

SYSTEMS AND INDUSTRIAL ENGINEERING SERIES



Enterprise Interoperability

*Smart Services and Business Impact
of Enterprise Interoperability*

Edited by

Martin Zelm, Frank-Walter Jaekel

Guy Doumeingts, Martin Wollschlaeger



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Introduction

The works in this book stem from research presented during 11 workshops and a doctoral symposium which were organized in the frame of the International Conference on Enterprise Interoperability (I-ESA 2018).

Most of the papers presented in this book originate from European or national research projects. One major goal of the I-ESA workshops is the exchange of knowledge to encourage an active debate of results between the presenters and the audience, which could inspire further research. The results of the discussions are reflected in the papers finalized after the conference and documented in the workshop reports.

With the conference subtitle “Smart services and business impact of enterprise interoperability”, the workshops elaborate results of research and industry transfer in the area of smart service-related technologies like next generation Internet, IoT, cloud-based platforms, artificial intelligence and advanced enterprise modeling for future manufacturing.

The I-ESA workshops were organized in three tracks, each track moving from research-oriented topics of wider scope towards particular application topics focusing on real benefits for industry.

Track A was composed of four workshops. The first workshop addressed embedded intelligence in manufacturing decision support, and elaborated on the business requirements of ICT solutions for directed trans-disciplinary information and knowledge-sharing capability. The second workshop elaborated the business impact of application use cases of enterprise interoperability (EI). In the third workshop, recent research on an operating system for virtual factory (vf-OS) was presented. The last workshop addressed issues in EI standardization management.

Track B consisted of four workshops. The first two workshops elaborated on smart services to enable semantic interoperability for industrial Big Data platforms to support digital transformation. Included was a position paper regarding the European Big Data Value Association for Smart Manufacturing Industry. The last two workshops addressed methodologies for predictive maintenance in Industry 4.0 and issues of higher education.

Track C was composed of three workshops. The first workshop focused on modeling and simulation for the design of advanced manufacturing systems including an ontology for enterprise modeling and the presentation of the first implementation of a new architecture, MDSEA for Industrie 4.0. The second workshop addressed methods and tools for product service systems (PSS) by proposing an innovation process and the use of a tool called the product service concept tree. The third workshop provided an outlook of the research into how interoperability solutions for crisis management could increase the resilience of smart cities.

The doctoral symposium presented the results of three dissertations in the field of flexible shop floor management. The results concern information systems for network organisations in the context of enterprise interoperability. The goal of the symposium was to discuss interactively the findings, issues or ideas between the participating PhD students and experienced participants from research and industry.

We would like to acknowledge the professional contribution of Andrea Koch to organize the papers for the delivery to the publisher.

Preface

Markets, stakeholders and information technologies will constantly evolve, making it challenging for a single organization to keep up with the competition. Modern production enterprises are responding to this challenge with Industries 4.0 and interoperable solutions in collaborative networks to become more reactive and innovative in both their organization and their production systems.

The International Conference on Enterprise Interoperability (I-ESA 2018) presented interoperable solutions for enterprises from the viewpoints of research and innovation (business impact). The workshops addressed Smart Services and new technologies like next generation internet (Internet of Things, cloud-based platforms, and artificial intelligence) applied in future manufacturing systems using digital transformation.

This book contains work that stemmed from 11 workshops and a doctoral symposium. One particular method used for each workshop was to exchange knowledge about actual research and applications and to interactively discuss issues and new ideas between the presenters and the audience of experts from research and industry.

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August 2018

PART 1

Embedded Intelligence

Part 1 Summary: Embedded Intelligence Discussion

Introduction

The research presented in this workshop involved 22 participants. The supporting presentations provided an in-factory perspective, a supply chain perspective, a technology perspective and a solution provider's perspective. The workshop contributors proposed the most important issues that should be addressed which were then discussed against four topics: (1) how do we best empower people?; (2) how do we enable effective knowledge sharing across multiple users with different viewpoints?; (3) what analytics techniques are needed/essential? and (4) how do we deploy and maintain ICT solutions to suit dynamic business environments? The results of the discussion are provided below against each of these topic areas.

How do we best empower people?

Within this area contributors identified the following topics: trust, skills and training, presenting decision support data, and integration of humans in the system.

Trust: *"How will operators accept new technology and culture change?"*

For successful automation and model building, a significant amount of data is required about the entire system. A large portion of this data should be obtained from the work force, including tacit knowledge. Trust would be essential to gain workforce involvement and ensure accurate data provision. Automated systems,

Chapter written by Bob YOUNG, Paul GOODALL, Richard SHARPE, Kate VAN-LOPIK, Sarogini PEASE and Gash BHULLAR.

autonomous agents and system models should provide a user with visibility of decisions. This should be easy to understand and interrogate.

Skills and training: *“How will we train people with no experience themselves to be good decision makers?”*

Dynamic embedded management will continue to be required. A human retains responsibility, and must have the ability to respond appropriately and intervene *when* exceptions, errors and emergency situations occur. Due to the reduced lifecycle of products and increased variability in processes, it would not be easy for someone to gain necessary or significant experience. Training should be provided for changing manual roles and strategic decision-making.

Presenting data for decision support: *“What are the tools required to make human decisions the right ones?”*

Complex, multi-system architectures should be easier to maintain and be user friendly, but how this could be achieved remained unclear. With complex systems that include autonomous and human elements it would be necessary for process and system models to be understood by human and machine. Process models for such systems could be excessively large and incomprehensible. Presenting processes in a manner easily understood by people would be necessary to support the generation of interoperable systems. Data presented for decision support should be simplified, potentially a summary of events and include both provenance and be easily interrogated. Interface to these data should be user friendly, visually pleasing and provide additional metadata to facilitate understanding.

A human in the system: *“How can we support/integrate the human worker?”*

The portion and abstraction of the system presented to the user should relate to the role they are expected to undertake. Interoperability will depend on successful communication and understandings between different organizations, groups and between the human and the system. Wearable technologies could be used to help support humans within these systems if they were ergonomically suitable. Legal and ethical questions arise if such tools are used to gather data about their users. Wearable technologies present an opportunity to develop a “digital human twin” however this concept presented concerns regarding ownership of such a twin and ethical use of the data.

How do we enable effective knowledge sharing across multiple users with different viewpoints?

Within this area contributors addressed three topics, with key findings listed as points below each topic.

The key features of an effective knowledge-sharing platform are for it to:

- support multiple users from various disciplines;
- use a common knowledge management language;
- be easily usable;
- be used and updated (user buy-in to managing and accessing the knowledge);
- be developed by experts, not developers;
- be easy to change and flexible to modification;
- define standards (e.g. for specific processes) and stick to them;
- have standard interfaces with interoperable layers;
- be a smart space for ontology sharing (using a semantic broker).

What tools and methods are currently used to store, manage, access and share knowledge?

- | | |
|---|------------------------------|
| – Databases | – Product Catalogues |
| – System models | – ISO Standards |
| – Wikis (often noted to be out of date) | – IBM Watson (AI) |
| – Ontologies | – INDUSTREWEB |
| – Human interaction (discussion and training) | – Solidworks PDM |
| – Scientific literature searches | – Written grant applications |
| – RDF triples | – Textbooks |

What problems should a future knowledge-sharing platform solve?

Note: all of the discussions in this area hinged on trust in the sources of knowledge where face-to-face interaction was considered of particular importance. In order to solve problems, a future knowledge-sharing platform should aim to:

- guarantee trust in sources of knowledge;

- ensure only experts ask the right (appropriate) questions;
- embed decision-making to provide the most useful solution;
- handle multi-process questions; respond to follow-up questions in light of previous questions;
- share knowledge only with trusted entities (security and data privacy);
- manage ownership of knowledge; ensure it is up to date and trusted;
- reflect the interactive process of learning (conversational).

What analytics techniques are needed/essential?

A broad discussion was held around the topic of data analysis, modeling, simulation and decision support for manufacturing with the aim of exploring the state of the art, identifying research challenges and suggesting routes to tackle these challenges. Listed below is a summary of the discussion areas and points raised.

Data and information uncertainty:

- it should not be assumed that the data is correct. Methods, measures and standards should be employed to assess if data is fit for purpose;
- how can we validate the analysis to determine if correlations are causations;
- can we include the scientific process?
- feedback data into models to enable continuous improvement;
- how should we determine if a sensor has failed or requires calibration?

People, skills and tools:

- domain experts need to be better integrated with the analysis team;
- good engineers need to be trained to ask the right questions;
- currently we can ask questions and use analytics to help answer them, but how can we be proactive – how do you know what you don't know?
- new software tools are being developed all the time; keeping up-to-date with the market is a challenge to ensure you are not reinventing the wheel;
- better integration is required to enable “plug and play” functionality.

Interoperability and sharing data within and between businesses:

- knowledge is wealth, so businesses are unlikely to freely share information;

- data represents a new opportunity for business;
- better tools and methods are required to utilize historical data for data analysis.

How do we design, deploy and maintain ICT solutions to suit dynamic business environments?

In this area the contributors discussed (1) what are the barriers to adopting cyber-physical systems (CPSs) for Industry 4.0 and interoperability?; (2) how can the challenges of design, development and adoption be dealt with? and (3) how can longevity within these systems be created, that is, how can you future-proof them?

From the discussions four main barriers to success were identified as a recurring focus in the group: (1) *flexibility*, (2) *culture*, (3) *awareness* and (4) *providers*.

There were concerns that the *flexibility* required to both interact with legacy components and cope with evolving systems was not currently achievable in systems. The lack of flexibility was attributed mainly to the numerous legacy components using numerous communication standards and protocols and the investment which would be required to not only interoperate with them but to adapt to any new components.

The second barrier of *culture* was discussed in terms of a business' unwillingness to share data. Reasons for this unease included the concern that a single supply chain member might become dominant by holding all other members' data and that there would likely be a lack of visibility of who would be using their data, how they would be using it and why.

The third barrier, which formed a common theme throughout the discussions, was industrialist *awareness*. This included their awareness of existing systems and benefits as well as the costs involved in development and deployment. Encompassed within this barrier is the concept of trust and the extent to which industrialists accept and agree with a presented system's benefits and costs.

The final discussed barrier to an interoperable environment, in which systems from different suppliers can interact, is whether or not major *providers* actually want to develop this functionality within their systems. Major providers may prefer not to allow third-party integration to their systems to keep customers investing in their in-house solutions.

Exploiting Embedded Intelligence in Manufacturing Decision Support

1.1. Introduction

There have been many advances in the ability to embed intelligence into products and manufacturing equipment in order to collect important data using wireless, intelligent systems of radio frequency identification (RFID) tags and networked sensors [XU 14]. Similarly, the ICT industries that support manufacturing businesses continue to expand and develop their range of decision support software across the full range of business requirements from shop floor systems, manufacturing execution systems, enterprise resource planning, product lifecycle management and supply chain management and so on. However, while each of these systems provide important capabilities, the ability to effectively interconnect them in a meaningful trans-disciplinary way is limited [HUB 14] and must be overcome if the visions of Industry 4.0, the fourth industrial revolution (4IR) and smart manufacturing are to be met.

In the continual need for manufacturing industry to strive for a competitive edge, the ICT industry should have the potential to deliver great benefit. Given the potential of ICT, a company's multiple decision makers should have ready access to high quality, timely information directed to meet their needs, on which to base critical business decisions. This paper highlights the technological progress that has been made towards meeting this manufacturing requirement and discusses the issues that still need to be resolved.

Chapter written by Paul GOODALL, Heinz LUGO, Richard SHARPE, Kate VAN-LOPIK, Sarogini PEASE, Andrew WEST and Bob YOUNG.

1.2. Key technologies

In this section the key technologies that we consider to be of major importance are highlighted and discussed in turn in terms of their current capabilities for manufacturing decision support. If we start from a decision support perspective the base level requirements are simply to (1) be able to collect the required data, (2) to direct the appropriate aggregated data to suit the needs of a range of users and (3) to define data analysis techniques to be able to answer specific sets of multi-user questions. However, meeting these needs is not straightforward and a range of issues must be resolved. There is a need to ensure that we can communicate up-to-date high quality information against an understanding of business knowledge across a range of business activities and to be able to build software platforms that can offer a dynamic way of directing information to support the trans-disciplinary needs of multiple users. In addition to the capabilities of embedded components to collect high quality real-time data, the main requirements of such a platform are proposed as falling into the following four key categories: (1) analytics technologies, (2) application services, (3) toolkits to empower workers and (4) interoperable knowledge environments, as illustrated in Figure 1.1. Each of these areas are discussed in turn in the following sections.

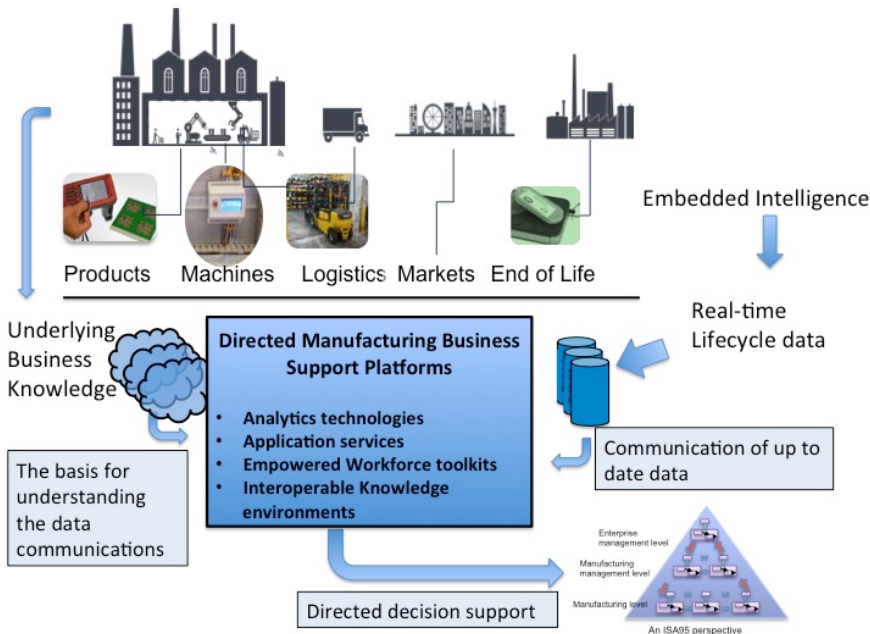


Figure 1.1. Overview of technologies for directed decision support.
For a color version of this figure, see www.iste.co.uk/zelm/enterprise.zip

1.2.1. Embedded Systems

A critical issue for any embedded system is the link between the physical world and the cyber world. The robustness of this link determines whether the system can be provided with accurate and timely measurements of the real world. In manufacturing, non-intrusive monitoring is significantly valued as it reduces requirements to pause a production line to maintain or scale infrastructure, avoiding associated productivity losses. Summarizing and extracting information from various sources of monitored contextual data, for example machine power consumption, tool vibration and asset location, then provides intelligent monitoring such as the ability to identify which components have been machined by a worn or damaged tool.

The identification of a physical object is the basis of any cyber–physical link and the methods of identification and continuous monitoring need to be appropriate to manufacturing environments, that is, they must be able to operate in harsh environments and be cost effective. Commonly used technologies are passive UHF RFID tags and wireless sensor networks (WSN) which to operate robustly may require a custom design, down to the selection of appropriate substrate, chip selection, antenna design and choice of sensors. Once physical objects can be identified, the level of intelligence can be extended to aspects such as problem notification, for example monitoring environmental conditions and decision making, such as requesting resources. As a physical object or product becomes more intelligent it must be able to access more processing power to be able to extract features from potentially numerous sensors (e.g. position, temperature, acceleration and humidity) and to interpret the results.

An example of an intelligent product's potential output is its location. Asset positioning precision increases with number of sensors, packets sent and traffic rate but is compromised by wireless packet loss that can inevitably be reduced by limiting the wireless transmissions in range of each other [PEA 17]. At the same time, an architecture of embedded sensors combined with prediction and optimization models can reduce the need for this type of continuous monitoring [PEA 18]. With an increasing demand on a product to be intelligent, the product's demand for power, internal storage and reliable and more frequent communication also increases. As intelligent products become more widespread within manufacturing, the requirement for security is also a key concern.

1.2.2. Analytics technologies

Data analytics refers to the process of examining and analyzing data with variable types to uncover hidden patterns, correlations and trends. The outcome of

this process is to uncover a business' valuable knowledge in order to increase operational efficiency and explore new market opportunities. Within manufacturing, data analytics is often reported as a machine learning solution to a business problem [ECK 17], disregarding the fact that data analytics exploits knowledge and tools from areas such as data mining, statistical analysis and data modeling.

The usefulness of data analytics is correlated with the time span covered by the gathered data and its analysis. In the first instance, the data regarding an immediate snapshot is useful in answering questions regarding what is currently happening. The second instance draws on historical data to answer what has happened via the detection of trends and correlations. At this point the understanding of why something happened is not yet achieved through data analytics. The understanding and abstraction of knowledge is the focus of the third instance of data analytics and this is where machine learning and data modeling fit in. Once an understanding of why something has occurred has been achieved it is necessary to understand its impact on the business. Tools such as process mining are appropriate at this stage [VAN 07]. Improving and expanding the results of data analytics across a range of instances requires an understanding of the increased complexity in the volume of data required, the integration between different data types and sources of data and the improved complexity of the analysis.

1.2.3. Application services

While analytics technologies provide techniques that can be generally applied to identify useful information, application services package these techniques in a reusable and on-going manner to support particular business needs. The process starts from a user application perspective and defines services that can support their needs. Examples of the sorts of services that can be defined are product/workpiece traceability, process monitoring, product/workpiece monitoring, logistics monitoring and performance assessment.

For these sorts of services to be effective it is necessary to have a clear understanding of the attributes, processes, resources and constraints that they must model and simulate in order to provide useful outputs. This can be challenging within real world manufacturing environments that are highly integrated into a supply chain, and are dynamic and constantly refining and updating their products, processes and resources. Challenges for application services include the ability to adapt to changing manufacturing environments, ensure they can scale to the needs of production and provide horizontal and vertical interoperability.

1.2.4. Empowered workforce toolkits

An important part of directed decision support is being able to present information to suit the needs of a range of decision makers throughout the business [JAR 17]. While it can be argued that the most important decisions are ensuring that the business makes the correct long-term strategic decisions, these are only effective if the short-term operational decisions are also made effectively and the data gathered are representative of the processes being completed. A problem associated with both small and “big” data is one of ensuring veracity [WHI 12]. Veracity may be affected by factors such as choice of sensors or filtering algorithms, and the users of the devices or processes being monitored. This human input can be supported by adopting a user-centric approach. When stakeholders are involved in changes they are more likely to adopt new processes and technology and develop the shared mental models that contribute to positive behavior.

While offering effective graphical user interfaces to suit strategic- and tactical-level decision makers are important, potentially the most important are those that enable rapid reaction to real-time data changes such as anomaly detection. The provision of appropriate real-time data may also be used to develop and supplement operator skills and abilities to improve efficiency and reduce operator stress.

The role of augmented reality in empowering the workforce is potentially where rapid benefits can be achieved. These toolkits can enable workers to: access information hands free, exploit digital twins to locate resources, products and people, be made aware of critical manufacturing issues that need immediate attention or maintenance or access online resources or be connected with an expert to advise on problem solutions.

1.2.5. Interoperable knowledge environments

There is a wide range of trans-disciplinary knowledge and expertise that must be brought together in a successful manufacturing business. Capturing the knowledge of each discipline, the relationships that exist between them, the different semantics that different groups use and ensuring that core knowledge remains secure are just a few of the problems that knowledge environments must achieve.

However, a key requirement for knowledge to be effective is for it to be sharable. It must therefore be captured within an interoperable knowledge environment. However, at the same time, a business’ core knowledge is critical to its success and needs to be secure so that it is only shared when appropriate.

A great deal of research effort has been targeted at formal ontologies as a route to knowledge exchange but has not produced the flexibility in knowledge base development that is needed. A new approach defining reusable reference ontologies is beginning to show potential [PAL 17] and is being further researched [MOR 17].

1.3. Concluding discussion

There are clearly huge business benefits to be gained from providing decision makers with high quality, accurate and timely information on which to base their decisions and inform their actions. Each of the areas mentioned above needs to be improved and enhanced for the full range of manufacturing business users to benefit.

At a basic level, real-time data can be communicated effectively. However, we are far short of the understanding needed to offer up the multiple different aggregations of information needed to satisfy the needs of trans-disciplinary business personnel. Just as importantly, the software platforms that start to offer solutions must be dynamically reconfigurable to match the rapid change requirements of manufacturing business.

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Test of the Industrial Internet of Things: Opening the Black Box

2.1. Introduction

The Internet of Things (IoT) is well known in the context of smart homes, smart cities and general consumer goods. Examples include refrigerators, coffee makers and heaters equipped with smart components and which are connected to the internet. Industry IoT raises especially in the context of smart factory and Industry 4.0. It has become an essential part in terms of the digital transformation in most of the business areas.

For example, in the manufacturing industry an approach is to have manufacture capabilities represented in terms of services accessible via intranet or even via cloud [JAE 17]. This creates questions like the following: is the cloud safe or is it accessible to everyone? Are the used cyber physical systems (CPS) and IoT compliant to the whole infrastructure? Is compliance to specific standards enough for real implementation?

With an industry focus, the expectations related to robustness, interoperability and especially security increases. However, IoT approaches remain similar comparing with the consumer area [WON 16, POL 17]. On the consumer side, the focus is much more related to low cost and therefore lower security and robustness. In contrast, IoT elements used in industry are not necessarily more mature in these aspects. In fact, currently they are more used in terms of a “black box” because of missing detailed knowledge and tools to prove the IoT components. This might be gateways but also protocols, machine controllers and software applications. Finally, the user has to rely on the supplier.

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Industrial cases have been identified that even if components are proved to be compliant to protocols such as OPC-UA [OPC 17], they do not work together with others because the standard can be implemented in different ways (see section 2.4). This can block the implementation of new manufacturing components such as machinery, monitors or sensors.

IoT test software and related labels or certificates are proposed to improve the situation such as in the German IoT-Test project [PRO 17]. This project uses standards for test software as well as IoT requirements such as described in ISO/IEC JTC 1. This has been combined with use cases and specific test requirements from IoT providers and end users [PRO 18] to get a clear view on the demands for such test features, also called testware [REN 16]. The objective is to provide the end users with more knowledge about the used IoT components to avoid unpleasant surprises as far as possible.

The paper focuses on emulating industrial scenarios and use cases to test and sharpen the testware because the testware developers usually do not have direct access to manufacturing lines. Moreover, the execution of a specific scenario can influence the real manufacturing process. Therefore, environments are proposed to demonstrate specific test cases to show the power of the testware. Moreover, an adaptor is presented to test CPS/IoT interfaces related to specific configurations of shop-floor-IT infrastructures.

2.2. Scoping

Regarding IoT tests and validations the following different cases can be distinguished (Figure 2.1):

- 1) providing a label or certificate illustrating a specific level of compliance to security, robustness and implementation of standards;
- 2) generic tests to prove an IoT element against a specific infrastructure. This relates to the check of a CPS network;
- 3) monitoring and runtime tests, which need to be setup within an IoT infrastructure such as a virus scanner.

Points one and two are the current targets of the IoT-T project. The IoT-T project works on a testlab [TES 18] to realize point one. However, for the industrial emulator and validation adaptor it is intended to focus on all three cases.

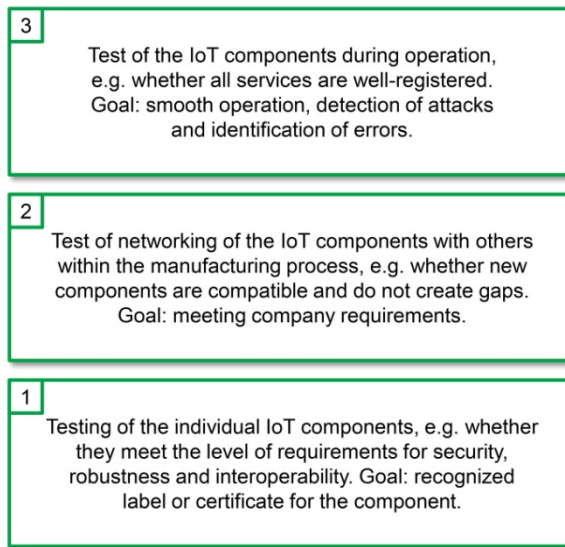


Figure 2.1. *Scopes related to potential testware and for the emulation*

2.3. Architecture of the industrial emulator

The industrial emulator aims to simulate different test cases to test the IoT test-ware as well as to demonstrate the relevance of the IoT test especially for industrial usage. The emulator should be usable by developers of IoT testware, independent of hardware components such as robots. This requires the emulation of the hardware components. In the best case scenario, machinery providers directly deliver these emulations of cyber physical systems (CPS). In any case, an adaptor is used to bridge different formats, specific implementations and provide a service interface. This approach allows an easy transformation from the emulated CPS to the real machinery. Moreover, the configuration of the adaptor will allow for the validation of interoperability demands.

The industry emulator follows the idea of manufacturing services, which can be combined to realize manufacturing processes as well as networks of manufacturing processes. The basis of the emulator is the model based on a modular shop floor IT system [JAE 17, RIE 14]. This allows that the specific configuration of a test case is designed by an enterprise model and afterwards executed by an execution engine. The execution requires an emulation of the manufacturing processes. CPS emulators provide the specific machinery data and behavior. To support the interoperability on the service side a CPS adaptor is used (Figures 2.2 and 2.3).

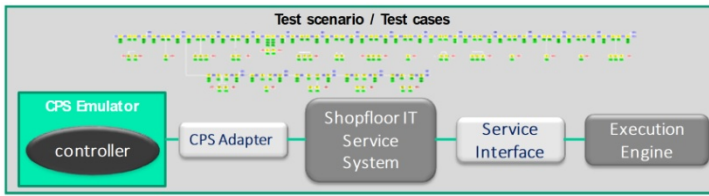


Figure 2.2. *Concept of the industrial emulation. For a color version of this figure, see www.iste.co.uk/zelm/enterprise.zip*

The CPS adaptor converts the specific formats and functionality of the CPS to a shop floor IT service system that allows the definition of specific services for the shop floor. Together with the service interface, it delivers the services to an execution engine.

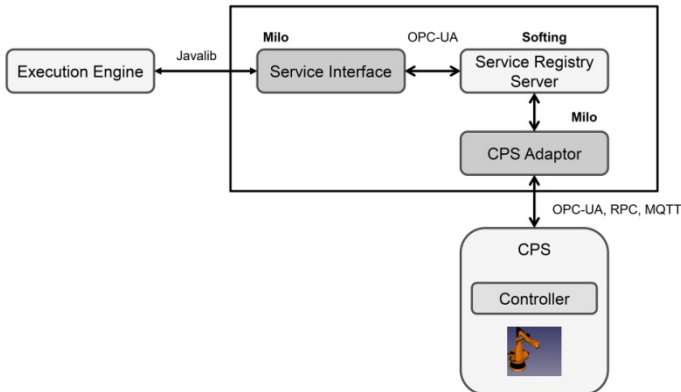


Figure 2.3. *Current technical realization. For a color version of this figure, see www.iste.co.uk/zelm/enterprise.zip*

In fact, to add a new CPS emulator or a real CPS only the interface between the CPS adaptor and the CPS needs to be realized. The execution engine enables the connection of the different CPS to realize the manufacturing network of cyber physical systems.

Figure 2.4 illustrates a test configuration for an availability test of services for an IoT system (here a robot). This test is intended to ensure that the specified services are available. This test must be fulfilled by a plant or system supplier and is based on precise specifications, which could be standardized in the future. Among other things, the aim is to ensure that new IoT systems can be safely integrated into existing IoT infrastructures and networks.

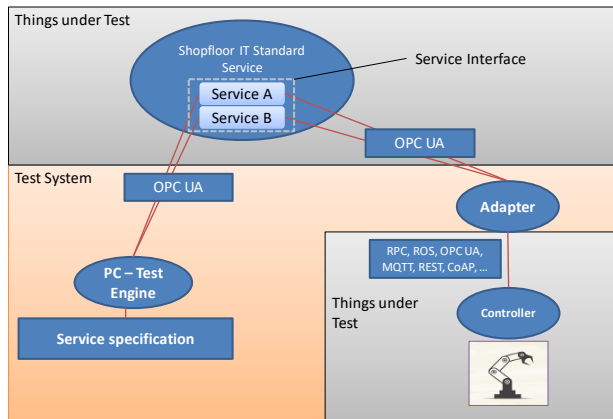


Figure 2.4. *Concept of the test scenario. For a color version of this figure, see www.iste.co.uk/zelm/enterprise.zip*

2.4. Application case

An industrial scenario derived from challenges related to the setup of smart new shop floor IT infrastructures illustrates the demand. Each of the equipment and machinery acts in terms of IoT with digital components (controllers) connected to the network (intra- or internet). Different machinery suppliers provide the equipment and machinery. They confirm them to be compliant to specific standards such as OPC-UA. However, during the setup of the infrastructure they appear non-interoperable because of specific interface configurations. One challenge is that OPC-UA can provide different security approaches. If the CPS uses different ones they might not work properly in the IT infrastructure. Furthermore, the set of supported functions could be different. Related to a report of the German Federal Office for Information Security (Bundesamt für Sicherheit in der Informationstechnik) [BSI 17] the security level of OPC-UA can be variable depending on the configuration. Therefore, it is also important to test potential security issues to create robustness against IT attacks.

2.5. Future work and conclusion

The aim is to support the “plug and produce” behavior of machine–tool interfaces. It becomes important in the context of smart and digital factory because it ensures a seamless plug and produce of new equipment into the shop floor IT infrastructure. It needs to cover different protocol aspects such as compliance tests for OPC-UA, MQTT, DDS, CoAP by using mostly existing open source tests. More importantly it needs to validate machine–tool interfaces against specific

interoperability, performance and security demands. This requires a configuration method of formats and demands. The configuration needs to be executable by a validation service. A CPS adaptor and an execution service will comprise the interface capability validation. The CPS adaptor will cover specific aspects of frameworks and protocols (OPC-UA, DDS, CoAP, MQTT, TCP/IP, etc.). The execution service runs the validation. Related to OPC-UA, both services are available as prototypes. At the time of writing, the configuration is in development and will be tested in summer 2018.

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Intelligent Decision-support Systems in Supply Chains: Requirements Identification

The research area on artificial intelligence and machine learning is pushing a trigger effect for the appearance of a new generation of intelligent decision-support systems (iDSS), which aim at achieving more efficient, agile and sustainable industrial systems. The implementation of intelligent DSS is conceived as a challenging issue for managing sustainable operations among the enterprises taking part in supply chains (SC), in an environment characterized by rapid changes and uncertainty. This paper establishes the state of the art and identifies new research challenges and trends for designing intelligent DSS, within the SC context (iDSS-SC).

3.1. Introduction

Current markets, globally operating, must work in an environment that demands agility and resilience of the enterprises; in which the decision-making process has to be as quick as possible, by considering all the information available that may affect the decision. The consideration of DSS has been widely addressed in the context of individual enterprises [GOU 17]. Nevertheless, enterprises are more and more aware about the establishment of collaborative relationships, and business, among its downstream and upstream partners [AND 16]. It is because of this that the DSS research area needs to extend individual DSS towards an extended DSS that covers the decision-making process performed within the supply chain (SC) [BOZ 09]. Moreover, novel SC-DDSs have to be profitable and include the

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new trends and advances achieved in the research areas of artificial intelligence and machine learning. Adapting these new solutions and approaches will create intelligent supply chain DSSs (iDSS-SC) with the aim of supporting the decision-making process in collaborative environments between SC partners.

It is also a reality that iDSS-SC should facilitate the inclusion of interoperability functionalities between SC partners, willing to carry out collaborative decision-making. Providing interoperability functionalities, when designing intelligent DSS, is the basis on which iDSS-SC must be built [PAN 07, CHE 08].

Working on this research line, the European Commission [EU 18] has launched several calls in the scope of H2020, that have resulted in the emergence of multi-country projects to address the object of discussion: intelligent and interoperable DSS in the SC context. To that extent, it is worth mentioning the following projects: C2NET, CREMA, MANTIS and vf-OS [C2N 15, CRE 15, MAN 15 and VFO 16]. Particularly, C2NET intends to be an intelligent DSS that covers all the planning processes of the supply chain, including replenishment, production and delivery planning. The collaborative, optimization and data collection framework modules developed allow individual enterprises and SCs to perform collaborative decisions based on real time information and in an automated way. The three aforementioned modules of C2NET are embedded in a cloud service and developed considering interoperability features. Regarding the CREMA and MANTIS projects, they are focused on developing intelligent DSS in the context of maintenance planning and proactive maintenance prediction. CREMA aims to simplify the establishment, management, adaptation, and monitoring of dynamic, cross-organizational manufacturing processes following Cloud manufacturing principles. MANTIS retrieves information from physical systems (e.g. industrial machines, vehicles, renewable energy assets), which are monitored continuously by a broad and diverse range of intelligent sensors, resulting in massive amounts of data. Intelligent systems are part of a larger network of heterogeneous and collaborative systems connected via robust communication mechanisms able to operate in challenging environments. In this context, MANTIS seeks to transform raw data into knowledge to create a new process of decision-making. Finally, the vf-OS project is more transversal in terms of its application as an iDSS-SC. vf-OS provides a portable, multitasking and multi-user operating system, which enables the creation of APIs to connect software, drivers to connect machines, and apps that contain modules such as data analytics, optimizers and so on. Apps are developed for their use as a DSS to facilitate the connection between different legacy systems, basing their deployment in interoperable functions; so that the developers do not have to deal with specific connection details and the heterogeneity of hardware and software systems that characterizes SC.

3.2. State of the art

This section introduces some concepts that could serve as a background for the design of intelligent DSSs in supply chains, namely business analytics, supply chain analytics, key performance indicators, machine learning, and data managing.

Business analytics (BA) and business intelligence (BI) are viewed as similar terms, which refer to different analytical capabilities for organizational business processes and decision support systems [CHA 13]. According to [ROB 10] BA enables the accomplishment of business objectives through reporting of data to analyse trends, creating predictive models for forecasting and optimizing business processes to achieve improved performance. BA aims to find “intelligence” within large volumes of the enterprise data (products, services, customers, manufacturing, sales, etc.).

Supply chain analytics (SCA) and supply chain intelligence (SCI) refer to BA for supply chain management, in uncertain business environments [TEE 97]. Seeing the SC as a set of four kinds of processes: plan, source, produce and deliver [API 17], SCI empowers decision makers with real-time performance insight across the extended supply chain. In this way, it allows continuous, KPI-based supply chain improvement. SCI helps organizations tackle the increased global complexity that impacts supply chains. It collects and presents crucial data from all trading partners in easy-to-use, customizable dashboards on a computer or tablet. SCI metrics illustrate where performance is weak or strong, allowing executives to make smart and strategic decisions [GT 18].

In all the above concepts, it is crucial to use key performance indicators (KPIs) and other metrics to monitor the enterprise and supply chain performance in several areas such as finance, production systems, marketing or planning. Therefore, technologies for gathering, storing and analyzing data are required for the proper measurement of KPIs. Accordingly, managing data stored in the enterprises' database's is a relevant challenge and becomes an important technical issue, especially when these data have to be exchanged with other SC partners. The need of technologies for addressing real time data gathering and analysis, catalyses research activities regarding sensors, IoT, CPS, linked data, data privacy, federated identity, big data, data mining, sensing technologies and so on.

Machine learning (ML) or intelligent machines (IM) refers to a specific area of artificial intelligence the objective of which is to develop techniques that allow machines to learn. It is applied to machine and sensor networks that analyze performance in predefined processes. It also explores the study and construction of learning methods and algorithms that can learn from and make predictions based on input data [CAM 09].

3.3. Trends in the research area of iDSS-SC

Taking as a starting point the state of the art described above, this section is devoted to identifying the next trends and concepts to be addressed in order to design and implement an iDSS-SC. A summary of the requirements needed to develop these kinds of iDSS-SCs that apply novel trends such as business analytics, business intelligence, supply chain analytics, key performance indicators, machine learning and data managing, is proposed. The requirements have been identified using a panel of experts working in the research area. iDSS-SCs must be accessible for all the partners of the supply chain. In this regard, systems and technologies in the cloud will favor the ubiquitous connection of all enterprises regardless of their location, as the previously noted H2020 projects demonstrate.

As stated before, SC intelligence (business analytics, supply chain analytics and machine learning) is based on data analysis processes, and transforms simple data into usable information, which is capable of supporting decision making by the analysis and prediction of the enterprise or SC behavior when different events occur. Therefore, data exchange among enterprises of the SC and the iDSS-SC is a key factor. Thus, data security and trust are two relevant concepts to address. In order to achieve SC visibility in all areas security issues – for example access rights – must be addressed.

Moreover, enterprises seek the easy facilitation of a connection between their legacy systems and the iDSS-SC. One important requirement is to design user-friendly cloud services that allow connection in real time, communication technologies to carry out teleconferences, or technologies that allow sending messages. In this research field, it is crucial to design and implement systems that generate alert messages when the iDSS-SC detects deviations. For the detection of deviations, the SC needs to define KPIs and their corresponding threshold values. An iDSS-SC will be able to monitor the defined KPIs, analyze potential deviations, and ultimately predict potential behaviors in the SC operations; these deviations and predictions will be communicated to the SC decision maker, via notifications from the cloud service in which the iDSS-SC is deployed. The notifications will be communicated to the subscribed SC stakeholders, making the security process more sustainable and considering the need to maintain high security and privacy controls.

iDSS-SC will be also able to create alternative decision-making scenarios, according to data gathered and processed for the KPIs identified. The generation of such scenarios will enable the decision maker to simulate different options of operating within the SC, taking into account diverse inter and intra-enterprise characteristics for more accurate decision making.

3.4. New research challenges

Considering the identified trends, new challenges and areas requiring further research in iDSS-SC, within the SC context, are identified:

- Automatic generation of not only *predefined* rules but also *predictive* rules. The aimed predictive rules can be created applying artificial intelligence technologies taking analytics as base data. Predictive analysis will allow the generation of predictive rules to figure out the future behavior of the SC system based on the current aggregated values extracted from the monitoring and measurement of KPIs. Predictive rules will enable the decision maker to identify how deviations can create new future scenarios. In this regard, the iDSS-SC must be able to identify that something not specifically modeled (predefined rules) can occur (predictive rules).

- Big Data, Data Analytics, and Machine Learning technologies have to be used for the *identification of patterns* and for the generation of potential scenarios when predictive rules are created, based on *KPI analysis*. The use of machine learning technologies should work with aggregated information and analyze *aggregate values* for *simulating patterns* with different scenarios, and make analytic predictions. SC decision makers will be able to anticipate future changes, or deal with current uncertainties, through the predictive functionalities of the iDSS-SC. Prediction will be handled taking into account the current behavior of KPIs and analyzing past behaviors that occurred in a given time period.

- Supply chain analytics must deal with lot of information gathered from SC stakeholders. In this regard, *data security* is a key factor when designing DSS in cloud platforms. Security when using artificial intelligence systems could be dealt with by analyzing all the information generated in the SC, and gathering sets of key variables that will be used to carry out learning and prediction processes. Moreover, data security and privacy that comes from the different companies that form the SC is also a key research area.

- Data aggregation can be faced with the definition of master KPIs to gather information (from the past and the present). SCAs must work within current master KPI values that will allow the identification of future potential behaviors. The designed iDSS-SC will support decision-makers about which decision to carry out and will provide an insight into the future effects of the decision made.

3.5. Conclusions

This paper carries out the state of the art and identifies new research challenges and trends for designing iDSS-SCs. Future work will be devoted to completing the

list of requirements needed to develop new iDSS-SCs according to the opinion of experts and industrial users.

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A Total Solution Provider's Perspective on Embedded Intelligence in Manufacturing Decision-support Systems

4.1. Introduction

“Embedded Intelligence” is being extracted from manufacturing equipment to generate information that improves productivity by reducing breakdown times and provides operators with effective knowledge to do their jobs more efficiently. It also supports engineers by storing knowledge on frequently occurring faults and breakdowns through the collection and analysis of captured data. The key to providing effective data for decision-support systems is a multifaceted approach to data collection. Multiple sources of data are pulled from shop floor devices and fed up to populate decision making systems at the enterprise level. The ability to collect this multi-process data is a major challenge considering that most companies (especially tiers 1 and 2 automotive suppliers, for example) have multivendor machines with a variety of control systems; this lack of interoperability makes the connectivity and collection of data difficult.

The challenge is to create an overarching system that can “glue” all the data sources together to give a coherent and meaningful single source of data that can be passed up the knowledge chain to provide valuable enterprise knowledge. This knowledge can of course be fed back down the chain to optimize processes on the shop floor.

This paper offers an approach to creating the “glue” that binds the knowledge chain.

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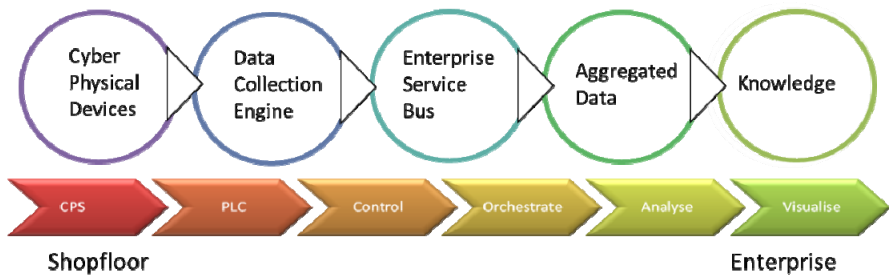


Figure 4.1. Knowledge chain of pulled data from the shop floor. For a color version of this figure, see www.iste.co.uk/zelm/enterprise.zip

4.2. Presenting knowledge for decision makers

In the manufacturing domain, as the roll-out of Industry 4.0 gathers momentum, the focus of increasing production, efficiency and reducing waste remains the “holy grail” for all manufacturing companies. To achieve this, it is vital to understand the connectivity aspects of an enterprise with respect to business processes, life-cycle management and understanding of the processes involved in the production process. The more “connected” an enterprise becomes, the better their chances of achieving the reduction of costs and increasing profits. The goal of connecting systems is to collect data for decision-support systems that can present themselves at many parts of the company. Taking a simplistic view, taking the production team for example, the usual focus of engineers and managers is to adopt a “pull” approach which takes data from shop-floor systems and presents it to management at board level to follow key performance indicators (KPIs) which are usually derived at this level. As can be seen in Figure 4.1, many defined layers are crossed to present the data required for the decision makers. These layers are normally points of hardware and infrastructure change. So generally, the cyber physical devices (CPDs) can be anything from proximity sensors to intelligent monitoring devices typically supplied by a wide variety of vendors with differing interface requirements such as voltage or current loop connections. These traditionally always interface with programmable logic controllers (PLCs and control systems) at the shop-floor level which again can come from a variety of vendors such as Siemens, Rockwell, Omron, Schneider Electric and so on. The orchestration software starts to link from the shop floor to IT systems which are normally office-based systems and usually linked to enterprise resource planning (ERP) systems. These systems are again provided by different vendors such as SAP or Oracle. Finally, the analysis and visualization is carried out at the intranet, edge (fog) or cloud level depending on the company’s data management policies but very much at the office level and again this could be provided by third