# Chapter 86
# Development of a Predictive Maintenance 4.0 Platform: Enhancing Product Design and Manufacturing

**Clint Saidy, Sruthi Puthan Valappil, Rhea McCaslin Matthews, and Abdel Bayoumi**

**Abstract** The current growth in digital technologies is transforming the working environment in all industries; even in traditional industries, scientists are experimenting with the Internet of Things (IoT), data analytics, sensor technology and most importantly machine learning. This paper addresses the use of predictive maintenance techniques to improve product lifecycle. The classical purpose of predictive maintenance is to diminish unexpected downtime, resulting in increased productivity and reduced production costs. However, the purpose of this study is to investigate and explore the potential of predictive maintenance and its relation to Industry 4.0, and product/process re-engineering through product lifecycle management (PLM), hence leading to Predictive Maintenance 4.0. During the operating phase of the product lifecycle, results from the Predictive Maintenance 4.0 model will not only help in predicting faults, but it will be crucial in product design and manufacturing advancement. This paper develops the architecture of a Predictive Maintenance platform connecting the industrial unit floor with design and manufacturing engineers. Feedback from the platform and interaction between different stakeholders from design, manufacturing, and operation will help in the advancement of the product itself.

## 86.1 Introduction

In recent years, advances to the Internet, the Internet of Things (IoT), big data, artificial intelligence, and new developments in digital technologies have given analog devices a digital footprint, allowing for greater interconnectivity and presenting opportunities to achieve higher levels of productivity within industry. This assimilation forms the basis of the so-called "Industry 4.0", being made possible by the extensive adoption of next-generation technologies by industrial firms [4, 7–9].

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A. Ball et al. (eds.), *Advances in Asset Management and Condition Monitoring*, Smart Innovation, Systems and Technologies 166,
https://doi.org/10.1007/978-3-030-57745-2_86

Industry 4.0 is the current trend of automation and data exchange in industrial settings and technologies. This approach allows for machines, systems, and users to be interconnected allowing for faster decision-making and lesser downtime. Predictive Maintenance 4.0 is the machine-assisted digital version of what humans have been doing in the past 40 years to ensure assets deliver value for organizations. It includes a holistic view of everything from data sources to collection and analysis to recommendation of actions. It also ensures asset function (reliability) and value (asset management).

### *86.1.1 Selecting the Application – Water Desalination*

The Government of Egypt has recently begun a national strategic plan to reclaim 1.5 million acres in selected desert areas. The government vision is to build new communities with sustainable high quality of life while promoting agriculture and cluster-based development. However, it is expected that these newly created communities will face challenges in securing fresh drinking water since the salinity of underground water reaches 7000 ppm in some of these desert areas. Reverse Osmosis (RO) is quickly becoming a dominant technology in the desalination industry. However, the energy consumption of an RO desalination plant is another critical factor that requires consideration since most of these communities are in remote locations off the national grid (Fig. 86.1).

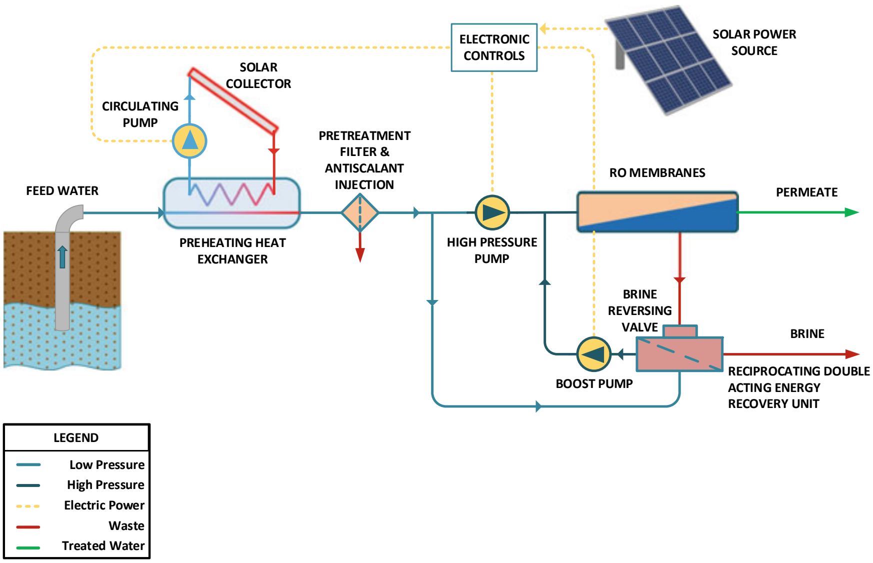


**Fig. 86.1** Schematic diagram of an RO desalination plant

The scope of the project is to develop an Industry 4.0 framework, including a digital twin of the water desalination plants system that will allow for self-diagnosis and system decision making to ensure optimal performance. These features enable remote monitoring and control of the desalination plant. The Digital Twin health monitoring system (HMS) will receive data from onboard sensors monitoring critical variables of the plant and compare it to the plant's historical and theoretical models of the plant. This enables the system to optimize its performance to achieve prolonged life and better efficiency. The current health of the system will be updated in real-time and shared with a remote decision making authority. If there is an anomaly in the readings, corrective action will be initiated and responsible personnel will be alerted to the new state of the system. The Internet of Things (IoT) enables this interconnected network of machines and people and the existence of a reliable, remotely operated, automated, decentralized ground water reverse osmosis (GWRO) treatment plant in the desert.

The main objective of this research is to maximize plant availability and smart monitoring of features incorporated in the plant to ensure reliable operation at optimal efficiency, and minimize maintenance burdens for the water desalination industry.

## 86.2 Literature Review

This so-called Industry 4.0 represents the fusion of modern manufacturing techniques with current communication and information technologies [5]. One facet of this integration with great potential in many industrial fields is Digital Twins [1, 4, 13]. Put broadly, Digital Twins represents the modeling of physical systems as digital counterparts, with the goal of improving productivity and efficiency [6]. The implementation of the twin lends itself to increased automation, reducing room for human error while increasing aforementioned productivity and efficiency [4, 9, 12]. Many authors have proposed different nuanced definitions on the concept of Digital Twins, which will be discussed below. The first definition was coined by NASA as, "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its…twin" [3]. Kritzinger differentiates this concept into three sub-categories; the Digital Model, The Digital Shadow, and the Digital Twin. With a Digital Model, the model and physical entity are linked through manual data. What happens to one doesn't affect the other; rather, the data must be manually transferred from one entity to another [6]. With a Digital Shadow, a Digital Model integrates an automatic one-way data flow between an existing physical object and its digital counterpart; a change in condition of the physical object leads to a change of condition in the digital representation, but not vice versa [6]. With a digital Twin, the data flows between an existing physical object and a digital object, so that a change in condition of the physical object directly leads to a change in condition of the digital representation and vice versa. Another key definition of the

Digital Twin suggests it is comprised of three components: the physical object, its digital counterpart, and the data that interconnects the two [8, 14]. Under this definition, "Digital twin reflects two-way dynamic mapping of physical objects and virtual models, specifically…the virtualization of physical entities" [8]. Another definition posits that the digital twin is comprised of "the flow of data, process and decisions captured in a software avatar that mimics the operation" [2]. As clearly seen, nuances exist between different interpretations of Digital Twins, but the core similarities remain [4, 11].

In this paper, we will use the concept of digital transformation and digital twin it in the development of a Predictive Maintenance 4.0 platform. This platform will allow health monitoring of systems and continuous feedback to user. Furthermore, this definition will be supported through the development and examination of a Predictive Maintenance 4.0 platform for water desalination systems.

### *86.2.1 The Application of Digital Twin in Industry*

While the implementation of Digital Twins has implications among many areas of industry, there are a few main fields that benefit from Digital Twins [8]. Digital Twins greatly rely upon data acquisition and provide benefits to real-time data acquisition [4, 13, 16]. With the digitization of previously only physical systems, the interconnectivity of Digital Twins allows for autonomous real-time data collection [8, 13, 16]. The acquisition of data in real time leads to many potential areas of improvement related to product lifecycle management (PLM). PLM "enables a company to grow revenues by improving innovation, reducing time-to-market for new products, and providing superb support and new services for existing products, as well as enables better support of customers' use of products" [13]. Many existing components of PLM rely on the acquisition and transformation of data from physical entities; with the introduction of Digital Twin modeling, PLM can further be expanded to interpret and factor in data from digital models, accounting for situations that are impossible or improbable to simulate in the physical world [4, 13, 15]. This application of Digital Twins has important implications—especially in the fields of aerospace and manufacturing. The aerospace industry, as many other industries, relies on "factors-of-safety" when designing products [3]. These "factors-of-safety" compound upon one another, which may lead to unnecessarily heavy configurations and reduced efficiency without improving the actual safety of the vehicle or the chances of success [13]. With the application of Digital Twins, real time modeling and predictive maintenance can be applied to any design, any step of the way, allowing for decreased redundancy in safety protocols, as well as improving the overall efficiency of the design [13, 15]. Similarly, the benefits can be extended to manufacturing as well. The application of Digital Twins, especially with regard to data analysis, could pinpoint bottlenecks in the manufacturing processes, derive both the causes and impacts of the problems, and recommend the proper solutions [6, 13]. It further brings together data from all steps of the product lifestyle, shortening the product development cycle, and improving quality, accuracy, reliability, and stability in manufacturing [6]. The mass collection of data allows for better simulated models reflected within the Digital Twin, which in turn leads to a better analysis of all phases and cycles of the manufacturing process [7]. In this paper, we will explore a more in-depth analysis of the application of Digital Twins in these fields, as well as other implications.

## 86.3 The Development of a Predictive Maintenance 4.0 Platform

This section details the rationale behind the architecture of a Predictive Maintenance platform connecting the industrial unit floor with design and manufacturing engineers. The main elements of this platform consist of: health monitoring, predictive analytics, and fault diagnosis and recommended actions. Feedback from the platform and interaction between different stakeholders from design, manufacturing, and operation will help in the advancement of the product itself creating the Predictive Maintenance 4.0 environment.

A critical factor in the success of the desert ground water treatment plant is the digital integration of the entire operation and the development of digital twins for each critical component. This Industry 4.0 framework will allow for an efficient GWRO system (Fig. 86.2).

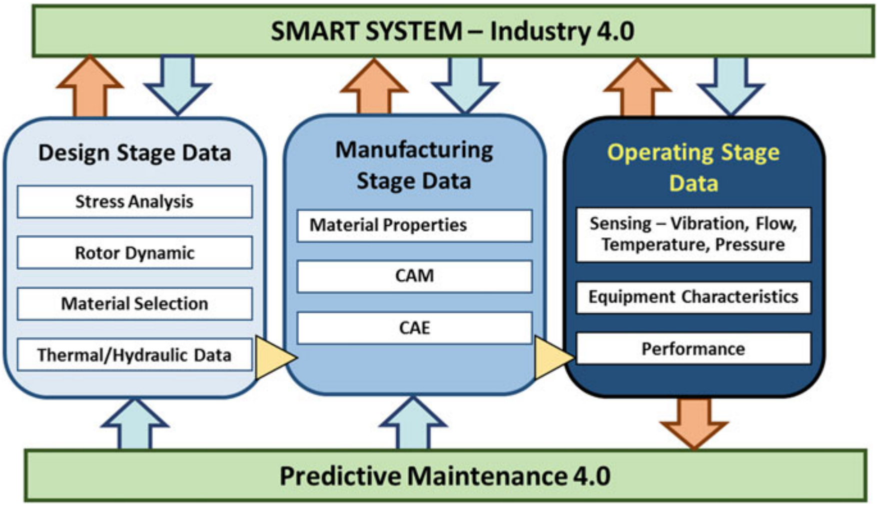


**Fig. 86.2** Enhancing design and manufacturing through predictive maintenance

Using a dashboard, all the data from different desalination plants around Egypt can be streamed up to the cloud and then used for analysis and presentation. Sensors are used to monitor the health of the component, and data is collected and models built to detect faults and develop trends based on the health and usage. In addition to dashboards, a virtual reality environment will be developed to display information and results.

### *86.3.1 Application: High Pressure Pump and Water Desalination*

The team will investigate what faults need monitoring to ensure an optimally functioning system. This is a critical step in developing a digital twin with the appropriate data models and algorithms. The critical components of the desalination system are solar panels, pumps, reverse osmosis membranes, energy exchanger/pressure recovery device and piping connecting everything together. Some common faults will include cavitation damage on the pump impeller, shaft misalignment, degraded bearings, recirculation in the pump, air in the system, scaling in RO membranes, fluid leakage, etc.

### *86.3.2 Collective Relevant Data*

A digitized system will be able to recognize negative changes in operation and adjust component performance to protect itself from further damage. It will also constantly adjust performance in response to variable factors, such as power fluctuation, changing flow rate, and environmental conditions, to ensure optimum efficiency is always achieved. For this to happen, the system must be "self-aware" which requires multiple types of sensors to be placed in critical locations in the system. These locations must be determined and data must be sampled appropriately to have accurate health monitoring and performance prediction.

### *86.3.3 Correlating Faults to Sensor Data and Developing Data Models*

The first step in this task is to process raw sensor data, which could include signal processing, vibration analysis, and feature extraction. In machine learning, feature extraction serves to build derived values (features) are intended to be informative and non-redundant from an initial set of measured data. The second step is to develop data models: Proper algorithms are needed to process the raw sensor data and turn it into useful information on the health of a component.

### 86.3.4 Designing a Health-Monitoring Dashboard

Software will be developed to process real-time data and distribute it to a networked monitoring system for human and machine use. Conditioned data will pass through a decision tree matrix so the pump can take appropriate action in response to the input. The machine learning and decision-making must be detailed and robust for an automated plant to be successful. Human decisions are still very critical in this type of HMS and so it is important that the data monitoring and analysis software are well designed.

### 86.3.5 Dashboard Development for Water Desalination

Sensors are used to monitor the health of the component, and data is collected and models built to detect faults and develop trends based on the health and usage. The data is then reflected on unique dashboards to easily relay information to users based on their needs. In addition to dashboards, a virtual reality environment was developed to display information and results.

Data is collected and transmitted to the web server application through a lightweight transfer protocol MQTT. MQTT is a publish/subscribe based messaging protocol that relays data through a central server called Mosquitto broker. It is designed for connections with remote locations and it is desirable in internet of things (IoT) because it is easy to add new devices without touching the existing infrastructure since new devices only need to communicate with the broker and they don't have to be compatible with other clients. Once the web server is subscribed to the MQTT broker it will receive the publishes from the device which is the sensor readings and this data is used to predict the health of the component. We have set the Quality of Service (QoS) value of the topic subscription to 2 which guarantees message delivery with no duplicates.

The software dashboard (web app) is built on Node JS which is a JavaScript framework for writing server-side applications. It allows triggering JavaScript programs from the command line without any browser involved. It is an excellent choice for building superfast and highly scalable Real-time web services because of the non-blocking asynchronous nature of the node. User interface (UI) part of the web application is implemented using HTML, CSS, JavaScript, jQuery, and Angular JS. After login to the web application user can navigate through different web pages and analyze the overall health score and performance of each plant. Fault detection dashboard (Fig. 86.5) is for real-time data visualization. Dynamic graphs will be displayed on this web page which can be refreshed in real-time and can be used to figure out the outliers.

Once logged into the software, a user, located at the control center, will have access to a map showing all plant locations, as well as an overall health score that describe the performance of each plant.

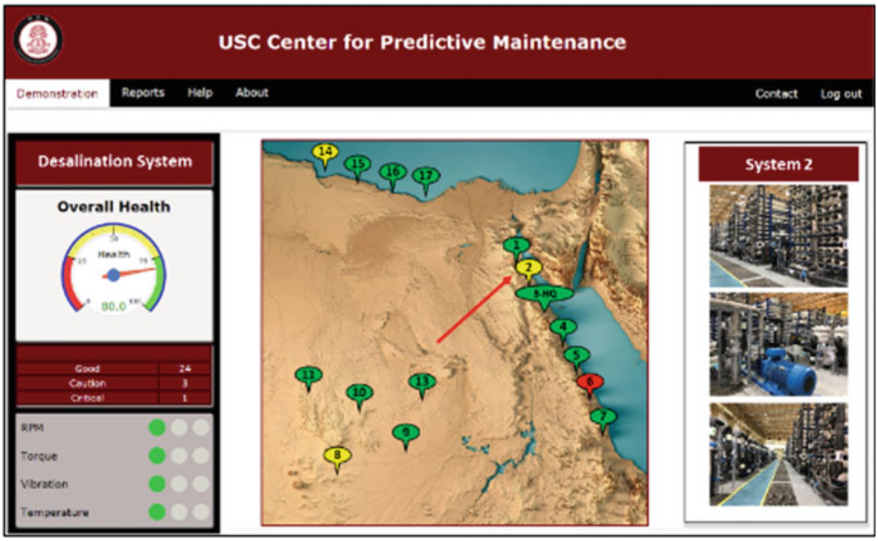


Fig. 86.3 Dashboard main screen

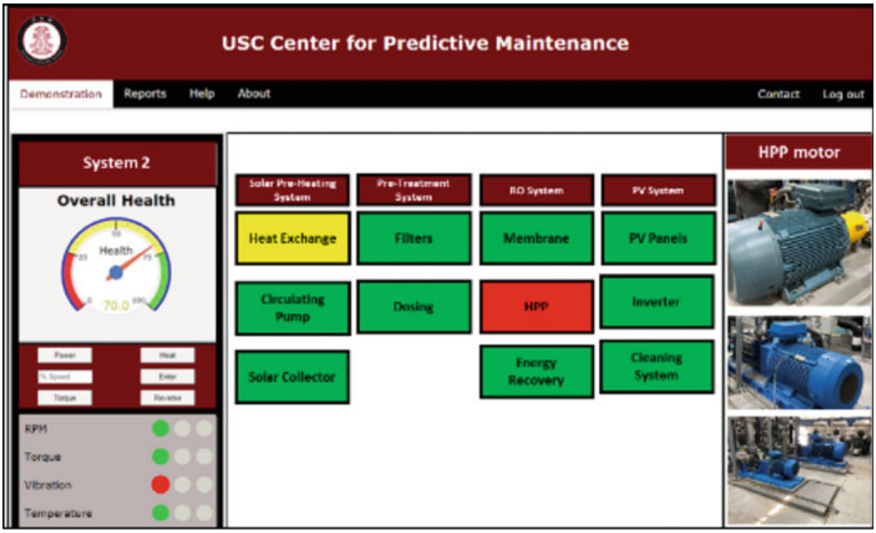


Fig. 86.4 Dashboard sub system

After being notified of an underperforming plant (Fig. 86.3), the user can monitor the specific performance of this plant. The data is then reflected into a unique dashboard for the specific plant showing which components are failing.

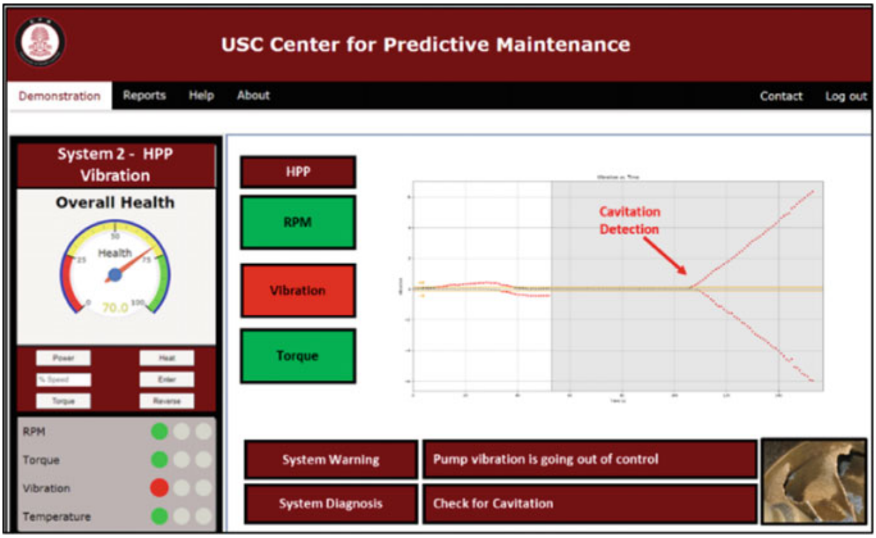


**Fig. 86.5** Dashboard fault detection - warning and diagnosis

Once observing that the main issue is related to the high pressure pump (Fig. 86.4), the user can select the component at hand in order to have a stronger understanding of the problem.

The dashboard will help the user understand the system warning, and propose a system diagnosis (Fig. 86.5). After the problem is diagnosed, the right stakeholder in the plant will be notified in order to check the issue and fix it. The rationale behind the fault detection algorithm is developed in Saidy et al. (2019) [10].

## 86.4 Conclusion

Effective data visualization is a key factor in the human digestion of data analysis. Figure 86.6 represents the smart system of systems where everything is connected as a digital twin (DT).

Our team will take historical data models and supplement them with theoretical models discussed above to create the digital twin of the pump and other GWRO system components that will process incoming data and make health decisions and predictions. These digital twins will result in "smart" components that are capable of knowing when to adjust in response to system changes without manual intervention. In a predictive maintenance 4.0 setting, a smart component should be fault tolerant and capable of safeguarding itself from operating under conditions that may reduce its life.

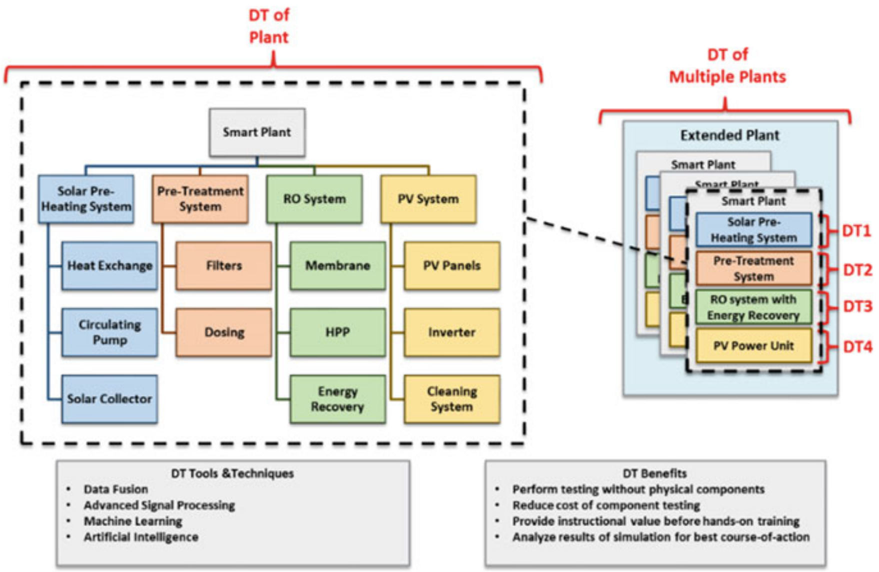


**Fig. 86.6** Smart system of systems

## References


1. Botkina, D., Hedlind, M., Olsson, B., Henser, J., Lundholm, T.: Digital twin of a cutting tool. Procedia CIRP **72**, 215–218 (2018)
2. Datta, S.P.A.: Emergence of digital twins. arXiv preprint arXiv:1610.06467 (2016)
3. Glaessgen, E., Stargel, D.: The digital twin paradigm for future NASA and US air force vehicles. In: 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference 20th AIAA/ASME/AHS Adaptive Structures Conference 14th AIAA, p. 1818, April 2012
4. Grieves, M., Vickers, J.: Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Transdisciplinary Perspectives on Complex Systems, pp. 85–113. Springer, Cham (2017)
5. Haag, S., Anderl, R.: Digital twin–proof of concept. Manuf. Lett. **15**, 64–66 (2018)
6. Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W.: Digital twin in manufacturing: a categorical literature review and classification. IFAC-PapersOnLine **51**(11), 1016–1022 (2018)
7. Negri, E., Fumagalli, L., Macchi, M.: A review of the roles of digital twin in CPS-based production systems. Procedia Manuf. **11**, 939–948 (2017)
8. Qi, Q., Tao, F.: Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. IEEE Access **6**, 3585–3593 (2018)
9. Rosen, R., Von Wichert, G., Lo, G., Bettenhausen, K.D.: About the importance of autonomy and digital twins for the future of manufacturing. IFAC-PapersOnLine **48**(3), 567–572 (2015)
10. Saidy, C., Xia, K., Kircaliali, A., Harik, R., Bayoumi, A.: The application of statistical quality control methods in predictive maintenance 4.0: an unconventional application of Statistical Process Control (SPC) charts in health monitoring and predictive maintenance. Int. J. COMADEM (2019)

11. Schleich, B., Anwer, N., Mathieu, L., Wartzack, S.: Shaping the digital twin for design and production engineering. CIRP Ann. **66**(1), 141–144 (2017)
12. Söderberg, R., Wärmefjord, K., Carlson, J.S., Lindkvist, L.: Toward a digital twin for real-time geometry assurance in individualized production. CIRP Ann. **66**(1), 137–140 (2017)
13. Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F.: Digital twin-driven product design, manufacturing and service with big data. Int. J. Adv. Manuf. Technol. **94**(9–12), 3563–3576 (2018)
14. Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., Guo, Z., Lu, S.C.Y., Nee, A.Y.C.: Digital twin-driven product design framework. Int. J. Prod. Res. **57**, 3935–3953 (2018)
15. Tuegel, E.J., Ingraffea, A.R., Eason, T.G., Spottswood, S.M.: Reengineering aircraft structural life prediction using a digital twin. Int. J. Aerosp. Eng. (2011)
16. Uhlemann, T.H.J., Schock, C., Lehmann, C., Freiberger, S., Steinhilper, R.: The digital twin: demonstrating the potential of real time data acquisition in production systems. Procedia Manuf. **9**, 113–120 (2017)