

**DEEP LEARNING-BASED MULTI-OBJECTIVE
RESOURCE ALLOCATION FOR INTERDEPENDENT
INFRASTRUCTURE NETWORK RESILIENCE**

BY

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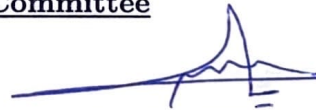
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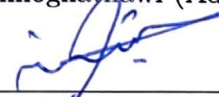
DEANSHIP OF GRADUATE STUDIES

This thesis, written by **QUSAI KARRAR** under the direction of his thesis adviser and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN INDUSTRIAL & SYSTEMS ENGINEERING**.

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To my family, For your unwavering support, love, and encouragement throughout this challenging journey. Your belief in me has been my greatest motivation, and this thesis is a testament to the sacrifices we've made together. Thank you for always being there and sharing in this endeavor's joys and struggles. This work is dedicated to you with all my love and gratitude.

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personal growth, I acknowledge your influence with profound thanks. This thesis stands as a collective effort, a reflection of the support, mentorship, and friendship that have surrounded me. I am humbled by the opportunity to contribute to the body of knowledge in my field, and I carry with me the invaluable lessons learned from each of you. With deepest gratitude, Thank you for being part of this journey.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	vi
LIST OF TABLES	xii
LIST OF FIGURES	xiii
ABSTRACT (ENGLISH)	xvi
ABSTRACT (ARABIC)	xx
CHAPTER 1 INTRODUCTION	1
1.1 Preface	1
1.2 Problem Statement	3
1.3 The Hypothesis	4
1.3.1 Minimize Restoration Costs	4
1.3.2 Maximize Infrastructure Network Resilience	5
1.3.3 Optimize Resource Allocation	5
1.3.4 Provide a Holistic Solution	5
1.3.5 Advance Predictive Modeling in Infrastructure Management . .	5
1.4 Research Objectives	6
1.4.1 Develop a Comprehensive Model	6
1.4.2 Predict Optimal Restoration Sequences	6
1.4.3 Consider Multi-Objective Optimization	6
1.4.4 Evaluate Model Performance	7
1.4.5 Optimize Resource Allocation	7

1.4.6	Provide Decision Support	7
1.4.7	Highlight Ethical Considerations	7
1.4.8	Contribute to Academic Knowledge	7
1.4.9	Promote Interdisciplinary Collaboration	8
1.4.10	Facilitate Practical Implementation	8
1.5	Thesis Outline	8
CHAPTER 2 BACKGROUND AND LITERATURE REVIEW		12
2.1	Interdependent Infrastructure Networks	12
2.2	Machine Learning Based Techniques	14
CHAPTER 3 MACHINE LEARNING BASED APPROACH		23
3.1	Data Generation and Preprocessing	23
3.2	Model Training and Validation	28
3.2.1	Linear Regression	28
3.2.2	Polynomial regression	32
3.2.3	Decision trees	33
3.2.4	KNN Regression	36
3.2.5	Random Forests Regression	38
3.3	Model Selection and Hyperparameter Tuning	41
3.4	Cross-Validation and Training Efficiency	43
3.5	Model Training Time	43
3.6	Evaluation Metrics	44
3.6.1	Mean Squared Error	44
3.6.2	Root Mean Squared Error	44
3.6.3	R-Squared	45
3.6.4	Mean Absolute Error	45
CHAPTER 4 DEEP LEARNING BASED APPROACH		46
4.1	Introduction	46
4.2	Artificial Neural Networks	52

CHAPTER 5 GEOMETRIC DEEP LEARNING BASED AP- PROACH	57
5.1 CONVOLUTIONAL NEURAL NETWORKS	59
5.2 MULTI-DIMENSIONAL GRAPHS	60
5.3 NETWORK EMBEDDING	64
5.4 Methodology	65
5.4.1 Model Architecture	66
5.5 Graph Neural Network Model Workflow	70
5.5.1 Model Implementation	72
5.5.2 Training Procedure	72
5.5.3 Significance of the Methodology	74
CHAPTER 6 DISCUSSION	75
6.1 Machine Learning Based Approaches	75
6.1.1 Performance of Individual ML Models	75
6.1.2 Linear Regression	76
6.1.3 Polynomial Regression	78
6.1.4 Decision Tree Regressor	80
6.1.5 KNN Regressor	82
6.1.6 Gradient Boosting Regressor	84
6.1.7 Radius Neighbors Regressor	86
6.1.8 Bayesian Ridge Regressor	88
6.1.9 Random Forest Regressor	88
6.1.10 Elastic Net Regression Model	89
6.1.11 Comparative Analysis	89
6.1.12 Key Findings and Implications	92
6.2 Deep Learning Based Approaches	93
6.2.1 Model Performance Analysis	94
6.2.2 Computational Efficiency Analysis	102
6.3 Geometric Deep Learning Based Approaches	106

CHAPTER 7	RECOMMENDATIONS AND CONCLUSION	118
7.1	Recommendations for Practical Implementation	118
7.1.1	Real-time Node Significance Assessment	119
7.1.2	Optimal Resource Allocation	119
7.1.3	Risk Mitigation Strategies	119
7.1.4	Emergency Response Planning	120
7.1.5	Continual Model Refinement	120
7.1.6	Interdisciplinary Collaboration	120
7.1.7	Ethical Considerations	121
7.2	Conclusion	121
7.3	Future Directions	122
APPENDIX A	MATHEMATICAL MODEL	124
REFERENCES		133
VITAE		149

LIST OF TABLES

3.1	Infrastructure Networks	26
3.2	Regression Models Hyperparameters	42
6.1	Regression Models Performance Metrics and Training Time	91

LIST OF FIGURES

2.1	Network performance during state transitions prior to, during, and after a disruptive event [1]	22
3.1	Nodes Locations.	25
3.2	Research Methodology	29
3.3	ML Models Development	40
4.1	DNN Model Development	55
5.1	GNN multi-dimensional graph[2]	63
5.2	GNN Model Pipeline[2]	69
6.1	RMSE Comparison	77
6.2	MAE Comparison	79
6.3	R2 Comparison	81
6.4	MSE Comparison	83
6.5	Training Time	85
6.6	Heat-map of Models Performance	87
6.7	R2 Comparison (more is better)	95
6.8	RMSE Comparison (less is better)	97
6.9	MSE Comparison (less is better)	99
6.10	MAE Comparison (less is better)	101
6.11	Training Time (less is better)	103
6.12	Heat-map of Models Performance	105
6.13	RMSE of the GNN model over epochs	108

6.14 MAE of the GNN model over epochs 110

6.15 MSE of the GNN model over epochs 112

6.16 R2 of the GNN model over epochs 114

LIST OF ABBREVIATIONS

CNN	Convolutional Neural Networks. 59, 60
DL	Deep Learning. 4–6, 9, 10, 15, 58
DNN	Deep Neural Networks. 10, 15, 53, 54
DT	Decision Tree. 2, 33–36, 38, 39
GCNs	Graph Convolution Neural Networks. 20
GNN	Graph Neural Networks. 4–6, 9, 10, 58, 60, 64–66
IIN	Interdependent Infrastructure Networks. 1–11, 16, 18, 19, 23, 24, 28, 46, 75
KNN	K Nearest Neighbors. 2, 36, 37
KPI	Key Performance Index. 15
MAE	Mean Absolute Error. 45
MIP	Mixed-Integer Programming. 24
ML	Machine Learning. 2–4, 6, 9, 10, 14–16, 27, 28, 33, 36, 38, 42, 52, 57–59, 64
MSE	Mean Square Error. 44

THESIS ABSTRACT

NAME: Qusai Karrar

TITLE OF STUDY: Deep learning-based Multi-objective Resource Allocation
for Interdependent Infrastructure Network Resilience

MAJOR FIELD: Industrial & Systems Engineering

DATE OF DEGREE: November 2023

In contrast to traditional regression algorithms, we harness the power of advanced machine learning techniques, including Linear Regression, Polynomial Regression, Decision Tree Regressor, K-Nearest Neighbors Regressor, Gradient Boosting Regressor, Radius Neighbors Regressor, Bayesian Ridge Regressor, Random Forest Regressor, and Elastic Net Regression. However, what sets this research apart is the integration of Deep Learning and Graph Neural Networks architecture. These sophisticated models undergo rigorous training and validation, showcasing their remarkable capabilities in predicting node significance while simultaneously minimizing restoration costs and maximizing infrastructure network resilience.

To assess model performance, we employ a comprehensive suite of evaluation

metrics such as Mean Squared Error (MSE), R-squared, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Notably, the Decision Tree Regressor, KNN Regressor, and Random Forest Regressor consistently outshine their counterparts, delivering the lowest MSE and RMSE scores.

This research holds significant practical implications, as it unveils the potential of our models for real-time node assessment, optimal resource allocation, risk mitigation, and emergency response planning within the complex fabric of Interdependent Infrastructure Networks. Our interdisciplinary approach underscores the importance of collaboration between infrastructure experts and data scientists, emphasizing ethical considerations and model refinement for responsible predictive modeling in critical infrastructure management.

This study represents a pioneering effort in advancing node significance prediction within Interdependent Infrastructure Networks. It provides indispensable tools for infrastructure operators and resilience planners, highlighting the pivotal role of data-driven decision support in safeguarding the functionality of Interdependent Infrastructure Networks and ensuring the well-being of modern society. By seamlessly integrating Machine Learning, Deep Learning, and Graph Neural Networks, this research pushes the boundaries of predictive modeling, paving the way for resilient and reliable infrastructure networks in an ever-changing world. *Interdependent Infrastructure Networks are the backbone of modern societies, vital for the delivery of essential services. This research centers on predicting the significance of nodes within these networks, which are crucial components of contemporary civilization. To enhance infrastructure resilience and reliability, this study leverages a combination of machine*

learning models, deep learning models, and graph neural networks in a novel approach. Our methodology explores developing and evaluating predictive models, primarily focusing on enhancing multi-objective resource allocation.

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ملخص الرسالة

الاسم:

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عنوان الدراسة:

تخصيص موارد متعدد الأهداف مبني على التعلم العميق من أجل مرونة شبكات البنية التحتية

التخصص:

الهندسة الصناعية والنظم

تاريخ الدرجة العلمية: نوفمبر 2023

شبكات البنية التحتية المترابطة هي عمود الحضارات الحديثة، وضرورية لتقديم الخدمات الأساسية. تركز هذه الدراسة على توقع أهمية العقد داخل هذه الشبكات، والتي تعتبر مكونات حاسمة في الحضارة المعاصرة. لتعزيز مرونة وموثوقية البنية التحتية، تستفيد هذه الدراسة من مزيج من نماذج التعلم الآلي ونماذج التعلم العميق وشبكات الأعصاب الرسومية بطريقة جديدة. تستكشف منهجيتنا تطوير وتقييم نماذج تنبؤية، مع التركيز بشكل أساسي على تحسين تخصيص الموارد متعدد الأهداف.

على عكس خوارزميات الانحدار التقليدية، نستفيد من قوة تقنيات التعلم الآلي المتقدمة، بما في ذلك الانحدار الخطي، الانحدار الكثير الحدود، مصنف شجرة القرار، المجاور الأقرب، K معزز التدرج، المجاور الأقرب بالنطاق، الانحدار الجسري البايزي، الغابة العشوائية، وانحدار الشبكة المرنة. ومع ذلك، ما يميز هذا البحث هو تكامل التعلم العميق وهندسة شبكات الأعصاب الرسومية. تخضع هذه النماذج المعقدة لتدريب وتحقيق صارم، مظهرة قدراتها الاستثنائية في توقع أهمية العقد مع تقليل تكاليف الاستعادة وزيادة مرونة شبكة البنية التحتية في الوقت نفسه.

لتقييم أداء النموذج، نستخدم مجموعة شاملة من المقاييس التقييمية مثل الخطأ المربع المتوسط، (MSE) ، مربع الخطأ المربع المتوسط الجذري، $(RMSE)$ ، والخطأ المطلق المتوسط. (MAE) من الجدير بالذكر أن مصنف شجرة القرار، المجاور الأقرب، K والغابة العشوائية يتفوقون بانتظام على نظرائهم، مسجلين أدنى درجات MSE و $RMSE$.

تحمل هذه الدراسة تأثيرات عملية هامة، حيث تكشف عن إمكانيات نماذجنا لتقييم العقد في الوقت الحقيقي، تخصيص الموارد الأمثل،

تخفيف المخاطر، والتخطيط للاستجابة للطوارئ داخل نسيج معقد لشبكات البنية التحتية المترابطة. يبرز نهجنا المتعدد التخصصات أهمية التع

CHAPTER 1

INTRODUCTION

1.1 Preface

Interdependent Infrastructure Networks, often abbreviated as IIN, represent a fundamental aspect of the contemporary urban landscape. These networks encapsulate the intricate dependencies that underlie the functioning of modern infrastructure systems. In this age of heightened complexity, where numerous services are deeply interwoven, the performance of one network is often contingent upon the seamless operation of another. Within the sphere of critical infrastructure, the term "critical infrastructure networks" encapsulates a diverse array of Interdependent systems and processes, primarily in private ownership. These networks function synergistically, collectively producing and delivering vital goods and services that constitute the lifeblood of modern societies. Essential components of contemporary urban existence, and critical infrastructure networks encompass electric power, water distribution, natural gas, transportation, telecommunications systems, and more. These networks form the backbone of society, serving as the cornerstone upon which the daily functioning of

cities and nations is built [3]. In recognition of their critical role, this research endeavors to enhance our understanding of their interdependencies, vulnerabilities, and strategies for resilient restoration.

The recognition and comprehension of these interdependencies become essential when assessing the resilience and reliability of critical infrastructure components. While these interconnections bolster the efficiency and capabilities of infrastructure services during normal operations, they can magnify vulnerabilities during periods of disruption. A malfunction in one network can trigger a domino effect, initiating a chain reaction of failures that can have far-reaching societal consequences.

Given the complex and Interdependent nature of IIN, the process of restoring functionality following disruptions is far from straightforward. The determination of the most efficient sequence and methodology for restoration assumes paramount significance, as it directly influences resource allocation and the mitigation of societal consequences. This research endeavors to harness the potential of machine learning (ML) techniques to predict the optimal restoration sequence. Employing a range of ML algorithms, including Linear Regression, Polynomial Regression, Decision Tree (DT) Regressor, KNN Regressor, Gradient Boosting Regressor, Radius Neighbors Regressor, Random Forest Regressor, and Elastic Net Regression, this study aims to pioneer a novel approach to infrastructure restoration. By marrying cutting-edge technological innovation with the imperatives of infrastructure resilience, this research seeks to make a substantial contribution to the field.

1.2 Problem Statement

The modern urban landscape is underpinned by a complex web of IIN, where the functionality of one network depends intimately not only on the physical performance of another but also on digital, operational, and policy-based interactions. This intricate interdependence is a hallmark of contemporary society, where essential services, such as electricity, telecommunications, water supply, natural gas, transportation, and more, are deeply intertwined. While these interconnections optimize the efficiency of infrastructure services under normal circumstances, they simultaneously amplify the vulnerability of these systems during disruptions, creating a pressing problem.

The problem lies in the need to comprehensively understand, model, and manage these dependencies within IIN to ensure their resilience and reliable operation. The consequences of disruptions within these networks can have far-reaching impacts, from service outages and resource misallocation to societal and economic consequences. The challenge is to develop effective strategies for infrastructure restoration that consider the complex, non-linear interdependencies present within IIN.

Current approaches to infrastructure restoration often lack the sophistication and adaptability required to address the multifaceted nature of IIN. As some traditional methods follow linear progression, assuming that the restoration of individual components can be isolated from the larger network context. However, this simplification overlooks the intricate cascade effects that disruptions can trigger within Interdependent networks.

Furthermore, while ML techniques have shown promise in various domains, their

full potential in addressing the intricate challenges of IIN has yet to be realized. Some existing research in this field primarily focuses on specific networks in isolation, neglecting the holistic, multi-objective restoration problem presented by interdependencies across networks.

Hence, the central problem addressed in this research is how to leverage advanced ML techniques, including DL models and GNN, to predict the most effective sequence and methodology for restoring functionality within IIN. By doing so, this study aims to optimize resource allocation, minimize restoration costs, and maximize infrastructure network resilience, providing a comprehensive solution to a pressing problem in contemporary infrastructure management.

1.3 The Hypothesis

The application of advanced ML techniques, including DL models and GNN, can significantly enhance the prediction accuracy of optimal restoration sequences within IIN. By leveraging these techniques, it is hypothesized that the research will:

1.3.1 Minimize Restoration Costs

Advanced ML models will enable the identification of restoration sequences that minimize resource allocation costs by minimizing the unmet demand cost during the restoration process while ensuring the efficient recovery of infrastructure networks.

1.3.2 Maximize Infrastructure Network Resilience

The incorporation of DL and GNN will lead to the identification of restoration sequences that maximize the overall resilience of IIN by considering complex interdependencies and cascading effects.

1.3.3 Optimize Resource Allocation

The models will offer insights into the most efficient allocation of resources during the restoration process, ensuring the timely recovery of critical services within IIN.

1.3.4 Provide a Holistic Solution

The research will contribute to a comprehensive, multi-objective approach to infrastructure restoration, addressing the intricate challenges posed by interdependencies across diverse IIN.

1.3.5 Advance Predictive Modeling in Infrastructure Management

By harnessing the potential of ML techniques, this research aims to advance the field of predictive modeling in critical infrastructure management, providing valuable tools for infrastructure operators and resilience planners.

The testing and validation of these hypotheses through rigorous experimentation and analysis will form the core of this research, with the ultimate goal of significantly enhancing the resilience and reliability of IIN in the face of disruptions and challenges.

1.4 Research Objectives

The primary objective of this research is to develop an innovative framework for multi-objective resource allocation in IIN that leverages advanced ML and DL techniques. To achieve this overarching goal, the following specific research objectives have been defined:

1.4.1 Develop a Comprehensive Model

To create a robust predictive model that captures the intricate interdependencies among IIN, integrating DL and GNN to account for the complex network topologies and dependencies.

1.4.2 Predict Optimal Restoration Sequences

Employ advanced ML algorithms to predict optimal restoration sequences for IIN during and following disruptions. These sequences should aim to minimize restoration costs while maximizing infrastructure network resilience.

1.4.3 Consider Multi-Objective Optimization

Investigate and incorporate multi-objective optimization techniques that take into account the competing goals of cost minimization and resilience maximization, providing a holistic approach to restoration.

1.4.4 Evaluate Model Performance

Conduct rigorous testing and validation of the developed models using synthetic data and case studies from diverse IIN to assess prediction accuracy, model generalization, and scalability.

1.4.5 Optimize Resource Allocation

Determine the most efficient allocation of resources, such as manpower, equipment, and materials, during the restoration process based on the predicted optimal sequences.

1.4.6 Provide Decision Support

Develop a decision support system that translates model predictions into actionable insights for infrastructure operators and resilience planners, facilitating informed decision-making during disruptions.

1.4.7 Highlight Ethical Considerations

Address ethical considerations related to data privacy, security, and responsible predictive modeling in the context of critical infrastructure management.

1.4.8 Contribute to Academic Knowledge

Contribute to the academic discourse by advancing the field of predictive modeling in infrastructure resilience and management, and disseminate research findings through

publications in reputable journals and conferences.

1.4.9 Promote Interdisciplinary Collaboration

Encourage interdisciplinary collaboration between infrastructure experts and data scientists to foster a holistic understanding of the challenges and opportunities presented by IIN.

1.4.10 Facilitate Practical Implementation

Provide practical tools and insights that can be applied by stakeholders in the fields of infrastructure operations, emergency response planning, and infrastructure resilience, ultimately enhancing the reliability and robustness of IIN.

These research objectives collectively form the foundation for this study, aiming to address the pressing challenges posed by the interdependencies within Interdependent Infrastructure Networks and contribute to the advancement of predictive modeling and resource allocation strategies in the domain of critical infrastructure management.

1.5 Thesis Outline

The structure of this thesis is organized into several key chapters, each contributing to a comprehensive exploration of the research topic, "Deep Learning-Based Multi-Objective Resource Allocation for Interdependent Infrastructure Network Resilience." The following sections provide a concise overview of each chapter's content and objectives:

BWSE 1. **Chapter 1:** Introduction

- Provides an introduction to the research problem and its significance.
- Presents the research objectives and hypotheses.
- Offers a brief outline of the subsequent chapters.

2. **Chapter 2:** Literature Review

- Surveys the existing literature related to IIN, resilience, and resource allocation.
- Discusses previous studies on ML, DL, and GNN applications in infrastructure management.
- Reviews relevant theoretical frameworks and models.

3. **Chapter 3:** Machine Learning Techniques

- Details the application of various ML algorithms, including Linear Regression, Polynomial Regression, Decision Tree Regressor, K-Nearest Neighbors Regressor, Gradient Boosting Regressor, Radius Neighbors Regressor, and Elastic Net Regression.
- Explains how these techniques contribute to the prediction of optimal restoration sequences.
- Describes the evaluation metrics and criteria used to assess the performance of machine learning-based restoration models.

4. **Chapter 4:** Deep Learning Techniques

- Explores the use of DL models, such as DNN in predicting optimal restoration sequences within IIN.
- Discusses the advantages and limitations of DL approaches in addressing the complexities of Interdependent networks.
- Presents the evaluation results and analysis of deep learning-based restoration sequences.

5. **Chapter 5:** Graph Neural Network Techniques

- Focuses on the application of GNN in predicting optimal restoration sequences and resource allocation strategies.
- Explores how GNN leverages the graph structure of IIN to enhance prediction accuracy.
- Provides an in-depth analysis of the outcomes and implications of GNN-based restoration models.

6. **Chapter 6:** Discussion

- Engages in a comprehensive discussion of the research findings, drawing insights from ML, DL, and GNN techniques.
- Highlights the practical implications of the study's results for infrastructure operators and resilience planners.
- Examines the ethical considerations related to predictive modeling in critical infrastructure management.

7. **Chapter 7:** Conclusion and Future Directions

- Summarizes the key findings and their contributions to the field.
- Restates the significance of the research objectives and hypotheses.
- Offers recommendations for future research and practice in the realm of IIN resilience and resource allocation.

8. **Appendices**

- Provides supplementary materials, including technical details, additional experimental data, and code samples.

9. **References**

- Lists all the sources and references used in the thesis, following a standardized citation format.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 Interdependent Infrastructure Networks

In the domain of restoration planning, the term "critical infrastructure networks" encompasses a broad spectrum of Interdependent systems and processes, predominantly owned by people and incorporated processes. These networks function in a synergistic manner, collectively producing and disseminating a continuous stream of vital goods and services that serve as the lifeblood of contemporary societies [3]. Integral to the functionality of modern societies, these critical infrastructure networks include electric power, water distribution, natural gas, transportation, and telecommunications systems, among others.

Traditionally, efforts in the field of critical infrastructure planning have mainly revolved around prevention and protection measures to safeguard against potential disruptions. However, the landscape of infrastructure planning has evolved over time

to encompass a broader perspective that extends to the capacity of infrastructure networks to withstand disruptions and recover promptly when faced with unforeseen challenges. The encompassing term for this capacity is "resilience" [4], a definition widely embraced by scholars and practitioners alike [5], [6], [1].

The study of critical infrastructure networks under the influence of disruptive events has witnessed significant maturation over the past thirty years. This evolution has been marked by a focus on identifying topological descriptors, e.g., [7], [8], [9], [10]. Simultaneously, researchers have proposed various methods and algorithms for the restoration of critical infrastructure networks after disruptive incidents. These approaches include determining the set of disrupted network components that require restoration to maximize network performance, assigning these components to work crews, establishing the sequence for their restoration, or pursuing integrated strategies, for example [11], [12], [13], [14].

Crucially, contemporary infrastructure networks are increasingly characterized by interdependence, where the functionality of one infrastructure network is relying on another in intricate ways. Interdependence manifests as a bidirectional relationship between two infrastructure networks, wherein the state of each network significantly influences or correlates with the state of the other [15]. Such interdependencies span various categories, including physical, cyber, geographical, and logical interdependencies. Physical interdependencies involve the exchange of outputs and inputs between networks, while cyber interdependencies rely on information transmission through information infrastructure. Geographical interdependencies result from shared local disruptive events, whereas logical interdependencies encompass all other forms of

interconnection.[15]

The intricate interdependencies among various infrastructure networks introduce a critical challenge: disruptions occurring within one infrastructure network can initiate a chain reaction of cascading disruptions across Interdependent networks. As a result, these interdependent networks exhibit heightened vulnerability to a spectrum of disruptive events, ranging from spontaneous component failures and deliberate malevolent attacks to unforeseen natural disasters [16]. The ripple effect of these disruptions across interdependent networks can culminate in the incapacitation of one or more networks, amplifying the complexity of the subsequent restoration efforts faced by decision-makers. This interplay of interdependencies underscores the pressing need for comprehensive strategies and methodologies to enhance the resilience and preparedness of infrastructure networks in the face of multifaceted challenges.[17], [18], [19], [20], [21], [22]

2.2 Machine Learning Based Techniques

The exploration of ML techniques in the context of network reliability and resilience has remained relatively limited. Prior research has made noteworthy contributions in this area. For instance, [23], [24], [25] employed support vector machines, decision trees, and clustering techniques to assess the reliability of network structures. Their approach involved simulating various network disruptions, calculating the source-sink flow within the network post-disruption, and characterizing the network's performance in binary terms, considering whether it met specific demand levels at the sink node.

Additionally, they utilized link capacity characteristics as predictive factors to ascertain the network’s binary performance, which in turn reflected its reliability.

The critical nature of infrastructure networks has been addressed by Jeddi et. al, [26] and the challenges in decision-making for their resilience. As these networks are characterized by interdependencies, multiple decision-makers, and uncertain information sharing, the authors propose an adaptive ML algorithm to incorporate predictions of other decision-makers’ actions into the restoration planning process of interdependent networks. Similarly, Singh et. al, [27] discuss the challenges posed by ultra-dense 5G and 6G wireless networks and the need for efficient network management and rapid service recovery in such environments. They highlight the difficulty of maximizing service recovery due to the lack of real-time KPI information during outages, leading to manual evaluation. To address this, the authors propose an intelligent proactive network recovery management scheme using DL. Their approach introduces a utilization-based ranking of wireless nodes, significantly reducing service downtime and enabling swift recovery. By predicting network KPI based on actual wireless data, their method achieves an impressive 54% improvement in service outage mitigation.

Nabian et. al, [28] conveyed the need for an efficient evaluation of the reliability of the infrastructure system in the context of natural disasters. They introduce a DL framework designed to accelerate infrastructure system reliability analysis. The framework comprises two DNN surrogates: one for accelerating the determination of network connectivity and the other that replaces various components within the analysis process. Through a simulation-based study of a California transportation network

under extreme earthquake scenarios, the authors demonstrate the effectiveness of their approach in significantly accelerating two-terminal reliability analysis with high prediction accuracy. Karim et. al, [29] tackle the challenges of post-fault restoration in modern power systems, which are prone to instability due to their operation at design limits. Traditional online methods struggle to identify events accurately in the stochastic post-fault scenario. They propose the use of feature selection in conjunction with ML to enhance decision-making for restoring multi-machine networks that become isolated due to faults. This method contributes to more precise decision-making in post-fault restoration processes.

Similarly, Talebiyan et. al, [30] contributed to the field by employing predictive models focusing on anticipating how decision makers, particularly utility operators, would respond to disruptions within interdependent decentralized networks. Their work centered on predicting network performance under various disruption scenarios. Our research extends the literature by implementing ML techniques for the prediction of the significance of the network nodes. We take into account both the disruptive event’s characteristics and the capacity attributes of the network. In particular, to our knowledge, there is no prior study that comprehensively addresses the prediction of node significance while considering both the characteristics of disruption and network capacity.

Critical Infrastructure Systems or Interdependent Infrastructure Networks IIN play an indispensable role in our contemporary world by facilitating essential services and promoting human interactions. Such systems range from electrical power grids to telecommunication setups and natural gas delivery mechanisms, underpin-

ning the economic vitality of nations. It is for this reason that numerous countries prioritize the consistent functionality of these systems and take measures to ensure their uninterrupted operation [31], [32].

The recent technological evolution, particularly in the realm of information technology, has led to a heightened Interdependentness among IINs. This has given rise to what can be termed as Interdependent Critical Infrastructure Systems [33], [34]. While ICISs exhibit the capacity to handle more complex challenges, their intertwined nature presents potential vulnerabilities. The interdependency between various systems introduces the risk of cascading failures. Specifically, a malfunction in one part of the system can trigger a domino effect, wherein dependent parts across different layers experience failures. This Interdependent collapse can be magnified across the entire Network of Networks, illustrating the magnitude of potential disruptions [35], [36], [37], [38].

Notably, research has indicated that the interplay between networks might diminish their overall robustness, in comparison to when they operate independently [39]. For example, a singular malfunction within an electricity node could instigate a chain reaction of failures, resulting in a breakdown of both the power grid and its allied communication network. A real-world manifestation of this scenario was evident during the 2003 Italian Blackout [40]. Consequently, there is an evident need for advanced mathematical methodologies that can elucidate the dynamics of network interdependencies and the associated vulnerabilities.

The realm of percolation theory has been instrumental in advancing our understanding of interdependent networks, specifically focusing on the intricate relationship

between power and communication systems. An influential contribution in this domain was made by Buldyrev [41], who formulated a framework that delves deep into the mechanics of cascading failures, highlighting key transition points. Subsequent research further enriched this area by extending the nuances of percolation theory to explore diverse facets of IIN. These studies encompassed aspects like partial coupling [42], degree associations [43], inter-affinities [44], modular designs [45], and strategic protective measures [46].

Simultaneously, other scholars approached the intricate web of ICISs through the lens of game theory [47]. Their research not only decoded the inherent structures and interdependencies but also proffered innovative strategies to bolster system resilience [48], [49], [22].

The academic discourse then took a pivot from merely understanding structural robustness to examining functional robustness within ICISs. Rosato et. al, [50] elegantly merged the DC power flow model with the TCP/IP network paradigm, introducing functional metrics tailored to assess ICIS robustness. Dong Hoon and his team [51] et. al, embarked on a mission to comprehend the ripple effect of failures across two types of interdependent networks, particularly emphasizing the role of the coupling coefficient in this propagation mechanism. Further research elucidated the ramifications of a power grid failure on hydraulic networks, highlighting the significant influence of correlation intensity and capacity coefficients on the functional susceptibility of Interdependent systems [52].

The integrity of real systems, while paramount, can be challenging to maintain given the inevitability of certain disasters. As such, the spotlight has recently been

on the system’s ability not only to resist and adapt to various disasters but also its capability to bounce back post-damage. In this context, the concept of ”resilience” within IIN has gained prominence. Resilience is typically characterized as the system’s aptitude to endure and rebound from both internal and external adversities [53].

In the pursuit of understanding resilience, scholars have presented various metrics and analytical models [54], [55], [56], [57]. A wide spectrum of research initiatives can be noted in this domain. To highlight a few: the evaluation of resilience and contrasting strategies in the face of natural disasters [58]; the nexus between community robustness and resilience optimization using memory optimization techniques [59]; resilience evaluation grounded on the system’s structural vulnerability function [60]; the juxtaposition of actual performance against expected outcomes in predefined fault conditions for resilience quantification [61]; the dual objective of enhancing resilience by minimizing both the temporal and financial burden of restoration tasks [62]; a comprehensive framework for gauging resilience amid varying seismic risks, factoring in both direct and ancillary repercussions [63]; resilience estimation techniques that marry system robustness with the inclinations of decision-makers [64]; the economic dimensions of resilience, with an emphasis on recovery expenditures [65]; a targeted analysis of resilience within the context of smart grids [66]; and advanced methodologies employing Bayesian networks [67] and the Copula function [68] for resilience assessment.

From the aforementioned discussion, it is evident that recent research trends have bifurcated, with some scholars delving into cascading failures to probe structural and functional robustness, while others predominantly concentrate on the post-disaster

recovery trajectory. Notably, there exists a gap, as comprehensive studies integrating both these facets are scant. Addressing this lacuna, the present paper endeavors to present a pioneering approach to resilience analysis. By harmoniously amalgamating fault propagation scrutiny with disaster recovery evaluation, this method seeks to bolster system resilience from multifarious angles.

In the initial forays into multi-dimensional graph analysis, the focus was primarily on community detection and clustering. Berlingerio et. al, [69] provided seminal insights into "multi-dimensional communities," introducing innovative metrics to refine the definition of density within such graphs. Subsequently, Papalexakis et. al, [70] developed algorithms designed to detect clusters across the multiple dimensions of a graph, laying the groundwork for multidimensional graph analysis.

As the field progressed, there emerged a special class of Graph Convolutional Networks or GCNs tailored for the complexities of multi-dimensional graphs. In this vein, [71] proposed a model that generates separate embeddings for each node within different dimensions, conceptualizing these embeddings as projections from a generalized representational space. They designed a GCNs aggregation mechanism that integrates the interactions among nodes within the same dimension as well as across different dimensions for a single node. In a complementary approach, [72] streamlined the multi-dimensional graph into a single-dimensional framework using a two-pronged technique. Their method first synthesized the various views through subspace analysis and then refined the network via manifold learning, subsequently applying a GCNs to the resulting simplified graph for further learning and analysis. In a similar context, [73] focused their efforts on extending node embedding algorithms to

the multi-dimensional graph setting, broadening the scope of node-centric analysis in these intricate networks.

The progression of these methodologies not only demonstrates the field’s adaptability but also its commitment to evolving alongside the increasing complexity of data structures. The movement from single-dimensional to multi-dimensional graph analysis is indicative of a broader trend in data science and machine learning – a trend towards more nuanced, comprehensive models capable of capturing the rich tapestry of relationships that define our digital and social ecosystems.

In this study, we consider the analysis of infrastructure networks that encompass multiple source and demand nodes, reflecting the common structure of real-world infrastructure systems. Recent literature has proposed several methodologies to assess resilience in such networks [74]. These methods include quantifying resilience through metrics such as the normalized shaded area under the performance function curve [75], employing topological measures [76], or considering the ratio between the probability of failure and recovery [77]. However, this paper adopts infrastructure networks with a resilience paradigm rooted in network performance [1], as depicted in Figure 2.1 and elaborated in previous works [78], [79], [80], [81], [82].

Figure 2.1 provides a visual representation of two fundamental dimensions of resilience: vulnerability and recoverability. Vulnerability in the context of a network pertains to the extent of damage incurred by the network when subjected to a disruptive event [83]. Conversely, recoverability signifies the swiftness with which a network rebounds to a predefined level of performance following a disruptive incident [84].

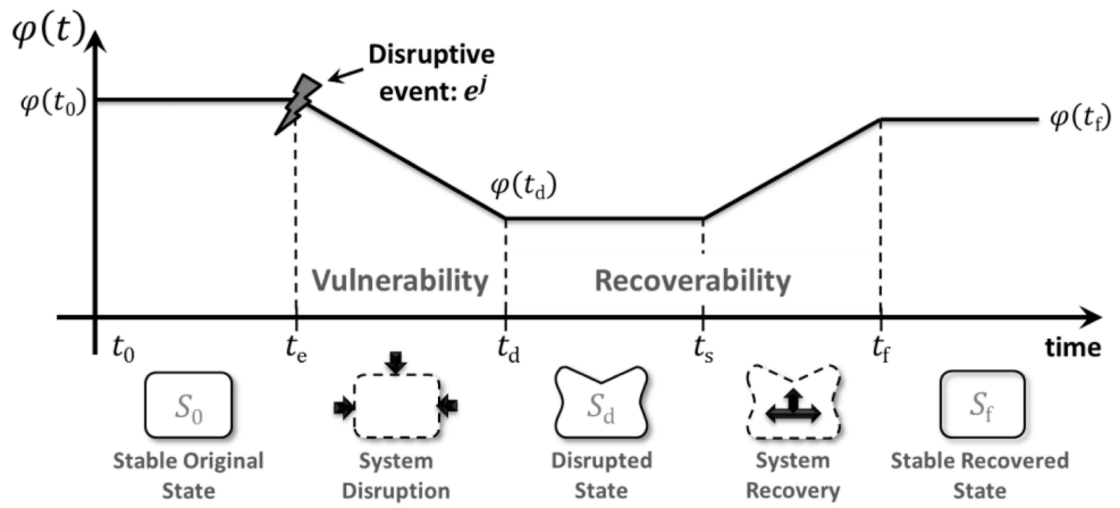


Figure 2.1: Network performance during state transitions prior to, during, and after a disruptive event [1]

CHAPTER 3

MACHINE LEARNING BASED APPROACH

3.1 Data Generation and Preprocessing

In this study, a mathematical model inspired by [16] had been used as a fundamental tool for data generation. The model serves as the basis for simulating restoration scenarios, as it takes into account both the enhancement of network resilience and the minimization of restoration costs. A data set that captures a wide range of restoration tasks, resource allocations, and associated costs, under varying disruption scenarios, had been systematically generated.

The study conducted by [16] is centered on the complicated problem of restoring IIN following a disruptive event while considering various scenarios of disruption. To address this challenge comprehensively, the authors put forth a multi-objective optimization model grounded in the principles of resilience-driven decision-making.

This model is formulated as a MIP framework, which serves the dual objectives of maximizing the resilience of the Interdependent infrastructure network system and minimizing the costs associated with the restoration process. These costs include various aspects, including flow, disruption, and restoration costs, providing a holistic perspective on the restoration problem.

One distinctive feature of our MIP restoration model is its consideration of temporal and resource constraints. The model offers a set of prioritized restoration tasks, facilitating the allocation and scheduling of available work crews. This allocation process is carried out with a keen awareness of the physical interdependencies that exist between infrastructure networks. The overarching goal is two-fold: to maximize the resilience of IIN while minimizing the overall cost incurred during the restoration process.

Although cost minimization is a common objective in restoration models within the literature, the distinguishing characteristic of the model used in this study lies in its emphasis on enhancing the resilience of the system of IIN. This entails restoring disrupted components to a level that ensures the system's performance aligns closely with its pre-disruption state, all while minimizing the associated costs encompassing flow, restoration, and disruption. The central focus of this restoration model is to increase the resilience of Interdependent infrastructure networks to a predefined threshold, thus optimizing the balance between resilience enhancement and cost reduction. Consequently, the model may not necessarily advocate for the restoration of all disrupted components, particularly those that do not significantly contribute to the overall system's resilience.

In this research, we address the challenge of obtaining data from the real infrastructure network, a common issue in research [85], [86]. To illustrate the effectiveness of our ML models, we use fictional interdependent infrastructure networks as shown in Figure 3.1. These synthetic networks are generated using an extended algorithm for proximal topology, which was initially introduced by [87] and further developed by [88]. The network generation process comprises two main phases: (i) the creation of individual networks and (ii) the establishment of interdependencies across these networks [89], [52]. Although fictional, these networks serve as a valuable proxy for real-world infrastructure networks, allowing us to develop and showcase our ML models effectively.

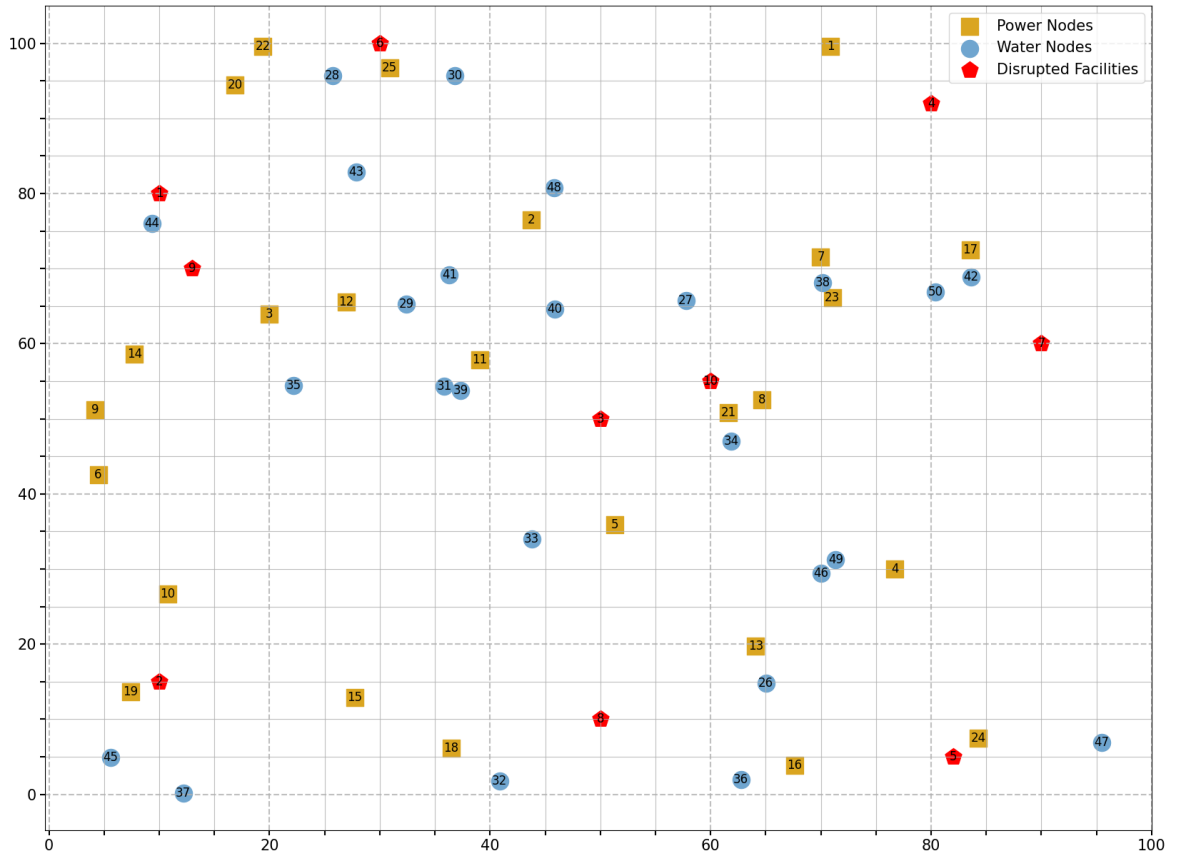


Figure 3.1: Nodes Locations.

Table 3.1: Infrastructure Networks

Network	Nodes			Links
	Supply	Demand	Total	
Power	5	20	25	28
Water	5	20	25	31

As summarized in Table 3.1, the networks used in the study have different key characteristics. Two types of networks, namely the Power and Water networks, are analyzed. In terms of nodes, both networks consist of a total of 25 nodes. Among these, 5 nodes serve as supply points, while the remaining 20 nodes represent demand locations. These networks exhibit a complex interconnection pattern. The Power network comprises 28 links, while the Water network is composed of 31 links and 18 interdependent links. Although the number of nodes is the same for all the networks utilized in this study, the number of links may be slightly different from one network to another. These nodes and links configurations are essential for understanding the structure and interdependencies of the infrastructure networks under investigation.

In the data generation process, we have employed seven essential predictors that collectively encompass the significant attributes characterizing nodes within infrastructure networks. These predictors offer a comprehensive representation of node characteristics, covering spatial information, resource supply and demand, cost considerations, and resilience status. To begin with, the initial two predictors capture the spatial aspect of the nodes through their X and Y coordinates, providing valuable geographical information on the distribution of the nodes. Additionally, we incorporate predictors reflecting the nodes' supply and demand quantities, shedding light on

resource flow dynamics within the network. Furthermore, our model integrates two key cost-related predictors: the restoration cost and the unmet demand cost. These factors are crucial in evaluating the economic implications of disruptions at different nodes of the network. Additionally, a binary feature is included that indicates the status of node disruption (1 for disrupted, 0 for intact). Finally, the target variable in our model quantifies the overall significance of each node within the infrastructure network. This comprehensive set of predictors empowers our ML approach to thoroughly assess node attributes, contributing to a more profound understanding of network resilience and restoration dynamics.

In our study, we carefully select specific parameters and distributions to ensure that our ML models provide valuable representations of real-world infrastructure networks. These choices, made without loss of generality, aim to capture the essential characteristics of such networks. For instance, we consider supply quantities associated with each supply node, assuming a uniform distribution within the range of 2000 to 3000. This range reflects the variability commonly observed in real-world infrastructure networks. In addition, we model demand quantities using a Gaussian distribution with a mean of 100 and a standard deviation of 200. This distribution accounts for the inherent uncertainty and demand fluctuations encountered in practical scenarios.

To simulate restoration cost values, we adopt a uniform distribution spanning from 20 to 50. This choice aligns with established research findings and serves as a basis for our analysis, as documented in [16]. Simultaneously, we maintain a constant cost of unmet demand, fixed at 60, to provide a stable reference point for our analysis.

Furthermore, our approach incorporates a binary disruption predictor, which allows us to distinguish between two primary disruption scenarios. In the first scenario, termed random disruption, nodes experience disruptions in a randomly selected manner, mirroring the unpredictability of real-world events. On the contrary, the second scenario, known as spatial disruption, involves the simultaneous disruption of nodes located in close geographic proximity, which is a common occurrence in actual infrastructure networks. To ensure the robustness and reliability of our ML models, we conduct repeated iterations of mathematical model solving. This process involves approximately 1300 runs and is implemented using the Gurobi optimization library in Python [90]. These iterations are undertaken to enhance the effectiveness of our ML approaches and contribute to the development of resilient restoration strategies tailored to real-world infrastructure networks.

3.2 Model Training and Validation

This section delves into the meticulous process of training and validating various regression models to ascertain their ability to predict the importance of nodes within IIN as shown in Figure 3.2. The primary objective is to discern the most proficient regression model that can provide precise and reliable predictions.

3.2.1 Linear Regression

The formal study of linear regression models constitutes a foundational aspect of statistical learning theory and is frequently deployed in predictive analysis. The premise

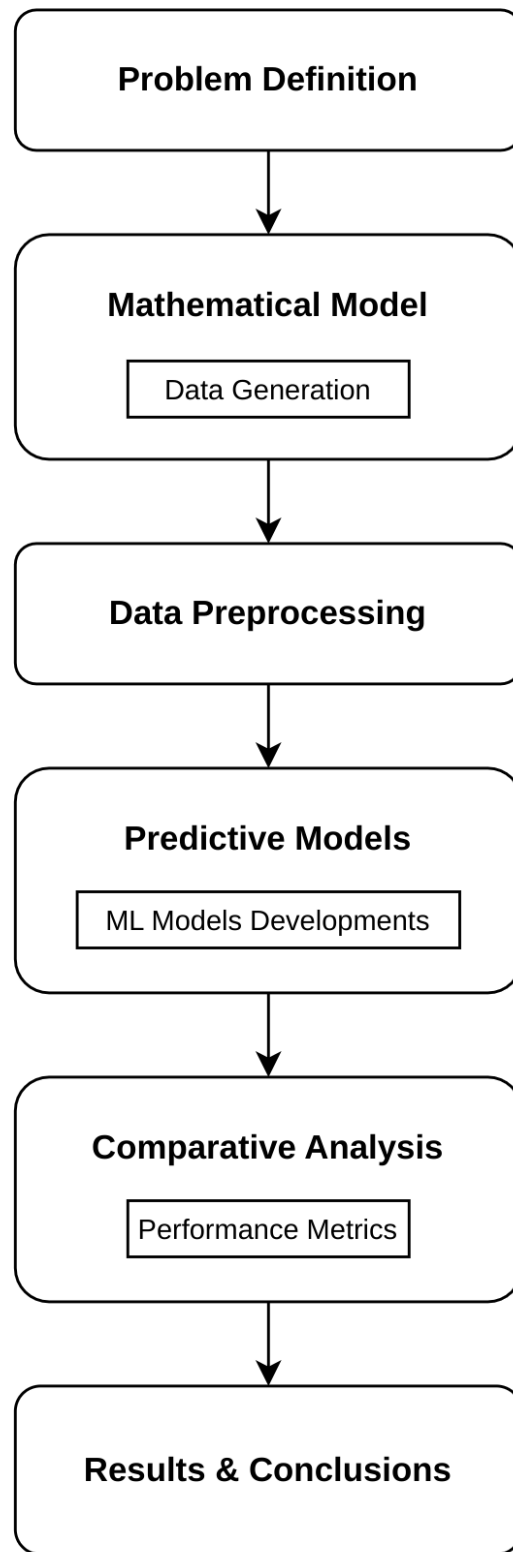


Figure 3.2: Research Methodology

of a linear regression model is to forecast an outcome based on the additive relationship between independent variables. The forecast or prediction ($\hat{y}$) is generated by calculating the weighted sum of the input features, plus a constant known as the bias term (θ_0), which is critical to adjust the model output independent of input values.

The generalized prediction formula for a linear regression, as delineated, can be mathematically represented as follows:

$$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n \quad (3.1)$$

Where, $\hat{y}$ is the forecasted value, n represents the total number of input features, x_i denotes the value of the i^{th} feature ($i=1, 2, \dots, n$), and θ_i signifies the i^{th} model parameter, which comprises both the bias term and the weights for each feature.

For computational efficiency, this equation is often expressed in a compact vectorized format:

$$\hat{y} = h_{\theta}(x) = \theta \cdot x \quad (3.2)$$

In this vectorized representation, θ stands for the parameter vector, including the bias term and feature weights, while x represents the feature vector, extending from x_0 to x_n , with x_0 conventionally set to 1 to accommodate the bias term in the dot product operation. The vector θ and the feature vector x undergo a dot product operation.

When these vectors are treated as column matrices, the prediction equates to a single-cell matrix resulting from the matrix multiplication of θ^T and x , where θ^T is

the transpose of θ , effectively converting it from a column vector to a row vector.

Moving beyond model representation to model training, the objective is to adjust the parameters (θ) such that the model optimally fits the training data. The quality of fit is typically quantified by the Root Mean Square Error (RMSE), a prevalent metric in regression analysis. However, for optimization purposes, the Mean Squared Error (MSE) is preferred due to its computational simplicity while yielding equivalent optimization results. The MSE is defined as follows:

$$\text{MSE}(\theta) = \frac{1}{m} \sum_{i=1}^m (\theta^\top x_i - y_i)^2 \quad (3.3)$$

Where, m indicates the number of instances in the training dataset, and $\theta^\top x_i$ and y_i correspond to the predicted and actual values for the i^{th} instance, respectively. It is imperative to note that minimizing MSE is synonymous with minimizing RMSE since the function that achieves the minimal value for MSE also achieves the minimal value for the square root of MSE, which is the RMSE.

Consequently, the training process for a linear regression model involves finding the parameter set (θ) that results in the lowest MSE for the given training data. This process of optimization is a critical step in ensuring that the model reflects the underlying data distribution with the highest possible accuracy. [91]. Algorithm 1 illustrates the training procedure of the linear regression.

Algorithm 1 Linear Regression Learning Algorithm

Require: Training dataset $D = \{(x^{(i)}, y^{(i)})\}_{i=1}^m$

Ensure: Learned model parameters θ

- 1: Initialize θ with random values or zeros
 - 2: **repeat**
 - 3: Calculate the hypothesis $h_{\theta}(x) = \theta^T x$
 - 4: Calculate the loss $J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$
 - 5: Update $\theta \leftarrow \theta - \alpha \frac{\partial}{\partial \theta} J(\theta)$
 - 6: **until** convergence criterion is met $=0$
-

3.2.2 Polynomial regression

Polynomial regression extends the linear regression framework to accommodate the non-linear relationships between the dependent and independent variables. Traditional linear regression models are inherently limited to linear associations. However, the complex and multifaceted nature of many real-world phenomena often necessitates a polynomial approach to better capture the dynamics at play.

The introduction of polynomial terms into the regression equation allows for the modeling of a curved relationship within the linear modeling paradigm. This process entails the generation of new features derived from the existing ones by raising them to various powers, hence the name *polynomial regression*.

A key advantage of polynomial regression is its capability to uncover the interactions between multiple features. It achieves this by incorporating not just the powers of individual features but also the interaction terms up to a specified degree. For example, given two features, a and b , and a polynomial degree of three, the enhanced feature set would include a^2 , a^3 , b^2 , and b^3 , along with interaction terms such as ab , a^2b , and ab^2 .

This enhancement is represented combinatorially by the formula:

$$\frac{(n + d)!}{d!n!} \tag{3.4}$$

where n denotes the original number of features and d is the degree of the polynomial. The factorial expression indicates the number of features generated through this polynomial expansion, emphasizing an exponential increase with respect to the polynomial degree.

Despite the potency of polynomial regression in capturing complex relationships, one must heed the potential for a combinatorial increase in feature space. This surge escalates both the computational burden and the susceptibility to overfitting, where the model becomes a reflection of the noise rather than the signal within the data. Consequently, the judicious application of polynomial regression is contingent upon a balanced choice of polynomial degree and rigorous validation strategies to ensure robust model generalization. Additionally, regularization may be employed to mitigate overfitting by imposing penalties on higher-order terms, thereby constraining the model's complexity. [91]

3.2.3 Decision trees

DT are a class of ML algorithms that stand out for their versatility and interpretability. They can be applied across a diverse array of tasks including classification, regression, and multi-output prediction problems. Recognized for their powerful capacity to model complex datasets, decision trees serve as the foundational building blocks of Random Forests, which rank among the most potent algorithms in the field of machine

learning today.

One of the significant advantages of DT is the minimal data preparation they require. Unlike many other algorithms that necessitate normalization or scaling of features, decision trees can be applied to raw datasets with little to no preprocessing, simplifying the workflow and reducing the potential for introduction of bias that can occur during data transformation.

The effectiveness of a DTs in classification tasks can be quantified through the Gini impurity measure. Gini impurity is an indication of node purity, where a score of zero reflects that a node contains instances of a single class. This purity metric helps to optimize the DTs during the training process by providing a clear criterion for the selection and prioritization of splits in the data. For instance, in a DTs classifying different types of Iris flowers, a node that perfectly classifies 'Iris setosa' would have a Gini score of 0, denoting pure classification.

The Gini impurity for a node i is calculated with the equation:

$$G_i = 1 - \sum_{k=1}^n p_{i,k}^2 \quad (3.5)$$

Where $p_{i,k}$ is the proportion of class k instances within the i th node. This mathematical representation succinctly encapsulates the weighted likelihood of classification missteps and aids in the tree's development to minimize such errors.

A distinguishing characteristic of DTs is their straightforward interpretability. The logic of a DT's classification process can be transparently viewed and understood, earning them the label of 'white box' models. This contrasts with more opaque 'black

box' models like Random Forests and neural networks, whose internal workings and logic are not as easily discerned. Although these models may exhibit high accuracy and predictive capability, delineating the exact reasoning behind specific predictions is often challenging. For example, when a neural network determines the presence of a person in an image, the rationale it uses—whether recognizing facial features or other contextual cues—is not readily apparent. On the other hand, DTs as explained in Algorithm 2 convey decision-making through an understandable series of rules. This clarity makes them particularly useful in scenarios where interpretability is paramount, such as medical diagnoses, credit scoring, or legal decision-making, where they can be manually applied for verification or in simple use cases like flower species classification.

[91]

Algorithm 2 Decision Tree Regression Learning Algorithm

Require: Training dataset D , Maximum depth d_{max} , Minimum split size s_{min}

Ensure: Decision tree regression model T

- 1: Let node N represent the entire dataset D
 - 2: Define a function $Split(N, d)$ that attempts to split node N using the best split criterion based on mean squared error reduction $BuildTreeN, d$
 - 3: **if** $d = d_{max}$ OR size of $N < s_{min}$ **then**
 - 4: Mark N as a leaf and set prediction to mean outcome in N
 - 5: **else**
 - 6: $Split(N, d)$
 - 7: **for** each child node C of N **do**
 - 8: $BuildTree(C, d + 1)$
 - 9: **end for**
 - 10: **end if**
 - 11: $BuildTree(N, 0) = 0$
-

3.2.4 KNN Regression

The k-nearest neighbor KNN classifier represents a shift from the machine learning models previously discussed, distinguishing itself as a non-parametric, instance-based learning algorithm. Unlike its counterparts, the KNN classifier is recognized as a lazy learner, a term that reflects its operational mechanism. This mechanism does not involve learning a generalizable discriminative function but rather retains the dataset, using it as a reference framework for making future classifications.

KNN's process can be outlined in three procedural steps: (1) selection of the quantity 'k' which denotes the number of nearest data points to consider and choosing an appropriate distance metric to measure proximity; (2) locating the 'k' closest neighbors to the new data point; and (3) assigning a class label based on the majority class present in this localized subset. This methodology underscores the KNN's real-time adaptation to newly acquired data, which is both a strength and a limitation.

The broader context of ML models includes parametric and non-parametric models. Parametric models, exemplified by algorithms like the perceptron, logistic regression, and linear SVM, infer parameters from training data to formulate a predictive function, independent of the training data thereafter. Conversely, non-parametric models, including DT and kernel SVM, adjust their complexity with the volume of training data, a trait evident in their inability to be summarized by a finite parameter set.

The categorization of KNN as a subtype of non-parametric models under instance-based learning emphasizes its distinctive attribute of memorization over learning

through abstraction. In lazy learning, specifically, the efficiency of memorizing comes at no cost during the training phase. However, the computation required to classify new instances escalates with the dataset's size, which may present challenges in terms of processing speed and storage capacity, particularly for large datasets.

Efficient querying in large datasets may be facilitated by advanced data structures such as k-d trees and ball trees, which can ameliorate computational burdens. Nevertheless, the KNN classifier remains effective for small to medium-sized datasets, as shown in various applications. For instance, in the pharmaceutical industry, KNN methods have been used to predict the dynamic properties of G-protein-coupled receptor (GPCR) inhibitors, underscoring its utility in high-stakes research. Moreover, KNN models have also been incorporated into language processing to optimize performance, demonstrating their relevance in cutting-edge computational linguistics.

In practice, while KNN's as illustrated in Algorithm 3 demand for computational resources grows with dataset size, its capacity for robust, flexible learning without the need for pre-training adjustments makes it a viable tool for addressing a range of practical problems, as evidenced by recent scholarly work in pharmacology and machine learning. [92]

Algorithm 3 K-Nearest Neighbors (KNN) Regression Learning Algorithm

Require: Training dataset $D = \{(x^{(i)}, y^{(i)})\}_{i=1}^m$, Number of neighbors k

Ensure: KNN regression model

- 1: **for** each test instance x **do**
 - 2: Find the k nearest neighbors in D to x
 - 3: Calculate the predicted output for x as the average of the output values of its k neighbors
 - 4: **end for**=0
-

3.2.5 Random Forests Regression

Ensemble methods are a class of algorithms that have become exceedingly prevalent in ML for their remarkable ability to deliver robust and high-performing classification models, particularly noted for their resistance to overfitting. These methods combine the strengths of various models to enhance performance and reduce the likelihood of an algorithm becoming too closely fit to the peculiarities of the training data. This section will focus on one ensemble technique in particular, the random forest algorithm.

The random forest algorithm is an extension of the DT regressor and operates on the principle of generating a 'forest' of trees where each tree is constructed using a random subset of data and features. The fundamental hypothesis underpinning random forests is that a collection of weak learners (individual decision trees) can be integrated to form a strong learner. Each tree in the forest is allowed to grow to its full depth, which results in high complexity and variance for individual trees. However, by averaging their predictions, the ensemble diminishes the individual trees' tendency to overfit, thereby yielding a more reliable and generalizable model.

Random forests scale well with large datasets and diverse problem sets, making them a versatile tool in the machine learning toolkit. They are particularly user-friendly because they require very few parameters to be set by the user, with the number of trees in the forest and the number of features considered at each split being the primary considerations. The robustness of random forests arises from their intrinsic design, which ensures that the diversity among the individual trees—achieved

through randomization—contributes to a collective decision-making process that is less prone to model the noise in the training data.

Moreover, random forests have an inherent measure of feature importance, given that they can indicate which features contribute most significantly to the predictive power of the model. This characteristic not only provides insight into the functioning of the model but also into the nature of the problem being solved.

The convergence of multiple DTs as illustrated in Algorithm 4 in a random forest leads to a consensus approach that mitigates the errors of individual trees and emphasizes common patterns, improving the predictive accuracy of unseen data. This method has been applied successfully in a wide array of domains, including but not limited to, bioinformatics, market analysis, and environmental modeling, where the benefits of its strong predictive capabilities and resilience to overfitting are critically important. [92]

Algorithm 4 Random Forests Regression Learning Algorithm

Require: Training dataset D , Number of trees T , Maximum depth d_{max} , Minimum split size s_{min}

Ensure: Random forest regression model RF

- 1: **for** $t = 1$ to T **do**
 - 2: Sample a subset of D with replacement to create a new dataset D_t
 - 3: Train a decision tree T_t using D_t with maximum depth d_{max} and minimum split size s_{min}
 - 4: Add T_t to the random forest RF
 - 5: **end for**
-

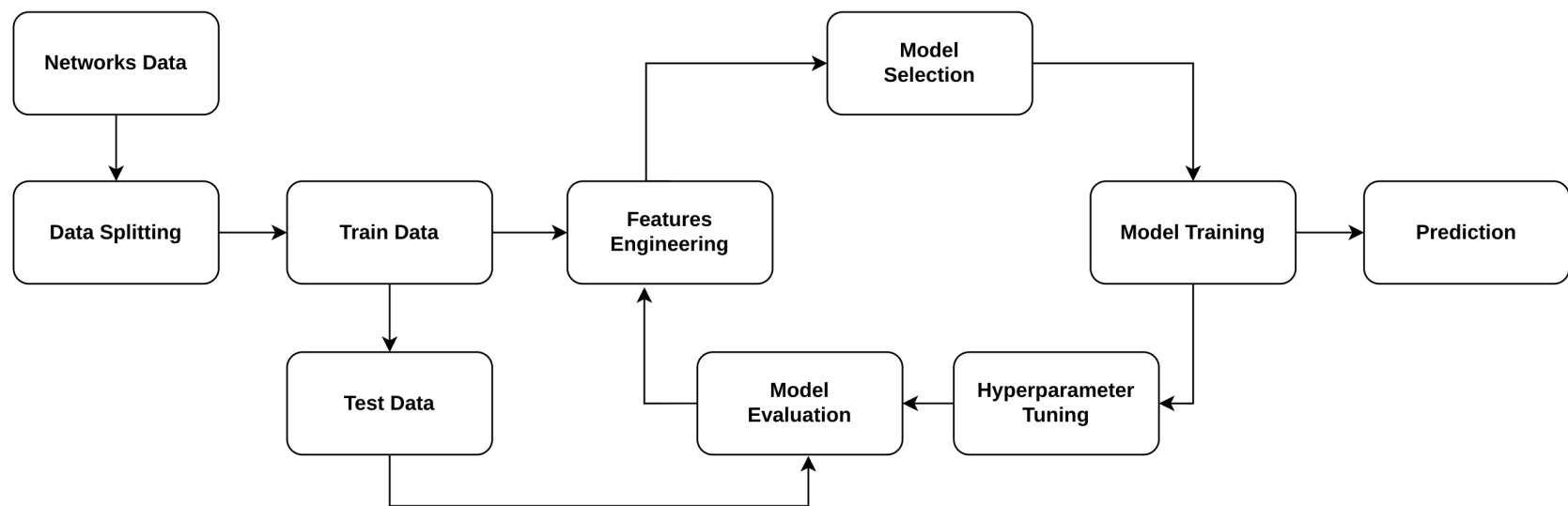


Figure 3.3: ML Models Development

3.3 Model Selection and Hyperparameter Tuning

In the process of developing our predictive models, we have taken a meticulous approach to model selection and hyperparameter tuning employing grid search techniques combined with cross-validation to optimize the efficacy of these models as illustrated in Figure 3.7. To ensure a comprehensive evaluation of various regression techniques within the context of our study, we have incorporated a diverse range of regression models, each possessing distinct characteristics and capabilities. For each regression model, an array of hyperparameters has been thoroughly examined to identify the configuration that minimizes the mean squared error on our dataset. This approach ensures that each model is fine-tuned to offer the highest predictive accuracy attainable.

The ensemble of regression models employed includes linear regression, polynomial regression, decision tree regression, k-nearest neighbor regression, gradient boost

regression, radius neighbor regression, Bayesian Ridge regression, random forest regression, and elastic net regression. By incorporating this diverse set of models, our objective is to thoroughly assess their performance and identify the most suitable candidate for our predictive tasks. This systematic exploration of regression techniques enhances the robustness and effectiveness of our ML approaches in predicting the importance of interdependent network nodes.

Table 3.2: Regression Models Hyperparameters

Model	Hyperparameter	Values
Linear Regression	<code>__fit_intercept</code>	[True, False]
	<code>__n_jobs</code>	[None]
	<code>__positive</code>	[False]
Polynomial Regression	<code>__degree</code>	[2, 3, 4]
	<code>__fit_intercept</code>	[True, False]
	<code>__positive</code>	[False]
Decision Tree	<code>__max_depth</code>	[None, 10, 20, 30]
	<code>__min_samples_split</code>	[2, 5, 10]
KNN	<code>__n_neighbors</code>	[3, 5, 7]
	<code>__weights</code>	['uniform', 'distance']
Gradient Boosting	<code>__n_estimators</code>	[10, 15, 20]
	<code>__learning_rate</code>	[0.01, 0.05, 0.1]
	<code>__max_depth</code>	[3, 5, 7]
Radius Neighbors	<code>__radius</code>	[1.0, 2.0, 3.0]
	<code>__weights</code>	['uniform', 'distance']
Bayesian Ridge	<code>__n_iter</code>	[100, 300, 500]
	<code>__alpha_1</code>	[1e-6, 1e-7, 1e-8]
	<code>__alpha_2</code>	[1e-6, 1e-7, 1e-8]
Random Forest	<code>__n_estimators</code>	[10, 20, 30]
	<code>__max_depth</code>	[None, 10, 20, 30]
	<code>__min_samples_split</code>	[2, 5, 10]
Elastic Net	<code>__alpha</code>	[0.001, 0.01, 0.1, 1, 10, 100]
	<code>__l1_ratio</code>	[0.1, 0.5, 0.9]

3.4 Cross-Validation and Training Efficiency

The expensive cross-validation process plays a pivotal role in assessing the generalization performance of the models. A K-fold cross-validation strategy has been adopted as shown in Table 3.2, where K is set to 10, thereby dividing the dataset into ten distinct subsets or "folds." Each fold is alternately employed as both a validation set and an integral part of the training set. This procedure is iterated ten times, ensuring that each fold assumes the role of a validation set exactly once. The results from these iterations are then amalgamated and averaged to yield a robust estimate of the model performance.

To accelerate the training process and optimize memory usage, a prudent batch-based training approach has been used. This approach strategically divides the dataset into smaller, manageable batches, deviating from the conventional method of training on the entire dataset at once. The benefits are twofold: maximize the utilization of available computational resources and ensure efficient execution of grid search and cross-validation procedures.

3.5 Model Training Time

An essential facet of model evaluation is related to the time taken for model training. This metric holds particular significance in real-world applications where computational efficiency is a crucial concern. The training times for each model have been meticulously recorded and are presented in minutes. These empirical data serve as a

valuable criterion for assessing the computational efficiency of the models, helping to judiciously select models for practical implementation.

3.6 Evaluation Metrics

In this section, a comprehensive evaluation of the trained regression models is carried out, using a variety of evaluation metrics. These metrics serve as the yardstick for gauging the models' proficiency in predicting the significance of nodes within Inter-dependent Infrastructure Networks. The evaluation metrics encompass the following key parameters:

3.6.1 Mean Squared Error

MSE, or Mean Squared Error, serves as a key metric to quantify the average squared difference between predicted values and actual observations. It provides an overarching assessment of the quality of a model's predictions, with lower MSE values signifying superior performance. For each model, we report the average MSE scores, providing a holistic view of their predictive capabilities.

3.6.2 Root Mean Squared Error

RMSE, or Root Mean Squared Error, represents the square root of MSE and offers a measure of the average prediction error in units congruent with the target variable.

This metric is invaluable for understanding the magnitude of errors generated by the model. Our analysis includes the average RMSE scores for each model, providing clarity on the degree of prediction precision.

3.6.3 R-Squared

The R^2 metric functions as an indicator of the efficiency with which a model elucidates the variance present in the target variable. It quantifies the proportion of variance in the dependent variable that can be foreseen from the independent variables. R^2 values range from 0 to 1, with higher values indicative of a better fit. Our reporting includes the average R^2 scores for each model, giving insight into their capacity to capture underlying patterns.

3.6.4 Mean Absolute Error

MAE, or Mean Absolute Error, measures the average absolute discrepancy between predicted values and actual observations. This metric offers a robust evaluation of prediction accuracy. For each model, we provide details on the average MAE scores, allowing a comprehensive evaluation of their predictive capabilities.

CHAPTER 4

DEEP LEARNING BASED APPROACH

4.1 Introduction

In this section, we utilized a mathematical framework developed by [16] for data generation. This model acts as a foundational platform for emulating recovery situations, considering both the improvement of network resilience and the reduction in recovery expenses. We methodically produced a dataset encompassing diverse recovery activities, resource distributions, and related costs under different disruption circumstances.

In this model, we consider a set of IIN, each identified as A , spanning a series of time intervals defined as $T = \{1, \dots, \tau\}$. Each network, denoted as a within A , comprises a series of nodes, referred to as M^a , and a network of links, referred to as P^a . We also identify subsets of nodes within each network: supply nodes $M_s^a \subset M^a$ and demand/consumption nodes $M_d^a \subset M^a$. The elements affected by disruptions in each

network a of A are designated as M'^a for nodes and P'^a for links. The supply amount at node i in M_s^a within network a from A is denoted by g_i^a , following a Gaussian distribution with specified mean and standard deviation, and assumed constant over time. The unmet demand at node i in M_d^a of network a from A during time interval t in T is represented as h_{it}^a . The cumulative unmet demand across all demand nodes in network a from A after recovery during time interval t in T is $\sum_{i \in M_d^a} h_{it}^a$. In this model, h_{it}^a symbolizes the extent to which network demand remains unmet, in contrast to g_i^a , which represents a consistent performance goal.

The economic aspect of network restoration involves assessing costs related to returning nodes and links to operational status. For a node i in M'^a and a link (i, j) in P'^a for a network a in A , restoration costs are denoted as rn_{it}^a for nodes and rl_{ijt}^a for links, where t is a time interval in T . The cost per unit of flow through link (i, j) in network a is q_{ij}^a , and the cost for unmet demand at node i is u_{it}^a . The total system cost, combining restoration, flow, and unmet demand costs, is expressed using binary decision variables v_i^a for nodes and w_{ij}^a for links, and a non-negative variable j_{ijt}^a for flow through a link during a time period t .

$$\sum_{a \in A} \sum_{t \in T} \left(\sum_{i \in M'^a} rn_{it}^a v_i^a + \sum_{(i,j) \in P'^a} rl_{ijt}^a w_{ij}^a + \sum_{(i,j) \in P^a} q_{ij}^a j_{ijt}^a + \sum_{i \in M_d^a} u_{it}^a h_{it}^a \right) \quad (4.1)$$

[16]

In discussing the operational resilience and restoration of complex networked sys-

tems, it is essential to establish a framework that allows for systematic analysis and efficient management of resources. Within this context, the concept of restoration duration is crucial. It refers to the time required to return a node or link in a network to its functional state after a disruption. This can be mathematically represented for a given node within a subset of nodes M'^a and a link (i, j) within a subset of links P'^a across various networks indexed by k , using the notation dn_i^k for nodes and dl_{ij}^k for links.

The capacity of each link (i, j) in network a , denoted as f_{ij}^a , is essential for understanding network constraints. Binary decision variables d_{it}^a (for nodes) and e_{ijt}^a (for links) represent the operational status of network components over discrete time periods. Where a value of 1 indicates functionality, while 0 indicates a failure or non-operational state.

To address the allocation of restoration efforts, binary decision variables l_{it}^{ar} for nodes and m_{ijt}^{ar} for links are introduced. These variables are used to schedule restoration tasks for work crews, denoted by r , who are equipped with the necessary expertise and tools to manage specific networks. The scheduling variable l_{it}^{ar} equals 1 if the node is being restored by crew r at time period t , with a similar interpretation for m_{ijt}^{ar} concerning links.

Furthermore, the Interdependentness of different networks is acknowledged through the interdependence variable Ξ , which identifies the physical dependency between nodes across different networks, capturing the essence of network interdependency in operational functionality. This variable enhances our understanding of

the cascading effects of network failures and the prioritization of restoration efforts. Through such modeling, stakeholders can better strategize the restoration process, ensuring a streamlined and effective recovery post-disruption. This analytical approach underscores the importance of preparedness and adaptive capacity in network infrastructure management.

The modeling endeavor is bound by a series of constraint groups: (a) flow regulation constraints within each network, (b) restoration timeframe constraints, (c) inter-network dependency constraints, (d) logical constraints correlating network flow with restoration activities, and (e) constraints that define the decision variables. Detailed explications and formulations for each group of constraints type are presented in the ensuing segments.

A. Network flow conservation Constraints: the constraints (3)-(6), ensuring the maintenance of flow at various node types within each infrastructure network. For the maintenance of flow within each network, several constraints are applied. These include:

$$\sum_{(i,j) \in P^a} j_{ijt}^a \leq g_i^a, \quad \forall i \in M_s^a, \quad a \in A, \quad t \in T \quad (4.2)$$

Equation (4.3) ensures the sum of flows on links emanating from supply nodes does not exceed the supply limit.

$$\sum_{(i,j) \in P^a} j_{ijt}^a - \sum_{(j,i) \in P^a} j_{jit}^a = 0, \quad \forall i \in M^a \setminus (M_s^a \cup M_d^a), \quad a \in A, \quad t \in T \quad (4.3)$$

Equation (4.4) assures that the flow is conserved at intermediary nodes within each

network.

$$\sum_{(j,i) \in P^a} j_{jit}^a + h_{it}^a = g_i^a, \quad \forall i \in M_d^a, \quad a \in A, \quad t \in T \quad (4.4)$$

Here, the balance of supply and demand at destination nodes is maintained, considering the unmet demand. This constraint assures that the flow is conserved at intermediary nodes within each network.

$$\sum_{(j,i) \in P^a} j_{jit}^a + h_{it}^a = g_i^a, \quad \forall i \in M_d^a, \quad a \in A, \quad t \in T \quad (4.5)$$

Here, the balance of supply and demand at destination nodes is maintained, considering the unmet demand.

B. Restoration Timeframe and Assignment Constraints: Restoration tasks are governed by a set of constraints ensuring timely and orderly execution. These include:

$$v_i^a = \sum_{r \in R^a} \sum_{t \in T} l_{it}^{ar}, \quad \forall i \in M^a, a \in A \quad (4.6)$$

$$w_{ij}^a = \sum_{r \in R^a} \sum_{t \in T} m_{ijt}^{ar}, \quad \forall (i, j) \in P'^a, a \in A \quad (4.7)$$

These equations determine the restoration status of nodes and links based on the completion of assigned tasks by respective crews.

C. Inter-Network Dependency Constraints: The functionality of nodes in Interde-

pendent networks is linked by the following constraint:

$$d_{it}^{\bar{a}} - d_{it}^a \leq 0, \quad \forall ((i, a), (\bar{i}, \bar{a})) \in \Xi, t \in T \quad (4.8)$$

This ensures the operational dependency between nodes across different networks.

D. Logical Constraints Linking Network Flow and Restoration: The model includes constraints that correlate the capacity and restoration status of network components with the permissible flow:

$$j_{ijt}^a - f_{ij}^a d_{it}^a \leq 0, \quad \forall (i, j) \in P^a, i \in M^a, a \in A, t \in T \quad (4.9)$$

$$j_{ijt}^a - f_{ij}^a e_{ijt}^a \leq 0, \quad \forall (i, j) \in P^a, a \in A, t \in T \quad (4.10)$$

These constraints dictate that the flow through any connection is dependent on the capacity and restoration status of nodes and links.

E. Decision-Making Variables and Associated Constraints:

Non-Negativity and Binary Nature of Decision Variables: The model imposes certain restrictions on the decision variables to ensure their practical applicability within the network's operational framework. These include:

$$h_{it}^a \geq 0, \quad \forall i \in M^a, a \in A, t \in T \quad (4.11)$$

This constraint mandates that the unmet demand (slack variable) at each node must

be non-negative, reflecting the absence of negative demand scenarios.

$$j_{ijt}^a \geq 0, \quad \forall (i, j) \in P^a, a \in A, t \in T \quad (4.12)$$

It ensures that the flow through each link in the network is non-negative, prohibiting reverse or negative flow values.

$$v_i^a, w_{ij}^a \in \{0, 1\}, \quad \forall i \in M^a, (i, j) \in P^a, a \in A \quad (4.13)$$

$$d_{it}^a, e_{ijt}^a \in \{0, 1\}, \quad \forall i \in M^a, (i, j) \in P^a, a \in A, t \in T \quad (4.14)$$

These constraints define the binary nature of the restoration status variables for nodes and links, indicating whether a component is restored (1) or not (0).

$$l_{it}^{ar}, m_{ijt}^{ar} \in \{0, 1\}, \quad \forall i \in M^a, (i, j) \in P^a, a \in A, t \in T, r \in R^a \quad (4.15)$$

The scheduling variables for restoration tasks by work crews are also binary, showing whether a specific task is scheduled (1) or not (0). The Deep Learning Model that has been developed to predict the nodes significance is discussed in the following section.

4.2 Artificial Neural Networks

Neural networks are a pivotal computational model in modern ML, especially noted for their proficiency in handling a wide array of data-driven tasks. In the context of supervised learning, where labeled datasets are employed, these networks excel in

discerning the intricate structure within high-dimensional data. They achieve this by approximating a function that maps input variables to output labels, often leveraging their inherent capability to model nonlinear relationships.

The architecture of a neural network is devised to simulate the processing attributes of biological neurons. Each artificial neuron within the network conducts a weighted sum of inputs, applies a nonlinear function (commonly an activation function), and produces an output that serves as an input for subsequent layers. This process is not static but evolves through a method known as 'training,' where the optimal weights of the network are iteratively adjusted based on the feedback from the error in output predictions.

The training process of neural networks hinges on optimization algorithms, with gradient descent and its variants being among the most utilized. By iteratively minimizing a loss function—a metric that quantifies the error between the predicted and actual values—neural networks refine their weights to improve prediction accuracy. The versatility of neural networks is further underscored by their ability to generalize from the learned data to new, unseen datasets, a feature that is fundamental to their widespread application.

A neural network's ability to capture nonlinearity is pivotal to its success across various domains such as image recognition, natural language processing, and predictive analytics. This nonlinearity, which allows for the modeling of complex and multifaceted patterns in data, is typically instantiated through multiple layers, giving rise to the term 'deep learning.' DNN, with their profound layering, have demonstrated remarkable performance improvements over traditional machine learning approaches.

The expansion of computational resources and the availability of large labeled datasets have catalyzed the rapid advancement of neural networks. Their growing sophistication allows for the tackling of increasingly complex tasks, offering a testament to the transformative power of neural networks in leveraging the latent knowledge embedded in data. As research progresses, the quest continues for novel neural network architectures and training methodologies that can further enhance their mapping efficiency from input spaces to desired output forms.

In the quest for advanced computational models capable of optimizing recovery strategies within complex systems, our study utilizes the Mixed Integer Programming (MIP) model presented in [80] as a fundamental point of departure. Recognizing the limitations imposed by the exhaustive computational demands of MIP, particularly when applied to scenarios of high dimensionality, we engage DNN to streamline the process. Our research employs a simulator that generates data reflective of the system’s dynamics, which is then used to train the DNN model, aiming to encapsulate the spatio-temporal characteristics inherent in the system’s operations.

Our DNN model as shown in Figure 4.1 and illustrated in Algorithm 5 is structured around a feed-forward design, a choice motivated by the architectural simplicity and proven efficiency of such designs in capturing linear and nonlinear relationships. Training is executed via backpropagation, an algorithm standard for its effectiveness in error correction throughout the network, thereby optimizing the model’s performance iteratively. The operational premise of our model is the transformation of system functionality states into a predictive framework for assessing the network’s response to disruptions. This is achieved through the input layer, where we utilize an

8-dimensional vector encoding specific node attributes. These attributes encompass a range of characteristics, including X and Y coordinates, supply/demand capacity, degree of connectivity, disruption status, restoration cost, and restoration duration. Each dimension of this vector encapsulates essential information about the immediate state and characteristics of the network's nodes.

The size and composition of the input layer are thoughtfully designed to align with the system's scope under examination. It comprises 8 neurons, each corresponding to one of the dimensions in the feature vector, allowing for the comprehensive representation of node attributes.

Our primary innovation revolves around the transformation of this multi-dimensional feature vector into a predictive signal that elucidates the priority and significance of each node's repair or restoration requirements. This conversion process plays a pivotal role in establishing the sequence of actions during recovery efforts, ensuring that resources are judiciously allocated to nodes of higher strategic importance.

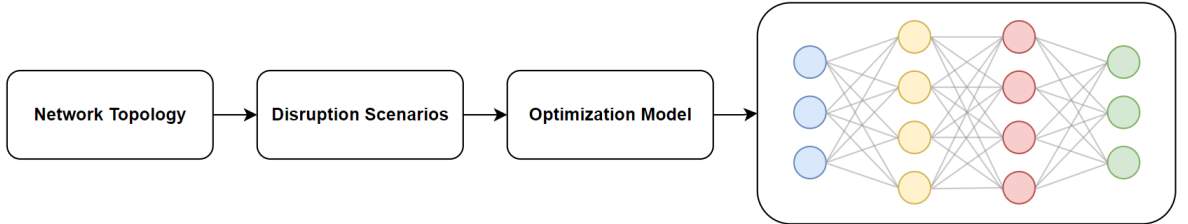


Figure 4.1: DNN Model Development

Algorithm 5 Deep Learning Model Learning Algorithm

Require: Training dataset D , Number of epochs E , Learning rate α , Batch size B ,
Network architecture N

Ensure: Deep learning model DL

- 1: Initialize weights and biases for the network architecture N
 - 2: **for** $e = 1$ to E **do**
 - 3: Shuffle the dataset D
 - 4: **for** each batch b in D of size B **do**
 - 5: Perform forward propagation on b using N to compute the output
 - 6: Calculate loss between the predicted output and the actual labels
 - 7: Perform backpropagation to compute gradients of the loss with respect to weights and biases
 - 8: Update weights and biases using gradients and learning rate α
 - 9: **end for**
 - 10: Optionally evaluate the model on a validation set and adjust hyperparameters if necessary
 - 11: **end for**
 - 12: Return the trained model $DL = 0$
-

CHAPTER 5

GEOMETRIC DEEP LEARNING BASED APPROACH

Graphs, as an integral data structure, play a vital role in representing objects (nodes) and their connections (edges), finding application in a wide range of fields from social sciences to natural sciences. The advent of ML has further elevated the importance of graphs, especially in complex domains such as social networks [93], [94], physical systems [95], [96], protein-protein interactions [97], and the construction of knowledge graphs [98]. The breadth of these applications underscores the adaptability and expressive power inherent in graph structures, making them indispensable in modern research and analysis.

Graphs are particularly significant in the realm of ML due to their non-Euclidean nature. Unlike traditional data structures, they offer a unique set of challenges and opportunities for researchers. Analytical techniques in this domain often focus on node classification, link prediction, and clustering. These methods are essential for

unraveling the intricate relationships and hidden patterns within the graph structure, thereby providing insights into the underlying data.

Within the sphere of DL, Graph Neural Networks or GNN have been a transformative development. GNNs are designed specifically to operate within the graph domain, differentiating them from conventional neural network architectures. Their direct engagement with graph structures allows for a more nuanced understanding and processing of the relationships between nodes and edges. This attribute of GNNs has led to their widespread adoption and acclaim, particularly due to their robust performance and high degree of interpretability. They have become a preferred method for graph analysis, leveraging the power of DL to extract meaningful insights from complex graph data.

The growing interest and application of GNNs signal a significant shift in the landscape of ML. It highlights the trend towards developing and implementing algorithms that are tailored to specific data structures, such as graphs. This tailored approach allows for more detailed and effective analysis, opening up new avenues for innovation and discovery in various fields of research. By leveraging the unique properties of graphs, GNNs facilitate a deeper understanding of data, contributing significantly to advancements in both theoretical and applied research domains.

This evolution of ML, with a focus on specialized techniques like GNNs, illustrates the ongoing pursuit of more sophisticated and efficient analytical tools. As researchers continue to explore the capabilities of GNNs and other graph-based methods, we can expect to see further advancements and novel applications in areas ranging from network analysis to computational biology, demonstrating the pervasive and growing

impact of graph-based analysis in the scientific community.

5.1 CONVOLUTIONAL NEURAL NETWORKS

Graph Neural Networks derive their foundational concept from Convolutional Neural Networks CNNs, a pivotal development in the evolution of deep learning. CNNs, excel in extracting and integrating multi-scale localized spatial features, contributing significantly to advancements across various ML domains. This success is largely attributed to key aspects of CNNs, such as local connections, shared weights, and multi-layer architectures. These elements are particularly relevant in the context of graph analysis, offering solutions to challenges inherent in this field.

Graphs epitomize locally connected structures, making the principles of local connection in CNNs especially pertinent. Shared weights, a concept crucial in CNNs, also find relevance in graph domain problems, offering computational efficiency over traditional spectral graph theory approaches. Furthermore, the multi-layer structure, vital for handling hierarchical patterns, proves beneficial in capturing features of varying scales within graph data.

Despite these similarities, a fundamental challenge arises when attempting to adapt CNNs to graph data. CNNs are intrinsically designed for regular Euclidean data, such as 2D images or 1D text sequences, both of which can be perceived as graph instances. However, the irregular, non-Euclidean nature of graphs complicates the direct application of CNN methodologies. The primary difficulty lies in defining localized convolutional filters and pooling operators for graphs, which are straightforward in Euclidean

domains. This barrier hinders the transformation of CNN approaches from Euclidean to non-Euclidean domains, necessitating innovative adaptations to leverage CNN-like techniques in graph analysis.

The quest to generalize CNNs to graph structures is not merely a theoretical endeavor but a practical necessity, given the vast potential applications of graphs in various scientific and technological fields. This challenge has spurred significant research efforts, aiming to reconcile the disparities between Euclidean and non-Euclidean data structures and to harness the power of CNNs in the expansive and complex world of graph data. The development of GNNs represents a critical step in this direction, embodying an attempt to bridge the gap between these two domains and unlock the capabilities of deep learning in graph-based analyses.

5.2 MULTI-DIMENSIONAL GRAPHS

Within the realm of graph theory and its applications, there has been a traditional predilection for the analysis of binary edge graphs. Such graphs presuppose a binary relationship between nodes – a straightforward yes-or-no, connected-or-not scenario. However, this binary perspective is a simplification that often fails to encapsulate the multifaceted nature of real-world networks. In more complex scenarios, nodes manifest multiple, diverse types of relationships, forging what is referred to as a "multi-dimensional graph" or, in other terminologies, a multi-view graph or a multi-graph. These networks are characterized by nodes connected by various types of relationships, each representing different interaction dynamics within the network.

An illustrative example of multi-dimensional graph complexity as illustrated in Figure 5.1 can be found in the online ecosystem of the video-sharing platform YouTube. Here, user interactions are multifarious and cannot be sufficiently represented by a single, uniform type of connection. Instead, interactions span across various dimensions – including but not limited to "subscription," "sharing," and "commenting" – each constituting a distinct form of relational engagement, as delineated by [71]. The non-independent nature of these relationship types indicates that models traditionally employed for single-dimensional graph analysis might not provide an optimal solution when applied to multi-dimensional structures.

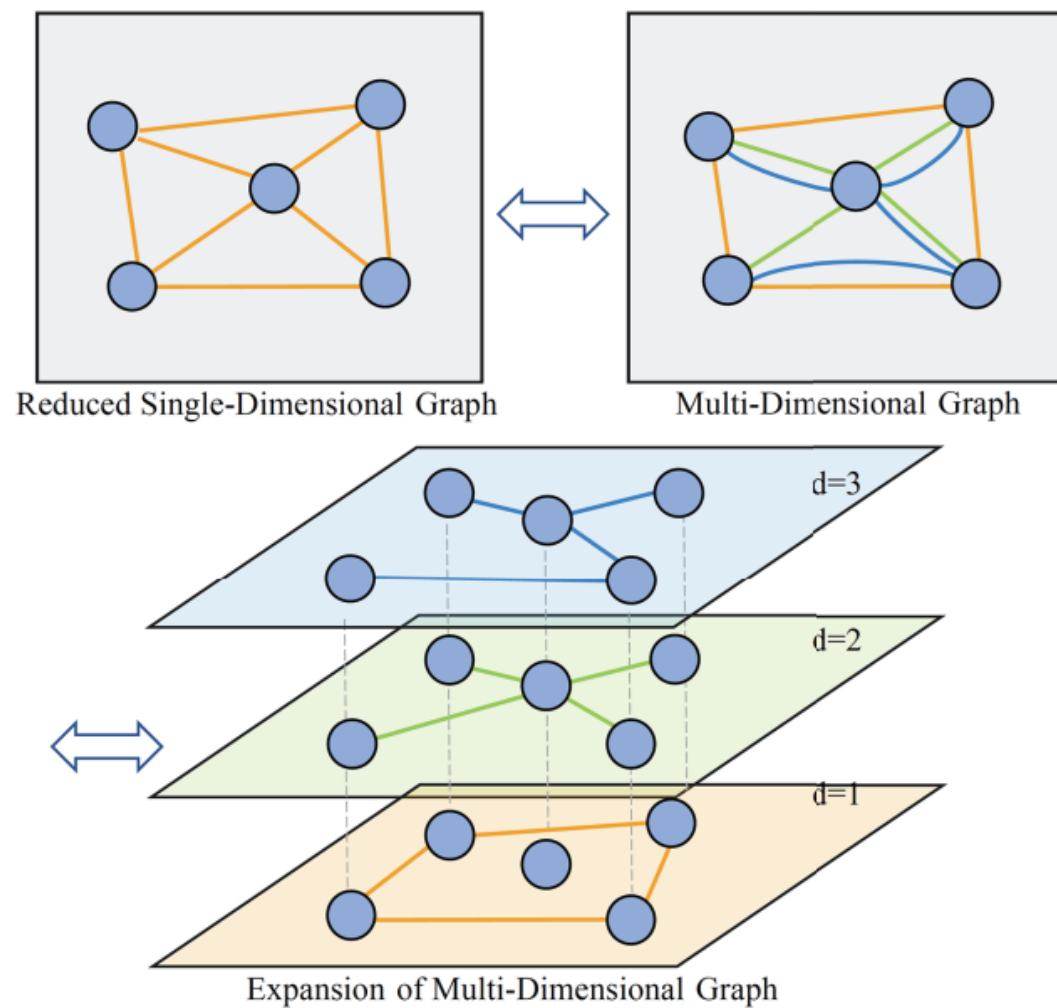


Figure 5.1: GNN multi-dimensional graph[2]

5.3 NETWORK EMBEDDING

Another key motivation for the development of GNNs stems from the field of graph embedding. This technique, as outlined by researchers like [99], [100], [101], [93] and others involves representing graph nodes, edges, or subgraphs as low-dimensional vectors. Traditional ML approaches in graph analysis have typically depended on manually crafted features, but this method often proves to be rigid and costly.

The concept of graph embedding draws inspiration from the success of representation learning, particularly evident in the field of word embedding, as demonstrated by [102]. An early and significant advancement in graph embedding was DeepWalk [103], which applied the SkipGram model, initially used in word embedding, to random walks generated on graphs. This approach laid the groundwork for subsequent methods like node2vec [104], LINE [105], and TADW [106], all of which marked significant progress in the field.

Despite these advancements, Hamilton et. al, [107] identified two major limitations in these initial graph embedding techniques. Firstly, the absence of shared parameters between nodes in the encoding process led to computational inefficiencies. This issue arises because the number of parameters needed increases linearly with the number of nodes, making the process less scalable. Secondly, these direct embedding methods demonstrated a lack of generalization capability. They were not equipped to handle dynamic graphs or to be generalized to new, unseen graph structures. This limitation severely restricted their applicability in dynamic and evolving graph scenarios, which are common in real-world applications.

These challenges highlighted the need for more advanced methods in graph representation, paving the way for the evolution of GNNs. The development of GNNs aimed to address these drawbacks by introducing more efficient and adaptable approaches to graph analysis, capable of handling dynamic changes and generalizing across various graph structures. This progression in graph embedding and analysis represents a significant stride in machine learning, particularly in the context of complex and large-scale graph data, where traditional methods fall short.

5.4 Methodology

This section illustrates the methodology employed in developing a GNN model, specifically tailored for enhancing the operational resilience of critical infrastructure systems by predicting each node’s significance in the network. The increasing complexity and Interdependency of such systems in contemporary society necessitate robust and intel-

ligent methods to forecast and mitigate disruptions. To this end, this research employs state-of-the-art artificial intelligence techniques, focusing on the application of GNNs for infrastructure robustness and recovery post-disruption.

5.4.1 Model Architecture

The GNN model, is architecturally designed as a subclass of `nn.Module` within the PyTorch framework. This architecture facilitates the incorporation of both graph convolutional and linear layers to process graph-structured data effectively. The model is structured to include:

1. **Graph Convolutional Layers:** Four GCN layers are implemented, gradually increasing in neuron count (512, 1024, 512, and `hidden_dim`). These layers are integral for capturing the complex, non-linear relationships inherent in graph-structured data. Each layer aims to refine the feature representation progressively, ensuring a comprehensive understanding of the graph's topology and node interactions.
2. **Linear Layers:** Following the GCN layers, four linear layers are introduced (`hidden_dim` to 1024, 1024 to 2048, 2048 to 512, and 512 to `output_dim`). These layers serve to further process the features extracted by the GCN layers, facilitating the transition from high-dimensional representations to the desired output dimension.
3. **Activation Functions:** The Rectified Linear Unit (ReLU) activation function is employed following each layer, introducing non-linearity and enhancing the

model's learning capability.

4. **Device Allocation:** The model is configured to operate on a CUDA-enabled device, leveraging GPU acceleration to handle the substantial computational requirements efficiently.

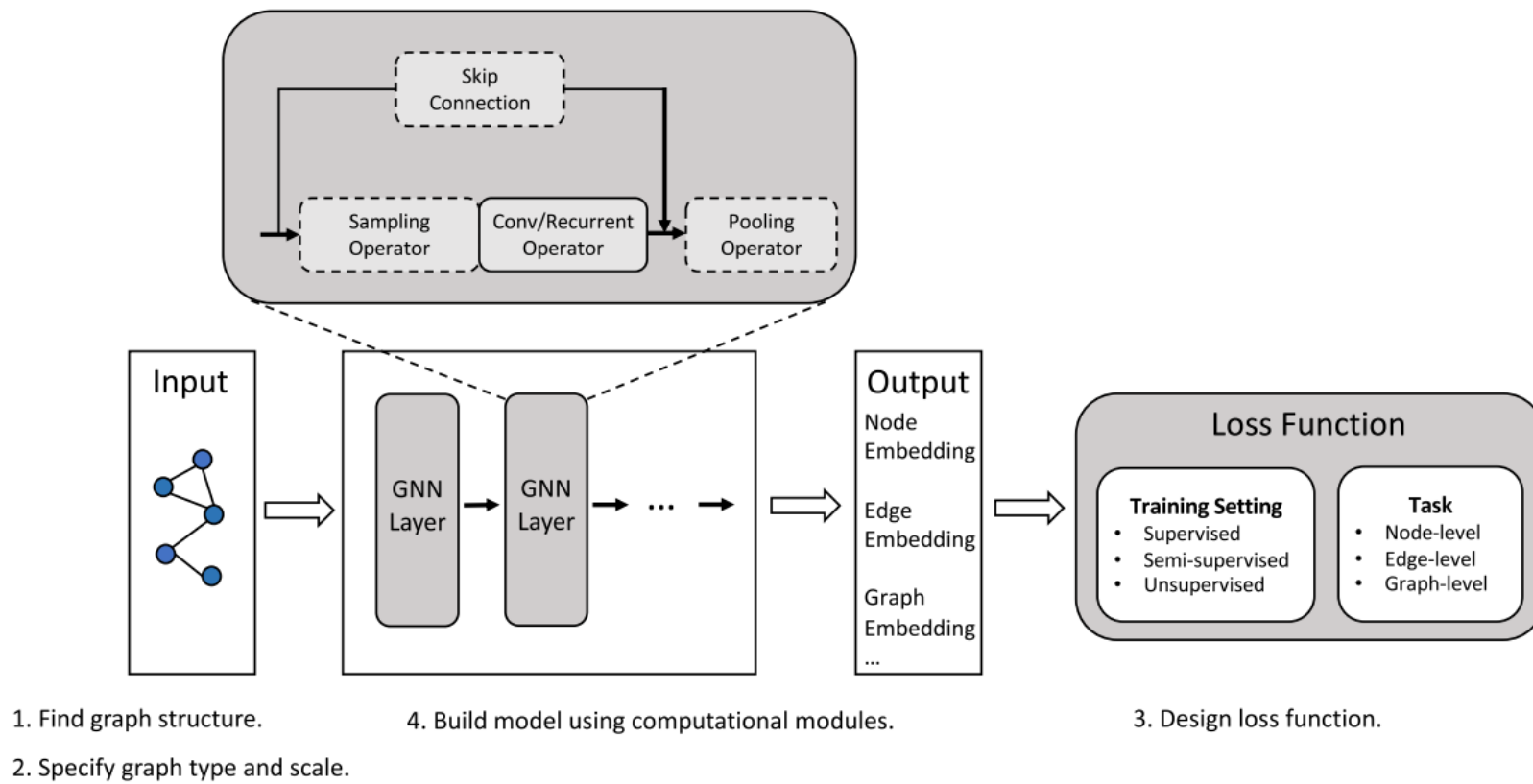


Figure 5.2: GNN Model Pipeline[2]

5.5 Graph Neural Network Model Workflow

Figure 5.2 delineates a systematic representation of the development workflow for a GNN model, encapsulating the journey from the input graph to the model’s final output and emphasizing the architectural and functional constituents of the GNN.

1. **Graph Structure Identification:** The initial phase of the workflow involves discerning the graph’s structural configuration, recognizing nodes and edges which are central to the graph’s representation and form the foundation for ensuing analysis within the GNN.
2. **Graph Type and Scale Specification:** Subsequent to the structure identification, the graph’s type and scale are specified, including its directionality, weighted nature, and the extent of its complexity. This specification is pivotal as it dictates the configuration of the GNN layers and the overarching model architecture.

3. **Model Construction Using Computational Modules:** The construction of the GNN model is executed using a variety of computational modules:

- *Sampling Operator:* Responsible for the selection of a node or edge subset, enabling efficient management of large-scale graphs.
- *Convolutional/Recurrent Operator:* These operators apply convolutions or recurrent transformations to graph data, aiding in feature extraction and information propagation.
- *Pooling Operator:* Aggregates information, contributing to dimensionality reduction and scale invariance.
- *Skip Connection:* Mitigates the vanishing gradient problem by providing an alternative gradient pathway during backpropagation.

4. **Output Generation:** The model processes the input and generates outputs, which include:

- *Node Embedding:* Vector representations of graph nodes, reflecting their properties and interrelations.
- *Edge Embedding:* Vector representations of edges, denoting the nodes' interconnections.
- *Graph Embedding:* A comprehensive vector representation of the entire graph, encapsulating its overarching structure and characteristics.

5. **Loss Function Design:** The final step is the formulation of a loss function congruent with the training setting (supervised, semi-supervised, or unsupervised)

and the task (node-level, edge-level, or graph-level). The loss function measures the discrepancy between the predicted output and the true labels, steering the model parameter optimization during the training phase.

This structured approach is quintessential for the development of GNN models, ensuring a cohesive progression from raw graph data to a machine learning-compatible format. The meticulous design and implementation of each stage are critical to the model's success in various tasks such as node classification, link prediction, or graph classification, thus contributing significantly to the domain of graph-based machine learning.

5.5.1 Model Implementation

Utilizing PyTorch for model implementation offers several advantages, including dynamic computation graphs and efficient memory usage, which are crucial for processing large-scale graph data. The model's implementation includes:

Initialization: Parameters for input, hidden, and output dimensions are defined, followed by the allocation of the model to a CUDA device for optimized computation.

Optimizer: The Adam optimizer is employed for updating network weights, selected for its efficiency in handling large datasets and its adaptive learning rate capabilities.

5.5.2 Training Procedure

The training of the GNN model encompasses several steps:

1. **Data Preparation and Loading:** Our Dataset has been prepared and loaded using PyTorch’s DataLoader. The batch size is set to 128, balancing computational efficiency and memory constraints.
2. **Loss Function:** A MSE criterion is adopted for quantifying the discrepancy between predicted values and actual labels, a standard choice for regression problems.
3. **Epoch-based Training:** The model undergoes training across 1000 epochs. Each epoch involves:
 - (a) Forward propagation of input data through the model: MSE loss computation and gradient calculation via backward propagation.
 - (b) Optimization step to adjust the model’s weights.
 - (c) Collection and storage of predictions and actual labels for metric evaluation.
 - (d) Metric Evaluation: Besides MSE, additional performance metrics such as RMSE, R2 score, and MAE are computed at each epoch. These metrics offer a comprehensive evaluation of the model’s predictive accuracy and generalization capability.
 - (e) GPU Memory Management: To optimize GPU memory utilization and prevent potential memory overflow, `torch.cuda.empty_cache()` is invoked after each training batch.
 - (f) Performance Visualization To assess the model’s training performance ef-

fectively, a visualization of the training metrics is implemented using Matplotlib. This visualization includes line plots of MSE, RMSE, R2 score, and MAE against the number of epochs. Such graphical representations provide an intuitive understanding of the model's learning trajectory, enabling the identification of trends and convergence behaviors.

5.5.3 Significance of the Methodology

This methodology leverages the advanced capabilities of GNNs, offering a novel approach to enhance the resilience of critical infrastructure systems. By adapting and customizing state-of-the-art machine learning techniques, this research provides a blueprint for future applications in infrastructure analysis and resilience enhancement. The comprehensive and meticulous training process, coupled with the detailed evaluation of model performance, ensures the reliability and robustness of the proposed GNN model in addressing real-world challenges in infrastructure systems management.

CHAPTER 6

DISCUSSION

6.1 Machine Learning Based Approaches

To advance the prediction of the significance of the nodes within IINs, we conducted an extensive evaluation of various regression models. This investigation aimed to shed light on the applicability and performance of these models in this specialized domain, with the goal of providing valuable insights and guidance to practitioners and researchers alike.

6.1.1 Performance of Individual ML Models

This subsection delves into the performance of individual ML regression models as summarized in Figure 6.6 and Table 6.1, evaluating their effectiveness in predicting node significance within infrastructure networks. We meticulously assess each model based on critical metrics like MSE, R2 scores, RMSE, and MAE, to determine their accuracy and ability to capture the complexities of the data, thereby informing the

optimal choice for infrastructure network analysis and restoration.

6.1.2 Linear Regression

Our initial evaluation revealed that the Linear Regression model, characterized by its efficiency with a training time of 0.65 minutes, displayed moderate performance across various metrics. Notably, it yielded competitive MSE scores, indicating its proficiency in minimizing prediction errors. Furthermore, the model demonstrated an average R^2 score, which signifies its ability to capture variations within network data. The RMSE scores remained within reasonable limits, further validating their suitability. Similarly, the MAE metrics were consistent with acceptable performance levels.

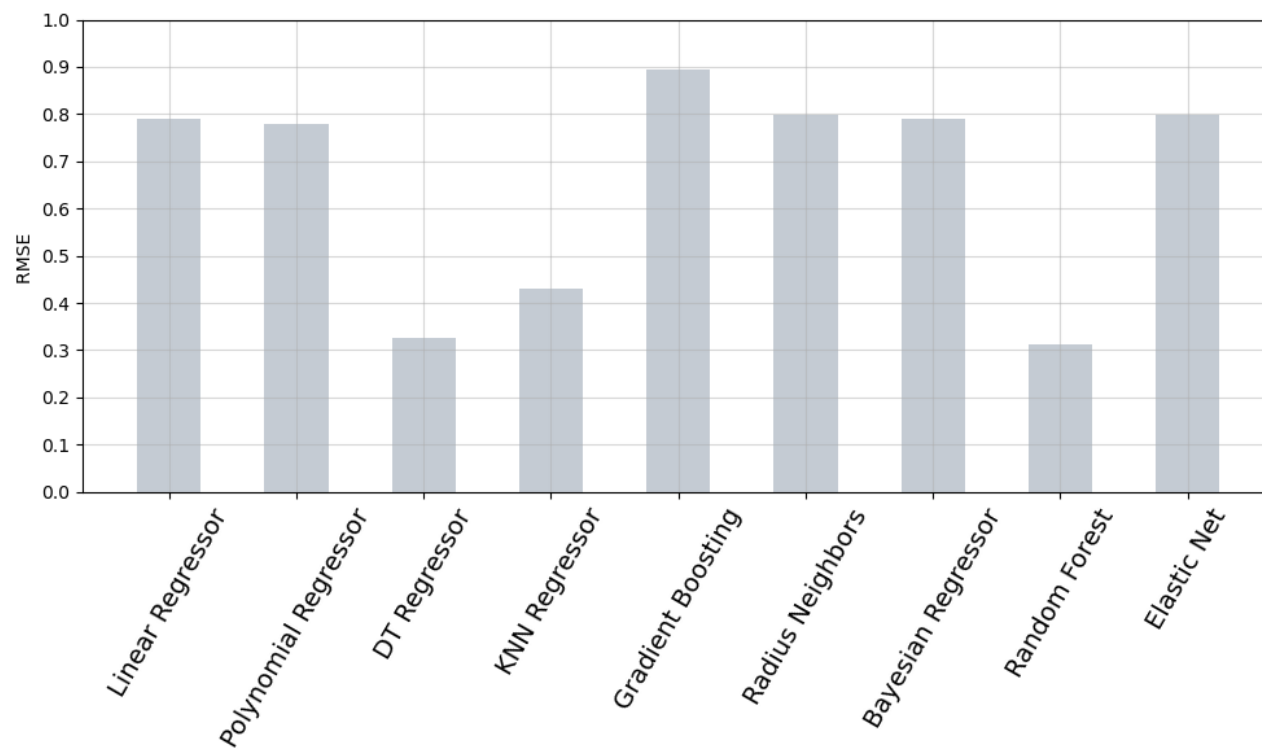


Figure 6.1: RMSE Comparison

6.1.3 Polynomial Regression

Despite its relatively longer training duration of 1.98 minutes, the Polynomial Regression model demonstrates promise in predicting node significance within interdependent infrastructure networks. This is evident from the competitive MSE scores it achieves, which indicates its effectiveness in minimizing prediction errors. Although the model presents an average R^2 score, indicative of its potential to elucidate variations in network data, it does so while effectively modeling intricate relationships within the dataset. Furthermore, RMSE scores remain reasonable, reinforcing the model's capacity to capture the underlying dynamics of interdependent infrastructure networks. Maintaining competitive MAE scores underscores the reliability of the model in offering precise predictions. Overall, the Polynomial Regression model showcases potential in predicting node significance, making it a viable choice for infrastructure network restoration tasks.

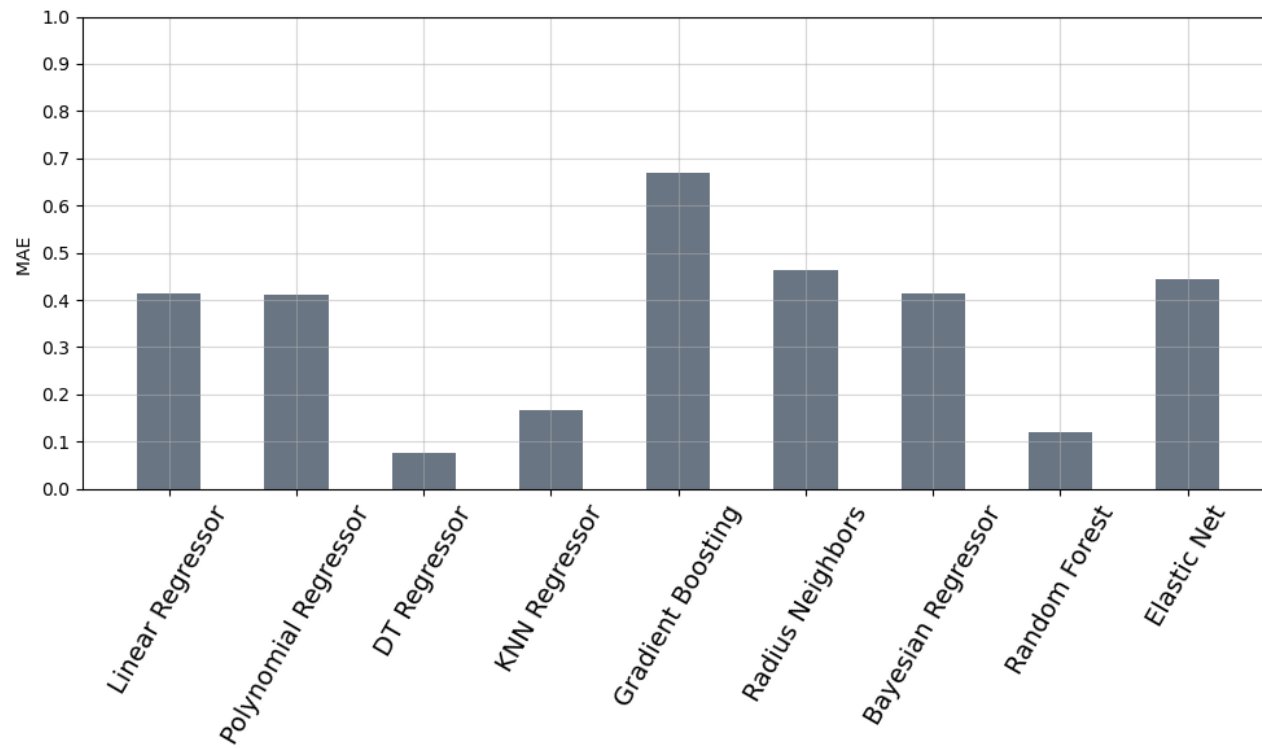


Figure 6.2: MAE Comparison

6.1.4 Decision Tree Regressor

The decision tree regression model, despite its longer training period of 2.42 minutes, emerged as a strong performer in our evaluation. It consistently achieved the lowest MSE scores, demonstrating a high degree of precision in predicting the significance of nodes. Remarkably high R2 scores were observed, indicating the model's proficiency in capturing intricate network relationships. The RMSE metric echoed these findings, providing further validation of its prediction accuracy. Impressively low MAE scores further substantiated the model's reliability for node significance prediction within these complex networks.

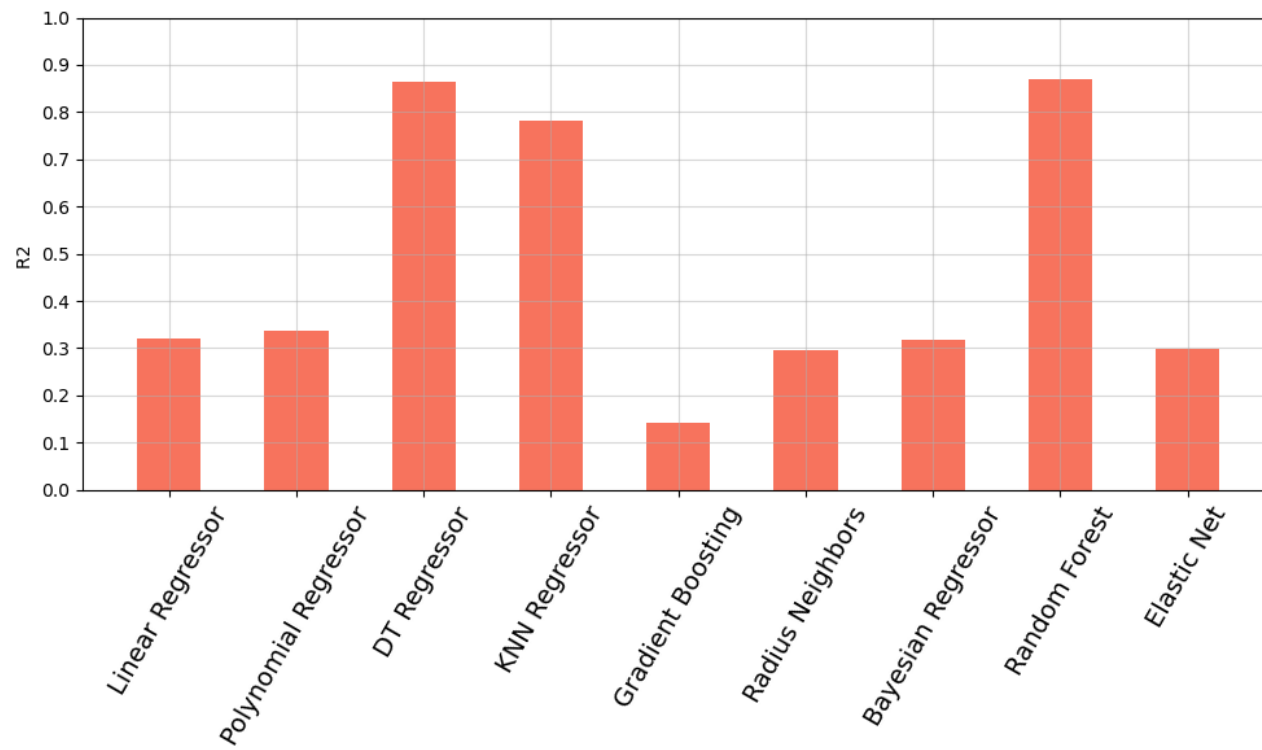


Figure 6.3: R2 Comparison

6.1.5 KNN Regressor

The KNN Regressor model presents a compelling performance profile, characterized by competitive MSE scores and commendable R2 scores. This balanced performance underscores its ability to provide accurate predictions within the context of infrastructure network node significance. Furthermore, the RMSE results reiterate its predictive capabilities by highlighting the model's ability to closely approximate the actual values. The model also maintains competitive MAE scores, further solidifying its effectiveness in capturing the underlying relationships in the data-set.

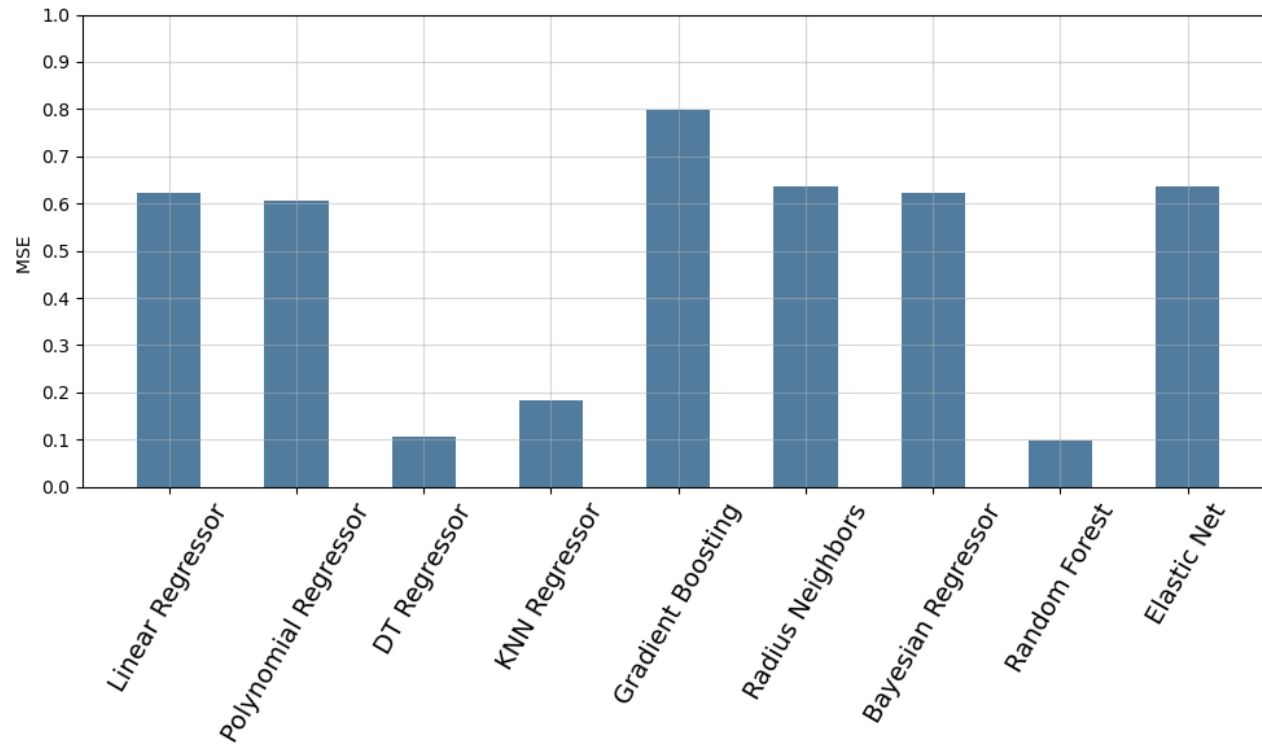


Figure 6.4: MSE Comparison

6.1.6 Gradient Boosting Regressor

The Gradient Boosting Regressor model, while demonstrating its predictive prowess, exhibits a trade-off in terms of training time. With a relatively longer training duration of 8.68 minutes, this model manages to achieve an average MSE score. This suggests its proficiency in predicting the significance of nodes within infrastructure networks. However, the model's R^2 scores are comparatively lower, indicating potential challenges in capturing intricate network relationships. RMSE and other evaluation metrics align with these observations, albeit with relatively higher MAE scores. These findings suggest that the Gradient Boosting Regressor excels in predictive accuracy but might require further optimization to enhance its efficiency.

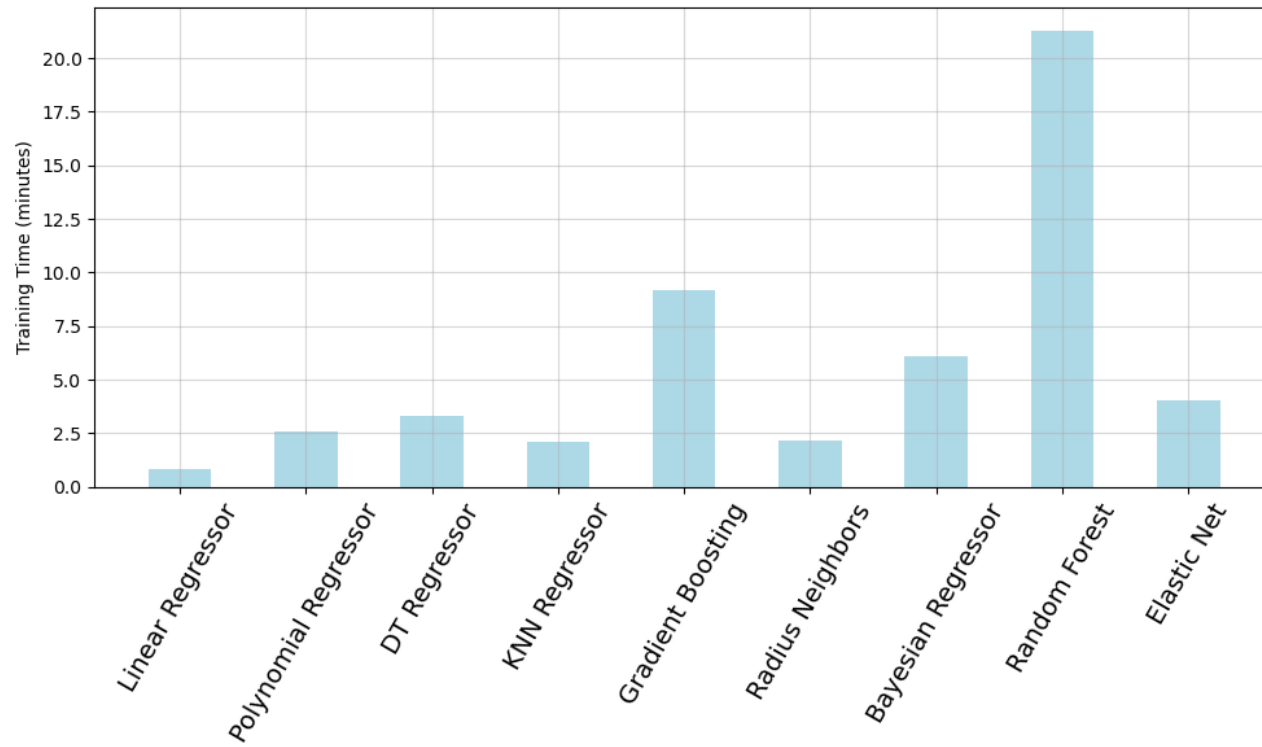


Figure 6.5: Training Time

6.1.7 Radius Neighbors Regressor

The Radius Neighbors Regressor model displays a competent performance profile, characterized by average MSE scores and a notable capability to capture data variance. This proficiency is evident from its R^2 scores, which indicate its ability to explain variations in the dataset. The RMSE and Explained Variance results validate these findings and establish the model's competitive edge. At the same time, the Radius Neighbors Regressor maintains competitive MAE scores, further affirming its reliability in capturing the essential aspects of the importance of the infrastructure network node.

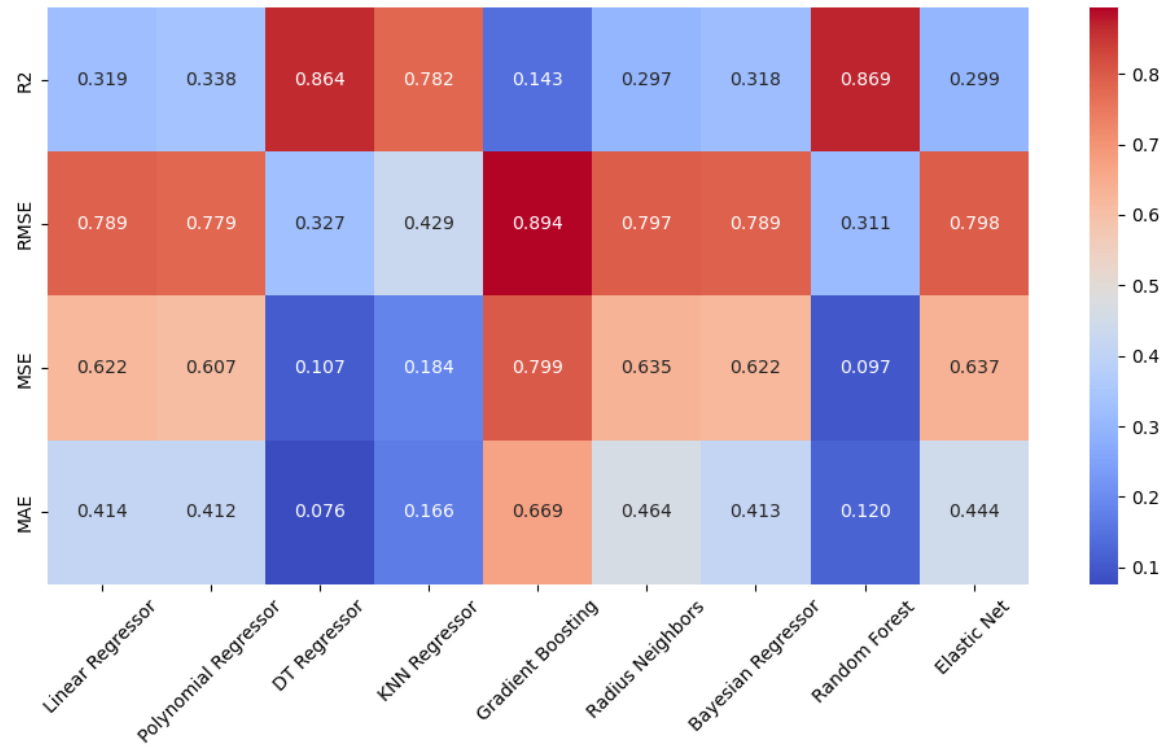


Figure 6.6: Heat-map of Models Performance

6.1.8 Bayesian Ridge Regressor

The Bayesian Ridge Regressor, evaluated along with other regression models, showed a moderate performance profile. It achieved an MSE score of 0.622, indicating its ability to estimate the significance of nodes within the infrastructure network. However, with an R2 score of 0.318, the model exhibited some limitations in capturing dataset variability compared to its counterparts. In terms of prediction precision, the Bayesian Ridge Regressor demonstrated RMSE and MAE scores of 0.789 and 0.413, respectively, implying reasonable predictive capabilities. Moreover, its training time of 6.11 minutes was within an acceptable range for the task complexity.

6.1.9 Random Forest Regressor

Remarkably, the Random Forest Regressor stands out as the top-performing model among the evaluated regressors. Despite a longer training period, this model achieves

the lowest MSE and the highest R2 scores, showcasing its exceptional predictive capabilities. These results highlight its efficacy in accurately determining node significance within infrastructure networks. The RMSE outcomes align with these findings, further solidifying the model's accuracy. Notably, the Random Forest Regressor maintains impressively low MAE scores, underscoring its reliability and precision.

6.1.10 Elastic Net Regression Model

The Elastic Net Regression model consistently exhibits competitive MSE scores across its predictions, emphasizing its reliability in predicting node significance within the context of infrastructure networks. The RMSE values further endorse the model's precision in approximating actual values, highlighting its predictive capabilities. Although the model maintains an average R2 score, suggesting its ability to capture data variance, it consistently yields competitive MAE scores. These observations collectively indicate that the Elastic Net Regression model provides reliable and accurate predictions while balancing the trade-offs between prediction error and model complexity.

6.1.11 Comparative Analysis

The regression models evaluated encompassed a diverse range, each characterized by distinct training times, computational requirements, and predictive capabilities. Our analysis commences with a summary of the key findings and discussions surrounding

each model’s performance, as illustrated in Table 6.1.

Table 6.1: Regression Models Performance Metrics and Training Time

Model	MSE	R2	RMSE	MAE	Minutes
Linear Regression	0.656	0.341	0.810	0.426	0.84
Polynomial Regression	0.641	0.356	0.801	0.423	2.57
DT Regressor	0.128	0.872	0.357	0.086	3.28
KNN Regressor	0.201	0.799	0.448	0.176	2.07
Gradient Boosting	0.869	0.126	0.932	0.699	9.20
Radius Neighbors	0.677	0.320	0.822	0.476	2.13
Bayesian Ridge	0.183	0.816	0.427	0.121	3.15
Random Forest	0.090	0.909	0.300	0.102	21.30
Elastic Net	0.676	0.321	0.822	0.453	4.02

6.1.12 Key Findings and Implications

In the evaluation of various machine learning regression models to predict the significance of nodes within interdependent infrastructure networks, several key findings have emerged.

Firstly, the Decision Tree Regressor model has consistently proven to be a standout performer in terms of predictive accuracy. It consistently achieved the lowest MSE scores, indicating a high degree of precision in predicting node significance. The model also exhibited remarkably high R^2 scores, underscoring its ability to capture intricate relationships within network data. Impressively low MAE scores further substantiated the model's reliability for node significance prediction. These findings have significant implications for decision-makers looking to enhance the resilience and efficiency of interdependent infrastructure networks.

Furthermore, the random forest regression model showcased exceptional perfor-

mance, boasting the lowest MSE and highest R2 scores, despite a longer training duration. This highlights the potential of ensemble methods, such as random forests, for predictive modeling within complex and interdependent systems. Decision-makers can consider leveraging ensemble techniques to achieve superior predictive accuracy when faced with challenging infrastructure network restoration tasks.

Lastly, our study underscores the importance of model selection based on specific task requirements. Whether the priority is accuracy, interpretability, or computational efficiency, our findings offer valuable insights to inform decision-makers' choices. The decision of which regression model to employ should be guided by the desired balance between predictive performance and practical considerations.

Overall, the key findings of our evaluation provide a solid foundation for informed decision-making in the context of restoring the infrastructure network and improving resilience. These findings contribute to the growing body of knowledge aimed at optimizing the management of interdependent infrastructure systems for a more sustainable and resilient future.

6.2 Deep Learning Based Approaches

The empirical evaluation of the proposed Deep Neural Network model is critical. The analysis presented in this section juxtaposes the performance of the proposed DNN model against traditional regression models, namely Linear and Polynomial regressions.

6.2.1 Model Performance Analysis

1. **Coefficient of Determination (R^2):** The proposed DNN model exhibits a robust predictive capacity with an R^2 score of 0.823, indicating that the model can explain approximately 82.3% of the variance in the target variable. This is substantially higher than the Linear and Polynomial Regressors, which demonstrate R^2 scores of 0.319 and 0.338, respectively. The inferior R^2 values of the Linear and Polynomial models signify a weaker fit to the data, which may be indicative of their limited capacity to capture complex, nonlinear relationships inherent in critical infrastructure datasets. Figure 6.3 and Figure 6.7 illustrate the R^2 of different models in terms of their ability to explain the variance in the target variable.

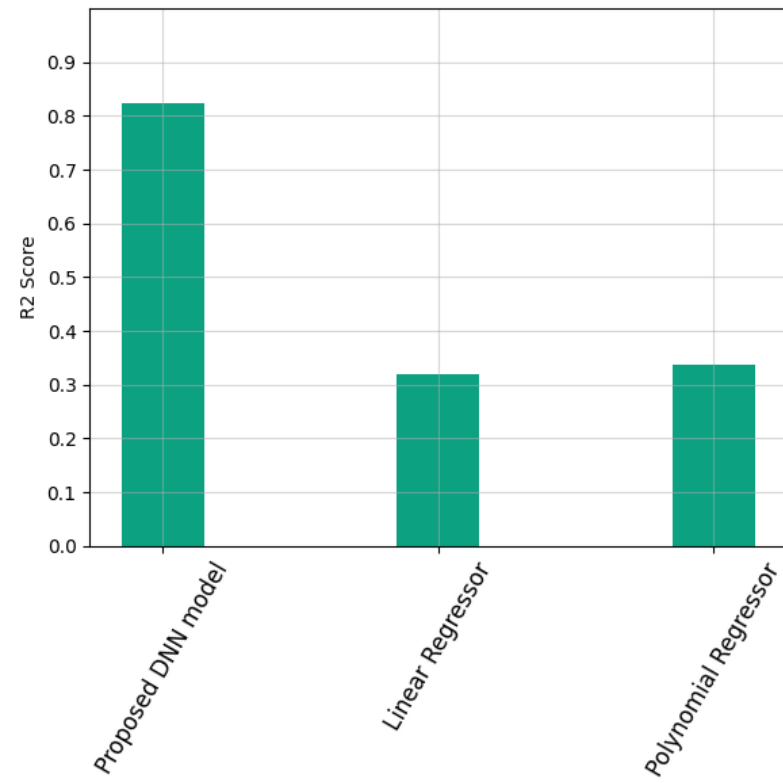


Figure 6.7: R2 Comparison (more is better)

2. **RMSE and MSE:** The proposed DNN model outperforms its counterparts with lower RMSE and MSE scores of 0.425 and 0.181, respectively. These metrics are critical, as they represent the average magnitude of the errors in the predictions, with lower values indicating better predictive performance. In contrast, the Linear and Polynomial Regressors report higher errors (RMSE scores of 0.789 and 0.779, and MSE scores of 0.622 and 0.607, respectively), which could potentially lead to less reliable predictions for post-disruption restoration planning. Figure 6.1, Figure 6.4, Figure 6.8, and Figure 6.9 illustrate the RMSE of the different models.

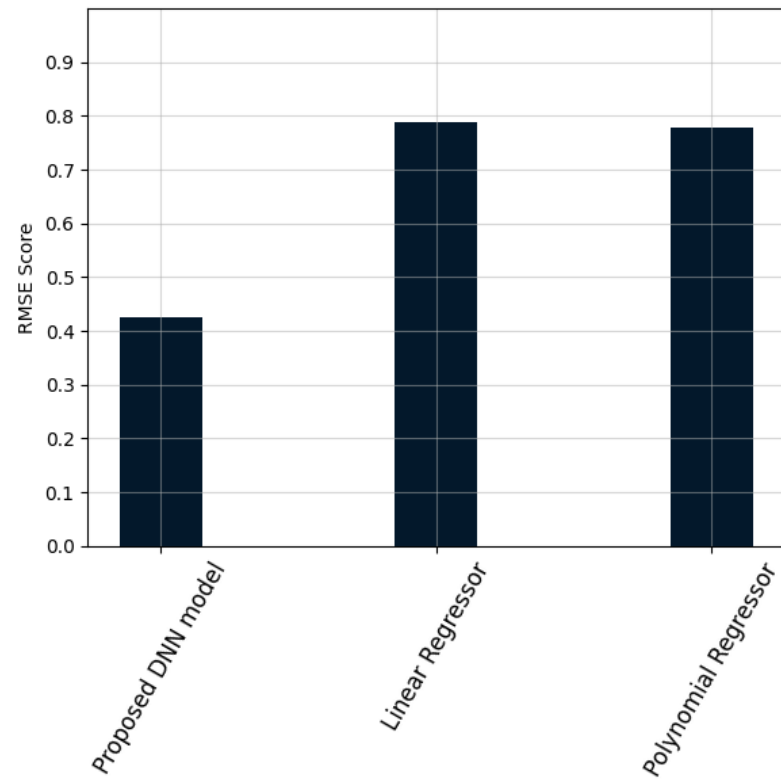


Figure 6.8: RMSE Comparison (less is better)

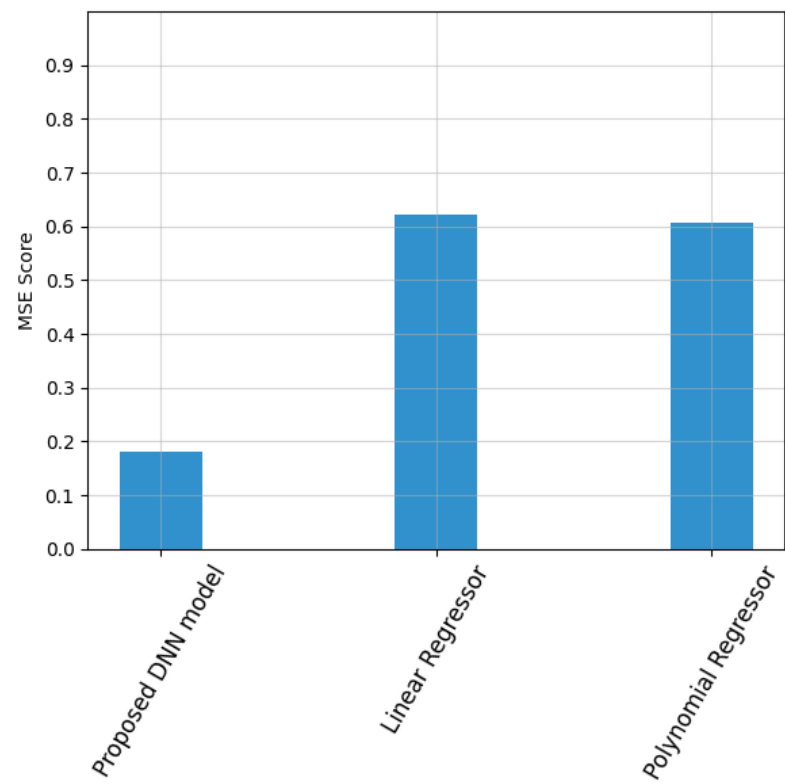


Figure 6.9: MSE Comparison (less is better)

3. **Mean Absolute Error (MAE):** The proposed DNN model maintains a leading performance with an MAE score of 0.268 as illustrated in Figure 6.2 and Figure 6.10. This is in stark contrast to the Linear and Polynomial Regressors, which have MAE scores of 0.414 and 0.412, respectively. The MAE is particularly insightful as it provides a clear measure of the average prediction error in the same units as the predicted value, emphasizing the practical superiority of the proposed DNN model.

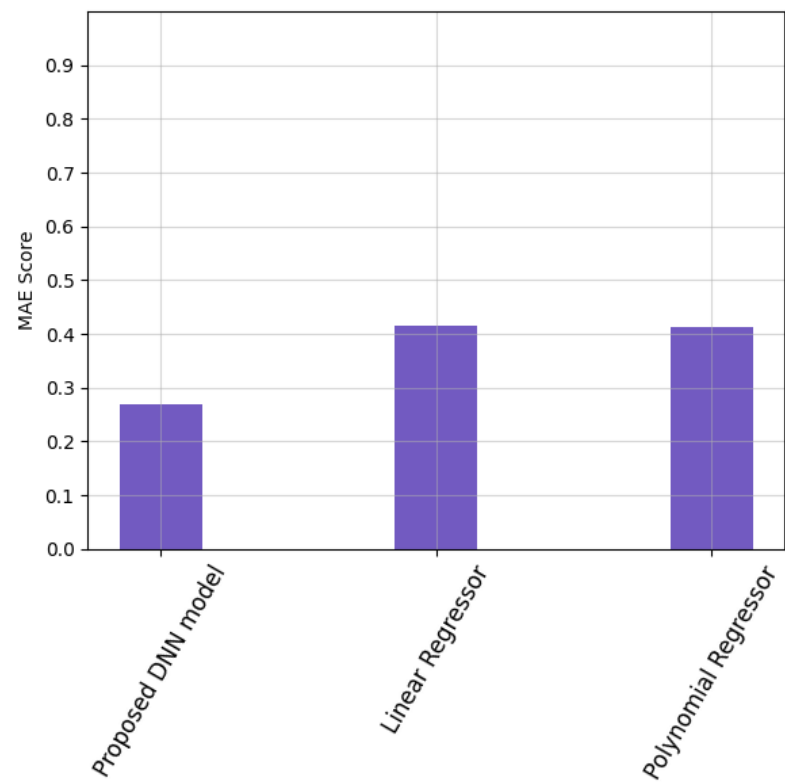


Figure 6.10: MAE Comparison (less is better)

6.2.2 Computational Efficiency Analysis

Training Time: The training time of the proposed DNN model as illustrated in Figure 6.5 and Figure 6.11 stands at 3.16 minutes, which is longer than the Linear Regressor (0.84 minutes) but shorter than the Polynomial Regressor (2.57 minutes). The extended training time for the DNN model is justified by its significantly improved predictive performance. The trade-off between training time and prediction accuracy is often a consideration in model selection; however, in critical infrastructure contexts where predictive accuracy is paramount for resilience and restoration, the DNN's longer training time is deemed acceptable.

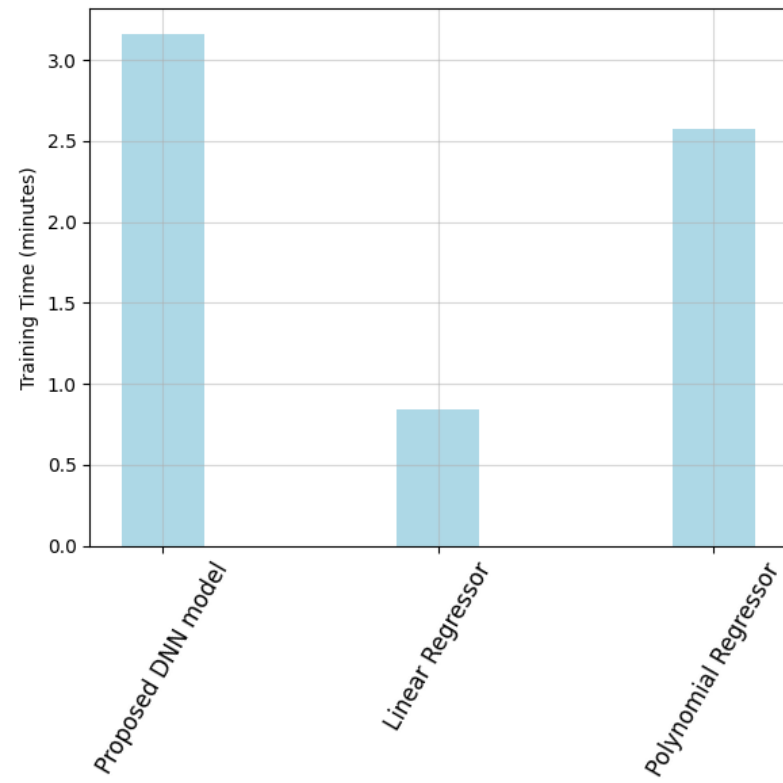


Figure 6.11: Training Time (less is better)

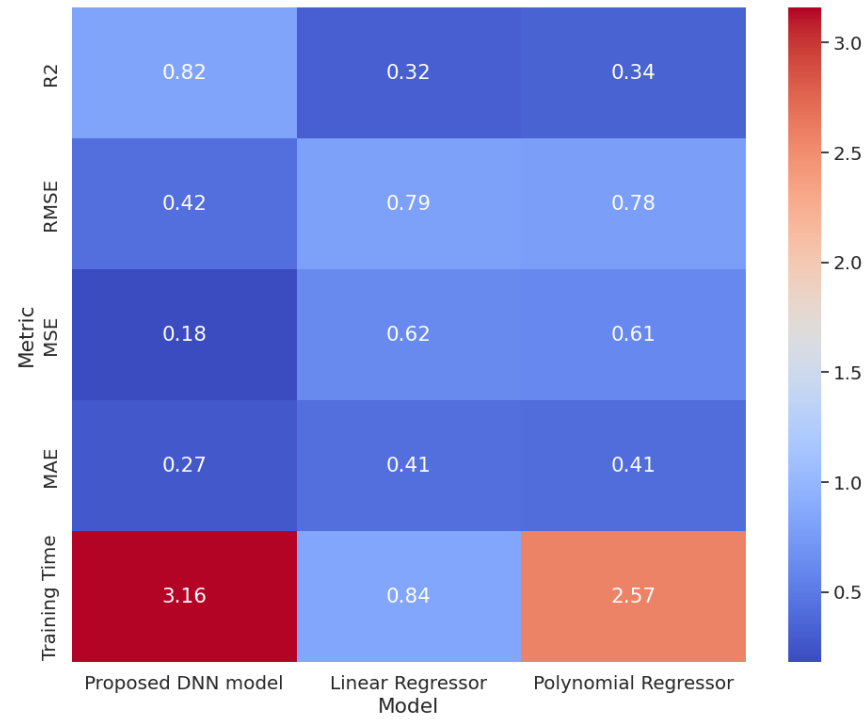


Figure 6.12: Heat-map of Models Performance

6.3 Geometric Deep Learning Based Approaches

In the process of developing a robust GNN model, utilizing the PyTorch framework, the model is initialized with predetermined input, hidden, and output dimensions, and is subsequently allocated to a CUDA device to capitalize on GPU acceleration capabilities.

The optimizer employed is the Adam optimizer, renowned for its adaptive learning rate features, which contribute to the efficient convergence of the model. The training loop is executed over 1000 epochs, a substantial number that reflects the intent to deeply train the model. Within each epoch, the model undergoes a sequence of forward and backward passes where the MSE loss is computed to quantify the prediction error. This loss not only guides the weight updates but also serves as the primary metric for evaluating the model's performance.

In addition to MSE (Figure 6.15), other metrics such as RMSE (Figure 6.13), R^2

(Figure 6.16), and MAE (Figure 6.14) are calculated. RMSE provides insight into the standard deviation of the prediction errors, R^2 indicates the proportion of variance in the dependent variable that is predictable from the independent variables, and MAE offers a linear score that summarizes the average magnitude of the errors in a set of predictions.

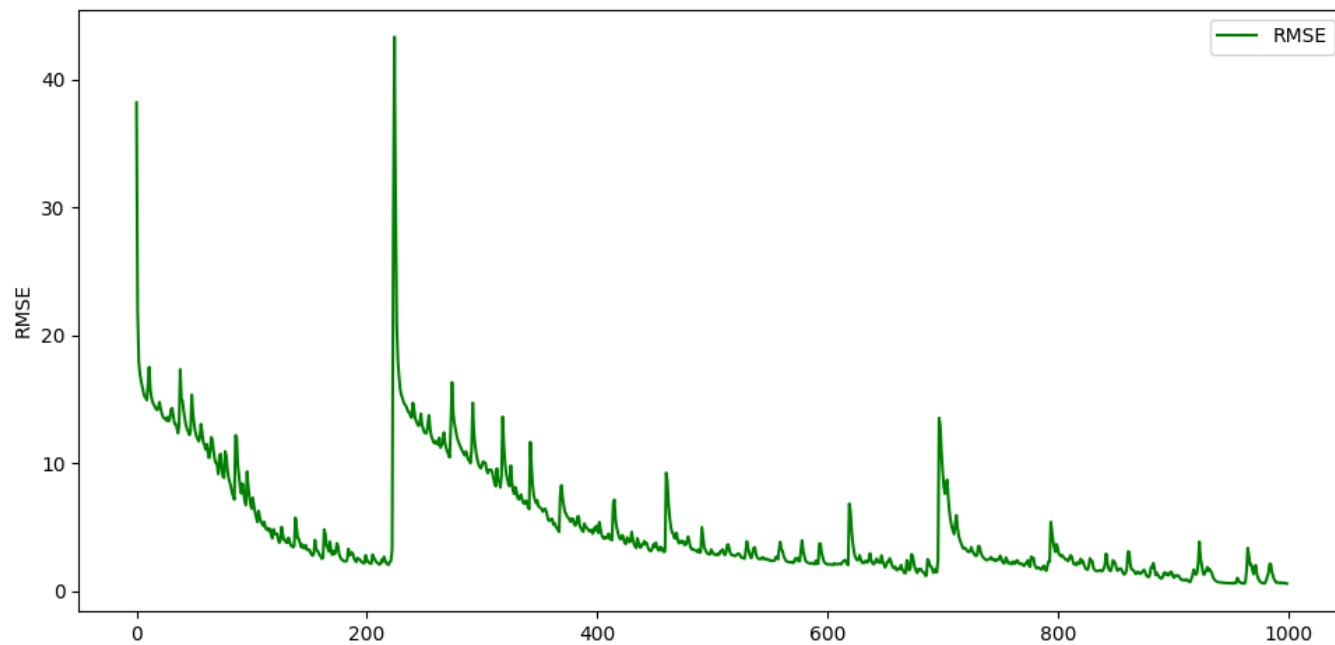


Figure 6.13: RMSE of the GNN model over epochs

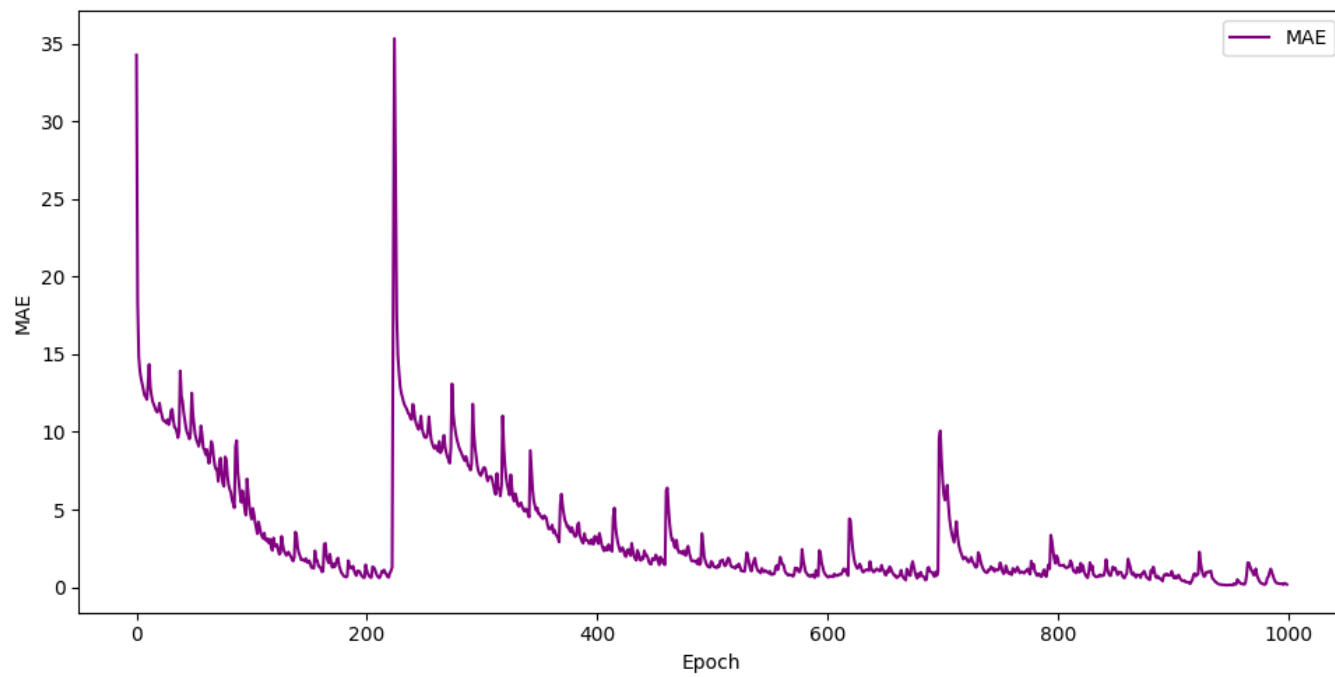


Figure 6.14: MAE of the GNN model over epochs

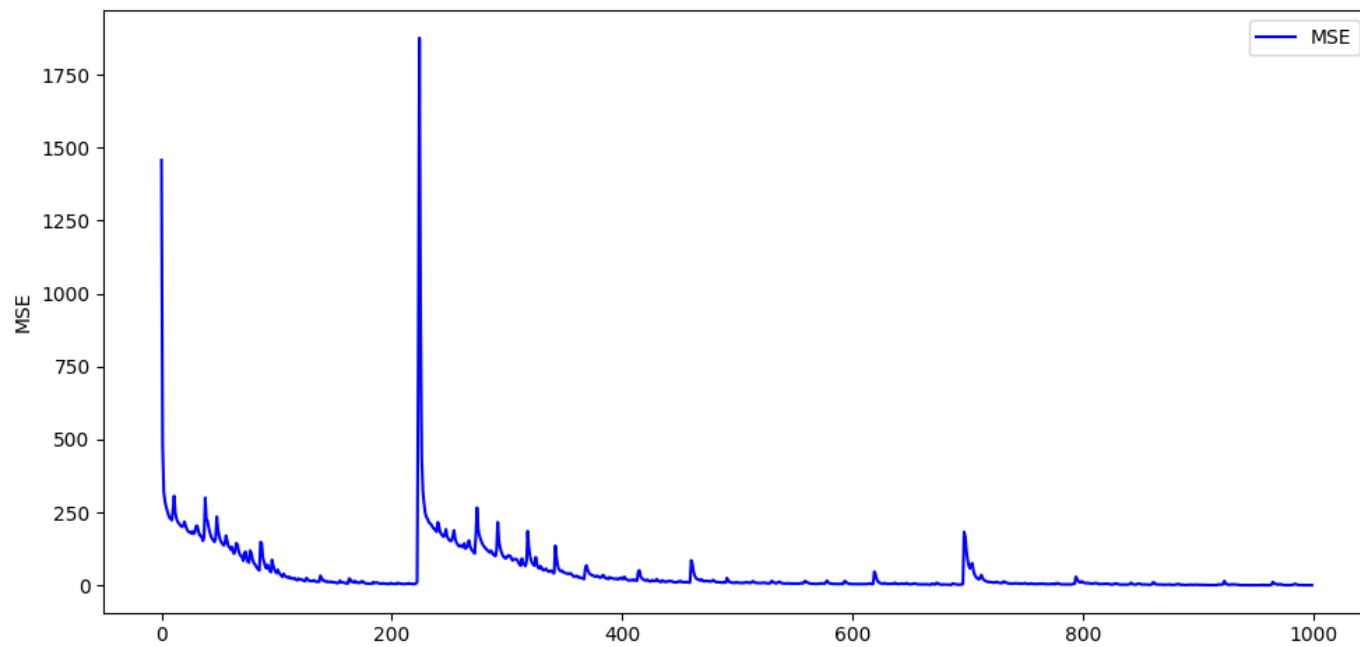


Figure 6.15: MSE of the GNN model over epochs

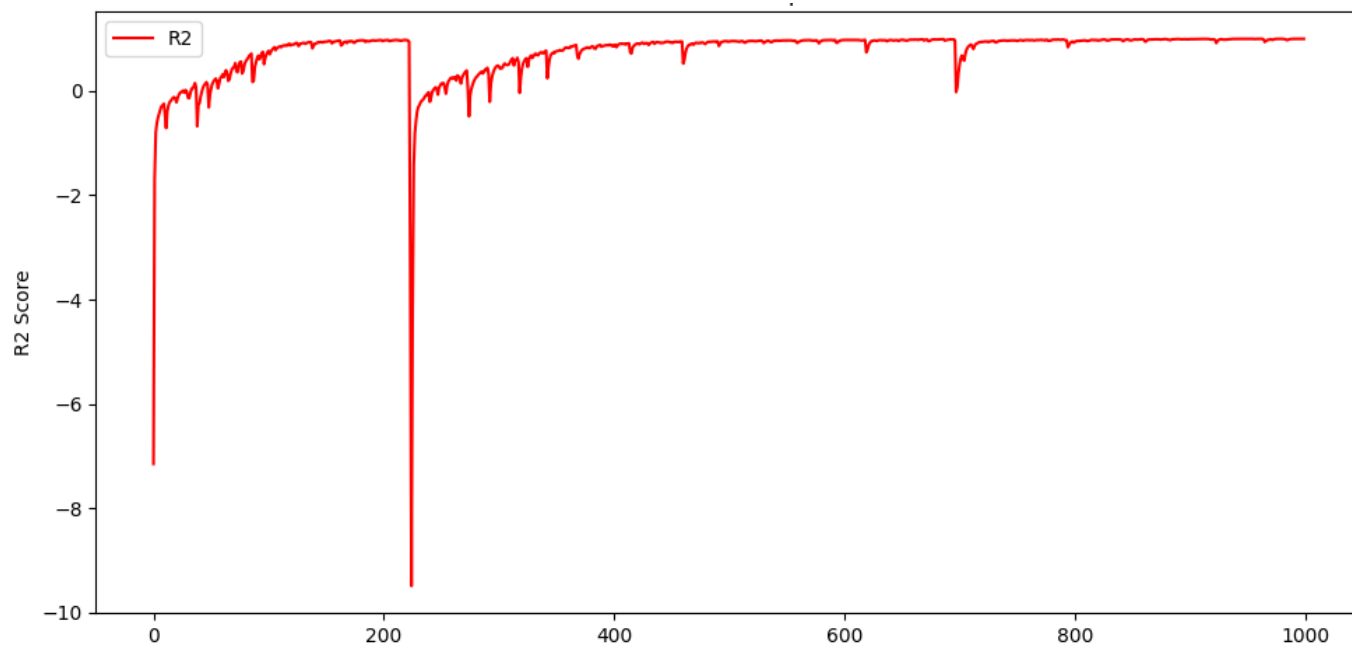


Figure 6.16: R2 of the GNN model over epochs

The visualization of these metrics, as shown in the provided figures, presents a nuanced understanding of the model's learning curve across epochs. Figures 6.13 - 6.18 indicate fluctuating levels of MSE, RMSE, and MAE, suggesting variability in the model's learning process, while the R2 score reveals the model's explanatory power, which appears to stabilize over time. Such visual feedback is indispensable for debugging and refining the model to ensure its robustness and reliability in application.

The trends depicted in the figure suggest the model experiences certain epochs with higher error, potentially due to the complexity of the data or learning rate adjustments. Over time, the model appears to achieve a decrease in loss and an increase in R2 score, signaling an improvement in its ability to predict and generalize from the training data. These insights, drawn from the plotted metrics, guide further fine-tuning of the model to achieve optimal performance, a testament to the iterative and empirical nature of machine learning model development.

During the final phases of the training process, the GNN showcased a commendable convergence towards optimal predictive performance. As evidenced by the progression

of epochs, the model's MSE demonstrated consistent improvement, indicative of the model's refined predictive capabilities. For instance, the MSE observed a decrement from 0.1689 at the 909th epoch to a slight reduction to 0.1622 at the 910th epoch, suggesting an upward trajectory in prediction accuracy.

Complementing the MSE, the RMSE, which offers insights into the prediction errors' standard deviation, also reflected this positive trend. With an RMSE of 0.4110 at the 909th epoch, decreasing slightly to 0.4028 at the 910th epoch, the model underscored its precision in estimating the target variable.

The R^2 score, which quantifies the fraction of the variance in the dependent variable that is predictable from the independent variables, consistently registered high, with values above 0.9990. This implies that the model could account for almost all the variance in the target variable, denoting a high degree of model fit.

The MAE, a metric that averages the absolute discrepancies between predicted and actual values, mirrored this downward trajectory, showcasing a continuous enhancement in the model's accuracy. As training neared completion, the MAE diminished significantly, reflecting the model's heightened precision in forecasting outcomes.

Despite the overall positive trend, the training process was not devoid of variability. For instance, a considerable increase in MSE to 15.8088 during the 922nd epoch indicated moments of elevated prediction error, which could be attributed to complex data patterns or an adaptive learning rate during training. However, this was followed by a steady recovery in model performance, culminating in an MSE of 1.4764 and RMSE of 1.2151 by the final epoch, epoch 1000.

The dataset's fluctuations are a natural aspect of the training process and are

instrumental in fine-tuning the model's parameters for robust generalization. The consistent enhancement of accuracy and reduction in error rates as training advanced reinforces the model's architecture and learning algorithm's effectiveness in discerning and predicting intricate patterns within the dataset. These results are not only a testament to the model's learning proficiency but also to its potential applicability in real-world scenarios where precision and reliability are paramount.

CHAPTER 7

RECOMMENDATIONS AND CONCLUSION

7.1 Recommendations for Practical Implementation

Successful training and evaluation of regression models to predict the significance of nodes in IINs provide valuable insights into potential practical implementations. These recommendations aim to guide the application of these models in real-world scenarios, leveraging their predictive capabilities to enhance decision-making processes in critical infrastructure management and resilience planning.

7.1.1 Real-time Node Significance Assessment

An immediate avenue for practical implementation involves real-time assessment of the significance of the node within the IINs. Training regression models, particularly those that demonstrate superior predictive performance, can be used to continuously assess the significance of the nodes. This real-time assessment can serve as an early warning system, alerting infrastructure managers to nodes that may be vulnerable or crucial to network functionality. Rapid response strategies can be devised based on these assessments, improving the overall resilience of the infrastructure.

7.1.2 Optimal Resource Allocation

In the face of budget constraints and limited resources, the predictive capabilities of the models can help optimize resource allocation. Decision-makers can utilize the node significance predictions to prioritize infrastructure maintenance, upgrades, or fortification efforts. By focusing resources on nodes deemed highly significant or vulnerable, infrastructure managers can maximize the network's resilience while operating within resource constraints.

7.1.3 Risk Mitigation Strategies

The models can also inform the development of tailored risk mitigation strategies. Infrastructure operators can use the predictions to identify critical nodes that, if disrupted, may lead to cascading failures. Armed with this knowledge, they can proac-

tively implement mitigation measures such as redundancy, diversification, or targeted hardening of specific nodes to minimize the potential impact of disruptions.

7.1.4 Emergency Response Planning

During crisis situations, such as natural disasters or cyberattacks, the rapid identification of critical nodes becomes paramount. The trained models can be integrated into emergency response systems to provide real-time assessments of node significance. This information can guide emergency responders and facilitate more informed decision-making on resource allocation and response prioritization.

7.1.5 Continual Model Refinement

To ensure that the models remain accurate and reliable in the evolving landscape of infrastructure, a continuous refinement strategy must be established. This involves regularly updating the training dataset with new data reflecting changes in the infrastructure network. Additionally, an ongoing evaluation of model performance against real-world outcomes is crucial to identify any deviations and re-calibrate the models as needed.

7.1.6 Interdisciplinary Collaboration

Effective practical implementation requires interdisciplinary collaboration between experts in infrastructure management, data science, and resilience planning. Close col-

laboration will facilitate the seamless integration of predictive models into existing infrastructure management systems and decision-making processes. Regular communication and knowledge sharing among these domains will ensure that the models align with the specific needs and objectives of infrastructure operators.

7.1.7 Ethical Considerations

Finally, the ethical implications of the use of predictive models in the management of critical infrastructure should not be overlooked. Transparent and responsible data handling practices, as well as ethical considerations related to privacy and bias, must be an integral part of any practical implementation. Adherence to ethical guidelines ensures that the benefits of using predictive models are realized without compromising societal values or individual rights.

These practical recommendations provide a comprehensive framework for leveraging regression models in the management and resilience planning of IINs while upholding ethical and responsible practices.

7.2 Conclusion

This study represents a comprehensive investigation into the prediction of node significance within the intricate domain of IINs. This research area holds significant relevance for real-world applications, considering its critical role in shaping resilient and efficient infrastructure management practices. The primary objective of the study was

to perform an extensive evaluation of various regression models, each distinguished by its training duration and predictive performance characteristics. The culmination of this investigation yields valuable insights and guidance that resonate with researchers, practitioners, and decision-makers operating within this intricate and Interdependent landscape.

The research journey embarked with a meticulous examination of each regression model's performance, encompassing a diverse array of performance metrics. These metrics comprised MSE, R2, RMSE, and MAE. In particular, the outcome of this analysis revealed the distinct strengths and limitations inherent to each model, thereby furnishing a nuanced understanding of their respective applicability within the specialized domain of IINs.

7.3 Future Directions

This study represents a foundational exploration of regression models for the prediction of the importance of the node in IINs. However, the field itself is marked by constant evolution, offering several avenues for future research and development.

Future investigations could delve into the integration of additional features, such as temporal dynamics and external factors, to increase predictive precision. Incorporation of these variables may further refine the models, making them more adept at capturing the nuanced changes and challenges that emerge within these complex networks.

Furthermore, the realm of ML offers an array of methodologies beyond regression

that hold substantial potential. DL techniques and graph-based models, for instance, present exciting possibilities for gaining deeper insights and advancing predictive capabilities within the context of IINs.

APPENDIX A

MATHEMATICAL MODEL

Model assumptions

The proposed optimization model for the restoration of interdependent infrastructure networks is underpinned by several key assumptions and considerations, which serve as foundational pillars for the development and application of this model. These essential facets include:

- **Infrastructure Network Components:** Each infrastructure network comprises a collection of components, denoting nodes and links. These components are susceptible to various forms of disruptions, such as manmade accidents, deliberate attacks, or natural disasters. However, it is important to note that cascading disruptions are not within the scope of this model and are a subject of potential future investigation.
- **Disruption States:** Components within each infrastructure network are characterized as either fully disrupted or entirely undisrupted following a disruptive

incident. The model does not account for partial disruptions or components operating at reduced capacity.

- **Variable Restoration Durations:** The restoration process for disrupted components is marked by variability in the time required for recovery. Unlike models with fixed restoration durations, this model accommodates the possibility that different components may necessitate varying periods for restoration.
- **Functional Component Restoration:** A fundamental premise of the model is that a disrupted component within an infrastructure network remains non-operational until it undergoes complete restoration. Partial recovery, where a component resumes limited functionality, is not considered in this context.
- **Capacity and Flow Parameters:** Within each infrastructure network, supply nodes, demand nodes, and links possess predefined attributes. These include known supply capacities for supply nodes, demand specifications for demand nodes, and flow capacities for links. These parameters play a pivotal role in shaping the model's optimization outcomes.
- **Fixed Flow Costs:** The model operates with the assumption that the cost associated with the flow through each link within an infrastructure network is both known and fixed. This deterministic view of flow costs informs the decision-making process during restoration efforts.
- **Interdependence Across Networks:** The model takes into account the physical interdependence that exists among different infrastructure networks. This

means that for a dependent node within an infrastructure network to regain functionality, it is contingent upon the operational status of specific node(s) from another interconnected infrastructure network.

- **Resource Availability:** The number of available work crews allocated for the restoration of disrupted components in each infrastructure network is a known quantity. Importantly, this allocation of infrastructure-specific resources can vary from one network to another, reflecting the diverse nature of restoration requirements.
- **Single Component Restoration:** Each work crew operating within an infrastructure network is capable of restoring only one disrupted component at any given time. The model adheres to a non-preemptive recovery process, meaning that a work crew cannot transition to another component until the restoration of the previous one is successfully completed.

These foundational assumptions and considerations collectively underpin the proposed optimization model, providing a structured framework for addressing the intricate challenges associated with the restoration of interdependent infrastructure networks. By embracing these assumptions, the model offers a systematic approach to decision-making in the context of infrastructure resilience and restoration planning.

Notation

Notation - Basic Network Structure and Elements

Notation	Description
T	The set of available time periods.
Ψ	The set of interdependent nodes.
R	The set of available work crews.
N	The set of nodes.
N_s	The set of source nodes.
N_d	The set of demand nodes.
L	The set of links.

Notation - Disruption and Restoration

Notation	Description
K	The set of disrupted nodes.
L'	The set of disrupted links.
dn_i	Signifies the restoration duration of node i .
dl_{ij}	Restoration duration of link $(i, j) \in L'$.
z_i	A variable indicating whether or not node $i \in N'$ is to be restored.
y_{ij}	A variable indicating whether or not link $(i, j) \in L$ is to be restored.

Notation - Operational and Cost Variables

Notation	Description
S_o	Total slacks at demand nodes before disruption.
S_d	Total slacks at demand nodes after disruption.
c_{ij}	Represents the cost of flow through link $(i, j) \in L$.
s_{it}	A variable indicating the amount of unmet demand at node $i \in N_d$ during time period $t \in T$.
x_{ijt}	A variable representing the flow through link $(i, j) \in L$ during time period $t \in T$.
b_i	Represents the amount of supply at node $i \in N_s$.
β_{it}	A variable indicating whether or not node $i \in N$ is operational at time period $t \in T$.
u_{ij}	Signifies the capacity of link $(i, j) \in L$.
α_{ijt}	A variable indicating whether or not link $(i, j) \in L$ is operational at time period $t \in T$.
γ_{it}^r	A variable indicating whether or not node $i \in N$ is restored by work crew $r \in R$ during time period $t \in T$.
fn_{it}	Represents the cost of restoration for node $i \in N'$ during time period $t \in T$.
fl_{ijt}	Denotes the cost of restoration for link $(i, j) \in L'$ during time period $t \in T$.
p_{it}	Signifies the cost of unmet demand in node $i \in N_d$ during time period $t \in T$.

Objective Functions

The research at hand encompasses two primary objectives: a resilience objective and a cost objective, each crucial in assessing the efficiency and effectiveness of the restoration process within a system of interdependent networks. These objectives serve as key guiding principles in decision-making and optimization efforts.

Firstly, the resilience objective, stands as a cornerstone in the restoration strategy. It is designed to maximize the overall resilience of the interdependent network system throughout the restoration time horizon. Resilience, in this context, signifies the system's ability to absorb disturbances, adapt to changing conditions, and ultimately maintain its functionality. By emphasizing resilience, the model seeks to ensure that the network can withstand disruptions, promptly recover from them, and continue to provide essential services.

Conversely, the cost objective introduces a pragmatic dimension to the restoration process. This objective is centered on the minimization of the total cost incurred during the restoration efforts. This cost is a composite metric, encompassing various components such as flow cost, restoration cost, and disruption cost, specifically, the cost associated with unmet demand. In essence, the cost objective aims to optimize resource allocation and decision-making to achieve restoration with the utmost economic efficiency.

These two objectives, resilience and cost, reflect the intricate balance that must be maintained when dealing with the restoration of interdependent networks. While resilience ensures the network's robustness in the face of disruptions, cost-efficiency

guarantees that resources are utilized judiciously, ultimately contributing to the overall sustainability and functionality of the interconnected infrastructure. By integrating these objectives into the decision-making process, stakeholders can work towards an optimal equilibrium between system resilience and cost-effectiveness, thus enhancing the system's overall performance and reliability.

Resilience objective:

$$\max \left[\sum_{t=1}^{\tau} \left(\frac{S_d - \sum_{i \in N_d} s_{it}}{S_d - S_o} \right) \right] \quad (\text{A.1})$$

Cost objective:

$$\min \sum_{t \in T} \left(\sum_{i \in N} f n_{it} z_i + \sum_{(i,j) \in L} f l_{ijt} y_{ij} + \sum_{(i,j) \in L} c_{ij} x_{ijt} + \sum_{i \in N_d} p_{it} s_{it} \right) \quad (\text{A.2})$$

Constraints

$$\sum_{(i,j) \in L} x_{ijt} \leq b_i, \quad \forall i \in N_s, t \in T \quad (\text{A.3})$$

$$\sum_{(i,j) \in L} x_{ijt} - \sum_{(j,i) \in L} x_{jit} = 0, \quad \forall i \in N \setminus \{N_s, N_d\}, t \in T \quad (\text{A.4})$$

$$\sum_{(j,i) \in L} x_{jit} + s_{it} = b_i, \quad \forall i \in N_d, t \in T \quad (\text{A.5})$$

$$x_{ijt} - u_{ij} \leq 0, \quad \forall (i, j) \in L, t \in T \quad (\text{A.6})$$

$$z_i = \sum_{r \in R} \sum_{t \in T} \gamma_{it}^r, \quad \forall i \in N' \quad (\text{A.7})$$

$$y_{ij} = \sum_{r \in R} \sum_{t \in T} \delta_{ijt}^r, \quad \forall (i, j) \in L' \quad (\text{A.8})$$

$$\sum_{i \in N'} \sum_{l=t}^{\min\{\tau, t+dn_i-1\}} \gamma_{il}^r + \sum_{(i,j) \in L'} \sum_{l=t}^{\min\{t, t+dl_{ij}-1\}} \delta_{ijl}^r \leq 1, \quad \forall r \in R, t \in T \quad (\text{A.9})$$

$$\beta_{it} \leq \sum_{r \in R} \sum_{l=1}^t \gamma_{il}^r, \quad \forall i \in N', t \in T \quad (\text{A.10})$$

$$\alpha_{ijt} \leq \sum_{r \in R} \sum_{l=1}^t \delta_{ijl}^r, \quad \forall (i, j) \in L', t \in T \quad (\text{A.11})$$

$$\sum_{t=1}^{dn_l-1} \beta_{it} = 0, \quad \forall i \in N' \quad (\text{A.12})$$

$$\sum_{t=1}^{dl_{ij}-1} \alpha_{ijt} = 0, \quad \forall (i, j) \in L \quad (\text{A.13})$$

$$\sum_{r \in R} \sum_{t=1}^{dn_i-1} \gamma_{it}^r = 0, \quad \forall i \in N' \quad (\text{A.14})$$

$$\sum_{r \in R} \sum_{t=1}^{dl_{ij}-1} \delta_{ijt}^r = 0, \quad \forall (i, j) \in L' \quad (\text{A.15})$$

$$\bar{\beta}_{it} - \beta_{it} \leq 0, \quad \forall ((i), (\bar{i})) \in \Psi, t \in T \quad (\text{A.16})$$

$$x_{ijt} - u_{ij}\beta_{it} \leq 0, \quad \forall (i, j) \in L, i \in N, t \in T \quad (\text{A.17})$$

$$x_{ijt} - u_{ij}\beta_{jt} \leq 0, \quad \forall (i, j) \in L, j \in N, t \in T \quad (\text{A.18})$$

$$x_{ijt} - u_{ij}\alpha_{ijt} \leq 0, \quad \forall (i, j) \in L', t \in T \quad (\text{A.19})$$

$$\sum_{t=1}^{dn_i^k-1} \beta_{it}^k = 0, \quad \forall i \in N'^k, k \in K \quad (\text{A.20})$$

$$\sum_{t=1}^{dl_{ij}^k-1} \alpha_{ijt}^k = 0, \quad \forall (i, j) \in L'^k, k \in K \quad (\text{A.21})$$

$$\sum_{r \in R^k} \sum_{t=1}^{dn_i^k-1} \gamma_{it}^{kr} = 0, \quad \forall i \in N'^k, k \in K \quad (\text{A.22})$$

$$\sum_{r \in R^k} \sum_{t=1}^{dl_{ij}^k-1} \delta_{ijt}^{kr} = 0, \quad \forall (i, j) \in L'^k, k \in K \quad (\text{A.23})$$

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