The Dissertation Committee for Yezhou Wang
certifies that this is the approved version of the following dissertation:

Security of Electric Power Systems: Cascading Outage Analysis, Interdiction Model and Resilience to Natural Disasters

Committee:

Ross Baldick, Supervisor

Surya Santoso

Alexis Kwasinski

Todd Humphreys

Mohit Tiwari

Eric Bickel

Security of Electric Power Systems: Cascading Outage Analysis, Interdiction Model and Resilience to Natural Disasters

by

Yezhou Wang, B.E.; B.E.; M.S.E.

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Dedicated to my family.

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**Security of Electric Power Systems:
Cascading Outage Analysis, Interdiction Model and
Resilience to Natural Disasters**

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Supervisor: Ross Baldick

Secure electric power system operation is key to social warfare. However, recent years have seen numerous natural disasters and terrorist attacks that threat the grid security. This dissertation summarizes the efforts to develop a model to analyze cascading outages, an interdiction model to analyze worst-case attacks on power grids, and research on grid resilience to natural disasters. The developed cascading outage analysis model uses outage checkers to systematically simulate the system behavior after an initial disturbance, and calculate the potential cascading outage path and electric load shedding. The new interdiction model combines the previously developed medium-term attack-defense model with the short-term cascading outage analysis model to find worst-case terrorist attack. The dissertation also reviews the research on power grid resilience to natural disaster, and develops a framework to simulate the impacts of hurricanes.

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Part I

Introduction

Chapter 1

Introduction

Electric power systems provide an essential source for the operation of the economy and for human well-being. Modern society is increasingly dependent on reliable, secure and cost-efficient electricity supply. However the electric grids, especially in U.S., are remarkably complex with some transmission lines spanning hundreds of miles. Terrorists could destroy key elements of the electricity generation and delivery system, causing blackouts that are unprecedented in this country in duration and extent [141]. In this dissertation, we try to develop models and tools to simulate the effects of deliberate attacks, find the worst possible scenarios, and develop techniques to mitigate the blackouts. At the same time, recent years have seen many large electricity blackouts across the globe due to natural disasters. The costs of such blackouts could be billions and the social warfare could be significantly damaged because of such events. Therefore, we conduct a survey on the existing state-of-art research of power system resilience to natural disaters, and try to develop models to simulate the impacts of natural disasters, and thus help decision makers be better prepared to such events. More specifically, we divide this dissertation into three parts, namely Cascading Outage Analysis, Integrated Interdiction Model, and Power Grid Resilience under Natural Disasters.

Many large blackouts are caused by a consecutive series of various outages following an initial disturbance. The understanding and simulation of such cascading outages are the foundation to provide reasonable assessment of power grid disturbances caused by deliberate attacks or natural disasters. Therefore, we build an enhanced cascading outage analysis tool to facilitate this function. In part two, we incorporate this cascading outage analysis tool to a worst-cast interdiction framework, in order to find out the worst-case attack scenario on a power grid. In part three, we survey the research on natural disasters and provide a framework for forecasting natural disasters related power outages.

The contributions in this work are:

- The enhancement of a Cascading Outage Analysis (COA) model and research on mitigation of cascading outages;
- Incorporation of the COA model into an interdiction framework and the development of an algorithm to solve the problem;
- Survey of state-of-art in power system resilience research on natural disasters and models to forecast hurricane-related outage.

This dissertation is based on the author's contribution in the papers [215], [214], [217], [216], [210], [218] and [219].

1.1 Background on Cascading Outage Analysis

Many large blackouts are caused by a consecutive series of various outages following an initial disturbance. Once enough critical components of a power system fail, the outages including transmission line, generator, and load trips can sequentially spread and lead to large blackouts [209]. Nevertheless, it is very difficult to identify critical components that represent weaknesses in the power system and to analyze cascading outages due to the lack of detailed blackout data and complicated electrical-physical interactions.

According to [209], [204], and [67], some major blackouts in North America due to cascading outages are shown in Table 1.1.

Table 1.1: Examples of Cascading Blackouts in North America [209], [204], and [67]

Date	Location	Customers Affected/MW Lost	Collapse Time	Nature of Collapse
Nov. 9, 1965	Northeast	30 million	13 minutes	Successive tripping of lines
July 13, 1977	New York City	1 million	1 hour	Successive tripping of lines and generators
Dec. 22, 1982	West Coast	12,350 MW	Few Minutes	Successive line tripping, protection coordination scheme failure
Dec. 15, 1994	Western U.S.	9,336 MW	N/A	Transient instability, successive tripping of lines, voltage collapse
July 2, 1996	Western U.S.	2 million	36 seconds	Successive tripping of lines, generators and voltage collapse
Aug. 10, 1996	Western U.S.	7.5 million	>1 minute	Voltage collapse
Aug. 14, 2003	Northeastern and Midwestern U.S. and Ontario, Canada	55 million	Few Minutes	Successive tripping of lines, generators and voltage collapse
Sep. 8, 2011	Southwestern U.S.	7 million	Few Minutes	Successive tripping of lines and islanding

1.2 Background on Interdiction Models

Secure electric power system operation is critical to society. It is noted in [141] that some blackouts would not immediately kill many people or make for spectacular television footage of bloody destruction. But if it were carried out in a carefully planned way, by people who knew what they were doing, it could deny large regions of the country access to bulk system power for weeks or even months. An event of this magnitude and duration could lead to turmoil, widespread public fear, and an image of helplessness that would play directly into the hands of the terrorists. If such large extended outages were to occur during times of extreme weather, they could also result in hundreds or even thousands of deaths due to heat stress or extended exposure to extreme cold. Therefore, it is important to think about what can be done to make them less vulnerable to attack, how power can be rapidly restored if an attack occurs, and how important services can be sustained while the power is out.

Deliberate attacks do not occur frequently, but when they do, they can be disastrous [164]. Trying to quantitatively evaluate the probability of such low-probability-high-consequence potential terrorist attacks is very challenging, resource demanding, and subject to inaccuracies. At the same time, the outcome of an attack depends strongly on the current system operation conditions during an attack, as well as the resources that terrorists have, both of which are also highly uncertain. Bienstock et al. [33] developed a model that includes a range of scenarios for the disruption. Chen et al. [50] use a probabilistic approach to $N-k$ analysis for naturally occurring events. However, given the uncertainties, the assumption made in the following work is that the system operators, or defenders, should consider a "worst case" analysis in order to correctly utilize a defense budget. Therefore, while the studies of [33] and [50] are valuable, we aim to identify the worst-case attacks on a certain system that an intelligent adversary might carry out.

Salmeron et al. [166] developed a bi-level optimization model that maximizes the medium-term "disruption" to the loads with given terrorist resources. A heuristic algorithm was also proposed to solve the problem to a near-optimal solution. In [6], a new algorithm called "Global Benders Decomposition" is proposed to guarantee the convergence of the bi-level optimization problem in [168]. Arroyo et al. [22] use a genetic algorithm to solve the interdiction problem. Romero et al. [164] proposed a three-level mixed-integer model, and used Tabu Search with an embedded greedy algorithm to seek an optimum defense strategy. The power flow subproblem of these four models is an "interdicted" DC optimal power flow model. Donde et al. [62] developed a nonlinear optimization problem to detect the fewest possible transmission line outages resulting in a system failure of specified severity. An AC optimal power flow model is used in that paper. Carrion et al. [164] uses a stochastic programming formulation to reinforce and expand a power system with the objective of reducing the impact of deliberate attack. Smith et al. [186] also studied different models and algorithms to solve network interdiction games.

While the optimal power flow (OPF) problem used in the interdiction models, either AC or DC, represents the economical operation (medium-term) of the power system by the Independent System Operators (ISOs), and maximizes the amount of load that can be served, it is a steady state optimization framework that does not consider short-term cascading outage effects. The phrase "medium-term" indicates a time window of minutes to hours or days, and the phrase "short-term" means a time window of seconds to minutes.

To our knowledge, no literature combined the short-term cascading effects and medium-term impacts of an interdiction.The primary contributions in this work are: incorporation of a novel COA model into the interdiction framework; and the development of an algorithm to solve the problem.

We note that it would never be possible to accurately identify terrorists' motivation, at least not before an attack [168]. Consequently the modeling of the attackers' objective function is problematic. In this dissertation, combined penalty costs associated with the amount of load shedding from a cascade and medium-term operation are used to represent the consequence of a potential terrorist attack.

1.3 Background on Natural Disasters Impact on Power Systems

Recent years have seen many blackouts due to natural disasters such as the 2005 Hurricane Katrina blackouts, 2011 Japan Earthquake blackouts, and 2012 Hurricane Sandy blackouts. Between 2003 and 2012, roughly 679 power outages, each affecting at least 50,000 customers, occurred due to weather events in U.S. [64]. Hines et al [89] describes 933 events causing outages from the years 1984 to 2006, and the data is presented in Table 1.2[1]. The study of natural disaster impacts on power grid can be traced back to 1930s, when the 1938 New England Hurricane struck the Boston Area [79]. In the last decades, there has been considerable progress in advancing methods for analyzing natural disaster related issues in power systems. At the same time, due to the complexity of the issue and its interdisciplinary nature, research activities are conducted sparsely across different domains. We summarize the natural disaster characteristics based on multiple sources such as [77], [89] in Table 1.3.

1.4 Layout of this dissertation

This dissertation is organized in three main parts:

- Part I: Cascading Outage Analysis, where cascading outage analysis models will be discussed in detail; mitigation techniques, examples and

[1] The totals are greater than 100% because some events fall into multiple initiating-event categories.

Table 1.2: Large Blackouts Causes in the United States [89]

Cause	% of events	Mean size in MW	Mean size in customers
Earthquake	0.8	1,408	375,900
Tornado	2.8	367	115,439
Hurricane/tropical storm	4.2	1,309	782,695
Ice storm	5.0	1,152	343,448
Lightning	11.3	270	70,944
Wind/rain	14.8	793	185,199
Other cold weather	5.5	542	150,255
Fire	5.2	431	111,244
Intentional attack	1.6	340	24,572
Supply shortage	5.3	341	138,957
Other external cause	4.8	710	246,071
Equipment failure	29.7	379	57,140
Operator error	10.1	489	105,322
Voltage reduction	7.7	153	212,900
Volunteer reduction	5.9	190	134,543

models are also discussed.

- Part II: Integrated Interdiction Model, where an analysis of power grid interdiction is presented.

- Part III: Power Grid Resilience under Natural Disasters, where a survey of current research on power grid resilience is conducted, and a tool to analyze power system security under hurricane threats is presented.

Conclusion is provided in the last part of the dissertation.

Table 1.3: Illustration of disaster characteristics based on multiple sources

Type	Impact Region	Predictability	Span/area	Affecting time
Hurricane, tropical storm	Coastal regions	24-72 hours, moderate to good	Large (radius up to 1,000 miles)	Hours to days
Tornado	Inland plains	0-2 hours, bad to moderate	Small (radius up to 5 miles)	Minutes to hours
Blizzard, Ice Storm	High latitude regions	24-72 hours, moderate to good	large, up to 1,000 miles	Hours to days
Earthquake	Regions on fault lines	Seconds to minutes, bad	Small to large	Minutes to days (after-shock)
Tsunami	Coastal regions	Minutes to hours, moderate	Small to large	Minutes to hours
Drought, Wild Fire	Inland regions	Days, good	Medium to large	Days to months

Part II

Cascading Outage Analysis

Chapter 2

Cascading Outage Analysis Model

Chapter 2 is based on author's contribution in [215], [216], [218]. The co-author Dr. Ross Baldick in these papers provided guidance, suggestions and review of the research work. Cascading outage is the main mechanism of large blackouts, and the duration of the sequence of cascading events can be very short. In the 2003 North-Eastern America Blackout [204], 14 high voltage transmission lines were tripped out within 5 minutes. In order to evaluate the short term impacts of a particular attack, the amount of short-term load shed should be calculated. Many efforts have been put into research to identify the cause of these events and the methods to mitigate them. Eppstein et al [62] has developed a Random Chemistry algorithm to identify the multiple contingencies that initiate cascading failure. Hazra et al [83] proposes pattern recognition and fuzzy estimation to calculate the cascading sequences of an event. Jie Chen et al [49] introduces a hidden failure model with an embedded DC model to study the cascading dynamics and mitigation. These methods are either very computationally expensive, or did not very accurately represent the system behaviour after the initial disturbances. Thus motivated, we propose an outage checker based algorithm to simulate the potential cascading outage of the system. Some of our previous work on developing sequential outage checker based COA analysis is presented in [91] and [215]. In this chapter, we provide an improved COA model, more detailed and accurate preventive equipment modeling, and case studies using the IEEE test systems.

2.1 Work flow of the COA

In previous models [91], [215], the cascading outage analysis is performed with sequential application of the checkers. This sequence is applied based on assumptions about the timing of various system protective actions subject to different criteria. For example, we assume the transient stability protection will detect rotor angle instability and trip generators before Under Frequency Load Shedding (UFLS) activates. The frequency relay will deploy UFLS before the over current relays trip the overloaded components, and over current relays will act before the under voltage relays trip out the loads or generators that experience voltage instability. However, in practice, the time of potential relay actions for the frequency relays, over current relays, and voltage relays could overlap. Once an element is tripped out (i.e., the line tripped out by the fastest relay), the system topology is changed accordingly, which will induce a sudden change of the power flow. The elements that were not tripped out will experience different loading, and could then be tripped by subsequent protective action. Therefore, in this report, simultaneous application of protection is modeled by the checkers and more detailed models of each protection scheme are implemented to provide a better representation of the sequence of the cascade. The approach is also reported in [217].

The analysis starts from a specification of the initial disturbances. Then the transient stability or rotor angle stability is checked by the Transient Stability Checker (TSC). If the generator rotor angle is larger than a certain threshold, say, 100 degrees, the generator will be automatically tripped and the analysis goes to the next cascading stage involving analysis with the TSC. If the system reaches a transiently stable state, the COA activates the three other checkers (frequency outage checker or FOC, overload outage checker or OOC, voltage outage checker or VOC) simultaneously. Each checker is implemented with a relay function to return a potential trip time. Then the COA determines the first element to trip (if any). If the topology changes, the COA will come to the next cascading stage and start the transient stability checker again. The workflow diagram is shown in Figure 2.1.

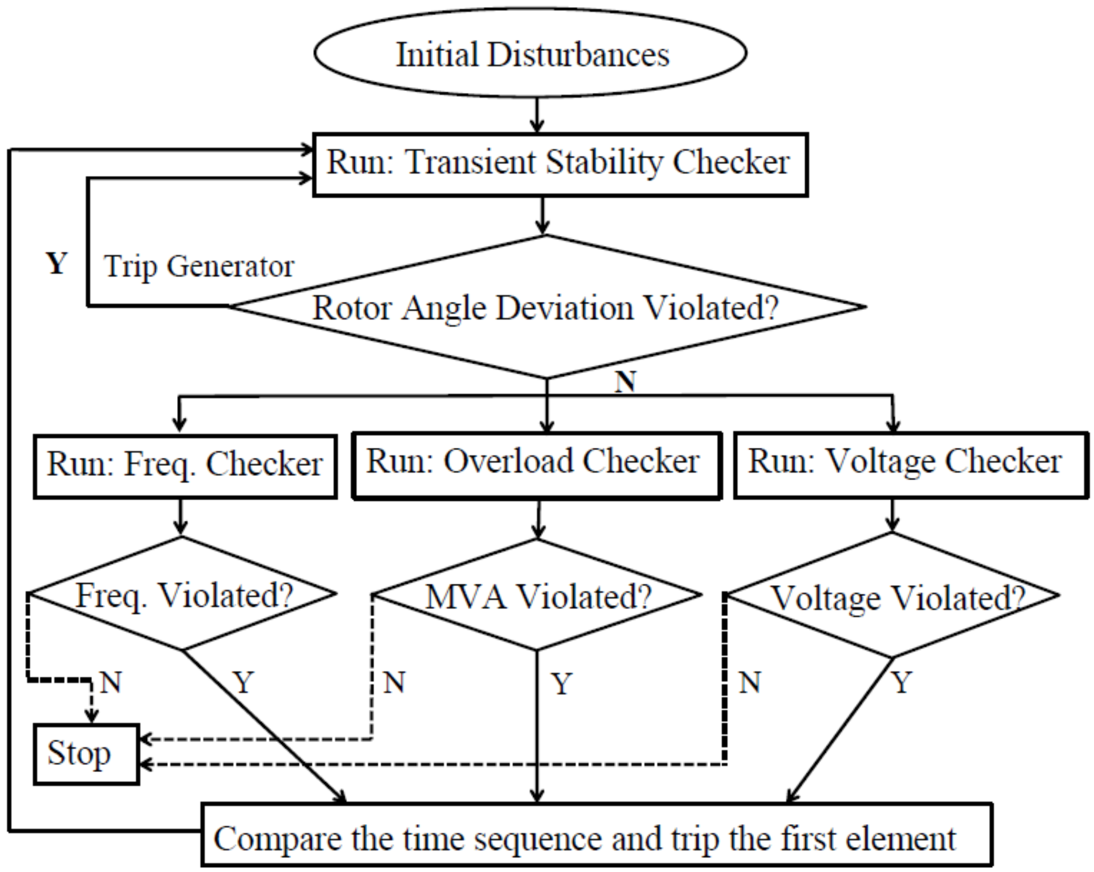

Figure 2.1: Work flow of the COA

2.2 Design of the Transient Stability Checker (TSC)

Transient stability, or rotor angle stability is the ability of the power system to remain in synchronism when subjected to large transient disturbances [93]. According to [126], the power system dynamic behavior can be represented as a set of differential equations (2.1) and a set of algebraic equations (2.2).

$$\dot{x} = f(x, y) \tag{2.1}$$

$$0 = g(x, y) \tag{2.2}$$

The solution of these two set of equations defines the electromechanical state of the power system at any instant in time. A disturbance in the network usually requires a change to both the network configuration and boundary conditions. These are modeled by changing the coefficients in the functions appearing on the right-hand side of equations (2.1) and (2.2).

In the context of transient stability under disturbances, these disturbances may include faults on transmission elements, loss of load, loss of generation, etc. Notice that the faults on the transmission elements, which are typically short-circuit to the facilities, if cleared and re-closed successfully, should not result in physical destruction of the assets. This is very different from the physical attack aimed at damaging the facilities, since permanent damage could contribute to long-term impacts on the system. A short-circuit type of attack could easily be initiated by applying conductive material (e.g. piece of metal, etc) to the transmission elements (e.g. overhead transmission lines, etc). Transient stability analysis has been performed in power system analysis by many methods. [231] and [58] use time-domain simulation to calculate the exact system response in time by implicitly numerically integrating the differential equations (1) and solve the algebraic equations (2) at each time step. The timedomain simulation is the most accurate method, but is slow in computation and does not provide any measurement of degree of system stability. Transient energy function (TEF) and potential energy boundary surface (PEBS) [71], [43], [52] methods avoid making numerical integration by constructing energy functions and comparing the system energy (when fault is cleared) to a critical energy value estimated by the energy fuctions to determine wherther or not the system will remain stable. These methods are fast in computation compared to the time simulation, and also able to provide useful information regarding the degree of stability or instability. However, they are only applicable to power system stability models having energy functions, and are not as accurate as numerical integration. Hybrid methods [129] combines the numerical integration and the energy functions method. As indicated in [217] we use time-domain simulation to perform the transient stability assessment because of its high accuracy. The time-domain simulation allows taking into account the full system dynamic model and consists in checking that inter-machine rotor angle deviations lie within a specific range of values. We choose to use time-domain simulation in this work.

Different models have been used to represent different dynamic characteristics of the generator. In our simulation, a "GENROU" model is selected to represent the round rotor generator. It is noticeable in [158] that the GENROU model provides a very good approximation of the behavior of synchronous generator. More than 2/3 of the machines in the 2006 North American Eastern Interconnect case (MMWG) are represented by GENROU models. Additionally, standard "IEEE T1" exciter model is used to represent a brushless alternating current (AC) exciter with a rotating rectifier, and "IEEE G1" governor model is used to represent the governor response model.

The transient stability checker uses the PowerWorld transient stability solver to numerically calculate the system response after a fault. If the rotor angle deviation of a generator is bigger than a certain threshold, say, 100 degrees, the generator will automatically be tripped. To illustrate this scheme more clearly, a simulation example is shown in Figure 2.2 and Figure 2.3.

The simulation is performed using IEEE RTS-96 one area test case [4]. The first scenario is a three phase fault applied on the transmission line from Bus 13 to Bus 11, circuit 1, at 1.0 second, and the relays cleared the fault at 1.1 second. Three generator rotor angles (Gen 13 unit 1, Gen 13 unit 2, Gen 23 unit 1) are plotted. As can be seen from the Figure 2.2, the system experienced some fluctuations, but finally remained stable.

Second scenario is performed under the same setting, but with a fault clearing time changed from 1.1 seconds to 1.3 seconds. As can be seen from the Figure 2.3, the generator angle deviations increase dramatically, and generator unit 1 at bus 13 is tripped out due to angle deviation larger than 100 degrees at roughly 1.324 seconds.

The implementation of transient stability enables the Cascading Outage Analysis (COA) model to include transient stability assessment (or rotor angle stability problem), and hence provides a more accurate representation of the system behavior.

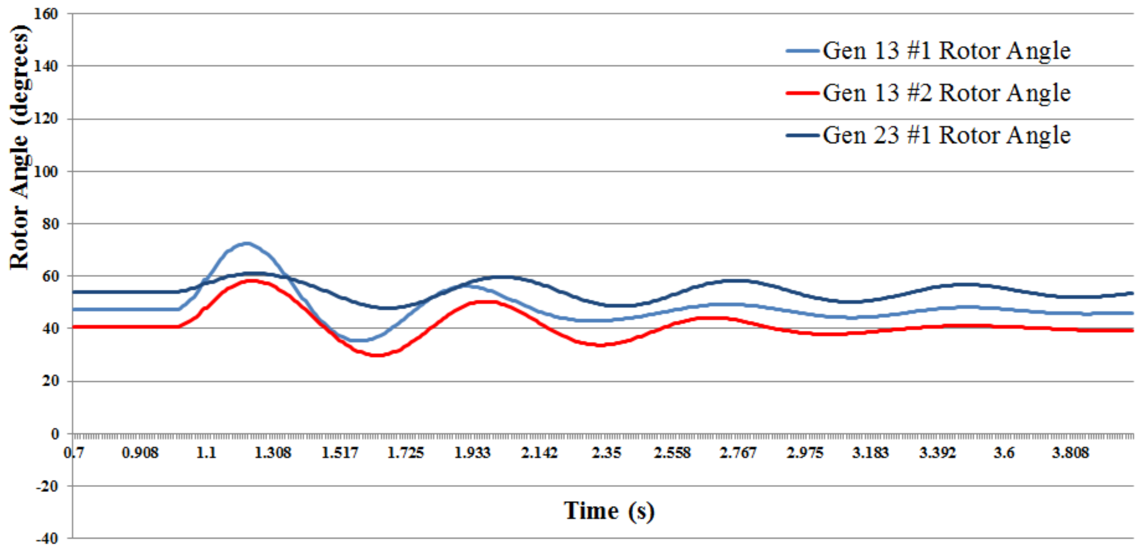

Figure 2.2: Generator angle for scenario one, stable swing

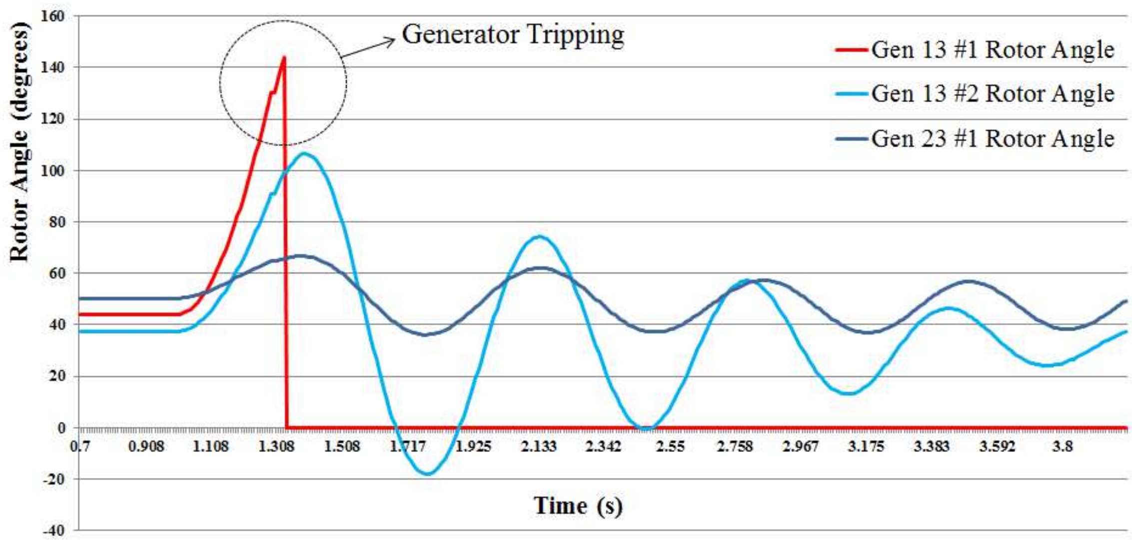

Figure 2.3: Generator angle for scenario two, unstable swing

2.3 Frequency Outage Checker (FOC)

Since the numerical integration method used in the transient stability checker is relatively computationally expensive, we limit the simulation time window to be 4 seconds, which is typically more than enough time to address the rotor angle deviation. However, if a mismatch of the generation and load happens, a subsequent frequency excursion will occur, typically after the rotor angle transient dies out. The frequency excursion may then trigger the over- or under-frequency protection. To represent this possibility, the frequency outage checker (FOC) is designed to model the protection behavior against system over or under-frequency events. In the frequency outage checker, a system frequency response (SFR) model [19] is used as a frequency response model. In the model, nonlinearities and all but the largest time constants in the equations of the generating units of the power system are neglected, with the added assumption that the generation dynamics are dominated by reheat steam turbine generators.[1] Topologically, the model replaces separate machines by a single large machine that is connected to the individual generator buses through ideal phase shifters. Consequently, the model produces an average frequency response shape of a system. In this report, frequency outages are specified in accord with the frequency outage standard from ERCOT [63]. According to this standard, when the system frequency violates a pre-determined threshold for a certain amount of time, the under frequency relays will operate to deploy under frequency load shedding. The equations (2.3) and (2.4) show the frequency response model that is used to calculate the frequency response.

[1]With increasing capacities of gas turbine and combined cycle gas turbines, this assumption is not literally true in, e.g. ERCOT. However, the resulting second order model for frequency may still be a reasonably accurate representation.

$$f(t) = \frac{RP_{step}}{(DR + K_m)2\pi}[1 + \alpha e^{-\varsigma\omega_n t} sin(\omega_r t + \phi)] + 60 \tag{2.3}$$

$$f(t) = K \tag{2.4}$$

where,

$$\omega_n^2 = \frac{DR + K_m}{2HRT_R}$$

$$\varsigma = (\frac{2HR + (DR + K_m F_H)T_R}{2(DR + K_m)}\omega_n)$$

$$\alpha = \sqrt{\frac{1 - 2T_R\varsigma\omega_n + T_R^2\omega_n^2}{1 - \varsigma^2}}$$

$$\omega_r = \omega_n\sqrt{1 - \varsigma^2}$$

$$\phi = \tan^{-1}(\frac{\omega_r T_R}{1 - \varsigma\omega_n T_R}) - \tan^{-1}(\frac{\sqrt{1 - \varsigma^2}}{-\varsigma})$$

In the above equations, R is governor droop, $\Delta\omega$ is incremental speed in per unit, F_H is fraction of total power generated by the HP turbine, T_R is reheat time constant in seconds, H is inertia constant in seconds, D is damping factor, K_m is mechanical power gain factor, P_{step} is disturbance magnitude in per unit and K is pre-defined threshold frequency.

Figure 2.4 shows how to obtain the under frequency time duration from the frequency functions. The time when the frequency first drops under the frequency threshold, t_1, and the time when the frequency first rises up to the threshold again, t_2, are determined to calculate the time duration $(t_2 - t_1)$. To determine the intersection of two functions (2.3) and (2.4), one could solve equation (2.5) by methods described in [233].

$$\frac{RP_{step}}{(DR + K_m)2\pi}[1 + \alpha e^{-\varsigma \omega_n t} sin(\omega_r t + \phi)] + 60 = K \tag{2.5}$$

If there are two solutions to (2.5), they are the values of t_1 and t_2. As a result, time duration for a specific threshold frequency can be obtained as $(t_2 - t_1)$. If there is no solution, the time-delay is not calculated, thus the frequency relay will not be triggered. If there is one solution, the frequency of the intersect is compared with the UFLS settings. When intersect frequency is lower than the UFLS threshold, the UFLS may still be deployed but the frequency may not restore to the pre-disturbance level. When the intersect frequency equal to the UFLS threshold, no UFLS scheme will be deployed. An example frequency curve is shown in Figure 2.4.

As seen in Figure 2.4, the lowest point of frequency value should be the first local minimizer of the frequency curve. This is due to the fact that the curve is a damped sine wave and the following local minimizers will be closer to 60 Hz. In an optimization problem like calculating minimum frequency f^{min}, the first order condition to find the local minimizer can be applied. If the derivative of the function at one point is zero, then this point is a local

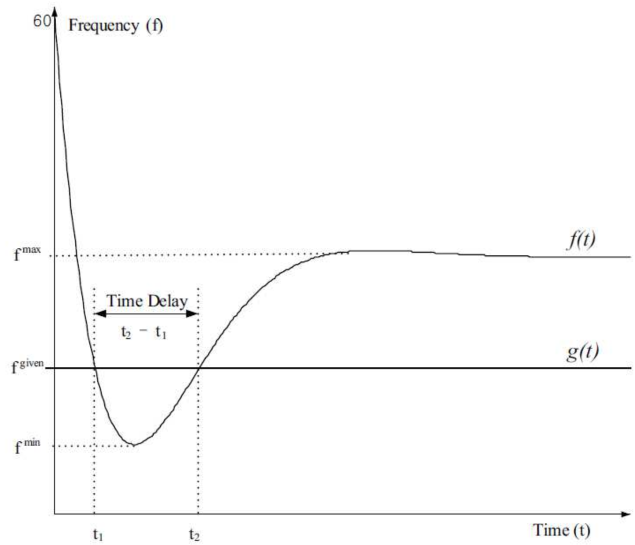

Figure 2.4: An example frequency drop curve

minimizer, maximizer, or inflection point. In this problem, finding a point t which satisfies the equation $\nabla f(t) = 0$ in the first cycle of the curve is necessary to obtain the time of minimum frequency.

After calculating the time duration in the FOC, it determines whether the calculated time duration (CTD) of frequency violation exceeds the set time duration (STD) of the protective relay. If STD is greater than CTD, the frequency checker selects the next generator according to a user defined order and compares two time duration values. If a frequency violation is detected in the calculation step, the FOC will return the time at which under frequency load shedding will be deployed. The time will later be used in cascading comparison algorithm.

2.4 Overload Outage Checker (OOC)

Line overloading for violating thermal limits is an important and common measure to identify the mechanism of cascading outages and to assess vulnerability to cascading outages [216]. In a cascading outage scenario pertinent to line overloading, a line outage can cause increased flows on other lines, potentially leading to overloading of the other lines. As a result, when a line violates the thermal limit, the overloaded lines may be tripped.

A normal inverse time-overcurrent model described in Siemens SIPROTEC 5 Current Relay [185] is implemented. The time when the over current relay trips the element is determined by (2.6).

$$T = \frac{0.14}{(\frac{I}{I_{th}})^{0.02} - 1} \cdot T_p[s] \tag{2.6}$$

Where I_{th} is the current threshold value of the relay. T_p is the setting value of the relay. The normal inverse current relay characteristic is shown in Figure 2.5. Note that in some cases a sag of a transmission line may result in a short circuit to other objects, e.g. a tree. This phenomenon was observed in 2003 North America blackout [204]. We are not modeling this issue in the COA.

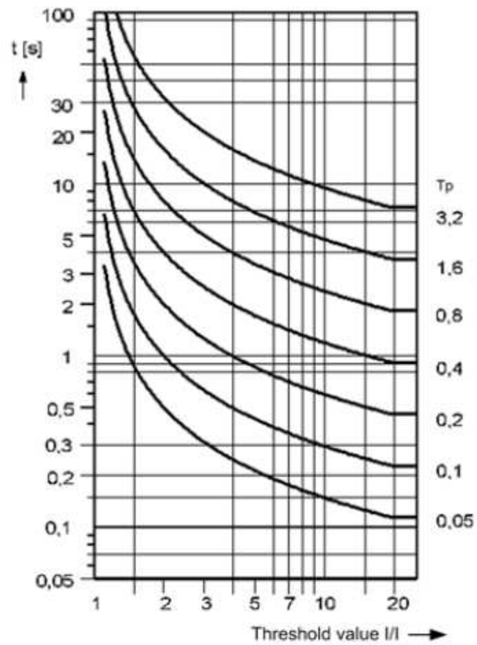

Figure 2.5: Normal Inverse Current Relay Characteristic [185]

2.5 Voltage Outage Checker (VOC)

Another typical character of cascading outages includes under (or over) voltage problem. When the system is highly stressed, the voltage profiles of power systems may decline. Similar to the line outage checker, when a voltage profile for a bus violates a pre-defined chosen threshold to maintain system stability, the voltage outage checker (VOC) may activate. If a bus voltage stays below the lower limit during the VOC process although the power flow calculation converges, load shedding action may be taken to maintain bus voltages within limits [216].

A standard Inverse time characteristic model described in ABB RXEDK

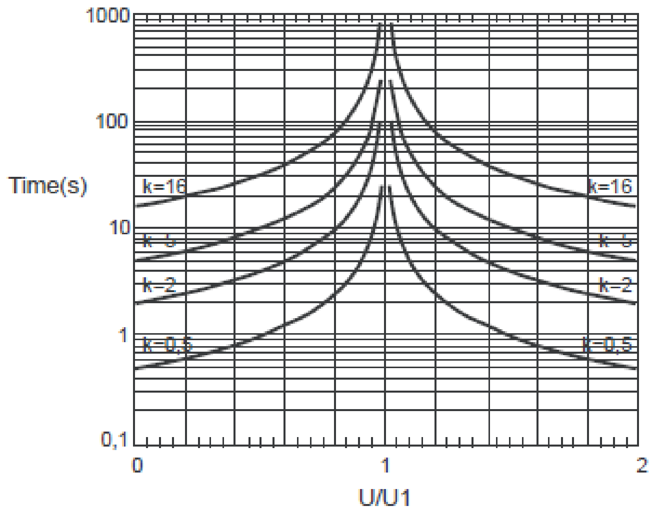

Figure 2.6: Inverse Voltage Relay Characteristic [11]

2H Time over/undervoltage relay [11] is implemented in voltage relay modeling. The time that under or over voltage relay trips the element is determined in (2.7) and (2.8).

$$Overvoltage : T = \frac{k}{\frac{U}{U1} - 1}[s] \tag{2.7}$$

$$Undervoltage : T = \frac{k}{1 - \frac{U}{U1}}[s] \tag{2.8}$$

Where k is the inverse time constant, $U1$ is the over/under voltage relay pick-up value, U is the user defined relay operating value. The inverse voltage relay characteristic curve is shown in Figure 2.6.

2.6 Implementation and case study of COA

Both the previous COA model discussed in [215] and the proposed improved COA model is implemented on a 2.5GHz dual core laptop with 4GB RAM. The simulations have been performed using IEEE 118 bus test case [2] and IEEE 300 bus test case [3]. Average simulation time is 3 seconds for previous COA model, and 3.5 seconds for the improved model. The increase of the computational time is due to the fact that three checkers (FOC, OOC, VOC) have to run every time the system passes through TSC stage to obtain potential tripping time, while in the previous model, the simulation stops or proceeds to the next cascading stage after one checker is activated. In our simulation, transmission line and transformer MVA limits are set relatively tight in order to illustrate the cascading scenarios.

The cascading outage analysis (COA) tool has been built on the Windows based Visual Basic Applications (VBA) [132] in order to support various distributed computing environments and interaction with other programs such as PowerWorld simulator [158] and MS Excel [131]. The implementation framework is shown in Figure 2.7. The high level control work flow, along with the relay models and frequency calculation algorithm are implemented using VBA. The AC power flow calculation and the numerical integration of the transient stability checker are based on the PowerWorld simulator results. A report including the post COA powerflow, transient rotor angle data, and the potential cascading outage data is given in multiple excel worksheets. A Graphical User Interface (GUI) is also designed to enable customized user in-

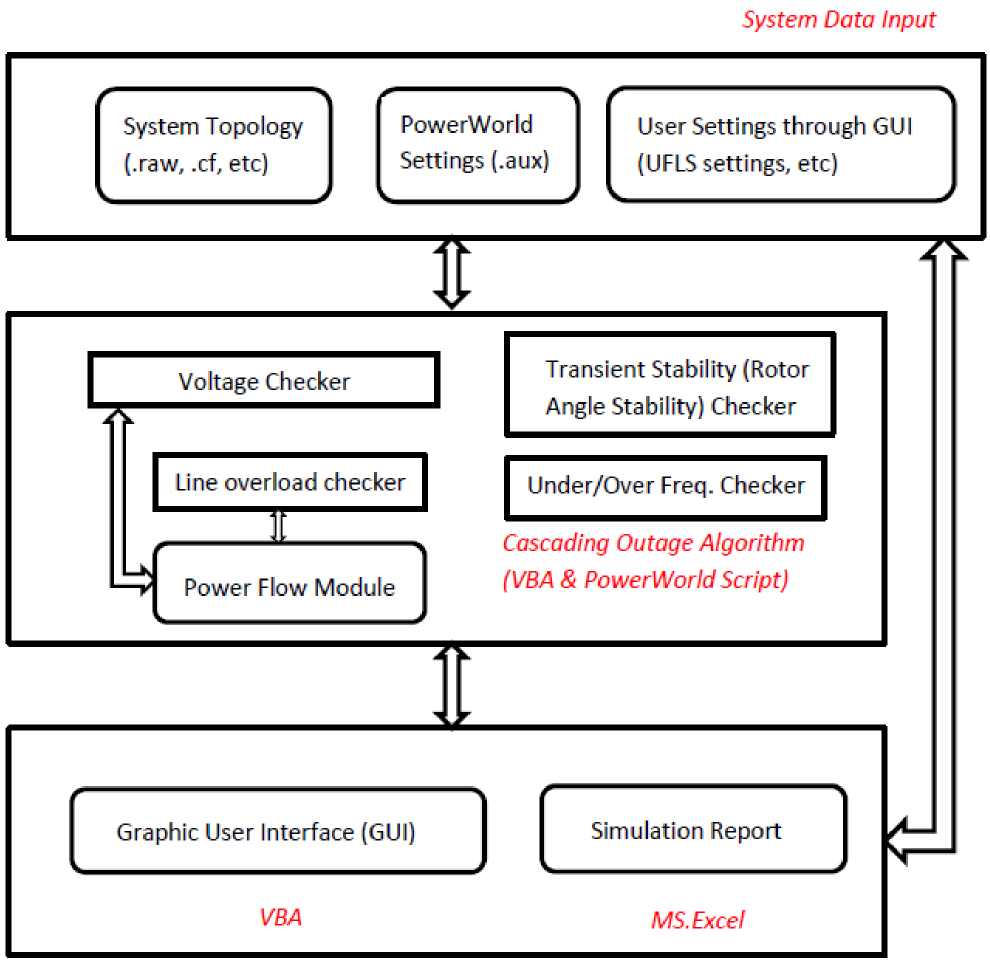

Figure 2.7: Implementation framework of the COA

put, settings, and to show a real-time simulation log. The design of the GUI is shown in Figure 2.8.

2.6.1 IEEE 118 Bus System

To illustrate operation of the COA and the difference between the previous COA model and the improved model, a particular initiating event is

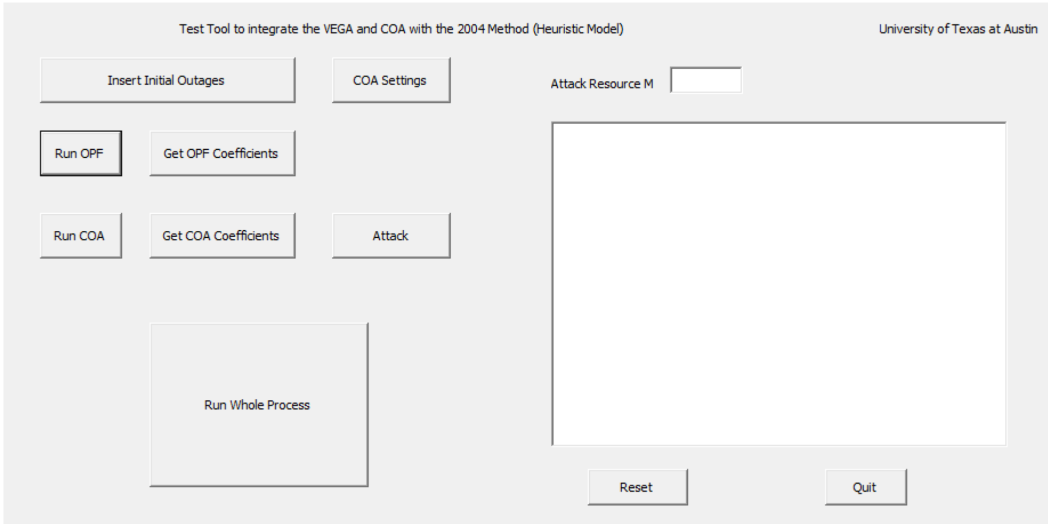

Figure 2.8: Graphical User Interface of the COA

chosen. In this IEEE 118 Bus System simulation, the initial disturbances are tripping transmission line 35-37-1, transformer 38-37-1 and transmission line 45-49-1. The cascading outage sequence simulated by the COA model described in [215] is shown in table 2.1. The cascading sequence simulated by the improved COA model is shown in table 2.2.

As can be seen from the results, when compared with previous work [215], the improved COA model proposed in this report indicated a different cascading path. However, the cascading events seen from the improved model are also shown in table 2.1 at analogous stages. The improved model provides a better representation of time sequence of the cascade, and avoids tripping out many elements that should not be tripped due to practical relay time setting. For example, at the first stage, as revealed from table 2.2, three lines are overloaded, but in fact only one line 45-46-1 will be tripped out because

Table 2.1: Cascading Sequence of IEEE 118 Bus Case using model in [215]

fromNum	toNum	ID	Category	Stage
15	33	1	Line Overload	1
45	46	1	Line Overload	1
68	81	1	Line Overload	1
15	19	1	Line Overload	2
18	19	1	Line Overload	2
19	34	1	Line Overload	2
34	43	1	Line Overload	2
37	40	1	Line Overload	2
39	40	1	Line Overload	2
40	42	1	Line Overload	2
41	42	1	Line Overload	2
42	49	1	Line Overload	2
42	49	2	Line Overload	2
65	68	1	Line Overload	3
23	24	1	Line Overload	4
26	25	1	Line Overload	4
47	49	1	Line Overload	4
49	69	1	Line Overload	4
Blackout				

of the shortest time delay (0.446s).

Table 2.2: Cascading Sequence of IEEE 118 Bus Case using improved model

fromNum	toNum	ID	Category	Stage	Time
45	46	1	Line Overload	1	0.446482
15	33	1	Line Overload	2	0.856211
19	34	1	Line Overload	3	1.118852
Blackout					

2.6.2 IEEE 300 Bus Test Case

Another simulation is performed on IEEE 300 Bus Test System. The initial disturbances are tripping transmission line 7002-2-1, and 3-1-1. The cascading outage sequence simulated by COA model proposed in [215] is shown in table 2.3. The cascading sequence simulated by the improved COA model is shown in table 2.4.

The improved model indicates similar cascading path at analogous stages, but the new model reveals the sequence of each protective device operation. At the time of 4.6386s, the system will be blacked out after 9 stages of cascading outage.

Table 2.3: Cascading Sequence of IEEE 300 Bus Test Case using model in [215]

fromNum	toNum	ID	Category	Stage
3	2	1	Line Overload	1
7	6	1	Line Overload	1
8	11	1	Line Overload	2
16	15	1	Line Overload	3
15	37	1	Line Overload	4
37	41	1	Line Overload	4
2	N/A	1	Load UnderVoltage	5
6	N/A	1	Load UnderVoltage	5
8	N/A	1	Load UnderVoltage	5
14	N/A	1	Load UnderVoltage	5
15	N/A	1	Load UnderVoltage	5
17	N/A	1	Load UnderVoltage	5
89	N/A	1	Load UnderVoltage	5
90	N/A	1	Load UnderVoltage	5
9031	N/A	1	Load UnderVoltage	5
9031	N/A	1	Load UnderVoltage	5
9032	N/A	1	Load UnderVoltage	5
9033	N/A	1	Load UnderVoltage	5
9035	N/A	1	Load UnderVoltage	5
9036	N/A	1	Load UnderVoltage	5
9037	N/A	1	Load UnderVoltage	5
9038	N/A	1	Load UnderVoltage	5
9040	N/A	1	Load UnderVoltage	5
9041	N/A	1	Load UnderVoltage	5
9042	N/A	1	Load UnderVoltage	5
Blackout				

Table 2.4: Cascading Sequence of IEEE 300 Bus Test Case using improved model

fromNum	toNum	ID	Category	Stage	Time(s)
7	6	1	Line Overload	1	0.5624
3	2	1	Line Overload	2	0.8844
8	11	1	Line Overload	3	1.2327
16	15	1	Line Overload	4	1.7786
15	37	1	Line Overload	5	2.1786
6	N/A	1	Load UnderVoltage	6	2.7604
2	N/A	1	Load UnderVoltage	7	3.3922
15	89	1	Line Overload	8	4.0316
15	90	1	Line Overload	9	4.6386
Blackout					

2.7 Summary and future work

In this chapter, a cascading outage analysis model (COA) is proposed and tested through the implementation and simulations discussed above. The model provides a way to evaluate the short term impacts of an attack, e.g. the amount of short-term load shed. The COA model applies four outage checkers, namely Transient Stability Checker, Frequency Outage Checker, Overload Outage Checker, and Voltage Outage Checker to simulate the system behavior after an initial disturbance, i.e. an attack. The proposed COA model is compared with the previous model, and has shown advantages including more accurate relay model representations and better cascading sequence calculation.

The cascading outage analysis has several limitations. Potential improvements include:

- The cascading outage analysis model does not consider breaker failures and back-up protection schemes such as zone-2 and zone-3 protection. The future work may include these models to reflect the real-world scenarios.

- The cascading outage analysis model uses a set of pre-determined parameters and settings for protection devices. In the industry applications, different coordinations and settings among various protection scehems may lead to different system behavior. Software such as CAPE could assist the optimization and design of the protection schemes [1].

- There are some control schemes in the power systems, including controlled islanding schemes and automatic tap changers, etc that are not modeled in the cascading outage analysis tool. These sophisticated models could be incorporated and studied to make the simulation results more reflective of reality.

Given the ability to simulate the potential cascades, a natural next step is to develop proper methods and mechanisms to mitigate and prevent cascading outages. In the next chapter, these issues are studied.

Chapter 3

Mitigation and Prevention of Cascading Outages

This Chapter is based on the Author's contribution in [210] and [219]. Co-authors in [210] have contributed to the editing and review of the paper. Dr. Jianhui Wang and Dr. Ross Baldick in [219] provided guidance and suggestions on the algorithms described in the paper. Techniques are used to prevent or mitigate potential cascading outages, including Special Protection Systems (SPS), Remedial Action Systems (RAS), and intentional islanding schemes. In this chapter, we review the current practice to mitigate the cascading outages, and propose a framework to design wide-area protection systems.

3.1 Mitigation and Prevention of Cascading Outages: Methodologies and Practical Applications

3.1.1 Background and Mitigation Techniques

Due to the complexity of the cascading outages, the methodologies and practical applications to mitigate such events are limited and subject to uncertainties. Measures for mitigating and/or preventing cascading outages depend on the type of event [209]. The process of determining preventive measures [99] is shown in Figure 3.1. As can be seen from the figure, control actions to immediately respond to the unforeseen events play a vital role to prevent cascades. Due to the infrequent deployment of such control actions, they are commonly implemented in devices or schemes called "Special Protection Schemes" or "Remedial Action Schemes". The North Electric Reliability Corporation (NERC) glossary defines a RAS as: An automatic protection system designed to detect abnormal or predetermined system conditions, and take corrective actions other than and/or in addition to the isolation of faulted components to maintain system reliability [5]. Considerable effort over the last several decades has been devoted to the research, various implementation and operational issues of SPS or RAS[1] [210], [147], [18], [199], [96], [106], [200], [157], [127]. The development and practical applications of SPS are given in [194], [211], [198], [6]. Most of the design and investment decisions are made to implement a single SPS scheme (e.g., line switching, generation trip) to tackle one particular line overload or other instability phenomena. However, for some severe $n-k$ contingencies, multiple instability phenomena could be present, and single SPS device implementations may not be able to relieve the system stress. According to [210], all recommendations learned by recent blackouts point towards the need for increased coordination between operators in terms of protection settings, real-time information exchanges, system studies and planning in an emergency state, and information sharing about system conditions of neighboring TSOs. However, current SPSs are primarily identified and developed

[1]For brevity, we use SPS to stand for both the Special Protection Schemes and Remedial Action Systems.

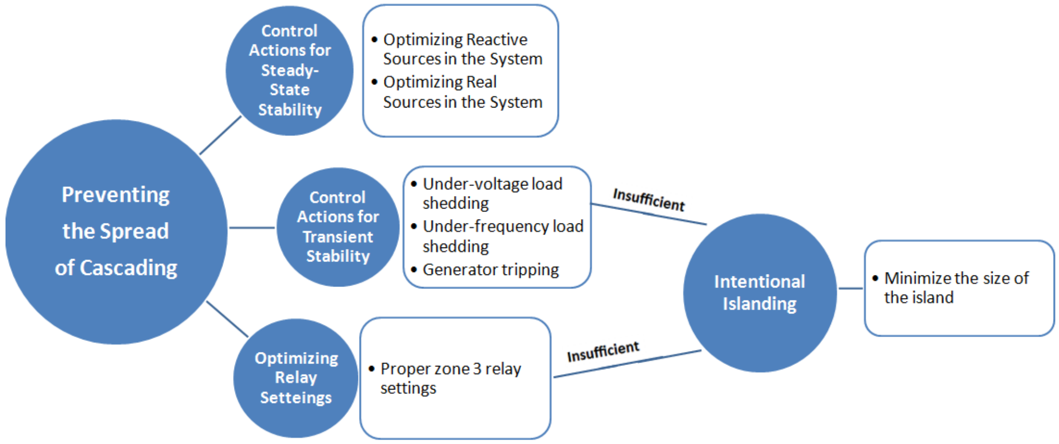

Figure 3.1: Preventive measures/islanding for different types of cascading events [210]

based on ad-hoc procedures [84].

3.1.2 Cases of successful and unsuccessful mitigation of cascading outages and lessons learned

This section presents examples of successful and unsuccessful mitigation of cascading outages, and summarizes lessons learnt after investigation of these events.

Cases of unsuccessful mitigation

In 2012, the largest case of unsuccessful mitigation occurred in India [44] with the loss of nearly 700 million customers. With the initial cause still under investigation, a severely weakened system coupled with large unscheduled interchanges led to highly loaded tie lines. Load encroachment (apparent impedance entering the protective zone) tripped these tie-lines after inadequate operator relief actions. The resulting power swings split-up the system where lines continued to trip from under-frequency/over-voltage actions which eventually caused total collapse of all three grids.

On the afternoon of September 8, 2011, an 11-minute system disturbance occurred in the Pacific Southwest, leading to cascading outages and leaving approximately 2.7 million customers without power [67]. According to the investigation report [67], the outages affected parts of Arizona, Southern California, and Baja California, Mexico. All of the San Diego area lost power, with nearly one-and-a-half million customers losing power, some for up to 12 hours. The disturbance occurred near rush hour, on a business day, snarling traffic for hours. Schools and businesses closed, some flights and public transportation were disrupted, water and sewage pumping stations lost power, and beaches were closed due to sewage spills. Millions went without air conditioning on a hot day. The sequence of the events are summarized below:

The loss of a single 500 kilovolt (kV) transmission line, namely Arizona Public Services (APS) Hassayampa-N. Gila 500 kV line (H-NG), which is a segment of the Southwest Power Link (SWPL), a major transmission corridor that transports power from generators in Arizona to the San Diego area, initiated the event. Power flows significantly increased through lower voltage systems to the north of the SWPL, while there was lower than peak generation levels in San Diego and Mexico. As a consequence, some sizeable voltage deviations and equipment overloads occured throughout the system. Significant overloading occurred on three of the Imperial Irrigation District (IID)'s 230/92 kV transformers located at the Coachella Valley (CV) and Ramon substations, as well as on Western Electricity Coordinating Council (WECC) Path 44, located south of the San Onofre Nuclear Generating Station (SONGS) in Southern California. The flow redistributions, voltage deviations, and resulting overloads had a ripple effect, as transformers, transmission lines, and generating units tripped offline, initiating automatic load shedding throughout the region in a relatively short time span. Just seconds before the blackout, Path 44 carried all flows into the San Diego area as well as parts of Arizona and Mexico. Eventually, the excessive loading on Path 44 initiated an intertie separation scheme at SONGS (RAS), designed to separate SDG&E from SCE. The SONGS separation scheme separated SDG&E from Path 44, led to the loss of the SONGS nuclear units, and eventually resulted in the complete blackout of San Diego and Comisiôn Federal de Electricidads (CFE) Baja California Control Area. During the 11 minutes of the event, the WECC Reliability Coordinator (WECC RC) issued no directives and only limited mitigating actions were taken by the Transmission Operators (TOPs) of the affected areas.

Cases of successful mitigation

In 2008 [140], an exceptionally rare event on the UK network resulted in frequency being outside the statutory limit for 9 minutes. Two large generators tripped within 2 minutes, which already exceeded the maximum credible loss, followed by two further units. This loss and further tripping of embedded generation in the distribution system caused frequency to drop to 48.795 Hz. This frequency drop was stopped by load shedding schemes and National Grid (TSO) was then able to restore system frequency and instructed affected DNOs to restore the dropped load within a range of 20-40 minutes. Only 1.5% of demand was shed instead of the expected 6.5% due to relay design accuracy. Successful coordination between the TSO and the DNOs meant that fewer customers were disconnected and system collapse avoided. In 2006, a major disturbance in Europe [202] highlighted the importance of coordination between operators. A planned outage by E.ON Netz (TSO), not properly evaluated for N-1 security, initiated the event. Also, the fact that one tie-line had different protection settings on each end connecting two TSOs was not considered in their evaluation. This line trip then initiated cascades throughout the UCTE system due to over-current distance protection and out of synchronism relays which caused the UCTE system to split into three areas. A blackout was narrowly avoided due to the actions of TSOs in their individual control areas. In both under-frequency areas, sufficient generation and load shedding allowed the restoration of normal frequency within 20 minutes. In the over-frequency area, where frequency increased further as wind farms that tripped in the disturbance came back on line, restoration took longer due to a lack of coordination between TSOs and DNOs.

3.1.3 Lessons Learned

While events are usually unique, there share many common factors such as a lack of coordination in key areas. A number of events highlighted the lack of coordination and information between TSOs operating in an interconnected region. All recommendations point towards increased coordination between operators in terms of protection settings, real time exchanges, system studies and planning and role in an emergency state, and system conditions of neighbouring TSOs. Also, a recommendation from [67] looked at the WECC Reliability Coordinator for coordinating actions in emergency situations as they have a bigger picture of events. Not only are there lessons to be learnt from coordination between operators, but the WECC 2011 event highlighted the need for RAS and SPS to be properly coordinated for protection within the TSO's own regions, but also across interconnected regions. When acting in an emergency state, operators need to be trained to deal with these situations and understand and act in an urgent manner.

3.2 Integrated wide-area protection design framework

Measures for mitigating cascading outages are discussed in [210], but investment and implementation of new wide-area protection schemes were not considered. Other frameworks are also discussed in [10, 13], but did not include a systematic approach to optimize the investment decisions regarding multiple protection actions. Based on these frameworks, we propose a two-step investment framework for design of wide-area protection systems to mitigate the cascading outages:

1. Identify the severe multiple contingencies that could potentially cause cascading outages, and the corresponding arming conditions when such contingencies may occur. Review existing budget constraints, available technologies (e.g., generation reduction, line switching, etc) to deploy and their associated deployment costs.
2. Construct an optimization program to find the optimal investment decision for various SPSs.

The initiating events for step one that are considered in this chapter are severe instantaneous multiple contingencies from extreme situations such as natural disasters or deliberate attacks. We do not consider probabilistic models of the initiating events due to the complexity of the existing framework. However probability models could be incorporated into this framework in the future. The investment decisions should be made upon clear understanding of the budget constraints and availability of the technologies. Figure 3.2 shows the most common SPS techniques currently deployed in WECC [210]. We use the three most commonly used technologies as available investment candidates (i.e., Generation Trip, Transmission Switching and Load Shed). The investment cost[2] for setting up the SPSs includes the deployment of specific measuring units to detect certain initiating events, a protected and secure communication channel, as well as the techniques used to conduct certain operations (e.g. controlled circuit breakers, specified generator controls, etc). The SPS arming configuration is important, and the system operator should carefully set the SPSs to be automatically armed when certain system operating points are met and the probability of multiple contingency occurrence is high. The cyber security of this system should also be studied carefully, and may induce additional costs as compared to other protection schemes. Since the focus of this paper is to present the basic investment framework, we do not discuss cyber security issues at this stage.

In Step two, the optimization programming model is formed to identify the investment strategy of the wide area protection systems. The purpose of using this programming model is to find the optimal locations and techniques where SPSs are implemented, so that the potential cascading outages could be mitigated, and at the same time budget constraints are satisfied. In this dissertation we assume the SPSs will be deployed simultaneously when the

[2]As the SPSs will be operated automatically, the operating cost of the SPSs is minimal and not considered in this paper.

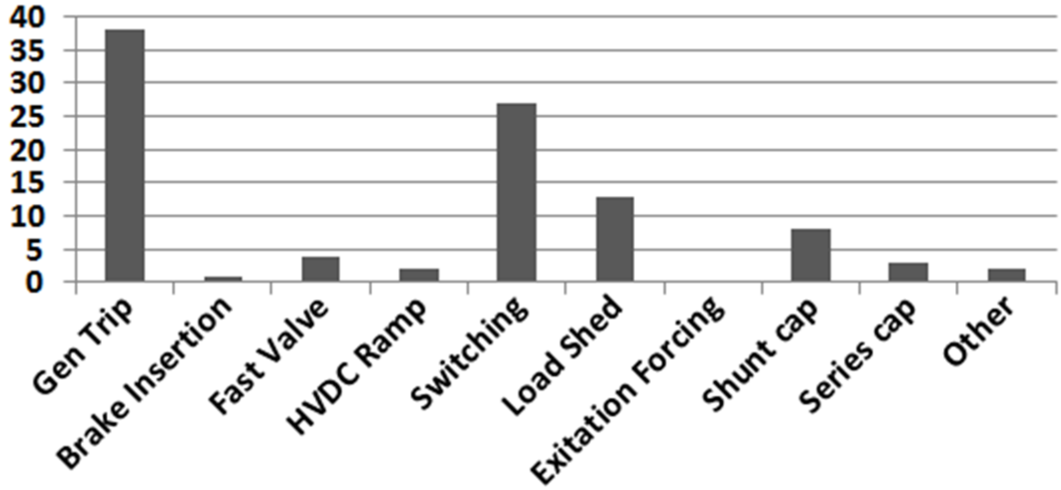

Figure 3.2: Percentage of SPS techniques deployed in WECC [210]

severe contingency happens.

If the cascading outage can not be avoided given a certain severe contingency and budget, many papers have discussed islanding strategies. [165], [32], [113], [213], [174]. Finally, if there is significant risk of having a blackout after a particular initiating event, black start schemes may be designed to ensure a fast and secure pick up of the load.

3.3 Future Direction in Mitigation of Cascading Outages

Both technical and cooperative advances are enabling new ideas to improve power system reliability. Driving demand for these new ideas are changes in generation characteristics, limitations in infrastructure installations, along with modern society's continuously increasing dependence on electric power. An important technical advance is the ability to measure the power system network state with precise time-stamps, and communicate these synchrophasor measurements at a high rate. Advances in communication infrastructure allow streaming measurements both between distributed control devices and between these devices and the control center. In North America, the American Recovery and Reinvestment Act (ARRA) [55], has participated with the installment and interconnection of hundreds of phasor measurement units (PMU) across the power system. Measurements are communicated within each utility and between the utilities and their regional coordinating center. This is bringing new monitoring capability which increases the situational awareness at each entity. PMUs provide a set of initial measurements that aid in detecting and mitigating voltage collapse [156]. Their advantages include a high processing rate and immunity from the convergence problems of nonlinear state estimation. For transient stability related outages, adding time-synchronized measurements of the generator rotor angle [236] will enable new protection and automated control [173]. The result is that generators stay synchronized during severe contingencies. Coordination between utilities provides the opportunity for future mitigation measures. In Europe, the ENTSO-E has proposed new recommendations [61]. Recommendations include harmonisation among UFLSs; developing a standard for the blocking of On Load Tap Changers (OLTC) and for Under-Voltage Load Shedding (UVLS) in the CE Synchronous Area; and ensuring high performance of line protections with respect to their original function (fault clearing) while implementing System Protection Schemes to protect the system against loss of stability.

3.4 Part Summary and Conclusion

In this part, we developed an improved framework of Cascading Outage Analysis model with four checkers, namely Transient Stability Checker, Frequency Outage Checker, Overload Outage Checker and Voltage Outage Checker. We implemented the algorithm and tested on IEEE test cases. We also discussed mitigation and prevention of cascading outages. In the next part, we incorporate the developed Cascading Outage Analysis model in an interdiction framework that considers both short- and medium-term impacts.

Part III

Integrated Interdiction Model

Chapter 4

Intergrated Model and Solution Algorithm

4.1 Introduction and I-DC-OPF Model

This part summarizes work on analyzing interdiction of electric power grids. The content of this chapter is based on author's contribution in [217]. The co-author Dr. Ross Baldick has contributed research ideas on the algorithms described in the paper and editing. An improved interdiction model to identify maximal electric grid attacks that incorporates both short-term (seconds to minutes) and medium-term (minutes to days) impacts of the possible attack has been proposed. The medium-term impacts are examined by an interdicted DC optimal power flow model (I-DC-OPF) building on previously reported work. The short-term impacts are addressed by a cascading outage analysis model (COA), as described in the part II, that uses a set of systematically applied checkers to perform the simulation of the cascading outage events and assess the short-term impacts of a blackout subsequent to specified terrorist attacks. An integer programming heuristic is applied that can utilize standard optimization software (e.g. CPLEX) to solve master problems generated by the heuristic. The proposed model has been verified using the IEEE 300 Bus Test System and IEEE RTS 96 Test System. Discussions of the results and future research plans are also presented in this dissertation.

As in [166] and [168], we also simulate the medium-term operation of a grid using a set of linearized DC optimal power flow models (DC-OPF). While the grid repair, restoration and the unit-commitment issues that arise as service is restored to different parts of the grid are important, we do not consider those long-term problems in this report. Some of these issues have been discussed in [34] and will be considered in the future work (see chapter 6). The objective function for I-DC-OPF includes terms for generation costs and for penalty costs associated with shed power or energy. The penalties approximate both the direct and indirect costs of the corresponding unserved demand.

We use the subproblem of the "interdicted power flow model" (IPF) as stated in [166] as the interdicted DC-OPF formulation. The formulation is shown below:

$$Formulation : I - DC - OPF(L, G, I; d, \boldsymbol{\delta})$$

$$z(\boldsymbol{\delta}) = \min_{P^G, P^L, S, \theta} \sum_g h_g P_g^G + \sum_i \sum_c q_{ic} S_{ic} \tag{4.1}$$

s.t.

$$P_l^L = B_l(\theta_{o(l)} - \theta_{d(l)})(1 - \delta_l^L)(1 - \delta_{o(l)}^I)(1 - \delta_{d(l)}^I), \forall l \in L, \tag{4.2}$$

$$\sum_{g \in G_i} P_g^G - \sum_{l \in L | o(l) = i} P_l^L + \sum_{l \in L | d(l) = i} P_l^L = \sum_c (d_{ic} - S_{ic}), \forall i \in I, \tag{4.3}$$

$$-\bar{P}_l^L(1-\delta_l^L)(1-\delta_{o(l)}^I)(1-\delta_{d(l)}^I) \leq P_l^L, \forall l \in L, \tag{4.4}$$

$$P_l^L \leq \bar{P}_l^L(1-\delta_l^L)(1-\delta_{o(l)}^I)(1-\delta_{d(l)}^I), \forall l \in L \tag{4.5}$$

$$0 \leq P_g^G \leq \bar{P}_g^G(1-\delta_g^G), \forall g \in G, \tag{4.6}$$

$$d_{ic}\delta_i^I \leq S_{ic} \leq d_{ic}, \forall i \in I, c \in C, \tag{4.7}$$

$$\theta_{i_0} = 0. \tag{4.8}$$

The objective function in (4.1) is the generation costs plus load-shedding costs in \$/h. Constraint (4.2) is linearized admittance constraints that approximate active power flows on lines. Constraint (4.3) maintains power-balance at the buses. Constraints (4.4), (4.5) and (4.6) set maximum power flows for lines and maximum generating-unit outputs, respectively. Our current implementation does not include contingency constraints, but these constraints could be included.[1] Constraint (4.7) ensures that load-shedding does not exceed demand. Constraint (4.8) sets the phase angle on the reference bus to 0.

[1]Under normal circumstances, power systems are operated to be secure with respect to single contingencies. In the event of a terrorist attack, however, insecure operation might be tolerated in order to serve as much load as possible.

4.2 Integrated interdiction model

This section introduces the integrated interdiction model that considers both short and medium term implications of an attack. The "interdictor" in our model, a group of terrorists, will make a coordinated set of resource-constrained interdictions (attacks) on the power grid. Before detailed discussion about the model, we state assumptions about the types of interdictions, similar to [166] and [168]:

- Line interdiction: All lines running physically in parallel at the point of an attack are opened. (Typically, these lines are mounted on the same towers, and an attack on one is an attack on all.)
- Transformer interdiction: The line representing the transformer is opened.
- Generator interdiction: The generator is disconnected from the grid.
- Bus interdiction: All lines and generators connected to the bus are disconnected.
- Substation interdiction: All buses at the substation are disconnected; this triggers the corresponding bus-interdiction effects just described.

We propose a new bi-level model:

$$\max_{\boldsymbol{\delta} \in \Delta} (z(\boldsymbol{\delta}) + \rho y(\boldsymbol{\delta})), \tag{4.9}$$

s.t.

$$\boldsymbol{M}\boldsymbol{\delta} \leq \bar{M}. \quad (4.10)$$

where $z(\boldsymbol{\delta})$ corresponds to the medium-term total cost of I-DC-OPF as discussed in previous section; $\rho y(\boldsymbol{\delta})$ corresponds to the total short-term load shedding cost subsequent to an interdiction specified by $\boldsymbol{\delta}$, where $y(\boldsymbol{\delta})$ is the amount of load shedding evaluated by the Cascading Outage Analysis (COA) model that was discussed in Chapter 2, and ρ is the load shedding penalty cost. All decision variables in the vector $\boldsymbol{\delta}$ are binary, $\bar{M}$ is the total terrorist resource (i.e. the number of terrorists), and entries in row vector $\boldsymbol{M}$ denote the number of resources required to interdict each of the system components. Constraint (4.10) limits the total resources that terrorists use for the interdiction plan to not exceed the resource limit $\bar{M}$. With this new bi-level optimization model, both the medium-term and short-term "pain" after an attack is addressed. In the actual implementation, several logical constraints are added to speed convergence and to avoid re-evaluating interdictions considered in earlier iterations. These logical constraints are discussed in section 4.3.3.

The choice of the load shedding penalty costs ρ in (4.9) and q_{ic} in (4.1) is crucial to the model[2] because they are directly used to evaluate the consequence of an attack $\boldsymbol{\delta}$. A higher medium-term load shedding penalty

[2]Our I-DC-OPF model is driven by generation and load shedding costs. However, load shedding penalty costs q_{ic} are typically much higher than generation costs h_g, so the load shedding penalty, if any, will offset the generation cost.

would lead to a choice of attack strategy to cause more medium-term shedding, while a higher COA penalty would lead to a very different attack strategy that causes more short-term load shed. On the one hand, more medium-term load shedding will lead to a longer-lasting system "pain," and the element replacement/repair costs might be higher than short-term cascading outage because most cascades are triggered by sequential system protection actions that do not directly damage the facilities. On the other hand, however, the short-term cascade, especially the total blackout, will be very noticeable and widespread, which could cause intense attention from the public, or even panic in society.

Note this interdiction model is a normative model based on assumptions on the terrorists' motivation, capability and resources. However due to the rarity of the terrorist attacks and uniqueness of each attack, it may be hard to produce the quantified inputs of this interdiction model. Therefore, other descriptive models based on intelligence and historical data may also help the ultimate decision on the defense schemes.

4.3 The heuristic algorithm to solve the integrated model

4.3.1 General Framework

Benders Decomposition (BD) [73], and Global Benders Decomposition (GLBD) [168] could potentially be used to solve the bi-level optimization problem in (4.9) because they could guarantee convergence of the optimum, if solved successfully. However they generally require construction of convexified "cuts," which in our case is very difficult due to the non-linear, non-convex nature of the cascading outage. Therefore, Benders Decomposition cannot be directly used in our new formulation (4.9), and we use a heuristic algorithm similar to that in [166] to solve the bi-level optimization problem described above, whose framework is schematically shown in Figure 4.1.

Heuristic algorithms, such as proposed in [166], do not guarantee convergence within a limited number of iterations, but could be solved relatively easily, and provide "reasonable" or "near optimal" solution. Theoretically, the heuristic will find the global optimum on or before the time when all feasible solutions are evaluated. In fact, a general observation to the interdiction problem is that the more assets an attack interdicts, the more cost the system will suffer. Therefore, the "worst case" attack strategy would most likely involve as much resource as the terrorists have.

4.3.2 Subproblem: I-DC-OPF and COA for a given interdiction plan

The initialization of the algorithm sets pre-attack coefficients and pre-attack interdiction binary variables to be 0. At the n-th iteration, given an interdiction plan $\boldsymbol{\delta}^n$ that maximizes the master problem, we re-calculate the I-DC-OPF model and COA model to obtain the new power flow patterns and total cost $z(\boldsymbol{\delta}^n)$ and $y(\boldsymbol{\delta}^n)$, in which case we expect some load shedding cost from I-DC-OPF and/or COA. The process continues by finding alternative sets of valuable assets to interdict that have not been identified at earlier iterations,

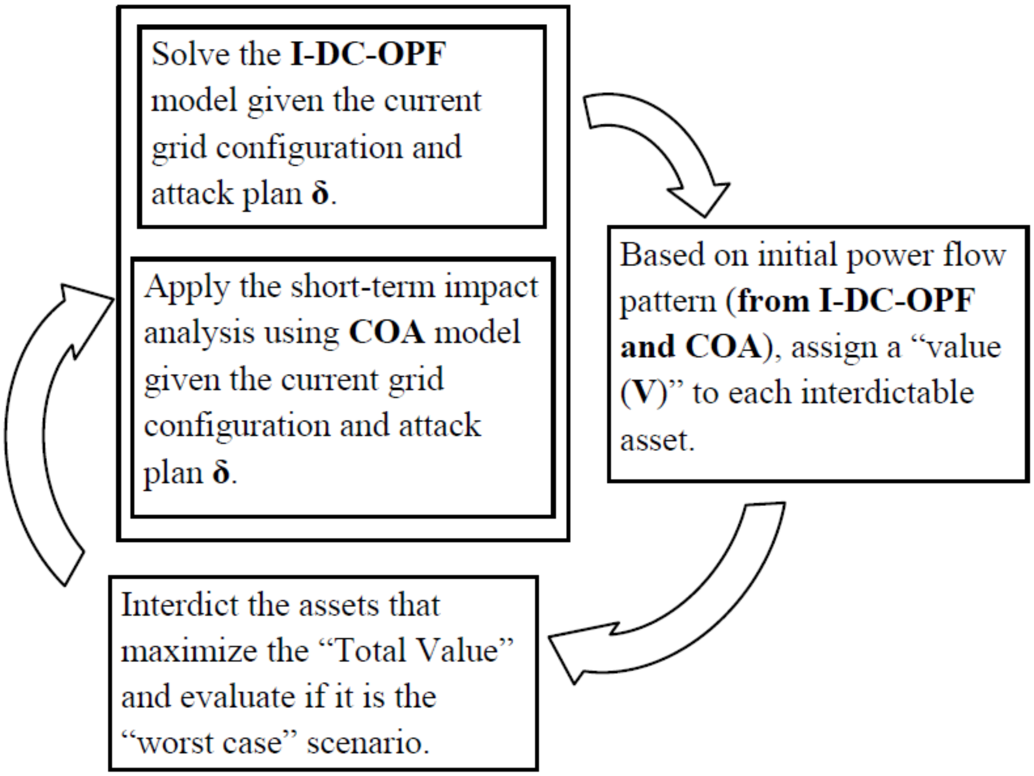

Figure 4.1: Proposed heuristic algorithm

and by evaluating load shedding of these interdiction plans.

4.3.3 Master Problem: Optimize a new interdiction strategy

The master problem uses the power flows from I-DC-OPF and COA at the initial iteration to calculate estimated coefficients, $\boldsymbol{V}_{OPF}$ and $\boldsymbol{V}_{COA}$, and also calculates a set of the combined values of elements $\boldsymbol{V}_{Total}$ used by the integer program $\boldsymbol{MP}(\boldsymbol{V}_{Total}, \boldsymbol{\delta}^1, \boldsymbol{\delta}^2, ..., \boldsymbol{\delta}^n)$ to solve for a newly optimized attack plan $\boldsymbol{\delta}^{n+1}$ and the subsequent total cost $\boldsymbol{\Phi}(\boldsymbol{V}, \boldsymbol{\delta}^{n+1})$. The results of each iteration will be compared with the previous solutions and the "worst case" plan will be updated. The coefficients for I-DC-OPF and COA are based on the power flow values from I-DC-OPF and COA respectively. The calculation for the values of each grid component in vector $\boldsymbol{V}_{OPF}$, for example, is shown below:

$$V_{OPF,g} = \boldsymbol{\varphi}^{Gen} P_g, \forall g \tag{4.11}$$

$$V_{OPF,l} = \boldsymbol{\varphi}^{Line}(|P_l| + \sum_{l' \in L_l^{Par}} |P_{l'}|), \forall l \tag{4.12}$$

$$V_{OPF,i} = \boldsymbol{\varphi}^{Bus}(P_i^{In} + P_i^{Out}), \forall i \tag{4.13}$$

$$V_{OPF,s} = \boldsymbol{\varphi}^{Sub} \sum_{l|l \in L_s} |P_l|, \forall s \tag{4.14}$$

The meaning of $\boldsymbol{V}_{OPF}$ and $\boldsymbol{V}_{COA}$ is to provide the "attractiveness", or the potential "benefit" of attacking each element, thus enabling the master problem to determine the worst case attack strategy. As shown in (4.11)-(4.14), calculation of the vectors $\boldsymbol{V}_{OPF}$ and $\boldsymbol{V}_{COA}$ is performed in a similar fashion to [166], where the $\boldsymbol{\varphi}$ multipliers are constant coefficients reflecting the relative value of interdicting each element, e.g., $\boldsymbol{\varphi}^{Gen} = 2$, $\boldsymbol{\varphi}^{Bus} = 5$, $\boldsymbol{\varphi}^{Line} = 1$, $\boldsymbol{\varphi}^{Sub} = 5$. After calculating $\boldsymbol{V}_{OPF}$ and $\boldsymbol{V}_{COA}$, $\boldsymbol{V}_{Total}$ is calculated by $\boldsymbol{V}_{Total} = \boldsymbol{V}_{OPF} \times \varpi_{OPF} + \boldsymbol{V}_{COA} \times \varpi_{COA}$. The values ϖ_{OPF} and ϖ_{COA} are the weights multiplied by the estimated vectors $\boldsymbol{V}_{OPF}$ and $\boldsymbol{V}_{COA}$ to send the Master Problem the "incentives" to attack each component. Different values of these weights will lead to different converging trajectory. For example, a larger $\boldsymbol{\varpi}_{OPF}$ will potentially make $\boldsymbol{V}_{OPF} \times \boldsymbol{\varpi}_{OPF}$ larger than $\boldsymbol{V}_{COA} \times \boldsymbol{\varpi}_{COA}$, thus create a higher incentive for the MP to attack heavily post-OPF loaded components. However, since the heuristic algorithm will ultimately choose the "worst case" by the combined cost of I-DC-OPF and COA, the effect of $\boldsymbol{\varpi}_{OPF}$ and $\boldsymbol{\varpi}_{COA}$ is primarily to affect the trajectory but not the best solution found to (9). In our case, we choose: $\boldsymbol{\varpi}_{OPF} = \boldsymbol{\varpi}_{COA} = 0.5$.

The combined and weighted power-flow pattern is then used to assign relative values to all the interdictable components of the power grid. These values are used to maximize the estimated value of the assets to be interdicted, while ensuring that the terrorist resources required for the interdiction plan are not exceeding the limit $\bar{M}$. Similar to section II.D in [166], we add five inequality constraints as logical constraints to speed the solution process. The meaning of these constrains are: do not interdict a bus i and a generator connecting to the same bus at same time; do not interdict a line and its terminal bus at the same time; do not interdict a line and its parallel line at the same time; do not interdict a bus i and a substation that contains bus i at the same time; and, do not interdict a line and the substation it is connected to at the same time. Another logical constraint as described in section II.C in [168] is also utilized to make sure the result of every iteration different from the previous results. Hence the master problem formulation becomes:

$\boldsymbol{MP}(\boldsymbol{V}_{Total}, \boldsymbol{\delta}^1, \boldsymbol{\delta}^2, ..., \boldsymbol{\delta}^n)$:

$$\max_{\boldsymbol{\delta}^{Line}, \boldsymbol{\delta}^{Gen}, \boldsymbol{\delta}^{Sub}, \boldsymbol{\delta}^{Bus}} \sum_{g \in G} V_g \delta_g^{Gen} + \sum_{l \in L} V_l \delta_l^{Line} + \sum_{i \in I} V_i \delta_i^{Bus} + \sum_{s \in S} V_s \delta_s^{Sub},$$

s.t.

$$\sum_{g \in G*} M_g^{Gen} \delta_g^{Gen} + \sum_{l \in L*} M_l^{Line} \delta_l^{Line} + \sum_{i \in I*} M_i^{Bus} \delta_i^{Bus} + \sum_{s \in S} M_s^{Sub} \delta_s^{Sub} \leq \bar{M},$$

$$\sum_{k \in K | \delta_k^{\hat{n}} = 1} \delta_k^{\hat{n}} + \sum_{k \in K | \delta_k^{\hat{n}} = 0} (1 - \delta_k^{\hat{n}}) \leq |K| - 1, \forall \hat{n} = 1, ..., n$$

$$\delta_g^{Gen} + \delta_i^{Bus} \leq 1, \forall g \in G_i^*, i \in I^*$$

$$\delta_l^{Line} + \delta_i^{Bus} \leq 1, \forall l \in L_i \bigcap L^*, i \in I^*$$

$$\delta_l^{Line} + \delta_{l'}^{Line} \leq 1, \forall l' \in L_l^{Par} \bigcap L^*, l \in L^*$$

$$\delta_l^{Line} + \delta_i^{Sub} \leq 1. \forall l \in L_s \bigcap L^*, s \in S^*$$

After obtaining this new attack plan $\boldsymbol{\delta}^{n+1}$ that solves $\boldsymbol{MP(V}_{Total}, \boldsymbol{\delta}^1, \boldsymbol{\delta}^2, ..., \boldsymbol{\delta}^n)$, the algorithm then goes back to the subproblem to check if it is the worst case so far by comparing the combined cost of the load shedding due to $\boldsymbol{\delta}^{n+1}$ with the cost of the previous worst case plan $\boldsymbol{\delta}^*$. The algorithm will iterate until the master problem is infeasible, or the total number of iteration reaches the pre-determined threshold N.

A more detailed, step by step description of this algorithm is shown as follows:

Input Data:

· Problem statement data (grid data, interdiction resource)

· N Total number of iterations

Initialization:

· Set $n = 1$ (iteration counter) and vector $\boldsymbol{\delta}^n$ to be zero.

· $\Phi^* \leftarrow \Phi^0$ Best interdiction plan initialized.

Solve Master problem:

· Calculate the vector of estimated values for I-DC-OPF model $\boldsymbol{V}_{OPF}$.

· Calculate the vector of estimated values for COA model: $\boldsymbol{V}_{COA}$.

- Calculate the combined vector of DC-OPF and COA model: $\boldsymbol{V}_{Total} = \boldsymbol{V}_{OPF} \times \varpi_{OPF} + \boldsymbol{V}_{COA} \times \varpi_{COA}$.
- Solve $\boldsymbol{MP(V}_{Total}, \boldsymbol{\delta}^1, \boldsymbol{\delta}^2, ..., \boldsymbol{\delta}^n)$ for new interdiction plan $\boldsymbol{\delta}^{n+1}$.
- If $\boldsymbol{MP(V}_{Total}, \boldsymbol{\delta}^1, \boldsymbol{\delta}^2, ..., \boldsymbol{\delta}^n)$ is infeasible, STOP.
- Otherwise, assign $n \leftarrow n + 1$, go to Subproblem.

Solve Subproblem:

- Solve I-DC-OPF for total operation cost and potential load shedding cost $z(\boldsymbol{\delta}^n)$.
- Solve COA model for potential load shedding cost $y(\boldsymbol{\delta}^n)$.
- Calculate the total disturbance cost $\Phi(\boldsymbol{\delta}^n) = z(\boldsymbol{\delta}^n) + \rho y(\boldsymbol{\delta}^n)$.
- If $\Phi(\boldsymbol{\delta}^n) > \Phi(\boldsymbol{\delta}^*)$ then $\Phi(\boldsymbol{\delta}^*) \leftarrow \Phi(\boldsymbol{\delta}^n)$.
- If $n \geq N$ then STOP.

Chapter 5

Implementation, Results and Future Work

5.1 Implementation and Simulation Results

In order to implement the models and algorithms, a graphical user interface is designed with the algorithm written in Visual Basic for Application [132], PowerWorld Scripts [158], Excel Scripts [131], and Cplex [92]. Within the code, the graphical user interface (GUI) is designed using the Visual Basic for Application; the PowerWorld simulator is used in the I-DC-OPF calculation, Transient Stability calculation, and the AC Power Flow calculation; Cplex is used to solve the integrated integer optimization problem; the frequency checker algorithm, along with the high-level control algorithm is implemented in Visual Basic for Applications.

With the GUI, the user will assign the attack resources, modify different control settings with respect to the cascading outage analysis, and run the interdiction model. The simulation result contains the post I-DC-OPF and COA power flow patterns, the load shed for OPF and COA modules, and the attack plan for each interdiction plan.

5.1.1 IEEE Reliability Test System RTS-96 and Integrated Tool Simulation

We have applied the proposed model and algorithm to 1996 IEEE Reliability Test System (RTS-96) [4]. Average simulation time for one iteration is 8 to 10 seconds on a 2.5GHZ laptop computer with 4GB RAM, excluding the initialization time that opens the solver connection and PowerWorld flow case. We restrict the number of iterations to $T = 500$ for all problems to limit the computation time. For a fixed interdiction resource $\bar{M}$ as described in $\boldsymbol{MP}(\boldsymbol{V}_{Total}, \boldsymbol{\delta}^1, \boldsymbol{\delta}^2, ..., \boldsymbol{\delta}^n)$ to solve for a newly optimized attack plan $\boldsymbol{\delta}^{n+1}$, the total simulation time is at most 1 hour, during which about 70 % of the time is used to solve the master problem, 20% of the time is to perform the cascading outage analysis and the I-DC-OPF calculations, and the rest of the time is due to running interfaces among the tools. Within Cascading Outage Analysis calculations, the time used for transient stability analysis is about 50%, and the time used for other three checkers is about 50%. Since we limited the number of iterations and computational time in this specific experiment, the proposed heuristic may miss relevant solutions.

While the computational time seems to be high for such a small system, the major increase of the computational burden for larger systems occurs in solving a larger integer master program. The cascading outage analysis model will run slower for large systems, but the computation time increases relatively slowly (a COA without transient stability checker can run the size of ERCOT system within 5 seconds). Solving the DC-OPF and running the interfaces are also not contributing significantly further to the computational efforts. At the same time, this “worst case” analysis is expected to be performed off-line so that the computational burden would not be a major concern.

We applied the algorithm to RTS-96 test system for three scenarios. We set the load shedding penalty cost for medium-term impacts to \$1000/MWh and set the short-term penalty to \$1000/MW in scenario 1. We also simulated two additional scenarios, each of which has one of the penalty costs dominating the other.

5.1.2 Interdiction Results

Figure 5.1 displays the results from the algorithm for the amount of load shed due to OPF, COA, and the total cost of the attack, respectively, in scenario 1, with the interdiction resource $\bar{M}$ varying from 0 to 22. Unlike in Salmeron et al. [166], it is quite noticeable that the amount of I-DC-OPF load shed is not monotonically non-decreasing. This is due to the effect of the jump in COA load shedding from resource $\bar{M} = 8$ to $\bar{M} = 10$. At $\bar{M} = 8$ the system will experience a comparably small cascading event, shedding 419MW of load, roughly 14.7 % of the total load. Thereafter, if we increase the interdiction resource to $\bar{M} = 10$, the attack could possibly create a total cascading blackout, meaning a total of 2850MW of load is shed, but only 765MW of load shedding in I-DC-OPF. In this case, although the attack has a lower medium-term cost compared with the previous attack, the total system cost is higher given our choice of penalty coefficients. It can also be observed that the load shedding of

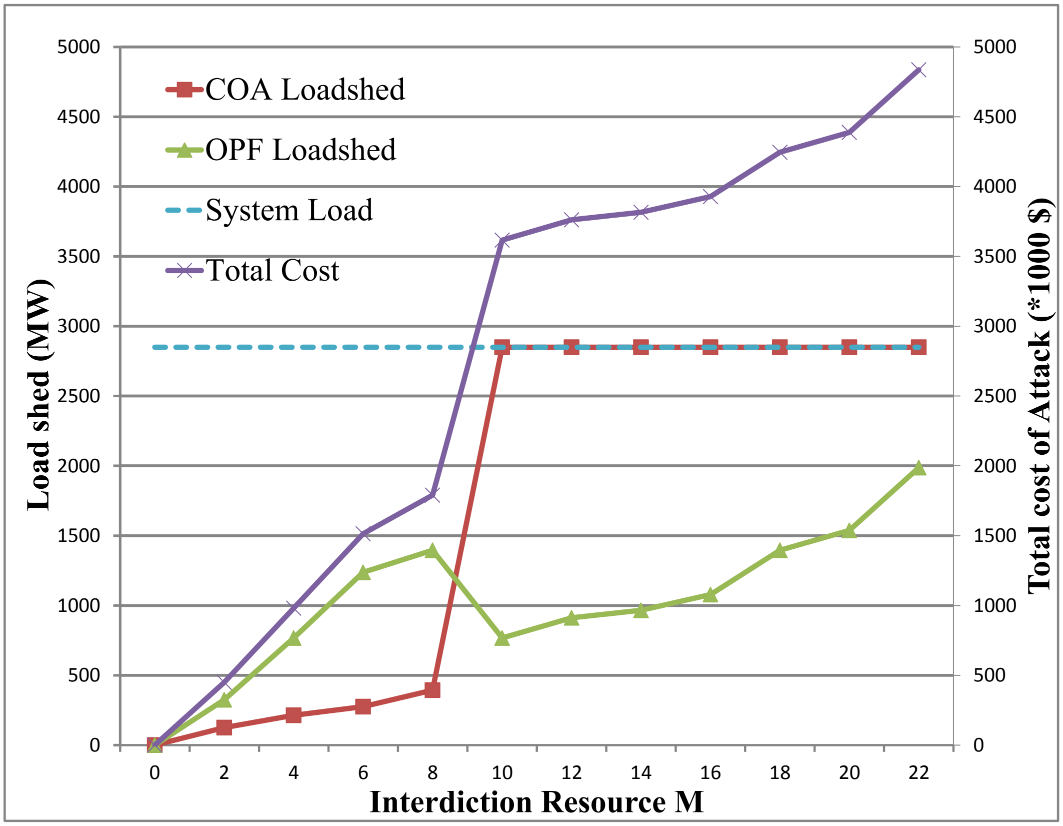

Figure 5.1: Simulation Results on RTS-96 Test Case, scenario 1

the cascading outage is monotonically non-decreasing. At the same time, once the resource is enough to trigger a total system blackout, more resources will not increase the COA load shedding. Therefore, the consequence of having more attack resources will be a higher medium-term load shedding only. In general, the total cost of the attack is monotonically non-decreasing.

Figure 5.2 and Figure 5.3 display the simulation results of scenario 2 and 3. Scenario 2 has medium-term penalty cost of $1000/MWh and short-term penalty of $0/MW. The results of scenario 2 are almost identical to the results in [166], which also only considers I-DC-OPF interdiction. Note that the OPF load shed is non-decreasing when interdiction resource increases because no short-term impacts are contributing to the total impact evaluation. High I-DC-OPF load shed with low cascading outage impact is primarily due to relaxed emergency transmission loading in short-term operation compared to sustained loading constraints in medium-term OPF. The results of scenario 3 have medium-term penalty cost of \$0/MWh and short-term penalty of \$1000/MW. It is demonstrated that although high cascading load shed is achieved, lower I-DC-OPF cost may occur due to the ability to reschedule power dispatch in I-DC-OPF.

5.1.3 Discussion

As mentioned in the Introduction, it is difficult to accurately understand the objective of the terrorists. As can be seen from our results and compared with the scenarios that only consider medium-term effects, such as the results from [166], the terrorists generally need a relatively large amount of resource to conduct an attack that results in large (e.g., larger than 80 %) medium-term load disturbance, while the resources needed to achieve a large short-term cascading events (e.g., cascading blackout) is much smaller. At the same time, the short-term cascades might be more socially visible, meaning a sudden large blackout would cause heavy media coverage. Therefore, each operator should conduct the study based on its own forecast, or understanding of the potential threats.

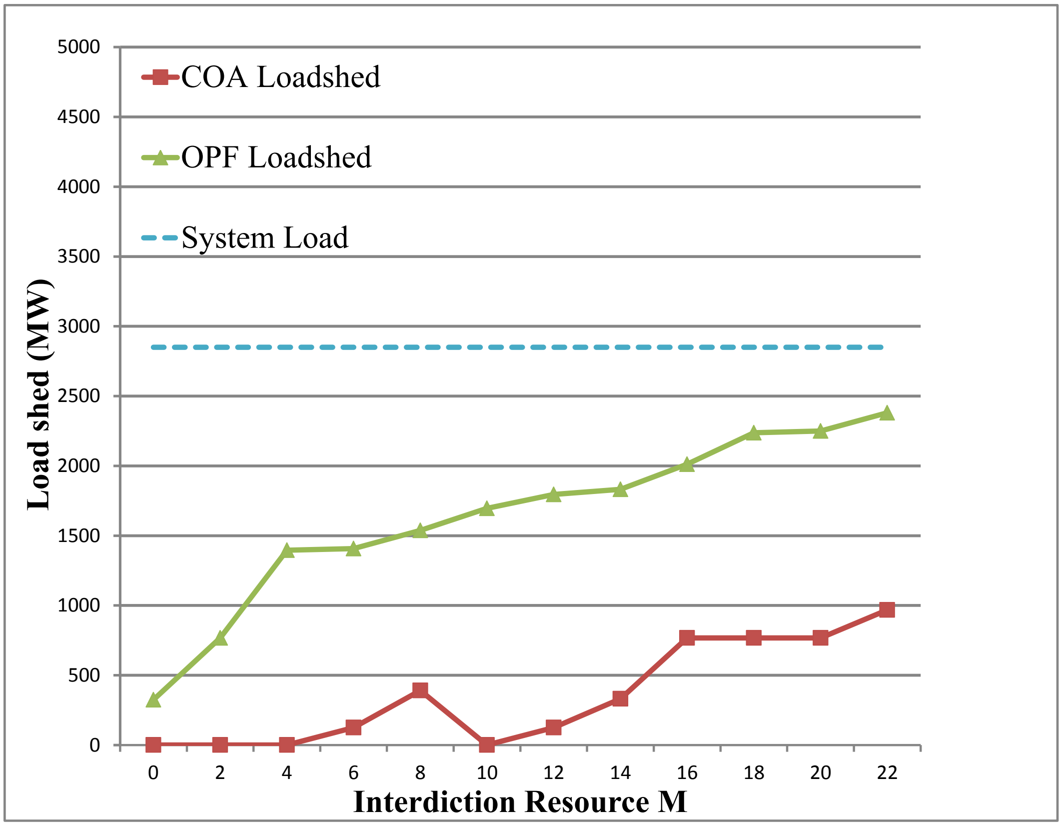

Figure 5.2: Simulation Results on RTS-96 Test Case, scenario 2

5.2 Summary and Future Work

In this chapter, the completed work is summarized and the directions of some future work are proposed. There are several limitations to our current work, including that we do not consider the restoration of power grids; do not consider cyber security threats to power system; the slow speed and poor convergence capability; and the lack of study on comparison of interdiction models and natural disaster analysis models. They are all important directions that we would like to further investigate in our future work.

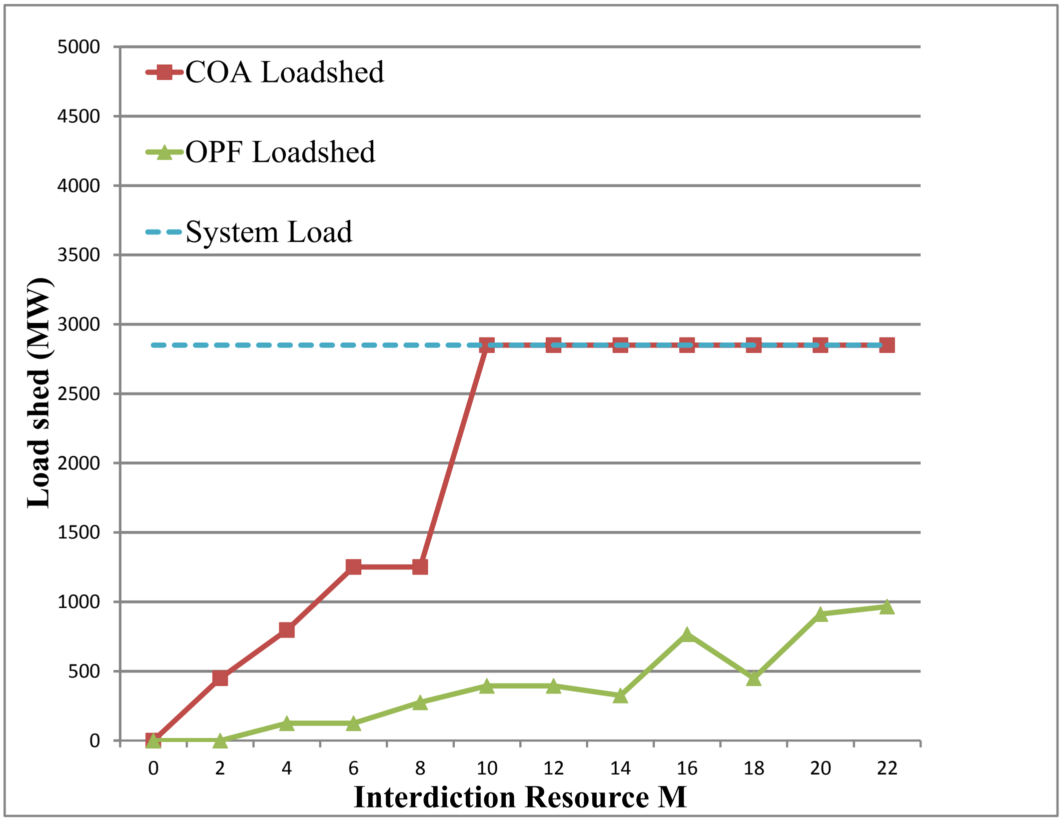

Figure 5.3: Simulation Results on RTS-96 Test Case, scenario 3

5.2.1 Incorporate restoration and cyber security attack models

As indicated in [141], "perhaps the most serious vulnerability to the various sensing, communication, and control subsystems that has developed in recent years, and which is now being rapidly rectified, has been lack of attention to connections from system control centers to the outside world. If these connections are not treated with great care, and if proper cyber security protection is not provided, they can in principle become a route for attackers from the outside world to create disruption, take control, and cause damage."

Recent studies and simulations [175], [54] have revealed that multiple types of attacks could be conducted to the power system through SCADA systems. Most of the cyber-related attacks are aimed at disrupting the service of one or more system components, either by physically destroying the physical facility, or by shutting down the facility without physical harm. We are not trying to study the detailed mechanisms of each attack, but rather our aim is to study how to allocate the limited defense budget to strengthen the protection against the critical components, which once attacked, could result in "worst case" consequences.

Based on studies on the level of difficulties and consequences of the attacks [175], we categorize the methods of attacks into four categories:

- Bomb or pure physical attack: the electric power facility (line, transformer, generator, bus, substation) is attacked and destroyed by attackers physically carrying weapons to the scene. Such attacks involve explosives and bomb attacks, etc and has been the default assumed method of attack in the work developed so far.

- Hybrid attack: the electric power facility is attacked by attackers that have to be physically near the scene, with the attackers gaining control of the facility and stopping service without destroying it. Such attack techniques include spoofing the PMU units that control a relay and opening an associated circuit breaker. [183]

- Cyber attack, non-destructive: the electric power facility is attacked by remote attackers that stop the service of the facility without destroying the asset. Such techniques include man-in-the-middle attacks, password spoofing attacks, etc.

- Cyber attack, destructive: the electric power facility is attacked by remote attackers that stop the service of the facility and destroy the asset. Such techniques include gaining control and feeding false control command to over speed the generators as described in [175], etc.

The key difference among the attacks are not only the ways they are conducted, but also the resources they need in order to be conducted, and the resulting restoration time/cost. For example, Figure 5.4 shows some example attack resource and repair times.[1]

Because of the large variation in the repair time among different attack techniques described above, we need to incorporate the repair and restoration cost to the model in order to get a better estimation of the attack consequence. The interdiction model including repair and restoration has been investigated in [166], [168]. In [166], a time-phased version of I-DC-OPF is created by using interdiction constructs to couple instances of DC-OPF, one for each system state that represents a stage or time period of system repair. Define $j = 1, 2, ..., J$ as the stages of the restoration, DUR^j as the time duration of stage j (i.e. hours). For example, we may have up to 7 stages of the restoration

[1] The specific numbers are for example purposes only. We have performed what we think are reasonable numbers but we do not currently have any specific empirical data.

Name of attack	Target of attack	Repair time	Resource needed	Reference scenario
Line attack (bomb)	Line L_{ab} connecting bus a and b	T^b_l, e.g. 48 hours	M^b_l, e.g. 2	A bomb is carried to a transmission tower and explodes.
Line attack (hybrid)	Line L_{ab} connecting bus a and b	T^h_l, e.g. 8 hours	M^h_l, e.g. 2	The PMU controlling the relay of a breaker has its GPS spoofed (the action happens with terrorists close to the PMU) and PMU is controlled to open the breaker.
Line attack (cyber)	Line L_{ab} connecting bus a and b	T^c_l, e.g. 6 hours	M^c_l, e.g. 1	The breaker is remotely controlled to open.
Gen attack (bomb)	Generator G_{ab} connecting bus a and b	T^b_g, e.g. 168 hours	M^b_g, e.g. 8	A bomb is carried to a generator and explodes.
Gen attack (cyber, non-destructive	Generator G_{ab} connecting bus a and b	T^{cn}_g, e.g. 12 hours	M^{cn}_g, e.g. 3	The generator is remotely controlled to be open.
Gen attack (cyber, destructive)	Generator G_{ab} connecting bus a and b	T^{cd}_g, e.g. 168 hours	M^{cd}_g, e.g. 6	The generator is remotely controlled to over speed and breaks down.
Bus attack (bomb)	Bus B_a	T^b_{bus}, e.g. 96 hours	M^b_{bus}, e.g. 6	A bomb is carried to a bus bar and explodes.
Substation attack (bomb)	Substation S_a	T^b_{sub}, e.g. 168 hours	M^b_{sub}, e.g. 8	A bomb is carried to a substation and explodes.
Substation attack (cyber)	Substation S_a	T^c_{sub}, e.g. 24 hours	M^c_{sub}, e.g. 8	The substation is remotely controlled to be shut down.

Figure 5.4: Description of modes of attack

based on repair time assumptions in Figure 5.4 (i.e. $j = 1, 2, ...7$). From hour 6 to hour 8, the damage of Line attack (cyber) is repaired, but all other damage having repair time longer than 6 hours is not repaired (i.e. $DUR^2 = 2$). The model described in [166] can be expressed as:

$$\max_{\boldsymbol{\delta} \in \Delta} \sum_{j=1}^{J} DUR^j z^j(\boldsymbol{\delta}), \tag{5.1}$$

s.t.

$$\boldsymbol{M}\boldsymbol{\delta} \leq \bar{M}. \tag{5.2}$$

Each instance $DUR^j z^j(\boldsymbol{\delta})$ is an I-DC-OPF model with topology at stage j. The topology is determined by the restoration process depending on how many components are online and functional. During a particular stage of restoration process (e.g. from hour 96 to hour 168 shown in Figure 5.4), the topology is assumed to remain the same.

Based on the model described above, we propose an expanded interdiction model considering the short term cascading effects and the sequencing of restoration:

$$\max_{\boldsymbol{\delta} \in \Delta} (\sum_{j=1}^{J} DUR^j z^j(\boldsymbol{\delta})) + \rho y(\boldsymbol{\delta}), \tag{5.3}$$

s.t.

$$\boldsymbol{M}\boldsymbol{\delta} \leq \bar{M}. \tag{5.4}$$

Expanding model (4.1), $\sum_{j=1}^{J} DUR^j z^j(\boldsymbol{\delta}) g$ corresponds to the total cost of multiple I-DC-OPF considering the restoration; $\rho y(\boldsymbol{\delta})$ corresponds to the total short-term load shedding cost subsequent to an interdiction specified by $\boldsymbol{\delta}$, where $y(\boldsymbol{\delta})$ is the amount of load shedding evaluated by the Cascading Outage Analysis (COA) model that was discussed in Chapter 2, and ρ is the load shedding penalty cost. All decision variables in the vector $\boldsymbol{\delta}$ are binary. Different from model (2.1), the decision variables include multiple attack modes to each facility. Logically, only one attack mode should be applied to one facility in a specific attack. The parameter $\bar{M}$ is the total terrorist resource (i.e. the number of terrorists), and entries in vector $\boldsymbol{M}$ denote the number of resources required to interdict each of the system components for each attack mode. Constraint (7.2) limits the total resources that terrorists use for the interdiction plan to not exceed the resource limit $\bar{M}$. The solution methods are also similar to the heuristic algorithm discussed in chapter 5. This model can be viewed as an extention of the integrated interdiction model (5.1) with consideration of the cyber attacks and restoration.

Preliminary experiments have been done on IEEE RTS 96 system [4]. Using the parameters provided in Figure 5.4, with total resource $M = 26$, the heuristic algorithm finds an attack scenario. The load shed over time is shown in Figure 5.5,[2] and the deployment of the attack resources is shown in Figure 5.6.

Future work includes more simulations, comparison with the scenarios without cyber attacks, and more rigorous study of the mechanisms of the cyber attacks.

[2]Note: durations of the repair stages shown in horizontal axis are not uniform.

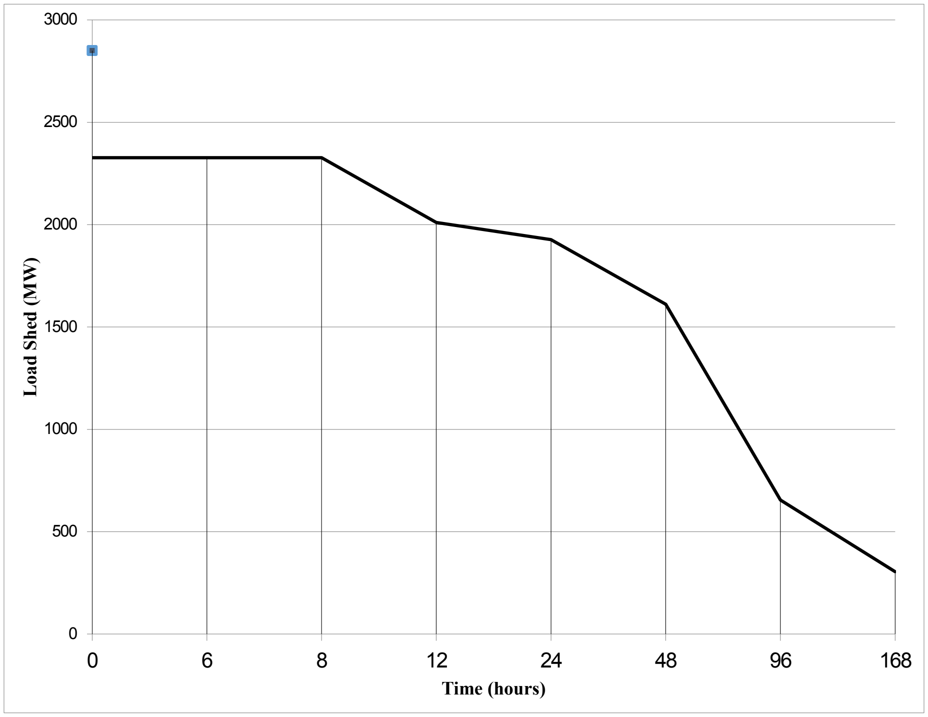

Figure 5.5: Load shed with time on RTS-96 Test Case, M=26

5.2.2 Improve the solution speed by new optimization methods

The limitations of this extension is that the computational burden becomes much higher than the models described in (2.1) and [166]. This is due to a large increase of decision variables for multiple attack modes, and the calculation of COA when compared to [166]. Therefore, we try to expedite the heuristic algorithm. At the same time, the heuristic algorithm does not guarantee the convergence of the problem. In [168], a "Global Benders Decomposition" algorithm has been used to solve the limitations discussed above. The decomposition relies on a sequence of upper-bounding (i.e., optimistic for the maximization problem) piecewise-linear functions for the interdictor's

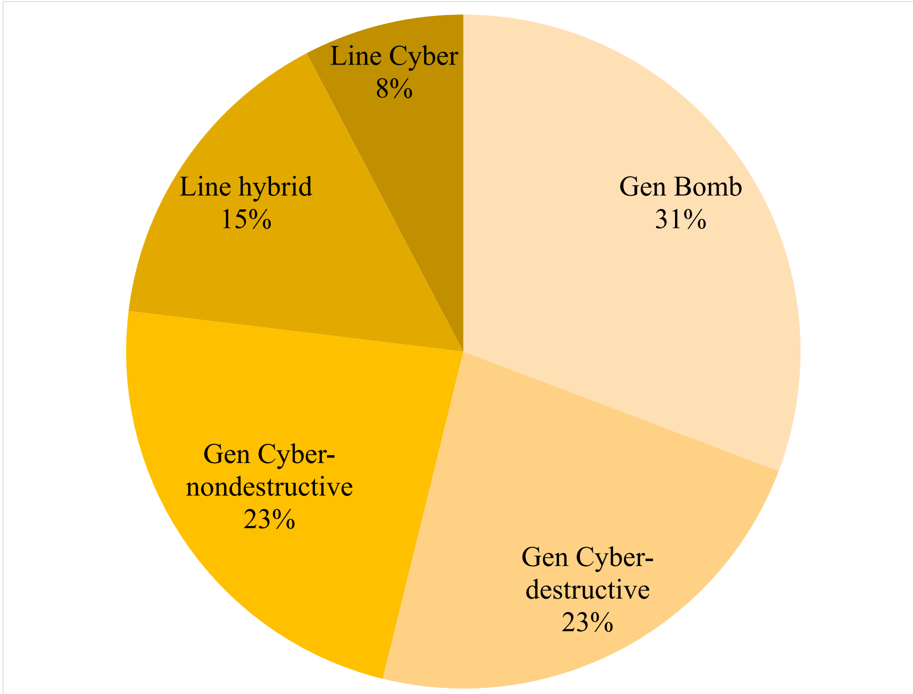

Figure 5.6: The attack resource deployment on RTS-96 Test Case, M=26.

objective. The maximum of the pointwise minima of those functions must converge to the optimal solution of IPF since only a finite number of interdiction plans exist; however, practical use of the decomposition rests on verifiably close-to-optimal solutions being found quickly.

In [168], for each interdiction plan $\boldsymbol{\delta}$, the interdictor's objective $z(\boldsymbol{\delta})$ is bounded by a cut:

$$z(\boldsymbol{\delta}) \leq z(\hat{\boldsymbol{\delta}}) + \sum_{k \in K} \alpha_k(\hat{\boldsymbol{\delta}})(\delta_k - \hat{\delta}_k), \forall \boldsymbol{\delta}, \hat{\boldsymbol{\delta}} \in \Delta \tag{5.5}$$

The cut is generated following an assumption:

- Assumption: Ignoring the short-term load-shedding due to interdiction-caused cascading failures, (a) the interdiction of a set of components, each carrying p MW of power, leads to the shedding of at most p MW of demand, and (b) the restoration of an interdicted component does not increase load-shedding.

Although the assumption does not hold strictly, [168] has demonstrated the efficiency and effectiveness of the method to solve interdiction problems. The major difference of the interdiction model described in [166] compared to the model in (7.1) is that we have short-term impacts, namely COA load shedding costs added to the objective. Inspired by the cut (7.5), we propose a new cut to tackle the inclusion of the short term COA cost:

$$z(\boldsymbol{\delta}) + \rho y(\boldsymbol{\delta}) \leq z(\hat{\boldsymbol{\delta}}) + \sum_{k \in K} \alpha_k(\hat{\boldsymbol{\delta}})(\delta_k - \hat{\delta}_k) + \rho \sum_{l \in L} P_l, \forall \boldsymbol{\delta}, \hat{\boldsymbol{\delta}} \in \Delta \tag{5.6}$$

In (7.6), we assume the upper bound of a potential cascading effect is the total system blackout, and has a cost of $\rho \sum_{l \in L} P_l$. Future work will focus on employing this cut structure to develop the extended Global Benders Decomposition method, in order to expedite the solution process. Note the assumption made in the proposed cut is likely to be conservative, because given limited resource, an attack may not achieve a total system blackout or load shedding that is close to the total system load. Therefore, the distance between the actual "worst case" attack load shedding and the bound calculated by the right hand side of (7.6) may be large, which may create challenges for the proper choice of convergence criteria.

In order to solve this challenge, we will also explore ways to establish less conservative bounds. An example solution could involve a pre-screening method (e.g. Random Chemistry method [62]) to identify whether the given attack resource is sufficient to cause a total system blackout. If the attack resource is sufficient to cause a system blackout, the upper bound described in (7.6) may be appropriate. If the attack resource is not sufficient to case a system blackout, a less conservative upper bound assumption may be applied (e.g. multiples of the largest power flow on components).

5.2.3 Summary

In this chapter, the completed work and contribution is summarized. The directions of some future work are proposed. We propose an extended framework that considers the restoration of power grids and the cyber security threats to power system. We will apply an extended Global Benders Decomposition cut structure and the subsequent screening methods to expedite the solution process of the interdiction problem. We will also conduct analysis on comparison of interdiction models and natural disaster models.

Part IV

Power Grid Resilience under Natural Disasters

Chapter 6

Survey on Research of Power Grid Resilience

6.1 Introduction

This chapter is based on the author's contribution in [218]. Dr. Chen Chen, Dr. Jianhui Wang and Dr. Ross Baldick in [218] contributed to the collection and discussion on the literature of the natural disasters research. Secure and reliable electric power grid operation is important to social wellbeing. Recent years have seen many blackouts due to natural disasters such as the 2005 Hurricane Katrina blackouts, 2011 Japan Earthquake blackouts, and 2012 Hurricane Sandy blackouts. Between 2003 and 2012, roughly 679 power outages, each affecting at least 50,000 customers, occurred due to weather events in U.S. [64]. Hines et al [89] describes 933 events causing outages from the years 1984 to 2006, and the data is presented in Table I[1]. The study of natural disaster impacts on power grid can be traced back to 1930s, when the 1938 New England Hurricane struck the Boston Area [79]. In the last decades, there has been considerable progress in advancing methods for analyzing natural disaster related issues in power systems. At the same time, due to the complexity of the issue and its interdisciplinary nature, research

[1]The totals are greater than 100% because some events fall into multiple initiating-event categories.

Table 6.1: Large Blackouts Causes in the United States [89]

Cause	% of events	Mean size in MW	Mean size in customers
Earthquake	0.8	1,408	375,900
Tornado	2.8	367	115,439
Hurricane/tropical storm	4.2	1,309	782,695
Ice storm	5.0	1,152	343,448
Lightning	11.3	270	70,944
Wind/rain	14.8	793	185,199
Other cold weather	5.5	542	150,255
Fire	5.2	431	111,244
Intentional attack	1.6	340	24,572
Supply shortage	5.3	341	138,957
Other external cause	4.8	710	246,071
Equipment failure	29.7	379	57,140
Operator error	10.1	489	105,322
Voltage reduction	7.7	153	212,900
Volunteer reduction	5.9	190	134,543

activities are conducted sparsely across different domains. We summarize the natural disaster characteristics based on multiple sources such as [77], [89] in Table II. The research on the issue of natural disasters on power systems can therefore be viewed in different aspects. To define the scope of this chapter, we first summarize the timeline of the response in the electric grid under natural disasters in Figure 6.1.

Paralleling the issues illustrated in Figure 6.1, we review the forecast models that are used to estimate the power outages as well as the asset dam-

Table 6.2: Illustration of disaster characteristics based on multiple sources

Type	Impact Region	Predictability	Span/area	Affecting time
Hurricane, tropical storm	Coastal regions	24-72 hours, moderate to good	Large (radius up to 1,000 miles)	Hours to days
Tornado	Inland plains	0-2 hours, bad to moderate	Small (radius up to 5 miles)	Minutes to hours
Blizzard, Ice Storm	High latitude regions	24-72 hours, moderate to good	large, up to 1,000 miles	Hours to days
Earthquake	Regions on fault lines	Seconds to minutes, bad	Small to large	Minutes to days (aftershock)
Tsunami	Coastal regions	Minutes to hours, moderate	Small to large	Minutes to hours
Drought, Wild Fire	Inland regions	Days, good	Medium to large	Days to months

ages; the corrective actions and emergency response, hardening and pre-storm preparation models; the restoration models that organize activities happening during or after the occurrence of the natural disasters. The scope of the work does not consider meteorological or geographical analysis of the natural disasters. While some traditional planning, operation and, restoration issues have appeared in the literature, we try to select and discuss the models and methods that could be applicable and relevant to natural disaster scenarios. The

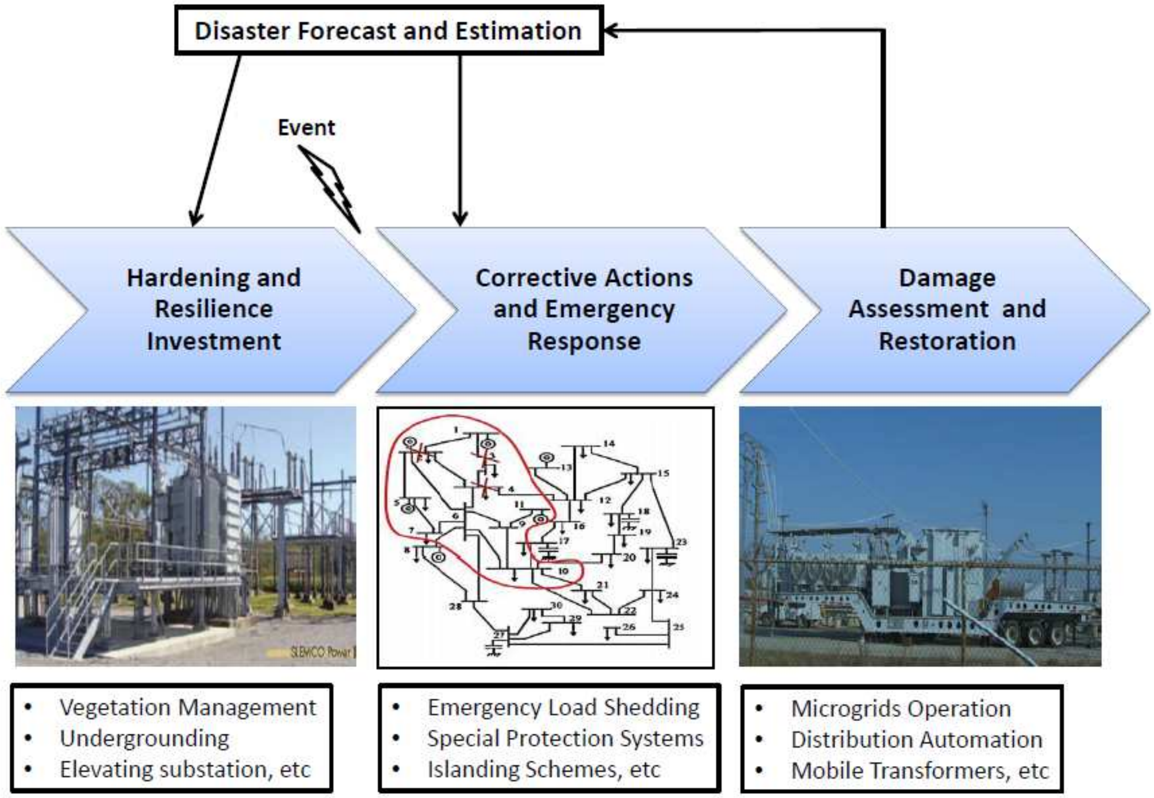

Figure 6.1: Timeline of the response in electric grid under natural disasters

references we review are mainly academic, especially in forecast models, and restoration techniques. On current hardening practices some of the references are from industry. The models, methodologies, and frameworks we review could be applied with no geographical restrictions. However, some examples shown in this chapter are mostly US concentrated.

The remainder of this chapter is divided as follows. Section 6.2 reviews the forecast models. Section 6.3 describes the experiences and practices for corrective actions, storm hardening programs, and pre-storm preparation activities. Section 6.4 discusses the models used to advance restoration processes. Section 6.5 provides challenges and suggestions for future work in the area of natural disaster impacts on power systems.

6.2 Forecast Models

6.2.1 Statistical Models

A range of models have been proposed in the literature to model power system damage, outage duration and restoration after natural disasters [138], [120], [80], [78], [77]. Most of the proposed methods, however, rely on damage assessments made after the occurrence of the extreme events [66], [148]. In this section we discuss some of the frequently used datasets, models and validation methods.[2]

6.2.1.1 Data and parameters

Many factors influence the susceptibility of electric power systems in a given geographic area to outages during natural disasters. Data required for statistical models can be divided into two categories, namely power system data and environmental data. The power system data usually includes the

[2]Most of the existing models emphasize finding the explanatory factors in power outages. While these factors and models could be used in both long-term hardening suggestions and short-term forecasting before the natural disasters, the on-line applications of short-term forecasting are challenging due to the difficulties to obtain update and validate real-time data. At the same time, different models stated in this chapter may suit some purposes better than the others. One example of the on-line prediction framework can be found in [181].

location and number of the customers, topology of the system, availability of the protection devices, etc.. The Transmission Availability Data System (TADS) managed by North American Electric Reliability Corporation (NERC) as well as its outage reports have collected outage data in a common format for U.S. transmission systems [144]. Other reports [37], [59] also provide some aggregated data for natural disasters.

Environmental data may vary with the disaster scenarios. Examples of such parameters as well as the possible source are listed below:

- Land and geometric characteristics of the area such as land use and land cover data, soil moisture levels, elevation characterisrics, land slopes, compound topographic index [136], [208].
- Disaster variables such as hurricane duration and intensity, approaching angle, landfall position, translation velocity, etc [142].
- Climatic characteristics, such as standardized precipitation index (SPI), annual and monthly precipitation [143].

6.2.1.2 Data fitting models

Generalized Linear Models (GLM): GLM has been used in [77], [78] to estimate the storm damage to power systems and the effects of tree trimming programs on power systems resiliency under hurricanes. For example, [78] used a negative binomial GLM to model power system failures, represented by equations (6.1) and (6.2):

$$f_Y(y|\alpha,\lambda) \sim \frac{\Gamma(y_i+\alpha)}{\Gamma(y_i+1)\Gamma(\alpha^{-1})} \times \left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_i}\right)^{\alpha^{-1}} \left(\frac{\lambda_i}{\alpha^{-1}+\lambda_i}\right), \tag{6.1}$$

$$log(\lambda_i) = \beta_0 + \sum_i \beta_i x_i, \tag{6.2}$$

where the vector x_i represents the explanatory variables, the vector β is the regression parameters to be estimated, and α is the overdispersion parameter of the negative binomial distribution that is observed in power system performance data.

Generalized Additive Models (GAM): The structure of a GAM differs from the structure of a GLM only in how the parameters of the conditional distribution are related to the covariates. For example, the link function shown in equation (6.2) can be changed to equation (6.3) to represent a non-linear smoothing function.

$$log(\lambda_i) = \beta_0 + \sum_i s(x_i) \tag{6.3}$$

Accelerated Failure Time (AFT) models: AFT models have been used by [138], [120] to estimate the power outage durations. The model relates the survival time to the explanatory variables through a linear relationship, as shown in equation (6.4):

$$ln(T_i) = X_t^T \beta + \sigma_i \tag{6.4}$$

where T_i is the survival time random variable, X_i is the vector of covariates, β is the vector of parameters, and σ_i is the vector errors that is assumed to be independently distributed. AFT is most typically fit using the method of maximum likelihood.

Tree Based Data Mining models (Classification And Regression Trees (CART) and Bayesian Additive Regression Trees (BART model)) [138]: CART are built by binary splitting of the data space into terminal nodes. In building regression trees the best splits s are chosen such that the sum of squared errors (or least absolute deviation) within each node t is minimized. A BART model comprises a set of small trees with each tree constrained by a prior to restrict each tree's contribution to the final model, making each individual tree a "weak learner". Fit and inference in BART are achieved through a Markov chain Monte Carlo algorithm.

Some other methods including Fuzzy Inference System (FIS) [122], Multivariate Adaptive Regression Splines method (MARS) and Cox Proportional Hazard models (COX PH) have also been used in the statistical forecast of the natural disaster impacts on power systems.

6.2.1.3 Measurement of fitting goodness and example

A typical way to measure the fitting goodness of a certain model is to compare the prediction results with the observed data. The mean absolute error (MAE), mean absolute deviation (MAD), mean squared error (MSE), and root mean squared error (RMSE) are often used as metrics to this comparison.

An example of the model implementation can be found in [78], where

Table 6.3: Comparison of Holdout Mean Absolute Errors (MAEs)

Model	MAE
BART	11.5
CART	11.7
GLM	21.4
GAM	13.6
BART/CART	10.3
BART/CART/GAM	10.4
BART/CART/GAM/GLM	12.0
Prediction by the Mean	20.0

model validation has been performed across four basic models, namely BART, CART, GLM, and GAM, as well as a combination of the methods to assess the pre-storm estimation of number of damaged poles in a distribution system. The variables used in the example include the parameters in Chapter 6.2.1.1). The pole replacement data consisted of the number of poles that were replaced in 456 grid cells (12,000 feet by 8,000 feet) due to damage in parts of Mississippi during Hurricane Katrina. There were 8,698 total pole replacements in this data set with 2,308 of these being poles owned by a telephone company but used by the power company and 6,390 being poles owned by the power company. The Comparison of Holdout Mean Absolute Errors (MAEs) based on detailed pole-level damage data on the basis of 150 random pre-selected samples (or “holdout” samples) is provided in Table 6.3.

6.2.2 Simulation Based Models

While most of the forecast models for power outages use statistical analysis, the accuracy of the estimates of the statistical approaches are critically dependent on (1) the appropriateness of the model used and (2) the sufficiency of the underlying data [138]. If an inappropriate or inappropriately developed model is used or if the data are insufficient to support the model development effort, the predictive accuracy of the statistical approach will be poor. At the same time, climate changes and other variances in natural occurrence could deviate the prediction results further from the future reality. Therefore, there is a value to understand the physical mechanisms of the damage, build simulation models that replicate the disaster occurrence and system response, and determine the proper preparation and hardening procedures.

One of the major causes of the equipment failures in natural disasters is due to the impacts of wind on transmission and distribution structures. There is a wide literature discussing the models and design of transmission and distribution structures subject to wind loading [171], [130], [81], [190], [68]. When designing transmission towers with conventional geometries and conductor arrangements the engineer has some design codes and guides available [139], [94], [205].

A simulation based approach to estimate the power outages or natural disaster related asset damages has been in [214] and an illustration of the approach is shown in Fig. 6.2. The core of the framework is the simulator that consists of (1) hurricane models, which associates the weather forecast parameters with the estimation of local environment for each power system components; (2) a set of generated initial disturbance following the hurricane models[3]; (3) a system outage simulator (Cascading Outage Analyzer) that evaluates the system condition following the initial disturbances. The output of the simulator could be system conditions such as power outages and damaged assets, as well as a series of hardening suggestions that help utilities to identify critical assets.

Numerous hurricane, transmission failure and outage models have been used in the previous research demonstrated in Fig. 6.2. [37], [214]. The simulation tool has the inputs of available weather forecast information, such as the landing positions, approaching angle, translation velocity, central pressure difference, maximum wind speed, and gust factor, to feed in to sample a failure rate-wind speed curve that generates the failed transmission line information as initial disturbances. This sampling processes can be replicated in a Monte-Carlo simulation framework. The initial disturbances, i.e. a set of failed transmission lines, are used in a developed Cascading Outage Analyzer, to produce the outage data under such a forecasted scenario. The hardening decisions are made to upgrade the most frequently observed outage paths.

We have developed a model based on this framework for hurricane impact simulation. The details of the model is discussed in Chapter 7.

[3]Many transmission and distribution failure models are developed by the statistical models or observations in Section 6.2.1

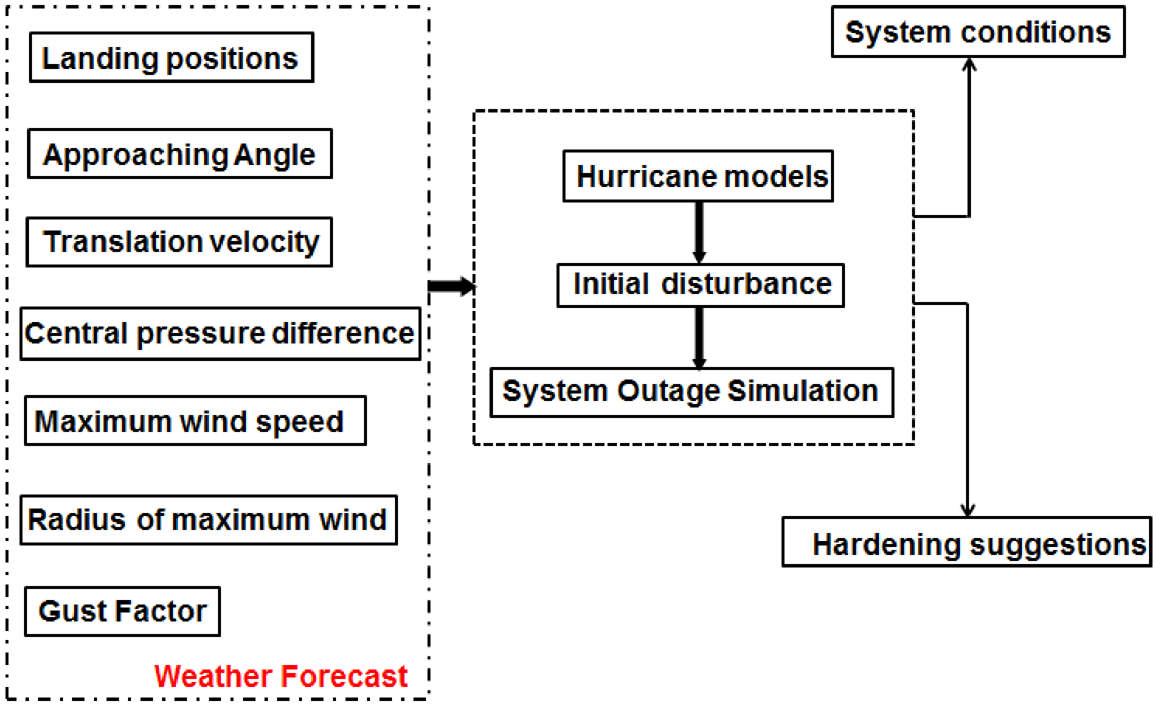

Figure 6.2: Example simulation framework for hurricane outage forecast

6.3 Corrective Actions, Hardening and Resiliency Activities

We define the corrective actions and emergency response as actions that are deployed during and right after natural disasters. When the natural disaster happens, due to the severity and uncertainty of the event, few corrective actions and emergency response actions are currently being deployed by utilities. Several papers discuss traditional measures to prevent large scale blackouts due to "multiple contingencies," which could potentially be used to help immediate natural disaster relief. Such activities may include deployment of Special Protection Schemes [210], [209] and Islanding Schemes [65], [213].

According to U.S. Department of Energy [206], hardening refers to physically changing the infrastructure to make it less susceptible to damage from extreme wind, flooding, or flying debris. Resiliency refers to the ability of an energy facility to recover quickly from damage to any of its components or to any of the external systems on which it depends. A summary of the existing practices to harden and increase resiliency of electric transmission and distribution system is shown in table 6.4.

Among the activities, elevating Substations, upgrading and under-grounding existing lines, and vegetation management are commonly used in current utility programs. We show some of the examples reported by the utilities in the following section.

Example 1: To prevent future flooding, as part of Southwest Louisiana Electric Membership Corporation's hardening plan, three substations that were flooded by Hurricanes Rita and Ike were elevated above the storm surge plus five feet, for a total of 13 feet above sea level. The cost of elevating the three substations was estimated at $5.2 million [206].

Example 2: To upgrade and harden the T&D lines against high wind, the public utility council of Texas (PUCT) has recommended that all new and replacement transmission structures installed within ten miles of the Texas coastline be designed to meet the current NESC (National Electric Safety Code) wind loading standards, assuming a maximum wind speed of 140 mph.

Table 6.4: Power Grid Hardening and Resiliency Activities [206]

Hardening	Activities
Flood Protection	Elevating Substations/control rooms/pump stations Relocating/constructing new lines and facilities
Wind Protection	Upgrading damaged poles and structures Strengthening poles with guy wires Burying power lines underground
Modernization	Deploying sensors and control technology Installing asset databases/tools
Resiliency	**Activities**
General Readiness	Conducting preparedness planning and training Complying with inspection protocols Managing vegetation Participating in mutual assistance groups Purchasing/leasing mobile transformers and substations Procuring spare T&D equipment
Storm-Specific Readiness	Facilitating employee evacuation and reentry Securing emergency fuel contracts Supplying logistics to staging areas

For 2009, Tampa Electric budgeted $10.7 million to replace 584 structures with steel or concrete poles, and 99 sets of insulators with polymer replacements [70]. Strengthening poles and towers by installing guy wires and upgrading crossarm materials is another common hardening method. Guying for extreme winds can cost $1,500 - $3,100 per pole [206].

According to [159], The estimated cost for constructing underground transmission lines ranges from 4 to 14 times more expensive than overhead lines of the same voltage and same distance. For example, a new 138 kV overhead line costs approximately $390,000 per mile as opposed to $2 million per mile for underground (without the terminals) [159].

Tree trimming is also the primary way that trees near distribution lines are managed [103]. In 2006, NERC introduced the Transmission Vegetation Management Program (Standard FAC-003-1) [145]. There are a number of papers discussing the vegetation maintenance scheduling models and techniques of overhead lines [103], [12], [228], [98], [95]. While these models do not directly consider natural disaster scenarios, they may be helpful for utilities to determine optimal strategy to allocate hardening resources.

Preparation of sufficient emergency generation units and black start units also plays a critical role in case of natural disasters. Generation planning does not normally consider the benefit of providing blackstart power and reduction of restoration time in natural disasters. However, optimal allocation of blackstart units and restoration procedure has been studied in [119] [193]. Such planning activities could significantly reduce the system restoration time, thus enhance the system resiliency.

6.4 Power System Restoration Techniques

After a power outage happens due to the damage from a natural disaster, the most important task for system operators is to restore the power system as quickly as possible to restore critical loads and minimize the economic loss to customers. In this section, we will first review the conventional power system restoration strategies and discuss new challenges for restoration from natural disasters. Then we will discuss two strategies to tackle these challenges, i.e., distributed generation and microgrids integration, and distribution automation with decentralized restoration.

6.4.1 Conventional Restoration Strategies

Power system restoration methods have been studied extensively in the literature [14] [115]. In general, the restoration process can be divided into three temporal stages: preparation, system restoration, and load restoration [69] [15]. In the first stage, the system status is assessed, initial cranking sources are identified and critical loads are located. During the second stage, the overall goal is reintegration of the bulk power network by designing an optimal generator start-up strategy utilizing black start (BS) and non-black start (NBS) units. Mathematical programming provides a powerful tool to tackle this problem, e.g. [119] [193]. In the third stage, the primary objective of restoration is to restore critical loads and minimize the unserved load, and the scheduling of load pickup will be based on the capabilities of available generators. This stage takes place after a part of the transmission system has been restored and electrical parameters such as frequency and voltage profile have been stabilized. Several approaches and analytical tools have been developed for load restoration strategies such as: expert systems [118] [48], fuzzy logic [114] [109], heuristic approaches [135] [201], and mathematical programming [97] [153] [152]. With emerging smart grid technologies, phasor measurement units (PMUs) based wide area monitoring system (WAMS) can enhance the information transmission as well as the system stability monitoring in the load restoration process [121].

However, power outages due to natural disasters have their unique features, which are different from those in typical outages, as shown in Table 6.5. These features are highly related to the characteristics of the natural disasters. For example, a storm may topple trees at several locations that snap utility poles to cause multiple faults causing a wide spreading outage, and these locations are dependent on the path of the storm, while in a typical outage, usually only one random fault causes the outage. Some severe disasters can even damage the transmission network, substations and generators, so that conventional restoration methods may not work effectively. In addition, natural disasters may also destroy other infrastructures which are interdependent with power grids (e.g., transportation, communications, water) so that the restoration will face even more difficulties. In comparison, a typical power outage usually does not have such issues. In this sense, conventional power system restoration strategies, which are designed for typical outages, may have more challenges for the recovery from outages as a result of natural disasters.

To cope with these challenges, new techniques, such as distributed generation, microgrids, distribution automation, and decentralized restoration strategies, may provide promising solutions to enhance the resilience of the grids, which will be in the following section. A few existing works have been done, e.g., using microgrids for system restoration after natural disasters, which will also be described.

Table 6.5: Differences between typical outages and natural disaster related outages

Typical Outages	Outages due to Natural Disasters
• Single fault due to one component failure	• Multiple faults due to catastrophic damage
• No stocastic feature involved in general analysis	• Uncertainty and stochasticity with the process of natural disasters
• No spatiotemporal correlation for the fault; fault happens randomly	• Spatiotemporal correlation for the faults due to natural disasters
• Most power generation units are working and stay connected	• Power generation units may be out of service
• Transmission and distribution network remain intact	• Transmission and distribution network are damaged and incomplete
• Only involve power grids infrastructure	• Have interdependence with other infrastructures
• Quickly repair and restore	• Difficult to repair and restore, e.g., debris after the disaster

6.4.2 DGs and Microgrids for Load Restoration

Generation availability is fundamental for all stages of power system restoration: stabilizing the system, establishing the transmission path, and picking up load [119]. As shown in Table 6.5, the lack of power availability during outages due to natural disasters casts huge challenges for conventional restoration strategies, which are based on the condition that most power sources are working and stay connected. To cope with generation unavailability during and after the natural disaster, distributed generation units (DGs) can be utilized to enhance the grid resilience by improving generation availability (e.g., fuel cells, microturbines, wind turbines, photovoltaic panels) [155]. Furthermore, microgrids can be employed to efficiently manage these DGs as well as other resources to improve the restoration for natural disasters. A microgrid is a small-scale power system typically on the medium- or low- voltage distribution feeder that includes distributed load and generation together with storage (e.g., flywheels, batteries) and protection devices, which are synchronized through an embedded management and control system [123] [220] [221]. Fig. 6.3 is a typical architecture of the microgrid that comprises different kinds of components [123].

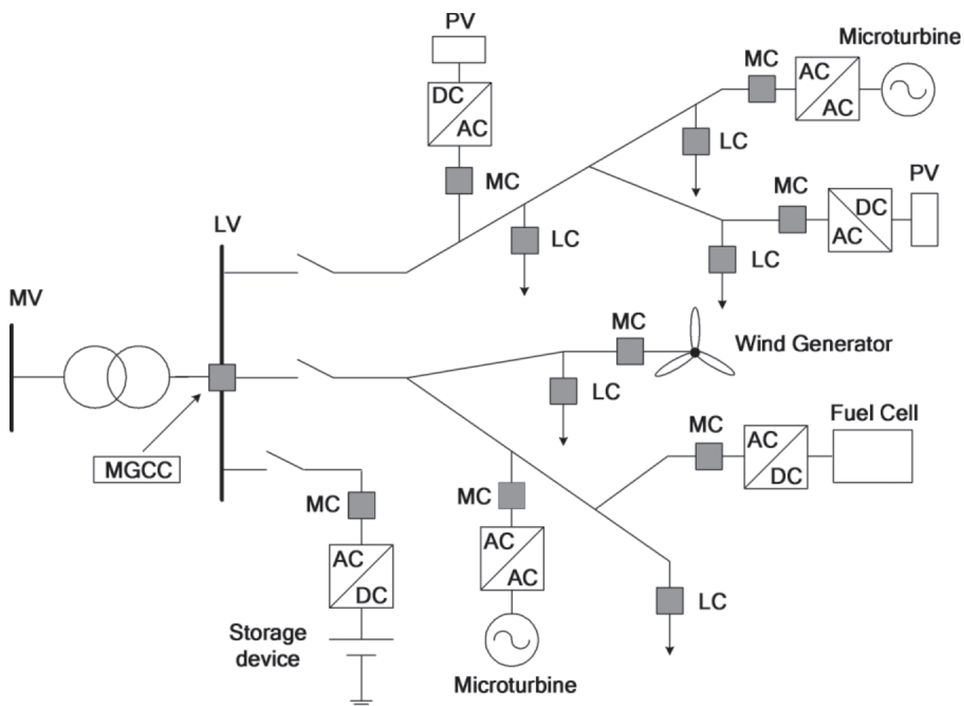

Figure 6.3: Microgrid architecture comprising microsources, storage devices, loads and control devices [123]

A key fundamental difference of microgrids with respect to conventional grids is that microgrids add active network components (i.e., DGs) at the distribution level, which provide more operational flexibility and reduce conventional power grid vulnerabilities caused by centralized generation and control architecture and long distances between power sources and loads [104]. This feature is even more important for the power system restoration after natural disasters. In addition, the observed uneven damage distribution of the natural disaster on distribution systems increase the resilience when applying microgrids for load restoration, as the chances of all microgrids being damaged are very low [104]. In this sense, microgrids will enhance the power system restoration after the disastrous event. The value of microgrids to achieve grid resilience has been recognized, and they are being adopted by some state governments and industries, and their technical, regulatory, and financial barriers for implementations are being studied, e.g., [9] [8].

Three specific uses of microgrids in power restoration are discribed in the following sections:

6.4.2.1 Microgrids aiding the conventional load restoration

In this scenario, the microgrids can serve as extra resource to enhance the conventional load restoration. This is especially useful for the area where no other suitable restoration path or source are available. In [112], the authors proposed graph-theoretic distribution system restoration strategy to embed the emerging microgrids that enhance the self-healing capability and allow the distribution system to recover faster in the event of an outage. The proposed method applies the spanning tree search algorithm to maximize the restored load and minimizes the number of switching operations without violations of operational constraints. The microgrids in the distribution system are modeled as virtual feeders. The authors in [133] presents a mathematical model to utilize microgrids to alleviate the outage in the absence of suitable restoration path/source.

6.4.2.2 Microgrids providing resources for bulk system restoration

In this scenario, the microgrids operate in the grid-connected mode, and can provide ancillary services such as blackstart to the bulk system restoration. For example, the authors in [42] developed a stochastic mixed integer linear program to assess the impact of coordinating microgrids as a blackstart resource to the regional grid or Regional Transmission Organization (RTO) after a natural disaster.

6.4.2.3 Microgrids in island mode for load restoration

In this scenario, the microgrids act in island mode in the event of disasters and serve critical loads like data center, hospital communities, and campuses by utilizing local generation and storage facilities. This operation mode requires special control for the frequency and voltage since no support is from the main grids. The power electronics inverters in this case act as voltage source inverter (VSI) to control the frequency and voltage [123]. In [134], the authors described the sequence of actions for a microgrid central controller

(MGCC) to perform service restoration, which is briefly described as the following steps: 1) sectionalize the microgrid around each microsource (MS) with BS capability; 2) build the low voltage (LV) network utilizing storage device; 3) synchronize small islands energized by MS; 4) connect the controllable loads to the LV network; 5) connect noncontrollable MS or MS without BS capability; 6) connect other loads; 7) change the control mode of MS inverters; 8) synchronize the microgrid with the medium voltage network. In [163], the authors further proposed a new distribution system architecture that allows the coordination among multiple microgrids for load restoration, and the corresponding sequence of actions are defined. Reference [74] the role of electric vehicles (EVs) as grid-supporting units to take advantage of their storage capacity and charging flexibility in the microgrids restoration. In [47], the authors proposed a microgrids formation scheme by utilizing the distributed generation to restore the critical loads after the natural disaster. Reference [222] proposed a self-healing strategy after natural disasters by sectionlization of the distribution system into microgrids. Other regional experiences such as shown in [170], [187] and [234] can also be utilized.

These three functions for power system restoration can be integrated in the microgrid energy management system (EMS). In [46], the authors introduce the hierarchical control of the Illinois Institute of Technology (IIT) microgrid, in which primary control is based on droop characteristics of distributed energy resources for the sharing the microgrid load; secondary control performs corrective action to mitigate frequency and voltage errors introduced by droop control; tertiary control manages the flow between the microgrid and the utility grid and provides normal operation as well as emergency restoration services.

6.4.3 Advanced Distribution Automation Techniques and Decentralized Restoration Strategies

Current power distribution systems are mostly operated under radial topology and limited number of line switches. However, to improve the reliability of distribution system, network topology with a large number remotely controlled automatic switches will be implemented [87]. With the Smart Grid Investment Grant (SGIG) by the U.S. Department of Energy (DOE) under the American Recovery and Reinvestment Act of 2009, several utilities have installed a large number of remotely controlled switches to enhance the topology flexibility of the distribution system, so called distribution automation [207]. These distribution automation pilot projects largely increase the reliability (e.g., System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI) of the distribution system [207], by reducing the number of customers affected and the restoration time. During the restoration after the natural disaster, distribution automation can be extremely helpful since several distribution lines may be destroyed due to the disaster. Reconfiguration of the topology of the network with remotely controlled switches provides opportunities to restore the outaged loads more quickly. This flexibility can also enhance the integration of distributed generation and storage, i.e., microgrids, into the distribution system for restoration. The authors in [155] proposed a method for integration of large scale of distributed generation into power system restoration by utilizing the fully implementation of remotely controlled switches.

Generally, the approaches to study service restoration in the distribution system can be roughly grouped into two categories: centralized methods and distributed methods [111]. The centralized methods normally depend on a powerful central facility to handle large amount of data with high communication capability requirement. This dependency is not suitable for next generation resilient distribution system in two aspects. Firstly, large amount of remotely controlled devices installed in the system would be an extensive burden on computation and communication will exert on the central controller. Secondly, the centralized strategy is prone to a single-point-of-failure of the central controller, especially in the scenario of the natural disaster. In this sense, decentralized power system restoration strategies, or the construction of multiple back-up control centers are needed to achieve grid resilience.

Several decentralized methods have been proposed for the power system restoration in the literature, e.g., [188] [146] [226] [162] [235], and they are based on multi-agent coordination schemes. In [188], a multi-agent system for load restoration is proposed, where description of the types of agents and their behaviors to exchange information and determine a feasible restoration path is specified. The authors in [226] proposed a distributed information discovery process for load restoration applying the average consensus algorithm, in which agents only communicate with their direct neighbors. In [146], the authors proposed a distributed algorithm for service restoration with distributed energy storage support following fault detection, location and isolation, as well as load restoration. The authors in [162] presented a conceptual multi-agent system design for autonomous bulk power system restoration. A dynamic team forming mechanism was proposed for agent coordination purposes. The authors in [235] proposed a cooperative two-layer multi-agent system to locate and isolate faults and decide and implement the switch operations to restore the out-of-service loads. Besides these research work, the decentralized methods have already been implemented in some distribution automation products, e.g., [172] [76]. With the decentralized methods, these remotely controlled automatic switch devices of distribution automation can achieve more resilient power system restoration scheme to mitigate the impact of natural disasters on customers.

6.5 Conclusion and Future Research Directions

This chapter reviewed the state-of-the-art of the impacts of natural disasters on power systems, and how the advanced smart grid technologies can be utilized to enhance the grid resilience. Due to the complexity of the issue, it involves interdisciplinary techniques such as statistics, meteorology, power engineering, optimization, communication and control, as well as policies and regulations. Based on the review, we observe several challenges and opportunities in future research, and this chapter lists three important directions in the next section.

6.5.1 Interdependence among Different Infrastructures

As discussed in Table 6.5, during a natural disaster, the resilience of the power system does not solely depend on the infrastructure of the power grids, but is also related to other infrastructures such as communication network, natural gas pipelines, transportation network, etc. For example, distributed generation such as internal combustion engine generator or microturbines will not work if the fuel or natural gas availability (also called lifeline infrastructures [104]) are destroyed by the natural disaster. To achieve a resilient power system, these lifeline infrastructures should be considered in the overall planning and operation before and after the natural disaster.

To do so, the impacts of lifeline infrastructures on the power system regarding the natural disaster need to be analyzed first. Several papers in the literature have already analyzed the interdependence between the power grids and natural gas infrastructure in the normal operation [178] [116]; however, the extension of these interdependence analyses from a resilience perspective has not been well studied. The co-simulation framework for the interdependent infrastructure is useful to evaluate the correlation between them. For example, based on the assessment, the optimization problem for planning of the infrastructure considering these dependencies can be formulated, in which the uncertainty of the infrastructure subject to the natural disaster can be integrated using stochastic or robust optimization techniques. At the operation level, optimal strategies utilizing the flexibility of the infrastructure (e.g., reconfiguration of network topology, demand response, distributed energy storage) can be designed using optimization techniques.

6.5.2 Operation and Control for Power System Restoration with DGs, Microgrids, and Distribution Automation

Integrating microgrids and distribution automation provide potential to improve the restoration process of the power system; however, challenges exist on the operation and control of the distributed generation and the remotely controlled switch devices to achieve the restoration goal while maintaining the frequency and voltage profile of the distribution system, especially in the island mode of the microgrids. During the disaster, the distributed generation and the remotely controlled switches may also be fully or partially damaged, so operation and control under this stringent condition need to be considered.

Advances in distributed optimization techniques [100] can be utilized to design the decentralized restoration scheme which is suitable for the natural disaster scenario. The impact of the device failure can be analyzed based on this decentralized framework which serves as the tertiary control level. The coordination between this scheme and primary and secondary control scheme need to be investigated accordingly.

6.5.3 Natural Disaster Impact Forecast, Hardening and Resilience Optimization

There lacks a clear link from the modeling of damages/outages to the future prediction and hardening guidance. The statistical methods described in section 6.2.1 heavily relies on the information that is localized (meaning heavily associated with the local geographies and power system structure) and subject to a specific event. Such case-dependent variance and uncertainty prevent the use of the model for future predictions. At the same time, the statistical methods do not look into the mechanisms of the development process of the blackouts/damages. Simulation based models may be able to provide more insights into causes of outages. But they are substantially more complex when detailed power system transmission and distribution information, as well as the other factors (e.g. vegetation information, accurate wind forecast, etc) are required. Such requirements may be hard to obtain, and subject to uncertainties.

When designing the hardening and resilience programs, utilities typically do not use systematic and rigorous optimization techniques. A common way of deploying the investment is to upgrade the previously damaged facilities, or choose certain techniques based on experience. Therefore, the identification and allocation of the budget may not be the most efficient. More research on how to optimize the hardening program investments could potentially save a large amount of money, as well as increase the resilience of the program. Some optimization methods and applications in the conventional power system research, such as [103], [12], [228], [98], [95] may be a helpful starting point.

Future research on forecast models is needed in two direction: 1) Establish models that links the forecast and the hardening investment guidance. For example, [37] provided some insights on the cost-benefit analysis of the infrastructure upgrades based on increasing NESC standard requirements. Such analysis may also be used in other types of hardening techniques, guided by the more accurate statistical and simulation models. 2) Enhancing the accuracy of the forecast by developing new statistical and simulation based models. This may require more data analytical models to be incorporated, as well as more open source data to be provided by the utilities. As discribed in section 6.2.2, we developed a tool to analyze power system security under hurricane threats based on the framework proposed in Figure 6.2. In the next chapter, this tool will be discussed in detail.

Chapter 7

Tool to Analyze Power System Security under Hurricane Threats

7.1 Introduction

This chapter is based on author's contribution in [214]. This chapter presents the efforts that aim to create a tool to analyze the power system security and safety under severe weather conditions such as hurricanes. The tool will be constructed in two parts, Cascading Outage Analyzer, and the Hurricane Model Generator. Further discussions on the potential applications to natural disaster relief and preparation are also provided. The schemes described in the chapter could be adopted by the utilities to reduce the costs of natural disasters, and increase the efficiency of the grid operation. While we try to represent what is happening in a hurricane event as accurate as possible, there are still a lot of assumptions and approximations in terms of modeling. Some of these assumptions and approximations are conservative to assess the consequence, while others are not. For example, considering the whole south and Houston zone lines under same wind condition certainly creates more severe results than reality, because the wind speed will not be maximum at each location at the same time; on the other hand, not considering the effects of storm surge and the subsequent substation/generator damage makes the results optimistic. Those issues should be acknowledged before applying the results.

7.2 General Framework

The tool to identify and analyze the hurricane threats to the power systems has a general framework as shown in Figure 6.2, which is repeated in Figure 7.1. The objective is to use the published and available weather forecast information, such as the landing positions, approaching angle, translation velocity, central pressure difference, maximum wind speed, and gust factor, to feed in to a hurricane model that generates the failed transmission line information as initial disturbance. The initial disturbance, i.e. a set of failed transmission lines, are used in developed Cascading Outage Analyzer, to produce the potential system conditions under such forecasted scenario, and the subsequent hardening suggestions.

7.3 Hurricane Model

As discussed in the general framework, it is vital to translate the available weather forecast information, to the actual projections of what transmission lines might experience outage during the event. Numerous studies [37], [224], [101], [124], [110] have been done to explain the relationship between high intensive wind (HIW) and the failure of transmission structure. The National Electric Safety Code [139] has set an “extreme wind loading” design criteria to the structures higher than 18 meters (60 ft.) above ground

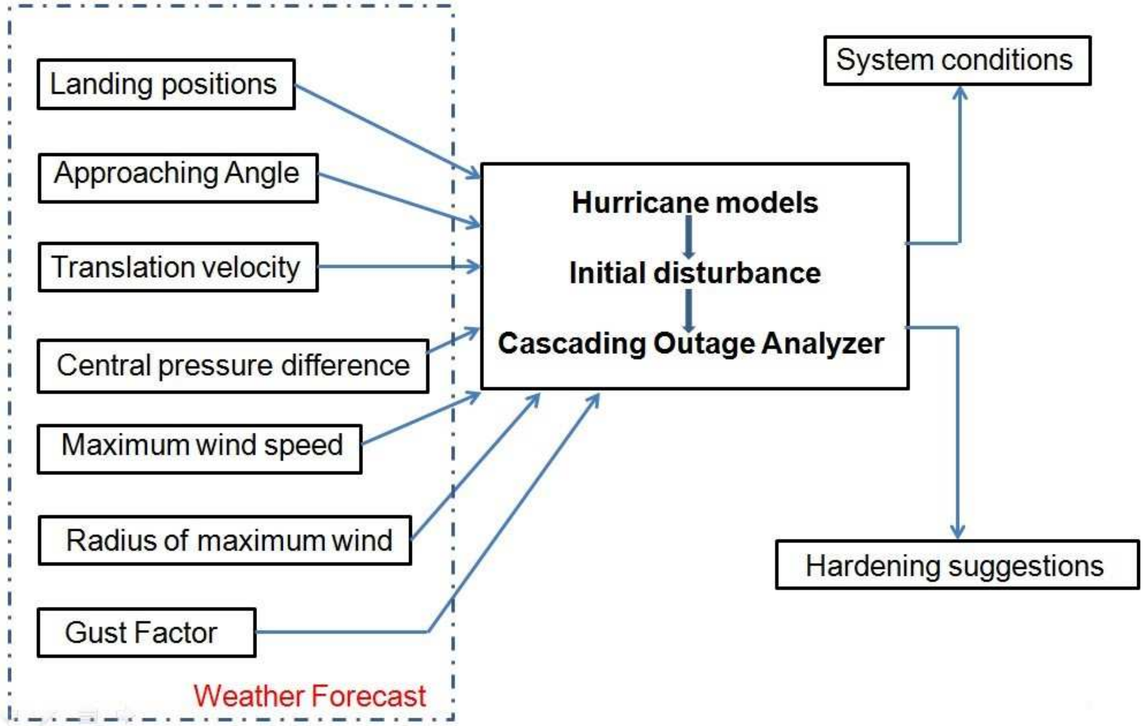

Figure 7.1: The general framework for hurricane outage forecast tool

or water. As most transmission line structures exceed this height, the extreme wind loading criteria is currently required for new construction in extreme wind regions. The report from Quanta Technologies [37] has identified the damage data from utilities and failure rate modeling produced the failure rate curve for existing structures, shown in Figure 7.2. The failure rate y as a function of gust speed x is:

$$y = 2 * 10^{-7} e^{0.0834x} \tag{7.1}$$

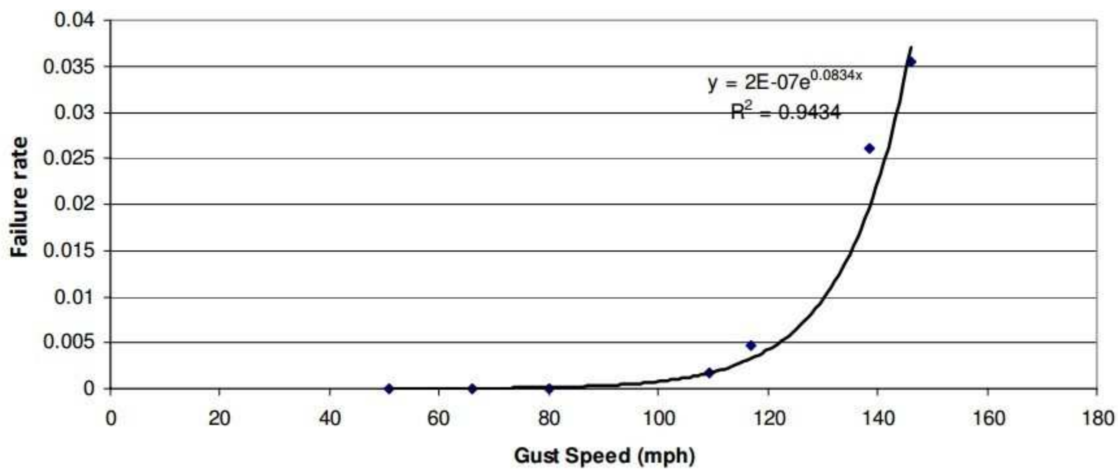

Figure 7.2: Failure rate of existing transmission lines

These data are based on existing transmission structures under NESC Grade B requirements and are equivalent to a wind loading standard of 105 mph. If the structures are replaced or rebuilt to the current NESC extreme wind loading criteria, they would need to meet a wind load requirement of up to 130 mph. The failure rate curve based on 130 mph design for transmission structure is shown in Figure 7.3. The failure rate y as a function of gust speed x is:

$$y = 2 * 10^{-8} e^{0.0834x} \tag{7.2}$$

Note that the unit of the failure rate in the figures is not identified in [37] and the authors of this study were not available to clarify. We assume that the failure rate is intended to be probability of failure per structure per hurricane event. At the same time, the focus of this chapter is not to accurately

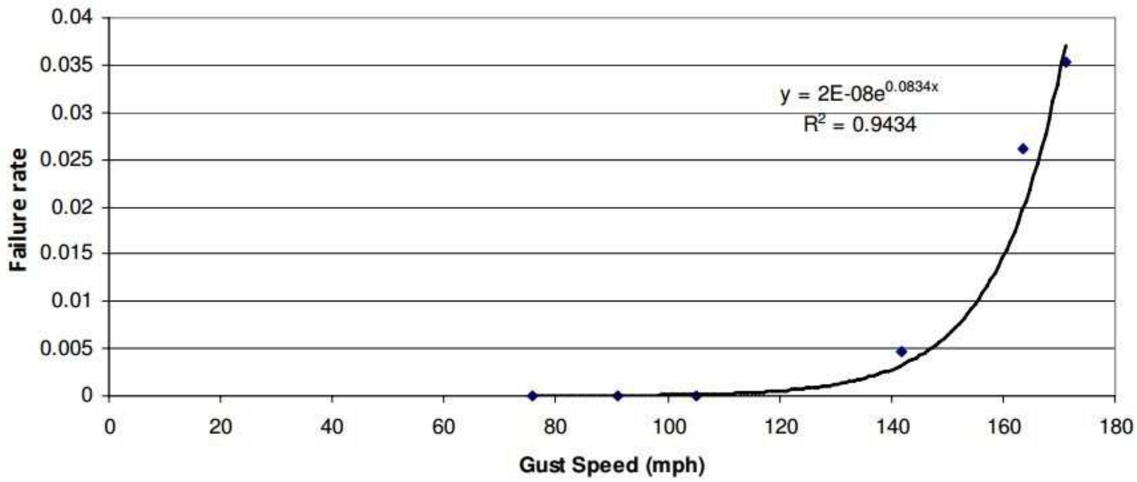

Figure 7.3: Failure rate of hardened transmission lines

estimate the failure rates of transmission structure under hurricanes, and we suggest every entity that is trying to use the tool needs to identify the failure rates of its transmission structures under certain wind speed. In modeling the transmission failure, several assumptions are stated as below:

- For a transmission line with multiple transmission structures, i.e., transmission towers, the failure of one of the transmission structure will lead to a trip of the transmission line.
- The failures of the transmission structures by wind are assumed to be independent. Notice once a transmission tower has failed, it is likely that the conductor attached to the transmission tower drags the towers next to the failed tower and induce subsequent failures. This will affect the calculation of the restoration, but will not affect the assessment of

probability of one transmission line failure, because once the initial failure occurs, the whole transmission line is assumed out of service. For a transmission line with n transmission structures, and failure rate of each transmission structure $y_1, y_2, ...y_n$, the failure rate of the transmission line will be $y_{line} = sum_{i=1}^{i=n} y_i$.

- The failure of the transmission structures is assumed to be a Poisson process, according to the exponential failure law. [31] The mean value of the time to failure, T_f, is $E\{T_f\} = \frac{1}{y}$. The probability density function (PDF) of the time to failure is given in equation 7.3, and the cumulative density function (CDF) of the time to failure is given in equation 7.4.

$$f_T f = y_{line} * e^{-y_{line} t}, t \geq 0, \tag{7.3}$$

$$F_T f(t) = 1 - e^{-y_{line} t}, t \geq 0. \tag{7.4}$$

- The hurricane event is divided into several time frames, e.g., fifty 5-minute time windows. For one time window, e.g., 5 minutes, the gust speed is assumed to be constant; therefore, the failure rate of the transmission line within the time window is constant. Once a transmission line is failed, it will not be restored within the hurricane event.

After the assumptions are made, for each simulated hurricane scenario, a sample of the transmission line failures is created by the steps 1 to 5 described below:

- Step 1: Acquire the weather forecast (e.g., sustained wind speed) and calculated gust wind speed at each location for an observation time window, e.g. the first 5 minutes of the hurricane.

- Step 2: Use equation 2 or 3 to find the failure rate of each transmission structure, and calculate each transmission lines failure rate, under assumption b.

- Step 3: Use the calculated failure rate, and equation 4, to apply the reverse CDF sampling to find a sample of the failure time of each transmission line.

- Step 4: Compare whether or not the sampled failure time is within the time of the studied period. If the sample time is longer, then the transmission line is not failed in the period, vice versa. Repeat the step for all transmission lines.

- Step 5: Repeat step 1 to 4 for all the time windows in the hurricane event.

It is noticeable that the set of transmission failures is generated based on the random numbers and the probability of failure, so a Monte-Carlo simulation is needed to generate enough sample, or “synthetic hurricanes to reflect the average expected situation of the level of hurricanes.

7.4 Cascading Outage Analysis model

The hurricane model creates a set of transmission line failures. In order to address the short-term consequence following a set of transmission line failures, sequential outage checkers to identify potential cascading process that might lead to large blackouts are proposed. In this cascading outage model, the line failures within a short time window, i.e., 5 minutes, are assumed as a set of simultaneously applied initial disturbance. The detailed implementation of the cascading outage analysis models has been discussed in Part I.

7.5 Storm hardening model

Some reports, such as [37], have discussed the storm hardening programs. Most of these programs are pointing to harden the components that are either closer to the coast, or close to the path of potential hurricanes. The rationale behind these programs is that the more those components are exposed to the wind, the more likely they will fail, thus more valuable to harden. However, as studied from the Cascading Outage Analysis model, and the historical events, such as [189], it is noticeable that the components occur in the cascading path are more valuable to harden, because not hardening those components would potentially lead to a large cascading outage, while the failure of lines close to the coast might only end up as localized blackout. The storm hardening model in this project is based on the Monte-Carlo simulation results of the hurricane models and Cascading Outage Analysis model. The Monte-Carlo simulation is used to generate a large number of synthetic hurricanes.

Each synthetic hurricane will contain all the information of the needed weather forecast, as shown in Fig. 1. After simulating the hurricanes through the Cascading Outage Analysis model, some components might repeatedly appear in the potential sequence of cascades, meaning it is more likely these components will fail in a hurricane initiated cascade. Therefore, these components will be identified as the targets for storm hardening model.

7.6 Implementation and results

7.6.1 Implementation and test case

In order to implement the models and algorithms, a new graphical user interface is designed with the algorithm written in Visual Basic for Application, PowerWorld Scripts, Excel Scripts. Within the code, the graphical user interface (GUI) is designed using the Visual Basic for Application; the PowerWorld simulator is used in Transient Stability calculation, and the AC Power Flow calculation; the frequency checker algorithm, along with the high-level Monte-Carlo algorithm is implemented by the Visual Basic for Applications. In our system an ERCOT 2008 summer planning case is used. Within the model, the total load is approximately 71 GW. The one-line diagram for this model is shown in Figure 7.4.

In the implementation, several assumptions are made, which could be enhanced as discussed in the future research:

- These lines are assumed to be exposed at same level of the wind during a hurricane.

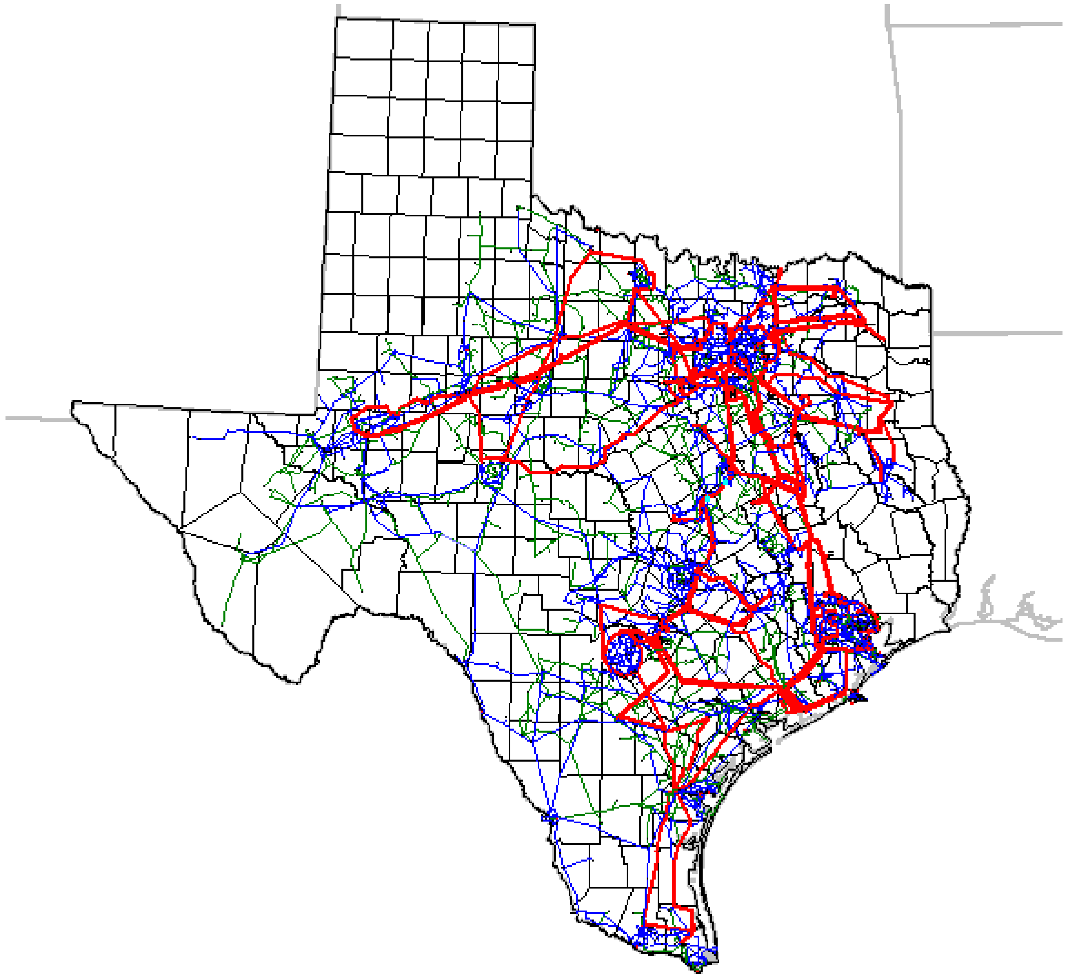

Figure 7.4: Network of ERCOT 2008 case

- The transmission lines, although different in lengths and number of transmission structures, are assumed to have 50 transmission towers in average.

- In order to calculate the failure rates, the time of the hurricane event is assumed to be 3 days.

7.6.2 Generation of one sample hurricane

In order to illustrate the hurricane model and the Cascading Outage Model, one sample hurricane is simulated. All transmission lines that are within, or have connecting bus in the south zone and Houston zone are selected, which represents 2278 transmission lines in total. One sample of hurricane is generated. We note that the average time to failure for sustained wind speed less than 80 mph is multiple years, therefore the probability of the transmission line failure in 5 minutes of 80 mph wind is negligible. In this sample of hurricane, the wind speed climbs from 90 mph in the beginning, to 125 mph in an hour, and comes down to 110 mph till 90 minutes, the end of the observation time. This hurricane is rated Category 3 according to the Saffir-Simpson Hurricane Scale. A sample of corresponding transmission line failures is created for this hurricane. In Figure 7.5, the sustained wind speed and the corresponding number of transmission line failures are shown.A total of 184 lines are out in the period of the hurricane.

Applying these transmission line failures to the Cascading Outage Analysis model, a cascade that involves three stages of outage, including load under voltage and line overload is detected, and the system experiences a total system blackout.

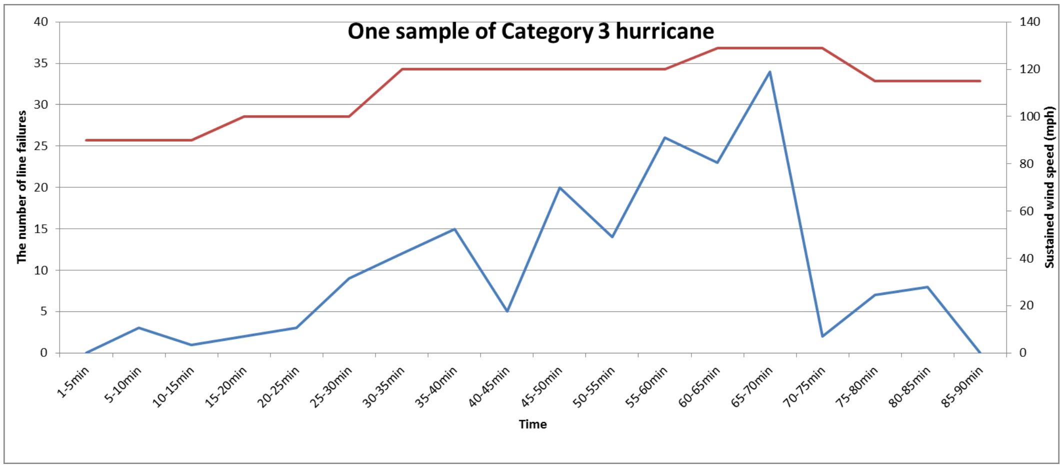

Figure 7.5: One sample of a category 3 hurricane

7.6.3 Monte-Carlo simulation

The Monte-Carlo simulation is used as discussed in the previous sections. Different levels of sample hurricanes are generated. The maximum wind speeds range from 70 mph to 120 mph. For each wind speed profile, 200 samples are generated. The Figure 7.6 shows the number of total transmission line outages for hurricanes with different top sustained wind speed. The ideal failure rate described in equation 7.1 is also plotted in this figure. As can be seen from the figure, the number of transmission line failures generally follows the trend of the failure rates, which is an exponentially increasing function of wind speed.

The number of total system blackouts, and the load shedding for the cases that do not black out are shown in the Fig. 10. Notice that when the hurricanes have a top wind speed of 110 mph, the probability of having a

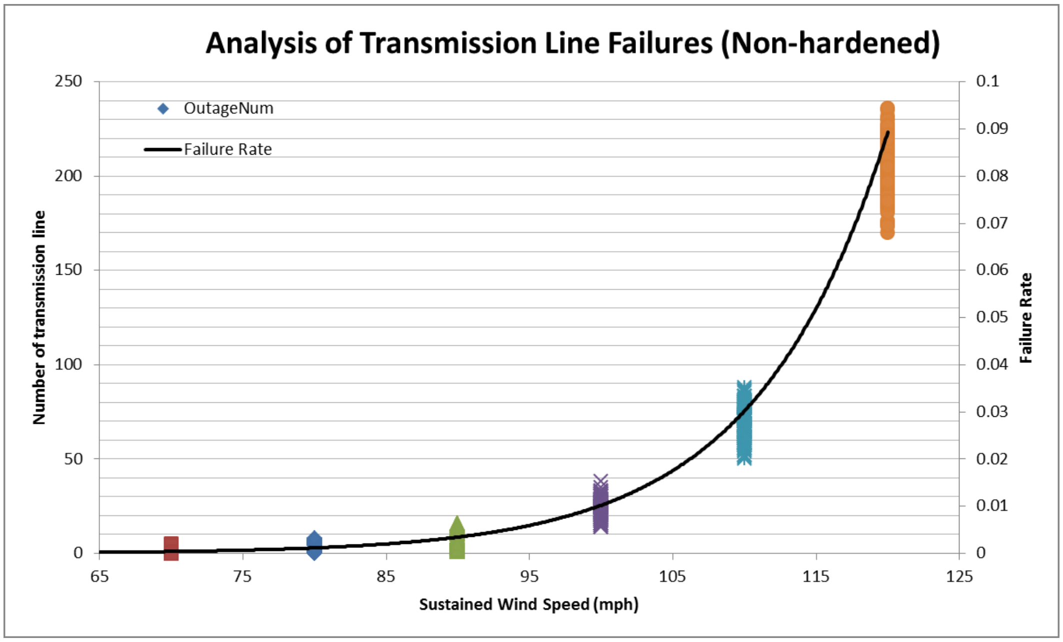

Figure 7.6: Number of transmission line failures in each level of hurricane

total system blackout in our simulation is 0.21, but when the top wind speed is increased to 120 mph, the probability of blackout increases to 0.82. This dramatic increase of probability of having a blackout is due to the exponential increase of number of transmission line failures.

7.7 Future work

As discussed in previous sections, the development of this tool involves numerous approximations and assumptions. Therefore, the author believes that there are a number of future enhancements that could be done in the future. Some of them are listed below:

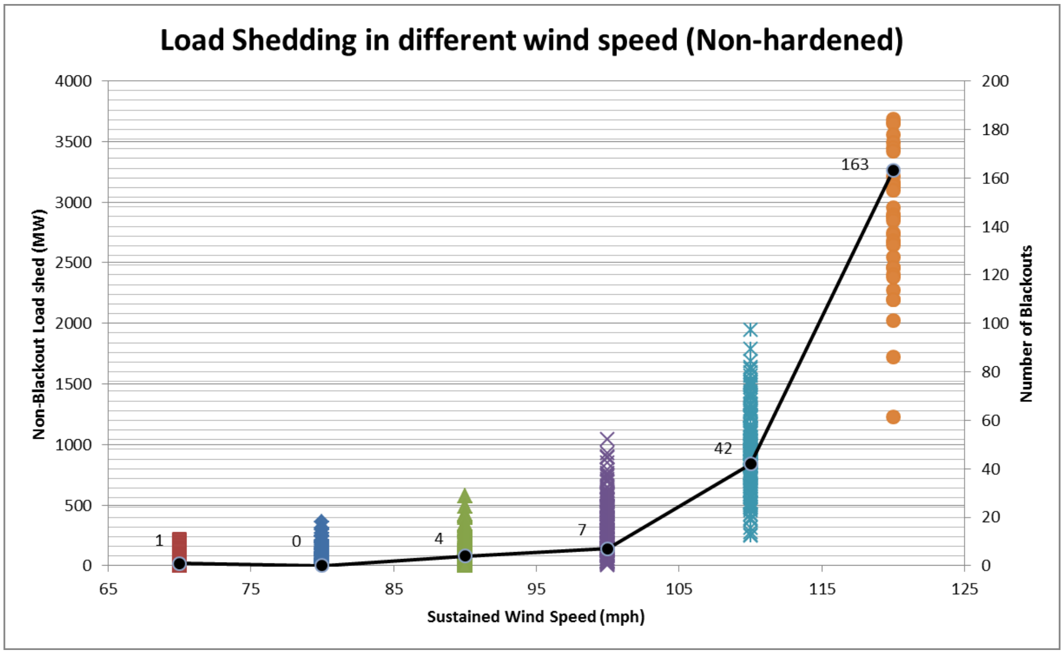

Figure 7.7: the load shedding in different level of hurricanes

- The transmission lines are assumed to be exposed at same level of the wind during a hurricane. Future research will try to differentiate the exposure of wind to the transmission lines based on the geographical information, and the wind profile.

- The transmission lines, although different in lengths and number of transmission structures, are assumed to have 50 transmission towers in average. Future research will try to differentiate the number of transmission structures based on geographical information.

- In order to calculate the failure rates, the time of the hurricane event is assumed to be 3 days. Additional flexibility will be introduced for the researcher to customize the selection.

- The translation velocity of the hurricanes, together with the wind profile change will be more accurately modeled in the hurricane models.

- The current authorities do have pre-cautious plans for the coming hurricanes, especially big ones, such as reducing the load, or evacuation. Our future research will also investigate these actions.

- The distribution system is not being modeled in the Cascading Outage Analyzer, but they play a significant role in blackouts of the system under hurricanes. Therefore the modeling of the distribution system will be explored.

- Facing a natural disaster, e.g. hurricane, precautions such as warning and evacuation may change the people's behaviors. Therefore, the electricity load shape may be very different. Future research may study this phenomenon and consider a more realistic load profile during the natural disasters.

- In this tool, the repair and restoration of the power system are not considered. However, decisions and implementations on repair and restoration play a vital role in natural disaster relief. At the same time, such decisions and implementations involve numerous human factors and infrastructure interdependency factors. Future studies on these issues may be very important.

Part V

Conclusions

In this dissertation, we discussed three main topics, namely cascading outage analysis, integrated interdiction model, and power system resilience under natural disasters.

In the cascading outage analysis part, an improved cascading outage analysis model is proposed. Four outage checkers, namely the transient stability checker, the frequency outage checker, the line outage checker and the voltage outage checker are implemented based on protective relay functions. The outage checkers are operated according to a newly proposed algorithm to determine the status of the resulting operating state or equilibrium. A case study of the improved cascading outage model using the IEEE 118-bus system and the IEEE 300-bus system is presented. Mitigation and prevention of cascading outage has also been discussed.

In the integrated interdiction model part, we propose an improved interdiction model to identify maximal electric grid attacks. The contribution of the model is that it incorporates both short-term (seconds to minutes) and medium-term (minutes to days) impacts of the possible attack. The medium-term impacts are examined by an interdicted DC optimal power flow model (I-DC-OPF). The short-term impacts are addressed by a cascading outage analysis model (COA) that uses a set of systematically applied checkers to perform the simulation of the cascading outage events and assess the short-term impacts of a blackout subsequent to specified terrorist attacks. An integer programming heuristic is applied that can utilize standard optimization software (e.g. CPLEX) to solve master problems generated by the heuristic. The proposed model has been verified using the IEEE 300 Bus Test System and IEEE RTS 96 Test System. Discussions of the results and future research plans are also presented.

In the power system resilience under natural disaster part, we consolidate and review the progress of the research field towards methods and tools of forecasting natural disaster related power system disturbances, hardening and pre-storm operations, and restoration models. A tool to analyze power system security under hurricane threats is proposed. It uses the published and available weather forecast information, such as the landing positions, approaching angle, translation velocity, central pressure difference, maximum wind speed, and gust factor, to feed in to a hurricane model that generates the failed transmission line information as initial disturbance. The initial disturbance, i.e. a set of failed transmission lines, are used in developed Cascading Outage Analyzer, to produce the potential system conditions under such forecasted scenario, and the subsequent hardening suggestions. Challenges and future research opportunities are also presented in this part.

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