



Digital Twin Applications for Predictive Maintenance of Industrial Machinery

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Received: 16 October 2025; **Accepted:** 30 December 2025; **Published:** 26 March 2026

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Abstract

Predictive maintenance depends on how faithfully a monitoring system tracks an individual machine's actual condition, and the digital twin -- a continuously updated virtual counterpart synchronized with a physical asset's live operating data -- has become the architecture most credited with improving that fidelity. This short communication synthesizes the literature on digital twin applications for predictive maintenance of industrial machinery, tracing the concept from its origins in product lifecycle management and aerospace structural health monitoring through Kritzinger et al.'s influential digital model/digital shadow/digital twin taxonomy, to applied frameworks for rotating-machinery fault diagnosis and remaining-useful-life estimation. Particular attention is given to two complementary strategies for the historical-failure-data scarcity that maintenance-focused machine learning routinely faces: generating synthetic fault data from a high-fidelity simulation to pre-train a diagnostic model, and modeling only healthy operating behavior so that deviation from it becomes the diagnostic signal. Applied case studies extend these architectures to specific, named industrial equipment, while the review literature is candid that the field has not converged on a shared implementation methodology and that many systems described as digital twins meet only the weaker, one-way-data-flow bar of a digital shadow. Read together, the literature supports digital twins as a genuinely productive predictive-maintenance architecture, particularly where failure data is scarce, while leaving implementation standardization and closed-loop automation as open problems.

Keywords: digital twin; predictive maintenance; fault diagnosis; industrial machinery; remaining useful life

1. Introduction

Industrial machinery fails on its own schedule, not on the schedule maintenance departments would prefer, and the two classic responses to that fact — run equipment to failure and repair it reactively, or service it on a fixed calendar regardless of its actual condition — both leave money and uptime on the table. Reactive maintenance concedes unplanned downtime and, often, collateral damage to adjacent components; calendar-based preventive maintenance wastes serviceable parts and still misses failures that develop faster than the schedule anticipates. Predictive maintenance (PdM) was conceived to split the difference: monitor a machine's actual condition and intervene only when the data say intervention is warranted [1]. What has changed over the past decade is not the goal of PdM but the fidelity of the model standing behind the prediction, and the digital twin — a live, continuously updated virtual counterpart of a physical asset — is the mechanism most recently credited with that improvement in fidelity [2].

The digital twin concept did not originate in maintenance engineering. Grieves and Vickers trace it to product lifecycle management, where the idea was to maintain a virtual model that mirrors a physical product closely enough to anticipate undesirable emergent behavior before it manifests physically [3]. NASA and the U.S. Air Force adopted the term for aerospace structural health monitoring, with Tuegel et al. proposing an "ultrahigh fidelity" per-tail-number aircraft model that integrates flight-condition data to predict structural life on an individual-airframe basis rather than a fleet-average basis [4]. Lee, Bagheri, and Kao's 5C cyber-physical systems architecture, developed independently around the same period, gave the underlying data pipeline — connection, conversion, cyber, cognition, configuration — a form that later digital twin implementations for manufacturing still largely follow [5].

What distinguishes a digital twin from an ordinary simulation model is the data loop: a digital twin ingests live operational data from its physical counterpart and, in the strongest formulations of the concept, feeds decisions back to that counterpart automatically, closing a bidirectional loop rather than serving as a one-off offline model [6]. Kritzinger, Karner, Traar, Henjes, and Sihn's frequently cited taxonomy makes this distinction

explicit, separating a "digital model" (no automated data exchange in either direction), a "digital shadow" (automated one-way flow from the physical asset to its virtual counterpart), and a "digital twin" proper (automated two-way flow, with the virtual model's outputs able to act back on the physical asset) [6]. That taxonomy matters for predictive maintenance specifically, because a system that only ingests sensor data without an automated path back to a maintenance decision is, by this definition, a digital shadow rather than a full digital twin, even if it is doing genuinely useful condition monitoring.

This short communication synthesizes the literature on applying digital twins to predictive maintenance of industrial machinery, concentrating on how the concept has been operationalized for fault diagnosis and remaining-useful-life estimation, what applied case studies and frameworks in this space have actually reported, and where the implementation literature identifies persistent gaps between the digital twin as an architectural ideal and as a deployed system.

2. Foundations and Definitions of the Digital Twin Concept

Tao, Zhang, Liu, and Nee's state-of-the-art review frames the digital twin as resting on three pillars that any maintenance-oriented implementation has to address: a physical entity, a virtual entity that models it, and a connection that keeps the two synchronized with live data [2]. Qi and Tao's companion comparison of digital twin and big data approaches to smart manufacturing is useful precisely because it clarifies what the digital twin adds on top of conventional data analytics: rather than treating operational data as an input to a general-purpose statistical model, a digital twin routes that data through a physics-grounded or physically informed model of the specific asset, which in principle gives it explanatory and predictive power a purely data-driven model lacks when operating conditions drift outside the range of historical training data [7].

Lu, Liu, Wang, Huang, and Xu's reference model for digital-twin-driven smart manufacturing situates predictive maintenance as one of several downstream applications a shared digital twin infrastructure can support, alongside process optimization and production scheduling, which is a useful corrective against treating maintenance-specific digital twins as an isolated technology rather than one application of a broader

manufacturing digital twin investment [8]. Jones, Snider, Nassehi, Yon, and Hicks's systematic review of how the digital twin concept has actually been characterized across the literature makes a related point from the definitional side: despite the proliferation of digital twin papers since roughly 2017, the field has not converged on a single agreed definition, and maintenance-focused digital twin papers in particular tend to adopt whichever subset of the general digital twin characteristics (fidelity, real-time synchronization, bidirectionality) best supports the specific diagnostic or prognostic claim being made [9]. Liu, Fang, Dong, and Xu's review of digital twin concepts, enabling technologies, and industrial applications similarly finds maintenance and health management to be among the most consistently reported application areas across the surveyed literature, alongside production planning and product design [10].

3. Digital Twin Architectures for Fault Diagnosis and Prognostics

Moving from definition to mechanism, the maintenance-specific digital twin literature splits fairly cleanly into two complementary tasks: fault diagnosis (identifying that a fault exists and what kind it is) and prognostics (estimating how much useful life remains before that fault becomes a failure). Wang, Ye, Gao, Li, and Zhang's digital twin framework for rotating machinery fault diagnosis pairs a physics-based model of the machine with data-driven refinement, using the digital twin to keep the diagnostic model synchronized with the physical asset's actual, evolving condition rather than relying on a static model trained once and never updated [11]. Because rotating machinery — motors, pumps, gearboxes, turbines — accounts for a large share of the rotating-equipment fleet in most industrial plants, this class of digital twin has attracted a disproportionate share of the applied literature relative to other machinery types.

A second, complementary line of work addresses the specific problem that historical failure data for a given asset is often scarce, since well-maintained industrial equipment is, definitionally, not supposed to fail very often. Xia, Shao, Williams, Lu, Shu, and de Silva's digital-twin-assisted deep transfer learning framework addresses this scarcity directly: a high-fidelity simulation model of the machine generates synthetic fault-condition data that a deep network is pre-trained

on, after which the pre-trained network is fine-tuned using only a small number of real measured samples from the actual asset, an approach the authors validate on triplex pump fault diagnosis and report as achieving effective one-shot adaptation with a single real target-domain sample, outperforming comparison data-driven methods that lack access to digital-twin-generated pre-training data [12]. Booyse, Wilke, and Heyns's Deep Digital Twin framework takes a related but distinct approach to the same scarcity problem: rather than simulating fault conditions to substitute for missing failure data, it trains a deep generative model exclusively on an asset's healthy operating data early in its life cycle, then flags deviations from the learned healthy-data distribution as evidence of incipient faults, explicitly avoiding any dependence on historical failure examples and demonstrating the ability to detect emerging faults and distinguish between failure modes across both steady and non-stationary operating conditions [13]. Both frameworks are, in effect, working around the same structural problem — maintenance-relevant failure data is inherently rare — from opposite directions: one manufactures synthetic failure data via simulation, the other sidesteps the need for failure data altogether by modeling normality instead.

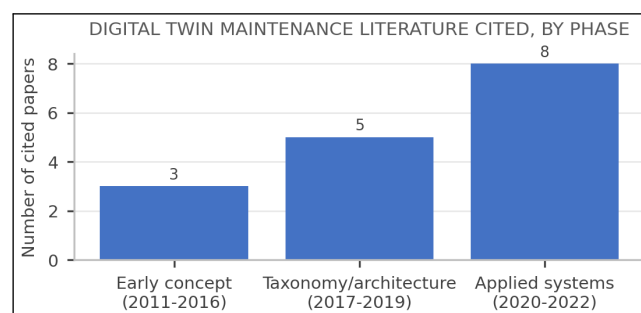


Figure 1: Publication timeline of the digital-twin-for-maintenance literature synthesized in this short communication, grouped into three phases -- early conceptual proposals, taxonomy and architecture formalization, and applied fault-diagnosis/prognostics systems -- by the number of cited papers falling in each phase [3,4,5,6,7,2,14,11,8,9,16,1,13,12,10,15].

4. Digital Twin-Driven Predictive Maintenance in Practice

Aivaliotis, Georgoulas, and Chrysosolouris's work on applying digital twins specifically to predictive maintenance in manufacturing formalizes the estimation of remaining useful time using a simulation-based digital twin of the physical asset, updating the model's degradation state from real

operational data so that the maintenance decision — when to intervene — is driven by the asset's actual, individually tracked condition rather than a population-average failure curve [14]. This is architecturally the clearest expression of the maintenance-specific digital twin idea: the virtual model does not merely diagnose a current fault but continuously projects the asset's condition trajectory forward to estimate when a maintenance threshold will be crossed.

Table 1: Applied digital twin frameworks and reviews for machinery fault diagnosis and predictive maintenance, and the specific maintenance-relevant contribution each cited source reports. [11,12,13,14,15,16].

Source	Machinery/Domain Focus	Reported Contribution
Wang et al. [11]	Rotating machinery (motors, pumps, gearboxes)	Couples a physics-based machine model with data-driven refinement so the fault-diagnosis model stays synchronized with the asset's evolving real condition
Xia et al. [12]	Triplex pump fault diagnosis	Digital-twin-generated synthetic fault data pre-trains a deep network, enabling effective one-shot fine-tuning on a single real measured sample
Booyse et al. [13]	General rotating and stationary assets	Deep generative model trained only on healthy operating data; flags deviation from learned normal behavior as incipient-fault evidence, with no historical failure data required
Aivaliotis et al. [14]	Manufacturing equipment, general	Simulation-based digital twin continuously updates an asset's degradation state from operational data to estimate remaining useful time
Yang et al. [15]	Industrial case-study equipment	Applied, named-equipment case study building a predictive maintenance model from a digital twin, representative of the shift toward deployment-grounded demonstrations
Errandonea et al. [16]	Cross-sector literature review	Finds maintenance among the most actively researched digital twin application areas, but reports no widely shared implementation methodology across studies

More recent applied work has continued to push toward deployment-grounded case studies rather than purely architectural proposals. Yang, Bao, and Zheng's digital twin approach to building a predictive maintenance model, presented with an accompanying industrial case

study, is representative of a broader shift in the applied literature away from describing digital twin architectures in the abstract and toward demonstrating them against a specific, named piece of equipment with a specific maintenance decision at stake [15]. Errandonea, Beltrán, and Arrizabalaga's literature review of digital twin applications for maintenance situates this shift in context, finding maintenance to be one of the most actively researched digital twin application areas precisely because the cost of a maintenance-driven production shutdown, particularly in sectors like energy and manufacturing, creates a direct financial incentive that other digital twin application areas do not always share to the same degree [16]. Zonta, da Costa, da Rosa Righi, de Lima, da Trindade, and Li's broader systematic review of predictive maintenance in Industry 4.0 situates the digital-twin-based approaches within a wider taxonomy of PdM methods, and is candid that predictive maintenance research remains a genuinely multidisciplinary undertaking spanning mechanical and reliability engineering on one side and machine learning and distributed computing on the other, a combination that not every research group, or every plant maintenance department, is equipped to field simultaneously [1].

Figure 1 places the literature synthesized in this short communication on a timeline, grouped into three loose phases: early conceptual work establishing the digital twin idea itself, a middle phase formalizing taxonomies and manufacturing-specific architectures, and a recent phase of applied fault-diagnosis and prognostics systems targeting specific machinery. The clustering is consistent with a field that spent roughly its first decade establishing what a digital twin is before spending its second producing systems that do something with the definition. Table 1 summarizes the specific maintenance-relevant contribution of the applied and framework-level papers reviewed above.

5. Implementation Challenges

None of the frameworks summarized above are free to build or run, and the applied literature is reasonably candid about what stands between the architecture and a working plant deployment. A digital twin capable of supporting fault diagnosis or remaining-useful-life estimation needs, at minimum, a sufficiently accurate physical or physics-informed model of the specific asset, a sensing and data infrastructure that keeps that model

synchronized with the real machine at a useful update rate, and — for the deep-learning-augmented frameworks in particular — either a simulation environment realistic enough to generate useful synthetic training data or enough measured operating data to characterize normal behavior before a fault appears [12,13]. Errandonea et al. note that despite the volume of maintenance-focused digital twin publications, the field still lacks a widely shared implementation methodology, with different groups building comparable systems from largely incompatible assumptions about what data is available and what fidelity of physical model is achievable for a given asset class [16].

There is also a definitional honesty problem the field has only partly resolved. Because Kritzinger et al.'s taxonomy sets a fairly demanding bar — automated, bidirectional data flow — a meaningful share of systems described in the applied literature as "digital twins" for maintenance are, by that taxonomy's own criteria, digital shadows: they ingest live sensor data and produce a diagnosis or a prognosis, but the resulting maintenance action is still routed through a human decision-maker rather than closing the loop automatically [6]. That is not necessarily a shortcoming, since automated intervention on safety-critical machinery is a higher-stakes proposition than automated diagnosis, but "digital twin" as used across this literature covers a wider range of actual system autonomy than the term's strictest definition implies.

6. Conclusion

The literature reviewed here supports a fairly bounded claim: digital twins, understood as continuously updated virtual models synchronized with a physical machine's live operating data, are a genuinely productive architecture for predictive maintenance of industrial machinery, particularly for fault diagnosis and remaining-useful-life estimation on rotating equipment where historical failure data is naturally scarce [11,12,13]. The strongest applied contributions work around that scarcity either by generating synthetic fault data from a simulation-grade model or by modeling healthy operation closely enough that deviation from it becomes the diagnostic signal, and both strategies are grounded in real deployed frameworks rather than purely conceptual proposals [12,13,14]. At the same time, the field has not fully closed the gap between the

digital twin as Kritzinger et al.'s taxonomy defines it and the digital-shadow-like systems a considerable share of the applied literature actually describes [6], nor converged on a shared implementation methodology a plant maintenance team could choose among competing frameworks with [16,9]. Those gaps are worth stating plainly, because the case for digital-twin-driven predictive maintenance is, on the evidence reviewed here, a genuinely strong one that does not need inflation to remain convincing.

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8. Declarations

Funding

This literature synthesis received no specific grant or funding from agencies in the public, commercial, or not-for-profit sectors.

Conflict of Interest

The authors declare that they have no competing interests relevant to this work.

Data Availability Statement

No new data were generated or analyzed for this short communication, which is a literature synthesis. All figures and comparisons are drawn from the cited published sources, and readers should consult the original studies for their underlying datasets and code.

Ethical Approval

Not applicable. This article synthesizes previously published literature and did not involve human participants, animal subjects, or the collection of primary experimental data by the authors.

Citation: Krawczyk A, Kozłowski M, Wojcik J. "Digital Twin Applications for Predictive Maintenance of Industrial Machinery." *J Eng Sci Future Technol* (2026): 001-006 doi: [10.5281/zenodo.22849429](https://doi.org/10.5281/zenodo.22849429)