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Experience from implementing digital twins for maintenance in industrial processes

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Abstract

The capability of estimating future maintenance needs in advance and in a timely manner is a prerequisite for reliable manufacturing with high availability in a production unit. Additionally, conducting planned maintenance efforts regularly and prematurely increases the service lifetimes and utilization rates of parts, which leads to more sustainable production. The benefits of predictive maintenance are obvious, but introducing it into a facility poses various challenges. In this study, digital twins of well-functioning machines are used for predictive maintenance. The discrepancies between each physical unit and its digital twin are used to detect the maintenance needs. A thorough evaluation of the method over a period of 18 months by comparing digital twin detection results with maintenance and control system logs shows promising results. The method is successful in detecting discrepancies, and the paper describes the techniques that are used. However, not all discrepancies are related to the maintenance needs, and the evaluation identifies and discusses the most common sources of error. These are often the results of human interaction, such as parameter changes, maintenance activities and component replacement.

Keywords Decision support systems · Digital twin · Data processing · Predictive maintenance · Industrial process · Remaining useful life · Anomaly detection

Introduction

The digital twin (DT) approach has shown promising results in different industrial case studies (Mattsson et al., 2019). DT is defined as an integrated multiphysics, multiscale, probabilistic simulation of an asset that can reflect the life of its corresponding twin using physical models and data (Glaessgen & Stargel, 2012). It is a virtual model of a physical system in digital space for simulating its behavior (Fei, 2018). For modern production equipment, there is a basis in the form of drawings and calculation models to create digital twins during the development of the machine.

Conventional industrial machines were classically manufactured decades ago, and typically, detailed parameter information is not available. Most small-, medium-, and even large-scale industries have deep roots and expertise in their fields using conventional industrial machinery. This is a resource to consider and take advantage of (Lin et al., 2016). Most of those industries are in transition from their current standards to Industry 4.0 (Tolkachev et al., 2020). These transitions are performed phase wise in a planned way either by digitalizing a small area of a production unit or by attaching necessary sensors to capture the uncertainties of critical machines (Hennig, et al., 2019). Industry 4.0 has emerged as a possible solution for extending manufacturing processes (Xu et al., 2018) and enables us to observe process disturbances and detect process anomalies at an early stage. The remaining useful life (RUL) also contributes to this solution and is used to estimate the remaining usable time of a machine or its assets based on health information and supplementary conditions (Si et al., 2011). Data play a crucial role; they are considered the lifeblood of Industry 4.0 and lead it toward

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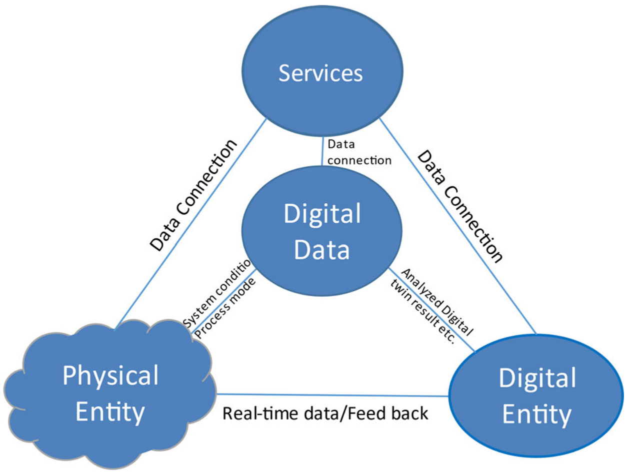

Fig. 1 A 5D digital twin model

smart manufacturing (Kusiak, 2017). The gathered data are available mostly in raw form and processed further in the data processing phase (). For analysis, an eminent method is the analysis of a physical equipment with a DT model to inspect its fluctuations with the power of a cyber-physical system (CPS).

Estimating the RUL and detecting anomalies are exciting areas of research. New algorithms and methods are being developed at a rapid pace with, for example, neural networks and statistical methods. Our evaluation is independent of the method used. What is not as well researched, however, is whether these methods can be applied in an industrial environment and which methods interact with the knowledge and experience that operators, process developers and maintenance personnel possess.

A five-dimensional DT (5D-DT) (Qinglin Qia et al., 2019) approach is used in this research to analyze the performance and maintenance need of various industrial machines and tools, known as physical entities (see Fig. 1).

The DT used in this research is designed for cyclic production and dedicated to specific machines and tools. Due to the age of the machines, inadequate system information, and frequent modifications of the process parameters, physics-based or white-box digital twins were not designed, where the design parameters were constructed from physical laws and well-established relationships (Rasheed et al., 2020). Therefore, we had to use a gray-box data-driven digital twin approach, which fits well in our (conventional industrial) scenario. The model structure is based on general physical equations, and the parameter values are estimated from measured data using system identification algorithms. We have applied DT methods to various processes, machinery, and tools in the steel industry. The pilot-phase results demonstrate that the DT faithfully represents the physical system in industrial applications. Depending upon need, it can be used for several industrial applications, such as process improvement, predictive maintenance, and RUL estimation. These industrial applications are denoted "Services" in Fig. 1.

Numerous scientific contributions are accessible concomitant to DT and its positiveness (Errandonea et al., 2020). However, in regard to practical implementation on live systems, various problems have been encountered, such as decision-making with complex processes and dynamic changes in system properties due to external activities. These problems were commonly neglected due to limited accessibility of data by considering only the ideal scenario (Garrido & Saez, 2019) or due to intense interest in highlighting only satisfactory results (Errandonea et al., 2020). The methods used for DT can give false alarm and missed opportunities. Even by developing an advanced model, similar problems could be encountered, as the production process is influenced by manual operator changes and external parameters.

Recent studies have shown that typical decision-making methods are moving from experience-based to data- and analysis-based methods (Qinglin Qi & Fei Tao, 2018). However, these problems are still considered critical in most industrial scenarios, as false alarms generated by the algorithms can not only cause emergency stops but also waste resources. In addition, they create a lack of trust among operators.

This study highlights and addresses the practical problems of DT analysis that are encountered in industrial implementation. We do not claim to have used the best algorithms in every part when developing our digital twin. Our target group was professionals in the steel industry; this applies to process developers, maintenance staff and operators. We have chosen methods that should be easily accessible to this target group and studied which questions arise during a practical implementation. Our ambition is that the results are generally valid for other methods and algorithms as well. The contribution of the paper is to highlight general problems, based on experience, of introducing digital twins in the process industry and to propose solutions to avoid these problems.

Digital twins were developed and analyzed in real processes. For 18 months, we evaluated this approach by comparison with other administrative systems and identified success factors and causes of false alarms and missed opportunities.

The remainder of the paper is organized as follows. Section "Theory" describes the underlying theory of digital twins and predictive maintenance. Then, DT development and evaluation are described in Sect. "Methods". The results section, namely, Sect. "Results", describes the detection of various types of maintenance needs, along with unwanted detections. The following section (Sect. "Discussion") discusses how unwanted detections can be avoided and presents the conclusions of this study.

Theory

In an industrial environment, data that are obtained from physical assets help DTs provide high-fidelity reflection throughout their service life. DTs can help increase production visibility, maintain optimal operation, and reduce energy consumption and maintenance costs. In this section, a framework for DTs is defined and used.

Digital twin frameworks

Various frameworks have been designed for DTs. However, the three-dimensional digital twin is widely accepted and can be considered the origin of DTs (Grieves, 2014). It consists of three major components: a physical space, a virtual space, and a connection between them. The physical space is a combination of a physical system, sensors, actuators, and related entities. The virtual space, which is also known as the digital or cyber space, is a probabilistic simulation model that analyzes and aggregates data to determine the condition of physical assets. To ensure seamless connection between the physical and virtual spaces, connections play a key role in exchanging information and commands between the spaces (Wanasinghe, et al., 2020). At the initial stage, three-dimensional DT research focused mainly on aerospace engineering for military products and restricted internet access (Tao, Zhang, & Nee, New requirements on Digital Twin, 2019).

In recent years, DTs have been introduced into various applications and have been utilized in daily use products. This has increased their characteristic requirements in terms of technology, application, modeling objects, and modeling methods. Therefore, the framework architecture of a three-component DT has been extended to a five-component framework architecture, which is also known as 5D-DT. Compared to the three-dimensional DT model, it provides broader prospects and higher efficiency. The 5D digital twin model contains five components: a physical object/entity, a digital model/entity, services, digital data, and connections between the components (Qinglin Qia et al., 2019). The two additional components, namely, digital data and services, enable various features and functions. Digital data can be other related software or databases. This model provides more accurate and comprehensive data processing. The 5D-DT digital model is illustrated in Fig. 1.

The physical object is the root of the digital model, which is a collection of physical entities (Wanasinghe, et al., 2020). In general, a physical object can be represented by a fluffy cloud due to its complexity, dependency, and influence on external parameters. Its main purpose is to perform specified tasks and produce output. Sensor data are the heart of a 5D-DT; they sense the physical object and use it to train and drive the DT model.

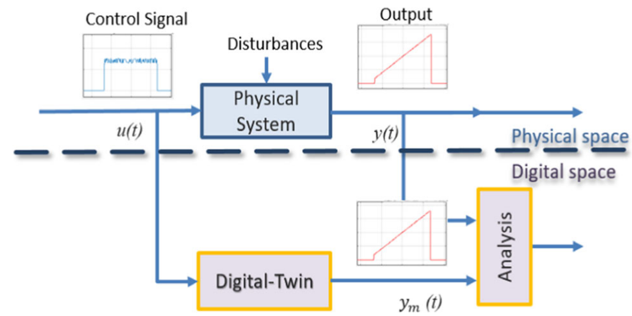

Fig. 2 Digital twin analysis

The physical object can be categorized into a unit-level, system-level, or system of system-level object. The unit-level physical object of a 5D-DT can be a device, a product, or a system component. It is classified as a small system with individual independence and cannot be further divided. Digital objects consist of digital model designs to reflect the physical properties, geometry, behavior, and similar characteristics.

The unit-level DTs are combined with a relationship to form a system-level DT, which includes data interoperation of units and common control, among other components. Unit-level DTs combine to form system-level DTs, systems of systems (SoSs) or organizational-level DTs in a similar manner by the combination of system-level DTs. Such entities offer higher performance and better functionality than a simple sum of constituent systems (Tao, Zhang, & Nee, Application-oriented three-level digital twins, 2019). This paper is mainly based on system-level DTs.

A SoS-level DT is characterized by precise decision-making, depth analysis, global optimization, and model interoperation. The digital data represent both physical and digital aspects, and connections connect components at each level to sync them together. The services in a 5D-DT typically consist of construction, calibration, and test services. System-level services focus mainly on providing services between physical objects and digital objects, such as monitoring and maintenance services for an essential machine unit. The services and data are more abundant at the SoS level due to high dependencies and increasingly complex physical and digital models, relationships, and interactions.

Predictive maintenance using digital twins

The basic idea is to study how a unit's behavior deviates from an idealized behavior. Idealization refers to the behavior of a new unit without failure and wear. The digital twin is used in this case to generate the idealized behavior, as shown in Fig. 2.

The idealized behavior is determined by studying the physical system. The purpose of any physical system is to transform the input into the desired output, for example, an industrial robot. Physical systems vary among applications, such as manufacturing and medical applications. The nature of an application could vary, and a system can be a simple system or a complex system that includes continuous and discrete processes (Engell et al., 2000). A complex system is typically a combination of nonlinear and interconnected functional units and structures (Xiang et al., 2018). An industrial system is usually designed for continuous processes, in which it performs designed tasks repetitively. It also assesses the input requirements through its controller, namely, through feedback calculation of interconnected process units to generate the desired control signal, which may vary from cycle to cycle (Pandit & Buchheit, 1999). In addition, the physical system is exposed to disturbances (e.g., material quality and ambient temperature). It is common for the DT to contain simplifications and delimitations in complexity. This is also why the physical entity in Fig. 1 is a cloud, while the digital equivalent is a box.

The data that are generated in the physical space are usually considered raw data, which barely provide useful information until they are processed further (Hashem, et al., 2015). In the first step, data are collected by various measures, and the physical system is sensed by a sensor application programming interface (PLC) and recorded by a data acquisition system. We use the iba system (ibaAg) for data acquisition, and it provides services up to the SoS level. Due to the characteristics of noise and other disturbances that are generated by multisource and multiscale manufacturing, most of the data must be cleaned before being processed further. The clean data are integrated and stored at a common central base for exchange and delivery to other dimensional levels. Based on the central storage data, the real-time and off-line data are analyzed and excavated through advanced analysis methods and tools, such as prediction models, classification, and feature extraction. The valuable information that is extracted from the ambiguous data is fed to the analyzer block to make suitable decisions for predictive maintenance.

The decision-making methods may vary depending on the application. It can be deviations from a reference cycle in a time domain or the study of health indicators. The health indicators can be properties in the time domain (such as max and min values or statistical parameters) or in the frequency domain (e.g., harmonics).

Modes in the Production Cycle

A production cycle has various operating modes or states, and the most frequent are start-up, operation, maintenance, and idle. Figure 3 shows different stages of the process, which depend on the production nature, maintenance need, operator influence, emergency stop, and other parameters. Since the behavior of the units is affected by the mode the machine is in, it is important to know which mode the machine is in.

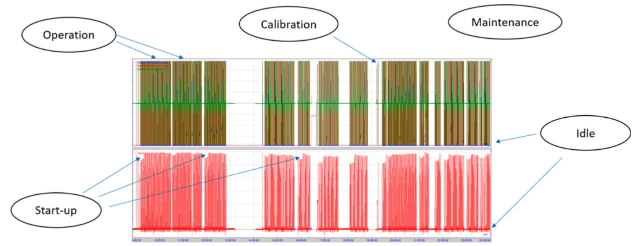

Fig. 3 Different stages of machines and tools during production

This applies both when the DT is created/designed/trained and when the result is evaluated. Sometimes, the measurable signals indicate the operating mode, whereas at other times, it is necessary to estimate the operating mode, which can be described with, e.g., a hidden Markov model.

Methods

To experimentally evaluate the problem of implementing DTs in industry, various machines and tools were studied. The DTs were designed according to the 5D-DT standard and driven using processed sensor data. Analyses were performed, and deviant behaviors were recorded. Then, the DT results were compared with a maintenance log. Data from 18 consecutive months were evaluated.

The testbed consisted of the process machinery and tools in the steel industry, in which various processes were upgraded to the Industry 4.0 standard. Most of the processes were complex, in which several small processes and tools synced together and formed a desired standard product. They involved nonlinear combinations and couplings of units. Various system behaviors were analyzed in the project. The complex processes were controlled by the PLC.

The health, performance, and efficiency of the system depended directly on the usage and maintenance. Planned maintenance activities were performed periodically, which mostly reduced the unplanned downtime but did not ensure the avoidance of emergency stops or forced maintenance. To improve the reliability, safety, and prevention of undesired maintenance, sensors were attached to the machines and tools, which sensed and recorded the system's environmental changes. A time synchronized data acquisition system was used by the iba system service provider, and it was adopted to record in-process measurements. The recorded raw signals were processed, and a data cleaning phase was conducted to remove data from when the machines or tools were in the calibration, waiting, or test mode. We did not have access to other data sources.

The central goal of the application of the DTs was to reflect the machine behavior, capture internal damage, and identify critical components that would lead to system failure.

Digital twin design

The systems under observation were machinery in the current industries, for which the entities did not have detailed information, such as datasheets or explanations. However, they were frequently maintained by experienced teams and operated by professional operators. These entities processed material and produced initial products, which were processed further to produce final products. The overall process that was shaped by the related machines and tools was driven by a controlled input signal that was manipulated by the PLC along with adjustable instructions that were given by the operator. The machinery and tools were usually affected by external stimuli such as disturbances, which were divided into two categories: 1) directly measured disturbances, e.g., disturbances in the temperature of the material, and 2) glitches that were observed through experience and product inspection, e.g., unusual tool behavior, and influenced the final product. The production was divided into several procedures, which were combinations of linear and nonlinear techniques. Nonlinearities have generally been approximated with linear behaviors within a specified work area, which can be justified by the observations that the control algorithms limit the work area and linear models reduce the number of calculations (Zawadzki & Różowicz, 2015).

Due to a lack of system information and frequent modifications of the system parameters, physics-based or white-box digital twins were not easily designed, where the design parameters were constructed from physical laws and well-established relationships (Rasheed et al., 2020). Therefore, we had to use a data-driven digital twin approach, as it fits well with our scenario. In the data-driven approach, the selected mode of the process was used to identify the physical system; for example, when a process operated in an optimum mode and produced satisfactory products, it also fulfilled the properties of the LTI system and postulated the model class when parametrized by limited but unknown parameter values. Process data were extracted for various purposes, such as performance estimation, equipment degradation or wear detection, RUL estimation, and maintenance prediction. The observed data were collected by constant sampling, thereby enabling us to choose a system representation in discrete form. In data-driven DT, pragmatic forecasting of the output was achieved by analyzing previous observations of measured data. The approach was to select or identify the unknown parameters to measure the output with less error. We used the regression method by considering previously recorded values. An autoregression with exogenous variable (ARx) model is an example of this approach.

The three basic entities that we used to construct the digital model were as follows: 1) A dataset was used to record production data from the process, where the measured signal was limited to the standard production, and calibration and bad production data were not included in the dataset. 2) The structure of the model was considered. Since the system could be identified from the collection of models, we considered the model by injecting process knowledge such as specified starting and stopping positions in combination with the formal properties of the twin model. Most of the entities were combinations of subsystems or SoSs. A split-up approach was used, in which subsystems were chosen. The DT of each subsystem was designed to analyze the dynamics. These subsystem DTs could be joined later mathematically to form a digital model of the whole system. 3) We identified the most suitable model based on performance when guided by the data in reproducing the measured data. Model validation was also included as a checkpoint, which ensured that the twin model was valid for the specified purposes. The model behavior with respect to its intended use and prior system knowledge that ensured the validity of the twin model built confidence in its reliability. The DT mathematical model was designed for use as a support tool for simulation and forecasting.

Evaluation

The machinery and tools under observation were maintained frequently by periodic and/or emergency maintenance, and some of the activities were related to quality inspection, component replacement, troubleshooting of faults, and emergency tool replacement. These activities were recorded in the maintenance log. For the studied production units, data from the maintenance log were saved separately and compared with the detections from the DT. The corresponding cases were successful cases. Cases in which the DT did not detect an event that was in the maintenance log were classified as missed opportunities; cases in which the DT detected an event that was not in the log were classified as false alarms.

Since the purpose is to gather experience of implementation in real industrial processes, we have chosen to classify the results based on the following three different classes.

Parameter settings

In most industries, production depends upon consumer demand and precise design. System parameters are commonly altered due to manual changes and natural wear. Based on expertise, the process operator or maintenance team realizes that changing certain parameters, e.g., speed limitations, could result in better production. In addition, with respect to process improvement, process engineers may apply process constraints and change parameter settings, e.g., restrict energy consumption through a logic controller to limit additional resource utilization and produce cost-efficient sustainable products. These parameter settings directly and/or indirectly modify the physical system dynamics. The twin models of such a system detect the parameter change activities either by manual changes or natural wear. It continuously analyzes data gathered from the data collection system and monitors system parameters in its analysis block.

Component replacement

The production process is a combination of several components, and the overall system performance and efficiency depend upon the health of each component. Re-equipping of the component can influence the performance of the overall system. In addition, misalignment and incorrect replacement can introduce contamination that affects system performance. These activities are part of periodic and/or emergency maintenance (when a component breaks and requires immediate action to continue the process). The twin model processes and extracts essential information from the collected data and identifies the characteristics and behavior of the new or re-equipped component. It points out the performance of the replaced component by comparing the DT model with its physical entity and indicates that either the component improves the process performance or it introduces impurities in the process.

Degradation

The lifespan of machines and tools is examined by observing from their initial deterioration stage to complete breakdown. When a machine or its essential component breaks, it not only reduces the process performance but also causes undefined production stoppage. In most of the observations, machines or their essential components experienced several degradation stages before failure. These stages are observed and calculated in the performance analysis block stationed between the DT and the physical system. The DT analyzes and aggregates data to determine the condition of the physical entities; it captures most of the external and internal fluctuations acting on the physical system.

Results

To test the effectiveness of the designed digital twin models, the analysis block in the digital domain was used to compare the performance of each individual physical system with its corresponding twin model. We collected information from the maintenance logs and detections from the DTs. In total, 47 observations were obtained. Successful detection occurred when a DT found a deviation that could subsequently be linked to a real deviation. This occurred in 33 cases, while 13 cases were missed detections, and one false alarm occurred. One false alarm is one too many, but since several hundreds of units were examined during the period, one false alarm may be acceptable (Table 1).

Table 1 Maintenance activities and DT responses

	Digital Twin	
	Detected	Missed
Log		
Activity	33	13
No activity	1	

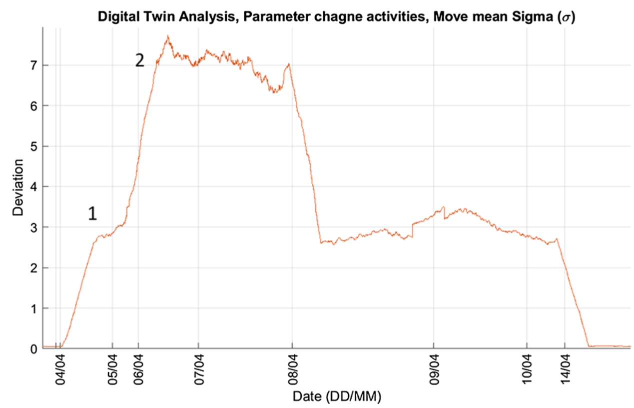

Fig. 4 Machine performance analysis via its twin model when the operator change system parameter settings at various occasions

However, false alarms can also include DT detection of deviations that do not correspond to maintenance needs. These can be parameter settings from the operator, maintenance efforts and planned replacement of components.

Parameter Settings

Several parameters were involved in the overall experimental process, and their changes could affect the performance. An example of such parameter changes is shown in Fig. 4.

The process operator changed three parameters that were considered essential in production, and their deviation could cause unsatisfactory production if they varied by themselves. The DT analysis reflects the process behavior with different deviation levels when the first two parameters were changed on April 04. The deviation between the twin and physical system increased and climbed to level 1. Later, the operator changed the third parameter, which was the initial process constraint. The system responded with a rapid jump, and the performance difference between the twin and the process increased to level 2. The high deviation fell later to level 1 when the operator reverted the third parameter to its original setting. In the end, the operator changed the first two parameters to their initial values. In response, the corresponding deviation returned to the original level.

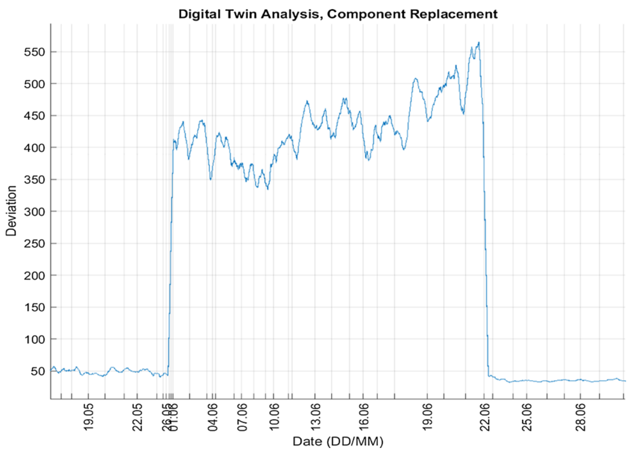

Fig. 5 Analysis of a machine's component, which showed how it affected the overall performance during its lifespan

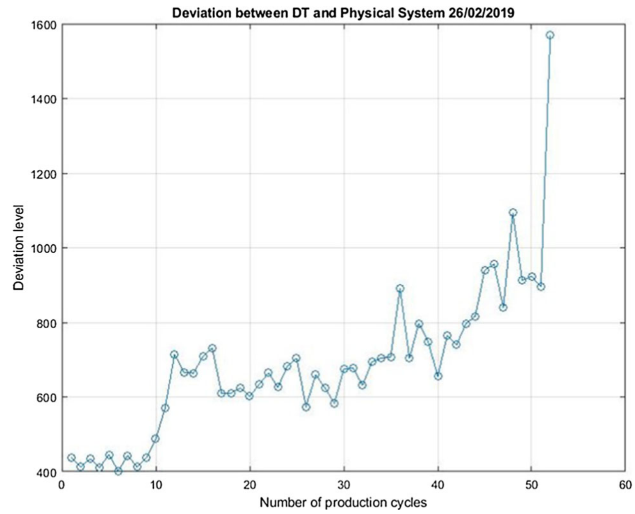

Fig. 6 Degradation analysis of an industrial tool that typically breaks down during the process

A deeper analysis shows that settings by the operator (that did not negatively affect the process) were detected on 10 occasions. According to the original definition, these were not false alarms but should be classified as such since they were not detections of maintenance needs.

Component Replacement

In most of the analyses, the SoS-level performance depended upon its essential subsystems or components. If any of the major components were replaced or degraded over time, this affected the performance of the final product, as shown in Fig. 5.

The maintenance team replaced one of the essential components to improve production. However, the replaced component did not fit well and caused contamination in the process. It is observed from the result that after replacement, the performance varied with a high floating level. In most of the component replacement activities, unsatisfactory syncing of the replacement not only ruined the production standard but also placed stress on the machines and consumed extra resources. The DT analysis showed the lifespan of the re-equipped component and how it affected the machine's performance. These responses were similar to those in Fig. 5. However, when the component fit well, it imposed less stress on the machine and led to satisfactory production, and the deviation between them remained at a constant level. A similar reflection is shown at the end of Fig. 5. When the team replaced the component again, the deviation level decreased to a low level, thereby indicating that the machine performed well.

Degradation

Degradation of the physical systems occurred in various stages due to utilization and environmental effects. If the process operator did not take the necessary action, equipment failure or breakdown occurred. Figure 6 shows the results of the equipment life analysis, where the equipment performance decreased with respect to its utilization and external effects. After a certain cyclic period, the deviation between the physical system and its twin gradually increased, which led to breakdown. We observed from a similar analysis that when the machine worked in an optimal mode, without any external parameter settings (either by the operator or the maintenance team), the deviation increased gradually to a threshold level before failure occurred. The prediction of such breakdowns is essential, and its successful implementation prevents failure and leads to standard production.

Degradation can be due to one or more reasons or failure modes. For each of the failure modes, a health indicator is calculated, and the deviation is registered. By using regression analysis, future deteriorations can be estimated. By setting a threshold for how large deterioration is acceptable, the RUL can be calculated. One condition, however, is that the measurement sequence does not contain parameter changes or component changes as in Sects. "Parameter Settings" and "Component Replacement".

Observed Problems

The results from the analyses are promising and provide valuable information. We were effectively able to measure the equipment degradation stages from fresh to complete failure, capture the process behavior, analyze the performance, and detect contamination when the essential component was repaired or replaced or when the operator changed the parameter settings. These pilot observations pave the way for implementation in a live system, but due to hurdles and complications (such as no explanations from the operator when he/she altered the system) and the complexity of regulating the parameter settings by the process operator (the process twin did not receive external feedback from the operator), the analyzer block considered these system change activities to be performance deviations and, in response, deceptively generated false alarms.

Similar to alterations of parameter settings, maintenance activities also resulted in deviations in the DT performance analysis. The maintenance activities were usually planned a couple of weeks in advance and typically covered a whole working day. The team usually inspected almost every part of the machinery, tools, and necessary equipment; replaced or repaired the necessary components that could affect the performance; and recorded these activities in the log afterward. In the future, data access to the maintenance logs (which would be in "Digital Data" in Fig. 1) will prevent false alarms during the maintenance activities. However, some activities were unplanned, which were usually performed during emergency stops and were reported instantly or after several days. This causes problems since the activities were not reported in a timely manner.

Activities that are related to maintenance and parameter settings are part of most industrial processes. In a pragmatic analysis, the overall process depends upon several individual processes that are driven by machines and tools. Each process correlates with other processes; therefore, any small misalignment could alter the system dynamics. In contrast, a DT is identified once; the maintenance activities for *component replacement* could cause the equipment state to become good, satisfactory, or bad. The system state is modified after parameter settings and component replacement, and the analyzer block sniffs these changes and produces high deviation even when the process leads to satisfactory production. This can be solved by updating the DT after maintenance activities. However, this could be difficult because a DT update after finding a bad or misaligned component could compensate for the idealized unit's behavior, and we were not able to detect whether the replaced component was good or bad.

Another major problem was setting an alarm for decision-making. Different types of production required different tool categories. The operator often switched tools from one category to another according to the production requirements and reused tools. When a tool broke, the operator often reused an old tool that was available and continued production. Lifetime data of most equipment from fresh to failure were not available. No records on equipment health, usage, or when the operator started using fresh tools were available. The RUL analysis results showed that from initial degradation to complete failure, a machine's performance deviated at a random level that varied from one breakdown to another. This can be improved by including process log information in the DT model.

Potential solutions

Regarding the problem of operators changing parameter settings, we see several solutions. One possibility is to include parameter values as part of the digital twin. However, it can cause the DT to become too complex. A simpler option is to create a look-up table where different parameter settings address a unique DT. A third option in order to avoid false alarms is that the DT can be turned off if parameter values are changed. To reduce the number of false alarms during maintenance, good communication is needed between computerized maintenance management systems (CMMS) and DT. This would allow the twin to be calibrated after a maintenance operation to adapt to new components. In addition, abnormally large deviations after a component change could warn of possible deficiencies in the new equipment.

Discussion

Machine degradation and performance deviation of industrial machinery and tools, which were analyzed using DTs, are the key factors in our research. During the analysis period, we observed that the designed DTs missed various machine deterioration activities, and in some cases, they did not reflect the true performance of the physical system under testing. This can be overcome by including unit-level DTs, which can also help enhance the overall monitoring strength and overcome missed opportunities.

Some analyses indicate false alarms due to changes in the parameter settings, which were usually altered either by process operators or after successful trial activities. The frequency of these false alarms can be reduced by including parameter settings in the DT model. However, the resulting model would be more complex. Alternatively, the monitoring of health parameters is paused when other than default parameter values are used.

Moreover, the maintenance of supply systems can also affect the performance, and it modifies the properties of the monitored systems. A connection to the maintenance system (see "Digital Data" in Fig. 1) can help tune a DT after maintenance. However, incorrect component maintenance could lead to an incorrect DT. Therefore, a plausibility analysis should be performed to sort out and warn of faulty spare parts before updating the properties of the DT.

Furthermore, changes or replacement of the components in the test system (after breakdown or maintenance activities) would also require adjustments in the DT. In such scenarios, unit-level DTs need to be updated individually and synchronized with system-level DTs. From the analysis and implementation experience, DT models have been further fine-tuned, and the new results give better performance.

Conclusions

From a thorough assessment of industrial DT models over a period of 18 months, we have demonstrated that DTs are a useful tool in real industrial processes, where various factors influence the physical system's properties. The results show that DTs can be used as assisting tools to monitor health and forecast failures at early stages.

Various industrial processes were examined, in which limited manufacturer information on machinery and equipment was available, such as data sheets. Gray box techniques were used to design the DTs. The designed twin models were used to facilitate successful detection of maintenance needs and tool degradation, performance analysis, and estimation of the RUL. The DTs ran in parallel with the physical system, performed satisfactorily and produced promising results. However, several problems were encountered in industrial implementation.

When a parameter was changed by the operator and/or by the maintenance team due to process needs, false alarms were generated, as the twin did not obtain information to update in time. In future work, an ideal production standard should be defined with the help of process workers and maintenance teams. Hence, after operational activities such as parameter setting and component changes, a trial test should be performed before starting production to match the physical system with the defined product standard. Furthermore, it is important to include a data exchange (interoperability) with other sources that are related to the DT, such as maintenance logs.

An interesting question is whether more advanced methods can avoid false alarms and give better predictions. Since the production units in the industries of interest to the paper are unique, are there resources (skills and economical) to implement and maintain more advanced algorithms, or is "good enough" good enough?

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Declarations

Conflict of interest The authors declare no conflict of interest in the presented research work.

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