QUANTIFYING POWER SYSTEM RESILIENCE IMPROVEMENT THROUGH NETWORK RECONFIGURATION IN CASES OF EXTREME EMERGENCIES

by

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A thesis submitted to the Graduate Council of
Texas State University in partial fulfillment
of the requirements for the degree of
Master of Science
with a Major in Engineering
August 2017

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DEDICATION

This M.Sc. thesis is delightfully dedicated to my loving parents (Fariba and Jalil), my dear sister (Paria), and my twin brother (Payman), for keeping my sprit up and without whom my achievements so far could never be accomplished. They are the ones who giving me life and always nursing me with affections and love. Their encouragement, support, and continued love have energized me throughout my life and specifically during the past couple of years abroad. God bless all of you.

ACKNOWLEDGEMENTS

I would like to express my very profound gratitude to my committee chair and thesis advisor, Prof. Semih Aslan, for his considerations, guidance, wisdom, patience, encouragements, and for advising me on each step of the journey that without all his supports this research would never have been successfully accomplished. Special thanks also to my committee members, Prof. Bahram Asiabanpour and Prof. Harold Stern for their time, attention, guidance, and exquisite support throughout the course of this master research.

I would also like to acknowledge all of my wonderful friends and colleagues and the department faculty and staff for making my time at the Ingram School of Engineering at Texas State University a wonderful experience in a healthy and friendly environment.

On top of all, I am truly indebted to my loving parents for their unfailing supports and encouragements both on and off water, without which, successful accomplishment of this advanced degree would not have been possible.

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LIST OF ABBREVIATIONS

A. Sets

$d \in D$ System demands (loads).

$g \in G$ System generators.

$t \in T$ Time step.

$k \in K$ System transmission lines.

$n \in N$ System buses.

$i \in I$ Iteration number for recovery process.

$\varepsilon \in \mathrm{E}$ Disruptive incident.

B. Variables

$P_{g_n}^t$ Active power output of generator *g* connected to the bus *n* at time *t* [MW].

$P_{k_{n,m}}^t$ Power flow through line *k* between bus *n* and bus *m* [MW] at time *t*.

β_k Switch action for line *k* (0: switch, 1: no switch).

$\theta_{n,m}$ Bus angle difference between bus *n* and bus *m*.

C. Parameters

$B_{k_{n,m}}$ Susceptance of link *k* between bus *n* and bus *m*.

C_{d_n} Value of lost load *d* at each load point *n*.

d_n Demand (in MW) at bus *n*.

M_k M-Value for transmission line k.

t_d Time at the end of a disruptive incident.

$P_{d_n,i}^{t|\varepsilon}$ Active power demand at bus n after the recovery action iteration i in response to the disruptive event ε at time t [MW].

P_d^T Total target active power demand in the system normal operating state [MW].

$P_{g_n}^{\max}$ Maximum generation limit for generator g at bus n [MW].

$P_{g_n}^{\min}$ Minimum generation limit for generator g at bus n [MW].

$P_{d_n lost}^{t|\varepsilon}$ Amount of lost demand at bus n at time t after disruptive incident ε [MW].

$P_{d_n}^{t_d|\varepsilon}$ Active power demand at bus n at the end of the disruption time [MW].

$P_k^{\max}$ Maximum power flow of line k [MW].

$P_k^{\min}$ Minimum power flow of line k [MW].

$\theta_n^{\max}$ Maximum bus angle difference at bus n.

$\theta_n^{\min}$ Minimum bus angle difference at bus n.

D. Power System Operational Resilience Indices

$R_{i,n,d,t}^{\lambda}$ The flexibility of demand d at load point n when adopting the network reconfiguration plan i at time t.

$R_{i,n,d,t}^{\vartheta}$ Recovery capacity of demand d at load point n when adopting the network reconfiguration plan i at time t.

$R^{\mu}_{i,n,d,t}$ Outage cost recovery of demand d at load point n when adopting the network reconfiguration plan i at time t.

$R^{\gamma}_{i,n,t}$ algebraic connectivity of the grid which depends on the load point n when adopting the network reconfiguration plan i at time t.

E. Power System Structural Resilience Indices

$R^{\tau}_{i,n,t}$ Sensitivity feature of grid resilience which depends on the load point n when adopting the network reconfiguration plan i at time t.

$\Omega^{\gamma}_{i,n,t}$ Resistance feature of grid resilience which depends on the load point n when adopting the network reconfiguration plan i at time t.

$C^{\gamma}_{i,n,t}$ Effective grid conductance which depends on the load point n when adopting the network reconfiguration plan i at time t.

ABSTRACT

Electricity grid complexity, together with diversity of critical infrastructures (CIs) such as generating units, transportation network, etc. are increasingly driving a complicated network that is vulnerable to unpredictable hazards. Disruptive events, whether they are natural catastrophes like floods, hurricanes, thunderstorms, or malicious cyber-physical attacks or even human-caused faults may have significant impacts on such real-time complex power networks composed of numerous interconnected structural and functional components. Because in the electric power grid, the electricity generated by large-scale power plants is transferred to a variety of commercial, industrial and residential customers via distribution and transmission networks, it can be disrupted over a vast geographical area when an unpredictable disaster occurs. From the 1980’s to 2014, both the frequency and intensity of weather-caused grid outages have been trending higher. For instance, due to a hurricane in 2008, more than 2.8 million residential/industrial customers in the Greater Houston area were affected by power outages, which lasted from a few days to several weeks, resulting in losses estimated at $24.9 billion to the U.S. government. With such drastic changes of weather conditions, the risk associated with transmission line insulation breakdowns may increase and power transformers (and other components) may be stressed and overloaded. Such faults may impose a risk to electric safety due to high fault currents, exposed faulted conductors, or other unsafe conditions. Therefore, having a proper and predictive resilience-based

strategy and corrective plans for dealing with the aftermath of such fatal phenomena is of great concern for electric utilities nationwide.

The task of improving resiliency of the electricity grid in the face of emergencies is challenging. While the term "*resilience*" is increasingly used in research articles, government documents, and the media, specific research focuses are still needed on quantifying the concept of resilience and making it usable in practice. Planning for enhanced system resilience has not been well explored, especially in the context of power transmission systems, and thus attention needs to focus on allocation of tangible resources, tradeoffs among various dimensions of system resilience, the relationship between community resilience and that of the built environment, and data-driven standards ensuring resilience.

There is a national push to model the electric grid in a smarter way as well as to introduce advanced technologies and control mechanisms into grid operations. One aspect of the smart grid aims at making better use of the current infrastructure. System operators may have the opportunity to harness the flexibility of the transmission system topology by temporarily removing transmission lines out of the system under authorized power system topology control, often called transmission line switching (TLS). By changing the way that electricity flows through the system, TLS can be employed either in emergency scenarios -to alleviate voltage violations, congestions and overloading conditions, and even load shed recovery-, or during normal operating conditions for higher economic benefits or loss improvements.

This research proposes a resilience-based smart grid application of harnessing the full control of transmission assets in the case of emergency scenarios, and the associated practical considerations aiming at improving preparedness and mitigation of the electric safety risks. Using resilience options concluded in this study, plans could be developed ahead of disruption time to provide operators with the opportunity to make the right decision at the time of disturbances.

1. INTRODUCTION

1.1 Problem Description

Electricity fuels our existence. Living without electricity in today's technological world is difficult to imagine. The electric grid is considered as the backbone of modern societies and is one of the most challenging and large-scale human-built systems to date. The power grid is a complex, interconnected network of generation, transmission, distribution, control, and communication technologies decentralized through a vast range of geographical regions and, hence, is widely exposed to external threats. The electricity grid can be impacted by natural events including severe storms, hurricanes, earthquakes, etc. and/or by malicious events such as cyber or physical attacks, among others [1], [2]. Safeguarding the nation's electric power grid and ensuring a reliable and affordable supply of energy are among the top priorities for the electric power industry. The electric sector's approach to protection of the grid critical infrastructure is known as "defense-in-depth," which includes preparation, prevention, response, and recovery for a wide variety of credible hazards to electric grid operations [3], [4]. The industry commonly recognizes that it cannot protect all assets from all threats. Its priorities are, instead, focused on protecting the most critical grid components against the credible contingencies: to build in system survivability and to develop contingency plans for response and recovery when either human-made or natural phenomena adversely affect the grid operations [5].

While well-known traditional reliability principles have been widely adopted in practice to have the grid operate securely and reliably under normal conditions and safely withstand credible contingencies (N-1 criterion), the concept of "resilience" to High

Impact Low Probability (HILP) incidents has remained less clarified and unfocused. HILP incidents include weather-driven natural disasters, as well as cyber security attacks with significant consequences. An example of an HILP event occurred on August 14, 2003, when large portions of the United States and Canada experienced an electrical power blackout, resulting in loss of electric power for several days. The outage affected a large area with an estimated 50 million people who experienced the loss of electricity. Estimates of the total costs in the US ranged between 4 and 10 billion dollars [6]. Another possible threat to the power grid is cyber-physical attacks and the potential disastrous impacts on synchrophasors [7]-[10]. One most likely target for terrorists is the large-capacity centralized sources of power generation, as a loss of a mother generator would heavily cut the electrical capacity. Any disruption on major substations with high-voltage transformers can also bring about the potentials for major electricity outages.

In such emergency scenarios, portions of the electric power system can be adversely affected with a compromised electrical safety, exposing the network to risk under an unstable condition with some equipment out of service. As a consequence of such HILP events, strategic centers whose functionality heavily depend on the continued supply of electricity (e.g. health centers, military stations, nursing homes, manufacturers, etc.) are subject to disruptions that contribute to significant economic loss and, even worse, loss of life for many people in need of special health care and nursing facilities at homes or hospitals. The question is how we can revive the system performance following by a disruptive event to its desirable and normal working condition and thus, improve the resiliency of the system in the face of potentially harmful grid disruptions.

1.2 Current Research Gaps and Proposal Importance

Many studies have been conducted on evaluating the reliability of bulk electric power systems and equipment; several metrics have been defined to measure the system and equipment reliability and maintainability over time [11]-[29]. However, the concept of reliability traditionally focuses on how to respond to several “known” and “credible” contingencies (outages) in the system. Reliability is mostly related to planning and maintaining electric operations under "N-1" scenarios, for instance, where "nodes" or "components" "fail" more or less one at a time (i.e., cascading), hopefully stopping cascading at one or two failures [30]-[33]. Thus reliability is largely about prevention, and less so about recovery. It is becoming more and more obvious that more attention is needed beyond the classical reliability-based view to have the lights on all the time. This need is evidenced by several catastrophic weather-caused grid outages, such as thunderstorms, hurricanes, heavy rain, etc. [34].

A new concept that has recently attracted much research attention is to ensure the “system resiliency.” Resiliency is the concept actually referring to the act of system recovery and how fast one is able to restore a defected system back to its normal operating condition. In the case of disturbances in the electricity grid, which may actually originate from extreme weather conditions, malicious cyber-attacks, or even human-caused faults, some parts of the system are out of service or some equipment might fail as a result. Within the context of the electric domain, and as the name implies, the word “resiliency” encompasses what actions need to be done to bring the electricity back as fast as possible and to have the load outages minimized [35], [36].

Resiliency may be thought of as planning and maintaining electric service under circumstances where multiple "nodes" or "components" "fail" more or less simultaneously, such as in a storm, and where the "N-1" planning rapidly becomes ineffective or irrelevant. Resiliency is somewhat in contrast to reliability in that it is generally more about recovery and mitigation of consequences, and less about prevention [37].

Determining techniques for improving the resiliency of the electricity grid in the face of emergencies that take the electricity out of service for a while and push the whole system to instability is challenging. Previous studies on this concept are mostly focused on the fact that a power system or a part of the network is out of electricity, some equipment (transmission lines, transformers, or customers) are out of service for a while, and the authors are trying to improve the system resiliency by prioritizing the affected equipment in terms of their importance for system resiliency to minimize the cost and maximize the system performance. Thus, the restoration plans would be triggered starting from the equipment with the highest priority for system resilience down to the rest. This will lead the system to be restored back to its reliable and normal condition, through prioritized maintenance of the failed equipment, with minimum outage cost.

1.3 Thesis Focuses

The proposed approach in this thesis is different in methodology and perspective from the past research. Instead of positioning the operator in a reactive mode in response to outages, the suggested decision making tool would help ahead of time to devise restorative plans if a given contingency (outage) is expected to happen. In this context, weather forecasts and environmental patterns would help the operators to know in advance what is probably going to happen in electric power systems. The work in this thesis is focused on improving the power system resiliency in case of emergencies through a known concept, called “topology control” through transmission line switching (TLS) actions. The suggested approach is to use the existent infrastructure, with minimum additional costs, to measure the resilience of the system by corrective TLS actions. By changing the topology of the system, the electricity flows change and there will be room for new operating states in the system that can recover the load outages very quickly. Imagine a system is working in its normal operating state and suddenly an unwanted disruption occurs that results in some equipment out of service. Contrary to what have been done in previous studies, such as to make a priority list of failed equipment based on system resiliency and plan accordingly, the idea is to take out some additional elements in the system (here transmission lines), changing the system topology, trying to recover the outages, and measuring the system resiliency by rerouting the flow in the system. Finally, a resilience-benefit analysis would be pursued to find the optimal TLS solution. The operator can then decide which options are the best at the moment to gain the highest resilience and impede the extra cost of lost equipment. This methodology is applicable when the extreme weather forecast or any other disruptions are expected.

2. LITERATURE SURVEY

2.1 Hazards in Electric Power System Delivery and Associated Consequences

2.1.1 Vulnerabilities in the Electric Power System

The power system is composed of extraordinarily interconnected components such as transmission and distribution lines, generators, transformers, and control centers that are decentralized through a vast number of regions. It is considered as the backbone of modern societies and one of the most challenging physical networks due to its complex interconnections which make it more vulnerable to possible hazards [1]. Disruptive events, whether they are natural catastrophes, e.g., floods, hurricanes, thunderstorms, etc., or malicious cyber-attacks or even human-caused faults, may have significant impacts on real-time complex power networks composed of numerous interconnected structural and functional components. Those emergencies may place the power system in danger, disable utilities (generation, transmission and distribution), and endanger lives. In the U.S, the infrastructure is extremely dependent on the existence of electricity, and any kinds of vulnerabilities in the electric power network results in much more impact beyond just keeping the lights turned on, affecting all other aspects of the life e.g. economic system, health centers, military stations, fueling infrastructure, data centers, and so on [38].

Figure 1 illustrates the typical power system topology and its vulnerability to

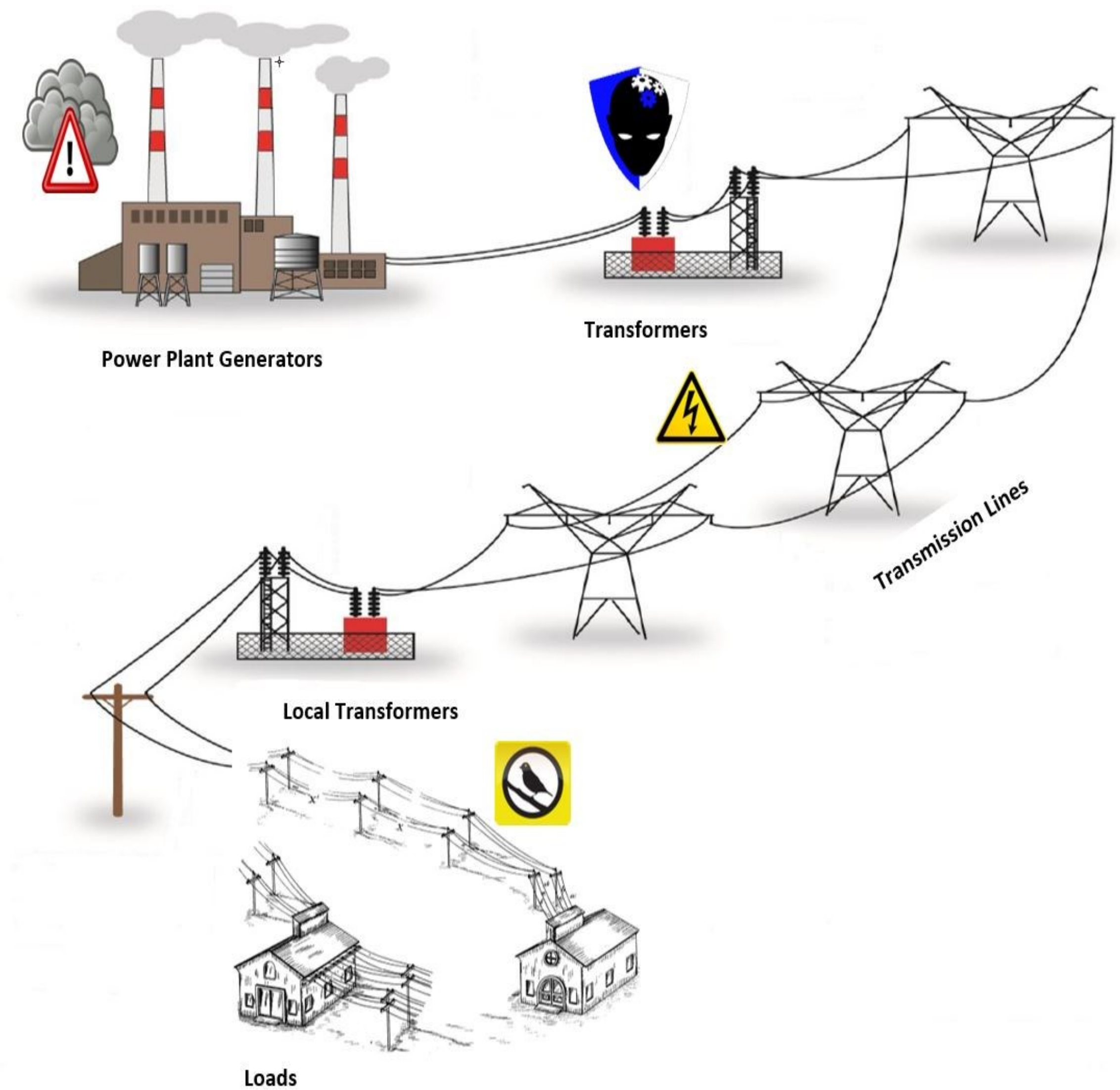


Figure 1. Power system topology and its associated vulnerabilities.

possible hazards. Today the power grid utilizes bulky central generation units which are located far from the customers. Using the transmission lines, the electricity is carried long distances. To maintain the voltage adjustment, the transformers are located near the power plants to increase the voltage level. Then, the voltage is reduced by the substation transformers near the end users and the power is carried into the distribution lines for delivery to end users. The main constraint is that unlike other forms of energy delivery systems such as natural gas pipelines, electric power cannot simply be sent via specific transmission or distribution lines wherever the dispatchers want. In a power grid, the electric current flows based on a set of security laws and it needs to be continuously adjusted to maintain all components synchronized [39]. Since the power system is a complex network with many interconnected components, when electrical imbalances occur in the system, the corrections must be done immediately to prevent the possible cascading failures from producing a domino effect through the whole network.

The power system is inherently vulnerable since it covers a vast range of area; transmission lines may span hundreds of miles and most critical facilities are unguarded. Moreover, many critical facilities and equipment are decades old and lack up-to-date technologies that could help mitigate outages. This puts the overall system in stress and increasingly vulnerable to the multiple failures that might follow, e.g. an organized attack on the power grid by terrorists that could adversely affect the interconnected facilities. If such large-scale extended power outages were to occur during times of severe weather conditions, they could also lead to hundreds of deaths due to heat stress or extended exposure to extreme cold. Following are discussed some of the vulnerabilities that a power system might face [38].

- *Physical Vulnerability*

Due to the vast geographical area the power system covers, disruption in the electric power supply can result from any problem in any part of the bulk power grid, including any failures in the transmission lines due to the collapsing of a small number of towers. Another vulnerable piece of equipment is large high-voltage transformer which can be targeted both from within and from outside the substations where they are located.

Usually, these transformers are custom-built, very large, and difficult to move if they need to be repaired following by a disruption.

- *Cyber Vulnerability*

The power system heavily relies on high-speed communication and centralized automated control centers. One of the most critical pieces of equipment used in the power system is the Supervisory Control and Data Acquisition (SCADA) [40]-[44] and Phasor Measurement Units (PMU) [7]-[10] that gather the real time data from the bus stations and send that data to the control centers for further security analysis or monitoring of system stability. These SCADA and PMU systems are very vulnerable to cyber-attacks. Attention must be concentrated in this domain to make sure that the system is secured because if they are targeted they can easily be manipulated and transmit wrong data to the control centers and thus the operators might implement wrong actions based upon data they are trusting. These actions might lead to cascading failures if the operator did not notice that the system is being attacked.

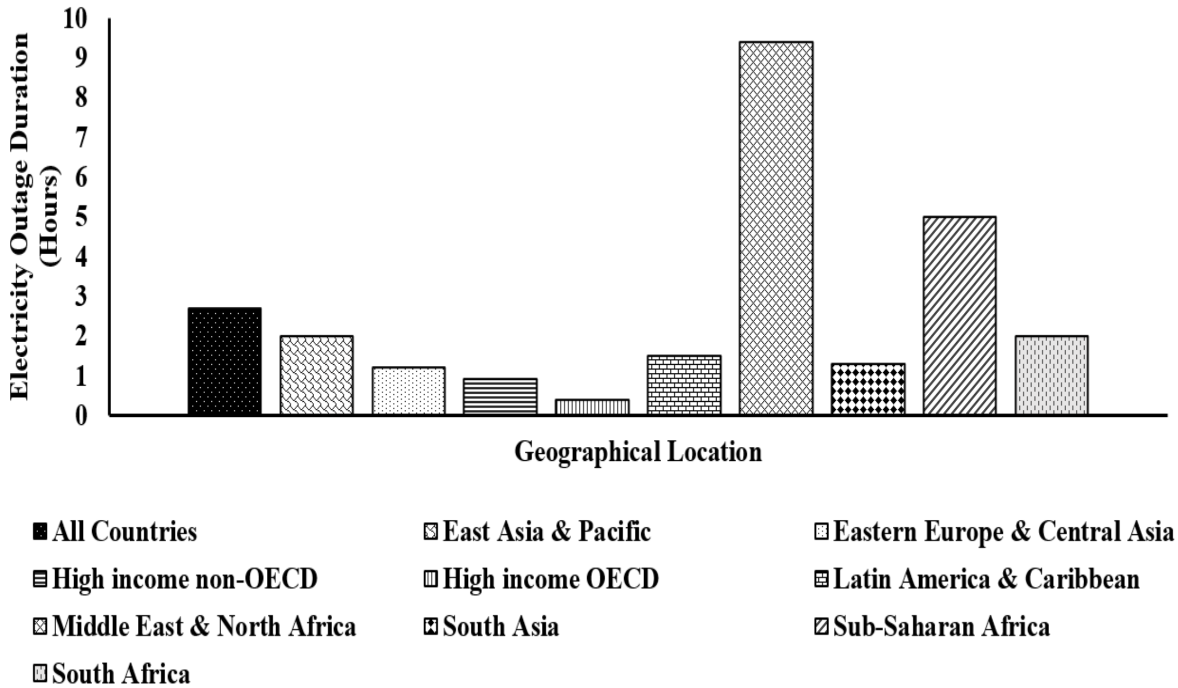
- *Human Vulnerability*

Workforce issues are significantly important to have a reliable supply of electricity, particularly if a terrorist action has occurred. Power system managers, operators, and line-crew are among the technical employees that must be carefully trained and be aware of their surrounding and responsibilities. Another problem is that it is hard to recruit enough new qualified workforce as many skilled engineers and technicians are close to being retired soon.

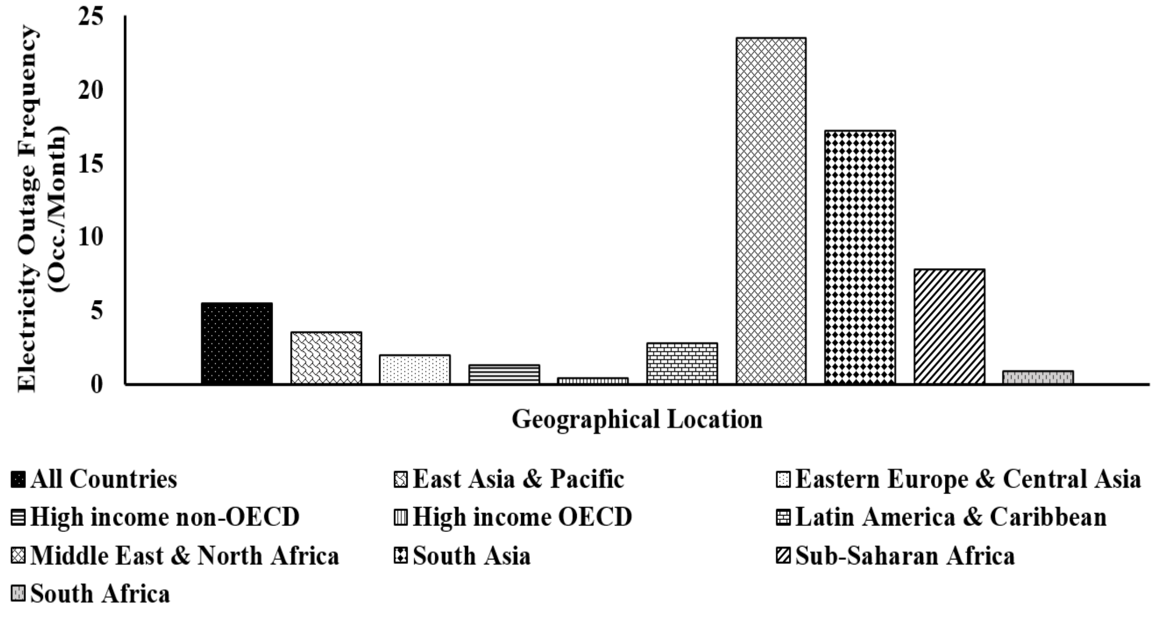
2.1.2 Electricity Outage Loss and Associated Consequences

As discussed in the previous section, power systems are very vulnerable to predicted and unforeseen hazards. Among those hazards, weather-driven hazards are the most common events that the power system might face. Following are some of the recently reported electricity outages and their consequences:

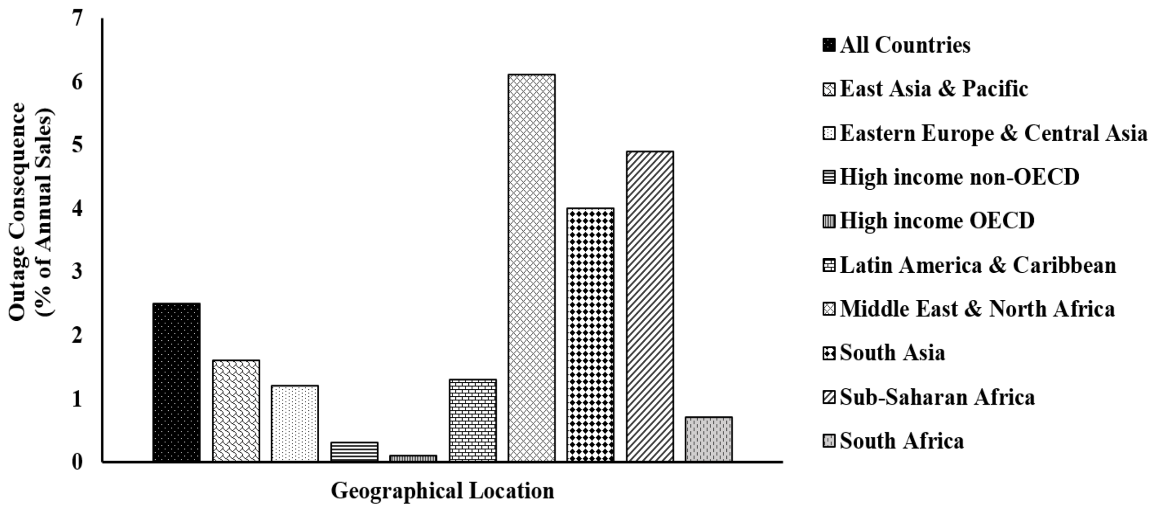
On August 14, 2003, large portions of the United States and Canada experienced an electrical power blackout, resulting in loss of electric power for days. Triggered by an environmental phenomenon -falling down trees on the power lines-, the outage affected a large area with an estimated 50 million people experiencing the loss of electricity. Estimates of the total costs in the United States ranged between 4 and 10 billion dollars [6] . In another case, in 2008, more than 2.8 million residential/industrial customers in the Greater Houston area were affected by power outages due to a hurricane, lasting to electricity outages of a few days to several weeks. This outage resulted in a huge financial loss estimated at $24.9 billion to the U.S. government [45]. During 2011 in the U.S., severe weather events resulted in huge economic losses approximating $55 billion. Fourteen of these events, each resulted in more than $1 billion in damages [38]. Figure 2 illustrates the statistics of the severe weather–driven HILP phenomena in 2014 and its global consequences regarding the extent, frequency, and duration of power outage [46].



(a) Electricity outage duration



(b) Electricity outage frequency



(c) Electricity outage consequence

Figure 2. Power outage statistics of HILP events in 2014.

Table 1 presents the statistics of the electricity outages regarding the number of the people affected, the outage frequency, and the outage duration only in the U.S. in 2015 [47].

Table 1. U.S. Electric Power Outages in 2015

Total Number of People Affected by Power Outages	Duration Outage (Minutes)	Number of Outages	Average Outage Duration (Minutes)	Average People Affected per Outage
13,263,473	175,821	3571	49	3714

2.2 Power System Resilience

Power systems are traditionally reliable during normal conditions and predictable incidents, but may not be adequately resilient to high-impact low-probability (HILP) events, such as severe weather phenomena and natural hazards. The term “resilience” is increasingly used in research journals, government documents, and the media, but work still remains on making resilience assessment usable. Methods for resilience planning are still a relatively unexplored area, including tangible resource allocation models, tradeoffs among the dimensions of resilience, the relationship between community resilience and the resilience of the built environment, and data-driven standards ensuring resilience.

Resiliency is an ability for a grid (either macro grid or micro grid) to restore itself, with little or no human intervention, to normal, reliable operations from any disturbances, outages, or blackouts. Resiliency should be enabled by advanced smart hardware and software technologies as well as streamlined processes [37]. One significant step in evolving the desired safety culture is to expand the operator’s awareness of electrical hazards across the system and focus on the recognition of when the system is, or may be, exposed to potential electrical hazard. Moreover, the operator’s awareness of weather-driven hazards to make a right decision effectively in response to the predicted ones is indispensable.

Most of these approaches to resilience interpretation and definition include aspects of a system withstanding disturbances, adapting to the disruption, and recovering from the state of reduced performance. Some of the recent efforts in resilience concepts are addressed as following:

In [48] a hierarchical outage management strategy is proposed to improve the resilience of a distribution system comprised of multi-microgrids against unforeseen emergencies. In this regard, having identified the essential elements and requirements for a resilient outage management scheme, a comprehensive framework is implemented and the roles and tasks of various management entities in a multi-microgrids power system are presented. In this case, by using a predictive control-based module the availability of all the resources will be properly scheduled in the first stage. In the second stage, the operator manages the possible power flow transfers among the microgrids and exploits the available capacities of microgrids' resources for feeding the unserved loads in stage I. The target optimization equation is formulated as a mixed integer linear programming (MILP) problem and finally an index is introduced to quantify the performance of the proposed method.

To increase the resilience of the power distribution system, an optimal hardening strategy is defined to protect against extreme weather conditions in [49]. This paper has used different grid hardening strategies, such as poles upgrading and vegetation management. A tri-level optimization algorithm is used to minimize both grid hardening cost and load shedding in extreme weather-driven events. In this regard, the first level is to find vulnerable distribution lines and select the corresponding hardening strategies, the second level is to identify the set of damaged distribution lines so that the loss caused by extreme weather events is maximized, and the last stage is to minimize the load shedding cost through the corrective prioritization of load and the set of out-of-service lines.

In [50], an effective decision-making algorithm is devised to minimize the cost of generation, customer load interruptions and restoration operation with the goal of proactive restoration plan improvement. In this paper, the authors presented a resource management model for repair and restoration of potential outages to the power system infrastructure. The goal is to minimize potential damages to power system infrastructure in a cost-effective manner. Finally, the results are verified through the standard IEEE

118-bus system.

Reference [51] focuses on the impact of severe weather to the resilience of power systems. To quantify the effect of the stochastic nature of weather parameters, a sequential Monte-Carlo-based time-series simulation model is introduced and the resilience of critical power system infrastructure is evaluated and tested using the IEEE 6-bus test system.

A supporting theory for enhancing resiliency of the critical electric power infrastructure in response to the likelihood of natural disasters is investigated in [52]. Three models are used to expedite the restoration process with the goal of minimizing the associated economic and physical disruptions. First, the outage model is conducted to illustrate the impact of weather-driven hazards such as a hurricane on power system components. Second, a resource allocation analysis is done and finally a deterministic post-hurricane recovery model is considered for managing the resources.

Reference [53] has described an approach for assessing the real-time operational resilience of power systems taking into account the impact of both weather and loading conditions, with focus on the impact of these system conditions on the failure probability of transmission lines. Operational resilience assessment refers here to the evaluation of power systems resilience by considering the effect of the real-time operating conditions that the system experiences.

A multi-systems joint restoration model to support interdependent systems' resilience assessment has been addressed in [54]. This paper provides a framework to assess interdependent systems' resilience and suggests optimum joint restoration sequences of interdependent systems, which is claimed as an effective strategy for rapid restoration and infrastructure resilience enhancement.

In [55], a new definition of system resilience and a resilience optimization framework are presented, then two network components importance measures are suggested, namely, the optimal repair time and the resilience reduction worth, beneficial for prioritizing restoration activities. The two measures quantify: 1) the failed components that should be repaired into the system are prioritized, and 2) the potential loss due to likelihood time delay in repairing of failed elements in the optimal system resilience is considered. This paper exploited a Monte Carlo-based method due to the stochastic nature of disruptive incidents and a probabilistic ranking approach using the Copeland's pairwise aggregation model to rank components' importance. This study is implemented using the IEEE 30-bus test system.

Fragility modelling, impact assessment and adaptation measures for power system resilience to extreme weather conditions are studied in [56]. Assessment of the resilience of transmission networks to extreme wind events is explored in [57], in which a sequential Monte Carlo based time-series model for evaluating the effect of weather on power system components is utilized, with focus on the wind impact on transmission lines and towers. Risk-based defensive islanding is suggested in [58] to boost the power grid resilience to extreme weather events, aiming to adaptively mitigate the cascading effects that may occur during weather emergencies. The resilience and flexibility of power systems to future demand and supply scenarios is studied in [59], where two case studies are reported for the Great Britain transmission network and the Cyprus network. The concept of demand-side resiliency through deployment of distributed energy resources (DER) including onsite generating units, batteries, and microgrids to enable electricity consumers to continue electricity use during power outages is investigated in [60]-[71]. Several time-dependent metrics for quantification of operational and infrastructure resilience in power systems are introduced in [72] where additional insights are provided to capture the degradation and recovery features of critical infrastructures in face of weather threats.

Proactive preparedness to cope with extreme weather events through resilience-oriented pre-hurricane resource allocation in power distribution systems is proposed in [73] using a new mixed-integer stochastic non-linear program. A heuristic to obtain the allocation plan by solving a MILP is also suggested and the impacts of resource transportation costs, initial distribution of electric buses, and hurricane severity on the allocation plans are discussed. The concepts, metrics, and a quantitative framework for power system resilience evaluation are suggested in [37], where a load restoration framework based on the smart distribution technologies is proposed. The concept of networked microgrids for enhanced power system resilience against extreme events is introduced in [74], through which an appropriate timely response would be possible in emergency conditions. In this study, metrics of the advanced information and communication technologies (ICTs) in microgrid-based distributed systems to support the power system resilience are proposed.

Technologies for early warning systems for timely prediction of disastrous weather outages are proposed in [74] and [76] to further enhance the system resilience by the use of effective remedial actions and preparedness in the face of severe weather-driven threats. In order to fulfill an effective emergency plan, reference [77] suggested a stochastic integer program aimed at finding the optimal schedule for inspection, damage evaluation, and repair in post-earthquake restoration of electric power systems with the objective of minimizing the consumers' outage duration. Approaches for joint damage assessment and restoration of power systems in face of natural disasters are suggested in [78] which include an online stochastic combinatorial optimization algorithm to dynamically update the restoration decisions after visiting each potentially damaged location, a two-stage method to evaluate the damage severity and then pursue the restoration plans, and a hybrid algorithm of both approaches that simultaneously considers both the damage assessment and system restoration plans. A general multi-objective linear-integer spatial optimization model for arcs and nodes restoration of disrupted networked infrastructure after a disaster is proposed in [79], in which the tradeoff between the problem objectives (e.g., system flow maximization and system cost minimization) could be optimally captured. An integrated network design and scheduling problem for restoration of the interdependent civil infrastructures was proposed in [80] through integer programming and was implemented on a realistic dataset of power infrastructure corresponding to Lower Manhattan in New York City and New Hanover County, North Carolina. Reference [81] investigated the challenges on how to schedule and allocate the routes to fleets of repair crews to recover the damaged power system in a timely manner. Extension of this work was presented in [82] through deployment of a randomized adaptive vehicle decomposition technique in order to improve the scalability of the model for large-scale disaster restoration of power networks with more than 24,000 components. A comprehensive survey of models and algorithms for emergency response logistics in electric distribution systems, including reliability planning with fault considerations and contingency planning models was presented in [83] and [84].

Many of the methods presented in this section could either mitigate the amount of loss outages or could even convert the attack that could lead to significant outages in a wide-range area into one with less damage potential. Cascading failures would be limited through isolating the affected areas from the other parts of the system. The damage intensity would be mitigated by a variety of means such as enhancing the system robustness; improving physical and cyber protections to critical parts of the system, and/or immunization of the system through splitting the system into microgrids.

2.3 Applications of Electricity Network Reconfiguration

2.3.1 Emergency Operating Scenarios

The TLS approach was employed in 1980s, as an efficient remedy to enhance system reliability and mitigate severe operating conditions such as line overloads, voltage violations, etc. [85]-[87]. While the benefits of harnessing the control of transmission lines have been acknowledged by previous research, the flexibility of the transmission grid to co-optimize the generation re-dispatch together with the network topology during steady-state operations has not been considered. Reference [88] provides an overview of the application of TLS as a corrective tool in response to a possible contingency. The problem formulation is further discussed and a comprehensive overview of the search technique to solve the problem is provided. Reference [86] proposes a method to alleviate line overloading due to any contingencies through utilizing transmission switching as a corrective framework. This method uses a heuristic technique which does not consider all TLS solutions and the effect of co-optimization of generation and the network reconfiguration. To find the best switching plan with the optimal number of the switching action iteration, a new technique was proposed in [89], which employs a sparse inverse algorithm. Reference [90] uses a binary integer programming technique to use switching actions as corrective approach to ease voltage violation and line overloads. A mixed integer linear program is proposed in [91], which determines the optimal transmission topology with the goal of minimizing the system losses, without taking into consideration co-optimizing the generation along with the transmission topology. The application of TLS with the goal of load-shed recovery in case of severe contingencies is investigated in [92] and [93]; A probabilistic robust optimization technique considering various uncertainties is utilized in [94] for corrective and in [95] for economic application of TLS, respectively. The authors claimed that all the solutions from the output of the research are feasible considering the worse uncertainty scenarios for the range of system operational states. References [96] and [97] used a real-time contingency analysis to address the scalability concerns of corrective TLS implementation on system reliability improvement in real-world large-scale networks.

The effect of TLS implementation on system transient stability requirements is addressed in [98], where application of TLS is considered as one of the last steps before the system collapses. In particular, this study proposes a dynamic corrective TLS strategy by taking into consideration the right time that TLS should be applied to ensure the system stability. The stability concerns of practical TLS implementations such as maintaining the system security margins and online stability checking are considered in [99]. The authors in [100] suggested a decomposition technique to solve the optimal transmission system reconfiguration taking into consideration the transient stability constraints. The impact of TLS applications in ensuring the N-1 reliability criterion and system stability requirements is investigated in [101]. More specifically, in this research, both the reliability and stability concerns of the robust corrective network reconfiguration formulation and solutions are explored.

2.3.2 Normal Operating Scenario

Co-optimizing the network topology with the generation dispatch creates the opportunity for the operator to simultaneously select the network topology with the proper generation unit. Being able to do the network topology optimization, the corresponding operator can not only choose any dispatch solution that is given in the original topology, but can also select further dispatch solutions that are feasible for other topologies. Needless to note that a generation dispatch solution is feasible just for one specific topology but not for a different topology since as topology changes, the power flow adjust itself in a new meshed network due to the Kirchhoff's laws. As a result, a variety of feasible dispatch solutions are generated by co-optimizing the generation with the network topology. The concept of harnessing the grid topology through TLS actions, coupled with generation dispatch optimization for the main sake of economic benefits has also been introduced and investigated in the literature [102], [103] .

The theory of dispatchable networks was first introduced in [102] where the dispatchable transmission rights were discussed to benefit the electricity market with greater economic efficiency and competition. Subsequently, optimal transmission line switching, was introduced for the main sake of gaining higher economic benefit in [104]. This research modeled a DCOPF formulation as a mixed integer programming (MIP) problem, and numerically analyzed the problem under different system loading conditions. Reference [103] made an extension on the work in [104] by conducting sensitivity analysis to see the impact of TLS implementation in normal operating condition on the nodal prices, load payments, generation revenues, and congestion rents. The realization of economic efficiency and market implications of the TLS actions along with the optimized generation dispatches are additionally studied in [105]. The N-1 reliable DCOPF-based topology control is investigated in [106], where TLS solutions are found in IEEE 118-bus and Reliability Test System (RTS) 96-test cases satisfying the N-1 standards while providing a considerable operation cost savings. Analyzing the grid controllability using TLS optimizations is investigated in [107] through multi-period N-1 reliable unit commitment equipped with TLS technology based on the duality concepts. The idea of having smart flexible transmission and flowgate bidding is discussed in [108] in which the TLS approach is applied allowing the network transmission line flows to surpass their rated capacity for a short period for a pre-specified regulatory penalty.

Because in large-scale systems iterating between DC-based topology control algorithms and AC power flow validation of TLS solutions may become intractable, AC-based topology control algorithms are proposed in [109] and implemented on a real-size power system through a Pennsylvania, Jersey, and Maryland (PJM) historical data case study. The impact of power system topology control assessment on system reliability performance is investigated in [110] to help the operator select the best economically TLS solutions under both DC and AC settings. Furthermore, the application of TLS in power systems under the normal scenario with the goal of getting economical TLS solution is analyzed in [111]. This study used a probabilistic method to evaluate the system migration to the system alert and emergency operating state following the TLS actions and assessed the reliability concerns of TLS decision making.

There are additional literature that have addressed other concerns regarding the TLS implementation: real-world TLS practical concerns and impact of frequent TLS implementation on circuit breaker reliability are investigated in [112]-[113]. Scalability issues of TLS implementation and the economic TLS solutions of the power systems are tested in [109], [114], and [115] for PJM transmission system, [116] for European electricity grid, [117] for ISO-New England, and [96] for Tennessee Valley Authority (TVA) and Electric Reliability Council Of Texas (ERCOT) networks. In [118], a decomposition optimization method, namely Alternating Direction Method of Multipliers (ADMM), is proposed to solve the scalability concerns of the TLS formulations for real-world large-scale power networks and some TLS solutions with lower computational cost are suggested.

Finally yet importantly, much literature has addressed the computational complexity of the TLS optimization problems aiming to find new algorithms to advance optimization technique and reduce the computational costs. In [119], a biddable dynamic TLS implementation integrated with the Optimal Power Flow (OPF) problem based on heuristic control approaches is introduced, through which it is claimed that the computational burden is improved up to four times better than the similar approaches in previous researches. Reference [120] suggested two heuristics relaying on the transmission line ranking parameters for the computational complexity enhancement of the TLS optimization problems. The first one solves a sequence of Linear Programming (LPs) equations removing one transmission line at a time and the other solves a sequence of Mixed integer programming (MIPs) formulations removing one transmission line at a time but with fewer binary variables. Tractable transmission control strategies that contain the sensitivity information from the economic dispatch optimizations to select the optimal number of transmission lines sequences are proposed in [121]. The application of LPs approximation to the current Alternative Current Optimal Power Flow (ACOPF)-based TLS formulations is explored in [122], where the TLS results shown much faster than the conventional nonlinear ACOPF-based formulations and yet with adequate accuracy.

3. POWER SYSTEM RESILIENCE

3.1 On the Concept of Resilience

Resilience is defined as the flexible ability of the system to reliably restore itself, with minimum human intervention, to its normal operating state following by any disturbances, outages, or blackouts [123], [124]. The concept of “resilience” mainly considers the unforeseen extreme failures of HILP nature, which cause huge damages and loss to the system, while the concept of “reliability” takes into account credible and most probable contingencies. Within the scope of engineering system resilience, it is always crucial to think about the challenges associated with both restoration and repair process in response to an electricity outage. For an outage of limited scale and consequence, the restoration process can be rapidly conducted, which will then allow sufficient time for the repair to bring the system back to its full operability. On the other hand, in widespread HILP outages, restoration itself may be a significant barrier. Metrics for the definition of power system resilience have not been efficiently explored yet. The most recently used terminologies for resilience are risk, hazard, vulnerability, and robustness [125], [126] which are discussed in Chapter 2.

Figure 3 illustrates the notion of resilience in case of disturbances and corresponding indicators. The functional definition of resilience can be represented using categorized districts of this curve as follows [127].

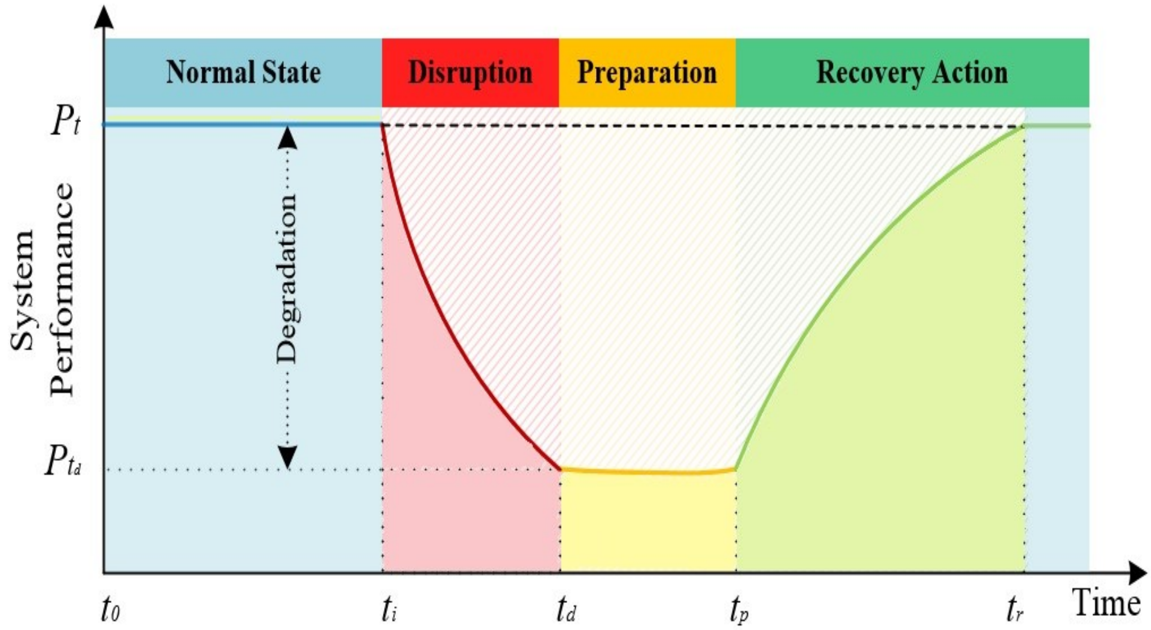


Figure 3. System interaction states in the face of a critical HILP disruption.

I. Phase 1: Normal State

During the normal operating state ($t_0 < t < t_i$), the system fully functions as expected. The main concern in dealing with a power system in this interval is continuous assurance of the grid stability and reliability. Having a sufficient estimation of the possible threats and predictive actions accurately planned could enhance the pre-disturbance resilience of the grid in case a contingency happens.

II. Phase 2: Disruption State

At the incident time t_i, an extreme HILP event strikes the system, affecting the grid with one (or several) component(s) out of the service resulting in degradation of the system performance ($t_i < t < t_d$). The level of performance reduction depends on the outage severity and system architectural design where the concepts of robustness and asset utilization matter. Robust grids regarding connectivity and resourcefulness, supported by smart grid technologies, can benefit from the operational flexibility required for limiting the resilience degradation when the disturbance is in progress during $t_i < t < t_d$.

III. Phase 3: Preparation State:

The system operators conduct a fast damage assessment in this state ($t_d < t < t_p$) to initiate the crew management plans, corrective actions (such as generation re-dispatch, repair and corrective maintenance, defensive islanding, etc.).

IV. Phase 4: Recovery/ Repair State:

It is considered as the process of restoring the system performance back to its normal and stable state ($t_p < t < t_r$). How fast the system resilience can be improved to its maximum level mainly depends on the network connectivity and flexibility, disturbance severity, recovery plans taken, and the operators' training. When the system restores from the disruptive event in the post-disturbance state ($t > t_r$), the impacts of the disruption on the system performance and resilience need to be assessed and fully analyzed. Such studies allow design and development of adaptive plans that can be taken to enhance the resilience of the critical infrastructure during similar unforeseen events that may happen in future.

3.2 Task Management for Power System Resilience Improvement

Under the resilience premises, Figure 4 demonstrates the critical task management chart for system resilience in the face of a disruptive event. Following steps should be considered to ensure the safety and resilience of the grid against disruptions.

- ***Identifying the Goals and Metrics*:**

To maximize the grid resilience and minimize the load outages following a contingency, the first step is to define the metrics for quantifying the system resilience.

- ***Characterizing the Threats:***

  One significant step in evolving the system to a desired safety and resilience culture is to expand the operators' awareness of electrical hazards across the system (arisen from natural disasters, cyber-attacks, human faults, etc.) and focus on how to make a right decision in a timely manner in response to the predicted vulnerabilities and outages.

- ***Grid Vulnerability and Risk Assessment:***

  A quantification method based on risk analysis should be attempted to understand the grid operational and infrastructure vulnerability in the face of the hazardous threats with the imposed consequence metrics assessed.

- ***Operational Recovery Decision Making:***

  Depending on the type and severity of the hazards and the risk metrics quantified, an optimal recovery model should be selected and implemented. A recovery model can include the corrective maintenance actions, replacement of damaged equipment, or operational decisions that use the inherent built-in flexibility of the grid.

As demonstrated in Figure 4, the resilience of the electricity grid to disruptive events can be enhanced through strategic actions in two chronological paradigms as follows [127]:

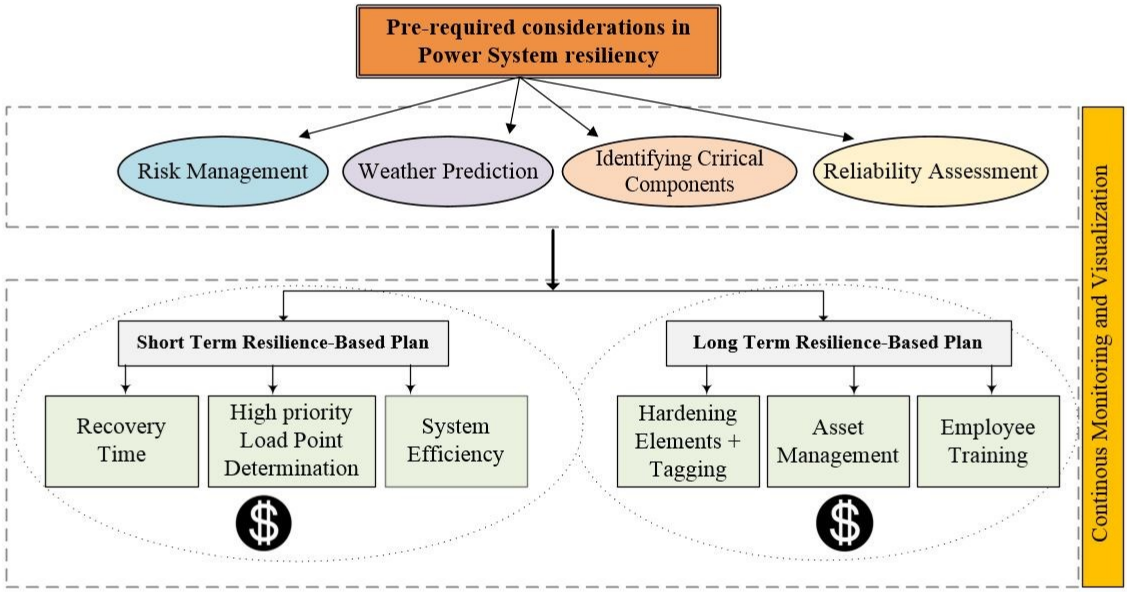


Figure 4. Short-term and long-term plan management for enhanced resilience of power systems in the face of probable disruptions.

- ***Long-Term Hardening:***

Due to the continuous exposure of the power grid to the external environment and hazardous conditions, it is crucial to plan for strengthening the network resilience over time and making design adjustments if needed. In so doing, the following strategies are reported in literature: power grid infrastructure upgrade [128]-[130]; tagging the components [131], [132]; vegetation management [133]; asset management [134], [135]; monitoring technologies [136]-[138], and crew training and education [139], [140] (see Figure 4.)

- ***Short-Term Recovery:***

Short term recovery includes the temporary remedial solutions in response to a given contingency or threat in power systems. Outage statistics in 2015 reveal that only 33.1% of firms worldwide owned or could share backup generators in case of emergencies [46]. A short-term recovery and restoration plan should be pre-planned to reduce the outage duration through a faster restoration process. An efficient recovery plan should have the capability to bring the system back to its maximum performance by rapidly feeding the critical load points in a prioritized manner.

Several metrics to quantify the grid resilience as well as a short-term mitigation algorithm for fast recovery of the load outages and enhanced resilience to extreme HILP conditions are suggested in Chapter 4.

4. PROPOSED METHODOLOGY

4.1 Proposed Metrics for Power Grid Resilience

This study considers several features of grid resilience grouped under two main concepts: (1) grid connectivity and robustness; (2) grid operational functionality. This thesis also proposes quantitative indices to measure the resilience performance of the grid in the face of disruptions. Such quantitative measures can also help in better comparing different recovery options and possible restoration plans (depending on how they affect the overall system safety and resilience), and hence, enhance the operator decision making.

4.1.1 Metrics of Graph Spectral Robustness

The power grid can be realized as a complex graph where the bus stations are considered as graph nodes and the transmission lines denote the connective lines between each graph node. Hence, to assure the grid robustness we are using the following metrics to evaluate the system resilience in the outcome of the case study, which will be discussed in Chapter 5.

- ***Algebraic Connectivity Metric***

The topology of a graph G can be represented by the Laplacian matrix. Suppose $[\gamma_1, \gamma_2, ..., \gamma_n]$ represents a non-decreasing vector of the eigenvalues of the Laplacian matrix. The algebraic connectivity is defined as the second smallest eigenvalue of the Laplacian matrix [141]. The grid robustness degree (in %) is presented in Equation 1.

$$R^{\gamma} = \left(\frac{\gamma_2^{S}}{\gamma_2^{S-1}}\right) \times 100 \tag{1}$$

where s denotes the system states. The index reflects the algebraic connectivity of the grid after any changes of network topology compared to the previous state of the grid. In other words, algebraic connectivity indicates the lower bound for grid link or node connections, where the higher the R^{γ}, the better the graph connectivity will be.

- ***Grid Sensitivity Metric***

It is a graph-oriented metric that quantifies the grid robustness against any topological changes and is calculated as follows:

$$\begin{cases} R^{\tau} = \left(\dfrac{2}{N-1}\right) \times Trace\left(L^{+}\right); \\ Trace(\mathrm{L}^{+}) = \displaystyle\sum_{i=1}^{n} l_{ii} = \sum_{i=1}^{n} \gamma_{l} \end{cases} \tag{2}$$

where N is the number of nodes in the network (here buses); L^{+} is the Moore-Penrose inverse of the Laplacian matrix of the grid graph, and Trace (L^{+}) is the sum of eigenvalues for a given grid topology. Note that a smaller value for R^{τ} reflects a higher grid robustness, as the network will be less sensitive to changes in its topology. To maximize the grid capacity, one should minimize the node/link criticality of the network. This index can be used to quantify the system reaction to any changes in the network topology [142].

- ***Grid Resistance Metric***

This metric calculates the effective resistance of the grid against any changes in the grid elements and configuration, e.g., transmission line or node removal, and is defined as follows:

$$\Omega^{\gamma} = N \times \sum_{i=1}^{N-1} \frac{1}{\gamma_i} \tag{3}$$

The following equation presents the normalized effective grid conductance, always with values within the [0, 1] interval, for better comparisons [143]:

$$C^{\gamma} = \frac{N-1}{\Omega^{\gamma}} \tag{4}$$

4.1.2 Metrics of System Operational Resilience

The main factors which the utilities are looking into are the operational metrics by which the operator can realize the impact of the corrective actions taken in the contingency analysis. The operational resilience metrics are suggested as follows [144] .

- ***Grid Flexibility Metric***

It demonstrates the level of system resourcefulness, enabling a faster recovery process. Network flexibility depends on the components' connectivity and the level of dependency to other elements. In a system with a sufficient number of generating units accessible to many load points, the re-dispatch process and corrective actions could be co-optimized as a temporary remedial solution for stabilizing the system facing a contingency. Moreover, the higher access to dispersed generating units, storage units, and fast-start units can be of great help in realizing a faster recovery process. The flexibility index is defined as the ratio of the system's level of performance following each recovery action to that of the system's normal condition. In other words, it is defined here as the amount of served demand following each recovery solution divided by the system's total demand to be met.

$$R_{i,n,d,t}^{\lambda} = \frac{\sum_{i \in I} \sum_{n \in N} P_{d_n,i}^{t|\varepsilon}}{P_d^T} \tag{5}$$

where, $P_{d_n,i}^{t|\varepsilon}$ is the active power demand at load point *n* after the recovery action *i* in response to the disruptive event ε at time *t*, and P_d^T is the target active power demand of the system in its normal and pre-disaster operating condition.

- ***Outage Recovery Value Metric:***

A resilient system should be able to minimize the electricity outage costs, i.e., the amount of total customer interruption costs that should be retrieved after each corrective action. It depends on the type of customers (residential, industrial, commercial, etc.) that are disturbed and should be recovered through the restoration plans. The proposed metric to quantify the outage cost recovery is as follows:

$$R_{i,n,d,t}^{\mu} = \sum_{i \in I} \sum_{n \in N} C_{d_n} \left(P_{d_n,i+1}^{t|\varepsilon} - P_{d_n,i}^{t|\varepsilon} \right) \tag{6}$$

where, C_{d_n} is the value of the lost load d at load point "*n*" (in \$/kWh) and $P_{d_n,i}^{t|\varepsilon}$ is the active power demand (MW) at load point *n* after implementation of the recovery plan *i* in response to a disruptive event ε at time *t*.

- ***Outage Capacity Recovery:***

In most cases in many engineering disciplines, the most significant resilience metrics involve how fast a recovery action can restore the interrupted function. The outage capacity recovery (in MW) determines the power capacity that could be restored through the recovery process within a certain time interval. In other words, the suggested index indicates the percentage of the recovered demand in each recovery step compared to the total demand lost following a disruptive event and can be quantified in (7):

$$R^{\vartheta}_{i,n,d,t} = \sum_{i \in I} \sum_{n \in N} \frac{\left(P^{t|\varepsilon}_{d_n,i} - P^{t_d|\varepsilon}_{d_n} \right)}{\left(P^{T}_{d} - P^{t_d|\varepsilon}_{d_n} \right)} \times 100 \tag{7}$$

where $P^{t_d|\varepsilon}_{d_n}$ is the active power demand (MW) at load point *n* at the end of the disruption time t_d.

4.2 Network Reconfiguration for Enhanced Resilience

Having faced an attack or disruption, the main focus for an electric utility is to restore the power to its customers. Many of the next steps are similar to those taken in response to a severe natural disaster i.e. damage identification, cleaning process, repair equipment and power outage restoration. Unlike some of the other threats, cyber-attacks may happen with no warning and destroy the key components. Some of these failed components may take days to weeks to replace. Physical protection of the components, boosting hardening strategies and improving electronic surveillance might help deter an attack. Training the operators and other workers to fully recognize and react to any possible major disruptions will be of great importance to limit the extent of outages and further cascading damages as well. Since it is impossible to completely eliminate all possible modes of failures, the utilities' managers should have a resilient plan to keep the major facilities operating in the event of power outages or at least restore the outages as soon as possible.

There are two challenging issues with most of the past works: (1) as it is hard to predict any form of hazards or contingency precisely, dispersed generation and storage units, whose allocation is planned previously, may not be readily available in the vicinity of the affected area in a timely manner; (2) prioritizing the damaged equipment in terms of importance and criticality for system resilience to repair and/or replace may be time-consuming, taking days to weeks, depending on the ability to bypass the failed substations or disrupted lines. This will lead the system to be restored back to its reliable and normal operating condition after the timely maintenance and replacement process.

It has been demonstrated in the previous literature that the topological reconfiguration of the power transmission system, in normal non-emergency scenarios, may improve the efficiency of power system operations by re-routing the electricity system-wide and enabling re-dispatch of the lower-cost generators [111]. Moreover, power system topology control through transmission line switching (TLS) actions is proved to be an effective remedy in response to emergency conditions in power systems. By changing the way electricity flows in the network, harnessing the built-in flexibility of the transmission system through TLS helps mitigate the voltage and overflow violations, transformer overloads, network loss improvement, etc. [145].

This research suggests the use of topology control for enhanced network resilience. A resilience-based Direct Current Optimal Power Flow (DCOPF)-based corrective topology control optimization is suggested in this study for timely recovery of the load outages and enhancing the system resilience in the face of HILP disruptions. The suggested topology control optimization in DC setting (where bus voltages are assumed to be 1 per unit, and the reactive power is neglected) is a mixed integer linear programming (MILP) formulation. The optimization model tries to maximize the system resilience [see objective function (8)] through optimal scheduling of system generating units as well as network topology (transmission lines connectivity). A binary variable that can take either 0 or 1 value is introduced for each transmission line in the network. The optimization output is the optimal resilience feature quantified as well as the optimal generating unit outputs and transmission line statuses. For demonstration purposes, the grid flexibility metric is utilized in this study to represent system resilience. As can be seen in (8), the optimization objective is to maximize the grid flexibility metric of resilience following a disruptive event at time *t*. The optimization problem is subject to several system and security constraints, as presented in (9)-(16).

$$\text{maximize } \sum_{n=1}^{N}\left(P_{d,n}^{t} - \mathrm{P}_{d_n,i}^{t|\varepsilon}\right) \tag{8}$$

$$P_{g_n}^{\min} \le P_{g_n}^{t} \le P_{g_n}^{\max} \quad \forall g \in G \tag{9}$$

$$P_{k}^{\min}.\beta_k \le P_{k_{n,m}}^{t} \le P_{k}^{\max}.\beta_k \quad \forall k \in K \tag{10}$$

$$\sum_{g\in\Omega_g} P_{g_n}^{t} - \sum_{m\in\Omega_B} P_{k_{n,m}}^{t} = \sum_{d\in\Omega_D}\left(P_{d_n}^{t} - \mathrm{P}_{d_n,i}^{t|\varepsilon}\right) \quad \forall n \in N \tag{11}$$

$$B_{k_{n,m}}.\left(\theta_{n,m}\right) - P_{k_{n,m}}^{t} + \left(1-\beta_k\right).M_k \ge 0 \quad \forall k \in K \tag{12}$$

$$B_{k_{n,m}}.\left(\theta_{n,m}\right) - P_{k_{n,m}}^{t} - \left(1-\beta_k\right).\mathrm{M}_k \le 0 \quad \forall k \in K \tag{13}$$

$$\theta^{\min} \le \theta_n - \theta_m \le \theta^{\max} \quad \forall k(m,n) \in K \tag{14}$$

$$\beta_k \in \left\{0,1\right\} \quad \forall k \in K \tag{15}$$

$$0 < P_{d_n lost}^{t|\varepsilon} < P_{d_n}^{T} \qquad \forall n \in N \tag{16}$$

where, *K*, *G*, and *N* are the sets of network transmission lines, generating units, and buses, respectively; $P_{g_n}^{t}$ is the active power output of generator *g* (in MW) connected to bus n at time t; $P_{g_n}^{t}$ is the power flow (in MW) through transmission line k between bus n and bus m, at time t; $P_{d_n,i}^{t|\varepsilon}$ is the amount of lost demand (in MW) at bus n due to disruptive event ε at time t which is constrained within the limits $\left[0, P_{d_n}^{t}\right]$; $B_{k_{n,m}}$ is the susceptance of transmission line k between bus n and bus m; β_k is the switch action for transmission line k between bus n and m (0: switch; 1: no switch); M_k is a user-specified large number greater than or equal to $\left|B_k\left(\theta_n^{\max} - \theta_n^{\min}\right)\right|$ which is selected to make the constraints nonbinding and relax those associated with Kirchhoff's laws when a transmission line k is removed from service; and $\theta_{n,m}$ is the bus angle difference between bus n and bus m. The output power of generating unit g at bus n is limited between its physical minimum and maximum capacities in (9). Constraint (10) limits the power flow across transmission line k connecting bus n to bus m within the minimum and maximum line capacities. Power balance at each node is enforced in (11), and Kirchhoff's laws are incorporated in (12) and (13). Voltage angle limits for each bus are set to -0.6 and 0.6 radians and are constrained in (14). The status of any transmission line k of the system is identified via an integer variable in (15). The demand loss at each bus is constrained to the maximum demand in (16). Parameter α introduced in (17) limits the number of open transmission lines in the optimal reconfigured network (i.e., 1-line, 2-line, etc. switches).

$$\sum_{k}\left(1-\beta_k\right) \leq \alpha \quad k \in K \tag{17}$$

The optimization engine is able to provide several sets of optimal solutions for any selection of α. Several topology control plans (in the form of a single or a sequence of TLS actions) can be provided for each forecasted disruptive event, considered as the recovery actions to be implemented during the restoration process. Note that the solutions are found in the system operational time frame (day-ahead) in response to critical contingencies. Each optimal TLS plan will migrate the system into a new operating condition with different levels of resilience and recovery. Depending on the resilience performance of the grid supplied with the provided solutions, the operator can select the final best reconfiguration plan for implementation, i.e., the one that improves the system resilience, safety and reliability the most.

4.3 Resilience Measurement of Power Grid with Transmission Line Switching

Having obtained the best practical solution from transmission line switching which ensures both the cost benefit and reliability of the system, we utilize those outputs in the new condition in power system topology to measure the network resiliency. By removing each line, the network topology is changed and thus, the power flow in the whole system adjusts itself with the new condition. After taking out each line, we measure the resiliency of the power system until it reaches its previous normal state performance. Figure 5 represents the system performance transition curve in the fault scenario. A quantifiable and time-dependent system performance function is the basis for the assessment of system resilience. It has a nominal value P_{t_0} under nominal operating conditions. The system operates in its normal condition at this level until suffering a disruptive event at a time t_i. The disruptive incident degrades the system performance to some level P_{t_d} at time t_d. Then, the recovery process is started right after the end of the disruption ($t_d < t < t_r$) for increasing the system efficiency until it is completely restored to its pre-disruption level.

Figure 5 illustrates the conceptual framework for computing the resilience metric. The following steps will be conducted to compute the resiliency of the system:

Suppose $R^{\lambda}_{i,n,d,t}$ is the resilience of a system at time t ($t > t_d$). $R^{\lambda}_{i,n,d,t}$ is here given the meaning of the cumulative system functionality that has been recovered at time *t*, normalized by the expected cumulative system functionality during this same time period. Graphically, $R^{\lambda}_{i,n,d,t}$ is represented by the ratio of the area with diagonal stripes S_1 to the area of the shaded part S_2. Mathematically, it is given as:

$$\max R^{\lambda}_{i,n,d,t} = \left\{ \frac{\sum_{n\in N} \mathrm{P}^{T}_{d_n} - [\sum_{n\in N}\left(\mathrm{P}^{T}_{d_n} - \mathrm{P}^{t_d|\varepsilon}_{d_n}\right) - \sum_{i\in I}\sum_{n\in N}\left(\mathrm{P}^{t|\varepsilon}_{d_n,i} - \mathrm{P}^{t_d|\varepsilon}_{d_n}\right)]}{\mathrm{P}^{T}_{d}} \right\} \cong \tag{18.a}$$

$$\min [\sum_{n\in N} \mathrm{P}^{t}_{d_n lost} - \sum_{i\in I}\sum_{n\in N}\left(\mathrm{P}^{t|\varepsilon}_{d_n,i} - \mathrm{P}^{t_d|\varepsilon}_{d_n}\right)]$$

$$\max R^{\lambda}_{i,\mathrm{d},\mathrm{n},t} \cong \min[1 - \frac{\sum_{i\in I}\sum_{n\in N}\left(\mathrm{P}^{t|\varepsilon}_{d_n,i} - \mathrm{P}^{t_d|\varepsilon}_{d_n}\right)}{\sum_{n\in N}\mathrm{P}^{t}_{d_n lost}}] = \max\left\{ \sum_{i\in I}\sum_{n\in N} \frac{\left(\mathrm{P}^{t|\varepsilon}_{d_n,i} - \mathrm{P}^{t_d|\varepsilon}_{d_n}\right)}{\left(\mathrm{P}^{T}_{d_n} - \mathrm{P}^{t_d|\varepsilon}_{d_n}\right)} \right\} \tag{18.b}$$

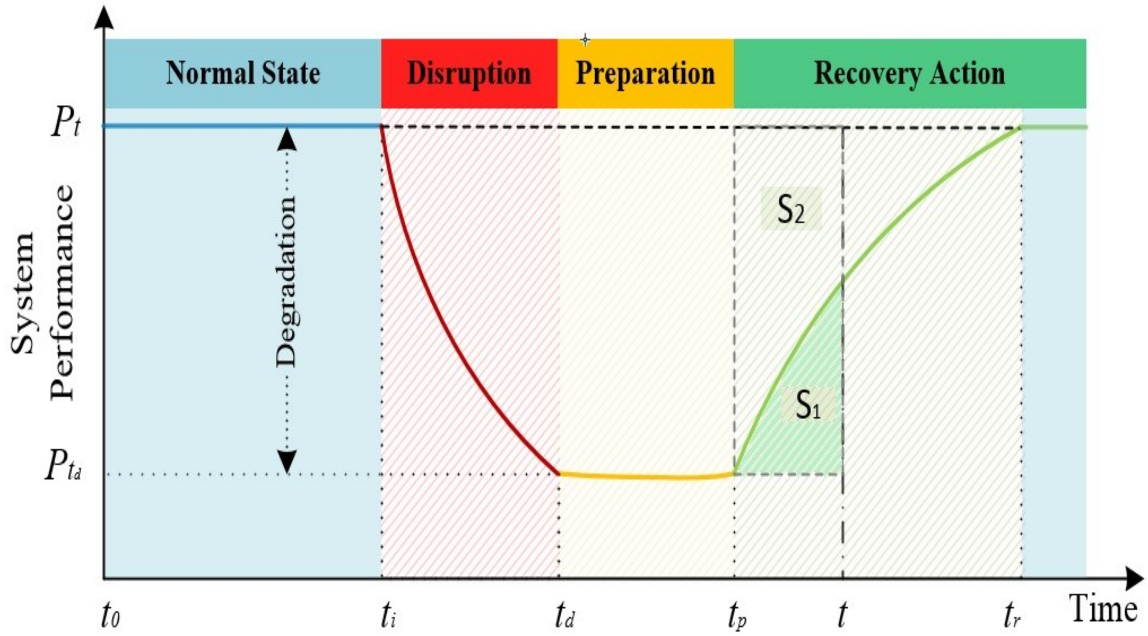


Figure 5. Conceptual illustration of system resilience quantification.

The following considerations about the given resilience definition are important: Here, the system resilience $R^{\lambda}_{i,n,d,t}$ defined in equation (18) calculates the cumulative recovered system performance following a disruption normalized by the target cumulative system performance in the normal state as if the system was not affected by the emergencies.

The system performance function P_t can be quantified by various metrics (e.g., the amount of flow or services delivered to the demand, the availability of critical resource allocation, the number of customers served, or the likelihood of economic activities for infrastructure systems), depending on which dimensions (i.e., technical, organizational, social and economic) of resilience the analysis focuses on. This study utilizes the amount of flow delivered to the demand nodes of a network as the performance level metric.

$R^{\lambda}_{i,n,d,t}$ is undefined when $t < t_d$, because the system is not exposed to disruptive incident and recovery is meaningless since no loss is subjected to the system. To carry out the analysis, each system element is transposed into a node or edge of the representative topological network. In this study, three different types of nodes are considered: generator nodes (where generate the electricity to feed the system), demand nodes (where customers are connected) and transmission nodes (without customers or sources). The mathematical model for the resilience optimization problem here considered involves an infrastructure network *G* (*N*, *L*) comprising a set of nodes *N* connected by a set of links *L*. The network nodes are classified into supply nodes N_S, and transmission node N_l. Each path $i, j \in L$ carries associated capacity $P_{i,j}$ while each supply node $g \in N_s$ has a supply capacity per time unit P^s_g and each demand node $j \in N_d$ has a demand P^d_j per time unit. The flow is delivered from the supply nodes to the demand nodes taking into consideration the flow capacity of the links and supply/demand capacity constraints. $P^t_{d,n}$ represents the amount of power received by demand node *n* at time *t*. The impact of the disruptive event is modeled by the removal of the element. System performance achieves its minimum value at this time ($t = t_d$, $i.e. P_{\min} = P(t_d)$). The goal is to achieve maximum system resilience over the whole restoration horizon T (i.e. $t_r - t_d$). In addition, the number of arcs that can be restored in each time period is constrained by the grid connectivity and stability checks. We focus on the role of various recovery decisions and actions in the task of optimizing the resilience of infrastructure networks subject to disruptive events. A resilience optimization model for infrastructure networks is first formulated taking into consideration the resilience metrics provided in Sections 4.1.1 and 4.1.2, and then the DC power flow is incorporated as extra constraints (i.e. equations (9)-(17)) when applying to power grids.

5. CASE STUDY: IEEE 118-BUS TEST SYSTEM

This research effort is tested and verified through a case study on the IEEE 118-bus test system which contains a total of 186 transmission lines, and 19 generating units, with the total capacity of 5859.2 MW, serving a total demand of 4519 MW. The optimization formulation for fast recovery in the face of HILP events, i.e., co-optimization of the generation re-dispatch and topology reconfiguration through TLS actions, is implemented with the main goal of maximizing the system resilience. The optimization problem and the analysis were run on a PC with an Intel(R) Core(TM) 2.9 GHz processor and 8 GB of RAM. The optimization allows the status of each transmission line as well as the optimized generation dispatch to be determined, overall comprising the recovery action. Several optimal TLS solutions taking into account different values for the maximum number of open transmission lines are obtained. This allows benefiting from a sequence of TLS actions that incrementally change the network topology, adjust the flow of power, and improve the system resilience.

In this study one non-trivial contingency, the outage of generator 13 (G13) which is the largest unit with the highest capacity in the studied network, is considered as an HILP disruptive event. Among the total 99 load points of the system, 26 load points are partially or fully affected by the weather-driven HILP phenomenon. The initial system-wide load outage caused by the G13 contingency is 805.2 MW, of which only 584.3 MW

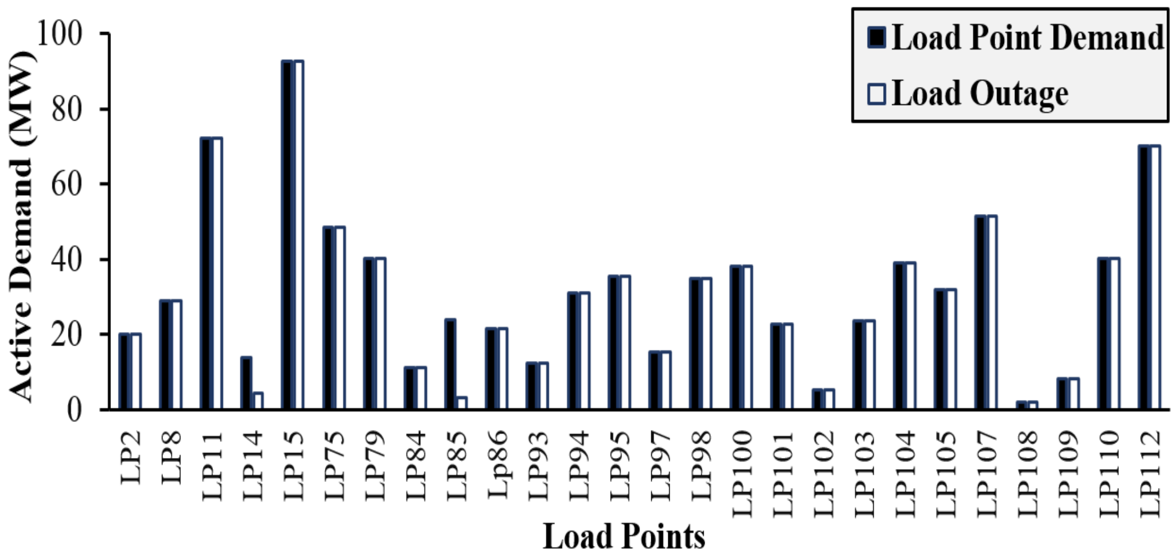


Figure 6. The impact of G13 contingency on network load points: Load outages and survived demand.

(72.6% of the system total load outage) can be recovered through the traditional generation re-dispatch-only practice. Figure 6 illustrates the load outages as a result of the studied contingency, and the demand survived at each bus. Hence, a co-optimization of generation re-dispatch and topology reconfiguration is pursued anticipating additional benefits in recovering the load outage in a timely manner.

5.1 Proof of Concept: TLS for Enhanced System Resilience

The proposed formulation for corrective resilience-based topology control is applied to the studied network faced with the G13 contingency, and various optimal topology control plans for outage recovery are found as depicted in Figure 7. The suggested recovery plans based on network topology control involve one or more TLS

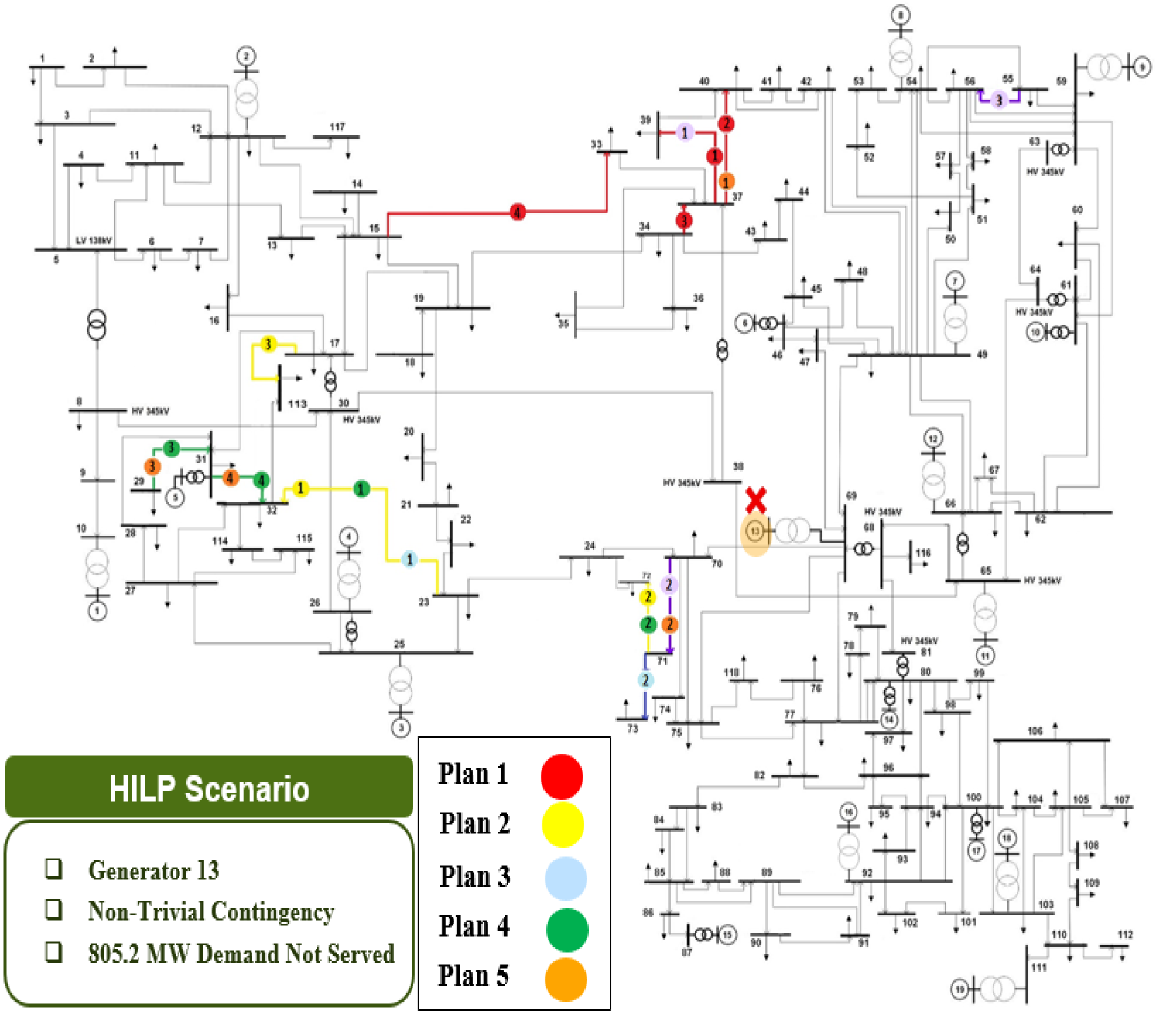


Figure 7. The optimal TLS sequences for enhancing the grid resilience in the face of the HILP event (an outage of G13).

actions in the form of a sequence that incrementally recovers the load outage and improve the system resilience. The grid flexibility metric [see (5)], representative of the system resilience, is quantified for each optimal restoration plan suggested via the optimization framework. Further details on the optimal TLS actions as well as their associated benefits in terms of load outage recovery are tabulated in Table 2.

Table 2. Line-Bus Connectivity of the Recovery Plans for Contingency G13: IEEE 118-Bus Test System

<table>
<tr><th>Line</th><th>From Bus</th><th>To Bus</th><th>Recovery Plan</th><th>Sequences of Optimal TLS Actions</th><th>Recovered Outage (MW)</th></tr>
<tr><td>40</td><td>29</td><td>31</td><td>RDO*</td><td>N/A</td><td>586.452</td></tr>
<tr><td>41</td><td>23</td><td>32</td><td>TLS Plan1</td><td>[52]-[53]-[50]-[44]</td><td>752.409</td></tr>
<tr><td>42</td><td>31</td><td>32</td><td>TLS Plan2</td><td>[41]-[112]-[178]-RD</td><td>753.57</td></tr>
<tr><td>44</td><td>15</td><td>33</td><td>TLS Plan3</td><td>[41]-[113]-RD</td><td>799.2</td></tr>
<tr><td>50</td><td>34</td><td>37</td><td>TLS Plan4</td><td>[41]-[112]-[40]-[42]</td><td>764.439</td></tr>
<tr><td>52</td><td>37</td><td>39</td><td>TLS Plan5</td><td>[53]-[110]-[40]-[42]</td><td>783.146</td></tr>
<tr><td>53</td><td>37</td><td>40</td><td rowspan="7" colspan="3">Grid Flexibility Features: Resilience State following Each Optimized Recovery Plan

*RDA: Re-Dispatch-Alone Practice
*RD: Re-Dispatch Action
*[x]: Transmission Line to be Switched Off.</td></tr>
<tr><td>79</td><td>55</td><td>56</td></tr>
<tr><td>110</td><td>70</td><td>71</td></tr>
<tr><td>112</td><td>71</td><td>72</td></tr>
<tr><td>113</td><td>71</td><td>73</td></tr>
<tr><td>178</td><td>17</td><td>113</td></tr>
</table>

Figure 8 illustratively proves the general concept and demonstrates the advantage of the proposed network reconfiguration strategy using TLS actions in the recovery of the load outages and enhancing the system resilience. As one can see from the resilience chart in Figure 8, the studied network faces an HILP event at time 10, and the system performance (here, the total system demand to be served) degrades to a minimum, resulting in 805.2 MW load outage in 10 minutes. At time 20, recovery actions should be initiated by the system operator to maintain the system safety and reliability performance

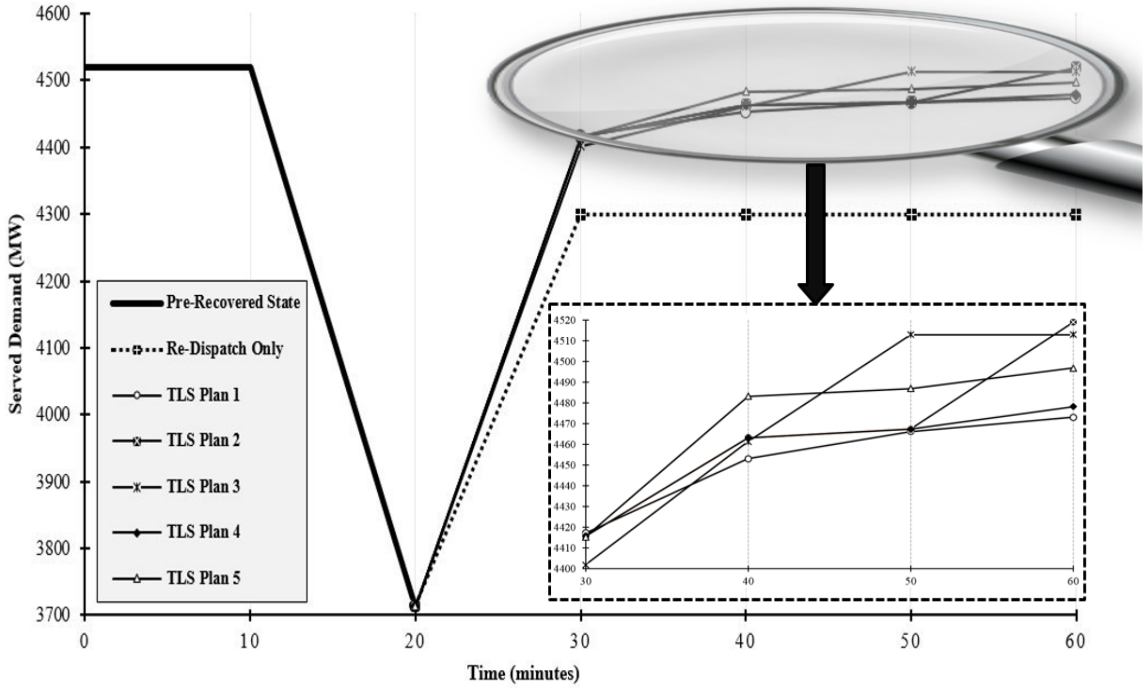


Figure 8. Load outage restoration through optimal corrective TLS plans.

through enhanced network resilience. As previously mentioned, the optimization engine is simulated in the operational planning time-frame (day-ahead) in response to this critical contingency and the solution recovery plans are ready to be implemented at time 20. For demonstration purposes, six recovery plans are compared, where the generation re-dispatch-only practice is also included.

It can be observed, from Figure 8, that while the load outage recovery through a 10-min re-dispatch practice at time 20 is significant (%72.6), all the other five restoration plans can further restore the interrupted loads, some of which leading to almost %100 load outage recovery. To put a figure on this, take the TLS Plan 5 as an example. This recovery plan involves 4 transmission line switching actions that need to be sequentially implemented together with the generation re-dispatch actions at each level, combined taking a 40 minutes implementation time leading to the %97.3 recovery of the system load outage (~%25 more than the re-dispatch-alone practice). Similar observations can be made for other optimal topology control plans presented, which highlights the benefits of employing the built-in network flexibility for corrective recovery actions for load restoration in this case.

Note: The implementation time requirement for each TLS action involved in a recovery plan is 10 min as it is accompanied by a generation re-dispatch process and restricted by the ramping up/down requirements of the system generating units. Hence, it takes 10, 20, 30 minutes to implement a 1-line, 2-line, and 3-line TLS plan, respectively.

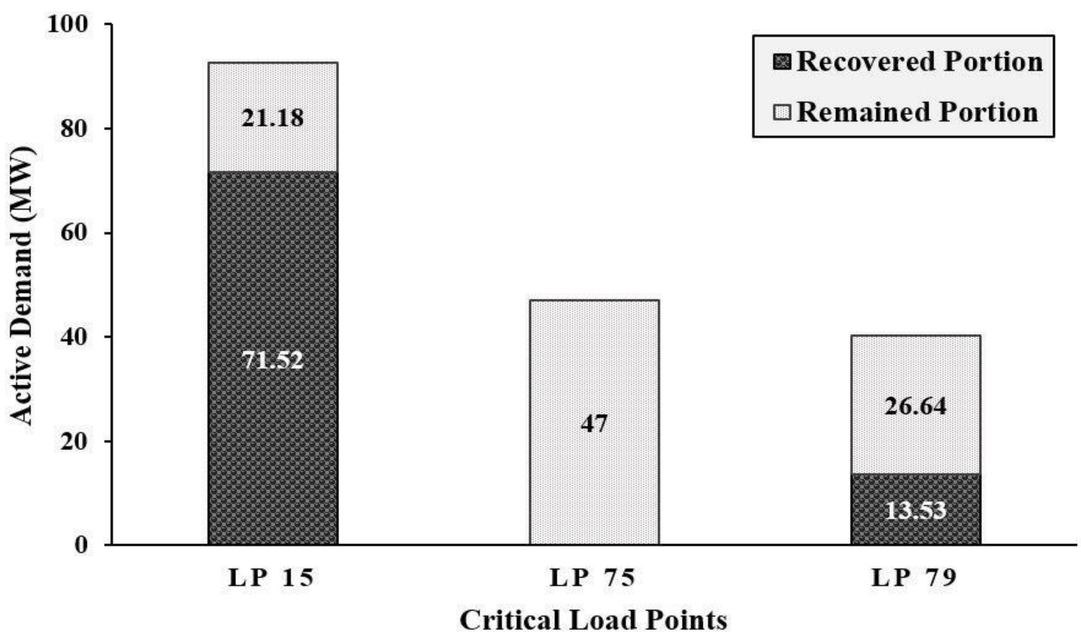
As the suggested optimization framework for outage recovery is able to suggest multiple recovery plans per forecasted contingency, the possibility of having at least one mitigation plan meeting all the other practical requirements (e.g., system stability, circuit-breaker reliability, electric safety considerations, etc.) is very high which is, thus, one more advantage of the suggested framework. With several optimal restoration options available, all of which providing significant load outage recovery, the operator needs to select one of such temporary plans for final implementation. Several key factors such as implementation duration (representative of how fast the system resilience can be improved), the amount of outage recovery (reflective of system robustness), and prioritized load point restoration, etc. could individually or collectively help the system operator make the best decision. In case of the studied example, although TLS plans 1, 2, 4, and 5 can all bring about potential for some benefits to the grid resilience, they recover the critical load points, those with the highest restoration priority, differently. In other words, critical load points may be restored faster in some recovery plans than in others.

In other special circumstances, e.g. less survivable systems, the system functionality might fall below a certain operation point following an HILP incident. In this case, it is vital to select the fastest temporary restoration plan first to bring the system back to its operational mode, regardless of other longer optimal plans with the highest outage restoration benefit. Thus, selection of the best plan for implementation also depends on the network configuration, customer types that are interrupted (e.g. commercial, industrial, residential, etc.), the operator's judgment and preference, as well as the goal he/she is seeking to improve the system overall safety and resilience.

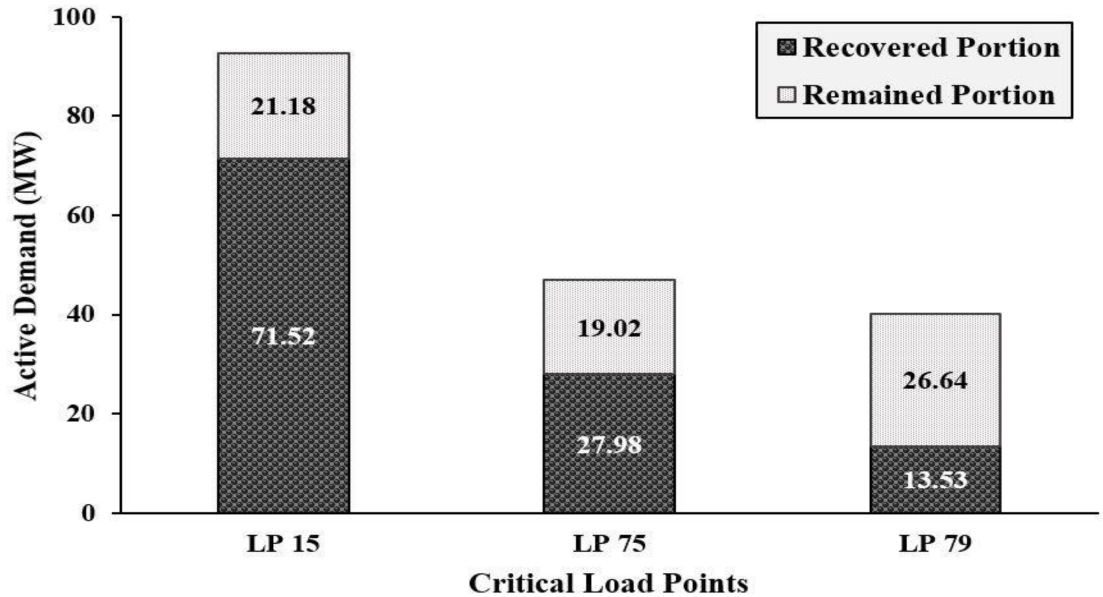
5.2 Impact of TLS on Restoration of Critical Load Points

As discussed earlier, the interrupted demand following an HILP incident may be of different types and criticality, thus imposing different outage costs and socio-economic consequences. The system operator must be aware of the grid geology and be prepared which restoration strategy to follow. Identifying the system critical load points in each region can be of great help in realizing a faster recovery and higher resilience. The impact of optimal network reconfiguration on the recovery of the critical load points of the studied network facing the HILP incident is further analyzed in this section. Of all disrupted load points (LPs), three are considered critical since LP15, LP75, and LP79 feed the industrial, commercial, and military demand sectors, respectively. The optimization objective (8) is adjusted to find the optimal restoration plans to recover the load outages in a timely manner considering the load point criticality.

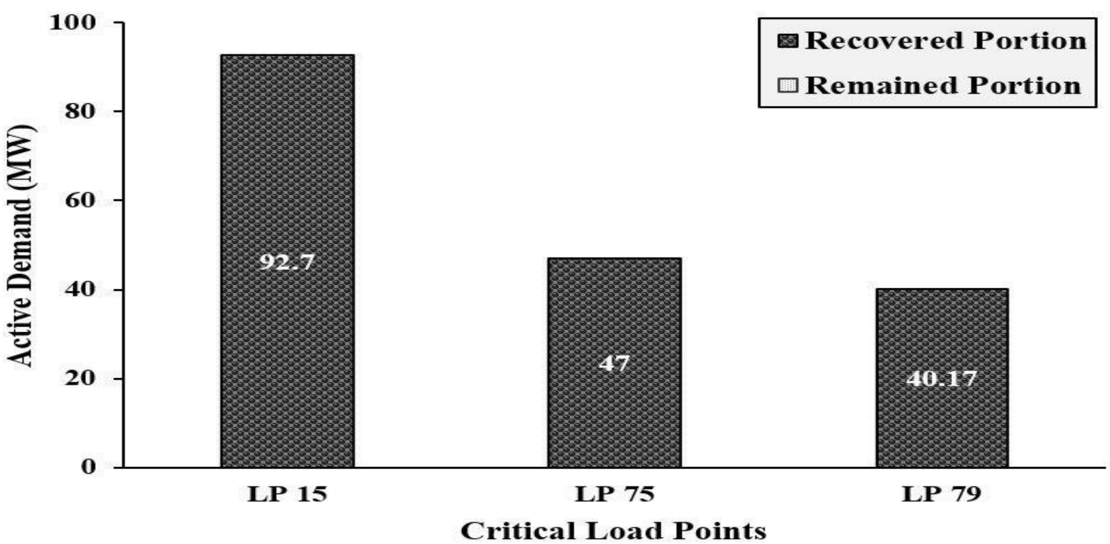
Figure 9 (a)-(c) illustrates how the proposed optimal recovery actions are able to restore the aforementioned critical load points incrementally. As can be seen in Figure 9, LP15, LP75, and LP79 were serving a total demand of 93 MW, 47 MW, and 40 MW, respectively, under system normal operating condition. With the HILP incident stroked at G13, all three of these load points are fully interrupted with %100 load outage consequence. The proposed optimization engine is able to suggest a recovery plan, among several others, consisting of a three-action TLS sequence (L52-L110-L79) that if sequentially implemented, can iteratively recover the demand associated with the target critical load points [this suggested restoration plan is shown in violet circles and lines in Figure 7]. Figure 9(a) shows how implementing the first TLS recovery action (opening transmission line 52) helps the load point restoration, with which 77.15% and 33.67% of the interrupted demand in the critical LP15 and LP79 are recovered, respectively, within 10 minutes. However, the demand at LP47 still remains fully interrupted with no recovery with this single TLS action. Subsequently, the second TLS action within the



(a) Critical load points restoration via 1st TLS action: L52.



(b) Critical load points restoration via 2nd TLS action: L52-L110.



(c) Critical load points restoration via 3rd TLS action: L52-L110-L79.

Figure 9. Demand restoration of critical load points through the implementation of an optimal corrective TLS sequence.

suggested recovery sequence is implemented (opening transmission line 110 while transmission line 52 remains switched out), and the interrupted demand in LP75 is recovered by 59.52% in 20 minutes [see Figure 9(b)], while no additional recovery could be realized for LP15 and LP79. Eventually, the suggested restoration sequence can be fully implemented in 30 minutes by performing the third TLS action (opening transmission line 79 while transmission lines 52 and 110 remain switched out), and according to the results presented in Figure 9(c), the entire interrupted demand in all critical load points of the system is fully restored in 30 minutes. Note that the TLS actions include switching the line out of service by opening the circuit breakers as well as a 10-min generation re-dispatch implementation. These combined actions realize incremental benefits in terms of power grid resilience against HILP incidents.

5.3 Grid-Scale Resilience Analysis

Generally speaking, an electric power grid with a higher number of transmission lines (i.e., a higher level of network redundancies) provides more flexible control over energy delivery with an increased power flow capacity. This higher flexibility offers higher elasticity to re-route the power flow system-wide, bypass the damaged equipment, and mitigate the risk of cascading failures and grid-scale outages.

Quantifying the network robustness is important for decision making on corrective restoration plans (either through topology control or microgrid operations) for enhanced resilience. Therefore, the grid resistivity and other robustness metrics are calculated as supplemental resilience metrics for each optimal recovery plan suggested through the optimization engine. Table 3 demonstrates the resilience metrics on grid robustness for each recovery plan formerly proposed in Table 2, where each network topology control plan impacts the system resilience differently. The network possesses the highest robustness in the base case condition. In general, the lower the resistance index is, the lower the system sensitivity is to any transmission line removal. The higher the other indices in Table 3 are, the better the grid capability is to withstand any topology changes. As the HILP incident strikes the network, its robustness changes. With several different optimal restoration plans proposed, the operator should consider selecting a final recovery plan that not only assures the highest outage recovery in a faster time frame, but also offers higher grid resilience. For instance, the proposed plan 3 is a recovery option composed of two TLS actions. While it restores 99.25% of the interrupted demand in 20 minutes, the network connectivity is much less than that for other plans as the switched lines are connected to a critical load point with a fewer number of transmission lines attached. So, switching out a line from that bus might put the grid at risk if another unpredicted contingency occurs during restoration.

Table 3. Grid Robustness Analysis for Each Suggested Recovery Plan in Response to Contingency G13

Recovery Plan	Grid Resistivity	Grid Connectivity	Grid Flexibility	Grid Conductivity
Base Case	2.2414	0.07440	6.324	0.0075
Plan 1	2.5147	0.07433	6.188	0.0067
Plan 2	2.3903	0.07414	6.222	0.0071
Plan 3	2.2950	0.02910	6.256	0.0073
Plan 4	2.4148	0.07414	6.188	0.0070
Plan 5	2.4099	0.07421	6.222	0.0070

6. CONCLUSION

Resilience is the ability of the system to restore itself, with little or no human intervention, to safe and reliable operation from any disturbances or outages. With the increasing exposure of the electricity grid to several sources of hazards arising from natural disasters or malicious cyber-attacks, realizing an enhanced resilience is essential through deployment of advanced hardware and software technologies as well as streamlined recovery processes and decision-making strategies.

This thesis proposes a resilience-based smart grid application of harnessing the full control of transmission assets in the face of emergency scenarios. The suggested approach employs network reconfiguration as a temporarily corrective tool in dealing with the forecasted contingencies for load outage restoration. Several resilience metrics corresponding to each proposed recovery plan are quantified, aiding the operator to make a more efficient decision on which one to implement. Results revealed that implementing the suggested recovery options quickly restores the load outages and improve the system overall safety and resilience.

APPENDIX SECTION

Here are the raw data that has been used in the investigated IEEE 118-Bus test case study discussed in Chapter 5. Following parameters and data are considered.

- Network Topology
- Bus Data
- Generator Data
- Line Data
- Bus Load Data

A. Network Topology

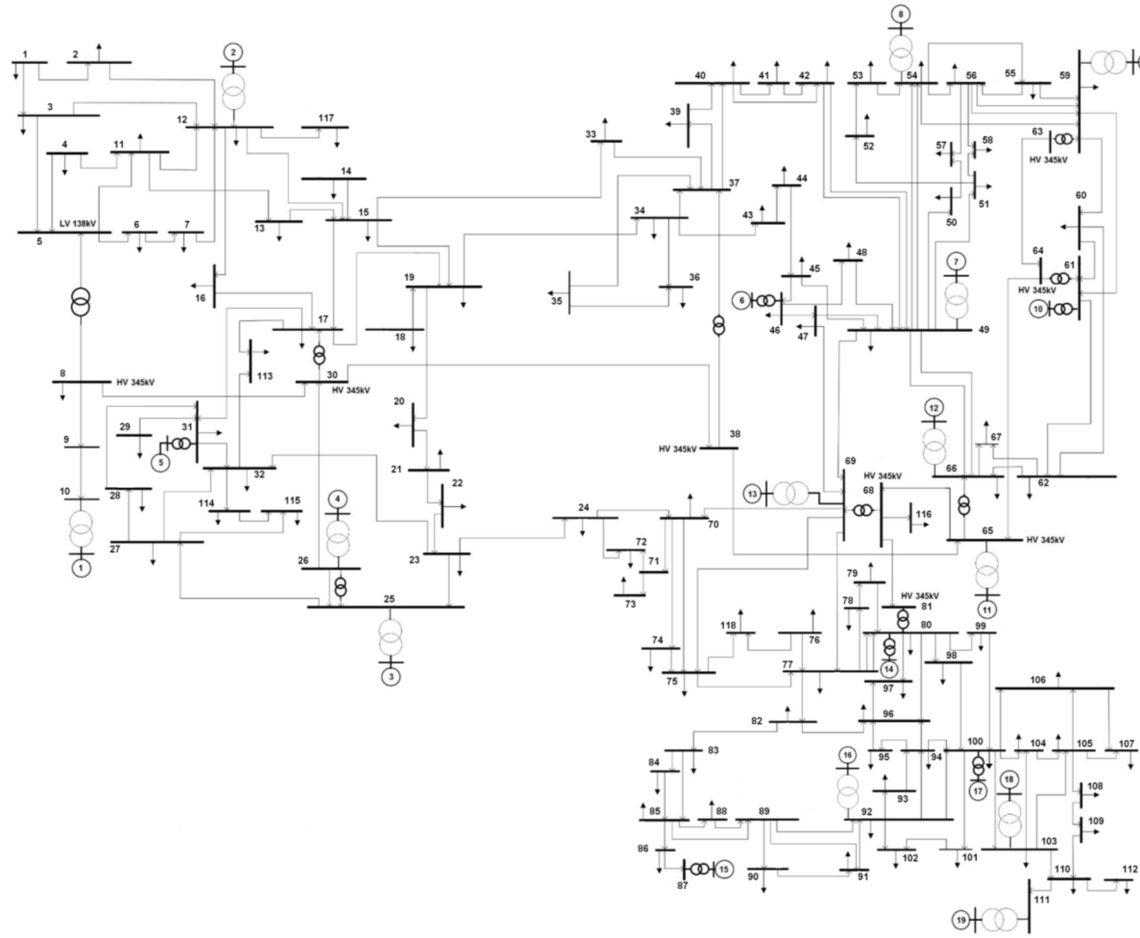


Figure 10. IEEE 118-bus test system one-line diagram.

B. Bus Data

Table 4. IEEE 118-Bus Test System Bus Data

Bus No.	**Conductance (G) (mhos)**	**Susceptance (B) (mhos)**	**Base Voltage (kV)**	**Voltage-Max (pu)**	**Voltage-Min (pu)**
1	0	0	138	1.06	0.94
2	0	0	138	1.06	0.94
3	0	0	138	1.06	0.94
4	0	0	138	1.06	0.94
5	0	-40	138	1.06	0.94
6	0	0	138	1.06	0.94
7	0	0	138	1.06	0.94
8	0	0	345	1.06	0.94
9	0	0	345	1.06	0.94
10	0	0	345	1.06	0.94
11	0	0	138	1.06	0.94
12	0	0	138	1.06	0.94
13	0	0	138	1.06	0.94
14	0	0	138	1.06	0.94
15	0	0	138	1.06	0.94
16	0	0	138	1.06	0.94
17	0	0	138	1.06	0.94
18	0	0	138	1.06	0.94
19	0	0	138	1.06	0.94
20	0	0	138	1.06	0.94
21	0	0	138	1.06	0.94
22	0	0	138	1.06	0.94
23	0	0	138	1.06	0.94

Table 4. Continued.					
24	0	0	138	1.06	0.94
25	0	0	138	1.06	0.94
26	0	0	345	1.06	0.94
27	0	0	138	1.06	0.94
28	0	0	138	1.06	0.94
29	0	0	138	1.06	0.94
30	0	0	345	1.06	0.94
31	0	0	138	1.06	0.94
32	0	0	138	1.06	0.94
33	0	0	138	1.06	0.94
34	0	14	138	1.06	0.94
35	0	0	138	1.06	0.94
36	0	0	138	1.06	0.94
37	0	-25	138	1.06	0.94
38	0	0	345	1.06	0.94
39	0	0	138	1.06	0.94
40	0	0	138	1.06	0.94
41	0	0	138	1.06	0.94
42	0	0	138	1.06	0.94
43	0	0	138	1.06	0.94
44	0	10	138	1.06	0.94
45	0	10	138	1.06	0.94
46	0	10	138	1.06	0.94
47	0	0	138	1.06	0.94
48	0	15	138	1.06	0.94
49	0	0	138	1.06	0.94
50	0	0	138	1.06	0.94
51	0	0	138	1.06	0.94

Table 4. Continued.					
52	0	0	138	1.06	0.94
53	0	0	138	1.06	0.94
54	0	0	138	1.06	0.94
55	0	0	138	1.06	0.94
56	0	0	138	1.06	0.94
57	0	0	138	1.06	0.94
58	0	0	138	1.06	0.94
59	0	0	138	1.06	0.94
60	0	0	138	1.06	0.94
61	0	0	138	1.06	0.94
62	0	0	138	1.06	0.94
63	0	0	345	1.06	0.94
64	0	0	345	1.06	0.94
65	0	0	345	1.06	0.94
66	0	0	138	1.06	0.94
67	0	0	138	1.06	0.94
68	0	0	345	1.06	0.94
69	0	0	138	1.06	0.94
70	0	0	138	1.06	0.94
71	0	0	138	1.06	0.94
72	0	0	138	1.06	0.94
73	0	0	138	1.06	0.94
74	0	12	138	1.06	0.94
75	0	0	138	1.06	0.94
76	0	0	138	1.06	0.94
77	0	0	138	1.06	0.94
78	0	0	138	1.06	0.94
79	0	20	138	1.06	0.94

Table 4. Continued.					
80	0	0	138	1.06	0.94
81	0	0	345	1.06	0.94
82	0	20	138	1.06	0.94
83	0	10	138	1.06	0.94
84	0	0	138	1.06	0.94
85	0	0	138	1.06	0.94
86	0	0	138	1.06	0.94
87	0	0	161	1.06	0.94
88	0	0	138	1.06	0.94
89	0	0	138	1.06	0.94
90	0	0	138	1.06	0.94
91	0	0	138	1.06	0.94
92	0	0	138	1.06	0.94
93	0	0	138	1.06	0.94
94	0	0	138	1.06	0.94
95	0	0	138	1.06	0.94
96	0	0	138	1.06	0.94
97	0	0	138	1.06	0.94
98	0	0	138	1.06	0.94
99	0	0	138	1.06	0.94
100	0	0	138	1.06	0.94
101	0	0	138	1.06	0.94
102	0	0	138	1.06	0.94
103	0	0	138	1.06	0.94
104	0	0	138	1.06	0.94
105	0	20	138	1.06	0.94
106	0	0	138	1.06	0.94
107	0	6	138	1.06	0.94

Table 4. Continued.					
108	0	0	138	1.06	0.94
109	0	0	138	1.06	0.94
110	0	6	138	1.06	0.94
111	0	0	138	1.06	0.94
112	0	0	138	1.06	0.94
113	0	0	138	1.06	0.94
114	0	0	138	1.06	0.94
115	0	0	138	1.06	0.94
116	0	0	138	1.06	0.94
117	0	0	138	1.06	0.94
118	0	0	138	1.06	0.94

C. Generator Data

Table 5. IEEE 118-Bus Test System Generator Data

U	Bus No.	P_g (MW)	Q_g (MVar)	Marginal Cost ($/MWh)	P_{max} (MW)	P_{min} (MW)	Q_{max} (MVar)	Q_{min} (MVar)
1	10	450	-5	0.217	550	0	200	-147
2	12	85	91.27	1.052	185	0	120	-35
3	25	220	49.72	0.434	320	0	140	-47
4	26	314	9.89	0.308	414	0	1000	-1000
5	31	7	31.57	5.882	107	0	300	-300
6	46	19	-5.25	3.448	119	0	100	-100
7	49	204	115.63	0.467	304	0	210	-85
8	54	48	3.9	1.724	148	0	300	-300
9	59	155	76.83	0.606	255	0	180	-60
10	61	160	-40.39	0.588	260	0	300	-100
11	65	391	80.76	0.2493	491	0	200	-67
12	66	392	-1.95	0.2487	492	0	200	-67
13	69	513.48	-82.39	0.1897	805.2	0	300	-300
14	80	477	104.9	0.205	577	0	280	-165
15	87	4	11.02	7.142	104	0	1000	-100
16	92	607	0.49	10	1100	0	9	-3
17	100	252	108.87	0.381	352	0	155	-50
18	103	40	41.69	2	140	0	40	-15
19	111	36	-1.84	2.173	136	0	1000	-100

D. Line Data

Table 6. IEEE 118-Bus Test System Transmission Line Data

Line No.	From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rate A (MVA)
1	1	2	0.0303	0.0999	0.0254	220
2	1	3	0.0129	0.0424	0.01082	220
3	4	5	0.00176	0.00798	0.0021	220
4	3	5	0.0241	0.108	0.0284	220
5	5	6	0.0119	0.054	0.01426	220
6	6	7	0.00459	0.0208	0.0055	440
7	8	9	0.00244	0.0305	1.162	220
8	8	5	0	0.0267	0	220
9	9	10	0.00258	0.0322	1.23	220
10	4	11	0.0209	0.0688	0.01748	220
11	5	11	0.0203	0.0682	0.01738	220
12	11	12	0.00595	0.0196	0.00502	1100
13	2	12	0.0187	0.0616	0.01572	880
14	3	12	0.0484	0.16	0.0406	220
15	7	12	0.00862	0.034	0.00874	1100
16	11	13	0.02225	0.0731	0.01876	220
17	12	14	0.0215	0.0707	0.01816	220
18	13	15	0.0744	0.2444	0.06268	220
19	14	15	0.0595	0.195	0.0502	220
20	12	16	0.0212	0.0834	0.0214	220
21	15	17	0.0132	0.0437	0.0444	220
22	16	17	0.0454	0.1801	0.0466	220

Table 6. Continued.						
23	17	18	0.0123	0.0505	0.01298	440
24	18	19	0.01119	0.0493	0.01142	220
25	19	20	0.0252	0.117	0.0298	220
26	15	19	0.012	0.0394	0.0101	220
27	20	21	0.0183	0.0849	0.0216	220
28	21	22	0.0209	0.097	0.0246	220
29	22	23	0.0342	0.159	0.0404	220
30	23	24	0.0135	0.0492	0.0498	220
31	23	25	0.0156	0.08	0.0864	220
32	26	25	0	0.0382	0	220
33	25	27	0.0318	0.163	0.1764	220
34	27	28	0.01913	0.0855	0.0216	220
35	28	29	0.0237	0.0943	0.0238	220
36	30	17	0	0.0388	0	220
37	8	30	0.00431	0.0504	0.514	440
38	26	30	0.00799	0.086	0.908	220
39	17	31	0.0474	0.1563	0.0399	220
40	29	31	0.0108	0.0331	0.0083	220
41	23	32	0.0317	0.1153	0.1173	440
42	31	32	0.0298	0.0985	0.0251	220
43	27	32	0.0229	0.0755	0.01926	660
44	15	33	0.038	0.1244	0.03194	220
45	19	34	0.0752	0.247	0.0632	220
46	35	36	0.00224	0.0102	0.00268	220
47	35	37	0.011	0.0497	0.01318	220
48	33	37	0.0415	0.142	0.0366	220
49	34	36	0.00871	0.0268	0.00568	660
50	34	37	0.00256	0.0094	0.00984	220

Table 6. Continued.						
51	38	37	0	0.0375	0	220
52	37	39	0.0321	0.106	0.027	220
53	37	40	0.0593	0.168	0.042	220
54	30	38	0.00464	0.054	0.422	220
55	39	40	0.0184	0.0605	0.01552	220
56	40	41	0.0145	0.0487	0.01222	440
57	40	42	0.0555	0.183	0.0466	220
58	41	42	0.041	0.135	0.0344	220
59	43	44	0.0608	0.2454	0.06068	220
60	34	43	0.0413	0.1681	0.04226	220
61	44	45	0.0224	0.0901	0.0224	220
62	45	46	0.04	0.1356	0.0332	660
63	46	47	0.038	0.127	0.0316	440
64	46	48	0.0601	0.189	0.0472	220
65	47	49	0.0191	0.0625	0.01604	220
66	42	49	0.0715	0.323	0.086	220
67	42	49	0.0715	0.323	0.086	220
68	45	49	0.0684	0.186	0.0444	220
69	48	49	0.0179	0.0505	0.01258	220
70	49	50	0.0267	0.0752	0.01874	220
71	49	51	0.0486	0.137	0.0342	220
72	51	52	0.0203	0.0588	0.01396	220
73	52	53	0.0405	0.1635	0.04058	220
74	53	54	0.0263	0.122	0.031	220
75	49	54	0.073	0.289	0.0738	220
76	49	54	0.0869	0.291	0.073	220
77	54	55	0.0169	0.0707	0.0202	220
78	54	56	0.00275	0.00955	0.00732	220

Table 6. Continued.						
79	55	56	0.00488	0.0151	0.00374	220
80	56	57	0.0343	0.0966	0.0242	220
81	50	57	0.0474	0.134	0.0332	220
82	56	58	0.0343	0.0966	0.0242	220
83	51	58	0.0255	0.0719	0.01788	440
84	54	59	0.0503	0.2293	0.0598	440
85	56	59	0.0825	0.251	0.0569	220
86	56	59	0.0803	0.239	0.0536	220
87	55	59	0.04739	0.2158	0.05646	220
88	59	60	0.0317	0.145	0.0376	220
89	59	61	0.0328	0.15	0.0388	220
90	60	61	0.00264	0.0135	0.01456	220
91	60	62	0.0123	0.0561	0.01468	220
92	61	62	0.00824	0.0376	0.0098	220
93	63	59	0	0.0386	0	220
94	63	64	0.00172	0.02	0.216	220
95	64	61	0	0.0268	0	220
96	38	65	0.00901	0.0986	1.046	220
97	64	65	0.00269	0.0302	0.38	220
98	49	66	0.018	0.0919	0.0248	220
99	49	66	0.018	0.0919	0.0248	220
100	62	66	0.0482	0.218	0.0578	220
101	62	67	0.0258	0.117	0.031	220
102	65	66	0	0.037	0	440
103	66	67	0.0224	0.1015	0.02682	220
104	65	68	0.00138	0.016	0.638	220
105	47	69	0.0844	0.2778	0.07092	220
106	49	69	0.0985	0.324	0.0828	220

Table 6. Continued.						
107	68	69	0	0.037	0	440
108	69	70	0.03	0.127	0.122	440
109	24	70	0.00221	0.4115	0.10198	220
110	70	71	0.00882	0.0355	0.00878	440
111	24	72	0.0488	0.196	0.0488	220
112	71	72	0.0446	0.18	0.04444	220
113	71	73	0.00866	0.0454	0.01178	220
114	70	74	0.0401	0.1323	0.03368	440
115	70	75	0.0428	0.141	0.036	220
116	69	75	0.0405	0.122	0.124	440
117	74	75	0.0123	0.0406	0.01034	440
118	76	77	0.0444	0.148	0.0368	440
119	69	77	0.0309	0.101	0.1038	220
120	75	77	0.0601	0.1999	0.04978	220
121	77	78	0.00376	0.0124	0.01264	220
122	78	79	0.00546	0.0244	0.00648	220
123	77	80	0.017	0.0485	0.0472	220
124	77	80	0.0294	0.105	0.0228	220
125	79	80	0.0156	0.0704	0.0187	220
126	68	81	0.00175	0.0202	0.808	220
127	81	80	0	0.037	0	220
128	77	82	0.0298	0.0853	0.08174	220
129	82	83	0.0112	0.03665	0.03796	220
130	83	84	0.0625	0.132	0.0258	220
131	83	85	0.043	0.148	0.0348	440
132	84	85	0.0302	0.0641	0.01234	220
133	85	86	0.035	0.123	0.0276	220
134	86	87	0.02828	0.2074	0.0445	220

Table 6. Continued.						
135	85	88	0.02	0.102	0.0276	220
136	85	89	0.0239	0.173	0.047	220
137	88	89	0.0139	0.0712	0.01934	220
138	89	90	0.0518	0.188	0.0528	220
139	89	90	0.0238	0.0997	0.106	220
140	90	91	0.0254	0.0836	0.0214	220
141	89	92	0.0099	0.0505	0.0548	220
142	89	92	0.0393	0.1581	0.0414	220
143	91	92	0.0387	0.1272	0.03268	220
144	92	93	0.0258	0.0848	0.0218	220
145	92	94	0.0481	0.158	0.0406	220
146	93	94	0.0223	0.0732	0.01876	220
147	94	95	0.0132	0.0434	0.0111	220
148	80	96	0.0356	0.182	0.0494	220
149	82	96	0.0162	0.053	0.0544	220
150	94	96	0.0269	0.0869	0.023	440
151	80	97	0.0183	0.0934	0.0254	660
152	80	98	0.0238	0.108	0.0286	220
153	80	99	0.0454	0.206	0.0546	220
154	92	100	0.0648	0.295	0.0472	660
155	94	100	0.0178	0.058	0.0604	220
156	95	96	0.0171	0.0547	0.01474	220
157	96	97	0.0173	0.0885	0.024	220
158	98	100	0.0397	0.179	0.0476	220
159	99	100	0.018	0.0813	0.0216	220
160	100	101	0.0277	0.1262	0.0328	220
161	92	102	0.0123	0.0559	0.01464	220
162	101	102	0.0246	0.112	0.0294	220

Table 6. Continued.						
163	100	103	0.016	0.0525	0.0536	220
164	100	104	0.0451	0.204	0.0541	220
165	103	104	0.0466	0.1584	0.0407	220
166	103	105	0.0535	0.1625	0.0408	220
167	100	106	0.0605	0.229	0.062	220
168	104	105	0.00994	0.0378	0.00986	220
169	105	106	0.014	0.0547	0.01434	440
170	105	107	0.053	0.183	0.0472	220
171	105	108	0.0261	0.0703	0.01844	220
172	106	107	0.053	0.183	0.0472	220
173	108	109	0.0105	0.0288	0.0076	220
174	103	110	0.03906	0.1813	0.0461	220
175	109	110	0.0278	0.0762	0.0202	220
176	110	111	0.022	0.0755	0.02	220
177	110	112	0.0247	0.064	0.062	220
178	17	113	0.00913	0.0301	0.00768	220
179	32	113	0.0615	0.203	0.0518	220
180	32	114	0.0135	0.0612	0.01628	220
181	27	115	0.0164	0.0741	0.01972	220
182	114	115	0.0023	0.0104	0.00276	220
183	68	116	0.00034	0.00405	0.164	220
184	12	117	0.0329	0.14	0.0358	220
185	75	118	0.0145	0.0481	0.01198	220
186	76	118	0.0164	0.0544	0.01356	220

E. Bus Load Data

Table 7. IEEE 118-Bus Test System General Load Data

Bus No.	**P_d (MW)**	**Q_d (MVar)**
1	51	27
2	20	9
3	39	10
4	39	12
6	52	22
7	19	2
8	28	0
11	70	23
12	47	10
13	34	16
14	14	1
15	90	30
16	25	10
17	11	3
18	60	34
19	45	25
20	18	3
21	14	8
22	10	5
23	7	3
24	13	0
27	71	13
28	17	7

Table 7. Continued.		
29	24	4
31	43	27
32	59	23
33	23	9
34	59	26
35	33	9
36	31	17
39	27	11
40	66	23
41	37	10
42	96	23
43	18	7
44	16	8
45	53	22
46	28	10
47	34	0
48	20	11
49	87	30
50	17	4
51	17	8
52	18	5
53	23	11
54	113	32
55	63	22
56	84	18
57	12	3
58	12	3
59	277	113

Table 7. Continued.		
60	78	3
62	77	14
66	39	18
67	28	7
70	66	20
72	12	0
73	6	0
74	68	27
75	47	11
76	68	36
77	61	28
78	71	26
79	39	32
80	130	26
82	54	27
83	20	10
84	11	7
85	24	15
86	21	10
88	48	10
90	440	42
91	10	0
92	65	10
93	12	7
94	30	16
95	42	31
96	38	15
97	15	9

Table 7. Continued.		
98	34	8
99	42	0
100	37	18
101	22	15
102	5	3
103	23	16
104	38	25
105	31	26
106	43	16
107	50	12
108	2	1
109	8	3
110	39	30
112	68	13
113	6	0
114	8	3
115	22	7
116	184	0
117	20	8
118	33	15

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