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POLYTECHNIQUE MONTRÉAL

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Scheduling of Repair Work Crew Routing for Power Network Restoration under Uncertainty

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Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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Antoine LEGRAIN, membre

DEDICATION

I dedicate my work to my mother, father and sisters.

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I would like to capture this opportunity to extend my deepest gratitude to those who played pivotal roles in various aspects of my research and the configuration of this thesis. Foremost, my sincere appreciation goes to Professor Michel Gendreau, my research director, whose unwavering guidance, patience, and support have been instrumental throughout the research process and the writing of this thesis. His encouragement has instilled confidence in my abilities. Additionally, I extend my gratitude to Professor Bernard Fortz, my research co-director, for dedicating their time, offering support, and providing valuable advice. Beyond my respected advisors, I wish to express my thanks to my committee members, Professor Thibaut Vidal, and Professor Antoine Legrain, for their commendable efforts. I am particularly grateful for their role as correction advisors, taking time from their busy schedules to precisely read, listen, and offer insightful comments on my research. Finally, I owe a debt of gratitude to my sister Melahat. Not only has she accompanied me on this journey to Polytechnique, offering unwavering love and support, but she has also been a valuable contributor to the writing of this thesis, providing advice on various aspects.

RÉSUMÉ

Le réseau électrique joue un rôle vital dans la société moderne, fournissant des services essentiels, stimulant la croissance économique et assurant la sécurité énergétique en s'appuyant sur son fonctionnement ininterrompu et efficace. Ce réseau est sujet à divers événements perturbateurs inévitables, qui peuvent avoir un impact imprévisible sur sa performance et entraîner des implications sociales importantes. Le sujet principal de cette thèse est l'opération de réparation et remise en service des réseaux de distribution après une catastrophe naturelle, avec un accent particulier sur la coordination des équipes de réparation et l'optimisation des opérations du réseau de distribution. À la suite de catastrophes majeures, l'un des principaux défis pour les exploitants est de gérer efficacement les équipes nécessaires pour réparer les lignes endommagées du réseau, rétablissant ainsi le fonctionnement normal du réseau. Les objectifs de cette thèse sont d'améliorer les pratiques actuelles et de fournir une assistance aux services publics dans leurs processus de prise de décision, permettant la restauration efficace du système rapidement et de manière sûre. Par conséquent, cette étude propose d'optimiser l'ordonnancement des réparations et le fonctionnement des réseaux de distribution en développant un modèle mathématique pour optimiser un cadre intégré qui planifie le travail des équipes de réparation et gère la remise en service du réseau de distribution. Deux approches distinctes sont présentées dans cette thèse. Tout d'abord, nous développons un programme linéaire déterministe en nombres entiers mixte (MILP) pour faciliter la restructuration du réseau et l'acheminement des équipes de réparation, afin de permettre une planification efficace des activités de réparation des lignes perturbées entre l'installation de production et les nœuds de distribution d'un réseau électrique. Deuxièmement, nous adoptons le modèle mathématique en introduisant un paramètre d'incertitude, convertissant le modèle MILP original en un programme linéaire mixte stochastique à deux étapes (SMILP) qui intègre une technique d'optimisation basée sur des scénarios. Ce modèle modifié est utilisé pour tenir compte des incertitudes quant aux temps de réparation dans le contexte du problème de réparation et de restauration. La première étape du SMILP consiste à dépêcher les équipes de réparation sur les lignes endommagées en fonction du temps requis pour les réparations. Le résultat des décisions de la première étape fournit un itinéraire pour les équipages, tandis que la deuxième étape est dédiée à la restauration du système de distribution dans tous les scénarios réalisés. Le modèle intégré vise à minimiser la somme des coûts de pénalité encourus en raison de la demande non satisfaite, ainsi que les coûts associés aux lignes inutilisables causées. Pour valider le modèle,

un exemple numérique est utilisé, avec des analyses approfondies de sensibilité, d'incertitude et de complexité démontrant la performance du modèle. Enfin, des discussions approfondies sont menées à partir des résultats obtenus.

ABSTRACT

The power network plays a vital role in modern society, providing essential services, driving economic growth, and ensuring energy security, relying on its uninterrupted and efficient operation. This network is prone to unavoidable disruptive events, which can unpredictably impact its performance and lead to significant social implications. The main topic of this thesis is the recovery operation of power networks after natural disasters, with a specific emphasis on coordinating crews and optimizing power network operations. In the aftermath of significant disaster events, one of the principal challenges for operators is effectively managing crews required to repair damaged lines in the network, thereby reestablishing normal network operations. The objectives of this thesis are to enhance current performance and assist utilities in their decision-making processes, enabling the efficient restoration of the system quickly and safely. Therefore, this study proposes optimizing repair scheduling and operation of power networks by developing a mathematical model for optimizing an integrated framework that schedules repair crews and manages the recovery of the power network. Two distinct approaches are presented in this thesis. Firstly, a deterministic mixed-integer linear program (MILP) is developed to facilitate the restructuring of the network and the routing of repair crews, aiding the efficient scheduling of repair activities for damaged lines between the generation facility and distribution nodes in a power network. Secondly, the mathematical model is adapted by introducing a parameter of uncertainty, converting the original MILP model into a two-stage Stochastic Mixed-Integer Linear Program (SMILP) incorporating a scenario-based optimization technique. This modified model addresses uncertainties in repair times within the repair and restoration problem context. The first stage of the SMILP involves the dispatch of repair crews to damaged lines based on the expected required time for repair. The outcome of the first stage decisions provides routes for the crews, while the second stage is dedicated to restoring the power network under all realized scenarios. The integrated model aims to minimize penalty costs incurred due to unmet demand and the costs associated with inoperable lines caused by link disruptions. A numerical example is utilized to validate the model, with extensive sensitivity, uncertainty, and complexity analyses demonstrating the model's performance. Finally, comprehensive discussions are drawn from the results obtained.

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LISTE OF SYMBOLS AND ABBREVIATIONS

SDVRP: Split Delivery Vehicle Routing Problem

MILP: Mixed Integer Linear Program

SMILP: Stochastic Mixed Integer Linear Program

CISs: Critical Infrastructure Systems

NOAA: The National Oceanic and Atmospheric Administration

NCEI: National Centers for Environmental Information

CHAPTER 1 INTRODUCTION

1.1 Research Motivations and Problem Statement

Power networks refer to interconnected and interdependent systems and processes that work collaboratively to generate and distribute energy (Ellis, 1997). Unfortunately, power networks are vulnerable to various disruptive events, particularly natural hazards, which can have unpredictable impacts on their performance and directly affect communities and people's daily lives (Helbing, 2013). Consequently, countries like the United States have been focusing on effectively and promptly responding to these disruptive events (Karagiannis G. M., 2017; O'Donnell, 2013; House, 2013). The United States have encountered a pronounced increase in power disruptions, primarily attributed to the convergence of an aging power infrastructure and a significant rise in severe natural disaster events. As indicated by a study released by the Executive Office of the President, between 2003 and 2012, there were approximately 700 significant power outage incidents resulting from natural disasters in the United States (Office, 2013). In 2016, power interruptions diverse across different regions of the United States, with average outage durations ranging from 27 minutes in Nebraska to as long as 6 hours in West Virginia, and an extensive 20-hour outage in South Carolina to the influence of Hurricane Matthew (Darling, 2018). A year later, in 2017, Hurricane Harvey left approximately 280,000 Texas residents without electricity (DiChristopher, 2017). Furthermore, the U.S. Department of Homeland Security reported that the profound impact of Hurricane Irma resulted in power outages for approximately 15 million customers (Sullivan, 2017). In 2017, the United States experienced 16 major incidents, each causing over $1 billion in damage. These events encompassed three hurricanes and eight violent storms as depicted in Figure 1.1. This pattern persisted in 2018, with 14 major incidents, including eight violent storms, two hurricanes, two winter storms, drought, and forest fires, illustrated in Figure 1.2.

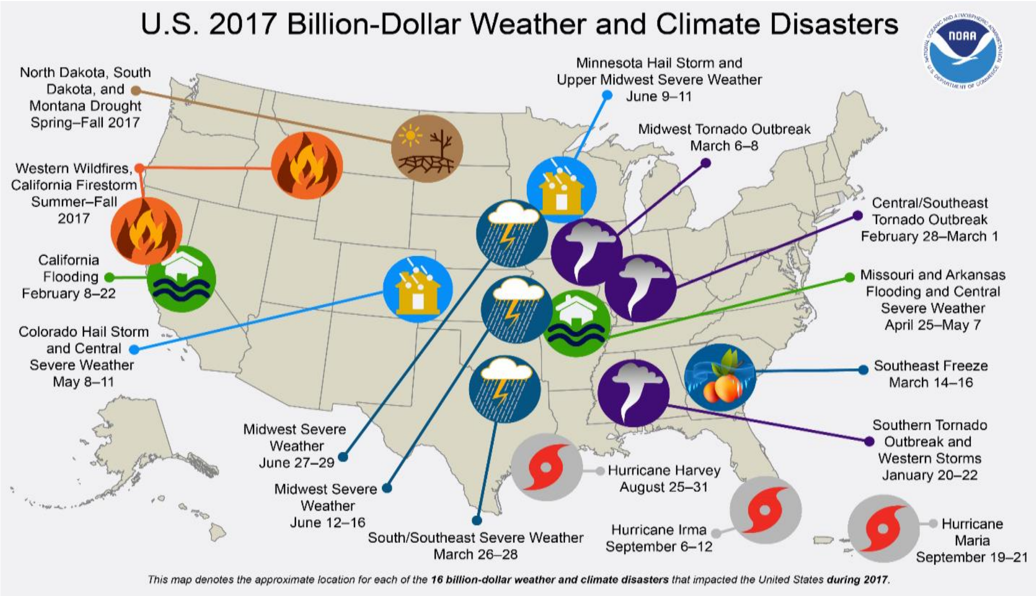

Figure 1.1: Map illustrating natural disasters that resulted in a minimum of one billion dollars in direct damages during 2017 (Smith, 2017)

The National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information (NCEI) have closely tracked significant weather and climate events affecting the United States (Smith, 2017). They have created a summary of the number of incidents and their associated costs from 1980 to 2017, presented in Figure 1.3.

In this context, disaster response typically encompasses two phases: a pre-disaster planning phase and a post-disaster recovery phase. Concerning the power network, the post-disaster recovery phase mainly focuses on quickly repairing and restoring the power network.

The disruption of electrical power in the aftermath of a hurricane or any natural disaster can lead to substantial disruptions. Enhancing the management of power outages and expediting the restoration are crucial objectives for utility companies. Dispatching repair crews and efficiently operating the network to restore services for clients represent essential responsibilities. The routing challenge associated with restoration of network is a complex combinatorial optimization problem, recognized for its difficulty. Integrating the operation of the power network with this routing problem will only contribute to the complexity of the overall problem.

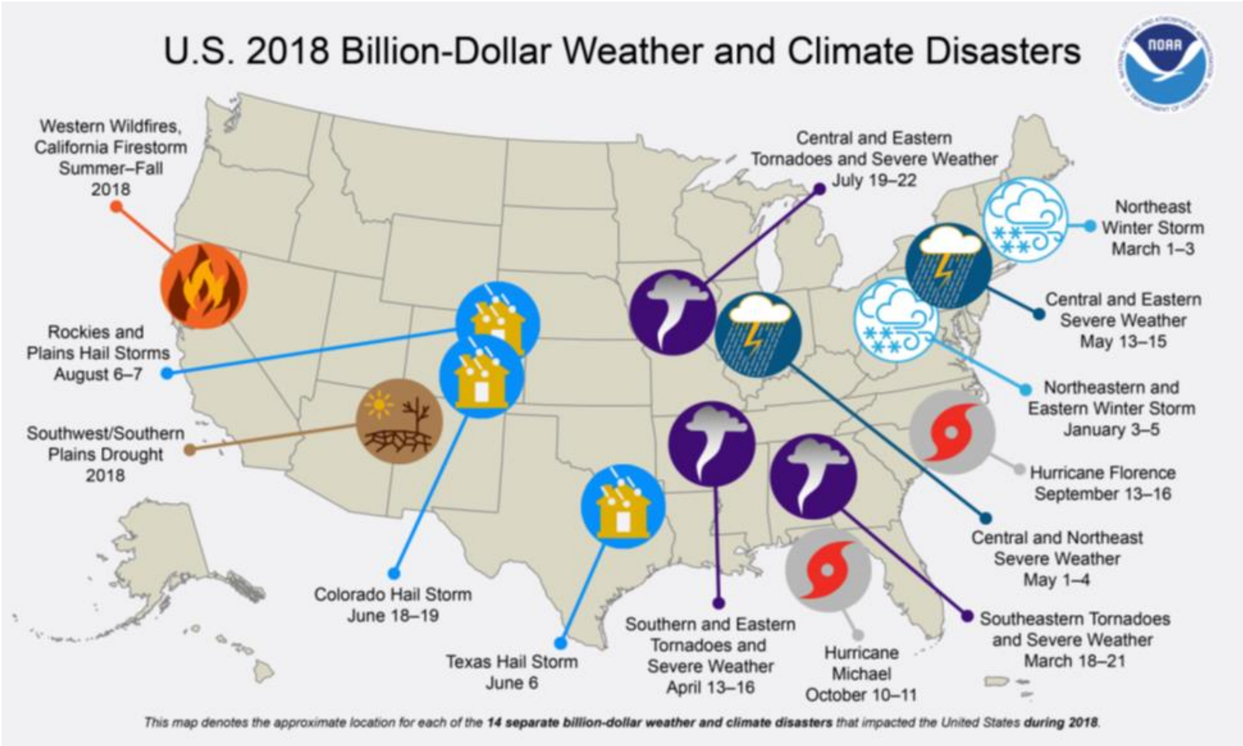

Figure 1.2: Map illustrating the impact of fourteen natural disasters that led to at least one billion dollars in direct damages in 2018 (Smith., 2019)

A frequently employed approach involves treating power network operation, restoration, and repair crew routing as separate problems. Nevertheless, in practice, network operation and repairs are closely interconnected. The restoration of the network that provides power to some demand nodes relies on the completion of necessary repairs. Utilities company typically rely on the operational expertise of their staff, which may not yield an optimal outage management plan. An optimization process that concurrently addresses crew scheduling and network operation can empower operators to make more knowledgeable critical decisions following outages. Our research aims to provide utilities with an enhanced decision-making framework for extreme events. This study concentrates on post-disaster operations within power networks, with a specific focus on repair and restoration efforts following disruptive events.

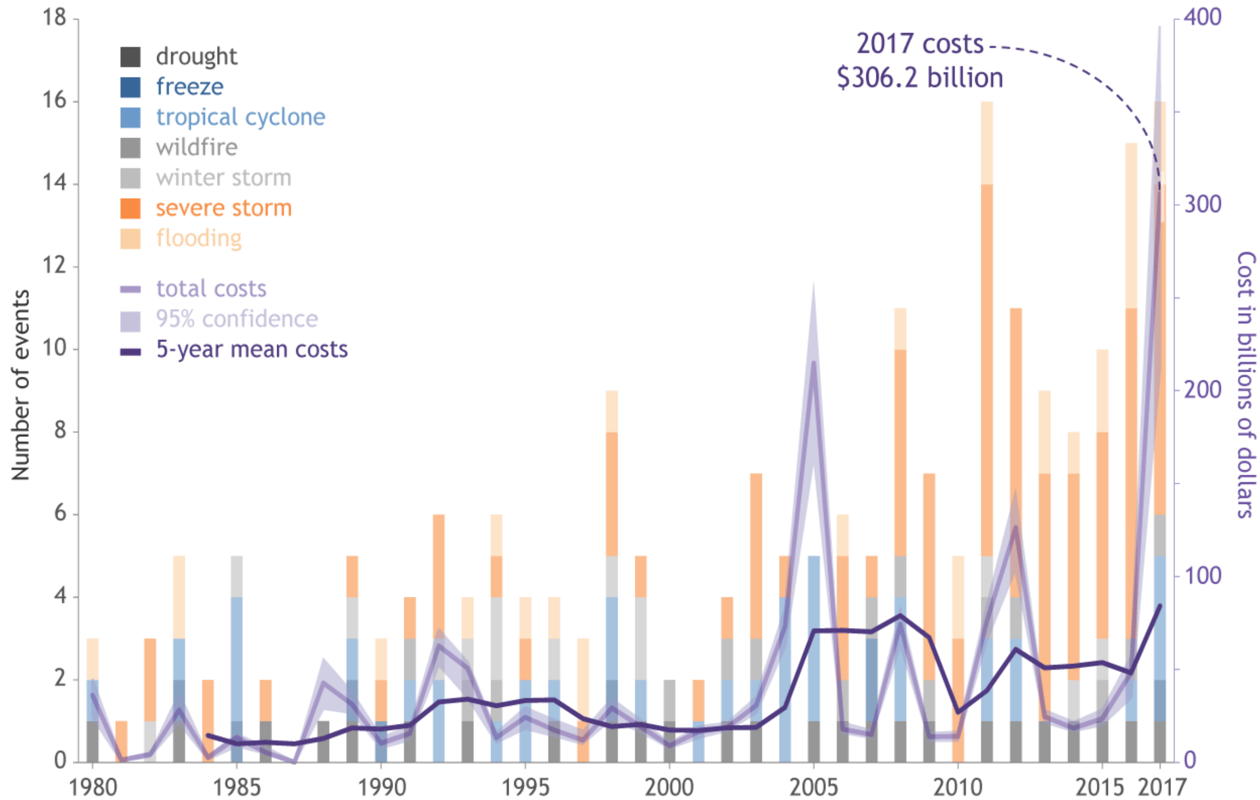

Figure 1.3: The number of events and yearly expenditure associated with natural disasters in the U.S. from 1980 to 2017 is derived from data provided by (Smith, 2017)

1.2 Research Objectives

The research objectives are designed to tackle the challenges associated with restoring damaged lines in a post-disaster power network. In this context, two approaches are presented in this thesis. We aim to:

- Develop a mathematical model for optimizing an integrated framework that schedules repair crews and manages the recovery of the power network. A deterministic mixed-integer linear program (MILP) is developed to optimize repair crew routing, efficiently scheduling repair activities for damaged lines between power network nodes.
- Develop a two-stage stochastic mixed-integer linear program (SMILP) that accounts for uncertain repair times in solving the repair and restoration problem, incorporating a scenario-based optimization technique. The first-stage involves dispatching and routing repair crews from the depot to damaged lines, while the second stage focuses on recourse actions for power network restoration. This model considers repair time uncertainty using

a uniform integer distribution. The objective of the developed model is to minimize the penalty costs associated with unmet demand and unrepaired lines in power restoration.

1.3 Research Contribution

We introduce an innovative mathematical framework that integrates the complex challenges of optimizing repair crew routing and the efficient operation of power networks. The model that we propose is a formulation that effectively combines these two interconnected problems. This model appropriately represents the inherent intricacies of addressing the repair-related problem, particularly by considering the uncertain repair time for damaged lines. The implementation of this model can be useful for utility providers in coordinating repair schedules and promptly restoring the regular operation of network in the aftermath of natural disasters. In summary, we have developed a two-stage (SMILP) approach to the optimization of service restoration within power networks, with a special focus on scenarios where repair times remain uncertain.

1.4 Organization of the Thesis

This thesis is organized into six chapters. Chapter 1 serves as the introduction, providing an overview of the research topic and its significance. It presents the research objectives, and contributions while outlining the structure of the thesis. Chapter 2 encompasses the literature review, investigating prior studies focused on power network restoration, the crew routing problem, the integration of crew routing in power network restoration, the incorporation of power flow conservation constraints in the models, and introduction to two-stage stochastic programming. The final section identifies research gaps and emphasizes the contributions made by the current research. Chapter 3 focuses on the mathematical models, presenting both a deterministic and a stochastic model for post-disaster power network restoration. The problem definition is discussed, and the formulations and notations are presented. The methodology for the proposed problem is presented in more detail in Chapter 4. In Chapter 5, we report the results of several computational experiments, including examining the effect of the number of scenarios, stochastic programming solution, out-of-sample analyses, and stability of the model. Moreover, we emphasize the significance of considering uncertainty in our model and conduct sensitivity analyses on the stochastic model. Finally, in the initial section of the Chapter 6, we presented the conclusion and research contributions. Subsequently, in the second part, we provided recommendations for future research.

CHAPTER 2 LITERATURE REVIEW

2.1 Overview

In this chapter, an overview of existing research is presented, providing background information on the management of power outages and the restoration of power networks after disasters. Section 2.2 is dedicated to the restoration of the power network, while Section 2.3 reviews the vehicle routing problem. Section 2.4 discusses efforts made to integrate crew routing and power recovery operations in disaster management. In Section 2.5, attention is given to incorporating power flow constraints into the power network problem. An introduction to two-stage stochastic programming is presented in Section 2.6. The final section summarizes the main gaps in current research and emphasizes the significant contributions of this thesis.

2.2 Power Network Restoration

In the domain of power network restoration, significant progress has been achieved, noticeable by the development of various algorithms and methodologies focused on power restoration (Liu, 2009; Wang Y. C., 2015; Toune, 2002; Pérez-Guerrero, 2008; Solanki, 2007). One commonly employed approach is the adoption of network reconfiguration, recognized for its effectiveness in the restoration of power networks (Butler, 2001). Insights into the reduction of outage through distributed generators have been revealed in recent studies. These investigations commonly employ mathematical models to simplify and enhance the optimization of the restoration process (Jabr, 2012; Ramos, 2005; Al Owaifeer, 2018).

2.2.1 Optimization Models for Restoration

The disruption of critical infrastructure systems (CISs) due to natural disasters can have significant negative impacts on society and the economy. Therefore, post-disaster restoration efforts are crucial to minimize customer downtime (Zhang H. L., 2018), and the rapid recovery of CISs is essential for minimizing social and economic impacts. Hence, to improve the efficiency and effectiveness of restoration processes, optimization models and algorithms have been developed by researchers. An optimization approach, which jointly considers the scheduling of restoration tasks, repair durations, team assignments, and routes, through an ant colony optimization algorithm is implemented in (Li Y. Z., 2019). The scheduling of inspection, damage assessment, and repair tasks to minimize power outage duration using a MILP, incorporating a genetic algorithm is addressed by (Xu N. G., 2007). The MILP models addressing power system restoration after natural disasters, with the goal of minimizing real power load interruptions and prioritizing load restoration based on lost load value, are presented in (Arab A. K., 2015). Post-disaster restoration planning models with consideration for repair and activation scheduling, aiming to maximize system load accommodation capability while minimizing restoration process time are developed by (Yan J. H., 2020). A co-optimization model is employed to integrate damage repair and power system operation, formulating optimal repair routes, unit output, and transmission switching plans in (Zhang H. B., 2018) is presented. Moreover, heuristic methods to solve scheduling repair sequences problem under limited resource availability are proposed in (Xu M. O., 2019).

2.2.2 Consideration of Uncertainty

The importance of considering uncertainties in restoration planning is emphasized, particularly for large-scale disruptions. Accordingly, a two-stage stochastic optimization approach to prioritize repair activities for CISs based on maximizing system resilience while considering uncertainties in the occurrence of disasters is presented in (Fang, 2019). An optimal maintenance strategy is being developed to minimize the loss of power transmission systems during extreme events, as presented in the article (Li Z. Y., 2020). An interval optimization method for post-disaster distribution network repair strategy, which considers various uncertainties in the repair process is proposed in (Xudong, 2018). Moreover, the uncertainty of repair times for damaged components by a two-stage stochastic model in paper (Xu M. O., 2022) is addressed. A two-stage SMILP, accounting for demand uncertainty and repair time uncertainty, to optimize distribution system operation and repair crew routing is employed by (Arif A. M., 2018).

Post-natural disaster considerations and the employment of stochastic programming to address uncertainties are featured in several articles (Xu N. G., 2007; Arab A. K., 2015). Therefore, a stochastic programming model is introduced in (Xu N. G., 2007; Zou, 2019) to schedule post-earthquake electric power restoration tasks. In (Arab A. K., 2015), uncertainties in component damage levels and restoration task durations are considered to examine the proactive restoration of an electric power system in the path of an approaching hurricane. A stochastic programming model is formulated by them, incorporating random parameters to represent damage levels and repair times for damaged components.

A model that accounts for uncertainties in disruptions, traffic demand, and costs associated with mitigation and repair actions is introduced in (Zou, 2019), while a two-stage stochastic optimization model to analyze the restoration of a CISs, considering uncertain repair times for damaged components and the availability of restoration resources, is proposed in (Fang, 2019). The post-disaster repair problem for electricity distribution networks is formulated as a scheduling problem with soft precedence constraints in (Tan, 2019). In conclusion, various optimization models and algorithms aiming to efficiently restore disrupted components of CISs after disasters are showcased in the reviewed literature.

2.3 Vehicle Routing Problem

Crew routing problem, as addressed in this thesis, is conceptualized as a Vehicle Routing Problem (VRP). VRP is a well-established combinatorial optimization problem, widely studied in operations research and applied mathematics. Recognized for its computational complexity, VRP presents a difficult challenge for obtaining optimal solutions efficiently. In its simplest form, VRP reflects the Traveling Salesman Problem (TSP), which involves a single vehicle, a depot (a starting point), and a set of locations to visit (similar to damaged lines in repair crew contexts) (Braekers, 2016). Several variations and modeling approaches are presented by VRP, typically utilizing Integer Programming (IP) or Mixed-Integer Linear Programming (MILP) (Ozbaygin, 2017). Graph theory and network flow models are also employed to represent VRP (Godinho, 2008). Additional models encompass knowledge-based approaches, time-space models, and Constraint Programming (CP) (Chiang, 2014; Yan S. C., 2015; Hojabri, 2018), which incorporate logical operations and relations.

2.4 Integration of Crew Routing in Power Network Restoration

While the field of power network restoration has been extensively studied, there has been a relative shortage of efforts focused on the integration of repair crew scheduling with recovery operations within the power network. In this section, the existing literature pertaining to this crucial intersection is reviewed.

2.4.1 Mathematical Models for Crew Routing and Repair Scheduling

One of the earliest instances of this integration is found in (Arab A. K., 2015), where a mathematical model for pre-hurricane crew mobilization was presented, specifically tailored to transmission networks. In the aftermath of a hurricane, (Arab A. K., 2015) also presented a MILP model for assigning repair crews to damaged components. However, it is worth noting that this model did not take into account critical factors like travel times and repair sequence, which are fundamental to efficient restoration processes. Another study focuses on the repair and restoration of transmission systems, combining the direct current (DC) optimal power flow problem with VRP to dispatch repair crews and maximize picked-up loads (Arif A. M., 2016).

Moreover, (Yan J. H., 2020) introduced a stochastic program aimed at allocating crews for inspection and repair tasks. Additionally, stochastic optimization techniques were applied to determine the optimal number of crews to be dispatched to potential damage locations. While a synchronized routing problem for restoring infrastructure networks after disruptive events is introduced in (Morshedlou N. G., 2018). For a more holistic view, (Van Hentenryck P. &., 2015) explored routing repair crews in transmission systems. They devised a two-stage approach to address the dual challenges of routing and restoration. In the first stage, a restoration ordering problem was addressed using MILP, with the assumption that only one damaged component could be repaired at each time step. The primary aim was to determine an optimal sequence of repairs that would maximize the restored loads. Subsequently, in the second stage, the crew routing problem was tackled employing Constraint Programming (CP), large neighborhood search, and a randomized adaptive decomposition. Additionally, a two-stage algorithm for emergency transportation and power recovery is proposed in Paper (Ghorbani, 2015), addressing the vehicle routing problem with charging relief. The effectiveness of this algorithm is highlighted by simulation results, which are validated through a real case study in Ichihara City, Japan.

Another approach to determining repair schedules was explored by the authors in (Zhang H. B., 2018), who leveraged queuing theory and stochastic point processes. An alternative perspective was presented in (Zhang H. L., 2018), where a dynamic programming model was introduced. This model focused on dispatching crews to manually operate switches within the distribution network. The restoration of virtual networks post-disaster is addressed in Paper (Ma, 2015), introducing the traveling repair crew problem and employing MILP models and heuristic algorithms. A combinational disruption recovery model for the vehicle routing problem with time windows in logistics is developed by (Wang X. R., 2012), with the proposed model being solved using a nested partition method.

Furthermore, effective solution methods for interdependent restoration planning and crew routing problems are presented in article (Morshedlou N. B., 2021), demonstrating the value of a MILP model and heuristic algorithms to solve restoration problem. Application of VRP to resource allocation in power distribution systems is explored in (Zapata, 2019), where utilizing exact techniques and metaheuristics for problem-solving is provided. The delivery of perishable goods is addressed by (Wu, 2020), while proposing a disruption recovery model incorporating split delivery and dynamic route choice, and a tabu search algorithm is used for the initial routing problem and disruption recovery plan generation. The focus of paper (Wang X. X., 2009) is disruption management in vehicle routing problems for logistics, with the offering of disruption management models and the design of a genetic algorithm for effective recovery.

Furthermore, the focus of article (Van Hentenryck P. B., 2010) is last-mile disaster recovery for power restoration, with a four-stage approach presented that efficiently schedules and routes repair crews for quick power network restoration after disasters in the United States. Scalability and the generation of high-quality solutions are demonstrated by this approach.

2.5 Incorporating Power Flow Conservation Constraint in Power Network

Understanding and accounting for power flow laws in electrical networks are crucial for the efficient operation and planning of the power network. Significant strides have been made by researchers, as demonstrated in (Küçükyazıcı, 2005), in incorporating operational constraints using power flow equations. These equations are designed to approximate Kirchhoff's first and second laws, ensuring energy flow balance between load and generation nodes.

Traditionally, solving the basic power flow problem necessitates the solution of a nonlinear program, addressing net active and reactive power balances that characterize the sinusoidal behavior of alternating current (AC) electrical networks in steady-state conditions. However, for modeling bulk power transfer between substations (nodes) in power networks, a pragmatic approach involves approximating the nonlinear AC system with a simplified linear direct current (DC) power flow model.

The non-linear AC power flow is often approximated as the linear DC power flow. This linearization process is instrumental in planning studies for high voltage networks, where linearized power flow equations are frequently used to obtain reliable approximations for circuit flows under specific operational constraints (Küçükyazıcı, 2005; Morshedlou N. G., 2018; Bienstock, 2007; Hong, 2015). These approximations are used as upper bounds on transmission line flows, which are crucial for maintaining network reliability.

Furthermore, linear models, such as the DC flow model, are increasingly adopted for network design purposes due to their adaptability and efficiency. For instance, the application of mixed-integer programming to address power grid blackout problems and the exploration of the relationship between the linear DC model and the nonlinear AC model for power systems are delved into in the article (Bienstock, 2007). It is found that, in the context of network design, the linear DC model offers a suitable alternative to the more complex AC model, demonstrating its effectiveness in practical applications.

Hence, integration of flow conservation constraints into network design problems, particularly in infrastructure systems like power network, has been the focus of several studies, including (Morshedlou N. G., 2018; Hong, 2015). These problems assume direct control overflows while respecting flow upper bounds on transmission lines. The DC power flow model can be readily incorporated into these design problems through a set of constraints that effectively manage power flow within the network.

This linear approximation relies on a set of simplifying assumptions. It is assumed that the transfer of active power in the power network is the primary consideration, neglecting the effects of active power losses in the transmission lines (Andersson, 2008). While these assumptions simplify the model, they allow for efficient analysis and planning of power networks.

In summary, the integration of flow conservation constraints in power networks is a critical aspect of network design, operation, and planning. The use of linear DC power flow models, driven by their efficiency and adaptability, has become a standard practice in the field. This approach enables complex network challenges to be addressed and the reliability of power systems to be maintained by researchers.

2.6 Introduction to Two-Stage Stochastic Programming

Stochastic programming (SP) is a method in mathematical modeling and optimization that deals with uncertain data. It is a widely recognized and conventional approach utilized in various real-world fields, including finance, healthcare, transportation, and energy planning (Birge, 2011). Stochastic programming has great importance in the real world due to its wide range of applications such as facility location problems (Louveaux, 1986; Pan, 2008; Gelareh, 2015) uncapacitated facility location problems (De Armas, 2017), transportation-location problems (França, 1982; Holmberg, 1999), location models with congestion (Boffey, 2007) location-routing problem (Laporte, 2007; Ahmadi, 2015; Salman, 2015), supply chain planning (Alonso-Ayuso, 2003), hub location (Castillo, 2009) ,and routing problem (Bozorgi-Amiri, 2016; Moreno, 2016; Vahdani, 2018).

Uncertainty in SP can extent from a limited number of potential outcomes (scenarios) to an infinite unlimited number of scenarios, where the probability distributions of the data are either known or estimated (Dupačová, 2000; Kaut M. &., 2003). Probability distributions are a fundamental assumption in stochastic programming. (Shapiro, 2021) showed that these distributions can effectively incorporate uncertain data by representing uncertain parameters as random variables.

One common formulation of a stochastic program is the two-stage approach, also referred to as the recourse model. In this framework, a decision is made in the first stage, subsequently, after the occurrence of the random event, a recourse decision is made in the second stage based on the first-stage decisions and the actual random event. When the number of events or scenarios is finite, a two-stage stochastic linear program can be represented as a single extensive linear programming model. In this representation, each constraint in the problem is replicated for each realization of the random data. However, in cases where the number of realizations is excessively large or infinite, the Monte Carlo sampling technique is employed to generate a manageable number of scenarios (Arif A. , 2019).

2.7 Research Gaps and Contributions

The significance of restoring power networks in the aftermath of disasters is emphasized in the discussed articles. In the concluding part of the literature review, which explores the integration of power network restoration and crew routing, frameworks have been proposed in some articles to enhance the efficiency of power network recovery in the immediate aftermath of disruptive events. However, a noticeable gap emerges due to the absence of a comprehensive mathematical model that integrates crew routing problem with power network operations. This model should specifically consider incomplete repairs in one period by one crew and the power flow conservation constraints of the power network.

To address this gap, a novel MILP model designed specifically for power networks is introduced in Chapter 3 of this thesis. Therefore, the goal is to establish an interconnected framework for the crew routing problem with power network operation. Furthermore, acknowledging the inherent uncertainty, an additional step is taken in this thesis by introducing a two-stage stochastic programming to handle uncertainty.

This innovative approach considers uncertainties in repair times, providing a structured framework for decision-making in uncertain post-disaster restoration situations. The model aims to quickly assign damaged lines to restoration crews, identifying the routes with the minimum total costs of inoperable links and unmet demands.

In summary, a substantial contribution is made by this thesis to the integration of crew routing and power network operation. Through the introduction of a novel MILP model designed for power networks and a two-stage stochastic approach, a complete framework is provided for effective decision-making in uncertain restoration environments. The proposed scenario-based two-stage stochastic programming model significantly improves the practicality and success of the restoration process by comprehensively considering all aspects corresponding to uncertainty in repair time.

CHAPTER 3 MATHEMATICAL MODELS

3.1 Overview

Natural disasters inflict significant damage on the infrastructure network, emphasising the rising importance of efficient disaster management in the power network. The effectiveness of disaster management is crucial for improving and expediting the restoration of power networks in the following of disaster events. In the aftermath of severe incidents, utility companies organise rapid response crews to repair the network, with the aim of restoring power quickly. At present, utility companies typically rely on past experiences for scheduling repairs, and they often treat network operation and repair scheduling as separate processes. Unfortunately, this conventional approach fails to account for the interdependent of crew routing and network operation challenges. This chapter introduces an innovative optimization strategy designed to assist utility operators in the restoration of power network, with a specific focus on the recovery of damaged lines in the aftermath of significant outages. In Section 3.2, we provide a comprehensive explanation of the problem definition. This section aims to offer readers a clear understanding of the scope of our work by explicating the integration the routing of repair crews with the operation of the power network, as well as the underlying assumptions and constraints that guide our research. In Section 3.3, we introduce a Mixed-Integer Linear Programming (MILP) model to optimize the routing of repair crews and network operations. Furthermore, in Section 3.4, we incorporate stochastic programming to address the uncertainty of repair time in restoration challenges. The primary objective of this section is to propose a two-stage Stochastic Mixed-Integer Linear Programming model (SMILP) for optimizing the operation of the power network and the routing of repair crews during outage restoration after natural disaster events while considering uncertainty in repair times of damaged lines. The first stage of this model focuses on dispatching repair crews to the damaged lines, while the second stage involves while assessing the level of restoration of the power network. Our objective is to enhance the decision-making process for power network restoration by proposing a more coordinated approach to crew scheduling and network operations.

3.2 Problem Definition

The proposed repair and restoration problem focuses on a power network after a natural disaster including a disruptive event affecting some transmission lines that are completely inoperative, when this network will be fully functional once all damaged links have been repaired. Hence, the suggested models aim to reestablish connectivity of the disrupted network by repairing damaged lines. We represent the power network as a graph $G = (N, A)$ where nodes (N) include generation facilities, intersection, and demand nodes. The edges (A) in this network aim to connect the mentioned nodes, and the set of damaged lines in the power network is defined as $A' \subseteq A$. Additionally, this study needs to solve a routing problem to transfer crews from a depot to damaged lines. Therefore, the routing problem can be defined on a complete graph with nodes and arcs $\overline{G} = (V, L)$. The node set V in the undirected graph contains the depot and damaged lines, and the arc set $L = \{(l, k) \mid l, k \in V; l \neq k\}$ represents the paths connecting each pair of nodes.

There is a connection between the graph of the power network and the routing network. Each node in the routing network can be seen as the equivalent of two nodes and one link in the power network. Consequently, the damaged lines in the power network (plus the depot) make up the set of nodes in the routing network. Considering the power network shown in Figure 3.1a, which includes two damaged lines, one depot, and some intersection nodes. To address our problem, we can transform power network G into the routing network $\overline{G}$ depicted in Figure 3.1b by identifying the paths between the damaged lines and the depot. To provide further clarification, the existing routing is illustrated in the power network (3.1a) through the use of dotted lines.

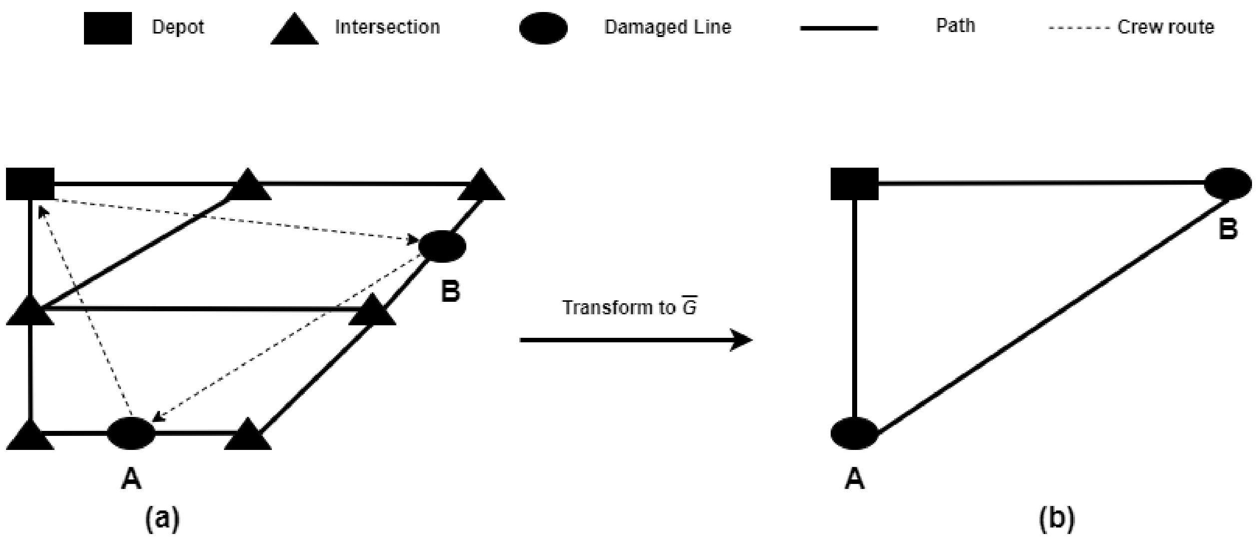

Figure 3.1:Example of transformation of power network G (a) to routing network $\overline{G}$ (b)

In this study, we classify the routing problem mentioned earlier as a Split Delivery Vehicle Routing Problem (SDVRP). This classification arises from the possibility of incomplete repairs to some damaged lines, and the process of restoration potentially involving more than one repair crew during the planning horizon. Also, each damaged line can be repaired by a limited number of crews.

Without loss of generality, the damaged lines are categorized at time $t = 0$, and these lines are repaired in subsequent time periods in the planning horizon. Besides considering repair times, the presented problem also considers the fixed travel time between each pair of nodes, which remains constant and is not influenced by uncertain events. The graph $\overline{G}$ is an undirected network which means that the travel time between nodes i and j is the same as the travel time from j to i (Akbari, 2017).

The problem involves finding a set of routes, starting, and ending at a depot, and we plan the routing of crews for the entire planning horizon. This depot has pre-defined location and there is no demand and processing time.

Each link in the power network has a defined capacity and we are interested in sending the maximum amount of flow from supply nodes to satisfy demand nodes, respecting the flow capacity of links and supply nodes' capacities. Moreover, electricity passes each transshipment node without any loss (Nurre, 2012).

Each damaged line has an associated repairing time, which depends on the characteristics of that line (e.g., severity of damage); it is expressed as the number of hours required for recovery. We also assume that recovery tasks can be started in a period and continued in following ones. We suppose that each damaged line remains inoperable until the related recovery process is completed.

One of the significant hurdles, as highlighted by Joint Research Centre (JRC) - the European Commission's science and knowledge service - is the uncertainty surrounding repair times (Karagiannis G. M., 2017). Therefore, in this study, the objective is to investigate the repair and restoration problem for a power network following a natural disruptive event, considering the inherent uncertainties in the repair times.

To address this objective, we propose two key approaches. First, we have formulated a deterministic Mixed-Integer Linear Program (MILP) aimed at addressing the challenge of repairing and restoring the power network. This MILP approach coordinates repair crews and the recovery operations of the power network. It effectively integrates both aspects to jointly tackle the repair and restoration of the power network. The objective of this integrated model is to minimize the sum of penalty costs incurred due to unmet demand, along with the costs associated with the inoperable lines caused by link disruptions. Second, we adapt the mathematical model by introducing an element of uncertainty, converting the original MILP model into a two-stage Stochastic Mixed-Integer Linear Program (SMILP) that incorporates a scenario-based optimization technique.

This modified model is employed to tackled the uncertainties in repair times in the context of the repair and restoration problem. The first stage involves the dispatch of repair crews to the damaged lines based on the expected required time for repairing. The outcome of the first stage decisions is to give us an optimal route of crews while the second stage is dedicated to the restoration of the power network under all scenarios. The second stage is implemented after the restoration begins and uncertainty is realized. In the second stage, we focus on decisions related to in the operation of power networks the power network, including the status of lines as either operative or inoperative, the total unmet demand in the network, as well as the proportion of damaged lines repaired by the crew in each period to achieve optimal service restoration.

3.3 Deterministic Model

The problem of restoring power network to minimize the effects during the whole recovery period involves two critical issues: (1) Determining the time of restoration of damaged lines, and (2) Assigning restoration tasks to repair crews.

This section focuses on the integrated repair and restoration problem, specifically dealing with dispatching of crews to expedite the repair of power systems and the restoration of damaged lines. A crucial aspect of this challenge is determining an optimal sequence for restoration, which plays a central role in the dispatching crew problem. However, the integration of repair and recovery introduces a combinatorial optimization aspect to the restoration process, significantly converting the nature of the fundamental optimization problem. The essence of the challenge lies in combining two highly intricate subproblems. Vehicle routing and power restoration, which may have conflicting objectives. When focusing uniquely on routing optimization, it can potentially lead to suboptimal restoration scheduling, while an optimized power restoration strategy may postpone routing and delay the overall restoration process.

Nomenclature for the Deterministic Model

Power network sets:

N_-	Set of demand nodes
N_+	Set of supply nodes
$N_=$	Set of intersection nodes
N	Set of all nodes $N = (N_- \cup N_= \cup N_+)$
A	Set of links in the power network $G = (N, A)$
A'	Set of disrupted links in the power network $G = (N, A)$, $A' \subseteq A$

Routing network sets:

V	Set of nodes and depot (node $\{1\} \in V$) in routing network $\bar{G} = (V, L)$
R	Set of vehicles/crews
$\bar{V}$	Set of demand nodes in routing network, $V - \{1\}$

Common parameters:

T	Set of time periods in the planning horizon

Parameters:

O_i	Installed power (MW) available in generation facility $i \in N_+$
D_i	Predicted power demand (MW) in load center $i \in N_-$
U_{ij}	Nominal transmission capacity of link $(i, j) \in A$
$\mathcal{E}_{ij}^t$	Cost (dollars) of inoperable transmission line $(i, j) \in A'$ at the end of period $t \in T$
δ	Maximum number of crews that can recover damaged lines in each period
θ_i	Penalty cost (dollars) $i \in N_-$
C_{lk}	Travel time in hours between the pair of nodes $(k, l) \subseteq L$
H	Working hours per day
$v\ (i, j)$	Node v in routing network represents damaged link $(i, j) \in A'$ in power system
μ_l	Repair time of link $l \in A'$
M	Very large number

Decision variables:

x_{lkr}^t	1, if crew $r \in R$ travels directly from node l to node k, $(l, k \in V)$ in period $t \in T$; 0, otherwise
q_{lr}^t	1, if crew r $\in R$ is assigned to the node $l \in V$ to repair this damaged line in period t, 0, otherwise
f_{ij}^t	Power flow on transmission line $(i, j) \in A$ at the end of period $t \in T$
β_{ij}^t	1, if damaged link $(i, j) \in A'$ will be operational at the end of period $t \in T$; 0, otherwise
z_i^t	Cumulative flow reaching demand node $i \in N_-$ at the end of period $t \in T$

y_{lr}^{t}	Proportion of disrupted node $l \in V$ that is repaired by crew $r \in R$ in period $t \in T$
w_{i}^{t}	Amount of unmet demand of node $i \in N_{-}$ at the end of period $t \in T$

3.3.1 Objective

In order to expedite the repair of damaged lines, we include the cost of inoperable lines in the objective function. Therefore, the cost of unmet demand is combined with the cost of inoperable lines as follows.

$$Min\, Z = \sum_{i \in N_{-}} \sum_{t \in T} \theta_i\, w_i^t + \sum_{(i,j) \in A'} \sum_{t \in T} \mathcal{E}_{ij}^t (1 - \beta_{ij}^t) \tag{3.1}$$

The first term in objective (3.1) minimizes the penalty cost of unmet demand, while the second term minimizes the cost of inoperable lines. We consider the penalty cost for unmet demand and penalize the inoperative lines to force the repair all lines. Moreover, the purpose of penalizing inoperable lines is to minimize the system restoration time.

3.3.2 Routing Constraints

Our purpose is to determine an optimal route for each crew to reach the damaged lines. The variable x_{lkr}^{t} and q_{lr}^{t} are keys in deciding whether the crew *r* travels include the path (*l*, *k*) with *l* preceding *k*. The routing constraints can be expressed as follows:

$$\sum_{k=1}^{|V|} x_{lkr}^t = q_{lr}^t \qquad \forall r \in R, t \in T, l \in V \tag{3.2}$$

$$\sum_{k=1}^{|V|} x_{klr}^t = q_{lr}^t \qquad \forall r \in R, t \in T, l \in V \tag{3.3}$$

$$\sum_{r=1}^{|R|} \sum_{k=1, k \neq l}^{|V|} x_{klr}^t = \sum_{r=1}^{|R|} \sum_{k=1, k \neq l}^{|V|} x_{lkr}^t \qquad \forall l \in V, t \in T \tag{3.4}$$

$$\sum_{k=1,k\neq l}^{|V|}\sum_{r=1}^{|R|} x_{klr}^t \leq \delta \qquad \forall l \in \bar{V}, t \in T \qquad (3.5)$$

$$\sum_{k\in\tilde{V}}\sum_{l\in\tilde{V}} x_{klr}^t \leq |\tilde{V}| - 1 \qquad \forall r \in R, t \in T, \tilde{V} \subseteq \bar{V}, 1 \notin \bar{V}, 2 \leq |\tilde{V}| \leq |\bar{V}| \qquad (3.6)$$

During each time period, Constraints (3.2) and (3.3) indicate that when a crew is assigned to node l, it must travel to and from that node. In relation to constraint set (3.4), it enforces flow conservation in routing, ensuring that if a crew reaches a damaged line, it proceeds to the next location in its route, and ultimately returns to the depot. Constraint set (3.5) guarantees that each node in the routing is visited by a limited number of crews in each time period. Constraint set (3.6) pertains to the elimination of subtours.

3.3.3 Power Network Operation Constraints

Flow conservation equations

The flow conservation equations express the balance of flow at each node of the power network. They ensure a consistent and efficient power flow throughout the network.

$$\sum_{j|(i,j)\in A} f_{ij}^t - \sum_{j|(j,i)\in A} f_{ji}^t \leq O_i \qquad \forall i \in N_+, t \in T \qquad (3.7)$$

$$\sum_{j|(i,j)\in A} f_{ij}^t - \sum_{j|(j,i)\in A} f_{ji}^t = 0 \qquad \forall i \in N_=, t \in T \qquad (3.8)$$

$$\sum_{j|(i,j)\in A} f_{ij}^t - \sum_{j|(j,i)\in A} f_{ji}^t = -z_i^t \qquad \forall i \in N_-, t \in T \qquad (3.9)$$

Constraints (3.7), (3.8), and (3.9) are network power flow conservation constraints in and out of supply nodes, intersection nodes, and demand nodes respectively.

Power network operation

$$w_i^t \geq D_i - z_i^t \qquad \forall\, i \in N_-, t \in T \quad (3.10)$$

$$z_i^t \leq D_i \qquad \forall i \in N_-, t \in T \quad (3.11)$$

$$f_{ij}^t \leq U_{ij} \qquad \forall (i,j) \in A,\, j \in \mathrm{N}, t \in T \quad (3.12)$$

$$f_{ij}^t \leq \beta_{ij}^t \times U_{ij} \qquad \forall (i,j) \in A',\, j \in \mathrm{N}, t \in T \quad (3.13)$$

Constraint set (3-10) calculates the amount of unmet demand for each demand node. Constraint set (3-11) ensures that the amount of delivered flow does not exceed the required value of the demand node. Constraint (3-12) ensures that the flow on link $(i, j) \in A \backslash A'$ does not exceed its capacity, and constraint set (3.13) enforces that flow can go through a transmission line at time *t* only if that link is operable at this time.

3.3.4 Connecting Routing and Power Network Operations

$$\beta_{ij}^t - \sum_{r=1}^{|R|} \sum_{t'=1}^{t} y_{v(i,j)r}^{t\prime} \leq 0 \qquad \forall (i,j) \in A', t \in T \quad (3.14)$$

$$y_{lr}^t \leq \sum_{k=1, k \neq l}^{|V|} x_{klr}^t \qquad \forall l \in \{2, .., |V|\}, r \in R, t \in T \quad (3.15)$$

$$\sum_{r=1}^{|R|} \sum_{t=1}^{|T|} y_{kr}^t \leq 1 \qquad \forall k \in \{2, .., |V|\} \quad (3\text{-}16)$$

$$\sum_{k=1, k \neq l}^{|V|} x_{klr}^t \leq M y_{kr}^t \qquad \forall l \in \{2, .., |V|\}, r \in R, t \in T \quad (3.17)$$

Constraint set (3.14) ensures that if link (i, j) $\in A'$ is operational at the end of period t, then its repair time must have been completed by the crews that have visited it in periods 1 to t. Constraint set (3.15) assures that repair work can be performed on a line l by crew r in period t only if this crew visits the corresponding node in this period. Constraint set (3.16) ensures that the repaired proportion of damaged line by different crews could be at most one during the planning horizon. Constraint (3.17) ensures that when a crew visits a line within a specified time period, the assigned crew is responsible for its repair. Additionally, this constraint prevents the existence of any unrepaired nodes within the routes of crews and there are no repairs needed anymore.

Working Hours

Constraint (3.18) guarantees that the total time, incorporating travel time between nodes and repair times is not greater than the specified working hours. The working hours constraint could be stated as follows.

$$\sum_{l=1,k\neq l}^{|V|} \sum_{k=1,k\neq l}^{|V|} C_{lk}\, x_{lkr}^{t} + \sum_{l=2}^{|V|} \mu_l y_{lr}^{t} \leq H \qquad \forall r \in R, t \in T \quad (3.18)$$

$$\beta_{ij}^{t}, x_{klr}^{t}, q_{lr}^{t} \in \{0, 1\} \quad (3.19)$$

$$f_{ij}^{t}, z_{i}^{t}, y_{lr}^{t}, w_{i}^{t} \geq 0,\ y_{lr}^{t} \leq 1 \quad (3.20)$$

Finally, domain of decision variables is specified in Eqs. (3.19) and (3.20).

3.4 Stochastic Model

In Section 3.3, we introduced a MILP model for addressing the repair and restoration problem, assuming a known and certain repair time for each damaged line. In practical utility situations, an optimization problem is typically solved to determine the optimal route for repair crews, who are subsequently dispatched to carry out necessary repairs, such as reconnecting damaged lines. To improve these processes, we proposed a MILP formulation that integrates both the repair crew routing and restoration problems. While post-disaster power network restoration involves actions like repairing and re-energizing the system, the durations of these activities are often uncertain (Xu N. G., 2007). To address this uncertainty, particularly regarding the repair time for each damaged link in the post-disaster power network, this section introduces a two-stage stochastic model for the repair and restoration problem. In this model, the first stage involves routing the repair crews, and the second stage focuses on the power network restoration. Building upon the mathematical model presented in Section 3.3, this section incorporates uncertainty and transforms the MILP model into a two-stage stochastic MILP (SMILP). Considering different realizations of uncertain parameter, the model aims to minimize the expected costs associated with unmet demand and inoperable lines as of its overarching objective.

Furthermore, two-stage stochastic programming and multi-stage stochastic programming are two approaches used to address uncertainties in optimization problems. In two-stage stochastic programming, it is assumed that all uncertain parameters are revealed at the beginning of the second stage, while in multi-stage stochastic programming, uncertain parameters are revealed during stages. Therefore, although multi-stage stochastic programming offers valuable insights, its application involves solving a significantly larger and more complex optimization model (Hu, 2018).

In some studies, two-stage stochastic programming is applied instead of multi-stage programming to obtain an accurate approximation of multi-stage programming in less computational time and with greater interactivity. In our proposed problem, we considered the two-stage stochastic programming model as an approximation of multi-stage programming. Moreover, this choice is made because, in our approach, crew routing decisions are initially fixed, resulting in fewer decision points in the optimization process.

Nomenclature for the Stochastic Model

Scenario notations:

S	Set of scenarios
P_s	Occurrence probability of scenario $s \in S$

Uncertain parameter:

μ_{ls}	Repair time of link $l \in A'$ under scenario $s \in S$

Decision variables:

x_{lkr}^t	1, if crew $r \in R$ travels directly from node l to node k $(l, k \in V)$ in period $t \in T$; 0, otherwise
q_{lr}^t	1, if crew $r \in R$ is assigned to node $l \in V$ to repair damaged line in period t in T; 0, otherwise
f_{ijs}^t	Power flow on transmission line $(i, j) \in A$ at the end of period $t \in T$ under scenario $s \in S$
β_{ijs}^t	1, if damaged line $(i, j) \in A'$ will be operational at the end of period $t \in T$ under scenario $s \in S$; 0, otherwise
z_{is}^t	Cumulative flow reaching demand node $i \in N_-$ at the end of period $t \in T$ under scenario s $\in S$
y_{lrs}^t	Proportion of disrupted node $l \in V$ that is repaired by crew $r \in R$ in period $t \in T$ under scenario $s \in S$
w_{is}^t	Amount of unmet demand of node $i \in N_-$ at the end of period $t \in T$ under scenario $s \in S$

3.4.1 Objective

$$Min\, Z = \sum_{s=1}^{|S|} P_s \,(\sum_{i\in N_-} \sum_{t\in T} \theta_i\, w_{is}^t + \sum_{(i,j)\in A'} \sum_{t\in T} \mathcal{E}_{ij}^t (1 - \beta_{ijs}^t)) \qquad (3\text{-}21)$$

The objective function in equation (3.21) relies on the realization of uncertainty, specifically the second-stage objective. Emphasizing the minimization of expected penalty costs associated to unmet demand, the first term takes precedence in addressing this concern. Simultaneously, the second term is dedicated to minimizing the cost associated with inoperable lines.

3.4.2 First-stage: Repair Crew Routing

The routing decision for each crew are the first-stage decision variables in the SMILP. The first-stage constraints remain independent of the uncertain parameters. The constraints are as follows:

$$\sum_{k=1}^{|V|} x_{lkr}^t = q_{lr}^t \qquad \forall r \in R, t \in T, l \in V \qquad (3.22)$$

$$\sum_{k=1}^{|V|} x_{klr}^t = q_{lr}^t \qquad \forall r \in R, t \in T, l \in V \qquad (3.23)$$

$$\sum_{r=1}^{|R|} \sum_{k=1,k\neq l}^{|V|} x_{klr}^t = \sum_{r=1}^{|R|} \sum_{k=1,k\neq l}^{|V|} x_{lkr}^t \qquad \forall l \in V, t \in T \qquad (3.24)$$

$$\sum_{k=1,k\neq l}^{|V|} \sum_{r=1}^{|R|} x_{klr}^t \leq \delta \qquad \forall l \in \bar{V}, t \in T \qquad (3.25)$$

$$\sum_{k\in\tilde{V}} \sum_{l\in\tilde{V}} x_{klr}^t \leq |\tilde{V}| - 1 \qquad \forall r \in R, t \in T, \tilde{V} \subseteq \bar{V}, 1 \notin \bar{V}, 2 \leq |\tilde{V}| \leq |\bar{V}| \qquad (3.26)$$

The constraints (3.22) to (3.26) are the same as the constraints (3.2) to (3.6) in the deterministic model of Section 3.3.

3.4.3 Second stage: Power Network Operation

In the second stage, the power network operates in response to realized scenarios. Utilizing second-stage decision variables, the system manages the operation of damaged lines. These second-stage variables, denoted by index $'s'$, are functions of the uncertain parameter μ_{ls}, representing repair times.

$$\sum_{j|(i,j)\in A} f_{ijs}^{t} - \sum_{j|(j,i)\in A} f_{jis}^{t} \leq O_i \qquad \forall i \in N_{+}, t \in T, s \in S \qquad (3.27)$$

$$\sum_{j|(i,j)\in A} f_{ijs}^{t} - \sum_{j|(j,i)\in A} f_{jis}^{t} = 0 \qquad \forall\, i \in N_{=}, t \in T, s \in S \qquad (3.28)$$

$$\sum_{j|(i,j)\in A} f_{ijs}^{t} - \sum_{j|(j,i)\in A} f_{jis}^{t} = -z_{is}^{t} \qquad \forall i \in N_{-}, t \in T, s \in S \qquad (3.29)$$

$$w_{is}^{t} \geq D_i - z_{is}^{t} \qquad \forall\, i \in N_{-}, t \in T, s \in S \qquad (3.30)$$

$$z_{is}^{t} \leq D_i \qquad \forall\, i \in N_{-}, t \in T, s \in S \qquad (3.31)$$

$$f_{ijs}^{t} \leq U_{ij} \qquad \forall (i,j) \in A, j \in \mathrm{N}, t \in T, s \in S \qquad (3.32)$$

$$f_{ijs}^{t} \leq \beta_{ijs}^{t} \times U_{ij} \qquad \forall (i,j) \in A', j \in \mathrm{N}, t \in T, s \in S \qquad (3.33)$$

$$\beta_{ijs}^{t} - \sum_{r=1}^{|R|} \sum_{t'=1}^{t} y_{v(i,j)rs}^{t'} \leq 0 \qquad \forall (i,j) \in A', t \in T, s \in S \qquad (3.34)$$

$$\sum_{l=1,k\neq l}^{|V|} \sum_{k=1,k\neq l}^{|V|} C_{lk}\, x_{lkr}^{t} + \sum_{l=2}^{|V|} \mu_{ls} y_{lrs}^{t} \leq H \qquad \forall r \in R, t \in T, s \in S \qquad (3.35)$$

$$y_{krs}^{t} \leq \sum_{k=1,k\neq l}^{|V|} x_{klr}^{t} \qquad \forall l \in \{2, .., |V|\}, r \in R, t \in T, s \in S \qquad (3.36)$$

$$\sum_{r=1}^{|R|}\sum_{t=1}^{|T|} y_{krs}^{t} \leq 1 \qquad \forall k \in \{2,..,|V|\}, s \in S \qquad (3.37)$$

$$\sum_{k=1,k\neq l}^{|V|} x_{klr}^{t} \leq M y_{krs}^{t} \qquad \forall l \in \{2,..,|V|\}, r \in R, t \in T, s \in S \qquad (3.38)$$

$$\beta_{ijs}^{t}, x_{klr}^{t} \in \{0,1\} \qquad (3.39)$$

$$f_{ijs}^{t}, z_{is}^{t}, y_{lrs}^{t}, w_{is}^{t} \geq 0,\ y_{lrs}^{t} \leq 1 \qquad (3.40)$$

In the stochastic model, the constraints (3.27), (3.28), and (3.29) imposing power flow conservation constraints in and out of supply nodes, intersection nodes, and demand nodes, respectively. Constraint set (3.30) calculates the unmet demand for each demand node under each scenario. The constraint set (3.31) has been designed to ensure that the delivered flow does not exceed the requirements of the demand node. Constraint (3.32), guarantees that the flow of the link $(i, j) \in A \backslash A'$ is no more than capacities of the links under different scenarios, and constraint set (3.33) imposes that the flow is permissible through a transmission line at time t only when the corresponding line is operational during that time across all scenarios. Constraint set (3.34) ensures that if the link $(i, j) \in A'$ is operational at the end of period t, then its repair time must have been completed by the crews that have visited it in periods 1 to t. Moreover, constraint set (3.35) in model guarantees that the total time, incorporating travel time between nodes and repair times is not greater than the specified working hours. Constraint set (3.36) assures the repair task could be performed on a line l by crew r in period t only if this crew visits the corresponding node in this period for each scenario. Constraint set (3.37) ensures that the repaired proportion of damaged line by different crews could be at most one during the planning horizon. Constraint (3.38) Ensures that when a crew visits a link within a specified time period, the assigned crew is responsible for its repair. Furthermore, this constraint prevents the existence of any unrepaired nodes within the crews' routes. Finally, domain of decision variables is specified in Eqs. (3.39) and (3.40).

CHAPTER 4 METHODOLOGY

In this chapter, we describe the solution method that was used to tackle the models proposed in Chapter 3. We focus mainly on solving the stochastic model of Section 3.4. We recall that this is a two-stage vehicle routing model in which the first stage focuses on designing routes for repair crews and the second stage on computing flows and restoration in the power network for different scenarios of damaged line repair times.

The description of our solution approach involves two major points: the general procedure that we used to solve a vehicle routing problem with subtour elimination constraints (SECs), which is described in Section 4.1, and the approach that we applied for the generation of scenarios in the model, which is explained in Section 4.2. It is the combination of these two points that ensures efficient routing of the crews and provides a reliable decision-making framework for power network recovery in the face of uncertainty.

4.1 Solving the Crew Restoration Routing Problem

Our solution methodology relies on utilizing the commercial mixed-integer linear programming (MILP) solver CPLEX, embedded into a Julia programming procedure. However, addressing large-scale problems poses significant computational challenges. Although the models presented in Chapter 3 are MILPs, CPLEX cannot just be applied directly due to the presence of subtour elimination constraints (SECs) in both models (constraints (3.6) in the deterministic model and constraints (3.26) in the stochastic one). These constraints ensure that crews' routes in each period do not contain suboptimal loops known as subtours. The objective is to create a single connected tour for each crew in each period, starting and ending at the designated depot. Unfortunately, explicitly stating all these constraints at the outset is practically infeasible, especially for instances with a large number of nodes. This is achieved by incorporating SECs in the problem formulation to eliminate subtours.

To address this challenge, we considered sub-tour elimination constraints as Lazy Constraints (Cuts). Lazy Constraints (Cuts) are employed to enhance the efficiency of solving integer and mixed-integer programs by selectively using constraints only when necessary. The application of lazy constraints involves the following steps. Initially, these constraints are relaxed, and progressively violated constraints are added to the original pool as they are identified in the optimal solutions of the relaxed problem. In Algorithm 1, when subtours are detected in the feasible solutions of relaxed problems, they are eliminated using appropriate cuts (SECs), treated as lazy constraints in CPLEX. For further clarification, we relax the constraints in the original formulation that are less likely to be violated. During the optimization process, we use the callback function to check any candidate IP solution; this callback function is automatically called by the commercial solver each time a new candidate solution is found. If any part of the current candidate integer solution violates the relaxed constraints, we reject the solution, and new constraints are added to the original pool to cut off that solution. Afterwards, we continue with the branch-and-bound process. This procedure allows CPLEX to concentrate on finding high-quality solutions while effectively addressing the subtour elimination requirement in a dynamic manner. This approach allows leaving out constraints from a problem that must be satisfied by any feasible solution but may not be required by the solver to find the optimal solution (Baldacci, 2011). By inspecting each integer solution during the branch-and-bound process and adding constraints only when needed, we achieve a smaller, more manageable model, leading to potential dramatic improvements in solution time for certain problems.

```
Store the current routing solution (set of routes) in an array
Initialize arrays to track visited nodes and next visited nodes
Identify nodes with outgoing arcs in the current solution
Calculate the number of outgoing arcs from each node
Determine the total number of outgoing arcs in the current solution
    For r ∈ set of routes, do:
        For t ∈ set of time periods, do:
            Reset the visited nodes array and the next visited nodes array
            Initialize a list of nodes with outgoing arcs for the current route and time period
            Calculate the number of outgoing arcs from each node for the current route and time period
            For i ∈ set of nodes in each route r, do:
                Calculate the next visited node
                If node i is not visited, do:
                    X ← mark node i and next visited node in route r as a subtour
                    While X≠ [], do:
                        first_visited_subtour ← next
                        add_subtour_elimination_constraint in first_visited_subtour
                        add corresponding subtour elimination constraints
```

Figure 4.1: The pseudo-code for the proposed subtour elimination algorithm

4.2 Scenario Generation using Monte Carlo Sampling

Addressing uncertain parameters through the incorporation of distributions presents computational complexities within stochastic models. To simplify and approximate these uncertainty parameters derived from distributions, a common approach is to constrain them to a specific number of realizations, a method known as scenario generation. However, a significant increase in the number of scenarios can considerably impact computational tractability.

The stochastic model of Section 3.4 relies on a set S of scenarios to represent the inherent uncertainty in line repair times. In our computational experiments, this finite set of scenarios is obtained using a Monte Carlo sampling procedure. This Monte Carlo sampling method generates a number $|S|$ of scenarios that are assumed to occur with probability $(1/|S|)$. This distribution suggests a balanced and comprehensive exploration of the uncertainty inherent in the restoration process. Therefore, this technique enables the generation of diverse and realistic scenarios for uncertain repair times.

Monte Carlo Sampling, a widely adopted method in decision-making dealing with uncertainty (Löhndorf, 2016), is strategically employed to simulate and analyze a range of possible outcomes. By simulating a large number of scenarios, it enables us to explore diverse possibilities and assess the impact of uncertain repair times on our power network restoration strategy. This approach enables the generation of multiple sets of scenarios, each capturing a unique expression of the stochastic nature of repair times. In our computational experiments, we have decided to use a uniform integer distribution on interval [1, 5] to provide a realistic representation of potential repair times for lines.

The fundamental idea of Monte Carlo simulation is to leverage the Strong Law of Large Numbers (Hewitt, 2021), ensuring convergence toward a stable and representative set of scenarios with increasing iterations. Therefore, when we use a sampling method, the strongest candidate for the source of the instability or bias is a lack of scenarios (Keutchayan, 2021). We know that, with an increasing number of scenarios, the discrete distribution converges to the true distribution. Hence, by increasing the number of scenarios, the set of scenarios will be closer to the true distribution (Goldreich, 2008; Knuth, 2014).

CHAPTER 5 COMPUTATIONAL EXPERIMENTS

We investigate the applicability of the proposed models to a portion of a power network. These models are coded in Julia 1.7.2 with JuMP 0.21, and the numerical experiments are executed on a server virtual machine (VM) with Core i7-7800X CPU and 128 GB of RAM.

We consider a test case involving a power network with 75 links following a natural disaster. We assume that the disaster damages 10 power lines in the network. The state of this network is illustrated in Figure 5.1. This figure shows the situation of the power network due to the outages before the repairs; i.e., the initial state of the system at time $t = 0$. It includes a depot, damaged lines, a supply node, intersection nodes, and demand nodes. We take into account the capacity of the supply node to generate energy and the ability of intersection nodes to pass the flow. Due to a lack of access to real data, we determine the values of parameters in the model based on uniform probability distribution, so the values for parameters are shown in Table 5.1.

Table 5.1: Parameter settings for the restoration problem in the power network

Parameter	Value
Supply capacity (KW)	O_i = *U (50-250)*
Intersection node capacity (KW)	U_{ij} = *U (15-25)*
Demand node capacity (KW)	D_i = *U (25-75)*
Travel time (Hour)	C_{lk} = *U (0.5,0.9)*
Penalty cost ($/per demand node)	$\theta_i = 300$
Inoperability cost ($/per damage link)	$\mathcal{E}_{ij}^t = 200$
Maximum number of repair crews (per damaged link per period)	$\delta = 2$
Repair time (hours)	μ_l = *U (1,5)*
Number of routing nodes (damaged lines)	$\bar{V} = 10$
Number of scenarios	*S = 10, 15, …, 100*
Time periods	*T = 2, 3, 4*
Number of available crews	*R = 2, 3, 4*
Working hours	*H = 8*

The models presented in Sections 3.3, and 3.4 are used to evaluate the impact of the extreme event. Scenarios related to repair times are generated using a discrete uniform distribution on the interval [1, 5]. Monte Carlo sampling is utilized to create 1000 interdependent repair time scenarios. Each scenario includes repair times for the 10 damaged lines. Table 5.2 displays samples of the repair time generated from the uniform distribution for 15 scenarios. Furthermore, the first node in the routing problem corresponds to the depot in our problem.

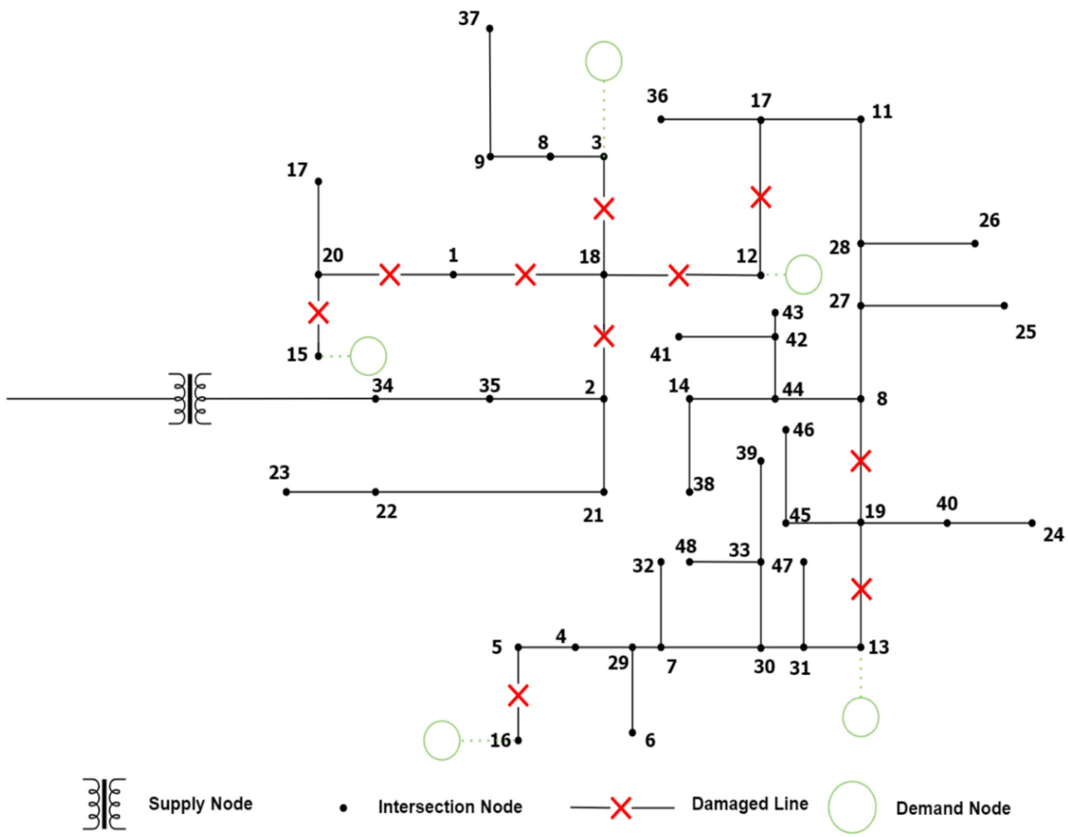

Figure 5.1: Initial state of the power network after 10 lines are damaged

Table 5.2: Samples of the repair times (in hours) for the 15 generated scenarios using the integer uniform distribution

Damaged line	*Routing node*	*Scenario 1*	*Scenario 2*	*Scenario 3*	...	*Scenario 15*
Line12-17	2	1	2	3	…	4
Line12-18	3	5	1	1	…	5
Line13-19	4	1	5	3	…	5
Line15-20	5	4	5	1	…	3
Line16-5	6	1	5	5	…	3
Line18-1	7	2	2	5	…	1
Line18-2	8	5	1	5	…	4
Line18-3	9	4	2	1	…	2
Line19-8	10	2	3	4	…	2
Line20-1	11	2	4	5	…	4

5.1 Basic Results: Examining the Effect of the Number of Scenarios

In this section, we examine the solutions of the stochastic model of Section 3.4 for our 75-link power network repair and restoration test case. In this context, we consider that three (3) crews are available for eight (8) hours in each period (day) to repair, the 10 damaged lines over a planning horizon of 2 time periods. To address this problem, we first establish in Table 5.3 the relationships between the damaged lines in the power network and the associated nodes of the routing network.

The objective values of 14 instances with different sets of scenarios are reported in Table 5.4. Additionally, the repair schedule of crews in each time period for the 15-scenario instance, obtained from CPLEX, are shown in Table 5.5. Furthermore, for better comprehension, the routing solutions of this instance for the first and second time periods, are depicted in Figures 5.2 and 5.3, respectively. All these results are obtained within a computational time limit of 86,400 seconds (24 hours). The optimal solution in instances involving more than 20 scenarios cannot be found by CPLEX.

Table 5.3: Correspondances between nodes in the routing network and lines in the power network

Nodes in the routing network	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
Damaged lines	Depot	12-17	12-18	13-19	15-20	16-5	18-1	18-2	18-3	19-8	20-1

Table 5.4: Results of the stochastic repair and restoration problem on the power network involving 10 damaged lines with different sets of scenarios

NO. SCENARIOS	OBJ	LOWER BOUND	GAP
10	109640	109640	0.0%
15	109800	109800	0.0%
20	109810	109810	0.0%
25	109816	109659.8838	0.14%
30	109806.6667	109574.6796	0.21%
35	110291.4286	109698.5637	0.54%
40	110045	109702.7782	0.31%
45	110244.4444	109715.0448	0.48%
50	110380	109768.268	0.55%
60	110740	109624.045	1.01%
70	110291.4286	109640.9124	0.59%
80	110707.5	109635.8935	0.97%
90	110202.2222	109640.3749	0.51%
100	110534	109624.8712	0.82%

Table 5.5: Optimal routes of crews for the 15-scenario instance

Crew number	Routes Schedule in Time period 1	Routes Schedule in Time period 2
Crew 1	Depot → 5 → 4 → Depot	Depot → 9 → 7 → 11 → Depot
Crew 2	Depot → 2 → 3 → 10 → Depot	Depot → 10 → 11 → Depot
Crew 3	Depot → 4 → 3 → 8 → Depot	Depot → 6 → 9 → Depot

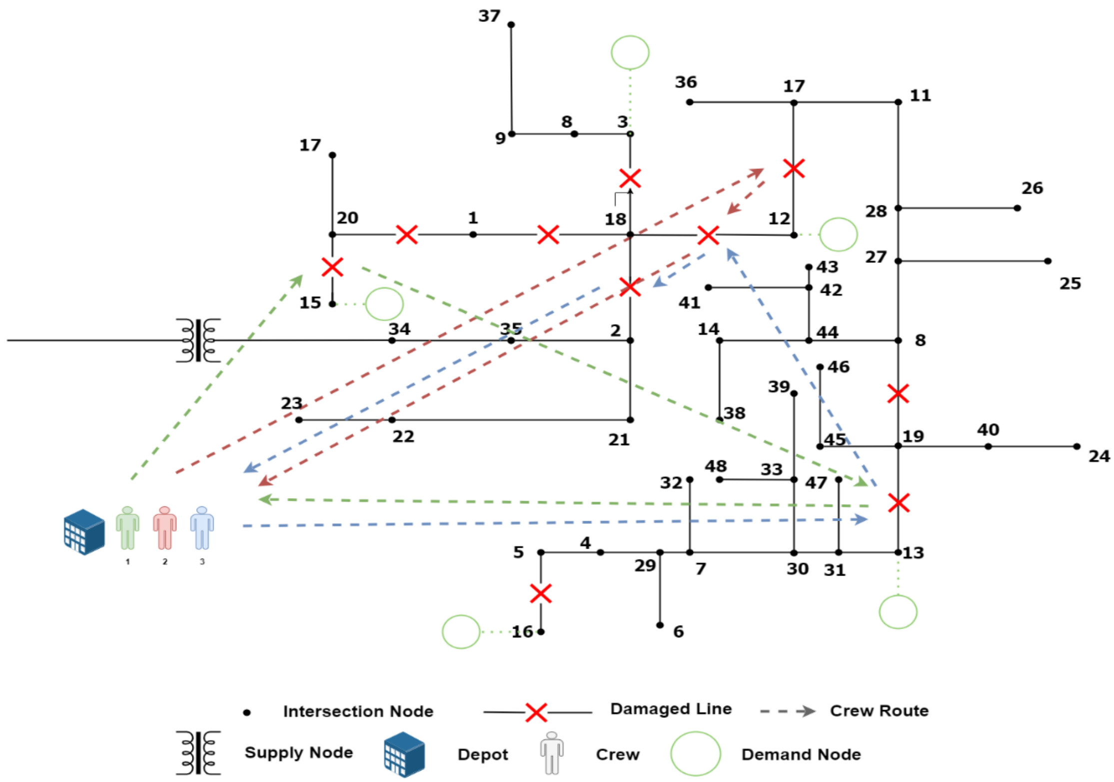

Figure 5.2: The routing solution for the first time period for the 15-scenario instance

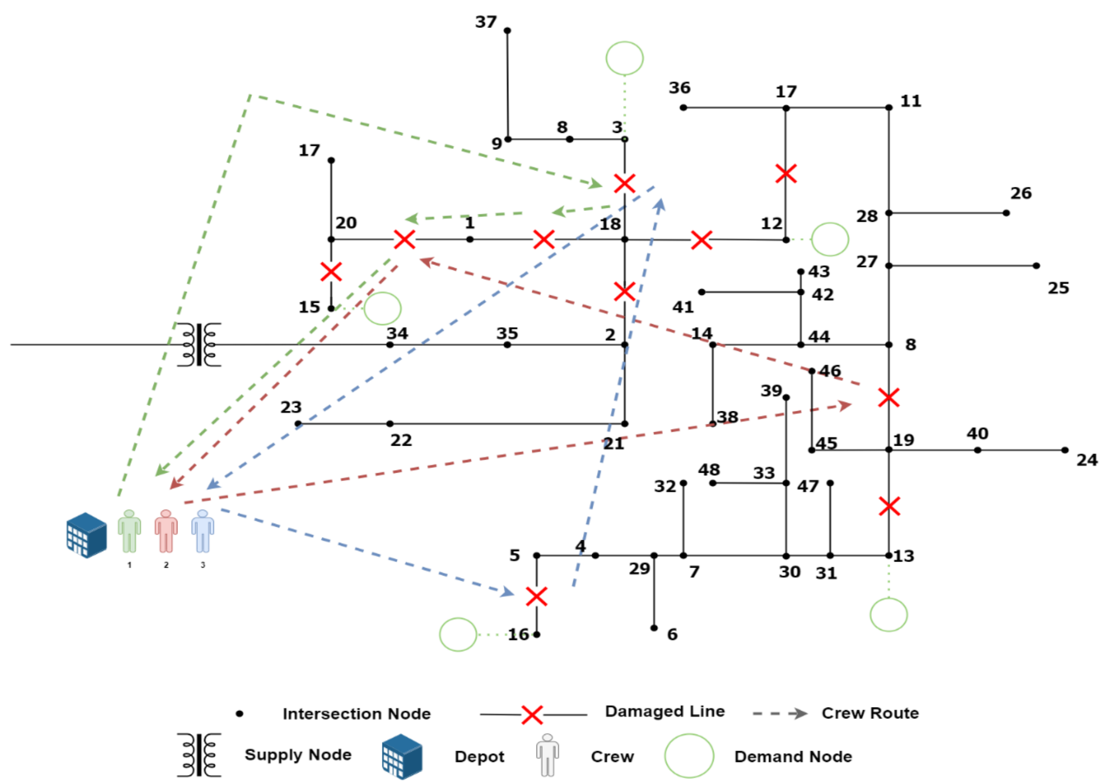

Figure 5.3: The routing solution for the second time period for the 15-scenario instance

5.2 Stochastic Programming Solution

To highlight the significance of accounting for uncertainty in our problem, we calculated two crucial measures: the Expected Value of Perfect Information (EVPI) and the Value of the Stochastic Solution (VSS). Accordingly, EVPI signifies the maximum amount that should be considered by a decision-maker to pay for perfect information before making a decision. The calculation entails comparing the expected value of the decision with perfect information to the expected value of the decision without perfect information. In the context of a two-stage stochastic program, EVPI is typically determined by calculating the difference in the objective function values between the optimal solution of the fully informed (perfect information) model referred to as Wait-and-See (WS) and the solution of the original (stochastic) model, known as Here and now (two-stage stochastic programming). The calculation includes evaluating the expected value over all possible scenarios, taking perfect information into account. The concept of EVPI essentially provides a lower bound for the objective value of two-stage stochastic programming model.

On the one hand, to determine the VSS measure, I will outline the process for calculating the EEV. The deterministic counterpart of the stochastic model, often referred to as the Expected Value (EV) problem, needs to be solved initially. This involves making decisions based on the expected values of uncertain parameters. We initiate by determining the expected repair time for a set of scenarios and solve the deterministic version by considering the expected value of repair time to attain the first-stage solution. Subsequently, we fix the first-stage variables in the two-stage stochastic model to address the second-stage problem and objective function associated with this set of scenarios. This involves making decisions in the second stage based on the actual realization of uncertain parameters. Furthermore, we replicate this procedure to obtain the EEV related to more sets of scenarios, including the previous set of scenarios.

The VSS is to be calculated by taking the difference between the expected of objective function values of the deterministic model and the objective function value obtained by considering the stochastic of the problem (Here and now solutions). Derived from references within the stochastic approach, large values of VSS highlight the critical importance of considering uncertainty in our decision-making process (Hu, 2018). To illustrate the impact of uncertainty in Table 5.6, we conducted our analysis on instances with up to 15 scenarios, which seem to make up a representative sample of the various aspects of our uncertain environment.

Table 5.6: Illustration of values in VSS and EVPI in different sets of scenarios

NO. SCENARIO	STOCHASTIC	EEV	WS	VSS	EVPI	LOWER BOUND	GAP
1	109200	119400	109200	10200	0	109200	0.0%
2	109600	114800	109300	5200	300	109600	0.0%
3	109533	113133	109333	3600	200	109533	0.0%
4	109600	114800	109300	5200	300	109600	0.0%
5	109600	113800	109280	4200	320	109600	0.0%
6	109600*	114767	109267	5167	333	109545	0.05%
7	109657*	115571	109314	5914	343	109599	0.05%
8	109675*	114825	109300	5150	375	109549	0.11%
9	109644*	114289	109311	4645	333	109524	0.11%
10	109640*	114800	109280	5160	360	109548	0.08%
11	109691*	115254	109309	5563	382	109499	0.12%
12	109717*	115617	109317	5900	400	109530	0.13%
13	109708*	115923	109323	6215	385	109482	0.15%
14	109714*	116171	109329	6457	385	109465	0.18%
15	109800**	116440	109360	6640	440	109800	0.0%

***** The optimal solution could not be obtained within the allocated computational time limit of 28,800 seconds

****** The optimal solution was attained in 43,955.33 seconds

******* All values in the table are rounded to nearest integer value

With 15 scenarios, the calculated EVPI amounts to 440, approximately 0.4% of the two-stage stochastic objective value. Concurrently, the VSS was found to be 6640, approximately 6% of the two-stage stochastic objective values. This substantial value for the VSS indicates the higher performance of the two-stage stochastic programming model compared to the deterministic model, emphasizing the necessity of considering uncertainty in our decision framework. As a practical consideration, we acknowledge instances where optimal solutions for the stochastic model in reasonable computational time limit were unattainable. In such cases, we present the lower bound for VSS and the upper bound for EVPI. Specifically, the value for the (EEV) is constant and using the non-optimal value of the two-stage stochastic model as an upper bound, the lower bound for the actual Value of Stochastic Solutions (VSS) can be derived. Similarly, ensuring a consistent and optimal value for Wait-and-See (WS) allows the value of EVPI to serve as the upper bound.

5.3 Out-of-Sample Analyses

In order to mitigate computational complexity, our objective is to pinpoint the number of scenarios that can yield a reliable estimation encompassing the entirety of scenarios (1000 scenarios). Reducing scenarios without compromising accuracy is crucial. Hence, Out-of-sample analyses are used in this study to confirm that a manageable number of scenarios effectively represents diverse outcomes, affirming the method's practical efficiency. In essence, this methodological framework, incorporating Monte Carlo Sampling with an integer uniform distribution, not only promises a realistic representation of uncertain repair times but also ensures a stable foundation for decision-making in power network restoration scenarios. We employ a stability test inspired from the proposals in (Kaut M. S., 2003) to assess the sensitivity of our objective function to varying scenarios, a process commonly known as out-of-sample validation. Our test involves solving the stochastic problems with instances based on a different number of scenarios and then comparing the resulting objective values. The model is supposed stable if these objective values are approximately equal. To perform this test, we generate 14 sets of scenarios that include from 10 to 100 scenarios. It should be noted that as we increase the number of scenarios, we keep scenarios that were used before. For instance, in a scenario set comprising 15 scenarios, scenarios 1 to 10 are duplicates from the set containing 10 scenarios. The two-stage stochastic model is solved for each set of scenarios. Then for each set of scenarios we fixed the values of the first stage decision variables and solved the second stage of our two-stage stochastic model considering 900 scenarios (scenarios from 101 to 1000). Because the first-stage decision variables are fixed in this model we can decompose it to 900 deterministic sub-problems results. The sensitivity analysis of the objective value versus the number of scenarios is conducted, and illustrated in Fig. 5.4. The results reveal minimal variation in the objective values and the reported average objective values are nearly identical. It should be noted that in certain experiments, as the number of scenarios increases, the two-stage stochastic model cannot be optimally solved within the computational time limit. The optimal solutions for the two-stage stochastic model were achievable within a 24-hour computational time only when the number of scenarios is 10, 15, or 20. Consequently, in some cases with a larger number of scenarios, the variation tends to increase.

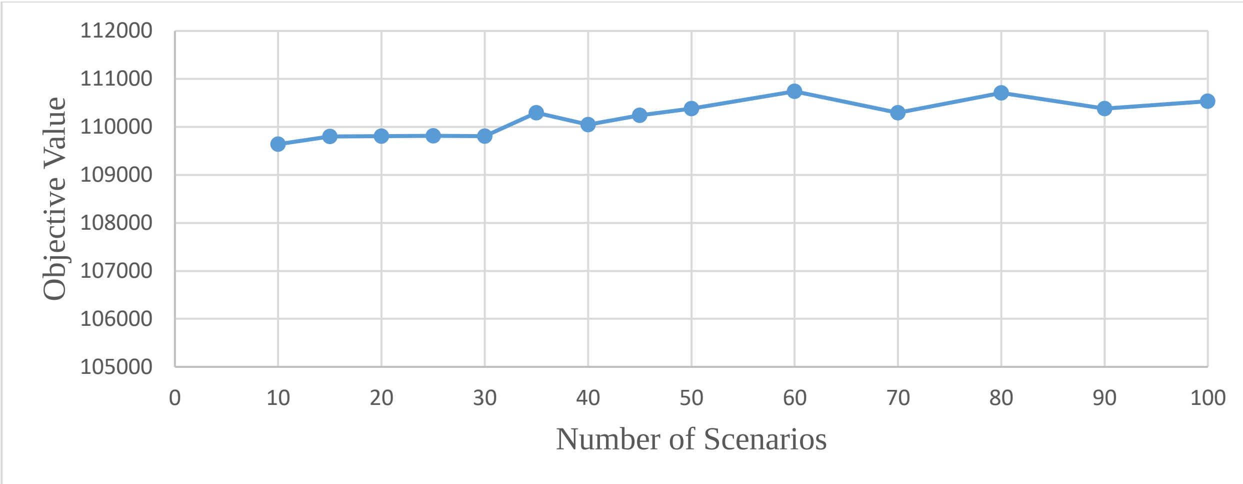

Figure 5.4: Sensitivity analysis of objective value versus the number of scenarios

To enhance the precision of our assessment, we calculate the standard deviation of the objective function values obtained from scenarios 101 to 1000, proceeding as in the procedure just described. To mitigate the influence of the expected value on our calculations, we use the coefficient of variation (CV) criterion to compare the effect of the number of scenarios. This criterion is formulated by dividing the standard deviation of 900 objective values obtained across scenarios by their corresponding expected values. The expected values and the standard deviation for different sets are shown in Table 5.7. The coefficient of variation values for different set of scenarios are displayed in Figure 5.5. As noticeable from Figure 5.5, the high (CV) criterion in the 10-scenario case can be attributed to the diversity observed in the objective values obtained in this context. Consequently, considering both the stability tests and the related results depicted in Figure 5.5, this set of 15 scenarios for repair times displays a high level of stability in our model. We believe that these scenarios adequately capture the uncertainties in our study. This sample is preserved and consistently utilized to address repair times in all instances of the problem across different test cases.

Table 5.7: The standard deviation and the expected values for different sets of scenarios

Number of scenarios	*S=10*	*S=15*	*S=20*	*S=25*	*S=30*	*S=40*	*S=45*	*S=50*	*S=60*	*S=70*	*S=80*	*S=90*
Standard deviation	2238.696	1550.789	1548.603	1550.789	1549.704	1550.789	1549.245	1548.603	1550.881	1522.856	1549.245	1548.603
Expected values	110332.4	110040.4	110035.3	110040.4	110039.1	110040.4	110042.9	110035.3	110039.1	110158.7	110042.9	110035.3

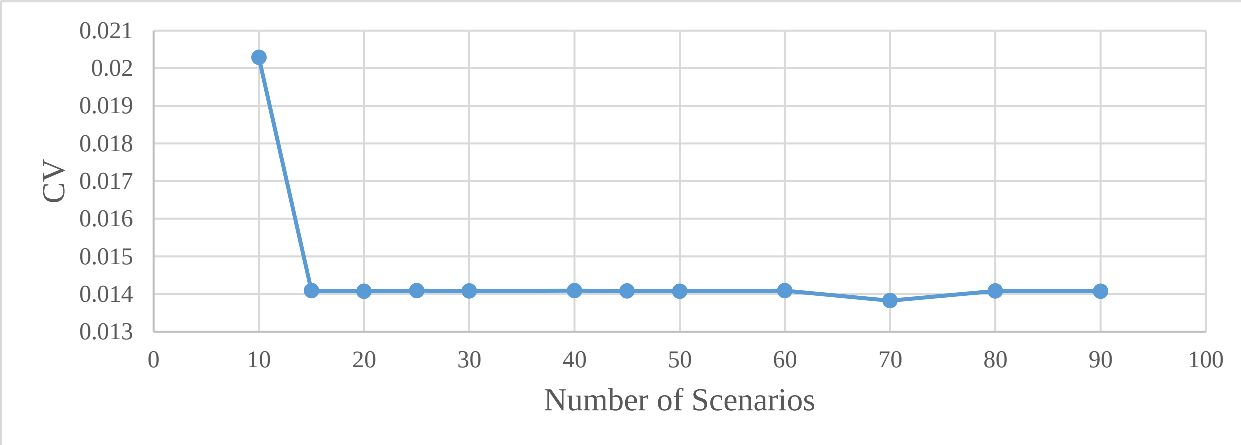

Figure 5.5: The coefficient of variation values for different sets of scenarios

5.4 Emphasizing the Significance of Considering Uncertainty in Our Model

In this section, we further examine the efficiency of the proposed two-stage stochastic programming model compared to the deterministic model. We consider solving three distinct formulations. First, we investigate the stochastic problem, considering 15 scenarios that account for varying repair times associated with damaged lines. Second, we examine the deterministic problem by considering the repair time of damaged lines equal to the mean values of them in the scenarios considered in the two-stage stochastic model. Lastly, we present a worst-case scenario, wherein all repair times related to damaged lines are consistently set to 5 hours (upper bound of the interval used for generating repair times in the scenarios). To elaborate on the approach, we initiated our analysis by addressing the stochastic problem and finding the optimal solution across a set of 15 scenarios, with 3 crews over 2 time periods. To compare the effects of considering uncertainty, we solved the two-stage stochastic programming model, the deterministic model with expected value of repair times, and the deterministic model with upper bound for repair times, separately. Then, for each model, we fixed the decisions obtained for the routing of crews (first-stage decision variables) and considered the second-stage problem using 100 scenarios (scenarios from 101 to 200). The objective values obtained are reported in Table 5.8.

Table 5.8: Comparing solutions to highlight the performance of the stochastic program

Method	*Optimal Objective Value*	*Differences between stochastic and alternative approaches*
Stochastic	$ 110148	-
ED	$ 115802	$ 5654
Worst-case	$ 114902	$ 4754

From Table 5.8, first, the outstanding performance of the stochastic programming model compared to the deterministic models. As reported in this table, the expected value of cost corresponding to penalty cost of unmet demand and inoperable links increases when the solution of the deterministic model is considered instead of the solution of the stochastic programming model. The expected cost value, pertaining to penalty costs associated with unmet demand and inoperable links, increases by $5654 when employing deterministic model with mean values of repair time. Additionally, there is an increase of $4754 when using the solution of the deterministic model with the worst-case scenario. This emphasizes the achieved cost-effectiveness and efficiency resulting by incorporating the stochastic approach. This outcome is expected, given that the stochastic problem considers the variability of natural disaster event outcomes unlike the deterministic solution in the context of the repair and restoration problem. This indicates that the stochastic model leads to a better restoration strategy. Solving the two-stage stochastic problem is thus more beneficial than solving a deterministic problem with expected repair durations. In the worst-case scenario, all repair times related to damaged lines are consistently set to 5 hours, which can lead to a more conservative and potentially less costly solution by about $900.

To further substantiate the validation of the stochastic model in contrast to the consideration of a deterministic model, results have been obtained across of different sets of scenarios, ranging from 10 to 100 in 13 instances, following the same methodology as previously explained. An important finding in this investigation emphasizes the significance of incorporating uncertainty related to repair times for damaged lines. Figure 5.6 provides a graphic comparison of the expected values of the objective function for the solutions of the deterministic and stochastic models. The outcomes reveal a significant difference in the results. This observation highlights the critical role of accounting for uncertainties in repair times, emphasizing the enhanced accuracy and practicality offered by the stochastic modeling approach.

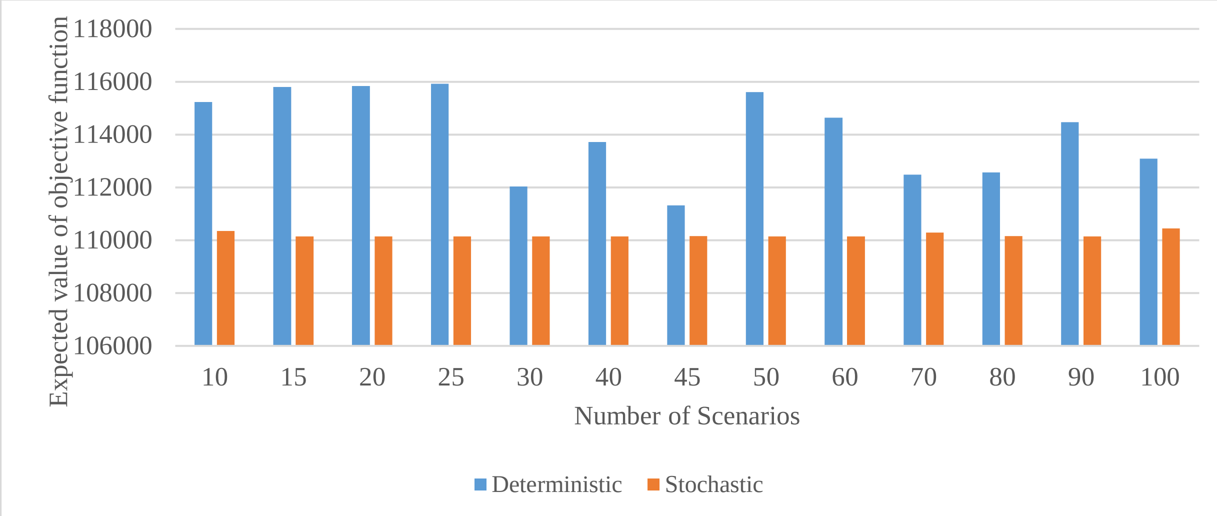

Figure 5.6:Performance of the stochastic program versus deterministic for different sets of scenarios

5.5 Sensitivity Analyses

In this section, we examine a number of variations of our stochastic programming model for power network repair and restoration. First, we analyze the impact of crew size on power network restoration. Next, we compare the Split Delivery Vehicle Routing Problem (SDVRP) with the traditional routing problem in terms of power network restoration. Finally, we investigate the impact of an increased number of damaged lines on stochastic repair and restoration problem.

5.5.1 Analyzing Crew Size Impact on Power Network Restoration

In this section, a detailed sensitivity analysis is conducted to determine the impact of the number of crews on the stochastic repair and restoration problem. Comparisons are made between the results with 3 crews in Table 5.9 and 2 crews in Table 5.10 across three time periods, for a network with 15 damaged lines under different sets of scenarios. The goal is to derive critical insights on the influence of crew size on optimizing the repair and restoration process. The investigation aims to identify optimal resource allocation, aiming to find the right trade-off between associated costs and the efficient repair of damaged lines post-disaster. This analysis is imperative in expediting the restoration of the power network to its normal operation. Moreover, it requires a thoughtful consideration of the costs associated with resource utilization.

Table 5.9: Results for different sets of scenarios when considering 3 crews in 3 time periods and 15 damaged lines

NO. SCENARIOS	OBJ	LOWER BOUND	GAP
10	206880	203299.3054	1.73%
15	208840	205369.7199	1.66%
20	208730	204730.1768	1.92%
25	210628	204663.7314	2.83%
30	210334	204296.3072	2.87%
35	214005.7143	204649.0887	4.37%
40	215130	204522.4492	4.93%
45	215651.1111	204146.9591	5.33%
50	217913.3333	204826.3222	6.01%

Table 5.10: Results for different sets of scenarios when considering 2 crews in 3 time periods and 15 damaged lines

NO. SCENARIOS	OBJ	LOWER BOUND	GAP
10	215530	214599.2419	0.43%
15	217593.3333	215599.7917	0.92%
20	216975	214864.7576	0.97%
25	218256	214207.3707	1.85%
30	219123.3333	213402.44	2.61%
35	218622.8571	213393.8795	2.39%
40	217512	212207.1785	2.44%
45	217857.7778	212222.8075	2.59%
50	219112.5	212618.9039	2.96%

Upon examination of the outcomes reported in both tables, it is revealed that the results in Table 5.9 consistently demonstrate a slightly better objective function compared to Table 5.10, implying that the additional crew marginally contributes to improved optimization. This suggests that the optimization potential may be influenced by crew size, but that the impact is marginal, once sufficient resources have been allocated to the task at hand. Furthermore, the trend of increasing percentage gaps in both Tables 5.9 and 5.10 indicates that achieving optimality becomes increasingly intricate with more scenarios. This observation points to a growing complexity in power network restoration challenges as the number of scenarios increases.

5.5.2 Comparing Split Delivery Vehicle Routing Problem (SDVRP) with Traditional Routing Problem in terms of Power Network Restoration

In this section, a comparative analysis is conducted between the split delivery vehicle routing problem (SDVRP) and the conventional single-route routing problem, similar to the Traveling Salesman Problem (TSP). The primary focus is on assessing the advantages of adopting SDVRP in the context of the repair and restoration problem. Two sets of results are presented, corresponding respectively to the use of SDVRP in Table 5.11, and the absence of SDVRP in Table 5.12, with the aim of displaying the impact on optimization outcomes. The parameters are kept constant, and the computational time limit is set at 86,400 seconds to ensure a fair evaluation.

Table 5.11: The results of solving the restoration problem for different sets of scenarios with SDVRP

NO. SCENARIOS	OBJ	LOWER BOUND	GAP
10	109640	109640	0.0%
15	109800	109800	0.0%
20	109810	109810	0.0%
25	109816	109659.8838	0.14%

Table 5.12: The results of solving the restoration problem for different sets of scenarios without SDVRP

NO. SCENARIOS	OBJ	LOWER BOUND	GAP
10	113480	111230.5709	1.98%
15	114540	111743.7632	2.44%
20	114520	111138.5343	2.95%
25	114516	110720.5549	3.31%

A definite advantage is demonstrated when SDVRP is employed, compared to the traditional single-route method. The analysis of the lower bounds of the restoration problem without SDVRP in Table 5.12 indicates that these exceed the objective function values when considering SDVRP in Table 5.11. This suggests that the number of repaired lines with SDVRP is greater than without its consideration. It emphasizes the limitations of the traditional routing approach in achieving solutions. In conclusion, this analysis highlights the significance of employing SDVRP in the repair and restoration problem, resulting in improved optimization outcomes.

5.5.3 Impact of Increased Damaged Lines on Stochastic Repair and Restoration

In this section, an exploration is performed with the deliberate purpose of increasing the complexity of our stochastic repair and restoration problem. The change considered involves an increase in the number of damaged lines, a critical parameter of the power network restoration problem. This modification is designed to enhance the resilience of the model, evaluating how well the expanded challenges posed by the increased number of damaged lines are managed. The results related to this adjustment are presented in Table 5.13. Our focus remains persistent in observing how the models are solved while considering an 86,400 seconds computational time limit.

Table 5.13: Increasing the number of damaged lines for instances with 15 scenarios

TEST	NO. SCENARIO	DAMAGED LINES	OBJECTIVE	LOWER BOUND	GAP%	COMP. TIME
1	15	25 Lines	116420.0000	106487.3823	8.53%	86399.86
2	15	30 Lines	118173.3333	102566.1031	13.21%	86399.92
3	15	35 Lines	211900	184437.1374	13.96%	86399.95

Analyzing of the results presented in Table 5.13, we clearly see that the difficulty of the problem increases significantly with the addition of more damaged lines. However, compared with the restoration problem examined in Section 5.1, the number of crews and time periods was not augmented. Despite this limitation, we note that, when the number of damaged lines goes from 10 to 25, the objective value only increases from 109,800 to 116,420, demonstrating that the allocated resources are probably sufficient to deal with the increased challenge. This is no longer true, when the number of damaged lines is further increased, as shown by the results obtained for 35 damaged lines. It then becomes apparent that additional resources are required to restore the operation of the power network in that situation.

CHAPTER 6 CONCLUSION AND FUTURE WORK

6.1 Conclusion and Research Contribution

Substantial damage to power network infrastructure can be caused by major disasters. Consequently, a careful planning of the recovery operations is imperative for utilities to ensure a quick and effective repair of the network. The efficient restoration of the network depends upon the proper utilization of crews. Hence, achieving a faster restoration time involves an effective response to disaster events, specifically coordinating repair crews with the recovery operations of power networks.

The use of mathematical programming in this thesis optimizes post-disaster repair scheduling and power network recovery. Operators are aided in significantly reducing restoration time through the optimization process. This thesis introduces a two-stage stochastic restoration optimization model, utilizing mixed-integer linear programming to address repair and restoration challenges under uncertainty in repair time. Acknowledging the post-disruption environment and inherent uncertainty, the two-stage stochastic model emphasizes the importance of uncertainty associated with restoration planning and repairing damaged line durations. Each crew is strategically assigned to a set of damaged lines for restoration in the model, optimizing the restoration sequence across scenarios to minimize the costs associated with the unrepaired disruption of the power network.

The main contributions of this thesis are the following:

- Development of a novel MILP model that combines repair crew routing and power network operation problems. This model can be utilized by operators for scheduling repairs and restoring normal operations after natural disasters, with decisions based on minimizing total costs related to unmet demand and inoperable damaged lines.
- Introduction of a new two-stage SMILP model for crew allocation, considering uncertainty in the repair time of damaged lines in power networks. The model efficiently demonstrates how uncertainty can be handled by stochastic programs in this context. The number of discrete uncertainty scenarios is reduced to a tractable size using an out-of-sample analysis.

The results highlight the significance of incorporating uncertainty through a two-stage stochastic programming, demonstrating its superiority over deterministic methods.

6.2 Future Work

6.2.1 Machine Learning for Repair Time Restoration

A more accurate estimation of repair times for damaged power lines can be achieved by incorporating machine learning techniques. This involves the utilization of historical data on repair times of damaged lines from past natural disasters. By employing machine learning tools to predict precise repair times, a more realistic mathematical model for power network restoration can be developed. This approach enables more comparable decisions to be made by utilities in the presence of the inherent uncertainty of the environment.

6.2.2 Exploring Alternative Formulations for the Stochastic Problem

The two-stage stochastic programming formulation proposed in this thesis relies on specifying, for each period, the nodes of the routing network visited by each crew. One could envision other ways of approaching the problem. For instance, one could create first-stage solutions that would specify a sequence of lines to be repaired over the complete planning horizon for each crew. This would lead to solutions better adapted to the uncertainty in repair times. It would require, however, a more complex solution procedure in the second stage.

Moving to a Multi-stage Stochastic Programming Model

The adoption of a multi-stage stochastic programming model is motivated by the necessity to react to new information on repair times as it becomes available. While considering the two-stage stochastic programming model, extending it to a multi-stage model enables the revision of decisions at each period based on previous realizations of uncertainty. While this is attractive from a mathematical modeling perspective, it must be recognized that solving a multi-stage mixed-integer stochastic problem would be quite difficult and challenging. In this case, the decisions can be revised by updating the remaining repair time for each damaged line. At the end of optimization process, decisions are more precise and applicable for real-world applications, but it requires more computational time.

6.2.3 Incorporating Resilience Metrics

Incorporating resilience metrics into the mathematical formulation as objective functions or constraints could enhance the overall resilience of the power network. This involves measures such as system reliability (Fang, 2019), guiding decision-making to prioritize restoration efforts in the face of future disruptions.

6.2.4 Hybrid Algorithm as Solution Approach

To effectively addressing large-scale restoration problems with damaged lines, it is necessary to explore proper solution algorithms such as exact or heuristic algorithms. Heuristics designed based on decomposition of the proposed model into a number of smaller sub-problems could be proper solution methods for the problem addressed in this thesis. Hence, the model proposed in this thesis can be decomposed into the SDVRP and the network design model. While heuristic methods can efficiently handle VRP models for large-scale problems, the network design model can be solved using the Benders decomposition algorithm within a reasonable time. Decomposing the problems into these sub-problems can significantly reduce the computational time of the large-scale problems. It should be mentioned that the proposed sub-problems could be solved iteratively, and the connection between the sub-problems is guaranteed by updating parameters or adding cuts.

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