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DEPENDABILITY ANALYSIS AND RECOVERY SUPPORT
FOR SMART GRIDS

by

Isam Abdulmunem Alobaidi

A THESIS

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MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

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MASTER OF SCIENCE IN COMPUTER SCIENCE

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Approved by

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ABSTRACT

The increasing scale and complexity of power grids exacerbate concerns about failure propagation. A single contingency, such as outage of a transmission line due to overload or weather-related damage, can cause cascading failures that manifest as blackouts. One objective of smart grids is to reduce the likelihood of cascading failure through the use of power electronics devices that can prevent, isolate, and mitigate the effects of faults. Given that these devices are themselves prone to failure, we seek to quantify the effects of their use on dependability attributes of smart grid. This thesis articulates analytical methods for analyzing two dependability attributes - reliability and survivability - and proposes a recovery strategy that limits service degradation. Reliability captures the probability of system-level failure; Survivability describes degraded operation in the presence of a fault. System condition and service capacity are selected as measures of degradation. Both reliability and survivability are evaluated using $N-1$ contingency analysis. Importance analysis is used to determine a recovery strategy that maintains the highest survivability in the course of the recovery process. The proposed methods are illustrated by application to the IEEE 9-bus test system, a simple model system that allows for clear articulation of the process. Simulation is used to capture the effect of faults in both physical components of the power grid and the cyber infrastructure that differentiates it as a smart grid.

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1 INTRODUCTION

Around the globe, power grids supply electricity to billions of consumers, often with a down time limited to a few minutes per year [1,2]. Since the social structures in most developed countries rely on continuous supply of electricity, massive disorders can happen when the power grid is unable to deliver electricity to consumers; all the joints of our life are completely paralyzed without electricity. For instance, vital services such as computer systems, transportation systems, and communications are quickly halted [3].

In August of 2011, the outage of an electrical line near San Diego led to a cascading failure and caused a blackout that affected more than 3 million people. The cause was disconnection of a major transmission line by overgrown trees [4]. The resulting shift of load to adjacent transmission lines caused an overload that cascaded through the grid. In a similar scenario, a cascading failure in Ohio kept millions of consumers without electricity for 15 hours [5]. Analysis of recent blackouts shows that their causes are largely similar. One segment of the system fails, the segments near it cannot cope with the increased load caused by the failure, so they fail. The resulting outages cascade through the grid and leave large areas without power.

It is impossible to replace even small portions of the power grid infrastructure each time an outage occurs, as doing so would necessitate expending significant time and effort which is prohibitively expensive. Practical and innovative solutions are required that allow the grid to tolerate localized outages without collapse. One such solution is to integrate cyber infrastructure (encompassing communication, computing, and control elements) that enables the intelligence required of a smart grid. The goal is to create a fortified and efficient power grid that outperforms its predecessors. However, failure is inevitable even in the most advanced cyber infrastructure,

and as such, evaluating, modeling, and predicting the reliability and survivability of smart grids are critical steps towards their broader use. Equally critical is creating decision support systems that guide recovery from failure in a fashion that maintains acceptable service levels.

This thesis presents methods for evaluation and analysis of system-level reliability and survivability for power grids, including smart grids. Also proposed are methods for determining the best strategy for recovery from outages. The proposed approach is illustrated through its application to the IEEE 9-bus test system and a smart grid created by fortifying this grid with power electronics devices capable of mitigating and isolating the effects of a line outage. Simulation of these grids with Power System Analysis Toolbox (PSAT) [6] and subsequent $N - 1$ contingency analysis were used to instantiate the models.

The first contribution of this thesis is to quantify the reliability of the IEEE 9-bus grid based on data from $N - 1$ contingency analysis. We also investigate the gains in reliability achieved by the addition of intelligent control devices to the system. Despite the importance of reliability as an indicator of dependability, it falls short in capturing degraded operation, and makes a binary prediction of the probability that the system will be operational. Survivability, which captures the effect of failure on the ability of a system to deliver the expected functionality, is better-suited to analysis of power grids, which are capable of providing degraded service despite the losses incurred as a result of component or subsystem failure. *The second contribution of this thesis is introducing a survivability index that quantifies the degradation experienced.* This index, which considers both the extent of component failure and the loss in service capacity, can be used to guide recovery efforts and provides a quantitative measure that can be used to compare the effectiveness of competing recovery strategies. *The third contribution of this research is to employ the proposed*

survivability metric in making decisions for the recovery process. Figure 1.1 depicts the overarching goals of our research.

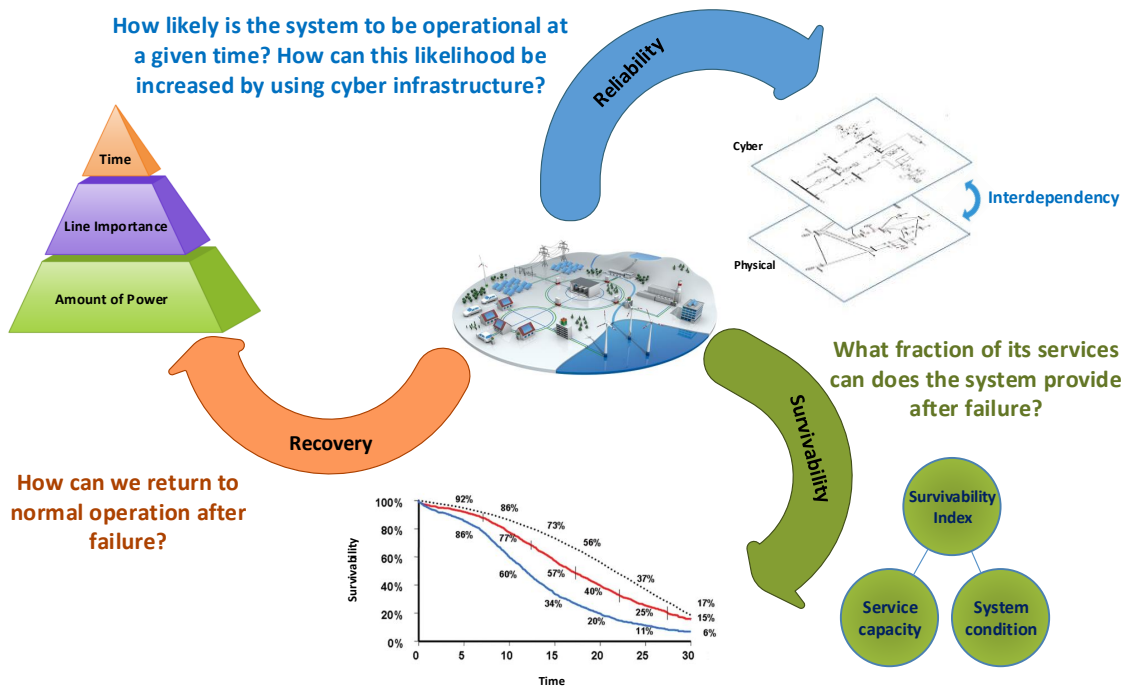


Figure 1.1. High-level abstraction of research objectives

The remainder of this thesis is organized as follows. Section 2 presents related literature on the analyses of reliability and survivability of power grids. In Section 3, we propose respective approaches for analysis of reliability and survivability, and explain how the proposed approach can provide information to guide recovery efforts. Section 4 presents a detailed case study on the IEEE 9-bus system and illustrates application of the proposed approach. Finally, Section 5 concludes this thesis and outlines future extensions to the research.

2 BACKGROUND AND RELATED WORK

Given the dependence of almost any other system on continuous supply of electricity, the power grid can be considered the most important of all critical infrastructures [7]. Smart grids, which are large-scale networked cyber-physical systems, have been introduced to the energy sector as part of efforts to increase the reliability, energy, and sustainability of the generation, distribution, and transmission of power. Regardless of their level of support from cyber infrastructure, power grids are comprised of numerous interconnected components whose operation (or failure) is dependent upon each other. Section 1 described two events where this interdependence led to large-scale and lengthy blackouts. These blackouts are the end result of cascading failure, which is defined as “the usual mechanism by which failures propagate to cause large blackouts of electric power transmission systems [8].” Refs. [9–11] present detailed investigations of cascading failures.

A notable study on the topic of cascading failures is presented in Ref. [9], where the authors investigate the impact of using local power sources by developing a simulation model to prove that local power sources can reduce the probability of cascading failure. A related study is presented in Ref. [10], where a model is proposed for vulnerability of a power grid to sequences of cascading events. The “vulnerability” term is defined in the context of cascading events and goes beyond the traditional concept of $N - 1$ or $N - 2$ system contingency. Component-level failures investigated in this study include outages of transmission lines and generators. In a relatively different study presented in [11], the authors studied the impacts of the topology of power grids on failure propagation by developing a DC power flow model. The conclusion reached was that reduced connectivity can improve performance.

While security attacks and accidental failures of transmission lines, generators, or transformers are examples of root causes for cascading failures, another potential cause is power grid congestion. A grid is considered congested when the existing transmission lines become incapable of accommodating the entire load demand during periods of emergency load conditions. One method of reducing transmission congestion is to balance the power flow using power electronics devices such as Flexible AC Transmission Systems (FACTS), which can enable increased utilization of the existing power grid infrastructure [12]. The success of these devices in directing the power flow to prevent and/or mitigate the effects of cascading failures has been demonstrated in many studies, including [13–15]. The topics discussed in these studies include optimal placement and configuration of FACTS devices, with the goal of achieving minimum total congestion.

Prediction of the effects of cascading failures can be accomplished through modeling of dependability attributes of a system. The specific dependability attributes to be chosen depend on the type of service a system provides and expected behavior of the system in face of disturbances. One such attribute is reliability, which is defined as the probability of failure-free operation of a system over a given duration of time, under given conditions [16]. Reliability has been extensively studied for power grid systems and modeled both qualitatively [17] and quantitatively [18, 19]. The authors of [17] have carried out analysis of the impact of demand response on the reliability of distribution systems. In this study, reliability evaluation of the power system is based on the static balance between load and generation (and existence of system facilities to meet the demand). Both analytical and simulation-based approaches for evaluating the reliability indices of distribution systems are presented in [18]. A graph-theoretical model is proposed in Ref. [19], where the goal is importance analysis.

The reliability model used in this thesis is based on the Markov Chain Imbeddable Structure (MIS), which provides a framework for quantitative reliability modeling of complex systems [20]. This technique is well-suited to analysis of an existing network with a known topology, in contrast to methods utilizing random networks, which are beneficial mostly in the design stage. A distinguishing factor of the work in this thesis is that the failure of both cyber and physical components of the smart grid are considered in evaluating dependability and guiding recovery efforts.

As an attribute of dependability, reliability takes a binary view of operation of a system, i.e., degraded operation, where partial functionality has been retained is considered equivalent to catastrophic failure. In contrast to availability analysis, which captures both failure and recovery, reliability analysis terminates upon failure of a system. This perspective falls short for modern critical infrastructures, which are expected to autonomously withstand attacks, remedy the consequences of failure, and recover in a timely manner. Survivability, defined as “the ability of a system to continue to function during and after a disturbance,” is more appropriate for a system that is expected to be resilient [21].

A representative qualitative study on survivability is [22], which presents a systematic approach for determining common and complementary characteristics of survivability. The approach includes definition, attributes, and evaluation measures for survivability.

The survivability of power grids is the topic of [23–26]. In [23], the authors propose a survivability index based on the combination of voltage support, voltage stability, and reliability of the system. The System Average Interruption Duration Index (SAIDI) - a metric commonly used to assess the consequence of failure - is extended to analysis of smart grids in [24]. This study is extended in [25] to propose an analytical model for survivability of a power grid, through initial state conditioning, state space factorization, and state aggregation. Another extension to [24] is presented

in [26], where survivability is assessed in terms of available power for each customer up to a specific time. This is in contrast to [26], which considers the total available power.

More specifically, in [25] the survivability index, denoted as $m_j(t)$, is determined based on Equation (2.1):

$$m_j(t) = N_j E \quad (2.1)$$

In Equation (2.1), N_j is the number of customers affected by a failure at section j , and E is energy demanded per user per unit time.

In contrast, the survivability index proposed in [26] is calculated as in Equation (2.2), where V is the survivability metric, P_n is the amount of available power after failure, P_o is the amount of available power before failure, L_n is the amount of power consumption by loads after failure, and L_o is the amount of power consumption by loads before failure.

$$V = \frac{\frac{P_n}{L_n}}{\frac{P_o}{L_o}} = \frac{P_n L_o}{L_n P_o} \quad (2.2)$$

One distinction of the survivability analysis proposed in this thesis from related studies is that we consider the system condition - the fraction of components that remain functional after failure - and the available power at the time of failure. Deteriorated system condition is conducive to cascading failure, and as such, the proposed metric is a more comprehensive predictor of survivability. A second distinction is that our work considers the fully-functional state of the system as the initial state for survivability analysis, in contrast to [25], where the state at the time of failure is considered the initial state. Beginning analysis from a fully-functional state facilitates linkage of reliability and survivability models, and more accurately reflects the extent of degradation that results from a failure or sequence of failures.

A more fundamental distinction is that our proposed analysis considers contingencies where the root cause is a fault in the cyber infrastructure. Despite the considerable research activity related to smart grids, dependability analysis of these systems is primarily focused on the effects of contingencies resulting from a fault in a physical component such as a transmission line.

In addition to reliability and survivability analysis, this thesis presents a method for guiding recovery efforts. Related studies include [25], where the strategy proposed is to reduce load demand on a failing system by providing sufficient backup power to temporarily meet demand. This increases the probability that the system will continue to function in spite of failure. In [26, 27], the strategy is to first recover the transmission line that supplies the greatest amount of power, then the line that supplies the second greatest amount of power, and so on. Both [26] and [27] neglect the duration of time associated with recovery of each line, which can affect the net service level achieved during the recovery process. The recovery method proposed in this thesis addresses this shortcoming by considering the rate of power recovery in determining the sequence of restoration efforts.

Figure 2.1 summarizes the literature cited in this section, and depicts the main categories of related work.

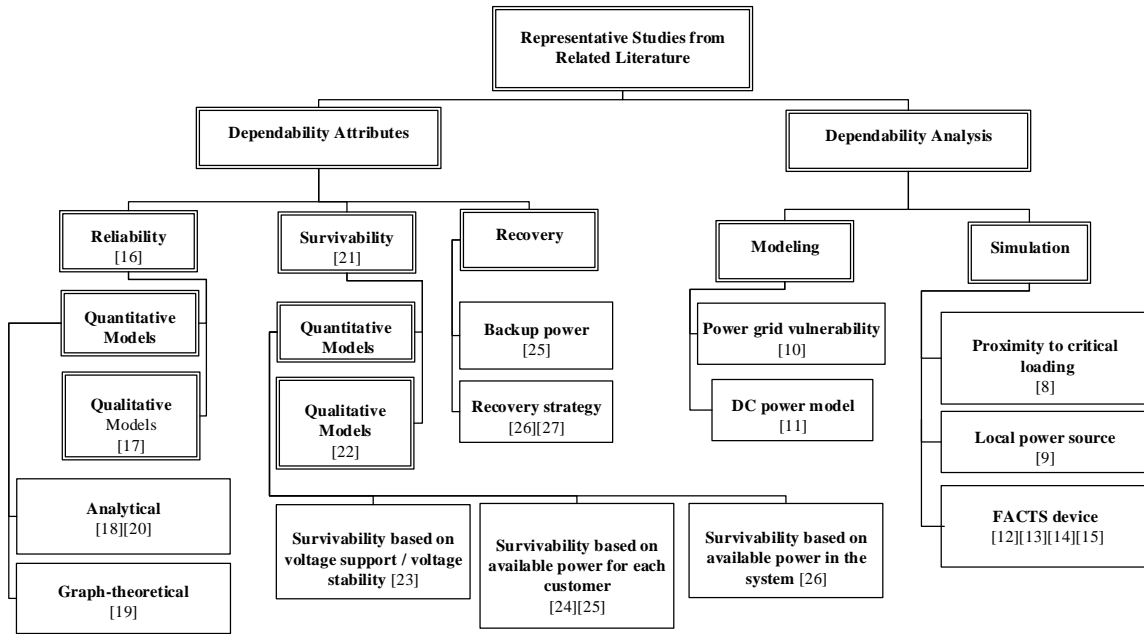


Figure 2.1. Representative studies from related literature

3 METHODOLOGY

This section discusses reliability and survivability modeling of a cyber-physical power grid, as well as a strategy for guiding fault recovery decisions. Reliability represents the system in a binary way; either functional or failed. Survivability captures the extent of system degradation and determines the retained system functionality. The proposed recovery strategy aims to achieve the highest potential survivability throughout the course of the recovery process, until the initial level of operational ability is restored - assuming that such restoration is possible.

3.1 RELIABILITY MODELING

Critical infrastructure systems such as the power grid are expected to be extremely reliable - a challenging feat, considering the complexity, scale, and interconnectedness of these systems [28]. Objective estimation, assessment, and prediction of the reliability of these systems is similarly challenging. Any meaningful representation of reliability should reflect both the state of components and the operational condition of the system. The MIS technique [20], which determines system-level reliability based on the state (functional or failed) of its constituent components, is well-suited to achieving this goal. This technique is comprised of four elements: matrix representation of system states, classification of each state as functional or failed, vector representation of the probability distribution for the initial system state, and matrix representation of state transition probabilities.

We illustrate the MIS technique through its application to a very simple test system: the IEEE 9-bus grid. This system has three generators, nine transmission lines, and three loads, as depicted in Figure 3.1. Among these components, outage of transmission lines is the event with by far the greatest impact on reliability. For

tractability, we focus on outage of transmission lines as representative of component-level failure in physical components of the grid. Each of the nine transmission lines can experience an outage, leading to a total of $2^9 = 512$ system states. Table 3.1 represents these states as a binary matrix. Each row of the table represents one of the 512 states. Each column represents the state of one transmission line. A '1' denotes that the transmission line is functional; a '0' denotes that it has experienced an outage.

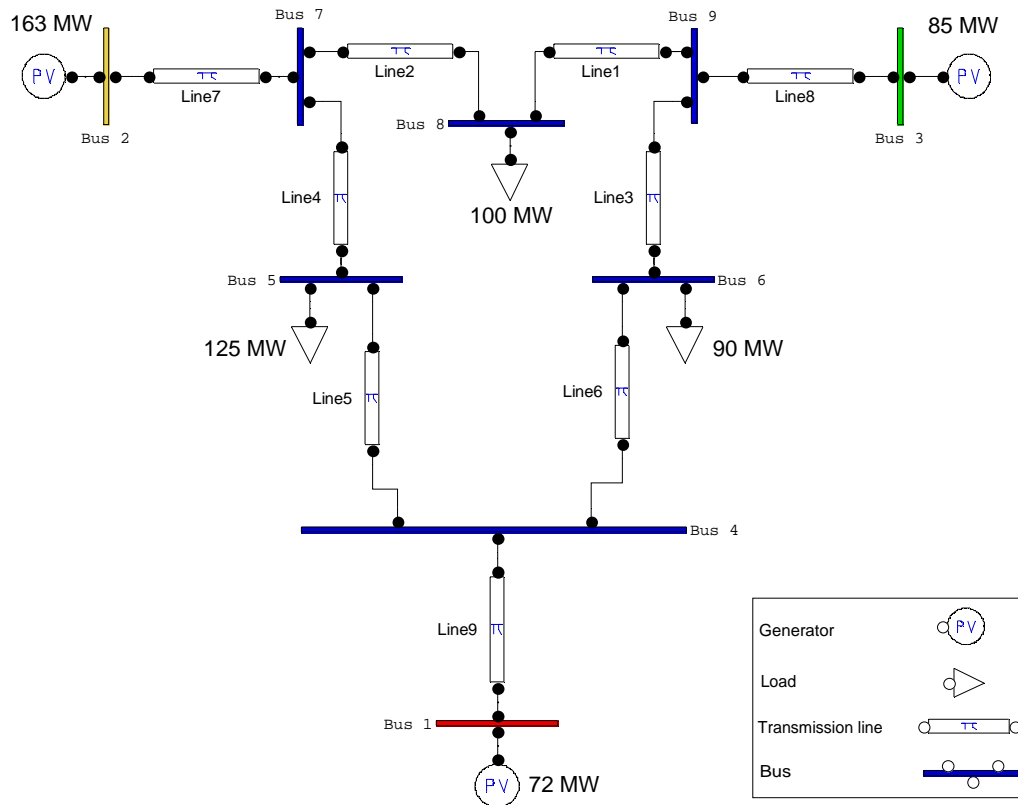


Figure 3.1. Sample test system: the IEEE 9-bus grid

Table 3.1. Matrix representation of system states for the IEEE 9-bus system

States	Transmission Lines								
	<i>TL1</i>	<i>TL2</i>	<i>TL3</i>	<i>TL4</i>	<i>TL5</i>	<i>TL6</i>	<i>TL7</i>	<i>TL8</i>	<i>TL9</i>
S_0	1	1	1	1	1	1	1	1	1
S_1	1	1	1	1	1	1	1	1	0
S_2	1	1	1	1	1	1	1	0	1
S_3	1	1	1	1	1	1	0	0	0
S_4	1	1	1	1	0	0	0	1	1
S_5	1	1	1	1	0	0	0	1	0
S_6	1	1	1	1	0	0	1	0	1
S_7	1	1	1	1	0	0	1	0	0
$S_8 - S_{503}$
S_{510}	0	0	0	0	0	0	0	0	1
S_{511}	0	0	0	0	0	0	0	0	0

Classification of the system states is represented by a 1×2^n vector denoted as \mathbf{u} . Element $\mathbf{u}[\mathbf{i}]$ is ‘1’ if the system is considered functional in state S_i , and ‘0’ otherwise.

The third element of the MIS model is a vector representing the probability of being in each of the 512 states when the system is initialized. In this vector, denoted as $\mathbf{\Pi}_0$, element i represents the probability of having an initial state of S_i , as is shown in Equation (3.1).

$$\mathbf{\Pi}_0 = [Pr(Y_0 = S_0), Pr(Y_0 = S_1), \dots, Pr(Y_0 = S_N)] \quad (3.1)$$

Linking the state matrix and initial state vector is a set of state transition probability matrices - one for each transmission line. In the Λ_k matrix, which reflects the effect of outage of transmission line k , element $p_{ij}(k)$ represents the probability of the system changing from state S_i to state S_j due to outage of the transmission line. For instance, if line $TL9$ fails, the state of the system will change from S_0 to S_1 , as shown in Table 3.1.

System-level reliability of the n -component system can now be determined as:

$$R_{sys} = \Pi_{\mathbf{0}} \prod_{k=1}^n \Lambda_k \mathbf{u} \quad (3.2)$$

The probabilities required for populating this model can be determined based on historical data or simulation. For the case studies presented in this thesis, we used the Power Systems Analysis Toolbox (PSAT), an open source Matlab toolbox for analysis and design of electric power systems [6]. The choice of simulator was based on the ability to simulate components of the cyber infrastructure of a smart grid with high fidelity and resolution.

To determine the net effect of introducing cyber infrastructure to a physical power grid, we compare the system-level reliability for the purely physical grid and the smart grid created by adding intelligent control. Each case, respectively, is described in one of the two subsections that follow. In both cases, we classify the system states by utilizing fault injection and $N - 1$ contingency analysis, i.e., we cause the components of the grid to fail, one-at-a-time, and observe the effects. In evaluating reliability, we consider the grid to have “failed” at the system level if cascading failure occurs, i.e., if the component failure caused by injection of a single fault results in failure of at least one other component. The data from $N - 1$ contingency analysis is used to populate the \mathbf{u} vector.

3.1.1 Reliability of a Purely Physical Power Grid Based on Equation (3.2), the reliability of a purely physical power grid can be represented as in Equation (3.3), where p_L denotes the reliability of a transmission line. For tractability, all lines have been assumed to be equally reliable. Relaxing this assumption requires only a minor change to the model, akin to changing a homogeneous Bernoulli trial to its non-homogeneous counterpart. $q_{TL} = 1 - p_{TL}$ is the unreliability of a line. n represents the number of transmission lines. M denotes the number of transmission lines whose outage does not cause a cascading failure.

$$R_{sys} = p_L^n + Mp_L^{n-1}q_L \quad (3.3)$$

3.1.2 Reliability of a Smart Grid To determine the effect of adding cyber infrastructure to a physical grid to create a smart grid, we add a number of FACTS devices to purely physical grid. The concept of FACTS devices refers to a family of power electronics-based devices that are able to enhance AC system controllability and stability and to increase the power transfer capability [12]. These devices were developed by the Electrical Power Research Institute (EPRI) in the 1980s. FACTS devices enhance the power grid with features such as increased transmission capacity, power flow control, and transient stability improvement [12].

In our simulations, we realized a smart grid by supplementing the simulated IEEE 9-bus system with Static Synchronous Series Compensators (SSSCs), a type of series FACTS devices that modifies the effective reactance of a line by generating and injecting a series voltage through the line [29].

The PSAT environment allows the user to install an SSSC device on any transmission line or bus and modify the configuration of the SSSC. We identified the parameter that had the greatest effect on the power flow balance: the Percentage Amount of Series Compensation (PASC) [13, 14]. This parameter ranges from 0 to

99. A value of 0 means the existence of SSSC device has no effect on the transmission line, even though it acts like a closed circuit breaker.

We added two FACTS devices to the IEEE 9-bus system to create its smart grid counterpart, as depicted in Figure 3.2. This number is unrealistically large for the scale of the network, but useful for illustration of the technique in a non-trivial case. Once the number of control devices is decided, two questions remain: where to place them, and how to configure their settings - in this case the PASC value. Exhaustive search for an optimal solution is prohibitively complex for any grid of non-trivial scale, but given the small scale of our example, feasible here. Details for our case study are presented in Section 4.1.2. For larger systems, approaches utilizing evolutionary computing have been proposed in the literature, e.g., in [30].

Per Equation (3.2), the reliability of the smart grid can be represented as:

$$R_{sys} = (p_L^n + Mp_L^{n-1}q_L) p_{SSSC_1} p_{SSSC_2} + \left(\sum_{\forall states \in S} p_L^{n-1}q_L \right) p_{SSSC_1} p_{SSSC_2} \quad (3.4)$$

where:

M is the total number of states where the system remains functional despite the outage of single line, whether or not SSSC devices are added.

S is the set of states where the system would have failed as a result of a single line outage, but remains functional due to the addition and correct configuration of the SSSC devices.

p_{SSSC_1} and p_{SSSC_2} are the respective reliabilities of the two SSSC devices.

If the system's reliability is increased by our choice of position and configuration for the SSSC devices, the \mathbf{u} vector will have a greater number of functional

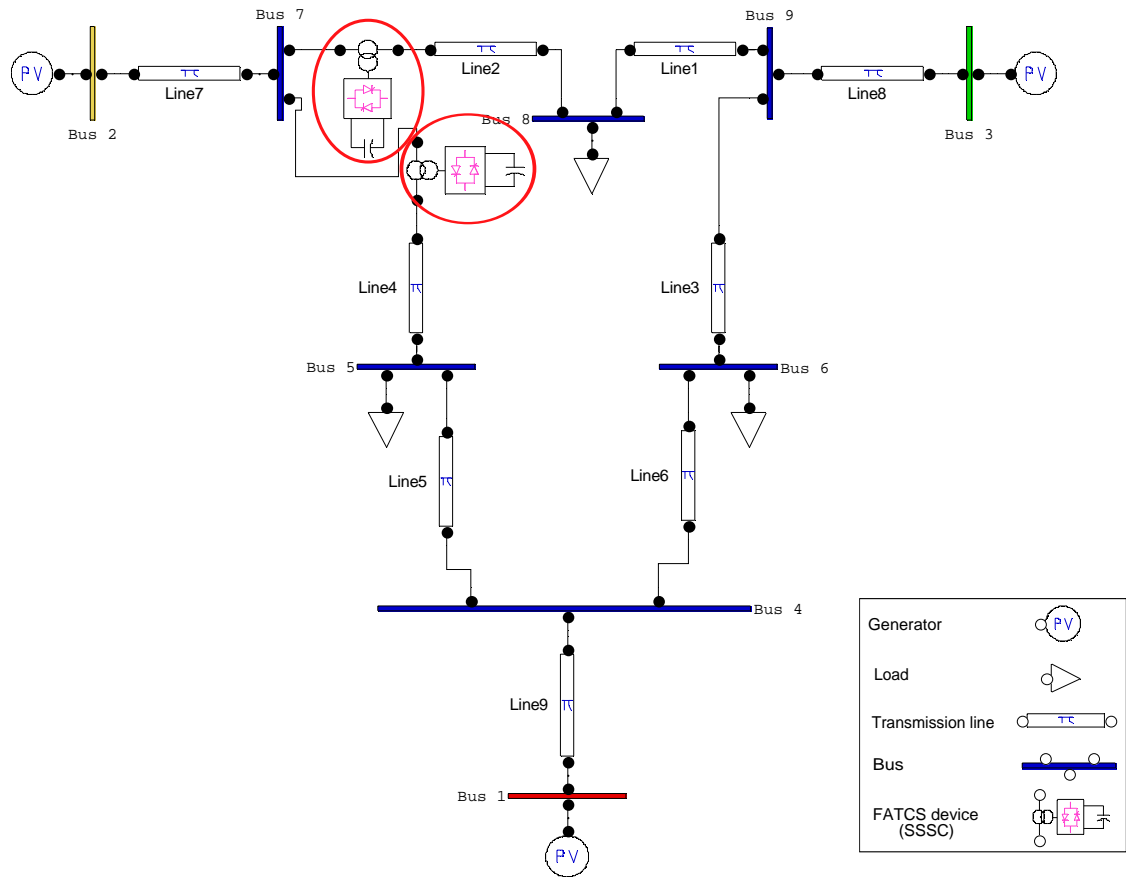


Figure 3.2. Smart grid created by adding two of SSSC devices to the IEEE 9-bus test system

states than its counterpart for the purely physical power grid. In other words, the set S will be non-null.

3.2 SURVIVABILITY ANALYSIS

The ability of a system to continue operating and provide service, albeit with lower performance, under adverse conditions (failure of one or more of its components) is broadly defined as survivability. In other words, survivability can be defined as the relationship between system conditions and service capacity, each of which is quantified as a number between 0 and 1.

In evaluating survivability, we consider both the condition and the service capacity of the system. For instance, assume there is a power grid that has 10 transmission lines, and three generators that provide total power of 400 MW. Assume a failure caused by outage of two transmission lines that connect a 100 MW generator to the power grid. The service capacity after failure would be 75% (of its nominal power under normal operating conditions), and the system condition would be considered 80% of its nominal condition, as two of the ten transmission lines have failed.

The system condition levels are defined based on transmission line outages that would cause a cascading failure that would affect the ability of the system to serve its load, i.e., an outage that would cause the available power to be less than the demand. The service capacity metric quantifies the inability to meet demand. Mathematically, the system condition at time t_i , denoted as $\alpha(i)$ is determined as:

$$\alpha(i) = 1 - \frac{d_i}{n - d_{i-1}} \quad (3.5)$$

In Equation (3.5), n is the total number of transmission lines and d_i is the number of transmission lines that have experienced an outage or are otherwise unavailable (unreachable) at time t_i .

The service capacity, (β) , is used to represent the impact of failure or outage on the ability of the grid to meet its power demand. At a given time t_i after a failure, the service capacity can be calculated as:

$$\beta(i) = \frac{P_G - P_L(i)}{LD} \quad (3.6)$$

where P_G is the power generated when the grid is fully functional, $P_L(i)$ is the power lost due to failure up to time t_i , and LD is the amount of power demand.

The survivability index depends on the power available and connectivity of the power grid after a failure, as well as the power demanded by loads. Equations 3.5 and 3.6 can be combined to yield the survivability index, denoted as SI :

$$SI = \begin{cases} 0, & \text{when } \alpha = 0 \text{ or } \beta = 0 \\ 1, & \text{when } (\alpha \geq \gamma \text{ and } \beta \geq 1) \\ \alpha * \beta, & \text{when } (\alpha < \gamma \text{ and } 0 < \beta < 1) \end{cases} \quad (3.7)$$

In Equation 3.7, γ is the minimum system condition that will prevent failure of a generator or inability to serve a load.

We can qualitatively describe the survivability index as follows:

- If one or more transmission lines have failed, but the generated power is not reduced to less than the demand in a specific time interval, then the SI value is 1. This means the system is stable.
- If all the transmission lines fail, or if a failure in the system reduces the generated power to zero, then the SI value will be 0.
- If one or more transmission lines fail and therefore reduce the generated power to less than the demand, in a specific time interval, then the SI value will be less than 1. This case is important for determining the level of degradation.

Based on the survivability index, five different levels of degradation were defined, as described in Table 3.2.

These values can be used to determine a recovery strategy, as described in the following section. In brief, the transmission line whose failure leads to the greatest degradation (lowest SI value) is considered the highest priority transmission line, the

Table 3.2. System degradation levels.

SI value	Degradation levels		Description
$SI = 1$	1	Stable	Failure of components with no impact
$0.8 \leq SI < 1$	2	Minor	Failure of components has little impact
$0.6 \leq SI < 0.8$	3	Moderate	Failure of components has modest impact
$0.4 \leq SI < 0.6$	4	Severe	Failure of components has high impact
$SI < 0.4$	5	Catastrophic	Failure of components leads to system collapse

transmission line whose failure leads to the second-lowest SI value is considered the second highest priority transmission line, and so on.

3.3 STRATEGY FOR RECOVERY FROM AN OUTAGE

The proposed recovery process is comprised of three stages. In the first stage, the load demand in the system is reduced after the occurrence of a failure. This will help the system temporarily meet demand. The second stage consists of repairing transmission lines, one-at-a-time, based the assumption of the availability of a single recovery team. In grids larger than our simple exam, this assumption can be relaxed to allow for concurrent recovery of multiple lines. The recovery sequence depends on the priority index of each transmission line, which is determined based on the contribution of the line to the survivability index.

The most important stage is the third stage. This stage involves increasing the generated power to meet the load demand and to reach the initial operational level. The recovery strategy aims to restore the system to full capacity in the shortest possible time. This goal guides the recovery sequence, prioritizing repair of the line that will enable the system to provide the highest amount of generated power in the

shortest time. For each transmission line, i we compute $O_i = \frac{P_r(i)}{D_r(i)}$, where $P_r(i)$ and $D_r(i)$, respectively, are the power recovered as a result of repairing line i and the time required for this recovery. The line with the greatest value of O - the recovery rate of power - is given the highest priority for recovery. The process is repeated until all transmission lines have been recovered.

4 SIMULATION ENVIRONMENT

This section illustrates the methods described in Section 3 through application to a simple test system - the IEEE 9-bus grid. The methods can be scaled to much larger grids; a small example was chosen in the interest of clarity and brevity. As briefly described in the previous section, the IEEE 9-bus test system, depicted in Figure 3.1 and repeated here in Figure 4.1 for ease of reference, is comprised of:

1. Nine transmission lines - three to deliver the power from the generators to the network and the rest to distribute the power.
2. Three generators, connected to buses 1, 2, and 3, respectively.
3. Three loads, connected to buses 5, 6, and 8, respectively.
4. Nine buses, connecting the transmission lines, loads and generators.

For simulation purposes, bus number 1, connected to the slack generator, is used as the reference bus. The generator capacity on bus 1 is 72 MW, the generator capacity on bus 2 is 163 MW, and the generator capacity on bus 3 is 85 MW. The load on bus 5 is 125 MW, the load on bus 6 is 90 MW, and the load on bus 8 is 100 MW [31, 32].

The following three subsections, respectively, illustrate reliability analysis (described in Section 3.1), survivability analysis (described in Section 3.2), and recovery (described in Section 3.3) for the example of the IEEE 9-bus test system and an analogous smart grid.

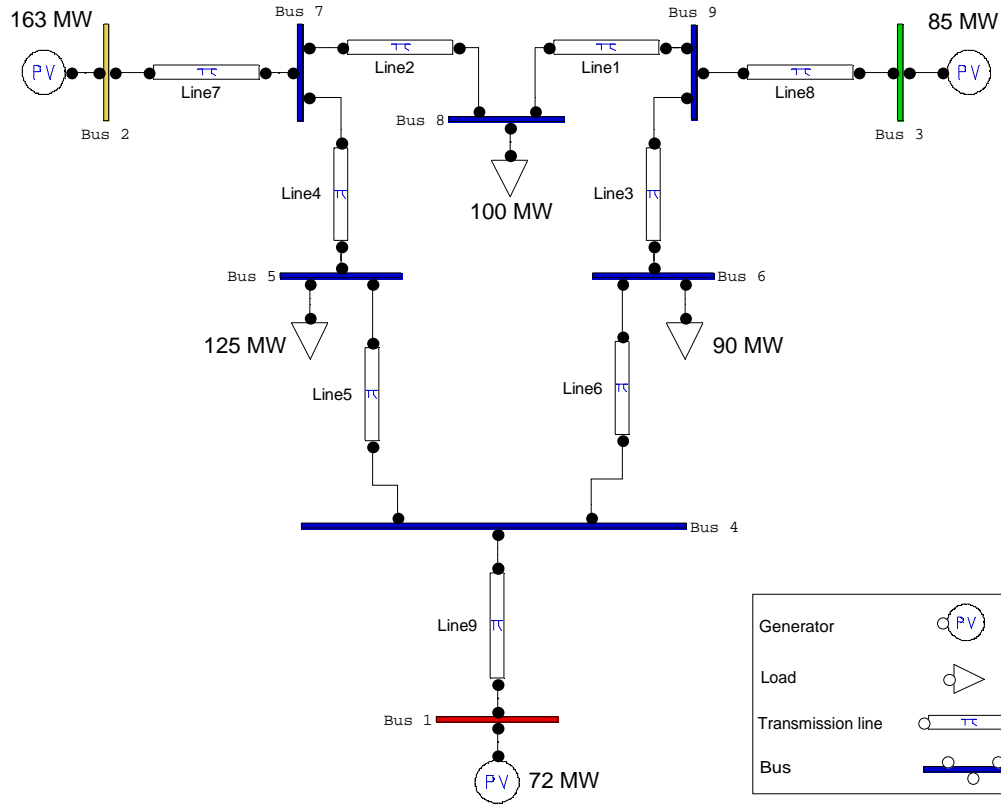


Figure 4.1. IEEE 9-bus test system

4.1 RELIABILITY ANALYSIS

In this section, we use simulation to populate the reliability models derived in Sections 3.1.1 and 3.1.2 for conventional and smart version, respectively, of the IEEE 9-bus system.

4.1.1 Reliability of a Purely Physical IEEE 9-Bus Grid.

The reliability of a purely physical (with no intelligent devices such as SSSC), denoted as R_{sys} , was derived as a function of the line reliability, p_L , in Equation 3.3 as $R_{sys} = p_L^n + Mp_L^{n-1}q_L$. This model reflects the reliability of a grid where only one transmission line outage can be tolerated at any given time. The outage of more than one line is

assumed to bring down the entire grid (due to its small size). This model will apply to any grid with equally reliable transmission lines. The value of p_L can be determined from the system history, or the specification of the transmission lines. The value of M , which reflects the number of transmission lines whose outage does not result in cascading failure. For our case study, this value is determined using simulation, with PSAT [6]. More specifically, we carried out $N - 1$ contingency analysis by causing an outage of one transmission line at a time, and conducting power flow analysis to determine whether a cascading failure would result. Table 4.1 shows the results of the simulation. This evaluation revealed that all but two transmission lines cause a cascading failure when they experience an outage. These transmission lines are lines 1 and 6, circled in Figure 4.2. The results show that $M = 2$, in other words, two states exist where the outage of one transmission line leaves the system functional. The system reliability can be represented as:

$$R_{sys} = p_L^9 + 2p_L^8 q_L \quad (4.1)$$

Table 4.1. Cascading failures of the purely physical IEEE 9-bus system

Line outage injected	First line to fail	Second	Third	Fourth	System state
1	1				Functional
2	2	4	7		Failed
3	3	4			Failed
4	4	2, 3	7		Failed
5	5	4	2, 3	7	Failed
6	6				Functional
7	7				Failed
8	8				Failed
9	9				Failed

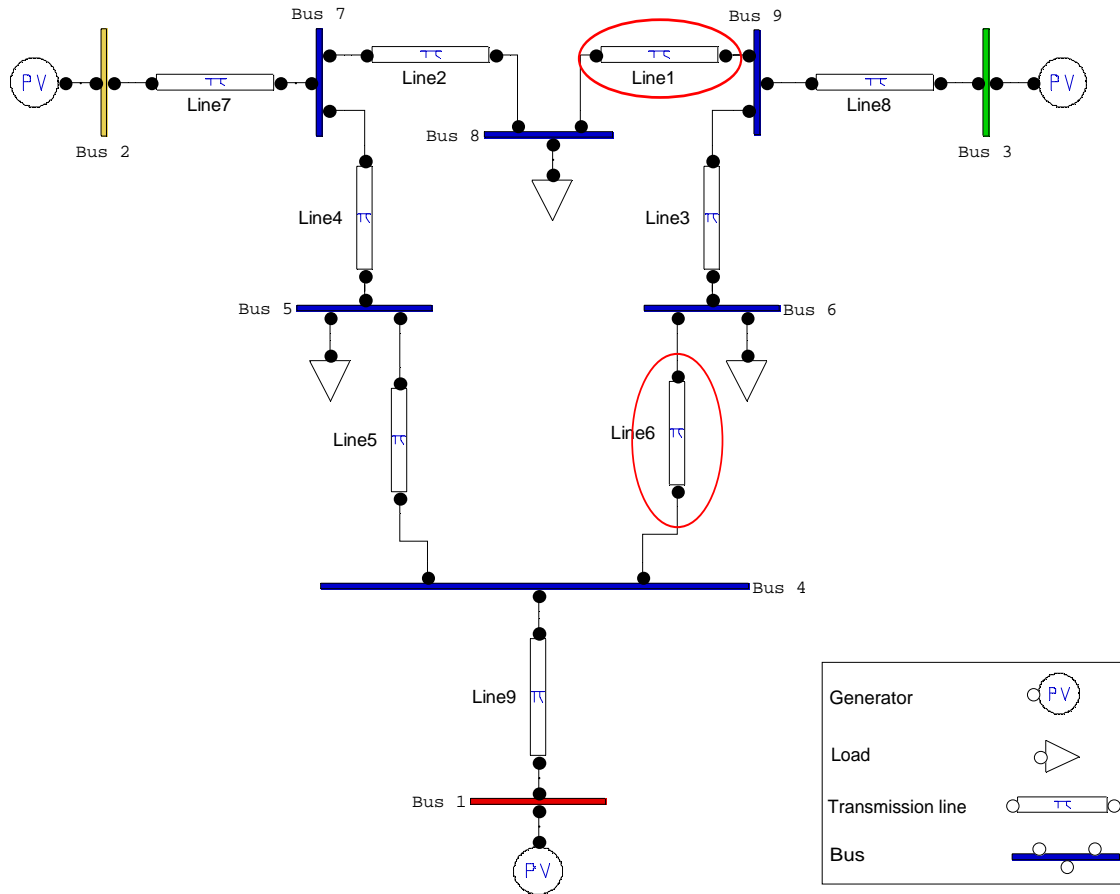


Figure 4.2. Transmission lines whose outage will *not* cause cascading failure

4.1.2 Reliability of a Smart Grid Based on the IEEE 9-Bus System.

As described in Section 3.1.2, in an effort to mitigate the effects of line outage and increase reliability, two SSSC devices were installed on the IEEE 9-bus system being simulated. Placement of the devices was determined by inspection - the small size of the grid resulted in only $\binom{9}{2} = 36$ cases to be investigated. As mentioned earlier, evolutionary computing approaches, e.g., [30] can be used if the size of the grid makes exhaustive inspection prohibitively costly.

Of the 36 cases investigated, only two configurations led to improvement of reliability of the system. This improvement is achieved by isolating a line outage

and preventing it from triggering a cascading failure. The first configuration that achieved reliability improvement involved placing the SSSCs on transmission lines 2 and 4, as shown in Figure 4.3. Similarly determined by inspection were the PASC values for the SSSC devices, which range from 0 to 99 and characterize the extent of series compensation carried out by the device. For the configuration of Figure 4.3, PASC values between 45 and 65 led to improvements in reliability. Utilizing the SSSC devices with this placement and configuration reduced the single-line contingencies that result in system-level failure from seven to four cases. The corresponding PSAT power flow simulation results are shown in Table 4.2. It is worth noting that the single-line contingencies resulting from outage of lines 7, 8, or 9 do not cause cascading failure of transmission lines, but still lead to a failed system state. The reason is that each of these lines connects one of the three generators to the remainder of the grid, and outage of any of these three lines will disconnect a generator and will leave the system unable to meet the load demand.

Table 4.2. Failure propagation in IEEE 9-bus smart grid, SSSCs on lines 2 and 4

Line outage injected	First line to fail	Second	Third	Fourth	System state
1	1				Functional
2	2				Functional
3	3				Functional
4	4	3			Failed
5	5				Functional
6	6				Functional
7	7				Failed
8	8				Failed
9	9				Failed

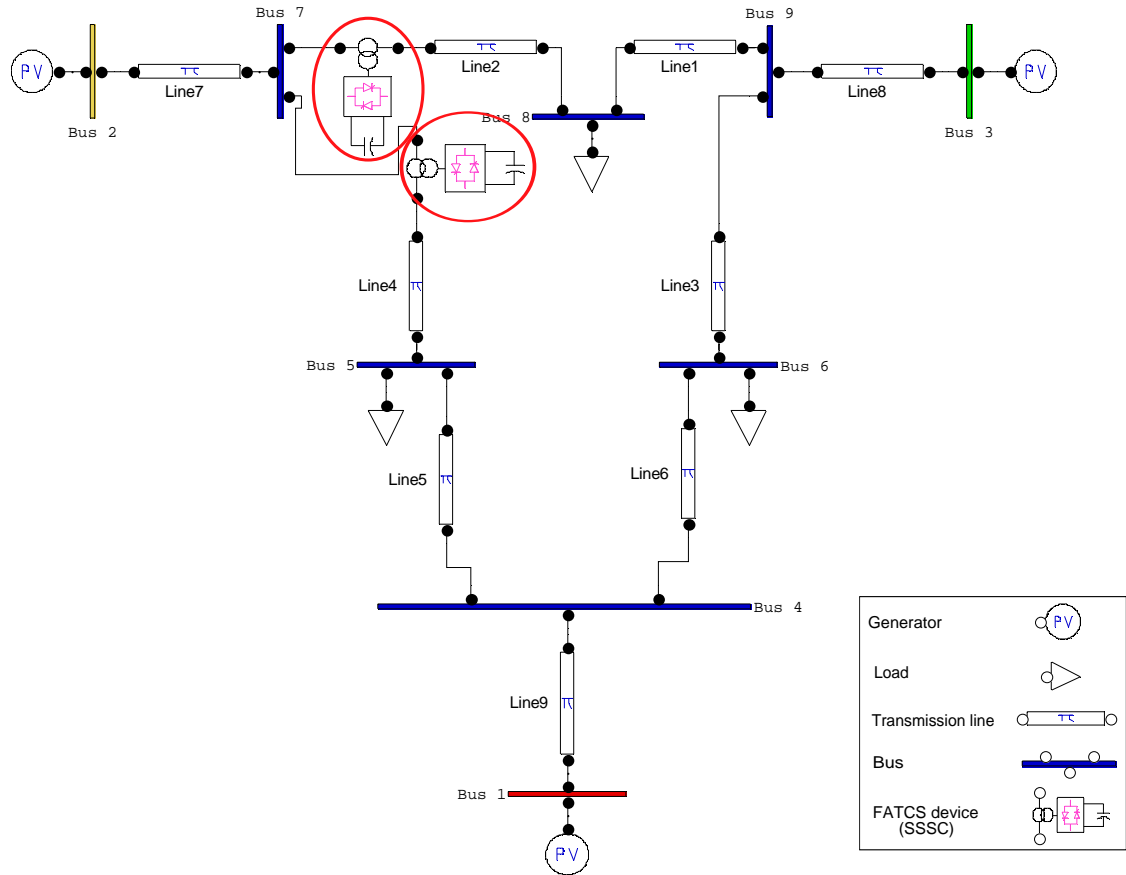


Figure 4.3. Configuration 1 for IEEE-9 smart grid: SSSCs on lines 2 and 4

The second configuration that improved reliability resulted from placing the SSSC devices on transmission lines 3 and 4, as shown in Figure 4.4. PASC values between 48 and 63 led to this improvement. This configuration also reduced the single-line contingencies that cause system-level failure from seven to four cases. The corresponding PSAT power flow simulation results are shown in Table 4.3.

Quantitatively, the two configurations were found to be identical in their effect on reliability. In both cases, using the two SSSC devices increased the number of states where the system remains functional despite single-line contingency from two to five states. Assuming that both SSSC devices are impervious to failure, the reliability of the grid can be represented as in Equation 4.2.

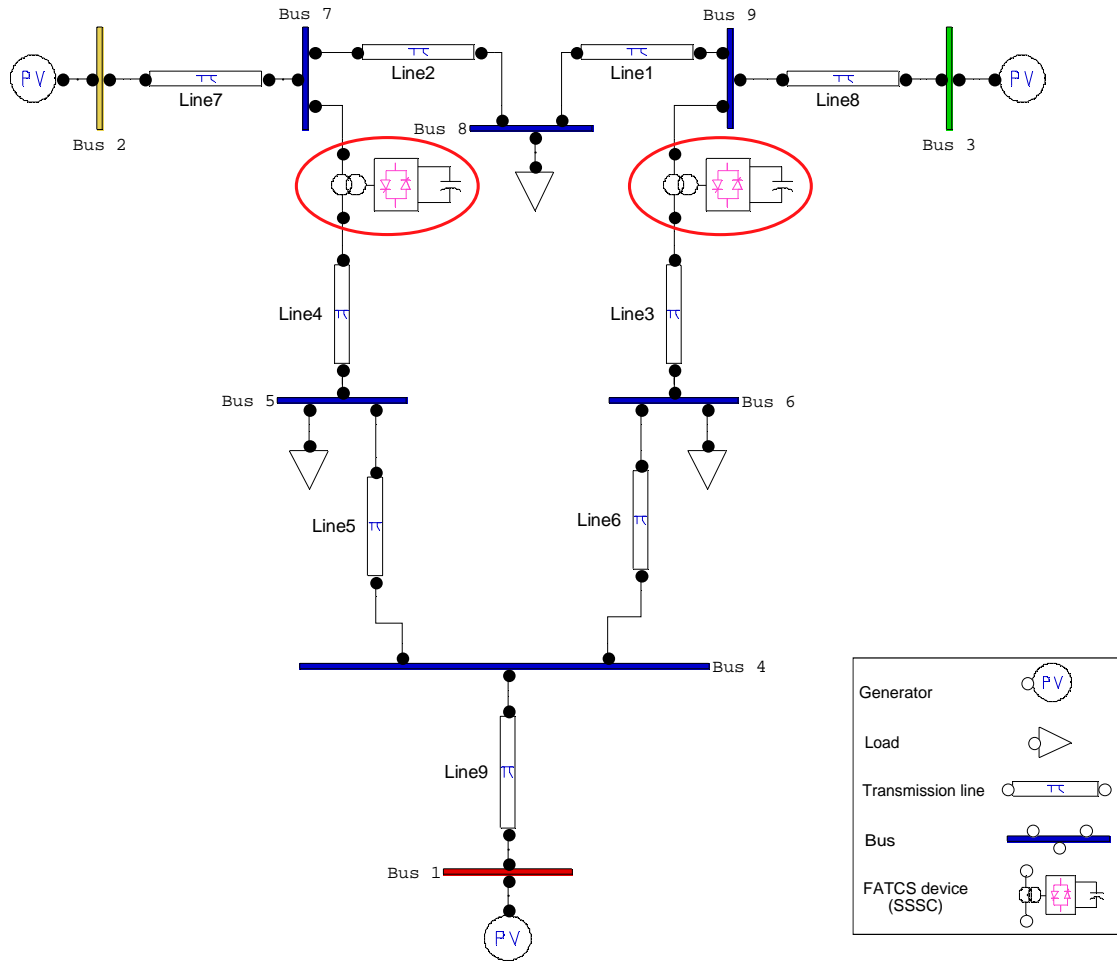


Figure 4.4. Configuration 2 for IEEE-9 smart grid: SSSCs on lines 3 and 4

$$R_{sys} = p_L^9 + 5p_L^8q_L \quad (4.2)$$

With the more realistic assumption that the SSSC devices are themselves prone to failure, Equation 4.3 represents the resulting reliability.

$$R_{sys} = (p_L^9 + 5p_L^8q_L) p_{SSSC_1} p_{SSSC_2} \quad (4.3)$$

Table 4.3. Failure propagation in IEEE 9-bus smart grid, SSSCs on lines 3 and 4

Line outage injected	First line to fail	Second	Third	Fourth	System state
1	1				Functional
2	2				Functional
3	3				Functional
4	4	2	7		Failed
5	5				Functional
6	6				Functional
7	7				Failed
8	8				Failed
9	9				Failed

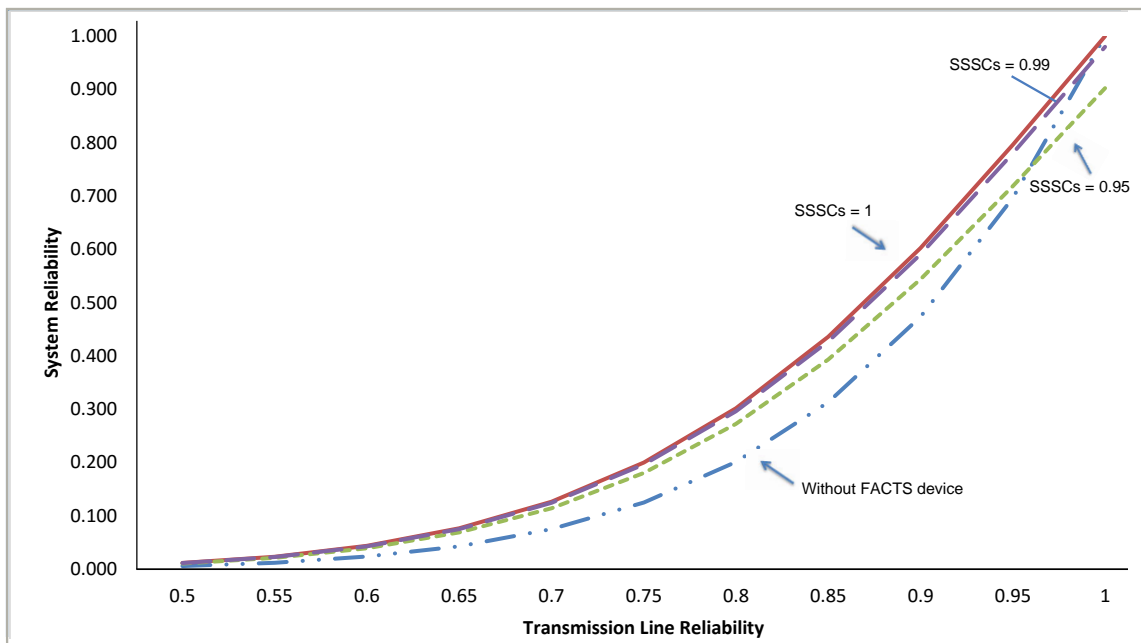


Figure 4.5. Reliability improvement with $p_{SSSC} = 1$, $p_{SSSC} = 0.99$, and $p_{SSSC} = 0.95$, respectively

Figure 4.5 illustrate the reliability improvement achieved by fortifying the IEEE 9-bus grid with two SSSC devices, for different values of transmission line and

SSSC reliability. It is worth noting that transmission line reliability is unlikely to reach values as low as 0.5 in anything other than disaster scenarios. In Figure 4.5, both SSSC devices are assumed to have the same reliability, denoted as p_{SSSC} .

4.2 SURVIVABILITY ANALYSIS

In Section 3.2, we described our proposed survivability index, which is based on the condition (extent of outage) in the grid and the resulting loss of capacity. In this section, we illustrate evaluation of this survivability index for the IEEE 9-bus grid, which generates 320MW of power using three generators. The three loads on the grid have a total demand of 315MW. In simulating the grid, we assume that each generator can exceed its rated capacity by 10% to compensate for failure of another generator, or in response to increased demand.

In the following subsections, we illustrate by example evaluation of the system condition, service capacity, and survivability index for the IEEE 9-bus grid.

4.2.1 Evaluation of System Condition After Line Outage The results of the $N - 1$ contingency analysis described in Section 4.1.1 demonstrated that in the absence of SSSC devices, seven of the nine possible single-line contingencies will cause system-level failure. The respective outage of four different lines will trigger a cascading failure, and respective outage of three others will disconnect a generator from the system. In reliability analysis, we are interested only in the end state of the system after a line outage, i.e., can the outage be tolerated or will it bring down the grid? Survivability analysis takes a more nuanced view and evaluates the system as it degrades (or recovers). One of the two components that determine the level of survivability (as defined by our metric) is the system condition, α , which is determined as in Equation 3.5: $\alpha(i) = 1 - \frac{d_i}{n-d_{i-1}}$. In brief, the system condition at time i is evaluated as the fraction of transmission lines that remain functional and reachable by that time.

A complication in evaluating the system condition is lines with unknown status. These transmission lines may be functional, but they are unreachable due to outage of one or more other lines. For the example of our case study, we begin with a fully-functional grid, where all nine transmission lines are operational. Now assume that line 2 experiences an outage at the end of the first time slot. This outage propagates to line 4 by the end of the second time slot. The second outage leaves line 7 unreachable. The question in such a situation is what to assume about the transmission line that becomes unreachable, as in the absence of communication, it is unknown whether the line is functional or has failed. If the line were simply omitted from the analysis, valuable information - namely, that line 7 had survived for at least two time slots - will be lost.

Table 4.4 illustrates evaluation of the system condition for this example, which is triggered by the outage of line 2. The value in columns 1 through 4 denotes the number of lines with that status. A line is considered at risk if it can potentially fail. A line is considered unavailable if it is known to have experienced an outage or is unreachable. The number of unavailable lines at time i is d_i . For the example of the IEEE 9-bus grid, $n = 9$.

The table was populated as follows. Of the nine transmission lines initially at risk, one line had failed by t_1 . The number of the functional transmission lines at t_1 was calculated as $9 - 1 = 8$, and the number of the transmission lines at risk at t_2 was calculated as $9 - 0 - 1 = 8$. When another transmission line fails by t_2 , the number of functional transmission lines becomes $8 - 1 = 7$, and the number of the transmission lines at risk at the beginning of time slot 3 (ending at t_3) becomes $8 - 0 - 1 = 7$. A third transmission line becomes unavailable during time slot 3. The number of functional transmission lines at t_3 was calculated as $7 - 1 = 6$, and so on.

Table 4.4. Evaluation of system condition over time

Time	At risk	Unreachable	Outages	Unavailable (d_i)	Functional	Condition
t_1	9	0	1	1	8	$1-(1/9)=0.89$
t_2	8	0	1	2	7	$1-(2/8)=0.75$
t_3	7	1	0	3	6	$1-(3/7)=0.57$
t_4	6	0	0	3	6	$1-(3/6)=0.5$

Table 4.5 shows how the α value for four time slots after each single-line contingency. Outage of lines 7, 8, or 9 will disconnect a generator and will immediately cause failure, and hence the contingencies corresponding to these three lines have not been included.

Table 4.5. System condition analysis for effective failures in IEEE 9-bus system

Injected contingency	System condition at time			
	t_1	t_2	t_3	t_4
Line 1	0.89	0.87	0.87	0.87
Line 2	0.89	0.75	0.57	0.50
Line 3	0.89	0.75	0.71	0.71
Line 4	0.89	0.63	0.33	0.20
Line 5	0.89	0.75	0.43	0.14
Line 6	0.89	0.87	0.87	0.87

4.2.2 Evaluation of Service Capacity After Line Outage The second component of the survivability index is the service capacity, β . As in Equation 3.6, the service capacity at time i , denoted as $\beta(i) = \frac{P_G - P_L(i)}{LD}$; where P_G is the power generated before the outage, $P_L(i)$ is the power lost by time i as a result of the outage, and LD is the load demand. Service capacity is reduced by transmission line

outages that cause overload and outage of the other transmission lines and/or cause a generator or load to be disconnected.

Tables 4.6 and 4.7 show the service capacity that remains after a single-line contingency is injected into the simulated IEEE 9-bus system. Table 4.6 evaluates service capacity for contingencies that result in disconnection of a generator bus from the system. Table 4.7 captures the result of contingencies that partition the power grid into two or more networks, i.e., outage of lines 3 and 4, respectively; as well as the result of outage of line 5, which disconnects a load bus from the system. The types of failures depicted in the second table increase the power generated in one part of the grid while decreasing the power generated in another part.

Table 4.6. Service capacity for outages that disconnect a generator bus

Injected contingency	Available power (MW)	Load demand (MW)	Service capacity β
1	322	315	1
2	172.7	315	0.54
6	322	315	1
7	172.7	315	0.54
8	258.5	315	0.82
9	272.8	315	0.86

4.2.3 Evaluation of Survivability and Degradation After determining the values of both system condition and service capacity, we can evaluate the *SI* (survivability index) of the grid using Equation 3.7 and determine the level of system degradation based on Table 3.2. The resulting values after injection of a single-line contingency on lines 1 through 6 are shown in Tables 4.8, 4.9, 4.10, 4.11, 4.12, 4.13, 4.14, 4.15 and 4.16; respectively.

Table 4.7. Service capacity for outages that partition the grid

Injected contingency	Available power (MW)	Load demand (MW)	Subsystem β	Overall β
3	272.8	100	2.72	0.33
	79.2	215	0.37	
4	93.5	100	0.94	0.32
	79.2	215	0.37	
5	93.5	100	0.94	0.63
	79.2	90	0.88	

Table 4.8. Survivability and degradation after injection of contingency on line 1

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	1	1	1
t_2	0.87	1	1	1
t_3	0.87	1	1	1
t_4	0.87	1	1	1

Table 4.9. Survivability and degradation after injection of contingency on line 2

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	1	1	1
t_2	0.75	0.54	0.41	4
t_3	0.57	0.54	0.31	5
t_4	0.50	0.54	0.27	5

Figure 4.6 compares the survivability index subsequent to the injection of respective single-line contingencies on lines 1 through 6. The outage of transmission line 4 results in the fastest and most drastic decrease in survivability. After line 4, lines 5, 3, and 2, in order, resulted in the greatest decrease in survivability. All

Table 4.10. Survivability and degradation after injection of contingency on line 3

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	1	1	1
t_2	0.75	0.33	0.25	5
t_3	0.71	0.33	0.23	5
t_4	0.71	0.33	0.23	5

Table 4.11. Survivability and degradation after injection of contingency on line 4

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	1	1	1
t_2	0.63	0.54	0.34	5
t_3	0.33	0.32	0.11	5
t_4	0.20	0.32	0.06	5

Table 4.12. Survivability and degradation after injection of contingency on line 5

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	1	1	1
t_2	0.75	1	1	1
t_3	0.43	0.63	0.27	5
t_4	0.14	0.63	0.09	5

four of these contingencies eventually cause SI to drop below 0.4, and as such, are considered catastrophic. In contrast, the outage of lines 1 and 6, respectively, do not affect survivability, i.e., $SI = 1$ despite these outages and the system remains stable.

Table 4.17 shows the survivability and degradation level attained at four time slots after each single-line contingency, and ranks each line according to its SI value, i.e., its importance to survivability. A rank of 1 is assigned to the most important

Table 4.13. Survivability and degradation after injection of contingency on line 6

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	1	1	1
t_2	0.87	1	1	1
t_3	0.87	1	1	1
t_4	0.87	1	1	1

Table 4.14. Survivability and degradation after injection of contingency on line 7

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	0.54	0.48	4
t_2	0.87	0.54	0.47	4
t_3	0.87	0.54	0.47	4
t_4	0.87	0.54	0.47	4

Table 4.15. Survivability and degradation after injection of contingency on line 8

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	0.82	0.73	3
t_2	0.87	0.82	0.71	3
t_3	0.87	0.82	0.71	3
t_4	0.87	0.82	0.71	3

line. This type of importance analysis can help in guiding recovery efforts, especially in cases where a single repair team is available and the lines can be repaired only one-at-a-time. It should be noted that in cases where cascading failure leads to disconnection of a generator bus and/or load bus, the line that causes disconnection of the generator should be the first to be repaired. The second line to be repaired should be the line causing disconnection of the load bus. This order ensures that the

Table 4.16. Survivability and degradation after injection of contingency on line 9

Time	System condition (α)	Service capacity (β)	SI	Degradation level
t_1	0.89	0.86	0.77	3
t_2	0.87	0.86	0.75	3
t_3	0.87	0.86	0.75	3
t_4	0.87	0.86	0.75	3

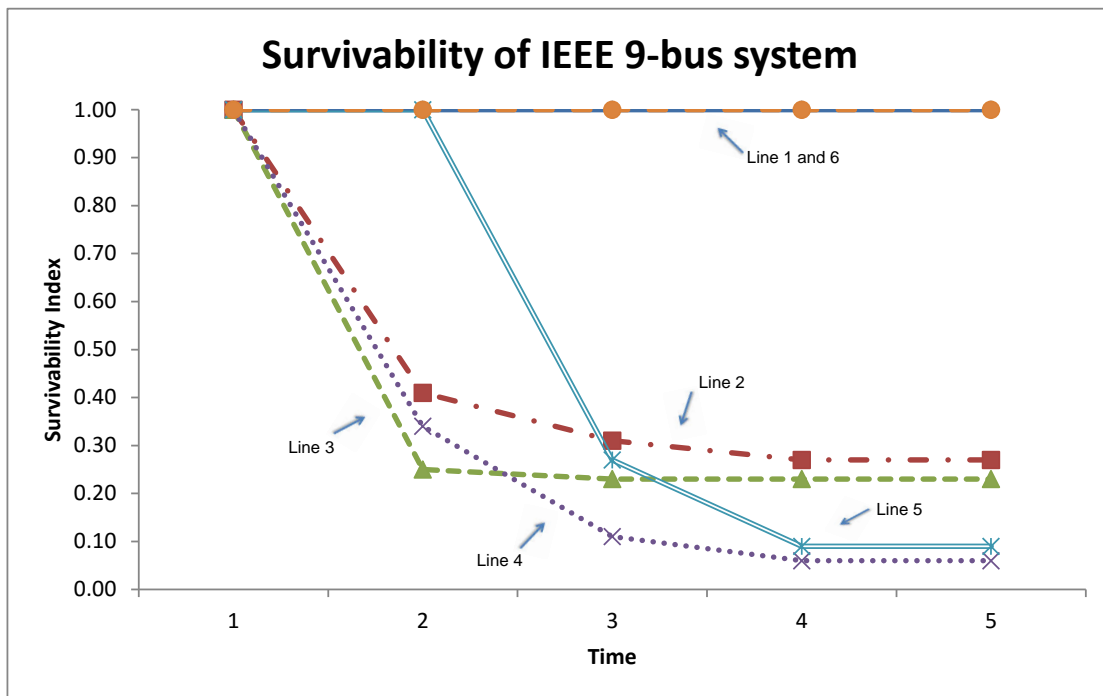


Figure 4.6. Survivability index after injection of single-line contingencies

amount of generated power increases before the power demand increases and leads to greater survivability.

4.3 RECOVERY STRATEGY

As an extreme example (for a grid of this size), we assume that five transmission lines have failed in the IEEE 9-bus system; two of them (lines 2 and 4) would

Table 4.17. Survivability and degradation at four time periods after single-line contingency

Line	SI	Degradation level	Importance
1	1.00	1	6
2	0.27	5	4
3	0.23	5	3
4	0.06	5	1
5	0.09	5	2
6	1.00	1	5

normally connect loads to the grid, and the remaining three (lines 7, 8, and 9) would connect the generators to the grid. Transmission line 7 connects a 163 MW generator to the system, transmission line 8 connects an 85 MW generator to the system, and transmission line 9 connects a 72 MW generator to the system.

We assume that each generator can provide 10% more power than its rated capacity if any one of the other generators fail. This would happen in response to load demand. If the power demand exceeds 110% of the generator's ability, the system becomes unstable.

We seek to use the information gleaned from survivability analysis to guide recovery efforts for this scenario. The proposed recovery strategy has three stages. The first stage works to balance the demand and supply, motivated by the fact that a temporary reduction in demand can keep the system stable until recovery efforts are completed. The second stage represents the repair of lines, one-by-one, in order of their importance to survivability (determined as in Section 4.2.3).

The third stage is the most important stage in the recovery process. This stage represents the repair of transmission lines used to connect to the generators, one-at-a-time. The goal of this effort is to recover the greatest amount of power as quickly as possible. In this example, lines 7, 8, and 9 are connected to generators. Assuming

that they would take an equal time to repair, we determine the best recovery sequence based on the power and capacity recovered. Table 4.18 summarizes the information used in deciding on a recovery sequence for lines 7, 8, and 9.

Table 4.18. Comparison of recovery strategies

Recovery sequence	After first repair		After second repair		After third repair	
	Recovered Power (MW)	Regained Capacity	Recovered Power (MW)	Regained Capacity	Recovered Power (MW)	Regained Capacity
9, 8, 7	79.2	25%	172.7	54%	320	100%
9, 7, 8	79.2	25%	258.5	80%	320	100%
8, 9, 7	93.5	29%	172.7	54%	320	100%
8, 7, 9	93.5	29%	272.8	85%	320	100%
7, 8, 9	179.3	56%	272.8	85%	320	100%
7, 9, 8	179.3	56%	258.5	80%	320	100%

As an example, the third recovery sequence in Table 4.18 is 8, 9, then 7. This sequence recovers 85 MW of power after the first repair (line 8). Adding in the potential 10% increase of power above the nominal capacity of the generator, the recovered power will be 93.5 MW. After the second repair (line 9), an additional 72 MW of power is recovered. Allowing for the 10% increase, this brings the total to 172.7 MW, which is 54% of the service capacity of the system. After the third repair, the 320 MW of power and the full service capacity are recovered.

All repairs have been assumed to be of equal duration, so the choice of recovery sequence is based on the power recovered as a result of each repair. A greedy approach is taken, whereby the line that yields the highest recovered power at each stage will be selected. Specifically:

Step 1 : First line to be repaired is the line that recovers the maximum power. The three possible values are 163, 85, and 72, corresponding to the repair of lines 7, 8, and 9, respectively. Line 7 is selected for the first repair.

Step 2 : The choice is now between recovery of line 8 or 9, which will yield 85 or 72 MW of power, respectively. Line 8 is selected for the second repair.

Step 3 : The only line yet to be repaired is line 9, which is selected as the third repair.

If the repair time would vary from line to line, the line whose repair would recover the maximum amount of generated power in the least amount of time would be selected for repair, meaning that the selection would be made based on the rate of recovery.

5 CONCLUSION AND FUTURE WORK

The goals of the research presented in this thesis were to: a) identify and illustrate methods for quantifying reliability and survivability for smart grids, and b) determine how to utilize this information in guiding recovery efforts. To this end, a Markovian model was proposed for reliability. The model can be applied to conventional or smart power grids, as it captures the system-level manifestation of component-level faults, regardless of whether these faults are the result of defects in cyber or physical components. The input to the model includes information on the initial state of the system, transition probabilities, and classification of each possible system state as functional or failed. This input information can be gleaned from historical data or simulation. Our work was based on the latter. We illustrated the approach using simulation of the classic IEEE 9-bus test system, and a smart grid created by fortifying this system with two SSSC devices that are intended to isolate failures and prevent cascades.

In evaluating survivability, we considered both the condition of the system, expressed as the fraction of functional components; and the service capacity, expressed as the fraction of load demand that can be met by the power available after an outage. The resulting survivability index is the basis for determining the level of degradation experienced by the system as a result of the outage. We illustrated the use of this survivability index in determining a recovery strategy that recovers the system capacity as quickly as possible. The methods proposed were illustrated through application to a simulated IEEE 9-bus grid.

The work presented in this thesis can be used in the design stage of smart grids to determine the most survivable design. It can be applied in the test stage to assess reliability and survivability. It can also be used to guide investments in

fortifying deployed systems. The end result of these efforts will be more reliable and survivable power infrastructures that are better able to fulfill their crucial role as the cornerstone of other critical infrastructures.

Future extensions to this work include validation with field data, stochastic modeling of survivability, extension of the work to other dependability attributes - in particular availability, and generalization of the approach to enable its application to other cyber-physical infrastructures, such as intelligent water distribution networks or transportation systems.

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