Digitalization possibilities and the potential of the Digital Twin for steam supply systems

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Kurzfassung

Möglichkeiten der Digitalisierung und das Potenzial des Digital Twin für Dampfversorgungssysteme

Digitalisierung führt zu einer weiteren Revolution industrieller Prozesse und eröffnet völlig neue Anwendungsmöglichkeiten. Die Zukunftsvisionen von Industry4.0 und Energy4.0, wie sie in dieser Arbeit zusammengefasst sind, zeichnen ein Bild beispielloser Vernetzung von Gegenständen und Dienstleistungen im Internet of Things. Sie versprechen einen noch nie dagewesenen Grad an Vernetzung, Flexibilisierung und Automatisierung von Produkten und Systemen, sowie enorme Potenziale zur Senkung von Kosten und Energieverbrauch sowie zur Steigerung der Nachhaltigkeit.

Als Auszug aus dem VGB-Forschungsprojekt DigiSteam, werden in diesem Beitrag die vielversprechendsten Möglichkeiten der Digitalisierung evaluiert und der Zusammenhang mit dem Konzept von Referenzarchitekturen, wie RAMI4.0, mit Fokus auf den Dampferzeugungssektor untersucht. Unter Anwendung der hier thematisierten theoretischen Grundlagen wird eine Adaption eines fünfdimensionalen Modells für einen Digitalen Zwilling von einem Dampferzeuger präsentiert, bestehend aus physikalischem Dampferzeuger, Kommunikationsmodell, virtuellem Dampferzeuger, Datenmodell und Servicemodell. Ein ganzheitliches Prognose- und System Health Management werden illustriert und Anwendungsfälle zeigen, dass die Systemüberwachung, -vorhersage und -optimierung stark verbessert werden kann.

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Digitalization is more and more becoming part of industrial processes and opens up completely new application areas. The visions of Industry4.0 and Energy4.0, as summarized in this article, both paint a picture of an unprecedented level of interconnectedness of devices and smart services in the Internet of Things. Systems and products will be created that have a high degree of networking, flexibility and automation. Because of these features, they have a huge potential for reducing cost, energy consumption and for improving economic sustainability.

In this article, as an excerpt from the VGB research project DigiSteam, the most promising possibilities offered by digitalization are evaluated with special focus on the steam supply sector. The connection with the concept of reference architectures, such as RAMI4.0, is discussed and the Digital Twin is introduced. Based on these theoretical fundamentals, an adaption of a five-dimensional Digital Twin model to a steam generator is presented. It consists of physical steam generator, communication model, virtual steam generator, data model and service model. A holistic Boiler Prognostics and System Health Management is outlined and with use cases, it is shown that system monitoring, prediction and optimization can be greatly improved by employing this Digital Twin.

1. Introduction

We are currently in the middle of what is often referred to as the fourth industrial revolution or *Industry4.0* (I4.0). Driven by the rapid development of Information and Communication Technologies (ICT), the integration of digital technologies is advancing rapidly in every industry sector, not least the energy sector. For the energy industry, new and more advanced technologies are becoming available that will heavily affect energy generation, transmission, distribution, storage, and even its consumption. These new technologies come at just the right time because they provide the tools to cope with the challenges that have emerged through the energy transition: changes in the regulatory framework, such as the liberalization of the energy market, and the increase of renewable and decentral energy generation. But these new technologies are not only a way to cope with challenges ahead, they also have great potential for increasing energy efficiency, reducing cost and even to generate completely new business models [1-3]. While some researchers warn that digitalization could increase energy consumption due to subsequent rebound effects and economic growth [4, 5], most researchers and organizations agree on the huge potential for reducing energy consumption and for increasing economic sustainability [2, 6-8]. In this way, digitalization can contribute immensely to meeting the increasingly stringent CO_2 reduction targets [2]. Just like any other revolution, I4.0 and the energy transition may be a threat or an opportunity. One way or the other: digitalization will heavily affect the energy sector and business actors have to carefully navigate this transition [8-10].

Within the energy sector, steam supply systems are of major importance. The growing demand for power plants and power generation processes has been fueling the demand for steam boiler systems substantially [11]. Digitalization technologies might be the key to unlock untapped optimization potential in steam supply systems, by supporting the optimal integration of technologies and utilization of infrastructure. For this reason, the VGB Research Foundation (https://www.vgb.org/en/vgb_research.html) has commissioned two parallel research projects in 2019 to take a close look at digitalization in the energy sector. *DigiPoll@Energy* [12] was conducted at the University of Duisburg-Essen (UDE). They assessed the current situation in industry regarding digitalization in the energy sector and expectations of industry leaders. *DigiSteam* [13] was carried out at TU Wien with the goal to identify opportunities through digitalization in the energy sector, especially in the field of steam supply systems. In that project, digitalization methods and their expected effect were assessed, and reference architectures, such as the Reference Architecture Model 4.0 (RAMI4.0), were evaluated. The Digital Twin (DT) was identified as one of the most promising digitalization applications to date. In this article, we present the most relevant results of the project *DigiSteam* and highlight our main findings.

2. Digitalization and Industry4.0

The aim of this section is to present a definition of and a broad overview on digitalization and digital technologies, as well as a discussion of the terms *Industry4.0* (I4.0) and *Energy4.0* (E4.0). Furthermore, reference architecture models are evaluated which provide the basis for successful implementation of I4.0 concepts.

The term *digitization* generally refers to the conversion of analogue data into a digital form. For the term *digitalization*, on the other hand, there is neither a universal definition nor is it used consistently. From a socio-economic perspective, the aim of digitalization is not only to convert analogue to digital signals but also to create value using digital content [14]. Digitalization also describes the connection between business processes, creation of efficient interfaces, and integrated data exchange and management [15]. In the context of industrialization, digitalization describes the transition to new, disruptive business cases driven by evolving Information and Communication Technologies (ICT), the automation and flexibilization of business operation and the interconnection of information, things and operatives [10]. Business models are already changing to take into account the increasing share of digital technologies as smart services [16]. In the present article, digitalization is seen in the context of industrialization. In our understanding, it refers to a more fundamental change than just digitizing existing processes or work products. To emphasize this fundamental change, the term *digital transformation* is also often used, especially if the change is happening on multiple levels, including the process level, organization level, business domain level and society level [9].

The term *Industry4.0* (I4.0) was first introduced in Germany in 2011, referring to the Fourth Industrial Revolution. In that sense, it is essentially equivalent to the definition of the digital transformation given in the previous paragraph. Just as with digitalization, there exists no universal definition of this term. However, I4.0 can be characterized in the following way [17]:

– The dynamic connection of internal and external data sources and
– the automated analysis and processing of thereby generated information
– for demand-driven preparation or control of processes,
– located at different points in the value chain of an industrial company,
– to make them faster, cheaper, customer-oriented, more efficient, resource-saving and flexible.

In analogy to I4.0, E4.0 characterizes the transition to energy systems of the fourth generation. These energy systems will be based on renewable, volatile energy carriers, a high amount of flexibilization, and interconnection between different industry sectors. Furthermore, they feature extensive application of digital technologies. The declared goal of E4.0 is to exploit efficiency- and flexibilization-potentials in processes to optimize the conversion, distribution and consumption of energy [18].

2.1 Digital (Enabling) Technologies of I4.0

Digitalization and consequently I4.0 are driven by recent developments within the area of digital base technologies. These technologies are also often referred to as *(key) enabling technologies*. Typical examples include next-generation sensors, Big Data, Machine Learning (ML), Artificial Intelligence (AI), the Internet of Things (IoT), Smart Services, Mechatronics and Advanced Robotics, Cloud Computing, Cyber Physical Systems (CPS), Additive Manufacturing, Digital Twins (DT), and Machine-to-Machine (M2M) communication [2]. Enabling technologies can both be implemented in new plants and retrofitted to existing plants. Out of the large number of key enabling technologies, we are going to focus on the four most relevant and address them in more detail: IoT, CPS, Big Data and AI or ML.

The backbone of every digital application in I4.0 is a (global) networking infrastructure. This role can be assumed by the IoT, which is defined as an interconnected world, where electronic sensors, actuators, and other digital devices are networked and connected with the purpose of collecting and exchanging data [19]. Other definitions also include features such as self-configuring capabilities, interoperable communication protocols and virtual personalities of "things" in the definition of IoT (Internet of Things European Research Cluster (IERC), Brussels: http://www.internet-of-things-research.eu; Internet of Things European Research Cluster (IERC), Brussels: http://www.internet-of-things-research.eu). Especially in the energy sector, an IoT based online monitoring system has a big potential, as has been demonstrated, for example, in a steel casting production line [19]. Most importantly, the IoT also satisfies elementary demands for the implementation of a DT [20].

The IoT also enables the creation of CPS, which connect the virtual space with the physical realityand integrates computing, communication and storage capabilities. A CPS works in real-time and it is reliable, secure, stable and efficient [21]. The core concepts of a CPS are computation, communication, and control. The goal is to achieve collaborative and real-time interaction between the real world and the digital world through feedback loops and the interaction between computational processes and physical processes [21]. The bi-directional connection between the real and the digital world also provides the foundation for a DT [22], as will be explained in more detail later.

Big Data describes ways of leveraging data rather than the data itself. It is maybe the most prominent enabling technology of all. It has even been claimed that "the world's most valuable resource is no longer oil, but data". Big data is usually defined by the five Vs: Volume, Velocity, Variety, Veracity and Value [23, 24]. *Big Data analytics* refer to techniques used to examine and process Big Data in a way that hidden underlying patterns are revealed, relationships are identified, and new insights concerning the application under investigation are generated [23]. The term Big Data is also interpreted as the ability to quickly acquire hidden value and information from heterogeneous and large amount of data [25]. Without doubt, there are numerous possibilities for leveraging Big Data, not least in the energy sector, where direct measurement of key process variables is extremely difficult, nearly impossible or simply unreliable [26-28]. Here, Big Data can help to monitor these key processes with higher accuracy. In this context it is often also referred to as Smart Data [29].

Automated methods to extract information from Big Data are ML or AI, among others. Often used synonymously, ML can be seen as a subset of AI that focuses on training a machine on how to learn [3]. ML technologies are related to pattern recognition and statistical inference. A ML model is capable of learning to improve the performance of a task, based on its own previous experience. While ML rather aims the creation of knowledge from experience (historic data), AI can more generally be defined as the attempt to create a human-like, cognitive intelligence with the ability to learn and to solve problems on its own [30]. AI and related technologies can enhance resource efficiency in industrial processes, which is a crucial factor for a successful realization of I4.0 [31]. Although AI and ML approaches are rather new and not yet mature, many industrial applications already exist. A review of such applications in the Austrian energy industry is given in the White Paper "Digitalization in Industry - an Austrian Perspective" [3].

2.2 Implementation Concepts and Reference Architectures

The realization of I4.0 and E4.0 is a complex design task, because the gradual integration of new technology in this complex overall framework must be seen in a holistic context. This requires intensive cooperation between experts of different disciplines such as electrical engineering, mechanical engineering and information technology (IT). Reference architectures provide common and consistent definitions of the system of interest, its compositions, and design patterns. Additionally, they provide a common terminology to discuss the specification of implementations [32].

In 2012, the Smart Grid Coordination Group published the Smart Grid Architecture Model (SGAM) [33], with the aim to establish a reference designation system to describe business cases as well as smart grid technical use cases. While SGAM was designed with the electrical energy sector in mind, the Reference Architecture Model 4.0 (RAMI4.0), a similar but more universal model was defined and presented by *Plattform Industrie 4.0 (https://www.plattform-i40.de)* in 2015 [34]. To achieve a common understanding of standards, tasks and use cases, three different aspects (dimensions) are combined in the RAMI4.0, as depicted in Figure 1. RAMI4.0 expands the hierarchy levels of IEC 62264, by Product and Connected World, defines six layers for an IT representation of an *Industry4.0* component, and considers the life cycle of products/systems according to IEC 62890 (http://i40.semantic-interoperability.org/). For a detailed description of the RAMI4.0, see, for example, [34, 35].

RAMI4.0 allows for step-by step migration of technology from the present industrial stage into the world of I4.0 [36], by breaking down tasks and workflows into manageable pieces [3]. The three dimensions support new technologies, applications and use cases in industry. Smart Services and their functional enhancements in the energy sector can easily be extended and used by a variety of other applications at different layers of the RAMI4.0 [37]. Furthermore, current and future standards and services can be located in RAMI4.0 to identify overlapping as well as missing standardization efforts.

Based on expert interviews in a recent study [38], the main fields for future potential in the energy sector were identified: (1) increasing transparency in the energy system, (2) flexibility in energy supply an (3) increase of energy efficiency [38]. According to that study, RAMI4.0 and SGAM can help to keep track of the complex design task of realizing E4.0 and focus on appropriate norms and standards. However, some pitfalls of RAMI4.0 were determined when applying it to an industrial reference use case [39]. It is clear that a more dynamic framework will be necessary to exploit the main fields for future potential during operation of energy systems.

3. The Digital Twin

Prominent concepts like *Industry4.0* (I4.0) or *Energy4.0* (E4.0) evoke a vision of the future industry and energy system, where enabling technologies are used extensively. They promise an unprecedented degree of networking, system flexibility and automation. The key is the consequent integration of the real/physical world with the virtual/digital world. While RAMI4.0 is a useful tool to identify areas where deeper integration is necessary, it cannot be used to do the actual integration. For this task, the Digital Twin (DT), as a high-fidelity digital mirror of its physical counterpart, is a promising concept to reach this convergence of the physical with the digital world. For this reason, the DT is considered a key technology for implementing the digital future in I4.0 and E4.0 [40, 41].

3.1 Review and Definition

The idea of the DT originates from an earlier concept of a physical twin, which was introduced by the American space agency NASA during the Apollo space program while testing operations on a replica on earth. Only in 2012 the concept was picked up again by NASA and continued under the name Digital Twin [42]. Since then, an al-

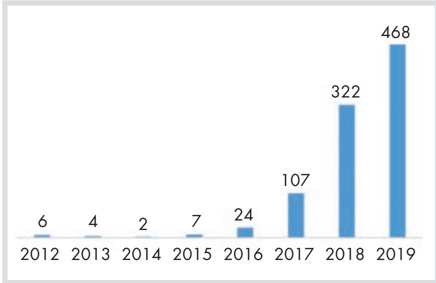

Fig. 2. Scientific Publications on DT from 2012 to 2019 (for more details, refer to the project report DigiSteam [13]).

most exponential increase in the number of scientific publications on DT has been recorded, as an extensive literature review [13] shows (see Figure 2).

In NASA's definition, the DT is a multiphysics, scalable and probabilistic image (simulation model) of a physical object or system that is used to map certain aspects of the real object, taking into account historical and real-time sensor data. However, there remains some controversy about the exact definition of the DT. There is a wide consensus, that also the bidirectional data exchange between physical and digital object in real time is a prerequisite for a DT [43].

After the DT concept was adopted by NASA (https://www.nasa.gov) in 2012, research and development on the DT was mainly driven forward in the field of aviation [44]. In recent years, the DT has found its way into more and more industry sectors, such as automotive, oil & gas and healthcare & medicine [45]. In 2018, DT was listed on top of the „Gartner-Hype-Cycle" (https://www.gartner.com), and the time in which DT is used as an applied concept within companies, has been put at 5 to 10 years.

With the rapid growth of the Internet of Things (IoT) and other Information and Communication Technologies (ICT), a large number of application possibilities, such as energy optimization, performance tuning, predictive maintenance and product optimization have been suggested. However, in order to make the most of these individual, already existing possibilities, a holistic approach is required. Here, the excellent scalability of the DT offers many benefits over the entire life cycle of an asset [46].

Despite the large number of promising approaches proposed in literature, a general lack of in-depth research on DT modeling is evident. Additionally, modeling methods for DTs are very heterogeneous, sometimes even inconsistent. In a recent literature review, the lack of a uniform modeling method was found to be very critical [47]. Thus, while DT implementations are considered to have huge potential, there is an urgent need to standardize interfaces and communication protocols, as well as a need for uniform DT modeling approaches to enable its practical introduction into industrial energy systems.

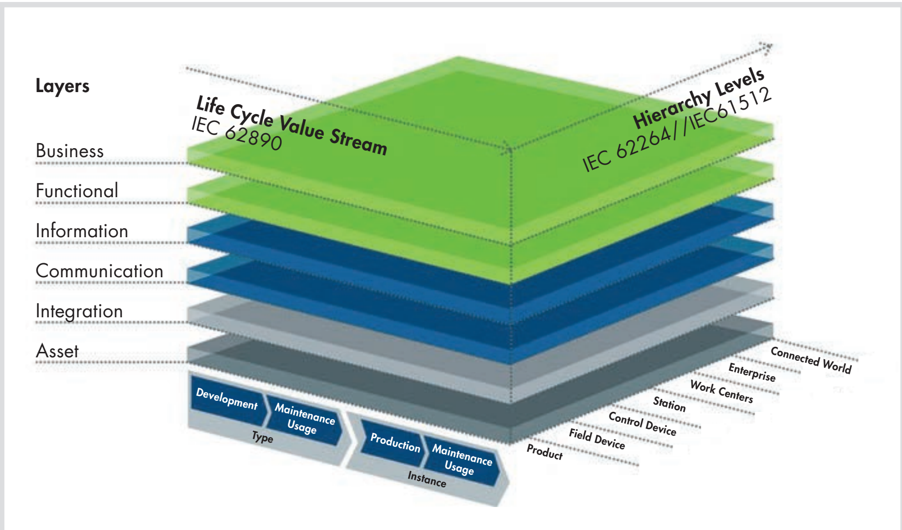

Fig. 1. RAMI4.0 [© Plattform Industrie 4.0, reproduced with permission].

3.2 Modelling Framework

To unify modeling of DTs, modeling frameworks have been introduced. An early DT modeling framework is the one by Grieves [48]. It is characterized by a three-dimensional approach (3D-DT), where the DT is described by the following three dimensions:

– The physical unit, i.e. the physical object or system, in the real world,
– the digital unit or system in the virtual world, also called virtual entity, and
– the connection between physical and digital entities through data and information.

This framework is very similar to the definition of a CPS (see Section). However, these dimensions do not present the extent to which new types of services are made available in this concept. Furthermore, data and information only act as connection between the real and virtual world. How this data is processed and the extent to which information can be retrieved from it is not made explicit. The rapid development of enabling technologies, omnipresent availability of data, and the need for services are the main reasons, why an extension of Grieves' 3D-DT framework was necessary [48, 49]. In order to prevent the pitfalls of unspecified data processing and restricted usability/servication, the model was extended by the following two dimensions by Tao et al. [50] to arrive at the 5D-DT:

– The data model, in which data from all sources is collected, managed and processed into usable information.
– The service model contains services resulting from the functionality of the DT and makes them available to the user of the DT.

With the help of the bidirectional connection and closed loop between physical and virtual space in the 5D-DT modeling approach, all components can be optimized and a significant increase in the physical object's performance can be achieved through the implemented services. The 5D-DT approach has recently been praised for its usefulness and generality in a number of contributions [20, 49-53]. In these publications, a wide range of use cases has been demonstrated and evaluated as well.

4. The Digital Twin of a Steam Generator

In this section, a digitalization concept based on a DT tailored to steam generation applications is presented. Applying the theoretical fundamentals and basic definitions that were assessed in the project *DigiSteam* [13] and outlined in the sections above, a five-dimensional DT-Model (5D-DTM) for a steam generator is outlined and discussed. A steam generator, as one of the most important thermal energy supply systems, is directly affected by the paradigm shift in

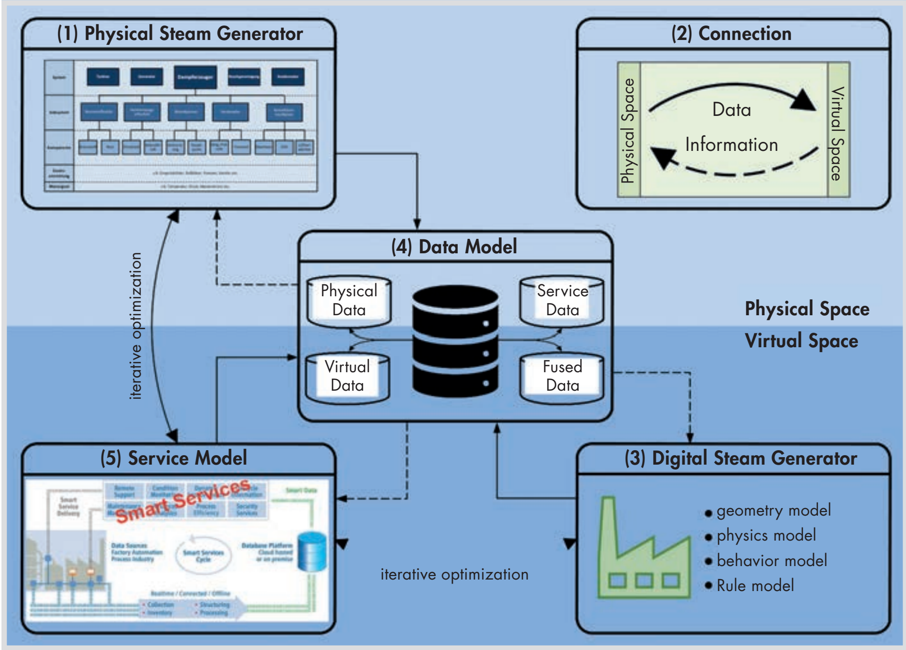

Fig. 3. 5D-DT model of a Steam Generator, adapted from [50]. The Physical Steam Generator (1) in the physical space is linked via the Connection dimension (2) to the virtual space, which consists of the Digital Steam Generator (3), i.e. virtual entity, the Data model (4) and the Service model (5).

Industry4.0 and *Energy4.0*. Steam generators will have to work in increasingly dynamic settings, which frequently leads to off-design conditions. For system operators, increasingly frequent load changes pose a great challenge to retain the economic operation of their systems [54]. Therefore, these difficult conditions are ideally suited to illustrate the advantages of a DT.

To illustrate the value creation by employing a Digital twin, a Smart Service system based on the 5D-DT concept is outlined: a holistic Boiler Prognostics and System Health Management (Boiler-PHM). It is shown that the system monitoring, prediction and optimization can be greatly improved. Figure 3 illustrates the 5D-DTM, based on the approach first presented by Tao et al. [50]. The DT consists of:

– Physical steam generator (i.e. physical entity)
– Connection between the respective dimensions (i.e. communication model)
– Digital steam generator (i.e. virtual entity)
– Data model
– Service model

Each aspect of modelling this 5D-DT is discussed in the following subsections. In Section 4.6 a demonstrative use cases and an economic evaluation is presented. A more in-depth treatment of this topic can be found in the final report of the *DigiSteam* project [13].

4.1 Physical entity

The physical entity consists of all functional subsystems and any physical sensor/actuator technology that is built into the steam supply system.

4.2 Communication model

The communication model in a 5D-DT fulfils the basic task of establishing connections between all other parts of the model, most importantly between the real and virtual space. It is only through this bidirectional communication infrastructure that the 5D-DT has the ability to access data from the physical entity and process it digitally to obtain relevant information. Essential characteristics of the communication model are real-time capability, integration of heterogeneous end-devices, scalability and security [55].

Exemplary communication infrastructures for I4.0 and Digital Twins based on IoT technology are given in [56, 57]. The use of open communications standards for industrial automation, notably OPC Unified Architecture (OPC UA) are highly encouraged in literature. OPC UA also provides the basis for further information modeling in the data model.

4.3 Virtual entity

The virtual entity of the DT is a high-fidelity representation of the physical entity. The virtual entity reproduces the geometry, physical properties, behaviours and rules of the physical entity in the virtual world [50]. The coupling of these four sub model classes is used to form a complete mirror image of the physical entity. In addition to this division in sub model classes, a modular modelling approach can be applied to reduce complexity of the virtual representation and increase the flexibility and scalability of the virtual entity. An example for such a modular design would be a hierarchical structure consisting of the system level, sub-system level, component level, auxiliary equipment and signal (sensor) level.

The geometric model of a virtual entity is commonly modelled based on 3D Computer-aided Design (CAD) models. Even though no functional properties or restrictions are stored in the geometric model, it serves as foundation for the physical, the behaviour and the rule model of the steam generator. These, in turn, serve to represent physical processes, state-specific behavioural patterns and the control behaviour of the entire steam generator system. These models combined must be able to represent all possible influencing variables and their interactions as well as the control behaviour of the system.

Three categories of simulation models can be distinguished [58]:

- White-box models uses a well-known physical relationship in mathematical form to describe a certain behavior.
- Black-box models, also known as (purely) data-driven models, are built on data only, without exploiting any physical knowledge.
- Grey-box models combine physical knowledge and empirical data, which often yields excellent results in practice [3, 58].

Typically, a combination of these simulation model categories is used with higher-level optimization models to create the functionality of the virtual entity.

4.4 Data model

In the data model, also known as information model or knowledge representation, static data for the description of different attributes of the physical entity is provided and dynamic status and operational data is processed. The heterogeneity of DT data, which is caused by the combination of different data sources working on different timelines, poses a big challenge for DT operation. Furthermore, a DT must be capable of extracting specific domain knowledge from experts or from existing data and making it accessible [59]. Therefore, DT need interpretable reliable data in standardized machine-readable formats [60]. With the help of the data model, anything from plain sensors to complex plants can be described in an semantically meaningful way [61].

To fully exploit the potentials of CPS, IoT and DT, proper data models should be employed, such as ontologies [62, 63]. Ontologies are explicit, semantic and formal representations of the relationships between concepts, data and entities in a domain [22]. They are the core semantic technology that provide intelligence embedded in the smart CPS [10] and can facilitate the integration of large amounts of data from various sources [64].

4.5 Service model

Digital transformation is driving I4.0 towards a service-oriented Product-Service-System. As a consequence, services in general and especially services related to physical products play an increasingly important role [65]. Users of the DT come from various industries with different technical requirements. This poses a challenge for the effective interaction between the DT and users/stakeholders. To solve the problem of interoperability and to enable innovative business models, the functions of the DT can be encapsulated into standardized services with user-friendly interfaces for easy and on-demand usage [49].

The service model includes services for physical and virtual entity. It optimizes the operation of the physical entity, and ensures the high fidelity of the virtual entity through automatic parameter adaptation during run-time. In general, services can be grouped into four basic types:

- Functional service: these define core business operations
- Enterprise service: these implement the functionality defined by the functional services
- Application service: these are confined to specific application content
- Infrastructure service: implements non-functional tasks such as authentication, auditing, security, and logging

More in-depth reviews of services and application scenarios can be found in [22, 66, 67]. Smart service architectures should provide interoperability by acting as foundation for data integration and data exchange between various applications as part of the DT functionality. Smart service architectures were, for example, proposed by the German electrical and electronic manufacturers association (ZVEI) [68] and in [37]. Therefore, the use of an ontology-based smart service architecture is highly encouraged for complex physical systems such as a steam generator.

4.6 Use Cases and Economic Evaluation

The DT can create value in all stages of the steam generator's live cycle: starting in the design phase, during product manufacturing and also in the operation and maintenance (o&m) phase [53]. A detailed discussion of many use cases can be found in the *DigiSteam* report [13]. In this article, we focus on value creation in the o&m pase, because it plays a particularly important role for steam generators.

Steam generators are designed to maintain a functional and efficient state over long periods of time with as little downtime as possible. To minimize downtime, monitoring and control strategies are applied. With conventional strategies data is collected and then evaluated by a team of engineers or a simple decision component to operate the system and draw conclusions on its current state. The system undergoes maintenance in regular intervals or whenever a part breaks. This approach can be labelled "offline monitoring and reactive control" (0). More advanced evolutionary stages of control concepts can be grouped, in ascending order of complexity, into online control (1), or condition monitoring, predictive maintenance (2) and proactive control (3) [69, 70].

To improve the operating performance of steam boilers, there already are a range of digital technologies available, that can readily be applied. Essential improvements that can be achieved by additional monitoring include the reduction of flue gas flows, reduction of pollutants, improvement of the ash quality, increase of the overall efficiency, reduction of corrosion [71]. In the context of digitalization and DT, so-called soft sensors or data-driven or virtual sensors are increasingly being considered. In contrast to conventional control methods, the usage of soft sensors has, for example, proven to lead to significant reductions in temperature and pressure fluctuations during operation [72]. In addition, soft sensors evidently provide high-quality quantification of synthesis gas caloric value. With currently available hardware sensors, this would not be possible at reasonable cost [26, 56].

Predictive maintenance is a procedure that improves the maintenance planning of systems in such a way that the current and predictive future system status can be included in the planning of maintenance measures and thus, downtime due to system failures is reduced. As a simple example, by consistent automated implementation of the RIMAP method (Risk Based Inspection and Maintenance Procedures for European Industry) [73], risk-based decision-making is achieved. Another example of a significant increase in productivity through a predictive maintenance strategy is presented in [74]. In this study, the dynamics of boiler efficiency and the expectations regarding heat demand are solved in an optimization model via dynamic programming, based on empirical operating data. It has been shown that the total operating costs of a steam generator in the observation period can be reduced by at least 8 %, compared to periodic maintenance (e.g. yearly) [74].

The most extensive and complex concept of monitoring and control that has been proposed is proactive operation control. The goal is to achieve an optimization of the overall system by considering all relevant aspects of the system. For this purpose, soft sensors and information of the predictive maintenance strategy are included in a holistic control strategy. The benefit of such a combined approach has been shown for fouling control [75-77], where big improvements could be achieved by taking maintenance information into account in the optimization and control strategy.

So where does the DT come in? The DT provides a platform for integrating all

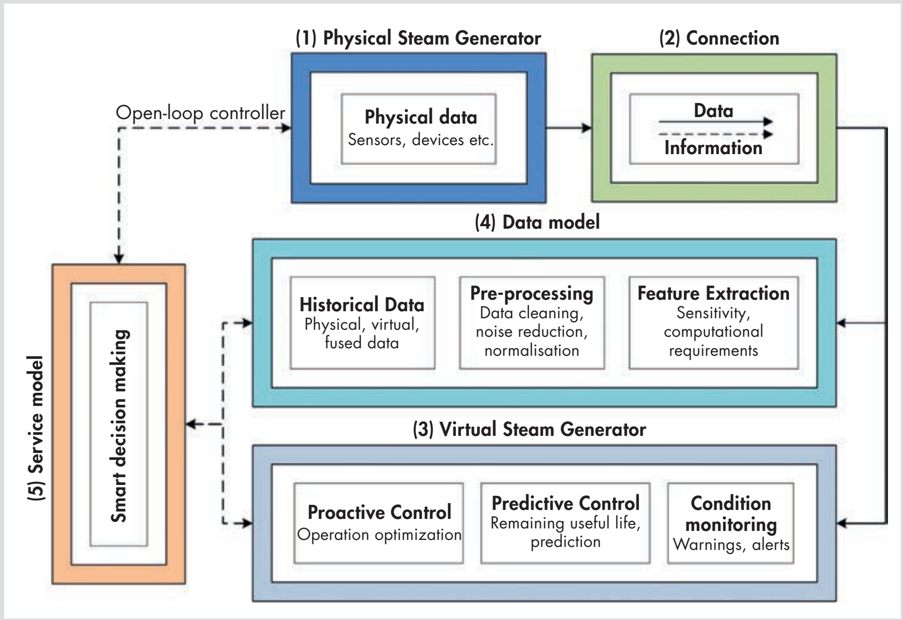

Fig. 4. Boiler System Health Management scheme according to [78] in the 5D-DT framework.

these smart services (soft sensors, predictive maintenance, proactive control), allowing them to communicate and giving them access to a shared data (knowledge) base. It allows the predictive maintenance service to access data from a soft sensor. It facilitates the information flow from the predictive maintenance service to the operation planning service, so that the next maintenance interval can be incorporated in the planning. The result is a holistic Boiler Prognostics and System Health Management, which has been adapted from [78]. Figure 4 illustrated this process in the 5D-DT framework.

This use case shows that even if many individual digitalization methods are already implemented in steam generators, they are not working at their full potential because they are isolated solutions, more often than not. With the help of the 5D-DT approach, these isolated solutions can be integrated into one single framework that allows all the components to communicate. This is made possible by setting up a central data management in the data model. By using extensive knowledge representation in the data model, the data is given meaning (Smart Data) and smart services can be extracted.

Another great advantage of the 5D-DT approach is that it can be built step by step, adding new services as needed. Starting from a very basic DT, the functionality can be extended continuously. The result is a comprehensive, holistic model that makes the DT more and more intelligent and creates value by a combination of smart services.

Conclusion and Outlook

The digital transformation and *Industry4.0* (I4.0) will have immense impact on the energy sector, including steam supply systems. It provides an opportunity for reducing cost and energy consumption and for improving economic sustainability. As novel digitalization methods are reaching a level of maturity that makes them ready for industrial implementation, opportunities but also challenges emerge. One big challenge is ensuring interoperability between services and the need to connect different systems and devices into a central knowledge base. These challenges were also highlighted in the recent survey and analysis in *DigiPoll@Energy* [12].

The reference model RAMI4.0 can aid the stepwise implementation of enabling digitalization technologies and, in this way, lead the way to I4.0 and E4.0. To make the most of opportunities offered by I4.0 and E4.0, the Digital Twin (DT) was identified as key application in the design, operation and maintenance phase. For the implementation of a DT standardized interfaces and data modelling via ontologies are the central part. During the ongoing digital transformation, RAMI4.0 can support the implementation of dynamic frameworks such as the presented 5D-DT of a steam generator.

DTs enable the horizontal integration of otherwise stand-alone digital services such as condition monitoring, predictive maintenance and operational optimization, to name just a few. The DT serves as a platform for these services that gives them access to a common knowledge base (Smart Data and models) and bi-directional communication with the real asset. It is considered a key technology to maximize the added value from enabling technologies and achieve a combined optimum of transparency, flexibility, economic sustainability and efficiency in energy systems.

Even though the benefits of advanced digitalization technologies like the DT in the steam supply sector are evident, they have not yet been implemented in industry. For this reason, interdisciplinary collaboration between scientists and industry is necessary to transfer these new technologies into practice and keep the competitive edge.

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Abbreviations and Acronyms

DT	Digital Twin
ICT	Information and Communication Technologies
I4.0	Industry4.0
E4.0	Energy4.0
RAMI4.0	Reference Architecture Model 4.0
ML	Machine Learning
AI	Artificial Intelligence
IoT	Internet of Things
CPS	Cyber Physical System
M2M	Machine-to-Machine communication
IT	Information Technology
SGAM	Smart Grid Architecture Model
3D-DT	three dimensional Digital Twin
5D-DT	five dimensional Digital Twin
PHM	Prognostics and System Health Management
OPC UA	OPC Unified Architecture
RUL	Remaining Useful Lifetime
RIMAP	Risk Based Inspection and Maintenance Procedures
o&m	operation and maintenance phase

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