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Digital transformation of manufacturing. Industry of the Future with Cyber-Physical Production Systems

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Abstract. This paper analyses the main research direction for the digital transformation of manufacturing and its important drivers: cloud services and resource virtualization that have led to the new *Cloud Manufacturing* (CMfg) model – an industrial replica of Cloud Computing. This model is adopted for the higher layer of the Manufacturing Execution System (*e.g.* the centralised, hierarchical System Scheduler), while its lower layers distribute intelligence through agent- and service orientation in the holonic paradigm. In this approach, Intelligent Manufacturing Systems are assimilated to Cyber-Physical Production Systems in which informational and operational technologies are merged, the shop floor physical reality being mirrored by virtual counterparts – the digital twins that represent abstract entities specific for the manufacturing domain: products, orders and resources. Industry 4.0 represents the vision for the Industry of the Future which is based on Cyber-Physical Production Systems that assure the flexible, dynamically reconfigurable control of strongly coupled processes. In this picture of the future manufacturing industry, the Industrial Internet of Things framework provides connectivity and interoperability to integrate communications between different kinds of things: products, orders and resources and legacy manufacturing devices to the web service ecosystem. The paper describes the scientific issues related to big data processing, analytics and intelligent decision making through machine learning in predictive resource maintenance, optimized production planning and control, lists solutions and proposes new research directions.

Key-words: 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 plant structures. This leads to the need for new control and management systems that exhibit efficiency, reality awareness, robustness, agility and reconfigurability while ensuring persistent resilience and sustainability of processes and context-dependent maintainability of manufacturing resources [1].

This presentation explains 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: i) resource instrumenting and virtualization, and ii) data analytics, machine learning and cloud services.

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 (twins) and ontologies. The definitions of these patterns require using advanced, integrated *information, communication and control technologies* (IC^2T) 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 centred on customers [3].

The key components of digital manufacturing are represented by *resource and process virtualization* leading to intelligent decisions through *machine learning* and *cloud services*.

Resource virtualization assumes the creation of extended digital models of the three categories of physical entities that are specific for manufacturing: products, resources and orders using the Digital twin technology. In the perspective of the digital, computer-based control of distributed manufacturing processes, the digital twins fulfil the role of "intelligent beings" that mirror parts of the reality, and need to be deployed in industrial systems where they interact with planning, scheduling and control entities in such way that no limitations relative to the corresponding reality, *e.g.*, controlled processes, are introduced.

The holistic view of the real capabilities, status and features of an entity (equipment, process, product) including its digital representation, execution context, history of behaviour, time evolution and status can be encapsulated in a digital twin – defined as an extended virtual model of a physical asset, process, product, that 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 plant entities [58, 59].

Resource virtualization also relates to the capacity of creating and managing *virtual machines* (VM) and represents the main enabling technology of *Cloud Manufacturing* (CMfg). Virtualization allows decoupling a set of physical computing or manufacturing resources from their use, thus permitting easy migration of a workload to other resources.

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 longterm global view and the rapid local reaction abilities to unexpected events.

Cloud services in manufacturing (CMfg in short) represent 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, it is considered that adopting CMfg in IaaS model on the production layer of enterprises with high production volumes and/or variable batch sizes and/or frequently changing product types is necessary in 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].

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 shape modelling techniques. 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.

Adopting cloud services for big data analytics and intelligent decision making through machine learning is based hence on the virtualization of shop-floor devices and a new organization of manufacturing control at global, batch level – the *Manufacturing Execution System* (MES).

2. The context: 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 IC^{2}T 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 physical world with 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) 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 this perspective, the digital transformation of manufacturing envisaged by Industry 4.0 is based on the paradigm of 3I technology advances:

I1. *Instrumenting* manufacturing resources (*e.g.*, machines and robots), products (*e.g.*, product carriers and subassemblies), and environment (*e.g.*, workplaces and lighting).

I2. *Interconnecting* orders, products / components / materials, and resources in a service-oriented approach using multiple communication technologies such as wireless, broadband Internet and mobile.

I3. *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, process optimization, 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. The research framework for digital transformation of manufacturing

We characterize the digital transformation of manufacturing processes and systems through a framework defined by four dimensions: (1) the research topic for the two transformation drivers: i) resource instrumenting and virtualization, and ii) data analytics, machine learning and cloud services; (2) the modelling approach for advanced control; (3) the architecture design for implementation, and (4) the scientific issues to be addressed.

3.1. The research drivers: Cloud services and resource virtualization

The research topic on the digital transformation of manufacturing is focused on two drivers: cloud services in manufacturing and resource virtualization.

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

- Transforms a pool of manufacturing resources (machines, their controllers and capabilities), products (recipes, client 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 can use *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, *e.g.*, 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, machine learning for predictions, tracking the complete production flow, etc. The adoption of cloud computing considers the virtualization of MES workloads [19]. While MES implementations to 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 [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].

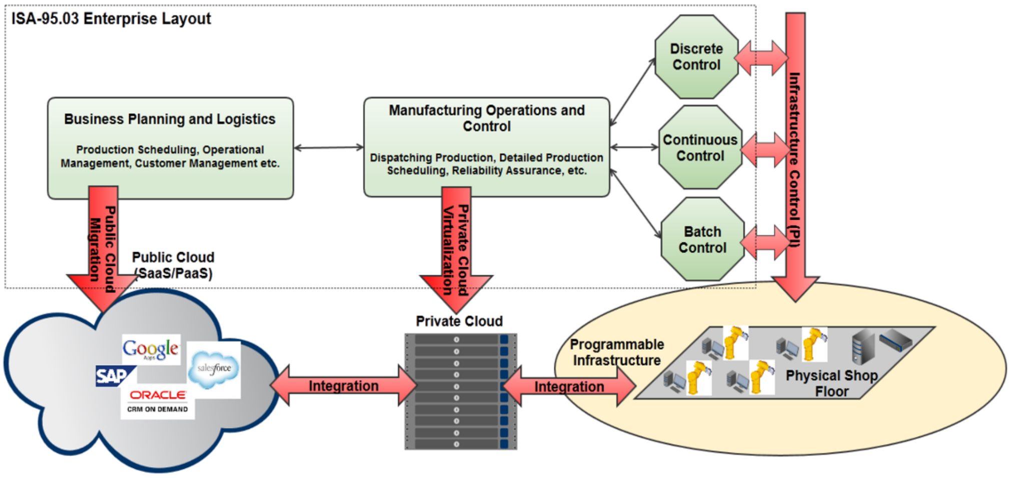

Fig. 1. Dual cloud adoption strategy for manufacturing enterprises and MES virtualization with programmable infrastructure (*adapted from* [33]).

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 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 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].

ii) Virtualization of shop floor devices

Virtualisation is based on the *Digital twin* (DT) concept. The digital twin is an emerging technology and a key consideration for interaction between the cyber and physical worlds [81]. The concept of digital twin, as defined by [82], is a digital information construct about a physical system that is created as an entity of its own. The digital information therefore forms the twin of the physical system and is linked to the physical system over its whole lifespan.

From the point of view of modelling reality there are two types of DT: a) DT with a physical counterpart or *data-driven* DT which relies on IoT to collect data; this model is used to synchronize the virtual twin with the physical counterpart and ii) DT without a physical counterpart or *model-driven* DT which is a digital simulation used for modelling, design, (analysis and forecasting). In the second case there is no IoT and no setup. Its usage case comprises different processes and views outcomes prior to developing infrastructure (resources and technology). Commonly used for *Product Lifecycle Management* (PLM), the term ‘product’ was extended to the terms ‘resource’ and ‘system’ used in manufacturing processes, and there exists now interest in aggregated DT for Smart Manufacturing [83].

The concept of digital twin was first introduced as a virtual representation of a manufactured asset, promoting the idea of comparing a DT to its engineering design to better understand what was produced versus what was designed (tightening the loop between design and execution). The following terms define a DT: 1) *Digital Twin Prototype* (DTP): A DTP describes information (the recipe) to create an asset, *e.g.*, the asset's 3D model, its Bill of Materials or Bill of Processes; 2) *Digital Twin Instance* (DTI): A DTI describes a single specific physical instance of an asset, *e.g.*, the list of exact part numbers that were used into production of this specific asset or the exact process steps that were followed in producing the given asset. DTI also contains the current operational states captured from the sensors connected to the asset; multiple separate physical assets could be manufactured using a single DTP, and each of them will have its own DTI; 3) *Digital Twin Aggregate* (DTA): A DTA is an aggregation of multiple DTIs, and it allows for querying information about a group of assets.

The industry implementations of digital twins typically fall into three categories:

1. *Simple device models*; they contain two primary sets of informations: i) the set of current values, measured by sensors on the device, that update the device's observed attributes and eventually report them; ii) the set of needs values the control application desires to be set on the device. In addition to these two primary sets of values, these DT implementations also store associated information like the #ID of the device, its current location and time of data acquisition, *e.g.* in a JavaScript Object Notation – type document [84].

2. *Embedded digital twins* (EDT); they are involved in all activities that imply their physical twins – *e.g.* an EDT is part of a resource control or a production management system. The connection between the physical model and the related virtual model is established in dual mode: by generating real time data using sensors, and by generating real time controls with help of a decision-making entity. An EDT is a single point of interaction and single source of information for its real-world counterpart [85].

3. *Networked twins*; networking provides every embedded twin with the capability to interact with the EDTs of its environment, thus mirroring an extended physical reality. For discrete shop floor batch manufacturing or continuous plant production process there will be a digital twin for the global plant which aggregates the digital twins for every resource. In the context of the ARTI reference control architecture open to reality awareness through resource virtualization, there is a separate twin for every equipment instance and each instance twin has a reference to the twin of its equipment type [86]. The aggregate twin tracks the plant infrastructure during its entire life cycle for control, reconfiguring, maintenance and design upgrading.

It is worth mentioning that an EDT that embodies its physical twin (*e.g.* an industrial process) may coexist and cooperate with a non-embedded DT that uses the model based on physics of the same closed loop process; both digital twins are fed with real time sensor data and by comparing their outputs deviations from a desired state trajectory or anomalies can be detected [86].

The main benefits brought by the digital twin concept are: a) *Visibility*: DTs allow visibility in the operations of equipment and of larger interconnected systems such as a manufacturing plant; b) *Prediction*: using various modelling techniques (physics- and mathematics-based), the DT model can be used to predict the future state of a process or resource; c) *Interaction with the model*: simulate conditions that are impractical to create in real life through what if analysis; d) *Documenting*: mechanisms to understand and explain behaviours of individual or interconnected resources; e) *Integration*: the DT model can be used to connect with backend business applications to achieve business outcomes in large systems: manufacturing value chain or plant production. Activity (order execution) intentions and resource allocation mechanisms are the DTs of the systems' decision making parts; predictive situation awareness is needed that can be reached making available a collective image through: i) virtual execution of decisions at complete horizon, at a frequency that exceeds its real-world counterpart, and ii) prediction of the physical twins' (resources) evolution [57].

Fig. 2 shows a 6-layer architecture of a Digital twin proposed for manufacturing cells [87].

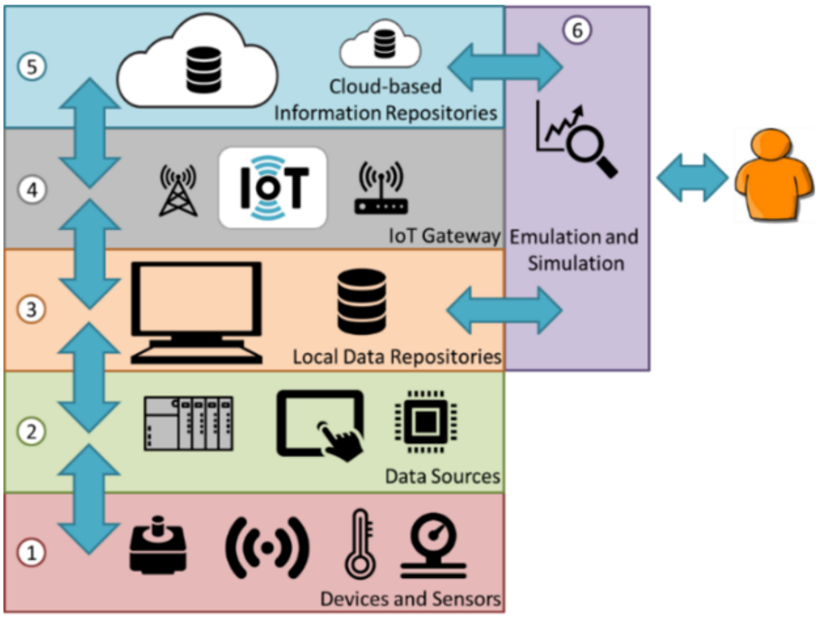

Fig. 2. 6-layer aggregate digital twin for a manufacturing cell (*Redelinghuys et al.*, 2019).

Layers 1 and 2 constitute the physical twin and consist of shop floor devices and data sources. Layer 3 consists of local data repositories; here, technologies such as the OPC UA serve as a vendor-neutral tool for collecting data from the data source layer 2 and sending it to the IoT gateway (layer 4). The IoT gateway is a custom developed software application that acts as a data-to-information conversion layer. It receives data from Layer 2, adds context if necessary and sends the information to the cloud repository (layer 5). Layer 5 stores historical information about the physical and digital twins. Layer 6 contains simulation and emulation tools, as well as user interfaces. Layer 6 also provides human interaction with the aggregated twin of the cell; the user can obtain a near real-time emulation through remote monitoring and also historical information from the cloud repository.

The concept of digital twin is important for the Industry of the Future in its implementing frameworks: *Industrial Internet of Things* (IIoT) and *Cyber Physical Production Systems* (CPPS), as they provide access to the world of interest and reality-awareness; planning and control systems can thus interact with the physical twins (resources, processes and products), influencing these elements into the desired behaviours.

The IIoT speeds up the usage of DTs for: 1) resource, operations and product monitoring (state, performances, energy consumption, timeliness, product quality, environment conditions) and 2) big data processing and insight extraction), while CPPS embed DTs in: 3) prediction, classification and detection based on machine learning (state, behaviour, performances; anomalies, failures; unexpected events) and 4) intelligent decision making in real time: global control (mixed product and operation scheduling, reallocating resources based on performance evolution); shop floor reengineering (resource team reconfiguring); diagnosis and predictive maintenance, and process resilience (reconfiguring set points, parameters and timing).

Resource virtualization is also needed for the virtualization of the *Manufacturing Execution System* (MES), *i.e.*, the creation of a virtualized layer for global manufacturing control tasks (the vMES); this 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 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. 3.

- *Shop floor resources* like robots, industrial vision systems, CNC machines, ASRS, 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.

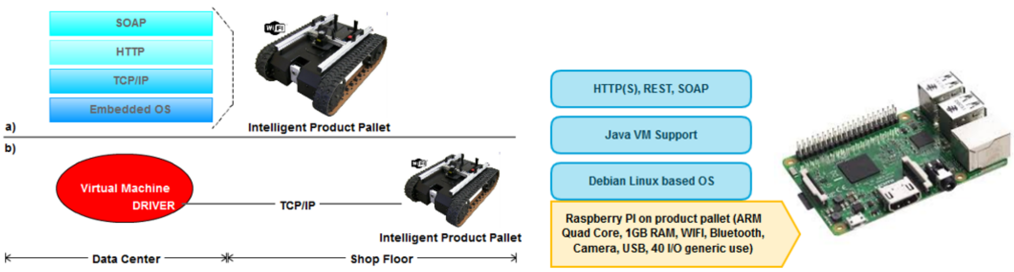

Fig. 3. Intelligent Product virtualization

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 (Arduino, Raspberry PI)

The binding between workload templates and virtualized resources is done using *shop floor profiles*, which are 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.

iii) 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*, the HA system includes 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 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 the cloud layer of a CPPS with 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 may be used as 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.

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 (Fig. 4). 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 (such as 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].

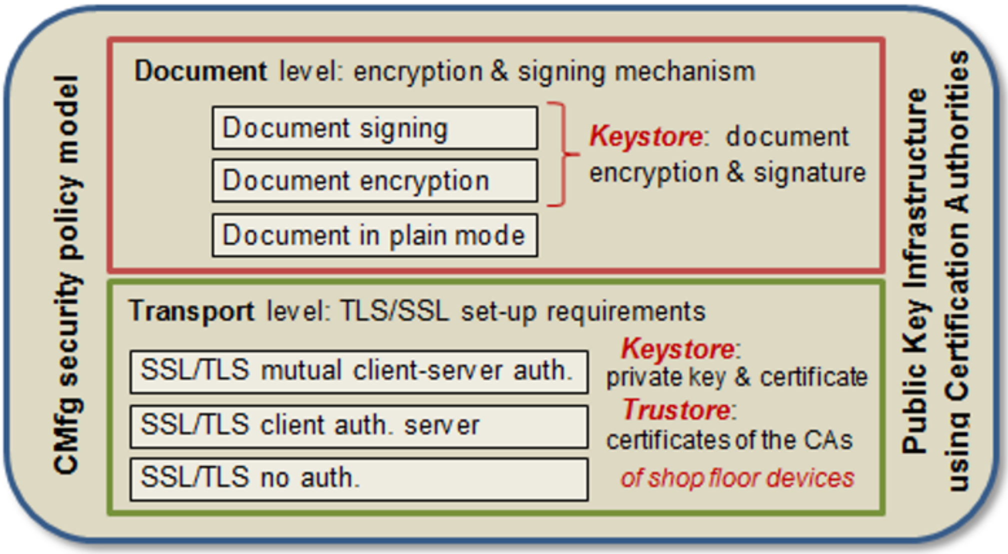

Fig. 4. Security policy model for shop floor device IoT integration in the CMfg platform of a CPPS

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].

One important research line is the integration of Infrastructure as a Service (IaaS) cloud platforms with manufacturing systems that include multiple resources at shop floor level. In order to use the cloud services offered in the IaaS infrastructure there are two approaches:

- To deploy the MES services inside the cloud system before production is started, or
- To deploy the MES services on-demand whenever they are needed.

The first approach offers the services just before the production starts and the manufacturing system can start the production without any delay. The problem with this approach is that the resources must be pre-provisioned, and the load of the services should be predicted; on line reconfiguration or deployment of the services adds downtime to the services due to the restart of the virtual machines implied in the process. Also, this approach will use more resources than needed and is less flexible.

The second approach is consuming the resources in an efficient and flexible way, offering elastic services and scaling faster than virtual machines; however, being an IaaS system, the provisioning of the services will require time which is translated in production delays.

A possible solution to be investigated is to use a combination of *virtual machines* deployed in cloud before the start of the production, and the services will run in containers executed on the virtual machines. The VMs accessed as services in the IaaS cloud will be the base for offering the static part of the services, and the containers which are deployed much faster than virtual machines will cover the dynamic services.

3.2. The modelling approach: Holonic manufacturing control, Multi-Agent Systems (MAS) and Service Oriented Architectures (SOA)

The distribution of intelligence within the manufacturing control system, as highlighted by Industry 4.0 concept, and the need for collaborative decisions of strongly coupled shop floor entities in the CPPS motivated researchers to adopt new modelling approaches for the global dynamic production control respectively frameworks for its implementing. In the literature, modelling of the control uses the *holonic manufacturing paradigm* in 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 set of abstract entities: 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.

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 manufacturing 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] and recently ARTI [48]. 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 in semi-heterarchical control topology. 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 structure is scalable and decoupled from the control algorithms which, by design, should preserve flexibility of the global holonic control and avoid introducing constraints and limitations such as myopia or the incapacity to react at unexpected events.

The most recently defined holonic reference architecture ARTI builds on PROSA and upgrades it for applicability for any type of CPPS by: i) *Generalisation*: the abstract manufacturing-related entities: product, resource, order and corresponding basic holons are replaced by generic ones, applicable beyond manufacturing to other classes of multi-resource production, logistics, supply, control and service activities; ii) *Reality awareness*: this architecture reduces the gap between the control software and the reality of interest defined by highly abstract elements (activities, resources and outcomes) mirrored by embedded digital twins.

The more abstract and generic interpretation of ARTI turns some scientific laws of the artificial [88] into unavoidable implications of bounded rationality:

- Flexible time-variant aggregation hierarchies are mandatory for the adaptation to a dynamic environment and thus hierarchies are time-variant (*e.g.* mirroring corresponding reality),

- Autocatalytic sets that include human resources are crucial for viability in CPPS,
- Intelligent beings are separated from intelligent agents, and decision-making technologies from the deployment of the selected decision-making mechanisms,
- Proactive behaviour and coordination require the ability to include the impact of future interactions, i.e., short term forecasts from the intentions of activity instances when multiple actors operate in a shared working space.

The holarchy for optimized and robust at disturbances (reality-aware) manufacturing control includes three classes of basic holons: *product holon, order holon* and *resource holon*, and one class of *expertise* (supervisory) *holon*. These classes are derived from the highly-abstracted, generic entities: "activity", "resource", "type" and "instance" of the ARTI holonic reference architecture represented in Fig. 5, in the form of the coloured ARTI-cube, which focuses on the relationship between (material) reality and the ICT-based production system.

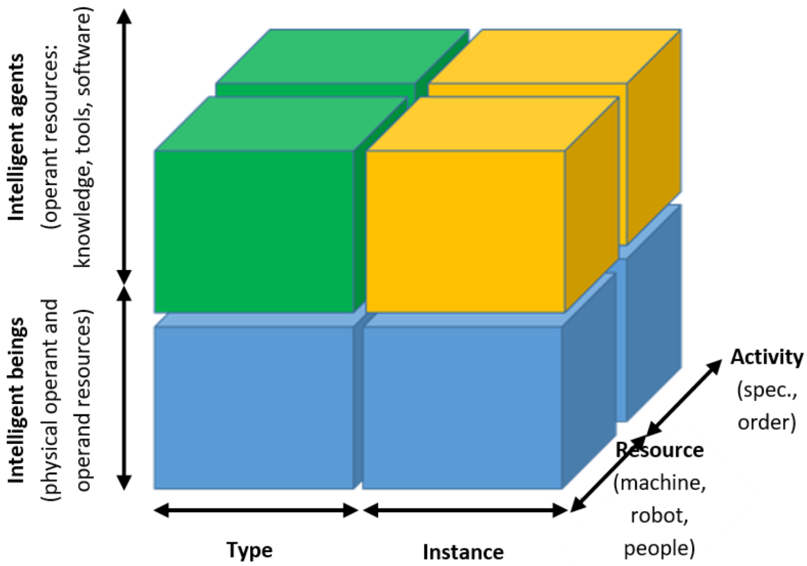

Fig. 5. The ARTI holonic reference architecture for IC^{2}T-based manufacturing, logistics, supply

Product holons contain the specifications (technical, logistics) formulated by the customer and are defined as *activity types*. Order holons become *activity instances* that are optimally calculated by the System Scheduler, while resource holons are subdivided into *types* (people, technology) and *instances* (*e.g.*, assigned personnel, used equipment).

Decoupling decision making (*i.e.* the plugins for production planning and capacity allocation) from the service processes becomes a top-level feature of the architecture, separating *intelligent agents* from *intelligent beings*. The agents are classified into *types* (*e.g.*, optimized planning methods, management principles) and *instances* (i.e., the connection of these concepts and mechanisms to intelligent control plug-ins and software tools). Expertise holons reside in the green cubes; the quality of supervision they assure upon batch production processes depends on how the yellow components connect them to the physical operands of the shop floor. Thus, ARTI subdivides an ICT-based production system to assure optimization and reality awareness.

The blue part of the ARTI holonic cube complies with the theory of flexibility (or design for the unexpected [38, 88]). The green part is founded on basic principles of, system- and data science, *e.g.*, mixed-integer programming, constrained optimization, recurrent neural network for resource state prediction, selected as needed in the batch planning and control stages. The yellow part is represented by the control technologies (instrumenting resources, detecting events) and software tools that implement the green methods; the yellow parts introduce limitations and restrictions that do not exist in the world of interest and their responsibilities should be limited as much as possible.

Activity and resources are formalized by distinct holons such that an activity is free to search and utilise suitable resources in an appropriate sequence and the resource can serve any activity that may desire it. The yellow software programs plan products, schedule operations, allocate resources, control the quality of products, maintain the necessary component stock, by implementing the green methods and algorithms. Humans are activity performers; they may cover multiple cubes in the ARTI model without inducing the penalties to the extent experienced by the yellow software agents.

The holistic view of the real capabilities, features and states of resource and activity instances (production orders, manufactured products and used resources) including their operating models, execution context, behaviour, and status in time should be encapsulated in *digital twins* that represent the blue ARTI parts – the intelligent beings.

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 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 (SOA) 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 shop floor and environment and easy reconfigurable process supervising and control solutions along the entire manufacturing value chain. 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 to efficiency criteria adopted by the manufacturer for sustainability, agility to market and product changes, 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.

4. 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.

i) 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 data and 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].

The 4-layer generic architecture specified below makes possible the integration of *Intelligent Manufacturing Systems* (IMS) in the Industrial Internet of Things framework, by deploying the specific role of a network of digital twins embedded in control functions: process optimization, reality-aware control, resource maintenance, product-driven automation:

- 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. 6). 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 and knowledge 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:* control, maintenance, traceability based on data analytics and machine learning for intelligent decision making. In digital production control, optimized planning and resource allocation will be based on measuring current parameter values and predicting states, behaviours and performances of processes and resources, while detection of anomalies and faults is based on classification and causal modelling. Historical data and time series of measured process and resource parameters are processed by data science methods (clustering, profiling as description of behaviors and detection of deviations, co-occurrence grouping, similarity matching, prediction, data reduction, classification, regression, and causal modelling) on this CPPS higher layer.

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.

The challenge is to integrate legacy manufacturing systems to the modern web service ecosystem of an IIoT. In typical industrial internet communications, there are barriers between parts of the internal network; these barriers exist because there are many different bus systems and protocols. In the higher levels of the ISA-95 model [20] XML-based protocols like PackML [89],

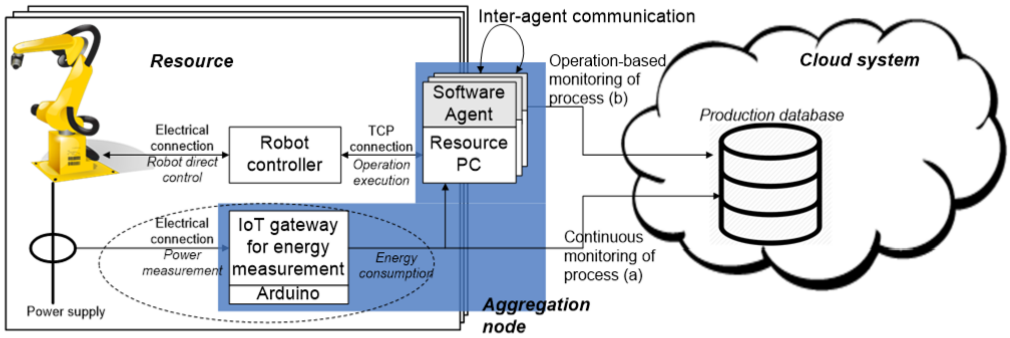

Fig. 6. Architecture of an aggregation node for a) continuous and b) operation-based data collection for digital twin implementation in CPPS

AutomationML [90] or B2MML [91] are used for the interoperability between ERP, MES and SCADA systems. On the lower levels there are many more compact protocols used on field buses (ModbusTCP [92], Profibus [93], OPC UA Binary [94], etc.) because of the advanced real-time requirements there. Also, there are often hardware limitations on the connected devices in this area, which prohibit the usage of high-level protocols for their communication.

One alternative is the use of a mediation device as middleware between the different network types. This device must be able to achieve the requirements of all connected networks and the protocols used there. Also, it should provide a big flexibility in its possible applications for the different needs of CPPS industrial components integration. In IIoT frameworks for digital manufacturing systems this middleware software is based on unified interfaces for the interoperability with protocols within the classes:

- "I/O" (low level): these protocols are members of the abstraction class named "I/O" and have the following characteristics: shared memory behaviour in data exchange; no incoming connection requests (polling necessary); data access over distinct addresses. This class includes mainly fieldbus protocols like Modbus TCP and Profibus, and other lightweight communication protocols like OPC UA Binary,
- "Webservice" (high level): these protocols are members of the abstraction class named "Webservice" and the nodes of the contained protocols use and/or offer web services. These protocols have the following characteristics: message-based data exchange; eventing is possible after publish-subscribe pattern; no hierarchy in involved network nodes, incoming and outgoing connection requests are possible.

The middleware software is based on interfaces for the interoperability with protocols within the classes "I/O" and "Webservice". These interfaces are designed to increase the modularity and extensibility of the software and to enable the integration of existing manufacturing systems into the IIoT (Fig. 7) [95].

The middleware could be *connected directly to a fieldbus*. This could be used to control a manufacturing system with the aid of its actuators, sensors and all other devices connected to the fieldbus. The second role contains this *mediation only*, but there is no control functionality included.

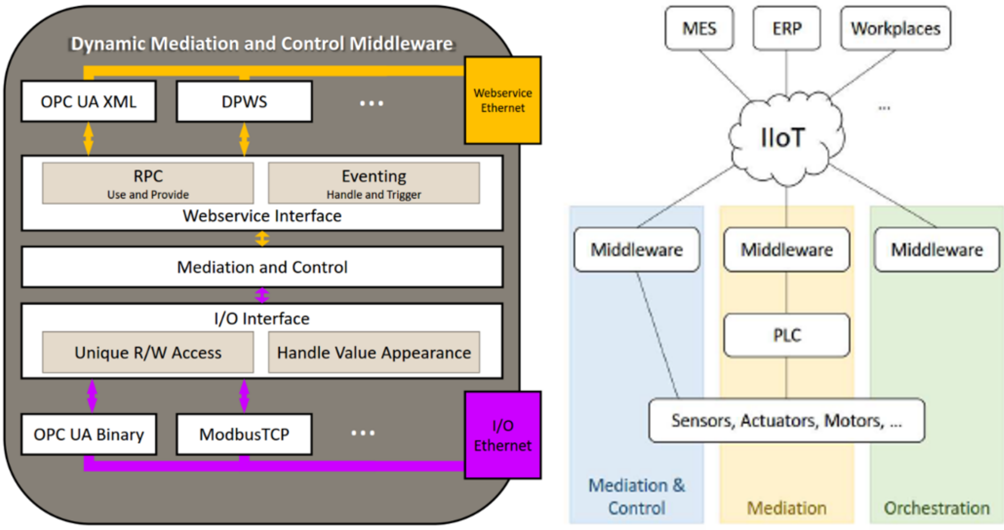

Fig. 7. Middleware for the integration of IMS in IIoT. *Left*: the interface and its software-modules; *Right*: possible roles of the middleware at an IIoT *(Kliesing, Colombo* 2016)

This task is completely fulfilled by PLCs, which could also match hard real-time requirements. The third suggested role is the *orchestration of foreign web service*, offered to other IIoT members, like MES or ERP systems.

ii) 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 [45].

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) and 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 [32, 47] address these concerns 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].

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 of devices and evaluating in the cloud the changes between their reported-last known, desired- target and current-live state with applied machine learning algorithms.

Fig. 8 shows the 4-layer structure of a CPPS with digital twins embedded in the supervised control of the production process of radiopharmaceuticals.

For the semi-continuous radiopharmaceuticals production process, each one of continuously controlled sub processes: target irradiation in the cyclotron, chemical synthesis and dispensing (portioning in vials with dilution) represents a physical twin; similarly, the installations have digital twins too.

There are multiple aggregations of DTs: 1) virtual twins of the three main sub processes in the production plant, and 2) predictive and decision-making twins projected in the supervisor for process resilience and global optimization. The DT layers are:

1. *Data acquisition and transmission:* the DT contains information about the acquisition and edge computing of process data and joining in time process data streams,

2. *Virtual twins of sub processes* that are needed to produce the bulk radiopharmaceutical product in a required quantity and with imposed characteristics (purity, radioactivity) and then portion it in a requested number of vials. The individual process models are aggregated at the level of the production plant to provide the necessary information about the entire production sequence,

3. *Data analysis:* these are predictive twins that are directly fed with process and device data and, using machine learning techniques, predict the evolutions of process parameters, product characteristics and equipment status and detect eventual deviations,

4. *Decision making:* these are twin projections on the highest aggregation layer that apply the insights into the evolution of processes and operations of resources in supervised production control. The role of the decision-making twins is twofold: advisor and trigger of appropriate corrective business processes in the time stages:

   - Off-line: i) assist configuring the parameters of sub processes in order to obtain the characteristics of products specified in the clients orders (using data from virtual sub process twins), and ii) assist the optimization of mixed order planning and production scheduling (using data from the virtual aggregated production process model). The high-level decision-making twin uses its global view on the plant's business processes (energy and raw material costs, revenue from regular and rush orders, etc.) to advise on the selection from the solution space for optimization.

- On line: signal the need to reconfigure the parameters of a sub process from which the predictive twin has identified an unexpected event *e.g.*, foreseen a critical process evolution or detected an anomaly, and evaluate the implications on subsequent sub processes.

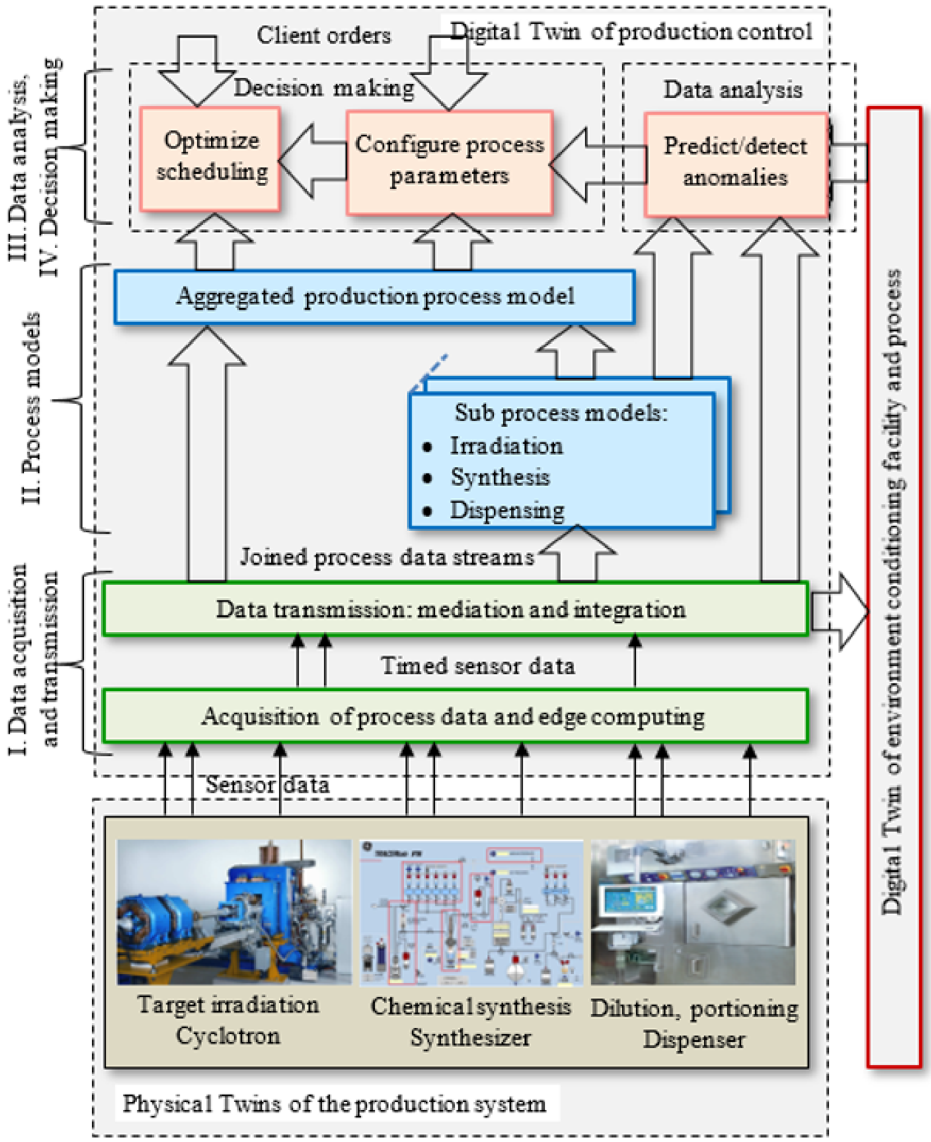

Fig. 8. CPPS with 4-layer aggregated digital twins embedded in supervised production control

The higher layers III and IV of the CPPS use the Plant Topology information and the Dynamic Rules Store. The Plant Topology data should be an integral part of the system's data model, representing its existing resources, their organizational structure and other relevant information such as connection interfaces and existing data sources. Through it, the CPPS can be instantiated in a way that allows virtualizing each of the system's elements and initiate the data acquisition. The CPPS is responsible for processing the collected data and reasoning with rule-based decision-making processes, and thus providing an earlier identification of faults, potential deviations or other critical events. The basis of this behaviour in DT layers III and IV is depicted in Fig. 9.

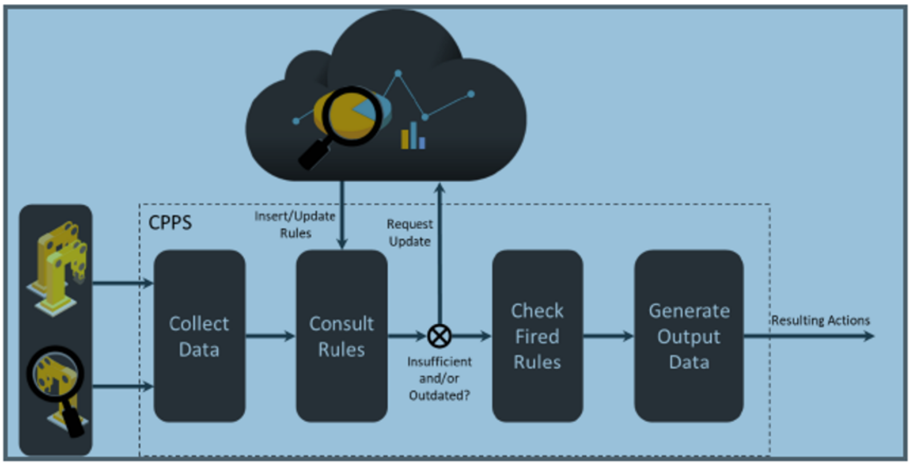

Fig. 9. Rule-based reasoning flow in the higher DT layers of the CPPS

These rules are contained in a Dynamic Rule Store and should be modelled using the system's common data representation format. The store can be updated dynamically during runtime by the Knowledge Management layer, if either as a result of the data analysis performed on the historical data it is found that certain changes are required to improve overall quality control, or if the CPPS requests an update from Knowledge Management due to having insufficient or outdated rules.

5. The scientific issues: Big data Analytics and Machine Learning

The digital transformation of manufacturing through resource virtualization, cloud services, applied AI and embedded digital models is based on intelligent decision making that complies with the theories of optimization, flexibility and reality-awareness [48]. These issues are addressed in the scientific literature and industry practice 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 of the contextual digital manufacturing enterprise that can be deployed across four layers:

1. *Gather data:* collect all relevant data from a variety of sources: process and resource sensors, embedded devices, microcontrollers and data concentrators,

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 parameter evolutions, 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.

The 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 listed. 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 (Fig. 10).

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 break-down); ii) *Intelligent Product Streaming:* IP data streams contain mostly location and status information about products.

Dealing with large amounts of real time data originating from various sources and having different formats requires a careful design of the messaging system architecture. Increased resource and product instrumenting and adoption of **Edge computing** paradigms in the IIoT framework leads to new types of data sources, that generate high quality information, but at the same time large volume. This information flow is only useful if it can be processed in real time or near real time, so decisions can be derived fast. Dividing the messaging platform in separate parameter domains (or topics) with established producer-consumer relations helps in logically dividing the load. This is how the distributed messaging platform should store and push data.

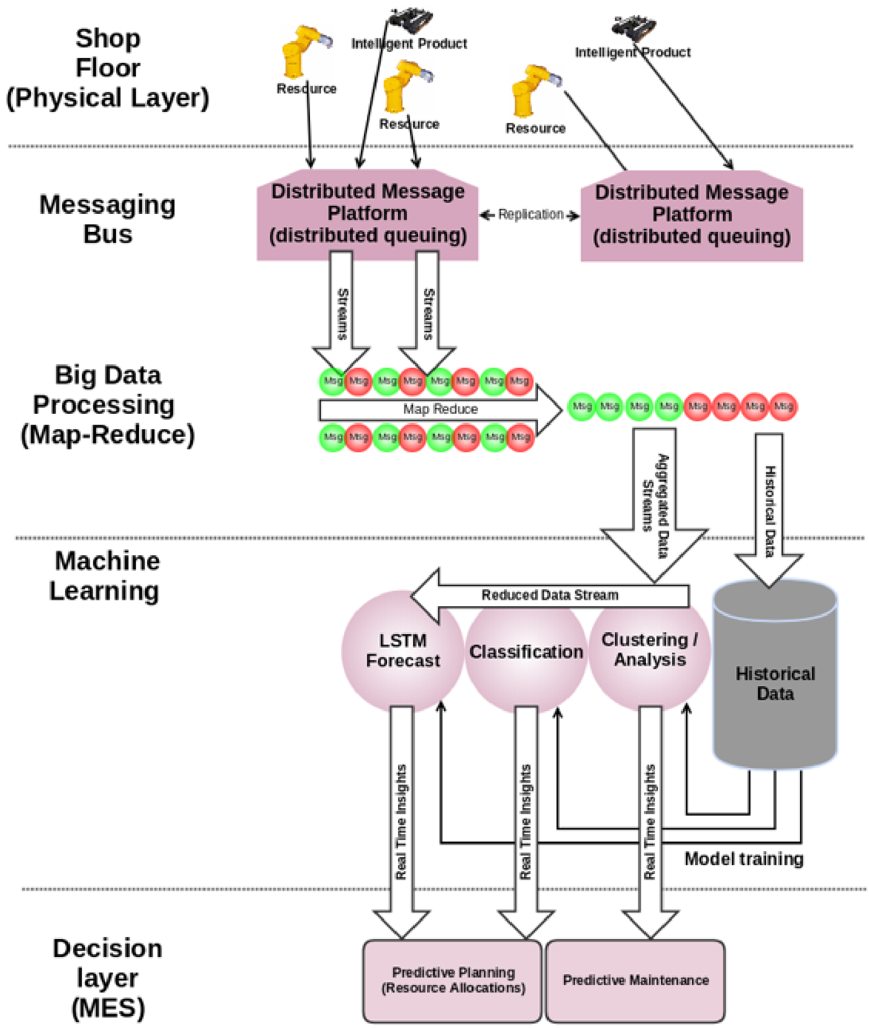

Fig. 10. Information flow in Big Data driven architecture with real time machine learning

However, topics must be seen at a logical level only, as over-structuring the topics at design time can reduce the flexibility of the platform on long term [15]. For example, it would make sense to use distinct topics for shop floor *resource messages* (including instant energy consumption data) and for *intelligent product messages* (comprising operation execution times). However, dedicating a topic to only one type of resource might cause issues as the shop floor capacity can change in time, and that will require changes in the map-reduce algorithms down the line. At the same time, the content of the messages sent can be different depending on the application, like instant energy consumption, motor temperature, axis vibration, and so on. Using a free format for payloads is essential but requires a complex meta-data definition for each attribute.

Traditionally the communication at shop floor level is established in a stack model, where the following data flows are identified: i) *Upstream*: consisting in events generated by lower level modules (*e.g.* resource breakdown, zero stock, QA failures, product tracking); ii) *Downstream*: dispatching of production orders, operations and resources selected to perform the operations, route calculation and optimization; iii) *Flat*: this kind of data flow is used when the original schedule cannot be followed due to unexpected events (resource breakdowns).

The stack-based data flow is a tightly coupled model, as each layer is coupled with two other layers and thus reduces the flexibility of the system. The introduction of a messaging system, acting as a service bus for the MES, assures loose coupling between modules at shop floor level. In this context, the messaging system needs to support the characteristics:

- *Event driven communication*: there is a high number of events generated at shop floor level that need to be handled by specific components,
- *Workflows*: the messaging system can launch and execute predefined workflows associated with specific events,
- *High number of messages*: it is vital to assure that high message throughput is possible,
- *Message transformation*: the role of the messaging system is to transform the messages to and from proprietary protocols (simple +5V dc signals, proprietary line protocols or high level TCP-based protocols) in a common standardized format. This is done by developing message convertors at any entry point and exit point of the bus,
- *Message validation*: filtering invalid messages at the edge of the processing system before they enter in the big data map-reduce.

Multi-Agent Systems were indicated 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 [51, 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 process monitoring and control.

A generic distributed, agent-based model to aggregate data and analytics in CPPS is shown in Fig. 11 [54].

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. Agents 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 (ML) is a very powerful tool to extract insights from big data; it has been traditionally 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 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].

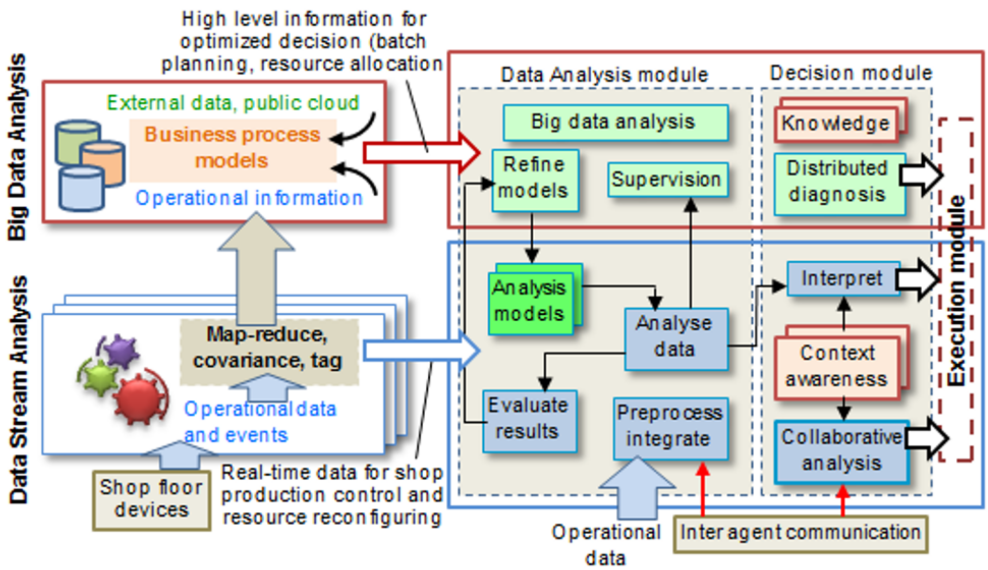

Fig. 11. Distributed, agent-based model of Big Data Analytics stages (operational, supervisory) in CPPS

From the perspective of Industry 4.0, 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.

Three types of machine learning applications that can be used for intelligent manufacturing control and predictive resource maintenance: 1) The first type tries to resolve the *prediction* problem, and the insights obtained can be used directly in the business layers for decision making or in fault detection systems. More specifically, the prediction problem is interpreted as the possibility to use a deep learning neural network to learn patterns and variations in numerical measurements, *i.e.* energy consumption, and then use the neural network to make forecasts for that measurement. This is especially useful when the data has temporal patterns that can be learned. 2) The second type deals with *classification* problems, in which the system tries to determine a class for every feature vector received. 3) The third type - *clustering* is represented by a set of algorithms that try to find similarities in non-labelled, multidimensional data and tag each feature vector accordingly. Examples of applications of the latter are quality assurance, image recognition for part picking and so on.

From an architectural perspective, the utilisation of machine learning approaches requires historical data storage that serves to train the machine learning models. Depending on the algorithm, being a supervised or non-supervised approach, the training and re-training would be done as a continuous process.

Industry of the Future needs the digital transformation of manufacturing which can be realized by developing new models of manufacturing control: Holonic Manufacturing Systems, Cloud manufacturing services, aggregated Digital twins embedded in manufacturing control (batch planning, shop floor reengineering), product-driven automation, intelligent products. These new models of digital manufacturing systems will be implemented as Cyber-Physical Production Systems in which intelligent agents representing strongly coupled physical entities: products, resources and orders tightly interact for the control of global tasks: batch planning, optimization of batch production, shop floor reengineering, resource maintenance, in line quality control, product traceability, etc.

Industrial Internet of Things represents a framework that allows pervasive instrumenting of shop floor resources and intelligent products in large-scale industrial systems; it distributes the data processing at the edge of the system using new technologies: IoT gateways, aggregation nodes and fog computing. Intelligence is distributed at shop floor level in heterarchical monitoring and control mode by clusters of Multi-Agent Systems that interact to manage in real-time processes, resources and products.

The interaction between the physical world and its virtual counterpart becomes possible by embedding Digital twins on the different layers of the CPPS and IIoT platforms. The systemic counterparts of the Digital twins associated to the abstract entities: products, resources and orders are the holons - the basic components of *Holonic Manufacturing Systems* (HMS). The new reference architectures for holonic manufacturing decouple the world of interest (represented by the physical twins of the shop floor entities and processes) from the intelligent control agents represented by methods and algorithms instantiated in software programs. The holons provide real-time feedback from the shop floor entities for all the control activities performed. The design is now divided into a reality-reflecting part and a decision-making part; the gap between (software) information processing and real-word aspects should be necessarily closed.

Embedding Digital twins in Intelligent Manufacturing Systems deployed as Cyber-Physical Production Systems provides access to the world-of-interest: the industrial plant, the manufacturing shop floor. Control systems and/or planners interact with the digital twins, influencing these intelligent beings into the desired behaviours

In the light of the theory of flexibility, Digital twins reflect their corresponding reality and can be used to build an IC^{2}T (*Information, Control and Communication*) infrastructure (a CPPS platform) that is knowledgeable about the real manufacturing world, without adding restrictions to this world. DTs are related to the concept of in-depth interoperability that concerns real-world interoperability, *i.e.*, safeguarding real-world interoperability when connecting their IT systems. When the corresponding elements in the world of interest can interoperate and collaborate, their IC^{2}T will not prevent it. After achieving conventional interoperability, the result effectively will be integration without having to modify or redevelop the systems within a CPPS system of systems.

The now emerging Industry 4.0-based Smart Factories implemented through CPPS with all the resources integrated, sharing information and coordinating their behaviours among each other, can adapt and organize in runtime to optimize at different levels (production, maintenance, energy consumption, etc). Moreover, with the advances in the *Industrial Internet of Things* (IIoT) and the increasingly large number of sensors and other data sources available on the shop-floor, the amount of extracted data is growing, and the traditional algorithms are no longer able to process these volumes of data. Hence, the big data analysis field is becoming more and more important in several areas to tackle this challenge.

This is often coupled with the usage of *Machine Learning* (ML), allowing manufacturers to obtain insights regarding their factory which would have been otherwise missed. In the present context, ML algorithms use computational methods to predict a manufacturing system's behaviour and/or improve its overall performance, enabling the development of tools capable of analysing data and perceive what are the underlying trends and correlations. Thus, ML-based approaches can be used to predict abnormal and unexpected events (failures, degradation, energy consumption, etc), generate warnings and advise the system and/or the operator regarding which course of action to take, assisting in diagnosis and maintenance tasks.

6. Conclusions

The perspective of future research resides in using the technological evolutions in IC^{2}T to develop new emerging concepts and solutions for manufacturing based on the instrumentation and interaction of a multitude of different interconnected and even decision-capable smart objects: products, orders and shop floor resources (belonging to industrial heterarchical systems in **IIoT**

frameworks), embedded or distant, with associated information counterparts (agents, holons) or purely digital. These "*bottom-up approaches*" lead to emerging behaviours that must be managed with more "*top-down approaches*" (hierarchical, cloud manufacturing controls), combined and integrated in Cyber-Physical Production Systems in hybrid (semi-heterarchical) topologies. Products, processes and industrial systems designed according to these concepts will be characterized by three important dimensions: smartness, safety and sustainability (Fig. 12).

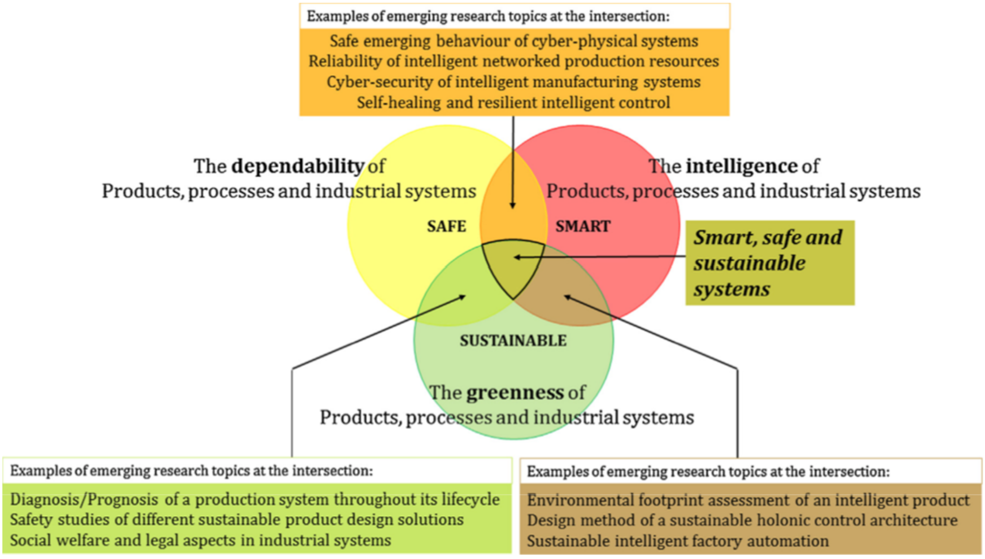

Fig. 12. The future of products, process and industrial systems in Industry 4.0 (*Trentesaux et al.*, 2016)

Future manufacturing systems will be conceived as Cyber-Physical Production Systems that use IC^{2}T strongly coupled components (sensing, actuating, computing, learning, controlling and communicating) embedded in physical objects, interconnected through several networks including the Internet, and satisfying global goals with a wide range of innovative applications based on digitalized data, information and services.

The drivers of these intelligent manufacturing systems are virtualization - based on the Digital twin technology and cloud services - based on the extension of Cloud Computing to the Cloud Manufacturing model. The semi-heterarchical control model of future manufacturing CPPSs uses the holonic paradigm and the distribution of intelligence through agentification in clusters of service-oriented Multi-Agent Systems. The specific functionalities of the two implementation platforms for 'Industry 4.0's intelligent manufacturing systems are:

- For *Industrial IoT frameworks*: pervasive instrumenting the multiple instances of the abstract class-entities: products, orders and shop floor resources (POR), distributed data processing at the edge of production systems using IoT gateways, aggregation nodes as edge computing technologies and decentralized cloud services through fog computing.
- For *Cyber-Physical Production Systems*: system interconnection, strongly coupling of abstract POR object classes and of their instances, semi-heterachical process planning and control dynamically reconfigurable, aggregating and embedding Digital twins in control and maintenance tasks, prediction-based production planning, resource allocation and

anomaly detection from big data streaming and machine learning in real time, secure data transfer with Software Defined Networks.

The scientific issues for future research are big data processing and analytics to extract insights from shop floor processes, and taking intelligent decisions through machine learning.

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