Challenges for the cyber-physical manufacturing enterprises of the future

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Abstract

This paper summarizes a vision of the challenges facing the so-called "Industry of the Future" as studied by the research community of the IFAC Coordinating Committee 5 on Manufacturing and Logistics Systems, which includes four Technical Committees (TC). Each TC brings its own vision and puts forward trends and issues important and relevant for future research. The analysis is performed on the enterprise-level topics with an interface too other relevant systems (e.g., supply chains). The vision developed might lead to the identification of new scientific control directions such as Industry 4.0 technology-enabled new production strategies that require highly customised supply network control, the creation of resilient enterprise to cope with risks, developments in management decision-support systems for the design, and scheduling and control of resilient and digital manufacturing networks, and collaborative control. Cobots, augmented reality and adaptable workstations are a few examples of how production and logistic systems are changing supporting the operator 4.0. Sustainable manufacturing techniques, such closed-loop supply chains, is another trend in this area. Due to increasing number of elements and systems, complex and heterogeneous enterprise systems need to be considered (e.g., for decision-making). These systems are heterogeneous and build by different stakeholders. To make use of these, an environment is needed that allows the integration of the systems forming a System-of-Systems (SoS). The changing environment requires models which adapt over time. Some of the adaptation is due to learning, other mechanisms include self-organisation by intelligent agents. In general, models and systems need to be modular and support modification and (self-)adaptation. An infrastructure is needed that supports loose coupling and evolving systems of systems. The vision of the overall contribution from the research community in manufacturing and logistics systems, over the next few years is to bring together researchers and practitioners presenting and discussing topics in modern manufacturing modelling, management and control in the emerging field of Industry 4.0-based resilient and innovative production SoS and supply networks.

1. Introduction

Integration in Manufacturing (IiM) is the first systemic paradigm to organise humans and machines as a whole system, not only at the field level, but at the management and corporate levels as well, producing an integrated and interoperable enterprise system. Business process software and Manufacturing Execution Systems are now available which meet the requirements of this fully computerised and automated integration. Major problems remain with respect to the interface between the enterprise corporate level and the manufacturing shop floor level: management and operation decisions within a closed loop are facilitated to pace the production according to the life-cycle dynamics of the products, processes and humans inside and outside the enterprise.

The role of research in the field is to create upstream conditions for technological breakthroughs, so that enterprise investment is not merely pulled by the incremental evolution of

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information technology (IT) (Monostori, et al. 2015). Recent literature extensively dealt with smart manufacturing trends in industry of future (Davis et al. 2015, Moghaddam and Nof 2017, (Thoben et al, 2017, Kusiak 2018). However, the future of the industry relies on collaboration networks, and cyber-physical production systems that can be established among companies, people and societies to generate shared knowledge and wealth (Giovannini, et al., 2015). A number of important enablers are needed to support the creation of successful collaborative networks, e.g., common reference models, effective interoperability mechanisms and approaches, supporting infrastructures based on open architectures, design and engineering methodologies to instantiate/duplicate already successful cases, and standardized market technologies and tools (Ollero, et al. 2002).

The analysis in this paper is performed on the enterprise-level topics with an interface to other relevant systems (e.g., supply chains). Enterprise engineering models and tools are necessary for the seamless integration of business and manufacturing models in order to completely describe an integrated manufacturing system's data. However, as of the time of writing, although some high-level standards are available for enterprise modelling and integration, they are not yet widely recognised as such or applied in industry (Panetto et al. 2012).

Forecasts place Information and Communication Technologies (ICT) at the core of new developments. Digital megatrends such as e-Tailing, e-Government, e-Manufacturing, Entertainment on demand, virtual education and a wide set of online services (finance, publishing, marketing) will be part of everyone life's. However, these applications and systems will need to satisfy several fundamental requirements for manufacturing:

- Enterprise integration and interoperability
- Distributed organization
- Model-based monitoring and control
- Heterogeneous systems and environments
- Open and dynamic structure
- Cooperation and Collaboration
- Integration and interoperability of humans with software and hardware systems
- Agility, scalability and fault tolerance
- Interdependent networks
- Service-oriented collaborative manufacturing platforms
- Data-driven analysis, modelling, control, and learning systems for decision-making support.

The following types of technology, which meet the requirements above, have been set forth as key success factors for next generation ICT manufacturing:

- Modular and adaptable, integrated equipment, processes, and systems that can be readily reconfigured
- System synthesis, modelling, and simulation for all manufacturing operations
- Software agents and symbolic artificial intelligence (AI)
- Cobots (Collaborative Robotics)
- Technologies that can convert information into knowledge for effective decision-making
- Enhanced human-machine interfaces
- Educational and training methods that would enable the rapid assimilation of knowledge
- Software for intelligent collaboration systems
- Product and process design methods that address a broad range of product requirements

- Innovative processes to design and manufacture new materials and components
- Manufacturing processes that minimise waste production and energy consumption
- Data-driven modelling, analysis and control
- Technologies supporting collaborative modelling, group learning
- Digital supply chain and smart operations
- Risk analytics for resilient production systems and supply chains
- Customised assembly systems for smart manufacturing when product and process are created simultaneously.

This paper does not pretend to be encyclopaedic and is not trying to cover “discrete manufacturing industry” in all its generality and specificity. It rather presents a vision of the challenges facing the so-called “Industry of the Future” as studied by the research community of the IFAC Coordinating Committee 5 on Manufacturing and Logistics Systems, which includes four Technical Committees, each one bringing its own vision and putting forward trends and issues important and relevant for future research. The grand challenges may be classified according to the following areas (Panetto and Molina, 2008), as shown in Table 1. The following sections will discuss, in relation with their specific domain, about specific challenges for the Cyber-Physical Manufacturing Enterprises of the Future.

CHALLENGES	BUSINESS	KNOWLEDGE	APPLICATIONS	COMMUNICATIONS (ICT)
Grand-Challenge 1. CPPS-based Manufacturing Plant Control	• Servitisation • Short lead-time to market • Data-driven performance management systems	• Biological transformation in manufacturing • Digitalisation of production	• Mass customisation • Big-data analytics • CPPS-based human interactions • Simulation models for CPPS-based manufacturing control	• IoT-enabled manufacturing • Cloud services • Smart manufacturing objects
Grand Challenge 2. Resilient digital manufacturing networks, collaborative control for Industry 4.0 and cyber-physical supply chains	• Business and strategy models • Strategic risk management • Customised supply network control • Customised flexible process-based services	• Business processes and operations in supply chains • Core competencies in the supply chains • Sharing principles and operation rules	• Collaborative software solutions • Simulation software for resilient and data-driven manufacturing systems • Tools for monitoring and control of disruptions in the supply chain	• Reliable communication networks • Broadband • Wireless applications • e-Work, e-Manufacturing, and e-Logistics
Grand Challenge 3. Cyber-physical System-of-Systems interoperability	• Integration of business information • Ontology mapping and matching • Consistent enterprise-wide decision-making structure	• Interoperability of models and processes • Shared ontology • Explicit knowledge • Knowledge management system	• Modular and reconfigurable systems • Component-based software solutions (Plug-in/Plug-out) • Symbolic artificial intelligence and software agents • Agent-based simulation software • Cobots and new Human / Machine Interaction with Robots	• Standards • Interfaces and mediators • Interoperability • Service buses • Technologies for collaborative learning
Grand Challenge 4. Interdependent networked systems and data analytics for decision support	• New networked model of business • AI and data-driven business • Risk and operations management through analytics from Big Data	• Modelling of interdependencies • Dynamical analysis • Behavioural pattern identification	• Tools for monitoring and control • Building resilient systems • Prescriptive and predictive modelling • Risk analysis and control	• Open platforms • Interactive applications

Table 1: Grand-Challenges for the Manufacturing Industry of the Future

2. CPPS-based (Discrete) Manufacturing Plant Control

Globally, a (discrete) manufacturing plant is a factory where goods/services are manufactured in accordance with customer/enterprise requirements and expected performance (Leitao, 2009). It can be assimilated with a Discrete Event System (DES) where each state refers to a product state within all its life cycle. This involves several processes, comprised of activities which support both the product state transformation through manufacturing resources and knowledge, and the shop floor level control of these transformations through the synchronization (in time and through time) of the product and information flows according to external demands and subject to the environmental context (Morel et al., 2007). The shop floor level is linked to the physical layer (sensing and actuating devices) and primarily implements real-time processing in different areas (e.g., monitoring, execution, supervision, tracking) by at least utilising an Industrial Control System (ICS), necessitating different performance and reliability requirements than those used for a typical IT system (Esmaeilian et al., 2016). In terms of engineering, control refers to logic control, loop control and supervisory control (Li et al., 2017a). Control is a key success factor for a plant because it directly impacts the plant's flexibility, productivity, modularity, etc. (Colledani et al., 2014). To support the necessary synchronization, control must consider all the interactions between the activities, processes and resources which make up the manufacturing system. The complexity of this system evolves in relation to the dynamics of the plant (e.g., time evolution, component age, customer/enterprise requirements, other requirements such as those in terms of norms and legislations).

(Diltis et al., 1991) consider four basic types of control architectures: centralised, hierarchical, modified hierarchical and heterarchical. This classification has been updated by (Morel et al., 2003) who proposes five levels according to different perspectives (Figure 1); this is in order to demonstrate a clear relationship between the particular feature of the system architecture and the theoretical and modelling paradigms to be implemented. The fifth level is representative of 'intelligent' as feature, such as that advocated by Intelligent Manufacturing System (IMS).

System Architecture Feature	Theoretical & Modelling Paradigms
5. Intelligent	Kenetics & MAS & HMS
4. Interoperable	Cognitics & Ontology & Object-Oriented
3. Integrated	Systemics & Systems Engineering
2. Hierarchical	Systems Theory & Automatic Control
1. Isolated	Empiricism & Ad hoc approach

Fig.1. Capability profile between architecture feature and the related theoretical and technical modelling framework (Morel et al., 2003)

Today and into the future, the story of this profile continues and targets a longstanding issue in manufacturing plant control by investigating new manufacturing plants as advocated by visions for 'Factory of the Future' or 'Industry 4.0'. This vision is of interest both for the industrial world (ex. EFFRA White paper[1], PWC white paper[2]) than the academic one (Reischauer, 2018)(Jardim-Goncalves et al., 2017).

Indeed, next generation industry holds the promise of increased flexibility in manufacturing, along with mass customisation, better quality, improved productivity and servitisation (Zhong

[1] Factory of the Future : Multi-annual roadmap for the contractual PPP under Horizon 2020 https://www.effra.eu/sites/default/files/factories_of_the_future_2020_roadmap.pdf

[2] Digital factory 2020: Shaping the Future of Manufacturing; PWC document, www.pwc.de

et al., 2017). It enables companies to cope with the challenges of producing individualised products as expected by customers with a short lead-time to market and at the cost of mass production (Rojko, 2017). These challenges can only be met by further developing the digitalisation of production systems as promoted by new manufacturing concepts, such as Internet of Things (IoT)-enabled manufacturing or cloud manufacturing in which data science, smart manufacturing objects (SMO) and services (e.g., RAMI model) are predominant. These new concepts have led to the introduction of new technologies/techniques such as IoT, advanced ICT, Big Data Analytics (BDA), cloud computing and the **Cyber-Physical Production System** (CPPS) (Monostori et al., 2016). However, these concepts cannot be reduced only to the assembly of new technologies (necessary but not sufficient step) within smart manufacturing platform or architecture (Davis et al., 2015) but require also a major extension of the paradigms at the 'intelligent' level (fifth level in Figure 1).

In that way, CPPS specialized for manufacturing has to be found on the CPS (Cyber-Physical System) principles which already poses many scientific issues in terms of its use in real applications (How to effectively model CPSs in real applications? (Nayak et al., 2016)). CPS promotes intensive connection and coordination between physical elements and computational software providing and using data accessing and data-processing services simultaneously (Alippi, 2014) (Figure 2). So, CPPS *consists of autonomous and cooperative elements and subsystems that are connected based on the context within and across all levels of production, from processes, through machines and up to production and logistics networks* (Monostori et al., 2016). It leads to consider CPPS from CPS as built on three basic capabilities (Cardin, 2019): Intelligence (computation), Connectedness (communication), and Responsiveness (control).

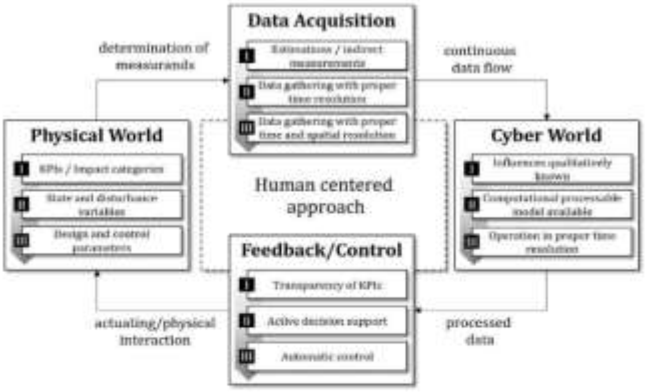

Fig. 2. CPS principle

Challenge 1.1 CPPS-based autonomous shop-floor systems

These capabilities allow to consider CPPS as a support to transform the manufacturing processes into highly distributed but interconnected networks of "entities" requiring new way of collaborations between these entities based, for example, on formalism of collaborative control theory (Nof, 2007) to found collaborative factory of the future (Moghaddam and Nof, 2017).

This compromise between autonomy and cooperation confers specific features to CPPS, such as self-organisation, self-maintenance (Iung et al., 2009), etc.

This has led to the reconsideration of the purpose of control/automation on the shop floor as an evolution of IMS concern (Figure 3) because CPPS offers innovative capabilities of self-awareness, self-prediction, self-reconfiguration in the face of internal and external changes. New manufacturing systems should be able to monitor physical processes, create a so-called "digital twin" of the physical world and make smart decisions through real-time communication and cooperation between humans, machines, smart equipment, sensors, and so forth.

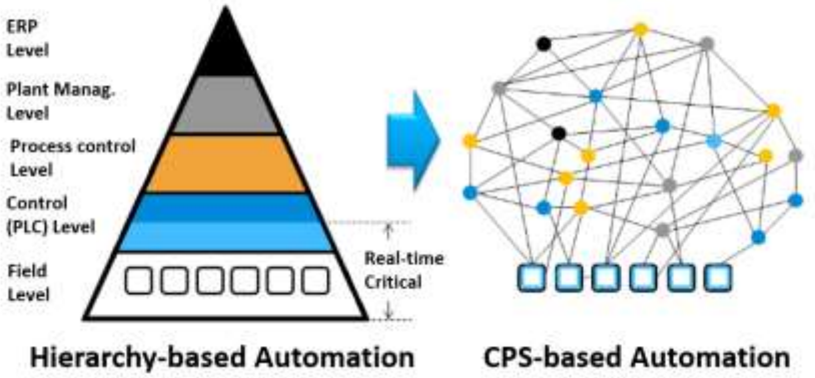

Fig.3. Positioning of CPS-based Automation (VDI/VDE, 2013)

The low level of CPS-based automation (focused on the shop-floor level) is responsible for the advanced connectivity which ensures real-time data acquisition from the physical world and information feedback from the cyber-space (high level). It materialises the two first layers (smart connection layer and data conversion layer) of the 5C architecture for CPS proposed by (Lee et al., 2015). The advanced connectivity is made possible through the collection and intelligent analysis of a massive amount of data (Big Data) gathered from numerous sources. In this way, the CPS-based machinery is equipped with prediction tools that process data to extract information and make real-time, informed decisions.

Challenge 1.2 From CPPS to biological transformation in manufacturing ("biologicalisation")

The advanced global features and capabilities of CPPS are also introducing a highest level in the complexity of the manufacturing system. One way to address this issue is proposed through the paradigm of "biologicalisation" (biological transformation in manufacturing): (Byrne et al., 2018) defined this *as the use and integration of biological and bio-inspired principles, material, functions, structures and resources for intelligent and sustainable manufacturing technologies and systems with the aim of achieving their full potential*. Indeed, CPS also creates opportunities to apply solutions inspired by biology to real practice, including to production systems, control systems and organisations. For example, the adage that "In biology, organisms adapt and evolve" can be transferred to self-organisation, self-reconfiguration, etc., in respect to environment changes (turbulences). These biologically inspired solutions primarily use artificial intelligence (computational intelligence) and machine learning approaches.

In conclusion, the question is how (discrete) manufacturing plant control is impacted by these new CPPS/Biologicalisation considerations (e.g., paradigm, architecture, modelling, technologies); consequently, the goal is to identify the additional scientific control orientations that must be investigated to support Challenge 1.1 and Challenge 1.2.
More precisely, the concrete issues faced may be summarized as research made in the following areas (including extracts from (Monostori et al., 2016), (Byrne et al., 2018), (Zhong et al., 2017), (Esmaeilian, 2016) (Lee et al., 2016) (Rabetino et al., 2017) (Nof, 2007)):

- Identification and modelling of the impacts of CPPS on manufacturing control;
- Integration of the biologicalisation principles in CPPS and in manufacturing control in general;
- Exploitation of collaborative control theory to support CPPS development at shop floor level
- Impact of the servitisation paradigm in manufacturing plant control;
- Development of Cyber-physical-biological solutions to master control complexity;

- Robustness of new control structure to maintain its function against external and internal perturbations;
- Reliability, robustness and (cyber)security of data produced and consumed at the shop floor level in respect to control objectives;
- Compromise between robustness, complexity and efficiency (performance indicators of the automation structure based CPPS and/or biologicalisation) to favour mastered plant operation;
- Self-aware and self-maintained control, machines, components;
- Adaptation and extension of new technologies to support CPPS-based control.

3. Resilient and digital manufacturing networks for Industry 4.0 and Cyber-Physical Supply Chains

Decision-support models range from optimisation and knowledge-based models to simulation models (discrete-event and continuous), all of them oriented to design and control of manufacturing and supply chain management. More specifically, the following models are usually considered in the decision-support systems for manufacturing and supply chains:

(a) Models of manufacturing tasks in production as well as assembly units, with the aim of designing the architecture of workstations, cells and production lines, quality assurance and maintenance;
(b) Models of manufacturing processes aiming at the design of procedures for process planning, production planning and control, job and activity scheduling, inventory control and logistics;

(c) Models of supply networks aiming at the design, planning and control of coordinated production-logistics systems;
(d) Models of Industry 4.0, CPS, computer-aided, communication-based and Internet-based procedures and processes with the aim of accomplishing the functions listed in (a) - (c).

Current developments and future trends in decision-support systems (DSS) for manufacturing and supply chain management are based on the principles of CPS and the intellectualisation of models and algorithms in smart manufacturing (Kusiak 2018). According to Zhuge (2011), the evolution from cyberspace and systems to the cyber-physical-social space and systems can be described by three extensions. It distinguishes two types of cyber spaces: the first allows users to read the information in cyberspace like the Web, and the other allows users to read and write information in cyberspace. Both rely on humans to add information to cyberspace in order to share it with others.

The first extension to this basic concept depicts the extension of cyberspace to physical space through various sensors. Any significant information in the physical space can be automatically sensed, stored, and transmitted through cyberspace. The IoT can be considered a kind of cyber-physical space.

The second extension is that user behaviours can be sensed and fed back into cyber-space to analyse patterns of behaviours, and humans can remotely control the actuators to behave in the physical space through cyber-space. This enables cyber-space to adapt its services according to the feedback, since behaviour change may indicate some psychological change.

In the third extension, i.e., the CPS, not only individuals' behaviours, but also social interactions can be fed back into cyberspace for further processing. Users are considered according to their social characteristics and relations, rather than as isolated individuals. Sensors are limited in their ability to collect all information in physical space, so users still need to directly collect significant information in physical space and then put it into cyberspace after analysis (including experiment). Users can also manipulate physical objects in physical space, which can also be fed back into cyberspace to reflect the real-time situation. Users' statuses, interests and knowledge evolve with social interaction and operations in cyberspace.

The aforementioned analysis can be presented as a digital cyber-physical supply chain framework (Fig. 4).

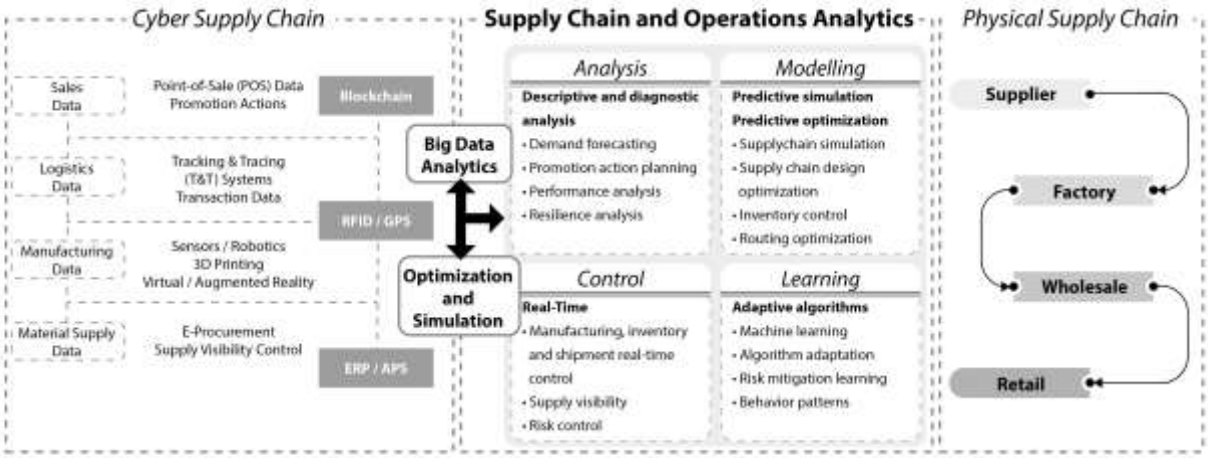

Fig. 4. Digital SC framework

Analysis of digital supply chain framework allows formulating two important Challenges.

Challenge 2.1 From competition between supply chains to competition between information services and analytics algorithms

When supply chain management was introduced into management practices, it was popular to say that *the company is as good as the supply chain behind it*. Later, the proposition was formulated again: competition is not between enterprises, but rather between their supply chains. Today and looking at the near future, specialists say that *the supply chain is as good as the digital technology behind it*. Consider two examples to support this proposition.

The first is the logistics service provider UPS. Development of additive manufacturing has led to the possibility of producing modules, components, and even end products in one place, and actually at any place in the supply chain (Feldmann and Pumpe 2017, Li et al. 2017b). This implies supply chain design changes, a lower number of supplier layers and suppliers as such and the reduced need for transportation, which is a threat to logistics companies. UPS and SAP developed a joint technology which allows UPS to manufacture items using 3D printing directly at distribution centres. This contributes to a faster and more efficient supply chain. Such an integration of production, sourcing, and distribution also positively influences the ability to react to possible disruptions in the supply chain. The second example is blockchain technology. Contracts in supply chains often involve multi-party agreements, with regulatory and logistic constraints. Further complexities may arise from operations in different jurisdictions, as well as dynamic features embedded in the contracts. The flow of information in a supply chain plays a critical role in the efficiency of operations. Regulatory processes (e.g., customs) can be expedited by improving confidence in documentation. This, in turn, will reduce wastage, risk and insurance premiums. IBM and Maersk are collaborating to create trust and transparency in global supply chains (IBM 2017). They are developing a distributed contract collaboration platform using blockchain technology. Maersk estimates that shipping a single container of flowers from Kenya to Rotterdam requires nearly 200 communications. How can the efficiency of the global supply chain be improved? In their approach, each distinct entity involved in the transaction is allowed to access this system. Shipping from the port of Mombasa requires signatures from three different agencies and six documents: the smart contract will automatically generate after the system receives the signatures. Simultaneously, when the documents about inspection, sealing of refrigerator, pick up by the trucker, and approval from customs as communicated to the port of Mombasa are uploaded, all participants can see the data in the meantime, allowing the relevant entity to prepare for the container.

These and further recent examples of digital technology applications to supply chains (Ivanov et al. 2018a, Ivanov et al. 2018b) support the new proposition that competition is not between the supply chains, but rather between the supply chain services and analytics algorithms behind the SCs. The services may be ordered in packages or as individual modules. Success in the supply chain service competition will be highly dependent on analytics algorithms in combination with optimisation and simulation modelling. Initially intended for process automation, digital technologies now disrupt markets and business models and significantly impact the development of supply chain management.

As such, new disruptive supply chain business models will arise where supply chains will not be understood as a rigid physical system with a fixed and static allocation of some processes to some firms. Instead, different physical enterprises will offer services in supply, manufacturing, logistics, and sales which will result in the dynamic allocation of processes and dynamic supply chain structures. Indeed, this idea is not really new. We can recall the virtual enterprises concept developed about 15-20 years ago. The supply chains in virtual enterprises were expected to be formed dynamically through so-called competence cells or agents networking (Teich 2003, Teich and Ivanov 2012, Ivanov and Sokolov 2012a,b). In essence, suppliers were integrated with a tool that contained their technological processes and related operational parameters (e.g., costs and lead-times). A customer was able to place an order specification, and an automatic algorithm was able to find the suppliers needed to be networked to fulfil this customer order. So, while the individual contributors (e.g., robots, sensors, radio frequency identification (RFID), agents, modular factories, etc.) are not really new, they are becoming more practical and companies more receptive to using them to stay competitive. In addition, an attempt to interconnect these local solutions using the progress in data processing technologies can be observed in practice. For example, with the help of smart sensors and plug-and-produce cyber-physical systems, stations in an assembly system are capable of changing the operation processing and setup sequences according to the actual order of incoming flows and capacity utilisation (Theorin et al. 2017). As such, this trend calls for new principles and models to support supply chain management in such future factories.

Challenge 2.2 From DSS to decision analysis, modelling, control and learning systems (DAMCLS)

The second observation concerns quantitative analysis methods in supply chain management. In the past decades, simulation and optimisation have played significant roles in solving complex problems in supply chain management. Successful examples include production planning and scheduling, supply chain design, and routing optimisation, to name just a few. However, many problems remain challenging because of their complexity and large scale and/or uncertainty and stochastic nature. In addition, the major application of optimisation and simulation methods in the last decades was seen in decision support, meaning that decision-makers had to manually provide model input and interpret the model output. On the other hand, the rapid rise of business analytics provides exciting opportunities for operations research and the re-examination of these hard optimisation problems, as well as newly emerging problems in supply chain and operations management (Fig. 5).

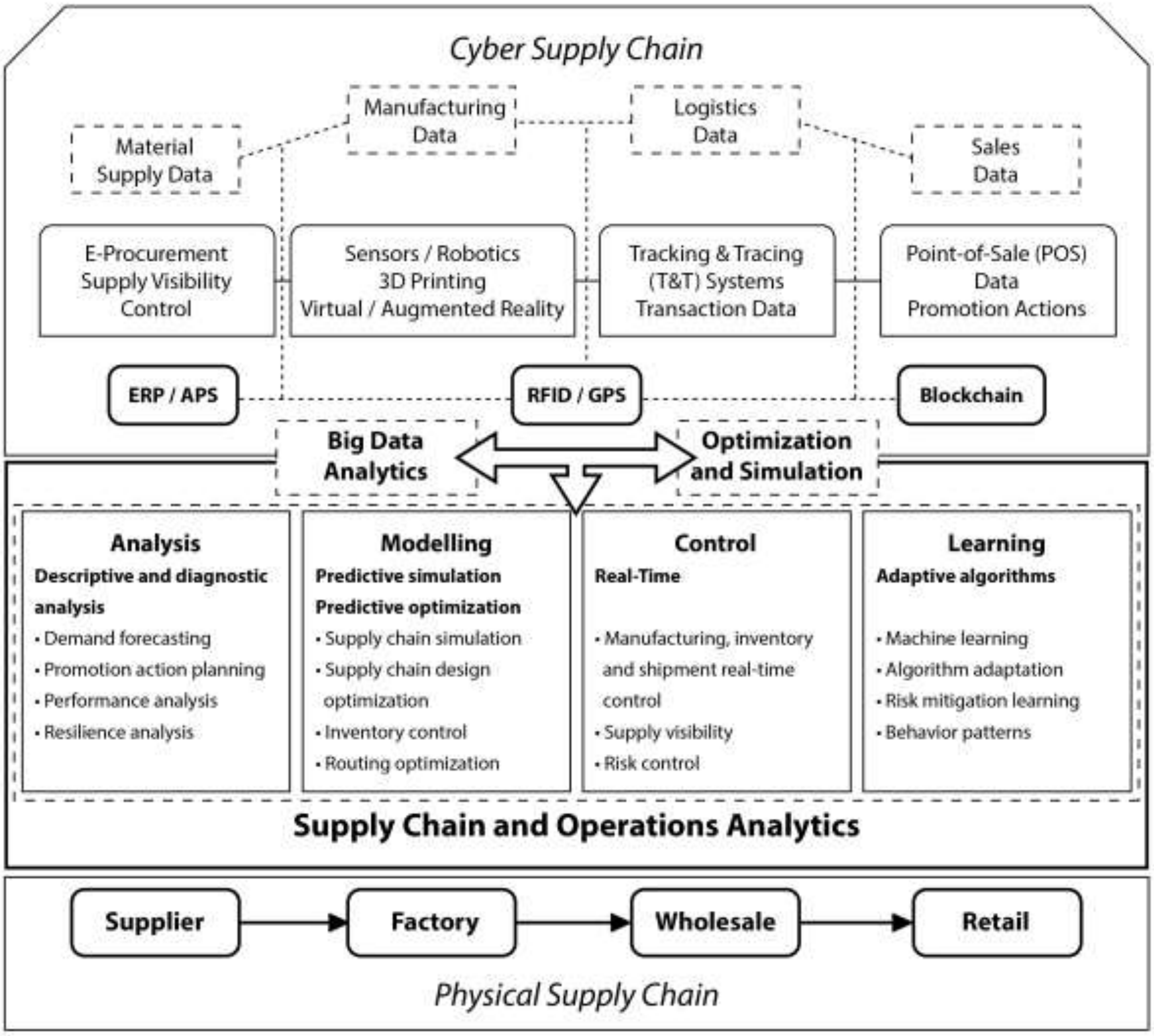

Fig. 5. Framework of decision analysis, modelling, control and learning system (DAMCLS)

Examples of supply chain and operations analytics applications include logistics and supply chain control with real-time data, inventory control and management using sensing data, dynamic resource allocation in Industry 4.0 customised assembly systems, improving forecasting models using Big Data, machine learning techniques for process control, supply chain visibility and risk control, optimising systems based on predictive information (e.g., predictive maintenance), combining optimisation and machine learning algorithms and simulation-based modelling and optimisation for stochastic systems.

The applications of supply chain and operations analytics can be classified in four areas, i.e.,

- Descriptive and diagnostic analysis,
- Predictive simulation and prescriptive optimization,
- Real time control, and
- Adaptive learning.

Sourcing, manufacturing, logistics, and sales data are distributed among very different systems, such as enterprise resources planning (ERP), RFID, sensors, and blockchain. BDA translated this data into information usable by AI algorithms in cyber supply chains and managers in physical supply chains. For example, electronic retailers are using their extensive transactional and behavioural customer data to offer customers new ways of trying, experiencing, and purchasing their products (e.g., Amazon with Alexa). AI is becoming more pervasive in the real world with every project, and of necessity it must be part of our simulations. It will not only be part of our simulations, our simulation will also help to develop AI. Resilience360 at DHL enables comprehensive disruption risk management by mapping the supply chain end-to-end, building risk profiles, and identifying critical hotspots in order to initiate mitigation activities and send alerts in near-real time mode about incidents that could disrupt the supply chain.

As such, a new generation of simulation and optimisation models can be observed that extends the DSS towards DAMCLS. The pervasive adoption of analytics and its integration with operations research shows that simulation and optimization are the key, not only to modelling physical supply chain systems, but also to learning and modelling cyber supply chain systems. In the near future, success in supply chain competition will be highly dependent on analytics algorithms in combination with optimisation and simulation modelling. Initially intended for process automation, business analytics techniques now disrupt markets and business models and significantly impact the development of supply chain management.

All in all, the future development of DSS for manufacturing and supply chain management are driven by transformations towards a digital factory evolving in DAMCLS (Fig. 5).

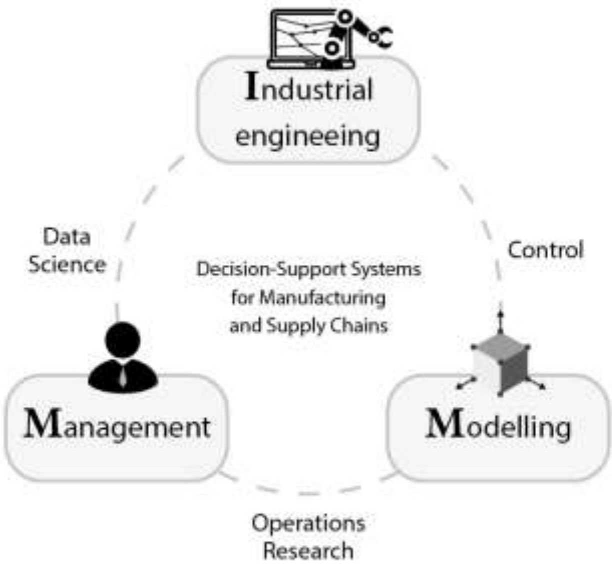

Fig. 6. Combination of industrial engineering, operations research, and data science as a multi-disciplinary research base for management decision-support in manufacturing and supply chain management

Fig. 6 shows the vision of a combination of industrial engineering, operations research, and data science as a promising multi-disciplinary research base that can contribute to the improvements of the DSS for manufacturing and supply chain management towards DAMCLS.

4. Cyber-Physical System-of-Systems (SoS) Interoperability

In an enterprise, dynamics in business are increased by new technical possibilities stemming from, e.g., the IoT, CPS, Digital Twin, S^3 Enterprise (Sensing, Smart, and Sustainable Enterprise). Much effort is currently put into technologies to sense the environment, digitalise observed systems and maintain a link between the physical and the digital/cyber (Weichhart et al. 2016). In an enterprise, there is an additional social element, which needs to be considered: the information sensed via such technologies is often relevant to more than one decision-maker (Agostinho and Goncalves, 2015). Semantic interoperability is relevant (Liao et al, 2016).

Semiotics is a field of investigation that is concerned with the meaning and semantics of signs. Since models are built on symbols and signs, semantic interoperability in an organisational context is highly relevant. The semantics of a sign is established between three elements: the sign, the referent/object and the interpretation (i.e., the concept) (Stamper et al. 2000).

In the context of the S^3 Enterprise, raw data from sensors is transferred into a data structure that is used to convey that information to an information processing system. This may be a machine (e.g. a robot), a piece of software, or a human. These systems will use the information, combine it with other information and take some action according to its meaning.

At any time, in the above, briefly sketched process, models might get modified. Organisational knowledge management is relevant for keeping the organisational members up-to-date (Firestone & McElroy 2005). The organisational knowledge life cycle of Fireston and McElroy (2005) provides organisational roles and specifies the features of organisational information systems. In this framework, the distributed organisational knowledge base (as a technical instrument provided by the organisation) is of fundamental importance. Here models, including facts and procedures, are stored and updated over time. The evolution of knowledge and models go hand-in-hand with the possibility and support for learning. Learning itself is a process that updates not only the mental models of the human and artificial agents involved, but also the models of the organisational knowledge base (Oppl and Stary 2014, Oppl and Hoppenbrouwers 2016).

In general, learning, sharing knowledge and connecting information systems highlights an important fact (Vernadat, et al. 2018): there are heterogeneous systems involved in the enterprise's SoS. Enterprise interoperability is a research field that is concerned with loosely coupled systems (Panetto, 2007). Enterprise interoperability goes hand-in-hand with enterprise integration. However, the term 'interoperability' highlights the decentralised nature of systems in a SoS (Weichhart, Stary and Vernadat 2018). There is no central point of view. Of course, this requires additional effort such as knowledge management (Vernadat, 2010). In order to manage and control firms, an increasing number of environmental, organisational and technological factors need to be taken into account, and captured in models for decision-making). This increases the complexity that must be handled by organisations. To manage the complexity of the enterprise's system in general, a SoS perspective is taken. A SoS perspective of the enterprise (Gorod et al. 2014) includes all socio, economic and technical systems that are necessary to make the enterprise work (in the general sense). General Systems Theory (GST) provides a basic theory for modelling systems, and aims to support the modelling process and abstraction (von Bertalanffy 1969). A system is composed of elements and has a certain purpose (or function) to fulfil (Boardman and Sauser 2006). The elements of a system are an inherent and integrated part of the system. Elements lose autonomy with respect to the purpose of the system they are a part of. In a SoS, the purpose remains with each system. This implies that systems in a SoS remain independent and may leave their super system.

In addition to structural complexity, there is an important dynamic perspective to be taken. This dynamic aspect leads to the observation that the enterprise is not only complex, but also an adaptive SoS (Agostinho and Jardim-Goncalves, 2015; Weichhart, Guedria and Naudet 2016). Complex adaptive system (CAS) (Holland 1996) research identified active sub-systems, called agents, which communicate and interact with their environment. However, interaction of agents is of such a dynamic nature that the overall system state may not be determined by the sum of the individual agents' behaviours. The communication and collaboration of the agents realises relationships which are not linear or directly related to each other.

The following figure (Fig. 7) builds on the European Interoperability Framework (EIF, 2017). The first level interoperability is seen from a societal perspective where organisations are resilient, sustainable, or not. On the second level, interoperability between multiple organisational units (e.g., departments, workers, etc.) is shown. Processes spanning multiple systems and agents have to be interoperable to maintain a running organisational system.

On the third level, the ontology-based semantics of sensed information and shared models is relevant. This level bridges technical systems with organisational systems (Giovannini et al. 2012). On the bottom of this figure, technical interoperability is discussed. This level concerns the IT and data-based interaction between systems.

The dark ellipses are concepts (discussed above). The framework is used to organise the major elements from modelling an enterprise to establish a knowledge-based, enterprise point of view.

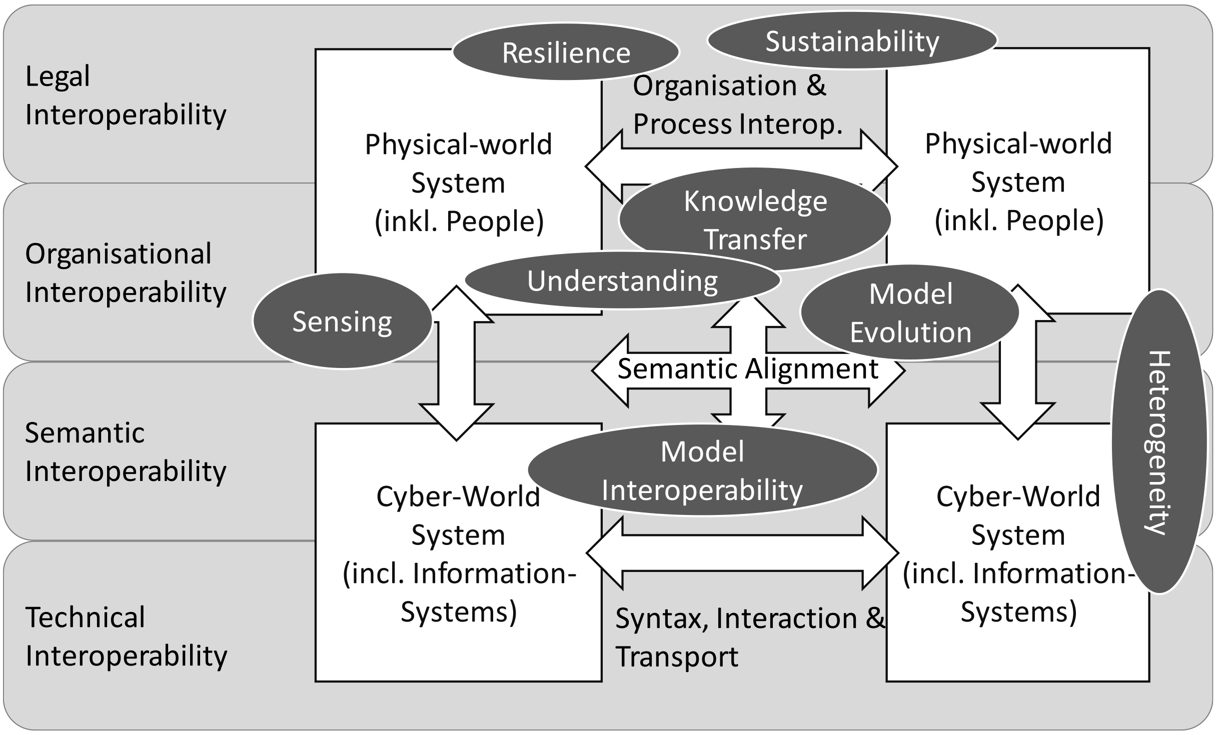

Fig. 7. Points of interest for the future model-based cyber-physical enterprise mapped to the European Enterprise Interoperability Framework.

Challenge 3.1 Enterprise models for knowledge management and collaboration

Approaches addressing this challenge may be summarized as research in information systems for (automatic) control in socio-technical enterprise systems-of-systems (SoS).

Enterprise integration supports a ubiquitous sensing system that digitalises everything and makes it available to human and artificial decision-makers. Several integration approaches provide an abstraction layer that unifies the exchanged data. An example for this is enterprise application integration using an enterprise service bus. Such a service bus is a central component, supporting a loose coupling between the other systems. The enterprise service bus also supports manual mapping between models to support data exchange between systems.

Interoperability is a term that, in addition to this, emphasizes that systems are decentralised. Interoperability aims at a very loose integration of systems. Loose integration / interoperability allows systems in a SoS to join or leave. Tight integration with strong dependencies does not allow this, and violates the idea of a system-of-systems. Enterprise interoperability emphasise a loose coupling, supporting an adaptive enterprise system-of-systems (Boardman and Sauser, 2006) that is composed of autonomous and intelligent agents. Enterprise modelling (EM) is needed for semantically interpretable information flows from sensors and people to actuators, including people. EM is also needed for knowledge exchange between artificial agents or other intelligent software modules.

Organisational knowledge management provides methods to guide human agents with respect to knowledge externalisation (and learning) to meet the challenges imposed by the external dynamics of changing environments (Giovannini, et al. 2015, Oppl and Hoppenbrouwers 2016). Structured externalised knowledge is a requirement to construct models and necessary for enterprise models.

Technologies for group modelling support the collaborative construction of models (Oppl 2017, Oppl 2017a, Weichhart 2015). These applications support the articulation of (partially shared) knowledge in groups. This collaborative construction of models is a form of group learning, enabling knowledge flows. Through the collaborative work on models, these evolve. The common activity also influences the mental models of the participants. This highlights a need for technologies that support knowledge management and the evolution of enterprise models. In particular, the interoperability of multiple enterprise models has to be assured.

Challenge 3.2 Process interoperability for collaborative control

One particular, important type of model are process models. Such models make flows between systems explicit. One of many challenges is the need in socio technical SoSs for processes to span artificial and human systems. For enterprise models, it is necessary to distinguish different flows like control flows, data flows, and physical flows (Weichhart, Stary and Vernadat 2018). The need for these different types of flows increases the complexity of the models. In the following one exemplary sub-type of enterprise model is discussed to highlight the key aspects of this challenge.

Collaborative robotics is a particular important research domain that requires to emphasis interoperability. Here two independent agents are executing a common process. These intelligent agents are interacting on physical and on cognitive level (Jones, Romero, Wuest 2018). The representation of physical and cognitive tasks is different for the human and the artificial agent, but needs to be shared (Weichhart, Pichler and Wögerer 2018). Process models are the important elements used to articulate and synchronize the execution of tasks between the agents in a loosely coupled SoSs. Different levels of automation and different levels of how tight these systems collaborate, inform the degree of task synchronization required (Fast-Berglund et al 2018, Weichhart et. al 2018).

A number of technologies and organisational measures on “how to support collaboration of human and artificial agents” have been elaborated using the term *Operator 4.0* (Romero et al 2016). Modern technologies are used to enhance the cognitive and physical possibilities of the worker, and make the execution of process more effective. For this collaboration of loosely coupled systems, interoperability of the execution of tasks by humans and by artificial agents needs to be assured (Åkerman and Fast-Berglund 2018). The interoperability aspect includes cognitive and physical processes (Jones, Romero, Wuest 2018). Models are required that support the articulation of cognitive and physical tasks and cognitive, physical flows between agents.

New approaches are required to model and represent SoSs. This includes in particular the flow perspective where physical and cognitive processes involve multiple systems. These approaches need to assure that human and artificial agents understand their tasks and the tasks of the others in order to have a smooth running work process. A misinterpretation of the next step a robot is going to execute may even put the human operator in danger.

In addition to understanding the collaborator's task, different levels of automation have to be possible during process execution, in order to address the physical and cognitive load of workers that are actually executing their parts of the processes (Fast-Berglund et al 2018). This in turn, requires processes and systems to be adapted. The process models and the used thechnologies must support dynamic re-planning of physical and cognitive flows (Weichhart et. al 2018, Weichhart, Pichler and Wögerer 2018).

In addition to the first challenge addressed in this section (enterprise models for knowledge management and collaboration), technologies for process interoperability require a dynamic infrastructure addressing the adaptability needs of the enterprise system-of-systems.

5. Interdependent networked systems and data analytics for Decision-Support

Large-Scale Systems (LSS) engineering as a branch of control and systems engineering can be traced back to half a century ago (Jamshidi, 1983). Large-scale complex systems have been traditionally characterised by a large number of variables, nonlinearities and uncertainties. Their decomposition into smaller, more manageable subsystems, possibly organised in a hierarchical form, has been associated with intense and time-critical information exchange and with the need for efficient decentralisation and coordination mechanisms.

Over the last decades, the world has witnessed an exponential growth in the level of complexity and interconnection among industrial and non-industrial systems, mainly fuelled by advances in computing, sensing, communication and control technologies. Physical and digital worlds are becoming increasingly intertwined, giving rise to systems such as CPS and IoT with emergent complex interactions. Firms of the present time operate in a highly complex networked environment and there is an ever more increased concern for integration of various technologies and economic, environmental and social aspects. Consequently, analysis and design of control must take into account more aspects and needs new skills and tools. At the same time, rapid advances in technologies provide effective tools and adequate technical infrastructures to support the design and implementation of control for large-scale complex system applications at present and in the future.

Challenge 4.1 Towards an integrated theory of complex interdependent networked systems.

There are more and more complex networks in manufacturing, including product design networks, manufacturing process networks, supply chain networks, logistics networks, sensor networks, resource services networks, social networks, etc. Furthermore, technology advances have been accelerating interactions among these networks, which may have a significant influence on the behaviour and performance of the whole system. Therefore, interdependent networks (also called ‘Network of Networks (NoN)’) has recently been viewed as a plausible model of many engineering complex systems (D'Agostino and Scala, 2014; Zuev and Beer, 2017) (). For example, node failures in one network may cause the failure of dependent nodes in other networks. This recursive process may lead to a cascade of failures throughout the whole network of networks. A dramatic real-world example is the electrical blackout in Italy on 28 September 2003: the shutdown of power stations led to the failure of nodes in the Internet, which in turn caused further breakdown of power stations. Over the years, there has been a stream of research on the resilience of different complex systems, including supply chain networks (Levalle and Nof, 2017). On the other hand, there has also been some research progresses on the cascading failures on network of networks, which have shown that some properties of a network of networks differ greatly from those of single isolated networks (Buldyrev et al., 2010).

It can be appreciated now that several traditional subfields of large-scale systems theory remain of significant interest, such as decentralised and hierarchical control, model reduction and optimisation (Mohammadpour and Grigoriadis, 2010). Traditional applications, such as power, gas, transportation, manufacturing, water systems agriculture, process industry, robotics and communication networks are still of interest. However, these application systems have been continuously developing and new challenges have emerged. In particular, we need to have an integrated theory for the analysis and control of complex interdependent networked systems.

Interdisciplinary collaboration is the key to achieve the goal. In recent years, there has been some efforts in exploring the links between network science and control engineering (Wang and Su, 2014; Wang 2014; Chankova, Hüttb and Bendul, 2018), although the starting points and objectives of a complex-network theoretician and a control engineer might be reversed (Abdallah and Tanner, 2007). On the other hand, Fig. 8 gives a framework for solving complex system problems by integrating data science, network science and domain science (Brugere, Gallagher, Berger-Wolf, 2018). However, new means to unify and integrate different models and methods that now exists in different fields such as control theory, network science, data science, mathematics and physics are needed to provide effective modelling, analysis and control of those emerging complex systems, including large-scale manufacturing systems.

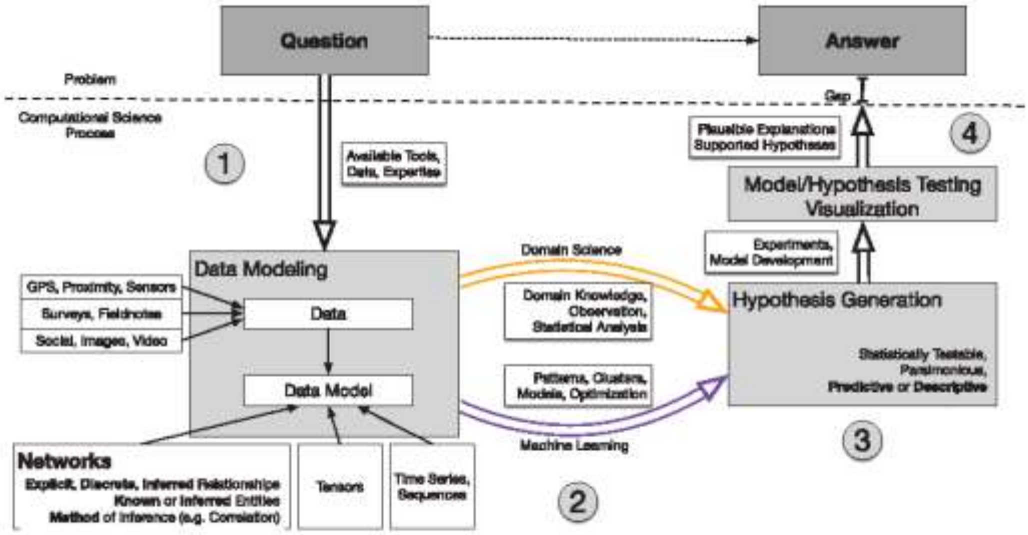

Fig. 8. A data-driven framework for solving complex questions (Brugere, Gallagher, Berger-Wolf, 2018).

Challenge 4.2 Towards AI and Data-driven modelling, analysis and control of manufacturing systems with multi-level, multi-scale and multi-temporal features.

We are entering an age of AI and Big-Data. A question attracting great interest is how to take advantage of the increasing availability of large amounts of data in modelling and control of complex systems (Åström and Kumar, 2014; Wang, 2014). For example, we may now make full use of those on-line and/or off-line process data to directly design controllers, predict system states, evaluate performance, make decisions, perform real-time optimisation and conduct fault diagnosis (Hou, Gao, Lewis, 2017). Advances in AI and related technologies will result in widespread use of smart systems in industry. Smart manufacturing systems can automatically adapt supply chains as circumstances evolve. Data-driven models and simulations may provide a predictive capability to anticipate system changes and also provide aids to manage these emerging complex systems. However, key foundational and systems research questions must be addressed to realize all these capabilities.

A modern manufacturing system should consider the whole lifecycle of product, the cooperation and integration of labour, process and resources within a single enterprise and among enterprises (Li et al., 2017c), which can be viewed as an interdependent network of networks (Fig. 9). We could expect that such kind of network interdependencies would be more and more ubiquitous. Furthermore, different levels (subnetworks) may have different scales and different temporal features. We need to have effective models to predict how the whole system responds to changes, failures or attacks. Theoretically, we need to have a better understanding and control of the dynamics of the processes that take place on network of networks. Interestingly, although temporality increases complexity, it also ensures a degree of flexibility which may enhance our ability to control them (Li et al., 2017d).

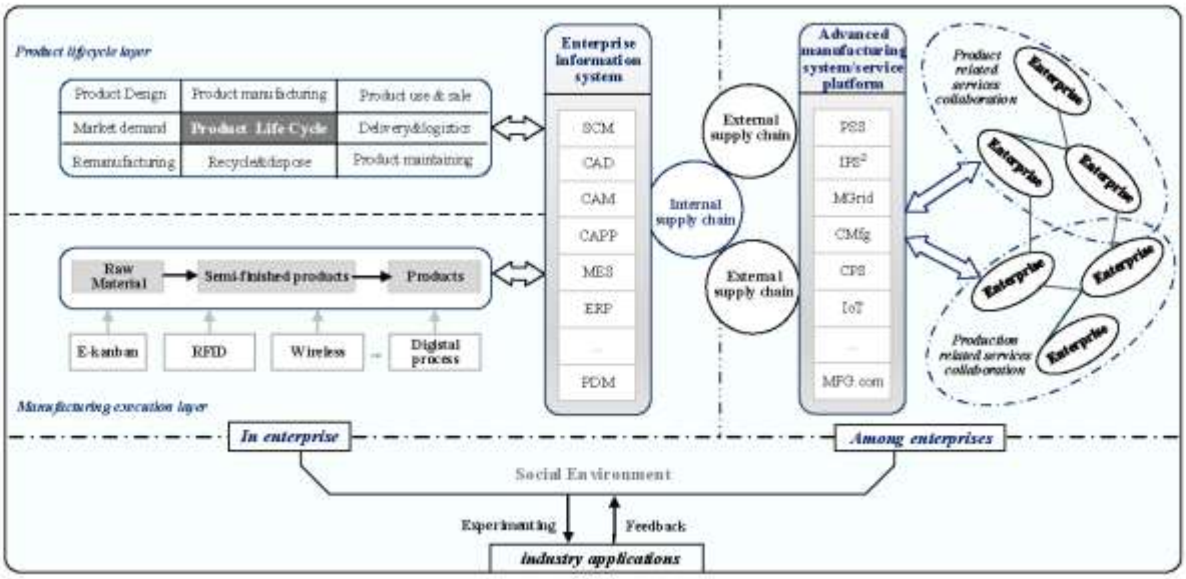

Fig. 9. A network framework model of manufacturing systems (Li et al., 2017c).

5. Conclusions

In continuation of the works already done on plant control with regards to IiM and IMS, which consider, respectively, architecture and systemics', cognitics' and kinetics' modelling paradigm, the global future trends require the investigation of the following question: How could manufacturing control in terms of architecture and paradigm modelling be impacted or extended by taking into account advanced CPPS and Biologicalisation principles as advocated by Industry 4.0? An answer to this might lead to the identification of new scientific control orientations, mainly that of cyber-physical-biological solutions robustness on new control system; self-aware and self-maintained control, machines and components; and the reliability, integrity, robustness and security of the CPPS data. While Industry 4.0 technology has enabled new production strategies that require highly customised supply network control (Ivanov et al. 2016), another trend is the creation of resilient supply chains to cope with risks (Olson and Wu 2015, Dolgui et al. 2018, Ivanov 2018). The ultimate objective of plans and future developments is therefore to facilitate developments in management DSSs for the design, scheduling and control of resilient and digital manufacturing networks and production systems (Frazzon et al. 2017, Amodeo et al. 2018). The vision of the overall contribution from the research community in manufacturing and logistics systems, over the next few years is to bring together researchers and practitioners presenting and discussing topics in modern manufacturing modelling, management and control in the emerging field of Industry 4.0-based resilient and innovative production SoS and supply networks (Battaïa et al. 2018). Human characteristics, such as age, gender, cultural background, and personality of operators are often neglected in traditional decision-making models used in the design and management of production and logistic systems. At the same time, new technologies are currently being developed that assist operators in their manual tasks and interact with these human characteristics (Battini et al. 2017). A specific focus is directed on collaborative control theory that opens the doors to decentralized, agent-based and bio-inspired coordination and control, adaptation and learning (Nof 2007). Cobots, augmented reality and adaptable workstations are a few examples of how production and logistic systems are changing supporting the operator 4.0 (Romero et al. 2016). Sustainable manufacturing techniques, such closed-loop supply chains, is another trend in this area. Due to increasing number of elements and systems, complex and heterogeneous enterprise systems need to be considered (e.g., for decision-making). These systems are heterogeneous and build by different stakeholders. To make use of these, an environment is needed that allows the integration of the systems forming a SoS. The changing environment requires models which adapt over time. Some of the adaptation is due to learning, other mechanisms include self-organisation by intelligent agents. In general, models and systems need to be modular and support modification and (self-)adaptation (Panetto, et al. 2016). An infrastructure is needed that supports loose coupling and evolving systems of systems.

The vision is to further investigate these new systems and study how they can be designed and managed with a human-oriented approach and with consideration of sustainable resource utilization in manufacturing and supply chains. The integration between practitioners and academics, thanks to case studies and experimental analysis, will guide the next steps of research to reach real and applicable results.

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