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A Systematic Literature Review of Self-Healing Mechanisms in Cyber-Physical Systems: Application to Robotic Manipulators

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***Abstract*—**Self-healing mechanisms enhance the reliability of cyber-physical systems (CPS) by addressing system faults autonomously. This systematic literature review investigates self-healing strategies in CPS, with a focus on robotic manipulators, to identify limitations, challenges, and future directions. Robotic manipulators play a critical role in precision tasks such as assembly, welding, and material handling in manufacturing and other industries. Their integration of mechanical actuators, sensors, and embedded software makes them particularly vulnerable to faults and failures. While fault-tolerant control (FTC) methods maintain functionality during faults, their reactive nature and limited recovery capabilities underscore the need for self-healing systems. These mechanisms integrate predictive maintenance, real-time diagnostics, and adaptive recovery, leveraging technologies such as Artificial Intelligence (AI), Digital Twins (DT), and the Internet of Things (IoT). This review identifies advancements in predictive maintenance and recovery strategies while addressing gaps such as the reliance on simulations, limited real-world validation, and the absence of comprehensive frameworks that seamlessly combine pre-failure and post-failure mechanisms. The findings offer insights into the development of intelligent self-healing frameworks that advance the evolution of CPS in Industry 4.0.

***Keywords-component*—self-healing; cyber-physical systems; fault tolerant; fault recovery; digital twin; Industry 4.0**

I. INTRODUCTION

Today's industrial and technological systems rely on cyber-physical systems (CPS) to ensure efficiency, safety, and productivity [1], [2]. These systems, characterized by the integration of control, communication, and distributed computing, support domains such as healthcare, transportation, and manufacturing [2]. Among CPS applications, robotic manipulators are particularly significant due to their role in precision tasks such as assembly, welding, and material handling. Their integration of mechanical actuators, sensors, and embedded software makes them vulnerable to faults and failures, which disrupt operations, degrade system performance, and compromise safety. This underscores the importance of effective fault management mechanisms [2].

Faults in robotic manipulators often arise from system degradation, operational wear, or environmental stress [3]. For example, ongoing operation can lead to actuator degradation that impacts precision and safety during tasks of assembly or material handling. Similarly, thermal stress can lead to actuator overheating that results in operational failures. These challenges emphasize the need for robust fault management mechanisms, where "robust" refers to a system's fault detection and isolation capabilities to perform its intended function even in the presence of noise and other sources of uncertainty [4]. Fault-tolerant control (FTC) has been used to address these issues by maintaining functionality after faults occur [5]. However, FTC generally operates reactively after faults occur, and lacks the ability to restore systems to their pre-failure state without human intervention [6].

Self-healing systems aim to overcome these limitations by having proactive fault prevention before faults and autonomous system recovery after faults. Through real-time monitoring, fault diagnosis, and autonomous recovery, self-healing systems address pre-failure scenarios by adjusting operational parameters. For post-failure scenarios, they restore systems to their pre-failure state without external intervention [6]. For robotic manipulators, self-healing enables continuous operation during assembly tasks by adapting to faults without halting production. Advances in enabling technologies such as artificial intelligence (AI)-driven diagnostics, digital twin (DT)-enabled simulations, and internet of things (IoT)-supported edge-cloud architectures facilitate these capabilities. These technologies enhance fault detection, recovery, and adaptation by integrating control, communication, and computation. Edge computing supports rapid local fault diagnosis and recovery actions, while cloud connectivity enables global data sharing, system updates, and predictive analysis. Compared to purely onboard systems, this integration allows CPS to adapt dynamically in real-time, maintaining operational continuity. By leveraging these technologies, self-healing in CPS can manage faults in decentralized industrial environments [7].

Several reviews have investigated fault tolerance in CPS, including robotic manipulators. Piardi et al. [2] examined fault-tolerant strategies in industrial CPS which emphasize redundancy and recovery mechanisms. However, the authors' analysis was focused on maintaining functionality during faults without exploring mechanisms for autonomous recovery or restoration to pre-failure conditions. Milecki and Nowak [5] reviewed FTC methods in robotic manipulators, highlighting advancements in fault detection and isolation but overlooked the integration of pre-failure prevention with post-failure recovery. Liang and Yin [6] explored self-healing mechanisms, providing insights into how biological principles of self-healing inspire applications in industrial systems. While these studies offer valuable perspectives, they highlight recurring limitations: the emphasis on fault tolerance rather than full system recovery and the lack of a cohesive mechanism integrating pre- and post-failure strategies which is the essence of self-healing.

This systematic literature review (SLR) contributes to the field by addressing these limitations. It focuses on self-healing mechanisms for robotic manipulators as examples of CPS, providing an exploration of how to integrate pre-failure and post-failure strategies to ensure reliability and autonomy—where reliability means the probability that systems perform without failure under stated conditions for a specific period, and autonomy refers to their ability to operate independently of external control or intervention [4], [8]. The review examines the role of enabling technologies, such as Digital Twins, in facilitating self-healing for these systems. The review identifies challenges and future directions for developing self-healing frameworks.

The remainder of this paper is organized as follows: Section 2 presents the background and outlines key concepts. Section 3 describes the methodology adopted for this review. Section 4 explores self-healing strategies for CPS through pre-failure and post-failure approaches. Section 5 discusses current limitations, challenges, and future research directions. Finally, Section 6 concludes with insights into the transformative potential of self-healing mechanisms in CPS.

II. Background and Key Concepts

Understanding self-healing mechanisms in CPS involves foundational concepts such as FTC, reliability-centered maintenance (RCM), life-extending control (LEC), and self-healing mechanism. These concepts address the two challenges of pre-failure prevention and post-failure recovery central to self-healing systems.

A. Fault-Tolerant Control Systems (FTC)

FTC systems maintain operational functionality during faults through fault detection, isolation, and corrective actions but generally do not restore systems to their pre-failure state [5]. FTC can be classified into [5]:

- **Passive FTC:** Operates offline by relying on pre-designed fault-handling mechanisms that do not adapt dynamically to unforeseen faults. For instance, a robotic manipulator may use fixed torque limits to prevent joint overloads during operation; these thresholds are predefined during system design and remain static regardless of fault type.
- **Active FTC:** Operates online by employing fault detection and isolation (FDI) techniques to dynamically identify faults and reconfigure the control system accordingly. An example is a robotic manipulator reassigning tasks to healthy joints when one actuator fails to ensure continued operation with minimal interruption.
- **Hybrid FTC:** Combines passive and active approaches by integrating predefined strategies with dynamic adaptability. For example, a robotic manipulator might use passive FTC to switch to a predefined safe mode when a sensor malfunction is detected, while simultaneously employing active FTC to adjust its trajectory in real time using redundant sensors to maintain task accuracy.

Corrective actions in FTC involve measures such as isolating faulty components, reallocating control effort, or switching to backup systems. However, these actions primarily focus on maintaining functionality during faults. In contrast, self-healing systems emphasize preventing faults before they occur and restoring the system to its pre-failure state after faults have been addressed.

B. Reliability-Centered Maintenance (RCM)

RCM identifies potential failure modes and optimizes maintenance actions using tools like Failure Modes and Effects Analysis (FMEA) and Fault Tree Analysis (FTA). While effective in high-risk systems, RCM's reliance on predefined failure modes limits adaptability to unexpected scenarios. Integrating RCM with self-healing mechanisms improves fault management in autonomous CPS [8].

C. Life-Extending Control (LEC)

LEC dynamically optimizes system performance as it extends the Remaining Useful Life (RUL) of components. For instance, stochastic models predict degradation rates in actuators by accounting for both gradual wear and random fluctuations [9]. These models enable controllers to reduce stress during peak loads, such as lowering motor torque in robotic arms to reduce wear. LEC focuses on delaying failures and lacks a post-failure approach to restore the system after a fault occurs [9].

D. Self-Healing mechanisms in CPS

A self-healing mechanism autonomously prevents faults before they occur and restores system functionality after failures, aiming to return the system to its pre-failure state [6]. Unlike FTC—which focuses reactively on maintaining functionality during faults (for example, by switching to redundant actuators to sustain operation after an actuator failure)—self-healing integrates both pre-failure prevention (such as employing LEC to reduce actuator degradation) and post-failure recovery (such as reinitializing software modules to resolve transient errors) [6]. Despite its ability to recover systems in ways that FTC cannot restore, self-healing remains constrained by permanent hardware failures—such as actuator damage—which require manual intervention. By combining proactive prevention with adaptive recovery, the self-healing mechanism transcends FTC's focus on operational continuity, offering a holistic approach to system resilience defined as the ability to absorb disturbances, adapt to faults, and recover its pre-failure state while maintaining operational objectives.

A DT, defined as a virtual replica of physical systems that dynamically simulates their real-time behavior, enhances self-healing mechanisms by enabling predictive maintenance and fault mitigation [7]. Through bidirectional communication between physical systems and their digital counterparts, a DT facilitates real-time data exchange, empowering self-healing systems to dynamically adjust or restore performance through informed actions. The subsequent section details the methodology for systematically reviewing how such technologies are designed and integrated into CPS frameworks.

III. Methodology

A. Search Methodology

SLR provides a structured and comprehensive approach to examining existing research on a specific topic or research question. Its primary goal is to collect, analyze, and synthesize all relevant evidence in a given area of study.

This SLR aims to achieve the following objectives:

- Analyze advances in FTC and self-healing mechanisms in CPS.
- Evaluate the strengths, limitations, and implementation contexts of existing approaches.
- Highlight existing research gaps and opportunities for improvement by identifying unresolved challenges and areas for further development.

B. SLR Planning

The SLR was designed to address the outlined objectives. Key concepts for the search query included **Self-Healing/FTC**, **Cyber-Physical Systems**, **Fault**, and **robotic manipulators**. These were expanded with keywords, synonyms, related terms, and truncations for comprehensive coverage. Logical operators such as **OR** connected synonyms within each concept, **AND** combined concepts, and **NOT** excluded irrelevant topics. The search query was structured as follows:

- Title **Self-Healing/FTC:** ("Fault tolerance control" OR "Fault-tolerant control" OR FTC OR "self-heal*" OR "resilience system* OR "resilient system*" OR "autonomous maintained" OR "reconfigur* autonomously" OR "self-configur*" OR "self-recover*" OR "PHM" OR "LEC").
- Topic **Cyber-Physical System (CPS):** ("cyber-physical system" OR "CPS" OR "Cyber physical system" OR "I-CPS" OR "ICPS" OR "cyber-physical warehouse" OR "real-time application*" OR "Cyber physical warehouse" OR "smart manufacturing" OR "intelligent system*" OR "experiment*" OR "simulation" OR "Internet connected" OR "AI-enabled" OR "Digital Twin" OR "DT").
- Topic **Fault:** ("Fault*" OR "Failure*" OR "degradation" OR "pre-failure" OR "Post-failure" OR "Anomal*" OR "not conform" OR "RUL").
- Abstract **robotic manipulators:** ("manipulator*" OR "AMR" OR "robot*" OR "machining process").
- **NOT** Topic ("bio*" OR "network" NOT "neural network") (note: the term "neural network" is included).

The search was conducted using Engineering Village, Web of Science, and Scopus, with a time range of 2015–2024 to capture advancements in self-healing for CPS, following the Industry 4.0 initiative in 2011, which led to an increase in FTC and LEC papers from 2015 onwards [2]. The search was limited to English-language journal articles and conference proceedings, yielding 207 results from Engineering Village, 171 from Web of Science, and 237 from Scopus.

C. Screening and Selection Process

Duplicates across the databases were removed by comparing titles and DOIs. This process yielded 472 unique publications. Titles were then reviewed to eliminate irrelevant studies, reducing the total to 109 publications. Subsequently, abstracts were examined to exclude unrelated studies, narrowing the list further to 46 publications. Full-text articles were carefully analyzed, resulting in 26 relevant publications after excluding works that did not meet the criteria. Finally, additional relevant studies were identified through forward and backward citation searches, leading to a final selection of 29 publications.

D. Knowledge Extracted from the SLR

The findings of this SLR provided critical insights into advancements in FTC and self-healing mechanisms, including:

- Advances in pre-failure mechanisms for fault prevention and post-failure strategies for fault recovery.
- Identification of research gaps, including the lack of integration between pre-failure mechanisms and post-failure strategies.
- Exploration of future directions such as the use of hybrid degradation models for pre-failure mechanisms.

IV. Self-Healing Strategies for Cyber-Physical Systems

We have seen in the literature that self-healing mechanisms in CPS aim to integrate pre-failure prevention and post-failure recovery strategies to address system faults comprehensively [6], [10]. This section examines these approaches, highlighting their applications, advancements, and existing gaps.

A. Pre-Failure Approaches

Pre-failure strategies focus on predicting and mitigating system degradation before it leads to faults. These strategies leverage tools such as DT, data-driven techniques, model-based methods, and health-aware control systems to extend the RUL of components and ensure reliability [6].

Model-based methods utilize mathematical models to capture the degradation dynamics of components, enabling predictive maintenance and life-extending strategies. Among these, stochastic differential equations (SDE) are widely employed in degradation modeling due to their effectiveness in representing stochastic behaviors influencing degradation rates. Si et al. [11] pioneered a nonlinear diffusion-based degradation model that transitioned from linear SDE to a nonlinear one incorporating a nonlinear drift coefficient. This approach improved RUL prediction accuracy by better capturing nonlinear degradation behaviors and deriving an analytical approximation for the first hitting time distribution. However, the model lacked integration with control systems for fault mitigation. Building on SDE-based models, Zhang et al. [12] formulated a degradation-incorporated state-space (DISS) model within a nonlinear model predictive control (MPC) framework, balancing actuator reliability and performance by treating degradation as a controllable state variable. Meng et al. [9] proposed a risk-quantified autonomous maintenance framework for robotaxis, integrating Prognostics and Health Management (PHM) with MPC. The framework utilized an SDE process to predict the RUL of motors and dynamically balanced motor performance and degradation. However, it relies on static operating conditions and lacks experimental validation. Similarly, Shen et al. [13] developed a predictive maintenance framework for quadrotor UAVs using a two-stage Kalman Filter and Laguerre function-based MPC. The framework incorporated SDE-based degradation modeling to improve reliability. However, it aggregated actuator health metrics, which neglects component interactions. Across these studies, a common limitation is their reliance on simulations without experimental validation, leaving both their practical effectiveness and the computational feasibility of integrating SDE-based degradation models with real-time parameter adaptation unconfirmed.

Data-driven methods, combined with DT, leverage historical and real-time data to model degradation, predict faults, and simulate system behavior under various conditions. Taha et al. [14] employed a Deep Reinforcement Learning (DRL) framework in CNC systems within a Digital Twin environment to optimize machining parameters. While it achieved significant improvements in operational efficiency, the framework lacked predictive degradation modeling. Mourtzis et al. [15] proposed a DT-based predictive maintenance framework focusing on robotic cell reliability, utilizing machine learning (ML) models for fault detection and RUL prediction. However, it primarily focused on detection, lacking autonomous maintenance actions and real-time adaptive control. Song et al. [16] introduced a DT-assisted fault diagnosis system for robot joints, achieving high diagnostic accuracy through synthetic data generation and deep learning. However, the system excluded maintenance actions and real-time control adjustments. Zagorowska et al. [3] surveyed degradation models, emphasizing their application in life-extending control strategies but noted limited integration with autonomous decision-making processes.

These studies collectively demonstrate significant advancements in pre-failure strategies and underscore the importance of using DT. However, they share common limitations. Many approaches rely on simulations without experimental validation, raising concerns about practical applicability. DT frameworks often focus on fault detection and RUL prediction without integrating autonomous maintenance actions. Additionally, static failure probabilities are frequently assumed, reducing adaptability to dynamic operational conditions.

B. Post-Failure Approaches

Post-failure strategies in CPS aim to maintain functionality and restore the system to its pre-failure state after faults occur [6]. Faults in CPS are broadly categorized as permanent (e.g., actuator lock, sensor failure), transient (e.g., external disturbances), or intermittent (e.g., sporadic actuator overheating) [17]. While FTC methods focus on sustaining functionality during faults, few studies address full recovery to pre-failure performance. Post-failure mechanisms predominantly address permanent faults, with limited focus on non-permanent or intermittent faults, such as overheating, which, if left unresolved, can escalate into permanent failures. Non-permanent faults like actuator overheating remain understudied, leaving gaps in fault management. Moreover, existing frameworks often struggle to differentiate non-permanent faults from operational noise, resulting in delayed or ineffective responses.

In the context of robotic manipulators, several FTC strategies have been proposed to maintain system performance during faults, often emphasizing functionality over restoring the system to its pre-failure state. Le and Kang [18] developed an active FTC strategy for actuator faults (e.g. loss of effectiveness, bias) using sliding mode control and extended state observers, emphasizing fault suppression. Xu and He [19] used adaptive fuzzy logic to address actuator and process faults, uncertain dynamics, and external disturbances. Rahali et al. [20] enhanced robustness against payload variations and actuator faults using an adaptive fuzzy type-2 backstepping controller. Chen et al. [21] and Long et al. [22] developed model-free and self-tuning FTC approaches, respectively, to handle actuator faults, disturbances, and input saturation. These studies exemplify a broader trend: intermittent anomalies are often treated as noise or uncertainty, with frameworks lacking mechanisms to specifically address non-permanent faults that can escalate into permanent failures [23], such as actuator overheating. While FTC methods robustly maintain functionality during permanent faults, they lack mechanisms to restore a system to its pre-failure state.

The limitations of single-agent systems extend to cooperative manipulators. Wu et al. [24] proposed an FTC framework for subsystems to compensate for each other's faults, but delays limited its effectiveness in real-time. Similarly, Freddi et al. [25] addressed faults in one arm of dual-arm systems using kinematic compensation, without considering the potential impact of faults in both arms simultaneously.

Learning-based approaches have emerged to address dynamic fault environments, yet their focus remains on tolerance rather than recovery. Yan et al. [26] integrated reinforcement learning (RL) with FTC to adaptively compensate for actuator faults in manipulators, leveraging neural networks for model-free diagnosis. However, their framework struggles with highly nonlinear fault dynamics and does not target system restoration. For sensor faults, Kommuri et al. [27] introduced a sliding mode observer-based FTC for bypassing faulty sensors, yet it lacked recovery mechanisms. Similarly, Cai et al. [28] developed a self-healing FTC framework aimed to restore sensors to their pre-failure state after faults, but only addressed specific nonlinear systems.

Mobile manipulators, increasingly integrated into CPS, face analogous challenges. Rayankula et al. [29] leveraged kinematic redundancy in both the manipulator arm and the mobile base to maintain functionality during locked joint faults but did not address recovery.

Restart-based strategies offer targeted solutions for transient faults but lack versatility in handling broader fault categories. Gao et al. [30] proposed an MPC-integrated self-healing framework to address transient actuator faults through system restarts, leveraging model predictive control to stabilize operations during recovery. However, this approach focuses solely on transient faults and neglects intermittent or evolving non-permanent faults, such as overheating, which demand adaptive mechanisms beyond restart procedures. Similarly, Zinn et al. [31] introduced a DRL-based FTC framework for automated production systems, focusing on temporary faults that require system restarts. However, they only focused on software faults.

For decentralized architectures in CPS. Nandanwar et al. [32] demonstrated decentralized active FTC in multi-robot systems, enabling coordinated fault management through distributed decision-making. However, their framework was constrained to predefined fault scenarios, failing to address unmodeled or evolving faults in dynamic environments. This study underscores a recurring pattern: decentralized architectures excel at fault detection and localized tolerance but can fall short in enabling adaptive, system-wide recovery.

Application-specific solutions further highlight the challenge of generalizability in self-healing systems. Taha et al. [33] developed a self-healing mechanism for CNC machines using Logical Analysis of Data (LAD) to detect and autonomously resolve process-related faults. While effective for managing deviations in machining processes, the approach does not extend to actuator or sensor faults, limiting its generalizability to CPS applications.

These post-failure approaches share limitations, focusing mainly on fault tolerance while often overlooking recovery mechanisms to restore pre-failure performance. Most studies target permanent faults, neglecting non-permanent ones like overheating, which are increasingly relevant in practice. Furthermore, real-time feasibility is unclear, as online optimization lacks experimental validation.

V. Limitations, Challenges, and Future Research Directions

A. Limitations in Current Research

While advancements in FTC and self-healing mechanisms for CPS have shown significant promise, several limitations persist in the current body of research. These limitations can be summarized as follows:

- Post-failure mechanisms predominantly address permanent faults, with limited focus on non-permanent ones, such as overheating, which, if left unresolved, can escalate into permanent failures.
- The majority of post-failure studies prioritize maintaining system functionality after faults rather than restoring systems to their pre-failure state. Moreover, efforts focused on restoration primarily address software faults, with limited attention to hardware issues.
- Most frameworks rely on simulations, with limited experimental studies, leaving uncertainties around their computational requirements for real-time deployment. Such experimental validation is crucial for confirming practical effectiveness and achieving higher technology readiness levels (TRL).
- There is a lack of integration between pre-failure mechanisms, which prevent fault escalation, and post-failure strategies aimed at system recovery. Combining these approaches would enhance fault management.

B. Challenges in Developing Self-Healing CPS

Developing self-healing CPS faces challenges, including:

- Pre-failure strategies like LEC rely on stochastic processes to approximate degradation due to insufficient real-world degradation datasets. This forces models to generalize from idealized assumptions, reducing accuracy in dynamic industrial settings.
- Existing frameworks struggle to differentiate non-permanent faults, which can escalate, from operational noise, resulting in delayed or ineffective responses. [34].
- Pre-failure strategies reduce actuator degradation to extend RUL but decrease tracking precision [9]. Conversely, post-failure FTC prioritizes precision to stabilize the system, creating conflicting control objectives. For example, torque redistribution in a 6-DOF manipulator during pre-failure phases may limit the available torque reserves needed for post-failure recovery maneuvers.

C. Future Research Directions

Future self-healing CPS research could focus on:

- Integrate physics-based degradation models with data-driven techniques to enhance RUL prediction accuracy, enabling adaptation of laboratory-calibrated models to real-world operating conditions.
- Develop adaptive MPC frameworks that dynamically balance RUL extension and fault recovery. For example, optimize joint torque limits during normal operation to reserve capacity for post-failure compensation, ensuring seamless transitions between modes.
- Develop fault detection algorithms with dynamic thresholding to accurately distinguish non-permanent faults from noise and prevent escalation into permanent failures.
- Shift from simulation-based studies to experimental validations in real-world settings, emphasizing validation

of computational efficiency and real-time performance. Collaborative research with industry partners can provide practical insights.

VI. Conclusion

This paper presents a systematic literature review of self-healing mechanisms in cyber-physical systems, with a focus on robotic manipulators. While fault-tolerant control has been studied for maintaining functionality during faults, its limitations in system recovery highlight the need for self-healing approaches. By integrating pre-failure prevention and post-failure recovery strategies, self-healing systems address these gaps, leveraging advanced technologies such as Artificial Intelligence and Digital Twin. Despite significant progress, challenges like limited experimental validation persist. Addressing these requires an interdisciplinary approach and enhanced industry collaboration to facilitate experimental validations in practical environments. Future research should focus on improving self-healing mechanisms to enhance CPS autonomy and reliability.

References

[1] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manufacturing Letters*, vol. 3, pp. 18–23, Jan. 2015.

[2] L. Piardi, P. Leitão, and A. S. de Oliveira, "Fault-tolerance in cyber-physical systems: Literature review and challenges," in *2020 IEEE 18th International Conference on Industrial Informatics (INDIN)*, Jul. 2020, pp. 29–34.

[3] M. Zagorowska, O. Wu, J. R. Ottewill, M. Reble, and N. F. Thornhill, "A survey of models of degradation for control applications," *Annual Reviews in Control*, vol. 50, pp. 150–173, Jan. 2020.

[4] M. D. Holloway, *Dictionary of industrial terminology*. Wiley, 2021. [Online]. Available: https://catalog.yln.info/ebookcentral/EBC6423303

[5] A. Milecki and P. Nowak, "Review of fault-tolerant control systems used in robotic manipulators," *Applied Sciences*, vol. 13, no. 4, p. Art. no. 4, Jan. 2023.

[6] H. Liang and X. Yin, "Self-healing control: Review, framework, and prospect," *IEEE Access*, vol. 11, pp. 79 495–79 512, 2023.

[7] M. Quamar and A. Nasir, "Review on fault diagnosis and fault-tolerant control scheme for robotic manipulators: Recent advances in AI, machine learning, and digital twin," 2024.

[8] A. Birolini, *Reliability engineering: Theory and practice*, 8th ed. Springer Berlin, Heidelberg, 2017, published: Hardcover (16 June 2017), Softcover (15 August 2018), eBook (19 May 2017).

[9] D. Meng, H. Chu, M. Tian, B. Gao, and H. Chen, "Risk-quantified autonomous maintenance of robotaxis using self-tuning model predictive control," *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1–13, 2024.

[10] J. Lee, M. Ghaffari, and S. Elmeligy, "Self-maintenance and engineering immune systems: Towards smarter machines and manufacturing systems," *Annual Reviews in Control*, vol. 35, no. 1, pp. 111–122, Apr. 2011.

[11] X.-S. Si, W. Wang, C.-H. Hu, D.-H. Zhou, and M. G. Pecht, "Remaining useful life estimation based on a nonlinear diffusion degradation process," *IEEE Transactions on Reliability*, vol. 61, no. 1, pp. 50–67, 2012.

[12] J. Zhang, T. Liu, and J. Qiao, "Solving a reliability-performance balancing problem for control systems with degrading actuators under model predictive control framework," *Journal of the Franklin Institute*, vol. 359, no. 9, pp. 4260–4287, Jun. 2022.

[13] F. Shen, W. Li, D. Jiang, and H. Mao, "Autonomous predictive maintenance of quadrotor UAV with multi-actuator degradation," *The Aeronautical Journal*, vol. 128, no. 1326, pp. 1789–1813, Aug. 2024.

[14] H. A. Taha, S. Yacout, and Shaban, "Deep reinforcement learning for autonomous pre-failure tool life improvement," *The International Journal of Advanced Manufacturing Technology*, vol. 121, no. 9, pp. 6169–6192, Aug 2022.

[15] D. Mourtzis, S. Tsoubou, and J. Angelopoulos, "Robotic cell reliability optimization based on digital twin and predictive maintenance," *Electronics*, vol. 12, no. 9, p. Art. no. 9, Jan. 2023.

[16] Z. Song, H. Shi, X. Bai, and G. Li, "Digital twin-assisted fault diagnosis system for robot joints with insufficient data," *Journal of Field Robotics*, vol. 40, no. 2, pp. 258–271, 2023.

[17] S. X. Ding, *Advanced methods for fault diagnosis and fault-tolerant control*, 1st ed. Berlin, Heidelberg: Springer Berlin, Heidelberg, 2021.

[18] Q. D. Le and H.-J. Kang, "An active fault-tolerant control based on synchronous fast terminal sliding mode for a robot manipulator," *Actuators*, vol. 11, no. 7, p. Art. no. 7, Jul. 2022.

[19] S. Xu and B. He, "Robust adaptive fuzzy fault tolerant control of robot manipulators with unknown parameters," *IEEE Transactions on Fuzzy Systems*, vol. 31, no. 9, pp. 3081–3092, Sep. 2023.

[20] H. Rahali, S. Zeghlache, and L. Benyettou, "Fault tolerant control of robot manipulators based on adaptive fuzzy type-2 backstepping in attendance of payload variation," *International Journal of Intelligent Engineering and Systems*, vol. 14, no. 4, pp. 312–325, Aug. 2021.

[21] Z. Chen, X. Wang, and Y. Cheng, "Model free based finite time fault-tolerant control of robot manipulators subject to disturbances and input saturation," *International Journal of Robust and Nonlinear Control*, vol. 32, no. 9, pp. 5281–5303, 2022.

[22] M. T. Long, W. Y. Nan, and N. V. Quan, "Adaptive robust self-tuning PID fault-tolerant control for robot manipulators," *International Journal of Dynamics and Control*, vol. 12, no. 2, pp. 477–485, Feb. 2024.

[23] F. Jia, F. Cao, and X. He, "Active fault-tolerant control against intermittent faults for state-constrained nonlinear systems," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 54, no. 4, pp. 2389–2401, 2024.

[24] W. Wu, Z. Cheng, R. Zhang, and B. Xu, "Fault diagnosis and fault tolerant control of two manipulators cooperation system," in *3rd International Conference on Artificial Intelligence and Advanced Manufacture*. Association for Computing Machinery, Mar. 2022, pp. 341–348.

[25] A. Freddi, S. Longhi, A. Monteriù, D. Ortenzi, and D. P. Pagnotta, "Kinematic fault tolerant control of a dual-arm robotic system under torque faults," in *2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA)*, Jul. 2018, pp. 1–6.

[26] Z. Yan, J. Tan, B. Liang, H. Liu, and J. Yang, "Active fault-tolerant control integrated with reinforcement learning application to robotic manipulator," in *2022 American Control Conference (ACC)*, Jun. 2022, pp. 2656–2662.

[27] S. K. Kommuri, M. Defoort, H. R. Karimi, and K. C. Veluvolu, "A robust observer-based sensor fault-tolerant control for PMSM in electric vehicles," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 12, pp. 7671–7681, Dec. 2016.

[28] M. Cai, X. He, and D. Zhou, "Self-healing fault-tolerant control for high-order fully actuated systems against sensor faults: A redundancy framework," *IEEE Transactions on Cybernetics*, vol. 54, no. 4, pp. 2628–2640, Apr. 2024.

[29] V. Rayankula and P. M. Pathak, "Fault tolerant control and reconfiguration of mobile manipulator," *Journal of Intelligent and Robotic Systems*, vol. 101, no. 2, p. 34, Jan 2021.

[30] S. Gao, M. Cui, X. Ma, and Y. Wang, "Self-healing control method combining model predictive control and restart strategy for 4WD mobile robot," in *2022 34th Chinese Control and Decision Conference (CCDC)*, Aug. 2022, pp. 1912–1917.

[31] J. Zinn, B. Vogel-Heuser, and M. Gruber, "Fault-tolerant control of programmable logic controller-based production systems with deep reinforcement learning," *Journal of Mechanical Design*, vol. 143, no. 072004, Apr. 2021.

[32] A. Nandanwar, V. K. Tripathi, and L. Behera, "Fault-tolerant control for multi-robotics system using variable gain super twisting sliding mode control in cyber-physical framework," in *2021 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, Jul. 2021, pp. 1147–1152.

[33] H. A. Taha, S. Yacout, and Y. Shaban, "Autonomous self-healing mechanism for a CNC milling machine based on pattern recognition," *Journal of Intelligent Manufacturing*, vol. 34, no. 5, pp. 2185–2205, Jun. 2023.

[34] G. Xiao and F. Liu, "Distributed fault-tolerant model predictive control for intermittent fault: A cooperative way," *ISA Transactions*, vol. 89, pp. 113–121, 2019.