ITEA-2018-17030
Daytime

Digital Lifecycle Twins for Predictive Maintenance

Deliverable: D1.3 Public summary report of project results

Due date of deliverable: (31-03-2022)
Actual submission date: (24-03-2022)

Start date of Project: 01 April 2019 Duration: 36 months

Responsible WP1: Philips

Revision: <outline, draft, proposed, accepted>

Dissemination level		
PU	Public	✓
PP	Restricted to other programme participants (including the Commission Service	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (excluding the Commission Services)	

0 DOCUMENT INFO

Author

Author	Company	E-mail
Ad de Beer	Philips	Ad.de.beer@philips.com

Documents history

Document version #	Date	Change
V0.1	14-05-2019	Starting version, template
V0.2	14-05-2019	Definition of ToC
V0.3	20-05-2019	First complete draft
Sign off	30-05-2019	Signed off version (for approval to Board members)
V1.0	04-06-2019	Approved Version to be submitted to ITEA office
V2.0	24-03-2022	Update on Daytime results

Document data

Editor Address data	Name: Ad de Beer Partner: Philips Address: HTC34-7-027 Phone: +31 6 1372 2049

Distribution list

Date	Issue	E-mailer
		Al_daytime_all@natlab.research.philips.com

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1 Executive summary

The concept of digital twin can provide solutions for the challenges faced in Smart Manufacturing, e.g. for Predictive Maintenance (PdM) techniques. Even though predictive maintenance and digital twins expected to have a high impact on future smart manufacturing and engineering, there are still very few functioning examples of digital twins being used for predictive maintenance in actual industrial practice. It is the gap DayTiMe is about to fill, integrating findings and solutions from several industrial use cases and using a generic value chain model.

Industry 4.0 describes an important technological advancement driving automation and data exchange in the manufacturing environment to provide smart production with its efficiency improvements, while setting the requirements and needs for necessary and essential tools to specifically enable the change. In smart production, improvements and adjustments to the production processes can be achieved with effective Internet of Things (IoT) tools that analyse and manage the sensor-collected data using Predictive Maintenance (PdM) techniques. PdM is a right-on-time maintenance strategy designed to determine the condition of in-service equipment to help predicting and deciding when maintenance actions should be performed. Maintenance tasks are performed only when warranted, leading to cost savings over routine or time-based preventive maintenance. The basis for PdM is the Condition-based Maintenance (CBM) concept. CBM techniques are already used in many industrial manufacturing areas, and the techniques include e.g. vibration analysis, lubricant contaminant analysis, and process performance monitoring, using information fusion techniques with multi-parameter measurements.

The targeted impact is striving for digitizing industry by improving the readiness and capability of product and production information to a secure data-driven value creation by:

- Identifying types of data relevant for performing functional PdM in respective use cases
- Specifying how data can be analysed effectively and lead to the identification of PdM measures
- Deriving how modelling techniques, in the sense of a digital twin, can be utilized to support PdM measures and how data analytics and machine learning can be included in these models
- Finding out how to utilize the collected information for further data-driven value creation based on Smart Services
- Generalizing these solutions for further industrial organizations

Technical outcomes will be:

- functioning pilots of industrial use cases
- Data acquisition and analytics techniques
- Digital twin models for the respective use cases
- Smart Service and data-driven business model blueprints

- A method toolbox for generalization and diffusion of these outputs in the industry

This project with a consortium of 19 partners, led by Philips Medical Systems BV, , supported by Philips Consumer Lifestyle and Philips Research meets the three challenges by deriving requirements from the industrial use cases in various industries, ranging from telecommunications to medical systems imaging to shipping industry. The project results will be widely disseminated to support digitizing European industry at large, which will benefit from efficient predictive maintenance techniques, with the project partners providing the enabler solutions to the market. The consortium is innovative in combining machine learning, simulations and modelling in order to achieve predictive maintenance. A unique feature of the projects is the integration of all industrial use cases in various fields within the same consortium to spread achieved learnings widely in industry.

2 The problem

The fourth industrial revolution, Industry 4.0, is an important trend driving the automation and data exchange in the manufacturing environment to provide more efficient shop floors, so-called Smart Manufacturing, while setting the requirements and needs for necessary and essential tools to specifically enable the change.
Industrial Internet of Things (IIoT) devices and systems form the basic enablers for industrial maintenance reliability and asset management by linking the real and virtual worlds together through sensors and Cyber-Physical Systems (CPS) that measure and monitor the production parameters, and by connecting different machines and devices together and to public/private cloud-solutions, that offer e.g. edge and/or fog computing capabilities. Improvements and adjustments to the production processes are using the so-called Predictive Maintenance (PdM) techniques. PdM is a right-on-time maintenance strategy designed to determine the condition of in-service equipment to help predicting and deciding when maintenance actions to be performed best and how. Maintenance tasks are e.g. performed only when warranted, leading to cost savings over routine or time-based preventive maintenance. The basis for PdM is the Industry 4.0-related Condition-based Maintenance (CBM) concept. CBM techniques are already used in many industrial manufacturing areas, and the techniques include e.g. vibration analysis, lubricant contaminant analysis, and process performance monitoring, using information fusion techniques with multi-parameter measurements.
In IoT predictive maintenance, two challenges that are related to data collection and analysis are crucial to enable the full and correct utilization of automated predictive maintenance techniques:
How to obtain high enough quality, labelled data from the industrial machines?
How to best apply these techniques to the collected data to provide engineers and technicians with analysed, relevant, and actionable condition-based maintenance information?
Gathering large volumes of raw, unlabelled data is relatively easy, but when building learning algorithms for IoT predictive maintenance platforms, it is important to keep in mind that the algorithm is only as good as the quality of data labelling. The challenge thus becomes to guarantee the availability of high-quality labelled data. The concept of digital twins can provide solutions to the above-listed challenges. A digital twin refers to digital replicas of physical assets, processes, and systems. For each physical product, a digital twin is created, and it accompanies the product throughout its lifecycle. It is created together with the product idea and serves as the first blueprint for production, then is made concrete during the product development process, and eventually remains inseparably linked to the product throughout the entire life cycle of the product.
The digital twin are beneficial in many ways. Examples are:

- Instead of the need to look at the factory reports, the digital twin simulations let engineers and technicians directly see the progress as the product moves along the manufacturing stages.

- Comparing the digital and physical product becomes easier as the twin model tracks the progress of the physical product development directly and clearly indicates deviations from the idealized processes.
- Tracking the state of the physical product under development through a replicated digital model lets individuals monitor the performance from anywhere.

Even though predictive maintenance and digital twins expected to have a high impact on future smart manufacturing and engineering, we still see very few functioning examples of using digital twins for predictive maintenance in actual industrial practice. It is the gap DayTiMe is about to fill.
Hence, we are committed to address crosscutting technological, economic and societal challenges:

- How are appropriate digital twin solutions for PdM designed, realized and operated?
- How can the business impact of those solutions be quantified and maximized?

3 The innovations

To address the challenges described in the previous section, the consortium follows a holistic and practical approach to implement predictive maintenance practices with the help of digital twins.

Various industrial use cases build the basis for research and development within DayTiMe and ensure that the solutions developed satisfy the actual industrial needs. Digital twins are developed for all the use cases. To have a functioning digital twin, it will be connected to the CPS to receive the relevant and acquired sensor data, and accompanied by respective models and simulations. The sensor data will be analysed via statistical methods, data analytics, and using machine learning algorithms. A specific goal for DayTiMe is to identify relevant parameters, means, and patterns, to provide opportunities for the technical predictive maintenance approach as well as data-driven business models and smart services. The impact of the approach will be measured throughout the development and fed back to providers to validate the chosen technical approach and solutions. Integrated demonstrators will be developed, to display predictive maintenance based on digital twins. Figure 1 displays the technology value chain of DayTiMe project.

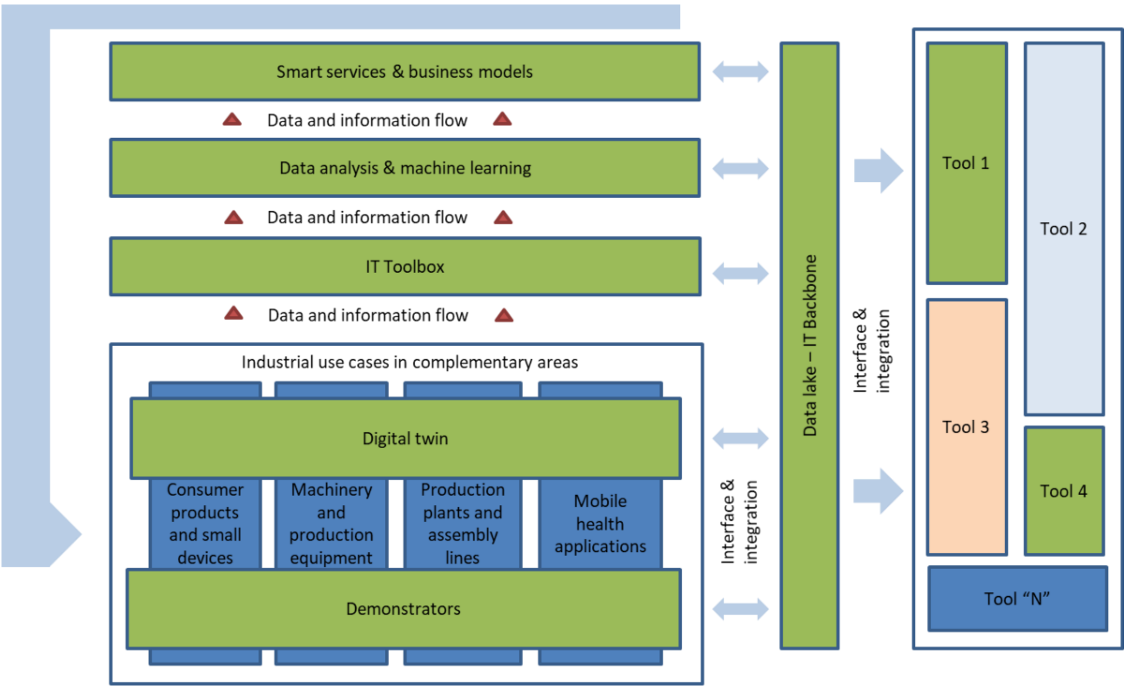


Figure 1: Technology Value Chain

The following specific innovations are developed and demonstrated:

3.1 A holistic view on digital twins for predictive maintenance

Within the context of smart production and digitization, demonstrators, testbeds, and sandboxes will be developed while simultaneously considering the actual

industrial practices. To create functional smart manufacturing processes, actual industrial practices are examined. Within this project, not only the practical examples (use cases) are examined, but also data analytics and the necessary IT-backbones were subject to investigation and development. In addition, the project replied to questions of which industrial database systems can process the vast amounts of data generated and which standards and formats will be necessary to be adopted or developed.
The project partners developed methods to fully and holistically utilise digital twins taking into consideration potential other smart services, such as feedback to design or sustainability assessment as well as the software architectural framework.

3.2 A cross-industrial approach

The term cross innovation describes cross-industry and interdisciplinary cooperation. On the one hand, this can take the form of a transfer of know-how between industries, looking for analogies in solving specific problems and transferring them to other sectors. The second form is cooperation in which innovations are developed across sectors and new things are created by bringing together sector-specific knowledge. This methodological approach delivers both, shorter development cycles, lower development costs and risks that can lead to disruptive extensions of the state-of-the-art. DayTiMe is not limiting itself to a specific high-risk innovation, but gaining potential from a holistic perspective concerning use cases (automotive, marine, manufacturing, plant maintenance) and application fields (process, methods, technology and information standards). Hence, as a result, DayTiMe identified success patterns and elaborate cross-industrial innovation blueprints. This generalisation allows a classification within the RAMI 4.0 model and supports the standardisation activities. The consortium assumes that this approach will on one hand deliver the best advances in competitiveness for all participants and one the other hand will guarantee a maximum impact of project results throughout society.

3.3 A tool-based approach

To achieve tangible results from the project, a toolbox is created to support the implementation of the developed concepts instead of creating a single holistic method or product. If you simply provide a global view of the solution provided by each use case, there will be no way to find the relationships between each of the solutions implemented in the different production systems. From the execution of the working program on the use cases of the projects, important findings and knowledge gains are won. These can be e.g. systematic procedures for setting up CPS and sensor-supported measurement systems, methods for digital twin implementation, methodologies for data processing etc. In order to give the partners of the consortium and further industrial players the opportunity to use these findings, they are converted into tools. These findings are combined in a method-tool box, aiming to support the whole process from CPS creation to data-driven business models. Interested organizations are able to choose their method according to their respective needs. This means that the toolbox is modular build, so that organizations or future customers can choose the tools suitable for their needs. With this segmentation, a vision of how to carry out the implementation of this type of solutions in different areas is generated; this provides more ideas to potential stakeholders in carrying out similar solutions for their business model.

3.4 Integration of machine learning algorithms to digital twins

The number and quality of results obtained in industrial applications across different domains has clearly proven the value added of machine learning, also in the predictive maintenance domain. However, data analytics algorithms, and machine learning in particular, until now have mainly been used only in specific parts of the analytics process (e.g., for anomaly detection when monitoring machine data).

The goal of DayTiMe was to perform a more thorough integration of machine learning concepts in digital twins, by

1) specifying a set of base models for common industry scenarios of predictive maintenance,
2) providing a methodology with corresponding toolset of tailored analytics functions and machine learning algorithms that are suitable for those scenarios and
3) lift the concept of digital twins beyond pure data storage and monitoring, to the level of modelling, control and behaviour prediction.

This will require

1) Tailoring existing and designing novel machine learning algorithms that are able to deal with the evolving and dynamic nature of the processes in the (physical) system's environment and are e.g., easily retainable, include transfer learning mechanisms to learn from similar systems/environments in case of unforeseen circumstances, etc.,
2) devising a methodology such that the (data-driven) machine learning algorithms can interact with physical and simulation-based models (i.e., hybrid modelling), and
3) coming up with an approach to let multiple ML models that are acting on a set of heterogeneous data sources work together (i.e., hyper modelling).

4 Use cases

The cluster of use case providers represents industrial partners, who will benefit predominantly, but not solely, through the development of predictive maintenance for their respective products. The clusters of partners providing IT-services, Data Analytics, simulation and modelling services are all technological enablers. Here, the partners will integrate the developed tools, methods or IT-solutions in their respective product or service portfolio to acquire new customers and strengthen their position on the existing markets.

4.1 Use Case Providers

The Netherlands

Royal Phillips: Royal Philips is a leader in cardiac care, acute care and home healthcare, as well as male shaving and grooming and oral healthcare. DayTiMe will enable Philips to transform in to digital service provider by giving advices tailored to the user. The two specific use cases are a MRI scanners and a smart shaver. The strategy for exploitation within the smart shaver use case is to explore new features and create more contact moment between Philips and the consumer and explore the digital twin as a future concept for this kind of products in the B2C domain. MRI Scanners are capital-intensive medical systems, used for diagnosis and image guided therapy in hospitals. The functionality of this equipment and has grown dramatically which makes maintenance of system, design and verification methods harder with every system release. To resolve this, knowledge of the actual use of the systems in hospitals is required. This information will be exploited to reduce the total cost of ownership.

Belgium

Yazzoom designs, installs, upgrades and services equipment for energy, defence, steel-making, the environment and other industry in general. Yazzoom designs, manufactures and maintains industrial steam production boilers Yazzoom has developed a set of physical models in order to design its boilers. These boilers are fully instrumented in order to deliver data to the SCADA of the full installation. The development of digital twins – integrating the physical models and the gathered SCADA data - of these industrial boilers will enhance the exploitation of the gathered SCADA data and support the follow-up of the operation of these machines throughout their lifecycle in light of a better product design and maintenance strategy.

Turkey

Triatech is experienced on producing innovative medication and medical supply management solutions, which also is a manufacturer. Thus, they will provide input about the applicability and suitability of the project to manufacturing systems. In addition, Triatech performs maintenance services therefore the information collected by the digital twin system will help them to create products with optimized maintenance issues. Since Triatech has the ability to utilize the project both on manufacturing and maintenance solutions, it will provide valuable test opportunities and feedback about the project.

Turkcell/VAS Telecom

Management in telecom systems, Network Insight, Optimization, Traffic Forecast, Network Plan and Simulation. The product will contribute to Turkcell in terms of customer satisfaction and operational sense. The product will be designed to be applicable to other operators also. This will create a new market for Turkcell.

UK:

Our self-funded partner C4FF is interested in exploiting DayTiMe platform and services in the UK SMEs with support from UK trade and industrial associations. The main exploitation route will be targeting our industrial SME members, local, regional and national (as well as their European network), The other interests and exploitation routes include providing consultancy, developing new RTD projects and integration of project outputs with our existing software systems, some with sophisticated artificial intelligence/neural network tools in decision making and optimization processes and in predicting failure in material flow or quality within supply chain and/or on factory floor. The knowledge gained and technology know-how of C4FF will be used to integrate the project outputs with our existing software systems and develop add-ons to potential clients' existing systems as well as for future developments.

5 Final results of Daytime

Mapping the demonstrators in the Daytime architecture

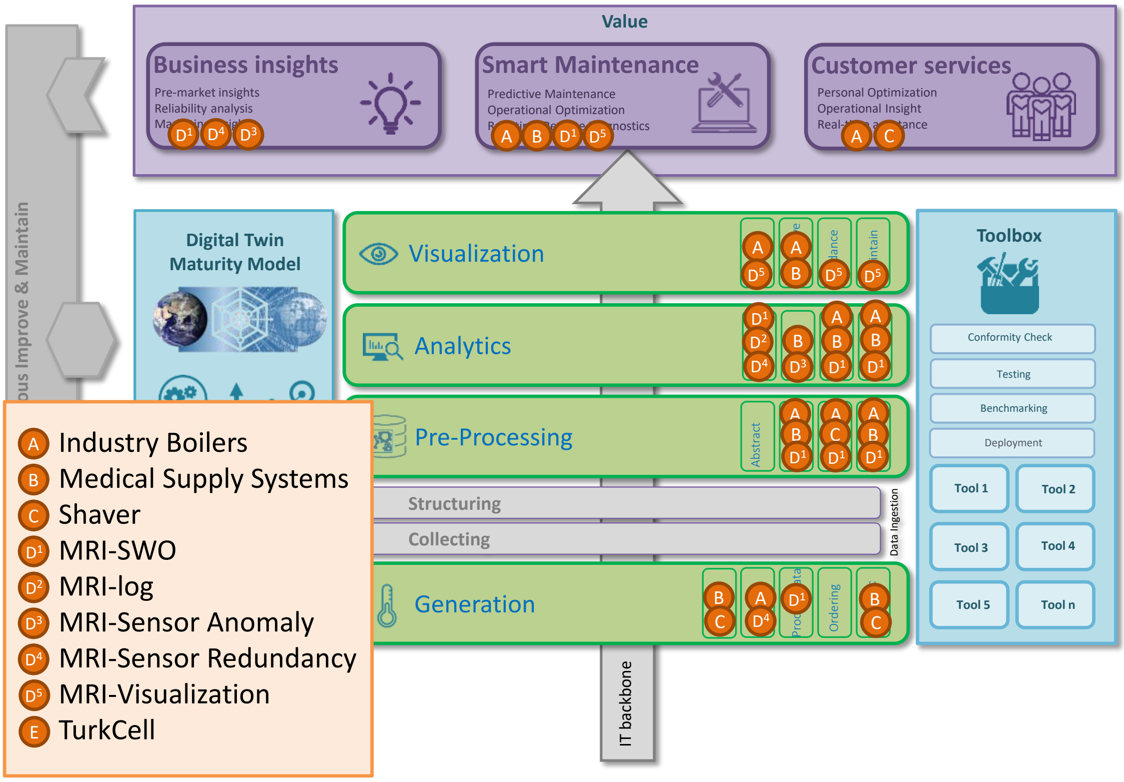
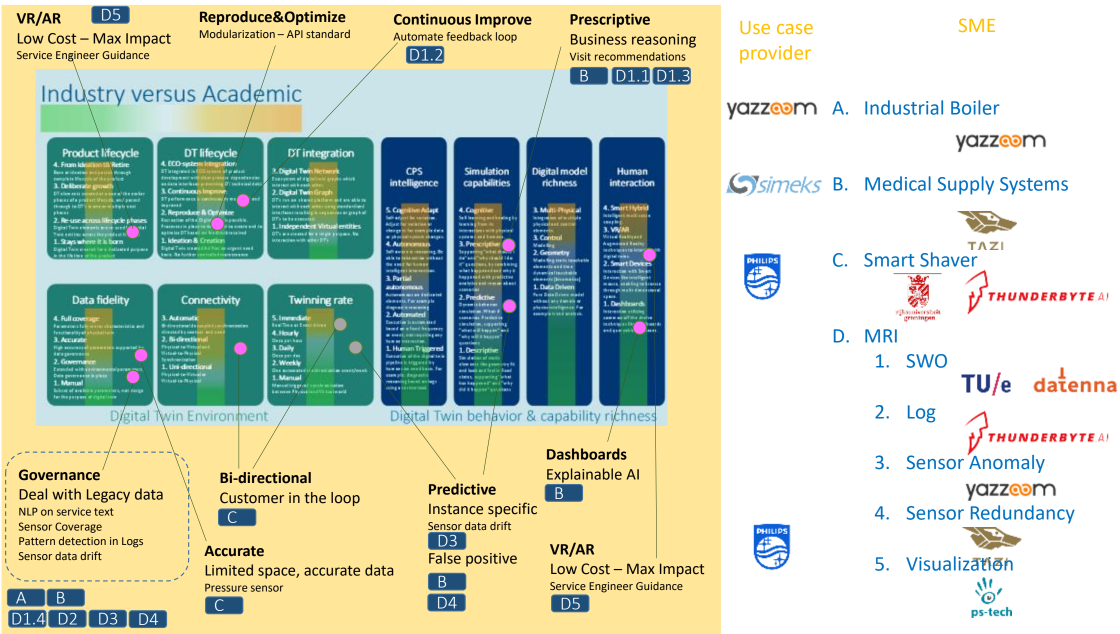


Figure 1: Mapping of DayTime Use-Cases on DayTime Architecture.

And in technical point of view.



5.1 Demonstrator: smart shaver

Innovation challenges addressed in this demo (PCL: use case provider)

The innovation challenge is to improve shaving satifaction by personalization of the shaving settings, by using two adjustable settings of the shaver: the pressure and the skin-cutter-distance. To measure the pressure, a special sensor is developed by RUG. Data from a user test (performed in 2021 and analyzed by ThunderbyteAI) is used as input for the digital twin developed.

Figure 2 - Shaver with a light ring indicating the used pressure

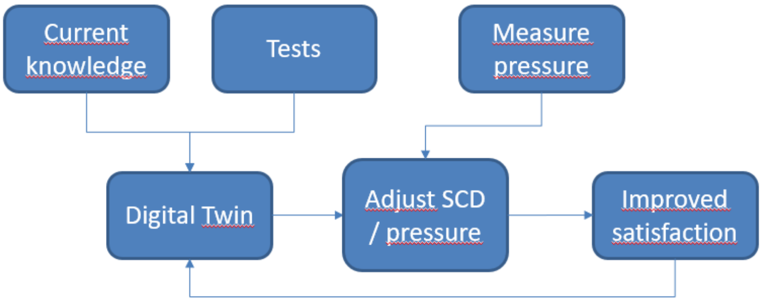


Figure 3 - Scematic overview of the shaver use case

In Figure 3 the general overview of the shaver use case is shown. Data from the performed test and current knowledge about shaving are used to determine the model (digital twin) that controls the adjustments for skin-cutter-distance and pressure of the user. These adjustments are also determined based on actual pressure measurements. The goal is that this will lead to improved satisfaction. The amount of improvement of this satisfaction and other remarks from the users, are input to further optimize the digital twin.

5.2 Demonstrator: MRI

The MRI demonstrator is split in different elements each addressing specific challenges in the domain of predictive maintenance.

- The SWO demonstrator addresses the challenge of utilizing human written re-ports with low fidelity and structure. Furthermore, it addresses the challenge of business reasoning; can part replacements and corrective actions be optimized for cost.
- The Log demonstrator addresses the challenge of finding anomalies in unstruc-tured logfiles during early testing across a limited number of physical proto-types.

- The Sensor anomaly demonstrator addresses the challenge of find anomalies in sensor data when dealing with limited number of physical twins which are oper-ated in different ways over physical twins and over time.
- The Sensor redundancy demonstrator addresses the challenge of finding pat-terns and cross-correlations in the huge amount of sensor data the physical twins deliver. The available sensor data is measured at different frequencies re-sulting in sparse multivariate time series data. Can unsupervised monitoring of sparse multivariate sensor data lead to insight when dealing with a limited num-ber of physical twins?
- The visualization demonstrator addresses the value aid of novel visualization techniques to bridge the gap between the insights delivered by the digital twins and the Service Engineer in the field who needs to translate the insights into ac-tions.

5.3 Demonstrator: anomaly detection in industrial sensor data.

For this demonstrator, we apply AI-based data-driven digital twins for modelling an industrial process and using that digital twin to subsequently detect faults in the process. Originally the industrial process that this use case would be based on was an industrial boiler. However, due to resource unavailability at the owner of the plant, a switch was made to a different process with similar properties and challenges, namely the Tennessee Eastman Process (TEP) [1]. The TEP is a well-studied benchmark in chemical engineering, consisting of a realistic simulation of an entire chemical production process based on 8 chemical components, and consisting of roughly five equipments involved:

- Reactor
- Condenser
- Separator
- Compressor
- Stripper

The dataset, while simulated, is realistic and shares many challenging properties with real-world industrial datasets which make AI-based modelling and anomaly detection difficult, namely:

- The dataset consists of high-dimensional timeseries data
- The process has long and possibly variable dead times due to various buffers and pipelines
- The underlying physical and chemical processes exhibit first- or second-order dynamics, which means that there is possibly no direct instantaneous relation between certain values in the process

The dataset consists of a large number of records (>250k), with over 50 variables. Training and deploying the model on this dataset takes less than 3 minutes.

5.4 Demonstrator: medication and medical supply management system

The use case performs medication and medical equipment management solution in hospitals. In this process, there can be too many problems with electro-mechanic component which are working in system. These problems cause downtime for the hospital's personal and cause poor patient therapy. The goal is to predict anomaly before couple of days. For this solution, AI model for digital twin technologies will be developed, based on current and test knowledge, and feedback from consumer in the market. Innovation challenges are:

- Gathering automatically working field raw data, readable data, hardware failure report and user experience report
- Development of an AI model
- Using customer feedback to improve the model
- Implementing the model to our use case
- Establishing information system communication

5.5 Demonstrator: GSM base stations and user-experience

Our demonstrator is intended to provide opinion for short-term fault/complaint estimations and long-term capacity planning, either by changing/increasing the capacity of an available station or establishment of new cells. Predictions are produced based on the data of most recent 6-days, yielding the two outputs for the next day (i.e. the 7th day), one for prediction of outage for a specific base station, and one for prediction of any customer complaints related to, or stemming from, that specific base station.

The demonstrator begins with the GSM base station data, that are collected periodically (several times a day) at a tool, called Ab Initio, and go through a series of ETL processes.
The data are sequenced in daily basis and prepared to be fed into the deep learning model, which acts as our Digital Twin for the base stations.

In the demonstrator, the user selects the dates of interest and trains the digital twin model first. Shortly after the running phase of the tool, the GSM base stations appear on a map. When the user selects one specific base station of his/her interest, that portion of the map is zoomed in and a popup info shows up. This small info window includes the related date, site ID, some site metrics such as average drop count, etc., and the predictions generated by the model, both for customer complaint probability and outage probability.

Besides daily predictions for customer complaints and site outages, another purpose of the use case is to provide useful information for capacity planning of GSM stations. This will be demonstrated by longer-period applications and different colors for the stations shown on the map. Lots of customer complaints, or too high/low values on some site metrics, will indicate capacity problems on specific sites. This will be addressed then either by increasing the available capacity, or adding new sites in the region, or changing the location of an available site, especially when too many connection problems occur.

6 The consortium

The DayTiMe project pursued a strongly iterative approach to the working plan, transparency of deliverables are achieved through constant exchange of information and a collaborative working environment.

The project includes 18 partners from four national consortia, which causes challenges regarding the collaboration environment. The DayTiMe partners are aware of this fact and have addressed this issue through several measures:
A detailed work structure with an iterative approach and a high number of collaboration and transparency in between different work packages did facilitate our planning. Collaboration within the project was supported by an IT-based collaboration platform, which was developed within WP1. The DayTiMe project was also managed through a matrix organisation: National consortia leaders were appointed and managed their respective national partners, while work package leaders focusses on the international work, which was conducted within the work packages. Some national consortia leaders has been chosen because of their long life experiences and strategically also as working package leaders in order to exploit synergies and to lead effectively. A steering committee consisting of all national consortia leaders and all work package leaders held monthly web meetings in order to secure effective and efficient collaboration. Plenary meetings were held biannual. National consortia and work package teams did meet on a monthly basis.

The DayTiMe partners new, that the collaboration environment must be detailed more in order to guarantee project success. A respective task (T1.3) was included in work package 1 for this purpose. Philips leaded the project management and collaboration. The assigned project manager was and is experienced in leading large research projects successfully.

7 The partners

7.1 Dutch consortium:

Datenna BV applies Natural Language Processing techniques to human-written text and also focuses on user interaction and leveraging expert user feedback to continuously improve predictive modelling

Eindhoven University of Technology will develop predictive maintenance optimization models and investigate continuous learning from the continuous flow of system usage data and the impact of data quality both on predictive maintenance and on continuous learning. **Philips Consumer lifestyle** provides a use case based on the Rota shaver. Philips brings already a connected shaver on the market and aim of the use case is to create more customer benefits in this connectivity. **Philips Electronics Nederland BV** is the national coordinator and will focus on big data analysis and AI technologies (such as machine learning, pattern mining). This is expected to unveil new insights from the actual product usage and create proactive/predictive models for preventing failures of the imaging systems. Philips is also leader of Work package 2 “Cyber-Physical Systems specification”.**Philips Healthcare** provides a use case based on Magnetic Resonance Imaging Systems. Since most of their systems are already connected to the Internet a vast amount of data is harvested, which shall be analysed within the context of the project goals.

PS-Tech will provide end-note forming visual a bridge between the developed digital twins and the users interacting with these twins. The **University of Groningen** will contribute their expertise in modelling and design of multi-domain physical systems and mechatronics system, as well as in the design of self-powered MEMS systems, which will support the design of self-powered sensor systems that can be embedded in the shaver. **Thunderbyte AI** will provide contributions to use case design, product design improvement, proactive and predictive patterns for imaging systems as well as personalized feedback for Smart Shavers users, and demonstration and validation. They serve as WP-leader for work package 5, Toolbox development.

7.2 Turkish Consortium:

Mangodo is going to provide the know-how on data analytics as well as the use-cases. With its expertise on web and mobile application development, it is going to help development of toolbox as a web application and during the dissemination phase, the knowledge on marketing will be used to wide-spread the project outputs. **Simeks** is specialized in medication and Medical Supply Management Systems manufacturing, sales and service. **Triatech** is experienced on producing innovative medication and medical equipment management solutions, which also is a manufacturer. **Turkcell/VAS Telecom** Management in telecom systems, Network Insight, Optimization, Traffic Forecast, Network Plan and Simulation. **Tazi** is focused on AML using streaming data. This project having connecting machines and sensors is expected to be a natural fit to improve and further advance tazi's realtime prediction capabilities and it's AML architecture.

7.3 United Kingdom

Centre for Factories of the Future Ltd (C4FF) will use its expertise in Artificial Intelligence and predictive technologies to develop modules for DayTiMe project.

7.4 Belgium Consortium:

Yazzoom acts as a use case provider and aims to develop digital twins of these industrial boilers to enhance the exploitation of the gathered SCADA data and support the follow-up of the operation of these machines throughout their lifecycle in light of a better product design and maintenance strategy. **Yazzoom** will contribute in R&D on algorithms for anomaly detection and drift detection on numerical machine data. They will specifically focus on the evaluation of these algorithms on the use cases of Philips Healthcare.