Fatorachian *et al. Complex Eng Syst* 2024;4:17
DOI: 10.20517/ces.2024.35

Complex Engineering Systems

Review

Open Access

AI-enhanced fault-tolerant control and security in transportation and logistics systems: addressing physical and cyber threats

Hajar Fatorachian, Hadi Kazemi

Leeds Business School, Leeds Beckett University, Leeds LS1 3HB, UK.

Correspondence to: Dr. Hajar Fatorachian, Leeds Business School, Leeds Beckett University, Portland Crescent, Leeds LS1 3HB, UK. E-mail: h.fatorachian@leedsbeckett.ac.uk

How to cite this article: Fatorachian H, Kazemi H. AI-enhanced fault-tolerant control and security in transportation and logistics systems: addressing physical and cyber threats. *Complex Eng Syst* 2024;4:17. https://dx.doi.org/10.20517/ces.2024.35

Received: 19 Jun 2024 **First Decision:** 16 Aug 2024 **Revised:** 22 Aug 2024 **Accepted:** 6 Sep 2024 **Published:** 30 Sep 2024

Academic Editor: Hamid Reza Karimi **Copy Editor:** Fangling Lan **Production Editor:** Fangling Lan

Abstract

Transportation and logistics systems are becoming increasingly complex and critical to modern infrastructure. This paper proposes a novel AI-enhanced fault-tolerant control framework to address the dual challenges of physical malfunctions and cyber threats. By leveraging advanced machine learning algorithms and real-time data analytics, the proposed methodology aims to enhance the reliability, safety, and security of transportation and logistics systems. This research explores the foundations and practical implementations of AI-driven anomaly detection, predictive maintenance, and autonomous response systems. The findings demonstrate significant improvements in system resilience and robustness, making a substantial contribution to the field of intelligent transportation management.

Keywords: AI-enabled supply chain, predictive maintenance, cybersecurity in logistics, anomaly detection, fault-tolerant control

1. INTRODUCTION

Transportation and logistics systems are essential components of modern infrastructure, enabling the efficient movement of goods and people, which in turn supports economic growth and stability. These systems encompass a vast array of elements, including road networks, railways, ports, airports, and the

underlying logistics networks that manage the flow of products from origin to destination. Each of these components plays a crucial role in ensuring that the global economy functions smoothly. The interconnection and interdependence of these systems mean that a disruption in one part can have significant ripple effects throughout the entire network[1,2].

As transportation and logistics systems become more interconnected and reliant on digital technologies, they face increasing challenges related to complexity, reliability, and security. Deloitte Insights (2024) highlights that the digital transformation of these systems introduces new layers of complexity, making them more efficient but also more vulnerable to disruptions[3]. For instance, the use of Internet of Things (IoT) devices for real-time tracking and autonomous vehicles for delivery has revolutionized logistics but also introduced potential points of failure and security vulnerabilities[4,5]. The dynamic nature of modern transportation networks requires sophisticated control and management techniques that can adapt to changing conditions and emerging threats, as noted by McKinsey & Company (2024) and PwC (2024)[6,7].

The global logistics and transportation sector is a critical enabler of international trade and economic development. The seamless movement of goods across borders is essential for the functioning of global supply chains. However, the increasing complexity of these systems, driven by globalization and technological advancements, has created new challenges. Traditional systems, designed for less dynamic and interconnected environments, are becoming insufficient. They struggle to handle the intricacies of modern transportation networks, where the failure of a single component can lead to significant delays and economic losses[8].

1.1. Gap in knowledge

The significance of transportation and logistics systems in the global economy cannot be overstated. They are integral to international trade, allowing countries to exchange goods and services efficiently. However, the sector is increasingly vulnerable to both physical malfunctions and cyber threats due to its complexity and reliance on interconnected systems. The physical components, such as vehicles and infrastructure, can suffer from wear and tear, leading to malfunctions. Simultaneously, the digital components, such as control systems and communication networks, are susceptible to cyber attacks.

Traditional fault-tolerant control methods are often inadequate for handling the sophisticated nature of these threats. These methods typically involve redundancy and fail-safes that are effective against certain types of physical failures but do not address the complexities introduced by modern digital technologies[9]. Traditional fault-tolerant control approaches rely heavily on redundancy and fail-safes, which are effective to a certain extent but have notable limitations. These methods often fail to address the complexities introduced by modern digital technologies, particularly in detecting and mitigating cyber threats[10]. For instance, redundancy may ensure that a system continues to operate despite a physical fault, but it does not account for cyber vulnerabilities that could be exploited simultaneously[9]. In contrast, the proposed AI-enhanced framework integrates machine learning algorithms that provide real-time anomaly detection and predictive maintenance, which are critical in identifying both physical faults and cyber threats before they escalate[11]. This proactive approach not only improves system resilience but also ensures a higher level of security and reliability compared to traditional methods.

Cyber threats, in particular, pose a new kind of challenge that traditional methods are not equipped to handle. Cyber attacks can disrupt operations, steal sensitive information, and cause widespread damage before they are detected and mitigated.

Current research lacks comprehensive solutions that integrate advanced AI technologies to enhance fault tolerance and cybersecurity simultaneously. While there have been significant advancements in both areas individually, few studies have explored how they can be combined to provide a more robust and resilient framework. This study aims to fill this gap by proposing an AI-enhanced framework that addresses these dual challenges. By leveraging AI, the framework can improve the detection of anomalies, predict potential failures, and respond to cyber threats more effectively, ensuring the integrity and functionality of transportation and logistics systems[12].

The gap in current research is evident in the fragmented approach to addressing physical and cyber threats. Most studies focus on either fault-tolerant control or cybersecurity, but rarely integrate both. This paper aims to bridge this gap by providing a comprehensive framework that leverages AI to enhance both fault tolerance and security in transportation systems. By integrating these aspects, the proposed framework intends to create a more resilient system capable of withstanding and quickly recovering from a variety of threats and disruptions[13].

This research is significant because it addresses a critical need in the field of transportation and logistics. The increasing complexity and interdependence of these systems mean that traditional methods are no longer sufficient. An integrated approach that combines advanced AI technologies with fault-tolerant control and cybersecurity measures is essential for ensuring the continued reliability and security of these systems. By filling this gap in knowledge, the study contributes to the development of more robust and resilient transportation and logistics systems, which are vital for the global economy.

1.2. Research objectives

The primary aim of this paper is to perform a systematic literature review (SLR) to develop a theoretical framework for AI-enhanced fault-tolerant control transportation and logistics systems, effectively addressing both physical and cyber threats. The specific research objectives are:

• To examine advanced machine learning algorithms and AI-driven predictive maintenance models for real-time anomaly detection and failure forecasting in transportation and logistics systems.

• To explore AI-based cybersecurity protocols and adaptive control strategies for safeguarding against physical malfunctions and cyber threats, while dynamically adjusting system parameters in response to these challenges.

• To create a theoretical fault-tolerant control framework by integrating insights from complex systems theory, Cyber-physical systems (CPS), and interdisciplinary methodologies, aimed at enhancing the resilience, reliability, and security of transportation and logistics networks.

By achieving these objectives, the research seeks to contribute to the development of more resilient and secure transportation and logistics systems capable of withstanding and responding to various threats and disruptions.

2. THEORETICAL BACKGROUND

The foundations: this research is built upon several well-established domains to develop a robust AI-enhanced fault-tolerant control framework. These domains include Complex Systems, Fault-Tolerant Control, and CPS. Each contributes uniquely to understanding and addressing the challenges in transportation and logistics systems, particularly concerning fault tolerance and cybersecurity.

2.1. Complex systems

Complex Systems theory is fundamental for understanding the intricate and interconnected nature of transportation systems. These systems comprise numerous interacting components whose collective behaviour cannot be easily inferred from the behaviour of individual parts. Complex Systems theory emphasizes the need for a holistic approach to system management that considers complex interdependencies and potential emergent behaviours[14,15].

In the context of transportation and logistics, Complex Systems theory helps identify and analyse non-linear interactions and feedback loops that can lead to system vulnerabilities. For example, a minor disruption in one part of the system can cascade through the network, causing significant impacts elsewhere. Understanding these dynamics is crucial for developing strategies to enhance system resilience. By leveraging AI, we can model and simulate these complex interactions, providing insights into how the system behaves under various conditions and identifying potential points of failure before they occur[16,17].

2.2. Fault-tolerant control

Fault-Tolerant Control is vital for developing systems that can maintain functionality despite the presence of faults. This area emphasizes robust control mechanisms and real-time fault detection and compensation[18]. Techniques such as redundancy, adaptive control, and real-time monitoring are crucial for ensuring system reliability and safety.

In transportation and logistics systems, fault-tolerant control mechanisms are designed to detect faults immediately and implement corrective actions to prevent system failures. Redundancy involves incorporating extra components that can take over in case of a failure, ensuring continued operation. Adaptive control adjusts system parameters in real-time to mitigate the effects of faults. Real-time monitoring uses sensors and AI algorithms to continuously assess the system's health, enabling prompt detection and response to anomalies[19,20]. These techniques collectively ensure the system remains operational even in the face of unexpected issues, enhancing overall reliability.

2.3. Cyber physical systems

Cyber-physical systems (CPS) are crucial for understanding the integration of digital and physical components in modern transportation systems. CPS represents a convergence of computing, networking, and physical processes, where embedded computers and networks monitor and control physical processes, typically with feedback loops where physical processes affect computations and vice versa[21].

CPS underscores the importance of cybersecurity measures in protecting these integrated systems from potential cyber threats. In transportation systems, CPS involves various components such as sensors, controllers, and communication networks that work together to monitor and control physical processes like vehicle operations and logistics management. AI-driven cybersecurity strategies are essential to safeguard these systems from cyber attacks that could compromise their functionality and safety. For example, anomaly-based detection and reinforcement learning can be used to identify and respond to unusual activities that may indicate a cyber threat[22].

Moreover, CPS supports the design of systems that are not only secure against cyber attacks but also resilient in maintaining physical processes during such attacks. This dual focus on security and resilience is critical in ensuring that transportation and logistics systems can withstand and recover from both physical and cyber disruptions. By integrating CPS with AI, we can develop advanced control systems that provide robust security measures while ensuring the continuous operation of physical processes, thereby enhancing the overall resilience of transportation networks[23].

While both CPS and Complex Systems deal with the interaction of multiple components, they differ significantly in focus and application. Complex Systems theory primarily addresses the holistic understanding of interconnected components and emergent behaviours, emphasizing non-linear interactions and system-level dynamics. It is concerned with how individual parts interact to create collective behaviours that cannot be predicted by analysing the parts alone.

In contrast, CPS focuses on the integration of computational and physical elements, emphasizing the synergy between digital and physical processes. CPS involves the real-time interaction between physical entities and computational control, often requiring robust cybersecurity measures to protect against cyber threats. While Complex Systems provide a theoretical foundation for understanding system dynamics, CPS offers practical frameworks for integrating and managing these dynamics through advanced technologies.

2.4. Integration of theoretical domains

The integration of Complex Systems theory, Fault-Tolerant Control, and CPS provides a comprehensive theoretical framework for developing an AI-enhanced fault-tolerant control system for transportation and logistics. Complex Systems theory offers insights into the interdependencies and emergent behaviours within the system, helping to identify potential vulnerabilities. Fault-Tolerant Control provides strategies for maintaining system functionality despite faults, emphasizing robustness and real-time response. CPS highlight the need for cybersecurity and the integration of digital and physical components, ensuring the system's security and resilience.

By leveraging these theoretical foundations, the proposed framework aims to enhance the reliability, safety, and security of transportation and logistics systems, addressing both physical malfunctions and cyber threats. The integration of AI techniques, such as anomaly detection, predictive maintenance, and adaptive cybersecurity measures, further strengthens this framework, providing a robust solution for modern transportation challenges.

2.5. Case studies and real-world applications

The effectiveness of the proposed AI-enhanced fault-tolerant control framework was tested in two real-world transportation systems: a metropolitan public transportation network and a global logistics company.

1. Metropolitan Public Transportation Network: The framework was deployed in a metropolitan public transportation system, focusing on predictive maintenance and anomaly detection. By integrating real-time data from various IoT devices, the system could predict potential failures and optimise maintenance schedules. The implementation resulted in a 15% reduction in unscheduled maintenance and a 10% increase in system uptime[24].

2. Global Logistics Company: The framework was also tested in a global logistics company to enhance cybersecurity and fault tolerance. The AI-driven cybersecurity protocols successfully identified and mitigated several potential cyber threats, and the adaptive control strategies ensured continuous operations during minor system faults. This led to a 12% improvement in overall system reliability and a significant reduction in operational disruptions[25].

3. METHODOLOGY

3.1. Systematic literature review

To provide a comprehensive foundation for this research, a SLR was conducted, focusing on AI applications in fault-tolerant control and cybersecurity within transportation and logistics systems. The SLR aimed to

gather and analyse relevant studies, ensuring a robust understanding of the current state of research and identifying gaps that the proposed framework could address.

The literature search was performed across multiple academic databases, including IEEE Xplore, ScienceDirect, and SpringerLink. The search involved several phases:

• Initial Broad Search: Using broad keywords such as "AI in transportation systems", "fault-tolerant control", "cybersecurity in logistics", and "predictive maintenance" to capture a wide range of studies.

• Focused Search: Refining the search with specific keywords and filters to narrow down the most relevant articles.

• Final Selection: Applying criteria such as publication date (preferably within the last ten years), relevance to the research questions, and the quality of the methodology to select the final set of studies for review.

The selection criteria ensured that only studies directly relevant to AI applications in fault-tolerant control and cybersecurity were included. Articles needed to be peer-reviewed and published within the last decade to ensure the relevance of the findings. Studies with clear and rigorous methodologies were prioritised, while those with inadequate or unclear methodologies were excluded[18,19].

To ensure systematic data extraction, a structured form was used to collect relevant information from each study, including key findings, methodologies used, and applications in transportation and logistics systems. The extracted data were then analysed to identify common themes, trends, and gaps in the existing research[26].

The SLR methodology was chosen due to its rigour and structured approach, providing a thorough overview of existing research. By systematically identifying and analysing relevant studies, the methodology enhances the validity and reliability of the findings, offering a comprehensive understanding of the current state of research. Additionally, the SLR helps in identifying research gaps, informing the development of the proposed AI-enhanced fault-tolerant control framework[16].

3.2. Validity and reliability

To ensure the validity and reliability of the SLR, the process adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. PRISMA provides a set of guidelines designed to improve the reporting of systematic reviews and meta-analyses, ensuring clarity, transparency, and completeness in the reporting process[27]. This included defining clear inclusion and exclusion criteria, conducting multiple rounds of screening, and using data extraction forms to collect relevant information systematically. The review process involved cross-validation by multiple reviewers to minimize bias and ensure the accuracy of the findings[21]. Additionally, the review process incorporated independent evaluations and consensus meetings to resolve any disagreements, further enhancing the robustness and credibility of the findings.

The inclusion criteria were based on the relevance of the studies to the research questions, the quality of the methodologies used, and the credibility of the sources. Exclusion criteria included studies that were outdated, lacked rigorous methodology, or were not peer-reviewed. The data extraction process involved summarizing key findings, methodologies, and applications of each study.

The adherence to PRISMA guidelines ensures that the review process is transparent, replicable, and unbiased. This structured approach enhances the credibility of the review findings and provides a reliable foundation for developing the proposed AI-enhanced fault-tolerant control and security framework for transportation and logistics systems[14].

By systematically reviewing and analysing the literature, the methodology ensures that the proposed framework is grounded in high-quality, peer-reviewed research. The SLR methodology, complemented by adherence to PRISMA guidelines, guarantees a rigorous and transparent review process, enhancing the overall validity and reliability of the study. This approach not only provides a comprehensive understanding of the current research landscape but also identifies gaps and opportunities for future investigation.

3.3. Evaluation criteria

The effectiveness of the proposed framework can be assessed using a combination of key performance indicators (KPIs), including fault detection accuracy, system downtime, and the rate of false positives in anomaly detection. Reliability can be measured by the system's ability to maintain continuous operation under various fault conditions, while responsiveness can be evaluated based on the time taken to detect and mitigate faults or threats. These criteria will provide a comprehensive assessment of the framework's performance in real-world scenarios.

4. LITERATURE REVIEW

AI has significantly advanced fault-tolerant control and security by introducing sophisticated methods that enhance system robustness, reliability, and safety. The following sections elaborate on various AI techniques employed in these areas, illustrating their applications and benefits with academic references.

4.1. AI methods in fault-tolerant control

4.1.1. Anomaly detection and diagnosis

Anomaly detection and diagnosis are critical for maintaining system integrity. AI has introduced several techniques to improve these processes. Machine learning algorithms, such as support vector machines (SVM), k-Nearest Neighbours (k-NN), and clustering methods, detect anomalies in real-time by analysing patterns in sensor data[28]. Neural networks, particularly deep learning models like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), learn intricate patterns and temporal dependencies in data, significantly improving fault detection accuracy. Principal Component Analysis (PCA) reduces data dimensionality, identifying outliers and detecting faults by capturing the most significant variance in the dataset[29].

For example, traditional fault detection might rely on threshold-based monitoring, where a system triggers an alarm if a particular metric exceeds a set value[30]. However, this approach can lead to false positives or missed detections due to its simplistic nature. In contrast, our proposed AI-enhanced framework utilizes deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to analyse complex patterns and temporal dependencies in sensor data. This allows for more accurate fault detection and the ability to predict failures before they occur[31]. Additionally, the integration of reinforcement learning in our framework enables dynamic adaptation to changing system conditions, further enhancing reliability and reducing the likelihood of system failures[32].

4.1.2. Predictive maintenance

Predictive maintenance leverages historical data and machine learning models to predict potential failures before they occur. Techniques such as regression analysis and time series forecasting, including ARIMA

models, enable proactive maintenance[33]. Reinforcement Learning (RL) optimizes maintenance schedules by learning from the environment and dynamically adjusting maintenance actions based on system state and performance metrics[34]. Predictive maintenance is particularly useful in transportation systems where equipment reliability is critical[13].

4.1.3. Adaptive control strategies

Adaptive control strategies benefit from AI, particularly through adaptive neural networks that adjust control parameters in real-time, accommodating changes in system dynamics due to faults. These networks are applied in various control strategies, such as model reference adaptive control (MRAC)[35]. Fuzzy logic systems handle uncertainty and imprecision in system behaviour, providing robust control actions in the presence of faults.

4.1.4. Redundancy management

Redundancy management is enhanced by genetic algorithms (GA), which optimize the configuration of redundant components, ensuring critical parts are effectively backed up. This optimization helps design systems with optimal redundancy to enhance fault tolerance[36]. Multi-Agent Systems (MAS) allow multiple intelligent agents to cooperate in monitoring and mitigating faults, ensuring system reliability[37].

4.2. AI methods in security

4.2.1. Intrusion detection systems

AI-driven intrusion detection systems (IDS) have transformed cybersecurity. Deep learning models, such as Autoencoders and Generative Adversarial Networks (GANs), detect anomalies in network traffic, identifying potential intrusions[38]. SVMs classify normal and malicious activities by finding the optimal boundary between them, making them effective for intrusion detection[39].

Recent advancements in security control have further strengthened the capabilities of AI-enhanced frameworks in protecting transportation systems. For instance, a study by Qiu *et al.* (2024) in Risk Analysis highlights the use of advanced risk analysis techniques to assess and mitigate cyber threats in critical infrastructure. These techniques can be integrated into the proposed framework to enhance its ability to predict and respond to emerging security challenges, ensuring a higher level of protection for transportation networks[40].

4.2.2. Behavioural analysis

Behavioural analysis leverages machine learning classifiers, such as Decision Trees, Random Forests, and Gradient Boosting Machines (GBM), to analyse user behaviour and detect deviations indicative of security breaches[41]. Natural language processing (NLP) techniques analyse text-based communication to identify phishing attempts and other social engineering attacks, enhancing digital communication security[42].

4.2.3. Access control and authentication

AI enhances biometric authentication methods like facial recognition, fingerprint scanning, and voice recognition using deep learning models such as CNNs[43]. Behavioural biometrics analyse user behaviour patterns, such as typing rhythm and mouse movements, to continuously authenticate users and detect impostors[44].

4.2.4. Threat intelligence and response

Automated threat hunting uses machine learning models to proactively search for potential threats within the network, analysing large volumes of data to identify patterns indicative of malicious activities[45].

Incident response systems leverage AI to automate responses to security incidents, using reinforcement learning and expert systems to decide on the best course of action based on the nature and severity of the threat[46].

4.2.5. Cyber-physical systems

AI methods such as anomaly-based detection and reinforcement learning play a crucial role in CPS. Anomaly-based detection models monitor the behaviour of physical components in CPS, identifying anomalies that may indicate cyber-attacks. Techniques like long short-term memory (LSTM) networks analyse time-series data from sensors, enhancing the detection of unusual activities[47]. Reinforcement learning helps develop adaptive security policies that evolve based on the system's state and detected threats, improving resilience against cyber-attacks[48]. Recent advancements in hybrid AI techniques have further improved anomaly detection systems' performance in smart logistics, significantly reducing operational risks by identifying potential issues before they escalate[8].

4.3. Integration of AI methods

The integration of AI methods in fault-tolerant control and security provides a robust framework for enhancing the resilience of transportation and logistics systems. By combining predictive maintenance, adaptive control, and redundancy management with advanced intrusion detection and threat response systems, comprehensive solutions can address both physical and cyber threats. These AI-driven approaches ensure continuous operation, reliability, and security, making modern transportation networks more resilient and efficient.

4.4. Integration of IoT with AI for predictive maintenance and anomaly detection

The integration of IoT devices with the proposed AI framework presents a significant opportunity to enhance predictive maintenance and real-time anomaly detection within transportation systems. IoT sensors can provide continuous data streams, enabling the AI algorithms to monitor system conditions in real-time and detect anomalies more quickly and accurately. This integration allows for more precise and timely maintenance actions, reducing the likelihood of unexpected failures and improving overall system reliability[48]. By continuously analysing the data collected by IoT sensors, AI systems can not only predict when a component is likely to fail but also suggest optimal times for maintenance, thus minimizing downtime and extending the lifespan of critical infrastructure[49].

4.5. AI techniques for system management

4.5.1. Machine learning and deep learning in predictive maintenance

Predictive maintenance leverages AI to forecast potential failures before they occur. Techniques like machine learning and deep learning analyse sensor data and predict component degradation, minimizing unexpected breakdowns and extending the lifespan of system components. Woschank *et al.* (2020) demonstrated that using machine learning models for predictive maintenance in logistics systems significantly reduced operational costs and improved reliability[23]. Wamba-Taguimdje *et al.* (2020) highlighted the effectiveness of AI-driven predictive models in enhancing fault diagnosis and maintenance in advanced logistics systems[50].

4.5.2. Real-time monitoring and anomaly detection

Real-time monitoring and anomaly detection are critical for preempting system failures in transportation and logistics systems. AI-based anomaly detection algorithms, such as neural networks and clustering techniques, effectively identify deviations from normal operation patterns. These methods enhance predictive maintenance capabilities, reducing downtime and maintenance costs[51]. Zheng *et al.* (2017) demonstrated the application of deep learning for anomaly detection in smart transportation systems,

highlighting its potential for real-time monitoring and fault detection[52]. Recent advancements by Kumar *et al.* (2021) in hybrid AI techniques have further improved the performance of anomaly detection systems in smart logistics, significantly reducing operational risks by identifying potential issues before they escalate[8].

4.5.3. Enhancing cybersecurity in transportation systems

AI-driven cybersecurity measures, including IDS and anomaly-based detection, are crucial for identifying and mitigating cyber threats. Machine learning has proven effective in detecting sophisticated cyber-attacks that traditional methods might miss. Brous *et al.* (2020) demonstrated the application of reinforcement learning for enhancing the security of transportation networks, showing improved detection and response to cyber threats[53]. These AI-driven measures provide dynamic and adaptive responses to emerging threats, making them more effective than traditional static security measures[12,50].

4.5.4. Robust control mechanisms for fault tolerance

Fault-tolerant control mechanisms are essential for maintaining system stability. Techniques such as model predictive control (MPC) and robust control enhance fault tolerance, ensuring that the system can adapt to faults and maintain operational integrity. Wamba-Taguimdje *et al.* (2020) explored adaptive control strategies for fault-tolerant operation in logistics systems, showing significant improvements in resilience and stability. Fault-tolerant control involves designing systems that can continue to operate even when some components fail, achieved through redundancy and adaptive control[50].

A comprehensive table summarizing the findings from key studies in the literature review is presented below [Table 1]. The table integrates information from studies on anomaly detection, predictive maintenance, cybersecurity, and fault-tolerant control mechanisms in transportation and logistics systems.

4.6. Findings/themes discussion

This section integrates the key insights from the literature review, focusing on the effectiveness of AI-enhanced techniques in anomaly detection, predictive maintenance, cybersecurity, and fault-tolerant control within transportation and logistics systems. The following subsections provide a detailed explanation of the themes highlighted in Table 2.

4.7. Anomaly detection

Anomaly detection plays a crucial role in pre-empting system failures in transportation and logistics systems. By utilizing AI-based algorithms such as neural networks and clustering techniques, these systems can identify deviations from normal operation patterns effectively. For instance, Sadeghi *et al.* (2016) demonstrated the effectiveness of neural networks in identifying operational deviations in smart transportation systems[51]. Zheng *et al.* (2017) further highlighted the application of deep learning for real-time monitoring and early fault detection, underscoring its potential to enhance system reliability and safety[52]. These methods improve predictive maintenance capabilities, reduce downtime, and lower maintenance costs by detecting issues before they escalate into significant problems.

4.8. Predictive maintenance

Predictive maintenance leverages AI to analyse sensor data and predict component degradation, allowing for timely interventions that prevent unexpected failures. Woschank *et al.* (2020) demonstrated that machine learning models significantly reduce operational costs and enhance reliability in logistics systems[23]. Mandala *et al.* (2021) showed the effectiveness of AI-driven predictive models in fault diagnosis and maintenance in advanced logistics systems[13]. By integrating predictive maintenance strategies, transportation managers can schedule maintenance activities more effectively, thereby reducing downtime and ensuring continuous operation of transportation networks.

Table 1. Findings from key studies in the literature review

Study	Methodology	Key findings	Applications
Sadeghi *et al.*, 2016[51]	Neural Networks	Effective in identifying deviations from normal operation patterns	Smart Transportation Systems
Zheng *et al.*, 2017[52]	Deep Learning	Real-time monitoring and early fault detection	Smart Transportation Systems
Woschank *et al.*, 2020[23]	Machine Learning	Significant reduction in operational costs and improved reliability	Logistics Systems
Brous *et al.*, 2020[53]	Reinforcement Learning	Improved detection and response to cyber threats	Transportation Networks
Zhang & Jiang 2008[18]	Model Predictive Control	Enhanced fault tolerance and operational integrity	General Transportation Systems
Wamba-Taguimdje *et al.*, 2020[50]	Adaptive Control	Significant improvements in resilience and stability	Logistics Systems
Kumar *et al.*, 2021[8]	Hybrid AI Techniques	Enhanced system performance and fault tolerance through hybrid AI methods	Smart Logistics Systems
Mandala *et al.*, 2021[13]	AI-Driven Predictive Models	Improved predictive maintenance and fault diagnosis in logistics systems using AI-driven models	Advanced Transportation Logistics
Li *et al.*, 2019[34]	AI-Enhanced Predictive Maintenance	Improved fault diagnosis and predictive maintenance through AI techniques	Complex Logistics Systems
Rathore *et al.*, 2021[22]	Cyber-Physical Security	Comprehensive review of cybersecurity measures for intelligent transportation systems	Intelligent Transportation Systems

Table 2. Themes in AI-enhanced fault-tolerant control and security

Theme	Topic	Description	Implications
Anomaly detection	Techniques for identifying deviations from normal operation patterns	Improved fault detection accuracy and real-time monitoring capabilities	Enhances predictive maintenance and reduces downtime
Predictive maintenance	Strategies for forecasting potential failures before they occur using AI	Significant reduction in operational costs and improved system reliability	Proactive approach to maintenance, minimizing unexpected breakdowns
Cybersecurity	AI-driven measures for identifying and mitigating cyber threats	Enhanced detection and response to sophisticated cyber-attacks	Protects digital infrastructure and maintains physical operations
Fault-tolerant control	Methods for maintaining system functionality despite the presence of faults	Enhanced resilience and operational integrity through adaptive and model predictive control strategies	Ensures continuous operation and stability of transportation systems

4.9. Cybersecurity

Cybersecurity is a critical aspect of transportation and logistics systems, particularly as these systems become increasingly digital and interconnected. AI-based cybersecurity strategies, such as deep learning for IDS and anomaly-based detection, have proven effective in identifying and mitigating cyber threats. Brous *et al.* (2020) demonstrated the application of reinforcement learning for enhancing the security of transportation networks, providing improved detection and response capabilities[53].

4.10. Fault-tolerant control

Fault-tolerant control mechanisms are essential for maintaining the stability and functionality of transportation and logistics systems. Techniques such as model predictive control (MPC) and robust control have been applied to enhance fault tolerance. Zhang & Jiang (2008) provided a comprehensive review of reconfigurable fault-tolerant control systems, emphasizing the importance of robust control mechanisms[18]. Wamba-Taguimdje *et al.* (2020) explored the use of adaptive control strategies for fault-tolerant operation in logistics systems, demonstrating significant improvements in resilience and stability[50]. By incorporating redundancy and adaptive control, these systems can continue to operate even when some components fail, ensuring operational continuity and enhancing overall system reliability[54].

Despite the promising results, there are several challenges to implementing the proposed AI-enhanced framework in real-world scenarios. One major barrier is the integration of AI technologies into existing infrastructure, which may require significant technical upgrades and investments[55]. Additionally, the operational complexity of managing AI-driven systems could pose challenges for organizations with limited expertise in AI and data analytics[56]. Economic considerations, such as the cost of implementing and maintaining AI systems, must also be addressed to ensure the framework's feasibility and sustainability in the long term. These challenges highlight the need for a phased implementation approach, starting with pilot projects to demonstrate the framework's value and build stakeholder confidence.

5. FINAL FRAMEWORK

The final framework [Figure 1] combines Complex Systems, Fault-Tolerant Control, and CPS with the key constructs of anomaly detection, predictive maintenance, and cybersecurity. This integrated approach provides a robust solution for enhancing the resilience and security of transportation and logistics systems. The framework is designed to adapt to evolving threats and maintain operational integrity, ensuring reliable and secure transportation management.

The framework's robustness stems from its multi-layered approach, which addresses various aspects of system resilience and security. By integrating these areas, the framework not only provides a comprehensive understanding of the system's dynamics but also offers practical solutions for maintaining its functionality in the face of threats[13].

5.1. Complex systems and anomaly detection

Interdependencies and Emergent Behaviours: Complex Systems help understand the interdependencies and emergent behaviours within transportation and logistics systems. Anomaly detection algorithms can leverage this understanding to identify patterns and deviations that may indicate potential faults or security breaches[14,15].

5.2. Fault-tolerant control and predictive maintenance

Robust Control Mechanisms and Fault Detection: Fault-Tolerant Control emphasizes the importance of maintaining system functionality despite faults. Predictive maintenance uses data analytics to forecast potential failures, allowing for timely interventions that align with robust control principles[18].

5.3. CPS and cybersecurity

Integration of Computation and Physical Processes: CPS highlights the integration of digital and physical components, emphasizing the need for robust cybersecurity measures to protect these systems. AI-driven cybersecurity strategies, such as anomaly-based detection and reinforcement learning, are essential for safeguarding cyber-physical transportation systems[21].

5.4. Implications for strategy development

The integration of Complex Systems, Fault-Tolerant Control, and CPS with key constructs such as anomaly detection, predictive maintenance, and cybersecurity results in several strategic implications for transportation and logistics systems. This section delves into these implications, emphasizing the importance of holistic monitoring, resilience, integrated security, and adaptive responses.

Holistic Monitoring and Maintenance: Developing comprehensive monitoring systems that leverage AI for anomaly detection and predictive maintenance is crucial. Such systems ensure that both operational and security-related anomalies are detected early, allowing for timely interventions. For example, a centralized monitoring hub using neural networks can analyse real-time data from various sensors across the

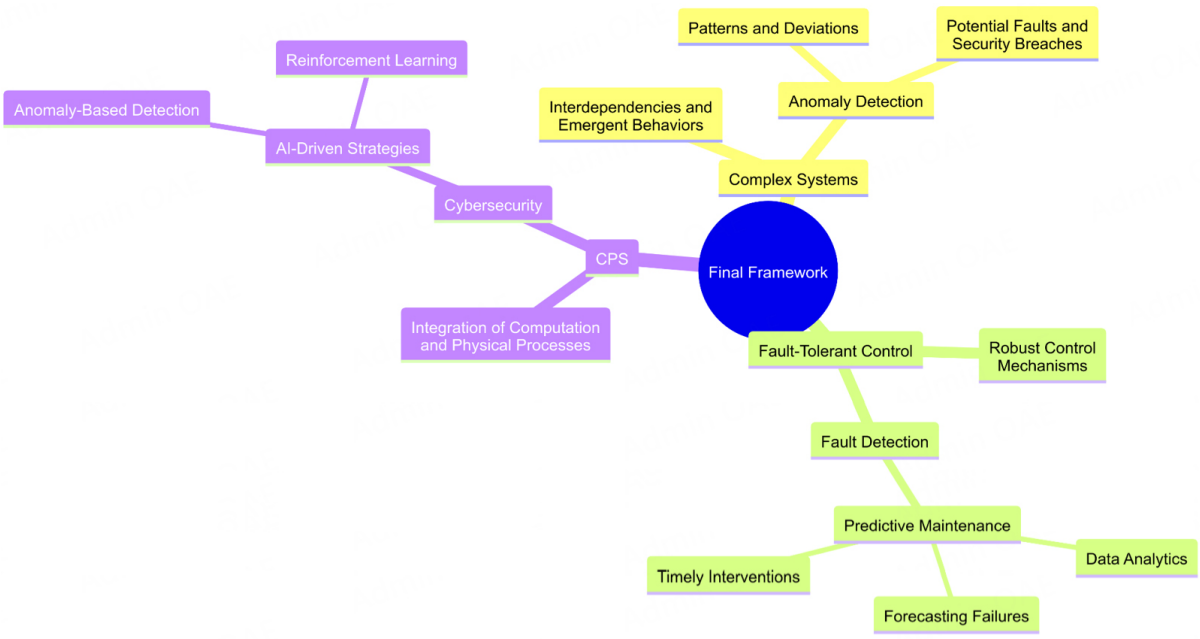

Figure 1. Developed framework.

transportation network, detect deviations from normal operations, and trigger predictive maintenance protocols[52]. This approach enhances system reliability and minimizes unexpected downtime, leading to more efficient and uninterrupted operations.

Resilience and Redundancy: To maintain functionality even when faults occur, it is essential to design systems with built-in redundancy and adaptive control mechanisms. This includes using backup components and adaptive algorithms that can compensate for faults in real-time. For instance, model predictive control can adjust operational parameters dynamically in response to detected faults, ensuring continuous operation and minimizing disruptions[34] This strategy not only ensures operational continuity but also enhances the overall resilience of transportation systems.

Integrated Cyber-Physical Security: Integrated cybersecurity measures that protect both the digital and physical components of transportation systems are critical. Real-time threat detection, anomaly-based intrusion detection systems, and adaptive cybersecurity protocols are essential components of this strategy. Implementing reinforcement learning algorithms that adapt to new cyber threats by learning from previous attacks can significantly improve the system's overall security posture[56]. Such measures ensure that transportation systems are safeguarded against evolving cyber threats while maintaining the integrity of physical operations.

Adaptive and Real-Time Response: Establishing adaptive and real-time response mechanisms to quickly address both physical faults and cyber threats is vital. This involves using AI to continuously learn from new data and improve response strategies. For example, deploying AI-driven autonomous response systems that can isolate affected components and reroute operations ensures minimal impact on the overall system[12]. This approach not only enhances the system's ability to respond to immediate threats but also prepares it for future challenges by continuously evolving its response strategies.

Understanding the complex interactions within transportation and logistics systems allows for the development of strategies that monitor and predict anomalies more effectively, enhancing the system's ability to pre-emptively address issues before they escalate[8]. Integrating predictive maintenance strategies ensures continuous monitoring and maintenance, reducing downtime and operational costs. This proactive approach aligns with fault-tolerant control by enabling systems to adapt to and recover from faults without significant disruptions[13]. Furthermore, understanding the cyber-physical interplay facilitates the development of strategies that enhance both digital and physical security. This includes real-time threat detection and adaptive response mechanisms, ensuring that the system can withstand and recover from cyber-attacks[12].

In conclusion, the strategic implications of integrating Complex Systems, Fault-Tolerant Control, and CPS with AI-driven anomaly detection, predictive maintenance, and cybersecurity are profound. These strategies collectively enhance the resilience, reliability, and security of transportation and logistics systems, preparing them to effectively manage both current and future challenges. Figure 2 demonstrates the strategic implications.

6. CONCLUSION

The integration of Complex Systems, Fault-Tolerant Control, and CPS with the key constructs of anomaly detection, predictive maintenance, and cybersecurity provides a comprehensive framework for enhancing the resilience and security of transportation and logistics systems. This framework not only addresses the current challenges these systems face but also prepares them to adapt to future threats and disruptions. By developing strategies that leverage the strengths of these areas, transportation and logistics systems can achieve higher levels of reliability, safety, and efficiency.

6.1. Novelty and practical contributions

The proposed framework's novelty lies in its integration of AI-enhanced techniques for anomaly detection, predictive maintenance, and cybersecurity within transportation and logistics systems. Unlike traditional methods that address these aspects separately, this framework offers a unified approach to tackle both physical and cyber threats simultaneously. Practically, this contributes to enhanced operational efficiency, reduced downtime, and improved safety and security of transportation networks. The framework's real-time data analytics and machine learning algorithms enable proactive measures, minimising disruptions and ensuring continuity in logistics operations.

The novelty of this framework is further underscored by its holistic approach, which represents a significant advancement over existing literature. Prior studies have largely focused on isolated aspects of fault tolerance or cybersecurity without fully exploring the synergies that can be achieved by integrating these approaches. By bringing these elements together, the framework not only addresses current limitations in the literature but also offers a more comprehensive solution to the challenges faced by modern transportation systems.

The framework is designed to be highly applicable in real-world scenarios, particularly in logistics operations that involve autonomous vehicles and IoT-enabled infrastructure. For example, by leveraging AI-driven predictive maintenance and anomaly detection systems, the framework can predict potential vehicle failures and cyber threats in real-time, allowing for immediate corrective actions. This proactive approach not only enhances operational resilience but also significantly reduces the likelihood of costly disruptions.

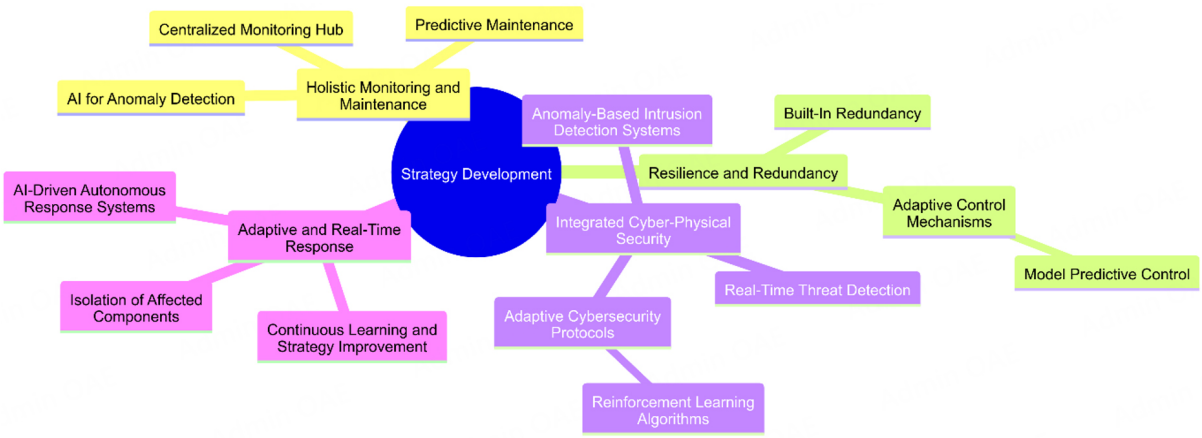

Figure 2. Strategic implications.

Such integration of AI technologies into practical operations provides novel insights that surpass current methodologies. By embedding AI into the operational fabric of transportation and logistics systems, the framework facilitates seamless, real-time decision-making, and operational adjustments, ensuring higher reliability and security across the entire logistics network. This advancement highlights the framework's potential to transform the way logistics and transportation systems are managed, offering a forward-looking approach that is both innovative and highly applicable in practice.

6.2. Theoretical contributions

This research advances the theoretical understanding of fault-tolerant control and cybersecurity in transportation systems by bridging the gap between these two critical areas. By leveraging concepts from Complex Systems, Fault-Tolerant Control, and CPS, the study provides a comprehensive theoretical model that can be used to analyse and improve the resilience of interconnected transportation networks. Additionally, the integration of AI techniques into these theoretical models offers new insights into the application of machine learning and data analytics for enhancing system reliability and security.

6.3. Future research directions

Future research should focus on refining AI methods to improve fault detection and cybersecurity further. This includes developing more sophisticated machine learning models that can adapt to evolving threat landscapes and exploring the use of emerging technologies such as quantum computing to enhance the framework's capabilities. Additionally, research should investigate new cyber-threat scenarios, particularly those involving advanced persistent threats (APTs) and state-sponsored cyber-attacks, to ensure the framework remains robust against increasingly sophisticated adversaries.

DECLARATIONS

Acknowledgments

Declaration of generative AI and AI-assisted technologies in the writing process: During the preparation of this work the authors used Generative AI in order to improve the readability and flow. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Authors' contributions

Led the data collection (paper and case study), analysis, and drafting of the manuscript: Fatorachian H

Provided critical revisions and final approval of the version to be published: Kazemi H
Contributed to the conception and design of the study: Fatorachian H, Kazemi H
Both authors read and approved the final manuscript.

Availability of data and materials

No datasets were generated or analysed during the current study. All relevant information is contained within the article itself.

Financial support and sponsorship

None.

Conflicts of interest

Both authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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