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Resilient Fault Detection and Recovery Mechanisms for Safety-Critical Industrial Control Systems under Cyber-Physical Threats

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RESEARCH ARTICLE

Abstract

Cyber-physical systems (CPS) that control critical industrial infrastructure face increasingly sophisticated threats that can compromise both security and safety functions. These systems require robust fault detection and recovery mechanisms capable of maintaining operational integrity under various attack vectors and environmental disturbances. This paper presents a novel framework for resilient fault detection and recovery in safety-critical industrial control systems that integrates model-based anomaly detection with adaptive reconfiguration strategies. We demonstrate that by combining formal verification methods with stochastic process modeling, detection accuracy improves by 27% while reducing false positives by 42% compared to conventional approaches. Our proposed recovery mechanism implements a hierarchical decision-making architecture that prioritizes safety-critical functions while gracefully degrading non-essential operations, achieving a mean time to recovery of 3.8 seconds in experimental evaluations. We validate the approach using both hardware-in-the-loop simulation and testing on an operational testbed representing a chemical processing facility under various attack scenarios. Results indicate that the proposed methodology maintains critical safety margins even when 68% of sensing infrastructure is compromised, significantly outperforming existing redundancy-based approaches while requiring minimal additional computational resources.

1 Introduction

Modern industrial control systems operate at the intersection of operational technology (OT) and information technology (IT), creating an expanded attack surface that traditional security measures inadequately address [1]. The integration of formerly isolated industrial systems with enterprise networks, cloud services, and Internet-connected devices has generated new vulnerabilities that sophisticated adversaries can exploit to cause physical damage, service disruption, or safety hazards. Recent incidents such as targeted attacks on water treatment facilities, power distribution networks, and manufacturing plants highlight the critical need for resilient control systems that can maintain essential safety functions even when compromised.

Traditional fault detection and isolation (FDI) mechanisms typically assume that failures occur randomly due to component degradation or environmental factors rather than as the result of intelligent adversaries who can adapt to defensive measures. Standard redundancy approaches rely on voting mechanisms that assume independence among redundant components—an assumption that sophisticated attacks can systematically violate [2]. Similarly, conventional recovery methods often implement simplistic failover strategies that may be predictable and thus susceptible to targeted subversion.

This research addresses these limitations by developing a comprehensive framework for resilient control systems that can detect anomalies, distinguish between accidental faults and malicious

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attacks, and implement appropriate recovery mechanisms under varying threat conditions. Our approach integrates concepts from control theory, cybersecurity, and formal verification to create defense-in-depth strategies appropriate for safety-critical industrial environments.

The primary contributions of this work include: (1) a formal model of resilience that quantifies the relationship between detection latency, recovery time, and safety margins; (2) a novel anomaly detection algorithm that leverages both physical system models and communication pattern analysis to identify inconsistencies indicative of attacks; (3) an adaptive recovery mechanism that implements context-aware reconfiguration strategies; and (4) a comprehensive validation methodology combining formal verification with experimental evaluation. [3]

Throughout this paper, we argue that resilience in cyber-physical systems cannot be achieved through isolated security measures but requires an integrated approach that considers both the physical dynamics of the controlled process and the computational infrastructure that implements control functions. By explicitly modeling attack vectors and their potential impact on system behavior, our approach enables proactive defensive measures rather than merely reactive responses.

The remainder of this paper is organized as follows. Section 2 presents the system model and threat assumptions that form the foundation of our work [4]. Section 3 details our anomaly detection methodology and its theoretical underpinnings. Section 4 introduces the mathematical modeling framework using stochastic hybrid systems. Section 5 describes the hierarchical recovery architecture. Section 6 outlines our implementation approach [5]. Section 7 presents experimental results and evaluation, and Section 8 concludes with a discussion of limitations and future research directions.

2 System Model and Threat Assumptions

Industrial control systems typically comprise a hierarchical architecture including field devices (sensors and actuators), controllers (PLCs, RTUs), and supervisory systems (SCADA, DCS). These components interact through various communication protocols to implement control loops that maintain desired process conditions. Our framework models this architecture as a directed graph $G = (V, E)$ where vertices V represent components (sensors, actuators, controllers, and computational nodes) and edges E represent communication channels between components. [6] [7]

Each component $v_i \in V$ is characterized by a state vector $x_i(t)$ that evolves according to a set of differential equations specific to its function. Sensors transform physical quantities into measurement signals, actuators convert control signals into physical actions, and controllers implement algorithms that determine appropriate control signals based on measurement inputs and control objectives. The physical process itself evolves according to its own dynamics, which may be linear or nonlinear, time-invariant or time-varying.

Communication channels $e_{ij} \in E$ transfer information from component v_i to component v_j with various properties including bandwidth limitations, latency characteristics, and potential information loss. We model communication as a stochastic process to account for network-induced uncertainties.

The threat model assumes an adversary with varying capabilities ranging from passive eavesdropping to active manipulation of both communication channels and component behavior [8]. Specifically, we consider attacks that may:

1. Compromise individual sensors to report incorrect measurements 2. Manipulate control signals to actuators 3. Modify controller logic or parameters [9] 4. Disrupt communication channels through jamming or packet manipulation 5. Compromise computational nodes to execute arbitrary code

An important distinction in our model is between attacks that target the information domain (cybersecurity) and those that directly impact physical components (physical security). The former typically aim to manipulate information flows within the system, while the latter seek to cause

direct damage to physical assets [10]. Our framework addresses both types of threats and their potential interactions.

We define a resilient control system as one that maintains essential functionality even when components are compromised or communication channels are disrupted. Specifically, a system is considered resilient if it satisfies three properties: (1) it detects deviations from normal operation within a bounded time; (2) it recovers acceptable performance within another bounded time after detection; and (3) throughout the attack and recovery process, critical safety properties are maintained.

Formally, let ϕ represent a set of safety properties that must be maintained (e.g., pressure remains below a critical threshold) [11]. For any attack scenario $a \in A$, where A is the set of all considered attacks, the system state trajectory $x(t)$ must satisfy ϕ at all times. Additionally, if t_d is the detection time and t_r is the recovery time, then the resilience objective is to minimize both while ensuring ϕ holds continuously.

This formulation allows us to quantitatively evaluate resilience as the system's ability to maintain safety properties under various attack scenarios and to recover normal operation efficiently once an attack is detected. The following sections detail our approach to achieving these resilience objectives through advanced detection and recovery mechanisms. [12]

3 Anomaly Detection Methodology

Our anomaly detection methodology integrates multiple approaches to identify potential attacks or faults: model-based detection, invariant checking, and communication pattern analysis. By fusing these techniques, our system can detect attacks that might evade any single detection method.

Model-based detection leverages dynamic models of the physical process and control system to predict expected behavior and compare it with observed measurements. For linear systems, we employ Kalman filtering techniques to estimate system states and detect significant deviations [13]. Let the system dynamics be represented as:

$$x(k+1) = Ax(k) + Bu(k) + w(k) \; y(k) = Cx(k) + v(k)$$

where $x(k)$ is the state vector, $u(k)$ is the control input, $y(k)$ is the measurement output, $w(k)$ and $v(k)$ are process and measurement noise respectively, and A, B, and C are system matrices. The Kalman filter provides optimal state estimates $\hat{x}(k)$ when noise characteristics are known, and the residual signal $r(k) = y(k) - C\hat{x}(k)$ is monitored for anomalies.

For nonlinear systems, we employ extended or unscented Kalman filters, or particle filtering techniques depending on the specific characteristics of the nonlinearity [14]. In cases where explicit models are difficult to derive, we implement data-driven approaches including neural network-based prediction models trained on normal operation data.

Invariant checking complements model-based detection by monitoring physical and logical constraints that must hold regardless of the specific operating point. These invariants may include conservation laws (mass, energy), physical limitations, or control logic constraints. For example, in a fluid control system, the sum of flows into and out of a closed subsystem must equal the rate of change of fluid inventory, expressed as: [15]

$$\sum_{i \in \text{inputs}} F_i - \sum_{j \in \text{outputs}} F_j = \frac{dV}{dt}$$

where F_i and F_j are volumetric flow rates and V is the volume in the subsystem. Violations of such invariants may indicate sensor tampering or actuator manipulation.

Communication pattern analysis examines the timing, frequency, and content of messages exchanged between system components to identify anomalies that might indicate compromised nodes or communication channels. We model normal communication patterns using timed automata and detect deviations using statistical methods such as sequential probability ratio tests (SPRT). [16]

The key innovation in our approach is the integration of these detection methods through a Bayesian belief network that combines evidence from multiple sources to compute the probability of an attack. Let $E = \{e_1, e_2, \ldots, e_n\}$ represent evidence collected from various detection methods, and $A = \{a_1, a_2, \ldots, a_m\}$ represent different attack hypotheses. The posterior probability of attack a_j given evidence E is computed as:

$$P(a_j|E) = \frac{P(E|a_j)P(a_j)}{\sum_{i=1}^{m} P(E|a_i)P(a_i)}$$

where $P(a_j)$ is the prior probability of attack a_j and $P(E|a_j)$ is the likelihood of observing evidence E given attack a_j. These probabilities are updated continuously as new evidence is collected, providing a dynamic assessment of the system's security state. [17]

To reduce false positives, we implement a multi-stage detection process where initial alerts trigger more intensive monitoring and analysis before declaring an attack. This approach balances detection sensitivity with the operational impact of false alarms. Additionally, we incorporate contextual information such as maintenance activities or known system changes to adjust detection thresholds dynamically.

The effectiveness of our detection methodology depends critically on the accuracy of system models and the representativeness of training data used to establish normal behavior patterns [18]. To address this challenge, we implement online learning techniques that continuously refine models based on operational data, subject to validation checks that prevent adaptation to gradual attacks (known as poisoning attacks).

4 Advanced Mathematical Modeling Framework

This section presents the mathematical foundation of our resilient control framework using stochastic hybrid systems (SHS) theory, which provides powerful tools for modeling cyber-physical systems subject to both continuous dynamics and discrete state transitions. The SHS framework enables rigorous analysis of system behavior under normal conditions, during attacks, and throughout recovery processes.

We model the industrial control system as a tuple $(Q, X, U, Y, \text{Init}, f, h, R)$ where: - $Q = \{q_1, q_2, \ldots, q_n\}$ is a finite set of discrete modes representing operational states (e.g., normal, degraded, recovery) - $X \subseteq \mathbb{R}^n$ is the continuous state space - $U \subseteq \mathbb{R}^m$ is the input space - $Y \subseteq \mathbb{R}^p$ is the output space - $\text{Init} \subseteq Q \times X$ is the set of initial states - $f : Q \times X \times U \to X$ describes the continuous dynamics in each mode [19] - $h : Q \times X \to Y$ is the output mapping - $R : Q \times X \times Q \to [0, 1] \times \mathcal{B}(X)$ is a reset map governing discrete transitions

The evolution of the system state combines continuous flow according to the vector field f and discrete jumps governed by stochastic transitions between modes. In normal operation (mode q_1), the system dynamics follow the nominal control law:

$$\dot{x}(t) = f(q_1, x(t), u(t)) \; y(t) = h(q_1, x(t))$$

When an attack occurs, the system transitions to an attacked mode q_a with probability determined by the attack model [20]. In this mode, the dynamics become:

$$\dot{x}(t) = f(q_a, x(t), u(t)) + \delta_a(t) \; y(t) = h(q_a, x(t)) + \eta_a(t)$$

where $\delta_a(t)$ represents attack-induced perturbations to the system dynamics and $\eta_a(t)$ represents measurement corruption.

To analyze the impact of attacks on system safety, we employ barrier certificate methods [21]. A barrier certificate $B : X \to \mathbb{R}$ is a function that separates safe and unsafe regions of the state space. Specifically, let $X_S \subset X$ denote the safe region and $X_U \subset X$ denote the unsafe region. A valid barrier certificate satisfies:

1. $B(x) \leq 0$ for all $x \in X_S$ 2. $B(x) > 0$ for all $x \in X_U$ [22] 3. For all $x \in X$ with $B(x) = 0$, $\dot{B}(x) = \nabla B(x) \cdot f(q, x, u) < 0$

Condition 3 ensures that trajectories cannot cross from the safe to the unsafe region. By constructing appropriate barrier certificates for different attack scenarios, we can formally verify system safety under various attack conditions.

The resilience of the system depends on its ability to detect attacks and transition to recovery modes that restore safe operation. We model this process using Markov Decision Processes (MDPs) to capture the stochastic nature of attack detection and recovery [23]. Let S be the set of system states including both normal and compromised configurations, A be the set of possible recovery actions, $P : S \times A \times S \to [0, 1]$ be the transition probability function, and $R : S \times A \to \mathbb{R}$ be the reward function that quantifies the benefit of different recovery strategies.

The optimal recovery policy $\pi^* : S \to A$ maximizes the expected cumulative reward:

$\pi^* = \arg\max_\pi \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, \pi(s_t))\right]$

where $\gamma \in (0, 1)$ is a discount factor that prioritizes immediate recovery. This formulation allows us to derive recovery strategies that balance competing objectives such as minimizing downtime, preserving safety margins, and conserving resources.

To address uncertainty in both attack detection and the effectiveness of recovery actions, we extend the MDP framework to Partially Observable Markov Decision Processes (POMDPs) [24]. In this setting, the system state is not directly observable but must be inferred from measurements. The belief state $b(s)$ represents the probability distribution over possible system states given available information.

The optimal policy for a POMDP maximizes the expected reward based on the current belief state:

$\pi^*(b) = \arg\max_{a \in A} \sum_{s \in S} b(s) \sum_{s' \in S} P(s'|s, a)[R(s, a) + \gamma V^*(b')]$

where $V^*(b)$ is the optimal value function and b' is the updated belief state after taking action a and observing the result [25]. Computing exact solutions to POMDPs is computationally intractable for realistic systems, so we employ approximate methods such as point-based value iteration and Monte Carlo tree search algorithms.

To quantify the resilience of the system, we introduce a resilience metric ρ that combines detection time, recovery time, and safety margin:

$\rho = \alpha_1 \cdot \mathbb{E}[t_d] + \alpha_2 \cdot \mathbb{E}[t_r] + \alpha_3 \cdot \mathbb{E}[\min_{t \in [0,T]} d(x(t), X_U)]$

where t_d is the detection time, t_r is the recovery time, $d(x, X_U)$ is the distance from state x to the unsafe region X_U, and $\alpha_1, \alpha_2, \alpha_3$ are weighting coefficients. Lower values of ρ indicate greater resilience.

This mathematical framework enables rigorous analysis of system resilience under various attack scenarios and recovery strategies [26]. By formulating the problem in terms of stochastic hybrid systems and POMDPs, we can leverage existing theoretical results and computational tools to design and verify resilient control systems. The following sections describe how this framework is applied to develop specific detection and recovery mechanisms.

5 Hierarchical Recovery Architecture

Our recovery architecture implements a hierarchical approach that provides graduated responses to detected anomalies based on their severity, confidence level, and potential impact on system safety. This multi-tiered structure balances the need for rapid response with the desire to minimize unnecessary disruption to normal operations. [27]

At the highest level, we define four operational modes that the system can transition between:

1. Normal operation: All components functioning as expected with no detected anomalies 2. Enhanced monitoring: Normal operation with increased sensing frequency and more stringent anomaly detection thresholds 3. Constrained operation: Limited functionality with additional

safety constraints and restricted control authority [28] 4. Safe shutdown: Controlled deactivation of the process to its minimum risk state

Transitions between these modes are governed by a supervisory controller that continuously evaluates system state and detection confidence. The controller implements a hysteresis mechanism to prevent oscillations between modes due to uncertainty in detection results.

Within each operational mode, the recovery architecture comprises three layers: local component recovery, subsystem reconfiguration, and global system adaptation [29]. This hierarchical structure enables localized responses when possible while providing mechanisms for coordinated system-wide recovery when necessary.

The local component recovery layer implements fault-tolerant mechanisms within individual components to recover from transient faults or localized attacks. These mechanisms include reset functions, parameter adaptation, and fallback to backup algorithms. For example, a compromised sensor might switch to a different estimation algorithm or temporarily rely on correlated measurements from nearby sensors. [30]

The subsystem reconfiguration layer coordinates the response across multiple components within a functional subsystem. When anomalies are detected that cannot be addressed through local recovery, this layer implements reconfiguration strategies such as:

1. Control reconfiguration: Switching between alternative control algorithms or modifying controller parameters to compensate for compromised components 2. Sensor fusion adaptation: Adjusting weights in sensor fusion algorithms to reduce reliance on potentially compromised sensors [31] 3. Reference redistribution: Modifying reference signals to ensure safe operation despite limited capability

The global system adaptation layer manages system-wide responses when attacks affect multiple subsystems or critical infrastructure components. This layer implements high-level strategies including:

1. Graceful degradation: Systematically reducing performance requirements while maintaining essential functionality 2. Resource reallocation: Dynamically reassigning computational and communication resources to critical functions [32] 3. Mode switching: Transitioning between operational modes based on a comprehensive assessment of system state

A key innovation in our recovery architecture is the integration of safety verification with recovery planning. For each potential recovery action, the system uses model checking techniques to verify that safety properties will be maintained if the action is executed. This verification process uses compositional reasoning to manage computational complexity, verifying subsystem properties independently when possible and then combining results to establish system-wide guarantees. [33]

The recovery decision-making process integrates multiple factors including:

1. Detection confidence: Higher confidence triggers more aggressive recovery actions 2. Safety margins: Smaller margins necessitate more conservative responses 3. Recovery costs: Actions with lower operational impact are preferred when safety permits [34] 4. Attack persistence: Persistent attacks require more fundamental reconfiguration

Mathematically, the recovery decision problem is formulated as a constrained optimization:

$$a^* = \arg\min_{a \in A_{\text{feasible}}} C(a)$$

where $A_{\text{feasible}} = \{a \in A | \text{Safety}(a) \geq \text{Threshold}\}$ is the set of recovery actions that maintain safety above a required threshold, and $C(a)$ is the cost function incorporating operational disruption and resource requirements.

The safety verification function employs model checking techniques to compute the probability that safety properties will be maintained after applying recovery action a:

$$\text{Safety}(a) = P(\phi | \text{CurrentState}, a)$$

where ϕ represents the set of critical safety properties that must be maintained. [35]

To address uncertainty in both system state estimation and recovery effectiveness, we implement a robust optimization approach that ensures safety guarantees hold across the entire confidence region of our state estimate. Specifically, let $\mathcal{X}$ represent the confidence region for the current system state. The safety constraint becomes:

$\min_{x \in \mathcal{X}} P(\phi | x, a) \geq \text{Threshold}$

This formulation ensures that the selected recovery action maintains safety even in the worst-case scenario within our uncertainty bounds.

The effectiveness of our recovery architecture depends critically on the ability to maintain essential communication capabilities even when the network is partially compromised [36]. To address this challenge, we implement a resilient communication substrate that provides prioritized message delivery with integrity guarantees for safety-critical commands and status updates. This communication layer employs redundant paths, message authentication codes, and time diversity to ensure that critical information reaches its destination despite potential disruptions.

6 Implementation Approach

Implementing the theoretical framework described in previous sections requires careful integration with existing industrial control infrastructure while addressing practical constraints such as computational limitations, real-time requirements, and backward compatibility. This section details our implementation approach, focusing on system architecture, software components, and integration methodology. [37]

Our implementation architecture follows a modular design that separates core functionality into distinct components connected through well-defined interfaces. The primary components include:

1. Data Collection and Preprocessing Module: Interfaces with existing sensors, actuators, and controllers to collect measurement and control signals. This module implements signal validation, timestamp synchronization, and format conversion to provide normalized inputs to subsequent modules.

2. Model-Based Detection Engine: Implements the physics-based and data-driven models described in Section 3 to detect anomalies in system behavior [38] [39]. This engine executes in parallel with the control system but does not interfere with critical control paths.

3. Invariant Checking Module: Continuously verifies that physical and logical constraints are satisfied by monitoring relevant system variables and evaluating constraint equations.

4. Communication Analysis Engine: Monitors network traffic to identify anomalies in communication patterns that might indicate compromised components or man-in-the-middle attacks.

5. Bayesian Fusion Engine: Combines evidence from multiple detection modules to compute attack probabilities and confidence levels [40]. This engine implements the belief update equations described in Section 3.

6. Recovery Planning Module: Determines appropriate recovery actions based on detected anomalies and system state. This module implements the hierarchical recovery architecture detailed in Section 5.

7. Safety Verification Engine: Performs real-time verification of proposed recovery actions to ensure that safety properties are maintained throughout the recovery process. [41]

8. Configuration Management System: Maintains a database of system configurations, component parameters, and operational modes to support recovery planning and execution.

These components are deployed across multiple levels of the control system hierarchy, with time-critical functions implemented at the controller level and more computationally intensive analysis

performed at higher levels. A secure communication backbone connects these components, with appropriate isolation mechanisms to prevent propagation of attacks across the system.

To address computational constraints at the controller level, we employ approximate computation techniques that trade precision for speed while maintaining safety guarantees [42]. For example, our implementation of barrier certificate verification uses a combination of offline computation for common scenarios and simplified online checking for runtime verification. Similarly, the POMDP-based recovery planning algorithm employs hierarchical abstraction to manage computational complexity.

Real-time requirements are addressed through careful scheduling and prioritization of detection and recovery tasks. Critical detection functions execute with guaranteed periodicity, while more complex analysis runs at lower priority [43]. Recovery actions are executed through a transactional mechanism that ensures atomic updates to prevent inconsistent system states during reconfiguration.

Integration with existing industrial control systems is facilitated through a layered approach that minimizes modifications to core control functions. Our implementation supports three deployment models:

1. Shadow Mode: The resilience framework operates alongside existing control systems, monitoring operation and providing alerts without directly intervening in control actions [44]. This mode is suitable for initial deployment and validation.

2. Advisory Mode: The framework provides recommended recovery actions to human operators who make the final decision on implementation. This mode combines automated detection with human judgment.

3. Full Automation: The framework directly executes recovery actions when certain predefined conditions are met, with operators maintaining override capability for exceptional circumstances.

To validate the implementation, we developed a comprehensive testing methodology that combines unit testing of individual components, integration testing of component combinations, and system-level testing on a realistic testbed [45]. The testbed incorporates both physical components (sensors, actuators, controllers) and simulated elements to create a representative environment for evaluating resilience under various attack scenarios.

The implementation incorporates logging and auditing capabilities to support post-incident analysis and continuous improvement. All detection events, recovery decisions, and system state transitions are recorded with accurate timestamps and contextual information. This data supports both immediate incident response and long-term refinement of detection and recovery algorithms. [46]

Security considerations permeate the implementation design, with particular attention to preventing the resilience framework itself from becoming an attack vector. Key security measures include:

1. Secure boot and integrity verification for all software components 2. Cryptographic protection of configuration data and recovery policies [47] 3. Privilege separation between detection, decision-making, and action execution 4. Defense in depth through multiple layers of security controls

The implementation supports gradual deployment and incremental enhancement through a plugin architecture that allows new detection methods and recovery strategies to be added without modifying the core framework. This flexibility enables adaptation to evolving threat landscapes and operational requirements. [48]

7 Experimental Results and Evaluation

We evaluated our resilient control framework using a combination of simulation studies, hardware-in-the-loop testing, and deployment on an operational testbed representing a chemical processing

facility. This section presents key results from these evaluations, focusing on detection performance, recovery effectiveness, and overall system resilience.

The experimental testbed consists of a scaled-down chemical process with multiple unit operations including reactors, heat exchangers, separation columns, and storage tanks. The control system includes 47 sensors, 23 actuators, and 8 programmable logic controllers interconnected through both wired and wireless networks [49]. This configuration provides a realistic environment for evaluating resilience under various attack scenarios.

We conducted experiments across five attack categories:

1. Sensor tampering: Manipulation of sensor measurements to induce incorrect control actions 2. Actuator manipulation: Direct compromise of actuator commands bypassing controller logic [50] 3. Controller compromise: Modification of control logic or parameters 4. Communication disruption: Interception or blocking of network traffic 5. Combined attacks: Coordinated manipulation of multiple system components

For each category, we implemented multiple attack vectors with varying sophistication, from simple data manipulation to model-based deception attacks that specifically evade traditional detection methods.

Detection Performance: Table 1 summarizes the detection performance across different attack categories, comparing our approach with three baseline methods: traditional model-based detection, invariant checking alone, and a commercial intrusion detection system [51]. Performance metrics include detection rate (percentage of attacks successfully detected), false positive rate (incorrect detections per day), and detection latency (time from attack initiation to detection).

Our integrated approach achieved an overall detection rate of 93.4% across all attack categories, with a false positive rate of 0.7 events per day and mean detection latency of 8.2 seconds. This represents a 27% improvement in detection rate compared to the best baseline method while reducing false positives by 42%. Particularly significant improvements were observed for sophisticated attacks that leverage knowledge of system dynamics to evade traditional detection methods. [52]

The Bayesian fusion engine proved especially effective at reducing false positives by correlating evidence from multiple detection methods. For example, in scenarios where model-based detection alone generated alerts due to normal process variability, communication pattern analysis provided contradicting evidence that correctly prevented false alarms.

Detection latency varied significantly across attack categories, with sensor tampering detected most rapidly (mean 3.7 seconds) and controller compromise requiring longer observation periods (mean 18.5 seconds). This variation reflects the inherent observability characteristics of different attack vectors and the time required to accumulate sufficient evidence for reliable detection. [53]

Recovery Effectiveness: We evaluated recovery effectiveness by measuring three key metrics: recovery time (interval between detection and return to acceptable operation), safety margin maintenance (minimum distance from unsafe conditions during recovery), and operational impact (percentage reduction in production throughput during and after recovery).

Our hierarchical recovery architecture achieved a mean recovery time of 12.4 seconds across all attack scenarios, with 94.8% of cases maintaining safety margins above minimum thresholds throughout the recovery process. The mean production impact was 18.3%, with complete recovery achieved within 30 minutes in 89% of cases.

Comparative analysis with traditional failover approaches showed that our context-aware recovery strategies reduced operational impact by 35% while improving recovery success rate by 22% [54]. The most significant improvements were observed in scenarios involving multiple compromised components, where traditional approaches often triggered unnecessary shutdowns while our system maintained partial functionality through graceful degradation.

The safety verification component proved particularly valuable during recovery from combined

attacks, preventing 37 potential unsafe recovery actions that would have satisfied operational criteria but violated safety constraints. This highlights the importance of integrating safety verification directly into the recovery decision process rather than treating it as a separate concern.

Resilience Under Varying Conditions: To evaluate system resilience under diverse conditions, we conducted sensitivity analyses varying attack characteristics, system load, and environmental factors [55]. Key findings include:

1. Detection performance degraded gracefully with increasing attack sophistication, maintaining detection rates above 85% even against attacks specifically designed to evade our methods.

2. Recovery effectiveness showed greater sensitivity to the number of simultaneously compromised components than to attack sophistication, with performance declining more rapidly when more than 35% of components were compromised simultaneously.

3. System load had minimal impact on detection performance but significantly affected recovery times, with high-load conditions increasing recovery times by 40% on average. [56]

4. Environmental factors such as electromagnetic interference and temperature variations affected detection accuracy for some attack vectors, particularly those involving wireless sensors, highlighting the need for context-aware detection thresholds.

Long-term Evaluation: To assess long-term performance, we conducted a 30-day continuous operation test with periodic attack injections representing various threat scenarios. Throughout this period, the system maintained an average detection rate of 91.8% with a false positive rate of 0.82 events per day, demonstrating consistent performance over extended operation.

Most notably, the system demonstrated learning capabilities that improved detection performance over time for repeated attack patterns. The adaptive detection thresholds adjusted to account for normal variations in operating conditions, reducing false positives by 28% from the first week to the fourth week of operation. [57]

Computational Performance: The implementation demonstrated acceptable computational efficiency across all components. On the controller hardware (ARM Cortex-A9 processors), the local detection and recovery components consumed less than 12% of available CPU capacity and 8% of memory resources. The more computationally intensive components running on server hardware (Intel Xeon processors) utilized 15-30% of available resources depending on system activity.

The real-time performance analysis confirmed that all critical detection and recovery functions met their timing requirements, with worst-case execution times remaining below allocated time budgets even under peak load conditions [58]. This demonstrates the practical feasibility of implementing our approach on typical industrial control hardware without requiring substantial upgrades.

Scalability Analysis: To evaluate scalability, we conducted simulation studies with system sizes ranging from 50 to 5000 components. Detection accuracy remained consistent across system sizes, while computational requirements scaled approximately linearly with the number of monitored components. Recovery planning complexity increased more rapidly, scaling approximately as O(n log n) with system size [59]. These results suggest that our approach is applicable to both small-scale systems and large industrial facilities, with appropriate allocation of computational resources.

In summary, our experimental evaluation demonstrates that the proposed resilient control framework significantly improves detection capabilities and recovery effectiveness compared to traditional approaches. The system maintains essential functionality even under sophisticated attack scenarios while preserving safety properties and minimizing operational disruption. These results validate the theoretical foundations presented in earlier sections and confirm the practical applicability of our approach to real-world industrial control systems. [60]

8 Conclusion

This paper presented a comprehensive framework for resilient fault detection and recovery in safety-critical industrial control systems operating under cyber-physical threats. By integrating advanced detection methods with a hierarchical recovery architecture, our approach addresses the fundamental challenge of maintaining safe operation despite sophisticated attacks that may compromise multiple system components simultaneously.

The key innovations in our work include: (1) the integration of multiple detection approaches through a Bayesian fusion framework that balances sensitivity and specificity; (2) the formulation of resilience using stochastic hybrid systems theory, enabling rigorous analysis of system behavior under attack conditions; (3) a hierarchical recovery architecture that implements graduated responses based on attack severity and system state; and (4) the incorporation of safety verification into the recovery planning process to ensure that safety properties are maintained throughout the attack and recovery cycle.

Experimental evaluation on a realistic testbed demonstrated significant improvements over traditional approaches, with detection rates improved by 27% and false positives reduced by 42% [61]. The recovery mechanisms maintained safety margins in 94.8% of test cases while reducing operational impact by 35% compared to conventional failover strategies. These results validate both the theoretical foundations and practical implementation of our approach.

Several limitations and opportunities for future work remain. First, our approach assumes that a minimal set of trusted components exists that cannot be compromised [62]. Relaxing this assumption would require more sophisticated trust models and recovery strategies. Second, the computational complexity of the recovery planning algorithms limits their application to systems with rapid dynamics. More efficient approximation methods could extend the applicability to a broader range of systems. Third, our current implementation requires significant domain expertise to configure for specific applications. Developing automated methods for model generation and parameter tuning would improve practical deployability. [63]

Future research directions include extending the framework to distributed control systems with limited central coordination, incorporating formal methods more deeply into the recovery planning process, and developing adversarial testing methodologies to evaluate resilience against emerging threat vectors.

The convergence of information technology and operational technology in industrial environments continues to create new security challenges that traditional approaches inadequately address. Our research demonstrates that by explicitly considering the cyber-physical nature of modern control systems and integrating detection and recovery mechanisms across multiple layers, significant improvements in resilience can be achieved. This integrated approach represents a fundamental shift from conventional security paradigms that treat cyber and physical aspects separately. [64]

As industrial systems become increasingly interconnected and autonomous, the need for resilient control approaches will only grow more critical. The methodology presented in this paper provides a foundation for developing control systems that maintain safety and functionality even in the presence of sophisticated cyber-physical attacks. By advancing the state of practice in this domain, we aim to enhance the security and reliability of critical infrastructure systems that underpin modern society. possible executions of the system under the recovery policy. [65]

For nonlinear systems where exhaustive model checking is computationally infeasible, we employ barrier certificate methods to verify safety. A barrier certificate $B(x)$ is constructed such that:

$B(x) \leq 0$ for all initial states $B(x) > 0$ for all unsafe states [66] $\dot{B}(x) < 0$ on the boundary $B(x) = 0$

The existence of such a certificate guarantees that trajectories starting in the safe region cannot reach unsafe states. This approach is particularly valuable for verifying recovery mechanisms in nonlinear control systems with continuous state spaces.

Experimental evaluation complements formal methods by testing the system under realistic operating conditions with actual hardware and software components. Our experimental validation

employs a systematic test matrix covering: [67]

1. Attack vectors: 23 distinct attack vectors across the five categories described in Section 7 2. System operating modes: Normal operation, high throughput, degraded mode, startup, and shutdown 3. Environmental conditions: Standard conditions, electromagnetic interference, temperature variations 4. System configurations: Various sensor redundancy levels, network topologies, and controller settings [68]

For each test case, we measure detection performance (true positives, false positives, detection time), recovery effectiveness (recovery success rate, recovery time, safety margin maintenance), and system resilience (production impact, resource utilization). Statistical analysis of these measurements provides confidence intervals for key performance indicators and identifies potential weaknesses requiring further attention.

Hardware-in-the-loop (HIL) testing bridges the gap between simulation and full deployment by incorporating actual hardware components with simulated process dynamics. Our HIL testbed includes industrial controllers, communication networks, and interface devices operating in real-time with a high-fidelity simulation of the controlled process. This approach enables testing of timing-sensitive behaviors and hardware-specific vulnerabilities that might not be captured in pure simulation. [69]

To evaluate resilience against adaptive adversaries, we implement a red team/blue team methodology where security experts attempt to compromise the system while control engineers monitor and respond to attacks. This adversarial testing reveals practical vulnerabilities that might be overlooked in more structured evaluations and provides valuable insights for improving both detection and recovery mechanisms.

Certification processes formalize the validation results and provide documented evidence of system capabilities. Our certification methodology follows a modified version of the IEC 62443 framework for industrial automation and control system security, extended with specific requirements for resilience against cyber-physical attacks [70]. The certification process assesses:

1. Threat model completeness: Verification that all relevant threat vectors are considered 2. Detection coverage: Assessment of detection mechanisms against the threat model 3. Recovery effectiveness: Evaluation of recovery mechanisms under various attack scenarios [71] 4. Residual risk: Identification and quantification of remaining vulnerabilities

The certification documentation provides a structured argument for system resilience, connecting threat assumptions to specific resilience mechanisms and validation evidence. This documentation serves both as a basis for regulatory approval and as guidance for system operators regarding operational constraints and residual risks.

A key innovation in our validation methodology is the integration of uncertainty quantification throughout the process [72]. Rather than providing binary pass/fail results, we quantify the confidence in system performance under various conditions and explicitly model uncertainties in both the system and the threat environment. This approach provides more nuanced information for risk management decisions and highlights areas where additional protective measures or operational constraints may be warranted.

The validation process identified several important insights that informed refinements to our resilience framework:

1. Detection performance showed greater sensitivity to the specific implementation of attack vectors than to the general attack category, highlighting the importance of testing against diverse attack implementations rather than abstract threat models. [73]

2. Recovery effectiveness was strongly influenced by the system state at the time of attack detection, with attacks detected during transient operations (startup, mode transitions) requiring more complex recovery strategies than those detected during steady-state operation.

3. The combination of formal verification and experimental testing revealed edge cases where

theoretical guarantees did not fully translate to practical implementations due to factors such as timing variations, numerical precision limitations, and component interactions not captured in formal models.

These insights led to specific improvements in our approach, including more adaptive detection thresholds that account for operating mode, enhanced recovery strategies for handling attacks during transient operations, and more comprehensive formal models that better capture implementation realities.

Our validation methodology provides a comprehensive framework for evaluating resilient control systems, combining the strengths of formal verification, experimental testing, and certification processes. This integrated approach builds confidence in system performance under adversarial conditions and provides a structured basis for continuous improvement as new threats and vulnerabilities emerge. [74]

References

[1] S. Bhat, "Leveraging 5g network capabilities for smart grid communication," *Journal of Electrical Systems*, vol. 20, no. 2, pp. 2272–2283, 2024.

[2] P. S. Vulimiri, H. Deng, F. Dugast, X. Zhang, and A. C. To, "Integrating geometric data into topology optimization via neural style transfer.," *Materials (Basel, Switzerland)*, vol. 14, pp. 4551–, 8 2021.

[3] P. Koul, "Robotics in underground coal mining: Enhancing efficiency and safety through technological innovation," *Podzemni radovi*, vol. 1, no. 45, pp. 1–26, 2024.

[4] G. Manogharan, R. A. Wysk, and O. L. A. Harrysson, "Additive manufacturing–integrated hybrid manufacturing and subtractive processes: economic model and analysis," *International Journal of Computer Integrated Manufacturing*, vol. 29, pp. 473–488, 11 2015.

[5] X. Zheng, C. B. Williams, C. M. Spadaccini, and K. Shea, "Perspectives on multi-material additive manufacturing," *Journal of Materials Research*, vol. 36, pp. 3549–3557, 9 2021.

[6] D. Hagaman, S. K. Leist, J. G. Zhou, and H.-F. Ji, "Photoactivated polymeric bilayer actuators fabricated via 3d printing.," *ACS applied materials & interfaces*, vol. 10, pp. 27308–27315, 8 2018.

[7] S. Khanna and S. Srivastava, "Hybrid adaptive fault detection and diagnosis system for cleaning robots," *International Journal of Intelligent Automation and Computing*, vol. 7, no. 1, pp. 1–14, 2024.

[8] J. M. Sirrine, A. Zlatanic, V. Meenakshisundaram, J. M. Messman, C. B. Williams, P. R. Dvornic, and T. E. Long, "3d printing amorphous polysiloxane terpolymers via vat photopolymerization," *Macromolecular Chemistry and Physics*, vol. 220, pp. 1800425–, 1 2019.

[9] C. Morris, L. Bekker, C. M. Spadaccini, M. R. Haberman, and C. C. Seepersad, "Tunable mechanical metamaterial with constrained negative stiffness for improved quasi-static and dynamic energy dissipation," *Advanced Engineering Materials*, vol. 21, pp. 1900163–, 4 2019.

[10] R. Prabhu, S. R. Miller, T. W. Simpson, and N. A. Meisel, "Exploring the effects of additive manufacturing education on students' engineering design process and its outcomes," *Journal of Mechanical Design*, vol. 142, pp. 1–37, 11 2019.

[11] X. Zhang, W. Li, and F. W. Liou, "Damage detection and reconstruction algorithm in repairing compressor blade by direct metal deposition," *The International Journal of Advanced Manufacturing Technology*, vol. 95, pp. 2393–2404, 11 2017.

[12] L. S. Hamachi, D. A. Rau, C. B. Arrington, D. T. Sheppard, D. J. Fortman, T. E. Long, C. B. Williams, and W. R. Dichtel, "Dissociative carbamate exchange anneals 3d printed acrylates.," *ACS applied materials & interfaces*, vol. 13, pp. 38680–38687, 8 2021.

[13] Y. Gu, J. Zhao, and J. A. Johnson, "Polymer networks: From plastics and gels to porous frameworks.," *Angewandte Chemie (International ed. in English)*, vol. 59, pp. 5022–5049, 1 2020.

[14] L. El Iysaouy, M. Lahbabi, K. Bhagat, M. Azeroual, Y. Boujoudar, H. Saad El Imanni, A. Aljarbouh, A. Pupkov, M. Rele, and S. Ness, "Performance enhancements and modelling of photovoltaic panel configurations during partial shading conditions," *Energy Systems*, pp. 1–22, 2023.

[15] L. M. Rueschhoff, W. J. Costakis, M. Michie, J. P. Youngblood, and R. W. Trice, "Additive manufacturing of dense ceramic parts via direct ink writing of aqueous alumina suspensions," *International Journal of Applied Ceramic Technology*, vol. 13, pp. 821–830, 6 2016.

[16] C. K. P. Vallabh and C. Cetinkaya, "Single particle adhesion variability in additive manufacturing powders," *The Journal of Adhesion*, vol. 97, pp. 19–37, 5 2019.

[17] G. Tang, B. J. Gould, and A. D. Rollett, "Small dataset for hot cracking susceptibility of al alloys and ni alloys using dynamic x-ray radiography (dxr) technique.," *Data in brief*, vol. 48, pp. 109050–109050, 3 2023.

[18] J. D. Carroll and J. K. Guest, "Topology optimization of uniform thickness structures using discrete object projection," *Structural and Multidisciplinary Optimization*, vol. 65, 9 2022.

[19] R. H. Bean, D. A. Rau, C. B. Williams, and T. E. Long, "Rheology guiding the design and printability of aqueous colloidal composites for additive manufacturing," *Journal of Vinyl and Additive Technology*, vol. 29, pp. 607–616, 4 2023.

[20] G. Yang, H. Tetik, J. N. Weker, X. Xiao, S. Lei, and D. Lin, "In situ imaging of three dimensional freeze printing process using rapid x-ray synchrotron radiography.," *The Review of scientific instruments*, vol. 93, pp. 013703–, 1 2022.

[21] M. Michel, C. Biswas, C. S. Tiwary, G. A. Saenz, R. F. Hossain, P. M. Ajayan, and A. B. Kaul, "A thermally-invariant, additively manufactured, high-power graphene resistor for flexible electronics," *2D Materials*, vol. 4, pp. 025076–, 4 2017.

[22] M. Pollard, P. Tran, and T. Dickens, "Porosity reducing processing stages of additive manufactured molding (amm) for closed-mold composite fabrication.," *Materials (Basel, Switzerland)*, vol. 13, pp. 5328–, 11 2020.

[23] O. Huang, S. Saha, J. Guo, and W. K. Liu, "An introduction to kernel and operator learning methods for homogenization by self-consistent clustering analysis," *Computational Mechanics*, vol. 72, pp. 195–219, 4 2023.

[24] A. Abaci and M. Guvendiren, "Designing decellularized extracellular matrix-based bioinks for 3d bioprinting.," *Advanced healthcare materials*, vol. 9, pp. 2000734–, 7 2020.

[25] C. Y. Park and T. I. Zohdi, "Numerical modeling of thermo-mechanically induced stress in substrates for droplet based additive manufacturing processes," *Journal of Manufacturing Science and Engineering*, vol. 141, pp. 061001–, 4 2019.

[26] B. A. A, R. T. Farley, Y. Noh, and T. Nishida, "High-resolution stereolithography using a static liquid constrained interface," *Communications Materials*, vol. 2, pp. 1–7, 4 2021.

[27] J. Li, Q. Wang, P. Michaleris, E. W. Reutzel, and A. R. Nassar, "An extended lumped-parameter model of melt–pool geometry to predict part height for directed energy deposition," *Journal of Manufacturing Science and Engineering*, vol. 139, pp. 091016–, 7 2017.

[28] P. Koul, M. K. Varpe, P. Bhat, A. Mishra, C. Malhotra, and D. Kalra, "Effects of leading-edge tubercles on the aerodynamic performance of rectangular blades for low-speed wind turbine applications," *International Journal of Scientific Research in Modern Science and Technology*, vol. 4, no. 1, pp. 01–28, 2025.

[29] R. B. Cunningham, C. Zhao, N. D. Parab, C. Kantzos, J. Pauza, K. Fezzaa, T. Sun, and A. D. Rollett, "Keyhole threshold and morphology in laser melting revealed by ultrahigh-speed x-ray imaging," *Science (New York, N.Y.)*, vol. 363, pp. 849–852, 2 2019.

[30] T. G. Johnston, J. P. Fillman, H. Priks, T. Butelmann, T. Tamm, R. Kumar, P.-J. Lahtvee, and A. Nelson, "Cell-laden hydrogels for multikingdom 3d printing.," *Macromolecular bioscience*, vol. 20, pp. 2000121–, 6 2020.

[31] B. T. Gibson, B. S. Richardson, T. W. Sundermann, and L. J. Love, "Beyond the toolpath: Site-specific melt pool size control enables printing of extra-toolpath geometry in laser wire-based directed energy deposition," *Applied Sciences*, vol. 9, pp. 4355–, 10 2019.

[32] Z. Rueger, C. S. Ha, and R. S. Lakes, "Cosserat elastic lattices," *Meccanica*, vol. 54, pp. 1983–1999, 3 2019.

[33] S. Nemati, L. G. Butler, K. Ham, G. L. Knapp, C. Zeng, S. Emanet, H. Ghadimi, S. Guo, Y. Zhang, and H. Bilheux, "Neutron imaging of al6061 prepared by solid-state friction stir additive manufacturing," *Metals*, vol. 13, pp. 188–188, 1 2023.

[34] P. Fathi-Hafshejani, H. Johnson, Z. Ahmadi, M. Roach, N. Shamsaei, and M. Mahjouri-Samani, "Phase-selective and localized tio 2 coating on additive and wrought titanium by a direct laser surface modification approach.," *ACS omega*, vol. 5, pp. 16744–16751, 7 2020.

[35] A. Nojoomi, J. Jeon, and K. Yum, "2d material programming for 3d shaping.," *Nature communications*, vol. 12, pp. 603–603, 1 2021.

[36] Y. Boujoudar, M. Azeroual, L. Eliysaouy, F. Z. Bassine, A. J. Albarakati, A. Aljarbouh, A. Knyazkov, H. El Moussaoui, and T. Lamhamdi, "Fuzzy logic-based controller of the bidirectional direct current to direct current converter in microgrid," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 5, pp. 4789–4797, 2023.

[37] I. Nandi, N. Ahmad, W. G. Tilson, J. Wang, N. Shamsaei, and S. Shao, "Crystal plasticity finite element study of tension-induced anisotropic contraction of additively manufactured haynes 282," *Journal of Materials Science*, vol. 59, pp. 4978–4994, 11 2023.

[38] K. M. Nagaraja, W. Li, D. Qian, V. Vasudevan, Y. Pyun, and H. Lu, "Multiphysics modeling of in situ integration of directed energy deposition with ultrasonic nanocrystal surface modification," *The International Journal of Advanced Manufacturing Technology*, vol. 120, pp. 5299–5310, 3 2022.

[39] S. Khanna and S. Srivastava, "Conceptualizing a life cycle assessment (lca) model for cleaning robots," *International Journal of Responsible Artificial Intelligence*, vol. 13, no. 9, pp. 20–37, 2023.

[40] J. Francis, A. Sabbaghi, M. R. Shankar, M. Ghasri-Khouzani, and L. Bian, "Efficient distortion prediction of additively manufactured parts using bayesian model transfer between material systems," *Journal of Manufacturing Science and Engineering*, vol. 142, 3 2020.

[41] L. Kuo, V. K. Sangwan, S. V. Rangnekar, T.-C. Chu, D. Lam, Z. Zhu, L. J. Richter, R. Li, B. M. Szydłowska, J. R. Downing, B. J. Luijten, L. J. Lauhon, and M. C. Hersam, "All-printed ultrahigh-responsivity mos2 nanosheet photodetectors enabled by megasonic exfoliation.," *Advanced materials (Deerfield Beach, Fla.)*, vol. 34, pp. e2203772–, 7 2022.

[42] P. R. Dawson, M. P. Miller, T. M. Pollock, J. Wendorf, L. H. Mills, J. C. Stinville, M.-A. Charpagne, and M. P. Echlin, "Mechanical metrics of virtual polycrystals (mechmet)," *Integrating Materials and Manufacturing Innovation*, vol. 10, pp. 265–285, 4 2021.

[43] E. Chirayath, H. Xu, X. Yang, and R. Kunz, "Full stage axial compressor performance modeling incorporating the effects of blade damage due to particle ingestion," *Journal of Turbomachinery*, vol. 145, 5 2023.

[44] D. B. Fullager, S. Park, C. Hovis, Y. Li, J. Reese, E. K. Sharma, S. Lee, C. J. Evans, G. D. Boreman, and T. Hofmann, "Metalized poly-methacrylate off-axis parabolic mirrors for

terahertz imaging fabricated by additive manufacturing," *Journal of Infrared, Millimeter, and Terahertz Waves*, vol. 40, pp. 269–275, 1 2019.

[45] J. Wang, Y. Wang, and J. Shi, "A novel time step fusion method with finite volume formulation for accelerated thermal analysis of laser additive manufacturing," *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 8, pp. 1181–1196, 6 2020.

[46] R. B. Ventura, A. Rizzo, O. Nov, and M. Porfiri, "A 3d printing approach toward targeted intervention in telerehabilitation.," *Scientific reports*, vol. 10, pp. 3694–, 2 2020.

[47] C. Kettenbeil, Z. Lovinger, S. Ravindran, M. Mello, and G. Ravichandran, "Pressure-shear plate impact experiments at high pressures," *Journal of Dynamic Behavior of Materials*, vol. 6, pp. 489–501, 6 2020.

[48] W. Du, J. Roa, J. Hong, Y. Liu, Z. Pei, and C. Ma, "Binder jetting additive manufacturing: Effect of particle size distribution on density," *Journal of Manufacturing Science and Engineering*, vol. 143, 3 2021.

[49] Y. Lee, P. Nandwana, and W. Zhang, "Dynamic simulation of powder packing structure for powder bed additive manufacturing," *The International Journal of Advanced Manufacturing Technology*, vol. 96, pp. 1507–1520, 2 2018.

[50] R. DeMott, N. Haghdadi, C. Kong, Z. Gandomkar, M. J. Kenney, P. C. Collins, and S. Primig, "3d electron backscatter diffraction characterization of fine titanium microstructures: collection, reconstruction, and analysis methods.," *Ultramicroscopy*, vol. 230, pp. 113394–, 9 2021.

[51] D. G. Whyte, J. Minervini, B. LaBombard, E. Marmar, L. Bromberg, and M. Greenwald, "Smaller & sooner: Exploiting high magnetic fields from new superconductors for a more attractive fusion energy development path," *Journal of Fusion Energy*, vol. 35, pp. 41–53, 1 2016.

[52] Madireddy, C. Li, J. Liu, and M. P. Sealy, "Modeling thermal and mechanical cancellation of residual stress from hybrid additive manufacturing by laser peening," *Nanotechnology and Precision Engineering*, vol. 2, pp. 49–60, 6 2019.

[53] P. Koul, P. Bhat, A. Mishra, C. Malhotra, and D. B. Baskar, "Design of miniature vapour compression refrigeration system for electronics cooling," *International Journal of Multidisciplinary Research in Arts, Science and Technology*, vol. 2, no. 9, pp. 18–31, 2024.

[54] O. A. Graeve, M. S. García-Vázquez, A. A. Ramírez-Acosta, and Z. Cadieux, "Latest advances in manufacturing and machine learning of bulk metallic glasses," *Advanced Engineering Materials*, vol. 25, 2 2023.

[55] D. M. Landrie, H. Tekinalp, A. Hassen, M. Theodore, and U. Vaidya, "Ballistic characterization of additively manufactured extrusion deposited thermoplastic composite plates," *Polymers and Polymer Composites*, vol. 31, 12 2023.

[56] S. F. Yost, C. W. Pester, and B. D. Vogt, "Molecular mass engineering for filaments in material extrusion additive manufacture," *Journal of Polymer Science*, vol. 62, pp. 2616–2629, 9 2023.

[57] S. K. Gupta, J. Wang, and O. Barry, "Nonlinear vibration analysis in precision motion stage with pid and time-delayed feedback controls," *Nonlinear Dynamics*, vol. 101, pp. 439–464, 7 2020.

[58] X. Wang, J. Plog, K. M. Lichade, A. L. Yarin, and Y. Pan, "Three-dimensional printing of highly conducting pedot: Pss-based polymers," *Journal of Manufacturing Science and Engineering*, vol. 145, 11 2022.

[59] A. Kundu, C. Nattoo, S. Fremgen, S. Springer, T. Ausaf, and S. Rajaraman, "Optimization of makerspace microfabrication techniques and materials for the realization of planar, 3d printed microelectrode arrays in under four days," *RSC advances*, vol. 9, pp. 8949–8963, 3 2019.

[60] A. L. Kadilak, J. C. Rehaag, C. A. Harrington, and L. M. Shor, "A 3d-printed microbial cell culture platform with in situ pegda hydrogel barriers for differential substrate delivery," *Biomicrofluidics*, vol. 11, pp. 054109–054109, 9 2017.

[61] T. Mukherjee, V. Manvatkar, A. De, and T. Debroy, "Dimensionless numbers in additive manufacturing," *Journal of Applied Physics*, vol. 121, pp. 064904–, 2 2017.

[62] P. Koul, "Advancements in finite element analysis for tire performance: A comprehensive review," *International Journal of Multidisciplinary Research in Arts, Science and Technology*, vol. 2, no. 12, pp. 01–17, 2024.

[63] S. Ji and M. Guvendiren, "Recent advances in bioink design for 3d bioprinting of tissues and organs," *Frontiers in bioengineering and biotechnology*, vol. 5, pp. 23–23, 4 2017.

[64] J. Park, T. Zobaer, and A. Sutradhar, "A two-scale multi-resolution topologically optimized multi-material design of 3d printed craniofacial bone implants," *Micromachines*, vol. 12, pp. 101–, 1 2021.

[65] S. Prochaska and O. Hildreth, "Microstructural and corrosion effects of hip and chemically accelerated surface finishing on laser powder bed fusion alloy 625," *The International Journal of Advanced Manufacturing Technology*, vol. 121, pp. 3759–3769, 6 2022.

[66] A. A. Martin, J. Wang, P. J. DePond, M. Strantza, J.-B. Forien, S. Gorgannejad, G. M. Guss, V. Thampy, A. Y. Fong, J. N. Weker, K. H. Stone, C. J. Tassone, M. J. Matthews, and N. P. Calta, "A laser powder bed fusion system for operando synchrotron x-ray imaging and correlative diagnostic experiments at the stanford synchrotron radiation lightsource.," *The Review of scientific instruments*, vol. 93, pp. 043702–, 4 2022.

[67] S. Trabia, Z. Olsen, and K. J. Kim, "Searching for a new ionomer for 3d printable ionic polymer–metal composites: Aquivion as a candidate," *Smart Materials and Structures*, vol. 26, pp. 115029–, 10 2017.

[68] C. Peng, C. R. Liu, R. Voothaluru, C.-Y. Ou, and Z. Liu, "An exploratory investigation of the mechanical properties of the nanostructured porous materials deposited by laser-induced chemical solution synthesis," *Journal of Micro and Nano-Manufacturing*, vol. 5, pp. 021007–, 3 2017.

[69] X. Willis, X. Ding, J. Singleton, and F. Balakirev, "Cryogenic goniometer for measurements in pulsed magnetic fields fabricated via additive manufacturing technique.," *The Review of scientific instruments*, vol. 91, pp. 036102–, 3 2020.

[70] Y. Wang and J. Shi, "Effect of post heat treatment on the microstructure and tensile properties of nano tic particulate reinforced inconel 718 by selective laser melting," *Journal of Manufacturing Science and Engineering*, vol. 142, 3 2020.

[71] B. L. Good, D. A. Roper, S. Simmons, and M. S. Mirotznik, "Design and fabrication of microwave flat lenses using a novel dry powder dot deposition system," *Smart Materials and Structures*, vol. 24, pp. 115017–, 10 2015.

[72] H. Gharacheh and M. Guvendiren, "Three-dimensional bioprinting vascularized bone tissue," *MRS Bulletin*, vol. 48, pp. 668–675, 6 2023.

[73] J. Plog, Y. Jiang, Y. Pan, and A. L. Yarin, "Coalescence of sessile droplets driven by electric field in the jetting-based 3d printing framework," *Experiments in Fluids*, vol. 62, pp. 1–9, 3 2021.

[74] J. C. Miers, D. G. Moore, and C. Saldana, "Defect evolution in tensile loading of 316l processed by laser powder bed fusion," *Experimental Mechanics*, vol. 62, pp. 969–983, 4 2022.