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Digital transformation of manufacturing through cloud services and resource virtualization

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A B S T R A C T

This editorial introduces the special issue in the Elsevier journal *Computers in Industry* that analyses how the digital transformation of manufacturing is speeded up by two important drivers: cloud services and resource virtualization, which are vital for implementing the main building blocks - Cyber Physical Production Systems and Industrial Internet of Things - in the “Industry of the future” framework. The context of this special issue is firstly presented, with a specific focus on the federative concept of Industry 4.0. A framework characterizing research activities led in the field of the digital transformation of manufacturing processes and systems is then introduced. This framework is used to present and position the 12 papers composing the special issue. Perspectives are finally introduced as a guideline for future work in the digital transformation of manufacturing through cloud services and resource virtualization.

Keywords: Digital manufacturing, Cloud services, Resource virtualization, Cloud manufacturing, Holonic manufacturing control Multi-agent system, Real-time data analysis, Machine learning, Digital twin, Cyber physical production system Industrial internet of things

1. Introduction

Markets are currently demanding customized, high-quality products in highly variable batches with shorter delivery times, forcing companies to adapt their production processes with the help of flexible, efficient and reconfigurable plants. This leads to the need for new management and control systems that exhibit better efficiency, robustness, responsiveness, agility and reconfigurability while ensuring persistent resilience and sustainability of processes and context-dependent maintainability of manufacturing resources [1].

This special issue puts the focus on how the digital transformation, as the one advocated by Industry 4.0 or “Industry of the future” concepts, can improve the sustainability and maintainability of manufacturing processes, products, systems and logistics through cloud services and resource virtualization.

The digital transformation or digitalization relates to the interaction between the physical and informational worlds and consists in the virtualization of reality-reflecting structural elements (products, orders and resources) managed in Service Oriented Architectures (SOA) for integration of technical and business layers of the enterprise [2]. Digital manufacturing can be defined as the digitalization of supply, production (with planning) and delivery operations of a networked company, and uses intensively digital models and ontologies. The definitions of these patterns require the design of advanced, integrated information, communication and control systems (IC²T) with core technologies

to establish a wide-ranging, Internet-scale platform for networked, intelligent production that will link effectively and scalably various stakeholders (technology providers, manufacturing plants, supply chains and service providers), thus enabling the emergence of a sustainable Internet economy for industrial logistics - agile relative to markets and oriented towards customers [3].

In this special issue, the focus is set on cloud services and resource virtualization as key aspects of the concept of digital manufacturing.

Cloud services in manufacturing (CMfg in short) represents an evolution of networked and service-oriented manufacturing models that comprise a pool of shop floor reconfigurable and interchangeable items, and may access a shared pool of computing devices according to cloud computing (CC) principles in which case CC is part of the CMfg model on IaaS (Infrastructure as a Service) abstraction level [4].

Manufacturing enterprises have already adopted cloud computing on the higher layers of business processes for supply, digital marketing and Enterprise Resource Planning (ERP) which are, however, not yet integrated in real time to production and logistics layers [5]. Cloud adoption at enterprise business and operations management layers promotes SaaS (Software as a Service)-based solutions to solve problems for globally optimizing the management of client orders, matching capacity and demand or increasing market share by client segmentation. While there is a clear acceptance that this category of cloud-based services assures smart management of networked companies and

complex manufacturing value chains, we consider that adopting CMfg in IaaS model at the production layer of enterprises with high production volumes and/or variable batch sizes and/or frequently changing product types is necessary for the smart digital factory of the future for sustainability and resilience of production processes [6].

Integrating high level SaaS cloud models with CMfg models at production level allows for service-oriented product development and mass customization, in which customers can order, configure, select, and use customized resources and services, ranging from computer-aided engineering software tools to after-sales services [7].

Resource virtualization relates to the capacity of creating and managing virtual machines (VM), and represents the main enabling technology of CC and hence of sustainable, robust, optimized and broadly-scoped performance CMfg. Virtualization allows decoupling a set of physical computing resources or manufacturing resources from its use, thus permitting easy migration of a workload to another resource during its execution.

Cloud services are a key attribute of digital manufacturing in the sense that they facilitate Direct Digital Manufacturing (DDM) which includes typically both novel 3D printing and digital modelling technologies. Through cloud services, the need for tooling and setup is reduced as parts are directly produced based on digital models; cloud services enable DDM by providing access to service-oriented networked product development patterns in which customers can select, configure and use customized resources, recipes and services. Also, cloud manufacturing has caused a shift from production-oriented processes to customer- and service-oriented ones by: (i) modelling manufacturing and control processes as services and aggregating them in optimized product making services, (ii) analysing big data and intelligent decision making for reality mirroring, robust, opportunistic and auto-configuring control, and (iii) integrating more tightly the business and production layers.

Resource virtualization is also a key element of digital manufacturing in the sense that, through the virtualization of shop floor devices of any kind (products, machines, tools, etc.), it is possible to balance effectively local computing abilities, e.g., close to manufacturing resources and intelligent embedded products, with global computing abilities, e.g. a private cloud manufacturing infrastructure. The Industrial Internet of Things (IIoT) technology, seamlessly integrating smart connected objects in the cloud, facilitates resource virtualization.

This stimulates also a *product centric approach*, in which the product directly requests processing, assembling and handling from available providers while it is in execution, delivery and use stages [8]. The virtualization of intelligent products allows moving some processing capabilities from the intelligent devices embedded on the product carriers to the cloud computing IaaS, to dynamically balance the optimized control with long-term global view and the rapid local reaction abilities to unexpected events.

Adopting cloud services through virtualization of shop-floor devices and MES (Manufacturing Execution System) computing tasks brings meanwhile new research issues, both at technical and conceptual level. The papers forming this special issue address key aspects of the digital transformation of manufacturing processes using cloud service and resource virtualization techniques, for which the authors suggest new innovative and disruptive approaches. The included papers describe the way digitalization is implemented, pointing out how the variety of data is managed and knowledge is extracted, analysed, capitalized and synchronized with the physical world in applications of manufacturing processes, products, and logistics. Some of the papers in this special issue are extended versions of chapters published in the proceedings volume edited after the 2016 edition of the SOHOMA

Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing held in Lisbon, Portugal in October 2016.

This editorial is organized as follows: firstly, in section 2, the context of this special issue is presented, with a specific focus on the federative concept of Industry 4.0. Secondly, in section 3, a framework characterizing research activities led in the field of the digital transformation of manufacturing processes is introduced. This framework will be used to present and position the papers composing this special issue in section 4. Perspectives are then introduced as a guideline for future work in section 5.

2. Context of the special issue: Factory of the future and Industry 4.0

The term Factory of the future (FoF) is used to indicate the new industrial revolution initiated by a new generation of manufacturing systems conceived to be adaptive, fully connected, analytical and highly efficient. This global FoF model describes a new stage of manufacturing fully automatized and using ever more advanced IC²T and intelligent devices. FoF is based on the main concepts of digitalization and interconnection of distributed manufacturing entities in a 'system of systems' approach: i) new types of production resources will be highly interconnected and self-organizing in the entire value chain, while products will decide upon their own production systems; ii) new types of decision-making support will be available from real time production data collected from resources and products [9].

A number of local initiatives that focus on common FoF topics have been developed: Industry 4.0 (Germany), Advanced Manufacturing (US), e-Factory (Japan) or Intelligent Manufacturing (China) with similar objectives and technological approaches. However, each of these initiatives addresses with different priorities the challenges that arise from the FoF concepts, and propose reference architecture models for overall factory of the future infrastructures.

Thus, Industry 4.0 focuses on cyber-physical production systems (CPPS) which will provide digital representation, intelligent services and interoperable interfaces in order to support flexible and networked production environments. Smart embedded devices will work together seamlessly via the IoT, and the centralized system controls will be transferred to networks of distributed intelligence based on machine-to-machine (M2M) connectivity at shop-floor level. Industry 4.0 fosters manufacturing digitalization [10], since it aims at:

- Efficiently controlling complex distributed systems as a society of autonomous units.
- Integrating the virtual world (where each physical element including: sensors, products, material processing, handling and transport resources and human operators is represented by a software unit) with the physical world in CPPS. This requires connectivity from any element of the virtual world to any embedded element of the physical world enabled, and smooth transfer of control from virtual to physical world.
- Optimizing decision making and efficiency (cost effectiveness, high performance and energy saving).
- Creating new business models and service-oriented approaches to value creation.

From our perspective, the digital transformation of manufacturing envisaged by Industry 4.0 is based on the paradigm of "3I" technology advances:

- Instrumenting manufacturing resources (e.g., machines and robots), products (e.g., product carriers and subassemblies), and environment (e.g., workplaces and lighting).

- Interconnecting orders, products / components / materials, and resources in a service-oriented approach using multiple communication technologies such as wireless, broadband Internet and mobile.
- Intelligent decision making in the manufacturing value chain, based on:
- Ontologies and digital twins – digital models of manufacturing resources, processes and products extended in time, space and operating context [11].
- New controls based on ICT convergence in automation, robotics, machine vision, agent based control, holonic organization, data science, machine learning, and implementing frameworks: Multi-Agent Systems (MAS), Cloud services, and SOA [2,12].
- Novel management of complex manufacturing value chains (supply, production, delivery, after-sales services) in virtual factories [13].

The relevant theoretical background lays today in data and knowledge management, and will lay tomorrow in big data analytics, machine learning and cognitive computing to apply Artificial Intelligence (AI) in the context of manufacturing and industrial logistics. The development and transfer of the “3I” advanced technologies for the industry is of strategic importance. These technologies aim at boosting competitiveness while targeting several aspects of manufacturing processes such as increasing resource efficiency, reducing waste and costs, and offering agility at product and market changes.

Industry 4.0 is seen as the convergence of nine digital industrial technologies: advanced robotics, additive manufacturing, augmented reality, simulation (will leverage real-time data to mirror the physical world in a virtual model which can include machines, shop floor operations, products, and humans), horizontal / vertical integration, cloud, cybersecurity, Big Data and Analytics, and the Industrial Internet [14]. Two major foundations of Industry 4.0 are represented by AI and IoT. Industry 4.0 is based on the concepts of horizontal and vertical integration:

- Vertical integration, SOA-based, along the enterprise axis from shop floor to business; IT systems are integrated at various hierarchical production and manufacturing levels.
- Horizontal integration, across the value chain from supply to after-sales services, along two axes: i) the axis of production processes (batch planning, product making) and stakeholders (suppliers, customers); ii) the axis of semi-heterarchical control layers [15] (e.g., Cloud System Scheduler and Delegate MAS with distributed intelligence [16]).

3. A research framework for the digital transformation of manufacturing

In this editorial, we characterize the digital transformation of manufacturing processes and systems through a framework defined by four dimensions, namely: the research topic for the two transformation drivers, the modelling approach for control, the architecture design for implementation, and the scientific issue to be addressed. This framework, presented hereinafter, will be used to position each of the twelve papers composing this special issue.

3.1. The research topic: cloud services and resource virtualization

As introduced, the research topic on the digital transformation of manufacturing relevant to this special issue is focused on two drivers: cloud services in manufacturing and resource virtualization.

Cloud manufacturing services define a dual control and computing model that:

- Transforms a pool of manufacturing resources (machines, their controllers and capabilities), products (recipes, customer requirements) and orders (producing modes, schedules, business specifications) into on-demand manufacturing services [17]
- Enables pervasive, on-demand network access to a shared pool of configurable high performance computing (HPC) resources (servers, storage networks, applications) that can be rapidly provisioned and released as services to various end-users e.g., shop-floor devices, higher MES layer, system scheduler, etc. with minimal management effort or service provider interaction [18]. This means that CMfg uses Cloud Computing (CC) facilities for high performance purpose.

The virtualization of the MES layer means that hardware and software resources of the CC platform are organized and managed in a pool model, allowing multiple beneficiaries, i.e., the MES workloads (manufacturing resources, products with embedded intelligence) to use them for computing tasks addressing global shop floor functionalities: scheduling the execution of the entire batch of products, monitoring the state and quality of services (QoS) of all assigned resources, tracking the complete production flow, etc. The adoption of cloud computing considers the virtualization of MES workloads [19]. While MES implementations in the pool of shop floor resources are different and usually depend on the control topology and modes (hierarchical, heterarchical), the MES functions refer mainly to the set of functions defined by level 3 of ISA-95.03 specifications [20,33].

Intensive computing activities on the MES layer can be performed in the CC platform due to its HPC capabilities: real time optimization of product scheduling and resource allocation at full batch horizon, work in process management and product traceability, monitoring the state, QoS and energy consumption of resources, preventive maintenance of resources and prediction of unexpected events using big data analysis and machine learning. Several MES specifications for the migration of workloads in the cloud have been proposed in [21]. The strategy for cloud adoption must result in a robust, highly available architecture in which the information flow can be synchronized with the material flow, and which is flexible enough to cope with dynamic reconfigurations of shop floor devices through APIs exposed and SOA choreography [22,23].

Cloud adoption in manufacturing enterprises with ISA-95 organization could gain from using a 2-layer public-private cloud-based software architecture with MES workload virtualization in a private cloud platform delivering services in the IaaS model, and having connectivity with external organizations, suppliers, clients and the internal shop floor processes for high level business tasks (ERP, SCM, demand managing, capacity planning, etc.) through access to public cloud services [24], see Fig. 1.

The private cloud platform implements in the IaaS model the centralized part of the MES layer by provisioning computing resources (CPU, storage, I/O) and global applications. One of these applications, the system scheduler, uses the HPC capabilities of the cloud for: configuring resource teams, batch planning, product scheduling, resource allocation [25], cell and production monitoring. The cloud MES communicates with its decentralized part in which intelligence is distributed among agentified and virtualized shop floor resources and products [26]; the Delegate MAS pattern (D-MAS) may be used for this decentralized part [16].

An emerging concept with strong impact in virtualized MES design is the *programmable infrastructure* (PI). PI provides a series of Application Program Interfaces (APIs) to the cloud software stack, including hypervisor, operating system and application

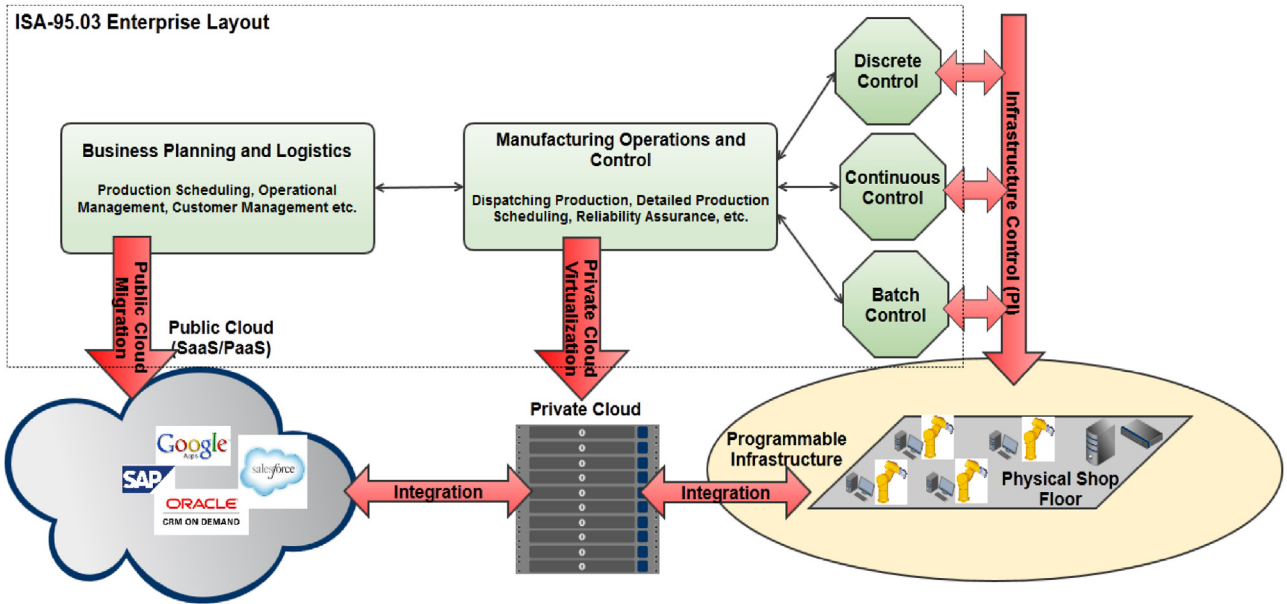


Fig. 1. Dual cloud adoption strategy for manufacturing enterprises and MES virtualization with programmable infrastructure (adapted from [33]).

layers, for accurate identification, monitoring, real time (re) configuration and control. This openness of the infrastructure, in contrast with legacy fixed infrastructure, allows the MES application logic to pre-program the infrastructure according to the estimated operations that would be required, and can be directly derived from the customer orders. The PI works with private cloud virtualization, as it deals with network (re) configuration [24].

Virtualization of shop floor devices: MES virtualization, i.e., the creation of a virtualized layer (the vMES), involves the migration of MES workloads that were traditionally executed on physical machines to the data centre, specifically to the private cloud infrastructure as virtual workloads. The idea is to run all the control software in a virtualized environment and keep only the physical resources (robots, machines, conveyor, etc.) with their dedicated real time controllers on the shop floor. This separation between hardware resources and software that controls them provides a new level of flexibility and agility to the manufacturing control system. From a virtualization perspective, two types of workloads are considered:

- *Intelligent products (IP)* are created temporarily in the production stage by embedding intelligence on the physical order or

product that is linked to information and rules governing the way it is intended to be made (with recipe, resources), routed, inspected and stored; this enables the product to support and/or influence these operations [27]. IP virtualization moves the processing from the intelligence embedded in the product to the to the virtual machine in the cloud using a thin hypervisor on the product carrier and WI-FI connection, either in a dedicated workload or in a shared workload to make decisions relevant to its own destiny [28,29], see Fig. 2.

- *Shop floor resources* like robots, CNC machines, conveyors etc.; their control architecture can vary depending on the manufacturer and technology used, but in general the resource is controlled by a PC-based workstation. The communication between the control workstation and the physical resource can be either standard TCP/IP based, or a proprietary wire protocol. If the resource can be accessed by TCP/IP directly, the workload is directly virtualized and a virtual network interface, which will be used to control the resource, is mapped to it. However, if a proprietary wire protocol is used, the virtualization process is more complex as it involves a local controller on the shop floor that would provide the physical interface for the wire protocol. This physical interface is virtualized and mapped through a specific driver to the virtualized workload over the network.

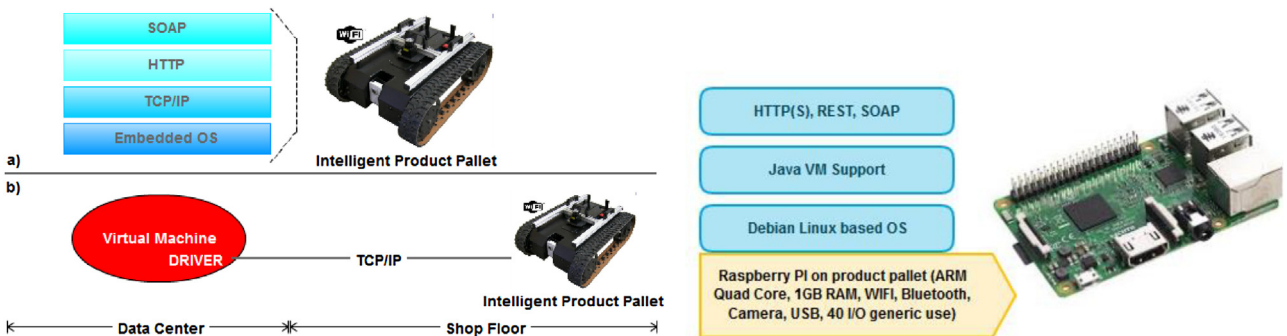


Fig. 2. Intelligent Product virtualization.

Left: a. Intelligence embedded on product carrier, hence on the product during its execution; b. IP virtualization mechanism; Right: IP based on mobile technology and standardized OS (e.g. Arduino, Raspberry PI).

The binding between workload templates and virtualized resources is done using *shop floor profiles*, which can be XML files and contain a partial or complete definition of the manufacturing system's virtual layout and mappings [24]. Shop floor profiles are workload centric and contain a list of workload definitions. The workload refers to a specific revision of a VM published in the service catalogue, a number of mapped virtual CPU cores, the amount of RAM memory allocated to the VM and the amount of disk space; the workload also contains references to a list of mapped resources, together with parameters passed.

High availability and policy-based security in CMfg: High availability (HA) of cloud services for manufacturing is an important issue for intensive data exchanges between cloud and shop floor devices. HA can be addressed by: i) providing HA at operating system level using VMs or ii) using HA at container (application) level; both methods try to eliminate all single points of failure at hardware and software level in cloud implementing MES functions.

From the point of view of *cyber security*, such a HA system is composed by two local networks with restricted access through firewalls; these networks are connected using an Open VPN solution. The first network hosts the production equipment and is completely isolated from internet attackers because no services are allowed to be accessed (isolation at firewall level). The equipment can communicate inside the network or with other services offered in cloud which are accessed through VPN, as shown in [30]. The second data network is hosted in cloud using the same solution; because the connection is done over VPN, the data sent through Internet is encrypted. Other HA CMfg solutions are described in [31,76].

The adoption of cloud computing in platforms for MES implementation raises new challenges for securing the data retrieved from shop floor devices and sent to resources [30].

There are four main issues concerning the integration in cloud of shop floor devices - resources and intelligent products - relative to security requirements: a) unauthorized access to information, b) theft of proprietary information, c) denial of service, and d) impersonation. To address these requirements, a policy-based mechanism is proposed in [32] to handle transport security by introducing a real time Public Key Infrastructure (PKI) platform using certification authorities to generate certificates on-the-fly and secure socket communication (Fig. 3).

Additionally, a document level encryption and signing mechanism may be introduced as a component of the policy for all MES messages exchanged between intelligent products, sensors, shop floor resources and different MES components.

This is required for securing parts of the architecture that cannot rely on transport layer security, due to functional requirements (i.e. content-based message routing at manufacturing service bus layer).

CPPS implementations have many communication end points for each device; this involves interactions between physical devices on the shop floor, vMES workloads and high level applications (public cloud hosted applications for supply chain management) for deployment. A *policy-based mechanism* that dictates the security requirements for each end point, including both transport layer and document layer security is compatible on both client and server side. The CMfg security policy model must define the document and transport aspects, and should be implemented in a real-time PKI platform using Certification Authorities (CAs) to generate certificates on the fly and secure socket communication [77].

The *document layer* governs the mechanisms used to secure the payload of the communication, while the *transport layer* specifies if the socket communication should be encrypted using SSL/TLS and if so, what kind of ciphers should be used [78]. The principal advantage of this policy-based approach is that, instead of individual configuration of each end point at the edge of the distributed environment, a centralized policy allocation can be used to automatically enforce security behaviour across the ISA 95 enterprise layers: business, Cloud MES, and D-MAS [32].

3.2. The modelling approach: holonic manufacturing control, MAS and SOA

Distributing intelligence within the manufacturing control system, as highlighted by Industry 4.0 concept and allowing for collaborative decisions of strongly coupled shop floor entities in the CPPS, motivated researchers to adopt new modelling approaches for the global dynamic control respectively frameworks for its implementing. In the literature, control modelling uses the holonic manufacturing paradigm and the service oriented architecture, while implementing is based on agent orientation and multi-agent systems.

The holonic manufacturing paradigm refers to a distributed control architecture that is based on the definition of a main set of assets: resources (technology, humans - reflecting the producer's profile, capabilities, skills), orders (reflecting the business solutions) and products (reflecting the client's needs, value propositions) - represented by autonomous holons communicating and collaborating in holarchies to reach a common production-related goal.

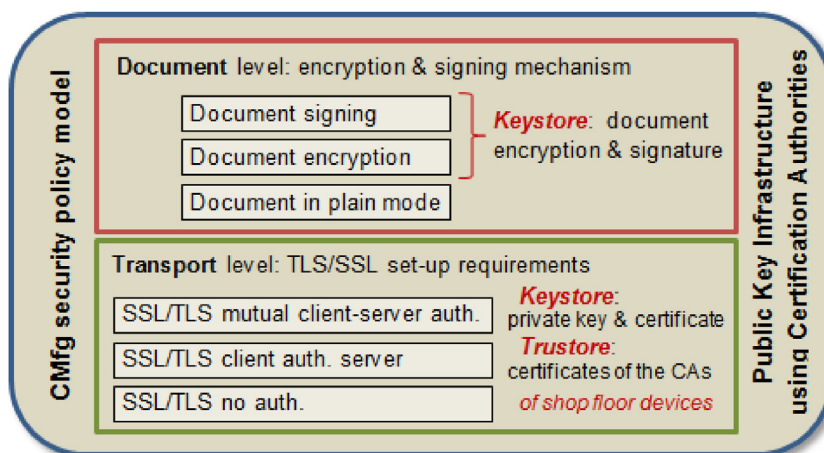


Fig. 3. Security policy model for shop floor device IoT integration in CMfg.

The holonic paradigm has been recognized in industry, academia and research as providing the attributes of flexibility, agility and optimality by means of a completely decentralized control architecture composed by a social organization of intelligent entities called holons with specific behaviours and goals, defined by reference architectures such as HABPA [27], PROSA [28] or ADACOR [29]. From the control perspective, in the dynamic organizations of holons (the holarchies), decision-making functional elements (e.g., scheduling, negotiating, allocating) are combined with reality-reflecting elements (resources, products, orders) modelled by *basic holons*. Staff or *expertize holons* can be included for the optimization of mixed batch planning, product scheduling and resource allocation. The coexistence of basic holons enhanced with staff holons decouples the system's robustness and agility from its optimization.

Holarchies allow for object-oriented aggregation, while the specialization incorporated in control architectures provides support for abstraction; in this way the holonic control paradigm has been increasingly transposed in control models of diverse types of industrial processes. The control system structure is scalable and decoupled from the control algorithms which, by design, should preserve flexibility of the global holonic manufacturing control and avoid introducing constraints and limitations such as myopia or the incapacity to react at unexpected events.

The information processing part of a holon acts as an informational counterpart (or software agent) of the holon's physical part (e.g. a resource, an order). In the context of holonic manufacturing, the loosely coupled networks of these software agents that cooperate to solve global production problems are multi-agent systems that constitute the implementing frameworks for holonic manufacturing control and reengineering of shop floor resource coalitions [34].

Mixed approaches were developed. For example, in [35], patterns of delegate MAS (D-MAS) are mandated by the basic holons representing structural production elements to undertake tasks reconfiguring operations scheduling and resource allocation in case of disturbances like resource breakdowns and performance degradation. Bio-inspired MAS for manufacturing control with social behaviour [36] or short-term forecasting of resource availability through ant colony engineering [37] are AI-based techniques for heterarchical control with MAS.

Because reality awareness and robustness of manufacturing control systems represent priorities of the industry, semi-heterarchical holonic models of manufacturing control were developed to offer a dual functional behaviour that combines cloud-based optimized system scheduling with agile, reactive scheduling that is done in real time by D-MAS. The semi-heterarchical manufacturing control architecture deals rapidly with unexpected events affecting orders in current execution, while computing in parallel at cloud level new optimized schedules for the rest of orders waiting to be processed; this operating mode reduces the myopia of the system at global batch level and preserves the system's agility [38]. MAS are then often used as implementing framework for holonic semi-heterarchical control models in Holonic Manufacturing Systems (HMS).

On the other hand the service-orientation paradigm defines the principles for conceiving decentralized control architectures that decompose processes into sub-processes handled as services, to later distribute them among the different available resources. Its focus is to leverage the creation of reusable and interoperable function blocks in order to reduce the amount of reprogramming efforts. The Service Oriented Architecture is more and more accepted as a natural technology, applicable to production processes and enterprise integration. Recent research works transposed the concepts of services in HMS to gives rise to a

new type of systems: *Service-oriented Holonic Manufacturing Systems*, reinforced by the use of a structure based on repeatability and reusability of manufacturing operations [2].

Holonic and multi-agent approaches provide dynamic feedback from the plant and environment and easy reconfigurable supervising and control solutions. In the holonic manufacturing paradigm, service orientation is used firstly to create orders according to the customer's preferences (the customer directly shapes the making of products through product holons in static mode) and secondly product intelligence is used to dynamically (re)schedule the operations for product making and to (re)configure the parameters of manufacturing processes when disturbances and changes occur in the system.

3.3. The architecture design: IIoT and CPPS

Once the modelling approach or paradigm is chosen for the control system and the cloud adoption decided (shared use of shop floor resources, eventually with cloud computing as IaaS), depending on the type and objectives of the production application – optimization, agility, vertical integration – the researchers have to design their Industry 4.0-oriented implementation framework through a dedicated architecture. In the literature, two main design approaches can be found, along with specific technologies: the Industrial Internet of Things and the Cyber Physical Production Systems. While CPPS - as a "system of systems" framework - is adequate for the integration of the higher layers (e.g., MES layer in the IaaS cloud platform), the IIoT organization allows distributing intelligence towards edge devices of the shop floor which cooperate through virtualization with the cloud.

These two implementing frameworks of Industry 4.0 are designed using the previously introduced control modelling and cloud digitalization approaches, the service orientation principles and the multi-agent technology distributing intelligence for control and information processing. Satisfying simultaneously optimization, robustness and agility criteria may lead to semi-heterarchical control topologies in which reality-reflecting structural elements (products, orders, resources) are strongly interconnected as cyber-physical components and retrieve in real time detailed information about the world-of-interest at the edge of the control system.

The Industrial Internet of Things framework includes infrastructure, technologies and applications that bridge the gap between the real industrial world and the virtual world. The Internet of Things is transposed in industrial environments, among which manufacturing, by the IIoT based on the convergence of information- and operation-technologies (IT, OT):

- IT considers the software, hardware, networking and communication technologies and system architectures that acquire, store, process, and deliver information to all parts of a manufacturing organization using HPC, SOA and AI techniques: centralized and geo-distributed cloud (fog and edge computing infrastructures) and digital twins [39,40].
- OT refers in the manufacturing domain to physical shop floor equipment, control software and hardware including: CNC and robot controllers, machine vision, sensors and programmable logic controllers, SCADA, embedded intelligence and holonic methods and patterns [41,42].

The integration of IT and OT in the IIoT is done in the scope of enabling the smart factory: new production controls and environment monitoring using connected devices that are able to collect, process and transmit data and information, embed intelligence and connectivity into virtualized shop floor entities, configure and execute computing tasks and applications that

analyse data and extract knowledge for decision support. IIoT is a disruptive technology allowing the manufacturing enterprise to directly access shop floor and remote industrial device data; it also decentralizes analytics and decision making, enabling real-time reconfiguring of resources and process optimization. While IT implements data access, processing and decision making solutions using a top-down approach which is method-oriented, OT uses ground-up solutions starting from end-point devices and integrating them in subsystems to build the complex manufacturing system in a problem-oriented approach [43,44].

As described in [45], Cyber-Physical Production Systems are systems of systems of autonomous and cooperative elements connecting with each other in situation dependent ways, on and across all levels of production, from processes through machines up to production and logistics networks, enhancing decision-making processes in real-time, response to unforeseen conditions and evolution along time.

Cyber-physical resources accomplish a common set of goals for the IIoT system through the exchange of order- and work-in-process information; they communicate and cooperate with each other and humans in real time. Via the Internet of Services, both internal and cross-organizational services are offered and utilized by participants in the value chain. The main focus of the Industry 4.0 platform is realizing strongly coupled manufacturing and logistics processes within CPPS based on advanced control systems (holonic, product-driven), embedded software systems in service orientation. CPPS pair a physical layer handled by IIoT technologies and a virtual layer handled by cloud computing technologies.

There are however major concerns about the OT-IT convergence. *Security* is the first one: accessing big data amounts from smart edge-of-network and end-point devices, and intensively transferring processed data in the Industrial Internet cause an increase in security vulnerabilities. Although OT devices still use proprietary technologies that make them less likely to be targeted for attacks (i.e. security by 'obscurity'), OT systems are no more self-contained having many connections to other IT systems. Because edge-of-network devices still use different protocols for sending and receiving data, there is a second issue of *interoperability*, which determines the need to have standardized communication protocols [46]. Papers in this special issue address these concerns [32,47] and propose solutions.

CPPSs are related with the IIoT by similar key characteristics: they dispose of Internet protocol addresses, use Internet technology and are part of an Internet of Everything in which they can be uniquely identified and addressed in the network. CPPSs represent the next innovation step in manufacturing, driven by: (1) intelligent representation of the reality by extended digital modelling and description of assets, products and processes; (2) linking of digital and physical domains by the Internet technology; and (3) convergence of IT and OT.

A new vision about cloud integration in CPPS designs considers that, instead of deploying global MES tasks in a CC infrastructure using IaaS models, a common set of cloud control building blocks that abstract the concept of device (resource, intelligent product) should be first built and then specialized to a particular production application. This model, proposed by researchers of the SOHOMA scientific community, is called Cloud Anything [18].

3.4. The scientific issues: big data analytics, machine learning and digital twins

The digital transformation of manufacturing through cloud services and resource virtualization allows for intelligent decision making that complies with the theories of flexibility and reality-awareness [48]. These issues are addressed in the literature mainly through three domains: big data analytics, machine learning and digital twins.

Big data integration, analytics and cognitive computing are currently integrated in an emerging 4-stage model for the contextual digital manufacturing enterprise that can be deployed across the four layers:

- 1) *Gather data*: collect all relevant data from a variety of sources: sensors, embedded devices, resource controllers.
- 2) *Connect to create the knowledge context*: dynamically extract features and create metadata from diverse data sources to continually build and update the context.
- 3) *Reason to take intelligent decisions*: analyse data in context to uncover hidden information and find new relationships. Analytics add to context via metadata extraction; use context to exploit information.
- 4) *Adapt*: compose recommended interactions, use context to deliver action; learn from history interaction patterns to design for the unexpected, optimize scheduling in MES and predict service degradation and resource failures allowing for preventive maintenance.

Big data analytics is related in the digital manufacturing context to acquiring and processing large amounts of shop floor data; three important dimensions should be considered when processing data: 1) aggregating at the right logical levels when data originates from multiple sources, 2) aligning the data streams in normalized time intervals and 3) extracting insights from real time data streams.

From our point of view, a streaming map-reduce architecture can solve the scale problem of big data acquisition when dealing with multiple real time signals across all three dimensions above defined. The most important feature of these streaming architectures is their distributed nature, allowing real time parallel stream processing in map-reduce fashion.

Map-reduce style aggregation of real time data streams from shop floor is a programming model well-suited to resolve a great variety of big data problems; the actual implementations must take care of distributed execution, resource allocation, failures and result aggregation.

The architecture defined in [49] uses the manufacturing service bus (MSB) model to collect real time metrics and events from shop floor devices: resources reporting their state and a set of KPIs, external sensors and products with embedded intelligence reporting work-in-process [50]. The information flow creates a high level loop such that real time data streams are flowing from the shop floor into MSB; from there, a series of map-reduce aggregations are performed, followed by machine learning on aggregated streams. The scheduling decisions are returned to the shop floor through message queuing. This approach allows for highly efficient use of computing resources, with horizontal scaling of the system.

The stream structures passing via the MSB are: i) *Resource Streaming*: shop floor resources typically send data encapsulated in events which are either periodic (monitoring data, functional parameters) or as a response to unexpected situations (resource breakdown); ii) *Intelligent Product Streaming*: IP data streams contain mostly location and status information about products.

MAS were indicated in [51] as a suitable approach to aggregate data and analytics in controlling the IIoT infrastructure of CPPS for manufacturing. Big data management (e.g., data, integration and analysis) comprises the essential mechanisms to integrate distributed, heterogeneous, dynamic, and stream data sources [52]. For this scope, the work described in [53] addresses two industrial levels, combining data analysis tasks: 1) at operational level, applying distributed data stream analysis for rapid response monitoring and control, and 2) at supervisory level, applying more robust and big data analysis for optimized planning and

scheduling of batches, resource team reconfiguring and intelligent decision-making.

In CPPS, the operational level is mainly related with the physical world represented by the IoT and the smart devices, also demanding the processing and analysis of real time data streams for efficient workflow and resource monitoring, and process control. The supervisory level is hosted in a virtual world defined by cloud-based infrastructure where robust software applications perform high level information processing for capacity and demand management and optimized decision-making, supported by big data analytics (DA).

By combining MAS with DA, two data analysis stages are attained: Big Data and Data Stream analysis. The first is related with the analysis of great volumes of heterogeneous data to extract valuable information for supporting the decision making, optimization and planning, while second is related with the analysis of the continuous operational data incoming from the shop floor, at real or near real-time, providing simpler information, but addressing the rapid response requirements of processes' monitoring and control (Fig. 4).

As an example, authors of [54] of this special issue propose a generic distributed, agent-based model to aggregate data and analytics in CPPS.

The model comprises two layers of agents and a set of components that define the agents' capabilities. On the lower layer agents are in charge of *stream data analysis* providing simple information about the processes, resources and products (e.g., operation status, consumed energy, resources' QoS, and events), subject to rapid response constraints. Agent retrieve and analyse the data from process devices; they can be embedded into devices (which become active entities) to perform distributed data analysis and intelligent monitoring, cooperating to identify problems or aggregate information about the system. On the upper layer, agents are *processing and analysing great amounts of historical and incoming data* from shop floor operations, contextual or external data; they aggregate information and retrieve knowledge for high level decision-making, optimization and dynamic re-planning of activities (e.g., QoS and performance degradation evaluation, event diagnosis, trends and forecasts). These agents can be deployed in the cloud-based MES, taking advantage of this type of HPC and service-oriented infrastructure and related software technologies (web and micro services, dev ops, virtualization, load balancing, etc.) to perform their tasks and manage lower level agents.

Machine learning is a very powerful tool to extract insights from big data; it has been usually used on static or historical data. However, if shop floor data can be obtained in real time and the machine learning algorithms can be run in a real time context with re-training on new data (e.g. in the cloud MES), then the insights become predictions, enabling real time decisions. Machine learning has been already used for short term prediction of some key performance indicators (KPIs), specifically *linear regression* for scalar predictions, and *k-means* for classification problems. In [55], Zhang proposes a real-time, data-driven solution that optimizes decision using a dynamic optimization model based on game theory. On the machine learning side, He [56] proposes a *k nearest neighbour* (KNN) approach to detect faults in the semiconductor manufacturing process. Scientific contributions of SOHOMA research in this field point at implementing map-reduce algorithms to forecast energy consumption patterns during production by using Long Short Term Memory (LSTM) neural networks [57].

From our perspective, CPPS implementations should use machine learning techniques to provide the following set of new functional characteristics for manufacturing control:

- Working on real time data streams from sensors rather than static data.
- Determining and learning the covariance between signals.
- Dynamically learning the patterns of the signals monitored.
- Dynamic scheduling of manufacturing operations based on real time data and predictions derived from it for the near future.
- Classifying the current state of the manufacturing system as healthy or faulty.
- Detecting faults of resources before service degradation occurs.
- Executing automated corrective actions.

Cloud and MAS combined with machine learning will solve Industry 4.0's needs for big data aggregation and analysis for intelligent decisions and actions in CPPS, i.e., reality-awareness, self-adaptation, reconfigurability, responsiveness, high availability, predicting behaviours and unexpected events.

Digital Twins for Industry 4.0: The holistic view of the actual capabilities and features of a device / product including its digital representation, execution context, history of behaviour and time evolution can be encapsulated in a digital twin – defined as a virtual model in the cloud of a product, process, physical asset, that

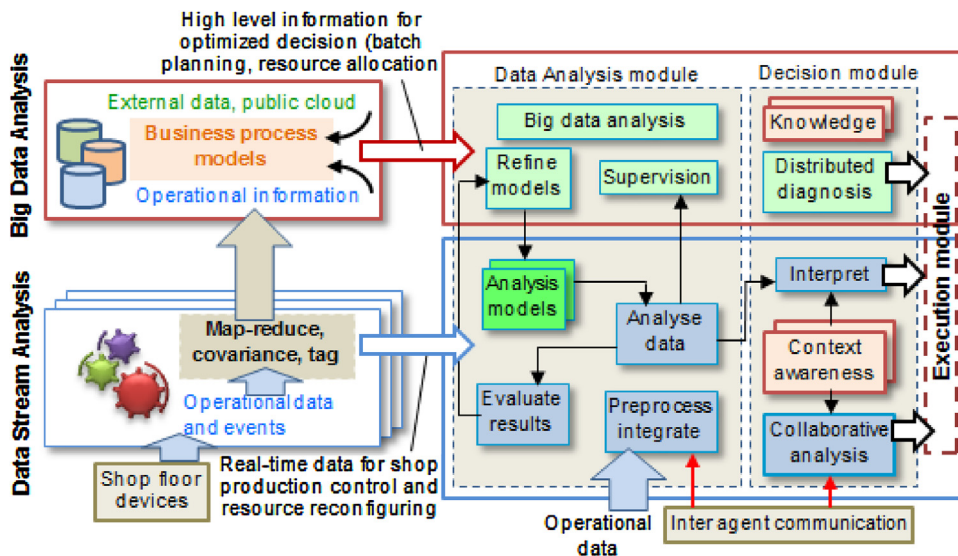


Fig. 4. Distributed, agent-based model of Big Data Analytics stages in CPPS (adapted from [53]).

is persistent even if its physical counterpart is not always on line / connected; this extended digital model can be shared in a cloud database with other shop floor devices [58,59].

The principle of *digital twin* (DT) is important for Industry 4.0 in its implementing frameworks: IIoT and CPPS, as they provide access to the world of interest; planning and control systems can thus interact with the physical twins (resources, products), influencing these intelligent elements into the desired behaviours. The IIoT speeds up the usage of DTs for: i) resource monitoring (energy consumption, faults); ii) prediction (state, performances, anomalies, failures); iii) simulating future behaviour (plan for the future); global control (reallocating resources based on reality-awareness); diagnosis and maintenance (combining data stream processing with machine learning). The pairing of the physical and virtual models collects operational / performance data at the edge the IIoT platform, bringing it into the digital twin simulation model of manufacturing resources which resides in the cloud. This provides data on how a resource is performing compared to its design goal, and closes the loop from the operations stage forward to the maintenance stage or backwards to the design stage.

From our point of view, the 4-layer generic CPPS architecture defined below allows materializing and deploying the specific role of a network of digital twins for digital manufacturing (e.g., reality-aware control, resource maintenance, product intelligence, etc.):

- Layer 1. *Physical twins and IoT gateways*: these are the shop-floor devices (resources, products), their controllers (programmable controllers, industrial controllers, embedded intelligence) and IoT gateways (acquisition and low level local data processing from sensors, external to resources)
- Layer 2. *Aggregation nodes*: these are groups of devices (IoT gateways, controllers) connected to a shop floor workstation (see Fig. 5). This node structure supports multiple communication protocols and is flexible enough to run streaming data and cloud communication software tasks. Layer 2 contains repositories of data located near the physical twin, such as local databases.
- Layer 3. *Digital twin information repositories in the cloud*: data bases that record and store the history of the physical twin and the current/latest available state of the physical twin, with acknowledged latencies.
- Layer 4. *Software application deploying the role of the DT*: in production control, optimized resource allocation is based on modelling the current behaviour of resources, while predicting unexpected events and resource maintenance is based on simulation software (that models future behaviours, states and performances) and data science insights (clustering, profiling as

description of behaviors and detection of deviations, co-occurrence grouping, similarity matching, prediction, data reduction, classification, regression, and causal modelling).

Layers 1 and 2 of this generic CPPS architecture use *edge computing* technologies to perform the computation on shop floor data downstream cloud services and upstream IoT services, at the edge of the physical network.

Control systems in CPPS will use networks of digital twins and ontologies to avoid introducing constraints relative to their consistent reality. These DT networks are based on pervasive instrumenting structural devices and evaluating in the cloud the changes between their reported-last known, desired- target and current-live state with applied AI algorithms.

4. Description of the papers composing the special issue

This section provides a short description of the 12 papers composing the special issue. Table 1 shows the coverage of the topics reflecting the four research dimensions of the framework for the digital transformation of manufacturing (DTM), analysed in chapter 3, by the 12 articles published in this special issue.

At MES level, cloud computing refers to virtualization of global applications such as mixed batch planning and job scheduling, product traceability or production tracking. In this context, the article entitled “A cloud-based manufacturing control system with data integration from multiple autonomous agents”, written by Silviu Răileanu et al., proposes a semi-heterarchical manufacturing control solution based on a private cloud infrastructure that collects data in real-time from intelligent devices associated to shop-floor entities: resources and products during their execution cycle [32]. The cloud platform acts as a centralized system scheduler that plans jobs and allocates resources optimally at batch level, and integrates real-time data and status information about manufacturing resources and orders from agentified, stationary or mobile shop floor devices. The paper reports an experimental evaluation of the data collection process (energy consumption) from measuring devices embedded on robots and of the data transfer in the cloud for updating the weights of resources bidding for jobs.

Establishing viable manufacturing management and control and scenarios for production structures requires iterative test-and-validation global simulations for solution validation and evaluation of KPIs. Virtual Manufacturing Systems (VMSs) with configurable virtual technologies may be used to compare existing manufacturing strategies and scenarios in order to conceive new shop floor layouts, logistic systems, material flows and control strategies

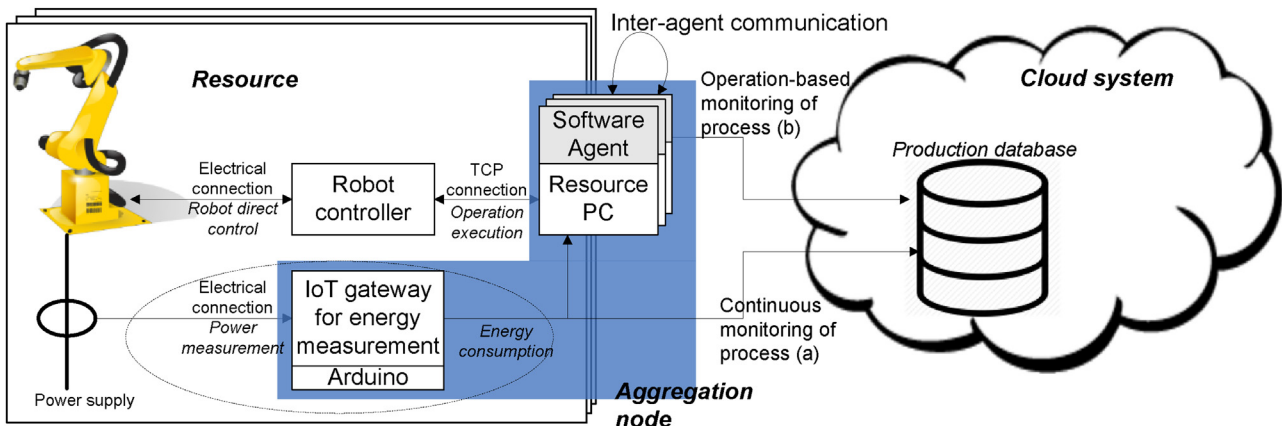


Fig. 5. Architecture of an aggregation node for a) continuous and b) operation-based data collection for digital twin implementation in CPPS.

Table 1

Coverage of the topics for the DTM framework by the 12 papers of the special issue.

Paper	Research topics		Modelling approach		Architecture design		Scientific issues		
	Resource/MES virtualization	Cloud Services/ CMfg	Distributed Intelligence/ MAS	Holonic control/ SOA	IIoT	CPPS	Big data/ Analytics	Cognition/ Machine learning	Digital twins
[32]	X	X	X	X	X				X
[60]		X	X		X		X		
[63]	X	X		X	X			X	
[64]		X	X	X		X	X	X	X
[54]	X	X	X	X		X	X	X	
[66]	X		X		X			X	X
[47]	X		X			X		X	
[69]	X			X		X		X	
[71]	X	X	X		X	X	X		
[72]		X	X	X		X			
[74]	X			X		X	X		
[75]	X		X			X	X		

leading to the best possible performances. The paper entitled “*Process Simulation Platform for Virtual Manufacturing Systems Evaluation*”, written by Radu Dobrescu et al., presents a cloud simulation platform and its associated services for the hybrid simulation of VMSs. The platform has a generic emulation-based architecture and switching mechanism which allows connecting either the digital, virtual factory and production models or the real manufacturing system to the cloud-based shop floor control. A Virtual Development Environment integrates new IC²T and concepts: embedded systems, hardware-in-loop, model-driven design and architectures, service-oriented agents, cloud services and edge computing [60].

One of the most noticeable trends in direct digital manufacturing investigates the utilisation of additive manufacturing technologies like 3D printing for local production of customised goods. Additive manufacturing technologies, and especially 3D printing, fall in the category of advanced manufacturing technologies required for mass customisation [61] due to their special manufacturing capabilities: customer-driven product design, flexibility, execution speed and easy reengineering [62]. Srinivasan et al. investigate in the paper “*Customising with 3D printing: The role of intelligent control*” “the suitability of 3D printing, as a rapid manufacturing technology, to handle customisation needs and to enhance the customization capabilities of conventional manufacturing systems [63]. The 3D printing technology implemented as digital manufacturing subsystem is able to handle the issues related to customisation: customer driven manufacturing; integration of product design and manufacturing systems; flexibility – reducing the need for tooling and setup by producing parts directly based on a digital model; management of inventory of great variety and of customised orders. The solution proposed in the paper is implemented using multi-agent based control in a real-life production environment.

CPPS move one step further Cyber-Physical Systems (CPS) that use specific technologies (big data analytics, self-configuring and machine learning) in the computation, control and communication tasks to advanced control-specific characteristics: reality awareness through digital twin patterns, strong coupling of processes and devices in holarchies, product-driven automation and control reconfigurability in semi-heterarchical topologies. The paper “*Classification of cyber-physical production systems applications: proposition of an analysis framework*” written by Olivier Cardin introduces a new analysis framework for classifying CPPS applications depending on their cognitive abilities, their application extent, the level of interaction with humans, the distribution of intelligence and the network technologies used [64]. Motivated

by the difficulties to compare and analyse dispersed CPPS developments, a framework is proposed to analyse current developments with focus on agility.

Real time analysis of data collected from the production system opens the path towards efficient scheduling of batch execution for large scale distributed manufacturing structures. Prediction of resource behaviours and shop floor events has a great potential to reduce manufacturing costs, by providing the information required for operational decisions like preventive maintenance, automatic remediation or scheduling optimization [65]. In this context, the paper “*Intelligent Data Analysis and Real-Time Supervision (IDARTS) framework*” written by Ricardo Silva Peres et al. presents a methodology and implementing solution for scalable, flexible and pluggable data analysis and real-time supervision of manufacturing systems, aligned with Industry 4.0 vision – the integration of a CPS at the edge with cloud computing. The proposed framework combines distributed data acquisition, machine learning and reasoning in real time to allow for predictive maintenance and quality control, reducing the impact of disruptive events in production. A MAS-based CPPS implementation that agentifies both shop floor devices and subsystems is described. IDARTS is able to support the plug-and-produce paradigm in the context of predictive manufacturing through dynamic system virtualization, coping with changes and disturbances at shop-floor level; it is designed to integrate real-time and historical data at device and system levels, enabling the adaptation of the real-time analysis and rule-based supervision algorithms after deployment. Finally, this framework supports context-aware self-reconfiguration of the manufacturing system’s parameters and human-machine interaction for corrective actions [54].

The intelligent product model was introduced as a means of motivating supply chains in which products and orders are central. Advances and ongoing research in developing IP applications concern information systems for physical products influencing their own movements through the supply chain. The basic concepts and characteristics of IP are also found in emerging technologies related to production, logistics and supply chains such as smart objects, objects in autonomous logistics and the Internet of Things. The focus in the paper “*Towards the deployment of customer orientation: A case study in third-party logistics*”, written by Vaggelis Giannikas et al., is put on the design of information systems that can support customer-orientation in logistics and its impact on existing operations and infrastructures [66]. The authors consider that the so-called product intelligence model for logically linking data and rules to a product provides a suitable approach for the deployment of customer-oriented

logistics [67,68]. The paper investigates implementation challenges of customer-oriented logistics via an in-depth case study with a third-party logistics company.

For Holonic Manufacturing Control, the agility and responsiveness respectively the robustness of the manufacturing system represent major objectives; generic approaches with high level abstraction were considered in last years' research. Such an approach is the semi-heterarchical control topology that allows dynamic reconfiguring of product scheduling and resource allocation. The dynamic service-oriented reconfiguration technique is at present an important topic in smart manufacturing systems, aligned with the CPPS context, and particularly with the Industry 4.0 initiative. Reconfigurability with service orientation are the main subjects developed in the paper "*Decentralized and on-the-fly agent-based service reconfiguration in manufacturing systems*" written by Nelson Rodrigues et al. The paper offers an agent-based approach to execute dynamic, online and decentralized service reconfiguration, where intelligent software agents detect events and identify reasons to reconfigure: resource breakdown, service performance degradation or production changeover, in proactive manner [47]. The proposed service reconfiguration solution is implemented by using the agent-oriented JADE framework and tested in a flexible manufacturing platform that contains five robotized workstations.

A similar topic of interest for Holonic Manufacturing Systems is approached in the paper "*On Rescheduling in Holonic Manufacturing Systems*" written by Carlos Pascal and Doru Pănescu. The motivation of the research results from the fact that optimally off-line scheduled production can be affected by several types of unexpected like: occurrence of rush orders, changes of production volume, resource breakdowns or degradation of their performances, variable duration unknown duration of maintaining processes and delayed delivery of raw materials, which imposes rescheduling or even repeating some operations in the manufacturing structure. An optimal schedule obtained with great computational effort may shortly become obsolete because of unforeseen dynamic changes. The paper presents in detail a holonic coordination method combining contract net protocol and distributed constraint satisfaction algorithms (DisCSP) for shop floor job rescheduling. This mechanism uses a coloured Petri net model as coordination protocol and a learning mechanism included in the DisCSP phase [69].

Several standards have emerged in the last period supporting the advances in SOA adoption, such as ESB (enabling SOA connectivity to integrate business applications, services and processes at enterprise level) or MIMOSA; together with the emergence of Cloud manufacturing, these standards open new directions in terms of multitenant manufacturing, where two or more organisations can share the shop floor or certain resources in order to realize batches of products. Securing these architectures becomes thus more important, as it does not refer only to physical security of the site, but extends to the communication between intelligent enterprise actors like ERP systems, shop floor resources, products with embedded intelligence during their execution, cloud resources, MES components and other external resources [70]. Cybersecurity is becoming of utmost importance due to the increasing use of cyber-physical systems in manufacturing tasks, and the extended access to information facilitated by the Industrial IoT. The paper "*Cyber Resilience Protection for Industrial Internet of Things: A Software-Defined Networking Approach*", written by Radu Babiceanu and Remzi Seker, argues that software-defined networks (SDN) that decouple the network data and control mechanisms are a promising solution addressing the security needs of distributed industrial applications [71]. A SDN-based manufacturing testbed and combined cybersecurity-resilience ontology to be used for the requirements capture of the virtual

manufacturing network design stages are first proposed. Then, the research presents a framework for SDN-based cybersecurity-resilience protection mechanisms for virtual manufacturing applications.

More than being a very attractive technology from the programming perspective, the Erlang technology ecosystem offers decisive benefits in industrial automation environments. The features and functionality offered by Erlang match holonic reference architectures for manufacturing control, like PROSA [48], much better in application software than intelligent agent tools. Erlang supports lightweight processes, allowing for one or more concurrent processes per activity or resource in the world of interest; it is extremely robust and offers mechanisms to handle process crashes, rendering applications with very high availability. The paper "*Erlang-based Holonic Controller for a Palletized Conveyor Material Handling System*", written by Karel Kruger and Anton Basson, presents an Erlang-based holonic control implementation for a modular conveyor system of a 10-workstation production cell [72].

Dual semi-heterarchical manufacturing control systems add to optimized scheduling and resource allocation computed in centralized mode agility, i.e. quickly reacting at unexpected events through intelligence distribution, agentification, and decentralization of the control [73]. By collecting and processing in real-time the resources' state and quality of services, the global optimization model can be re-run in the cloud MES adapted to the current shop floor and environment operating conditions reducing thus the myopia of the system at global batch level. In the paper "*The design space of production planning and control for Industry 4.0*", Julia Bendul and Henning Blunck have reviewed literature from multiple research domains and the various theoretical findings and design approaches reported therein, to create a classification of design decisions through which the emergence of myopic behaviour in distributed manufacturing control systems can be controlled [74].

A similar topic is addressed in the paper "*Decentralised vs. Partially Centralised Self-Organisation Model for Mobile Robots in Large Structure Assembly*" written by Spartak Ljasenko et al. who introduce the concept of self-organisation in complex distributed assembly systems using robots [75]. It is argued that in centralized scheduling, shop floor reconfiguration and other hardware changes usually require considerable modifications in the software. Distributed, agent-based systems provide a natural solution to these problems by reducing the processing load on the central entity in hybrid systems, or by removing it completely in fully decentralised systems. Other reasons for adopting decentralization are: the heterogeneous environment, the need for scalability, robustness and agility by reconfiguring rather than by reprogramming, and the collaboration in strongly coupled CPPS components.

5. Conclusions and perspectives of future research

This special issue brings contributions to the digital transformation of manufacturing through cloud services and resource virtualization, which are vital for implementing the main building blocks - Cyber Physical Production Systems and Industrial Internet of Things - in the "industry of the future" framework.

The 12 selected articles address the principles, patterns, context and IT-OT convergence requirements for the digital transformation of manufacturing, and focus on two important speed-up drivers: virtualization of resources and adoption of cloud services. Yet the complexity rises when handling and using big data, analytics and machine learning must be considered. Manufacturing reality should be reflected within these models and architectures through digital twins, closing the gap between information processing and real-world aspects.

Some challenges remain to be dealt with in future research:

- **Conceptual:** improved design of the control systems based on a more abstract and generic understanding and interpretation of holonic reference architectures, increased reality-awareness bringing the control layer closer to processes, decision mechanisms for unexpected events, prediction and detection of anomalies based on machine learning.
- **Societal:** allocation of humans as activity performers without experiencing the penalties to the extent incurred by the IT, human integration in CPS, autonomy of artificial decisional entities, legal aspects [79], ethical behaviour of autonomous CPS [80].
- **Environmental:** adaptation to dynamic environments, energy saving, waste reduction, risk management.
- **Technical:** high performance computing in the Cloud for real time optimization with distribution of intelligence in D-MAS patterns for robustness at disturbances, service orientation of production and control processes, cybersecurity, in-depth interoperability at physical level, big data management, embedding intelligence on products, interaction of control systems and planners with networks of digital twins for access to the world of interest.
- **Technological:** efficient integration of new information, communication and control technologies: pervasive instrumenting at plant level, resource and product virtualization, merging CMfg and CC infrastructures, edge and fog computing, Software Defined Networks.

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