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Maintenance planning using a digital twin: principles and case studies

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ABSTRACT

We present a set of principles for guiding proponents and developers of digital solutions for maintenance planning. Maintenance planning is a good arena in which to use a digital twin (DT) due to varied and evolving operational, environmental and business circumstances, and issues of risk, safety, and reliability. Therefore, the work in this paper is important. Application of the principles is illustrated using two case~~s~~ studies on monitoring and restoration in the seawater desalination industry: one relating to reverse-osmosis membrane elements; the second to submerged seawater-intake pumps. Both systems provide unique and complicated contexts, both operational and environmental, that justify the development of bespoke maintenance plans. The contribution of the paper is to show, in a systematic way, according to the proposed design principles, how to develop a digital twin for planning maintenance interventions for an engineered object. The principles are derived hierarchically in the paper beginning with basic principles of effective and efficient maintenance and then moving to the principles of maintenance planning and so on to principles for DT design for maintenance planning. We aim to: provide a tool for maintainers in industry; and initiate academic discussion about DT suitability, capability, ownership, deployment, and return on investment. The proposed set of principles is: original because maintenance planning with DTs is emerging; useful for industry and application; and rigorously grounded in maintenance planning theory.

1. Introduction

1.1. Motivation and contribution

A critical part of Industry 4.0 is the digitalisation of maintenance, both technologically and managerially. A key driver of digitalisation in maintenance is the availability of data and associated analytics [1], and different approaches have been developed to exploit data to inform maintenance decisions, among which is the Digital Twin (DT) [2]. Introduction of these approaches into maintenance practice has reportedly driven the evolution of maintenance strategy, evidenced by a shift [3–5] from conventional time (use)-based and condition-based maintenance to predictive [6] and prescriptive maintenance [7]. It may be argued that these latter ideas simply highlight appropriate application of the former—that is, proper application of use-based and condition-based maintenance involves prediction and prescription. Nonetheless, the concept of prescriptive maintenance emphasizes proactive and (so called) “smart” maintenance planning by prescibing the course of action based on predicted asset condition that uses field data and mathematical modeling [8,9]. However, despite the availability of the various modeling approaches, and many attempts by different industries, successful or wide adoption of these approaches by the industry is rarely reported. Many factors may have contributed to this situation [1,10], which may range from infrastructure availability, security [11, 12] to trust [13], and expectations among others.

The DT is offered as a digitalization tool. However, despite its acclaim as a promising technology for digital transformation [14], there is no universal definition of the term DT, see e.g. Glaessgen and Stargel [15] versus Grieves [16] versus Semeraro et al. [17], and as also reviewed by Wright and Davidson [18], Fuller et al. [1], and Agrawal and Fischer [19]. Nonetheless, a DT is generally accepted to be a digital representation of a physical entity. The entity may be an object, a system or a process, or a combination of these. The general aim is to use the DT to proactively identify issues or opportunities arising, while allowing the approach to evolve as data are collected. The capability to prescribe actions may or may not be included in the definition [15,17]. The key

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constituents of a DT can be stated as data, models, information, and connectivity [20]. Connectivity manifests most simply as data transfer from the physical entity to the DT. More sophisticated DTs are envisaged to have cognitive capability [21] and to be intelligent automata embedded in the physical entity [22]. A DT can be data-driven [14], physical model-based [23,24] or hybrid [25]. Whatever the basis for the DT, fundamentally a DT is a model [26]. A DT may be perceived at different levels of abstraction, depending on the purpose of application [27], and, for example, may or may not encode decision-support (Fig. 1). Claims about autonomy may be exaggerated and not helpful for industry practice. Most simply, a DT might be described as a simulator. Nonetheless, it is a simulator that aligns with the digitalization trend in industry.

Use of a DT can underpin a life cycle approach [10], and work in this area is emerging [28], although reported applications are often narrower, with specific works, for example, relating to inspection and component swapping of drilling risers [29], maintenance planning for windfarms [30], manufacturing [31–34], urban facilities [35], tunnel operations and maintenance [36], cutting tool monitoring and replacement [37], pump condition monitoring [38,39], gearbox fault diagnosis [40] and prediction [27], bearing condition monitoring [41], motor winding condition monitoring [42], aviation maintenance [43], maritime engineering [44], battery management [45,46], and nuclear energy safety [47]

More generally, DT usage is growing exponentially, as judged by number of publications by year with “digital twin” in the title—such growth is demonstrated for maintenance in particular in Errandonea et al. [28]. Also, there exist frameworks and principles for construction of DTs for specific application domains, for example, supply chain risk assessment [48], structural engineering [49], safety analysis and risk assessment for engineered objects more generally [50], prognostics and health management [51,52], facilities operation and management [25], and manufacturing [53], and specific methodological domains, for example, DT integration [54], and DT quality assessment [27]. Furthermore, availability of principles and frameworks has been identified as positively contributing to the adoption of DTs by industry [55–57]. Nonetheless, our review of the literature has identified that no generic principles are available to guide DT design for maintenance planning, the focus of this paper. This further evidences the findings of Centomo et al. [58] and Zhong et al. [59] regarding the design of maintenance decision support driven by a DT. Our purpose is to fill this gap in the literature.

Furthermore, in synthesizing these issues there are evidently contradictions. Digitalization (data and analytics) is offered to industry as a means for improvement, but modeling (data and analytics) lacks a track record of industry-application. DTs are offered as a digitalization tool but clarity and principles for their use are lacking. Therefore, we think there is an opportunity to provide clarity about DTs, to present principles for their use, and to demonstrate the use of DTs in engineering asset management. Thus, this paper addresses these issues directly and develops a pathway to appropriate application of a DT to support engineering asset management and decision support for maintenance planning in particular. This is the contribution of this paper.

1.2. Decision support for maintenance planning

In maintenance planning, decision-making support is vital [60]. While maintenance planning theory is well developed, viz maintenance concept in Gits [61], Pintelon & Parodi-Herz [62] and Ben-Daya et al. [63], maintenance requirements analysis in Liyanage et al. [64] and Dwight et al. [65], maintenance policy in Burhanuddin et al. [66], and reliability-centered maintenance (RCM) in [67], decision-making support is often neglected. Labib [68] evaluated the implementation of computerised maintenance management systems and found mainly use for data management and little on the development of decision support systems. Thus, maintenance plans may simply reproduce OEM recommended and/or regulated schedules [69]. Indeed, the evidence from industry is that time-based schedules and reactive maintenance predominate [70,71]. Furthermore, reliance on the OEM manual may be often due to a lack of a deep understanding of the EO [72] and may disregard the economic and environmental context of operation ([67], chapter 1; [73,74]).

Meanwhile, the availability of modeling tools to assist the development of maintenance strategy grows [75] without evidence for their use [76]. Lack of reporting of successful implementations may be for various reasons: misunderstanding of modeling capabilities; misrepresentation of their utility; unavailability of unreasonably demanded and unattainable data; scarcity of research about implementation.

Our view is that the DT concept offers industry the technology to encode novel models of degradation and repair, and to provide decision-support for maintenance planning when a complicated operating regime leads to significant variation in component degradation rates which itself leads to uncertainty about appropriate maintenance interventions and implies the need for condition information. This is somewhat different to using DTs for anomaly detection, failure prediction, and diagnosing the causes of failures and the symptoms. Reporting of this type of work dominates the literature on the use of DTs in maintenance and reliability [5,6,9,28]. Therein, DTs inform when to undertake actions. In some cases, the DTs support the decision-making of what to undertake.

There is a presumption then that a DT that supports decision-making will be sophisticated and will require considerable investment. Therefore, we expect that at least initially DTs will be developed for high value, critical systems, with complex behaviour, so that the developer can expect a return on investment, and that this return should be measurable. Thus, we conclude that there exist questions and issues about the design of a DT. It is our purpose to address exactly these kinds of issues, in the context of maintenance planning, to keep the discussion grounded. This practical grounding will ensure that our discussion is not abstract. Further, we will present a “set of principles”, illustrated with two case studies, as a solution, as means to implementation, to bridge the gap between academia and industry, between the DT concept and a decision-support tool, and as one link in the path of Industry 4.0 from concept to realization.

1.3. Contents of the paper

This paper presents a set of principles for the design of a DT for providing decision-support for maintenance planning. Our intention is that this set of principles should serve two purposes: (i) to guide the

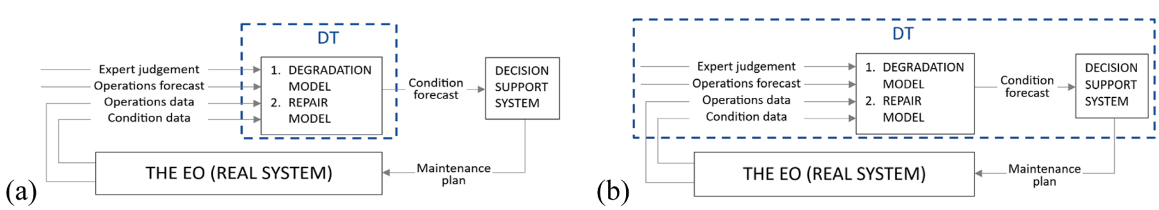

Fig. 1. Schematic of DT extent: (a) DT as a modeling tool; (b) DT as a decision-making tool.

maintainer in the development, and to gain support for the development, of a decision-support system (tool for industry); (ii) to contribute to the academic debate on the nature of a DT (research discussion). The principles are presented and discussed next. We ground the discussion in a practical reality (maintenance planning) so that we can avoid abstraction and demonstrate the application of the principles in a cognate area. Thus, Sections 3 and 4 describe two case studies on DT development. The exposition there focuses on how the principles informed the development. The paper finishes with a discussion of limitations (disconnect between model and reality) and future directions (autonomy).

2. Principles for the design of a DT for maintenance planning

We now discuss design principles for DTs for maintenance planning (MP) and present these principles within a hierarchy of maintenance principles. We start with the foundations of this hierarchy: principles for maintenance and planning a maintenance program themselves. Then, principles for DT design for maintenance are developed as sub-principles of these more fundamental principles (Table 1). Thus, the principles are developed from the general towards the particular. We present 24 principles, four on each of six levels. Fewer principles would simplify the presentation but likely hinder application, so we do not attempt to condense them. Presenting these principles in this way is novel and useful: novel because to our knowledge we are the first to propose such a hierarchy or set of principles; useful because our very purpose is to provide a guide for operators and maintainers to develop their own maintenance planning solutions.

Note, we define a principle as a foundational statement in a chain of reasoning. Further, the principles we present do not attempt to provide a complete set of principles for planning a maintenance program. This is beyond the scope of the paper. We present only those that we think are necessary for DT development based on experience gained from case studies that we describe later. The set of principles are thus limited, but nonetheless their number and scope can be expanded as and when necessary. Further, while there exist vertical connections between the principles at successive levels and these connections were used to develop the principles, they are not presented in Table 1 because their existence is not a requisite for application of the principles. Nonetheless, these connections are described in the detailed discussion of the principles below.

Table 1
Hierarchy of principles for DT design for decision support maintenance planning.

Level 1. General principles of operation, degradation, and safety			
1.1 An engineered object (EO) in operation and not maintained will eventually fail	1.2 An EO to exist only if the cost of safe operation is bearable	1.3 Failure of an EO is not always the responsibility of maintenance	1.4 Sustainability (longevity, maintainability, reuse, recycling) to be designed into the EO
Level 2. General principles of maintenance			
2.1 Planned maintenance typically to be preferred to unplanned maintenance	2.2 Operations (O) and Maintenance (M) are co-dependent, regardless of whether their management is separate	2.3 Maintenance stakeholders, including O and M, act according to their own priorities	2.4 Maintenance to be perceived as valuable (value-creating) rather than a cost
Level 3. Sub-principles of planned maintenance			
3.1 Better maintenance planning derives from better knowledge of the EO, its operational environment and business objectives	3.2 Maintenance must understand the causes of degradation and failure and the effect of repairs and use this knowledge	3.3 Maintenance performance baseline to be established so the benefit of additional investment in maintenance can be known	3.4 Planned maintenance actions and protocols for execution to be decided by the stakeholders who share the maintenance plan
Level 4. Sub-principles of how to manage/decide/determine/specify planned maintenance			
4.1. Failure data are useful for deciding the focus of investment in maintenance	4.2. Maintenance should evolve as: the EO ages; knowledge of it changes; and business objectives and operational environment evolve	4.3. Maintenance to be managed systematically using a maintenance management system (CMMS) so that cues are announced and actions recorded	4.4. Maintenance requirements interact with operations, logistics, and spare-parts inventory requirements
Level 5. Sub-principles for the development of a DT for maintenance planning			
5.1 DT to be dedicated to the maintenance requirements of a unit of an EO	5.2 The development cost of a DT is bearable for only some units of an EO	5.3 The development cost of a DT with O and M capability to be shared by O and M	5.4 Development to be documented and a user-guide to be produced
Level 6. Sub-principles for the design of a DT for a specific unit			
6.1 DT to be integrated with EO, its CMMS, sensors and data collection.	6.2 DT to model degradation and repair	6.3 Known unknowns to be represented in the DT	6.4 Competing maintenance policies to be testable in the DT

2.1. Level 1. General principles of operation, degradation, and safety

Gits [61], the pioneer of maintenance theory, Kobbacy and Murthy [77], in their overview, and Ben-Daya et al. [63], in their seminal text on maintenance engineering, all clearly state that an unmaintained engineered object (EO) will fail eventually. This is the defining principle of maintenance and engineering asset management (Principle 1.1) [78, 79], and is a restatement of the second law of thermodynamics (tendency towards disorder). Note, this principle does not imply the converse: that all maintenance will make the system more ordered (better). Indeed, the very act of doing maintenance may precipitate degradation/failure [80–82].

Where failure has implications for safety (of persons, the environment and such like), then the consequences of failure must be bearable by the stakeholders, otherwise the EO should cease operation and be made safe or scrapped. Waeyenbergh & Pintelon [83] and Riane et al. [84] make this point. This is the second fundamental principle (Principle 1.2). Equivalently, safety is the concept of specifying an acceptable risk for operations, the margin of safety [85,86], and it should be the priority of the operator to operate its EO within this margin of safety [87]. In addition, awareness of the state of the EO relative to unacceptable failure or performance is necessary and determined as a probability [88].

Maintenance cannot make operation of an EO free from failure because uncontrollable risks may exist [89,90]. For example, transportation is risky no matter how well vehicles are maintained. This is Principle 1.3.

Sustainability is a fundamental part of asset management [91] so we include Principle 1.4. A seminal work in this respect is Iung and Levrat [92], who discuss among others the lack of consideration of the decommissioning phase of an EO and reticence to accept used components into new products. More recent works on the importance of sustainability in maintenance are reviewed in Ghaleb and Taghipour [93].

2.2. Level 2. General principles of maintenance

We think it is reasonable to claim that the entire maintenance and engineering asset management literature (and practice aside) is predicated on the notion that planned maintenance is preferable to unplanned maintenance. Further, while there can exist cases where an operate to failure (OTF) policy has acceptable cost and risk consequences [68], acknowledging such requires degree of planning that includes for example adequate spares provisioning [94]. Thus, Principle 2.1 is the first general principle of maintenance.

Planning maintenance requires the cooperation of maintenance stakeholders, not least the operator and the maintainer (Principle 2.2). Further, there may be many stakeholders with agency (e.g. the asset owner if different from the operator, the original equipment manufacturer, customers and clients, community and society generally, insurers, warranty providers, consultants, regulators) with their own priorities [95], and maintenance planning must take account of competing priorities (Principle 2.3). Thus, for example, asset owners and warranty providers may engage consultants as auditors, auditors typically base their assessment on common assumed standards, so that the planned maintenance program is routinely based on the time-based maintenance schedule of OEM manuals. This way, consultants persuade the time-based method out of lack of a deep understanding of the business of an organisation and the environment in which the EO operates [72]. Regulators will naturally prioritise public safety over maintenance cost-saving and, as a result, tend to address maintenance with the same perspective [96]. Owners and operators may be contracted to use OEMs for spare parts [69], and frequently maintenance policies are directly copied from OEM manuals, which may be biased by commercial interests [97] or based on ignorance of the operating environment.

Planning requires investment, and investment in maintenance is rational if maintenance creates value, albeit indirectly. The notion of maintenance as an unproductive cost-centre [98,99] is changing to one of maintenance as value-creating [100]. This is Principle 2.4. Further, sustainability is an important contributor to value (Principle 1.4) [101].

2.3. Level 3. Principles of planned maintenance

It is uncontroversial that better understanding of the EO and its operational environment leads to better planning of maintenance (Principle 3.1) [63–65,84]. It is rational that knowledge of degradation and failure and the effect of repair (noting repair may take different forms) should inform maintenance planning (Principle 3.2) [102]. Many works make the case for establishing baselines for maintenance expenditure and EO performance [72,103–106] so that the return on investment in maintenance can be measured (Principle 3.3). Finally, Principle 3.4 follows from Principles 2.2 and 2.3, that is, the stakeholders with agency must agree the maintenance program if it is to be supported and implemented successfully [95].

2.4. Level 4. Principles of how to plan maintenance

First, we make a strong and controversial claim about the usefulness of failure data for planning maintenance. Our view is that their usefulness and the attention given to them is often overstated. Operational failures (failures of components during operation) are typically rare, an individual circumstance is often unique, and analyses of failure data are obsolete because, meanwhile, an EO has evolved. An exception is when the installed base of EOs is very large e.g. van Staden et al., [107]. A consequence is the interest in subjective methods for reliability analysis [88]. Nonetheless, investment focus can be guided by analysis of operational failures and interventions (Principle 4.1) [65].

Next, an EO evolves as it ages and its maintenance program should evolve accordingly (Principle 4.2). Thus, for example, maintenance priorities for a new plant will differ for an established plant which will differ for a retiring plant, and programs should be adapted accordingly [65,108]. Further, maintenance must be managed systematically, so that the triggers for action are announced, and outcomes recorded (Principle 4.3), implying the use of a maintenance management system (CMMS) [68,109,110]. Finally, maintenance requirements interact with operations, logistics, and spare parts inventory (Principle 4.4), and all other functions within an organisation and its supporting organisations. Therefore, these functions must be coordinated with maintenance activities, so that maintenance interventions do not unnecessarily interrupt production. Thus, for example, spare-parts unavailability extends downtime, while excessive spare-parts inventory is costly [111, 112].

2.5. Level 5. Principles for the development of a DT for maintenance planning

This layer of the hierarchy deals with the fundamentals of DT design, so we discuss it in detail. We assume the existence of a maintenance program (maintenance concept) (the set of rules that recommend what maintenance is required and when) for an EO, and that the maintenance concept is operationalised using a maintenance management system, CMMS.

2.6. DT to be dedicated to the maintenance requirements of a unit of an EO (5.1)

The argument for this principle is that the alternative is impractical. We use an analogy to make our case. Consider the evolution of computerised ICS since the 1960s. The ICS evolved in two different philosophies: Decentralised Control Systems (DCS), which are the standard in the oil-and-gas and power generation sectors; and Programmable Logic Controllers (PLC) and later with a Human-Machine-Interface (HMI), which are the standard in discrete manufacturing. Nowadays, both architectures can do technically the same thing. However, their philosophies are different. PLC/HMI is a lean architecture, but the System Integrator (SI) must program everything from scratch, using a significant amount of resource. The philosophy of DCS on the other hand is that engineering by the SI should be minimised, with the SI focusing on configuration rather than programming. Therefore, DCS has a library of standard control blocks for each EO [113]. However, each customer has different demands, so the DCS vendors respond by adding more options. Ultimately, control blocks are big, with much functionality, and resource-heavy and complicated, while particular functionality may be hidden or not fully supported. Then, an SI must develop bespoke solutions. The issue is analogous for a DT module of a CMMS that intended to cover all the units of an EO. However, the particulars of an EO under specific environmental and operational conditions are so diverse that an “out of the box” solution would be inefficient. Such a DT would have to be tailored to the particular category of EO to perform effectively. Integrating a tailored DT with an existing CMMS requires significant customisation of the CMMS software, and implementation often fails this alignment [110]. Therefore, our proposal is to dedicate the design of a DT to the particular maintenance requirements of an EO or category of EOs operating in a specific environment under a given business conditions, while presenting a set of principles that is not application specific. Consequently, each EO has its own DT in this architecture, but the DT is designed for a specific EO type. A DT designed for a specific category of EO further simplifies the DT design process since specific maintenance requirements can be picked out one at a time, and the design concept is divided into manageable segments.

2.7. The cost of developing a DT is bearable for only some units of the EO (5.2)

Time, knowledge, skills, and high implementation costs are often significant barriers to the development of useful solutions [114]. A production facility has numerous EOs each with many units. The plant in our first case study (Section 3), as an example, has approximately 23,500 assets registered in the CMMS, including items such as tools. Developing a DT for even a fraction of these units will be too costly. Therefore, the decision-maker must prioritise and focus on investment, guided by Principles 3.1 (criticality), 3.3 (benefit), 3.4 (consensus). Of course, this does not imply that EOs not associated with a DT do not have a planned maintenance program; such a program would be established by other means.

Finally, there are practical issues associated with DT design. Cost-sharing of the development of a DT (Principle 5.3) is a consequence of Principle 2.2 (O and M dependence) and Principle 2.3 (stakeholder priorities). Development should be documented and a user-guide produced (5.4)—such documentation will provide developers and users with an explanation of what the system does, how it operates, and how it should be used [115]. We do not discuss software environments for the development of DTs because this is not in the scope of a set of principles.

2.8. Level 6. Principles for the design of a DT for a specific unit

Notionally, the preceding principles pertain to matters of engineering management. Now we describe the specific principles for what characteristics a good DT for maintenance planning should possess.

2.9. DT to be integrated with the EO, its CMMS, sensors, and data collection (6.1)

An EO will have many units and so a consequence of Principle 5.1 is an architecture like Fig. 2, in which DTs are integrated with but external to the CMMS. Presuming that data collection and storage are within the CMMS, then the necessary data for planning maintenance is available to a DT. Data themselves can be generated by inspection or continuously, using integrated sensors or otherwise. Suppose the operational technology (OT) system, that is, the platform that collects the sensor data, and CMMS are not directly integrated. In that case, the DT should further be data-driven by the OT database. This is connectivity of the DT and EO essentially in its simplest from. Note, in Fig. 2, we are presuming that there exists objective data that is used by the DT. Nonetheless, a DT may be a purely physical-model based and/or use subjective data alone. Also, contrary to the scheme in Fig. 2, DTs might be integrated, although typically DTs are "one-off" because interoperability and interchangeability present significant development challenges [56,116,117]. Finally, while the diagram indicates the connection of work orders to the database, it is implicit that work orders derive from the maintenance concept, and the specific maintenance policy therein.

2.10. DT to model degradation and repair (6.2)

This principle follows from Principle 3.4 (knowledge of degradation and repair) and an assumption that data related to degradation and repair are more than are provided by sensors and data collectors. It is not untypical that large volumes of sensor data provide little by way of information about condition [118], and that processing and analysis of sensor data is necessary for decision-making. Modeling encodes the expert knowledge of operators and maintainers [119–121], and fundamentally, a DT is a model [26,122,123].

2.11. Known unknowns to be represented in the DT (6.3)

Degradation and the effects of maintenance interventions are stochastic [124]. These random factors are the known unknowns of maintenance planning, and models of them are a fundamental part of the DT. Specifically, the state (degradation) of a unit of an EO and the effect of a repair on it will not be known with certainty by the agent, and there will be greater uncertainty about the state of the unit as the forecast horizon is extended [96]. Thus, these uncertainties must be encoded in the DT. Further, this implies limitations of DTs because: i) models are approximations to reality [125]; ii) unknown unknowns by definition (unanticipated: events, circumstances, variability) cannot be encoded [126].

2.12. Competing maintenance policies to be testable in the DT (6.4)

Maintenance interventions (repairs, replacements, overhauls) are a consequence of degradation (Principle 1.1) and their effects are varied and uncertain. Further, repair cannot be seen separately from degradation [64,66]. Therefore, the impact of degradation, and maintenance policies to remediate degradation, must be learned [127]. Testing maintenance policies on an operating, physical unit is at best costly and tedious and at worst unacceptable [128]. If maintenance policies can be tested using a DT, well before observation of the lifecycle of the physical unit, decision-time, cost, and risk will be reduced [129]. Therefore, a DT for maintenance planning that is fit-for-purpose must be capable of testing competing maintenance policies.

These above are our proposed principles. Next, we describe in the first case study what a DT built to these principles will look like. The second case study describes a DT in development, wherein the problem, the supporting data, and the specification for the DT are described. A key point is that DT development must be demonstrably led by the principles rather than various actions being labelled as evidence of a principle.

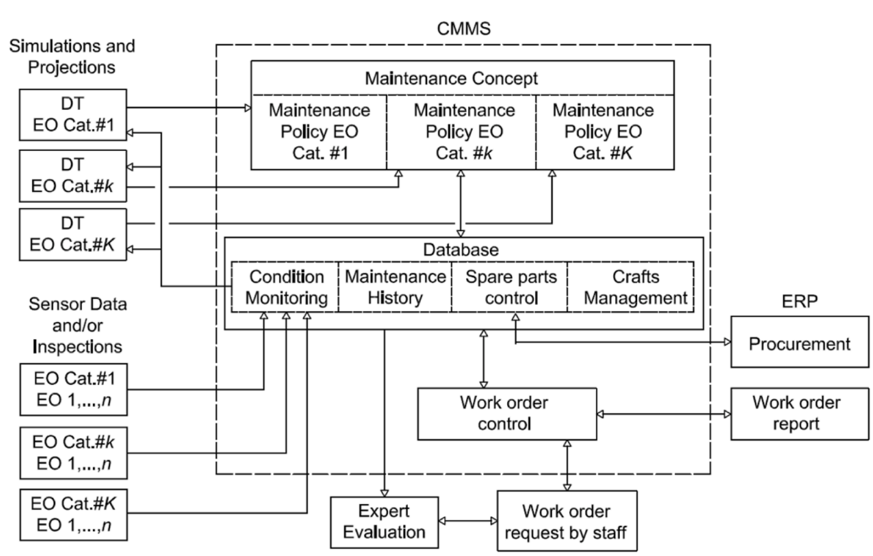

Fig. 2. Schematic of CMMS and DT integration.

3. Case study 1: Repair of membranes in reverse osmosis desalination

3.1. Summary

We show in this case study how the principles guided the design of a DT for maintenance planning. The DT quantifies the hidden degradation-state of membrane-elements in a reverse osmosis (RO) pressure vessel (the EO) over time (Principle 6.2, "DT to model degradation and repair"). The effects of repairs (cleaning, swapping, replacements) are uncertain and modeled in the DT (Principle 6.3, "unknowns modeled in the DT"). The DT uses real-time data from the EO to update decision support (connectivity). The DT is used to evaluate different, competing repair (restoration) policies (Principle 6.4, "competing policies to be testable in the DT") that could not evaluated directly on the EO. A preliminary analysis of maintenance performance at the plant [130] justified the investment necessary to develop the DT (Principle 5.2, "cost of development of DT only bearable for some units in an EO"). The DT itself models an idealised pressure vessel (Principle 5.1, "DT dedicated to maintenance requirements of a unit of an EO"), and maintenance policies tested on the DT are regarded as providing a good indication of the effectiveness of maintenance of all the seawater vessels in the plant.

3.2. Problem description

The Carlsbad Desalination Plant is the biggest and most sophisticated desalination plant in the Western Hemisphere. The RO system at this plant has 1792 pressure vessels, arranged in 14 parallel sub-systems (called trains), each with 128 vessels in parallel. Each train operates independently. Normal demand for potable water (204,000 m^3/day) is met when 13 to 14 trains are operating, depending on the seawater temperature.

Eight identical (when new) membrane-elements are loaded into a vessel to form one continuous membrane. In simple terms, the saline side of the membrane of a vessel has one input at the front (pre-treated seawater) and one at the rear (rejected brine), and on the other side of the membrane a vessel has two outputs: potable water at the front; brackish water at the rear that is desalinated again in another RO system. The membrane is permeable to water but not salt, but water must be pushed through the membrane under high pressure. Membrane-elements have a spiral micro-structure that resists saline flow and results in a small pressure-drop across the vessel on the saline side. This *pressure-differential* is continuously monitored for each train, and post-processed as the daily *normalised pressure-differential* (NPD) (Fig. 3). As the elements in a train degrade, the NPD increases. Discontinuities in the NPD are at maintenance interventions.

A significant factor in the degradation of membranes is biofouling due to seasonal algae blooms—Matin et al. [131] estimate the annual cost of biofouling in the desalination industry at $15 billion. Biofouling increases the pressure-differential due to the build-up of biofilm in the micro-structure of membrane-elements. The degradation of vessels in a train is homogeneous due to inherent load-variation (more worn vessels work less hard). However, the degradation of membranes in a vessel is heterogeneous. This is because algae adhere more to more worn elements, and the effect of algal contamination is indirect.

At the Carlsbad plant, degradation was greater than expected in the first year, and the operator was faced with the possibility to stop a train if the pressure-differential rose above 3.5 bar. Short-term relief was achieved by swapping worn front elements with less worn rear elements. Cleaning, the commonly applied intervention, had some effect, but renewal of the most worn elements was required. Complete replacement of all elements is prohibitively expensive, so partial replacement and swapping policies were sought. However, the degradation of the individual elements in a vessel is hidden, and incorporating internal sensors for monitoring is impossible. Therefore, it was not obvious which elements should be replaced and which should be swapped. Also, if elements required renewal on a regular basis, why bother with cleaning? Therefore, decision support using modeling was sought. The project developed a simulator, a digital twin (DT), of degradation at an element level within an idealised vessel, calibrated using operational (NPD) data collected at the plant. The DT has been used by the operator to compare long-term degradation and cost projections for various, competing repair policies.

3.3. Modeling degradation and repair of membranes

The DT models an idealised pressure vessel. It models degradation and repair (Principle 6.2, "DT to model degradation and repair"). Implicity, it is assumed that vessels degrade homogeneously, so that NPD measured at train level represents pressure-differential at a vessel level. Elements degrade heterogeneously, and degradation is unobserved at an element level. The DT models degradation at an element level, attributable to the causes described above (biofouling) (Principle 3.2, "maintainers must understand causes of degradation and effects of repair"), to quantify the effects of swapping, cascading and selective replacement of elements.

A vessel comprises 8 fixed sockets. Socket i ($i = 1, \ldots, 8$) contains an element whose degradation-state at time t is $X_{i,t}$. The (unobserved) pressure-differential across socket i is $P_{i,t}$, and the (observed) pressure-differential across the vessel is

$$P_t = \sum_{i=1}^{n} P_{i,t},\ i = 1, \ldots, 8,$$

because the elements are in series. When an element is new, its state is set to 1, and when a vessel is new (all elements are new) its pressure-differential is P_0.

The hydraulics of saline flow in an RO vessel implies that the pressure-differential $P_{i,t}$ across socket i at time t depends both on the state of the element in socket i and the position of the socket (Principle 3.1, "better maintenance derives from better knowledge of an EO"). Therefore, it is assumed that

$$P_{i,t} = \omega_i P_0 X_{i,t},\ i = 1, \ldots, 8 \tag{1}$$

with ω_i ($i = 1, \ldots, 8$) a set of known constants such that $\sum_{i=1}^{8} \omega_i = 1$.

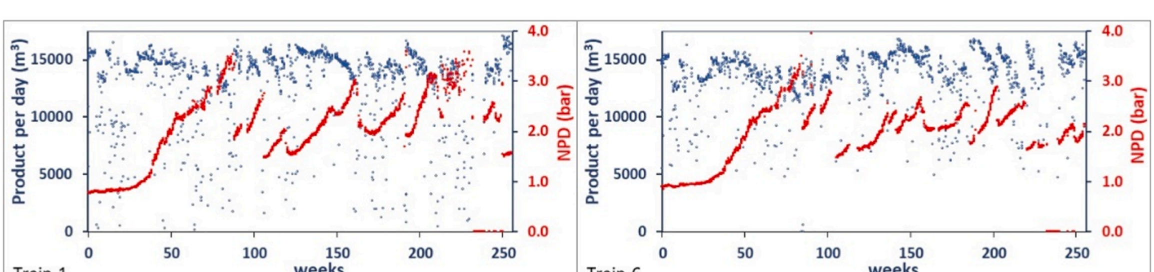

Fig. 3. Product flow and normalised pressure-differential (NPD) for two trains (to 31.8.2020).

These constants are the pressure-position distribution, representing the pressure variation due to position, which arises broadly because salt becomes more concentrated towards the rear of the vessel (Principle 3.1). The calculation of the constants is described in Van Rooij, Scarf, and Do [132].

The degradation-rate of an element depends on the input condition (extent of algal contamination of the seawater), the position of the element, and the state of trailing elements (elements further along the vessel). Using a discrete time interval of one day, and denoting the degradation-increment in the element in socket i from day $t-1$ to day t by $\Delta X_{i,t} = X_{i,t} - X_{i,t-1}$, we have

$$\Delta X_{i,t} = \kappa_t \alpha^{i-1} \left\{ \sum_{j=i+1}^{8} X_{j,t-1} \Big/ (8-i) \right\}^{\theta}, \ (i=1,\dots,7) \Delta X_{8,t} = \kappa_t \alpha^7, \qquad (2)$$

where κ_t is the input (seawater) condition on day t, $\alpha \in (0,1)$ is a single parameter that quantifies preferential biomass growth on leading elements, and $\theta > 0$ quantifies the degradation in an element due to degradation in the trailing elements (because leading elements at the front "work harder" when trailing elements are degraded). Thus, the variation in extrinsic degradation (κ_t), the intrinsic degradation (α), and the degradation rate-state interaction (θ) [118,133,134] are all modeled. Eq. (2) applies when a train is online (operating). When offline (not operating), elements are not "working" so that $\Delta X_{i,t} = \kappa_t \alpha^{i-1}$ for all i. Thus, elements in a vessel form a multi-component system with non-identical components, stochastic degradation dependence between components, economic dependence (shared setup cost), and structural dependence (elements are accessed sequentially). This complexity necessitates a bespoke (dedicated) DT (Principle 5.1, "DT dedicated to maintenance requirements of a unit of an EO").

Vessels are restored (repaired) by partial replacement of elements and swapping of elements or cleaning. When the element in socket i is swapped with the element in socket j at time t, it is supposed that

$$X_{i,t^+} = X_{j,t^-}, \ X_{j,t^+} = X_{i,t^-},$$

where t^- and t^+ denote the times immediately prior- and post-repair. When the element in socket i is replaced at time t, it is supposed that

$$X_{i,t^+} = 1.$$

Thus, the effects of replacement and swapping are deterministic. In practice, cascading elements (e.g. 2345678N whereby element 1 is discarded, element 2 is placed in socket 1, and so on, and a new element is placed in socket 8) is considered a good policy because front elements generally degrade faster. The partial cascade, 234N5678, is another interesting policy because it is less costly than 2345678N. The former can be executed by opening only one end of a vessel.

The effect of cleaning is stochastic. Vessels are cleaned to remove biomass with elements in-situ. Operators use two cleaning methods: C1 (low pH rinsing followed by high pH rinsing); C2 (soaking in sodium bisulfate followed by C1). We assume the cleaning effect, $\delta_k (k = 1,2)$, is proportional to the degradation of an element. Thus,

$$X_{i,t^+} = (1-\delta_k)\left(X_{i,t^-} - 1\right) + 1 = (1-\delta_k) X_{i,t^-} + \delta_k, \ (i=1,\dots,8), \ (k=1,2),$$

so that $P_{t^+} = (1-\delta_k) P_{t^-} + \delta_k P_0$, which implies

$$P_{t^+} - P_{t^-} = -\delta_k (P_{t^-} - P_0). \qquad (3)$$

Thus, the cleaning effect is proportional to the excess pressure-differential. The cleaning parameter is such that if $\delta_k = 0$, $P_{t^+} = P_{t^-}$ (no effect), and if $\delta_k = 1$, $P_{t^+} = P_0$, (renewal).

3.4. Parameter estimation and forecasting

We estimate parameters using a variety of methods that we discuss briefly here. Van Rooij, Scarf, and Do [132] present full details. The preferential-biomass-growth parameter, α, is estimated by weighing worn elements in a random sample of vessels and comparing observed and model-predicted weights (Fig. 4). A time-invariant parameter is estimated for each train. The seawater condition parameter, on the other hand, is time-varying, and is estimated in such a way that forecasts of future condition can be made in order to compare competing repair policies (Principle 6.4, "competing policies to be testable in the DT"). For each train, we initially assume

$$\kappa_t = (\kappa_2 - \kappa_1) e^{-\beta \tau}, \qquad (4)$$

where κ_1 is the condition up to the known start of the first algal bloom and κ_2 is the condition thereafter. Thus, Eq. (4) models the persistence of bio-fouling [135] as exponential decay, where τ is days since seasonal-algae-bloom end. Then, with known α, $\kappa_1, \kappa_2, \beta, \theta$ are estimated for each train using particle filtering (PF). Strictly, iteration between estimation of α and the PF is required.

Next, to find a set of values of daily seawater condition for forecasting, we use

$$\kappa_t = (P_t - P_{t-1}) \Big/ \left\{ P_0 \sum_{i=1}^{8} \alpha^{i-1} f(x,i)^{\theta} \omega_i \right\},$$

where $f(x,i) = \sum_{j=i+1}^{8} X_{j,t-1}/(8-i)$ for $i < 8$ and $f(x,8) = 1$, which follow from Eqs. (1) and (2). Note, the function f serves as a shorthand in this equation, noting that the eighth element is last in a vessel. This yields 70 series of values of κ_t ($t = 1,\dots,365$) (five years of data for each of the 14 trains) . Then, each of these series is smoothed to increase the contrast in degradation between periods of algae blooms and non-algae blooms, giving $\tilde{\kappa}_{t,j}$ for $t = 1, \dots, 365$; $j = 1, \dots, 70$. Three moving-average smoothing regimes, with windows of width 5, 10 and 20 days, were tested for robustness. Finally, the $\tilde{\kappa}_{t,j}$ are bootstrapped [136] to provide five-year projections of daily seawater condition (seawater condition on day t of each year is sampled with replacement from $\tilde{\kappa}_{t,j}$, ($j = 1,\dots,70$), thus modeling another known unknown (Principle 6.3, "unknowns modeled in the DT"), the condition of the seawater in the near and medium-term.

For each cleaning event, Eq. (3) was used to calculate a value of the cleaning effect (Fig. 5). For the projections where a cleaning method was used, the cleaning effect was bootstrapped from these values.

3.5. Digital twin of a RO train

There are three modules in the DT, (i) data analysis, (ii) planning, (iii) the simulator, schematically as Fig. 1(b). The DT first imports data (observed NPD, product flow) and maintenance history from the CMMS, and estimates parameters. In the user-interface (Fig. 6), simulated NPD paths can be compared with a real path, with real paths updated in real time. This real-time updating is the connectivity from EO to DT (Principle 6.1, "DT to be integrated (connectivity)". Repair policies are compared in the planning module, using simulated paths and the costs of policies. Connectivity from DT to EO is offline; essentially human decision-maker plans maintenance using knowledge obtained at the user-interface. The user-interface displays the modeled NPD (red pen, Fig. 3), calculated using the simulator that runs in the background, the observed NPD (black pen), and the NPD implied by the modeled degradation of each element in each socket (other coloured pens). Then, a repair policy is selected, and the DT simulates an ensemble of forecasts (grey ribbon, 100 simulations) over the specified horizon (five years).

At the user-interface, policies are compared using risk (% of NPD paths in ensemble forecast that cross the pressure threshold) and cost (Fig. 7). Policies 10, 11, and 12 have an acceptable risk (median < 15 % on the 3.5 bar risk-measure), and Policy 12 stands out in terms of risk and cost. Under Policy 10, element replacement was 356784NN annually for four trains and 234N5678 for the others, in rotation, and cleaning was two C2 per train per year. Policy 12 had more cleans (three

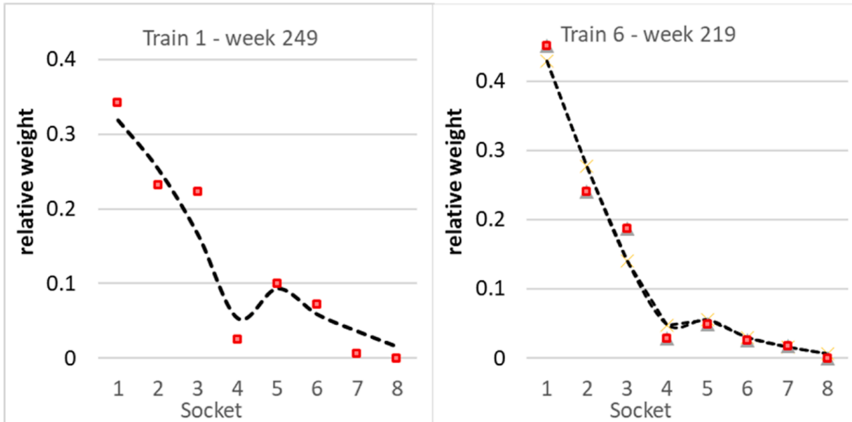

Fig. 4. Observed element weights (■) and modeled degradation-states (—) for two trains.

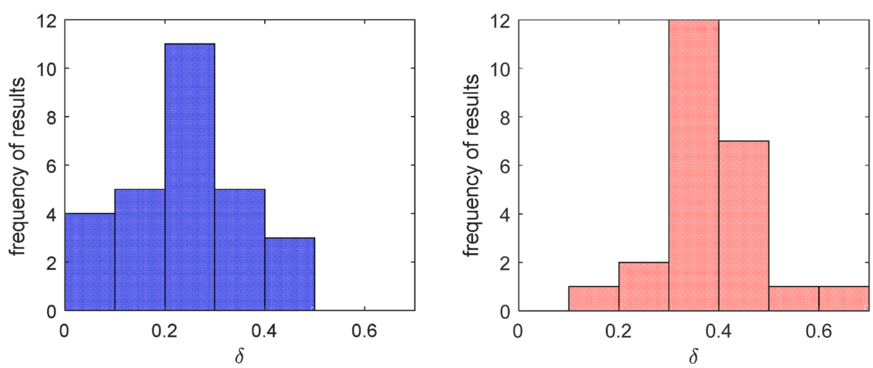

Fig. 5. Histograms of the cleaning effects: left—C1 (mean 0.24, standard deviation 0.13); right—C2 (mean 0.38, standard deviation 0.10).

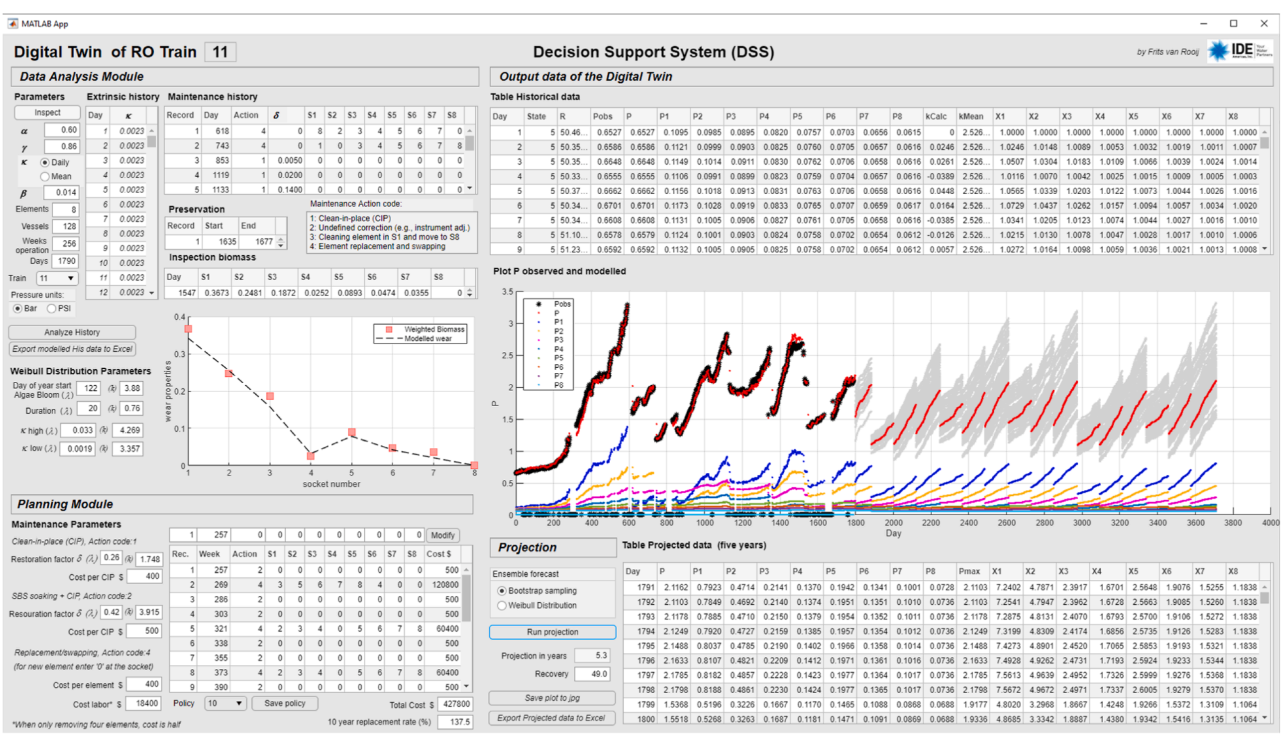

Fig. 6. The user-interface showing real-time pressure data from the EO and forecast envelopes (middle figure right column).

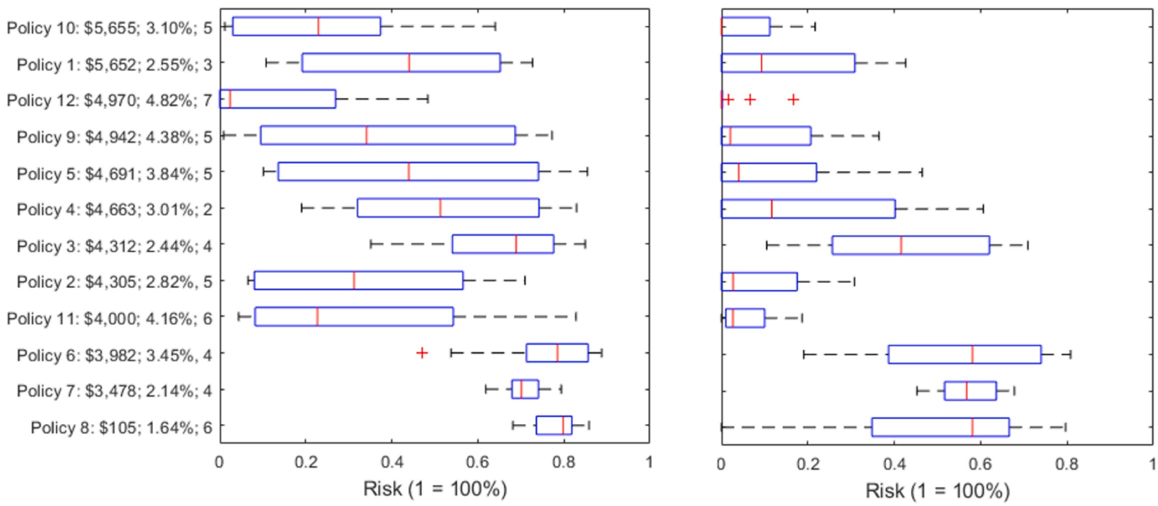

Fig. 7. Policies ranked by total cost ($000 s) and showing downtime per train (%), number of stops per train per year, and boxplots of risk measure (left, 3 bar; right, 3.5 bar) across 14 trains.

C2 per year) but fewer replacements, 2356784N in year 1 and 2345678N in years 2–5. Policy 12 was desirable but infeasible because the plant then lacked the cleaning capacity, so Policy 11 was a feasible version of Policy 12 with a different year 1 (one C1, two C2, and no element replacement or swapping). The status quo (Policy 1) was like Policy 10 except the cleaning rate was lower (one C2).

The DSS also facilitates sensitivity analysis. The risk-measure decreases with the length of the smoothing window of the seawater condition, while there is no change in the risk-ranking of the policies. Choosing this window is a step in the analysis, with a longer smoothing window giving clearer differentiation of periods of algae blooms.

4. Case study 2: Digital twin for a centrifugal pump

4.1. Summary

The single-stage centrifugal pump is widely used in the water industry. Centrifugal pumps in marine applications undergo two kinds of degradation: mechanical or chemical processes that typically affect bearings, seals, and the impeller; adhesion of marine life, e.g., mussels, that affects pump performance. Both can increase power consumption, reduce the pump's ability to provide flow, and finally lead to failure. For submersible pumps offshore, scheduling timely inspections to determine condition of the pump and determining appropriate interventions are difficult problems. This case describes the development of a DT, as a work-in-progress, for estimating pump condition and remaining time to intervention without the need for sophisticated instrumentation or physical inspections. The specification of the DT is described with reference to the principles (Table 1). Connectivity from EO to DT will be established through real-time data input from the EO to the DT. In due course, the DT will give warning alarms for action in real time; this is the connectivity from DT to EO.

4.2. Problem statement

Operations and maintenance manuals of OEM always stipulate a time-based trigger for pump overhaul. However, for large submersible pumps overhaul based on condition is likely more cost-effective, in part due to the large set-up cost (Principle 3.1, "better maintenance derives from better knowledge of an EO"). Unfortunately, the pump condition is not always directly observable (Principle 6.3, "unknowns modeled in the DT"). Operations and Maintenance companies of offshore drilling rigs deal with this by operating these marine submersible pumps for a few years without any intervention and then replacing them with a new pump (Principle 1.1, "an EO in operation and not maintained will eventually fail") [137]. These pumps are located in very deep water, complicating any maintenance. Submersible pumps that transfer seawater to the shore are located in comparatively shallow water, so that maintenance intervention is considered cost-effective. Nonetheless, the difficulty of maintenance interventions justifies the cost of the development of a DT (Principle 5.2, "cost of development of DT only bearable for some units in an EO")

In this case, the EO (the system) is two intake pumps (Principle 5.1, "DT dedicated to maintenance requirements of a unit of an EO"), located in the Pacific Ocean, 760 m offshore and at a depth of 10 m. They supply raw seawater to a reverse osmosis desalination plant, at a mean flow of 1042 m^3/hr. The pumps each weigh 3.3 tonnes. Typically, one pump operates while the other idles (hot standby). Aside from wear of bearings, seals, and the impeller, marine growth at a pump's suction obstructs the intake, and this degradation manifests as increased power consumption, and reduction of pump pressure (head) and/or flow [138] (Principle 3.2, "maintainers must understand causes of degradation and effects of repair"). Degradation reaches a critical threshold if a pump can no longer provide the flow required to meet peak demand. Maintenance of a pump requires plant shutdown, and a barge and divers to unhook the intake pipe and lift the pump to the surface for inspection, cleaning, and servicing by the maintenance team. The problem is to provide a tool for planning operations and maintenance (Principle 2.1, "planned maintenance typically preferred to unplanned", Principle 2.2, "operations and maintenance are co-dependent", Principle 3.4, "maintenance protocols to be decided by stakeholders who share the maintenance plan") so that the system is maintained before it goes critical.

At installation, pump capacity (maximum flow the pump can deliver) exceeds plant requirements. An onshore valve controls flow to meet demand at the plant by "throttling" (partial closure), resulting in an increase in pressure (pump head). As a pump degrades, its ability to provide flow reduces, so that throttling reduces, and the head decreases (Fig. 8). Put simply, once the limit for throttling reduction is reached, the pump must be maintained.

The maintenance decision-problem can be restated conceptually as follows. Define the peak demand for flow as Q_P. Suppose the maximum possible flow (minimum throttling) of the pump at time t (since last maintenance) is $Q_{\max,t}$. The quantity $Q_{\max,t}$ is not observed (Principle 6.3, "unknowns modeled in the DT"), but can be estimated (modeled) using the observed history of $(P_{\text{obs}}, Q_{\text{obs}}, H_{\text{obs}})$ (power, flow, head), the theoretical pump affinity laws [139], and the OEM design-performance specification (Principle 6.2, ""DT to model degradation and repair""). The objectives are: (i) to forecast $Q_{\max,t}$ and hence that T such that the

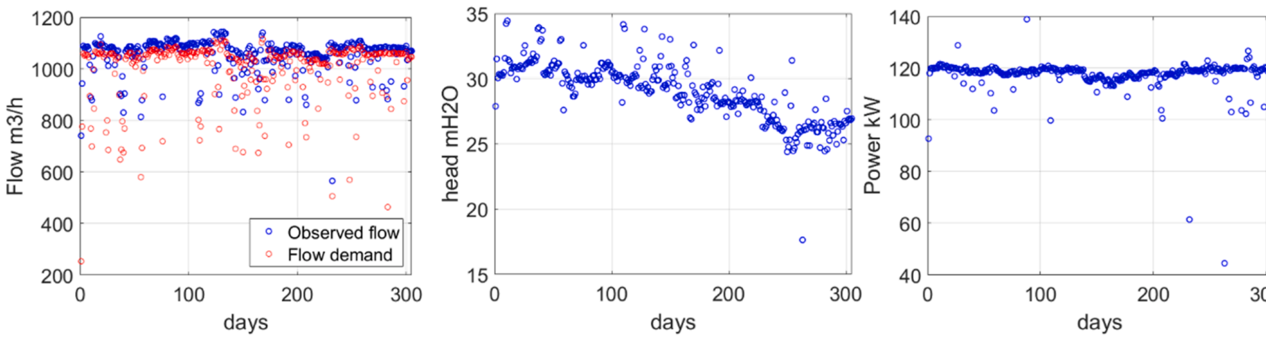

Fig. 8. Observed flow and flow demand (left), observed pump head (middle), and observed power consumption (right) of the newer pump versus days since its installation.

maximum possible flow becomes critical ($T = \inf\{t : Q_{\max,t} < Q_P\}$); (ii) to allow different operations and maintenance policies (switching, flow-demand control, varying maintenance interval) to be compared in a virtual environment (Principle 6.4, "competing policies to be testable in the DT"); (iii) to provide some autonomous capability for decision-making about the timing and nature of interventions.

The pumps differ in age and design. The newer pump [140] is more efficient than the older pump (b. 2019). Maintenance requires good weather, a large barge with a crane and crew, divers, environmental monitoring personnel, and the actual maintenance personnel. Oil changes are performed on the barge. Removing marine growth from the pump suction and vault screens (cleaning) can be done by divers. The pump is not removed, so no barge is needed. Any other maintenance is performed onshore, requiring power and control cable disconnection, transportation to the workshop, and an additional crane. The fixed setup cost is typically more than twice the maintenance cost for the pump.

Pumps can be switched during operation of the plant, simultaneously shutting down the operating pump and bringing up the idling pump. However, before cleaning by divers, both pumps must be stopped for safety. Thus, cleaning and any other maintenance intervention requires plant shut down, so that in all cases premature intervention must be planned.

4.3. DT specification

The DT will support planning decisions that are not straightforward. Oil-changes are on-barge interventions, and doing so for both pumps one after another reduces logistics costs. However, preferential operation of the new pump over the older one may be better (Principle 4.2, "maintenance should evolve as the EO evolves"), so that the required oil-change frequencies for the two pumps would be different. On the other hand, marine growth obstructs pump suction causing cavitation (wear) (Principle 3.1, "better maintenance derives from better knowledge of an EO"), so it is important to undertake cleaning on time. Currently, measuring the extent of marine growth requires inspection by divers, and the associated logistics and plant shutdown. Thus, the DT will model the maximum flow the pump can deliver using data (e.g. Fig. 8 and records of previous interventions) (Principle 6.2, "DT to model degradation and repair"), in the short term, the DT will provide decision support for planning inspections, cleaning, and oil-changes so that interventions are timely and cost-effective (Principle 6.4, "competing policies to be testable in the DT") for both operations and maintenance (Principle 3.4, "maintenance protocols to be decided by stakeholders who share the maintenance plan"). The cost-benefit of the development and use of the DT will be analysed two years after initial roll-out (Principle 3.3, "maintenance performance baseline to be established"). Furthermore, cleaning and oil-changes are partial repairs, so that in the longer term, the effects of these repairs and other interventions (component replacements) on pump performance will be learned (Principle 6.2, "DT to model degradation and repair"). Then, the DT will have the capability to trigger overhaul and spare-part procurement (Principle 4.4, "maintenance requirements interact with operations, logistics, and spare-parts inventory").

The DT will be more than a one-off modeling solution. The DT will use the modeling solution adaptively and be integrated with the plant maintenance management and data collection systems (Principle 6.1, "DT to be integrated (connectivity)"). The DT will serve maintenance (M) and operations (O) (and other stakeholders e.g. supply chain manager; regulatory compliance officer) (Principle 3.4, "maintenance protocols to be decided by stakeholders who share the maintenance plan") through a decision support system (user-interface), with the capability to compare competing policies dynamically (connectivity), as new information about degradation and repair, and configuration and operational circumstances arises (Principle 4.2, "maintenance should evolve as the EO evolves"). This extended capability requires significant investment to which O and M are committed (Principle 5.3, "development cost of DT to be shared by operations and maintenance").

5. Discussion

We present a set of principles for guiding proponents and developers of digital solutions for maintenance planning. Application of the principles is illustrated using two cases studies based in the seawater desalination industry. The first relates to membrane elements in reverse-osmosis pressure vessels, and their monitoring and restoration, and the second to submerged seawater-intake pumps. Both these systems, engineered objects (EOs) in the terminology of the paper, are high-value, critical systems (for the delivery of potable water) and provide unique and complicated contexts, both operational and environmental, that justify the development of bespoke maintenance plans. The contribution of the paper is to show, in a systematic way, according to the proposed design principles, how to develop a digital twin of an EO for planning maintenance interventions for the EO.

The principles themselves are derived hierarchically in the paper beginning with basic principles of effective and efficient maintenance. As such they are generally relevant to maintenance planning. The presentation of these principles in the paper serves two purposes: to provide a novel framework for maintainers in industry; to lead discussion among researchers about DT design for maintenance and reliability and their suitability, capability, ownership, deployment, and return on investment. Much of the literature so far on DTs for maintenance and reliability describes solutions to particular problems that use particular models. To our knowledge, this paper is the first to discuss principles for their development. Furthermore, we see this work as an initial step towards the development of software that would support the practical use of the principles in industry. Such a tool would translate an agreed, comprehensive theoretical structure into an actionable format.

We discuss the nature of DTs, what defines them, concluding broadly that a DT encodes a model in a manner that is aligned with the digitalization trend in industry. While some proponents insist of capabilities for automation and autonomy, we take a more inclusive view that a DT should provide: a digital representation of an EO that is sufficiently accurate to be useful; decision support for planning. With regard to automation, there exists a tension: on the one hand maintenance that is planned without close human oversight may be productive (efficient) but on the other hand high-value, critical systems for which the cost of development of a DT is bearable are unlikely to be subject to maintenance that is planned without human oversight. Nonetheless, there may be circumstances (e.g. an installed base of very many EOs maintained by an OEM) where automation is desirable. Autonomy, in the sense that the DT (or the DSS within which the DT sits) learns good policy, is we think appealing but somewhat speculative.

Maintenance planning is a good arena in which to use DTs because operational and environmental circumstances are often unique, EOs may be immature with data scarce, or EOs and their environment may have evolved, been modified, redesigned, retrofitted, cannibalized with data plenty but superfluous. Then, a good simulator can provide useful knowledge quickly to support decision-making albeit for a digital representation of a real entity. This then provides general justification for the importance of the work in this paper.

What the paper does not do is: discuss in detail architectures for DT design; present an exhaustive set of principles for planning a maintenance program; explore matters of verification and validation of DTs and of simulators. These are beyond the scope of the paper.

To summarise, we think our proposed set of principles is original, because only recently are DTs being developed for maintenance planning, useful because we think industry-based maintainers can use these principles, rigorous because we position the principles within the context of work to date on the principles of maintenance planning, and important because maintenance planning presents decision-makers with unique circumstances. Operational and environmental variations, considerations of safety, and evolving business objectives characterise these unique circumstances. We hope these principles, or the development of them by other researchers in future, will provide the blueprint for developing a DT for maintenance planning.

Author statement

Please consider the revision of the manuscript “Maintenance planning using a digital twin: principles and case studies” for the virtual special issue “Maintenance Modelling”. This manuscript describes work that was presented at MIMAR 2023.

CRediT authorship contribution statement

Richard Dwight: Writing – original draft, Validation, Methodology, Conceptualization. **Wenxu Li:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Frits van Rooij:** Writing – original draft, Validation, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Phil Scarf:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

As corresponding author I can confirm there has been no conflict of interest in preparation of the manuscript “Maintenance planning using a digital twin: principles and case studies”.

References

[1] Fuller A, Fan Z, Day C, Barlow C. Digital twin: enabling technologies, challenges and open research. IEEE Access 2020;8:108952–71.
[2] Singh M, Fuenmayor E, Hinchy E, Qiao Y, Murray N, Devine D. Digital Twin: origin to future. Appl Syst Innov 2021;4:36.
[3] Ahmed U, Carpitella S, Certa A, Izquierdo J. Feasible Framew Maint Digit Process 2023;11:558.
[4] Rødseth H, Schjølberg P, Marhaug A. Deep digital maintenance. Adv Manuf 2017;5:299–310.
[5] Silvestri L, Forcina A, Introna V, Santolamazza A, Cesarotti V. Maintenance transformation through industry 4.0 technologies: a systematic literature review. Comput Ind 2020:123.
[6] van Dinter R, Tekinerdogan B, Catal C. Predictive maintenance using digital twins: a systematic literature review. Inf Softw Technol 2022;151:107008.
[7] Consilvio A, Sanetti P, Anguìta D, Crovetto C, Dambra C, Oneto L, Sacco N. Prescriptive maintenance of railway infrastructure: from data analytics to decision support. In: 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS); 2019. 5-7 June 2019.
[8] Matyas K, Nemeth T, Kovacs K, Glawar R. A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Ann 2017;66:461–4.
[9] Zonta T, da Costa C, da Rosa Righi R, de Lima M, da Trindade E, Li G. Predictive maintenance in the industry 4.0: a systematic literature review. Comput Ind Eng 2020;150:106889.
[10] Lim K, Zheng P, Chen C. A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives. J Intell Manuf 2020;31:1313–37.
[11] Aggarwal P, Narwal B, Purohit S, Mohapatra A. BPADTA: blockchain-based privacy-preserving authentication scheme for digital twin empowered aerospace industry. Comput Electr Eng 2023;111:108889.
[12] Feng H, Chen D, Lv H, Lv Z. Game theory in network security for digital twins in industry. Digit Commun Netw 2024;10:1068–78.
[13] Korotkova N, Benders J, Mikalef P, Cameron D. Maneuvering between skepticism and optimism about hyped technologies: building trust in digital twins. Inf Manag 2023;60:103787.
[14] Semeraro C, Lezoche M, Panetto H, Dassisti M. Data-driven invariant modelling patterns for digital twin design. J Ind Inf Integr 2023;31:100424.
[15] Glaessgen E, Stargel D. The digital twin paradigm for future NASA and U.S. Air Force vehicles. In: 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics And Materials Conference 20th AIAA/ASME/AHS 14th AIAA; 2012. p. 1818.
[16] Grieves M, Vickers J. Origins of the digital twin concept. Fla Inst Technol 2016;8:3–20.
[17] Semeraro C, Lezoche M, Panetto H, Dassisti M. Digital twin paradigm: a systematic literature review. Comput Ind 2021;130:103469.
[18] Wright L, Davidson S. How to tell the difference between a model and a digital twin. Adv Model Simul Eng Sci 2020;7:1–13.
[19] Agrawal A, Fischer M. What is digital and What are we twinning?: a conceptual model to make sense of digital twins. Handbook of digital twins. CRC Press; 2024. p. 13–29.
[20] Yoon S. Building digital twinning: data, information, and models. J Build Eng 2023;76:107021.
[21] Ozturk GB, Ozen B. Artificial intelligence enhanced cognitive digital twins for dynamic building knowledge management. Handbook of digital twins. CRC Press; 2024. p. 354–69.
[22] Zheng X, Lu J, Kiritsis D. The emergence of cognitive digital twin: vision, challenges and opportunities. Int J Prod Res 2022;60:7610–32.
[23] Hinchy E, Carcagno C, O'Dowd N, McCarthy C. Using finite element analysis to develop a digital twin of a manufacturing bending operation. Procedia CIRP 2020;93:568–74.
[24] Sílvia R, Lauro C, Ana H, Davim J. Development of FEM-based digital twins for machining difficult-to-cut materials: a roadmap for sustainability. J Manuf Process 2022;75:739–66.
[25] Zhao G, Cui Z, Xu J, Liu W, Ma S. Hybrid modeling-based digital twin for performance optimization with flexible operation in the direct air-cooling power unit. Energy 2022;254:124492.
[26] Lv Z. Overview of digital twins. editor. In: Zhihan Lv ip, editor. Handbook of digital twins. CRC Press; 2024.
[27] Liu J, Liu X, Vatn J, Yin S. A generic framework for qualifications of digital twins in maintenance. J Autom Intell 2023.
[28] Errandonea I, Beltrán S, Arrizabalaga S. Digital Twin for maintenance: a literature review. Comput Ind 2020;123:103316.
[29] Liu S, Guzzo J, Zhang L, Kumar U, Myers G. Ultra-deepwater drilling riser lifecycle management system. Procedia Manuf 2020;49:211–6.
[30] Fox H, Pillai A, Friedrich D, Collu M, Dawood T, Johanning L. A review of predictive and prescriptive offshore wind farm operation and maintenance. Energies 2022;15:504.
[31] Frantzén M, Bandaru S, Ng A. Digital-twin-based decision support of dynamic maintenance task prioritization using simulation-based optimization and genetic programming. Decis Anal J 2022;3:100039.
[32] Gosavi A, Le VK. Maintenance optimization in a digital twin for Industry 4.0. Ann Oper Res 2024;340:245–69.
[33] Jingyu L, Weixi J, Chen C, Su X. Maintenance architecture design of equipment operation and maintenance system based on digital twins. Proc Inst Mech Eng B: J Eng Manuf 2024;238:1971–90.
[34] Neto A, Carrijo B, Brock J, Deschamps F, de Lima E. Digital twin-driven decision support system for opportunistic preventive maintenance scheduling in manufacturing. Procedia Manuf 2021;55:439–46.
[35] Bujari A, Calvio A, Foschini L, Sabbioni A, Corradi A. A digital twin decision support system for the Urban Facility Management process. Sensors 2021;21:8460.

[36] Yu G, Wang Y, Mao Z, Hu M, Sugumaran V, Wang Y. A digital twin-based decision analysis framework for operation and maintenance of tunnels. Tunn Undergr Space Technol 2021;116:104125.
[37] Xie Y, Lian K, Liu Q, Zhang C, Liu H. Digital twin for cutting tool: modeling, application and service strategy. J Manuf Syst 2021;58:305–12.
[38] Almuraia A, He F, Khan M. AI-driven maintenance optimisation for natural gas liquid pumps in the oil and gas industry: a digital tool approach. Processes 2025; 13-5:1611.
[39] Wang J, Zhang Z, Liu Z, Han B, Bao H, Ji S. Digital twin aided adversarial transfer learning method for domain adaptation fault diagnosis. Reliab Eng Syst Saf 2023; 234:109152.
[40] Xia J, Huang R, Chen Z, He G, Li W. A novel digital twin-driven approach based on physical-virtual data fusion for gearbox fault diagnosis. Reliab Eng Syst Saf 2023;240:109542.
[41] Li S, Jiang Q, Xu Y, Feng K, Wang Y, Sun B, Ni Q. Digital twin-driven focal modulation-based convolutional network for intelligent fault diagnosis. Reliab Eng Syst Saf 2023;240:109590.
[42] Kohtz S, Zhao J, Renteria A, Lalwani A, Xu Y, X Z, Wang P. Optimal sensor placement for permanent magnet synchronous motor condition monitoring using a digital twin-assisted fault diagnosis approach. Reliab Eng Syst Saf 2023:109714.
[43] Sun J, Yan Z, Han Y, Zhu X, Yang C. Deep learning framework for gas turbine performance digital twin and degradation prognostics from airline operator perspective. Reliab Eng Syst Saf 2023;238:109404.
[44] Li S, Brennan F. Digital twin enabled structural integrity management: critical review and framework development. Proc Inst Mech Eng M: J Eng Marit Environ 2024;238:707–27.
[45] Anandavel S, Li W, Garg A, Gao L. Application of digital twins to the product lifecycle management of battery packs of electric vehicles. IET Collab Intell Manuf 2021;3:356–66.
[46] Qu Y, Shu W, Qiu L, Kuan YC, Chiang SHW, Chang JS. A low-profile high-efficiency fast battery charger with unifiable constant-current and constant-voltage regulation. IEEE Trans Circuits Syst I: Regul Pap 2020;67(11):4099–109.
[47] Wan C, Li W, Yang B, Ling S, Fu G, Hong Y. Digital twin model and platform based on a dual system for control rod drive mechanism safety. Reliab Eng Syst Saf 2025;261:111075.
[48] Ivanov D, Dolgui A. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Prod Plan Control 2021;32:775–88.
[49] Chiachío M, Megía M, Chiachío J, Fernandez J, Jalón ML. Structural digital twin framework: formulation and technology integration. Autom Constr 2022;140: 104333.
[50] Zio E, Miqueles L. Digital twins in safety analysis, risk assessment and emergency management. Reliab Eng Syst Saf 2024:110040.
[51] Ma S, Flanigan KA, Bergés M. State-of-the-art review and synthesis: a requirement-based roadmap for standardized predictive maintenance automation using digital twin technologies. Adv Eng Inform 2024;62:102800.
[52] Toothman M, Braun B, Bury S, Moyne J, Tilbury D, Ye Y, Barton K. A digital twin framework for prognostics and health management. Comput Ind 2023;150: 103948.
[53] Huang Z, Fey M, Liu C, Beysel E, Xu X, Brecher C. Hybrid learning-based digital twin for manufacturing process: modeling framework and implementation. Robot Comput Integr Manuf 2023;82:102545.
[54] Robles J, Martín C, Díaz M. OpenTwins: an open-source framework for the development of next-gen compositional digital twins. Comput Ind 2023;152: 104007.
[55] Botín-Sanabria DM, Adriana-Simona M, Peimbert-García RE, Ramírez-Moreno MA, Ramírez-Mendoza RA, Lozoya-Santos J. Digital Twin technology challenges and applications: a comprehensive review. Remote Sens (Basel) 2022; 14:1335.
[56] Qamsane Y, Moyne J, Toothman M, Kovalenko I, Balta E, Faris J, Barton K. A methodology to develop and implement digital Twin solutions for manufacturing systems. IEEE Access 2021;9:44247–65.
[57] De Donato L, Dirnfeld R, Somma A, De Benedictis A, Flammini F, Marrone S, Saman Azari, Vittorini V. Towards AI-assisted digital twins for smart railways: preliminary guideline and reference architecture. J Reliab Intell Environ 2023;9 (3):303–17.
[58] Centomo S, Dall'Ora N, Fummi F. The design of a digital-twin for predictive maintenance. In: 2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 1; 2020. p. 1781–8.
[59] Zhong D, Xia Z, Zhu Y, Duan J. Overview of predictive maintenance based on digital twin technology. Heliyon 2023. 9-4.
[60] Vatn J. Industry 4.0 and real-time synchronization of operation and maintenance. editors. In: Haugen S, Barros A, van Gulijk C, Kongsvik T, Vinnem JE, editors. Safety and reliability–safe societies in a changing world. Trondheim, Norway: CRC Press; 2018. p. 681–6.
[61] Gits C. Design of maintenance concepts. Int J Prod Econ 1992;24:217–26.
[62] Pintelon L, Parodi-Herz A. Maintenance: an evolutionary perspective. editors. In: Kobbacy KA, Murthy DN, editors. Complex system maintenance handbook. London: Springer; 2008. p. 21–48.
[63] Ben-Daya M, Kumar U, Murthy DN. Introduction to maintenance engineering: modelling, optimization and management. Dhahran, Saudi Arabia; Lulea, Sweden; Brisbane, Australia: Wiley; 2016.
[64] Liyanage JP, Lee J, Emmanouilidis C, Ni J. Integrated E-maintenance and intelligent maintenance systems. editors. In: Ben-Daya M, Duffuaa SO, Raouf A, Knezevic J, Ait-Kadi D, editors. Handbook of maintenance management and engineering. Springer; 2009. p. 499–544.
[65] Dwight R, Scarf P, Gordon P. Dynamic maintenance requirements analysis for asset management. editors. In: Berenguer Gralland, Soares Guedes, editors. Advances in safety, reliability, and risk management. London: Taylor and Francis; 2012. p. 847–52.
[66] Burhanuddin MA, Halawani SM, Ahmad AA. An efficient failure-based maintenance decision support system for smalland medium industries. editor. In: Jao C, editor. Efficient decision support systems: practice and challenges from current to future. BoD–Books on Demand; 2011. p. 195–210.
[67] Smith A. Reliability-Centered maintenance. New York: McGraw-Hill; 1993.
[68] Labib A. Computerised maintenance Management Systems. editors. In: Kobbacy KA, Murthy DP, editors. Complex system maintenance handbook. Springer Series in Reliability Engineering; 2008. p. 416–35.
[69] Murthy D, Jack N. Maintenance outsourcing. editors. In: Kobbacy KA, Murthy DP, editors. Complex system maintenance handbook. Springer Series in Reliability Engineering; 2008. p. 373–93.
[70] Adenuga OD, Diemuodeke OE, Kuye AO. Maintenance in marginal oilfield production facilities: a review. World J Eng Technol 2022;10:691–713.
[71] Alsyouf I. Maintenance practices in Swedish industries: survey results. Int J Prod Econ 2009;121:212–23.
[72] Dwight R. Searching for real maintenance performance measures. J Qual Maint Eng 1999;5:258–75.
[73] Tam A, Chan W, Price J. Optimal maintenance intervals for a multi-component system. Prod Plan Control 2006;17:769–79.
[74] Tiddens W, Braaksma J, Tinga T. Decision framework for predictive maintenance method selection. Appl Sci 2023;13:2021.
[75] de Jonge B, Scarf PA. A review on maintenance optimization. Eur J Oper Res 2020;285:805–24.
[76] da Costa L, Cavalcante C. A review on the study of maintenance effectiveness. Pesqui Oper 2022:42.
[77] Kobbacy K, Murthy D. An overview. editors. In: Kobbacy K, Murthy D, editors. Complex system maintenance handbook. Springer Series in Reliability Engineering; 2008. p. 1–18.
[78] da Silva R, de Souza G. Modeling a maintenance management framework for asset management based on ISO 55000 series guidelines. J Qual Maint Eng 2021;28: 915–37.
[79] Parra Márquez C, Crespo Márquez A, González-Prida Díaz V, Gómez Fernández J, Kristjanpoller Rodríguez F, Viveros Gunckel P. Economic impact of a failure using life-cycle cost analysis. In: Márquez A, Díaz V, Fernández J, editors. Advanced maintenance modelling for asset management: techniques and methods for complex industrial systems. Springer; 2018. p. 213–43.
[80] Crocker J. Effectiveness of maintenance. J Qual Maint Eng 1999;5:307–14.
[81] James AT, Gandhi OP, Deshmukh SG. Assessment of failures in automobiles due to maintenance errors. Int J Syst Assur Eng Manag 2017;8:719–39.
[82] Pyy P. An analysis of maintenance failures at a nuclear power plant. Reliab Eng Syst Saf 2001;72:293–302.
[83] Waeyenbergh G, Pintelon L. A framework for maintenance concept development. Int J Prod Econ 2002;77:299–313.
[84] Riane F, Roux O, Basile O, Dehombreux P. Simulation based approaches for maintenance strategies optimization. editors. In: Ben-Daya M, Duffuaa SO, Raouf A, Knezevic J, Ait-Kadi D, editors. Handbook of maintenance management and engineering. Springer; 2009. p. 133–53.
[85] Novak J, Farr-Wharton B, Brunetto Y, Shacklock K, Brown K. Safety outcomes for engineering asset management organizations: old problem with new solutions? Reliab Eng Syst Saf 2017;160:67–73.
[86] Pintelon L, Muchiri PN. Safety and maintenance. editors. In: Ben-Daya M, Duffuaa SO, Raouf A, Knezevic J, Ait-Kadi D, editors. Handbook of maintenance management and engineering. Springer; 2009. p. 612–48.
[87] Grechuk B, Zabarankin M. Risk averse decision making under catastrophic risk. Eur J Oper Res 2014;239:166–76.
[88] Aven T. The reliability science: its foundation and link to risk science and other sciences. Reliab Eng Syst Saf 2021;215:107863.
[89] Hansson SO. ALARA: what is reasonably achievable?. editors In: Oughton D, Hansson SO, editors. Social and ethical aspects of radiation risk management. Oxford, UK: Elsevier; 2013. p. 143–55.
[90] Verhulst E. Applying systems and safety engineering principles for antifragility. Procedia Comput Sci 2014;32:842–9.
[91] Ghaleb M, Taghipour S. Assessing the impact of maintenance practices on asset's sustainability. Reliab Eng Syst Saf 2022;228:108810.
[92] Iung B, Levrat E. Advanced maintenance services for promoting sustainability. Procedía CIRP 2014;22:15–22.
[93] Ghaleb M, Taghipour S. Evidence-based study of the impacts of maintenance practices on asset sustainability. Int J Prod Res 2023;61:8719–50.
[94] Scarf PA, Syntetos AA, Teunter R. Joint maintenance and spare-parts inventory models: a review and discussion of practical stock-keeping rules. IMA J Manag Math 2024;35:83–109.
[95] Söderholm P, Holmgren M, Klefsjö B. A process view of maintenance and its stakeholders. J Qual Maint Eng 2007:19–32.
[96] Duffuaa SO, Raouf A. Planning and control of maintenance systems. modelling and analysis. 2nd ed. Dhahran, Saudi Arabia; Lahore Pakistan: Springer; 2015.
[97] Diallo C, Aït-Kadi D, Chelbi A. Integrated spare parts management. editors. In: Ben-Daya M, Duffuaa SO, Raouf A, Knezevic J, Ait-Kadi D, editors. Handbook of maintenance management and engineering. Springer; 2009. p. 191–222.
[98] Alsyouf I. Measuring maintenance performance using a balanced scorecard approach. J Qual Maint Eng 2006;12:133–49.

[99] Muchiri P, Pintelon L. Performance measurement using overall equipment effectiveness (OEE): literature review and practical application discussion. Int J Prod Res 2008;46(13):3517–35.
[100] El-Akruti K, Dwight R, Zhang T. The strategic role of engineering asset management. Int J Prod Econ 2013;146:227–39.
[101] Barbieri G, Hernandez JD. Sustainability indices and ram analysis for maintenance decision making considering environmental sustainability. Sustainability 2024;16:979.
[102] Ben-Daya M, Duffuaa S. Overview of maintenance modeling areas. editors. In: Ben-Daya M, Duffuaa S, Raouf A, editors. Maintenance, modeling and optimization. Kluwer Academic Publisher; 2000. p. 3–35.
[103] Åhrén T, Aditya A. Maintenance performance indicators (MPIs) for benchmarking the railway infrastructure: a case study. Benchmarking: Int J 2009;16:247–58.
[104] Mobley RK. An introduction to predictive maintenance. 2nd ed. Knoxville, Tennessee: Butterworth-Heinemann (Elsevier Science USA); 2002.
[105] Parida A. Study and analysis of maintenance performance indicators (MPIs) for LKAB: a case study. J Qual Maint Eng 2007;13:325–37.
[106] VanHorenbeek A, Pintelon L. Development of a maintenance performance measurement framework—Using the analytic network process (ANP) for maintenance performance indicator selection. Omega (Westport) 2013;42:33–46.
[107] van Staden HE, Deprez L, Boute RN. A dynamic "predict, then optimize" preventive maintenance approach using operational intervention data. Eur J Oper Res 2022;302(3):1079–96.
[108] Ruiz PP, Foguem BK, Grabot B. Generating knowledge in maintenance from Experience Feedback. Knowl Based Syst 2014;68:4–20.
[109] Bakri A, Januddi M. Computerized-based maintenance. Systematic industrial maintenance to boost the quality management programs. Cham: Springer; 2020. p. 69–78.
[110] Catt PJ. A tailorable framework of practices for maintenance delivery. J Qual Maint Eng 2022:28. -1.
[111] Carnero Moya M. The control of the setting up of a predictive maintenance programme using a system of indicators. Omega Int J Manag Sci 2004;32:57–75.
[112] Topan E, Eruguz AS, Ma W, van der Heijden MC, Dekker R. A review of operational spare parts service logistics in service control towers. Eur J Oper Res 2020;282:401–14.
[113] Mazur DC, Stewart BG, Clark HE, Paes R. Industrial petrochemical applications - analysis of programmable logic controllers and distributed control systems. IEEE Ind Appl Mag 2021:36–44. July/August.
[114] Noor HM, Mazlan SA, Amrin A. Computerized Maintenance Management System in IR4.0 adaptation - a state of implementation review and perspective. In: IOP Conf. Series: Materials Science and Engineering, 1051; 2021.
[115] Aghajani E, Nagy C, Vega-Márquez O, Linares-Vásquez M, Moreno L, Bavota G, Lanza M. Software documentation issues unveiled. In: IEEE/ACM 41st International Conference on Software Engineering (ICSE); 2019. p. 1199–210.
[116] Liu S, Lu Y, Li J, Shen X, Sun X, Bao J. A blockchain-based interactive approach between digital twin-based manufacturing systems. Comput Ind Eng 2023;175: 108827.
[117] Mahmood K, Shamshad S, Saleem M, Kharel R, Das A, Shetty S, Rodrigues J. Blockchain and PUF-based secure key establishment protocol for cross-domain digital twins in industrial Internet of Things architecture. J Adv Res 2024;65: 155–63.
[118] Assaf R, Do P, Nefti-Meziani S, Scarf P. Wear rate–state interactions within a multi-component system: a study of a gearbox-accelerated life testing platform. J Risk Reliab 2018;232:425–34.
[119] Apeland S, Aven T. Risk based maintenance optimization: foundational issues. Reliab Eng Syst Saf 2000;67:285–92.
[120] Dibsdale C. Holistic prognostics. editors. In: Redding L, Roy & R, editors. Through-life engineering services: motivation, theory, and practice. Springer; 2014. p. 71–82.
[121] Van Noortwijk J, Dekker A, Cooke R, Mazzuchi T. Expert judgment in maintenance optimization. IEEE Trans Reliab 1992;41:427–32.
[122] Liu M, Fang S, Dong H, Xu C. Review of digital twin about concepts, technologies, and industrial applications. J Manuf Syst 2021;58:346–61.
[123] Tao F, Xiao B, Qi Q, Cheng J, Ji P. Digital twin modeling. J Manuf Syst 2022;64: 372–89.
[124] Dohi T, Kaio N, Osaki S. Basic preventive maintenance policies and their variations. editors. In: Ben-Daya M, Duffuaa S, Raouf A, editors. Maintenance, modeling and optimization. Kluwer Academic Publisher; 2000. p. 155–83.
[125] Box G. Science and statistics. J Am Stat Assoc 1976;71:791–9.
[126] French S. Cynefin, statistics and decision analysis. J Oper Res Soc 2013;64: 547–61.
[127] Percy D. Maintenance based on limited data. editors. In: Kobbacy K, Murthy D, editors. Complex system maintenance handbook. Springer Series in Reliability Engineering; 2008. p. 133–54.
[128] Lind S, Nenonen S, Kivistö-Rahnasto J. Safety risk assessment in industrial maintenance. J Qual Maint Eng 2008;14:205–17.
[129] Nakagawa T. Imperfect preventive maintenance models. editors. In: Ben-Daya M, Duffuaa S, Raouf A, editors. Maintenance, modeling and optimization. Kluwer Academic Publisher; 2000. p. 201–14.
[130] van Rooij F, Scarf P. Towards a maintenance requirements analysis for maximizing production. In: Beer Michael, Zio Enrico, editors. Proceedings of the 29th European Safety and Reliability Conference. Singapore: Research Publishing; 2019. p. 684–90. editors.
[131] Matin A, Laoui T, Falath W, Farooque M. Fouling control in reverse osmosis for water desalination & reuse: current practices & emerging environment-friendly technologies. Sci Total Environ 2020:1–20. https://doi.org/10.1016/j.scitotenv.2020.142721. Retrieved from.
[132] van Rooij F, Scarf P, Do P. Planning the restoration of membranes in RO desalination using a digital twin. Desalination 2021;519:115214.
[133] Bian L, Gebraeel N. Stochastic framework for partially degradation systems with continuous component degradation-rate-interactions. Nav Res Logist 2014;61: 286–303.
[134] Do P, Assaf R, Scarf P, Iung B. Modelling and application of condition-based maintenance for a two-component system with stochastic and economic dependencies. Reliab Eng Syst Saf 2019;182:86–97.
[135] Battin TJ, Kaplan LA, Newbold JD, Hansen CME. Contributions of microbial biofilms to ecosystem processes in stream mesocosms. Nature 2003;426:439–41.
[136] Efron B, Tibshirani RJ. An introduction to the bootstrap. Chapman and Hall/CRC; 1994.
[137] Minette R, SilvaNeto S, Vaz L, Monteiro U. Experimental modal analysis of electrical submersible pumps. Ocean Eng 2016;124:168–79.
[138] Stoffel B. Assessing the energy efficiency of pumps and pump units. Darmstadt, Germany: Elsevier, Europump; 2015.
[139] Beebe RS. Predictive maintenance of pumps using condition monitoring. New York: Elsevier Science & Technology Books; 2004.
[140] Zhao J, Feng H, Chen Q, Garcia de Soto B. Developing a conceptual framework for the application of digital twin technologies to revamp building operation and maintenance processes. J Build Eng 2022;49:104028.