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# A Digital Failure Twin Model For PHM: From Concepts To Maturity Levels

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**Abstract**—In the context of industry 4.0, traditional reliability engineering has the opportunity to greatly benefit from the big data generated by Industrial Internet of Things (IIoT) and the advancement of industrial intelligence technologies. To make full use of the opportunities emerging in the era of industry 4.0, a Digital Failure Twin (DFT) is proposed as a dynamic virtual modeling framework that encompasses various dimensions such as model, data, connection, and computation. This framework is designed to simulate and forecast the failure behavior of complex real-world systems throughout their entire life cycle, enhancing Prognostics and Health Management (PHM) application, ultimately leading to improved reliability, safety, and operational efficiency. Five maturity levels of a DFT model are defined to support the development and implementation of DFT in practice. This evolution entails transitioning from static failure modeling based on historical data to dynamic predictive maintenance capabilities integrated with artificial intelligence. The potential application of the DFT framework on prognostics and health management is also discussed. Through the discussion, we show that introducing the DFT in prognostics and health management could improve operational and maintenance planning and reduce failure occurrence, as the framework could provide an accurate and up-to-date prediction of the evolution of the failure behavior.

**Keywords**—component; digital failure twin, conceptual model, maturity level, prognostics and health management

## I. INTRODUCTION

Prognostics and Health Management (PHM) is a promising technology that could enhance the reliability, safety, and efficiency of complex systems [1]. PHM predicts and diagnoses the health status of a system, anticipates its future condition, and makes informed decisions regarding maintenance activities. PHM's significance is evident in various industries such as aerospace, manufacturing, energy, and transportation due to its abilities to:

- enhance the reliability and safety of a system by predicting potential failures and preventing catastrophic events.
- predict conditions allowing for condition-based maintenance, which is more cost-effective and improves operational availability compared to traditional scheduled maintenance practices.
- improve operational efficiency by reducing downtime and preventing unexpected failures, thus facilitating more effective resource planning and optimization.

Traditional PHM methodologies can be generally categorized into two main approaches: data-driven [2] and model-based [3]:

- The data-driven approach relies on historical data to identify patterns and predict the remaining useful life of a system. It employs statistical analysis, probabilistic models, and AI algorithms to examine large operational and performance datasets, uncovering correlations and patterns that suggest potential failure modes. One major challenge of this approach is the need for extensive run-to-failure data to train the remaining useful life (RUL) prediction algorithms. However, obtaining such data can be difficult or impossible due to high costs, safety risks, or rare system failures. This limitation results in reduced accuracy and reliability of data-driven PHM failure predictions.
- The model-based approach relies on physical and mathematical models that describe a system's behavior under various operating conditions. Based on the principles of physics governing the system's operations, these models can simulate potential failures and predict remaining useful life. However, a significant drawback of this approach is that prediction models are static and typically developed offline, which may not accurately reflect the real-time operating conditions. Developing

such models requires deep technical expertise due to the complexity and resource-intensive nature of understanding a system's physics.

To address these limitations, a new approach is needed that amalgamates the advantages of both methods while tackling their drawbacks. A promising solution is to leverage the advanced simulation and model updating capability from digital twin technologies, and combined with the data-driven capabilities in traditional PHM methods.

A digital twin is a virtual copy of a physical entity that is utilized to enhance business outcomes through the understanding, prediction, and optimization of performance [4]. The term was first introduced by Grieves during his university class [5], and was later popularized by General Electric and NASA [6]. Extensive literature has explored this concept [7]. Digital twins offer advanced abilities in data collection, system simulation, and model updating, making them a promising method to overcome the constraints faced by data-driven and physics-based PHM approaches.

- For data-driven approaches, the challenge is to obtain sufficient run-to-failure data. Digital twins can assist in addressing this issue by simulating diverse failure scenarios and producing synthetic data that can be utilized for training predictive algorithms. As a result, the reliance on actual failure data is greatly reduced, enabling the creation of more resilient and dependable prediction models.
- The model-based approach faces challenges related to the static nature of models and their inability to reflect real-time system conditions. This drawback can be overcome by introducing digital twins, as they have the capability to integrate real-time data from sensors installed on the physical system. As a result, digital twins can continuously update the model to reflect the current status and operating conditions of the system. This feature enables digital twins to generate more accurate failure predictions that reflect the actual state of the system.

Digital twins are entities that are constantly learning from data and can update their predictive models using advanced machine learning and artificial intelligence techniques. This results in a better understanding and forecasting of system behavior, leading to more reliable failure predictions. This technology bridges the gap between data-driven and model-based approaches by utilizing the advantages of both methods, resulting in a more comprehensive, accurate, and dynamic prediction of system failures and RUL.

In order to effectively utilize digital twins for the purpose of supporting PHM, it is essential that a digital twin model should not only simulate normal behavior, but also failure behavior. To address this issue, a conceptual model known as the Digital Failure Twin (DFT) is developed and a discussion on its application opportunities on PHM is given in this paper. The DFT is a specialized form of digital twin that concentrates on simulating and predicting failure behaviors within a system by integrating potential failure modes, their causes, and effects into the digital twin model. It employs real-time data, advanced

simulations, and machine learning algorithms to anticipate failures, identify their root causes, and recommend preventive measures. By concentrating exclusively on failure behavior, the DFT can enhance the predictive capabilities of PHM and result in improved system reliability and safety.

The rest of this paper is organized as follows: Section II presents the definition, the conceptual model and four key elements of the DFT. Section III introduces the five maturity levels of a DFT model. Subsequently, the application of DFT to support Prognostics and Health Management (PHM) is explored in Section IV. Finally, the paper concludes with a discussion and future work in Section V.

## II. DIGITAL FAILURE TWIN: DEFINITION AND CONCEPTUALIZATION

Digital Failure Twin (DFT) is defined in this paper as a universal framework to accurately model and simulate the failure behavior of real-world asset, process, person or organization in the virtual space. The developed failure behavior model should be able to connect to the physical entity so that the model structure and prediction results can be updated dynamically to catch any changes due to functional or failure behavior of the physical entity. The developed DFT model can be used as a digital copy of the physical entity and support dynamic risk assessment, reliability analysis and PHM of the asset throughout its entire lifecycle.

A conceptual model for the DFT is presented in Fig. 1. As shown in Fig. 1, a DFT should cover the following four essential aspects, i.e., model, data, connection and computation.

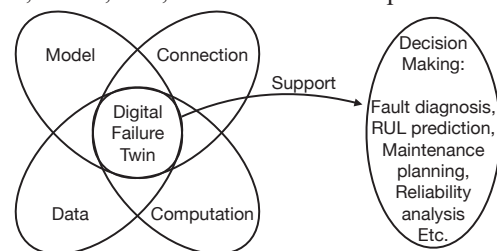


Figure 1. DFT conceptual model

### A. Model

The “model” in the DFT framework refers to a high-precision model to simulate the failure behavior, as well as the normal behavior of the physical entity. The DFT model for normal behavior is usually developed through implementing computer-aided design models, simulation software, and sensor information from the physical setup. The DFT model for failure behavior will be discussed in details in Sect. 3

### B. Data

The “data” pertains to the gathering, manipulation, and examination of both current and past data originating from the physical entity. Data may originate from a variety of sources, such as sensors, operational logs, and maintenance records. These data points are then processed using analytical tools to extract knowledge regarding the system's actions and potential malfunctioning patterns.

### C. Connection

The integration of the DFT with the physical system and the real-time exchange of data between them represents another crucial element of the DFT, i.e., the connection. As a result, the prediction of a DFT and/or the model structure of the DFT itself can be updated to accurately reflect the current state of the physical system, allowing for updates to its simulations and predictions as conditions change.

### D. Computation

The Digital Failure Twin (DFT) relies heavily on computation to accurately predict the normal and failure behavior of the physical entity. Its functions involve data processing, modeling and simulation, machine learning, and real-time analytics. Computing systems are responsible for managing and processing the large amounts of data that a DFT uses. The ability to analyze data in real-time and update the digital twin is one of the key capabilities of a DFT, which requires a high-performance computation system that can process incoming data swiftly, perform real-time analytics, and update the digital twin's status.

As can be seen from Fig. 1, DFT is a modeling and simulation framework that targets at failure behavior of the physical entity. A conventional digital twin model framework, as described in ISO 23247 [8] and supported by Asset Administration Shell [9], does not explicitly discuss how to describe failure behavior in a digital twin and how to develop such a digital twin model. Rather, the main objective is to model and simulate the normal operation behavior of the physical quantity. Therefore, compared to a conventional digital twin, the DFT framework

additionally analyze possible failure modes, their causal factors, and their impact on the system's functionality. Additionally, it develops tactics for averting and reducing the impact of failures.

### III. MATURITY LEVELS OF A DIGITAL FAILURE TWIN MODEL

Out of the four dimensions in a DFT framework, the “model” plays a central role and interacts with the other dimensions to fulfil the intended functions of DFT. To support the development and implementation of a digital failure twin model in industry, as shown in Fig. 2. The proposed five levels offer progressively more sophisticated capabilities and predictive accuracy. The required model capability in each level is defined from three aspects:

- How to model the failure behavior (Modeling)?
- How to use the digital failure twin model to simulate the failure behavior (Simulation)?
- How to update the model prediction and model structure (Updating)?

As the digital failure twin model moves from the lowest level (L0 - initial level) to the highest one (L4 - integrated level), the digital failure twin model will evolve from a static model purely based on historical data, to a fully connected model being able to simulate and update the performance and failure behavior with high precision dynamically. A detailed description of the five maturity levels can be found in TABLE I.

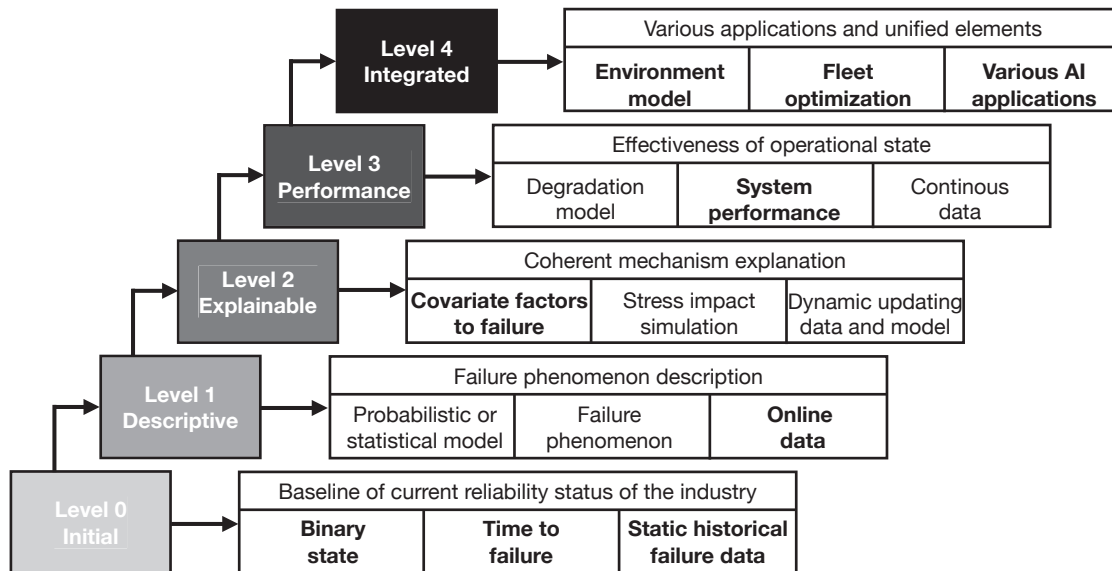


Figure 2. Maturity levels of a DFT model

TABLE I. DFT MATURITY LEVEL

| Level      | L0 - Initial   | L1 - Descriptive   | L2 - Explainable   | L3 - Performance  | L4 - Integrated   |
|------------|--|--|--|---|---|
| Modeling   | <ul style="list-style-type: none"> <li>- Failure behavior is characterized by a binary state variable (representing system state or time-to-failure)</li> <li>- Statistical models are used for failure behavior modeling based on historical data.</li> </ul> | <ul style="list-style-type: none"> <li>- As the previous level.</li> </ul>   | <ul style="list-style-type: none"> <li>- Modeling object: Time to failure/state</li> <li>- The model is explainable in terms of failure cause: Covariates are used to relate time to failure distribution to failure-inducing factors.</li> <li>- Model parameter is estimated based on observational data: TTF<sub>i</sub>, stress<sub>i</sub></li> </ul> | <ul style="list-style-type: none"> <li>- The performance of a normal functioning system is modeled first.</li> <li>- Then, failure mechanisms and their impact on the performance model is modeled.</li> <li>- Time-to-failure is calculated as the time instant when system performance no longer satisfies functional requirements..</li> <li>- Compare to L2: Need to consider explicitly the failure process, not just data-driven</li> </ul> | <ul style="list-style-type: none"> <li>- Failure behavior: The same as L3</li> <li>- Model of the environment: Production scheduling, temperature</li> <li>- From individual DFT to a fleet of DFTs.</li> </ul> |
| Simulation | <ul style="list-style-type: none"> <li>- System state or time to failure is simulated.</li> <li>- No detailed process that leads to a failure is considered in the modeling/simulation.</li> </ul>   | <ul style="list-style-type: none"> <li>- As the previous level.</li> </ul>   | <ul style="list-style-type: none"> <li>- Able to simulate how stress (covariate) impact the TTF</li> </ul>   | <ul style="list-style-type: none"> <li>- System performance and its variation over time is simulated.</li> <li>- Time-to-failure distribution is calculated based on system performance.</li> </ul>   | <ul style="list-style-type: none"> <li>- Additional information about usage/environment (production planning, etc)</li> </ul>   |
| Updating   | <ul style="list-style-type: none"> <li>- Model parameters estimated offline from historical failure data and are not updated during operation.</li> </ul>  | <ul style="list-style-type: none"> <li>- Online data on failure events and failure times collected periodically</li> <li>- Model structure and parameter updated dynamically using Bayesian updating.</li> </ul> | <ul style="list-style-type: none"> <li>- Dynamic updating, based on TTF and covariance data</li> </ul>   | <ul style="list-style-type: none"> <li>- Continuous updating, based on condition-monitoring data on performance.</li> </ul>   | <ul style="list-style-type: none"> <li>- Environment model can be updated</li> <li>- More power application based on the integrated model</li> </ul>  |

### A. Level 0: Initial

The initial level (L0) is the entry level of the maturity hierarchy of a DFT. It represents the current practice of traditional reliability and failure behavior modeling without introducing digital twin technologies. In this level, the failure behavior is modeled by a binary state variable (time-static case) or a continuous random variable representing time to failure (time-dependent case [10]). Probabilistic and statistical models are developed to describe the failure behavior and the model parameters are directly estimated from historical failure data (failure event data in the time-static case and failure time data in the time-dependent case [11]). Once the model is developed, it can be used to simulate the system state or time to failure directly, without considering the detailed process that leads to a failure. In this level, the model is not connected to the physical entity and, therefore, is offline and static, and not updated over time.

### B. Level 1: Descriptive

L1 is called descriptive level, as in this level, the failure behavior is modeled in the same way as L0: a probabilistic or statistical model is developed for system state or time to failure directly, and the model parameters are calibrated based on historical data. This is a pure description of what happened in the past without considering the actual cause and process leading to failure. In terms of simulation capabilities, a L1 digital failure twin is as the L0 one as well, where the system state variable or

time to failure is simulated directly, without involving the simulation of actual failure causes and processes. Compared to L0, a L1 model mainly improves in terms of its updating capability. At the L1 level, online data on failure events and failure times have to be collected periodically, and the model structure and prediction need to be updated dynamically based on these online data. The primary tool employed here is Bayesian updating [12]. This technique allows for the dynamically updating the probability of a hypothesis as new evidence comes in during the operation of a system or a fleet of systems. Therefore, the model can provide an up-to-date estimation of the failure behavior, although the description of the failure behavior is still crude based on descriptive models.

### C. Level 2: Explainable

Advancing to the L2 explainable level, the main difference in terms of failure behavior description is that, the model no longer limits itself to the description of the failure behavior in terms of system state variable or time-to-failure. Rather, a statistical model is developed to relate the system state variable or time-to-failure to some interdependent variables, so called covariates representing potential contributing factors to failures (modeled as covariates), e.g., stress, temperature, voltage. A covariate model is often used to describe the statistical relation between lifetime and its influencing factors [13]. When used to simulate the failure behavior, a digital twin model can be used first to simulate the current value of the influencing factors (e.g., stresses) based on the operational conditions [14]. These

influencing factors are then injected to the failure behavior model to further simulate the failure behavior in terms of failure time/failure probability. This model leverages real-time updating observational data and dynamic stress (covariate) simulation to understand and predict the time to failure for physical entities, taking into account a variety of contributing factors.

#### D. Level 3: Performance

Proceeding to the L3, the performance level, the failure behavior can be described in a more detailed way. The model identifies and simulates the normal performance of the system. Then, the main degradation and failure mechanisms are modeled and simulated. By investigating the impact of the failure and degradation processes on the performance, the time to failure can be accurately predicted. When applied to simulate the failure behavior, the DFT model in this level can simulate both the normal performance and the failure/degradation processes. In such a way, the evolution of the system performance over time can be simulated. The dynamic updating data handled by the model at this juncture is typically continuous, predicated upon condition-monitoring data on performance, which more accurately embodies and forecasts system behavior and performance over time.

#### E. Level 4: Integrated

Culminating at the L4 integrated level, the DFT leverages advanced machine learning algorithms to make proactive failure predictions and the focus shifts to the application perspective, with the intent to elucidate physical functionality, failure behavior simulation, and dynamically forecast the time to failure with a view towards facilitating technical value creation. At this stage, the model frequently integrates artificial intelligence algorithms for predictions, problem-solving, and strategy alignment. It synchronizes operations and decisions with the conditions of the dynamically updated environment model, such as temperature, thereby offering a comprehensive approach towards reliability analysis, fault diagnosis, dynamic risk assessment, remaining useful life prediction, maintenance planning, production scheduling, and enhancement of system performance. Also, in this level, the DFT is not just on a single asset, but includes a fleet of assets and the operational profiles and environment for each individual in the fleet.

Advancing through the maturity levels amplifies the predictive precision, flexibility, and general efficiency of the DFT. At elevated levels of maturity, the DFT can furnish more prompt and precise prognostications of failures, enabling more efficacious preventative procedures and diminishing the likelihood of unforeseen system breakdowns.

The various levels of maturity in DFT provide increasing insights into failure behavior and enable more precise simulations. In its initial stages, DFT is capable of offering fundamental insights and failure forecasts based on historical system performance. However, as it advances, DFT can provide real-time insights, predict future failures using real-time data and even enhance its predictive accuracy and organizational value by learning and improving autonomously.

## IV. APPLICATION OF DFT TO SUPPORT PHM

Generally speaking, there are at least two main tasks in PHM: The first is to accurately predict the remaining useful life while the second is to plan preventive maintenance activities based on the predicted RUL. As the DFT evolves from level 0 to level 4, the support it can provide to PHM evolves as well. A level-0 DFT does not have the capacity to update the model parameters/behavior. Rather, the failure behavior is mainly characterized based on historical time-to-failure/failure event data. In this level, the DFT cannot be used to support remaining useful life prediction. Maintenance planning can still be made based on the historical data. For example, if one can estimate the lifetime distribution of an item from historical data, the optimal maintenance time can be determined by minimizing the expected cost rate.

Compared to level-0, a DFT model in level-1 obtains the capability to update the failure behavior model (in terms of lifetime distribution or failure probabilities) based on observational data collected during operation. The observational data used to update a level-1 DFT model are mainly failure time/event data from similar products. Remaining useful life prediction can also be made using the same observational data in a Bayesian framework. Unlike traditional RUL prediction methods based on condition-monitoring data, here, the RUL prediction is made based on the failure data from similar products. The RUL is updated because we have new information on the lifetime of the population. Once the RUL prediction is done, the maintenance planning can be done in the same way as in level-0.

A level-2 DFT model encodes physical knowledge on the failure contributing stresses as covariates in a statistical model to predict time-to-failure. During operation of the system, these contributing stresses can be monitored. Then, the condition-monitoring data can be used to update the estimation of the remaining useful life. Compared to the prediction in level-1, which is still a prediction for the whole population, the RUL predicted in level-2 has moved from a population-wide prediction to an individual-level prediction, as the item-specific failure-inducing covariates are monitored and used for RUL prediction. The predicted RUL can, then, be used to support maintenance planning.

In level-3, the DFT simulates not only the evolution of failure process, but also the normal functioning principle of the item. Both the performance and failure-inducing stresses of the item are monitored. RUL prediction is made by first updating the parameters in the failure model, and then integrate the failure model in the performance simulation model to determine the degradation of system-level performance. Then, the RUL is calculated by checking the moment when the system-level performance cannot satisfy its functional requirement. The performance of the item can also be used to support fault detection and diagnosis.

In level-4, the DFT not only simulates a single product, but a fleet of products and their operating environment. On this level, the DFT can support PHM on a single component level, but, more importantly, on a fleet level. RUL prediction is made for each individual in the fleet. Then, a fleet-level maintenance

planning is conducted, considering the health state of each item, and also the fleet-level operational constraints like availability of service, maintenance slot, economic dependency arising from grouping of maintenance activities, etc.

## V. CONCLUSIONS AND FUTURE WORKS

This paper presents the Digital Failure Twin (DFT) as an advanced modeling framework for failure behavior. Following the DFT framework, the decision-maker could benefit from a digital copy of a physical system that can simulate and forecast system failures. The DFT incorporates four essential components, namely model, data, connection and computation. As the DFT evolves over time, it can provide more advanced capabilities and predictive accuracy that can benefit the organization. The widespread implementation of DFTs in various industries could benefit a number of decision-making problems, e.g., efficient operation planning, maintenance planning, fault diagnosis, RUL prediction and prediction maintenance. In particular, we discussed in details how could a DFT model in different maturity level help the RUL prediction problem.

Future studies may investigate methods to overcome these challenges and boost the efficiency of DFTs. Case studies serve as tangible instances for the application of the Digital Failure Twin (DFT) concept across diverse industries. One of the future work is to apply this model on use cases. Possible ones are:

### A. Case Study 1: Adoption of DFT in the Energy Sector:

The employment of DFT models in energy system can reduce the probability of unanticipated failures and the ensuing interruptions by simulating system operations under various scenarios utilizing dynamic optimization in the frequency domain and periodic analysis. A use case of energy system incorporates components including energy management system, solar panel, train brake generator, battery, communication system, among others. As DFT models mature, their failure prediction accuracy improves, leading to more optimized plant operations and a reduced risk of power outages.

### B. Case Study 2: Usage of DFT in Manufacturing Sector:

In the manufacturing industry, the DFT framework can be employed to mitigate the impact of unexpected assembly line failures, which can lead to significant production delays and cost escalations. Using past data on assembly line performance, DFT models can simulate operations, identify patterns, and predict potential failures. A case study of open-source mini-production system with two first-person camera robot arms and one conveyor belt is installed to realize functions such as interconnected system component close collaboration for intelligent palletization, quality inspection. The system undergoes in-depth parametric and digitization conversions to facilitate multi-scale, multi-domain, multi-source model/data fusion and online system performance monitoring, health state estimation, and reliability optimization with various sensors. Through this proactive approach, DFT enables timely preventive measures, reducing the impact of failures on production timelines and costs.

### C. Case Study 3: Application of DFT in Aerospace Industry:

The aerospace sector's intricate systems, if failed, can have devastating consequences. To mitigate this, a DFT can predict engine malfunctions by simulating operations under various scenarios and identifying potential failure points. By using a run-to-failure dataset with time-series data from four distinct sets and each containing simulated information for 100 aircraft engines [15], the DFT integrates real-time data from engine sensors, enhancing its predictive accuracy, enabling preventive maintenance, and significantly reducing the risk of catastrophic engine breakdowns.

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