

UNIVERSITY OF CALIFORNIA, MERCED

SMART PREDICTIVE MAINTENANCE ENABLED BY
DIGITAL TWINS AND PHYSICS INFORMED SMART
BIG DATA

BY

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Smart Predictive Maintenance Enabled by Digital Twins and Physics
Informed Smart Big Data

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To Gokce
my light and my Lúthien, forever

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Abbreviations

AI Artificial Intelligence

AlexNet AlexNet convolutional neural network

ANOVA Analysis of Covariance

BD Big Data

CS Cloud Systems

CWT Continuous Wavelet Transform

DC Direct Current

DCNN Deep Convolutional Neural Network

DL Deep Learning

DMD Dynamic Mode Decomposition

DMDc Dynamic Mode Decomposition with Control

DT Digital Twins

DWT Discrete Wavelet Transform

EC Edge Computing

FOPTD First Order Plus Time Delay

FRF Frequency Response Function

GoogLeNet GoogLeNet convolutional neural network

HIL Hardware-in-the-Loop

IAI Industrial Artificial Intelligence

IDC International Data Corporation

ILSVRC ImageNet Large Scale Visual Recognition Challenge

IoT Internet of Things

MIMO Multi-input Multi-output

ML Machine Learning

NSF Natural Sciences Foundation

ResNet Residual neural Network

RF Radio Frequency

RFIM Radio Frequency Impedance Matching

RG Relative Gain Array

SAS Smart and Autonomous Systems

SBD Smart Big Data

SI The International System of Units

SINAD Signal-to-Noise and Distortion Ratio

SLDO Simulink Design Optimization Tool

SNR Signal-to-Noise Ratio

SPM Smart Predictive Maintenance

STD Standard Deviation

STFT Short-Time Fourier Transform

WVD Wigner-Ville Distribution

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Abstract

Smart Predictive Maintenance Enabled by Digital Twins and Physics
Informed Smart Big Data

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In classical control engineering, optimality and robustness have been the main concerns of the control design and maintaining good performance. On the other hand, the third main concern can be considered as smartness with the inevitable grow of Digital Transformation and Industry 4.0 together with the influence of key enabling technologies like Artificial Intelligence (AI), Machine Learning (ML), Big Data (BD) and Edge Computing (EC). These core technologies enable users to increase capabilities of the systems not only for the design of the complex structures with smart control applications but also for maintaining a successful operation afterwards. For this reason, smartness can be considered as one of the most important requirements of maintenance strategies. Many engineering applications require a proper maintenance strategy to address the degradation and failure in the machines, processes and complex systems. In this context, maintenance methodologies play a key role depending on the application type and complexity of the requirements. Reactive and preventive maintenance strategies lead high downtime or waste useful life where they are not handy for a proper maintenance of complex systems. On the other hand, predictive maintenance strategy enables users to find optimal time and part selection to reduce downtime and maximize equipment lifetime. With the introduction of smartness to the predictive maintenance, a new frontier of Smart Predictive Maintenance (SPM) is aimed in this thesis to address main obstacles of traditional predictive maintenance workflow. To introduce smartness into the predictive maintenance framework, key enabling technologies of Digital Twins (DT) and physics-informed Smart Big Data (SBD) is utilized. To enhance the framework, development of the Digital Twin with behavioral matching process and utilization of existing knowledge in the Smart Big Data is demonstrated. The argument of the SPM is supported by a set of case studies including physics-informed transfer learning for fault classification, smart selection of control elements and error recovery for the Radio Frequency Impedance Matching (RFIM) system. Results of the example studies show that SPM is a new and effective systematic approach that can improve maintenance strategies, health monitoring and fault diagnosis applications.

Appendix B

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- F. Guc, Z. Yumrukcal, and O. Ozcan, “Nonlinear identification and optimal feedforward friction compensation for a motion platform,” *Mechatronics*, vol. 71, p. 102 408, 2020.

Book chapters

- F. Guc and Y. Chen, “Backlash quantification in control systems using noises with outliers: A benchmark study,” in *Outliers in Control Engineering: Fractional Calculus Perspective*, P. D. Domański, Y. Chen, and M. Ławryńczuk, Eds. De Gruyter, 2022, pp. 149–156. DOI: doi:10.1515/9783110729122- 008. [Online]. Available: <https://doi.org/10.1515/9783110729122-008>.

Workshops

- F. Guc, Y. Chen, J. Viola, P. Domanski, and J. Wang, Smart predictive maintenance (spm) of mechatronic systems based on smart big data (sbd) and digital twins (dt), A Half Day Tutorial at the 9th IFAC Symposium on Mechatronic Systems (Mechatronics 2022), the 16th International Conference on Motion, and Vibration Control (MoViC 2022) Jointly held at University of California, Los Angeles on September 7-9, 2022.

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- F. Guc and Y. Chen, “Ball-bearing fault diagnosis with physics informed transfer learning,” in *IFAC World Congress*, 2023, pp. 1–4.
- F. Guc and Y. Chen, “Smart predictive maintenance and error recovery for transmission line effects on rf impedance matching performance,” in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers, 2023.
- F. Guc and Y. Chen, “Smart predictive maintenance enabled by digital twins and smart big data: A new framework,” in *2022 IEEE 2nd International Conference on Digital Twins and Parallel Intelligence (DTPI)*, IEEE, 2022, pp. 1–4.
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