ASSET ANALYTICS OF SMART GRID INFRASTRUCTURE FOR RESILIENCY ENHANCEMENT

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Doctor of Philosophy
in Industrial Engineering

by
Ali Arab
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FOR RESILIENCY ENHANCEMENT

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To those who strive for peace, justice, and sustainability

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Abstract

First, a post-hurricane restoration model for power grid which considers the economics of disaster is introduced. The physical and economic constraints of the system, including unit commitment and restoration constraints, are incorporated in the proposed model. The aim is to restore the hurricane-related damages to electric power system infrastructure in an economic and customer-centered manner, without violating the physics of the system, in order to mitigate the aftermath of natural disasters.

Second, a proactive resource allocation model for repair and restoration of potential damages to the power system infrastructure located on the path of an upcoming hurricane is proposed. The objective is to develop an efficient framework for system operators to restore potential damages to power system components in a cost-effective manner. The problem is modeled as a two-stage stochastic integer program with recourse. This model can improve proactive preparedness of the decision makers to cope with emergencies, especially those of nature origins, in order to minimize the restoration cost, and enhance the resilience of the power system.

Third, a model is proposed to incorporate the impact of potential damage due to hurricane in the maintenance scheduling of the power infrastructure components located in hurricane prone areas. The power infrastructure deterioration process, as well as two competing and independent failure modes, i.e., failure due to loss of reliability and failure due to hurricane damages are integrated into the model. Moreover, the interrelationship between the component, the grid, and the associated downtime cost dynamics are analyzed. The problem is modeled as a Markov decision process with perfect state information.

Fourth, the impact of El Niño/La Niña phenomenon which has shown to induce seasonal effects on hurricane arrivals in long-term climatological horizon is considered in asset management strategies of the electric power systems. An integrated infrastructure hardening and condition-based maintenance scheduling model for critical components of the

power systems is developed. The partially observable Markov decision processes are used to formulate the problem. The survival function against hurricane is derived as a dynamic stress-strength model, and is incorporated in the proposed framework.

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Chapter 1

Introduction

The extreme weather conditions and natural disasters can have a devastating impact on lifeline infrastructure systems. In this dissertation, a set of related problems are addressed, and asset analytics for smart grid infrastructure in order to enhance the resilience of the system is proposed. This chapter presents an overview, motivation and importance of research, problem statement, objective of the research, contributions, N-gram analysis of the title, and organization of this dissertation.

1.1 Overview

Natural disasters, particularly the storms are still the *Achilles heel* of the electricity infrastructure as one of the most critical lifeline systems and of utmost importance to our daily lives. After over half a century from publication of one of the earliest studies on efficient response to hurricanes, motivated by Hurricane Carla that slammed into the Gulf Coast and moved onward into the United States and Canada [1], the issue of efficient response to hurricanes and other natural disasters seems to remain in its immature stage. Storms can result in significant economic, social, and physical disruptions, and cause considerable inconvenience for residents living in disaster areas due to loss of electricity, water and communication [2]. Even the notion of *"after a storm comes a calm,"* is not the case for the electric power systems. The electric power grid transfers the electricity generated by large-scale power plants to a variety of industrial, commercial, and residential customers via transmission and distribution networks, and hence it can be disrupted over a vast geographical area when a hurricane strikes. For instance, following Hurricane Ike in 2008, more than 2.8 million customers in the Greater Houston area experienced a power outage, which lasted from a few days to several weeks. Figure 1.1 depicts the power outage map in

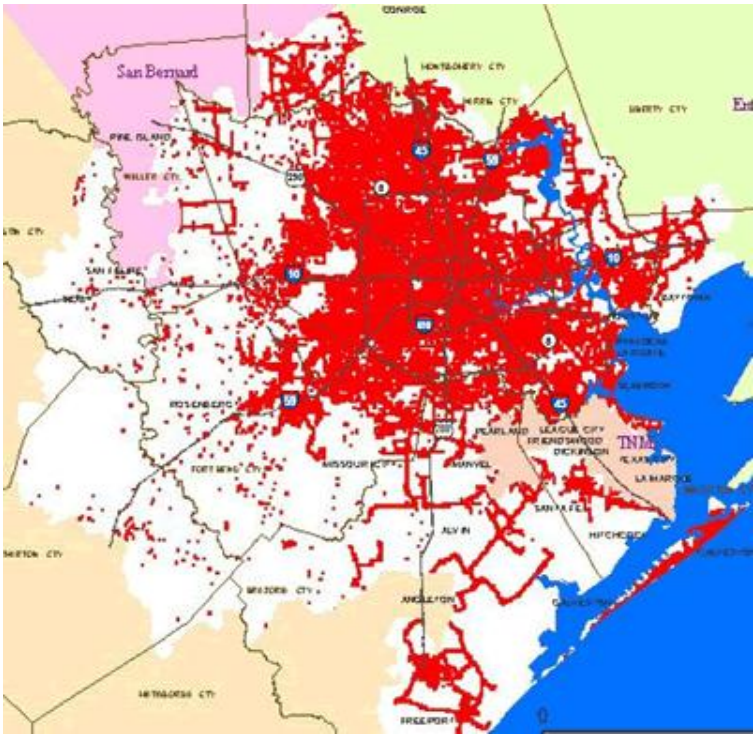

Figure 1.1 Power outage map in the Greater Houston area after Hurricane Ike

the Greater Houston area after the Hurricane Ike [3]. The total damage from Hurricane Ike in the U.S. coastal and inland areas was estimated at $24.9 billion [4]. Therefore, dealing with the aftermath of such disasters is of great concern of utilities and governments.

The level of complexity and interdependency of systems, either in urban or rural settings, increases with time. These complex and interdependent systems are extremely vulnerable to disasters. Development of mitigation strategies which outflanks the process of risk transference of mega-disasters is the key to successful management of disasters. In this context, *resistance* refers to the capacity to withstand disaster without change, while *resilience* refers to its capacity to *"bounce back"* to a pre-disaster condition [5]. Based on definition from [6], *"local resiliency with regard to disasters means that a locale is able to withstand an extreme natural event without suffering devastating losses, damage, diminished productivity, or quality of life and without a large amount of assistance from outside the community."* The term *storm* can alternatively be used for *hurricane*, *typhoon*, and *cy-*

clone. According to the National Oceanic and Atmospheric Adminstration [7], hurricanes, cyclones, and typhoons are the same phenomenon, but they can be classified depending upon the location the storms originate. The term *hurricane* is used in the Atlantic and Northeast Pacific; while it is called *typhoon* in the Northwest Pacific; and *cyclone* is used for the same phenomenon in the South Pacific and Indian Ocean.

1.2 Motivation and Importance of Research

The increasing trend of natural disasters which is believed by scientific communities to be due to the climate change has not received adequate attention by governments, policy makers, and international community. Only in the United States, storm-related damages to the power grid result in approximately $270 million in annual repair costs [8]. The disastrous effects of the storms and hurricanes on the reliability and economics of the electric power grid infrastructure as one of the critical lifeline systems from one side, and the lack of enough research work and practical decision making tools to keep pace with the increasing trend of such disasters from other side are the main motives of dedicating the proposed research to this area. Utilizing engineering solutions to improve the quality of life and well-being of the society is a strong driver to enhance research in such a critical area of public safety management. Of course, providing efficient strategies and decision making tools which are currently lacking in practice in order to be used by utilities is another motive.

National disaster policy plays an important role to protect the safety of citizens, security of businesses and national economy, and also the national security of each country. For instance, in the United States, the Disaster Mitigation Act (DMA) of 2000 provided the legal requirements of Federal Emergency Management Agency (FEMA) for disaster mitigation planning and implementation efforts by State, local and Indian Tribal governments. DMA 2000 amended the existing Disaster Relief and Emergency Assistance Act of 1988 by offsetting the disaster policies from postdisaster into a predisaster mitigation paradigm.

Following devastating aftermath of hurricane Sandy, the Sandy Recovery Improvement Act (SRIA) of 2013 and the accompanying Disaster Relief Appropriations Act of 2013 were signed into law [9]. The passed legislations during the recent years have constantly shifted the policies in favor of proactive and preventive actions toward disasters in order to improve the *resistance* and *resilience* of the critical infrastructure. The importance of this research is in its pragmatic approach to cope with the real world problem of disaster management in power grid infrastructure by using scientific and engineering solutions in order to provide practical solutions which are inline with utility companies' and public policy decision makers' paradigm of resiliency enhancement to tackle the problem.

1.3 Problem Statement

In this dissertation, we model a comprehensive set of asset management strategies to address the decision making needs of next generation smart grid infrastructure in short-, mid-, and long-term planning horizons. The aim is to push the frontiers of engineering solutions to cope with the devastating impacts of natural disasters (particularly storms and hurricanes) on electric power infrastructure.

A joint restoration and unit commitment model for recovery of damaged power systems due to hurricane is lacking in the literature. Intuitively, the physics of the system along with the economics of disaster, i.e., the resource cost, the opportunity cost of load interruption, and the unit commitment problem, need to be considered in restoration model. Otherwise, the obtained restoration schedule can be either sub-optimal or infeasible in practice. Different combinations of restoration schedule and operational configuration of the system need to be searched in solution space to find a cost-effective restoration plan.

Although variety of problems for power system planning in hurricane-prone areas have been addressed in the literature, to the best of our knowledge a few of them provide a comprehensive and generic approach for proactive resource allocation in preparedness

phase for hurricanes. An efficient decision making tool is required to be developed for proactive restoration planning of power systems to minimize the expected customer load interruption cost, restoration operation cost, and electricity generation cost.

The stochastic and independent effects of damage due to hurricane in maintenance scheduling of a power system infrastructure is lacking in the literature. The survival probability of component against hurricane during each period as well as the dynamic downtime cost of the component during each period need to be considered for a cost-effective preventive maintenance strategy of power system infrastructure.

A holistic view to the global and long-term climatological effects of phenomena such as El Niño/La Niña are lacking in the power systems literature, and perhaps in practice. A cost-effective asset management strategy for an integrated condition-based maintenance and hardening of the power system infrastructure when the component is subject to operational degradation as well as failure due to hurricane needs to be developed to fill this gap in the literature and practice.

1.4 Research Objectives

A model to minimize the customer load interruption cost, restoration operation cost, and electricity generation cost needs to be developed. The output of the proposed model is expected to provide the post-hurricane restoration schedule, generation unit commitment states, power dispatch, and transmission configuration of the system in the post-disaster phase. The proposed decision making model not only should determine the restoration schedule, but also provides a practical and cost-effective operational configuration for major components of the power system during the restoration time horizon.

A proactive resource allocation model to mobilize the maintenance crew for repair and restoration of potential damages to the power system infrastructure located on the path of an upcoming hurricane is another objective of this research. The aim is to develop an

efficient framework for system operators to minimize the expected subsequent costs of potential damages to power system components in a systematic manner.

The next objective is to incorporate the hurricane effects in mid-term preventive maintenance scheduling of the grid infrastructure in hurricane prone areas. The dynamics of downtime cost of component across the planning horizon, and its interplay with preventive maintenance schedule should be studied and incorporated in the model.

Finally, as last objective, an integrated infrastructure hardening and condition-based maintenance model for the critical components of the electric power system needs to be developed. The long-term climatological effects of El Niño/La Niña on hurricane arrivals will be considered to analyze the reliability function of the infrastructure. The aim is to construct a mathematical model which simultaneously considers the reliability of the infrastructure against hurricane arrivals under long-term climatological effects, its functional state due to degradation, and the cost dynamics of the proposed asset management strategy under various scenarios.

1.5 Contributions

Although variety of problems for electric power grid recovery in natural disasters have been addressed in the literature, few provide a comprehensive and generic approach for resource allocation which simultaneously considers the physics of the power grid along with the economic aspects of the disaster. This dissertation investigates the issue from a new and generic perspective by proposing following models:

- A generic post-hurricane restoration model which considers the physics and economics of the system;
- A stochastic pre-hurricane restoration model which mobilizes the restoration resources in a proactive manner.

Variety of maintenance planning models for power infrastructure have been proposed, but incorporating the effect of hurricanes in maintenance strategies is lacking in the literature. This dissertation investigates the subject by proposing the following models:

- A mid-term maintenance scheduling model based on perfect state information from infrastructure, considering the hurricane effects on reliability of the system, and the fluctuating outage cost during planning horizon;
- A long-term integrated infrastructure hardening and condition-based maintenance model based on imperfect state information from infrastructure, considering climatological effects of global weather conditions.

1.6 N-gram Analysis of the Title

The title of this dissertation represents the keywords that describe the proposed research work. The N-gram is a data mining tool which estimates the ratio of frequency of using a word or a sequence of words over the rest of the words in textbooks during a given period. This index can be used to analyze the emphasis on a particular subject over time. *Asset*, *Analytics*, *Infrastructure*, *Resiliency*, and *Enhancement* were the 1-grams, and *Smart Grid* was the 2-gram analyzed using *N-gram Google* from 1800 until present as shown in Figure 1.2. The term *Smart Grid* was shown to be frequently used in the textbooks from year 2000. The usage of this term has increased by 700% during a decade. It was also shown that the term *resiliency* is more common in American English compared to British English. The term *Resilience* which can alternatively be used is more common in British English compared to American English.

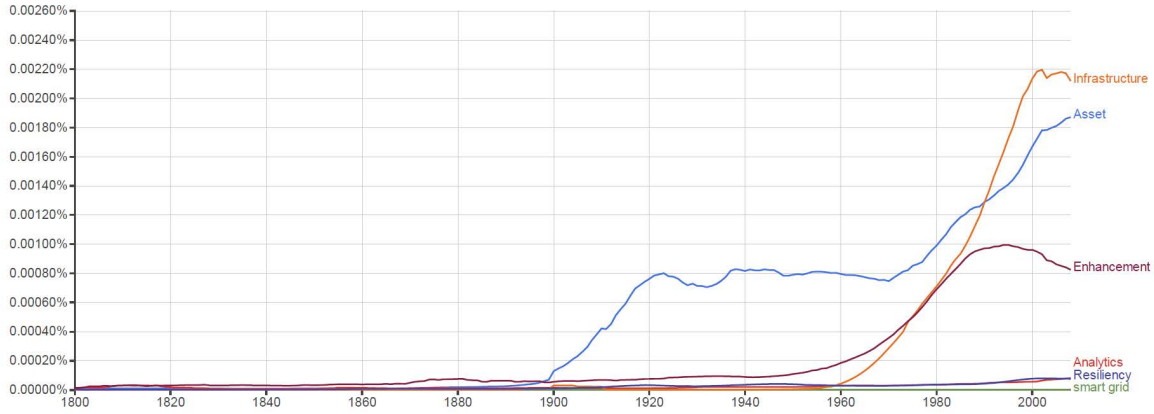

Figure 1.2 N-gram analysis of the dissertation title

1.7 Organization of the Dissertation

The proposed research work spans a wide spectrum of models for asset management of electric power infrastructure incorporating the effects of hurricane. The related research work in the literature including the problem domain and the solution domains are reviewed in the next chapter. In Chapter 3, an economic model for restoration of damaged power system in post-hurricane phase is introduced. In Chapter 4, a stochastic scheme will be applied to develop a decision making tool for proactive allocation of resources to the infrastructure susceptible to damage due to hurricane. In Chapter 5, a dynamic maintenance scheduling model considering the hurricane effects will be developed. In Chapter 6, an integrated infrastructure hardening and condition-based maintenance model considering El Niño/La Niña effects is presented. Finally, in Chapter 7, the concluding remarks are made, a summary of findings will be presented, and directions for future research are provided.

Chapter 2

Literature Review

In this chapter, first, the problem domain of the asset management of power systems and related research work is presented. A brief history along with some bibliographical references on methodological background and solution techniques used in this dissertation are then provided.

2.1 Problem Domain Review

There is a vast literature on asset management and analytics of power systems. The most relevant research work is divided to emergency planning, physical behavior, outage prediction, resource allocation, maintenance planning, reliability analysis, and restoration planning.

2.1.1 Emergency Planning

In this context, [10] reviewed and discussed the research problems and models for substations and/or distribution feeders planning under normal and emergency conditions. A case study on hurricane planning and rebuilding the electrical infrastructure along the Gulf Coast, for hurricane Katrina was presented in [11]. A risk assessment method for infrastructure technology planning to improve the power supply resiliency to natural disasters was proposed in [12]. Reduced cost as well as power supply availability were considered as two fundamental decision factors in their hurricane planning approach. In [13], a stochastic integer program was proposed to find the optimal schedule for inspection, damage evaluation, and repair in post-earthquake restoration of an electric power system. The aim was to minimize the mean time that each customer is without power. A comprehensive survey of models and algorithms for emergency response logistics in electric distribution systems,

including reliability planning with fault considerations and contingency planning models were presented in [14, 15].

2.1.2 Physical Behavior

In context of physical behaviour analysis of power system infrastructure in hurricane events, [16] analyzed the resilience of power systems based on the power distribution infrastructure and its interaction with the biophysical environment, and the way the restoration processes are prioritized. It was concluded that even though the infrastructure does not have any significant effect on outage duration, the interaction between infrastructure and the biophysical environment significantly affects outage duration. Reference [17] proposed a comprehensive strategy for mitigation of hazards with the aim of creating resilient cities which are able to withstand disasters. The hazard mitigation practices, the definition of the resilient city, and discussion on importance of resilience, and the ways that these principles can be applied to physical and social elements of cities were presented, as well. A data mining approach to evaluate the impact of soil and topographic variables on accuracy of the power outage prediction models in hurricane events was proposed in [18]. The results indicate that certain land cover variables could be reasonable proxies for the power system and could be incorporated in the model when detailed information about the power system is not available. In [19], a method for characterization of the behavior of networked infrastructure, including power delivery systems in natural hazard events such as hurricanes was presented. The model also included resilience and interdependency measures. The proposed model could be utilized to develop design strategies for improved infrastructure resiliency in natural disasters. Reference [20] proposed a probabilistic framework for vulnerability analysis of distribution poles subject to hurricane hazards considering the impact of a changing climate. The results indicate that changing climate and the age of the poles significantly increase the failure rate of distribution poles. The impact of tropical cyclones on United States power systems, under climate change scenarios was analyzed in [21].

2.1.3 Outage Prediction

Outage prediction is an important tool for ensuring an efficient response to hurricanes. In this context, [22] introduced a method for estimating the restoration time of electric power systems after hurricanes and ice storms. Using large dataset of six hurricanes and eight ice storms, accelerated failure time models were developed to forecast the duration of each probable outage. In [23], negative binomial regression models for prediction of outages due to hurricane were developed. The number of transformers in the area, maximum wind gust speed, the power company affected, and a hurricane effect turned out to be the most explanatory variables. Diagnostic statistics such as pseudo R-squared values were used for model selection purposes. Their adopted zip code-based model could be used for prediction of the likely outage rates prior to the hurricane events. In another work, [24] used regression analysis and data mining to develop models to estimate the number of utility poles that will be damaged based on damage data from past storms. Results indicate that hurricane-related damages to the poles can be predicted in an accurate manner, given the past damage data are available and adequate. However, the availability of past data could be a challenging issue which limits the efficiency of models in practice. Reference [25] compared the regression methods and data mining techniques for predicting power outage durations after hurricane strikes. The accuracy of Bayesian additive regression trees (BART) outperformed the other models in their study. In [26], an outage-forecasting model which is able to accurately estimate the hurricane-induced outages using fewer number of input variables was proposed. The power outage duration models and the key variables along with their degree of influence on predicting hurricane-induced outage durations were proposed in [27]. The development of a hurricane power outage prediction model for U.S. coastlines using publicly available data was proposed by [28]. The application of the model for Hurricane Sandy was demonstrated, and the impacts of some historic storms on U.S. energy infrastructure were analyzed.

2.1.4 Resource Allocation

In context of resource allocation for restoration of power systems, [29] presented three mathematical goal programming models for locating the repair units and restoring the transmission and distribution lines in an efficient manner. The first model finds the optimal repair-unit dispatch tactical plan with a forecast of adverse weather conditions. The second model derives the optimal repair-unit location for a short-term strategic plan under normal weather conditions. The third model finds the optimal number of repair units for a long-term strategic plan. In another work, a mixed-integer programming model and a general column-generation approach for inventory decision making of power system components throughout a populated area in order to maximize the amount of power served after disaster restoration was proposed [30]. In [31], the service restoration considering the restrictions on emergency-response logistics was studied with the objective of minimizing the customers interruption cost. The reconfiguration and the resources dispatching issues were considered in a systematic way in order to derive the optimal time sequence for every step of the restoration plan. In [32], a decision-making model to manage the required resources for economic power restoration operation was proposed. The optimal number of depots, the optimal location of depots, and the optimal number of repair crews were determined by their model in order to minimize the transportation cost associated with restoration operation. In [33], a decision support tool for improvement of information used by electric utilities for managing restoration of power distribution components damaged due to large-scale storms was described. The circuit layout, the placement of protective and switching devices, and the location of customers were taken into account to allocate the crew resources to manage the storm outage in a cost-effective manner.

2.1.5 Maintenance Planning

Preventive maintenance plays an important role to keep the grid infrastructure in good condition and improve the reliability of the system. In context of maintenance scheduling for power systems, [34] presented a decomposition approach for transmission line maintenance scheduling in a restructured power system. The proposed model comprises a master problem, and sub-problems, while the first one solves the maintenance problem, and the latter ones solve the transmission and voltage problem. The results indicate that constraints on transmission and voltage have impacts on line maintenance schedule which lead to increased maintenance cost. Reference [35] presented a game-theoretic framework for the maintenance strategy analysis to be used by generation companies (GENCOs). The problem is formulated as a multistage dynamic noncooperative game with complete information, while the players are defined as the profit maximizing GENCOs, and the payoff for each player would be the profit obtained from the energy auction market. The obtained results demonstrated that the maintenance schedule could be one of the most important strategic behaviors of power system players. Reference [36] proposed an approach for security-constrained coordination of generation and transmission maintenance outage scheduling, which can be used by Independent System Operators (ISOs) and vertically integrated utilities. The proposed approach enables the coordination of the optimal maintenance schedule of transmission lines and generation units, with security-constrained unit commitment of generation units. In addition, the optimal allocation of fuel and emission allowance are considered in their model. The results suggest that coordination of maintenance schedule with unit commitment of components would improve the system security, resulting in reduced probability of blackouts in power systems. Reference [37] presented an efficient mixed-integer linear programming model for long-term maintenance scheduling of overhead lines. The proposed model minimizes the total cost of the system, i.e., the incurred costs due to maintenance tasks which have not been performed, and the costs associated with performing maintenance tasks while maintaining the system reliability. In [38],

a stochastic model for the optimal long-term maintenance scheduling of transmission lines and generation units coordinated with short-term security-constrained unit commitment was developed. Random contingencies of transmission lines and generation units, load forecast errors, and fuel price fluctuations were simulated as scenario trees using the Monte Carlo simulation. Lagrangian relaxation was used to decompose the problem into maintenance and stochastic unit commitment subproblems. The results demonstrate the potential savings in operation costs realized by using the proposed model. Reference [39] addressed the tradeoff between transmission system adequacy, and the market operation alteration in their bilevel model for transmission line maintenance scheduling.

In a two-part paper, [40] and [41] developed a two-stage maintenance optimization model in short-term and mid-term for a transformer. The proposed model was formulated as a mixed-integer linear program. The actual and expected condition of the transformer as well as the constraints on $N-1$ contingency of the system are considered in the model. The results demonstrate the solution quality and computational efficiency of the proposed model. In another two-part paper [42,43], a comprehensive reliability-centred maintenance framework for power distribution systems was presented. The underlying concepts, algorithm, and mathematical models were described in Part I, while, the application of the proposed framework was presented in Part II.

As a maintenance strategy, frequent inspection of civil infrastructure including power systems is neither practical nor cost-effective. Reference [44] proposed a partially observable Markov decision process (POMDP) model for inspection, maintenance, and repair of civil infrastructures. The proposed model minimizes discounted life-cycle costs of the infrastructure. The decision variables determine *when* and *how* to inspect and repair the infrastructure in question, i.e. a bridge. The formulated problem is solved by modifying the original one-pass algorithm which provides exact solutions for problem. In another work [45], the same authors presented the theory and algorithm of partially observable Markov decision processes and its application in maintenance management of civil in-

frastructure. An algorithm was established and related topics in structural maintenance management were discussed.

Recent research demonstrates the advantage of applying the POMDPs in asset management of power systems. The most relevant research work are [46] and [47]. Reference [46] studied the optimal preventive maintenance strategies for wind turbines by considering their operations under stochastic weather conditions. The problem was modeled as POMDP in an infinite horizon. The weather constraints, the lengthy lead time to deliver the maintenance services, and generation loss due to downtime were incorporated in the model. Furthermore, several structural properties, i.e., a set of closed-form expressions for the optimal policy were derived in their study. In [47], a wind turbine system with multi-level deterioration and multiple failure modes was studied. The season-dependent condition-based maintenance was modeled using POMDP with heterogeneous parameters. A backward dynamic programming algorithm was used to solve the model numerically. The results indicate that the dynamic condition-based maintenance strategy achieves significant improvements in costs and reliability compared to the static model and the current industry practices.

Analysis of monotonicity and other structural properties of the optimal policy can be utilized for heuristic use in the POMDP models, and coping with the "curse of dimensionality" of this class of problems. As one of the most relevant research work in this area, [48] studied the structured maintenance policies on interior sample paths. The problem of adaptively scheduling maintenance actions for a multi-state deteriorating system with hidden failure was modeled as POMDP. The structural properties of the optimal policy to minimize the expected maintenance cost was extended in their study. In another study [49], maintenance policies for systems with condition monitoring and obvious failures were investigated. The problem of adaptively scheduling perfect and imperfect observations and preventive maintenance actions for a system with Markovian deterioration and obvious failures was modeled. The POMDP was used to formulate the problem in order to mini-

mize the expected long-run average cost per unit time. The structural properties to devise a closed-form heuristic for the case with perfect information were derived and adjusted to be used for the case with imperfect information.

2.1.6 Reliability Analysis

The weather effects on reliability of the power systems is an undeniable issue that have received the attention of utility companies and research communities in recent years. Effective reliability assessment of electric power systems has a great impact on quality of services, and significantly contributes in total operation costs of the utilities. In context of topological aspects of power grid and its effects on hardening the system against hurricane, [50] proposed two models to solve power systems blackout problems using mixed-integer programming. The optimization problems relevant to the prevention of large-scale blackouts in transmission grids subject to a set of stochastic damage scenarios were considered. The first model makes a decision on which transmission lines to be expanded in capacity in order to guarantee that after damage to transmission lines in different scenarios all power flows are within desired capacities. The second model considers the dynamics of cascades in order to find an optimal reinforcement plan that can passively survive a potential cascade. In [2], hurricane damage predictions and topological assessment to characterize the impact of hurricanes on reliability of power systems were combined. Component fragility models were applied to predict failure probability for individual transmission and distribution power network elements, simultaneously. The damage model was calibrated using power network component failure data for Hurricane Ike strike at the Greater Houston area in 2008. Their research demonstrates that topological features, such as network meshedness, centrality, and clustering, as well as the compact irregular ring mesh topology need to be considered in storm hardening activities.

In the context of cost-effectiveness of power infrastructure hardening, [51] proposed

a probabilistic model for analyzing electric power infrastructure risk mitigation investments. A parametric model was proposed to evaluate the tradeoffs between wetland restoration and infrastructure hardening for power grid. A hybrid economic input-output life-cycle analysis was used to analyze the model. The result indicates that wetland restoration and undergrounding of power infrastructure are not preferred over keeping them without wetland protection. In another study, [52] proposed a system dynamics-based analysis of cost-effectiveness of hurricane mitigation strategies for power distribution poles. They illustrated the systemic and dynamic natures of long-term maintenance and replacement strategies on both cost-effectiveness and performance of the systems under hurricane effects. Different aspects of adverse weather on reliability and asset management of power infrastructure were considered in [53–56].

Despite the given attention to weather effects, a holistic view to the global and long-term climatological effects of phenomena such as El Niño/La Niña are lacking in the power systems literature, and perhaps in practice. According to National Oceanic and Atmospheric Administration [7], *"El Niño is characterized by unusually warm ocean temperatures in the Equatorial Pacific, as opposed to La Niña, which characterized by unusually cold ocean temperatures in the Equatorial Pacific. El Niño is an oscillation of the ocean-atmosphere system in the tropical Pacific having important consequences for weather around the globe."* There are number of interesting research work in actuary science and risk theory research community who have considered this issue in hurricane arrival analysis. For instance, [57] considered the seasonal effects and El Niño/La Niña phenomenon to model the hurricane arrival times. The Non-homogeneous Poisson processes were used for modelling the fluctuations of hurricane arrivals due to seasonality in intensity function as a result of El Niño/La Niña phenomenon.

2.1.7 Restoration Planning

In context of restoration, [58] studied the budgeted and the minimum weighted latency variants of recovery problem of large-scale power outage due to a major disaster. The problems for general case, as well as, trees and bipartite networks as special case were studied. In [59], a mixed-integer program to model the recovery of the transmission networks damaged due to disasters was formulated. The model considered the repair crew constraints as well as the penalty cost of unserved loads to find the recovery schedule which minimizes the cost of power outage. Reference [60] used a mixed-integer programming framework for modeling the optimal supply restoration of the faulty power distribution systems. A two-step decomposition method was developed to derive the optimal configuration as well as the optimal switching sequence of the power distribution system. In another research work, [61] studied three approaches for joint damage assessment and restoration of the power systems after natural disaster. The proposed approaches include i) an online stochastic combinatorial optimization algorithm which dynamically makes the restoration decisions once each potentially damaged site is visited, ii) a two-stage method that first evaluates the extent of the damage and then restores the system, and iii) a hybrid algorithm of both approaches which simultaneously performs the damage evaluation and system restoration tasks. The results indicate that the first approach is able to provide solutions with higher quality for the joint damage assessment and recovery problems. In [62], a general multi-objective linear-integer spatial optimization model for arcs and nodes restoration of disrupted networked infrastructure after disaster was presented. The proposed model addressed the tradeoff between maximization of the system flow and minimization of system cost. Reference [63] proposed an integrated network design and scheduling problem for restoration of the interdependent civil infrastructure. The problem was formulated using integer programming, and analyzed on realistic dataset of power infrastructure of the Lower Manhattan in New York City and New Hanover County, North Carolina. The results indicate that the proposed model can be used for real-time as well

as long-term restoration planning. In another study, [64] considered *"the last-mile restoration"* of power systems, i.e., how to schedule and allocate the routes to fleets of repair crews to recover the damaged power system as quick as possible. The power restoration and vehicle routing were decoupled to improve the computational efficiency of the model. The proposed model outperformed the models which were practiced in the field in terms of solution quality and scalability. This work was extended in [65] by applying randomized adaptive vehicle decomposition technique in order to improve the scalability of the model for large-scale disaster restoration of the power networks with more than 24,000 components. In another work, [66] presented a scalable approach for restoration of the interdependent gas and power infrastructure. Mixed-integer programming was used to obtain minimum restoration set and optimal restoration ordering. Randomized adaptive decomposition was applied in order to improve the solution quality and computational efficiency.

2.2 Solution Domain's History

Various techniques have been used to model and solve the proposed problems in this dissertation. The major techniques include the mixed-integer programming, the linearization techniques, the two-stage stochastic programs with recourse, Benders decomposition, the Latin hypercube sampling (LHS), the scenario reduction techniques, the dynamic stress-strength models, the Markov decision processes (MDPs), and the partially observable Markov processes (POMDPs). In this section, the history of each technique is briefly reviewed, and relevant references for readers are provided.

2.2.1 Mixed-integer Programming

Linear programming (LP) and mixed-integer programming (MIP) are well-known subjects in Operations Research and engineering community. It is perceived by many that the modern LP and MIP started with the work of George Dantzig in 1947 at UC Berkley

and U.S. Air Force. However, the fact of the matter is that many other scientists have also made incredible contributions to the subject, and some science historians even claim that the origins of the subject predate Dantzig's contribution. However, the undeniable fact of the matter is the Dantzig's groundbreaking contribution to the LP and MIP [67]. From the mid 1960s to the late 1990s, fundamental theoretical work in integer programming and combinatorial optimization were proposed. Important parts of proposed theoretical and computational developments were inspired by pioneering work of Dantzig [68]. Detailed history of MIP can be found in [67].

The subject of MIP has continued its progress during the recent years by introduction of state-of-the-art solvers, heuristics, and methodologies. However, further developments of the field are yet to come. The recent progress of the subject can be found in [69].

2.2.2 Linearization Techniques

It is said that modelling of complex systems using MIPs is more of an art than an exact science. In many MIP models, formulating a problem as a linear program can be problematic. That is the case for MIP models that are formulated in this dissertation. There are plenty of tips and tweaks that can be applied for modeling integrality of quantities, *if-then* statements, enforcing at least k out of p restrictions, and nonlinear product terms. Under some circumstances, nonlinear terms can be converted into linear terms by the change of variables and the use of linear constraints. An interesting tutorial on this subject can be found in [70].

2.2.3 Two-stage Stochastic Program with Recourse

When parameters of a deterministic mathematical program are substituted with random variables, a stochastic program comes in use. A common approach to model uncertainty in mathematical programming problems is through a two-stage stochastic program

in which a long-term (first stage) anticipatory decision needs to be made before the full information about the outcome of the substituted random variables for parameters of the problem and also short-term (second stage) decisions known as *recourse* actions become available. The goal is to make a *here-and-now* (versus *wait-and-see*) decision to minimize the total expected costs of making both the first and second stage decisions [71]. One of the earliest studies in this area was proposed by Dantzig [72] when he was with Rand Corporation. Stochastic integer programs are the same type of problems, except some decision variables are required to be integer. As mentioned in [73], the first solution technique developed for stochastic integer program was a cutting plane algorithm by Wollmer [74]. References [73, 75, 76] are among major contributions of the stochastic integer programs with recourse.

2.2.4 Benders Decomposition

Benders decomposition proposed by Jacques Benders [77] is one of the well-known algorithms to solve large-scale mixed integer programs through exploiting the structure of the problem. This algorithm decomposes a MIP problem into a master problem and a subproblem to be solved in an iterative manner. The algorithm has been well received in electric power community to solve problems such as unit commitment [78], optimal power flow [79], network expansion planning [80], and transmission switching [81]. The generalized Benders decomposition was proposed in [82], the convergence properties of Benders decomposition was studied in [83], and extension of the generalized Benders decomposition to be used for a larger class of problem was presented in [84].

2.2.5 Latin Hypercube Sampling

A conventional approach for assessment of uncertainty in models is to apply Monte Carlo sampling. This technique yields reasonable estimates for the distribution of an under-

lying random variable if the sample size is relatively large. However, since a large sample size reduces the computational efficiency, other uncertainty estimation methods which can provide more accurate estimates such as the Latin hypercube sampling (LHS) method were developed [85]. The LHS was developed in [86] based on the idea of sample stratification to use a constrained Monte Carlo sampling scheme. An analysis of applying LHS to a large computer model was presented in [87]. A study on application of LHS method for sensitivity analysis was proposed in [88, 89]. A comparison of LHS method with other techniques can be found in [90].

2.2.6 Scenario Reduction Techniques

Many solution techniques for stochastic programs are based on discrete approximations of the uncertainty in a form of scenario tree with associated probabilities. However, considering all possible scenarios to form the deterministic equivalent of the original stochastic program results in inflation of the model which reduces the computational efficiency and in some cases makes the problem intractable to solve. This obstacle can be handled by approximating the equivalent deterministic program by a model that has a much smaller number of scenarios. This process is called scenario reduction [91]. The underlying scenario reduction algorithms can be found in [91–93].

2.2.7 Stress-strength Analysis

Stress-strength analysis is an important area of applied statistics which its simplest definition is to assess the reliability of a component or a system with the strength represented by a random variable Y, against the exposure to a stress represented by a random variable X, i.e., $P(X < Y)$. According to [94], for the first time the idea was proposed by Birnbaum in [95]. The idea was later developed in [96], and has reached to its methodological maturity in early 2000. According to the same authors, the term *stress-strength*

appeared in [97] for the first time. Detailed explanation on evolution of the subject can be found in [94].

2.2.8 Markov Decision Processes

According to the World Heritage Encyclopedia [98], Markov decision processes (MDPs), named after Andrey Markov, is a mathematical framework to formulate sequential decision making problems under circumstances that part of system is random and part of the system can be controlled by decision maker. MDPs have been known at least from 1950s by the work of Richard Bellman with Rand Corporation [99]. The next breakthrough was published by Ronald Howard in [100]. More details on related algorithms and recent advancements of the subject can be found in [101, 102].

2.2.9 Partially Observable Markov Decision Processes

A partially observable Markov decision processes (POMDPs) is a generalization of the MDPs which allows uncertainty in the state of the system. This generalization of MDPs to POMDPs results in computational burden to solve the model [103]. A survey on POMDPs can be found in [103]. A study on Operations Research approaches to find the optimal policies in POMDPs was proposed in [104]. A set of exact and approximate algorithms for stationary POMDP models can be found in [105]. Approaches to exploit the structure of large scale POMDP problems for efficient solutions can be found in [106].

Chapter 3

Grid Restoration Considering the Economics of Disaster

Even though variety of problems for power system restoration have been addressed in the literature, but to the best of our knowledge none of them provides a comprehensive approach for grid restoration which simultaneously considers the physics of the system along with the economics of disaster. In this chapter, an efficient post-hurricane restoration planning model is developed which in addition to the physics of the restoration, considers the unit commitment problem and generation costs, the value of lost load, and the economics of restoration resources. The flexibility of the proposed model enables its application in any other post-disaster restoration problems. In following sections, first the notation is introduced. Next, the proposed model is described, and the problem formulation is presented. Afterward, the numerical results are illustrated on an IEEE 118-bus test system. Finally, the concluding remarks are made.

3.1 Notation

The notation used for problem formulation is as follows.

Indices:

b	Index for buses
i	Index for generation units
l	Index for transmission lines
t	Index for time

Sets:

N_b	Set of components connected to bus b

Parameters:

C_b	Hourly crew cost per person for bus b repair
C_l	Hourly crew cost per person for line l repair
C^g_{it}	Generation cost of unit i at time t

C_{it}^{sd}	Shutdown cost of unit i at time t
C_{it}^{su}	Startup cost of unit i at time t
D_{bt}	Load demand at bus b at time t
DR_i	Ramp-down rate limit of unit i
DT_i	Minimum downtime of generation unit i
M	Large positive constant
P_i^{max}	Maximum power generation capacity of unit i
P_i^{min}	Minimum power generation capacity of unit i
R_t^{max}	Number of available repair crew at time t
R_b^{min}	Number of hourly required crew to repair bus b at time t
R_l^{min}	Number of hourly required crew to repair line l at time t
TTR_b	Mean time to repair for bus b
TTR_i	Mean time to repair for unit i
TTR_l	Mean time to repair for line l
UT_i	Minimum uptime of generation unit i
$VOLL_{bt}$	Value of lost load at bus b at time t
α_{ib}	Element of unit i and bus b in generation-bus incidence matrix
β_{lb}	Element of line l and bus b in line-bus incidence matrix

Variables:

I_{it}	Commitment state of generating unit i at time t; 1 if committed, otherwise 0
LI_{bt}	Load interruption at bus b at time t
P_{it}	Real power generation of unit i at time t
PL_{lt}	Power flow of line l at time t
SD_{it}	Shutdown state of unit i at time t; 1 if shutdowns at time t, otherwise 0
SU_{it}	Startup state of unit i at time t; 1 if starts at time t, otherwise 0
u_{bt}	Repair state variable of bus b at time t; 1 if on repair, otherwise 0
UR_i	Ramp-up rate limit of unit i
v_{lt}	Repair state variable of line l at time t; 1 if on repair, otherwise 0
w_{lt}	Outage state of line l at time t; 0 if damaged, otherwise 1
y_{it}	Outage state of unit i at time t; 0 if damaged, otherwise 1
z_{bt}	Outage state of bus b at time t; 0 if damaged, otherwise 1

3.2 Model Description

Due to the hurricane, the major infrastructure of power system including generating units, transmission lines, and buses along with their downstream distribution lines are subject to damage. After the hurricane, the utility companies conduct a damage assessment by an aerial survey of the power network in the affected areas as well as a ground check by inspectors [3]. Damage assessment determines whether a component has damaged at all,

and if damaged, estimates the required time to repair and restore the component in question. Each bus along with its downstream distribution lines are aggregated and considered as one component. Therefore, the time to repair for each bus and its downstream distribution lines are aggregated in our model as well. The information on the damage state and the time to repair for the generating units are posted by generation companies (GENCOs) to the Independent System Operator (ISO) to be shared by other participants of the market. We consider two states for each component: *damaged*, if the component in question is encountered major damage, thus it is offline and needs to be repaired to be restored; and *functional*, if it has not been damaged at all, or minor damage has occurred and the component in question is able to continue its functionality.

After determining the initial *damaged* or *functional* state of each component, the restoration resources, i.e. the crew should be allocated to repair the damaged equipments in an optimal fashion. The resource allocation, however, is subject to the criticality of the load to be restored as well as costs associated with seizing the resources in each particular time and location. In this regard, the objective of the problem is defined as to minimize the customer interruption cost plus the restoration resource cost and power generation cost. The interruption cost is the amount of the interrupted load times the value of lost load (VOLL). From economic point of view, VOLL is considered as an opportunity cost which is defined as the average amount of money that each type of customer (e.g., residential, commercial, or industrial) is willing to pay for each MWh in order to avoid load interruption [107]. VOLL can also represent the criticality of loads to be supplied, in which more critical loads, such as hospital and water treatment facilities, have a higher VOLL, and therefore, must be restored and supplied with a higher priority. This value can be adjusted based on load criticality in a way that key facilities such as hospitals, water treatment plants and public service facilities are given a higher priority to be restored.

The post-hurricane restoration model is considered as a deterministic problem. As shown in Figure 3.1, after assessment of the extent of damage to each component in the

system, the time to repair for component in question is estimated and the criticality of the loads are calculated. Afterward, the restoration resources are allocated and sequence of activities and system configuration including the repair schedule, the power generation by each generating unit, and power flow in each transmission line during each time period of the restoration planning horizon are determined.

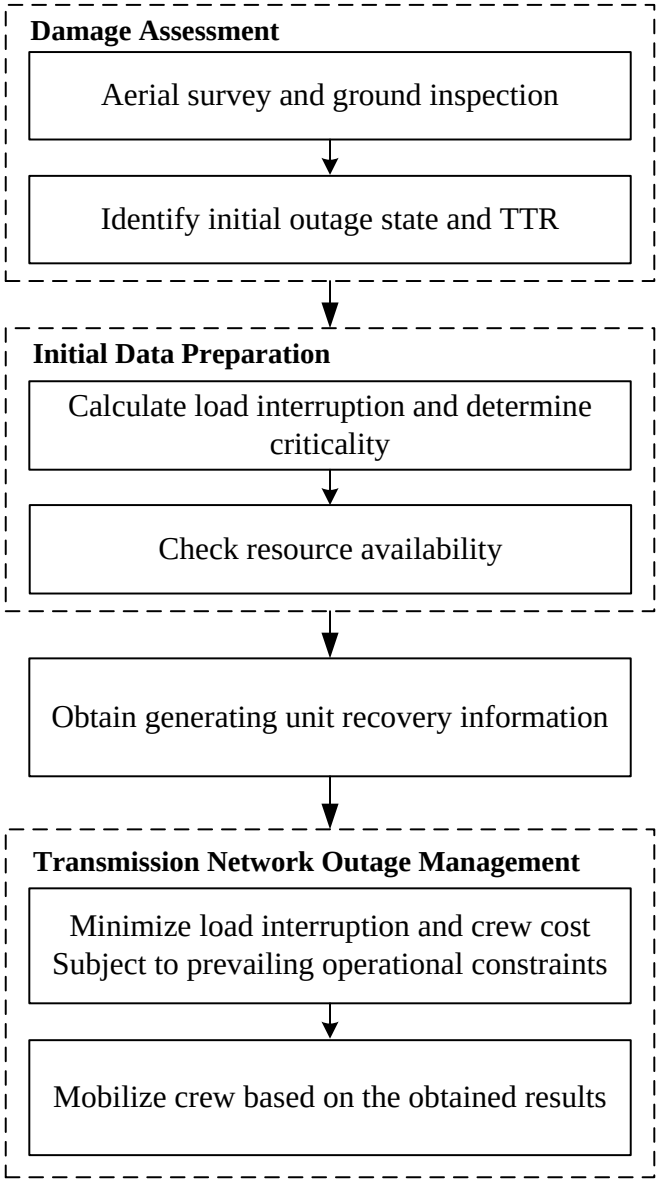

Figure 3.1 The schematic view of the proposed restoration framework

3.3 Problem Formulation

In this section, the objective function and constraints for the model are formulated as a mixed-integer linear program.

3.3.1 Objective Function

The objective is to minimize the customer load interruption cost, the restoration operation cost, and the energy generation cost as

$$\min_{u,v,LI,P,I,SU,SD} \sum_t \sum_b C_{bt} R_b^{min} u_{bt} + \sum_t \sum_l C_{lt} R_l^{min} v_{lt} + \sum_t \sum_b VOLL_{bt} LI_{bt} + \sum_t \sum_i \Big(C_{it}^g P_{it} I_{it} + SU_{it} + SD_{it} \Big), \quad (3.1)$$

where the first term represents the cost of resources allocated to the buses (and their downstream distribution lines), the second term is the cost of resources allocated to transmission lines, the third term represents the total cost of load interruption over the restoration planning horizon, and the fourth term indicates the generation cost of all the units feeding the system, including the fuel costs, the startup costs of generating units committed to generate, and the shutdown costs of generating units decommitted from generation. As shown in (3.1), the restoration cost of buses (and their aggregated downstream distribution lines) is the summation of the product of the number of allocated resource(s) to each bus, and the cost of each unit of resource seized by buses. In the same manner, the restoration cost of transmission line is the summation of the product of the number of allocated resource(s) to each transmission line, and the cost of each unit of resource allocated to transmission lines. The binary decision variable u_{bt} takes the value of 1, if the resource is allocated to bus b at time t; otherwise it takes the value of 0. In the same way, v_{lt} takes the value of 1, if line l seizes the required resource(s) at time t; otherwise its value would be 0. Obviously as shown in (3.1), the fourth term which calculates the generation cost is not a linear term.

By defining a new variable F_{it} where, $F_{it} = P_{it}I_{it}$ and plugging it into (3.1), and adding constraints (3.2)-(3.5), the objective function is linearized as follows:

$$F_{it} \leq P_{it}^{max} I_{it}, \ \ \forall i, \forall t, \tag{3.2}$$

$$F_{it} \geq 0, \ \ \forall i, \forall t, \tag{3.3}$$

$$F_{it} \leq P_{it}, \ \ \forall i, \forall t, \text{ and} \tag{3.4}$$

$$F_{it} \geq P_{it}^{max}(I_{it} - 1) + P_{it}, \ \ \forall i, \forall t. \tag{3.5}$$

3.3.2 Damage State Modeling

Binary state variables y_{it}, z_{bt}, and w_{lt} are defined to represent the *damaged* or *functional* state of generation unit i at time t, bus b along with its downstream distribution lines at time t, and transmission line l at time t, respectively. Binary state variable y_{it} is defined to be equal to 0, if due to hurricane, the generating unit i was damaged, and has not been restored up to time t; otherwise it is equal to 1. The time that it takes from beginning of planning horizon for a damaged generation unit to be repaired and brought back to the system is represented by TTR_i. If the component has not undergone any damage, the time to repair TTR_i is set to 0. In the case of vertically integrated utilities, it is assumed that generation units are able to restore their facilities by their own means, as soon as hurricane ends. In the case of restructured power market, it is considered that the Transmission & Distribution (T&D) company has no control over the restoration of generating units, but the generating units' repair schedules are posted to ISO and is accessible for T&D company to incorporate it in the restoration scheduling of its own infrastructure in a coordinated manner. Therefore, the damage state of generation units is modeled as

$$y_{it} = 0 \text{ if } t \leq TTR_i \text{ ; otherwise } y_{it} = 1, \ \ \forall i, \forall t. \tag{3.6}$$

However, since *if-then* constraint is not allowed in linear programming, constraint (3.6) is decomposed and rewritten as

$$t - My_{it} \leq TTR_i, \ \ \forall i, \forall t \text{ and} \tag{3.7}$$

$$My_{it} \leq TTR_i, \ \ \forall i, \forall t = 0, 1, ..., TTR_i. \tag{3.8}$$

The damage state of transmission lines and buses are modeled as

$$0 \leq w_{l(t+1)} - \Big(\sum_{k=1}^{t} v_{lk} - TTR_l + 0.5\Big)/M \leq 1 \ \ \forall l, \forall t \text{ and} \tag{3.9}$$

$$0 \leq z_{b(t+1)} - \Big(\sum_{k=1}^{t} u_{bk} - TTR_b + 0.5\Big)/M \leq 1 \ \ \forall b, \forall t, \tag{3.10}$$

where constraints (3.9) and (3.10) present the relationships among binary state variables w_{lt} and z_{bt} with repair decision variables v_{lt} and u_{bt}, respectively. If the transmission line l at time t is on *damaged* state, the binary variable w_{lt} which represents the line damage state would be equal to 0. Once it is repaired, the value of w_{lt} becomes 1 and remains the same up to the end of the restoration planning horizon. v_{lt} is the decision variable for repair of line l, in a sense that, when the line l is under repair at time t, the v_{lt} takes the value of 1, otherwise it is 0. In the same way, z_{bt} is the binary state variable for bus b, which is equal to 0 when the bus b at time t is in *damaged* state; Once it is repaired, the value of z_{bt} becomes 1 and remains the same up to the end of the restoration planning horizon. u_{bt} is the decision variable for repair of bus b, which takes the value of 1, when the bus in question is under repair, otherwise it is equal to 0.

Each damaged line or bus should receive the required time and resources to be restored. In this model, it is assumed that once the restoration operation on a particular component is started, it should be continued at least for duration of time to repair (TTR) of

the component. Therefore,

$$\sum_{k=t}^{t+TTR_l-1} v_{lk} \geq TTR_l(v_{lt} - v_{l(t-1)}), \ \ \forall l, \forall t \text{ and} \tag{3.11}$$

$$\sum_{k=t}^{t+TTR_b-1} u_{bk} \geq TTR_b(u_{bt} - u_{b(t-1)}), \ \ \forall b, \forall t. \tag{3.12}$$

Constraints (3.11) and (3.12) guarantee that sufficient time and resources are allocated to each damaged component to be repaired. Moreover, these constraints eliminate partial repair operation on each damaged component.

3.3.3 Resource Constraint

The objective function of the restoration model is also constrained by resource limitation. This limitation is modeled as

$$\sum_{l} R_{lt} v_{lt} + \sum_{b} R_{bt} u_{bt} \leq R_t^{max}, \ \ \forall t. \tag{3.13}$$

Constraint (3.13) represents the maximum amount of resources that can be allocated to the whole system in each time period.

3.3.4 Load Balance Constraint

The physics of the power system also imposes several constraints to the objective function of the post-hurricane model. The load balance is given by

$$\sum_{i \in N_b} P_{it} + \sum_{l \in N_b} PL_{lt} + LI_{bt} = D_{bt}, \ \ \forall b, \forall t. \tag{3.14}$$

The bus load balance equation (3.14) as a constraint ensures that the injected power to a bus from connected transmission lines and generating units is supplying the whole bus

load; however, if the injected power is not sufficient, the load supply would be interrupted by the load interruption variable (LI_{bt}). The load interruption variable is a nonnegative variable. Therefore, the system has to generate and supply not more than demand at each bus b during time period t.

3.3.5 Real Power Generation Constraints

The real power generation in each unit i is bounded with its damage state, commitment state along with its minimum and maximum generation capacity as

$$P_i^{min} y_{it} I_{it} \leq P_{it} \leq P_i^{max} y_{it} I_{it}, \ \ \forall i, \forall t, \tag{3.15}$$

where as shown, the real power generation turns out to be a nonlinear constraint which needs to be linearized. To do so, by defining a new variable $n_{it} = y_{it}.I_{it}$, this constraint is decomposed and linearized as follows:

$$P_i^{min} n_{it} \leq P_{it} \leq P_i^{max} n_{it}, \ \ \forall i, \forall t, \tag{3.16}$$

$$n_{it} - y_{it} \leq 0, \ \ \forall i, \forall t, \tag{3.17}$$

$$n_{it} - I_{it} \leq 0, \ \ \forall i, \forall t, \tag{3.18}$$

$$-n_{it} + y_{it} + I_{it} \leq 1, \ \ \forall i, \forall t, \text{ and} \tag{3.19}$$

$$n_{it} \geq 0, \ \ \forall i, \forall t. \tag{3.20}$$

It is important to notice that if a generating unit is not in *functional* state, it cannot be committed for generation. Therefore, the following coupling constraint of unit commitment and damage state holds all the time, i.e.,

$$I_{it} \leq y_{it}, \ \ \forall i, \forall t. \tag{3.21}$$

The damage state of bus(es) connected to each generating unit also can impose another constraint on real power generation. This constraint is modeled as

$$-M \sum_{b} \alpha_{ib} z_{bt} \leq P_{it} \leq M \sum_{b} \alpha_{ib} z_{bt}, \ \ \forall i, \forall t, \tag{3.22}$$

where α_{ib} is the element of unit i and bus b in generation-bus incidence matrix. As shown in (3.22), if a connected bus to a generation unit is damaged, the associated generating unit becomes offline.

3.3.6 Power Flow Constraints

The damage state of each transmission line l at time t poses a constraint on power flow within line l at time t in a sense that if the line is in *functional* state, the power flow at line l at time t can be in either direction up to the maximum power flow capacity of the line. The effects of outage state of associated components to a transmission line are modeled as

$$-PL_l^{max} w_{lt} \leq PL_{lt} \leq PL_l^{max} w_{lt}, \ \ \forall l, \forall t, \tag{3.23}$$

$$-M \sum_{b} \beta_{lb}^{from} z_{bt} \leq PL_{lt} \leq M \sum_{b} \beta_{lb}^{from} z_{bt}, \ \ \forall l, \forall t, \text{ and} \tag{3.24}$$

$$-M \sum_{b} |\beta_{lb}^{to}| z_{bt} \leq PL_{lt} \leq M \sum_{b} |\beta_{lb}^{to}| z_{bt}, \ \ \forall l, \forall t, \tag{3.25}$$

where β_{lb}^{from} includes all the positive elements of the bus-line incidence matrix and β_{lb}^{to} includes all the negative elements of the bus-line incidence matrix. If a transmission line is damaged, the power flow within that line will be equal to 0 as modeled in (3.23). In addition, if any of the buses connected to each transmission line is damaged, the power flow in that particular line cannot exist in any direction and is set to be equal to 0, as shown in (3.24) and (3.25).

An important constraint that must hold all the times to avoid violation of the physics of the system is the transmission line power flow constraint which is defined based on bus voltage angle as

$$-M(1-w_{lt}) - M(1-\sum_{b}|\beta_{lb}|z_{bt}) \leq PL_{lt} - \frac{\sum_b \beta_{lb}\delta_b}{x_l}$$
$$\leq M(1-w_{lt}) - M(1-\sum_{b}|\beta_{lb}|z_{bt}), \ \ \forall l, \forall b, \forall t. \quad (3.26)$$

3.3.7 Startup and Shutdown Costs Constraints

The startup and shutdown costs have been defined in the objective function as positive variables to avoid using additional extra binary state variables to improve the computational efficiency of the program. Therefore, from [108] and [109], the startup and shutdown cost variables are bounded to the following constraints:

$$SU_{it} \geq C^{su}_{i\tau}\left(I_{it} - \sum_{k=1}^{\tau} I_{i(t-k)}\right), \ \ \forall i, \forall t, \forall \tau = 1, ..., ND_i, \quad (3.27)$$

$$SU_{it} \geq 0, \ \ \forall i, \forall t, \quad (3.28)$$

$$SD_{it} \geq C^{sd}_{it}\Big(I_{i(t-1)} - I_{it}\Big), \ \ \forall i, \forall t, \text{ and} \quad (3.29)$$

$$SD_{it} \geq 0, \ \ \forall i, \forall t, \quad (3.30)$$

where ND_i is the number of time intervals of the startup cost function for generating unit i.

3.3.8 Ramp-up and Ramp-down Constraints

The mechanical and thermal inertia that should be overtaken in order to decrease (ramp-down) or increase (ramp-up) the real power generation of a thermal generating unit

from one time period to the next can also pose constraints other than the minimum and maximum real power generation at each generating unit during each unit time [110]. A computationally efficient mixed-integer linear formulation for the ramp-up rate, shutdown ramp, ramp-down rate, minimum uptime, and minimum downtime were proposed in [109] as shown in (3.31)-(3.39). The ramp-up rate, the shutdown ramp rate, and ramp-down rate constraints are as follows:

$$P_{it} - P_{i(t-1)} \leq UR_i I_{i(t-1)} + UR_i^{su}\Big(I_{it} - I_{i(t-1)}\Big) + P_i^{max}\Big(1 - I_{it}\Big), \ \ \forall i, \forall t, \quad (3.31)$$

$$P_{it} \leq P_i^{max} I_{i(t+1)} + DR_i^{sd}\Big(I_{it} - I_{i(t-1)}\Big), \ \ \forall i, \forall t, \text{ and} \quad (3.32)$$

$$P_{i(t-1)} - P_{it} \leq DR_i I_{it} + DR_i^{sd}\Big(I_{i(t-1)} - I_{it}\Big) + P_i^{max}\Big(1 - I_{i(t-1)}\Big), \ \ \forall i, \forall t. \quad (3.33)$$

3.3.9 Minimum Uptime and Downtime Constraints

In thermal generating units, the temperature change can only occur gradually. Thus, when a generating unit is running, it should not be decommitted immediately (minimum up time); and once the unit is offline, it requires some time before it can be committed (minimum down time) [111]. From [109], the minimum uptime constraints are shown in (3.34)-(3.36) as follows:

$$\sum_{t=1}^{G_i} \Big(1 - I_{it}\Big) = 0, \ \ \forall i, \quad (3.34)$$

$$\sum_{k=t}^{t+UT_i-1} I_{ik} \geq UT_i\Big(I_{it} - I_{i(t-1)}\Big), \ \ \forall i, \forall t = G_i + 1, ..., NT - UT_i + 1, \text{ and} \quad (3.35)$$

$$\sum_{k=t}^{NT} \Big(I_{ik} - (I_{it} - I_{i(t-1)})\Big) \geq 0, \ \ \forall i, \forall t = NT - UT_i + 2, ..., NT, \quad (3.36)$$

where $G_i = Min\{NT, (UT_i - U_i^0)I_i^0\}$ is the number of primary time periods that generation unit i is online, U_i^0 is the number of time periods up to the beginning of the planning horizon before generating unit i becomes online, and I_i^0 is the primary commitment state of generating unit i. From [109], the minimum downtime constraints are shown in (3.37)-(3.39) as follows:

$$\sum_{t=1}^{L_i} I_{it} = 0, \ \ \forall i, \tag{3.37}$$

$$\sum_{k=t}^{t+DT_i-1} \Big(1 - I_{ik}\Big) \geq DT_i\Big(I_{i(t-1)} - I_{it}\Big),$$

$$\forall i, \forall t = L_i + 1, ..., NT - DT_i + 1, \text{ and} \tag{3.38}$$

$$\sum_{k=t}^{NT} \Big(1 - I_{ik} - (I_{i(t-1)} - I_{it})\Big) \geq 0, \ \ \forall i, \forall t = NT - DT_i + 2, ..., NT, \tag{3.39}$$

where $L_i = Min\{NT, (DT_i - S_i^0)(1 - I_i^0)\}$ is the number of primary time periods that generating unit i is offline, and S_i^0 is number of periods up to the beginning of planning horizon that generating unit i has been offline.

There is a possibility for circumstances that the interrupted load is fully recovered, while some generating units, transmission lines and buses still have not been repaired. The reason is that other redundant generation units, transmission lines, and buses may compensate the outage of some of the components in question. Therefore, the restoration time horizon might be terminated by partial restoration of the system, while later on due to potential load increments, the system might not be able to supply all electricity demands. To ensure that all damaged components are repaired by the end of planning horizon, the following constraint should hold

$$\sum_i y_{i(NT)} + \sum_b z_{b(NT)} + \sum_l w_{l(NT)} = NG + NB + NL. \tag{3.40}$$

3.3.10 Decomposition Strategy

Benders decomposition for mixed-integer programming is an efficient strategy, when the original problem is large-scale and difficult to solve, while the Benders subproblem and the relaxed master problem are much more tractable to solve. In order to employ the decomposition strategy for the proposed problem, we consider the continues variable vector as $\mathbf{X} = [LI_{bt}^T, P_{it}^T, PL_{lt}^T, SU_{it}^T, SD_{it}^T]^T$, the binary variable vector as $\mathbf{Y} = [u_{bt}^T, v_{lt}^T, y_{it}^T, z_{bt}^T, w_{lt}^T, I_{it}^T]^T$, the cost coefficient matrix of the integer variables in the objective function as $\mathbf{C^T}$ composed of $C_{bt}R_b$ and $C_{lt}R_l$, and the cost coefficient matrix of the continues variables in the objective function as $\mathbf{D^T}$ composed of $VOLL_{bt}$ and $\mathbf{1}$. We also consider that $\mathbf{A}$ and $\mathbf{B}$ represent the coefficient matrix of $\mathbf{X}$ and $\mathbf{Y}$ in the constraints, respectively. Finally, $\mathbf{H}$ is considered to represent the right hand side matrix of the constraints. Now we can rewrite the proposed MIP model in the following abstract form

$$\min_{X,Y} \mathbf{C^T X} + \mathbf{D^T Y}, \tag{3.41}$$

$$\text{s.t.} \quad \mathbf{AX} + \mathbf{BY} \geq \mathbf{H}, \ \ \forall \mathbf{Y} \in \{0,1\}, \forall \mathbf{X} \geq 0. \tag{3.42}$$

For instance, in constraint (3.31), the coefficients of variables P_{it} and $P_{i(t-1)}$ of vector $\mathbf{X} = [LI_{bt}^T, P_{it}^T, PL_{lt}^T, SU_{it}^T, SD_{it}^T]^T$, are -1 and 1, respectively; and the coefficients of the rest of the continues variables are equal to 0. The coefficients of the integer variables I_{it} and $I_{i(t-1)}$ of vector $\mathbf{Y} = [u_{bt}^T, v_{lt}^T, y_{it}^T, z_{bt}^T, w_{lt}^T, I_{it}^T]^T$, are $UR_i - UR_i^{su}$ and $UR_i^{su} - P_i^{max}$, respectively; while the coefficients of the rest of the integer variables are equal to 0. Also, the corresponding element of aforementioned constraint in matrix $\mathbf{H}$ takes the value of $-P_i^{max}$. The proposed MIP problem is decomposed into a master problem and a subproblem. The master problem is set as an integer program, while the subproblem is set as a dual linear program (without any integer variable). Considering $\mathbf{U}$ as the dual variable vector for the subproblem, the Benders decomposition algorithm for the proposed model is shown in Algorithm 3.1 [112].

The master problem has lower number of constraints than original problem. In each iteration, after solving the master problem, the subproblem evaluates the obtained solution of the master problem to check the feasibility of the subproblem. As shown, in each iteration of the algorithm, if the dual LP subproblem turns out to be unbounded, the feasibility cuts are generated and will be added to the IP master problem; otherwise the optimality cuts are generated to be added to the master problem (the constraints with θ represent the optimality cuts). This iterative process will be continued until an acceptable relative gap (ε) between upper bound and lower bound of the original problem is obtained. The value of ε is considered to be 0.05 for this study.

Algorithm 3.1 Benders decomposition for mixed-integer program

---

$\{$initialization$\}$
Lower bound (LB):$= -\infty$, Upper bound (UB):$= +\infty$
while UB $-$ LB $> \varepsilon$ **do**
$\{$solve dual LP subproblem$\}$
$\max_U \{\sum_t \sum_b C_{bt} R_b^{min} \bar{u}_{bt} + \sum_t \sum_l C_{lt} R_l^{min} \bar{v}_{lt} + (H - B\bar{Y})^T U \mid A^T U \leq C, U \geq 0\}$
  if Unbounded **then**
  Get unbounded ray $\bar{U}$
  Add cut $(H - BY)^T \bar{U} \leq 0$ to IP master problem
  else
  Get extreme point $\bar{U}$
  Add cut $\theta \geq \sum_t \sum_b C_{bt} R_b^{min} u_{bt} + \sum_t \sum_l C_{lt} R_l^{min} v_{lt} +$
  $(H - BY)^T \bar{U}$ to master problem
  UB $:= \min \{$UB$, \sum_t \sum_b C_{bt} R_b^{min} \bar{u}_{bt} + \sum_t \sum_l C_{lt} R_l^{min} \bar{v}_{lt} + (H - B\bar{Y})^T \bar{U}\}$
  end if
$\{$solve IP master problem$\}$
LB $:= \min_Y \{\theta \mid cuts\}$
end while

3.4 Numerical Results and Analysis

The IEEE 118-bus system is used to analyze the proposed post-hurricane restoration model. The system has 118 buses, 54 generation units, 186 branches, and 91 load sides.

Further details on IEEE 118-bus system can be found in Appendix A. The system setup is shown in Tables 3.1–3.3. Among damaged buses, B1, B2, B3, B4, and B11 are load buses, feeding their downstream distribution lines, while B5 is not a load bus. From [107], the value of lost load is considered to be \$3.706/kWh for industrial loads, \$6.979/kWh for commercial loads, and \$0.110/kWh for residential areas. The value of lost load for critical loads, e.g., medical centers and water treatment plants are misstated in micro and macro economic approach. However, due to the crucial importance of these critical loads, the value of lost load in an *ad hoc* manner is considered to be \$10/kWh to impose higher priority to these areas. In this analysis, as shown in Table 3.1, bus B1 is considered as commercial load, bus B11 as industrial load, bus B4 as critical load, and the rest of the load buses in the system are considered as residential loads. The time to repair in Tables 3.1 and 3.2 indicate the estimated duration of the repair for buses and transmission lines, respectively; while the time to repair in Table 3.3 shows the time it takes from the beginning of the restoration planning horizon to repair and restore each damaged generating unit.

Table 3.1 Damaged buses and time to repairs

Bus Number	Time to Repair (Hours)	Load Type
$B1$	24	Commercial
$B2$	11	Residential
$B3$	18	Residential
$B4$	15	Critical
$B5$	5	N/A
$B8$	4	Residential
$B11$	22	Industrial

Table 3.2 Damaged transmission lines and time to repairs

Line Number	Time to Repair (Hours)
$L1$	20
$L2$	18
$L10$	16
$L14$	10
$L16$	22

Table 3.3 Damaged generation units and time to repairs

Unit Number	Time to Repair (Hours)
$G1$	17
$G2$	12
$G3$	24
$G5$	8

The repair crew is considered to be the only limited resource that is allocated to repair the damaged components. It is assumed that each damaged bus requires 12 repair crews/hour, while for each damaged transmission line 18 repair crews/hour are required. Although depending on skill levels different crew costs can be considered, we assume that all repair crews have equal skill levels; hence, they are equally paid (we could think of it as a bundle of resources which their average wage is used as an input into our model). The hourly wages for repair crews varies based on the working shift and types of repair. For repairing the buses and downstream distribution lines, the average wages are assumed to be \$60/hour at shift 1 (8:00 A.M.–4:00 P.M.), \$70/hour at shift 2 (4:00 P.M.–12:00 A.M.), and \$80/hour at shift 3 (12:00 A.M.–8:00 A.M.); for repairing the transmission lines, the average wages are assumed to be \$65/h at shift 1, \$75/hour at shift 2, and \$85/hour at shift 3. Without loss of generality, it is assumed that all generation units are incurred identical generation, startup, and shutdown costs. From [113], the generation cost is considered to be \$0.3509/kWh. The shutdown cost is assumed to be \$250 per shutdown for each generation

unit. The startup cost is assumed to be $150 within the first hour after last shutdown. For each additional hour (up to eight hours), an incremental cost of $25 would be added to the startup cost. Restoration planning horizon starts at 8:00 AM.

The following scenarios are considered to analyze the model and impacts of economic considerations in post-hurricane restoration:

Scenario I: The problem is solved without considering the economics of disaster, i.e., only load interruption is minimized.

Scenario II: The problem is solved with consideration of the VOLL and repair cost.

Scenario III: The problem is solved with full economic consideration, i.e., VOLL, repair cost, and generation cost.

Scenario IV: The impact of maximum number of available resources (repair crews) on restoration is analyzed for five different cases. The number of crews ranges from 50 in Case 1, with an increment of 25 in other cases, up to 150 for Case 5.

The proposed model implemented on the IEEE 118-bus system setup is composed of 162,481 decision variables, which 22,308 of them are integer variables. The model also is constrained with 352,514 equations. The model is decomposed into an IP master problem and a dual linear subproblem, and is solved using Benders decomposition method. The optimal restoration schedule for buses and transmission lines for Scenarios I to III are shown in Tables 3.4 and 3.5, respectively. The simulated costs of implementing Scenarios I and II, as well as the optimal restoration cost of system with full consideration of economics of disaster (Scenario III) are shown in Table 3.6. As shown, implementation of Scenario I which merely minimizes the interruption regardless of economic issues in grid restoration process results in 12.3% increase in opportunity cost of lost load as an index to measure the social welfare. The overall restoration cost in this scenario increases by about 5% compared to Scenario III. In Scenario II, even though the objective function minimizes both lost load cost and repair crew cost, the induced impairment in the objective function results in even higher opportunity cost of lost load and total restoration cost. Scenario III as a

comprehensive economic restoration model, which was used as a benchmark for Scenarios I and II, provides the most economic restoration scheme and establishes an equilibrium between generation cost, lost load cost, and repair cost.

Table 3.4 Optimal repair schedule for buses in Scenarios I-III

Bus	Scen. I	Scen. II	Scen. III
B1	1-24	1-24	1-24
B2	1-11	1-11	1-11
B3	1-18	1-18	1-18
B4	1-15	1-15	1-15
B5	1-5	3-7	1-5
B8	1-4	1-4	6-9
B11	1-22	1-22	1-22

Table 3.5 Optimal repair schedule for transmission lines in Scenarios I-III

Line	Scen. I	Scen. II	Scen. III
L1	5-24	84-103	92-111
L2	7-24	1-18	1-18
L10	6-21	19-34	95-100
L14	5-14	74-83	71-80
L16	1-22	28-49	48-69

Table 3.6 Performance indices for Scenarios I-III (costs $\times 10^3$)

Index	Scen. I	Scen. II	Scen. III
Total Cost	\$30,188	\$30,261	\$28,764
Lost Load Cost	\$17,893	\$18,000	\$15,929
Generation Cost	\$12,099	\$12,067	\$12,640
Resource Cost	\$196.92	\$194.76	\$193.62
Lost Load (MWh)	2174.62	2,275	3,902

The optimal schedules for Cases 1 to 5 of Scenario IV's buses and lines are shown in Tables 3.7 and 3.8, respectively. As it was expected, the load on B4 which is classified as critical load is restored as early as possible in all scenarios. The repair operations on

commercial and industrial loads are initiated from early stage of the planning horizon to restore these costly interruptions. On the other hand, the restoration of the transmission lines in vast majority of the cases are postponed to the middle or late stage of the planning horizon.

Table 3.7 Optimal repair schedule for buses in Scenario IV

Bus	R_t=50	R_t=75	R_t=100	R_t=125	R_t=150
B1	27-50	1-24	1-24	1-24	1-24
B2	16-26	16-26	17-27	1-11	1-11
B3	28-45	25-42	1-18	1-18	1-18
B4	1-15	1-15	1-15	1-15	1-15
B5	1-5	1-5	1-5	1-5	4-8
B8	49-52	27-30	27-30	6-9	6-9
B11	6-27	1-22	1-22	1-22	1-22

Table 3.8 Optimal repair schedule for transmission lines in Scenario IV

Line	R_t=50	R_t=75	R_t=100	R_t=125	R_t=150
L1	17-36	7-26	95-114	92-111	93-112
L2	59-76	47-64	6-23	1-18	1-18
L10	53-68	96-111	89-104	95-100	92-107
L14	1-10	25-34	71-80	71-80	71-80
L16	45-66	23-44	46-67	48-69	35-56

Table 3.9 summarizes the total restoration cost, opportunity cost of the lost load, generation cost, resource cost, the amount of lost load, and the last time span that system still experiences partial load interruption in Scenario IV. Due to the physics and economics of the problem, the restoration operations will continue for a longer period than required time to eliminate partial load interruption in the system for each case, as shown in Figure 3.2. The higher level of restoration resources results in shorter interruption time in the system. Thus, the load interruption and operations duration diagram diverges by increasing the resource level, as illustrated in Figure 3.2. On the other hand, the higher resource

level will extend the restoration planning horizon to complete the remaining operations in a cost-effective manner, i.e. by allocating less expensive resources, and configuring a more economic generation unit commitment.

Table 3.9 Performance indices for different cases in Scenario IV (costs $\times 10^3$)

Index	R_t=50	R_t=75	R_t=100	R_t=125	R_t=150
Total Cost	\$37,713	\$29,377	\$28,798	\$28,764	\$28,762
Lost Load Cost	\$24,952	\$16,562	\$15,966	\$15,929	\$15,926
Generation Cost	\$12,547	\$12,598	\$12,629	\$12,640	\$12,641
Resource Cost	\$213.24	\$216.00	\$203.46	\$193.62	\$194.10
Lost Load (MWh)	6,544	5,098	4,232	3,902	3,875
Interruption Time	50 h	42 h	27 h	24 h	24 h

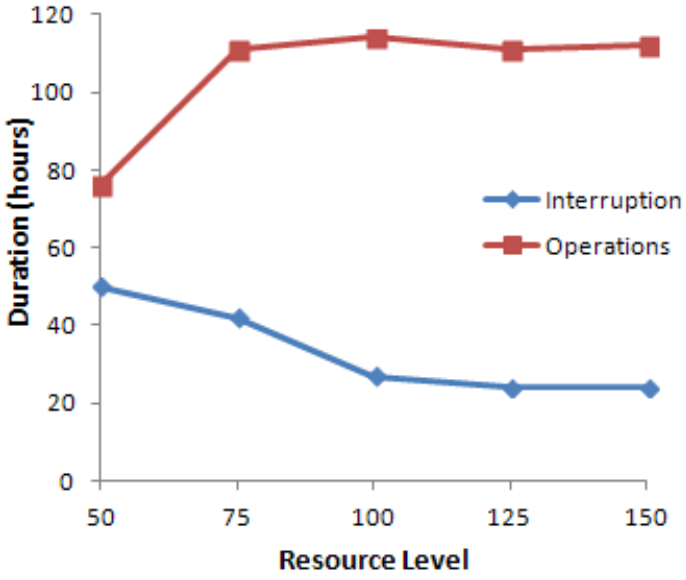

Figure 3.2 Interruption vs. operations duration for different scenarios.

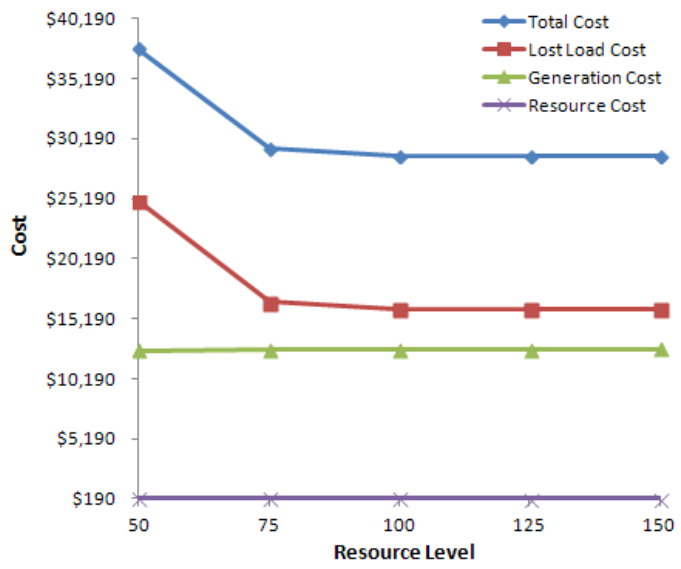

Figure 3.3 Optimal restoration cost breakdown for different scenarios (costs $\times 10^3$).

As shown in Table 3.9, higher resource level results in lower amount of aggregated lost load in the system. The higher level of restoration resources results in lower total restoration cost. This cost dynamics is significantly due to impact of resource level on opportunity cost of load interruption, as illustrated in Figure 3.3. Interestingly, by securing higher level of restoration resources, the trend of the total resource cost turns out to have a descending pattern. However, the total restoration resource cost is much lower than other cost components. In the first glance, the generation cost might be perceived to have low sensitivity to the resource level. But, surprisingly, considering different restoration planning horizon length for different cases in Scenario IV, the average power generation of each kWh for Cases 1 to 5 are \$0.5663, \$0.3848, \$0.3721, \$0.3847, and \$0.3762, respectively. Therefore, the average generation cost depends on the number of available restoration resources.

3.5 Conclusions

An economic model was proposed to support the post-hurricane decision making process for restoration of electric power infrastructure. The result demonstrates that the proposed model is able to find the optimal restoration schedule of damaged components of power system in a cost-effective manner. The opportunity cost of lost loads, the repair cost, and the generation costs were considered as economic indices. It was demonstrated that economy of disaster needs to be an important part of restoration plan. Moreover, the numerical results show that the restoration resource level significantly impacts on the total incurred cost of restoration of the system. The results suggest that investing on restoration resources is paid off in a sense that by securing enough restoration resources, a considerable restoration cost saving can be realized. Moreover, the higher level of resources would significantly shorten the partial restoration of the system. It was shown that the number of available resources has a significant impact on the average cost of power generation. This study suggests that incorporation of the unit commitment problem, value of lost load, and repair crew cost into the restoration decision making model plays a crucial role to implement an economic restoration of the grid.

Chapter 4

Pre-hurricane Proactive Planning

When according to weather forecast, a hurricane is on its way and about to be striking in an area, efficient proactive restoration planning for power system could significantly improve the resilience of the system. Consider a power system which all or some of its entities including generation units, transmission lines, buses and the downstream distribution lines of load buses are located on the path of an upcoming hurricane. The objective is to proactively allocate and mobilize the on-hand resources in order to enable quick response capability of utility companies to repair and restor potential damages to their facilities in a way that minimizes the expected incurred costs to the system. In addition, estimation of required resources which need to be outsourced in order to efficiently cope with the aftermath of the hurricane is another critical issue for improving the resilience of the system.

4.1 Notation

In this chapter, we borrow notation from Chapter 3. In addition, the following notation is used to describe the model, and formulate the problem.

Indices:

s	Index for scenario

Parameters:

A_c^l	Cross sectional area of line l
CD_l	Drag coefficient
F_{wind}^l	Wind force on line l
F_{brk}^l	Maximum perpendicular force that the line l is able to withstand
g	Wind gust speed
HI_l	Hazard importance for line l
$p(s)$	Probability of scenario s
q_b^+	Recourse penalty coefficient for bus b
q_l^+	Recourse penalty coefficient for line l
TC_l	Terrain correction
WS_l	Wire strain

γ_b	Probability of damage for bus b
γ_i	Probability of damage for generation unit i
γ_l	Probability of damage for line l
φ	Air density

Variables:

T_b	Random time to repair of bus b
T_i	Random time to repair of generation unit i
T_l	Random time to repair of transmission line l
$X_{bt}^{+}(\xi)$	Recourse activity for bus b at time t
$X_{lt}^{+}(\xi)$	Recourse activity for line l at time t
ϑ_i	Random initial state of unit i after hurricane strikes; 0 if damaged, otherwise 1
ξ	A multivariate random variable
ϕ_b	Random initial state of bus b after hurricane strikes; 0 if damaged, otherwise 1
ψ_l	Random initial state of line l after hurricane strikes; 0 if damaged, otherwise 1

4.2 Model Description

The damage state of components after hurricane strike are modeled as random variables ψ_l, ϑ_i, and ϕ_b for transmission line l, generation unit i, and bus b (and its downstream distribution lines), respectively. These random variables are considered to have two states: *damaged* and *functional*; thus, they can be modeled by Bernoulli random variables which take the value of 1, when after the upcoming hurricane the component in question is still *functional*, and value of 0, when the component in question is *damaged*. As parameters of aforementioned Bernoulli random variables, γ_b, γ_i, and γ_l are probability of damage for bus b (and its downstream distribution lines), generating unit i, and transmission line l, respectively.

As earlier explained in Chapter 2, various models have been proposed to the literature for modeling weather-related failure rate and probability of damage of power system components. However, without loss of generality, and because of their nice properties, we choose models that have been used in [2]. The probability of damage for substations and generating units in urban and suburban areas are represented by Lognormal fragility curves. Thus, the probability of damage for a given wind gust speed (g) considering the

local terrain and structural characteristics is obtained as

$$\gamma_k = \int_{-\infty}^{g} \frac{1}{\sqrt{2\pi}\sigma_k} exp\left(\frac{-(ln(x)-\mu_k)^2}{2\sigma_k^2}\right) dx, \tag{4.1}$$

where $k \in Set\{b, i\}$, μ_k is the logarithmic mean, and σ_k is the logarithmic standard deviation of the relevant fragility curve.

The wind force on transmission line l could be calculated with following standard design equation of American Society of Civil Engineers (ASCE) considering the wind gust speed, as

$$F_{wind}^{l} = \varphi \cdot TC_l \cdot HI_l \cdot WS_l \cdot CD_l \cdot A_c^l \cdot g^2, \tag{4.2}$$

where g^2 is the squared wind gust speed, and A_c^l is the cross sectional area of line l; parameters φ is the air density, TC_l is the terrain correction, HI_l is the hazard importance, WS_l is the wire strain, CD_l is the drag coefficient, which all are defined in Practice Report 113 of ASCE [114]. Assuming the transmission lines to be *Zebra* aluminum/steel conductor, the damage probability of line l is calculated as the ratio of wind load F_{wind}^{l} to the maximum perpendicular force that the line is able to withstand, F_{brk}^{l}, as

$$\gamma_l = \min\left(\eta \frac{F_{wind}^{l}(g)}{F_{brk}^{l}}, 1.0\right), \tag{4.3}$$

where, η is a parameter which is used to match the line fragility estimates with historical failure data [2].

Once the resources are allocated to each damaged component, the required repair and restoration resources are seized by the component in question up to the time when repair operation is completed. Therefore, the time to repair for each damaged component has a direct impact on the dynamics of resource allocation. The time to repair of each potentially damaged component is stochastic in its nature, which could be modeled by a random variable and may take various probability distributions. Random variables T_b,

T_i, and T_l correspond to time to repair for bus b (and its downstream distribution lines), generating unit i, and transmission line l, respectively. The probability distributions most often used to model the time to repair are the Exponential, Gamma, Normal, and Lognormal [115]. In this research, without loss of generality, it is assumed that the time to repair random variables to be defined by the Weibull density function as

$$f_{T_k}(t) = \begin{cases} \frac{\rho_k}{\lambda_k}\left(\frac{t}{\lambda_k}\right)^{\rho_k - 1} e^{-(t/\lambda_k)^{\rho_k}} & \text{if } t \geq 0, \\ 0 & \text{otherwise,} \end{cases} \tag{4.4}$$

where ρ_k is the shape parameter, λ_k is the scale parameter, and $k \in \{b, i, l\}$.

Considering the stochastic nature of the pre-hurricane problem, the resources should be allocated in a way that minimizes the expected cost of decisions made before the hurricane strikes and its stochastic outcomes be realized. Therefore, the problem turns out to be a two-stage stochastic problem; thus the stochastic programming with recourse could be utilized to model this problem. The aim is to allocate resources in a way that minimizes the sum of our original first-stage resource allocation costs and the expected recourse costs. For each possible stochastic circumstances, a *recourse* or second-stage activity can be performed to compensate the violation of the constraints – if there is any [116].

Figure 4.1 shows the schematic view of the proposed pre-hurricane restoration planning framework. As shown, by incorporating the physical characteristics of each component and forecasted information on maximum wind speed, the probability of damage is calculated. The stochastic time to repair for each damaged component is obtained from historical records. Considering the resource availability, and criticality of each probable load lost, the resources are primarily allocated to components in different locations. The lack of resources are obtained by recourse variables to have an efficient plan for responding to the hurricane. The optimal value of second-stage decision variables such as load interruption, power generation, and power flow in each line are determined, but are not to be performed necessarily. These values are the simulated optimal system configuration if the hurricane strikes, which help the decision maker to make a sound proactive decision,

i.e. the optimal resource allocation and the additional amount of resources that needs to be outsourced from other utility companies.

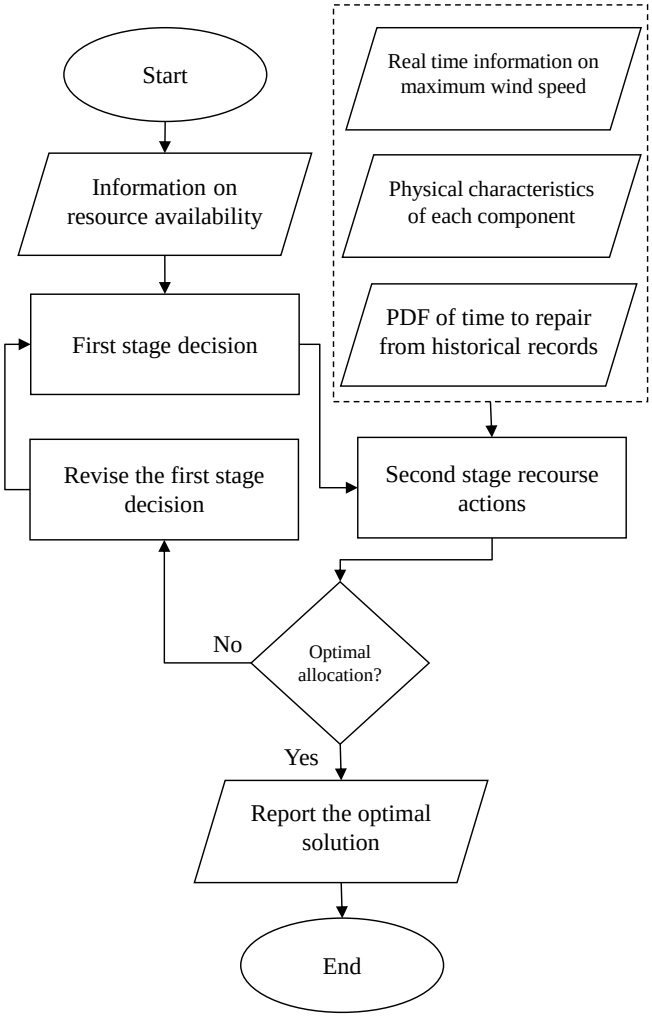

Figure 4.1 The schematic view of the proposed pre-hurricane planning framework

4.3 Problem Formulation and Methodology

As earlier explained, the pre-hurricane model is formulated as a two-stage stochastic linear program with recourse. The general formulation of a two-stage stochastic linear

program with recourse is as

$$\min_{x} \quad z = cx + \boldsymbol{Q}(x),$$

$$\text{s.t.} \quad Ax = b,\ x \in X, \tag{4.5}$$

where c is the cost vector in $\mathbb{R}^{n_1}$, b is RHS vector in $\mathbb{R}^{m_1}$, A is matrix of size $m_1 \times n_1$, and function $\boldsymbol{Q}(x)$ is the second stage value function (expected recourse cost function) defined as

$$\boldsymbol{Q}(x) = \mathbb{E}_{\xi}[Q(x, \xi(\omega))], \tag{4.6}$$

where

$$Q(x, \xi(\omega)) = \min_{y}\{q(\omega)y | Wy = h(\omega) - T(\omega)x,\ y \in Y\}, \tag{4.7}$$

where y is the recourse variable, $q(\omega)$ is the recourse penalty coefficient, W is the recourse matrix of size $m_2 \times n_2$, and ξ is a random N-vector in (Ω, A, S) probability space [73].

4.3.1 Objective Function

The objective of the pre-hurricane model is to minimize the cost of decisions primarily made on restoration resource allocation, the expected cost of customer load interruption, the expected cost of additional recourse actions to complete the restoration, and the expected cost of energy generation during the restoration planning horizon, after the hurricane strikes. Considering the stochastic program with recourse modeling structure, the problem is formulated. The objective function of proposed pre-hurricane restoration model is formulated as

$$\min_{u,v} \sum_t \sum_b C_{bt} R_b^{min} u_{bt} + \sum_t \sum_l C_{lt} R_l^{min} v_{lt}$$

$$+ \mathbb{E}_\xi \Bigg[\min_{LI,P,I,SU,SD} \sum_t \sum_b VOLL_{bt} LI_{bt}$$

$$+ \sum_t \sum_i \Big(C_{it}^g P_{it} I_{it} + SU_{it} + SD_{it} \Big) \Bigg], \quad (4.8)$$

where the first term represents the cost of resources primarily allocated to the buses (and their downstream distribution lines), and the second term is the cost of resources primarily allocated to transmission lines. The expected value operator represents the expected second-stage (recourse) function, where the first term in the expected value operator is the total cost of load interruption over the restoration planning horizon, and the second term is the total generation cost including fuel costs, the startup costs and the shutdown costs of generation units. The first term in the recourse function can be linearized in a similar manner as post-hurricane objective function. Although all decision variables in the pre-hurricane objective function are the same as the post-hurricane objective function of Chapter 3, but due to uncertainty of the problem, the resource allocation decisions are made in the first-stage, while the rest of decisions are made in the second stage as shown in (4.8). This definition of the recourse function is based on costs that are imposed to the system as a result of probable operations and configuration of the system, probable load interruption of the system, probable commitment/decommitment states, and probable real power generation of the units, after a potential hurricane strikes.

4.3.2 Common Constraints with Post-hurricane Model

The following constraints are in common with post-hurricane model described in Chapter 3.

- Resource constraints

- Load balance constraints
- Real power generation constraints
- Power flow constraints
- Startup and shutdown cost constraints
- Ramp-up and ramp-down constraints
- Minimum uptime and downtime constraints

4.3.3 Damage State of Generating Units

The initial damage state of each generating unit, y_{i0} is modeled with a random variable $\vartheta_i \sim Bernoulli(\gamma_i)$ as earlier explained. If the random variable ϑ_i is 0, it means the generation unit i is *damaged*; hence it is offline and needs to be restored. The state of a damaged generating unit does not change, unless the restoration operation is performed on that. On the other hand, if the random variable ϑ_i takes the value of 1, it indicates that the generation unit is *functional* and ready to be committed for generation from the beginning of the restoration planning horizon. It is assumed that if a generating unit is in *functional* initial state, its state will remain the same up to the end of restoration planning horizon, as modeled in following constraints

$$y_{i0} = \vartheta_i, \ \ \forall i \text{ and} \tag{4.9}$$

$$y_{it} = 0 \text{ if } t \leq (1 - y_{i0})T_i \text{ ; otherwise } y_{it} = 1, \ \ \forall i, \forall t, \tag{4.10}$$

where $T_i \sim Exponential(\lambda_i)$. Since, *if-then* constraint is not allowed, we write it in the following linear form

$$t - My_{it} \leq (1 - \vartheta_i)T_i, \ \ \forall i, \forall t \text{ and} \tag{4.11}$$

$$y_{it} \leq \vartheta_i, \ \ \forall i, \forall t = 0, ..., T_i. \tag{4.12}$$

4.3.4 Damage State of Buses

The initial damage state of each bus z_{b0} is represented with random variable $\phi_b \sim Bernoulli(\gamma_b)$. If the random variable takes the value of 1, it indicates that the initial state of the bus in question is considered as *functional*. Again, it is assumed that if a bus is initially in *functional* state ($z_{b0} = 1$), it will remain in the same state up to the end of the planning horizon. On the other hand, if this random variable takes the value of 0, then it is considered as *damaged* state. In this case, the bus will remain in the same state up to the time that restoration operation is completely performed on that, as

$$z_{b0} = \phi_b, \ \ \forall b, \tag{4.13}$$

$$0 \leq z_{b(t+1)} - \Big(\sum_{k=1}^{t} u_{bk} - T_b + 0.5\Big)/M \leq 1, \ \ \forall b, \forall t, \text{ and} \tag{4.14}$$

$$\sum_{k=t}^{t+T_b-1} u_{bt} \geq T_b(u_{bt} - u_{b(t-1)}), \ \ \forall b, \forall t, \tag{4.15}$$

where $T_b \sim Exponential(\lambda_b)$, and u_{bt} is the binary variable determined in the first stage problem for primary resource allocation to bus b at time t. The combination of stochastic variable for time to restoration, T_b, along with u_{bt} could make circumstances that result in infeasibility of the constraint (4.14) and (4.15). Therefore, set of recourse actions represented by binary variable $X^+_{bt}(\xi)$ are required to compensate lack of required resources for each bus in each unit of time. Therefore, constraints (4.14) and (4.15) are modified and rewritten as

$$0 \leq z_{b(t+1)} - \left(\sum_{k=1}^{t} \Big(u_{bk} + X^+_{bk}(\xi)\Big) - T_b + 0.5\right)/M \leq 1 \ \ \forall b, \forall t \text{ and} \tag{4.16}$$

$$\sum_{k=t}^{t+T_b-1} \Big(u_{bk} + X^+_{bk}(\xi)\Big) \geq T_b\Big(u_{bt} + X^+_{bt}(\xi) - u_{b(t-1)} - X^+_{b(t-1)}(\xi)\Big), \ \ \forall b, \forall t, \tag{4.17}$$

where,

$$u_{bt} + X_{bt}^{+}(\xi) \leq 1, \ \ \forall b, \forall t. \tag{4.18}$$

4.3.5 Damage State of Transmission Lines

In the same way as the generating units and buses, the initial damage state of transmission lines is modeled with a random variable $\psi_l \sim Bernoulli(\gamma_l)$. If a transmission line is damaged due to the hurricane, the binary initial state variable (w_{l0}) of that transmission line becomes equal to 0, and remains the same up to the time that required resources are allocated and the restoration operation is fully performed. On the other hand, if it does not undergo any damage, the w_{l0} takes the value of 1. In this case, it is assumed that w_{lt} keeps the value of 1 up to the end of planning horizon. The pertaining constraints are as follows:

$$w_{l0} = \psi_l, \ \ \forall l, \tag{4.19}$$

$$0 \leq w_{l(t+1)} - \Big(\sum_{k=1}^{t} v_{lk} - T_l + 0.5 \Big) / M \leq 1, \ \ \forall l, \forall t, \text{ and} \tag{4.20}$$

$$\sum_{k=t}^{t+T_l-1} v_{lk} \geq T_l (v_{lt} - v_{l(t-1)}), \ \ \forall l, \forall t, \tag{4.21}$$

where $T_l \sim Exponential(\lambda_l)$ is the time to repair for transmission line l, and v_{lt} is the binary decision variable of the first stage problem indicating the resource allocation on line l at time t. The combination of some outcomes of random variable T_l with first stage decision variable v_{lt} could lead to infeasibility of constraints (4.20) and (4.21). Using the same logic as used for (4.14) and (4.15), the constraints (4.20) and (4.21) are modified as

$$0 \leq w_{l(t+1)} - \left(\sum_{k=1}^{t} \Big(v_{lk} + X_{lk}^{+}(\xi) \Big) - T_l + 0.5 \right) / M \leq 1 \ \ \forall l, \forall t \text{ and} \tag{4.22}$$

$$\sum_{k=t}^{t+T_l-1} \Big(v_{lk} + X_{lk}^{+}(\xi)\Big) \geq T_l\Big(v_{lt} + X_{lt}^{+}(\xi) - v_{l(t-1)} - X_{l(t-1)}^{+}(\xi)\Big), \ \ \forall l, \forall t, \tag{4.23}$$

where $X_{lt}^{+}(\xi)$ is the recourse variable for line l at time t, and

$$v_{lt} + X_{lt}^{+}(\xi) \leq 1, \ \ \forall l, \forall t. \tag{4.24}$$

4.3.6 Penalization of Recourse Activities

As earlier explained, the recourse activities in the second stage problem are performed to compensate the lack of required resources that have not been allocated in the first stage. Mathematically, the recourse variables $X_{bt}^{+}(\xi)$ and $X_{lt}^{+}(\xi)$ are also used to avoid infeasibility in the problem due to lack of primary allocated resources in some stochastic circumstances. However, the recourse actions should be penalized in the recourse function to minimize the total costs. Therefore, by including the recourse activities' cost, the recourse function is modified as

$$Q(u,v,\xi) = \min_{LI,F,SU,SD,X_l^{+},X_b^{+}} \sum_t \sum_b VOLL_{bt} LI_{bt}(u,v,\xi)$$

$$+ \sum_t \sum_i \Big(C_{it}^{g} P_{it} I_{it} + SU_{it} + SD_{it}\Big) + \sum_l \sum_t q_{lt}^{+} X_{lt}^{+}(\xi) + \sum_b \sum_t q_{bt}^{+} X_{bt}^{+}(\xi). \tag{4.25}$$

4.3.7 Scenario-based Modeling

The expected recourse cost function is obtained by

$$\mathcal{Q}(u,v) = \mathbb{E}_{\xi}[Q(u,v,\xi)] = \sum_{\xi_l^1} \cdots \sum_{\xi_l^{NL}} \sum_{\xi_b^1} \cdots \sum_{\xi_b^{NB}} \sum_{\xi_i^1} \cdots \sum_{\xi_i^{NG}} \int_{\xi_{T_l}^1} \cdots \int_{\xi_{T_l}^{NL}} \int_{\xi_{T_b}^1} \cdots \int_{\xi_{T_b}^{NB}}$$

$$\int_{\xi_{T_i}^1} \cdots \int_{\xi_{T_i}^{NG}} \left(\prod_l p(\xi_l) \prod_b p(\xi_b) \prod_i p(\xi_i) \right) Q(u,v,\xi)$$

$$d(F(T_l^1)) \ldots d(F(T_l^{NL}) d(F(T_b^1)) \ldots d(F(T_b^{NB})) d(F(T_i^1)) \ldots d(F(T_i^{NG})). \tag{4.26}$$

Obviously, calculating the above integration is not an easy task, if is possible; Moreover, due to large number of scenarios, the computational efficiency of the optimization routine will be significantly lowered. Since there is no closed-form solution for (4.26) available, an alternative method is to solve the problem using a scenario-based approach. Therefore, all variables for pre-hurricane model except u_{bt} and v_{lt} should be considered as scenario-based variables, i.e., I_{its}, P_{its}, LI_{bts}, PL_{lts}, θ_{bts}, SU_{its}, SD_{its}, y_{its}, z_{bts}, w_{lts}, X^{+}_{lts}, and X^{+}_{bts}; where s is index for scenario. Therefore, the objective function is rewritten as follows:

$$\min_{u,v} \sum_{t}\sum_{b} C_{bt}.R_b^{min}u_{bt} + \sum_{t}\sum_{l} C_{lt}R_l^{min}v_{lt}$$

$$+ \sum_{s} p(s)\Bigg[\min_{LI,F,SU,SD,X_l^+,X_b^+} \sum_{t}\sum_{b} VOLL_{bt}LI_{bts}(u,v,\xi)$$

$$+ \sum_{t}\sum_{i}\Big(C_{it}^{g}P_{its}I_{its} + SU_{its} + SD_{its}\Big) + \sum_{l}\sum_{t} q_{lt}^{+}X_{lts}^{+}(\xi) + \sum_{b}\sum_{t} q_{bt}^{+}X_{bts}^{+}(\xi)\Bigg], \tag{4.27}$$

where $p(s)$ is the probability of scenario s.

4.3.8 Nonanticipativity

An important issue that should be considered in solving stochastic programs is that the decisions should not depend on the outcome of ξ, denoted as nonanticipativity concept [116]. One way to enforce nonanticipativity requirement is the Birge's method [117]. Let S_s^t be the set of scenarios that are identical to scenario s at time t. The following nonanticipativity constraints should hold

$$\left(\sum_{\acute{s}\in S_s^t} p(\acute{s})\right) LI_{bts} = \sum_{\acute{s}\in S_s^t} p(s) LI_{bt\acute{s}}, \;\; \forall b, \forall t, \forall s, \tag{4.28}$$

$$\left(\sum_{\acute{s}\in S_s^t} p(\acute{s})\right) P_{its} = \sum_{\acute{s}\in S_s^t} p(s) P_{it\acute{s}}, \;\; \forall i, \forall t, \forall s, \tag{4.29}$$

$$\left(\sum_{\acute{s}\in S_s^t} p(\acute{s})\right) PL_{lts} = \sum_{\acute{s}\in S_s^t} p(s) PL_{lt\acute{s}}, \;\; \forall l, \forall t, \forall s, \tag{4.30}$$

$$\left(\sum_{\acute{s}\in S_s^t} p(\acute{s})\right) I_{its} = \sum_{\acute{s}\in S_s^t} p(s) I_{it\acute{s}}, \;\; \forall i, \forall t, \forall s, \tag{4.31}$$

$$\left(\sum_{\acute{s}\in S_s^t} p(\acute{s})\right) SU_{its} = \sum_{\acute{s}\in S_s^t} p(s) SU_{it\acute{s}}, \;\; \forall i, \forall t, \forall s, \tag{4.32}$$

$$\left(\sum_{\acute{s}\in S_s^t} p(\acute{s})\right) SD_{its} = \sum_{\acute{s}\in S_s^t} p(s) SD_{it\acute{s}}, \;\; \forall i, \forall t, \forall s, \tag{4.33}$$

$$\left(\sum_{\acute{s}\in S_s^t} p(\acute{s})\right) X^+_{lts}(s) = \sum_{\acute{s}\in S_s^t} p(s) X^+_{lts}(\acute{s}), \;\; \forall l, \forall t, \forall s, \text{ and} \tag{4.34}$$

$$\left(\sum_{\acute{s}\in S_s^t} p(\acute{s})\right) X^+_{bts}(s) = \sum_{\acute{s}\in S_s^t} p(s) X^+_{bts}(\acute{s}), \;\; \forall b, \forall t, \forall s. \tag{4.35}$$

4.3.9 The Proposed Solution Scheme

In this section, first the scenario construction and reduction method is introduced. Next, the decomposition strategy to solve the problem is explained.

4.3.9.1 Scenario construction and reduction

Due to presence of continues random variables, i.e., the Weibull distribution for time to repair of each damaged component, the stochastic data process of the proposed models,

ξ has an infinite support. To make the problem tractable, the stochastic data process ξ needs to be redistributed to provide a finite support with the reduced (optimal) number of scenarios. While Monte Carlo sampling can yield reasonable estimates for the distribution of an underlying random variable, but it requires relatively large sample size which reduces computational efficiency. To cope with this issue, other uncertainty estimation techniques such as the Latin hypercube sampling method which can provide more accurate estimates with smaller sample size were developed [85]. We use the Latin hypercube sampling [118] to replace ξ by a scenario tree approximation ξ_{tr} which has a finite, but large number of scenarios. The Latin hypercube sampling guarantees that the whole range of values for a random variable is sampled. For a sample size of N, the Latin hypercube sampling technique selects N different values from each of random variables by dividing the range of each random variable into N non-overlapping intervals. Then by shuffling and pairing these values constructs N scenarios, each with probability of $1/N$.

The next step is to reduce the number of scenarios into a computationally tractable size. Various reduction techniques are available to be applied for different applications. For the constructed probability measure of $\xi_{tr} = \sum_{k=1}^{N} \frac{1}{N} s_k$, it is required to determine an index set $K_*^{'} \subset \{1, ..., N\}$ of given cardinality $\#K_*^{'} = N - N^{'}$ and a probability measure $\tilde{\xi}_* = \sum_{k'=1, k' \notin K_*^{'}}^{N} p_{k'}^{*} s_{k'}$ such that

$$\hat{\mu}_c(\xi_{tr}, \tilde{\xi}_*) = \inf \left\{ \hat{\mu}_c \left(\xi_{tr}, \sum_{k=1, k \notin K_*^{'}}^{N} p_{k'} s_{k'} \right) : K_*^{'} \subset \{1, ..., N\}, \#K_*^{'} = N - N^{'}, \right.$$

$$\left. \sum_{k' \notin K_*^{'}} p_{k'} = 1, p_{k'} \geq 0, k^{'} \notin K^{'} \right\}, \quad (4.36)$$

where *Kantorovich functional* $\hat{\mu}_c(\xi_{tr}, \tilde{\xi}_*)$ is an estimation of the probability distance $\zeta_c(\xi_{tr}, \tilde{\xi}_*)$. Problem (4.36) can be solved through variety of techniques, but due to accuracy of backward reduction algorithm, we solve it through this method. Readers are referred to [91] for the detailed explanation of the backward scenario reduction algorithm.

4.3.9.2 Decomposition strategy

By construction of the scenario three and reducing it to a tractable number of scenarios, the proposed two-stage stochastic program with recourse is converted to its deterministic mixed-integer program equivalence. Benders decomposition for mixed-integer programming is an efficient strategy, when the original problem is large-scale and difficult to solve, while the Benders subproblem and the relaxed master problem are much more tractable to solve. In order to employ the decomposition strategy for the proposed problem, we consider the continues variable vector as $\mathbf{X} = [LI_{bts}^T, P_{its}^T, PL_{lts}^T, SU_{its}^T, SD_{its}^T]^T$, the binary variable vector as $\mathbf{Y} = [u_{bt}^T, v_{lt}^T, X_{bts}^+, X_{lts}^+, y_{its}^T, z_{bts}^T, w_{lts}^T, I_{its}^T]^T$, and the cost coefficient matrix of the integer variables in the objective function as $\mathbf{C^T}$, and the cost coefficient matrix of the continues variables in the objective function as $\mathbf{D^T}$. We also assume that $\mathbf{A}$ and $\mathbf{B}$ represent the coefficient matrix of $\mathbf{X}$ and $\mathbf{Y}$ in the constraints, respectively. Finally, $\mathbf{H}$ is assumed to represent the right hand side matrix of the constraints. The problem is decomposed into a master problem and a subproblem. The master problem is set as an integer program, while the subproblem is set as a dual linear program (without any integer variable). Considering $\mathbf{U}$ as the dual variable vector for the subproblem, the Benders decomposition algorithm for the proposed model is shown in Algorithm 4.1 [112].

4.4 Numerical Analysis

The IEEE 118-bus system is considered to study the proposed model. The component of the system located on the path of the upcoming hurricane along with the associated probability of damage, as well as the scale parameter of the Weibully distributed time to repair are given in the first three columns of Tables 4.1–4.3. The shape parameter of the Weibull distribution for all components are assumed to be equal to 1.

Algorithm 4.1 Benders decomposition for equivalent MIP problem

{initialization}
Y := initial feasible integer solution
Lower bound (LB):= $-\infty$, Upper bound (UB):= $+\infty$
while UB $-$ LB $> \varepsilon$ **do**
{solve dual LP subproblem}
$\max_U \{\sum_t \sum_b C_{bt} R_b^{min} \bar{u}_{bt} + \sum_t \sum_l C_{lt} R_l^{min} \bar{v}_{lt}$
$+ \sum_s \sum_l \sum_t p(s) q_{lt}^+ \bar{X}_{lts}^+ + \sum_s \sum_b \sum_t p(s) q_{bt}^+ \bar{X}_{bts}^+$
$+ (H - B\bar{Y})^T U \mid A^T U \leq C, U \geq 0\}$
if Unbounded **then**
Get unbounded ray $\bar{U}$
Add cut $(H - BY)^T \bar{U} \leq 0$ to IP master problem
else
Get extreme point $\bar{U}$
Add cut $\theta \geq \sum_t \sum_b C_{bt} R_b^{min} u_{bt} + \sum_t \sum_l C_{lt} R_l^{min} v_{lt}$
$+ \sum_s \sum_l \sum_t p(s) q_{lt}^+ X_{lts}^+ + \sum_s \sum_b \sum_t p(s) q_{bt}^+ X_{bts}^+$
$+ (H - BY)^T \bar{U}$ to master problem
UB := $\min \{$UB$, \sum_t \sum_b C_{bt} R_b^{min} \bar{u}_{bt}$
$+ \sum_s \sum_l \sum_t p(s) q_{lt}^+ \bar{X}_{lts}^+ + \sum_s \sum_b \sum_t p(s) q_{bt}^+ \bar{X}_{bts}^+$
$+ \sum_t \sum_l C_{lt} R_l^{min} \bar{v}_{lt} + (H - B\bar{Y})^T \bar{U}\}$
end if
{solve IP master problem}
LB := $\min_Y \{\theta \mid cuts\}$
end while

Table 4.1 Damage probabilities and TTR scale parameter for units

Unit Number	Damage Probability	TTR Scale Parameter
$G26$	0.15	8
$G38$	0.35	8
$G39$	0.50	16
$G40$	0.45	16
$G41$	0.35	8
$G42$	0.20	8
$G43$	0.80	12
$G44$	0.25	12
$G45$	0.40	12

Table 4.2 Damage probabilities, TTR scale parameters, and derived allocations for buses

Bus Number	Damage Probability	TTR Scale Parameter	Schedule (Case I)	Schedule (Case II)	Schedule (Case III)
$B62$	0.70	10	1-10	1-10	1-8
$B85$	0.20	10	1-9	1-9	1-3
$B86$	0.40	10	1-8	1-8	1-5
$B87$	0.15	7	25-28 46-65	N/A	9-10
$B88$	0.1	10	N/A	N/A	3-4
$B89$	0.05	10	96-107	N/A	1-2
$B90$	0.60	10	1-18	1-18	1-7
$B91$	0.10	7	3-4	5-6	6-7
$B92$	0.30	10	1-4	1-4	1-4
$B93$	0.05	7	1-8	1-8	2-3
$B94$	0.40	10	1-30	1-30	1-5
$B95$	0.20	10	1-8	1-8	2-4
$B96$	0.25	10	1-11	1-11	1-4

Table 4.3 Damage probabilities, TTR scale parameters, and derived allocations for lines

Line Number	Damage Probability	TTR Scale Parameter	Schedule (Case I)	Schedule (Case II)	Schedule (Case III)
$L91$	0.20	10	1-3 67-90	N/A	3-5
$L92$	0.30	10	41-63	N/A	5-8
$L100$	0.10	10	1-2 25-38	N/A	1-2
$L101$	0.35	10	1-8	N/A	5-9
$L131$	0.70	10	46-87 1-4	N/A	2-9
$L132$	0.55	10	1-8 72-81	1-8	1-7
$L133$	0.30	15	1-3	2-4	1-6
$L134$	0.25	15	5-7	N/A	2-6
$L135$	0.35	10	1-13 95-107	1-13	3-7
$L136$	0.20	10	2-6	N/A	1-3
$L137$	0.20	15	44-74	N/A	1-4
$L138$	0.15	15	70-89	N/A	4-7
$L139$	0.15	15	24-38	N/A	4-7
$L140$	0.35	10	97-106	N/A	1-5

The value of lost load is considered to be \$3,706/MWh for industrial loads, \$6,979/MWh for commercial loads, and \$110/MWh for residential areas [107]. The load on bus B62 is industrial, while loads on buses B88, B92, and B93 are commercial. The rest of the loads are considered as residential. The repair crew is considered to be the only limited resource that is allocated to repair damaged components. It is assumed that each damaged substation requires 10 repair crews/hour, while each damaged transmission line requires 15 repair crews/hour. The wages for repair crews of substations are assumed as follows: \$60/hour at shift 1 (8:00 A.M.–4:00 P.M.), \$70/hour at shift 2 (4:00 P.M.–12:00 A.M.), and \$80/hour at shift 3 (12:00 A.M.–8:00 A.M.). An incremental rate of \$5/hours is added to the wage of transmission lines' repair crew. The generation cost is considered to be \$35.09/MWh [113]. The shutdown cost for each generating unit is assumed to be \$250. The startup cost is assumed to be \$150 within the first hour after last shutdown. For each additional hour (up to eight hours), an incremental cost of \$25 is added to the startup cost. Three cases are considered for analysis as follows:

Case I (full restoration): The primary resources are considered as unconstrained. The restoration of all components are enforced. The aim is to find the optimal value for the maximum amount of resources required for full restoration.

Case II (partial restoration): The primary resources are constrained to obtained value in Case I. The restoration is not enforced for all damaged components. The aim is to analyze the economic dynamics of the restoration, regardless of system-level reliability.

Case III (expected value problem): The expected value problem of the proposed model is solved. The aim is to find the value of stochastic solution (VSS) for the problem.

All three cases are analyzed in a 120-hour restoration planning horizon. As Latin hypercube sampling method is used for scenario construction, in an *ad hoc* manner 3,000 independent scenarios (which is a sufficiently large sample size for this sampling scheme) are generated for Cases I and II [85]. With the use of the backward reduction algorithm [91], the number of scenarios are reduced to 10, with associated probabilities of 0.336, 0.011,

0.017, 0.065, 0.029, 0.308, 0.115, 0.012, 0.057, and 0.05. All three cases are solved using the Benders decomposition method. First, the proposed model is solved for Case I to find $R^{max}(t)$, i.e., the maximum resource level required to restore the entire system. After obtaining $R^{max}(t)$, this value is imposed as a constraint in Case II in order to study system behavior, when the system-level reliability is not considered. The derived value for $R^{max}(t)$ in Case I is 210 crew/hour. The fourth and fifth columns of Table 4.2 respectively show the optimal schedule of resources that need to be allocated to damaged substations in Case I and II; while the fourth and fifth columns of Table 4.3 respectively represent allocation of resources to transmission lines in Cases I and II. The adjacent allocation schedules to each component are merged, while the overlapping allocations are removed from the results (associated costs are also deducted in the latter case).

As shown in the results, there are components in the system which have multiple allocations, i.e., B87, L91, L100, L131, L132, and L135 in Case I. These multiple allocations perform as an insurance for the system to different scenarios that can occur when the hurricane strikes. On the other hand, there are components in the system without any allocated resources. The reason is due to low expected cost of damage to these components. This phenomenon also occurs in Case II due to partial restoration which ignores the system-level reliability. Due to economic dynamics of the system, i.e., the cost sensitivity of system to functional state of each component, Case II does not allocate resources to some components of the system which do not have considerable expected economic risk. Furthermore, presence of redundant components in the system that can compensate the offline state of other components is another reason for observed behavior. However, from the system-level reliability perspective, the restoration scheme of Case II is not always preferable.

For Case III, rather than deriving a scenario-based solution, the expected value of the parameters are plugged into the proposed model. The last columns of Tables 4.2 and 4.3 show the optimal resource allocation in Case III for substations and lines, respectively. As shown in Figure 4.2, the total expected cost of restoration in Case III is $15,581,870 which

is higher than Cases I and II (i.e., $15,343,980 and $15,065,320, respectively). Therefore, the value of stochastic solution which is the difference between the stochastic solution and the expected value solution is $237,890 and $516,550, for Cases I and II, respectively. The expected load interruptions for Cases I, II, and III are 1,469 MWh, 1,467 MWh, and 1,761 MWh, respectively. While the expected load interruption cost for Case III is significantly higher than Cases I and II, the generation cost of Case I is slightly lower than two other cases.

As shown in Figure 4.3, the optimal resource level for all three cases starts with a high value, but is dramatically dropped by the end of the fist working shift. As results show, Cases I and II have a similar pattern for optimal resource allocation from the beginning of shift 2 until the end of shift 3. The total resource costs for Cases I, II, and III are $373,575, $114,450, and $70,725, respectively. While Case I has the highest, and Case III has the lowest resource allocation cost, Case II has the most cost-effective strategy to restore the system. However, due to contingency of the system to unexpected failures and faults, the partial restoration strategy of Case II does not provide the desired system-level reliability in the normal operating condition. On the other hand, the full restoration strategy of Case I provides higher system-level reliability in expense of a higher resource allocation cost. Considering this trade-off, decision makers can choose the desirable strategy based on their system operation preferences.

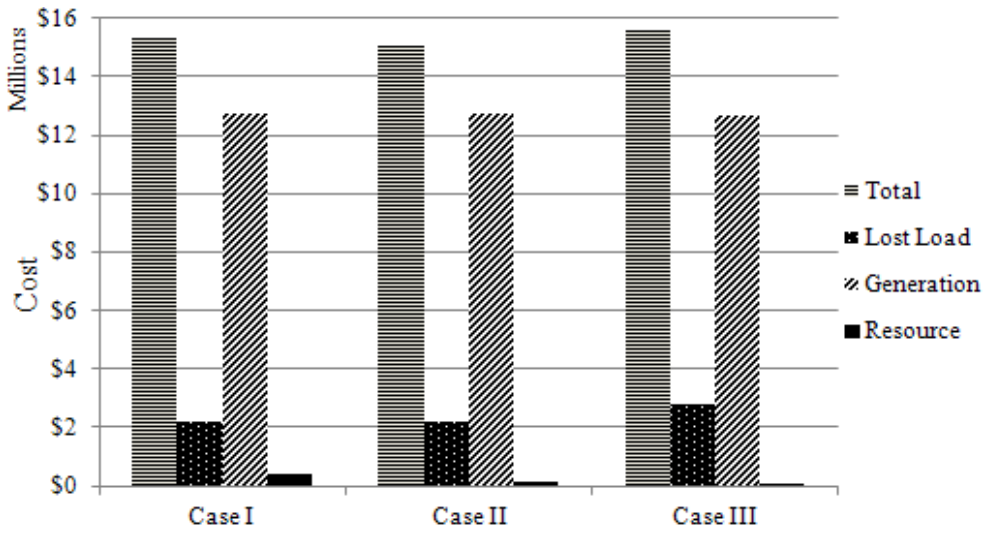

Figure 4.2 Expected cost breakdown for three scenarios

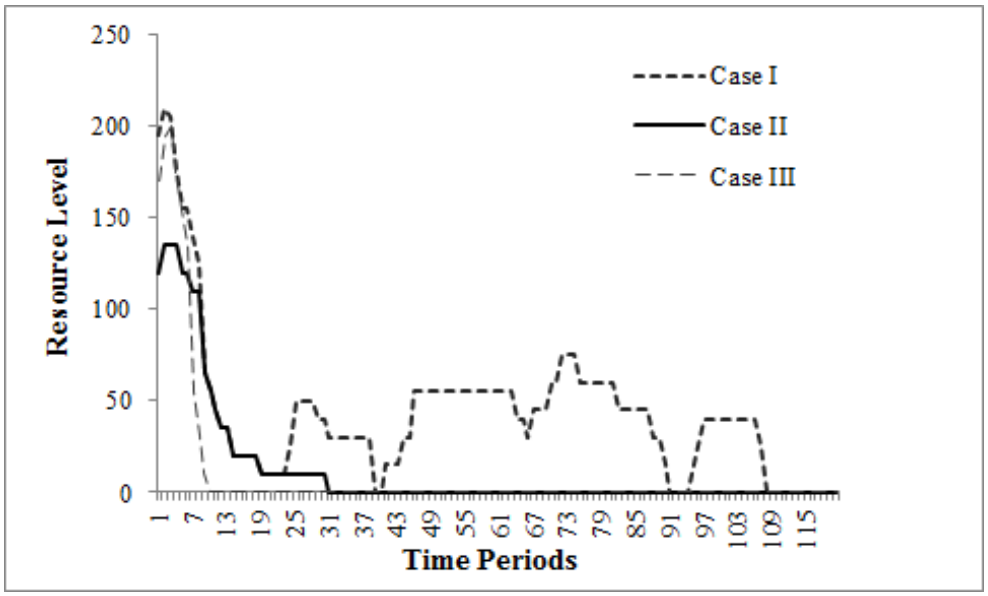

Figure 4.3 Optimal resource level for for three scenarios

4.5 Conclusions

A stochastic model to support decision making process for power system restoration in pre-hurricane phase was introduced. The model was formulated as a two-stage stochastic

problem with recourse. After scenario reduction, the large scale equivalence of the universe problem was solved using Benders decomposition. Two strategies, i.e. the full restoration, and the partial restoration strategies were analyzed; and the value of stochastic solution was calculated. The value of stochastic solution as an index, obviously justifies the advantage of obtaining it over expected value solution. The numerical results demonstrates the merits and disadvantages of each strategy. While the partial restoration strategy provides a more cost-effective restoration plan, it may not provide the same system-level reliability that full restoration strategy secures. However, decision makers can choose the best strategy based on operations policy of the utility company.

Chapter 5

Dynamic Maintenance Planning Incorporating Hurricane Effects

An effective preventive maintenance program plays a critical role in improving the reliability of electric power systems. In this chapter, the impact of potential damage due to hurricane is incorporated in the power system maintenance scheduling problem. The proposed model considers component deterioration, as well as two competing and independent failure modes, i.e., failure due to deterioration and failure due to hurricane damages. Furthermore, the interrelationship between the component, the grid, and the associated downtime cost dynamics are incorporated in the problem. The downtime cost of the power system due to component outage is formulated using mixed-integer programming. The obtained downtime cost is used in a stochastic dynamic programming model to derive the optimal maintenance policy for the component.

5.1 Notation

The notation used for problem formulation are shown as follows.

Indices:

b	Index for buses
i	Index for generation units
l	Index for transmission lines
t	Index for time

Sets:

$A(j)$	Action space when system is in state j
B_b	Set of components connected to bus b

Parameters:

$C(a)$	Immediate cost of action a
C_{it}	Generation cost of unit i in period t
$d_t(j)$	Probability of deterioration from state j to $j+1$ in period t

D_{bt}	Electricity demand at bus b in period t
DT_t	Downtime cost in period t
$f_t(j)$	Probability of failure in period t, when it is in state j
g	Maximum wind gust speed that component is able to withstand
h_t	Probability that component is not affected by hurricane in period t
M	Large positive constant
P_i^{max}	Maximum generation capacity of unit i
P_i^{min}	Minimum power generation capacity of unit i
PL_l^{max}	Maximum power flow capacity of line l in period t
$VOLL_{bt}$	Value of lost load at bus b in period t
λ_t	Hurricane arrival rate in period t
α_{ib}	Element of unit i and bus b in generation-bus incidence matrix
β_{lb}	Element of line l and bus b in line-bus incidence matrix

Variables:

I_{it}	Commitment state of generating unit i at period t; 1 if committed, otherwise 0
G_m	Random variable for wind gust speed of mth hurricane
LI_{bt}	Load interruption at bus b in period t
P_{it}	Real power generation of unit i in period t
PL_{lt}	Power flow of line l in period t
s_t	State of the system at decision epoch t
$V_t(s_t)$	Expected minimum cost of the system from decision epoch t to the end of planning horizon
w_{lt}	Outage state of line l in period t; 0 if offline, otherwise 1
y_{it}	Outage state of unit i in period t; 0 if offline, otherwise 1
z_{bt}	Outage state of bus b in period t; 0 if offline, otherwise 1
δ_{bt}	Bus voltage angle

5.2 Model Description

Consider a power system located in a hurricane-prone area. A component of this power system is under consideration for the preventive maintenance program. The component is subject to failure due to two independent and competing random failure processes: The failure due to aging and deterioration, and failure due to hurricane strike. In addition to failure risk, the component is subject to degradation over time. As the component ages and deteriorates, the probability of failure increases. Furthermore, the associated cost to bring the component to as-good-as-new condition increases. On the other hand, as illustrated

in Figure 5.1, regardless of the reliability condition of the component, when a hurricane strikes, it can affect the functional state of the component. In addition, the risk of hurricane strike varies from one season to another. Therefore, the overall risk of failure of the component over the planning horizon, i.e., before, during and after hurricane season is dynamically changing. Furthermore, the downtime cost of the component is changing due to variation of demand for electricity and generation cost over the planning horizon. The trade-off arises between the risk of failure and subsequent downtime cost of the component from one side, and unutilized capital invested on asset management on the other side. Therefore, this dynamic cost of failure needs to be addressed in preventive maintenance programs of the components.

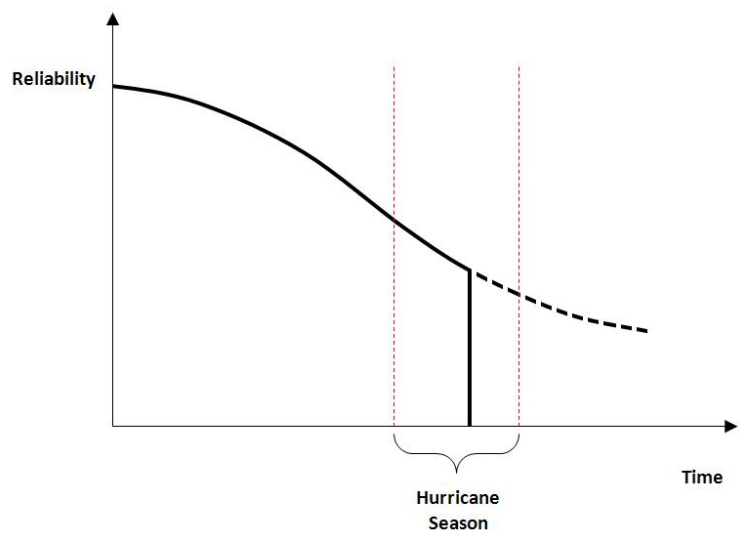

Figure 5.1 Reliability of a single component of the system subject to hurricane damage

Variety of probability density functions have been proposed in the literature to fit the probability density function for time to failure for different components of the power system, e.g. [40,41]. The probability distributions that are most often used to model the time to repair are Exponential, Gamma, Normal, and Lognormal [115]. The Poisson distribution is used to model the hurricane arrival rate to the system [57]. However, along with hurricane

arrival rate, the maximum wind gust speed that the component is able to withstand needs to be considered to evaluate the probability of failure.

We consider $k+2$ different states for the component as

$$S = \Big\{1, ..., k, k+1, k+2\Big\},$$

where states $1, ..., k$ represent the condition of the component while it is functional; the larger the state of the component is, the more the component is deteriorated (therefore, state 1 means *as-good-as-new*). State $k+1$ represents component failure due to aging and deterioration, and state $k+2$ shows component failure due to hurricane damage. Figures 5.2 and 5.3 show the transition diagrams of the system.

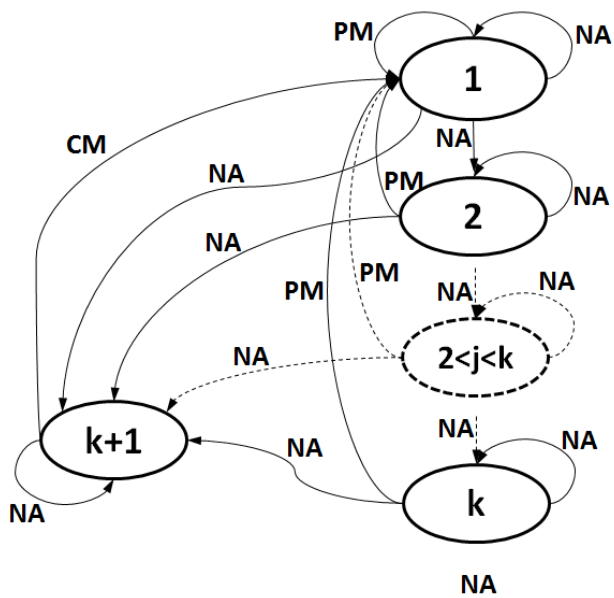

Figure 5.2 State transition diagram related to degradation

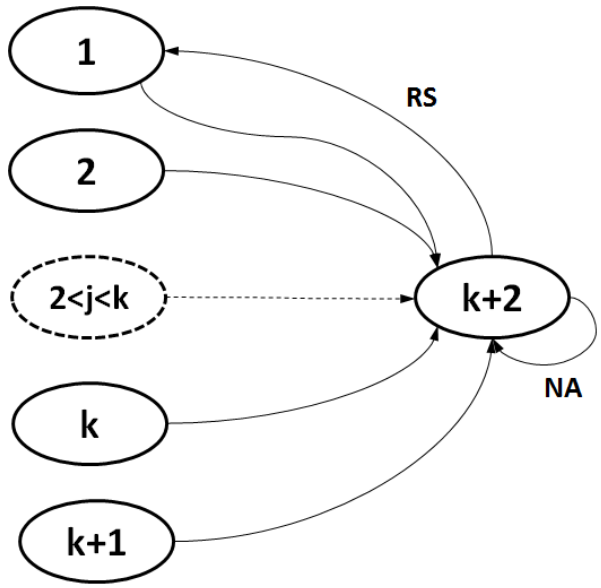

Figure 5.3 State transition diagram related to hurricane

When the component is in state $j = 1, ..., k$, there are two actions available in each decision epoch: *no action*, denoted by NA_j; and *preventive maintenance*, denoted by PM_j. It is assumed that by preventive maintenance, the reliability of the component is fully restored and the component is brought back to state 1. However, the cost of preventive maintenance increases by the condition of the component, i.e., $C(PM_k) > C(PM_{k-1}) > ... > C(PM_1)$. Zero cost is considered to be associated with NA_j action. The action space when the component is in state j is represented by $A(j) = \{NA, PM_j\}$, $j \in \{1, ..., k\}$.

Once the component goes to failure state $k+1$, we can either take *no action*, NA (and proceed to the next decision epoch) or we can immediately perform corrective maintenance, CM, with the cost of $C(CM)$. Therefore, the action space for component in state $k + 1$, is $A(k + 1) = \{NA, CM\}$. Finally, when the component fails due to hurricane damage, the action space is $A(k + 2) = \{NA, RS\}$; where action NA is the same as described for previous cases, and action RS means to *restore* the component into functional state. The cost associated with the restoration is $C(RS)$, where $C(RS) > C(CM) > C(PM_k) > C(PM_{k-1}) > ... > C(PM_1)$.

If the component remains in failed condition during a period, say period t, the downtime cost DT_t is incurred. The downtime cost can be computed by solving two mixed-integer programming problems in order to find the difference in minimum system cost during each period when the component is in the functional state and when it is offline due to failure.

5.3 Problem Formulation and Methodology

We formulate the problem as a finite horizon Markov Decision Process (MDP) with decision epochs $T = \{1, 2, ..., N\}$. In particular, we consider $N = 52$ weeks for an annual preventive maintenance program.

5.3.1 Transition Probabilities

The state transition probabilities need to be evaluated to model the problem. First, the probability that the component is not affected by hurricane is considered. This probability is composed of the probability that the hurricane does not occur at all, plus the probability that hurricane strikes but damage does not occur, during each period t with length of τ. The hurricane arrivals follow a Poisson process with $\tau = 1$ week, and average arrival rate λ_t in period t [57]. The survival of component against each wind gust speed G_i of each strike of hurricane can be modeled by the Lognormal distribution [2]. The probability that

the component is not affected by hurricane strikes during period t is modeled as

$$h_t = \sum_{m=0}^{\infty} P\Big\{G_1 < g, G_2 < g, ..., G_{N(\tau)} < g, \ |N(\tau) = m\Big\} P\Big(N(\tau) = m\Big)$$

$$= P\Big(N(\tau) = 0\Big) + \sum_{m=1}^{\infty} \Big[P\Big(G < g\Big)\Big]^m P\Big(N(\tau) = m\Big)$$

$$= \frac{\exp\Big(-\lambda_t\tau\Big)\Big[-\lambda_t\tau\Big]^0}{0!} + \sum_{m=1}^{\infty} \left[\Phi\left(\frac{\ln(g) - \mu_G}{\sigma_G}\right)\right]^m \frac{\exp\Big(-\lambda_t\tau\Big)\Big[\lambda_t\tau\Big]^m}{m!}$$

$$= \exp\Big(-\lambda_t\tau\Big)\left(\sum_{m=0}^{\infty} \frac{\left[\Phi\Big(\frac{\ln(g)-\mu_G}{\sigma_G}\Big)\lambda_t\tau\right]^m}{m!}\right), \quad (5.1)$$

where g is the maximum wind gust speed that the component can withstand, $N(\tau)$ is the number of hurricane strikes during each period, μ_G is the average wind gust speed, σ_G is the standard deviation of the wind gust speed, and $\Phi(\cdot)$ is the CDF of the Normal distribution. Using

$$\sum_{k=0}^{\infty} \frac{z^k}{k!} = \exp(z),$$

we obtain

$$h_t = \exp\Big(-\lambda_t\tau_t\Big)\left(\exp\left[\Phi\Big(\frac{\ln(g) - \mu_G}{\sigma_G}\Big)\lambda_t\tau\right]\right)$$

$$= \exp\left[\lambda_t\tau\left(\Phi\Big(\frac{\ln(g) - \mu_G}{\sigma_G}\Big) - 1\right)\right]. \quad (5.2)$$

The failure probability of the component increases in its state. If the component is in state $j \in \{1, ..., k\}$ at the beginning of period t, $f_t(j)$ denotes the probability that the component fails due to aging and deterioration, and $f_t(j+1) > f_t(j)$ for $j \in \{1, ..., k-1\}$.

On the other hand, $d_t(j)$ represents the probability that the component will deteriorate to state $j+1$ in period t for $j \in \{1, ..., k-1\}$, if the component is in state j at the beginning of period t, and $d_t(j+1) > d_t(j)$ for $j \in \{1, ..., k-1\}$. $1 - d_t(j)$ denotes the probability that the state of the component remains the same in period t. That is, the component can at most deteriorate by one level in each period. This transition probability is considered only in the event that the failure due to aging and hurricane damage do not occur in that particular period and state. However, if the failure occurs, the deterioration transition will not occur; and thus this probability cannot be considered in that case.

5.3.2 Model Formulation

The optimality equation for the finite horizon MDP can be written as

$$V_t(s_t) = \min_{a \in A(s_t)} \left\{ r_t(s_t, a) + \sum_{j \in S} p_t(j|s_t, a) V_{t+1}(j) \right\}, \tag{5.3}$$

where $V_t(s_t)$ is the minimum total expected cost, when the component is in state s_t in the beginning of period t; $r_t(s_t, a)$ is the expected cost of taking action a in state s_t in period t, and $p_t(j|s_t, a)$ is the transition probability of going to state j in the next decision epoch, given the component is currently in state s_t and action a is taken. At each decision epoch, when the component is in functional state, i.e., $s_t = j$ where $j \in \{1, ..., k\}$, we can either do nothing, or we can perform preventive maintenance. Therefore, the optimality equation for this state is written as

$$\begin{aligned} V_t(j) = \min \Bigg\{ & C(NA) + h_t \Bigg(f_t(j) V_{t+1}(k+1) \\ & + \Big(1 - f_t(j)\Big) \Big(d_t(j) V_{t+1}(j+1) + \Big(1 - d_t(j)\Big) V_{t+1}(j) \Big) \Bigg) \\ & + \Big(1 - h_t\Big) V_{t+1}(k+2), \;\; C(PM_j) + W_t(1) \Bigg\}, \end{aligned} \tag{5.4}$$

where

$$W_t(1) = h_t\Bigg(f_t(1)V_{t+1}(k+1)$$

$$+ \Big(1 - f_t(1)\Big)\Big(d_t(1)V_{t+1}(2) + \Big(1 - d_t(1)\Big)V_{t+1}(1)\Big)\Bigg)$$

$$+ \Big(1 - h_t\Big)V_{t+1}(k+2), \quad (5.5)$$

where the first expression in the curly braces represents the total expected cost of action NA (doing nothing), while the second expression represents the total expected cost of action PM_j (performing preventive maintenance in state j), given the component is in state j in decision epoch t. The total expected cost of action NA is composed of following costs: the first term represents the expected cost of action NA in period t (which is zero), the second term is the total expected cost for periods $t+1, ..., N$, if action NA is taken in period t, if the hurricane occurs in period t but it does not result in damage or the hurricane does not occur. The third term is the total expected cost for periods $t+1, ..., N$, if action NA is taken and the hurricane occurs and damages the component. The same order of the expected cost breakdown holds for total expected cost of PM_j in the second expression in the curly braces.

When the component goes to failure state, i.e., $s_t = k+1$ we can either take *no action*, or we can perform *corrective maintenance* on component. By taking no action, an expected downtime cost of DT_t is incurred. In the next subsection, we explain how to compute the associated downtime cost of a component in the power system. The optimality equation for this state of the component is given as

$$V_t(k+1) = \min\Bigg\{ C(NA) + DT_t + h_t\Big(V_{t+1}(k+1)\Big)$$

$$+ \Big(1 - h_t\Big)V_{t+1}(k+2), \;\; C(CM) + W_t(1)\Bigg\}, \quad (5.6)$$

where the first expression in the curly braces of equation (5.6) shows the total expected cost of taking no action, and the second expression represents the total expected cost of doing corrective maintenance on the component. The total expected cost of taking no action is composed of following elements: the expected cost of taking no action (which is zero) in period t, the expected downtime cost during period t, the total expected cost for periods $t+1, ..., N$, if the component is not affected by hurricane in period t, and the expected cost from decision epoch $t+1$ to the end if the component fails due to hurricane. The total expected cost of doing corrective maintenance is as follows: the expected cost of corrective maintenance operation in period t, the total expected cost for periods $t+1, ..., N$ if the hurricane does not occur or if it occurs but does not affect the component in period t, and the total expected cost for periods $t+1, ..., N$ if the component fails due to hurricane in period t.

Finally, when the component fails due to hurricane, i.e., $s_t = k+2$, there are two actions available: doing nothing (NA), and restoring the component to its functional state (RS). The optimality equation for this state is

$$V_t(k+2) = \min\left\{C(NA) + DT_t + V_{t+1}(k+2), C(RS) + W_t(1)\right\}. \tag{5.7}$$

By taking no action on restoration and postponing the action to the future, an expected downtime cost DT_t is incurred in period t. On the other hand, as shown in (5.7), if restoration operation is performed, an expected restoration cost in period t is incurred. The expected future cost of performing restoration action in this state is the same as the expected future cost of performing corrective maintenance, when the component is in the failure state.

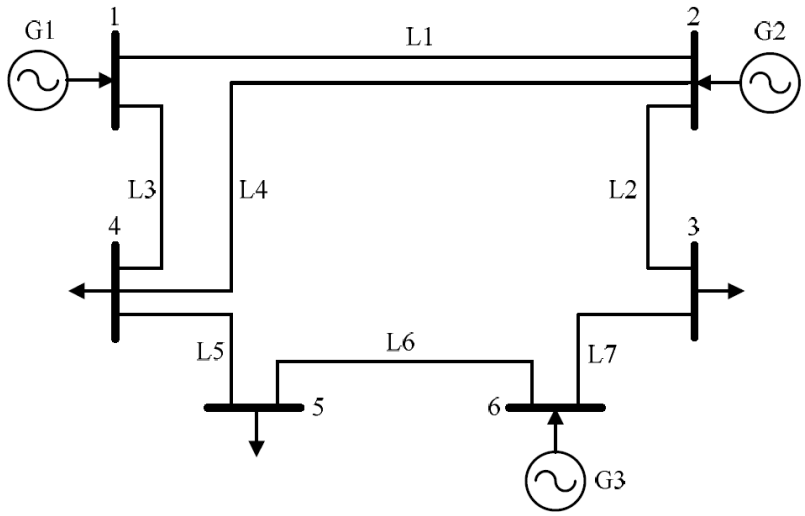

Figure 5.4 IEEE 6-bus system

5.3.3 Downtime Cost

When the component goes through downtime, it can affect the whole configuration of the electricity grid operation. For instance, as shown in Figure 5.4, if the transmission line which connects bus 2 to bus 3 goes offline, generator 2 will not be able to supply any portion of the load 1 in the system. Therefore, the generation unit commitment status along with power dispatch configuration of the grid will be affected. It can result in higher generation cost to supply the load. Furthermore, if the system is not able to supply the load, the load will be interrupted which results in incurring opportunity cost of load interruption. Therefore, the downtime cost, DT_t in a particular period t is considered to be the difference in the minimum system operation cost when the component is online and when it is offline. The minimum operation cost is obtained through following objective function

$$\min_{LI,P,I} \sum_t \sum_b VOLL_{bt} LI_{bt} + \sum_t \sum_i C_{it} P_{it} I_{it}, \tag{5.8}$$

where b is index for buses, C_{it} is the generation cost of unit i in period t, I_{it} is the commitment state of generating unit i at period t (1 if committed, otherwise 0), l is the index for transmission lines, LI_{bt} is the load interruption at bus b in period t, P_{it} is the power

generation of unit i in period t, and $VOLL_{bt}$ is the value of lost load at bus b in period t. The first term represents the total opportunity cost of load interruption, and the second term represents the generation cost of the system. This objective function is subject to following physical constraints which we borrow from Chapter 3 as

$$\sum_{i \in B_b} P_{it} + \sum_{l \in B_b} PL_{lt} + LI_{bt} = D_{bt}, \ \forall b, \tag{5.9}$$

$$P_i^{min} y_{it} I_{it} \leq P_{it} \leq P_i^{max} y_{it} I_{it}, \ \forall i, \tag{5.10}$$

$$-M \sum_b \alpha_{ib} z_{bt} \leq P_{it} \leq M \sum_b \alpha_{ib} z_{bt}, \ \forall i, \tag{5.11}$$

$$-PL_l^{max} w_{lt} \leq PL_{lt} \leq PL_l^{max} w_{lt}, \ \forall l, \tag{5.12}$$

$$-M \sum_b \beta_{lb}^{from} z_{bt} \leq PL_{lt} \leq M \sum_b \beta_{lb}^{from} z_{bt}, \ \forall l, \tag{5.13}$$

$$-M \sum_b |\beta_{lb}^{to}| z_{bt} \leq PL_{lt} \leq M \sum_b |\beta_{lb}^{to}| z_{bt}, \ \forall l, \text{ and} \tag{5.14}$$

$$\begin{aligned} &-M(1 - w_{lt}) - M(1 - \sum_b |\beta_{lb}| z_{bt}) \leq PL_{lt} - \\ &\qquad \frac{\sum_b \beta_{lb} \delta_{bt}}{x_l} \leq M(1 - w_{lt}) + M(1 - \sum_b |\beta_{lb}| z_{bt}), \ \forall l, \forall b, \end{aligned} \tag{5.15}$$

where B_b is set of components connected to bus b, D_{bt} is the electricity demand at bus b in period t, i is the index for generation units, M is a large positive constant, P_i^{max} is the maximum generation capacity of unit i, P_i^{min} is the minimum power generation capacity of unit i, PL_{lt} is the power flow of line l in period t, PL_l^{max} is the maximum power flow capacity of line l in period t, w_{lt} is the outage state of line l in period t (0 if offline, otherwise

1), y_{it} is the outage state of unit i in period t (0 if offline, otherwise 1), z_{bt} is the outage state of bus b in period t (0 if offline, otherwise 1), α_{ib} is the element of unit i and bus b in generation-bus incidence matrix, β_{lb} is the element of line l and bus b in line-bus incidence matrix, and δ_{bt} is the bus voltage angle.

Equation (5.9) represents the load balance equation, (5.10) models the power generation capacity, (5.11) models the impacts of outage state of associated buses to each generation unit's functional state, (5.12) shows the transmission line flow limits, (5.13) and (5.14) represent the impacts of outage state of connected buses to each transmission line's functional state, and (5.15) models the bus voltage angle constraint. Further details on these constraints can be found in Chapter 3.

5.3.4 Solution Method

The optimality equations are solved using backward induction algorithm which is described in Algorithm 5.1 [102]. The algorithm starts from last period and the optimal policy for all periods are sequentially constructed. The algorithm goes one period back to find the optimal policy when there is one period to go. Afterward, in the next iterations of algorithm, it continues going back one more period in order to find the optimal sequence of actions. This process is iterated until it reaches to the beginning of planning horizon. At this point, given the initial state of the system, the optimal sequential policy for the whole planning horizon is constructed.

5.4 Numerical Results and Analysis

The IEEE 6-bus system is considered to evaluate the effectiveness of the proposed model as shown in Figure 5.4. The system is composed of three generating units, six buses, and seven transmission lines. Line 1 which connects buses 1 and 2 is considered for

Algorithm 5.1 The Backward Induction algorithm [102]

Step 1: Set $n = T$ and $V_T(s_T) = r_T(s_T)$

Step 2: Set $n = n - 1$ and compute $V_t(s_t)$ for each $s_t \in S$

$$V_t(s_t) = \min_{a \in A_{s_t}} \left\{ r_t(s_t, a) + \sum_{j \in S} p_t(j|s_t, a) V_{t+1}(j) \right\}$$

$$\text{Set } A^*_{s_t,t} = \arg\min_{a \in A_{s_t}} \left\{ r_t(s_t, a) + \sum_{j \in S} p_t(j|s_t, a) V^*_{t+1}(j) \right\}$$

Step 3: If $n = 1$, stop. Otherwise, return to step 2.

preventive maintenance program. The value of lost load per MWh for bus 4 (commercial load) is considered as \$6,979, for bus 5 (industrial load) as \$3,706, and for the rest of the loads (residential loads) as \$110. The generation cost for generators 1, 2, and 3 are \$35.09, \$38.05, \$46.02 per MWh, respectively. The rest of the system setups are the same as the IEEE 6-bus system provided in [119]. The hourly load profile over the year has been aggregated into weekly load profile as shown in Figure 5.5.

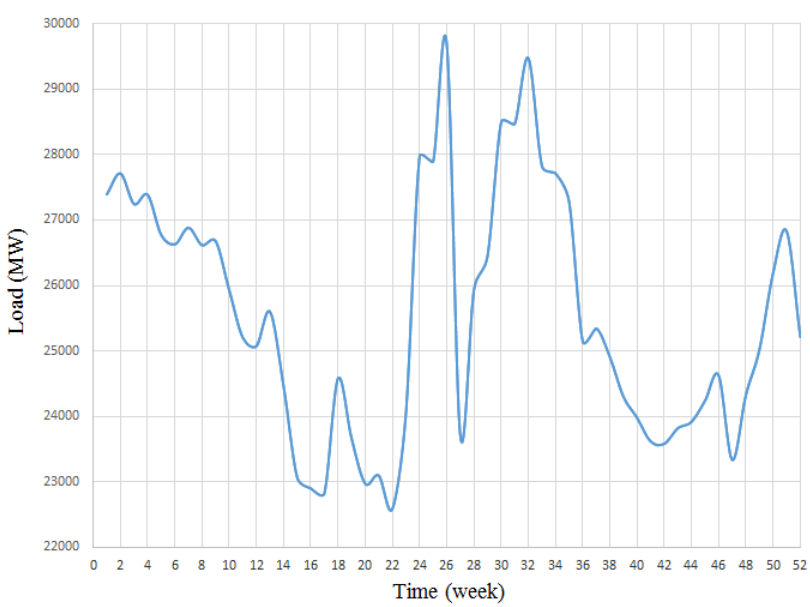

Figure 5.5 Aggregated load profile in a 52-week horizon for the IEEE 6-bus system

The transmission line 1 is considered to function in three different functional states (k=3). State 4 is considered as failure due to aging and deterioration, while state 5 is considered to be the failure due to hurricane damage. Based on hurricane data from 1800 through 2000 [57], the hurricane arrival rate λ_t for each week t from June through November are calculated as 0.027, 0.042, 0.1, 0.062, 0.25, 0.01. Based on maximum wind gust speed that the transmission line can withstand, the probability of survival from each hurricane is assumed to be 0.65. The transition probabilities are assumed as follows: $f_t(1)$ =0.005, $f_t(2)$ =0.01, $f_t(3)$ =0.015, $d_t(1)$ =0.01, $d_t(2)$ =0.02, and $d_t(3)$ =0.025. In addition, the maintenance costs are assumed as follows: $C(PM_1)$ =\$1,200, $C(PM_2)$ =\$1,200, $C(PM_3)$ =\$2,500, $C(CM)$ =\$7,000, and $C(RS)$ =\$12,000.

The MIP problem is solved to obtain the downtime cost of the transmission line 1 per week for 52 weeks. Once the transmission line goes offline, the load is not interrupted, but the generation cost increases. The annual system operation cost over the year if the transmission line 1 is operational is \$46,623,900; while, when it is offline, the annual system operation cost will increase to \$47,970,980. However, the cost difference in each week, i.e., the downtime cost varies based on load fluctuations over the planning horizon.

Incorporating the obtained downtime cost per week, the optimality equation is solved using the backward induction algorithm. The result is shown in the optimal policy lookup Table 5.1. As expected, when the component is in state 1, the optimal policy is always to take *no action*. When the component is in state 2, the optimal policy is to take no action from week 23 through week 40. However, the optimal policy for the remainder of the year is to perform *preventive maintenance* in order to bring the component into *as-good-as-new* condition. As intuitively expected, performing preventive maintenance actions during hurricane season does not have any economic value. When the component is in state 3, the optimal policy is always to perform preventive maintenance. In the case that the component is failed due to aging and deterioration, the optimal policy is to perform the *corrective maintenance* immediately. Similarly, when it is failed due to hurricane, the optimal policy

Table 5.1 Optimal maintenance decision lookup table

System State	Weeks 1-22	Weeks 23-40	Weeks 41-52
1	NA	NA	NA
2	PM	NA	PM
3	PM	PM	PM
4	CM	CM	CM
5	RS	RS	RS

is to *restore* it without any delay. As expected, regardless of the cause of failure, when the component is filed, it needs to be brought back to functional condition as soon as possible.

Table 5.2 presents the expected annual maintenance costs with and without preventive maintenance programs. We observe that the expected cost saving due to implementing the preventive maintenance program is the highest (39%), when the initial state of the component is 3. The expected annual maintenance costs by implementing the derived optimal schedule are as follows: \$10,317, \$11,517, \$12,817, \$17,317, and \$22,317 if the state of the component at the beginning of the year is 1, 2, 3, 4, and 5, respectively. If the preventive maintenance program is not implemented, and fire fighting corrective maintenance strategy in the case of failure is the only maintenance plan, the annual expected maintenance costs are as follows: \$10,317, \$14,447, \$17,881, \$17,950, and \$22,950, if the state of the component at the beginning of the year is 1, 2, 3, 4, and 5, respectively. Therefore, the expected cost saving due to implementing preventive maintenance program if the initial state of the component is 1, 2, 3, 4, and 5 is 0%, 25%, 39%, 3%, and 4%, respectively.

Table 5.2 Annual cost with and without preventive maintenance program

Initial State	Exp. Cost (No PM)	Exp. Cost (With PM)	Cost Saving
1	$10,317	$10,317	0%
2	$14,447	$11,517	25%
3	$17,881	$12,817	39%
4	$17,950	$17,317	3%
5	$22,950	$22,317	4%

5.5 Conclusions

A MDP model was developed to find the optimal maintenance policy of a component of power grid. Using MIP, the downtime cost per period was obtained. The hurricane effect probabilities were derived and incorporated in the model. The MDP problem was solved using the backward induction algorithm. The results show that the cost saving due to implementing the preventive maintenance program is significant. However, the amount saved depends on the state of the component at the beginning of the planning horizon. The proposed model can be used effectively for any major component of the power grid.

Chapter 6

Infrastructure Hardening and Condition-Based Maintenance Considering El Niño/La Niña Effects

Global climatological phenomena such as El Niño/La Niña can induce seasonality on hurricane arrival rates in long term. Effective asset management of electric power systems has a great impact on quality of services, and significantly contributes to reducing the total operation costs of the utilities. In this chapter, an integrated infrastructure hardening and condition-based maintenance model, considering long-term climatological effects of El Niño/La Niña on hurricane arrival is presented. The aim is to provide a comprehensive asset management strategy for power grid infrastructure located in hurricane prone areas.

6.1 Notation

The notation used for problem formulation is shown as follows.

Indices:

t	Index for time periods

Functions:

$I(\cdot)$	Indicator function
$N_t(\tau)$	Number of hurricane arrivals in period t
$V_t(\boldsymbol{\pi}, z)$	Minimum expected cost-to-go in state $(\boldsymbol{\pi}, z)$ at decision epoch t
$\Lambda(t)$	Cumulative intensity function of non-homogenous Poisson process at time t
$\Phi(\cdot)$	CDF of normal distribution

Parameters:

c	El Niño cycle length
C_a	Immediate cost of taking action a
DT_t^a	Downtime cost in period t due to action a
n	Number of time periods for which the hardening action will be effective
T	Length of planning horizon
β	Discount factor

λ_t	Hurricane arrival rate in period t
μ	Mean of a normal random variable
σ^2	Variance of a normal random variable
τ	Length of each period

Probabilities:

$F(\boldsymbol{\pi})$	Probability of failure in next period, given it is functional in current period
H_t^0	Hurricane survival probability in period t, if system is not in hardened state
H_t^1	Hurricane survival probability in period t, if system is in hardened state
p_{ij}	Transition probability from state i to state j
$R(\boldsymbol{\pi})$	Probability of survival in next period, given it is functional in current period
π_i	Probability that the system is in state i

States:

$\boldsymbol{e}_i$	Extreme state i
s	Original deterioration state
S	Original state space
S'	Partially observable state space
z	Infrastructure hardening state
$\boldsymbol{\pi}$	Information state
$\tilde{\boldsymbol{\pi}}(\boldsymbol{\pi})$	Information state in the next period, if it is currently in information state $\boldsymbol{\pi}$

Variables:

CM	Corrective maintenance
G	Wind gust speed random variable
G'	Random variable for strength of system, given it is not in hardened state
G''	Random variable for strength of system, given it is in hardened state
HH	Hardening against hurricane
IN	Inspection
NA	No action
PM	Preventive maintenance
RS	Restoration

6.2 Model Description

Consider a critical component of power system infrastructure located in a hurricane-prone area. From this point forward, this component of the infrastructure is alternatively called the *system*. The system is subject to breakdown due to two independent and competing random failure processes: failure as a result of maximum deterioration, and failure as a result of hurricane strikes. In addition to the failure risks, the system is subject to

progressive deterioration over time. As the system deteriorates over time, the probability of failure increases. Furthermore, the associated cost to bring the system to *as-good-as-new* condition increases. On the other hand, regardless of the deterioration condition of the system, when a hurricane strikes, it can result in failure of the system. However, the risk of a hurricane strike varies from one season to another, and from one year to another year due to periodic nature of the phenomenon, and long-term climatological effects of El Niño/La Niña on hurricane arrivals [57]. Therefore, the overall risk of failure of the system over the planning horizon is dynamically changing. In addition, the downtime cost of the system can be nonstationary due to variation of demand for electricity and generation cost over the planning horizon. The trade-off arises between the risk of failure and the associated expected downtime cost of the system, and the capital invested on asset management.

Using online data from the Supervisory Control and Data Acquisition (SCADA) system, the failure condition of the power system infrastructure can be detected. It is assumed that the failure due to hurricane strikes can be fully observed and distinguished from failure due to maximum deterioration. On the other hand, the deterioration level of the system can be *partially observed* from the probabilistic reliability function or condition monitoring systems, given the system is still in functional state. In order to fully observe the deterioration level of the system, inspections are required to be performed. However, frequent inspections of the system is neither practical, nor cost-effective. Therefore, a mixture of full and partial observations can be utilized for making maintenance and hardening decisions.

6.2.1 State Space

We consider a two-dimensional state (s, z) in order to describe the state of the system. The first element (s) represents the deterioration level of the system, while the second element (z) shows the hardening state of the system. When $s \in \{1, ..., k\}$, the system is functional. As s increases from 1 to k, the system deteriorates. That is, $s = 1$ indicates that

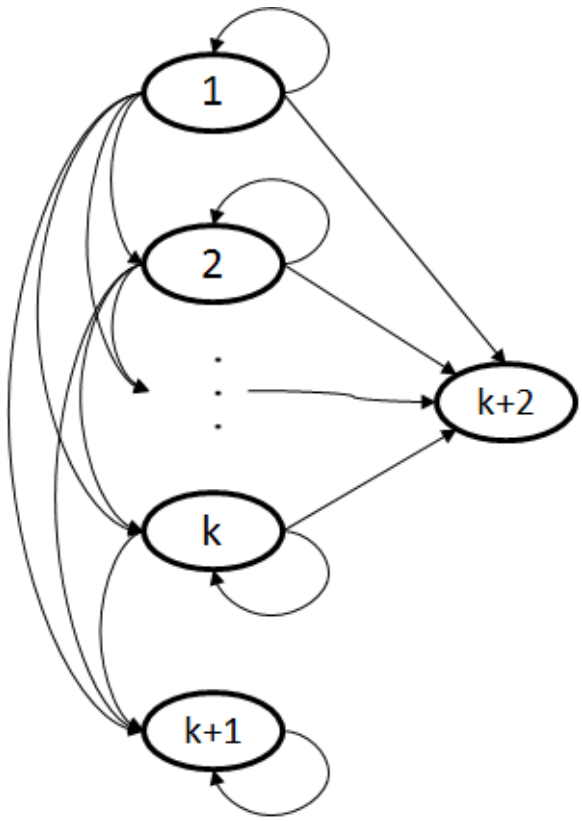

Figure 6.1 Original state transition diagram

the system is in the *as-good-as-new* condition, while $s = k$ indicates the most deteriorated functional state of the system. We also consider two *failure* modes (states) for the system: failure due to maximum deterioration, denoted by $s = k + 1$, and failure due to damage by hurricane, denoted as $s = k + 2$. Figure 6.1 shows the transition diagram for the first element of the state space.

The second element of the state of the system, i.e., z, is a nonnegative integer which represents the number of time periods that the system will be in the *hardened* state. z can be interpreted as a countdown timer for hardening measures that are of temporary nature. For instance, tree trimming as a hardening measure will be in effect for a few years and needs to be repeated after a certain period of time depending on geographical and other environmental factors. When the hardening measure is taken, immediately the hardening state for the system is brought to its maximum value n, i.e., the length of time interval

during which the hardening measure will be in effect. By passing each time period after last hardening, the value of z is reduced by one unit. When the effect of last hardening measure expires (which takes n time periods from last hardening), then we have $z = 0$. Regardless of deterioration level of the system as well as the hardening measures which are taken, the system can fail due to hurricane, if it cannot withstand the hurricane's wind forces.

Overall, the *original state space* of the system is defined as

$$S = \Big\{(s, z); s \in \{1, ..., k+2\}; z \in \{0, ..., n\}\Big\}. \tag{6.1}$$

Without a full observation, the exact deterioration state of a functional system cannot be known. On the other hand, in many cases such as power infrastructure, frequent inspection of the system is not practical. One approach to overcome this barrier is to incorporate the probability of being in a particular state at each decision epoch. To model this uncertainty, a probability distribution can be used to define the state of the system as the decision maker's belief about the underlying state of the system. To this end, the state of the system is defined as

$$(\boldsymbol{\pi}, z) = \Big([\pi_1, ..., \pi_k, \pi_{k+1}, \pi_{k+2}], z\Big), \tag{6.2}$$

where π_i is defined as the probability that the system is in state i with $i \in \{1, ..., k+2\}$, while $\boldsymbol{\pi}$ is known as *information state* in the literature [48]. The combination of the first element (information state) and the second element (hardening state) represents the state of the system. The state space under the POMDP, i.e., the *partially observable state space* is defined as

$$S' = \Bigg\{\Big([\pi_1, ..., \pi_k, \pi_{k+1}, \pi_{k+2}], z\Big);\ 0 \leq \pi_i \leq 1, \forall i;$$
$$\sum_{i=1}^{k+1} \pi_i = 1 \oplus \pi_{k+2} = 1; z \in \{0, ..., n\}, n \in \mathbb{N}_0; \Bigg\}, \tag{6.3}$$

where $\oplus$ is the logic operator for *exclusive or*, and $\mathbb{N}_0$ is the set of nonnegative integers.

If the state of the system is fully observable and known, i.e., an element of the information state is equal to 1, then the remaining elements of information state take the value of 0. This known state is called an *extreme state*, $\boldsymbol{e}_i$. For instance $\boldsymbol{e_1}$ indicates that the system is known to be in the *as-good-as-new* condition; or $\boldsymbol{e}_{k+1}$ indicates that the system is certainly in the state of failure due to deterioration.

When the system is functional, then $\sum_{i=1}^{k} \pi_i = 1$. When the system is nonfunctional, it is either in failure state due to deterioration ($\boldsymbol{\pi} = \boldsymbol{e}_{k+1}$), or in the failure state due to hurricanes ($\boldsymbol{\pi} = \boldsymbol{e}_{k+2}$). Since both the failure states are fully observable, there are no probabilities associated with them in the partially observable state space when the system is functioning. Our policy is to immediately perform the *corrective maintenance* when the system fails due to deterioration, and immediately perform *restoration* when it fails due to hurricanes. Therefore, when the system is functional, we always have $\pi_{k+1} = 0$ and $\pi_{k+2} = 0$.

6.2.2 Hurricane Survival Modeling

The strength of power structures and the stress of wind gusts in hurricane strikes can be modeled by the lognormal distribution [2, 120]. Consider that the wind gust speed is a random variable distributed as $G \sim LogNor(\mu_G, \sigma_G^2)$. The maximum wind gust speed that the system can withstand is a random variable distributed as $G' \sim LogNor(\mu_{G'}, \sigma_{G'}^2)$ when the system is not in the hardened state ($z = 0$); and $G'' \sim LogNor(\mu_{G''}, \sigma_{G''}^2)$ when the system is in hardened state ($z > 0$). The following definition and assumptions are needed for continuing the discussion.

Definition 1: Suppose X and Y are normally distributed. If X has a smaller variance, or greater mean than Y, then random variable X *second order stochastically dominates (SSD)* random variable Y, denoted as $X \succeq_{SSD} Y$ [121].

Assumption 1: When the system is in hardened state, then the mean of its strength against wind stress is higher than when it is in non-hardened state ($\mu_{G''} > \mu_{G'}$).

Assumption 2: After hardening the system, the variance of strength does not increase ($\sigma^2_{G''} \leq \sigma^2_{G'}$).

Proposition 1: Random variable G'' second order stochastically dominates (SSD) random variable G', denoted as $G'' \succeq_{SSD} G'$.

Proof: As both G' and G'' are lognormally distributed, considering Assumptions 1 and 2, the relationship between corresponding means and between corresponding variances of normally distributed random variables $\ln(G')$ and $\ln(G'')$ still holds. Since, $\ln(G'') \succeq_{SSD} \ln(G')$, then $G'' \succeq_{SSD} G'$. ■

Assumption 3: Arrival of any two hurricane strikes and their associated wind gust speeds are considered to be independent from each other.

Using a dynamic stress-strength model which both stress (i.e., the wind gust speed) and strength (i.e., the maximum wind gust speed that the system can withstand) are random variables, the probability that the system is not affected by hurricane strikes during period t, i.e., from decision epoch t until decision epoch $t+1$ is modeled as

$$H_t^0 = \sum_{m=0}^{\infty} P\Big\{G_1 < G_1', G_2 < G_2', ..., G_{N_t(\tau)} < G'_{N_t(\tau)}, \, |N_t(\tau) = m\Big\} P\Big(N_t(\tau) = m\Big)$$

$$= \sum_{m=0}^{\infty} \Big[P\Big(G < G'\Big)\Big]^m P\Big(N_t(\tau) = m\Big), \quad (6.4)$$

where H_t^0 is the probability of survival in non-hardened state, and $N_t(\tau)$ is the number of hurricane strikes in period t. The annual seasonal pattern and long-term periodic behavior of hurricane arrivals considering El Niño/La Niña effects need to be addressed using an appropriate model. Therefore, the probability of hurricane arrivals from the beginning of planning horizon until time $t' = \tau t$ can be modeled using a nonhomogeneous Poisson (NHP) process as

$$P\Big(N(t^{'}) = m^{'}\Big) = \frac{\exp\Big(-\Lambda(t^{'})\Big)\Big(\Lambda(t^{'})\Big)^{m^{'}}}{m^{'}!}, \tag{6.5}$$

where $\Lambda(t^{'})$ is the cumulative intensity function for the NHP process. In [57], $\Lambda(t^{'})$ was derived for a double-beta periodic intensity model to describe the effects of El Niño/La Niña on hurricane arrivals. By replacing $N_t(\tau)$ with $N(t^{'})$ in (6.4) the reliability function of the system against hurricane considering El Niño/La Niña is obtained. However, this approach is useful for risk analysis of a power system component, when memoryless property is not desired. Another alternative approach is to directly use the average hurricane arrival rate in each period t within the long-term El Niño/La Niña cycle $c \gg t$, i.e., λ_t and use a homogenous Poisson process to model the hurricane arrival rate during each long-term El Niño/La Niña cycle in a piecewise manner. In the latter approach, the survival probability of system against hurricane is independent from previous periods; hence, the memoryless property for transition probabilities to failure state due to hurricane holds.

We can write

$$P\Big(G < G^{'}\Big) = P\Big(\frac{G}{G^{'}} < 1\Big) = P\Big(\ln(G) - \ln(G^{'}) < 0\Big), \tag{6.6}$$

where $\ln(G) \sim N(\mu_G, \sigma_G^2)$ and $\ln(G^{'}) \sim N(\mu_{G^{'}}, \sigma_{G^{'}}^2)$. By standardizing these random variables, and plugging the Poisson probability mass function in the hurricane survival function (6.4), we have

$$H_t^0 = \sum_{m=0}^{\infty}\left[\Phi\left(\frac{\mu_{G^{'}} - \mu_G}{\sqrt{{\sigma_G}^2 + {\sigma_{G^{'}}}^2}}\right)\right]^m \frac{\exp\Big(-\tau\lambda_t\Big)\Big(\lambda_t\tau\Big)^m}{m!}, \tag{6.7}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the normal distribution. Using the following geometric series

$$\sum_{q=0}^{\infty}\frac{r^q}{q!} = \exp(r), \tag{6.8}$$

we obtain

$$H_t^0 = \exp\left[\tau\lambda_t\left(\Phi\Big(\frac{\mu_{G'} - \mu_G}{\sqrt{{\sigma_G}^2 + {\sigma_{G'}}^2}}\Big) - 1\right)\right]. \tag{6.9}$$

This function computes the probability of not being affected by hurricanes in period t given the system is not in hardened state ($z = 0$). In the same manner, the probability of survival of the system in period t when it is in hardened state ($z > 0$), denoted as H_t^1 is modeled by replacing $\mu_{G'}$ and $\sigma^2_{G'}$ with $\mu_{G''}$ and $\sigma^2_{G''}$, respectively. Therefore, the transition probability of failure due to hurricanes in period t, depending on the hardening state of the system which can be either $z = 0$, or $z > 0$ is obtained as $1 - H_t^0$, or $1 - H_t^1$, respectively.

6.2.3 Transition Probabilities

First, suppose that the system is currently functional with information state $\boldsymbol{\pi}$. The probability that the system will survive until the next decision epoch, given there is no hurricane effect, is referred as the *conditional reliability* function, $R(\boldsymbol{\pi})$. This function is defined as

$$R(\boldsymbol{\pi}) = \sum_{i=1}^{k}\sum_{j=1}^{k} \pi_i p_{ij}, \tag{6.10}$$

where p_{ij} is the transition probability from state i to state j in the original state space S, and $\sum_{j=1}^{k+1} p_{ij} = 1, \forall i \in \{1, ..., k+1\}$. As shown by [49], based on the law of conditional probability, the information state at the beginning of the next decision epoch, given the system will be still functional, is

$$\tilde{\pi}_j(\boldsymbol{\pi}) = \begin{cases} \frac{\sum_{i=1}^{k} \pi_i p_{ij}}{R(\boldsymbol{\pi})}, & j = 1, ..., k, \\ 0, & \text{otherwise.} \end{cases} \tag{6.11}$$

Therefore, the system makes a transition to the next information state with probability $R(\boldsymbol{\pi})$ as

$$\tilde{\boldsymbol{\pi}}(\boldsymbol{\pi}) = \left\{\Big[\tilde{\pi}_1(\boldsymbol{\pi}), \tilde{\pi}_2(\boldsymbol{\pi}), ..., \tilde{\pi}_k(\boldsymbol{\pi}), 0, 0\Big]; 0 \leq \tilde{\pi}_i(\boldsymbol{\pi}) \leq 1, \quad \forall i = 1, ..., k\right\}. \tag{6.12}$$

If the current information state is $\boldsymbol{\pi}$, the probability that the system fails due to deterioration (if there is no hurricane effect) is obtained by

$$F(\boldsymbol{\pi}) = \sum_{i=1}^{k} \pi_i p_{i,k+1} = 1 - R(\boldsymbol{\pi}). \tag{6.13}$$

Therefore, given the system is not affected by hurricane, with probability $F(\boldsymbol{\pi})$ it makes a transition to the *extreme* state $\boldsymbol{e}_{k+1}$.

Regardless of the deterioration state of the system, it can be damaged by hurricane strikes. As derived in the previous subsection, in each period t, depending on the hardening state of the system, i.e., either $z = 0$ or $z > 0$, the functional state of the system makes a transition to the *extreme* state $\boldsymbol{e}_{k+2}$ with probabilities $1 - H_t^0$ or $1 - H_t^1$, respectively.

Recall that the second element of the state of the system (the hardening state) is used as a counter which shows the number of remaining time periods that the hardening action will be in effect. Therefore, if $z = u$ at decision epoch t, then regardless of the information state, with probability one, z makes a transition to $z^{'} = \max(0, u-1)$ denoted by $(u-1)^+$ at decision epoch $t+1$.

6.2.4 Action Space

The following actions constitute the action space at each decision epoch:

- No action (NA);
- Inspection (IN);
- Preventive maintenance (PM);
- Corrective maintenance (CM);
- Restoration (RS);
- Hardening (HH).

When the system is functional, two actions are always available at each decision epoch: *no action* (NA) and *inspection* (IN). When the inspection action is taken, the exact functional state of the system is revealed. Subsequently, following each inspection, the decision maker can choose to either take *no action*, or to perform a *preventive maintenance* (PM_i) based on the condition of the system (i.e., the revealed deterioration level i), denoted by the extreme information state $\boldsymbol{e}_i$. By performing the preventive maintenance, the reliability of the system is fully restored and the system is brought back to the *as-good-as-new* condition. The immediate cost of preventive maintenance increases in deterioration state of the system, i.e., $C_{PM_k} > C_{PM_{k-1}} > ... > C_{PM_1}$. Obviously, zero cost is associated with NA and C_{PM_1} actions. Therefore, a sub-action space when it is revealed by *inspection* that the system is in deterioration state i, is represented by $\{NA, PM_i\}$ where $i \in \{1, ..., k\}$.

Due to the high cost of outage and its consequences in system-level reliability of the grid, once the system goes to failure state $\boldsymbol{e}_{k+1}$, we immediately perform *corrective maintenance*, denoted by CM, at an immediate cost of C_{CM}. Likewise, when the system fails due to hurricane damage, we instantaneously restore the system by taking *restoration* action, denoted by RS. The cost associated with the restoration is C_{RS}, where $C_{RS} \geq C_{CM} > C_{PM_k}$. Furthermore, in order to quantify the changing downtime cost which is associated with the breakdown of the system during different periods of the year, a separate downtime cost which is a function of time can be considered for the system.

Finally, in each decision epoch there is another type of action available, i.e., *hardening* action (HH), at a cost of C_{HH} to strengthen the system against upcoming hurricanes. This action does not fully eliminate the damage risk due to hurricane strikes, but significantly reduces the risk of such damages. The hardening strategy and its subsequent effects varies depending on infrastructure and its geographical location. These strategies include but are not limited to vegetation management, undergrounding of distribution and transmission lines, distributed generation, and modernization of the smart grid [122]. Two types of effects, i.e., *temporary* and *permanent* effects can be perceived for the hardening strat-

egy. For instance, vegetation trimming considering the growing nature of the trees from one side, and environmental protection and regulatory issues from the other side will be in effect for a certain period of time. Therefore, such a hardening action with *temporary* effects has to be scheduled and repeated in specific time intervals [122]. On the other hand, engineering solutions such as undergrounding of transmission lines, or installation of spacer cables and Cutout-Mounted Reclosers [123] result in *permanent* effects during the life-cycle of the infrastructure.

6.3 Problem Formulation and Methodology

6.3.1 Problem Formulation

The problem is formulated as a finite horizon POMDP. To construct the optimality equation, first the expected cost of each action needs to be specified. The optimality equation for the proposed model is constructed as

$$V_t(\boldsymbol{\pi}, z) = \begin{cases} CM_t(\boldsymbol{e}_{k+1}, z), & \boldsymbol{\pi} = \boldsymbol{e}_{k+1}, \\ RS_t(\boldsymbol{e}_{k+2}, z), & \boldsymbol{\pi} = \boldsymbol{e}_{k+2}, \\ \min\Big\{NA_t(\boldsymbol{\pi}, z), & \\ \qquad IN_t(\boldsymbol{\pi}, z), HH_t(\boldsymbol{\pi}, z)\Big\}, & \text{otherwise}, \end{cases} \tag{6.14}$$

where $V_t(\boldsymbol{\pi}, z)$ is the minimum total expected cost-to-go when the system is in information state $\boldsymbol{\pi}$ and hardening state z at decision epoch t. As shown, when the system is in the fully observable information states, i.e., the *failure* due to hurricane ($\boldsymbol{e}_{k+1}$), or *failure* due to aging and degradation ($\boldsymbol{e}_{k+2}$), the corresponding actions are immediately taken to bring the system back to the *as-good-as-new* condition. When the system is functional, the most cost-effective action among NA, IN, and HH needs to be taken in that decision epoch.

When *no action* is taken at decision epoch t, given the state of the system is $(\boldsymbol{\pi}, z)$ the expected cost-to-go can be written as

$$NA_t(\boldsymbol{\pi}, z) = W_t(\boldsymbol{\pi}, z), \tag{6.15}$$

where

$$\begin{aligned} W_t(\boldsymbol{\pi}, z) = &\left[H_t^1 I(z > 0) + H_t^0 I(z = 0)\right] \\ &\beta\left[R(\boldsymbol{\pi})V_{t+1}\Big(\tilde{\boldsymbol{\pi}}(\boldsymbol{\pi}), (z-1)^+\Big) + F(\boldsymbol{\pi})V_{t+1}\Big(\boldsymbol{e}_{k+1}, (z-1)^+\Big)\right] \\ &+ \left[1 - \Big(H_t^1 I(z > 0) + H_t^0 I(z = 0)\Big)\right]\beta V_{t+1}\Big(\boldsymbol{e}_{k+2}, (z-1)^+\Big), \end{aligned} \tag{6.16}$$

where $(z-1)^+$ is the positive part of $(z-1)$ defined as $f(x)^+ = \max(f(x), 0)$, and $I(\cdot)$ is the indicator function. The first term in (6.16) represents the total expected cost in period t if the system is not affected by hurricanes. It considers two possible outcomes which can result either in continuing the functionality of the system until period $t+1$, or system failure due to deterioration. The second term in (6.16) presents the expected cost in period t if the system fails due to hurricane. We assume that the failure due to hurricane overrides any other states of the system, and takes the information state into $\boldsymbol{e}_{k+2}$.

If the *hardening* measures are taken, they do not guarantee that the system will survive against hurricane, but significantly reduce the chance of failure if the hurricane strikes. The expected cost-to-go by taking the *hardening* action is obtained by

$$\begin{aligned} HH_t(\boldsymbol{\pi}, z) = C_{HH} + H_t^1\beta\left[R(\boldsymbol{\pi})V_{t+1}\Big(\tilde{\boldsymbol{\pi}}(\boldsymbol{\pi}), n-1\Big) + F(\boldsymbol{\pi})V_{t+1}(\boldsymbol{e}_{k+1}, n-1)\right] \\ + (1 - H_t^1)\beta V_{t+1}(\boldsymbol{e}_{k+2}, n-1), \end{aligned} \tag{6.17}$$

where n is the number of periods that hardening will be in effect. By taking the *hardening* action, an immediate cost of C_{HH} is incurred and the system continues to evolve. Since

hardening is performed discrete from the system, we do not consider a downtime cost associated with this action. As shown in the second and third terms of (6.17), by hardening the system, the hurricane survival probability in period t immediately increases to H_t^1, so the risk of being affected by hurricane is reduced. By taking this action in decision epoch t, the hardening state of the system instantaneously makes a transition to n with probability 1.

Once the system fails due to the hurricane, the *restoration* action must be taken immediately. The expected cost-to-go associated with the *restoration* action is given by

$$RS_t(\boldsymbol{e}_{k+2}, z) = C_{RS} + DT_t^{RS} + W_t(\boldsymbol{e}_1, z). \tag{6.18}$$

By restoration, the system is brought to the *as-good-as-new* condition. As shown in (6.18) by taking the *restoration* action, the restoration cost as well as downtime cost are immediately incurred to the system. In addition, $W_t(\boldsymbol{e}_1, z)$ which represents the expected cost-to-go based on the evolution of a renewed system at decision epoch t is incurred. In our model, without loss of generality, we assume that renewing the system by taking the *restoration* action does not have any impact on the *hardening* state of the system.

When the system fails due to deterioration, it needs to be repaired immediately. The *corrective maintenance* action is taken to bring the system to the *as-good-as-new* condition. The expected cost-to-go when the *corrective maintenance* action is taken is modeled as

$$CM_t(\boldsymbol{e}_{k+1}, z) = C_{CM} + DT_t^{CM} + W_t(\boldsymbol{e}_1, z), \tag{6.19}$$

where the first term is the corrective maintenance cost, and the second term is the downtime cost. Similar to (6.18), the third term in (6.19) represents the expected cost-to-go from period t for a system in an *as-good-as-new* condition.

With transition probabilities, the deterioration level of a functional system can be partially observable. The only way to reveal the exact deterioration state of a functional system is to perform the *inspection* action. However, inspection of the system at each

decision epoch is not cost-effective. Therefore, a sound decision about inspection of the system is required to be made. After inspection, with respect to the condition of the system, a proper decision regarding preventive maintenance action can be made. Therefore, the expected cost-to-go associated with taking the inspection action is obtained as

$$IN_t(\boldsymbol{\pi}, z) = C_{IN} + \sum_{i=1}^{k} ACT_t(\boldsymbol{e}_i, z)\pi_i, \tag{6.20}$$

where

$$ACT_t(\boldsymbol{e}_i, z) = \min\Big\{NA_t(\boldsymbol{e}_i, z),\ PM_t(\boldsymbol{e}_i, z)\Big\}, \tag{6.21}$$

where C_{IN} is the immediate inspection cost, and $PM_t(\boldsymbol{e}_i, z)$ is the expected cost-to-go of the corresponding *preventive maintenance* action. As a result of preventive maintenance, the system is returned to the *as-good-as-new* condition. The expected cost-to-go is given by

$$PM_t(\boldsymbol{e}_i, z) = C_{PM_i} + DT_t^{PM_i} + W_t(\boldsymbol{e}_1, z). \tag{6.22}$$

The proposed formulation is a generic model for systems in which the hardening action has *temporary* effects. A special case of this generic formulation can describe the systems in which the hardening action has *permanent* effects during the life-cycle of the system. To do so, simply the value for n needs to be chosen sufficiently large, i.e., $n \geq T$.

6.3.2 Solution Method

The optimality equations are solved using the backward induction algorithm [102]. The algorithm starts from the last period and the optimal policy for all periods are sequentially constructed. In order to use backward induction to solve for optimal policy in the proposed POMDP model, we approximate the sample path denoted by Ω as *a priori*. The sample path is defined as a sequence of information states evolving over time by taking *no*

action [49]. To this end, we need to construct a sample path from the initial belief state $\boldsymbol{\pi^0}$. Furthermore, the sample path that starts from each functional extreme information state needs to be constructed. Therefore, using (6.11), we construct $k+1$ sample paths denoted by $\Omega_{\boldsymbol{\pi}^0}$, $\Omega_{\boldsymbol{e}_1}$, ..., $\Omega_{\boldsymbol{e}_k}$. As explained earlier, due to a high cost of outage, our policy is to immediately perform *corrective maintenance* once the systems goes to *failure* state due to deterioration, and *restore* once it goes to *failure* state due to hurricanes. Therefore, once the system goes into the extreme states $\boldsymbol{e}_{k+1}$ or $\boldsymbol{e}_{k+2}$, it will not evolve by taking no action. However, since based on our policy the system is immediately brought back to the *as-good-as-new* condition in such circumstances, the system evolves on the sample path $\Omega_{\boldsymbol{e}_1}$. Hence, there is no need to construct the sample paths $\Omega_{\boldsymbol{e}_{k+1}}$ and $\Omega_{\boldsymbol{e}_{k+2}}$.

In order to construct a sample path from a starter information state, e.g., $\boldsymbol{\pi}$, using (6.11) we obtain the first element (i.e., an information state) of the sample path by $\tilde{\boldsymbol{\pi}}^{\boldsymbol{1}} = \tilde{\boldsymbol{\pi}}(\boldsymbol{\pi})$, and the second element by $\tilde{\boldsymbol{\pi}}^{\boldsymbol{2}} = \tilde{\boldsymbol{\pi}}(\tilde{\boldsymbol{\pi}}(\boldsymbol{\pi}))$, and so forth. A sample path $\Omega_{\boldsymbol{\pi}}$ emanating from $\boldsymbol{\pi}$ is defined as $\{\tilde{\boldsymbol{\pi}}^{\boldsymbol{1}}, \tilde{\boldsymbol{\pi}}^{\boldsymbol{2}}, ..., \tilde{\boldsymbol{\pi}}^{\boldsymbol{L}}\}$, where $L \equiv \min\{l : \|\tilde{\boldsymbol{\pi}}^{\boldsymbol{l}}(\boldsymbol{\pi}) - \tilde{\boldsymbol{\pi}}^{\boldsymbol{l-1}}(\boldsymbol{\pi})\| \leq \varepsilon\}$. The last information state in the sample path, i.e., $\tilde{\boldsymbol{\pi}}^{\boldsymbol{L}}$ is an *absorbing state* in which from this point forward the deterioration of the system shows a stationary behavior [47, 49]. As it is proven in [124], as long as the discrete time Markov chain is acyclic, there exists L for any $\varepsilon > 0$. By constructing the described sample paths for $\Pi = \{\boldsymbol{\pi^0}, \boldsymbol{e}_1, ..., \boldsymbol{e}_k\}$, the set $\Psi(\Pi) = \bigcup_{\boldsymbol{\pi} \in \Pi} \Omega_{\boldsymbol{\pi}}$ includes all of the information states that the system can reach in its evolution. Therefore, without compromising the accuracy, the solution space is significantly reduced which results in higher computational efficiency of the POMDP solution algorithm.

Algorithm 6.1 The POMDP solution algorithm

Step 1. Select an unchosen $\boldsymbol{\pi}' \in \Pi = \{\boldsymbol{\pi}^{\mathbf{0}}, \boldsymbol{e}_1, ..., \boldsymbol{e}_k\}$;
Set $|\Pi| = |\Pi| - 1$.

Step 2. Set $\boldsymbol{\pi} = \boldsymbol{\pi}'$; and $l = 1$.

Step 3. Compute $R(\boldsymbol{\pi})$ and $F(\boldsymbol{\pi})$ using (6.10) and (6.13).

Step 4. Generate the new information state $\tilde{\boldsymbol{\pi}}^{\boldsymbol{l}}(\boldsymbol{\pi})$ using (6.11).

Step 5. Set $\boldsymbol{\pi} = \tilde{\boldsymbol{\pi}}^{\boldsymbol{l}}(\boldsymbol{\pi})$; and $l = l + 1$.

Step 6. If $\|\tilde{\boldsymbol{\pi}}^{\boldsymbol{l}}(\boldsymbol{\pi}) - \tilde{\boldsymbol{\pi}}^{\boldsymbol{l-1}}(\boldsymbol{\pi})\| \leq \varepsilon$ stop; Otherwise, return to step 3.

Step 7. Generate sample path $\Omega_{\boldsymbol{\pi}}$.

Step 8. If $|\Pi| > 0$, return to step 1.

Step 9. Set $\Psi(\Pi) = \bigcup_{\boldsymbol{\pi} \in \Pi} \Omega_{\boldsymbol{\pi}}$.

Step 10. Set $t = T$;
Set $V_T(\boldsymbol{\pi}, z) = 0, \forall \boldsymbol{\pi} \in \Psi(\Pi), \forall z \in \{0, ..., n\}$.

Step 11. Set $t = t - 1$;
Compute H_t^0 and H_t^1 using (6.9);
Using (6.14) compute $V_t(\boldsymbol{\pi}, z), \forall \boldsymbol{\pi} \in \Psi(\Pi), \forall z \in \{0, ..., n\}$;
Set optimal policy $A_t^*(\boldsymbol{\pi}, z) = \arg\min V_t(\boldsymbol{\pi}, z)$.

Step 12. If $t = 1$, stop; Otherwise, return to step 11.

Algorithm 6.1 shows the steps of the POMDP solution algorithm. As shown, the initial belief state and the extreme states play a central role in constructing the reduced information state space of the system. Cardinality of set Π is denoted by $|\Pi|$ in the algorithm. Steps 1 to 8 construct the sample paths emanating from each information state member of the set Π. These steps are iterated until the corresponding sample paths emanating from every and each member of the set Π are obtained. Note that in step 6, the Euclidean norm of the difference of two consecutive information states emanated from a information state

$\boldsymbol{\pi}$ is computed and compared with the small value ε. When this norm becomes smaller than ε, the associated sample path $\Omega_{\boldsymbol{\pi}}$ reaches to its steady state behavior and no longer evolves. In step 9, the reduced information state space of the system, i.e., $\Psi(\Pi)$ is formed, where $\Psi(\Pi) \subset S'$. Step 10 incorporates the terminal values of the system at the end of planning horizon at decision epoch T. We assume that at the end of planning horizon the system is overhauled regardless of its condition. Therefore, without loss of generality, the terminal values for all states are assumed as $r_T(\pi, z) = 0$.

Step 11 computes the minimum expected cost-to-go and finds the optimal policies in a backward manner. This step is iterated until the optimal actions for all decision epochs in the entire planning horizon are obtained. As explained, an MDP equivalent of the POMDP problem with reduced state space is solved to find the optimal solution for the proposed model. This approach enables one to solve a non-stationary problem for an exact solution. This conversion of the POMDP to its MDP equivalent results in inflation of the problem size. However, this inflation has already been minimized through steps 1 to 9 as earlier explained. As shown, a considerable number of states and associated computations are eliminated without significant compromise on the accuracy of the model.

6.4 Numerical Analysis

In this section, we analyze a standard oil-filled transformer in order to illustrate the application and effectiveness of the proposed model. Dissolved Gas-in-Oil Analysis (DGA) is widely used in power industry as a useful diagnostic tool for evaluating the health condition of transformers. Measurement of certain gases generated in an oil-filled transformer in operation is a reliable indicator of an existing malfunction that may result in failure, if not corrected. The failure mechanisms include severe overloading, pump motor failure, arcing, partial discharge, and low-energy sparking, among others. These failure mechanisms

which can occur singly or simultaneously, decompose the insulating materials and form variety of combustible and noncombustible gases. Normal operation of a transformer can also result in the formation of various gases [125]. As shown in Table 6.1, based on key gas concentration limits, a four-level criterion was developed in [125] to identify the deterioration level of a transformer (TDCG in the Table 6.1 stands for Total Dissolved Combustible Gas). Deterioration level 1 represents *as-good-as-new*, while deterioration level 4 represents *failure* or near failure condition. Deterioration levels 2 and 3 represent the system with *minor* and *major* deteriorations, respectively.

For our analysis, we use data from [126]. In their study, the same deterioration levels and key gas concentration limits as [125] are considered, while condition 4 is considered to be a *failure* due to deterioration. By analyzing the historical data from condition monitoring of multiple transformers of the same type and manufacturer, they estimated the weekly transition probability matrix as

$$\mathbf{P_w} = \begin{bmatrix} 0.9917 & 0.0083 & 0.0000 & 0.0000 \\ 0 & 0.9936 & 0.0064 & 0.0000 \\ 0 & 0 & 0.9891 & 0.0109 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{6.23}$$

Since the length of each period in our model is $\tau = 1$ month, we need to use a monthly transition probability in our analysis. Without loss of generality, we assume each month to be exactly four weeks. Therefore, the following 4-period (monthly) transition probability matrix for the underlying discrete-time Markov chain is used in our analysis:

$$\mathbf{P_m} = \begin{bmatrix} 0.9672 & 0.0325 & 0.0003 & 0.0000 \\ 0 & 0.9746 & 0.0249 & 0.0005 \\ 0 & 0 & 0.9571 & 0.0429 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{6.24}$$

where $\mathbf{P_m} = \mathbf{P_w^4}$.

Table 6.1 Dissolved key gas concentration limits $(\mu L/L(ppm))$

Key Gas	Hydrogen (H_2)	Methane (CH_4)	Acetylene (C_2H_2)	Ethylene (C_2H_4)	Ethane (C_2H_4)	Carbon monoxide (CO)	Carbon dioxide (CO_2)	TDCG
Deterioration level 1	$<$100	$<$120	$<$35	$<$50	$<$65	$<$350	$<$2500	$<$720
Deterioration level 2	101-700	121-400	36-50	51-100	66-100	351-570	2500-4000	721-1920
Deterioration level 3	701-1800	401-1000	51-80	101-200	101-150	571-1400	4001-10000	1921-4630
Deterioration level 4	$>$1800	$>$100	$>$80	$>$200	$>$150	$>$1400	$>$10000	$>$4630

In order to consider the long-term climatological effects of El Niño/La Niña, the problem needs to be solved for at least one long-term El Niño/La Niña cycle. From [57], we consider this cycle as c =5 years. From the same study, we use the mean number of hurricane arrivals for each month t, denoted as λ_t during each El Niño/La Niña cycle for the Atlantic hurricanes, estimated from a data set of 102 years. On the other hand, the planning horizon needs to be long enough to study the economic impacts of capital expenditures on engineering solutions for the hardening strategy with *permanent* effects. Based on these considerations, we solve the problem for planning horizon of T =120 months, i.e., for two consecutive El Niño/La Niña cycles. We also assume that the planning horizon starts at the beginning of the first El Niño/La Niña cycle.

The discount factor is assumed as β =0.99, and the threshold value for the Euclidean norm as ε =0.01. From [126], the inspection cost is considered as C_{IN} =\$100, the minor maintenance cost as C_{PM_2} =\$1,000, the major maintenance cost as C_{PM_3} =\$10,000, and the corrective maintenance cost as C_{CM} =\$100,000. We set the restoration cost to C_{RS} =\$100,000 (same as corrective maintenance cost). The minor maintenance is done online, while the major maintenance is performed offline [126]. Therefore, the downtime cost for minor maintenance is $DT_t^{PM_2}$ =0. In [126], the downtime costs for major maintenance and also corrective maintenance have been aggregated into the corresponding maintenance cost. From [120], the mean of the logarithm of wind gust speed and its standard deviation are considered as μ_G =3.85 and σ_G =0.427, respectively. The parameters associated with hurricane hardening actions varies based on geographical location, and structural characteristics of the infrastructure in question. Without loss of generality, we assume the following parameters for our analysis: the cost of hurricane hardening action with *temporary* effects is assumed as \$3,000, and the number of time periods that it will be in effect is assumed to be n =24 months; the cost of hurricane hardening action with *permanent* effects is assumed to be \$20,000; the mean of the logarithm of structure's strength and its standard deviation *without* hardening are $\mu_{G'}$ =4.7 and $\sigma_{G'}$ =0.1, respectively; the mean

Table 6.2 Parameter values for numerical analysis

Parameter	Value	Source
β	0.99	Assumption
ε	0.01	Assumption
C_{IN}	\$100	[126]
C_{PM_2}	\$1,000	[126]
C_{PM_3}	\$10,000	[126]
C_{CM}	\$100,000	[126]
C_{RS}	\$100,000	Assumption
C_{HH} (temporary)	\$3,000	Assumption
C_{HH} (permanent)	\$20,000	Assumption
$DT_t^{PM_2}$	0	[126]
$DT_t^{PM_3}$	Aggregated	[126]
DT_t^{CM}	Aggregated	[126]
DT_t^{RS}	Aggregated	Assumption
μ_G	3.85	[120]
σ_G	0.427	[120]
$\mu_{G'}$	4.70	Assumption
$\sigma_{G'}$	0.1	Assumption
$\mu_{G''}$ (temporary)	4.90	Assumption
$\sigma_{G''}$ (temporary)	0.1	Assumption
$\mu_{G''}$ (permanent)	5.00	Assumption
$\sigma_{G''}$ (permanent)	0.1	Assumption
λ_t (constant)	1.64	[57]
λ_t (variable)	Varying	[57]

of the logarithm of structure's strength and its standard deviation *with temporary* hardening effects are $\mu_{G''}$ =4.9 and $\sigma_{G''}$ =0.1, respectively; and, the mean of the logarithm of structure's strength and its standards deviation *with permanent* hardening effects are $\mu_{G''}$ =5 and $\sigma_{G''}$ =0.1, respectively. Table 6.2 summarizes the parameter values used for numerical analysis.

To illustrate the problem and the impacts of different asset management strategies, we analyze six cases as follows:

Case 1: Hurricane effects are considered. Preventive maintenance, corrective maintenance and restoration are available for the system. In addition, tree trimming is used as a

hardening strategy with *temporary* effects, i.e., n =24 months.

Case 2: Hurricane effects are considered. Preventive maintenance, corrective maintenance and restoration are available for the system. In addition, structural reinforcement is used as a hardening strategy with *permanent* effects.

Case 3: Hurricane effects are considered. Preventive maintenance, corrective maintenance and restoration are available for the system. There is no hardening strategy.

Case 4: Hurricane effects are considered. Corrective maintenance, and restoration are available for the system. However, preventive maintenance and hardening strategy are eliminated from asset management.

Case 5: There is no hurricane affecting the system. Preventive maintenance, corrective maintenance and restoration are available for the system.

Case 6: There is no hurricane affecting the system. Only corrective maintenance is available for the system.

In order to analyze the implications of incorporating El Niño/La Niña, we analyze two scenarios for Cases 1 to 4, as follows:

Scenario I: The El Niño/La Niña effects on hurricane arrivals are considered. Therefore, nonhomogeneous hurricane arrival rates λ_t for Poisson processes are used to describe the El Niño/La Niña effects on hurricane arrivals in the model.

Scenario II: The El Niño/La Niña effects are ignored. Instead, a homogeneous hurricane arrival rate for Poisson process (i.e., λ_t =1.64 per month, $\forall t \in \{1, ..., 120\}$) is used to model the hurricane arrivals.

We implemented Algorithm 6.1 in MATLAB and ran it for each case/scenario on a workstation with Core 2 Quad 2.33 GHz CPU and 8 GB memory. In addition to solving the problem, we simulate the obtained results from Scenario II of Cases 1 to 4 to evaluate the derived policies from scenario with homogenous hurricane arrivals in an envi-

ronment which hurricanes follow a nonhomogeneous arrival rate due to El Niño/La Niña phenomenon. The aim is to analyze the opportunity cost of ignoring the El Niño/La Niña effects for deriving the optimal policies.

In continuation, the numerical results on optimal policy for the system in the entire makespan of a long-term El Niño/La Niña cycle (i.e., $c = 5$ years) are described, and the dynamics of optimal policies in the hurricane and off-hurricane seasons during different years of the cycle are discussed.

In Scenario I of Case 1, for the first year of the cycle, it is optimal to take *no action* as long as the probability of being in state 1 (π_1) is greater than 0.904 during hurricane season; while it is optimal to take *no action* when the probability of being in state 1 is greater than 0.875 for the rest of the first year. Once the probability of being in state 1 goes below the corresponding thresholds, it is optimal to *inspect* the system. Once inspection is performed, with respect to the revealed deterioration level of the transformer, the required maintenance needs to be delivered in order to bring the deterioration level of the transformer into state 1, i.e., *as-good-as-new* condition. The optimal period to perform infrastructure hardening (i.e, tree trimming) is in period 6, i.e., at the beginning of the first hurricane season in the El Niño/La Niña cycle. In the second year, it is optimal to perform inspection once the probability of being in state 1 is less than 0.904 regardless of the time of the year. Since the performed hardening in the middle of year 1 is still in effect, there is no hardening action required for year 2. In the third and fourth years of the cycle, as long as the π_1 is greater than 0.875, it is optimal to take no action; otherwise, the *inspection* and subsequent maintenance actions are required to be taken. The optimal time to perform the second infrastructure hardening action is at the beginning of the hurricane season of the third year. The third hurricane hardening action is taken at the beginning of the hurricane season of the fifth year of the El Niño/La Niña cycle. The optimal *inspection/no action* decisions in the fifth year are similar to the first year of the cycle.

Table 6.3 The expected life-cycle costs for Case 1 to 4

Case #	Scenario I	Scenario II	Simulated Model	Time (min)
1	\$108,461	\$109,023	\$108,975	<10
2	\$74,317	\$74,785	\$74,785	<250
3	\$285,969	\$296,406	\$286,166	<3
4	\$298,334	\$308,580	\$298,333	<3

In Scenario II of Case 1, it is always optimal to perform *inspection*, once the probability of being in state 1 goes below 0.875; Otherwise, it is optimal to take *no action*. The first hardening action is performed at the beginning of the planning horizon. The second and third hardening actions are taken at the beginning of the third and fifth year, respectively.

In the first two years of El Niño/La Niña cycle in Scenario I of Case 2, it is optimal to do *inspection* once π_1 becomes less than 0.904 and 0.875 in hurricane and off-hurricane seasons, respectively. In the remaining three years of the cycle, it is always optimal to do *inspection* once π_1 drops below 0.875. Otherwise, *no action* is the optimal strategy. The optimal time to perform the hardening action with *permanent* effect (i.e, structural reinforcement) is at the beginning of the hurricane season in the first year. In Scenario II of this case, it is always optimal to take *no action* as long as the probability of being in state 1 is greater than 0.875; otherwise, *inspection* is the optimal action. In this scenario, the hardening action is performed at the beginning of the planning horizon.

In the first, second, third, and fifth year of the cycle in Scenario I of Case 3, it is optimal to perform the *inspection*, once π_1 is less than 0.875 and 0.904 in hurricane and off-hurricane seasons, respectively. However, in year 4, it is optimal to *inspect* once the probability of being in state 1 becomes less than 0.875; In Scenario II of Case 3, it is always optimal to do inspection, once π_1 becomes less than 0.904; Otherwise, it is optimal to take *no action*. As described, we have not taken any hardening measures in this case.

Table 6.3 shows the expected life-cycle cost of the transformer as well as the com-

Table 6.4 The expected life-cycle costs for Case 5 and 6

Case #	Expected Cost	Time (min)
5	\$5,744	<2
6	\$37,830	<2

putation time in different cases and scenarios. As shown for Case 4, considering the El Niño/La Niña effects, the expected life-cycle cost of transformer, when no preventive maintenance and infrastructure hardening measures are taken significantly increases by 175%, 301%, and 4.3% compared to Scenario I of Cases 1, 2, and 3, respectively. However, if the El Niño/La Niña effects are not considered (Scenario II), the reactive asset management strategy in Case 4 results in 183%, 312%, and 4.1% increase in expected life-cycle cost compared to Cases 1, 2, and 3, respectively.

In Case 5 in which there is no hurricane effects (because of being located in a non-hurricane prone area), the asset management strategy excludes hardening measures. The results indicate that similar to Scenario II of Cases 1, 2, and 3 in which the risk factor does not change over the planning horizon, the system needs to be *inspected* once the probability of being in an *as-good-as-new* condition (state 1) drops to below a threshold of 0.875. Otherwise, *no action* is required to be taken. In Case 6, for the same environmental circumstances as described for Case 5, we analyze the life-cycle cost of the system by not maintaining it, unless it fails due to deterioration. As shown in Table 6.4, the life-cycle cost of the system increases by 550% compared to Case 5.

Figure 6.2 illustrates the structure of optimal policy along the sample path for the system marked with probability thresholds of 0.875 and 0.904. As shown, probabilistically, it takes four months for a system in an *as-good-as-new* condition to reach the threshold of 0.904, while it takes five months to reach a probability threshold of 0.875. Therefore, in the case that the transformer is not equipped with real-time condition monitoring devices, the corresponding time intervals for reaching to these threshold values can be used for decision

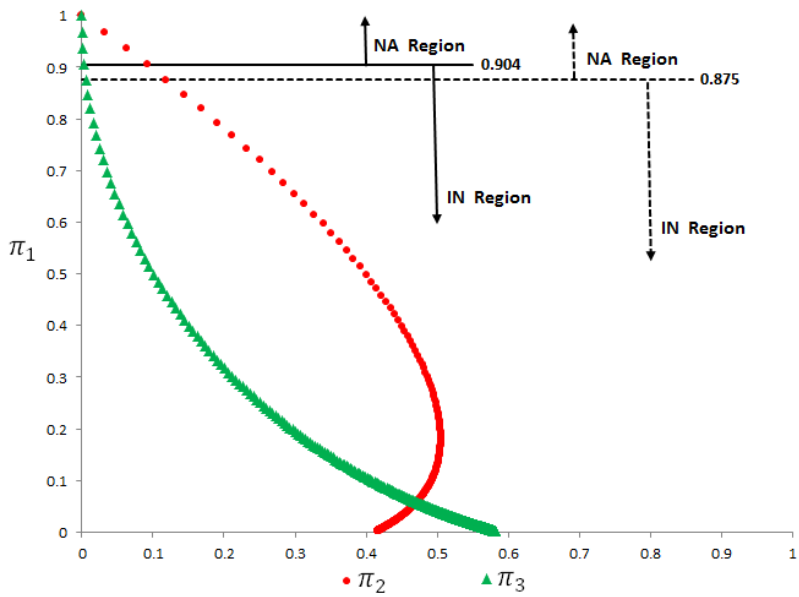

Figure 6.2 Structure of optimal policy on sample path

making on maintenance planning for the transformer. For instance, in Case 6, it is optimal to inspect the transformer every five months, while in year 1 of Scenario I of Case 1, the optimal inspection time interval from last inspection are four and five months in hurricane and off-hurricane seasons, respectively.

We simulated the impacts of implementing the optimal policies from scenarios with homogeneous hurricane arrival pattern, in an environment subject to El Niño/La Niña effects. The expected life-cycle cost of implementation of such policies are \$108,975, \$74,785, \$286,166, and \$298,333, for Cases 1, 2, 3, and 4, respectively. Therefore, the expected loss/opportunity cost due to implementing such inaccurate policies for Cases 1, 2, 3, and 4 are 0.005, 0.006, 0.036, and 0.034. As illustrated in Figure 6.3, the expected life-cycle of the transformer by implementing the derived policies from homogeneous hurricane arrival models in asset management strategies which include full maintenance options and hardening measures are not significant, while in the strategies with no hardening measures are considerable.

The cost of damage to transformer due to hurricane and the subsequent cost of inter-

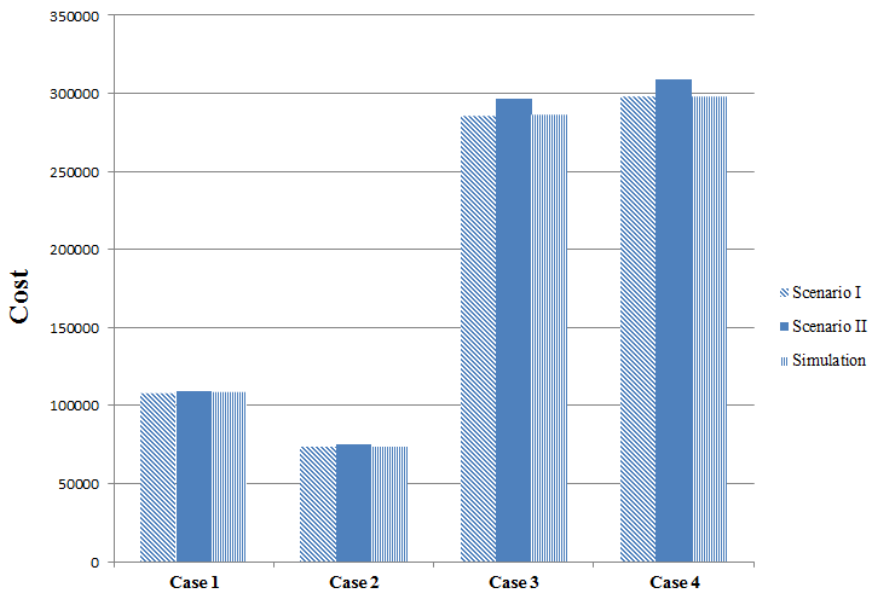

Figure 6.3 Comparison of expected cost-to-go and simulated model

ruption due to long lead time of this critical asset is relatively high. Based on [126], from 1997 to 2001, the average property damage cost and the interruption cost of each damaged transformer in the U.S. were about $1,736,586 and $1,312,657, respectively. Even though in our study we assumed a relatively low restoration cost for hurricane related damages to the transformer (i.e., $100,000), in all cases and scenarios the optimal policy is to *harden* the system at every decision epoch which there is a chance of hurricane. This finding shows the importance of hardening measures in the cost dynamics of the asset management of critical power infrastructures located in hurricane prone areas.

Finally, as shown in Table 6.3, the computation time increases with the number of periods that hardening action will be in effect. As explained in Section 6.3.2, the size of information space has significantly been reduced in our model. For instance, the sample path emanating from extreme state e_1 reaches to its steady state after 39 iterations (versus 120 iterations). Hence, the reduction in the size of the information space that needs to be evaluated is realized, which results in improved computational efficiency of the model.

6.5 Conclusions

In this chapter, we proposed a new model for asset management of power infrastructure to integrate the long-term maintenance with hardening strategy and restoration activities. We used the POMDP with a mixed-state space, i.e., a stochastic partially observable information state and a deterministic hardening state as a framework to formulate the problem. Utilizing the long-run steady state behavior of system deterioration, we significantly reduced the size of information space which resulted in improved computational efficiency of the backward induction algorithm without significantly compromising the accuracy of the optimal solution. The results indicate that the optimal maintenance decisions are sensitive to the hurricane seasons in El Niño/La Niña cycles. We simulated the derived optimal policies from systems with homogeneous hurricane arrival rates (which statistically are inaccurately distributed), in an environment with nonhomogeneous hurricane arrival pattern (that is proven to be more accurately describing the reality) which considers El Niño/La Niña effects. The simulation results indicate that the opportunity cost for the system when the derived policies based on homogeneous hurricane arrival assumption are implemented, cannot always be significant. The reason can be due to the long-term and cyclic nature of the hardening strategies which remain in effect. However, the use of homogeneous hurricane arrival models to find the optimal policies can result in significant overestimation of the total life-cycle cost in the grid scale. This overestimation can lead to unrealistic budget constraints which prohibit a cost-effective and productive asset management strategy in the utility company level. The results also demonstrate the importance of hardening strategy in asset management of the critical power infrastructure due to the considerable impacts of the failure due to hurricanes and the subsequent interruptions on cost dynamics of the system.

Chapter 7

Summary, Conclusions, and Extensions

Transformation of the conventional power systems into the next generation smart grids calls for rethinking of many common approaches which are currently in practice. Despite significant advances in integration of information and communication technologies into power systems, the issue of physical and cyber resiliency of the grid seems to remain in its early stage. External physical disruptions such as natural disasters and in particular, storms and hurricanes, can have devastating impact on the reliability and normal operation of the grid. The recent examples of such disruption are the Hurricane Ike of 2008 in the Gulf Coast, the Hurricane Sandy of 2012 which affected the East Cost of the U.S., and Typhoon Haiyan of 2013 in the Southeast Asia. The increasing trend of these types of disasters which is perceived by many to be due to climate change, and the vulnerability of the smart grid infrastructure, as one of the most critical lifeline system of today's urban and rural settings, call for action on enhancing the resistance and resiliency of the grid via employing efficient engineering solutions.

7.1 Summary and Conclusions

In Chapter 1, an overview of the proposed research was provided. The motivation and importance of the proposed research, the problem statement, and the research objectives were outlined and introduced. As the current paradigm of the real world practices are shifting to prevention, proactiveness, and resiliency enhancement, the main approach in this dissertation was to be inline with this paradigm.

In Chapter 2, the most relevant research work in the literature of asset management in power system was reviewed. The literature was divided into emergency planning, physical behavior, outage prediction, resource allocation, maintenance planning, reliability assess-

ment, and restoration planning. Moreover, the history and bibliography of the solution methods used in different parts of this dissertation were briefly reviewed. The reviewed subjects included mixed-integer programming, linearization techniques, two-stage stochastic program with recourse, Benders decomposition, Latin hypercube sampling, scenario reduction techniques, stress-strength analysis, Markov decision processes, and partially observable Markov decision processes.

In Chapter 3, a post-hurricane restoration planning model for electric power infrastructure considering the economics of disaster was proposed. Various economic issues surrounding the restoration problem including value of lost load, resource cost, and unit commitment problem were considered in the model. The problem was modeled as a MIP, and was solved using Benders decomposition. The results indicate that the proposed model is able to effectively find the optimal restoration schedule of damaged components of power system in a cost-effective manner. It was revealed that the total incurred cost of restoration of the system is sensitive to the available restoration resource level. The results suggest that investing on restoration resources is paid off in a sense that by securing adequate restoration resources, a considerable restoration cost saving can be realized. It was also demonstrated that the available restoration resource level has a significant impact on the average cost of power generation. The results show that incorporation of the unit commitment problem into the restoration problem results in a more cost-effective solution. It is concluded that restoration problem should not be solved without consideration of the economic aspects of restoration, i.e., unit commitment problem, value of lost load, and direct restoration resource cost. The optimal restoration schedules show that in general, restoration of the buses have higher priority compared to transmission lines, as the model in all scenarios intends to restore buses in the very early stage of restoration process.

In Chapter 4, a stochastic model to support decision making process for power system restoration in pre-hurricane phase was introduced. The model was formulated as a two-stage stochastic program with recourse. In order to make the problem tractable to solve,

it was transformed into an equivalent large-scale deterministic problem. To improve the computational efficiency of the solution, the large-scale deterministic problem was scaled down by using backward scenario reduction technique. The final problem was solved using Benders decomposition. Two strategies, i.e., the full restoration, and the partial restoration were analyzed; and the value of stochastic solution was calculated. The value of stochastic solution justified the advantage of obtaining stochastic solution over expected value solution. The numerical results indicated that the partial restoration strategy provides a more cost-effective restoration plan. However, the partial restoration may not provide the same system-level reliability that full restoration strategy secures. Nonetheless, decision makers can choose the best strategy based on financial and operational priorities within the utility. As solving stochastic problem is preferred over expected value problem, it is also reasonable to invest on forecasting technologies to improve the accuracy of the proactive restoration strategy. Furthermore, in general, the partial restoration strategy can be a more efficient option for utilities to eliminate the load interruption before fully recovering the system-level reliability of the grid.

In Chapter 5, a dynamic maintenance scheduling model which considers the stochastic degradation of the infrastructure, along with the stochastic effects of hurricane in a mid-term planning horizon was developed. MDP was employed to model the maintenance problem. MIP was used to find the outage cost of the component in different periods to be incorporated in the maintenance scheduling model. The hurricane survival probabilities during different periods were derived by using dynamic stress-strength analysis, and was incorporated in the model. The problem was solved using the backward induction algorithm. The results show that the cost saving due to implementing the preventive maintenance program is significant. However, the amount saved depends on the initial state of the component at the beginning of the planning horizon. In general, it is concluded that for a component which has an acceptable operational condition, the preventive maintenance during hurricane season should be eliminated. However, the preventive maintenance on a

component of the grid which is operating below a certain reliability threshold needs to be immediately performed, regardless of the time during the year.

In Chapter 6, POMDP was used to develop an integrated model for infrastructure hardening and condition-based maintenance of the critical components of the electric power systems. The long-term climatological effects of El Niño/La Niña phenomenon were considered in development of the proposed model. Utilizing the long-run steady state behavior of system deterioration, we significantly reduced the size of information space which resulted in improved computational efficiency without compromising the accuracy of the model. The dissolved gas analysis (DGA) was used to model the transition states of an oil-filled transformer. The problem was solved using backward induction algorithm, and optimal policies were derived. The results indicate that, due to the long-term and cyclic nature of the hardening strategies which remain in effect, the opportunity cost for deriving policies without consideration of seasonal effects of El Niño/La Niña phenomenon cannot always be significant. However, ignoring this phenomenon can result in significant overestimation of the total life-cycle cost in the grid scale. This overestimation can lead to unrealistic budget constraints which prohibit a cost-effective and productive asset management strategy in the utility company level. The hardening strategy was shown to play a critical role in long-term asset management of the power infrastructure under hurricane effects.

7.2 Extensions

Number of interesting issues in resiliency enhancement of the power systems are left for the future research. The proposed restoration models in this dissertation are based on DC estimation of the power system. Even though that DC estimation has shown to be practical, but greater accuracy of the AC models can result in even higher efficiency of the proposed post-hurricane restoration model. An efficient linearization scheme for AC

system has been proposed in Appendix C. Integration of the proposed scheme into joint unit commitment and restoration of power system can be an interesting area for the future research. Consideration of different types of resources in proactive resource mobilization can make the proposed model a more interesting problem. It was assumed that after hurricane, all routes and vehicles to be available and not to be affected by hurricane strike. Consideration of the probability of the damage on routes and vehicles, along with vehicle routing optimization in the model can create a challenging problem for the future research.

The proposed dynamic maintenance planning under hurricane effects considers only a single component of the grid. Consideration of multiple components and their outage cost dynamics along with the budget constraints can be modeled in a game theoretic framework to find the equilibrium of the asset management strategy in a hurricane prone area. Beside the interesting methodological improvements which can be made, analyzing the practical aspects of implementation of such model can be another area for future research. The proposed POMDP framework for integrated infrastructure hardening and condition-based maintenance scheduling considers two dimensions for the state of the system. However, only one state of the system follows a random variable. The solution methodology for solving the POMDPs with multiple dimensions as random variables for the state of the system is another interesting area for methodological development.

The proposed models were analyzed for vertically integrated utilities. However, deregulation of the power markets requires new engineering solutions for a cost-effective recovery planning of the grid. Distributed optimization and game theoretic frameworks can be used in future research to address these issues. Scarcity of operational and business data, and conflict of interests among different entities and players in the deregulated market call for development of innovative engineering techniques and efficient business solutions. Finally, integration of smart grid technologies in asset management and resiliency enhancement of the grid is another fertile area for future research.

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Appendices

Appendix A: IEEE 118-Bus Testing System

In this appendix, the related data on IEEE-118 bus system including its schematic view, generation unit data, transmission line data, the data related to the buses associated with lines, and load profiles are presented [119].

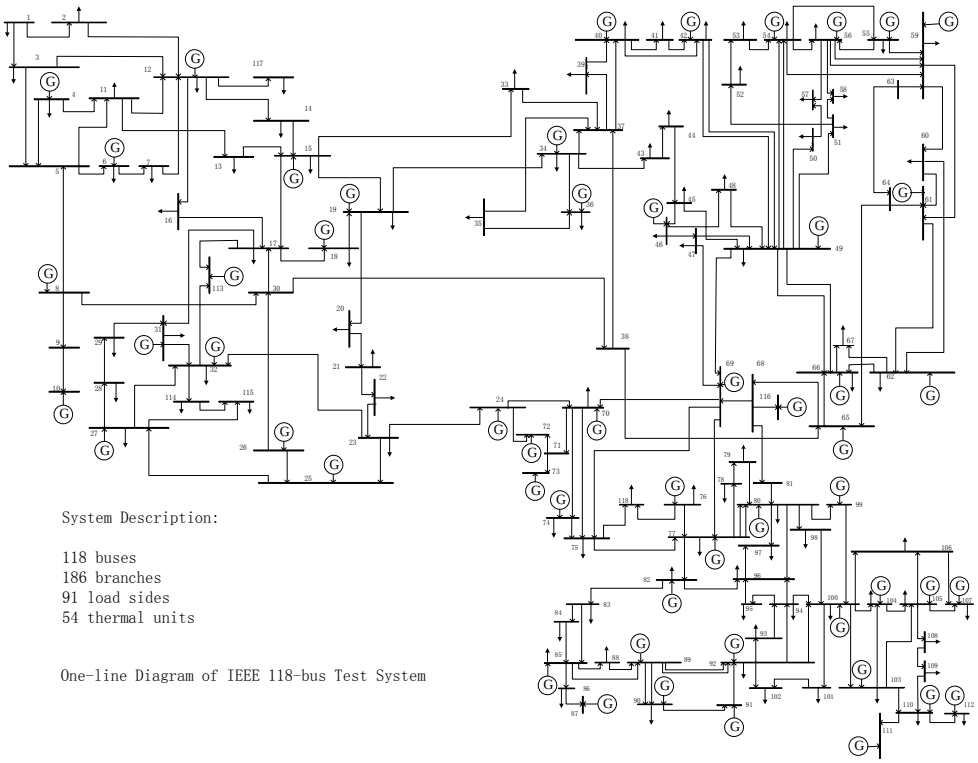

Figure A.1 Schematic view of IEEE 118 bus testing system

Table A.1 Generation units data for IEEE 118-bus system

Unit Index	Unit Name	Unit ID	Unit Type	Bus No	Pmin	Pmax	Qmin	Qmax	Min ON	Min OFF	Ramp Up	Ramp Down
1001	TG1	1	T	4	5	30	-300	300	1	1	30	30
1002	TG2	1	T	6	5	30	-13	50	1	1	30	30
1003	TG3	1	T	8	5	30	-300	300	1	1	30	30
1004	TG4	1	T	10	150	500	-147	200	10	10	500	500
1005	TG5	1	T	12	100	300	-35	120	10	10	300	300
1006	TG6	1	T	15	10	30	-10	30	1	1	30	30
1007	TG7	1	T	18	25	100	-16	50	5	5	100	100
1008	TG8	1	T	19	5	30	-8	24	1	1	30	30
1009	TG9	1	T	24	5	30	-300	300	1	1	30	30
1010	TG10	1	T	25	100	300	-47	140	8	8	300	300
1011	TG11	1	T	26	100	350	-1000	1000	8	8	350	350
1012	TG12	1	T	27	8	30	-300	300	1	1	30	30
1013	TG13	1	T	31	8	30	-300	300	1	1	30	30
1014	TG14	1	T	32	25	100	-14	42	5	5	100	100
1015	TG15	1	T	34	8	30	-8	24	1	1	30	30
1016	TG16	1	T	36	25	100	-8	24	5	5	100	100
1017	TG17	1	T	40	8	30	-300	300	1	1	30	30
1018	TG18	1	T	42	8	30	-300	300	1	1	30	30
1019	TG19	1	T	46	25	100	-100	100	5	5	100	100
1020	TG20	1	T	49	50	250	-85	210	10	10	250	250
1021	TG21	1	T	54	50	250	-300	300	10	10	250	250
1022	TG22	1	T	55	25	100	-8	23	5	5	100	100
1023	TG23	1	T	56	25	100	-8	15	5	5	100	100
1024	TG24	1	T	59	50	200	-60	180	11	11	200	200
1025	TG25	1	T	61	50	200	-100	300	10	10	200	200
1026	TG26	1	T	62	25	100	-20	20	5	5	100	100
1027	TG27	1	T	65	100	420	-67	200	10	10	420	420
1028	TG28	1	T	66	100	420	-67	200	10	10	420	420
1029	TG29	1	T	69	80	300	-99999	99999	10	10	300	300
1030	TG30	1	T	70	30	80	-10	32	4	4	80	80
1031	TG31	1	T	72	10	30	-100	100	1	1	30	30
1032	TG32	1	T	73	5	30	-100	100	1	1	30	30
1033	TG33	1	T	74	5	20	-6	9	1	1	20	20
1034	TG34	1	T	76	25	100	-8	23	5	5	100	100
1035	TG35	1	T	77	25	100	-20	70	5	5	100	100
1036	TG36	1	T	80	150	500	-165	280	10	10	500	500
1037	TG37	1	T	82	25	100	-9900	9900	5	5	100	100
1038	TG38	1	T	85	10	30	-8	23	1	1	30	30
1039	TG39	1	T	87	200	650	-100	1000	10	10	650	650
1040	TG40	1	T	89	150	500	-210	300	10	10	500	500
1041	TG41	1	T	90	8	20	-300	300	1	1	20	20
1042	TG42	1	T	91	20	50	-100	100	1	1	50	50
1043	TG43	1	T	92	100	300	-3	9	8	8	300	300
1044	TG44	1	T	99	100	300	-100	100	8	8	300	300
1045	TG45	1	T	100	100	300	-50	155	8	8	300	300
1046	TG46	1	T	103	8	20	-15	40	1	1	20	20
1047	TG47	1	T	104	25	100	-8	23	5	5	100	100
1048	TG48	1	T	105	25	100	-8	23	5	5	100	100
1049	TG49	1	T	107	8	20	-200	200	1	1	20	20
1050	TG50	1	T	110	25	50	-8	23	2	2	50	50
1051	TG51	1	T	111	25	100	-100	1000	5	5	100	100
1052	TG52	1	T	112	25	100	-100	1000	5	5	100	100
1053	TG53	1	T	113	25	100	-100	200	5	5	100	100
1054	TG54	1	T	116	25	50	-1000	1000	2	2	50	50

Table A.2 Transmission lines data for IEEE 118-bus system

Index	Name	I	J	CID	Status	R	X	B	RATEA	RATEB	RATEC
1	BR1	1	2	1	1	0.0303	0.0999	0.0254	100	0	0
2	BR2	1	3	1	1	0.0129	0.0424	0.01082	100	0	0
3	BR3	4	5	1	1	0.00176	0.00798	0.0021	500	0	0
4	BR4	3	5	1	1	0.0241	0.108	0.0284	100	0	0
5	BR5	5	6	1	1	0.0119	0.054	0.01426	100	0	0
6	BR6	6	7	1	1	0.00459	0.0208	0.0055	100	0	0
7	BR7	8	9	1	1	0.00244	0.0305	1.162	500	0	0
8	BR8	8	5	1	1	0	0.0267	0	500	0	0
9	BR9	9	10	1	1	0.00258	0.0322	1.23	500	0	0
10	BR10	4	11	1	1	0.0209	0.0688	0.01748	100	0	0
11	BR11	5	11	1	1	0.0203	0.0682	0.01738	100	0	0
12	BR12	11	12	1	1	0.00595	0.0196	0.00502	100	0	0
13	BR13	2	12	1	1	0.0187	0.0616	0.01572	100	0	0
14	BR14	3	12	1	1	0.0484	0.16	0.0406	100	0	0
15	BR15	7	12	1	1	0.00862	0.034	0.00874	100	0	0
16	BR16	11	13	1	1	0.02225	0.0731	0.01876	100	0	0
17	BR17	12	14	1	1	0.0215	0.0707	0.01816	100	0	0
18	BR18	13	15	1	1	0.0744	0.2444	0.06268	100	0	0
19	BR19	14	15	1	1	0.0595	0.195	0.0502	100	0	0
20	BR20	12	16	1	1	0.0212	0.0834	0.0214	100	0	0
21	BR21	15	17	1	1	0.0132	0.0437	0.0444	500	0	0
22	BR22	16	17	1	1	0.0454	0.1801	0.0466	100	0	0
23	BR23	17	18	1	1	0.0123	0.0505	0.01298	100	0	0
24	BR24	18	19	1	1	0.01119	0.0493	0.01142	100	0	0
25	BR25	19	20	1	1	0.0252	0.117	0.0298	100	0	0
26	BR26	15	19	1	1	0.012	0.0394	0.0101	100	0	0
27	BR27	20	21	1	1	0.0183	0.0849	0.0216	100	0	0
28	BR28	21	22	1	1	0.0209	0.097	0.0246	100	0	0
29	BR29	22	23	1	1	0.0342	0.159	0.0404	100	0	0
30	BR30	23	24	1	1	0.0135	0.0492	0.0498	100	0	0
31	BR31	23	25	1	1	0.0156	0.08	0.0864	500	0	0
32	BR32	26	25	1	1	0	0.0382	0	500	0	0
33	BR33	25	27	1	1	0.0318	0.163	0.1764	500	0	0
34	BR34	27	28	1	1	0.01913	0.0855	0.0216	100	0	0
35	BR35	28	29	1	1	0.0237	0.0943	0.0238	100	0	0
36	BR36	30	17	1	1	0	0.0388	0	500	0	0
37	BR37	8	30	1	1	0.00431	0.0504	0.514	100	0	0
38	BR38	26	30	1	1	0.00799	0.086	0.908	500	0	0
39	BR39	17	31	1	1	0.0474	0.1563	0.0399	100	0	0
40	BR40	29	31	1	1	0.0108	0.0331	0.0083	100	0	0
41	BR41	23	32	1	1	0.0317	0.1153	0.1173	100	0	0
42	BR42	31	32	1	1	0.0298	0.0985	0.0251	100	0	0
43	BR43	27	32	1	1	0.0229	0.0755	0.01926	100	0	0
44	BR44	15	33	1	1	0.038	0.1244	0.03194	100	0	0
45	BR45	19	34	1	1	0.0752	0.247	0.0632	100	0	0
46	BR46	35	36	1	1	0.00224	0.0102	0.00268	100	0	0
47	BR47	35	37	1	1	0.011	0.0497	0.01318	100	0	0
48	BR48	33	37	1	1	0.0415	0.142	0.0366	100	0	0
49	BR49	34	36	1	1	0.00871	0.0268	0.00568	100	0	0
50	BR50	34	37	1	1	0.00256	0.0094	0.00984	500	0	0
51	BR51	38	37	1	1	0	0.0375	0	500	0	0
52	BR52	37	39	1	1	0.0321	0.106	0.027	100	0	0
53	BR53	37	40	1	1	0.0593	0.168	0.042	100	0	0
54	BR54	30	38	1	1	0.00464	0.054	0.422	100	0	0
55	BR55	39	40	1	1	0.0184	0.0605	0.01552	100	0	0
56	BR56	40	41	1	1	0.0145	0.0487	0.01222	100	0	0

Table A.2 Transmission lines data for IEEE 118-bus system (continued)

Index	Name	I	J	CID	Status	R	X	B	RATEA	RATEB	RATEC
57	BR57	40	42	1	1	0.0555	0.183	0.0466	100	0	0
58	BR58	41	42	1	1	0.041	0.135	0.0344	100	0	0
59	BR59	43	44	1	1	0.0608	0.2454	0.06068	100	0	0
60	BR60	34	43	1	1	0.0413	0.1681	0.04226	100	0	0
61	BR61	44	45	1	1	0.0224	0.0901	0.0224	100	0	0
62	BR62	45	46	1	1	0.04	0.1356	0.0332	100	0	0
63	BR63	46	47	1	1	0.038	0.127	0.0316	100	0	0
64	BR64	46	48	1	1	0.0601	0.189	0.0472	100	0	0
65	BR65	47	49	1	1	0.0191	0.0625	0.01604	100	0	0
66	BR66	42	49	1	1	0.0715	0.323	0.086	100	0	0
67	BR67	42	49	2	1	0.0715	0.323	0.086	100	0	0
68	BR68	45	49	1	1	0.0684	0.186	0.0444	100	0	0
69	BR69	48	49	1	1	0.0179	0.0505	0.01258	100	0	0
70	BR70	49	50	1	1	0.0267	0.0752	0.01874	100	0	0
71	BR71	49	51	1	1	0.0486	0.137	0.0342	100	0	0
72	BR72	51	52	1	1	0.0203	0.0588	0.01396	100	0	0
73	BR73	52	53	1	1	0.0405	0.1635	0.04058	100	0	0
74	BR74	53	54	1	1	0.0263	0.122	0.031	100	0	0
75	BR75	49	54	1	1	0.073	0.289	0.0738	100	0	0
76	BR76	49	54	2	1	0.0869	0.291	0.073	100	0	0
77	BR77	54	55	1	1	0.0169	0.0707	0.0202	100	0	0
78	BR78	54	56	1	1	0.00275	0.00955	0.00732	100	0	0
79	BR79	55	56	1	1	0.00488	0.0151	0.00374	100	0	0
80	BR80	56	57	1	1	0.0343	0.0966	0.0242	100	0	0
81	BR81	50	57	1	1	0.0474	0.134	0.0332	100	0	0
82	BR82	56	58	1	1	0.0343	0.0966	0.0242	100	0	0
83	BR83	51	58	1	1	0.0255	0.0719	0.01788	100	0	0
84	BR84	54	59	1	1	0.0503	0.2293	0.0598	100	0	0
85	BR85	56	59	1	1	0.0825	0.251	0.0569	100	0	0
86	BR86	56	59	2	1	0.0803	0.239	0.0536	100	0	0
87	BR87	55	59	1	1	0.04739	0.2158	0.05646	100	0	0
88	BR88	59	60	1	1	0.0317	0.145	0.0376	100	0	0
89	BR89	59	61	1	1	0.0328	0.15	0.0388	100	0	0
90	BR90	60	61	1	1	0.00264	0.0135	0.01456	500	0	0
91	BR91	60	62	1	1	0.0123	0.0561	0.01468	100	0	0
92	BR92	61	62	1	1	0.00824	0.0376	0.0098	100	0	0
93	BR93	63	59	1	1	0	0.0386	0	500	0	0
94	BR94	63	64	1	1	0.00172	0.02	0.216	500	0	0
95	BR95	64	61	1	1	0	0.0268	0	500	0	0
96	BR96	38	65	1	1	0.00901	0.0986	1.046	500	0	0
97	BR97	64	65	1	1	0.00269	0.0302	0.38	500	0	0
98	BR98	49	66	1	1	0.018	0.0919	0.0248	500	0	0
99	BR99	49	66	2	1	0.018	0.0919	0.0248	500	0	0
100	BR100	62	66	1	1	0.0482	0.218	0.0578	100	0	0
101	BR101	62	67	1	1	0.0258	0.117	0.031	100	0	0
102	BR102	65	66	1	1	0	0.037	0	500	0	0
103	BR103	66	67	1	1	0.0224	0.1015	0.02682	100	0	0
104	BR104	65	68	1	1	0.00138	0.016	0.638	500	0	0
105	BR105	47	69	1	1	0.0844	0.2778	0.07092	100	0	0
106	BR106	49	69	1	1	0.0985	0.324	0.0828	100	0	0
107	BR107	68	69	1	1	0	0.037	0	500	0	0
108	BR108	69	70	1	1	0.03	0.127	0.122	500	0	0
109	BR109	24	70	1	1	0.00221	0.4115	0.10198	100	0	0
110	BR110	70	71	1	1	0.00882	0.0355	0.00878	100	0	0
111	BR111	24	72	1	1	0.0488	0.196	0.0488	100	0	0
112	BR112	71	72	1	1	0.0446	0.18	0.04444	100	0	0

Table A.2 Transmission lines data for IEEE 118-bus system (continued)

Index	Name	I	J	CID	Status	R	X	B	RATEA	RATEB	RATEC
113	BR113	71	73	1	1	0.00866	0.0454	0.01178	100	0	0
114	BR114	70	74	1	1	0.0401	0.1323	0.03368	100	0	0
115	BR115	70	75	1	1	0.0428	0.141	0.036	100	0	0
116	BR116	69	75	1	1	0.0405	0.122	0.124	500	0	0
117	BR117	74	75	1	1	0.0123	0.0406	0.01034	100	0	0
118	BR118	76	77	1	1	0.0444	0.148	0.0368	100	0	0
119	BR119	69	77	1	1	0.0309	0.101	0.1038	100	0	0
120	BR120	75	77	1	1	0.0601	0.1999	0.04978	100	0	0
121	BR121	77	78	1	1	0.00376	0.0124	0.01264	100	0	0
122	BR122	78	79	1	1	0.00546	0.0244	0.00648	100	0	0
123	BR123	77	80	1	1	0.017	0.0485	0.0472	500	0	0
124	BR124	77	80	2	1	0.0294	0.105	0.0228	500	0	0
125	BR125	79	80	1	1	0.0156	0.0704	0.0187	100	0	0
126	BR126	68	81	1	1	0.00175	0.0202	0.808	500	0	0
127	BR127	81	80	1	1	0	0.037	0	500	0	0
128	BR128	77	82	1	1	0.0298	0.0853	0.08174	100	0	0
129	BR129	82	83	1	1	0.0112	0.03665	0.03796	100	0	0
130	BR130	83	84	1	1	0.0625	0.132	0.0258	100	0	0
131	BR131	83	85	1	1	0.043	0.148	0.0348	100	0	0
132	BR132	84	85	1	1	0.0302	0.0641	0.01234	100	0	0
133	BR133	85	86	1	1	0.035	0.123	0.0276	500	0	0
134	BR134	86	87	1	1	0.02828	0.2074	0.0445	500	0	0
135	BR135	85	88	1	1	0.02	0.102	0.0276	100	0	0
136	BR136	85	89	1	1	0.0239	0.173	0.047	100	0	0
137	BR137	88	89	1	1	0.0139	0.0712	0.01934	500	0	0
138	BR138	89	90	1	1	0.0518	0.188	0.0528	500	0	0
139	BR139	89	90	2	1	0.0238	0.0997	0.106	500	0	0
140	BR140	90	91	1	1	0.0254	0.0836	0.0214	100	0	0
141	BR141	89	92	1	1	0.0099	0.0505	0.0548	500	0	0
142	BR142	89	92	2	1	0.0393	0.1581	0.0414	500	0	0
143	BR143	91	92	1	1	0.0387	0.1272	0.03268	100	0	0
144	BR144	92	93	1	1	0.0258	0.0848	0.0218	100	0	0
145	BR145	92	94	1	1	0.0481	0.158	0.0406	100	0	0
146	BR146	93	94	1	1	0.0223	0.0732	0.01876	100	0	0
147	BR147	94	95	1	1	0.0132	0.0434	0.0111	100	0	0
148	BR148	80	96	1	1	0.0356	0.182	0.0494	100	0	0
149	BR149	82	96	1	1	0.0162	0.053	0.0544	100	0	0
150	BR150	94	96	1	1	0.0269	0.0869	0.023	100	0	0
151	BR151	80	97	1	1	0.0183	0.0934	0.0254	100	0	0
152	BR152	80	98	1	1	0.0238	0.108	0.0286	100	0	0
153	BR153	80	99	1	1	0.0454	0.206	0.0546	100	0	0
154	BR154	92	100	1	1	0.0648	0.295	0.0472	100	0	0
155	BR155	94	100	1	1	0.0178	0.058	0.0604	100	0	0
156	BR156	95	96	1	1	0.0171	0.0547	0.01474	100	0	0
157	BR157	96	97	1	1	0.0173	0.0885	0.024	100	0	0
158	BR158	98	100	1	1	0.0397	0.179	0.0476	100	0	0
159	BR159	99	100	1	1	0.018	0.0813	0.0216	100	0	0
160	BR160	100	101	1	1	0.0277	0.1262	0.0328	100	0	0
161	BR161	92	102	1	1	0.0123	0.0559	0.01464	100	0	0
162	BR162	101	102	1	1	0.0246	0.112	0.0294	100	0	0
163	BR163	100	103	1	1	0.016	0.0525	0.0536	500	0	0
164	BR164	100	104	1	1	0.0451	0.204	0.0541	100	0	0
165	BR165	103	104	1	1	0.0466	0.1584	0.0407	100	0	0
166	BR166	103	105	1	1	0.0535	0.1625	0.0408	100	0	0
167	BR167	100	106	1	1	0.0605	0.229	0.062	100	0	0
168	BR168	104	105	1	1	0.00994	0.0378	0.00986	100	0	0

Table A.2 Transmission lines data for IEEE 118-bus system (continued)

Index	Name	I	J	CID	Status	R	X	B	RATEA	RATEB	RATEC
169	BR169	105	106	1	1	0.014	0.0547	0.01434	100	0	0
170	BR170	105	107	1	1	0.053	0.183	0.0472	100	0	0
171	BR171	105	108	1	1	0.0261	0.0703	0.01844	100	0	0
172	BR172	106	107	1	1	0.053	0.183	0.0472	100	0	0
173	BR173	108	109	1	1	0.0105	0.0288	0.0076	100	0	0
174	BR174	103	110	1	1	0.03906	0.1813	0.0461	100	0	0
175	BR175	109	110	1	1	0.0278	0.0762	0.0202	100	0	0
176	BR176	110	111	1	1	0.022	0.0755	0.02	100	0	0
177	BR177	110	112	1	1	0.0247	0.064	0.062	100	0	0
178	BR178	17	113	1	1	0.00913	0.0301	0.00768	100	0	0
179	BR179	32	113	1	1	0.0615	0.203	0.0518	500	0	0
180	BR180	32	114	1	1	0.0135	0.0612	0.01628	100	0	0
181	BR181	27	115	1	1	0.0164	0.0741	0.01972	100	0	0
182	BR182	114	115	1	1	0.0023	0.0104	0.00276	100	0	0
183	BR183	68	116	1	1	0.00034	0.00405	0.164	500	0	0
184	BR184	12	117	1	1	0.0329	0.14	0.0358	100	0	0
185	BR185	75	118	1	1	0.0145	0.0481	0.01198	100	0	0
186	BR186	76	118	1	1	0.0164	0.0544	0.01356	100	0	0

Table A.3 Load profile data for IEEE 118-bus system

Index	Name	ID	BusNo	Status	PL	QL
1	Load1	1	1	1	54.14	28.66
2	Load2	1	2	1	21.23	9.55
3	Load3	1	3	1	41.4	10.62
4	Load4	1	4	1	31.85	12.74
5	Load5	1	6	1	55.2	23.35
6	Load6	1	7	1	20.17	2.12
7	Load7	1	11	1	74.31	24.42
8	Load8	1	12	1	49.89	10.62
9	Load9	1	13	1	36.09	16.99
10	Load10	1	14	1	14.86	1.06
11	Load11	1	15	1	95.54	31.85
12	Load12	1	16	1	26.54	10.62
13	Load13	1	17	1	11.68	3.18
14	Load14	1	18	1	63.69	36.09
15	Load15	1	19	1	47.77	26.54
16	Load16	1	20	1	19.11	3.18
17	Load17	1	21	1	14.86	8.49
18	Load18	1	22	1	10.62	5.31
19	Load19	1	23	1	7.43	3.18
20	Load20	1	27	1	65.82	13.8
21	Load21	1	28	1	18.05	7.43
22	Load22	1	29	1	25.48	4.25
23	Load23	1	31	1	45.65	28.66
24	Load24	1	32	1	62.63	24.42
25	Load25	1	33	1	24.42	9.55
26	Load26	1	34	1	62.63	27.6
27	Load27	1	35	1	35.03	9.55
28	Load28	1	36	1	32.91	18.05
29	Load29	1	39	1	27	11
30	Load30	1	40	1	20	23
31	Load31	1	41	1	37	10
32	Load32	1	42	1	37	23
33	Load33	1	43	1	18	7
34	Load34	1	44	1	16	8
35	Load35	1	45	1	53	22
36	Load36	1	46	1	28	10
37	Load37	1	47	1	34	0
38	Load38	1	48	1	20	11
39	Load39	1	49	1	87	30
40	Load40	1	50	1	17	4
41	Load41	1	51	1	17	8
42	Load42	1	52	1	18	5
43	Load43	1	53	1	23	11
44	Load44	1	54	1	113	32
45	Load45	1	55	1	63	22
46	Load46	1	56	1	84	18
47	Load47	1	57	1	12	3
48	Load48	1	58	1	12	3
49	Load49	1	59	1	277	113
50	Load50	1	60	1	78	3
51	Load51	1	62	1	77	14
52	Load52	1	66	1	39	18
53	Load53	1	67	1	28	7
54	Load54	1	70	1	66	20
55	Load55	1	74	1	68	27

Table A.3 Load profile data for IEEE 118-bus system (continued)

Index	Name	ID	BusNo	Status	PL	QL
56	Load56	1	75	1	47	11
57	Load57	1	76	1	68	36
58	Load58	1	77	1	61	28
59	Load59	1	78	1	71	26
60	Load60	1	79	1	39	32
61	Load61	1	80	1	130	26
62	Load62	1	82	1	54	27
63	Load63	1	83	1	20	10
64	Load64	1	84	1	11	7
65	Load65	1	85	1	24	15
66	Load66	1	86	1	21	10
67	Load67	1	88	1	48	10
68	Load68	1	90	1	78	42
69	Load69	1	92	1	65	10
70	Load70	1	93	1	12	7
71	Load71	1	94	1	30	16
72	Load72	1	95	1	42	31
73	Load73	1	96	1	38	15
74	Load74	1	97	1	15	9
75	Load75	1	98	1	34	8
76	Load76	1	100	1	37	18
77	Load77	1	101	1	22	15
78	Load78	1	102	1	5	3
79	Load79	1	103	1	23	16
80	Load80	1	104	1	38	25
81	Load81	1	105	1	31	26
82	Load82	1	106	1	43	16
83	Load83	1	107	1	28	12
84	Load84	1	108	1	2	1
85	Load85	1	109	1	8	3
86	Load86	1	110	1	39	30
87	Load87	1	112	1	25	13
88	Load88	1	114	1	8.49	3.18
89	Load89	1	115	1	23.35	7.43
90	Load90	1	117	1	21.23	8.49
91	Load91	1	118	1	33	15

Table A.4 Buses data for IEEE 118-bus system

Index	Name	No	Type	BaseKV	VM	VA	GL	BL	VM_Min	VM_Max
1	BUS1	1	0	0	0.95661	-10.613	0	0	0.94	1.05
2	BUS2	2	0	0	0.97187	-9.492	0	0	0.94	1.05
3	BUS3	3	0	0	0.96838	-9.954	0	0	0.94	1.05
4	BUS4	4	2	0	0.998	-7.46	0	0	0.97	1.05
5	BUS5	5	0	0	1.00127	-7.084	0	0	0.94	1.05
6	BUS6	6	2	0	0.99	-8.363	0	0	0.97	1.05
7	BUS7	7	0	0	0.98922	-8.431	0	0	0.94	1.05
8	BUS8	8	2	0	1.015	-3.846	0	0	0.97	1.05
9	BUS9	9	0	0	1.04908	0.03	0	0	0.94	1.05
10	BUS10	10	2	0	1.05	4.161	0	0	0.97	1.05
11	BUS11	11	0	0	0.98534	-8.461	0	0	0.94	1.05
12	BUS12	12	2	0	0.99	-8.17	0	0	0.97	1.05
13	BUS13	13	0	0	0.9685	-9.379	0	0	0.94	1.05
14	BUS14	14	0	0	0.98362	-8.574	0	0	0.94	1.05
15	BUS15	15	2	0	0.97	-7.991	0	0	0.97	1.05
16	BUS16	16	0	0	0.98353	-8.223	0	0	0.94	1.05
17	BUS17	17	0	0	0.99422	-5.88	0	0	0.94	1.05
18	BUS18	18	2	0	0.973	-6.782	0	0	0.97	1.05
19	BUS19	19	2	0	0.96522	-7.809	0	0	0.97	1.05
20	BUS20	20	0	0	0.96208	-8.157	0	0	0.94	1.05
21	BUS21	21	0	0	0.96385	-7.473	0	0	0.94	1.05
22	BUS22	22	0	0	0.97522	-5.948	0	0	0.94	1.05
23	BUS23	23	0	0	1.00268	-2.651	0	0	0.94	1.05
24	BUS24	24	2	0	0.992	-3.982	0	0	0.97	1.05
25	BUS25	25	2	0	1.05	3.201	0	0	0.97	1.05
26	BUS26	26	2	0	1.015	4.482	0	0	0.97	1.05
27	BUS27	27	2	0	0.968	-5.956	0	0	0.96	1.05
28	BUS28	28	0	0	0.96147	-6.839	0	0	0.94	1.05
29	BUS29	29	0	0	0.96292	-6.891	0	0	0.94	1.05
30	BUS30	30	0	0	0.99153	-3.546	0	0	0.94	1.05
31	BUS31	31	2	0	0.967	-6.439	0	0	0.96	1.05
32	BUS32	32	2	0	0.96872	-5.386	0	0	0.96	1.05
33	BUS33	33	0	0	0.97367	-8.739	0	0	0.94	1.05
34	BUS34	34	2	0	0.991	-7.992	0	0	0.97	1.05
35	BUS35	35	0	0	0.98723	-7.963	0	0	0.94	1.05
36	BUS36	36	2	0	0.98693	-7.815	0	0	0.97	1.05
37	BUS37	37	0	0	0.99643	-7.776	0	0	0.94	1.05
38	BUS38	38	0	0	0.97176	-5.037	0	0	0.94	1.05
39	BUS39	39	0	0	0.97263	-9.578	0	0	0.94	1.05
40	BUS40	40	2	0	0.97	-9.742	0	0	0.97	1.05
41	BUS41	41	0	0	0.96673	-9.956	0	0	0.94	1.05
42	BUS42	42	2	0	0.985	-7.725	0	0	0.97	1.05
43	BUS43	43	0	0	0.98352	-8.976	0	0	0.94	1.05
44	BUS44	44	0	0	0.98913	-7.885	0	0	0.94	1.05
45	BUS45	45	0	0	0.98982	-6.566	0	0	0.94	1.05
46	BUS46	46	2	0	1.005	-3.151	0	0	0.97	1.05
47	BUS47	47	0	0	1.01882	-3.482	0	0	0.94	1.05
48	BUS48	48	0	0	1.02103	-3.685	0	0	0.94	1.05
49	BUS49	49	2	0	1.025	-3.205	0	0	0.97	1.05
50	BUS50	50	0	0	1.00272	-4.259	0	0	0.94	1.05
51	BUS51	51	0	0	0.96993	-5.58	0	0	0.94	1.05
52	BUS52	52	0	0	0.95996	-6.167	0	0	0.94	1.05
53	BUS53	53	0	0	0.94746	-6.142	0	0	0.94	1.05
54	BUS54	54	2	0	0.955	-4.492	0	0	0.95	1
55	BUS55	55	2	0	0.95542	-4.539	0	0	0.95	1
56	BUS56	56	2	0	0.95671	-4.744	0	0	0.95	1
57	BUS57	57	0	0	0.97334	-4.939	0	0	0.94	1.05
58	BUS58	58	0	0	0.96197	-5.522	0	0	0.94	1.05
59	BUS59	59	2	0	0.985	-5.118	0	0	0.97	1.05

Table A.4 Buses data for IEEE 118-bus system (continued)

Index	Name	No	Type	BaseKV	VM	VA	GL	BL	VM_Min	VM_Max
60	BUS60	60	0	0	0.99328	-3.126	0	0	0.94	1.05
61	BUS61	61	2	0	0.995	-2.397	0	0	0.97	1.05
62	BUS62	62	2	0	0.998	-2.859	0	0	0.97	1.05
63	BUS63	63	0	0	0.97098	-3.138	0	0	0.94	1.05
64	BUS64	64	0	0	0.98518	-2.132	0	0	0.94	1.05
65	BUS65	65	2	0	1.005	-0.354	0	0	0.97	1.05
66	BUS66	66	2	0	1.05	-1.199	0	0	0.97	1.05
67	BUS67	67	0	0	1.02022	-2.756	0	0	0.94	1.05
68	BUS68	68	0	0	1.00291	-0.56	0	0	0.94	1.05
69	BUS69	69	3	0	1.035	0	0	0	0.97	1.05
70	BUS70	70	2	0	0.98493	-5.176	0	0	0.97	1.05
71	BUS71	71	0	0	0.98685	-5.998	0	0	0.94	1.05
72	BUS72	72	2	0	0.98	-5.29	0	0	0.97	1.05
73	BUS73	73	2	0	0.991	-7.175	0	0	0.97	1.05
74	BUS74	74	2	0	0.958	-6.439	0	0	0.95	1
75	BUS75	75	0	0	0.97388	-5.419	0	0	0.94	1.05
76	BUS76	76	2	0	0.943	-5.21	0	0	0.94	1
77	BUS77	77	2	0	1.006	-3.226	0	0	0.97	1.05
78	BUS78	78	0	0	1.01258	-3.735	0	0	0.94	1.05
79	BUS79	79	0	0	1.01625	-3.86	0	0	0.94	1.05
80	BUS80	80	2	0	1.04	-2.803	0	0	0.97	1.05
81	BUS81	81	0	0	0.99518	-1.386	0	0	0.94	1.05
82	BUS82	82	2	0	1	-4.327	0	0	0.97	1.05
83	BUS83	83	0	0	0.99536	-4.25	0	0	0.94	1.05
84	BUS84	84	0	0	0.98687	-3.499	0	0	0.94	1.05
85	BUS85	85	2	0	0.985	-2.81	0	0	0.97	1.05
86	BUS86	86	0	0	0.9927	-0.458	0	0	0.94	1.05
87	BUS87	87	2	0	1.015	5.694	0	0	0.97	1.05
88	BUS88	88	0	0	0.99121	-3.477	0	0	0.94	1.05
89	BUS89	89	2	0	1.005	-2.031	0	0	0.97	1.05
90	BUS90	90	2	0	0.985	-5.733	0	0	0.97	1.05
91	BUS91	91	2	0	0.98	-5.934	0	0	0.97	1.05
92	BUS92	92	2	0	0.99	-2.84	0	0	0.97	1.05
93	BUS93	93	0	0	0.99583	-3.729	0	0	0.94	1.05
94	BUS94	94	0	0	0.99686	-4.058	0	0	0.94	1.05
95	BUS95	95	0	0	0.98761	-4.74	0	0	0.94	1.05
96	BUS96	96	0	0	0.99965	-4.556	0	0	0.94	1.05
97	BUS97	97	0	0	1.01493	-4.031	0	0	0.94	1.05
98	BUS98	98	0	0	1.02353	-3.955	0	0	0.94	1.05
99	BUS99	99	2	0	1.01	-4.436	0	0	0.97	1.05
100	BUS100	100	2	0	1.017	-2.644	0	0	0.97	1.05
101	BUS101	101	0	0	0.99798	-3.587	0	0	0.94	1.05
102	BUS102	102	0	0	1.00002	-3.191	0	0	0.94	1.05
103	BUS103	103	2	0	1.01	-2.374	0	0	0.97	1.05
104	BUS104	104	2	0	0.971	-2.091	0	0	0.97	1.05
105	BUS105	105	2	0	0.99412	-1.861	0	0	0.97	1.05
106	BUS106	106	0	0	0.98175	-3.146	0	0	0.94	1.05
107	BUS107	107	2	0	0.952	-3.487	0	0	0.97	1.05
108	BUS108	108	0	0	0.98403	-0.773	0	0	0.94	1.05
109	BUS109	109	0	0	0.98011	-0.288	0	0	0.94	1.05
110	BUS110	110	2	0	0.97379	1.349	0	0	0.97	1.05
111	BUS111	111	2	0	0.98	3.736	0	0	1	1.06
112	BUS112	112	2	0	0.975	2.634	0	0	0.97	1.05
113	BUS113	113	2	0	0.993	-4.632	0	0	0.97	1.05
114	BUS114	114	0	0	0.96343	-6.185	0	0	0.94	1.05
115	BUS115	115	0	0	0.96296	-6.273	0	0	0.94	1.05
116	BUS116	116	2	0	1.005	-0.519	0	0	0.97	1.05
117	BUS117	117	0	0	0.98241	-8.213	0	0	0.94	1.05
118	BUS118	118	0	0	0.95815	-5.778	0	0	0.94	1.05

Appendix B: IEEE 6-Bus Testing System

In this appendix, the data related to IEEE 6-bus system, including the schematic view, generation unit data, transmission line data, the buses associated with lines, and load profile are presented [119].

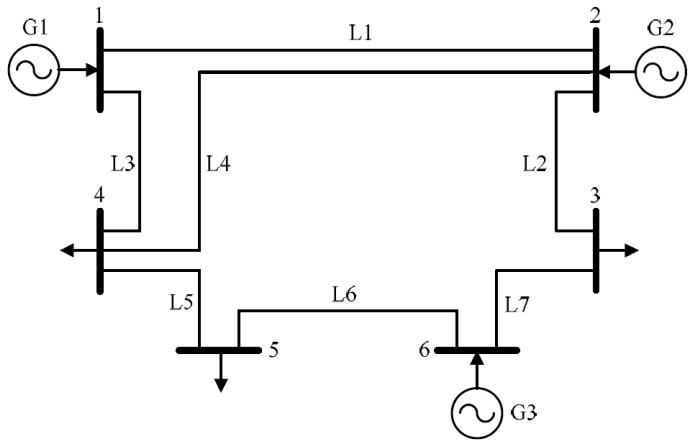

Figure B.1 Schematic view of IEEE 6-bus testing system

Table B.1 Generation units data for IEEE 6-bus testing system

Unit	Pmin (MW)	Pmax (MW)	Min On (h)	Min Off (h)	Ramp (MW/h)
G1	100	220	4	4	55
G2	10	100	3	2	50
G3	10	40	1	1	20

Table B.2 Transmission lines data for IEEE 6-bus testing system

Line No.	From Bus	To Bus	X (pu)	Flow Limit (MW)
1	1	2	0.170	200
2	2	3	0.037	100
3	1	4	0.258	100
4	2	4	0.197	100
5	4	5	0.037	100
6	5	6	0.140	100
7	3	6	0.018	100

Table B.3 Hourly aggregated load profile data for IEEE 6-bus testing system

Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Load (MW)	166.4	156	150.8	145.6	145.6	150.8	166.4	197.6	226.2	247	257.4	260
Hour	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Load (MW)	257.4	260	260	252.2	249.6	249.6	241.8	239.2	239.2	241.8	226.2	187.2

Table B.4 Bus load percentage data for IEEE 6-bus testing system

Bus No	Load (%)
3	20
4	40
5	40

Appendix C: A Linearization Scheme for AC Networks

According to [127], [128], the following assumptions make it possible to use the DC network for modeling/analyzing a problem: i) the susceptance is large relative to the impedance, ii) the phase angle difference is small enough to approximate $\sin(\delta_{nt} - \delta_{mt}) \approx \delta_{nt} - \delta_{mt}$, and iii) the voltage magnitudes are close to 1.0 and do not change significantly; However, due to considerable topological changes in the network, the above mild assumptions can be violated in restoration process. Therefore, it is important to develop AC based framework for restoration planning of power systems. In this appendix, a linearization scheme for AC approximation is proposed.

The Proposed Linearization Method

Since all the restoration constraints in AC model are either quadratic or can be represented as a quadratic function, they can be plotted as an ellipse. Therefore, we can approximate them as a polygon or polyhedron by adding linear constraints. For instance, consider the generator capability curve as

$$P_{it}^2 + Q_{it}^2 \leq S_i^2, \ \ \forall i, \forall t,$$

which is a quadratic equation of a semi ellipse (in fact, the power capability curve is a circle which is a special case of ellipse). As shown in Figure C.1, by dividing the semi ellipse into k slices, each with angle γ_k, we can approximate the feasible region of the generator capability curve as a semi polygon. P_{max} and Q_{max} are considered as the length of semi major and semi minor axes of the ellipse, respectively. The corresponding equation for each side of the polygon (i.e., each line that cuts the semi ellipse) is obtained by

$$\frac{P_{it} - P_{max}\cos\gamma_k}{Q_{it} - Q_{max}\sin\gamma_k} = \frac{P_{max}\cos\gamma_{k+1} - P_{max}\cos\gamma_k}{Q_{max}\sin\gamma_{k+1} - Q_{max}\sin\gamma_k}, \ \ \forall k.$$

Therefore, we have,

$$Q_{it} - \left(\frac{Q_{max}\left(\sin\gamma_{k+1} - \sin\gamma_k \right)}{P_{max}\left(\cos\gamma_{k+1} - \cos\gamma_k \right)} \right) P_{it} \leq$$

$$Q_{max}\left(\sin\gamma_k - \frac{\cos\gamma_k\left(\sin\gamma_{k+1} - \sin\gamma_k \right)}{\cos\gamma_{k+1} - \cos\gamma_k} \right), \ \forall k,$$

Due to the symmetric shape of semi ellipse, the following constraints are imposed for the inner linear approximation of its lower half as

$$Q_{it} + \left(\frac{Q_{max}\left(\sin\gamma_{k+1} - \sin\gamma_k \right)}{P_{max}\left(\cos\gamma_{k+1} - \cos\gamma_k \right)} \right) P_{it} \geq$$

$$-\, Q_{max}\left(\sin\gamma_k - \frac{\cos\gamma_k\left(\sin\gamma_{k+1} - \sin\gamma_k \right)}{\cos\gamma_{k+1} - \cos\gamma_k} \right), \ \forall k.$$

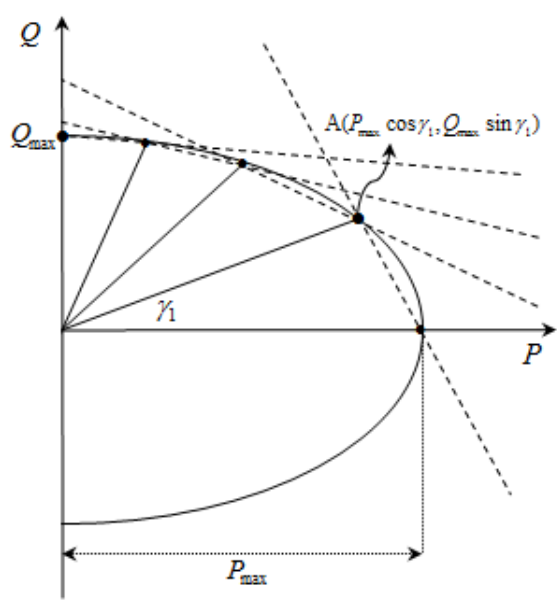

Figure C.1 Inner polyhedral linearization of the generation capability curve

Appendix D: Publications & Presentations

Journal Papers from Doctoral Dissertation:

- A. Arab, A. Khodaei, S. K. Khator, K. Ding, V. Emesih, and Z. Han, "Stochastic Pre-hurricane Restoration Planning for Electric Power Systems Infrastructure," *IEEE Transactions on Smart Grid*, Vol. 6, No 2, 1046-1054, 2015.

- A. Arab, A. Khodaei, Z. Han, and S. K. Khator, "Proactive Recovery of Electric Power Assets for Resiliency Enhancement", *IEEE Access*, Vol. 3, 99-109, 2015.

- A. Arab, E. Tekin, A. Khodaei, S. K. Khator, and Z. Han, "Infrastructure Hardening and Condition-based Maintenance for Power Systems Considering El Nino/La Nina Effects," *IEEE Transactions on Reliability*, (Under review).

- A. Arab, A. Khodaei, S. K. Khator, Z. Han, "Post-hurricane Power Grid Restoration Considering the Economics of Disaster," (to be submitted to *IIE Transactions*).

Journal Papers beside Doctoral Dissertation:

- A. Arab and Q. Feng, "Reliability Research on Micro and Nano Electro-Mechanical Systems: A Review," *International Journal of Advanced Manufacturing Technology*, Springer, Vol. 44, No. 9-12, 1679-1690, 2014.

- Q. Feng, K. Rafiee, E. Keedy, A. Arab, D. W. Coit, and S. Song "Reliability Analysis and Condition-based Maintenance for Multi-stent Systems with Stochastic-dependent Competing Risk Processes," *International Journal of Advanced Manufacturing Technology*, Springer (Accepted).

- A. Arab, A. Khodaei, S. K. Khator, Z. Han, "Sustainable Strategic Management of the Utilities of the Future: A Resource-based View on Smart Grids" (Working paper).

Conference Papers/Presentations from Doctoral Dissertation:

- A. Arab, E. Tekin, A. Khodaei, S. K. Khator, and Z. Han, "Dynamic Maintenance Scheduling for Power Systems Incorporating Hurricane Effects," *IEEE Smart Grid Communication Conference*, Venice, Italy, 2014.

- A. Arab, A. Khodaei, S. K. Khator, K. Ding, and Z. Han, "Post-hurricane Transmission Network Outage Management," *IEEE Great Lakes Symposium on Smart Grid and the New Energy Economy*, Chicago, IL, 2013.

- A. Arab, A. Khodaei, S. K. Khator, K. Ding, and Z. Han, "Optimal Restoration Planning for Smart Grid under Natural Disaster," *Poster Presentation at UT Energy Forum*, Austin, TX, 2014.

- A. Arab, A. Khodaei, S. K. Khator, Z. Han, "A Linearization Scheme for AC Power Systems," (Working paper).

Conference Papers/Presentations beside Doctoral Dissertation:

- A. Arab, S. K. Khator, Q. Feng, and Z. Han, "Control Theoretic Angiography Scheduling of Implanted Stents in Human Arteries," *Annual Industrial & Systems Engineering Research Conference*, Nashville, TN, 2015.

- A. Arab, E. Keedy, Q. Feng, S. Song, and D. W. Coit, "Reliability Analysis for Implanted Multi-stent Systems with Stochastic Dependent Competing Risk Processes," *Annual Industrial & Systems Engineering Research Conference*, Puerto Rico, 2013.

- F. Sangare, A. Arab, M. Pan, L. Qian, S. K. Khator, and Z. Han, "RF Energy Harvesting for WSNs via Dynamic Control of Unmanned Vehicle Charging" *IEEE Wireless Communications and Networking Conference*, New Orleans, LA, 2015.

- J. Sosa, A. Arab, E. Tekin, M. Bennis, S. K. Khator, and Z. Han, "Smart Energy Pricing for Utility Companies Using Reinforcement Learning," (Working paper).