An Overview of Trends and Developments of Internet of Things Applied to Industrial Systems

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***Abstract*—Advances in the domain of electronics and information and communication technology provide a tremendous set of new possibilities and services. The development of the Internet of Things concept where different sensors, actuators, and control devices are connected together and where functions are provided to the Internet, is on the way to be used also in various industrial domains. A new age of intelligence in such industrial systems is being formed. Hence, the aim of this work is to provide an overview about ongoing research and technology developments related to the digitalization of industrial systems applying the IoT approach. This review covers the domain of manufacturing, as an example for discrete systems, and the power and energy domain, as an example for continuous systems. Important domain standards and future research directions are identified and discussed also.**

***Index Terms*—Industrial Systems, Information and Communicator Technology, Internet of Things, Manufacturing, Power and Energy Systems, Standards.**

I. Introduction

Recent advances in the domain of electronics and Information and Communication Technology (ICT), especially in the area of Internet technology, provide a tremendous set of new possibilities and corresponding services. The development of the Internet of Things (IoT) concept, where different sensors, actuators, and control devices are connected together and where functions are provided to the Internet, is on the way to be used also in various industrial domains [1], [2]. A new age of intelligence in such systems is being formed [1]. There is an ongoing transformation of traditional monolithic, hierarchical, and centralized legacy control and data acquisition systems to network-based automation and control architectures.

The aim of this paper is to provide an overview about ongoing research and technology developments related to the digitalization of industrial systems applying the IoT approach. Especially, the domains of manufacturing, as an example for discrete systems, and power and energy systems, as an example for continuous systems, are covered in this review. Important domain standards and future research directions are identified and discussed also.

Following this introduction, Section II discusses IoT-based trends and developments as well as standardization activities in the domain of manufacturing systems whereas the power and energy domain is covered in Section III. An outlook about research trends and future needs is provided in Section IV. This review paper is concluded with Section V.

II. Manufacturing Domain

A. Overview of the Domain

Today, the manufacturing and production industry has to cope with mass-customized products and a growing number of product and part variants. Also a shorter time-to-market and shortened product life-cycles can be observed mainly due to consumer demands. Corresponding manufacturing systems and production plants must be constructed in a way to react on this market changes and consumer demands; they need to be highly flexible and adaptable. Besides the needed physical flexibility (mainly on the mechanical and electrical layout) also adaptability on the logical level (mainly monitoring, automation and control algorithms; ICT architectures and concept) is required. Recent developments in electronics and ICT provide the basis for the realization of flexible solutions.

B. Research Trends and Developments

The following trends and developments in the domain of manufacturing systems from the digitalization point of view are now discussed.

1) Automation with Industrial Internet of Things: Industrial IoT (IIoT) is undoubtedly perceived as a key enabling technology for the digitalization of industrial systems. The Industrial IoT's role is to enable seamless collection of data from the shop floor and make it available for advanced data analysis in order to further improve performance of production processes, as depicted in Figure 1. There is a clear parallel to traditional closed-loop control systems known from control theory, where the controlled process variable is monitored and the *controller* generates a control action to bring the controlled

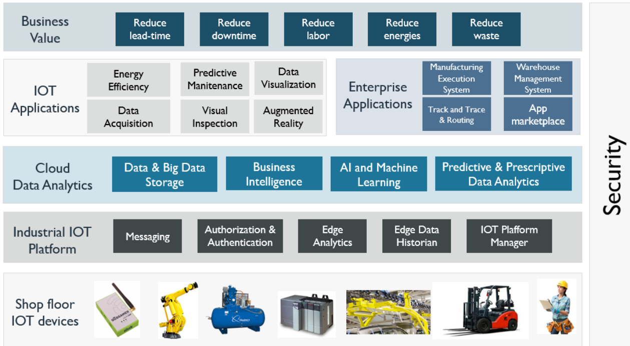

Fig. 1. Overview of the Industrial IoT concept.

process variable to a desired value. There is another parallel between the mathematical model used by the controller as a replica of the physical system behavior and the contemporary concept of a *digital twin* [3].

Despite mentioned parallels, IIoT enables to elevate manufacturing control to a new level. The key enablers are recent advancements in electronics and in ICT that are finding way to industry. Nowadays, a variety of *IoT devices* appear in form of low-cost and always connected smart sensors or micro-computers that connect physical *things* to the Internet. The connectivity is usually supported by new low-power wide-area networks such as LoRaWAN, Sigfox, Nb-IOT or LTE Cat M1 [4]. Such IoT devices are powerful enough to run data analytics *on the edge* to perform distributed intelligent decisions close to where data originate. Moreover, *IoT Platforms* serve as software foundations for running industrial IoT applications. These environments provide different features and services like device management, message routing, complex event processing, authentication and authorization, and Application Programming Interfaces (APIs) for data access. Contrary to traditional industrial systems based on server-client technology, where the client has to poll the server for data updates, IoT platforms apply *publish-subscribe* mechanism.

There is a wide range of *IoT Applications* supported by IoT devices and IoT platforms such as remote metering, real-time plant floor data acquisition, real-time machine status monitoring, energy management, environmental monitoring, asset tracking, and inventory management [5].

2) Solving Complex Problems with Artificial Intelligence: Artificial Intelligence (AI) has a long tradition of applications in industrial systems. Broadly defined as the study of intelligent agents that collect data from their environment and make autonomous decision to maximize the expected reward given their goals. The AI field thus incorporates a wide range of approaches, from non-adaptive systems (rules engines, expert support systems), through fuzzy logic, to a large host of probabilistic methods including machine learning.

The belief that artificial neural networks with a larger number of hidden layers could effectively learn representation of complex problems from input data has a long history [6]. While effective methods for training artificial neural networks has been known since the 1970s (error back-propagation), practical application to networks with typically more that 2-3 hidden layers suffered from numerical problems during training (so called vanishing and/or exploding gradients).

Since almost a decade, such kind of learning approaches underwent major developments enabled by three factors: *(i)* availability of large data sets, *(ii)* availability of large computing power, and *(iii)* advances in algorithms. Training networks with hundreds of layers and millions of free parameters ("weights") is currently feasible and so-called deep architectures—and corresponding Deep Neural Networks (DNNs) [7], [8]—significantly moved the frontier of machine learning in many applications.

3) Application Fields for Artificial Intelligence: The above outlined advanced approaches are being increasingly used in the manufacturing domain in the following application fields:

a) Deep Learning for Image and Video Recognition: The field of computer vision up to year 2010 was dominated by complex, multi-step image processing pipelines combining image transformation, filtering, feature detection and extraction steps (here called "classical computer vision" approaches). While these pipelines work very well in many contexts (particularly in well controlled environments like manufacturing lines), they require laborious hand-crafting of features and fine tuning. This process (so called feature engineering) is essentially "guided" representation construction. It is exactly at this step where DNN offer the largest leverage compared to classical methods. DNN can automatically build up (learn) a hierarchical, multilevel representation from the input data, where each successive layer internalizing finer, lower scale features, based on inputs. The development focus is thus shifted from feature engineering to network architecture.

Performance of computer vision algorithms is annually compared in several object recognition contests and the year 2012 was the first time that a DNN beat the classical methods [9] using a convolutional architecture first proposed in 1998 by [10]. Ever since, DNNs have been achieving state-of-the-art results on object recognition tasks in all major image and video recognitions with new architectural innovations being introduced each year. Since 2015, DNNs in some of the competitions are even surpassing super-human accuracy (the Resnet architecture of [11]). For a recent review of the field we refer the [12] and references therein.

Given that the representation learning by DNNs is automatized and far more general and complex compared to the manually engineered features in classical approaches, the main advantages of DNNs for image and video recognition compared to classical approaches are: *(i)* increased accuracy, *(ii)* more robust models, *(iii)* saved engineering time, and *(iv)* continuous model improvement during data collection.

These desirable properties of deep learning algorithms come at costs of: *(i)* larger model complexity (and thus often longer training and prediction times), *(ii)* larger computational hardware requirements, and *(iii)* larger training datasets requirements. The requirement on the size of the data set depends on applications—complex tasks require more input data. Fortunately, application of DNNs on problems with relatively similar structure can take advantage of so called transfer learning (for a review see [13]). Here, we can take a network that was already trained on a different (often larger data set), remove the final few layers and re-train it on our, smaller data set. Improvements of sample efficiency of DNNs (how much can the network learn per input sample) is one of the most researched areas in deep learning.

To sum up, the application of convolutional DNNs for image and recognition opens new frontiers in machine vision in accuracy and robustness. The application of DNN in industrial context include thus automation of parts and products classification, visual quality control, machine vision for robots and automated guided vehicles, and further more.

b) Time Series Analysis and Forecasting: Further major area of interest for industrial applications is times series analysis and forecasting. Most of the data collected from manufacturing systems comes in the form of time series (i.e., ordered pairs of time-stamp and measurement values like power, temperature, torque, etc.). The increased presence of industrial IoT devices further underlines this trends by allowing data collection from cost effective sensors.

Just as convolutional DNNs allowed major breakthroughs in image processing (see above), so called Recurrent Neural Networks (RNNs) play a similar role for sequential data (primarily time series, but also for text and speech, etc.). RNNs, first introduced by [14], work by allowing the network weights to be shared across time, effectively introducing "memory" into the systems. This memory was initially only very short term (due to gradient vanishing) but a major advance came with the design of so called Long Short-Term Memory models (LSTM, [15]) that allowed information flow over much longer time periods and the network to learn features across different time scales. Applications of RNN in industrial systems include time series prediction and classification as well as the processing of audio signals.

c) Anomaly Detection and Predictive Maintenance: One particularly interesting application of deep learning techniques is in the field of condition monitoring of industrial assets. Here a particular subclass of DNNs, so called *autoencoders* [8], can play a role of essentially non-parametric twins, by building up a compressed representation of the given physical system (asset) for the purposes of detecting anomalous states.

Anomaly detection reacts when the system is already entering an unusual (potentially dangerous) state. This, depending on application, might be too late for reaction (perhaps except shutdown). We speak about predictive maintenance, when the time horizon before warning and the potential failure is extended so that more complex planning and intervention can take place [16]. While the superior predictive power of DNN could help in theory to predict potential failures with longer foresight, we are often encountering issues with data set sparsity: failures are typically relatively rare occurrences and therefore not often sufficient to train a DNN (though a simpler model with fewer parameters might work). While the potential of this technology is large, its practical applicability is currently limited by finding a proper use case, with a preference for systems with many uniform, expensive assets (e.g., wind turbines), rather than those found in manufacturing conditions.

d) Reinforcement Learning for Automation, Robotics and Process Control: The final area where deep learning can have a large impact within industrial systems is in the area of reinforcement learning—the design of software agents acting to maximize a reward signal extracted from a virtual or physical environment. Here, Deep Reinforcement Learning (DRL) [17] made huge advancements in the recent years, crowned by mastering the games of go, chess and shogi at super-human level with a single architecture from scratch and only using self-play within a < 24 hour learning period [18]. While these successes are very encouraging they come from areas where enormous amount data can be automatically generated (self-play, computer games, simulated environments.). DLR remains still the most sample in-efficient (see above) area of deep learning, training is computationally very demanding and often unstable and there are several further obstacles (reward function design, escaping local optima, etc.).

For these reasons the deployment of DRL in real environments is up to now very limited. Theoretical work is however rapidly progressing (see [17] for demonstration of approx. factor 4 increase of training efficiency) and many promising new venues have been recently explored, e.g. learning from "instructional" videos [19] or from sparse human preferences [20]. DRL is therefore expected in the future to play an important role in automation and robotics similar to e.g., convolutional DNNs in image recognition.

C. ICT Interoperability and Standardization

There are attempts to provide reference architectures and methodologies for IIoT systems in order to ensure interoperability of connected components, products, services, algorithms, and people. There are two major, highly complementary architectures—*Industrial Internet Reference Architecture* (IIRA) from the Industrial Internet Consortium and the *Reference Architectural Model Industrie 4.0* (RAMI 4.0) by Plattform Industrie 4.0 [21]. Especially, the later has been developed to address the aforementioned requirements and needs of IIoT approaches and solutions across the different hierarchical control levels in manufacturing systems and across the life cycle value stream as outlined in Figure 2.

ICT plays the central role in realizing IIoT solutions. Therefore, traditional industrial protocols for machine-to-machine communication such as Profinet, EtherNet/IP, or EtherCAT and automation approaches need to be complemented or replaced with a variety of new protocols from the IoT era. Following is a list of more influential ones:

- *MQ Telemetry Transport (MQTT)* is one of the most dominant protocols in IoT applications these days [22]. Its history dates back to 1999 when it was released as a protocol suitable for low-bandwidth and low-power

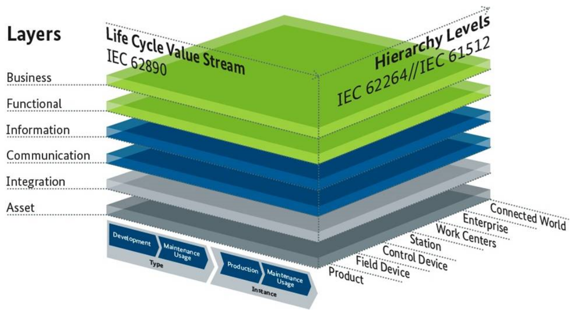

Fig. 2. Reference Architecture Model for Industry 4.0 (RAMI 4.0) [21].

devices. It is based on publish-subscribe model—the messages, which are organized in topics, are distributed by the *message broker* among clients, which publish messages on given topic and receive notifications from the broker if a message on subscribed topic appears. There are three levels of Quality of Service (QoS) to chose from—at most once, at least once, exactly once—to offer different levels of data delivery guarantees.

- *Advanced Message Queuing Protocol (AMQP)* is a binary, application layer protocol designed to support a variety of messaging applications and communication patterns. Similarly to MQTT it provides delivery guarantees such as at most once, at least once, and exactly once. It suggests authentication and/or encryption based on SASL and/or TLS [23]. Developed for banking applications it is now finding its way also to industry.
- *Data Distribution Service (DDS)* is a data-centric middleware standard designed for mission-critical systems. It provides the real-time, many-to-many, managed connectivity required by high-performance machine applications. It can efficiently deliver millions of messages per second to many simultaneous receivers. The QoS is taken seriously in DDS. There are more than 20 QoS parameters, covering reliability, volatility, liveliness, resource utilization, filtering and delivery, ownership, redundancy, timing deadlines, and latency [24].
- *IEC 62541 OPC Unified Architecture (OPC UA)* is the successor of very popular OPC which dates back to 1996. OPC UA is recommended as one of the standards that meet the requirements of both the IIRA and RAMI 4.0. It is providing complimentary services to established industrial automation protocols and is used mainly for distribution of data from processes amongst the factory systems. The idea of OPC UA is centered on object models with the aim to provide a standardized approach to address event handling, security, information modeling, and standard interfaces. Initially it was designed as producer-consumer architecture, but the emergence of chips with integrated OPA UA or implementation of publish-subscribe protocol makes OPC UA hot candidate to be used in (not only Industrial) IoT applications [25].
- *IEC 61499 Functions Blocks* enhances the traditional scan-based execution of Programmable Logic Controllers (PLC) with an event-based execution model and a distributed control architecture. IEC 61499 can be seen as an extension to common IEC 61131-based PLC systems addressing the needs of IIoT systems and devices [26].

III. Power and Energy Systems

A. Overview of the Domain

Several change drivers are causing a fundamental shift in energy management practices in the electric power grid which include: *(i)* growing demand for electricity, *(ii)* new regulation and legislation supporting renewable energy resources, *(iii)* the emergence of electrified transportation, *(iv)* deregulation of electric power markets, and *(v)* innovations in smart grid technology [27]. Perhaps nowhere will the impact of the energy management change drivers, identified in the previous chapter, be felt more than at the grids periphery. Distributed generation in the form of solar Photovoltaics (PV) and small-scale wind will be joined by a plethora of Internet-enabled appliances and devices to transform the grids periphery to one with two-way flows of power and information [28], [29].

B. Trends and Developments

From the digitalization point of view in following major trends and developments in the power and energy systems domain are discussed.

1) Automation with Energy Internet of Things: This work argues that the challenges of activating the grid periphery maybe addressed by deploying the Energy Internet of Things (EIoT) as a scalable energy management solution. In essence, energy management may be viewed as a control loop where dispatchable devices, be they traditional large-scale centralized generators or millions of small-scale Internet-enabled devices, must meet the three power system control objectives: balanced operation, line congestion management, and voltage control. These objectives can be achieved despite the presence of disturbances like customer load or variable energy generation from solar PV and wind resources. Fortunately, EIoT is fundamentally a control loop consisting of small-scale sensing technologies, wireless and wired communication, distributed control algorithms, and remotely controlled actuators. And yet, despite EIoT having all of the components of a scalable energy management control loop, the challenge is to continue to integrate more of these technologies in a such a fashion that the control objectives are achieved well into the future.

Figure 3 serves to guide the discussion of the EIoT concept as a networked control loop where a strong development of ICT has converged with the electric grid [30], [31]. Such a structure is consistent with the Strategic Research Agendas (SRAs) of European Research Cluster on the Internet of Things (IERC) and later the Alliance for Internet of Things Innovation (AIOTI) [32]. Here, the EIoT is depicted as a three-layer architecture [33]. The physical layer consists of physical devices with their associated network-enabled sensors and actuators. The network layer consists of complementary access and core networks. Finally, the application and control layer support the physical and business objectives of energy management [34].

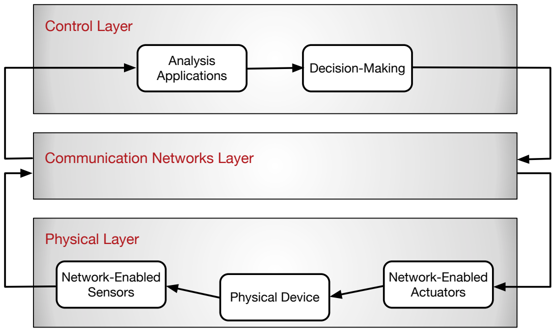

Fig. 3. The development of IoT within energy infrastructure as networked control loop [27].

2) Network-Enabled Physical Devices: In many ways, the development of network-enabled physical devices forms the heart of EIoT. Here, it is important to appreciate the tremendous heterogeneity and relative placement within the electric power system. EIoT extends well beyond network-enabled devices that measure and actuate traditional primary electric power system variables in the transmission system. They also include devices that monitor and control secondary variables associated with wind, solar, hydro, and natural gas generation so as to bring about the new challenges of variable energy integration, the energy-water nexus, and interdependent energy infrastructures. The distribution system is also incorporating new devices such as smart meters and other "grid modernization" technologies. Finally, the distribution system has it own set of demand-side secondary variables that describe the physical behavior of smart homes, buildings, and industry. Within the home, these include "smart" versions of traditional electrical items (outlets, switches, appliances, etc.) as well as electrified versions of traditional non-electrical devices (electric vehicles, water and space heating, etc.). These many devices vary tremendously in size, power consumption, use case, and on-board computing.

3) Network Layer: This tremendous heterogeneity of network-enabled devices demands several complementary and mutually co-existing communication networks. Traditionally, the power system has used proprietary networks within the jurisdiction of grid operators and utilities. These transmitted data over wired networks (e.g., power line carrier & fiber optics) as well as wide-area wireless networks such as SCADA (supervisory control and data acquisition). However, with "grid modernization", telecommunication networks are increasingly playing a role. Cellular data networks, and in particular 4G and LTE, have the potential to transmit relatively high bandwidth across long distances. Furthermore, WiMax networks can provide connectivity at the grid periphery at the neighborhood length-scale. Finally, a large part of EIoT will require private area networks; be they wired Ethernet, WiFi, Z-wave, ZigBee or Bluetooth. Naturally, industrial energy management applications will continue leverage preexisting industrial Internet infrastructure in addition to these private area network options.

4) Application and Control Layer: The application and control layer is responsible for achieving technical and economic objectives of energy management. Whereas traditionally, power systems operations and control has relied on *centralized* algorithms in market operation and *decentralized* algorithm for real-time control, EIoT-based control relies on *distributed* control algorithms. In this regard, physical devices will not just have their digital counterparts with their associated IP address and *agent* but will also have the ability to communicate and coordinate with other agents in *multi-agent system algorithms* so as to achieve these objectives [35]. Perhaps the earliest works on the multi-agent systems in power systems were focused in modeling electricity markets in a deregulated power industry [36], [37]. Agent-based applications then diversified to various aspects of power systems control and operations such as balancing, scheduling, line control and protection, and frequency and voltage regulation [38], [39]. Finally, as discussion of an activated grid periphery has developed in the smart grid literature, several multi-agent system framework have been developed to provide self-healing mechanisms for microgrids [40] and some have even demonstrated resiliency of such microgrids under several reconfigurations [40]. While this area of EIoT has received a significant attention, significant theoretical and applied research is required to bring distributed control algorithm into mainstream practice.

C. ICT Interoperability and Standardization

The implementation of EIoT as an automated solution rests upon a significant effort to develop effective standards. Early on, initiatives were launched at national, European and international levels [41], [42]. For example, important standards have been identified at European level under Mandate M/490 [43] as outlined in Figure 4. The topic has also been addressed in the work of standardization organizations such as IEC [44], IEEE [45], and NIST [46]. These work have led to improved interoperability in EIoT.

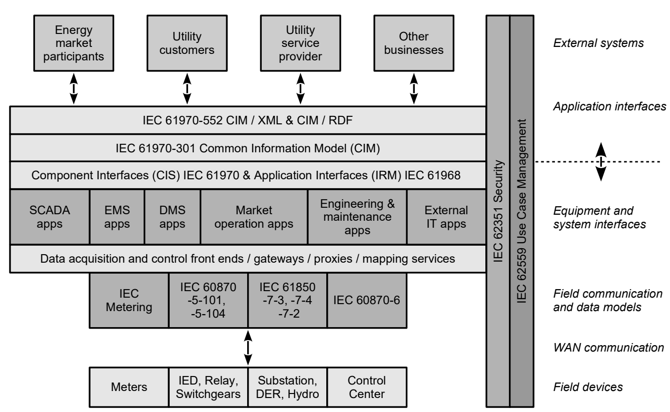

Fig. 4. Overview of important EIoT standards (adopted from [47]).

In particular, the following EIoT standards are directly relevant [47], [48]:

- *IEC TR 62357 Seamless Integration Architecture (SIA)* aims to provide a framework for current energy-related ICT approaches of IEC TC 57. For this purpose, they are related to each other and combined within the framework of a reference architecture for the identification and resolution of inconsistencies between the standards to obtain a seamless framework.
- *IEC 61970 Common Information Model (CIM)* specifies a domain ontology, i.e., it provides a kind of knowledge-base with a special vocabulary for power systems. One goal is to support the integration of new applications in order to save time and costs and another one to facilitate a simple exchange of messages in multi-vendor systems. The IEC offers an integration framework based on a common architecture and data model. In addition, the architecture is platform independent. The main application of IEC 61970 is the modeling of topologies.
- *IEC 61968 Distribution Management* extends CIM for Distribution Management Systems (DMS). These extensions relate in particular to the data model. The main use case is the exchange of XML-based messages. For this, further use cases for different DMS are specified.
- *IEC 62325 Market Communications* is also an extension to CIM where the data model and messages are extended. However, the focus here is on market communication for EU and US-style electricity markets.
- *IEC 62351 Security for Smart Grid Applications* addresses ICT security for power system management with the goal to define a secure communication infrastructure for the environment of energy management systems with end-to-end security. This implies that secure communication is specified for protocols used in IEC 61970, IEC 61968 and IEC 61850.
- *IEC 61850 Substation Automation and Distributed Energy Resource (DER) communication* focuses on the communication and interoperability at device level. The focal topics are the exchange of information for protection, monitoring, control and measurement, the provision of a digital interface for primary data and a configuration language for the systems and devices. This is implemented by a hierarchical data model, abstractly defined services, mappings of these services to current technologies and an XML-based configuration language for the functional description of devices and systems.
- *IEC 62559 Use Case management* deals with a steadily increasing system EIoT complexity and number of players as well as disciplines. In such a complex system, use cases help to structure and organize all relevant information for a technical solution. Therefore, in IEC 62559 five phases are identified for the development of use cases and the identification of requirements. On top of this, a description template is also provided, containing a narrative and visual representation of the use case.

Also under the EU mandate M/490, the Smart Grid Architecture Model (SGAM) was developed (see Figure 5. Shortly described, it is a structured approach for modeling and design of use cases for power and energy systems. Its basis is a three-dimensional framework consisting of domains, zones, and layers. These allow the engineer to structure the use case design in a clear and concise way. The original goal of this reference architecture was to identify standardization needs in EIoT applications/smart grids.

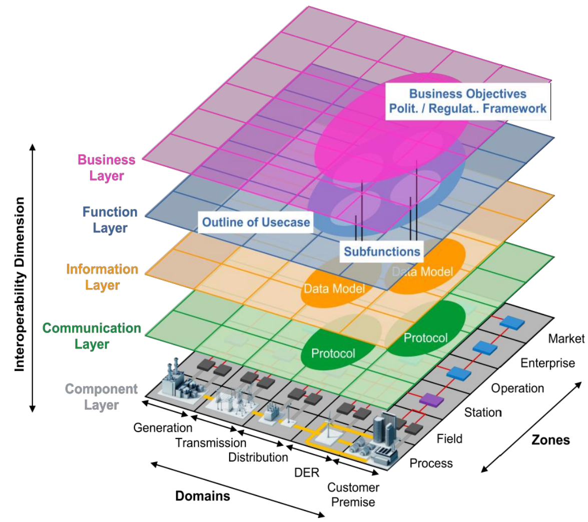

Fig. 5. Reference Architecture for EIoT (SGAM) [49].

However, it has been further developed to design architectures for technical solutions. Therefore, the SGAM was combined with the use case methodology from IEC 62559. A field of application is given by the fact that the design of future energy automation and management systems requires system operators/energy utilities to analyze and compare different technical solutions for determining which of these could be best implemented in their networks [50].

Moreover, also approaches from IIoT domain like MQTT, OPC UA, or IEC 61499 getting attention from the power and energy systems domain.

IV. Discussion of Future Needs and Research

Despite ongoing research, development, and standardization in the manufacturing domain and in power and energy systems as discussed above there are still room for improvements and further research in order to address challenging future needs and requirements. In particular the following fields of improvements can be identified.

A. Enhanced Machine-to-Machine Communication

The machine-to-machine communication in mission critical IoT applications require a *deterministic messaging* on standard Ethernet. Technologies such as Time Sensitive Networking (TSN) as defined by IEEE 802.1Q will attract attention to provide guarantees of delivery and minimized jitter using time scheduling [2]. Also the integration of proper information and data models in such TSN networks is still an open issue. The combination of OPC UA together with TSN approaches seems to be a proper choice.

B. Cyber Security

Cyber security is is an important aspect for IIoT solutions but also for critical infrastructures like EIoT. The goal is to deal with requirements for trust in communication entities and transferred data [51]. It is both hardware security at the level of IoT devices as well as software security to guarantee end-to-end message encryption and authorization & authentication of devices, users, and services.

C. Handling of Big Data and Data Analytics

The handling of big data streams from networked sensor, actuator, and control devices is another hot topic in research and development [52]. Compared to traditional systems, there is a tremendous increase in collected data which need to be collected, pre-processed, and stored on the one hand side in real-time or near real-time on the one hand side but they have to be analyzed and processed on the other side. Proper approaches which are suitable for industrial environments need to be developed. Combining big data handling solutions with corresponding data analytics methods and corresponding algorithms is still a highly challenging field of interest.

D. Enhanced Engineering Methods and Tools

The previously mentioned digitalization trends are leading to fundamental changes in operating manufacturing plants and power and energy systems. As a consequence, also the implementation and deployment of these solutions and corresponding applications is changing. Plant operators, utilities, component vendors, software and service providers, and other stakeholders are confronted with an increasing engineering complexity, resulting in higher engineering costs and development time. The provision of proper engineering approaches, development methods, and corresponding tools will reduce the engineering complexity, safe time and money. As an attempt to improve existing engineering solutions, the use of Model-Driven Engineering (MDE) for automation is one research trend that can be observed during the recent years. A number of approaches use MDE to improve the specification and design process, together with support for requirement identification [53]–[55].

E. Interdisciplinary Training and Education

Besides the above outlined technical research and development trends there is also an urgent need for well educated researchers and engineers which are able to understand challenging problems in the domain of industrial systems from an interdisciplinary point of view [56], [57]. Future curricula and training activities need to take care to teach the interdisciplinary aspects of IIoT (i.e., understanding of mechanical, electrical, ICT/IoT, automation and control topics) or EIoT (i.e., understanding of electrical/power, ICT/IoT, control and optimization topics) approaches and solutions but they need to take also care on cyber security and big data issues.

V. Conclusions

Technology development in the domain of ICT provide new possibilities. Approaches like the IoT approach where a huge number of devices are nowadays connected together via Internet-based services and functions are being increasingly used in industrial environments like in the manufacturing domain or in power and energy systems.

This paper provided an overview of ongoing research and developments in the aforementioned areas with a focus on digitalization applying the IoT concept. From this survey it can be concluded that industrial systems are moving in the same direction; IoT approaches, concepts, technologies, and solutions are becoming more commonly used. This provides a tremendous set of new possibilities and new services and business models are on the way to be developed.

However, there is still room for future research and technology developments. Interesting and promising fields of research are related to *(i)* enhanced machine-to-machine communication, *(ii)* cyber security, *(iii)* handling of big data and data analytics, as well as the *(iv)* provision of proper engineering approaches and tools. Besides of those technical issues a focus need to be put also on the interdisciplinary training and education of researchers and engineers in order to keep track in a digitalized world.

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