Next Generation Digital Twin

Proceedings of TMCE 2018, 7-11 May, 2018, Las Palmas de Gran Canaria, Spain
Edited by: I. Horváth, J.P. Suárez Rivero and P.M. Hernández Castellano

NEXT GENERATION DIGITAL TWIN

Stefan Boschert
Corporate Technology
Siemens AG
stefan.boschert@siemens.com

Christoph Heinrich
Roland Rosen
Corporate Technology
Siemens AG
{christophheinrich, roland.rosen}@siemens.com

ABSTRACT

The vision of the Digital Twin itself refers to a comprehensive physical and functional description of a component, product or system together with all available operational data. This includes more or less all information which could be useful in all - the current and subsequent - lifecycle phases. One of the main benefits of the Digital Twin for mechatronic and cyber-physical systems is to provide the information created during design and engineering also at the operation of the system. The comprehensive networking of all information, shared between partners and connecting design, production and usage, forms the presented paradigm of next generation Digital Twin. This will bridge the gap between physics-based design simulation and its use in operation and service phases. Based on the example of a point machine the benefits of using the Digital Twin are shown.

KEYWORDS

Digital Twin, operation assistance, simulation, mechatronics, cyber-physical system

1. INTRODUCTION

The vision of the Digital Twin itself refers to a comprehensive physical and functional description together with all available operational data of a component, product or system, which includes more or less all information which could be useful in all - the current and subsequent - lifecycle phases. In [2] we defined the (simulation aspects of the) Digital Twin as follows:

The Digital Twin refers to a description of a component, product or system by a set of well aligned executable models with the following characteristics:

- The Digital Twin is the linked collection of the relevant digital artefacts including engineering data, operation data and behaviour descriptions via several simulation models. The simulation models making up the Digital Twin are specific for their intended use and apply the suitable fidelity for the problem to be solved.
- The Digital Twin evolves along with the real system along the whole life cycle and integrates the currently available knowledge about it.
- The Digital Twin is not only used to describe the behaviour but also to derive solutions relevant for the real system.

Based on this comprehensive description, the main goal and challenge is then how to support all stakeholders during all lifecycle phases with their tasks in order to increase productivity. In this contribution we review the methodological basis and present a first approach, the next generation Digital Twin (nexDT).

Today, modelling and simulation is a standard process in system development, to support design tasks or to validate system properties for example. But also first simulation-based solutions are realized for optimized operations and failure prediction. In general, simulation technology offers the chance to integrate data- and physics-based approaches and to reach the next level of merging the real and virtual world in all life cycle phases. The Digital Twin for mechatronic and cyber-physical systems allows that information created during design and engineering is also available and ready for evaluation during the operation of the system. This is nowadays often neglected, as design and operation are mainly disconnected life cycle phases from the point of data usage. By using simulation models, it becomes possible to interpret measurements, operational and fleet data in a different way rather than just detecting deviations from the norm. Several modes of failure can be simulated for the current situation trying to reproduce the actual measurement signals. The comparison of the simulated signals with measured ones can help to identify the failure mode.

The integrated use of data- and physics-based models promises an efficient approach for optimized operation of cyber-physical systems and analytics and diagnostic solutions for their complex components. The next generation Digital Twin will transport data, information and executable models of all system elements from development – delivered by the component supplier – to operation. This information can be used for the cost-effective development of assist systems during operation, e.g. autopilot solutions for production systems and service applications. Application examples are improved maintenance solutions which explain anomalies and identify potential failure causes. This networking of information also allows for the increased use of field data in the development of variants and follow-up products. The value creation process is closed by a feedback loop.

In chapter 2 we will present the paradigm of next generation Digital Twin. A first realization is shown on an example of a point machine for train switches in chapter 3. Main focus besides the planning of the Digital Twin is the use of engineering models in operation and the integration of fleet data. We will close with a short summary and outlook.

2. NEXT GENERATION DIGITAL TWIN

2.1. Digital Twin concept

The vision of the Digital Twin has been the subject of numerous publications and white papers in recent years. Common understanding of the Digital Twin in these publications is that it is seen as a concept for a virtual equivalent or a dynamic digital representation of a real system [4, 6]. In [6], Grieves dates the first mention of the term Digital Twin to a presentation to industry at University of Michigan in 2002 at an event for the formation of a PLM-Center. A more prominent use and distribution of the term was later, e.g., multiple mentions can be found in NASA roadmaps [12]. Here, the Digital Twin refers to the virtual equivalent of satellites which were not accessible for inspections and scenario investigation once shot into space.

In [8] the manufacturing context (production system itself as well as production processes) is emphasized whereas in [5] products and their development play a dominant role. The emphasized role in design phases is underlined in [7] by the attribute that the Digital Twin is first born. In this context of system design, especially for dimensioning tasks, validation and virtual commissioning high fidelity models are often mentioned. This clarifies the general objective that the Digital Twin corresponds to the real system or, so to speak, the real twin with a high accuracy. The latter also proves that this part of the idea of the Digital Twin has long been pursued in the modeling and simulation community. The purpose of multiphysics simulation and system simulation is to accurately replicate and answer detailed questions and system relationships [11].

The connection to PLM shows two further important characteristics of the Digital Twin idea, the consideration and integration of data and information beyond simulation models and the lifecycle spanning aspect. Another key point results from the connectivity of all devices and systems and ubiquitously available computing power as elements of the IoT, Industrie 4.0 and Industrial Internet [4, 8, 14]. This networking between devices but also to software systems allows that during the usage of the system a linkage between both twins is possible. In particular, the use of a system can be the operation of a plant or infrastructure as well as the use of a product. Regardless of the type of implementation, i.e., either the Digital Twin is embedded on the device or available on cloud or edge computer, a loop between the real world and the digital world and back to the real thing is possible [9]. In [10] this connection is presented as a prerequisite for autonomous systems. The Digital Twin realized the self-awareness and controls the behaviour with the system environment.

The inclusion of the IoT perspective and cloud-based IoT operation systems, e.g., in [14], extends the described loop to greater closed innovation loops. This is expressed by specific names for Digital Twins for different tasks and areas. The digital product twin includes all design artefacts of a product, the digital production twin covers models for the manufacturing process and production system itself and a digital performance twin derives insight from utilization data and analyzes actual performance.

The collection of data out of running systems is a source of information and for knowledge which can

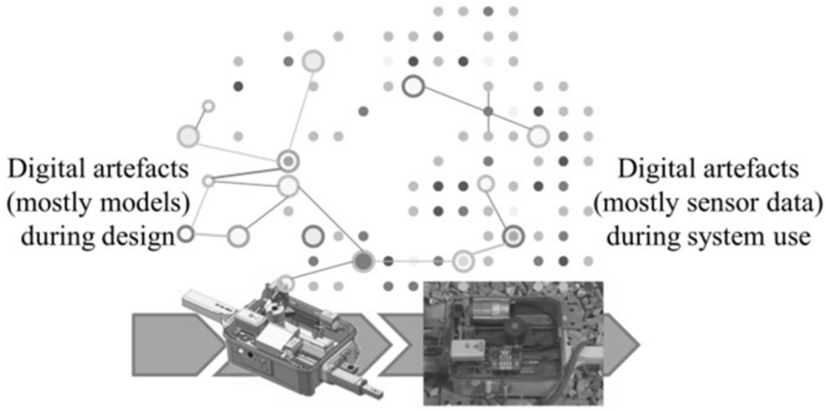

Figure 1: Next generation Digital Twin uses semantic technologies to connect all kind of information. Rings represent engineering and simulation models; dots stand for data. The connection of these models via semantic technologies is shown as lines. This general relation is valid throughout the lifecycle**.**

be used for system improvements and new product generations. The feedback loop to development and PLM systems is closed.

2.2. Next generation Digital Twin paradigm

The weakness of the comprehensive definition of a Digital Twin is that it can be misunderstood as a twin which is suitable for all kind of tasks. Of course, this is a too extensive interpretation.

This motivates that we will speak in our revised definition of a set of models. The Digital Twin refers to a description of a component, product, system or process by a set of well-aligned, descriptive and executable models:

- The Digital Twin is the semantically linked collection of the relevant digital artefacts including design and engineering data, operational data and behavioural descriptions.
- The Digital Twin evolves with the real system along the whole life cycle and integrates the currently available and commonly required data and knowledge.

This definition generalizes the description of the Digital Twin which we have given in [2] for the simulation viewpoint by the inclusion of descriptive models and data which are relevant for development and also gathered in operation (or usage) lifecycle phases.

The consistent continuation of this concept idea leads to the next generation Digital Twin as a visionary paradigm. It covers several aspects which will increase the performance of different systems and increase efficiency in all lifecycle phases:

- Creation and deployment of several – a set of – simulation models, which have a defined purpose and validity range. This set evolves along the lifecycle whereby new models are added regarding the intended function or at least with the anticipation of the later use.
- The provision of descriptive data and information which are valuable for different stakeholders.
- Realization of interconnectedness of all digital artefacts by semantic technologies.
- Anchoring in all lifecycle phases and the support of the transformation to the next phase.
- Linkage between the real and the digital world by mastering the synchronization of measured, sometimes big data, and the virtual representation.
- The Digital Twin (or a part of it in the sense of a set) can be an element of the product itself and delivered with it as well or can be a stand-alone service forming its own business models.
- Closing the feedback loop, not only back to the real system but also to early lifecycle phases, maybe for the development of new system versions or product generations.

2.3. The value network aspect of nexDT

In figure 1 the connection of all models and data is shown. The rings represent engineering and simulation models and the filled dots represent different kinds of data. All information can be connected by using semantic technologies, represented by the lines as sketched in the figure. In particular, the linkage allows the bundling of design

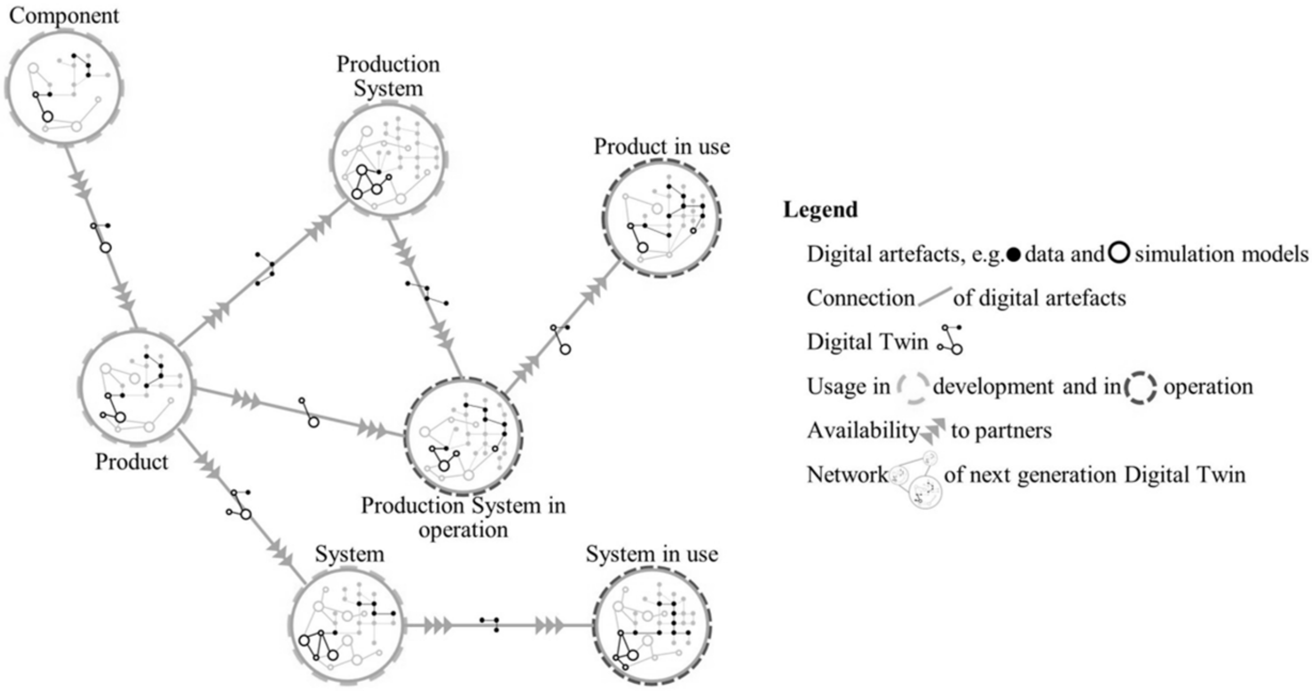

Figure 1 Next generation Digital Twin paradigm links different twins and connects it to a value network

models with measurement data. This comprehensive information is in principle available in all lifecycle phases. This enables the efficient realization of new solutions, e.g., for operation and service purposes.

A specific part of the connection is the synchronization of measurement data coming from the real system in use with the Digital Twin. In chapter 3.3 we will show this aspect by an example for a new service by the application of a point machine for train networks.

In figure 2 the value network of Digital Twins as well as the connection of all digital artefacts in next generation Digital Twin paradigm is shown. Digital artefacts, e.g., data of all kinds, descriptive and simulation models, are linked by using semantic technologies. With approaches such as the Knowledge Graph [1, 3], information can be linked and later retrieved by different stakeholders at any time. Specific digital artefacts build a Digital Twin. As already mentioned, this single Digital Twin cannot fulfil all purposes and tasks in all lifecycle phases. Therefore, a set of Digital Twins is needed, where each Digital Twin has a well-defined objective. Of course, with a suitable design of the digital twin it can be used for several tasks. In this sense the Digital Twin is delegated for a series of tasks and can be used in different lifecycle phases.

A big advantage of this paradigm lies in the creation of improved value chains. Digital Twins from a supplier can be used from a product designer for his development. The provision of Digital Twins between partners or in general the realization of the next generation Digital Twin paradigm can be done in several ways. This ranges from big cloud applications and ecosystems to individually defined exchange formats. Specific Digital Twins can be embedded in the component or device and accompany the real twin once manufactured. A further aspect in the relationship between suppliers and integrators is the degree of transparency. This can be done in two ways, on the one hand by using encapsulated models to guarantee IP protection for the supplier and on the other hand by open models for realizing integrated development processes. System integrators can in turn use this information to realize a larger system, e.g., a car manufacturing factory or a whole train. The next step in the chain depends on the application. Information of a designed product is valuable for the development or reconfiguration of the production system that should produce the product. Accordingly, a Digital Twin of the product can be combined with Digital Twins of the production system. This refers to the development of the production system including engineering and virtual commissioning tasks as well as the operation of the plant itself. When the product is made the Digital Twin can be further used. Enriched by sensor data and collected information on the use of the product the Digital Twin supports the

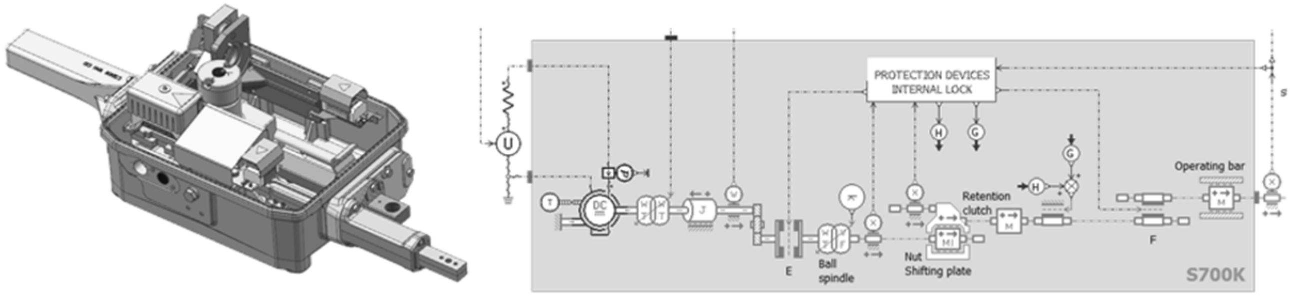

Figure 2 Multi-body model (left) and component based multiphysics model (right) of point machine S700K

optimized application of the product itself. In the understanding of the interconnectedness of all information these data and in the end knowledge are available for the development of product variants and new product generations.

If the planning, construction and operation of the production plant or an infrastructure is the focus, the general application of the next generation Digital Twin paradigm follows the same principles. Digital Twins of a product, in this case equipment of the production system, are used during development of the production system. And as above described for products, the available data and knowledge can help to improve the production and the design of new production systems.

Another aspect should be mentioned as well. During product development most digital artefacts refer to a type of a product. After production a larger number of instances are created. This means that Digital Twins are now valid for multiple instances, enhanced by production information. Conversely, data can now be collected from all instances. This leads to the generation of fleet data, which can also be used in new applications and services.

3. USE OF DIGITAL TWIN IN OPERATION

3.1. Point machine for train switches

Railroad switches also called turnouts or points are a key element of the rail network infrastructure. They are distributed all over the network and its maintenance is crucial to guarantee safety and undisturbed operation. Within a railway network the turnouts are responsible for a high amount of the operational costs as monitoring and maintenance is mainly manual. Points Diagnostics systems like the Sidis W compact [13] from Siemens are used to monitor the current condition of the point machine by analyzing the electrical power demand of the drive and point machine operation module. However, a prediction of the future behaviour remains difficult. The interaction of a railway switch and its drive (point machine) is complex. On both subsystems many different parameters act in a way that it will be difficult to predict its behaviour.

The use of physics-based models as shown in figure 3 promises an efficient and cost-effective extension of such systems as not only real data but also the immanent physics is used to identify potential chinks in dependence of the current load, maintenance condition or operating hours. It can be further used to explain anomalies and identify potential failure causes and, thus, improve the maintenance process.

3.2. Planning the Digital Twin

As already mentioned in section 2.2, the Digital Twin can become part of the product itself enhancing the original functionality of the product. In this case the additional functionalities covered by the Digital Twin can already be designed in the same way as normal product features. Or, when the concept of Digital Twin is already broadly realized, the functionalities can be assembled based on existing (simulation) modules provided by the Digital Twin. In our example physics-based simulation models as well as live data from the points diagnostics system are used to identify a possible malfunction of the turnout. Therefore, a “template” of this Digital Twin feature is specified during the conceptual design phase. This template describes how the different components are linked together and interact. During the ongoing design and construction process it will be successfully filled with (sub-)models as soon as they are created and finally results in a complete system model that fulfils the specified product functionalities. Defining the template already during the early planning helps to ensure that the simulation models are created at the time when lowest effort is needed: during the component development. It is however also possible to create the models afterwards, but at a higher cost, as implicit knowledge may have been lost.

This idea will be illustrated for the example of an enhanced points diagnostics system: The new functionality brought in by the Digital Twin is the identification of possible root causes of malfunctions in contrast to its pure detection. This feature will be realized by a system model that consists of a simulation model based on the physics of the point machine and track on one side. Another component of the system model is measurement data from the live system. The architecture of this system model will be specified in the concept phase (it is a product feature), however, its components are not yet available, as details of the physical realization are not yet cleared (figure 4 top). And obviously live data are not available as well. But it is already possible to specify the content of the data (in our case measurement of the power consumption of the electric motor of the point machine during operation). This leads directly to a requirement for the simulation model that should describe the physical behaviour of point machine and track: This model should also give the power consumption of the motor. A possible candidate that could give this information is a multi-body simulation model used to verify the kinematics of the point machine. Such a model combines the geometrical object description with kinematic features like joints and hinges to simulate possible motions of the system. Together with realistic forces and accelerations predictions on the kinematic behaviour of the system can be done. A more abstract – and therefore less numerically expensive – model to fulfil this functionality is a component-based 1-d multiphysics model of the point machine (see figure 4 bottom left).

During the design of the point machine, like for all other mechatronic systems, several models (descriptive and simulation) are created. They all have a dedicated purpose during its creation: verification of design hypotheses during the development. Using the nexDT design paradigm already in this phase the additional requirement from the system model is known and the model owners are aware of it. Therefore, it is easy to add this functionality or derive a (sub-)model with the desired functionality alongside with the phase-specific model (“failure identification”, figure 4 bottom right). This minimizes the effort in setting up the simulation. If the model for operation phase would have been prepared only at the time when it is needed, many design features and models would no longer be available as they are specific to the design phase and will probably no longer be maintained after its initial use. The nexDT offers the possibility to keep the models in focus also after the initial (primary) use.

3.3. Digital Twin during operation phase

The system model allows simulating the operation of the point machine for a customer/site specific configuration. Depending on the complexity of the underlying system the implementation can be done at different locations, ranging from embedded logic in the control unit of the drive over included as an assistance module for the switch operator to cloud based as service on demand e.g. for maintenance worker. In the suggested set-up (assistance system) the failure identification module compares the measurement data from the live system with results from the physics-based simulation. This direct comparison is possible as by design the results of the two input sources (simulation model, points diagnostics system) are comparable.

As soon as the failure identification module detects a significant deviation of the two models it raises a notification in the dashboard and analyzes possible root causes of the failure, also displayed to the operator.

As usually every turnout has an individual configuration, the failure identification module has to be configured individually. However, there exist several situations where different turnouts show a similar behaviour as they are somehow connected to each other. E.g., turnouts that are locally close to each other are subject to similar environmental conditions like temperature or rainfall. Including this kind of information in the analysis via nexDT is shown in the following section.

3.4. Hybrid analysis and fleet data

Especially the connection between the Digital Twin and operational data offers a wide range of new services from failure detection and diagnosis, as mentioned in the previous section, over predictive maintenance to faster product improvement and development.

The connection of the Digital Twin and a physical instance is established via sensors. Ideally sensor data is received and processed in real-time. But if we think of data being submitted to a cloud and

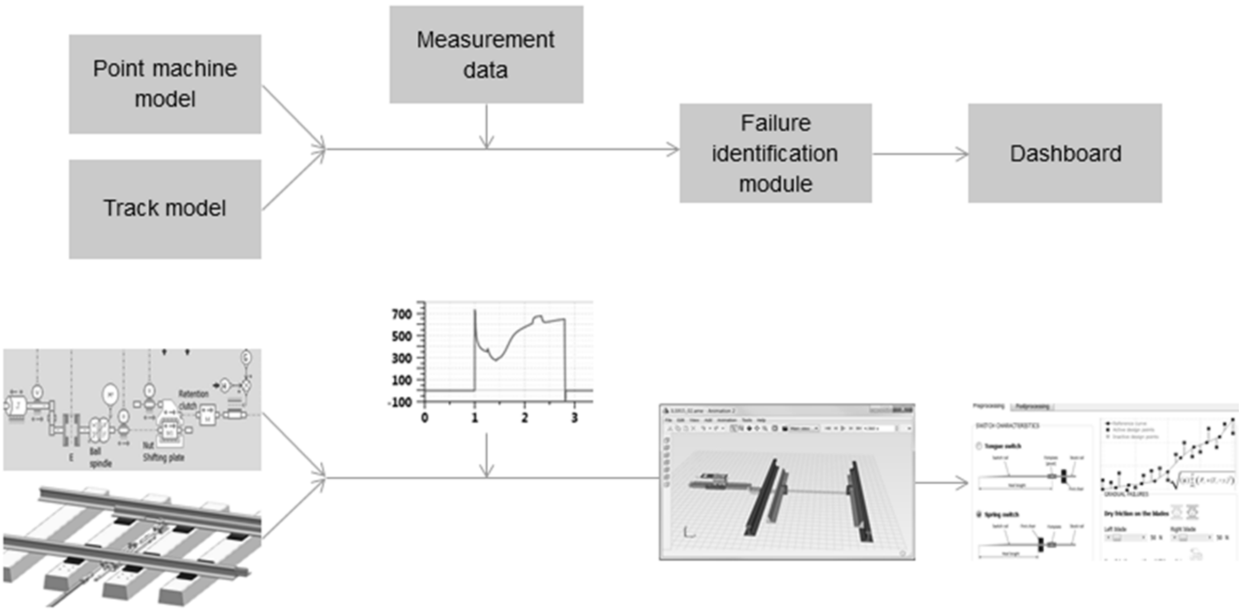

Figure 3 Architecture (top) and realization (bottom) of assist system based on Digital Twin functionalities

processed there, synchronization and a proper delay management gets important due to different time constants. Depending on the application such sensors measure physical quantities like accelerations, displacements, strains, temperatures or current signature and power in case of point machines. In this situation it is relevant not only to monitor data, but also to detect and diagnose failure states as well as give recommendations for future operation or maintenance. We have seen in sections 3.1 - 3.3 how physics-based or model-based approaches contribute to this goal.

A second approach is to purely rely on data and use artificial intelligence algorithms on it. This has the drawback that without a large and old fleet new services are out of reach due to a lack of data. But in this situation simulation models help to test the system virtually in different environments or failure modes. Fleet data is so to speak generated by using simulation models and variants of it. This approach even applies for unique items. Once having products in operation this data can then be gradually enriched by data from the field.

Another part of fleet data stems from service and maintenance. Today, maintenance data are usually completely disconnected from models of the design phase as well as from sensor data. The latter is of course often due to a lack of sensors at all. This disconnection has to be overcome such that it gets possible to match findings in the field with measured data taking the environmental conditions into account as well as the load history, which is a necessary input for data analytics and highly beneficial for model-based approaches.

In summary, a combination of physics-based and data-based approaches in combination with findings from service is recommended. It is required that all ingredients have to be semantically connected for a specific instance of a product. This hybrid model is then employing physics-based models matched with sensor data in the early phase of a fleet. The older the fleet gets and the more data are acquired, data-based approaches in combination with service findings get a larger weight.

Having talked about different sensor data and their further processing we haven't defined the term fleet yet. In principle a fleet consists of products that show a certain similarity. This similarity can be geometrically or related to parameters or the behaviour in operation. Concerning the first an example would be a fleet of industrial electric motors of a certain type. All motors have many parts in common (that can be scaled) but differ in shaft height and the number of pole pairs but also in wear and age. In case of the point machine for railroad switches, as mentioned before, there is a large number of geometrically identical instances belonging to the same fleet. But the age and the location where they are mounted are having a large effect on their behaviour and remaining lifetime. That means a reasonable sub-classification within in a larger fleet can be based on comparable environmental conditions.

The definition of similarity criteria to define a fleet and to find similarities within a fleet has to be also based on hybrid models combining physics-based insights with data analytics. One means to do that is a knowledge graph that everybody experiences when searching in Google and additional useful information is provided. In our case this graph consists of all members of the fleet as well as their models, sensor data, data from maintenance as well as age and others. By means of similarity search algorithms on that graph similar fleet members can be found, e.g., point machines of similar age and wear in similar environmental conditions as the latter have significant impact on the functionality.

Using similarity search within a fleet, new services lay at hand. In case of the point machine we can deduce from the knowledge of a subset of a fleet to a specific device having required similarities in common. Concretely, if we are interested in the future behaviour of a point machine of a certain age in certain surroundings similarity search on the knowledge graph provides other point machines in similar surroundings that are as old or older. The already known aging behaviour can then be adopted to the point machine of interest and new knowledge is generated. The same holds, e.g., for a fleet of electric motors in a plant where usually many different motors are installed. By deducing knowledge in terms of ageing models from the already existing fleet the whole plant operation can be optimized to also optimally plan maintenance intervals. That means that predictive maintenance services can be provided on high quality data. Noteworthy, similarity search can also identify drawbacks in design leading to new insights for the design phase of the next generation product.

4. SUMMARY AND OUTLOOK

In summary, employing models and data from the Digital Twin allows for the realization of new services with low effort. Especially their combination, i.e., engineering or simulation models on the one hand and measurement data on the other hand, is key. The latter makes it possible to create hybrid models guaranteeing high quality analyses. Moreover, similarity search on a knowledge graph comprising all devices of a fleet provides knowledge for a specific device by searching for similar devices in a fleet.

The presented next generation Digital Twin is the paradigm to connect digital artefacts and to build a whole value network. Making no claims for being complete, this paradigm needs further concretization and implementation. But a specific realization in case of a point machine has already given a first impression on the achievable benefits. Having a general implementation of the next generation Digital Twin available, the field of application is almost unlimited.

In future, efforts have to be spent in how to connect product lifecycle management systems, cloud solutions and further data artefacts as well as devices. Further challenges lie in the structuring of models and data, e.g., by using official standards, as well as their semantic annotations. Additionally, methods and algorithms for the synchronization of measurement data with the Digital Twin have to be developed. Although we are aiming at a quite general approach, the realization of the next generation Digital Twin paradigm for a specific application domain can have its own challenges that have to be solved.

REFERENCES

[1] Banerjee, A., Dalal, R., Mittal, S., Pande Joshi, K., Generating Digital Twin models using Knowledge Graphs for Industrial Production Lines, InProceedings, Workshop on Industrial Knowledge Graphs, co-located with the 9th International ACM Web Science Conference 2017, June 2017

[2] Boschert, S., Rosen, R. (2016): “Digital Twin – The Simulation Aspect”. In P. Hehenberger, D. Bradley (Eds.), Mechatronic Futures Challenges and Solutions for Mechatronic Systems and their Designers (pp 59-74). Springer-Verlag, 2016

[3] Canedo, A., Industrial IoT Lifecycle via Digital Twins, in: Proc. Elev. IEEE/ACM/IFIP Int. Conf. Hardware/Software Codesign Syst. Synth., 2016: p. 29

[4] GE 2017. The Digital Twin. Compressing time-to-value for digital industrial companies, White Paper. https://www.ge.com/digital/sites/default/files/The-Digital-Twin_Compressing-Time-to-Value-for-Digital-Industrial-Companies.pdf

[5] Gossens, P. 2017. Industry 4.0 and the Power of the Digital Twin.

https://www.maplesoft.com/contact/webforms/Whitepapers/industry4.aspx

[6] Grieves, M. (2014). Digital Twin: Manufacturing Excellence through Virtual Factory Replication, White Paper. http://www.apriso.com/library/Whitepaper_Dr_Grieves_DigitalTwin_ManufacturingExcellence.php

[7] Jung, N., Depew, C. 2017. Building a Digital Twin of Your Process Plant with Unified Lifecycle Simulation. White Paper. https://software-solutions.schneider-electric.com/unified-lifecycle-simulations-with-simcentral

[8] Overton, J., Brigham, J. C. (2017). The Digital Twin. Data-driven simulations innovate the manufacturing process, White Paper. http://www.dxc.technology/analytics/insights/138984-the_digital_twin_data_driven_simulations_innovate_the_manufacturing_process

[9] Parrot, A., Warshaw, L 2017. Industry 4.0 and the digital twin. https://dupress.deloitte.com/dup-us-en/focus/industry-4-0/digital-twin-technology-smart-factory.html

[10] Rosen, R., von Wichert, G., Lo, G., Bettenhausen, K. D. (2015) About the Importance of Autonomy and Digital Twins for the Future of Manufacturing, INCOM 2015.

[11] Schenk, T., Gilg, A. B., Mühlbauer, M., Rosen, R., Wehrstedt, J. C. (2016): Architecture for modeling and simulation of technical systems along their lifecycle. In Computing and Visualization in Science, January 2016, Volume 17, Issue 4, pp 167–183, Springer

[12] Shafto, M. (Chair), Conroy, M., Doyle, R., Glaessgen, E., Kemp, C.; LeMoigne, J., Wang, L. 2010. NASA Technology Roadmap. DRAFT Modeling, Simulation, Information Technology & Processing Roadmap Technology Area 11. https://www.nasa.gov/pdf/501321main_TA11-MSITP-DRAFT-Nov2010-A1.pdf

[13] Sidis W compact points diagnostics system. Siemens AG 2010 Order No: A19100-V100-B927-X-7600

[14] Siemens 2017. MindSphere. The cloud-based, open IoT operating system for digital transformation, White Paper. https://www.plm.automation.siemens.com/media/global/en/Siemens_MindSphere_Whitepaper_tcm27-9395.pdf.