Digital twin service patterns for maintenance management of operational rail assets

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ABSTRACT: Digital twins entail the entangled use of a software representation of a real asset with engineering sensors to communicate the state and behaviour of an asset. This work focuses on how digital twin technology may specifically proffer maintenance management in rail networks and rolling stock through their value adding property, servitization. These digital services are structured through a portfolio of digital twin service patterns, which hinge on the generic configuration of digital twin building blocks to deliver a specific value. This idea springboards off the iconic concept, "design patterns" in object orientated programming which entail standardized high-level solutions to commonly recurring problems. Design templates are provided for specific services that mirror asset behaviour, provide virtual sensing, detect anomalies, and match the fingerprint of a specific response. The service patterns are presented through a graphical model that depicts the detail of cyber-physical interactions.

1 INTRODUCTION

Though digital twins (DT) are not a new concept, access to their abilities for use by a wider group of stakeholders is emergent. Drazen et al. (2019) cites the use of system-of-system DT deployments and their specific utility in pro-active condition-based maintenance. The authors attribute the successful commercial deployment of these twins to advances in several enabling technologies such as high-performance computing, advanced data analytics, and artificial intelligence. DTs have evolved as a "solution without a problem". It is a technology that offers convincing potential, however, there seems to be space for innovation in the formulation of use-cases that enable its full exploitation.

The plethora of literature on DTs, attests to the fact that DT technology is increasingly well established, yet rail-related accounts are somewhat isolated at the time of writing. The term, *digital twin* is defined and adopted differently in various application sectors. As such, the sparsity of DTs in published rail literature is more ascribed to adopted terminology than an absence of existing applications. To clarify the proposed contribution of the present work, the following sections are devoted to a brief background that describes an inclusive definition and attributes of a DT.

2 DIGITAL TWINS

2.1 *Evolution and definition*

The earliest DTs, enabled by Computer Automated Design, conveyed the descriptive essence of an object, without the requirement of its physical presence. Since, DTs have progressed to increasingly actionable, dynamic presentations that do not only follow form, but can reflect behaviour and increasingly rich information (Grieves & Vickers, 2017). Today, DTs potentiate the ability to design, test, manufacture and use the virtual version of an asset or system. This bolsters the development of digital services towards increasing understanding of engineering products, the anticipation of responses in unforeseen conditions and the prediction of emergent behaviours (Grieves & Vickers, 2017).

A widely adopted definition (Niederer et al., 2021) states that a DT is a set of virtual information constructs that mimics the structure, context and behaviour of an individual or unique physical asset, that is dynamically updated with data from its physical twin throughout its life-cycle, and that ultimately informs decisions that realize value. A complimentary definition by Minerva et al. (Minerva et al., 2020) echoes that a DT is a comprehensive software representation of an individual physical object which reflects its properties, conditions, and behaviours through models and data.

In these definitions the essential components of a DT system may be identified including a *physical asset*, *digital representation*, and the *entanglement* between the two through sensor feeds or controlling actions from the user or virtual counterpart. Literature is somewhat contradicting as to a common understanding of the digital representation and entanglement aspects (Kritzinger et al., 2018; Tekinerdogan & Verdouw, 2020). The present work adopts the most inclusive definition (Erikstad, 2017; Minerva et al., 2020; Niederer et al., 2021) of a DT as follows:

1. The *physical asset* could refer to a single component, an assembly, or a system of assemblies. Kutzke et al. (2021) state that a physical system could be represented by an aggregate of several distinct and potentially different DTs, each driven by the functions of individual subsystems that comprise the full system. Therefore, based on the intended use of a DT a single asset may be represented by multiple DTs.
2. The *digital representation* may also be referred to as a virtual counterpart, software clone or a logical object (Minerva et al., 2020). The digital representation is to capture the essential physical manifestation of the real asset in a digital format (Erikstad, 2017). At a minimum, this twin should contain all required information to fully characterize the physical asset for the intended function of the twin. This may be achieved through physics-based-, data-driven or hybrid (combination of physics-based and data-driven) models. Although very accurate, ultra-high-fidelity representations may lead to models which are hard to implement because of the high computational effort, requirement for domain specific knowledge and time-intensive development (Aivaliotis et al., 2019). Alternatively, simpler models may offer reasonable estimation of asset responses, at the cost of lower reliability and accuracy.
3. The link which enables communication between the real asset and virtual representation is termed *entanglement* (Minerva et al., 2020) where the intention of a DT is a one-to-one coupling with a unique real asset (Erikstad, 2017). Entanglement is characterized by three properties namely (Minerva et al., 2020):
    a. *Connectivity* - the direct or indirect means through which updates in state and/or behaviours can be realized between real and softwarized assets.
    b. *Promptness* - quantifies how timely communication between the real asset and its digital representation takes place. It is important that the latency of the digital reflection is negligible compared to the needs of the intended use of the DT.
    c. *Association* - refers to the direction of communication between the real asset and its digital counterpart. The communication can be uni-directional (typically from the physical asset to digital counterpart) or bi-directional where virtual to physical information flow may additionally be enabled.

When considering connectivity, promptness and association, entanglement can be defined as *weak* (where information is inferred by indirect observations), *simple* (uni-directional link, not necessarily real-time with links that may be interrupted) or *strong* where a constant bi-directional link is established, and the digital representation may be the controlling instance (Minerva et al., 2020) and may be ultimately automated.

The present study elects to define DTs to include weak, simple, and strong physical/digital entanglements. Det Norske Veritas (2020) suggest a framework whereby a DT may be structured into manageable functional elements with capability levels ranging between *disconnected (level 0)* or *connected* (levels 1 to 5) as shown in Fig.1. The culmination of the functionality of the elements and their connections is classified into DTs that are standalone, descriptive, diagnostic, predictive, prescriptive or autonomous (Det Norske Veritas, 2020). Erikstad (2019) delineated DT maturity similarly and cautioned that the level of insight the DT is expected to deliver, will be associated with complexity and cost, thereby stressing the need for a systematic and purposeful design practice.

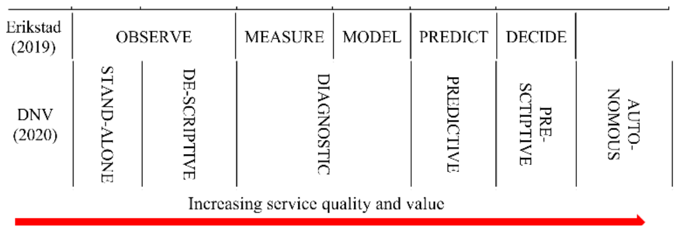

Figure 1. DT maturity, cost, and complexity.

Finally, it should be realized that use cases for DT are transpiring *throughout the asset life cycle.* Macchi et al. (2018) highlight the capability of DT to reflect an asset from inception to end of life and to impact strategic, tactical, and operational control levels. DTs could be concurrently developed alongside new products to reflect their state and behaviour throughout the design and manufacturing stages. Pedersen et al. (2021) propose to distinguish between *living* and *prototyping* DTs. The latter represents a system scenario sans direct coupling to real-time observations for design or planning actions.

2.2 *Contribution*

It is acknowledged that rail sector stakeholders are complex enterprises with major capital investments in existing rail assets and infrastructure. With this in mind, the present scope *includes solutions that enable retrofitting* of DT instances onto existing rail assets in operation (middle of life to end of life). Furthermore, the contribution is pitched to assist in maintenance management where it is desired to optimize the condition and performance of assets in balance with activities that aim to reduce breakdowns, increase up-time, and promote reliability. In an effort to move away from case-specific DT examples, to more generic, widely applicable solution templates, the concept of DT *service patterns* by Erikstad & Bekker (2021) is leveraged. The present work builds on earlier service patterns by concrete depiction of cyber-physical interactions that employ a graphical model by Kapteyn et al. (2021).

2.3 *Layout*

First, the methodology is introduced through introduction of the graphical method of Kapteyn et al. (2021)(Section 3.1) and the originally proposed service patterns by (Erikstad & Bekker, 2021) (Section 3.2). Next the results in Section 4 reflect a graphical evolution of service patterns for mirroring, virtual sensing, anomaly detection and fingerprint recognition. The practical value of each pattern is further illustrated through reference to literature examples from the rail sector. Finally, discussions are offered relating to the challenges and benefits of DTs that emerge from research on the presented service patterns in Section 5.

3 METHOD

3.1 *Graphical model for cyber-physical interactions*

Kapteyn et al. (2021) recognized the need to depict the interactions between the digital and physical counterparts of DTs which would enable solution templates and robust DT implementations at scale. The proposed probabilistic graphical model enables a formal mathematical representation of a DT which draws on well-established theory and methods from Bayesian statistics, dynamical systems, and control theory. The present work adopts this model, with some extensions to explain service patterns through which digital twins may be leveraged to support decisions in condition-based and predictive maintenance.

The physical asset and virtual counterpart are represented as a set of dynamically coupled systems that evolve over time through their state spaces (Kapteyn et al., 2021). Interactions are enabled through observed data and control inputs. The mathematical representation comprises six quantities which are listed and explained in Fig. 2.

To depict the cyber-physical interaction sequence for digital service patterns some minor extensions of this graphical model were required:

1. It was required to differentiate that observations and *quantities of interest arise because of specific conditions*. This was enabled by addition of subscripts such as $|A$ "given A" and $|B$ to differentiate between observations and quantities of interest that arise under different operational scenarios.
2. In some illustrations it was necessary to communicate clearly that the service pattern infers quantities of interest that are not included in the physical observed data. Here it was elected to use classical definitions from mathematics relating to sets. E.g., such that observations from set $\mathbb{B}$ are not contained in set $\mathbb{A}$ or $\mathbb{B} \notin \mathbb{A}$.

3.2 *Patterns of in-service implementation*

Design patterns describe the solution to a recurring problem in such a way that the solution can be re-used in a multitude of versatile applications (Gamma et al., 1996). Gamma et al. (1996) identified twenty-three core patterns in software systems which each capture the underlying architectural and algorithmic solutions to a specific problem independent of programming language and application area. These patterns added value as common solution templates for the software development community. Erikstad (2018) was first to adopt the concept of design patterns to structure the functionality of DTs into four groupings namely structural, creational, insight and computational patterns.

In later work by Erikstad & Bekker (2021) design pattern thinking was applied to identify a set of eight patterns for digital services based on DT (see Table 1).

Table 1. DT service patterns (Erikstad & Bekker, 2021).

Name	**Value provided by digital service**
Virtual sensor	Provide insight into asset behaviour on locations without sensor observations.
Context sensor	Provide insight into loads and operational context by inverse inference on asset behaviour.
Fingerprint	Understand asset operations by matching against a catalogue of behavioural patterns.
Anomaly	Early detection of faults and critical conditions by comparing observed and predicted behaviour.
Root cause	Identify root cause of observed deviations by reverse engineering physics-based simulations.
Scout	Anticipate near/future behaviour / performance by fast forwarding current operations using simulations and predictive statistics.
Life counter	Aggregate miniscule incremental loads to better exploit actual life capacity and avoid failures
Mirror	Recreate complete immersive operators experience to manage remote assets

Here, a DT-based service pattern is defined as *a common, high level, conceptual solution for realizing (partly or fully) a digital service, based on a DT that delivers value to stakeholders by decision support and/or improved insight related the asset's state or operational behaviour* (Erikstad & Bekker, 2021).

4 RESULTS

In the context of maintenance management, digitalisation of the rail sector has resulted in trains and tracks that are increasingly equipped with sensors and software. Remote stakeholders attain awareness of the state and behaviour of their assets through technologies such as condition monitoring. Condition-based and predictive maintenance strategies have long been advocated for their potential reduction in un-planned, costly breakdowns and avoidance of unnecessary repairs (Nunes et al., 2023). Condition-based maintenance utilizes on-line sensing techniques from which asset degradation information may be inferred (Jardine et al., 2006). Maintenance actions are triggered by the condition of an asset, thereby saving labour, and reducing downtime, reducing costs, and increasing production. Condition monitoring could rely on visual inspection, inspection measurements or permanent instrumentation. It is specifically in the spheres of condition-based maintenance that DTs may increase the clarity of condition assessment (Kutzke et al., 2021). Particularly in function- or safety-critical systems.

Werner et al. (2019) contribute a holistic maintenance strategy by formulating an approach which utilizes a DT to mitigate the reported lack of a systematic predictive maintenance approaches. DT technology is perfectly situated to advance activities related to *diagnostics* (fault isolation and identification) and *prognostics* (failure mode evolution) in condition-based monitoring regimes.

The following sections detail the contribution of four service patterns, which aim to generalize how DT technology can be explicitly harnessed towards services that benefit maintenance management.

4.1 *Mirror*

A mirror DT enables the reflection of the asset in its current state through timely sensor feeds and appropriate dashboarding to the user. In Fig.3 the interaction between physical and digital entities of the mirror pattern are depicted as they evolve. The physical state of the asset, S_1, is obtained through sufficient sensor (or other) physical observations, O_1. Physical state inputs and observation data are used to realize the digital state reflection, D_1 of the asset and deliver the required quantities of interest (Q_1) as reward, R_1. When the asset receives a new control action U_1 the physical state of the asset is updated, and the digital counterpart evolves to update the reflection of the asset.

The mirror pattern delivers *digital visibility* and situational awareness (Drazen et al., 2019) to remote stakeholders. The implementation of this DT pattern could be as simple as an annotated plant model with clickable links to view sensor feeds and asset specifics or alternatively, be highly sophisticated with immersive contextual modelling or extensive augmented reality features. This pattern is associated with maturity on a descriptive level and requires sensor feeds or observations linked to the asset state, behaviour, and context.

Applications in asset monitoring make use of this pattern which is widely adopted throughout broader industrial applications and the rail industry over the last decades. In South Africa, Busatta & Moyo (2015) proposed a monitoring system comprising arrays of accelerometers, strain gauges and crack sensors to monitor a single span of a highly-trafficked viaduct structure. This investment aims to understand the deterioration rate of an aging structure and the detection of defects amidst usage trends such as increasing axle loads, number of wagons and number of trains. No further details were provided with regard to the dashboards or value-adding algorithms. Sangat et al. (2016) emphasize the need to determine the real-time position of trains and wagons with high accuracy as inputs to safety-related and maintenance decisions. Here, rapidly executed algorithms and suitable data structures mitigate errors owing to delays in signal arrival time, thereby ensuring accurate train location mappings despite high volumes of geo-spatial data.

4.2 *Virtual sensor*

A virtual sensor (see Fig.4) delivers digitally generated insights into asset behaviour beyond the measures that are available from a set of physical observation data.

A physical asset operates at a state, S_t, and is equipped with sensors to provide observations, $O_{\mathbb{A},t}$ from a set of sensors in collection $\mathbb{A}$. The observations sufficiently enable the replication of the digital state of the asset, D_t. The digital representation is now be queried to infer a quantity of interest which is outside the measured set of observations, $Q_{\mathbb{B},t}$, where $\mathbb{B} \notin \mathbb{A}$.

As an example, the location of a critical stress "hotspot" may differs from the measurement location on a real asset. The measurement can serve as input to enable the digital replication of the physical state. A virtual measurement may then be extracted from the desired location on the digital model (Erikstad & Bekker, 2021). Alternatively, data-driven or reduced-order models could be trained to infer the desired responses from historical data or simulations. The maturity level of a virtual sensor twin surpasses a descriptive level DT and requires an investment in modelling efforts.

Bernal et al. (2023) aimed to extend on automated train control systems by developing a digital twin to predict the instantaneous wagon derailment risk. The model could deliver rapid results through a surrogate model which was derived from a multitude of computations using a sophisticated multi-body simulation model. As such the surrogate model enabled the instantaneous determination of a performance quantity which is not directly measured.

4.3 *Anomaly*

The anomaly pattern (see Fig.5) detects abnormal behaviour of the physical asset when sensor responses deviate from expected responses obtained through a virtual model which is exposed to the same context or load (Erikstad & Bekker, 2021).

The physical asset is exposed to a control action, U_i, and/or an operational environment with conditions, A. As a result, the asset is in a physical state, S, at time, t, given environmental inputs, A, and control inputs U, denoted as $S_{t|A,U}$.

The digital representation receives information about the control action and / or observational data $O_{t,U,A,}$ related to the context and / or control inputs on the asset which enable a digital output response, measured as a quantity of interest, $Q_{t|A,U}$. Meanwhile, observation data, $O_{t|A,U}$ is captured. The intent with this pattern is that the digital representation delivers the ideal / expected response, which serves as a benchmark for the detection of physically deviant behaviour within a tolerance, σ. If the deviation between the physical observation and digital quantity of interest is significant this enables the automated detection of anomalous asset responses.

An anomaly DT provides the advantage of digital vigilance and the potential automation of manual, repetitive tasks. At a minimum, this pattern requires a digital model to deliver the expected response as well as a physical feed of observation for comparison.

Recently, Mosleh et al. (2022) proposed a methodology for the automatic detection of wheel flats on train wheels by distinguishing between healthy and defective wheels. This low-cost solution employs a single-sensor monitoring system where wheel state classifications are enabled through an un-supervised algorithm which was developed using advanced signal processing and more extensive sensing equipment.

4.4 *Fingerprint*

The fingerprint matches the response of an operational asset to a catalogue of response patterns which are pre-generated using a digital model or earlier diagnostic / qualification measurements.

An example of a fingerprint pattern is shown in Fig.6 where it is desirable to recognize response patterns under conditions which are denoted $A...j$. Prior to the operational deployment of the fingerprint DT, a digital model is used to generate a matching set of quantities of interest, $Q_{A...j}$, which correspond to intended observations on the real asset in operation. When the asset is deployed it may assume several physical states $S_{i|j}$ at instances t_i which are measured by purposely positioned sensors that capture observational data $O_{i,j}$. If the instantaneous observation $O_{i,j}$ matches any of the fingerprint quantities $Q_{0|j}$, the reward is that the condition of the asset can be automatically identified and flagged to inform stakeholders.

This pattern could be used to diagnose a type of failure or response in operational assets. Virtualized sensor feeds can be generated for early-stage failure scenarios without requiring that the system should physically have operated in this response mode before. This addresses the typical lack of failure data in condition-based monitoring applications. Alternatively, expert diagnostics can be softwarized to assist in the interpretation of anomalous asset behaviour. The automation of the identification of response patterns can alleviate laborious manual tasks and leverage digital vigilance. This pattern lends itself to high levels of customization and adaptability as the catalogue may be extended as new states of interest arise.

Limitations include that noisy measurements from real responses may deviate from digitally simulated fingerprints in a catalogue. This DT requires a maturity level that corresponds to diagnostic capabilities. In their recent review article Van Dinter et al. (2022) conclude that the development of reliable predictive maintenance models is challenging owing to the lack of semi-healthy or failure data. Especially since predictive maintenance aims at interventions that should be optimized before the asset encounters failure. Here, the use of a fingerprint DT could serve to generate estimations of pre-failure responses to inform a predictive maintenance approach.

5 DISCUSSION

5.1 *Cost*

It is interesting to observe that the instantiation of a DT solution may require a transient investment. In the development stage costs could be incurred to fund data acquisition and sensing, data analytics and labelling, extensive simulation, and the generation of response surfaces.

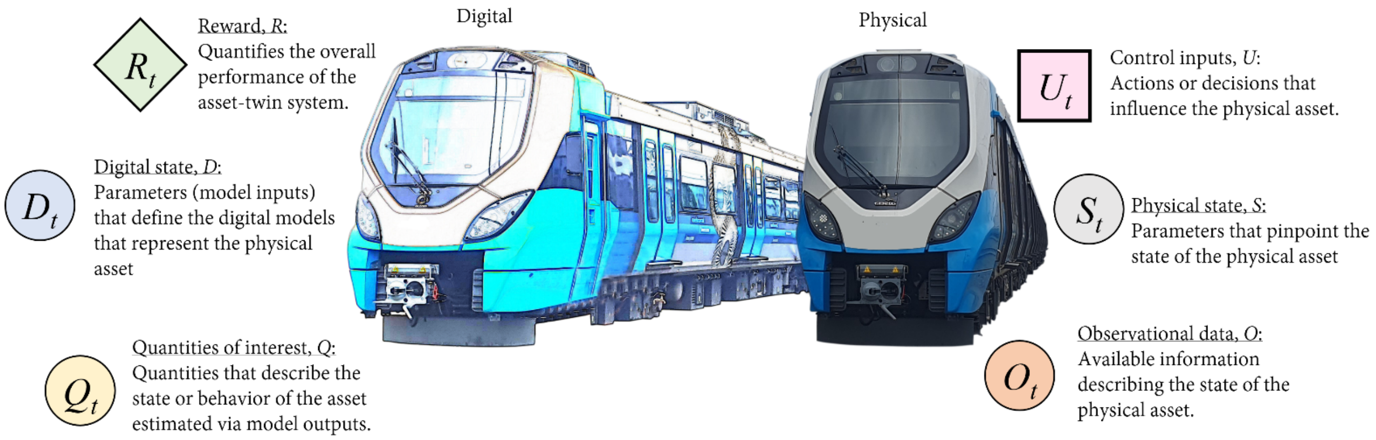

Figure 2. A summary of the six quantities used in the graphical model by Kapteyn et al. (2021).

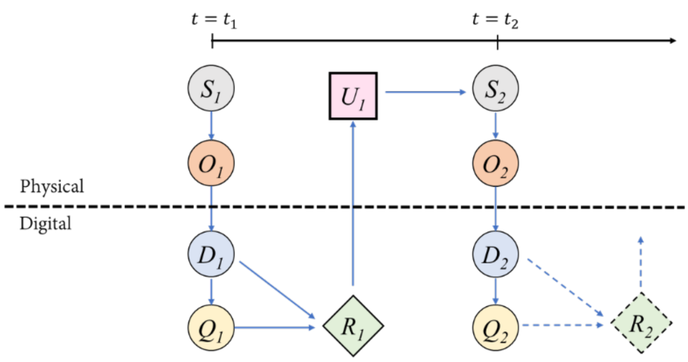

Figure 3. The mirror pattern.

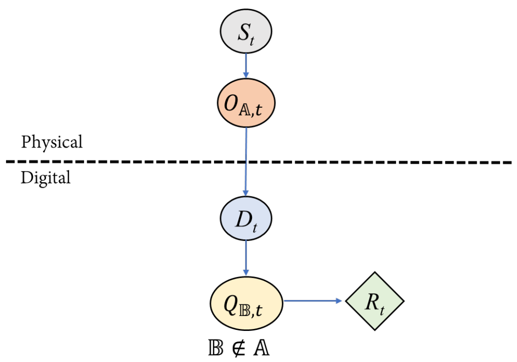

Figure 4. The virtual sensor.

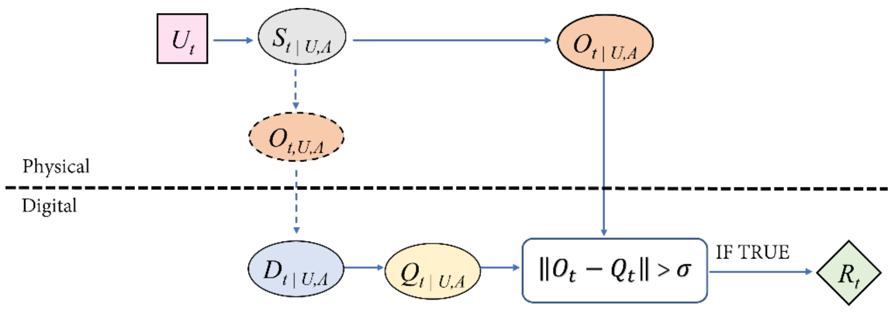

Figure 5. The anomaly pattern.

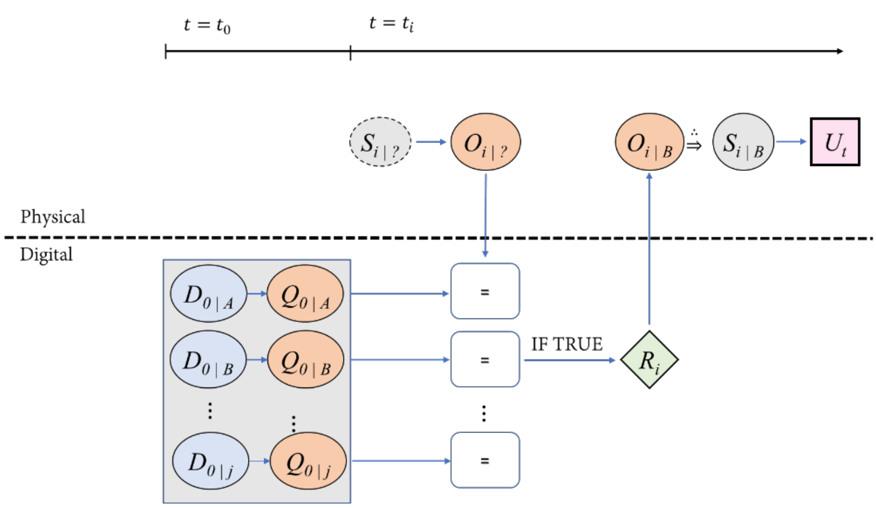

Figure 6. The fingerprint pattern.

In the operational phase a leaner infrastructure could serve the remainder of the DT lifecycle to deliver the required value. As discussed by Erikstad (2019) the increased sophistication and maturity of DTs will require greater complexity and entail increased costs. Currently, the most common examples of DTs are evident in monitoring applications and DTs that deliver a service on a descriptive level.

5.2 *Challenges*

Proprietary ringfencing entails the challenge related to the lack of model sharing between rail operators, infrastructure managers and train producers. Living DTs will serve multiple stakeholders for distinct purposes in each of their specific roles, which calls for greater cooperation and sharing the benefits of the DT.

Security concerns arise with increased remote access to sensitive information and the possibility of criminality through this access. Another concern includes topics such as retaining the competitive edge through proprietary intellectual property.

The reliability of information from DTs can only be ensured through the quality assurance of each functional element. Additionally, assurance is required to ensure the obtained data and models are complete in their representation of information that should influence decisions.

In itself DT infrastructure will require maintenance, expertise and entail costs to ensure proper functioning.

5.3 *Advantages*

Uhlenkamp et al. (2019) state that prognostic health management of assets have been hampered by uncertainty in the material behaviour, operational conditions and loads that products face in deployment. As such DT-enabled coupling between operational data and virtual models springboards a means through which uncertainties in asset health management (material behaviour, operational context, and loads) can be reduced. Kutzke et al. (2021) mention that DT technology is used to facilitate reliability and increased robustness by providing awareness to system operators and maintainers. This technology adds additional predictive capacity to anticipate degradation in their real counterparts. This predictive ability is attributed to the fact that a DT aggregates numerous data sources and technologies to create a snapshot of the state and behaviour of an operational system. A core function of living DT solutions purposes to assist in decision aiding, with the following advantages which enable CBM on a novel scale:

1. DT technology is an *aggregator* of data and tools with the ability to realize information sharing and convenient communication towards decision support. The ability to reflect a physical asset with a digital counterpart allows the components and users of a DT to be widely distributed, even during operation.
2. It is now possible *to observe, analyse, and understand real-world interactions and impacts on different objects at a very granular level.* Suitable applications involve those where the unpredictability of behaviour and complexity in interactions and /or change of states are relevant (Minerva et al., 2020).
3. DTs enable *automation* of manual and repetitive tasks. For example, manual maintenance inspections may be augmented through indicator data, obtained from a sensor array. This data may be automatically recorded, processed, and transmitted without a direct man hour requirement. The impact entails an increased capacity to conduct a higher volume of inspections, thereby increasing data volumes which in turn may lead to trending models and enhanced predictions.
4. DT enables stakeholders to be geographically removed from operational assets. This *digital visibility* unhinges benefits such as remote operation or inspection of assets that are traditionally inaccessible. Expertise may be remotely contracted with greater efficiency, lower cost as and a prompter time horizon an overview of the operational asset can be obtained without the express requirement of physical presence.
5. Given the correct data resolution / fidelity and sufficient calculation efficiency, gathered data may be *softwarized expertise*. Much the same as specialist software may place thousands of man hours' worth of programming at the fingertips of an analyst, advanced diagnostics may be deployed and enhanced throughout the life cycle of a DT as better tools / algorithms evolve. These tools may also be application specific, where, for instance, AI algorithms are trained in situ, using the data from a specific asset of fleet of assets to deliver tailored results.

Digital vigilance: Digital records are impartial, relentless and do not require rest or sleep. The quality of observations will not decrease because of boredom or decreasing attention span. These logs are useful in determining if assets were incorrectly operated or establishing the conditions or sequence of events at the time of failure. Tasks that dispose workers to boredom or unaccommodating hours could be transferred in full / or part to a digital watchman, for example round-the-clock environmental observations.

6 CONCLUSION

The increased entanglement of physical and digital assets through DT beckons future potential for maintenance management, particularly condition-based and predictive maintenance. Asset health management has been hampered by uncertainty in the material behaviour, operational conditions and loads that products face in deployment. DTs provide a highly granular means through which engineering knowledge and asset state can be combined to reduce these unknowns towards tailored decisions. Four DT service patterns were presented to illustrate how an asset can be mirrored digitally, exposed to anomaly detection, virtual sensing, and response pattern recognition through cyber-physical interactions. These services leverage benefits from DTs such as aggregation of diverse data, remote operation, automation, softwarized expertise and digital vigilance.

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