Digital Twin of a Rotating Shaft for Predictive Maintenance Using Matlab Simulink and Simscape

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Introduction

In modern manufacturing, the predictive maintenance of rotating machinery has become increasingly important due to the rising costs of downtime and mechanical failures. One of the emerging technologies to address this challenge is the Digital Twin, which is a virtual representation of a physical asset, updated in real-time through sensor data. Digital twins allow engineers to simulate, predict, and optimize machine performance, enabling proactive maintenance and reducing unexpected failures.

This report presents a bibliography of relevant sources for the Digital Twin project of a rotating shaft. The sources include books, research papers, online resources, and industry standards. Each source is summarized and evaluated for relevance, key findings, and contribution to the project. The purpose of this annotated bibliography is as follows.

1. provide a comprehensive overview of previous research and knowledge on digital twins, rotating shafts, and predictive maintenance.
2. Identify best practices, methodologies, and tools applicable to the project.
3. Demonstrate the depth of research that supports the implementation of the project.

Annotated Bibliography

1 Raja Singh, R., et al. (2023)

Title: *Building a Digital Twin Powered Intelligent Predictive Maintenance System for Industrial AC Machines*
Journal: Machines, 11(2), 212. MDPI Journal

Summary

Raja Singh and colleagues (2023) proposed a comprehensive digital twin (DT) framework for predictive maintenance of industrial AC machines. The paper introduces a hybrid approach that combines:

- A physics-based digital twin model of the machine,
- Sensor data acquisition from the real physical system, and
- Artificial intelligence algorithms for fault detection and Remaining Useful Life (RUL) prediction.

The study demonstrates that integrating digital twins with machine learning can significantly reduce unplanned downtime, improve maintenance scheduling, and optimize operational efficiency. The authors modelled the AC machine's critical components, collected real-time operational data, and trained a deep learning model (LSTM) to predict degradation trends. Their results showed high fault detection accuracy and timely RUL estimation compared to traditional preventive maintenance techniques.

Key Concepts

Relevance to This Project

This study forms the core foundation of our project. Raja Singh et al. proposed a digital twin-powered predictive maintenance system integrating physics-based modelling and AI analytics to monitor AC machines. Their approach bridges the gap between real-time simulation and machine learning for RUL estimation — a concept central to our work.

Our project extends their methodology by focusing on a specific subsystem — the rotating shaft. While the original paper analysed entire electrical machines, our digital twin zooms in on shaft-level behaviour, modelled using MATLAB Simulink and Simscape.

We chose this paper because:

- It establishes a complete predictive maintenance framework combining simulation and AI.
- It validates the digital twin concept through experimental testing.
- It supports our goal of integrating fault simulation, signal analysis (FFT/RMS), and predictive modelling (LSTM).
- It demonstrates industrial relevance and feasibility.

Thus, our project builds upon their concept by extending it to component-level fault analysis, enabling targeted predictive maintenance for shafts, bearings, and drivetrain systems.

Concept	Explanation
Digital Twin Integration	The study defines the DT as a real-time, bidirectional digital replica of the physical AC machine. It continuously synchronizes simulated and real sensor data to reflect true system behaviour.
Hybrid Modeling (Physics + AI)	Combines simulation-based models with AI-driven analytics. The physics model provides interpretability, while AI improves prediction accuracy.
Predictive Maintenance Workflow	Establishes a complete workflow — from model creation, data collection, fault diagnosis, and prediction of RUL — forming a blueprint for modern intelligent maintenance systems.
Data Fusion for Fault Detection	Uses both simulated and real sensor data to train predictive models, overcoming the scarcity of labelled failure data.
Industrial Validation	Applies the system on industrial AC machines to demonstrate real-world applicability, proving that DTs can make predictive maintenance more reliable and cost-efficient.

2 Han, T., et al. (2022)

Title: *Overview of Predictive Maintenance Based on Digital Twin Technology*
Journal: Mechanical Systems and Signal Processing, 165, 108377.

Summary

Han et al. review the evolution of digital twin-based predictive maintenance systems, focusing on structure, data flow, and implementation challenges. They categorize digital twins into:

- Data-driven,
- Physics-based, and
- Hybrid approaches.

The paper highlights the importance of virtual testing and simulation for fault modelling, as physical experiments are costly and time-consuming.

Key Concepts

Concept	Explanation
Hybrid Digital Twin	Integrates simulation and AI for accurate prediction and system adaptability.
Virtual Fault Modeling	Uses simulated data to mimic real-world degradation for algorithm training.
Data Synchronization	Real-time communication between digital and physical twins.
Challenges in DT Design	Includes computational cost, data integration, and model fidelity.

Relevance to This Project

Han et al. provide one of the most extensive reviews of digital twin (DT) technology applied to predictive maintenance. They categorize DT implementations into three levels — physics-based, data-driven, and hybrid — and discuss how each can be used for condition monitoring and prognosis.

This paper helped shape our project's architecture by guiding us to adopt a hybrid digital twin approach:

- Physics-based modelling through MATLAB Simscape for realistic simulation of shaft dynamics and fault conditions.
- Data-driven analysis using FFT, RMS, and later LSTM for data interpretation and predictive modelling.

Han et al. also emphasizes that one of the current challenges in DT-based maintenance is the lack of virtual data for fault scenarios, as physical experiments are expensive and time-consuming. Our project directly addresses this gap by generating synthetic run-to-failure data through Simulink simulations, allowing the creation of fault-rich datasets for training predictive models.

Their review also reinforced the importance of interoperability between simulation tools and AI frameworks, which guided our decision to use MATLAB — since it allows seamless integration between Simscape models and deep learning toolboxes.

In short, Han et al. (2022) provided the strategic direction and research justification for developing a hybrid, simulation-based predictive maintenance system — forming the theoretical backbone of our implementation.

3 Qi, Q., Tao, F. (2018)

Title: *"Digital Twin and Big Data Toward Smart Manufacturing and Industry 4.0: 360 Degree Comparison."*
DOI: 10.1109/ACCESS.2018.2793265

Summary

Qi and Tao introduced the conceptual framework of digital twins in the context of Industry 4.0 and smart manufacturing. They compared digital twin technology to big data systems and showed how DTs provide real-time predictive intelligence through physics-based models synchronized with operational data. The paper emphasized the role of DTs in creating cyber-physical systems capable of autonomous decision-making and continuous optimization.

Key Concepts

Concept	**Explanation**
Digital Twin Ecosystem	Integrates simulation and AI for accurate prediction and system adaptability.
Industry 4.0 Alignment	DTs as key enablers for smart, data-driven manufacturing.
Cyber-Physical Systems	Real–virtual integration for real-time control and optimization.
Predictive Analytics	DTs use real-time data to predict performance and maintenance needs.

Relevance to This Project

Qi Tao's work is a cornerstone publication in Industry 4.0 research. It defines the digital twin as a bi-directional connection between a physical system and its virtual counterpart, enabling real-time synchronization, predictive intelligence, and adaptive decision-making.

This paper gave our project its strategic motivation — showing that digital twins are not just models, but active components of smart manufacturing ecosystems. It helped us frame our project as part of the industry 4.0 paradigm, where digital twins serve as the foundation for autonomous predictive maintenance.

The authors also compared digital twin architecture vs. big data systems, concluding that a DT provides more interpretability and precision for physical systems because it integrates real physics models (like our Simulink shaft model) with analytics. This justified our decision to use a Simulink-based twin instead of purely data-driven approaches.

In summary, Qi Tao (2018) guided the conceptual positioning of our project — linking it to the larger vision of smart manufacturing and cyber-physical systems.

4 Tiboni, M., Zappa, E., Gobbi, M. (2022).

Title: *"A Review on Vibration-Based Condition Monitoring of Rotating Machinery.."Applied Sciences, 12(3), 972.*
DOI: https://doi.org/10.3390/app12030972

Summary

Tiboni et al. (2022) present a comprehensive review of vibration-based condition monitoring (VBCM) techniques used in rotating machinery such as motors, turbines, and shafts. The paper highlights that vibration is one of the most sensitive indicators of machine health, as most mechanical faults manifest first as changes in vibration patterns. The authors examine the complete workflow of vibration-based diagnostics, starting from sensor selection and signal acquisition, to feature extraction, and finally to fault classification using traditional and machine learning (ML) methods. They categorize faults such as unbalance, misalignment, bearing defects, looseness, and shaft cracks, describing how each produces distinct vibration signatures in both the time and frequency domains. The review also discusses the transition from classical analysis (FFT, RMS, envelope analysis) to modern approaches that combine AI algorithms (like SVM, CNN, and LSTM) with vibration data for automatic fault diagnosis.

Key Concepts

Concept	Explanation
Vibration-Based Condition Monitoring (VBCM)	A diagnostic method where vibration data is continuously recorded to detect mechanical anomalies early.
Fault Signature Identification	Each mechanical fault (e.g., unbalance, misalignment, crack) produces unique frequency-domain patterns identifiable through spectral analysis.
Feature Extraction Techniques	Use of RMS, FFT, kurtosis, crest factor, and wavelet transform to extract numerical indicators of machine health.
Predictive Analytics	Integration of supervised and deep learning models (e.g., ANN, CNN, LSTM) to automate the detection and classification of vibration anomalies.
Condition-Based Maintenance (CBM)	Transition from scheduled maintenance to predictive maintenance by using real-time vibration monitoring.

Relevance to This Project

This paper directly supports the fault detection and analysis component of our Digital Twin of a Rotating Shaft Project.

It validates that vibration analysis is the most reliable signal source for identifying early-stage mechanical faults in rotating shafts.

Tiboni et al. (2022) provided the theoretical foundation for our signal processing methods:

- RMS (Root Mean Square) – quantifies overall vibration energy, used as a health indicator.
- FFT (Fast Fourier Transform) – transforms vibration signals into frequency spectra to locate fault-related harmonics.

Their classification of faults (unbalance, misalignment, bearing wear, looseness) guided our fault injection design in MATLAB Simulink, ensuring that the simulated conditions represent real industrial faults.

Furthermore, the paper emphasizes the importance of data-driven learning in vibration-based monitoring, reinforcing our decision to later integrate LSTM (Long Short-Term Memory) models for predictive analytics — similar to the advanced systems described in the review.

By linking traditional vibration analysis (FFT, RMS) with AI-driven fault recognition, this paper bridges the gap between our digital twin's simulation phase and its future AI-based predictive maintenance phase.

5 MATLAB Simulink Documentation (2024)

Title: *"Simscape Rotational Reference — Modeling Mechanical Systems." MathWorks Documentation*

Summary

This official documentation provides mathematical formulations and practical examples for modelling rotational mechanical systems in Simscape. It explains the use of rotational inertia, spring-damper systems, torque sources, and sensors — all of which form the foundation of our shaft digital twin. It also provides solver configurations and parameter setup guidelines to ensure numerical stability and realistic simulations.

Key Concepts

Concept	Explanation
Simscape Library	Provides prebuilt physical modelling components for mechanical systems.
Parameterization	Defines how inertia, damping, and stiffness affect rotational motion.
Physical–Simulink Interface	Use of PS–Simulink converters for signal exchange and plotting.
Solver Configuration	Crucial for achieving stable simulation behaviour.

Relevance to This Project

This technical documentation from MathWorks was essential for the practical implementation of the digital twin model. It provided the equations and block-level understanding needed to build the rotating shaft system using:

- Inertia blocks (for mass moment of inertia),
- Rotational Dampers (for friction and bearing losses),
- Rotational Springs (for shaft stiffness),
- Torque Sources and Sensors for measuring and controlling system dynamics.

It also guided the correct configuration of solver settings, physical signal conversion (PS-Simulink), and measurement scaling to ensure numerical stability and physical realism.

This documentation helped translate theoretical digital twin design into a working Simulink model, making it the primary technical resource for model creation and verification.

6 Zhao, R., et al. (2019)

Title: *"Deep Learning and Its Applications to Machine Health Monitoring: A Survey." Mechanical Systems and Signal Processing, 115, 213–237.*
DOI: 10.1016/j.ymssp.2018.05.050

Summary

Zhao et al. explore the role of deep learning in predictive maintenance and health monitoring. The paper compares various neural architectures — CNNs, RNNs, and LSTMs — for machinery fault detection and RUL prediction. It emphasizes that traditional ML techniques (SVM, Decision Trees) struggle with nonlinear and time-dependent data, while LSTM networks can learn long-term temporal patterns in vibration or torque signals, making them ideal for fault prognosis.

Key Concepts

Concept	**Explanation**
Deep Learning in Maintenance	Using DL models for automated fault diagnosis.
LSTM Networks	Capture long-term temporal dependencies in sequential data.
Feature Learning	DL models extract patterns automatically from raw sensor signals.
RUL Prediction	Estimate remaining life before failure using time-series data.

Relevance to This Project

Zhao et al. explore the role of deep learning (DL) in machinery health monitoring, highlighting how DL models outperform traditional machine learning in handling nonlinear, time-dependent data.

Their review identifies LSTM (Long Short-Term Memory) networks as particularly powerful for RUL prediction because they can learn long-term dependencies in sequential vibration or torque data.

This paper forms the theoretical foundation for our Phase 4, where the digital twin's synthetic data (FFT, RMS, time-domain signals) will be used to train an LSTM model for predicting the Remaining Useful Life (RUL) of the shaft.

The paper also discusses challenges such as limited labelled datasets and overfitting, which we address through synthetic data generation from our Simulink model — exactly as recommended in the study.

Thus, Zhao et al. (2019) directly supports the AI integration phase of our digital twin project, enabling predictive maintenance beyond simple fault detection.