A Survey on Resilience Optimization in Complex Socio-Technical Systems

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Abstract

This survey paper explores the resilience optimization of complex socio-technical systems through a multidisciplinary lens, focusing on interconnected networks and human-machine interfaces. The study emphasizes the necessity of enhancing system resilience against cascading failures by analyzing and optimizing complex networks. Key areas include the integration of human factors and interactions, leveraging system dynamics to model intricate interactions. The paper reviews recent advancements in network theory, machine learning, and system dynamics, highlighting methodologies such as the Planar Maximally Filtered Graph (PMFG) and Dynamic Network Alignment (DNA) for analyzing network structures and dynamics. It also discusses the role of multiplex and higher-order networks in capturing interdependencies and enhancing resilience. Furthermore, the paper addresses the impact of human factors on network resilience and the optimization of human-machine interactions to improve system adaptability. Strategies for mitigating cascading failures are explored, including adaptive network interventions and multichannel stabilization. Case studies across domains, such as financial systems and urban environments, illustrate practical applications of resilience optimization frameworks. The survey concludes by identifying challenges and future research directions, emphasizing the need for more sophisticated models and computational methods to address the complexities of socio-technical systems. This comprehensive examination provides valuable insights for both academic research and practical applications, contributing to the development of robust and adaptive socio-technical systems.

1 Introduction

1.1 Resilience Optimization in Socio-Technical Systems

Resilience optimization in socio-technical systems enhances the robustness and adaptability of intricate networks in response to disturbances. This involves strategies that enable systems to absorb shocks, adapt dynamically, and recover efficiently from adverse events. The integration of human and machine components necessitates a sophisticated approach to resilience, emphasizing the dynamics and structural organization of the network [1]. The complexity of socio-technical systems, influenced by both internal and external factors, can lead to extreme events, highlighting the need to understand their origins and causal pathways [2].

In network dynamics, resilience optimization is crucial for maintaining collective robustness, particularly when specific components are disrupted [3]. The multifaceted nature of human behaviors complicates this process, necessitating an integrated approach that considers the complexities of social systems [4]. Moreover, resilience optimization is vital during sustainability transitions, where integrating heterogeneous elements is essential [5].

The interconnectedness of educational systems, characterized by complex relational processes, significantly influences learning outcomes and decision-making, underscoring the importance of

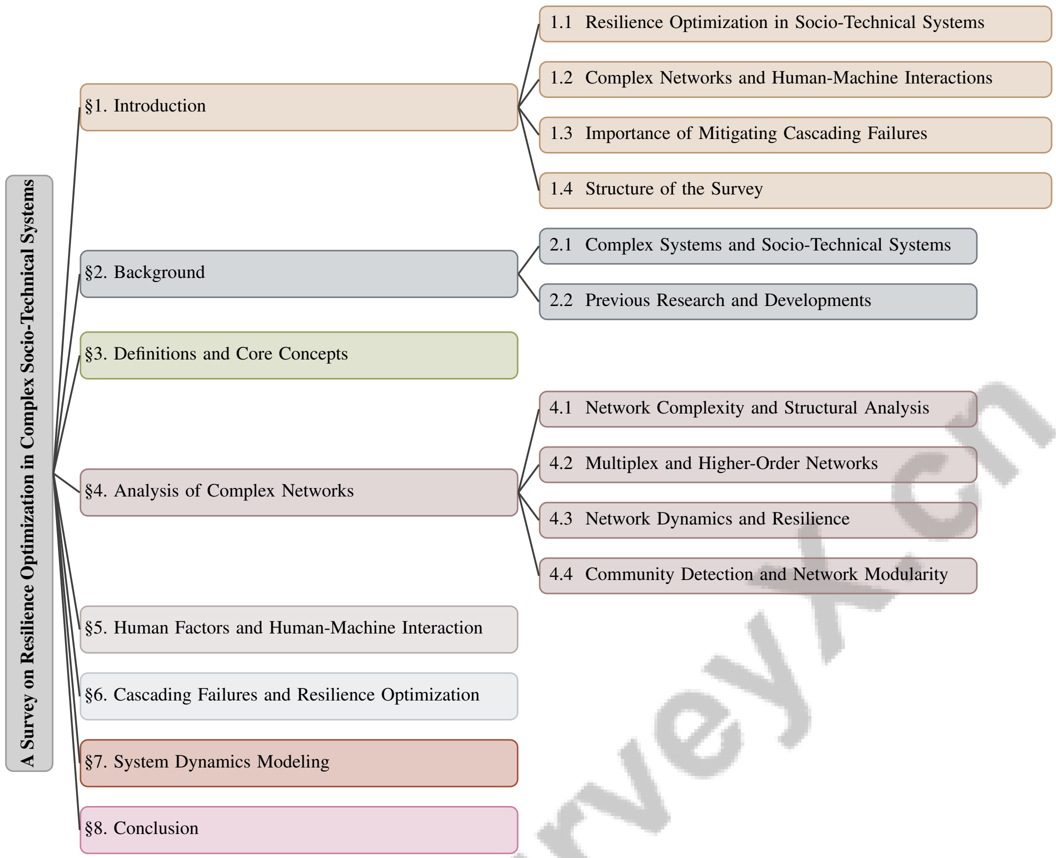

Figure 1: chapter structure

resilience in these contexts [6]. Techniques like the Planar Maximally Filtered Graph (PMFG) retain crucial information from complex correlation-based graphs, highlighting the need for resilience optimization [7]. Additionally, the organization of strong links within networks enhances resilience by promoting robust clustering and connectivity [8].

Aligning heterogeneous networks improves our understanding of complex systems, emphasizing the limitations of methods focusing solely on topological properties rather than dynamic interactions [9]. Thus, resilience optimization is not merely about maintaining stability but also about fostering adaptability and innovation in response to unforeseen challenges.

1.2 Complex Networks and Human-Machine Interactions

The interplay between complex networks and human-machine interactions is fundamental to socio-technical systems. Complex networks describe the multifaceted relationships and interdependencies among various components [6]. Their ability to retain functionality amid external perturbations or internal failures is crucial for resilience. Understanding the structure-dynamics relationship is essential, as optimization efforts can lead to unexpected sensitivities affecting system stability [8].

Human-machine interactions significantly influence the dynamics of socio-technical systems, especially with the integration of advanced artificial intelligence (AI) technologies, which introduce complexities and uncertainties. As AI systems gain autonomy, the potential for unexpected behaviors and misalignment with human values increases. This necessitates a comprehensive understanding of interconnected components, as these interactions impact decision-making processes and the effectiveness of both human and machine agents in contexts like education [10, 6, 11]. These interactions encompass not only direct interfaces but also cooperative work processes and emergent complexities, which are vital for the adaptive capabilities of socio-technical systems.

Integrating information theory into complex systems analysis enhances our understanding of information flow and causation, emphasizing the significance of communication in socio-technical

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interactions. A systems-theoretic perspective advocates for a comprehensive approach to understanding complex systems, categorizing research within frameworks that address hierarchical structures and their interactions. This is essential for accurately extracting the hierarchical organization of networks, facilitating a multi-scale description that captures dynamic relationships and emergent properties [12, 13, 14, 11, 15]. Such frameworks enhance our understanding of knowledge production in complex contexts and support modeling, control, and decision-making processes necessary for managing these intricate systems.

The integration of communication and evolutionary theories, exemplified by the Triple Helix model, enhances our understanding of the interplay between complex networks and human-machine interactions, emphasizing triadic interactions and hierarchical organization. This approach addresses the limitations of traditional pairwise analyses while incorporating advanced modeling techniques, such as hybrid node-link communities and machine learning algorithms, to reveal insights into the functional properties and evolutionary processes of complex systems across various domains [16, 17, 18, 11, 19]. This model illustrates interactions among university, industry, and government, highlighting the importance of redundancy and meaning in information exchange. Collectively, these perspectives underscore the critical role of complex networks and human-machine interactions in enhancing the resilience and adaptability of socio-technical systems.

Furthermore, incorporating AI components into cyber-physical systems (CPS) necessitates a focus on modeling, analysis, and safety requirements, emphasizing the significance of these interactions. Complex networks often exhibit intricate multilayered interactions among nodes, which are essential for understanding their dynamics. These multilayer networks allow nodes to engage in various relationships that co-evolve across different layers, necessitating advanced analytical approaches like the Multiplex PageRank centrality measure, which considers layer interdependence when assessing node importance. Methods for identifying hybrid node-link communities and extracting hierarchical organizations further illustrate how interplay between layers can reveal structural properties and dynamics that would remain obscured if analyzed independently [20, 21, 22, 11, 19]. In social networks, modeling interactions between potentially violent and nonviolent agents reflects real-world scenarios, such as terrorism, while the complexity of international trade networks illustrates the multifaceted nature of socio-technical systems. Epidemic spreading in interconnected networks highlights the importance of capturing complex interdependencies and structural heterogeneity. The limitations of traditional models focusing on pairwise interactions emphasize the critical role of higher-order interactions—such as triadic interactions—in understanding complex systems. Recent advancements in network analysis tools address these patterns, significantly enhancing our understanding of dynamics across various fields, from biology to socio-economic networks. Emerging frameworks for causal inference are shifting focus from pairwise relationships to multivariate interactions, emphasizing the need to incorporate higher-order structures, such as hypergraphs and simplicial complexes, to accurately capture real-world complexities [18, 11, 23, 24, 25]. The self-organization of networks through evolutionary adaptation and environmental pressures on optimal configurations are critical for understanding network dynamics. The interconnected nature of real-world systems and the influence of network structure on global performance are emphasized in the literature, underscoring the necessity of capturing correlation structures in evolving complex systems.

1.3 Importance of Mitigating Cascading Failures

Mitigating cascading failures in socio-technical systems is essential due to intricate interdependencies that can escalate minor disturbances into large-scale disruptions. Such failures threaten the stability and functionality of critical infrastructures, including energy grids, communication networks, and financial systems, integral to modern society [26]. The unpredictability of extreme events, often deviating from conventional expectations, further emphasizes the need for effective mitigation strategies to maintain system stability [27].

The inherent complexity of socio-technical systems poses significant challenges in predicting and managing rare yet impactful states, necessitating a robust understanding to avert potential crises [26]. Overlapping modular structures within networks can exacerbate vulnerability to random failures, highlighting the critical need to address cascading effects to preserve resilience [28]. Furthermore, large endogenous changes within complex systems can lead to catastrophic crashes without external triggers, underscoring the importance of preemptive measures to mitigate such failures [29].

Implementing effective network interventions is compounded by vast state and action spaces and the limited authority of system managers, emphasizing the complexity of mitigating cascading failures [30]. Therefore, developing innovative methodologies and frameworks to address these complexities is imperative for enhancing resilience against cascading failures.

1.4 Structure of the Survey

This survey conducts an in-depth analysis of resilience optimization in complex socio-technical systems, focusing on the interplay between social and physical infrastructures, systemic risk management, and decision-making frameworks that enhance recovery efficiency and self-reliance in urban environments. By integrating quantitative measures and hierarchical modeling techniques, the study aims to provide insights into the critical functionalities and interdependencies defining resilience across various domains, ultimately contributing to the design of robust systems capable of withstanding diverse disruptions [31, 32, 1, 11, 12].

The paper begins with an introduction to resilience optimization concepts, emphasizing their significance in maintaining socio-technical systems' robustness amid disturbances. Following this, we explore the intricate dynamics of complex networks and human-machine interactions, highlighting their pivotal roles in shaping resilience.

The survey transitions to a discussion on the critical importance of mitigating cascading failures, which pose significant threats to socio-technical system stability. This section underscores the necessity for effective strategies to prevent minor disruptions from escalating into large-scale systemic failures. Subsequently, the background section reviews previous research and developments in resilience optimization within complex systems.

In the definitions and core concepts section, we define key terms and explore their interrelations, establishing a foundational understanding for subsequent analysis. The analysis of complex networks section examines network structure and dynamics, discussing methodologies for assessing resilience and identifying vulnerabilities. This is followed by a focus on human factors and human-machine interaction, analyzing their impact on system resilience and exploring optimization strategies.

The survey further investigates cascading failures and resilience optimization, presenting adaptive strategies and case studies illustrating practical applications. The system dynamics modeling section explores using system dynamics to simulate interactions and predict behavior, incorporating agent-based and simulation models.

The conclusion synthesizes key findings and insights, emphasizing the development of a comprehensive knowledge framework for complex systems, the application of unsupervised methods for extracting hierarchical organization in diverse networks, and the introduction of tools for higher-order network analysis. It discusses relevant theoretical frameworks underlying these findings and proposes future research directions to enhance our understanding and management of complex systems across various domains [23, 11, 12]. This structured approach ensures a thorough examination of resilience optimization in complex socio-technical systems, providing valuable insights for academic research and practical applications.The following sections are organized as shown in Figure 1.

2 Background

2.1 Complex Systems and Socio-Technical Systems

Complex systems are characterized by intricate interdependencies and dynamic interactions among components, leading to emergent behaviors that are not predictable from individual elements [33]. These systems span biological, social, and technological domains, exhibiting stochastic and nonlinear behaviors that contribute to their unpredictability [26]. Understanding the link between interacting elements and emergent properties underscores the importance of self-organization, crucial for grasping the stability and adaptability of complex systems [29].

Network theory provides a robust framework for modeling complex systems, capturing multibody interactions through higher-order connectivity patterns such as network motifs and hypergraphs [34]. These representations are vital for understanding structural and dynamical properties, including epidemic propagation in interconnected networks, where network coupling significantly influences thresholds and dynamics [35]. The robustness of complex networks, which maintain functionality

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despite local disturbances, underscores the necessity of understanding their adaptability [28]. Additionally, the relationship between hierarchical structures and fractal dimensions can simplify complex mathematical modeling through fractal analysis [36].

Socio-technical systems, a subset of complex systems, integrate human and machine components, necessitating a synthesis of social and technical elements for effective functioning [37]. Their complexity arises from multiple interaction layers and variability in human behaviors and technological responses. The interdependence of network layers and agent dynamics emphasizes the multifaceted nature of socio-technical systems, where optimizing network properties can significantly impact stability and performance across various domains [38]. The absence of robust mechanisms to model multichannel contagion and stabilization strategies in interconnected financial markets exemplifies the challenges faced by these systems [39].

Theoretical frameworks merging statistical physics with sociological insights are essential for understanding agent interactions and their implications for collective behavior within these systems [40]. This complexity necessitates methodologies capable of capturing the full spectrum of interactions and dependencies in both complex and socio-technical systems. Moreover, integrating AI components, which often exhibit non-deterministic behavior, into cyber-physical systems (CPS) requires stringent verification and adherence to safety and liveness standards, underscoring the challenges in managing complex socio-technical environments [41]. Understanding how increasing complexity in AI systems may lead to performance plateaus or regressions, especially beyond critical thresholds, is crucial for effective system design and management.

The evolution of multi-function networks, where subnetworks co-evolve based on local dynamics and network structure, further illustrates the intricacies of complex systems [42]. Additionally, cascading failures in scale-free interdependent networks highlight the critical role of specific network structures in either mitigating or exacerbating these failures, emphasizing the need to understand topological and temporal properties in evolving networks [43]. Balancing privacy and performance in these systems showcases the dynamic interplay between the components of complex systems and their emergent properties. The interconnectedness of educational components extends beyond individual relationships to encompass institutional and systemic factors, demonstrating the broad applicability of complex systems theory across various domains [6].

2.2 Previous Research and Developments

Significant advancements in resilience optimization within complex socio-technical systems have emerged by addressing traditional network analysis limitations. Conventional methods, such as the Minimum Spanning Tree (MST), inadequately filter complex data, highlighting the need for more sophisticated approaches [7]. Recent studies emphasize the importance of multilayer networks for a comprehensive understanding of complex systems, capturing the intricacies of interconnected layers often overlooked by single-layer analyses [21].

Advancements in machine learning have further contributed to the field, particularly through algorithms capable of extrapolating bifurcation behaviors from stationary data. This approach, utilizing next-generation reservoir computing, presents a novel method for predicting critical transitions in complex systems [44]. Additionally, research on network dynamics indicates that functional similarities within networks are often more indicative of system behavior than topological structures alone, prompting a shift in focus toward dynamic interactions [9].

Transport in complex networks has garnered attention, with research emphasizing the manipulation of network topology to enhance transport robustness, crucial for understanding various natural and human-engineered processes [43]. The organization of strong and weak links within networks remains a focal point for future research, as targeted adjustments in weight organization can significantly improve network robustness [8].

In educational systems, network analysis has provided a nuanced understanding of relational dynamics, offering improvements over previous methods [6]. This approach highlights the potential for network analysis to inform resilience optimization strategies across diverse fields.

Statistical methods have played a pivotal role in advancing the understanding of complex biological systems, with differential network analysis enabling the identification of structural changes

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and interactions [45]. Nonetheless, challenges persist, particularly regarding data availability and methodological rigor, which can affect the reproducibility and generalizability of findings [46].

The concept of nestedness has been extensively explored across various fields, yielding valuable insights into network stability and resilience [47]. These insights contribute to a broader understanding of how complex systems can be optimized for resilience, ultimately informing the development of more robust and adaptive socio-technical systems.

In examining the intricacies of socio-technical systems, it is essential to recognize the underlying structures that govern their behavior. Figure 2 illustrates the hierarchical structure of core concepts and interrelations in these systems, emphasizing the complexity and emergent behavior inherent within them. This figure categorizes the main themes into several key areas: socio-technical systems, emergent concepts, modeling frameworks, advanced computational techniques, and future research directions. By doing so, it highlights the dynamic interplay and optimization strategies that operate within these domains, providing a comprehensive overview that enhances our understanding of the subject matter.

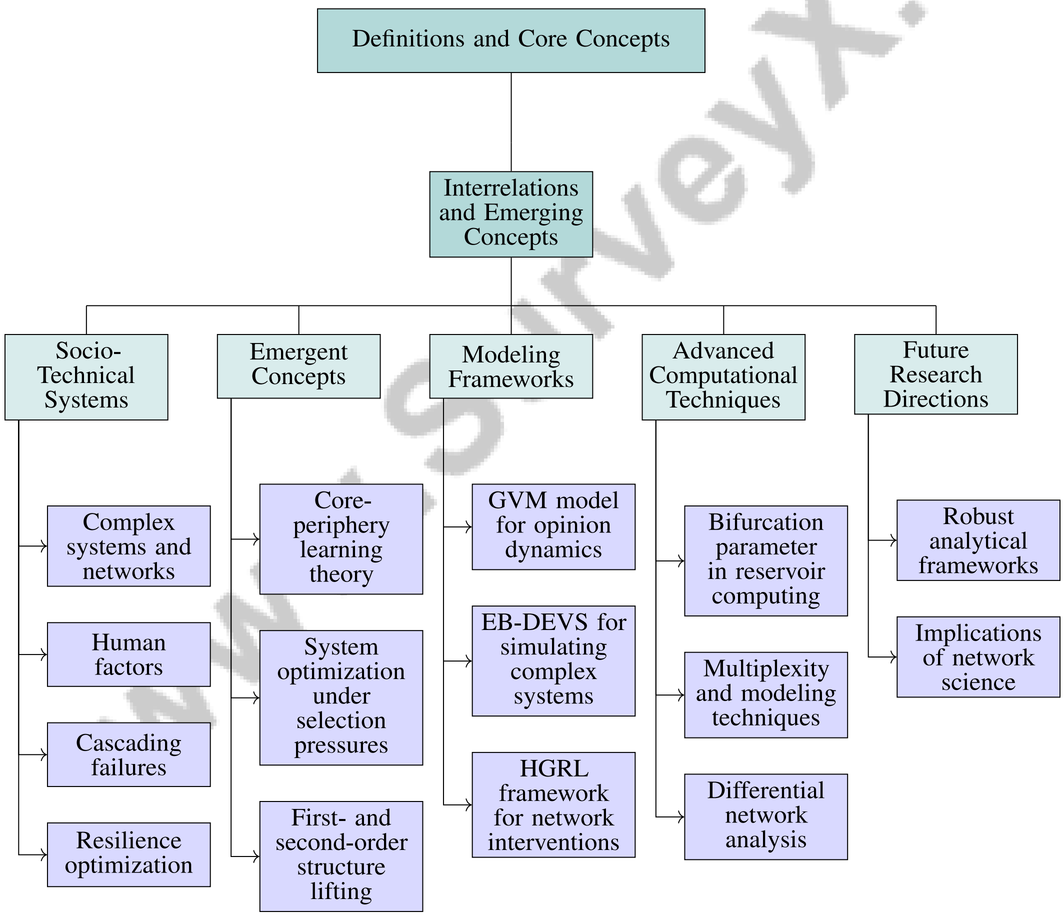

Figure 2: This figure illustrates the hierarchical structure of core concepts and interrelations in socio-technical systems, emphasizing the complexity and emergent behavior of such systems. It categorizes the main themes into socio-technical systems, emergent concepts, modeling frameworks, advanced computational techniques, and future research directions, highlighting the dynamic interplay and optimization strategies within these areas.

3 Definitions and Core Concepts

3.1 Interrelations and Emerging Concepts

Understanding socio-technical systems necessitates examining the intricate interrelations among complex systems, networks, human factors, cascading failures, and resilience optimization. These systems, characterized by self-organization, emergent behavior, and chaos-fractal dynamics, offer insights into the predictability of extreme events [33]. Their dynamics often align with multi-type branching diffusion processes, incorporating spatial dynamics and external influences critical for forecasting such events [29].

Emergent concepts such as core-periphery learning theory highlight that while a network's core enables rapid responses, its periphery is vital for fostering innovation [48]. This perspective supports the notion that systems optimize behavior under selection pressures [49]. Techniques like first- and second-order structure lifting enhance the modeling of initial microscopic states in complex systems, improving system optimization [50].

The GVM model, integrating polyadic interactions and nonlinearity, provides a framework for understanding opinion dynamics and the complex interplay between group interactions and system behavior [51]. Additionally, the balance between information flow and response diversity in network formation, assessed via density matrices, underscores the importance of adaptive strategies [35].

Emerging methodologies, such as EB-DEVS, extend traditional modeling formalisms to capture emergent properties through hierarchical and modular structures, offering a robust framework for simulating complex systems [52]. Modular assurance cases and contract-based designs simplify complexity management, ensuring system reliability [10].

The HGRL framework, combining Graph Neural Networks with Reinforcement Learning, exemplifies an innovative approach to network interventions in multi-agent systems with limited authority [30]. This highlights the role of advanced computational techniques in enhancing system resilience.

Furthermore, integrating a bifurcation parameter into reservoir computing architectures allows for predicting dynamics in unexplored parameter regions, advancing the understanding of system behavior under variable conditions [44]. The concept of multiplexity, where multiple interaction layers affect overall system behavior, underscores the complexity of real-world systems, necessitating sophisticated modeling techniques [53].

Differential network analysis aids in identifying changes in network edge sets while maintaining a fixed node set, especially valuable in biological systems where edges are inferred from node measurements [45]. This approach is crucial for understanding how network structures evolve in response to external stimuli.

As illustrated in Figure 3, the key interrelations and emerging concepts in the study of socio-technical systems highlight complex systems, network dynamics, and modeling techniques as primary categories. Each category encompasses specific elements that contribute to the understanding and optimization of these systems.

Future research should focus on developing robust analytical frameworks that integrate diverse methodologies and explore the implications of network science in practical applications [46]. These interrelations and emerging concepts emphasize the need for a holistic approach in resilience optimization, highlighting the dynamic interplay of network structures, human factors, and system dynamics to foster robust and adaptive socio-technical systems.

4 Analysis of Complex Networks

4.1 Network Complexity and Structural Analysis

Analyzing network complexity involves understanding the intricate interactions and connectivity patterns that define these systems. The PMFG method, as described by Tumminello et al. [7], constructs graphs by iteratively connecting strongly correlated nodes while maintaining topological constraints, thereby elucidating structural complexity. Transport dynamics within networks, modeled using Kirchhoff's equations, highlight the significant influence of network topology on transport efficiency and resilience [43]. Shojaie [45] categorizes network inference methods based on marginal

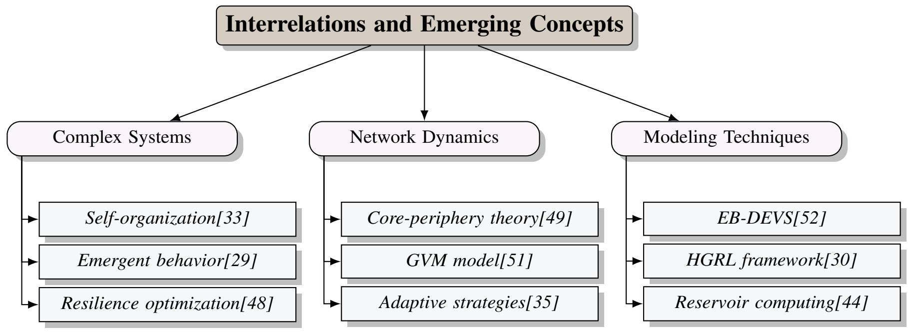

Figure 3: This figure illustrates the key interrelations and emerging concepts in the study of socio-technical systems, highlighting complex systems, network dynamics, and modeling techniques as primary categories. Each category encompasses specific elements that contribute to the understanding and optimization of these systems.

and conditional associations, emphasizing the need to understand diverse associations contributing to network complexity.

The Dynamic Network Alignment (DNA) method proposed by Langendorf et al. [9] aligns networks by comparing node dynamics through diffusion kernels and Shannon's entropy, revealing the interplay between network topology and dynamics. De Domenico et al. [21] discuss a multilayer framework categorizing research on network dynamics, essential for understanding inter-layer interactions. Varley et al. [42] employ tools like attractor counts to investigate network dynamics, providing insights into dynamic properties emerging from structural complexity.

Advanced methodologies enhance understanding of complex networks, informing strategies for optimizing resilience and managing networks. Techniques such as mixed methods for knowledge production and unsupervised hierarchical organization extraction facilitate analysis across domains, from transportation to biological systems. Recognizing overlapping modular structures in network robustness reveals vulnerabilities often overlooked by traditional models, improving management strategies for complex systems [54, 28, 11, 12].

4.2 Multiplex and Higher-Order Networks

Examining multiplex and higher-order networks is crucial for understanding complex systems' resilience, as these models represent interactions and interdependencies more accurately than traditional approaches. Multiplex networks accommodate multiple interaction types across different layers, vital for analyzing system dynamics and resilience [55]. The Multiplex Measures for Higher-Order Networks framework quantifies hyperedge properties and community structures within multiplex hypergraphs, enhancing understanding of structural complexities and inter-layer interactions [56]. Multiplex PageRank assesses node importance by considering inter-layer influence on rankings, highlighting cross-layer interactions' role in system resilience [20].

Research on multiplex network structures reveals their capacity to facilitate cooperative dynamics, where heterogeneous benefits and costs across dimensions promote cooperation, crucial for resilience [57]. Classifying methods based on layer coupling types, such as mutual percolation and transport dynamics, provides a comprehensive perspective on multiplex networks' multifaceted nature [53].

4.3 Network Dynamics and Resilience

Network dynamics are essential for understanding resilience, as they dictate responses to perturbations. Temporal networks, characterized by dynamic interactions, offer insights into network stability through correlation matrices that analyze temporal changes [58]. The exploration of multilayer structures enhances understanding of dynamics compared to single-layer models [21].

The dual response mechanism in complex systems, where the core mobilizes rapid responses while the periphery adapts to new stimuli, underscores the interplay between network components [59]. Communicability metrics indicate transitions from independent to coordinated behavior, crucial for understanding adaptive dynamics and network functionality [37]. Self-organized cooperative

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criticality in coupled systems illustrates the significance of local dynamics in maintaining stability, as small-scale interactions can lead to large-scale resilience [2]. Assessing community structure robustness through critical thresholds provides insights into networks' capacity to withstand perturbations [60].

4.4 Community Detection and Network Modularity

Community detection and network modularity are vital for understanding the internal organization and dynamics of complex networks. The NLC method enhances hybrid community identification, addressing limitations of traditional detection methods [19]. Optimizing multislice modularity facilitates community detection across multiple data layers without prior specifications, essential for multilayer network analysis [61]. A robust framework for characterizing communities is provided by Tumminello et al. [62], effectively identifying significant attributes in heterogeneous datasets. The MULTITENSOR model, introduced by De Bacco et al. [22], captures multilayer community structures, revealing overlapping communities and interdependencies that contribute to overall network resilience.

In financial markets, community detection methods uncover mesoscopic structures and correlations beyond traditional classifications [63], highlighting the importance of these techniques for risk management. Network community analysis, particularly in directed networks, enhances understanding of information flow and influence, optimizing performance and resilience [34]. These methodologies significantly contribute to insights into complex networks' structural and functional properties. By employing advanced analysis methods, researchers can deepen their understanding of dynamics, aiding in formulating effective strategies to enhance resilience and adaptability of socio-technical systems across various domains [46, 31, 59, 54].

5 Human Factors and Human-Machine Interaction

5.1 Impact of Human Factors on Network Resilience

Human factors significantly shape the resilience of complex networks, influencing both their structural and dynamic aspects. [64] highlights the importance of stakeholder involvement, showing that human-centric methodologies can enhance system resilience by aligning technological solutions with human needs, crucial for maintaining network connectivity and functionality. The organization of strong links within integrative networks, as discussed by [8], underscores the advantage of high clustering coefficients, which ensure resilience despite the removal of weaker links. This structural robustness is vital for networks influenced by human factors to withstand disruptions. Moreover, the dynamics of cooperation in multiplex networks illustrate how topology affects human interactions, impacting resilience through cooperative behaviors [53].

Modeling complex interactions in socio-technical systems is essential for understanding human factors' impact on network resilience. The approach by [34] enhances the understanding of directed interactions by identifying local communities, highlighting the role of human factors in network dynamics, especially where information flow is critical. Cascading failures in real-world systems are closely tied to network topology, significantly influenced by human factors. [53] emphasizes the need to understand these influences to develop strategies that strengthen network resilience, integrating both social and technical elements.

5.2 Optimizing Human-Machine Interactions

Optimizing human-machine interactions is essential for enhancing socio-technical systems' resilience, impacting operational efficiency and adaptability. Hierarchical models provide a structured framework for improving these interactions, supporting dynamic decision-making processes [65]. This approach facilitates systematic adaptation, ensuring human-machine systems remain robust under varying conditions. The concept of multiplex networks, as discussed by [20], enriches understanding by emphasizing inter-layer influences, allowing identification of critical influence points to optimize interactions and bolster system resilience. This interconnectedness indicates that changes in one aspect can cascade across the network.

Furthermore, the introduction of graph hierarchies offers insights into network resilience and robustness [66]. By leveraging hierarchical levels, it is possible to better understand the structural and functional dynamics of human-machine interactions, enabling targeted interventions to enhance system stability and performance. This comprehensive approach underscores the importance of considering both hierarchical structures and the multiplex nature of networks in optimizing interactions.

6 Cascading Failures and Resilience Optimization

6.1 Adaptive Strategies for Resilience Optimization

Method Name	Adaptive Strategies	Network Interventions	System Robustness
HGRL[30]	Adaptively Influence Agent	Targeted Interventions Network	Preventing System Collapse
NG-RC[44]	Dynamic Adjustments	Optimize Network Structures	Withstand Disruptions
PMFG[7]	Dynamic Adjustments	Optimize Network Structures	Withstand Disruptions

Table 1: Overview of adaptive strategies, network interventions, and system robustness across different methods. The table compares the HGRL, NG-RC, and PMFG methods, highlighting their unique approaches to enhancing resilience in complex systems through adaptive strategies and network interventions.

Adaptive strategies are pivotal in enhancing the resilience and adaptability of complex socio-technical systems by leveraging dynamic network properties to maintain stability and functionality. Table 1 presents a comparative analysis of various methods focusing on adaptive strategies, network interventions, and system robustness as explored in recent research. Multichannel stabilization strategies, as detailed by [39], outperform traditional single-channel methods by facilitating concurrent operations across interconnected markets, thereby strengthening system resilience. The HGRL framework, discussed by [30], underscores the effectiveness of adaptive network interventions in multi-agent systems, even under constrained authority, optimizing network structures through adaptive strategies that manage complex interactions and dependencies.

Research by [43] on node properties affecting transport collapse times provides insights into enhancing network resilience. Understanding these properties allows for targeted interventions to prevent transport collapses, thereby stabilizing the system. The NG-RC method, introduced by [44], offers a novel approach for predicting tipping points and simulating non-stationary dynamics through polynomial transformations of input data, crucial for identifying critical transitions in complex systems and facilitating proactive resilience optimization.

The PMFG method, as outlined by [7], serves as a tool for filtering complex information. Future research should refine this method and explore its applicability across various network types, aligning with adaptive strategies focused on continuous improvement and adaptation for maintaining system robustness. Insights from the survey by [53] highlight the importance of diverse coupling strategies in shaping system robustness and dynamics, particularly regarding percolation and cascading processes, emphasizing the need for adaptive strategies that consider the multifaceted nature of interactions within multiplex networks.

6.2 Case Studies and Practical Applications

Method Name	Methodological Techniques	Application Domains	Resilience Optimization
SDSP[67]	Symbolic Dynamics	Financial Systems	Risk Management
S[68]	Symbolic Dynamics	Multiplex Networks	Risk Management
BCM[11]	Block-diagonal Fitting	Metabolic Networks	Risk Management
CCDC[63]	Community Detection	Financial Systems	Risk Management
EB-DEVS[69]	Symbolic Dynamics	Artificial Societies	Live Identification
HON+[70]	Higher-order Dependencies	Dynamic Networks	Anomaly Detection
NG-RC[44]	Polynomial Transformations	Power System Model	Bifurcation Parameter

Table 2: Overview of advanced methodologies applied in resilience optimization across various domains, highlighting their methodological techniques, application domains, and specific resilience optimization focuses. This table summarizes the contributions of different methods to enhancing system robustness and adaptability in complex socio-technical systems.

Resilience optimization in complex socio-technical systems is exemplified through various case studies employing advanced methodologies. Table 2 presents a comprehensive summary of the advanced methodologies utilized in the case studies for resilience optimization in complex socio-technical systems, detailing their methodological techniques, application domains, and specific areas of resilience enhancement. The symbolic dynamics technique, as demonstrated by [67], provides quantitative insights into complex systems, particularly in share price movements, enhancing resilience optimization by improving the understanding of dynamic behaviors in financial systems. In multiplex networks, the method proposed by [68] elucidates inter-layer network connections, offering insights into the organization of knowledge in physics through collaboration network analysis, highlighting essential interdependencies for maintaining functionality amidst disruptions.

The hierarchical organization of complex networks is effectively revealed through the method demonstrated by [11], uncovering modular relationships crucial for understanding system organization and enhancing resilience. Community detection methods applied to financial time series datasets, including major stock indices like SP 500 and FTSE 100, offer practical applications for resilience optimization [63]. By identifying meaningful mesoscopic structures, these methods inform risk management and investment strategies, thereby bolstering financial network robustness.

The simulation of emergent behavior in artificial societies, explored by [69], provides insights into socio-technical system dynamics. Models such as the Dissemination of Culture and SIR epidemic models demonstrate the applicability of these frameworks in understanding emergent phenomena and optimizing resilience. Efficient modeling of higher-order dependencies, as shown by [70], significantly outperforms FON-based methods in detecting anomalies, emphasizing the importance of incorporating higher-order dependencies in dynamic network modeling for effective anomaly detection, crucial for resilience optimization.

The NG-RC method, reiterated by [44], remains vital for predicting tipping points and simulating non-stationary dynamics, aiding in identifying critical transitions in complex systems. The case study on the collaboration network of Oscar-winning actors, presented by [48], illustrates the model's real-world applicability, emphasizing the importance of understanding network growth dynamics for resilience optimization. Findings on non-stationary patterns in complex systems, such as epileptic seizures, explored by [71], highlight practical applications for resilience optimization, informing strategies to manage and mitigate impacts.

Lastly, the study of hidden dependencies and spreading vulnerability using real-world temporal network data from systems like schools and hospitals reveals correlations between entropy and vulnerability [72]. This research is instrumental in developing robust public health systems through resilience optimization against epidemic spread. The discussed case studies and practical applications illustrate various methodologies employed in resilience optimization, showcasing their potential to significantly enhance the robustness and adaptability of complex socio-technical systems across multiple domains, including infrastructure, information networks, and social frameworks. Utilizing quantitative measures aligned with the National Academy of Sciences' definition of engineering resilience, these methodologies assess critical functionality over time, providing insights into integrated system resilience and robustness. Decision-making frameworks for managing systemic risks, particularly in the context of cyber threats, offer structured approaches adaptable to various complex systems, demonstrating the effectiveness of tailored interventions and cost management strategies in enhancing overall network resilience [31, 1].

7 System Dynamics Modeling

7.1 Agent-Based and Simulation Models

Agent-based and simulation models are pivotal to system dynamics modeling, offering a framework to analyze complex interactions and emergent behaviors within socio-technical systems. These models operate across multiple scales, optimizing computational efficiency while preserving detail, and employ mechanisms like the EB-DEVS formalism to derive global properties from local interactions. This approach facilitates the exploration of social processes and emergent behaviors, enhancing understanding of communication structures and feedback loops to support macro-level decision-making [69, 73, 74, 15]. By simulating autonomous agents' actions and interactions, these models capture micro-level dynamics leading to macro-level phenomena, offering insights into system resilience and adaptability.

Higher-order network analysis tools, as described by [23], improve the predictive capabilities of agent-based models by identifying key structural features and interaction patterns within networks through clustering algorithms based on motif participation. This allows for explicit modeling of higher-order interactions, leading to more accurate system behavior predictions.

Simulation models, particularly those grounded in system dynamics, provide a macroscopic perspective by capturing intricate feedback loops and time delays characteristic of complex systems. They integrate mathematical and computational techniques to analyze dynamic interactions within hierarchical structures, improving control and decision-making. By incorporating expert knowledge and data-driven approaches, such as neural networks, these models enhance the representation of complex dynamical systems across various fields [75, 76, 77, 15]. Such models are crucial for assessing the long-term implications of strategies and interventions, enabling decision-makers to evaluate potential impacts on system resilience through scenario simulation and stress-testing.

The integration of agent-based and simulation models leverages their complementary strengths: agent-based models depict the diversity and adaptability of individual agents, while simulation models provide an overarching view of system dynamics and feedback mechanisms. This synergy facilitates modeling hierarchical structures and emergent phenomena, enabling dynamic multi-level simulations that balance resource use with information fidelity. The interplay between stability and information integration underscores the importance of balancing robustness and flexibility, essential for accurately simulating complex phenomena [65, 42, 74]. Together, they form a comprehensive toolkit for exploring the resilience of socio-technical systems, guiding strategies to enhance robustness and adaptability in the face of complex challenges.

7.2 Integration of Human Factors in System Dynamics

Incorporating human factors into system dynamics modeling is crucial for capturing the complexity and adaptability of socio-technical systems. Human factors include decision-making frameworks that manage systemic risks, cognitive perceptions influenced by scale-free properties, and social interactions affecting conflict resolution and organizational dynamics. These elements significantly impact system behavior and resilience, guiding interventions for risk mitigation and shaping stakeholder understanding of critical functionalities in complex infrastructures [31, 78, 1]. Embedding these factors into system dynamics models allows researchers to better understand how human interactions and decision-making influence overall system performance and stability.

The load-capacity model for multilayer networks, as discussed by [79], provides a theoretical framework for integrating human factors into system dynamics. This model analyzes how human-driven changes in load and capacity can trigger cascading effects across network layers, impacting system resilience. Simulating these interactions enables system dynamics models to capture the non-linear and emergent behaviors arising from complex human-machine interactions.

Future research should prioritize integrating human factors into urban systems modeling, as highlighted by [80]. Urban systems are inherently complex, with diverse human activities influencing their dynamics. Incorporating human factors into system dynamics models of urban environments enhances understanding of the intricate interactions between human behavior, infrastructure, and environmental factors, crucial for developing strategies to improve urban resilience and sustainability.

Additionally, exploring complex models of module failures and intentional attacks, as suggested by [28], can enrich system dynamics modeling by elucidating vulnerabilities in socio-technical systems. Simulating scenarios involving disruptions and module failures can yield valuable insights into network robustness and resilience, informing strategies for risk mitigation and system stability enhancement.

Integrating human factors into system dynamics modeling establishes a robust framework for analyzing and enhancing the resilience of socio-technical systems, particularly in the face of complex challenges such as natural disasters, urban growth, and interdependencies between social and physical infrastructures. This approach facilitates evaluating critical functionality—defined by stakeholder performance metrics—across various domains, including physical, informational, and social systems. Advanced modeling techniques, such as multi-level directed acyclic graphs and interdependent coupled networks, enable researchers to identify optimal design parameters that balance resilience and robustness, ultimately improving recovery dynamics in urban environments and enhancing decision-making in complex systems [32, 1, 15]. By capturing the interplay between human behavior and system dynamics, these models serve as powerful tools for exploring adaptive capacities and informing resilience optimization strategies.

8 Conclusion

8.1 Theoretical Frameworks and Future Directions

The pursuit of resilience optimization in socio-technical systems is an evolving field, continuously adapting to address the intricate interdependencies inherent in these networks. Future research should focus on integrating complex network structures and exploring system heterogeneity to gain deeper insights into their stability and adaptability. Extending concepts from the Grand Canonical Minority Game to various systems could further enhance our understanding of stability dynamics and crash avoidance. The application of advanced algorithms to manage internal conflicts in fields like chemical and material sciences could enrich our comprehension of complex interrelations within socio-technical systems. Moreover, leveraging information flow as a tool for network intervention presents a promising avenue for enhancing social welfare and fostering cooperation among agents, which is crucial for optimizing resilience in multi-agent systems.

Exploring the dynamics of TSE-complex systems in relation to biological systems may reveal valuable insights into synergies and emergent behaviors. Refining data collection methodologies and analyzing the impact of network structures on educational policy could lead to more effective strategies for enhancing resilience in educational systems. Additionally, the development of differential network analysis methods for non-Gaussian contexts, particularly in directed networks, is essential for addressing the complexities inherent in biological data. Improving the computational efficiency of techniques for analyzing networks with explicit temporal dynamics could broaden the applicability of these frameworks to real-world scenarios.

In multilayer networks, advancing the measurement of inter-layer edges and investigating new dynamical processes could provide a more comprehensive understanding of interactions within these complex systems. Pursuing these research directions will enable scholars to establish more robust frameworks for resilience optimization, ultimately contributing to the stability and adaptability of socio-technical systems in an increasingly complex environment.

8.2 Challenges and Future Directions

The field of resilience optimization in complex socio-technical systems faces several challenges that demand thorough exploration and innovative solutions. A primary challenge is the limited resource capacities and the strategic placement of resource nodes, which significantly influence system viability and robustness. Future research must develop strategies for optimal recovery that address these constraints, ensuring systems can effectively withstand and recover from disruptions.

In network dynamics, there is a need to expand the focus beyond small networks to include tensor networks for analyzing larger dynamics, which could provide deeper insights into the structural complexities and dynamic behaviors of extensive networks. Understanding the impacts of multiple sources and drains on transport dynamics is crucial for network design across various applications. The complexity of multiplex networks presents another challenge, necessitating the refinement of existing models and the exploration of new coupling mechanisms. Future research should examine emergent phenomena arising from complex interdependencies within these networks to enhance understanding of their resilience and adaptability.

Addressing the computational demands of exhaustive mining of triadic interactions is critical, as this process can be resource-intensive. Developing specialized metrics for higher-order networks is essential for better understanding and classifying detected anomalies. Moreover, capturing complex non-linear relationships in networks remains a challenge; future studies should investigate more sophisticated dynamical properties to address this issue. In system dynamics, challenges include navigating nonlinear systems and heterogeneous subsystems, complicating model reduction and resilience optimization. Future research should refine model reduction methods to better accommodate these complexities. Additionally, exploring the evolution of agent behaviors and communication strategies within models is vital, applying frameworks to specific real-world systems to validate their applicability.

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By addressing these challenges and exploring future directions, researchers can develop more robust frameworks for resilience optimization, ultimately enhancing the stability and adaptability of socio-technical systems.

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