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## Abstract

The increasing complexity of interdependent infrastructure networks has heightened the vulnerability of critical systems to cascading failures, where disruptions in one network trigger widespread consequences across others. Graph Neural Networks (GNNs) have emerged as a powerful tool to model these complex interdependencies, offering promising applications in failure prediction and resilience enhancement. This chapter explores the application of GNNs in modeling cascading failures within interdependent networks, focusing on their ability to capture spatial, temporal, and dynamic relationships between various network components. Key challenges in collecting large-scale, high-quality data for GNN-based models are addressed, with a particular emphasis on overcoming issues related to data completeness, scalability, and real-time adaptability. Additionally, the chapter examines hybrid modeling approaches, integrating GNNs with traditional simulation techniques to improve the accuracy and robustness of failure propagation predictions. Through case studies and recent advancements, this work demonstrates how GNNs can be leveraged to better understand, predict, and mitigate cascading failures in critical infrastructure. The integration of GNNs into existing frameworks for failure prediction offers an innovative pathway toward building more resilient infrastructure systems in an increasingly interconnected world.

**Keywords:** Graph Neural Networks, Cascading Failures, Infrastructure Networks, Failure Prediction, Hybrid Models, Resilience.

## Introduction

The vulnerability of interdependent infrastructure networks to cascading failures has become an increasing concern in modern society [1]. These networks, which include power grids, transportation systems, communication networks, and water supply systems, are interconnected and often rely on shared resources and common pathways [2]. A disruption in one network component can trigger a chain reaction, affecting other components in unexpected ways [3]. The complexities associated with understanding the propagation of these failures have made it difficult to develop reliable models that predict failure sequences and system responses [4]. Traditional approaches, such as system dynamics models and agent-based simulations, have been useful in analyzing such failures; often fail to capture the intricate relationships that exist between different infrastructure domains [5]. In this context, new methodologies that can handle the complexities of these interconnected systems are needed [6].

Graph Neural Networks (GNNs) have emerged as a promising tool for addressing these challenges [7]. GNNs excel at modeling complex, relational data, making them highly effective in simulating the interactions between various nodes and edges in a network [8]. By learning from large-scale historical data, GNNs can dynamically model the behavior of infrastructure networks, accounting for both spatial and temporal dependencies [9]. This capability makes them an ideal choice for studying cascading failures, where disruptions in one part of the network propagate to others in a nonlinear fashion [10]. GNNs also offer advantages in their ability to generalize across different network types, providing flexibility in applying the same methodology to various types of interdependent systems [11].

One of the primary challenges in applying GNNs to interdependent infrastructure networks was the need for large-scale, high-quality data [12]. Infrastructure systems are dynamic, with frequent changes in load, operational status, and environmental factors [13]. Collecting real-time data that accurately reflects the state of the system was essential for training GNN models [14]. The data was often sparse, incomplete, or inconsistent due to limitations in sensor coverage, sensor malfunctions, or communication issues between components [15]. These data quality issues can hinder the ability of GNNs to make accurate predictions and can lead to unreliable failure propagation models [16]. To overcome this challenge, efforts must be made to enhance data collection infrastructure, improve sensor technology, and implement more sophisticated data processing techniques, such as data imputation or anomaly detection, to handle missing or inconsistent data.