation of Industry 4.0 manufacturing machines, which will exhibit extraordinary SR* capabilities.

A 'future-state model' for these next-generation Industry 4.0 SR* machines, is represented by: reconfigurable DC and DZC machines/systems, intelligent CPS architectures, virtualization modelling, and enabling modular scalable technical frameworks, as depicted in Figs. 17 and 18.

Both models identify an abstraction of complex control and

Table 4
Key Progression Narrative References to SR* Definition.

Ref (×)	Narrative
3.1.3	RMSs are considered holistically, from an individual machine/system perspective, to a collective of machines/systems.
3.2.1	Machine control loops are compounded when viewing the machine as a unit within a cell, a system, and a plant. This represents the horizontal and vertical integration of sensing, actuating, control, management, and logistics systems. Often commercially referred to as the merger, or convergence, of the Operational Technology (OT) domain, and the wider Integrated Technology (IT) domain. Furthermore, this abstraction of control throughout layers of computational devices and networks is academically referred to as a Cyber Physical System (CPS).
3.2.4	Collectively, the new digital manufacturing horizontal and vertical connectivity and interoperability (e.g. industrial standards in RAMI 4.0 "digital ecosystem"), identifies a shift away from strictly centralization hierarchical designs and towards more technically agile, distributed and decentralized designs, which is characteristically fundamental in RMSs. Comparably, the equivalent, or 'mirroring', of distributed and decentralized computing infrastructure (IT), is observed in distributed and decentralized machine/process control (OT).
3.2.5	When considering the classification of control systems holistically, it is important to take into account the system's control composition, horizontal and vertical relationships, intelligence, and behavior. For example, a Decentralized Control (DZC) system 'composition' would need to be resilient to single points of failure. While, an intelligent DZC would act or "behave" in some way to overcome the issue. This Smart Reconfigurable (SR*) adaptive capability is supported by several distributed and decentralized machine intelligence paradigms.
3.3.2	While these paradigms can be considered inclusively or cross referenced to create hybrid models, a 'hypothesis' is that they are collectively exploring the cyber-physical, or metaphysical domain of decentralized and distributed control, with layered intelligence; where one paradigm is an enabler of another, and each paradigm represents, or supports an advancing intelligent control state for systems, such as: machines, systems, factories, and enterprises.
3.3.3	The state-of-the-art computational landscape, or 'technology stack', which supports vertical and horizontal integration and CPS intelligence; can be further encapsulated by three computational layers, namely: the Edge, the Fog, the Cloud. Philosophically this represents the 4th industrial (r)evolution of the centralized 'biological mind', transcending to the distributed cyber physical "digital mind".
3.3.4	The variation in advanced intelligence paradigms, and supporting Edge, Fog, Cloud technology, has led to the emergence of several "Smart Machine" architectures, or models. These models act as convergence points in literature for applied research and technology development. Observably, there are similarities in their abstraction of the machine control intelligence, virtualization, modularity, universal service integration, and collaborative communication. Objectively, these models can form part of, or integrate with, the CPS 5C architecture and its maturity model.
3.3.6	In the present research review, machine control and artificial intelligence (AI) have been presented through distributed and decentralized theory, layered computation technology, and future-state machine models. All of these support and form part of CPS architectures, which enable the dynamic integration and aligning of various algorithms, to unlock "smarter" machine capabilities.
3.3.6	This sequence of analytical capability and closed-loop control is mirrored in the CPS 5C architecture, from connection, conversion, cyber analytics, cognition, to (re) configuration. Uniquely, this convergence of 'Smart' analytics and 'Reconfigurable' control capabilities, has the potential to produce unique synergies in Smart Reconfigurable (SR*) machines.

Table 5
Key Conceptual Alignment References Points for Next Generation Industry 4.0 SR* Machines.

Ref (¤)	Topic	Sequence & Advancement	Key Alignment
3.2.1	Closed Loop Control	Input, Logic, Output, System, Measurement, →	Feedback
3.2.1	Horizontal & Vertical Integration	IT & OT Convergence, ICT, AI →	Cyber Physical Systems
3.2.4	Industry 4.0 Standards	New Horizontal & Vertical Connectivity →	"The Digital Ecosystem"
3.2.5	RMS (Individual & Collective)	I4.0, IT & OT mirroring, Open Architectures, →	DC & DZC
3.2.5	Decentralized Control	Passive and Resilient redundancy, →	Adaptive Behavior
3.3.6	Adv. Monitoring	Sensing, DAQ, Processing, Decision Support, →	Adaptive Control
3.3.6	Analytical Capabilities	Descriptive, Diagnostic, Predictive, →	Prescriptive Analytics
3.3.1	CPS 5C Architecture	Connection, Conversion, Cyber, Cognition, →	(re)Configuration
3.3.1	CPS Maturity Model	Basic Operation, Insight, Decision Support, →	Self Optimization
3.3.3	CPS Intelligence	Technology Landscape (Edge, Fog, Cloud) →	"The Digital Mind"
3.3.4	AI Paradigms	Technology Landscape (Edge, Fog, Cloud) →	"Smart Machine Modelling"
Ref (»)	A RMS Foundation		
3.1.2	Modularity, Integrability, Customization, Convertibility, Scalability, Diagnosability, Mobility, Adaptability		
3.1.2	Changeable structures, Simultaneous operations, and Open control architectures.		
3.1.4	Coupling and decoupling: Hardware, Software, Information, Communication		

intelligent capabilities within higher-level 'cyber' computational environments, while maintaining real-time control capabilities within lower-level control systems. Objectively, virtualization provides a universal method to harmoniously bind distributed and decentralized systems together. Therefore, a virtual model is a pivotal point between IT and OT system integration, offering data sources and services, standardizing communication, and governing high-to-low level decision making. Furthermore, virtual models become accessible resources in the Industry 4.0 "digital ecosystem", due to their standardized Service Oriented Architecture (SOA); and further gain access to other digital resources/ services seamlessly. The alignment of data and communication standards can further enable access to a universal form of individual and collective intelligence in the Industry 4.0 "digital mind". Therefore, enabling "turn-key" advanced control and intelligence capabilities.

Within these future-state models, Machine customization can be supported through Modularity, e.g. modular technical frameworks; to promote simplified reconfigurable programming, and holistic machine control. Design considerations for hierarchical/remote control can be considered proactively, e.g. unified programming and data standards; with common understanding of acceptable limits, e.g. adaptive tasks vs production tasks. The combination of which aims to empower each skilled developer with the tools and specification they need to individually and collectively develop, and expand the capabilities of the SR* machine, across its lifecycle. Fundamentally, this recognizes the importance of human centricity beyond the HMI, and throughout collective CPS design and hierarchical control.

Finally, advanced 'future-state' modelling can be recognized in the research and development of intelligent orchestration and virtualization in 5G enabled environments, blockchain for Open Manufacturing (OM), and increased autonomy and optimization via closed-loop simulation.

6. Conclusion

6.1. Smart reconfigurable machines

In succinct conclusion, this paper has provided a fundamental research review of RMS, machine control, and machine intelligence, in order to propose objective answers to two proposed research questions, relating to: (1) reconfigurable design and industry adoption; and (2) enabling present and future state technology. Uniquely, the result of this effort has established a vision for next generation Industry 4.0 Smart Reconfigurable (SR*) machines, which aim to:

- Close control-loops vertically and horizontally, from Connection, Conversion, Cyber, Cognition, to Configuration
(IT & OT, CPS architecture & maturity).
- Provide "turn-key" integration and intelligence capabilities for individual and collective machines/systems (digital ecosystem, and the digital mind).
- Harness the synergy between reconfigurable capability, and distributed intelligence (extraordinary capabilities).
- Simplify the complex, and become a bridge for academic and industry collaboration, and Industry 4.0 innovation.
(AI: decomposition, virtualization, simulation)

From the authors perspective, the potential impact the technologies reviewed in this paper will have on the manufacturing sector, is apparent in the RMS examples referenced throughout the paper. For context, key RMS examples have ranged from: reconfigurable collaborative and cellular robots, distributed fractal factories, additive processing chains, and distributed modular processes; with further references made to reconfigurable machine tools, assembly machines, and inspection machines. These individual and collective systems offer solutions to ease the management and automation of complex, customized and individualized manufacturing processes; and fundamentally enable a rapid adjustment of production capacity and functionality over time. Presently, to achieve this, these solutions are designed to be both smart and reconfigurable, with new enabling technology innovations in distributed and decentralized control and artificial intelligence systems. The impact of which is most significant to machines that are reconfigurable and/or flexible, as such these systems have the "capability to autonomously change". This is a key factor when closing the loop in artificially intelligent systems, such as Cyber Physical Systems (CPS) from: data connection, conversation, analytics, artificial cognition, to (re)configuration; as such these systems will have the "intelligence to know when and what to change". The potential impact this could have to manufacturing systems is estimated in obtaining new levels of efficiency with new levels of autonomy, such as adaptive behavior; for optimizing product flows, production scheduling, and maintenance activities. Presently, there is ample opportunity to develop these next gen systems, as throughout this paper we have attempted to demystify the collective research efforts and draw focus on enabling technologies. As such, the status quo for centralized design is being challenged, as integrated technology is becoming interface technology within larger distributed and/or decentralized networks. All of which should break down barriers to change, with autonomous hardware, software, and information; which is representative of a 4th industrial revolution.

6.2. Future research opportunities

Potential future SR* research opportunities, can be seen in:

Architecture / Frameworks - A current challenge is the present-state maturity of smart machine models, architectures and CPS frameworks. As such, there is an opportunity to create open-source technical SR* architectures with development/operation resources to assist SME adoption, and LME consideration. Key to this framework is its open-access, intuitive HMI reconfigurations, universal application, modular customization, value-added connected services, an ease-of-use "plug-and-produce" mentality, and a focus on high-speed automation. Key references: Section 3.2.4 - 'Vertical Integration', Section 3.3.3 - 'Technology Landscape', Section 3.3.4 - 'Smart Machine Modelling', and Section 3.3.6 - 'Smart Reconfigurable Synergy - Orchestration'.

Business Impact - An ideal future-state of SR* machines would be full-scale reconfigurable autonomy. However, this could be highly impractical and highly costly, and therefore a balance is needed, taking into account the change/reconfigurable cost, speed, and frequency, as depicted in Fig. 16. As such, there is an opportunity to provide more 'business impact cost analysis' studies, to examine the effects of faults in the centralized production systems, in contrast to RMS. This would be an incentive to incorporate higher levels of reconfigurable DZC designs, to increase reliability through redundancy, and adaptive control behaviors. Key reference: Section 3.1.3 - 'individual and collective', Section 3.1.4 - 'expanded research'.

Speed and Volume – RMSs seek to maximize both capability and capacity with increased speed and volume. Therefore, enabling research to achieve this in both hardware, software, information and communication systems is paramount. For example, the abstraction of controls through virtualization counterintuitively provides another link in the control/communication chain, which could potentially reduce automation speeds. Therefore, further research is required to understand the scope of synchronization methods, such as bi-level communication; to

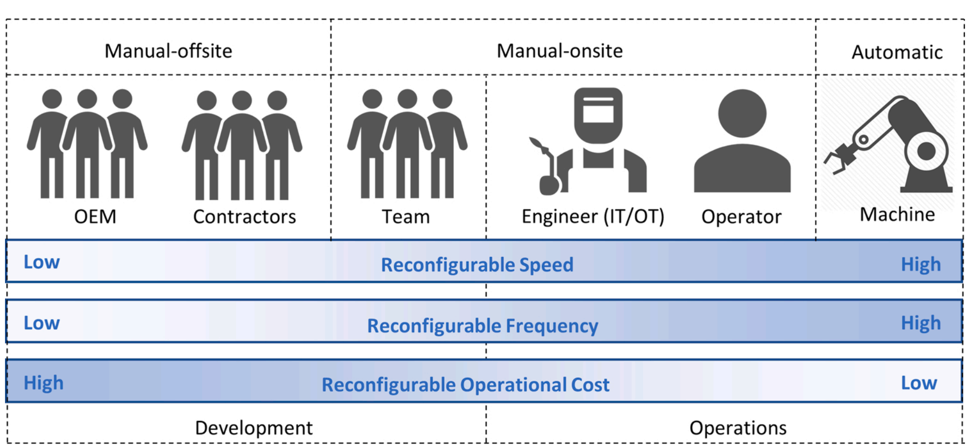


Fig. 16. Level of Reconfigurable Provider.

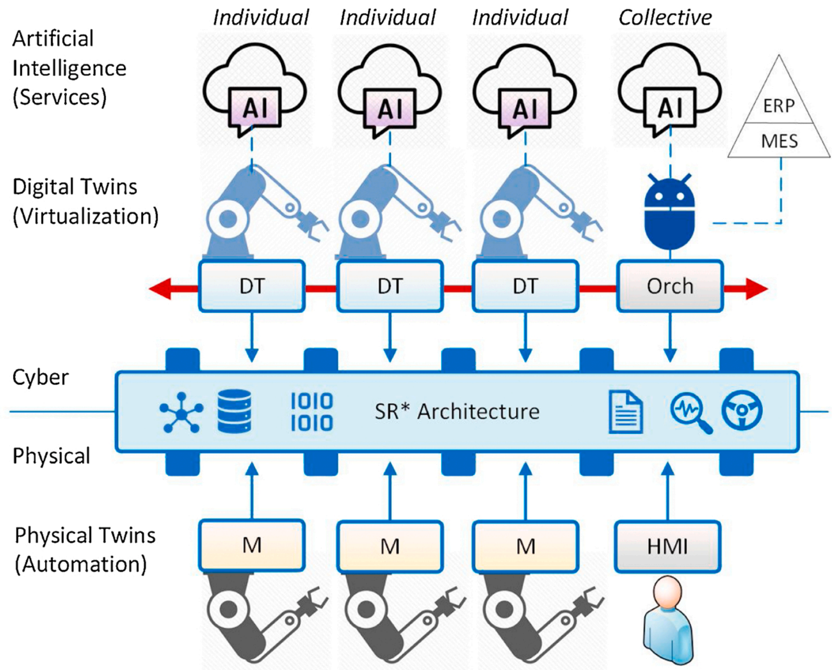


Fig. 17. Future-state model "Plug and Produce" architecture.

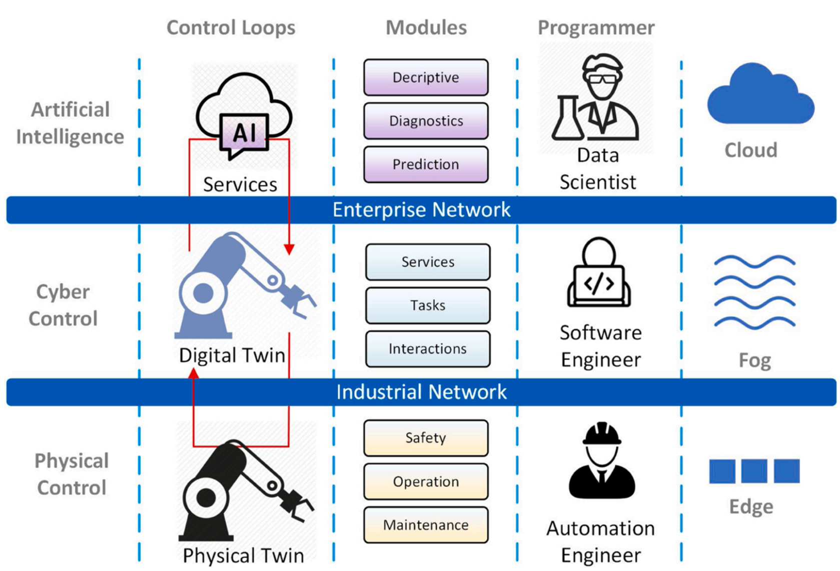


Fig. 18. Future-state model "Modularity" framework.

achieve optimal performance. Key reference: Section 3.3.4 - 'Smart Machine Modelling – Digital Twin'.

Retro-Fitting - An ideal future-state of SR* manufacturing would be the mass deployment of reconfigurable machines. However, the current heterogeneous nature of manufacturing technology/processes and new/legacy equipment, does not easily support this full vision. Potentially only "factories of the future", designed outright, could maximize that potential value. As such, there is an opportunity to investigate the retro-fitting of present state and legacy manufacturing equipment within virtualization models, and CPS architectures. Key reference: Section 3.3.4 - 'Smart Machine Modelling - Asset Administration Shell'.

Sensing / Actuation – SR* machines have the "capability to autonomously change, and the intelligence to know when and what to change". Therefore, machines need to be designed with wider internal and external actuation and sensing considerations. As such, exploring both common and unique mechanisms to both sense issues and overcoming issues is paramount. This will also have to consider a return on investment, as new sensing and actuation must bring value, and not exacerbate the negative high costs associated with RMS. Key reference: Section 3.3.6 - 'Smart Reconfigurable Synergy - Self-maintenance'.

Digital Ecosystems/Mind – The standardized digital ecosystem, frameworks, and technology stacks, offers a means for universal service integration, and modular intelligence plugin capabilities. As such, there are opportunities to review and develop Software-as-a-Service (SaaS) solutions in the Edge, Fog, and Cloud, to enable ubiquitous SR* capabilities for next generation SR* machines. Key reference: Section 3.3.3 - 'Technology Landscape', Section 3.3.4 - 'Smart Machine Modelling - Software-defined Cloud manufacturing architecture'.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgments

This publication has emanated from research supported in part by a research grant from Science Foundation Ireland (SFI) under Grant Number SFI 16/RC/3918 (Confirm SFI Research Centre for Smart Manufacturing), co-funded by the European Regional Development Fund. With special thanks to Sean Nolan from the Confirm Centre for his work in establishing the cross university collaboration which was pivotal to the creation of this paper.

References

[1] HORIZON 2020 in brief. European Commission; 2014. https://doi.org/10.2777/3719.
[2] Lasi H, Fettke P, Kemper H-G, Feld T, Hoffmann M. Industry 4.0. Bus Inf Syst Eng 2014;6:239–42. https://doi.org/10.1007/s12599-014-0334-4.
[3] Trentesaux D. Distributed control of production systems. Eng Appl Artif Intell 2009;22:971–8. https://doi.org/10.1016/j.engappai.2009.05.001.
[4] Zhong RY, Xu X, Klotz E, Newman ST. Intelligent manufacturing in the context of industry 4.0: a review. Engineering 2017;3:616–30. https://doi.org/10.1016/J.ENG.2017.05.015.
[5] Wooldridge M, Jennings NR. Intelligent agents: theory and practice. Knowl Eng Rev 1995;10:115–52. https://doi.org/10.1017/S0269888900008122.
[6] Valckenaers P, Van Brussel H. Holonic manufacturing execution systems. CIRP Ann Manuf Technol 2005. https://doi.org/10.1016/S0007-8506(07)60137-1.
[7] Lee J, Bagheri B, Kao H-A. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manuf Lett 2015;3:18–23. https://doi.org/10.1016/j.mfglet.2014.12.001.
[8] Lu Y, Liu C, KI-K Wang, Huang H, Xu X. Digital Twin-driven smart manufacturing: connotation, reference model, applications and research issues. Robot Comput Integr Manuf 2020;61:101837. https://doi.org/10.1016/j.rcim.2019.101837.
[9] Koren Y, Heisel U, Jovane F, Moriwaki T, Pritschow G, Ulsoy G, et al. Reconfigurable manufacturing systems. CIRP Ann Manuf Technol 1999. https://doi.org/10.1016/S0007-8506(07)63232-6.
[10] Andersen A-L, Brunoe TD, Nielsen K, Rösiö C. Towards a generic design method for reconfigurable manufacturing systems: analysis and synthesis of current design methods and evaluation of supportive tools. Int J Ind Manuf Syst Eng 2017;42:179–95. https://doi.org/10.1016/J.JMSY.2016.11.006.
[11] Koren Y, Gu X, Guo W. Reconfigurable manufacturing systems: Principles, design, and future trends. Front Mech Eng 2018;13:121–36. https://doi.org/10.1007/s11465-018-0483-0.
[12] Hofmann E, Rüsch M. Industry 4.0 and the current status as well as future prospects on logistics. Comput Ind 2017;89:23–34. https://doi.org/10.1016/j.compind.2017.04.002.
[13] Tisdell CA. Economic, social and political issues raised by the COVID-19 pandemic. Econ Anal Policy 2020. https://doi.org/10.1016/j.eap.2020.08.002.
[14] Kumar MS, Raut DRD, Narwane DVS, Narkhede DBE. Applications of industry 4.0 to overcome the COVID-19 operational challenges. Diabetes Metab Syndr Clin Res Rev 2020;14:1283–9. https://doi.org/10.1016/j.dsx.2020.07.010.
[15] Porvair adapts manufacturing to fight Covid-19. Filtr Ind Anal 2020;2020:3. https://doi.org/10.1016/S1365-6937(20)30096-4.
[16] Rapaccini M, Saccani N, Kowalkowski C, Paiola M, Adrodegari F. Navigating disruptive crises through service-led growth: the impact of COVID-19 on Italian manufacturing firms. Ind Mark Manag 2020;88:225–37. https://doi.org/10.1016/j.indmarman.2020.05.017.
[17] Mehrabi MG, Ulsoy AG, Koren Y. Reconfigurable manufacturing systems: Key to future manufacturing. J Intell Manuf 2000;11:403–19. https://doi.org/10.1023/A:1008930403506.
[18] Ateekh-Ur-Rehman, Subash Babu A. Reconfigurations of manufacturing systems—an empirical study on concepts, research, and applications. Int J Adv Manuf Technol 2013;66:107–24. https://doi.org/10.1007/s00170-012-4310-1.
[19] Koren Y, Shpitalni M. Design of reconfigurable manufacturing systems. J Manuf Syst 2010;29:130–41. https://doi.org/10.1016/J.JMSY.2011.01.001.
[20] Fox S. Moveable factories: how to enable sustainable widespread manufacturing by local people in regions without manufacturing skills and infrastructure. Technol Soc 2015. https://doi.org/10.1016/j.techsoc.2015.03.003.
[21] Bauernhansl T. In: Bauernhansl T, ten Hompel M, Vogel-Heuser B, editors. Die vierte industrielle revolution – der weg in ein wertschaffendes produktionsparadigma BT - industrie 4.0 in produktion, automatisierung und logistik: anwendung · technologien · migration. Wiesbaden: Springer Fachmedien Wiesbaden; 2014. p. 5–35. https://doi.org/10.1007/978-3-658-04682-8_1.
[22] Lu Y, Xu X. Cloud-based manufacturing equipment and big data analytics to enable on-demand manufacturing services. Robot Comput Integr Manuf 2019. https://doi.org/10.1016/j.rcim.2018.11.006.
[23] Bortolini M, Galizia FG, Mora C. Reconfigurable manufacturing systems: literature review and research trend. J Manuf Syst 2018;49:93–106. https://doi.org/10.1016/J.JMSY.2018.09.005.
[24] El Zaatari S, Marei M, Li W, Usman Z. Cobot programming for collaborative industrial tasks: an overview. Rob Auton Syst 2019. https://doi.org/10.1016/j.robot.2019.03.003.
[25] Abele E, Chryssolouris G, Sihn W, Metternich J, ElMaraghy H, Seliger G, et al. Learning factories for future oriented research and education in manufacturing. CIRP Ann 2017;66:803–26. https://doi.org/10.1016/j.cirp.2017.05.005.
[26] Benitez GB, Ayala NF, Frank AG. Industry 4.0 innovation ecosystems: an evolutionary perspective on value cocreation. Int J Prod Econ 2020;228:107735. https://doi.org/10.1016/j.ijpe.2020.107735.
[27] Zheng C, Qin X, Eynard B, Bai J, Li J, Zhang Y. SME-oriented flexible design approach for robotic manufacturing systems. J Manuf Syst 2019;53:62–74. https://doi.org/10.1016/J.JMSY.2019.09.010.
[28] Koren Y, Wang W, Gu X. Value creation through design for scalability of reconfigurable manufacturing systems. Int J Prod Res 2017. https://doi.org/10.1080/00207543.2016.1145821.
[29] Yelles-Chaouche AR, Gurevsky E, Brahimi N, Dolgui A. Reconfigurable manufacturing systems from an optimisation perspective: a focused review of literature. Int J Prod Res 2020. https://doi.org/10.1080/00207543.2020.1813913.
[30] Monostori L, Kádár B, Bauernhansl T, Kondoh S, Kumara S, Reinhart G, et al. Cyber-physical systems in manufacturing. CIRP Ann 2016;65:621–41. https://doi.org/10.1016/j.cirp.2016.06.005.
[31] Instrument Society of America. ISA–95.00.01, Part 1: Models and terminology. 200AD.
[32] Zezulka F, Marcon P, Vesely I, Sajdl O. Industry 4.0 – an Introduction in the phenomenon. IFAC-PapersOnLine 2016;49:8–12. https://doi.org/10.1016/J.IFACOL.2016.12.002.
[33] Scholz S, Mueller T, Plasch M, Limbeck H, Adamietz R, Iseringhausen T, et al. A modular flexible scalable and reconfigurable system for manufacturing of Microsystems based on additive manufacturing and e-printing. Robot Comput Integr Manuf 2016;40:14–23. https://doi.org/10.1016/J.RCIM.2015.12.006.
[34] Adamietz R, Giesen T, Mayer P, Johnson A, Bibb R, Seifarth C. Reconfigurable and transportable container-integrated production system. Robot Comput Integr Manuf 2018;53:1–20. https://doi.org/10.1016/J.RCIM.2018.02.008.
[35] Nikolakis N, Senington R, Sipsas K, Syberfeldt A, Makris S. On a containerized approach for the dynamic planning and control of a cyber - physical production system. Robot Comput Integr Manuf 2020;64:101919. https://doi.org/10.1016/J.RCIM.2019.101919.
[36] Kim D-Y, Park J-W, Baek S, Park J-B, Kim H-R, Park J-I, et al. A modular factory testbed for the rapid reconfiguration of manufacturing systems. J Intell Manuf 2019. https://doi.org/10.1007/s10845-019-01471-2.
[37] Park KT, Lee J, Kim H-J, Do Noh S. Digital twin-based cyber physical production system architectural framework for personalized production. Int J Adv Manuf Technol 2020;106:1–24. https://doi.org/10.1007/s00170-019-04653-7.
[38] Liu M, Ma J, Lin L, Maogen G, Wang Q, Liu C. Intelligent assembly system for mechanical products and key technology based on internet of things. J Intell Manuf 2014;28:1–29. https://doi.org/10.1007/s10845-014-0976-6.
[39] He C, Guan Z, Gong Y, Wang C, Yue L. Automated flexible transfer line design problem: sequential and reconfigurable stages with parallel machining cells. J Manuf Syst 2019;52:157–71. https://doi.org/10.1016/J.JMSY.2019.05.005.
[40] Koren Y. General RMS characteristics. Chapter 3. Comparison with Dedicated and Flexible Systems. Reconfigurable Manuf Syst Transform Factories; 2006. https://doi.org/10.1007/3-540-29397-3_3.
[41] Dashchenko AI. Reconfigurable manufacturing systems and transformable factories. 2006. https://doi.org/10.1007/3-540-29397-3.
[42] Koren Y. The global manufacturing revolution: product-process-business integration and reconfigurable systems. 2010. https://doi.org/10.1002/9780470618813.
[43] Koren Y, Fotsoh C, Najid N-M, Martin P, Wang G, Bortolini M, et al. Reconfigurable manufacturing systems: from design to implementation. Springer Nature Switzerland AG 2020;2020.
[44] Dictionary.com 2020. www.dictionary.com.
[45] Landers RG, Min BK, Koren Y. Reconfigurable machine tools. CIRP Ann Manuf Technol 2001. https://doi.org/10.1016/S0007-8506(07)62120-9.
[46] Bi ZM, Lang SYT, Verner M, Orban P. Development of reconfigurable machines. Int J Adv Manuf Technol 2008;39:1227–51. https://doi.org/10.1007/s00170-007-1288-1.
[47] Bi ZM, Lang SYT, Shen W, Wang L. Reconfigurable manufacturing systems: the state of the art. Int J Prod Res 2008;46:967–92. https://doi.org/10.1080/00207540600905646.
[48] Andersen A-L, Brunoe TD, Nielsen K. Reconfigurable manufacturing on multiple levels: literature review and research directions. In: Umeda S, Nakano M, Mizuyama H, Hibino N, Kiritsis D, von Cieminski G, editors. Adv. Prod. Manag. Syst. Innov. Prod. Manag. Towar. Sustain. Growth. Cham: Springer International Publishing; 2015. p. 266–73.
[49] Wang Y, Zhang G, Han L. A methodology of setting module groups for the design of reconfigurable machine tools. Int J Adv Manuf Technol 2019. https://doi.org/10.1007/s00170-019-03337-6.
[50] Moghaddam SK, Houshmand M, Saitou K, Valilai OF. Configuration design of scalable reconfigurable manufacturing systems for part family. Int J Prod Res 2020;58:2974–96. https://doi.org/10.1080/00207543.2019.1620365.
[51] Prasad D, Jayswal SC. Reconfigurability consideration and scheduling of products in a manufacturing industry. Int J Prod Res 2018. https://doi.org/10.1080/00207543.2017.1334979.

[52] Gadalla M, Xue D. An approach to identify the optimal configurations and reconfiguration processes for design of reconfigurable machine tools. Int J Prod Res 2018. https://doi.org/10.1080/00207543.2017.1406674.
[53] Bortolini M, Galizia FG, Mora C, Pilati F. Reconfigurability in cellular manufacturing systems: a design model and multi-scenario analysis. Int J Adv Manuf Technol 2019. https://doi.org/10.1007/s00170-019-04179-y.
[54] Haddou Benderbal H, Benyoucef L. Machine layout design problem under product family evolution in reconfigurable manufacturing environment: a two-phase-based AMOSA approach. Int J Adv Manuf Technol 2019. https://doi.org/10.1007/s00170-019-03865-1.
[55] Saliba MA, Azzopardi S, Pace C, Zammit D. A heuristic approach to module synthesis in the design of reconfigurable manufacturing systems. Int J Adv Manuf Technol 2019. https://doi.org/10.1007/s00170-019-03444-4.
[56] Wiendahl HP, ElMaraghy HA, Nyhuis P, Zäh MF, Wiendahl HP, Duffie N, et al. Changeable manufacturing - classification, design and operation. CIRP Ann Manuf Technol 2007. https://doi.org/10.1016/j.cirp.2007.10.003.
[57] Farid AM. Measures of reconfigurability and its key characteristics in intelligent manufacturing systems. J Intell Manuf 2017;28:353–69. https://doi.org/10.1007/s10845-014-0983-7.
[58] Saliba MA, Zammit D, Azzopardi S. Towards practical, high-level guidelines to promote company strategy for the use of reconfigurable manufacturing automation. Robot Comput Integr Manuf 2017;47:53–60. https://doi.org/10.1016/J.RCIM.2016.12.002.
[59] Gauss L, Lacerda DP, Sellitto MA. Module-based machinery design: a method to support the design of modular machine families for reconfigurable manufacturing systems. Int J Adv Manuf Technol 2019;102:3911–36. https://doi.org/10.1007/s00170-019-03358-1.
[60] Najid N-M, Castagna P, Kouiss K. In: Benyoucef L, editor. System engineering-based methodology to design reconfigurable manufacturing systems BT - reconfigurable manufacturing systems: from design to implementation. Cham: Springer International Publishing; 2020. p. 29–55. https://doi.org/10.1007/978-3-030-28782-5_3.
[61] Bortolini M, Botti L, Galizia FG, Mora C. In: Benyoucef L, editor. Safety, ergonomics and human factors in reconfigurable manufacturing systems BT - reconfigurable manufacturing systems: from design to implementation. Cham: Springer International Publishing; 2020. p. 123–38. https://doi.org/10.1007/978-3-030-28782-5_6.
[62] Abdelzaher T, Diao Y, Hellerstein J, Lu C, Zhu X. Introduction to control theory and its application to computing systems. Perform Model Eng 2008:185–215. https://doi.org/10.1007/978-0-387-79361-0_7.
[63] Lee E. Cyber physical systems: design challenges. Electr Eng Comput Sci 2008: 363–9. https://doi.org/10.1109/ISORC.2008.25.
[64] Alphonsus ER, Abdullah MO. A review on the applications of programmable logic controllers (PLCs). Renew Sustain Energy Rev 2016;60:1185–205. https://doi.org/10.1016/j.rser.2016.01.025.
[65] John K-H, Tiegelkamp M. IEC 61131-61133: programming industrial automation systems.. 2001. https://doi.org/10.1007/978-3-662-07847-1.
[66] Plaza I, Medrano C, Blesa A. Analysis and implementation of the IEC 61131-3 software model under POSIX Real-Time operating systems. Microprocess Microsyst 2006. https://doi.org/10.1016/j.micpro.2006.06.001.
[67] Thramboulidis K. Towards an object-oriented extension for IEC 61131. IEEE Int. Conf. Emerg. Technol. Fact. Autom. ETFA 2012. https://doi.org/10.1109/ETFA.2012.6489673.
[68] Caro D. Automation network selection: a reference manual. Third. ISA; 2016.
[69] Vyatkin V. IEC 61499 as enabler of distributed and intelligent automation: state-of-the-art review. IEEE Trans Ind Informatics 2011. https://doi.org/10.1109/TII.2011.2166785.
[70] NI. Introduction to the Distributed Control and Automation Framework (DCAF). White Pap n.d. https://www.ni.com/en-ie/innovations/white-papers/18/introduction-to-the-distributed-control-and-automation-framework.html#section–810865512 (accessed August 10, 2020).
[71] ISA. ANSI/ISA-88.01 batch control part 1 : models and terminology. 1995.
[72] Nøkleby C. PackML unit/machine implementation guide. 2016.
[73] Hollnagel E. Handbook of cognitive task design. 2003. https://doi.org/10.1201/9781410607775.
[74] Nachreiner F, Nickel P, Meyer I. Human factors in process control systems: the design of human-machine interfaces. Saf Sci 2006. https://doi.org/10.1016/j.ssci.2005.09.003.
[75] Magrini E, Ferraguti F, Ronga AJ, Pini F, De Luca A, Leali F. Human-robot coexistence and interaction in open industrial cells. Robot Comput Integr Manuf 2020. https://doi.org/10.1016/j.rcim.2019.101846.
[76] Hartson R, Pyla P. What are UX and UX design?. Chapter 1 In: Hartson R, Pyla P, editors. UX B.. second ed. Boston: Morgan Kaufmann; 2019. p. 3–25. https://doi.org/10.1016/B978-0-12-805342-3.00001-1.
[77] Wang W, Zhang X, Li Y, Li Y. Open CNC machine tool's state data acquisition and application based on OPC specification. Procedia CIRP 2016;56:384–8. https://doi.org/10.1016/j.procir.2016.10.061.
[78] Xu XW, He Q. Striving for a total integration of CAD, CAPP, CAM and CNC. Robot Comput Integr Manuf 2004;20:101–9. https://doi.org/10.1016/j.rcim.2003.08.003.
[79] Hao Y, Helo P. The role of wearable devices in meeting the needs of cloud manufacturing: a case study. Robot Comput Integr Manuf 2017. https://doi.org/10.1016/j.rcim.2015.10.001.
[80] Sand O, Büttner S, Paelke V, Röcker C. smARt.ASsembly – projection-based augmented reality for supporting assembly workers. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics); 2016. https://doi.org/10.1007/978-3-319-39907-2_61.
[81] Longo F, Nicoletti L, Padovano A. Smart operators in industry 4.0: a human-centered approach to enhance operators' capabilities and competencies within the new smart factory context. Comput Ind Eng 2017. https://doi.org/10.1016/j.cie.2017.09.016.
[82] Scholten B. Integrating ISA-88 and ISA-95. Isa expo 2007. 2007.
[83] Morgan J, O'Donnell GE. The cyber physical implementation of cloud manufactuirng monitoring systems. Procedia CIRP 2015;33. https://doi.org/10.1016/j.procir.2015.06.007.
[84] Hoffmann M, Meisen T, Jeschke S. OPC UA based ERP agents: enabling scalable communication solutions in heterogeneous automation environments. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics); 2017. https://doi.org/10.1007/978-3-319-59930-4_10.
[85] Munz H. Requirements for time sensitive networks in manufacturing. Why right now? because industry 4.0 needs it. IEEE 8021 TSN Stand Meet 2015:40 (accessed February 25, 2021), https://www.ieee802.org/1/files/public/docs2015/tsn-munz-requirements-for-tsn-in-manufacturing-0515-v01.pdf.
[86] Morgan J, O'Donnell GE. Enabling a ubiquitous and cloud manufacturing foundation with field-level service-oriented architecture. Int J Comput Integr Manuf 2017:30. https://doi.org/10.1080/0951192X.2015.1032355.
[87] Wollschlaeger M, Sauter T, Jasperneite J. The future of industrial communication: automation networks in the era of the internet of things and industry 4.0. IEEE Ind Electron Mag 2017. https://doi.org/10.1109/MIE.2017.2649104.
[88] Sisinni E, Saifullah A, Han S, Jennehag U, Gidlund M. Industrial internet of things: challenges, opportunities, and directions. IEEE Trans Ind Informatics 2018;14:4724–34. https://doi.org/10.1109/TII.2018.2852491.
[89] Köksal Ö, Tekinerdogan B. Obstacles in data distribution service middleware: a systematic review. Future Gener Comput Syst 2017. https://doi.org/10.1016/j.future.2016.09.020.
[90] Pérez H, Gutiérrez JJ. Modeling the QoS parameters of DDS for event-driven real-time applications. J Syst Softw 2015. https://doi.org/10.1016/j.jss.2015.03.008.
[91] Pisching MA, Pessoa MAO, Junqueira F, dos Santos Filho DJ, Miyagi PE. An architecture based on RAMI 4.0 to discover equipment to process operations required by products. Comput Ind Eng 2018. https://doi.org/10.1016/j.cie.2017.12.029.
[92] Grángel-Gonzalez I, Baptista P, Halilaj L, Lohmann S, Vidal ME, Mader C, et al. The industry 4.0 standards landscape from a semantic integration perspective. IEEE Int. Conf. Emerg. Technol. Fact. Autom. ETFA 2017. https://doi.org/10.1109/ETFA.2017.8247584.
[93] Industry 4.0 standards. Enterprise Information Systems; 2016 (accessed July 28, 2020), http://i40.semantic-interoperability.org/.
[94] Ye X, Hong SH. An AutomationML/OPC UA-based industry 4.0 solution for a manufacturing system. IEEE Int. Conf. Emerg. Technol. Fact. Autom. ETFA 2018. https://doi.org/10.1109/ETFA.2018.8502637.
[95] OPC UA information model for IEC 61131-3. OPC Foundation, PLCopen. PLCopen and OPC Foundation; 2018. p. 1–61.
[96] Siemens. OPC UA methods for the SIMATIC S7-1500 OPC UA server. 2018.
[97] WAGO. A PLUG-IN MAKES WAGO CONTROLLERS IOT-READY. 2020 (accessed October 2, 2020), https://www.wago.com/us/open-automation/cloud-connectivity/iot-plc-controller-with-mqtt.
[98] Sparkplug specification version 2.2. Eclipse Foundation; 2019.
[99] Liu Y, Xu X. Industry 4.0 and cloud manufacturing: a comparative analysis. J Manuf Sci Eng Trans ASME 2017. https://doi.org/10.1115/1.4034667.
[100] Gerrikagoitia JK, Unamuno G, Urkia E, Serna A. Digital manufacturing platforms in the industry 4.0 from private and public perspectives. Appl Sci 2019. https://doi.org/10.3390/app9142934.
[101] Monostori L. Cyber-physical production systems: roots, expectations and R&D challenges. Procedia CIRP 2014;17:9–13. https://doi.org/10.1016/j.procir.2014.03.115.
[102] Sharma KLS. Overview of industrial process automation. Elsevier Inc; 2011. https://doi.org/10.1016/C2011-0-04273-4.
[103] Grigoriev SN, Martinov GM. Research and development of a cross-platform CNC kernel for multi-axis machine tool. Procedia CIRP 2014;14:517–22. https://doi.org/10.1016/j.procir.2014.03.051.
[104] Sharma KLS. Overview of industrial process automation. second edition 2016.
[105] Mehta BR, Reddy YJ. Industrial process automation systems: design and implementation. 2014. https://doi.org/10.1016/C2013-0-18954-4.
[106] Bakule L. Decentralized control: an overview. Annu Rev Control 2008;32:87–98. https://doi.org/10.1016/j.arcontrol.2008.03.004.
[107] Essers MS, Vaneker THJ. Design of a decentralized modular architecture for flexible and extensible production systems. Mechatronics 2016. https://doi.org/10.1016/j.mechatronics.2015.08.009.
[108] Baran P. On distributed communications: I. Introduction to distributed communications networks. 2018. https://doi.org/10.7249/rm3420.
[109] Rahman M, Ranjan R, Buyya R. Decentralization in distributed systems: challenges, technologies, and opportunities. Adv. Distrib. Comput. Internet technol. Trends issues. Hershey, PA, USA: IGI Global; 2012. p. 386–99. https://doi.org/10.4018/978-1-61350-110-8. ch018.
[110] Buckholtz B, Ragai I, Wang L. Cloud manufacturing: current trends and future implementations. J Manuf Sci Eng Trans ASME 2015. https://doi.org/10.1115/1.4030009.
[111] Li Z, Wang WM, Liu G, Liu L, He J, Huang GQ. Toward open manufacturing a cross-enterprises knowledge and services exchange framework based on blockchain and edge computing. Ind Manag Data Syst 2018;118:303–20. https://doi.org/10.1108/IMDS-04-2017-0142.

[112] Baillieul J, Antsaklis PJ. Control and communication challenges in networked real-time systems. Proc IEEE 2007. https://doi.org/10.1109/JPROC.2006.887290.
[113] Mařík V, McFarlane D. Industrial adoption of agent-based technologies. IEEE Intell Syst 2005. https://doi.org/10.1109/MIS.2005.11.
[114] Leitão P. Agent-based distributed manufacturing control: a state-of-the-art survey. Eng Appl Artif Intell 2009. https://doi.org/10.1016/j.engappai.2008.09.005.
[115] Chen J, Cao X, Cheng P, Xiao Y, Sun Y. Distributed collaborative control for industrial automation with wireless sensor and actuator networks. IEEE Trans Ind Electron 2010. https://doi.org/10.1109/TIE.2010.2043038.
[116] Dotoli M, Fay A, Miśkowicz M, Seatzu C. An overview of current technologies and emerging trends in factory automation. Int J Prod Res 2019. https://doi.org/10.1080/00207543.2018.1510558.
[117] Kusiak A. Fundamentals of smart manufacturing: a multi-thread perspective. Annu Rev Control 2019;47:214–20. https://doi.org/10.1016/j.arcontrol.2019.02.001.
[118] Babiceanu RF, Chen FF. Development and applications of holonic manufacturing systems: a survey. J Intell Manuf 2006;17:111–31. https://doi.org/10.1007/s10845-005-5516-y.
[119] Colombo AW, Jammes F, Smit H, Harrison R, Lastra JLM, Delamer IM. Service-oriented architectures for collaborative automation. In: 31st Annu. Conf. IEEE Ind. Electron. Soc. 2005; 2005. p. 6. https://doi.org/10.1109/IECON.2005.1569325. pp.-.
[120] Atzori L, Iera A, Morabito G. The internet of things: a survey. Comput Networks 2010;54:2787–805. https://doi.org/10.1016/j.comnet.2010.05.010.
[121] Lim KYH, Zheng P, Chen CH. A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives. J Intell Manuf 2019. https://doi.org/10.1007/s10845-019-01512-w.
[122] Qi Q, Tao F, Hu T, Anwer N, Liu A, Wei Y, et al. Enabling technologies and tools for digital twin. J Manuf Syst 2019. https://doi.org/10.1016/j.jmsy.2019.10.001.
[123] Cândido G, Barata J, Colombo AW, Jammes F. SOA in reconfigurable supply chains: a research roadmap. Eng Appl Artif Intell 2009;22:939–49. https://doi.org/10.1016/j.engappai.2008.10.020.
[124] Leng J, Liu Q, Ye S, Jing J, Wang Y, Zhang C, et al. Digital twin-driven rapid reconfiguration of the automated manufacturing system via an open architecture model. Robot Comput Integr Manuf 2020;63:101895. https://doi.org/10.1016/j.rcim.2019.101895.
[125] Russell S, Norvig P. Artificial intelligence: a modern approach. Prentice Hall; 2009.
[126] Monostori L, Váncza J, Kumara SRT. Agent-based systems for manufacturing. CIRP Ann Manuf Technol 2006;55:697–720. https://doi.org/10.1016/j.cirp.2006.10.004.
[127] Wang S, Wan J, Zhang D, Li D, Zhang C. Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. Comput Networks 2016. https://doi.org/10.1016/j.comnet.2015.12.017.
[128] Mathews J. Organizational foundations of intelligent manufacturing systems — the holonic viewpoint. Comput Integr Manuf Syst 1995;8:237–43. https://doi.org/10.1016/0951-5240(95)00021-6.
[129] Jammes F, Smit H. Service-oriented paradigms in industrial automation. IEEE Trans Ind Informatics 2005;1:62–70. https://doi.org/10.1109/TII.2005.844419.
[130] Derler P, Lee EA, Vincentelli AS. Modeling cyber–physical systems. Proc IEEE 2012;100:13–28. https://doi.org/10.1109/JPROC.2011.2160929.
[131] Cruz Salazar LA, Ryashentseva D, Lüder A, Vogel-Heuser B. Cyber-physical production systems architecture based on multi-agent's design pattern—comparison of selected approaches mapping four agent patterns. Int J Adv Manuf Technol 2019. https://doi.org/10.1007/s00170-019-03800-4.
[132] Tao F, Qi Q, Wang L, Nee AYC. Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison. Engineering 2019;5:653–61. https://doi.org/10.1016/J.ENG.2019.01.014.
[133] Tao F, Cheng J, Qi Q, Zhang M, Zhang H, Sui F. Digital twin-driven product design, manufacturing and service with big data. Int J Adv Manuf Technol 2018; 94:3563–76. https://doi.org/10.1007/s00170-017-0233-1.
[134] Bussmann S. An agent-oriented architecture for holonic manufacturing control. First open work. IMS eur.. Lausanne, Switzerland: ESPRIT Working Group on IMS; 1998. p. 12.
[135] Giret A, Botti V. Holons and agents. J Intell Manuf 2004;15:645–59. https://doi.org/10.1023/B:JIMS.0000037714.56201.a3.
[136] Fischer K, Schillo M, Siekmann J. Holonic multiagent systems: a foundation for the organisation of multiagent systems. In: Mařík V, McFarlane D, Valckenaers P, editors. Holonic multi-agent syst. Manuf., vol. 2744. Berlin Heidelberg: Springer; 2003. p. 71–80. https://doi.org/10.1007/978-3-540-45185-3_7.
[137] Wang L, Haghighi A. Combined strength of holons, agents and function blocks in cyber-physical systems. J Manuf Syst 2016. https://doi.org/10.1016/j.jmsy.2016.05.002.
[138] Xu LD, He W, Li S. Internet of things in industries: a survey. IEEE Trans Ind Informatics 2014;10:2233–43. https://doi.org/10.1109/TII.2014.2300753.
[139] Leu J, Chen C, Hsu K. Improving heterogeneous SOA-Based IoT message stability by shortest processing time scheduling. IEEE Trans Serv Comput 2014;7:575–85. https://doi.org/10.1109/TSC.2013.30.
[140] Lu Y. Industry 4.0: a survey on technologies, applications and open research issues. J Ind Inf Integr 2017;6:1–10. https://doi.org/10.1016/j.jii.2017.04.005.
[141] Oztemel E, Gursev S. Literature review of Industry 4.0 and related technologies. J Intell Manuf 2020. https://doi.org/10.1007/s10845-018-1433-8.
[142] Leitão P, Colombo AW, Karnouskos S. Industrial automation based on cyber-physical systems technologies: prototype implementations and challenges. Comput Ind 2016;81:11–25. https://doi.org/10.1016/J.COMPIND.2015.08.004.
[143] Negri E, Fumagalli L, Macchi M. A review of the roles of digital twin in CPS-based production systems. Procedia Manuf 2017;11:939–48. https://doi.org/10.1016/j.promfg.2017.07.198.
[144] Leng J, Zhang H, Yan D, Liu Q, Chen X, Zhang D. Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop. J Ambient Intell Humaniz Comput 2019. https://doi.org/10.1007/s12652-018-0881-5.
[145] El-Sayed H, Sankar S, Prasad M, Puthal D, Gupta A, Mohanty M, et al. Edge of things: the big picture on the integration of edge, IoT and the cloud in a distributed computing environment. IEEE Access 2017. https://doi.org/10.1109/ACCESS.2017.2780087.
[146] Porambage P, Okwuibe J, Liyanage M, Ylianttila M, Taleb T. Survey on multi-access edge computing for internet of things realization. IEEE Commun Surv Tutorials 2018. https://doi.org/10.1109/COMST.2018.2849509.
[147] Satyanarayanan M, Simoens P, Xiao Y, Pillai P, Chen Z, Ha K, et al. Edge analytics in the internet of things. IEEE Pervasive Comput 2015. https://doi.org/10.1109/MPRV.2015.32.
[148] Shafique M, Theocharides T, Bouganis CS, Hanif MA, Khalid F, Hafiz R, et al. An overview of next-generation architectures for machine learning: roadmap, opportunities and challenges in the IoT era. Proc. 2018 Des. Autom. Test Eur. Conf. Exhib. DATE 2018 2018. https://doi.org/10.23919/DATE.2018.8342120.
[149] Ochoa-Ruiz G, Aguilar-Lobo LM, Bevan R, de Lamotte F, Diguet JP. Towards Dynamically Reconfigurable SoCs (DRSoCs) in industrial automation: state of the art, challenges and opportunities. Microprocess Microsyst 2018. https://doi.org/10.1016/j.micpro.2018.07.002.
[150] Barton D, Gönnheimer P, Schade F, Ehrmann C, Becker J, Fleischer J. Modular smart controller for industry 4.0 functions in machine tools. Procedia CIRP 2019. https://doi.org/10.1016/j.procir.2019.04.022.
[151] Goldschmidt T, Hauck-Stattelmann S, Malakuti S, Grüner S. Container-based architecture for flexible industrial control applications. J Syst Archit 2018. https://doi.org/10.1016/j.sysarc.2018.03.002.
[152] Wei H, Shao Z, Huang Z, Chen R, Guan Y, Tan J, et al. RT-ROS: a real-time ROS architecture on multi-core processors. Future Gener Comput Syst 2016. https://doi.org/10.1016/j.future.2015.05.008.
[153] Zhao Z, Barijough KM, Gerstlauer A. DeepThings: Distributed adaptive deep learning inference on resource-constrained IoT edge clusters. IEEE Trans Comput Des Integr Circuits Syst 2018. https://doi.org/10.1109/TCAD.2018.2858384.
[154] Teerapittayanon S, McDanel B, Kung HT. Distributed deep neural networks over the cloud, the edge and end devices. Proc - Int Conf Distrib Comput Syst 2017. https://doi.org/10.1109/ICDCS.2017.226.
[155] Oteafy SMA, Hassanein HS. IoT in the fog: a roadmap for data-centric IoT development. IEEE Commun Mag 2018. https://doi.org/10.1109/MCOM.2018.1700299.
[156] Aazam M, Zeadally S, Harras KA. Deploying Fog Computing in Industrial Internet of Things and Industry 4.0. IEEE Trans Ind Informatics 2018. https://doi.org/10.1109/TII.2018.2855198.
[157] Arkian HR, Diyanat A, Pourkhalili A. MIST: Fog-based data analytics scheme with cost-efficient resource provisioning for IoT crowdsensing applications. J Netw Comput Appl 2017. https://doi.org/10.1016/j.jnca.2017.01.012.
[158] Bonomi F, Milito R, Zhu J, Addepalli S. Fog computing and its role in the internet of things. MCC'12 - Proc. 1st ACM Mob. Cloud Comput. Work 2012. https://doi.org/10.1145/2342509.2342513.
[159] Da Xu EL, Xu EL, Li L. Industry 4.0: state of the art and future trends. Int J Prod Res 2018. https://doi.org/10.1080/00207543.2018.1444806.
[160] O'Donovan P, Gallagher C, Leahy K, O'Sullivan DTJ. A comparison of fog and cloud computing cyber-physical interfaces for Industry 4.0 real-time embedded machine learning engineering applications. Comput Ind 2019. https://doi.org/10.1016/j.compind.2019.04.016.
[161] Moghaddam M, Cadavid MN, Kenley CR, Deshmukh AV. Reference architectures for smart manufacturing: a critical review. J Manuf Syst 2018. https://doi.org/10.1016/j.jmsy.2018.10.006.
[162] Ciavotta M, Alge M, Menato S, Rovere D, Pedrazzoli P. A microservice-based middleware for the digital factory. Procedia Manuf 2017;11:931–8. https://doi.org/10.1016/j.promfg.2017.07.197.
[163] Xu X. From cloud computing to cloud manufacturing. Robot Comput Integr Manuf 2012;28:75–86. https://doi.org/10.1016/j.rcim.2011.07.002.
[164] Ren L, Zhang L, Tao F, Zhao C, Chai X, Zhao X. Cloud manufacturing: from concept to practice. Enterp Inf Syst 2015. https://doi.org/10.1080/17517575.2013.839055.
[165] Ray PP. A survey of IoT cloud platforms. Futur Comput Informatics J 2016. https://doi.org/10.1016/j.fcij.2017.02.001.
[166] Wang XV, Wang L, Mohammed A, Givehchi M. Ubiquitous manufacturing system based on Cloud: a robotics application. Robot Comput Integr Manuf 2017. https://doi.org/10.1016/j.rcim.2016.01.007.
[167] Mourtzis D, Vlachou A, Zogopoulos V. Cloud-based augmented reality remote maintenance through shop-floor monitoring: a product-service system approach. J Manuf Sci Eng Trans ASME 2017. https://doi.org/10.1115/1.4035721.
[168] Sicari S, Rizzardi A, Coen-Porisini A. 5G in the internet of things era: an overview on security and privacy challenges. Comput Networks 2020;179:107345. https://doi.org/10.1016/j.comnet.2020.107345.
[169] Leng J, Ruan G, Jiang P, Xu K, Liu Q, Zhou X, et al. Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: a survey. Renew Sustain Energy Rev 2020. https://doi.org/10.1016/j.rser.2020.110112.

[170] Leng J, Jiang P, Xu K, Liu Q, Zhao JL, Bian Y, et al. Makerchain: a blockchain with chemical signature for self-organizing process in social manufacturing. J Clean Prod 2019. https://doi.org/10.1016/j.jclepro.2019.06.265.
[171] Leng J, Yan D, Liu Q, Xu K, Zhao JL, Shi R, et al. ManuChain: combining permissioned blockchain with a holistic optimization model as Bi-Level intelligence for smart manufacturing. IEEE Trans Syst Man Cybern Syst 2020. https://doi.org/10.1109/TSMC.2019.2930418.
[172] Strobel V, Ferrer EC, Dorigo M. Managing byzantine robots via blockchain technology in a swarm robotics collective decision making scenario: robotics track. Proc Int Jt Conf Auton Agents Multiagent Syst AAMAS 2018;1:541–9.
[173] Garrocho CTB, Ferreira CMS, Jnior ASS, Cavalcanti CFMC, Oliveira RAR. Blockchain-based process control and monitoring architecture for vertical integration of industry 4.0. 2020.
[174] Fraunhofer. PLUG and WORK – interoperability for Industrie 4.0 based on existing industry standards. 2020. https://www.iosb.fraunhofer.de/servlet/is/51300/.
[175] Derigent W, Cardin O, Trentesaux D. Industry 4.0: contributions of holonic manufacturing control architectures and future challenges. J Intell Manuf 2020. https://doi.org/10.1007/s10845-020-01532-x.
[176] Chaplin JC, Bakker OJ, De Silva L, Sanderson D, Kelly E, Logan B, et al. Evolvable assembly systems: a distributed architecture for intelligent manufacturing. IFAC-PapersOnLine 2015. https://doi.org/10.1016/j.ifacol.2015.06.393.
[177] O.P.C. Unified architecture part 10: programs. OPC Foundation; 2017.
[178] Dorofeev K, Zoitl A. Skill-based engineering approach using OPC UA programs. Proc. - IEEE 16th Int. Conf. Ind. Informatics, INDIN 2018 2018. https://doi.org/10.1109/INDIN.2018.8471978.
[179] Iigo-Blasco P, Diaz-Del-Rio F, Romero-Ternero MC, Cagigas-Muiz D, Vicente-Diaz S. Robotics software frameworks for multi-agent robotic systems development. Rob Auton Syst 2012. https://doi.org/10.1016/j.robot.2012.02.004.
[180] Wan J, Tang S, Shu Z, Li D, Wang S, Imran M, et al. Software-defined industrial internet of things in the context of industry 4.0. IEEE Sens J 2016. https://doi.org/10.1109/JSEN.2016.2565621.
[181] Nayak NG, Durr F, Rothermel K. Software-defined environment for reconfigurable manufacturing systems. Proc. - 2015 5th Int. Conf. Internet Things, IoT 2015 2015. https://doi.org/10.1109/IOT.2015.7356556.
[182] Lopez F, Shao Y, Mao ZM, Moyne J, Barton K, Tilbury D. A software-defined framework for the integrated management of smart manufacturing systems. Manuf Lett 2018;15:18–21. https://doi.org/10.1016/j.mfglet.2017.12.015.
[183] Kreutz D, Ramos FMV, Verissimo PE, Rothenberg CE, Azodolmolky S, Uhlig S. Software-defined networking: a comprehensive survey. Proc IEEE 2015. https://doi.org/10.1109/JPROC.2014.2371999.
[184] McKeown N, Anderson T, Balakrishnan H, Parulkar G, Peterson L, Rexford J, et al. OpenFlow: enabling innovation in campus networks. Comput Commun Rev 2008; 38:69–74. https://doi.org/10.1145/1355734.1355746.
[185] Tao F, Zhang M, Liu Y, Nee AYC. Digital twin driven prognostics and health management for complex equipment. CIRP Ann 2018. https://doi.org/10.1016/j.cirp.2018.04.055.
[186] Xu X. Machine Tool 4.0 for the new era of manufacturing. Int J Adv Manuf Technol 2017. https://doi.org/10.1007/s00170-017-0300-7.
[187] Liu C, Xu X. Cyber-physical machine tool - the era of machine tool 4.0. Procedia CIRP 2017. https://doi.org/10.1016/j.procir.2017.03.078.
[188] Liu C, Vengayil H, Lu Y, Xu X. A cyber-physical machine tools platform using OPC UA and MTConnect. J Manuf Syst 2019. https://doi.org/10.1016/j.jmsy.2019.04.006.
[189] Altintas Y, Brecher C, Week M, Witt S. Virtual machine tool. CIRP Ann Manuf Technol 2005. https://doi.org/10.1016/s0007-8506(07)60022-5.
[190] Kamath V, Morgan J, Ali MI. Industrial IoT and digital twins for a smart factory : an open source toolkit for application design and benchmarking. 2020 glob. Internet things summit. 2020. p. 1–6. https://doi.org/10.1109/GIOTS49054.2020.9119497.
[191] Pirvu BC, Zamfirescu CB, Gorecky D. Engineering insights from an anthropocentric cyber-physical system: a case study for an assembly station. Mechatronics 2016. https://doi.org/10.1016/j.mechatronics.2015.08.010.
[192] Zhou J, Zhou Y, Wang B, Zang J. Human–Cyber–Physical systems (HCPSs) in the context of new-generation intelligent manufacturing. Engineering 2019. https://doi.org/10.1016/j.eng.2019.07.015.
[193] Wang L, Gao R, Váncza J, Krüger J, Wang XV, Makris S, et al. Symbiotic human-robot collaborative assembly. CIRP Ann 2019. https://doi.org/10.1016/j.cirp.2019.05.002.
[194] Liu Q, Zhang H, Leng J, Chen X. Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system. Int J Prod Res 2019. https://doi.org/10.1080/00207543.2018.1471243.
[195] Leng J, Yan D, Liu Q, Zhang H, Zhao G, Wei L, et al. Digital twin-driven joint optimisation of packing and storage assignment in large-scale automated high-rise warehouse product-service system. Int J Comput Integr Manuf 2019. https://doi.org/10.1080/0951192X.2019.1667032.
[196] Liu Q, Leng J, Yan D, Zhang D, Wei L, Yu A, et al. Digital twin-based designing of the configuration, motion, control, and optimization model of a flow-type smart manufacturing system. J Manuf Syst 2020. https://doi.org/10.1016/j.jmsy.2020.04.012.
[197] Alexopoulos K, Nikolakis N, Chryssolouris G. Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. Int J Comput Integr Manuf 2020. https://doi.org/10.1080/0951192X.2020.1747642.
[198] Kaur MJ, Mishra VP, Maheshwari P. The convergence of digital twin, IoT, and machine learning: transforming data into action. Internet Things 2020. https://doi.org/10.1007/978-3-030-18732-3_1.
[199] Min Q, Lu Y, Liu Z, Su C, Wang B. Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry. Int J Inf Manage 2019. https://doi.org/10.1016/j.ijinfomgt.2019.05.020.
[200] Teti R, Jemielniak K, O'Donnell G, Dornfeld D. Advanced monitoring of machining operations. CIRP Ann Manuf Technol 2010;59:717–39.
[201] Kandukuri ST, Klausen A, Karimi HR, Robbersmyr KG. A review of diagnostics and prognostics of low-speed machinery towards wind turbine farm-level health management. Renew Sustain Energy Rev 2016;53:697–708. https://doi.org/10.1016/j.rser.2015.08.061.
[202] Roy R, Stark R, Tracht K, Takata S, Mori M. Continuous maintenance and the future – foundations and technological challenges. CIRP Ann Manuf Technol 2016. https://doi.org/10.1016/j.cirp.2016.06.006.
[203] Ivanov D, Dolgui A, Sokolov B. Applicability of optimal control theory to adaptive supply chain planning and scheduling. Annu Rev Control 2012. https://doi.org/10.1016/j.arcontrol.2012.03.006.
[204] Li K, Xiao W, lin Yang S. Scheduling uniform manufacturing resources via the Internet: a review. J Manuf Syst 2019. https://doi.org/10.1016/j.jmsy.2019.01.006.
[205] Öztürk C, TunalI S, Hnich B, Örnek A. Cyclic scheduling of flexible mixed model assembly lines with parallel stations. J Manuf Syst 2015. https://doi.org/10.1016/j.jmsy.2015.05.004.
[206] Wuest T, Weimer D, Irgens C, Thoben KD. Machine learning in manufacturing: advantages, challenges, and applications. Prod Manuf Res 2016. https://doi.org/10.1080/21693277.2016.1192517.
[207] Wang J, Ma Y, Zhang L, Gao RX, Wu D. Deep learning for smart manufacturing: methods and applications. J Manuf Syst 2018;48:144–56. https://doi.org/10.1016/j.jmsy.2018.01.003.
[208] Panicucci S, Nikolakis N, Cerquitelli T, Ventura F, Proto S, Macii E, et al. A cloud-to-edge approach to support predictive analytics in robotics industry. Electron 2020. https://doi.org/10.3390/electronics9030492.
[209] Taylor ME, Stone P. Transfer learning for reinforcement learning domains: a survey. J Mach Learn Res 2009.
[210] Devin C, Gupta A, Darrell T, Abbeel P, Levine S. Learning modular neural network policies for multi-task and multi-robot transfer. Proc - IEEE Int Conf Robot Autom 2017. https://doi.org/10.1109/ICRA.2017.7989250.
[211] Lee J, Ghaffari M, Elmeligy S. Self-maintenance and engineering immune systems: towards smarter machines and manufacturing systems. Annu Rev Control 2011; 35:111–22. https://doi.org/10.1016/j.arcontrol.2011.03.007.
[212] Frei R, McWilliam R, Derrick B, Purvis A, Tiwari A, Di Marzo Serugendo G. Self-healing and self-repairing technologies. Int J Adv Manuf Technol 2013. https://doi.org/10.1007/s00170-013-5070-2.
[213] Dijkman R, Dumas M. Service-oriented design: a multi-viewpoint approach. Int J Coop Inf Syst 2004. https://doi.org/10.1142/S0218843004001012.
[214] Chafle G, Chandra S, Mann V, Nanda MG. Decentralized orchestration of composite web services. Proc. 13th Int. World Wide Web Conf. Altern. Track, Pap. Posters, WWW Alt. 2004 2004. https://doi.org/10.1145/1013367.1013390.
[215] Docker Inc. Getting started with orchestration. 2020. https://docs.docker.com/get-started/orchestration/.
[216] Thames L, Schaefer D. Software-defined cloud manufacturing for industry 4.0. Procedia CIRP 2016. https://doi.org/10.1016/j.procir.2016.07.041.