RELIABILITY EVALUATION OF COMPOSITE POWER SYSTEMS INCLUDING THE EFFECTS OF HURRICANES

A Dissertation

by

YONG LIU

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December of 2010

Major Subject: Electrical Engineering

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Approved by:

Chair of Committee,	Chanan Singh
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	Natarajan Gautam
Head of Department,	Costas N. Georghiades

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ABSTRACT

Reliability Evaluation of Composite Power Systems Including the Effects of Hurricanes.

(December 2010)

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Chair of Advisory Committee: Dr. Chanan Singh

Adverse weather such as hurricanes can significantly affect the reliability of composite power systems. Predicting the impact of hurricanes can help utilities for better preparedness and make appropriate restoration arrangements. In this dissertation, the impact of hurricanes on the reliability of composite power systems is investigated.

Firstly, the impact of adverse weather on the long-term reliability of composite power systems is investigated by using Markov cut-set method. The Algorithms for the implementation is developed. Here, two-state weather model is used. An algorithm for sequential simulation is also developed to achieve the same goal. The results obtained by using the two methods are compared. The comparison shows that the analytical method can obtain comparable results and meantime it can be faster than the simulation method.

Secondly, the impact of hurricanes on the short-term reliability of composite power systems is investigated. A fuzzy inference system is used to assess the failure rate increment of system components. Here, different methods are used to build two types of fuzzy inference systems. Considering the fact that hurricanes usually last only a few

days, short-term minimal cut-set method is proposed to compute the time-specific system and nodal reliability indices of composite power systems. The implementation demonstrates that the proposed methodology is effective and efficient and is flexible in its applications.

Thirdly, the impact of hurricanes on the short-term reliability of composite power systems including common-cause failures is investigated. Here, two methods are proposed to archive this goal. One of them uses a Bayesian network to alleviate the dimensionality problem of conditional probability method. Another method extends minimal cut-set method to accommodate common-cause failures. The implementation results obtained by using the two methods are compared and their discrepancy is analyzed.

Finally, the proposed methods in this dissertation are also applicable to other applications in power systems.

To my parents, my wife and my daughter

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NOMENCLATURE

ANFIS	Adaptive Neuro-Fuzzy Inference System
CCF	Common-Cause Failure
FES	Fuzzy Expert System
IMFR	Increment Multiplier of Failure Rate
M-FIS	Mamdani-Type Fuzzy Inference System
NERC	North American Electric Reliability Corporation
RTS	Reliability Test System
S-FIS	Sugeno-Type Fuzzy Inference System

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CHAPTER I

INTRODUCTION

In this chapter, the background of the research reported in this dissertation is introduced first, then the objectives of this dissertation are listed, and the organization of this dissertation is given in the end.

1.1 Introduction

Adverse weather such as hurricanes can significantly affect the operation of power systems, and it can jeopardize system reliability. In recent years, the hurricanes in the United States have caused hundreds of thousands of customers losing power supply. Moreover, due to the interdependency of various infrastructural systems, even brief power interruption may affect communication, water distribution, traffic signaling, and other lifeline systems [1]-[3]. Predicting the impact of hurricanes on power system reliability can help utilities for better preparedness and make appropriate restoration arrangements [2]-[3].

The impact of adverse weather on the reliability of power systems has been investigated in the past decades, i.e. the average effect of adverse weather over a long period of time. Some weather models have been proposed to evaluate power system reliability considering the effect of weather, e.g. two-state weather model [4] and three-state weather model [5].

This dissertation follows the style of *IEEE Transactions on Power Systems*.

When the effect of weather is considered, the states of the components of power systems can become dependent. For instance, when two-state weather model is used, usually a set of linear equations need to be solved by using Markov process [6]. However, this becomes impractical when applied to large power systems considering the fact that the number of system components is large. To solve this problem, usually Monte Carlo simulation can be used. But, due to its inherent nature of random experiments, simulation process can take long time to converge. In [6], Markov cut-set method was proposed to simplify the analytical approach. Its basic idea is that Markov process can be only applied to system minimal cut-sets as well as their unions, and its application to all system components is unnecessary. Although this method was described for some simple transmission configurations, it has not been developed for application to composite power systems, especially the nodal indices.

In this dissertation, algorithms are developed to implement Markov cut-set method and simulation method to evaluate the impact of adverse weather on the long-term reliability of composite power systems including system and nodal indices [7]. The obtained results by using different methods are compared and analyzed [7].

Usually, hurricanes last only a few days but their effect is drastic. Thus, the short-term impact of hurricanes, i.e. their dynamic impact during their durations, need to be investigated as their impact may not be reflected properly in the long term indices. Since a composite power system covers a large area, the weather models in [4]-[5] are not applicable and instead the regional weather model proposed in [8]-[9] can be used.

In this dissertation, the impact of hurricanes on the short-term reliability of composite power systems is investigated and the common-cause failures of system components are also considered. A common-cause failure refers to the simultaneous failures of multiple components due to a common cause [10], e.g. those of transmission lines installed on a same tower.

It has been known for a long time that the failure rate of a transmission or a distribution line is a function of the weather that it is exposed to and the failure rate of the transmission (distribution) line can be much higher in adverse weather than that in normal weather [11]. In this dissertation, a fuzzy inference system combined with regional weather model is used to assess the failure rate increment of system components cause by hurricanes. Additionally, different methods are proposed to build different types of fuzzy inference systems [12]-[14]. After the incremental failure rates of system components are obtained, short-term minimal cut-set method is proposed to compute the time-specific system and nodal reliability indices of composite power systems [13]. Here, only the independent failures of system components are considered.

Next, two methods are proposed to investigate the impact of hurricanes on the short-term reliability of composite power systems including common-cause failures [15]-[16]. One of them uses a Bayesian network to alleviate the dimensionality problem of conditional probability method when numerous common-cause failures are modeled [15]; the other method extends minimal cut-set method to accommodate common-cause failures [16]. The obtained results by using the two methods are compared and the difference is analyzed [16].

Finally, it is shown that the evaluation methods proposed in this dissertation are also applicable to distribution systems [17] and other applications [18], e.g. operational reliability, and intermittent renewable energy.

1.2 Objectives

The objectives of this dissertation are as follows:

1) Investigate the impact of adverse weather on the long-term reliability of composite power systems. The evaluation results can be used in power system planning.
2) Investigate the impact of hurricanes on the short-term reliability of composite power systems. The evaluation results can be used in power system operation.
3) Investigate the impact of hurricanes on the short-term reliability of composite power systems including the common-cause failures of components. Thus, the impact of hurricanes on the operational reliability of composite power systems can be predicted more accurately.

1.3 Organization of the Dissertation

This dissertation is organized as follows: in Chapter II, basic concepts of power system reliability and some weather models are introduced; in Chapter III, the investigation of the impact of adverse weather on the long-term reliability of composite power systems is presented; in Chapter IV, the investigation of the impact of hurricanes on the short-term reliability of composite power systems is presented; in Chapter V, the investigation of the impact of hurricanes on the short-term reliability including the common-cause failures of components is presented; finally, in Chapter VI, the evaluation methods proposed in this dissertation is summarized and their possible extensions are discussed.

CHAPTER II

POWER SYSTEM RELIABILITY EVALUATION

In this chapter, some basic concepts of power system reliability are introduced first; then, two models to consider the effect of weather are introduced.

2.1 Basics of Power System Reliability

Generally, reliability is defined as the ability of a system or component to perform its required functions under stated conditions for a specified period of time [19]. A key element of this definition is that the concerned system or component should operate under stated conditions. Operational environment such as weather is such a condition which should be addressed in reliability evaluation. The effect of adverse weather on power systems and other infrastructural systems are introduced in the next section.

For power systems, North American Electric Reliability Corporation (NERC) defines reliability as "the degree to which the performance of the elements of [the electrical] system results in power being delivered to customers within accepted standards and in the amount desired." Actually, NERC's definition of reliability includes two concepts: *adequacy* and *security*. *Adequacy* is defined as "the ability of the system to supply the aggregate electric power and energy requirements of the consumers at all times." NERC defines *security* as "the ability of the system to withstand sudden disturbance." In other words, *adequacy* refers to that sufficient system resources are available to meet predicted load with reserve for contingencies; *security* refers to that the system remains reliable even in contingent cases.

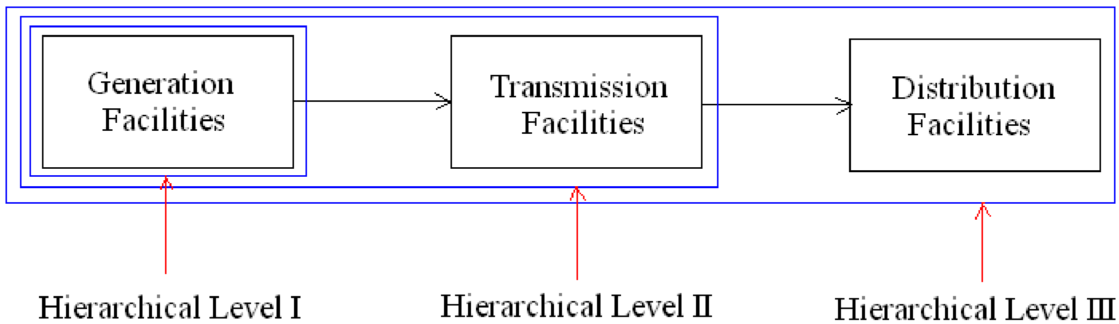

Fig. 1: Functional Zones and Hierarchical Levels

It is noted that most present probabilistic techniques for power system reliability evaluation are used for adequacy assessment. The available probabilistic techniques to assess the security of power systems are limited. Accordingly, most reliability indices used at the present time are adequacy indices.

The reliability evaluation can be implemented in different segments of a power system, i.e. functional zones, as well as the combinations of them which shapes the hierarchical levels shown in Fig. 1 [20].

The evaluation methods at different hierarchical levels of a power system can be different. For instance, at hierarchical level II the configuration of a transmission system is usually in a meshed fashion, and the effects of load flow, overload alleviation, generation rescheduling need to be considered. In contrast, at hierarchical level III the configuration of a distribution system is usually radial. Thus, power flow is usually not considered in distribution systems. Generally, the evaluation methods for power system reliability fall into two categories: analytical and simulation. The details of the algorithms to implement them are described in the following chapters. Clearly, the reliability assessment at hierarchical level III becomes very complex as it involves all three functional zones. Thus, the distribution system is usually analyzed as a separate part.

In this dissertation, the impact of hurricanes is investigated at hierarchical level II which is usually called a composite power system or a bulk power system. But, the proposed evaluation methods in this dissertation are also applicable to distribution systems. This is discussed in detail in Chapter VI.

2.2 Weather Models

2.2.1 Two-state weather model

In [4], each transmission line was assumed to operate in a two-state fluctuating environment as shown in Fig. 2, and Markov method for the whole transmission system was used to evaluate its reliability. In Fig. 2, the arrows represent the transition of component states. For simplicity, only the transition of the states of one component is illustrated.

Advantages of two-state weather model are its simplicity and easy implementation. This weather model can be used for long-term applications in power systems, e.g. power system planning. In this dissertation, it is used to evaluate the impact of adverse weather on the long-term reliability of composite power systems. But, for a composite power system the number of components is large, and applying Markov process to all components is impractical. In this dissertation, Markov cut-set method in [6] is used to solve this problem. The details are given in the next chapter.

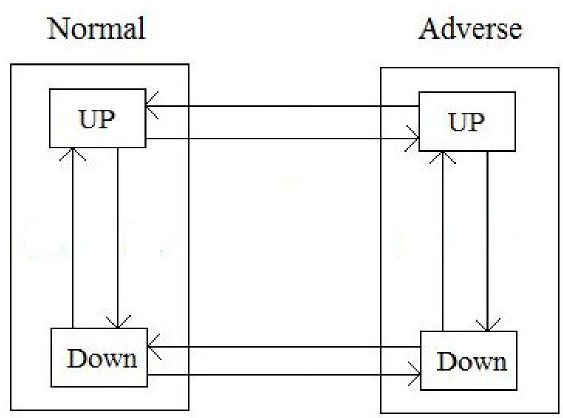

Fig. 2: Two-State Weather Model (Simplified)

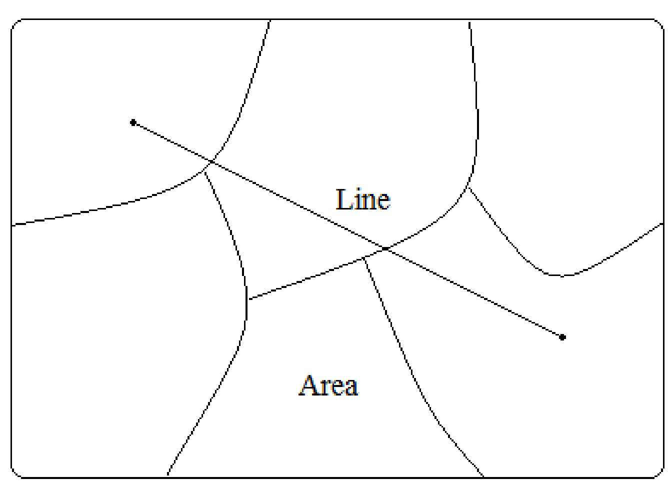

Fig. 3: Regional Weather Model

2.2.2 Regional weather model

An assumption adopted by previous weather model is that all system components are exposed to the same weather at a time. This is not true considering the fact that hurricanes develop and dissipate over time, i.e. the impact of hurricanes on a power system can be different temporally and spatially.

In [8]-[9], the regional weather model as shown in Fig. 3 was used to recognize the regional effects of weather that transmission lines are exposed to and Monte-Carlo simulation was used to evaluate the reliability of composite power systems.

In [2]-[3], similar regional weather model was applied to distribution systems and statistical regression method was used to predict the number of outages caused by hurricanes in each geographic unit.

2.2.3 Disaster impact on infrastructural systems

The impact of adverse weather on other infrastructural systems has been investigated in the literature. For instance, in [21] a regional weather model similar to that in [2]-[3] was used to evaluate the performance of cellular networks during hurricanes. Moreover, the impact of other natural disasters on power systems has been investigated. For instance, in [22] simulation method was used to investigate the restoration process of power systems after earthquakes.

CHAPTER III

RELIABILITY EVALUATION OF COMPOSITE POWER SYSTEMS USING MARKOV CUT-SET METHOD

The impact of adverse weather on the long-term reliability of power systems have been investigated during the past decades. Usually, two-state weather model [4] is used to evaluate the effects of fluctuating weather on power system reliability. As a result, the states of system components are not independent anymore. To solve this problem, usually simulation method can be used. In this chapter, Markov cut-set method [6] is used to achieve the same goal and algorithms to implement this method are developed. For the purpose of comparison, algorithm to implement sequential simulation is also developed, and the results obtained by using the two methods are compared and analyzed.

This chapter is organized as follows: in Section 3.1 relevant researches using two-state weather model are reviewed; in Section 3.2 the assumptions adopted in this chapter are listed; in Section 3.3 minimal cut-set method is briefly introduced and the developed algorithms for Markov cut-set method are presented; in Section 3.4 Monte Carlo simulation is briefly introduced and the developed algorithm for sequential simulation is presented; in Section 3.5 the analytical and simulation methods proposed are applied to the modified IEEE reliability test system (RTS). The results obtained by using the two methods are presented and compared; finally, in Section 3.6 main conclusions obtained in this chapter are summarized.

3.1 Literature Review

In the reliability evaluation of power systems, usually the states of system components are assumed to be independent, and system reliability indices are calculated by using the methods based on the multiplication rule of probabilities [23]. But, in some cases, for instance, when the effect of fluctuating weather or common-cause failures is considered, the previous assumption is invalid. The main weather models used include two-state weather model [4] and its variant [5]. Generally, two kinds of methods can be adopted, namely analytical [4], [6], [23] and Monte Carlo simulation [24].

Generally, simulation method mimics the operational process of a physical system by using random experiments and obtains system reliability indices using statistical inference. Generally speaking, simulation method is suitable when complex system operational conditions are considered. In [24], basically two kinds of simulation methods are described: random sampling and sequential simulation. Generally, random sampling assumes that component states are independent and system states, i.e. the combinations of component states, are uncorrelated. Sequential simulation is more flexible and is suitable to simulate the effect of fluctuating weather. Relevant details are given in Section 3.4.

However, by the nature of simulation method, its convergence may need acceleration by using other techniques [24]. On the other hand, the Markov process used in [4] is accurate within the distribution assumptions, but it is only applicable to relatively small systems considering that the solution of 2^{n+1} linear equations is required [6]. Here, n is the number of system components.

To alleviate the dimensionality problem, a method was proposed in [23] to reduce the state space by merging system states and systematically deleting low probability states. In [6], Markov cue-set method was proposed to evaluate the reliability of transmission and distribution systems considering the effects of fluctuating weather. In [6], minimal cut-set method was used to compute system reliability indices, and Markov process was applied to the components of a minimal cut-set or a union of minimal cut-sets to alleviate the computational burden. Markov cue-set method is based on the concept that if two-state weather model is used, the reliability indices of a minimal cut-set or a union of minimal cut-sets can be calculated by applying Markov process only to its members, and the application of Markov process to all system components simultaneously is unnecessary. Thus, if the minimal cut-sets up to some order (e.g. third-order, i.e. the maximum number of components) are determined, only a limited number of linear equations need to be solved at a time. For example, considering a system of 500 components, if the entire system is to be modeled by using Markov process, there will be 2^{501} number of states and thus as many equations to be solved. However, if the maximum number of the components in a minimal cut-set or a union of minimal cut-sets is say 6, then by using Markov cut-set method, the highest number of equations to be solved at a time is 2^7 . This can make the difference in the practical applicability of Markov process.

However, in [6] Markov cut-set method was applied to a simple 5-component system, and the minimal cut-sets were determined by using simple enumeration method and the connectivity criterion in transmission and distribution systems. Additionally, nodal reliability indices were not computed, and the comparison with simulation method was not given in [6].

In this chapter, Markov cut-set method is used to investigate the impact of adverse weather on the long-term reliability of composite power systems. From previous discussion, it is clear that a key step of Markov cut-set method is the identification of minimal cut-sets. In this dissertation, this is modeled as a linear constrained optimization problem to shorten computational time. Since enumerating all minimal cut-sets of a power system is impractical and unnecessary, the algorithm of computing the bounds of minimal cut-sets is also developed. An important new feature is the method for computing nodal indices as these indices are important for assessing the impact of adverse weather as well as extensions to distribution systems.

3.2 Assumptions

In this chapter, the following assumptions are adopted:

1) Voltage is assumed as 1pu at each bus and DC power flow is used.

2) The distribution of state residence times is assumed exponential. Thus, Markov process can be used to compute reliability indices.

3) All reliability indices computed are steady state indices. Thus, the probability of a system state can be obtained by using the steady state condition of Markov process.

4) All system components have two possible states: success or failure.

3.3 Markov Cut-Set Method

In this section, the developed algorithms for implementing Markov cut-set method are presented in detail. Firstly, minimal cut-set method is briefly introduced; then, the algorithm for identifying system and nodal minimal cut-sets is presented; finally, the algorithm for computing the bounds of minimal cut-sets is presented.

3.3.1 Minimal cut-set method

A cut set is a set of components whose failures alone could cause system failure. Here, the definition of system failure is rather broad and it can be any kind of anomaly defined. In this dissertation, system failure refers to the load shedding at any node of a composite power system. A minimal cut-set has the further property that it has no proper subset of components whose failures alone could cause system failure. Here, the term "component" is also used in a broad sense. It can be any device in a power system and even can be a condition or a function whose presence or absence could cause system failure.

The basic idea of minimal cut-set method is to first identify the minimal cut-sets of a power system, and then use the following equations of probabilities to compute the reliability indices [6].

$$p_f = \sum_i p\left(\overline{C_i}\right) - \sum_{i<j} p\left(\overline{C_i} \cap \overline{C_j}\right) + \sum_{i<j<k} p\left(\overline{C_i} \cap \overline{C_j} \cap \overline{C_k}\right) - \cdots + (-1)^{m+1} \cdot p\left(\overline{C_1} \cap \overline{C_2} \cap \cdots \cap \overline{C_m}\right) \tag{1}$$

$$f_f = \sum_i p\left(\overline{C_i}\right) \cdot \overline{\mu_i} - \sum_{i<j} p\left(\overline{C_i} \cap \overline{C_j}\right) \cdot \overline{\mu_{i+j}} + \sum_{i<j<k} p\left(\overline{C_i} \cap \overline{C_j} \cap \overline{C_k}\right) \cdot \overline{\mu_{i+j+k}} - \cdots + (-1)^{m+1} \cdot p\left(\overline{C_1} \cap \overline{C_2} \cap \cdots \cap \overline{C_m}\right) \cdot \overline{\mu_{1+2+\cdots+m}} \tag{2}$$

$$d_f = p_f / f_f \tag{3}$$

where

p_f	=	failure probability
C_i	=	minimal cut-set i
$\overline{C_i}$	=	event that all members of C_i fail
$\overline{C_i} \cap \overline{C_j}$	=	joint event that all members of both C_i and C_j fail
m	=	number of minimal cut-sets
f_f	=	failure frequency
μ_i	=	repair rate of component i
$\overline{\mu_i}$	=	$\sum_{i \in C_i} \mu_i$
$\overline{\mu_{i+j}}$	=	$\sum_{i \in C_i \cup C_j} \mu_i$
d_f	=	mean duration of failure

In practice, enumerating all the minimal cut-sets of a power system and using (1)-(3) to compute the exact values of reliability indices are impractical and unnecessary. Instead, the minimal cut-sets are usually determined up to a desired order and the following equations are used to compute the bounds of the reliability indices to approximate the results of (1)-(3):

$$p_f^u = \sum_i p\left(\overline{C_i}\right) \tag{4}$$

$$p_f^l = \sum_i p\left(\overline{C_i}\right) - \sum_{i<j} p\left(\overline{C_i} \cap \overline{C_j}\right) \tag{5}$$

$$f_f^u = \sum_i p\left(\overline{C_i}\right) \cdot \overline{\mu_i} \tag{6}$$

$$f_f^l = \sum_i p\left(\overline{C_i}\right) \cdot \overline{\mu_i} - \sum_{i<j} p\left(\overline{C_i} \cap \overline{C_j}\right) \cdot \overline{\mu_{i+j}} \tag{7}$$

where

p_f^u	=	first upper bound of p_f
p_f^l	=	first lower bound of p_f
f_f^u	=	first upper bound of f_f
f_f^l	=	first lower bound of f_f

By using inclusion-exclusion formula, a sequence of increasingly closer bounds of the reliability indices can be obtained [25].

Following the above introduction, Markov cut-set method can be implemented as follows:

1) Determine the minimal cut-sets up to the preset order and the ones of higher order are ignored.

2) Compute the reliability indices of the minimal cut-sets and their unions. Here, the multiplication rule of probabilities is not applicable anymore. Instead, the algorithm developed in Subsection 3.3.4 can be used.

3) Use (3)-(7) to compute the reliability indices.

3.3.2 Identification of minimal cut-sets

In the literature, numerous methods have been proposed to generate minimal cut-sets to evaluate the reliability of large complex systems [26]-[34]. However, these graph-based methods mainly explore the connectivity feature of networks and are not suitable for the reliability evaluation of composite power systems considering the capacity and admittance of transmission lines. In [31], [33], although the link capacity of networks were considered, the proposed algorithms are only suitable for some general networks considering the fact that generation rescheduling and load shedding have to be considered in composite power systems. In [29], although the proposed method was implemented in power systems, the previous issues were not addressed.

Normally, a composite power system can be modeled as a capacitated-flow network subjected to some operational constraints, such as generation-load balance, generator capacity limits and voltage magnitude limits. In reliability evaluation, usually the analysis of failure effects should be implemented after the occurrence of a system event, i.e. determining the resultant system state is success or failure as defined. In a composite power system, after a system event occurs, e.g. the outage of a generator or the tripping of a transmission line, usually the output of generators is rescheduled first. If the violation of system constraints cannot be remedied, usually load shedding is finally executed.

In this dissertation, the identification of minimal cut-sets is modeled as a constrained linear optimization problem to reduce computational time. When the voltage is considered, the proposed algorithm can be easily extended to the AC model.

Mathematically, the objective is to minimize the amount of load shedding M_D if necessary and meantime the following constraints are satisfied:

Balance of active power flow:

$$P_G = P_D - P_{LD} \tag{8}$$

where

P_G = active power of total generator output

P_D = active power of system load

P_{LD} = active power of total load shedding

Transmission line capacity limit:

$$P_{i,j} \leq P_{i,j}^{\max} \tag{9}$$

where

$P_{i,j}$ = active power flow in transmission line from bus *i* to *j*

$P_{i,j}^{\max}$ = upper limit of $P_{i,j}$

Generator capacity limit:

$$P_g \leq P_g^{\max} \tag{10}$$

where

P_g = active power output of generator *g*

$P_g^{\max}$ = upper limit of P_g

Load shedding limit:

$$P_d \leq P_d^{\max} \tag{11}$$

where

P_d = active power shedding of load *d*

$P_d^{\max}$ = upper limit of P_d

The algorithm to determine the minimal cut-sets of a composite power system up to the preset order is as follows:

1) Choose an n-order arbitrary combination of system components.
2) Check all the existing lower-order minimal cut-sets to examine if they are the subsets of the combination in Step (1): if yes, go back to Step (1); if not, go to the next step.
3) Run the optimization routine on the condition that these n components are out of service simultaneously.
4) Examine if load shedding is needed: if yes, these components make up an n-order minimal cut-set; otherwise, not.
5) Check if all the n-order combinations of system components have been examined: if not, go back to Step (1); if yes, forward to the next step.
6) Check if the pre-set order of the combinations is reached: if yes, stop; if not, forward to the next step.
7) Set $n = n + 1$ and go back to Step (1).

The proposed algorithm has some advantages as follows:

1) The implementation is simple. Since linear optimization is widely used in various applications in power systems, the proposed algorithm can be implemented by slightly modifying the current software.
2) It is easy to extend this algorithm to incorporate more system operational considerations. For instance, it is simple to extend it to the AC model.
3) It is easy to compare the proposed algorithm with other methods since linear optimization is also used in other analytical and simulation methods to analyze the failure effects. For example, the number of calling the optimization routine can indicate the efficiency of a reliability evaluation method.

4) It can be used to compute system and nodal reliability indices. Although simulation method can achieve the same goal, the computation may be more expensive. This is discussed in detail in the next subsection.

However, a practical composite power system may have a large number of components. Even if the minimal cut-sets are determined to a small order, their number can be still very large. This problem can be further alleviated by using the approaches proposed in [35]. The basic idea is that using learning methods to classify system states as success or failure. Thus, the computational time can be reduced further. It should be pointed out that this problem is shared by analytical and simulation methods. Some intelligent methods can accelerate the algorithms of both of them.

***3.3.3 System and nodal minimal cut-set*s**

As mentioned previously, the proposed algorithm can identify nodal minimal cut-sets too. Actually, it can identify system and nodal minimal cut-sets simultaneously. Thus, the computation of nodal reliability indices can be much simplified.

When a minimal cut-set is determined, the information about the nodes which suffer loss of load is saved. Thus, in the end there are two *lists*, first a *list* of all minimal cut-sets and then an additional *list* of nodes that have loss of load corresponding to each minimal cut-set. To compute system reliability indices, all the minimal cut-sets are used, i.e. they are system minimal cut-sets. To compute the reliability indices of a node, only those minimal cut-sets which have it suffering loss of load are used, i.e. they are the nodal minimal cut-sets. It should be pointed out that most of the computation time is spent in identifying the minimal cut-sets. The time taken by the computation of (3)-(7) is relatively small. Since the nodal minimal cut-set are the subsets of system minimal cut-sets, no additional time is needed for nodal reliability indices as far as the identification of minimal cut-sets is concerned. The only additional time needed is for the use of (3)-(7) for the calculation of nodal reliability indices and this is not significant. This point will be further illustrated in Section 3.6.

When simulation method is used to obtain nodal reliability indices, as pointed out in the above discussion, a system failure may have different effects at different nodes, i.e. it may only have some nodes suffering loss of load. Usually, for a power system the number of system states which are success is much greater than that of system states which are failure. Considering the fact that the number of system states that cause a node suffering loss of load is smaller than that of system states which are failure, the converge of simulation method is slower to simulate nodal reliability indices than that simulating system reliability indices.

3.3.4 Calculation of probabilities

Another key step of implementing Markov cue-set method is to compute the probabilities of a minimal cut-set or a union of minimal cut-sets. In this subsection, an improved algorithm is developed to compute the bounds of the reliability indices. This algorithm can automatically generate the transition rate matrix of a minimal cut-set or a union of minimal cut-sets, thus the computation of system and nodal reliability indices can be much easier. This algorithm is an improvement of the method proposed in [36]. The improvements are summarized as follows:

1) Although the algorithm in [36] is applicable to *n*-component system, it is different from that in this dissertation. The index *n* in [36] is 'fixed' whereas in this chapter *n* is 'variable'. In other words, the algorithm in [36] is applicable to fixed-dimension problems whereas the algorithm developed here is applicable to variable-dimension problems. This is needed as the number of the components of a minimal cut-set or a union of minimal cut-sets keeps on changing.
2) The algorithm in [36] is for single-state weather model whereas in this chapter the algorithm is applicable to two-state weather model considering the effects of fluctuating weather. Thus, the transition rate matrix produced here comprises four sub-matrices, and they are generated in sequential steps and finally all the diagonal elements are updated.
3) The core parts of two algorithms are different. The core part of the algorithm in [36] is based on “number” processing whereas in this chapter it is based on “bit” processing. Relevant details are given in the following discussion.

To illustrate the proposed algorithm to compute the bounds of the reliability indices, a simple example is given first. Here, the two-state weather model in Chapter II for a single component is used. It is reproduced in Fig. 4. and necessary parameters are added.

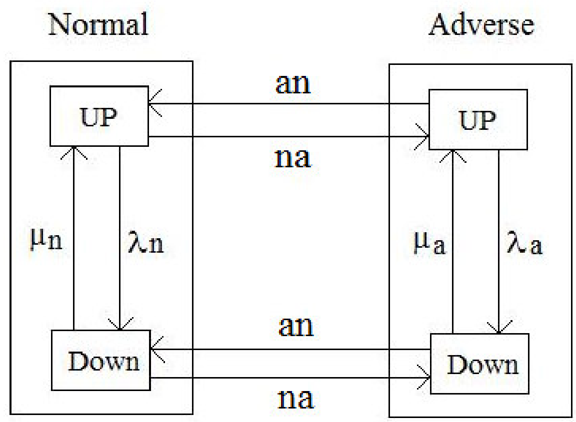

Fig. 4: Two-State Weather Model (Parameterized)

here

λ_n	=	failure rate in normal weather
μ_n	=	repair rate in normal weather
λ_a	=	failure rate in adverse weather
μ_a	=	repair rate in adverse weather
na	=	transition rate from normal weather to adverse weather
an	=	transition rate from adverse weather to normal weather

In this chapter, the impact of adverse weather on the long-term reliability of composite power systems is of interest. Thus, the steady state condition of Markov process can be used to compute the probabilities, i.e. the following equation can be obtained.

$$\begin{pmatrix} -(\lambda_n+na) & \mu_n & an & 0 \\ \lambda_n & -(\mu_n+na) & 0 & an \\ na & 0 & -(\lambda_a+an) & \mu_a \\ 0 & na & \lambda_a & -(\mu_a+an) \end{pmatrix} \cdot \begin{pmatrix} P^n_{up} \\ P^n_{down} \\ P^a_{up} \\ P^a_{down} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{12}$$

where,

P^n_{up} = success probability in normal weather

P^n_{down} = failure probability in normal weather

P^a_{up} = success probability in adverse weather

P^a_{down} = failure probability in adverse weather

However, the above equations cannot be directly solved to compute the probabilities because they are linearly correlated, i.e. they are not independent. Now, we have the following equation:

$$P^n_{up} + P^n_{down} + P^a_{up} + P^a_{down} = 1 \tag{13}$$

Then, we can replace say the fourth row of (12) as follows:

$$\begin{pmatrix} -(\lambda_n + na) & \mu_n & an & 0 \\ \lambda_n & -(\mu_n + na) & 0 & an \\ na & 0 & -(\lambda_a + an) & \mu_a \\ 1 & 1 & 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} P^n_{up} \\ P^n_{down} \\ P^a_{up} \\ P^a_{down} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} \tag{14}$$

Now, the above equations can be solved appropriately to compute the probabilities. The previous discussion shows that a key step to compute the probabilities is to generate the transition rate matrix.

For a minimal cue-set or a union of minimal cue-sets, generally the following equation can be used to compute the steady state probabilities:

$$A'P = B \tag{15}$$

where

A'	=	obtained from $A = \begin{pmatrix} NN & AN \\ NA & AA \end{pmatrix}$ by replacing the elements of an arbitrary row *k* by summing vector 1
NN	=	$2^n \times 2^n$ transition rate matrix in normal weather
AA	=	$2^n \times 2^n$ transition rate matrix in adverse weather
NA	=	$2^n \times 2^n$ transition rate matrix from normal weather to adverse weather
AN	=	$2^n \times 2^n$ transition rate matrix from adverse weather to normal weather
n	=	order of a minimal cut-set or a union of minimal cut-sets
P	=	a column vector whose *i*th element is the steady state probability of system state *i*
B	=	a vector of zeros with the *k*th element set to 1

Actually, only the sum of the state probabilities in two weathers which correspond to the minimal cut-set or the union of minimal cut-sets, needs to be calculated.

Next, the algorithm to generate matrix *A* is presented in detail. The basic idea is as follows:

1) Generate the transition rate sub-matrices in different weathers.

2) Generate the transition rate sub-matrices between two weathers.

3) Update the transition rate sub-matrices in Step(1).

Generating NN

NN is a sub-matrix whose elements are as follows:

$$NN_{i,i} = -\sum_j NN_{j,i}$$

$NN_{i,j} \quad = \quad \lambda^{n}_{j,i}$

$\lambda^{n}_{i,j} \quad = \quad$ transition rate from system state i to j in normal weather

The algorithm used to determine $\lambda_{i,j}$ is as follows: for *NN* the number of system states is 2^n and each system state is represented by an n-bit binary vector on the principle - for each bit the binary number is 1 or 0 if the state of the corresponding component is success or failure.

1) Firstly, number $\underbrace{00\cdots0}_{n}$ is assigned to state 1. From state 2 to $2^n - 1$, the binary representation of each system state is as follows:

   - From state 2 to state $\binom{n}{1}+1$, the corresponding binary vectors are in the following form: $\underbrace{10\cdots0}_{n}$, $\underbrace{01\cdots0}_{n}$, $\cdots$, $\underbrace{00\cdots1}_{n}$.

   - From state $\binom{n}{1}+2$ to state $\binom{n}{1}+\binom{n}{2}+1$, the corresponding binary vectors are in the following form: $\underbrace{11\cdots0}_{n}$, $1\underbrace{01\cdots0}_{n}$, $\cdots$, $\underbrace{00\cdots11}_{n}$.

   $\vdots$

   - From state $\binom{n}{1}+\binom{n}{2}+\cdots+\binom{n}{n-2}+2$ to state $\binom{n}{1}+\binom{n}{2}+\cdots+\binom{n}{n-1}+1$, the corresponding binary vectors are in the following form: $\underbrace{11\cdots10}_{n}$, $\underbrace{11\cdots01}_{n}$, $\cdots$, $\underbrace{01\cdots11}_{n}$.

- Finally, vector $\underbrace{11\cdots1}_{n}$ is assigned to state 2^n.

2) From system state *i* to *j*, if there is one and only one bit of their binary vectors being different, forward to the next step; if not, $\lambda_{i,j} = 0$. Here only the change of the state of one component at a time is considered, i.e. common-mode failures are not considered.

3) Suppose that the change of the state takes place at the *l*th bit of two binary vectors: if it is $0 \rightarrow 1$, $\lambda_{i,j} = \mu_l$; otherwise, $\lambda_{i,j} = \lambda_l$.

4) If all the pairs of system states are examined, stop; if not, go back to Step (2).

Generating AA

AA is a sub-matrix whose elements are as follows:

$$AA_{i,i} = -\sum_j AA_{j,i}$$

$$AA_{i,j} = \lambda^a_{j,i}$$

$\lambda^a_{i,j}$ = transition rate from system state *i* to *j* in adverse weather

The algorithm to generate *AA* is the same as that to obtain *NN* except that the transition rates in adverse weather are used instead.

Generating NA and AN

Both *NA* and *AN* are diagonal sub-matrices and they are easy to produce. *NA* is a sub-matrix whose elements are as follows:

$$NA_{i,i} = \lambda_{N \rightarrow A}$$

$\lambda_{N \rightarrow A}$ = transition rate from normal weather to adverse weather

AN is a sub-matrix whose elements are as follows:

$$AN_{i,i} = \lambda_{A \to N}$$

$\lambda_{A \to N}$ = transition rate from adverse weather to normal weather

Update NN and AA

Finally, *NN* and *AA* are updated as: $NN = NN + NA$ and $AA = AA + AN$.

In previous discussion, the relevant reliability parameters, i.e. the transition rates, are assumed to be known. Here, these parameters can be obtained as follows.

Parameters in different weathers

Usually, average reliability parameters are ready to use or can be easily obtained by using simple conversion. For example, usually the mean time to failure or mean time to repair of a component is known. Then, the failure rate or repair rate is just the reciprocal of mean time to failure or mean time to repair. But, the average reliability parameters are undistinguished in different weathers. In the next chapter, a simple approach is proposed to differentiate the reliability parameters in different weathers.

Parameters between two weathers

These parameters can be obtained by using a method similar to that obtaining the average parameters, i.e. computing the reciprocal of mean time in normal weather or mean time in adverse weather to obtain the corresponding transition rate.

3.4 Simulation Method

In this section, the algorithm to simulate the impact of fluctuating weather on composite power system reliability is presented. Firstly, the basic concepts of sequential simulation are introduced; then, the proposed simulation algorithm is presented; finally, some possible improvements to simulation method are discussed.

3.4.1 Sequential simulation

Generally, the evaluation techniques of power system reliability fall into two categories: analytical and simulation. Analytical method is usually based on some mathematical models and calculates reliability results using mathematical derivation. Basically, analytical method enumerates some dominant system states in state space which have non-trivial probabilities. In contrast, simulation method usually does not depend on specific mathematical models. Instead, it simulates the operational process of a physical system, and repeat the simulation till termination criterion is satisfied. Finally, the reliability indices are obtained by using statistical inference [37].

As mentioned in the beginning of this chapter, basically there are two main simulation techniques: random sampling and sequential simulation [24]. The major difference of these two methods is as follows: random sampling assumes that component states are independent and consecutive simulations are also independent with each other; in contrast, sequential simulation simulates system operation literally over time. Actually, this method simulates a Markov chain chronologically. Thus, it is more flexible than random sampling and it is used to simulate the effects of adverse weather on the reliability of composite power systems in this chapter.

Generally, there are two methods to control the advance of sequential simulation: fixed time interval method and next event method [24]. Fixed time interval method advances the simulation in step of a constant time interval Δt . Next event method advances the simulation in a temporal sequence which is determined by the occurrence order of system events. Here, a system event refers to the change of the state of a component or weather. In this chapter, the next event method is used.

A main step of sequential simulation is to generate the random residence time of a component at a state and then determine the next most imminent event. The former issue is discussed next and the latter issue is explained in Subsection 3.4.4.

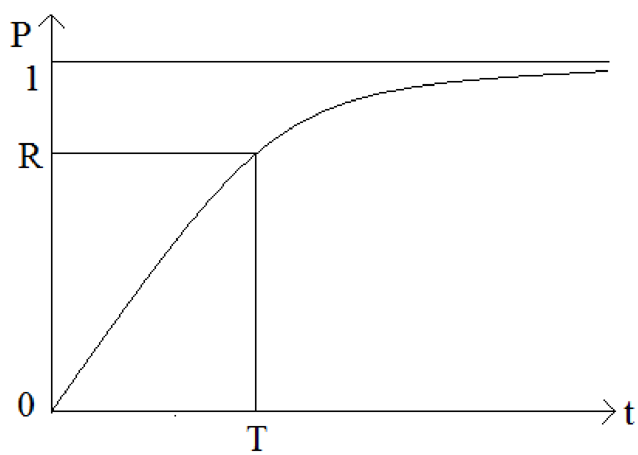

Fig. 5: Function Inversion

To generate the random time that a component resides at a state, usually the function inversion approach as shown in Fig. 5 can be used [24]. In this chapter, the residence time of component state is exponentially distributed. Firstly, a random number within $[0,1]$ is generated; then, the value of the corresponding residence time on the horizontal axis can be obtained by inversing the exponential function. Mathematically, the cumulative distribution function of an exponential distribution is as follows:

$$P = 1 - e^{-\alpha t} \tag{16}$$

here,

α = rate parameter

Then, the residence time can be computed as follows:

$$t = -\frac{\ln(1-P)}{\alpha} \tag{17}$$

When α is replaced by failure rate λ or repair rate μ, the residence time of a component at success state or failure state can be obtained accordingly.

3.4.2 Estimation and convergence

As in the analytical method, here frequency and duration indices are simulated. An advantage of sequential simulation is that the estimation of reliability indices is simpler than that in random sampling. The estimates of p_f, f_f are as follows:

$$\overline{p_f} = \frac{\sum_{i=1}^{N} T_i}{N} \tag{18}$$

$$\overline{f_f} = \frac{\sum_{i=1}^{N} f_i}{N} \tag{19}$$

where,

$\overline{p_f}$ = estimate of p_f

$\overline{f_f}$ = estimate of f_f

N = a sufficiently large number (e.g. the number of years)

T_i = system failure time during the *i*th cycle

f_i = system failure frequency during the *i*th cycle (e.g. the frequency from success to failure)

Then, the mean duration of system failure d_f can be computed as follows:

$$d_f = \frac{\overline{P_f}}{\overline{f_f}} \tag{20}$$

Apparently, $p_f = E(T_i)$ and $f_f = E(f_i)$.

In this dissertation, the coefficient of variation of an estimate is used to terminate the simulation, i.e. when it is less than a preset value. The coefficients of variation of $\overline{p_f}$, $\overline{f_f}$ are as follows:

$$COV_p = \frac{\sqrt{Var(\overline{p_f})}}{\overline{p_f}} = \frac{\sqrt{\frac{1}{N}\overline{Var(p_f)}}}{\overline{p_f}} \tag{21}$$

$$COV_f = \frac{\sqrt{Var(\overline{f_f})}}{\overline{f_f}} = \frac{\sqrt{\frac{1}{N}\overline{Var(f_f)}}}{\overline{f_f}} \tag{22}$$

where,

COV_p = coefficient of variation of $\overline{p_f}$

COV_f = coefficient of variation of $\overline{f_f}$

$Var(\overline{p_f})$ = variance of $\overline{p_f}$

$Var(\overline{f_f})$ = variance of $\overline{f_f}$

$Var(p_f)$ = variance of p_f

$Var(f_f)$ = variance of f_f

$\overline{Var(p_f)}$ = estimate of $Var(p_f)$ and is equal to $\frac{1}{N}\sum_{i=1}^{N}\left(T_i - \overline{p_f}\right)^2$

$\overline{Var(f_f)}$ = estimate of $Var(f_f)$ and is equal to $\frac{1}{N}\sum_{i=1}^{N}\left(f_i - \overline{f_f}\right)^2$

3.4.3 Confidence interval

As discussed previously, T_i, f_i are random variables and their expected values are p_f, f_f respectively. Now, suppose that their variances are σ_T^2, σ_f^2 respectively. Then, their sample variances are as follows:

$$S_T^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(T_i - \overline{p_f}\right)^2 \quad (23)$$

$$S_f^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(f_i - \overline{f_f}\right)^2 \quad (24)$$

where,

S_T^2 = sample variances of T_i

S_f^2 = sample variances of f_i

Then, $Z_T = \frac{\overline{p_f} - p_f}{S_T/\sqrt{N}}$, $Z_f = \frac{\overline{f_f} - f_f}{S_f/\sqrt{N}}$ have *t*-distribution [23], and the $100\%(1-\alpha)$ confidence intervals of p_f, f_f are as follows:

$$P_r\left(\overline{p_f} - A_{\alpha/2}\frac{S_T}{\sqrt{N}} < p_f < \overline{p_f} + A_{\alpha/2}\frac{S_T}{\sqrt{N}}\right) = (1-\alpha) \quad (25)$$

$$P_r\left(\overline{f_f} - A_{\alpha/2}\frac{S_f}{\sqrt{N}} < f_f < \overline{f_f} + A_{\alpha/2}\frac{S_f}{\sqrt{N}}\right) = (1-\alpha) \quad (26)$$

where,

$$A_{\alpha/2} \quad = \quad 100(1-\alpha/2)th \text{ percentile of } t\text{-distribution}$$

Actually, confident interval is an interval estimation in contrast to the point estimation introduced in the last subsection, and it can provide another perspective on the estimates.

3.4.4 Simulation algorithm

The algorithm of sequential simulation to assess the effects of fluctuating weather is as follows:

1) Each system state is represented by an (n+1)-bit binary vector. From bit 1 to n, each binary number is 1 or 0 if the state of the corresponding component is success or failure. The last bit indicates the state of weather and it is 1 or 0 if weather is normal or adverse.
2) For an arbitrary combination of n+1 binary numbers, examine the last bit: if it is 1, the transition rates of all components in normal weather are used; otherwise, the transition rates of all components in adverse weather are used.
3) Compare the residence times of all components and weather at their current states, and the smallest one determines the next most imminent event. Here, the change of weather state is also treated as an event.
4) Update all residence times on the principle: each one minus the smallest one, and the one being 0 will get a new time.
5) Check the type of the event: if it is the change of the state of weather, go back to Step (2); if it is the change of the state of a component, go to the next step.

6) After the event has happened, check if the obtained system state is failure (here the same criterion as that in the analytical method is used): if true, the corresponding event time is saved; otherwise, go to the next step directly.
7) Check if the system state before this event is failure: if false, the transition of system state is counted; otherwise, go to the next step directly.
8) Update all values: estimates, coefficients of variation, confidence intervals.
9) Check if termination criterion is matched: if true, stop; if not, go back to Step (1).

3.4.5 Possible improvements

As in the analytical method, most of the computational time is spent on analyzing failure effects, i.e. determining a system state is failure or not. This can be improved by using the methods mentioned in the last section. Due to the characteristics of simulation method, there are two other improvements which can be implemented. One is that some intelligent methods can be used to improve the selection of system states [24]; the other is that variance reduction method can be used to accelerate the convergence of simulation [23].

3.5 Implementation

In this section, the analytical and simulation methods proposed are applied to the modified IEEE reliability test system [38], and the results obtained by using the two methods are compared and analyzed.

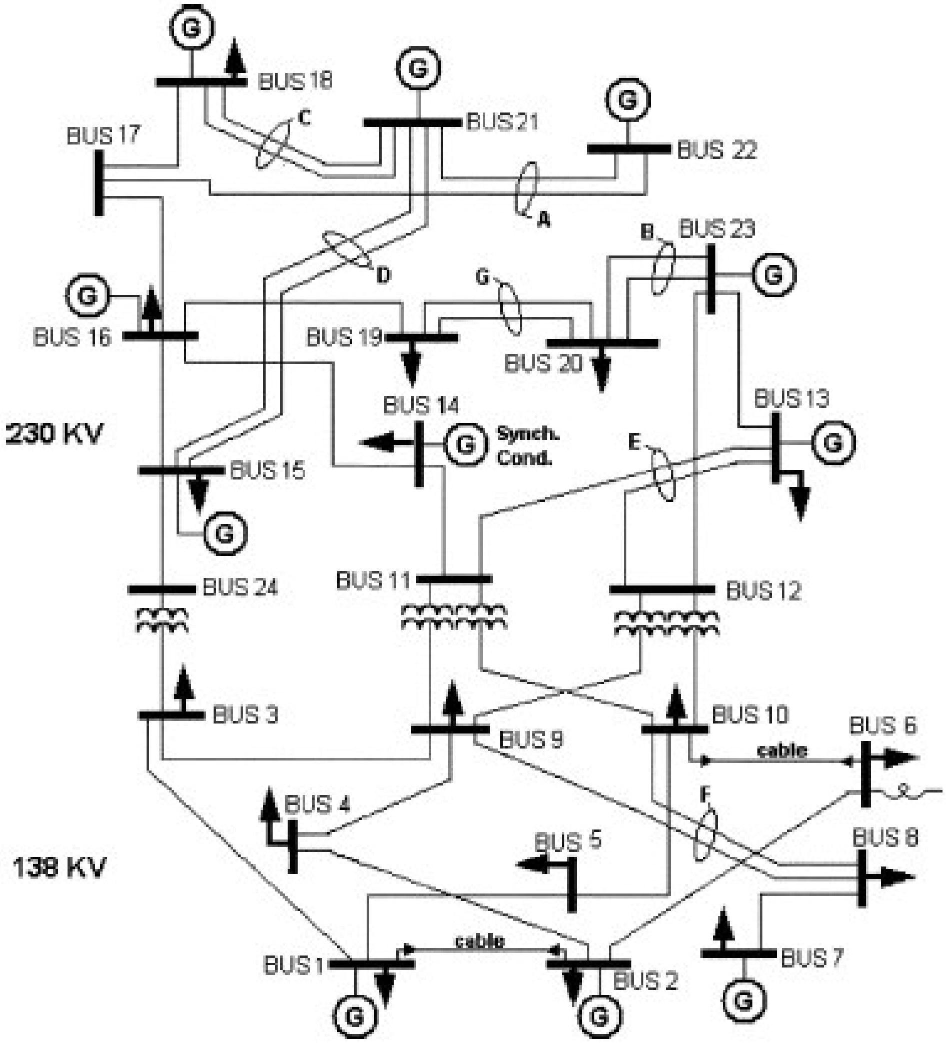

Fig. 6: IEEE Reliability Test System [39]

3.5.1 Test system

The single-line diagram of IEEE reliability test system is shown in Fig. 6. There are 32 generators ranging from 12 MW to 400MW, 24 buses, and 38 transmission lines and transformers. The transmission part of the test system generally consists of two voltage levels: 138 KV and 230 KV.

Considering that the transmission part of the test system is relatively over-reliable [40]-[41], the test system is modified as: the installed capacities of all generators and the load at each bus are increased 1.5 times. Accordingly, the annual peak load 4275 MW is used as the system load, i.e. the system load is constant. But, the proposed methods are also applicable when varied system load is used. Additionally, for the purpose of illustration, all the generators in Table 7 and all the transmission lines in Table 11 in [38] are assigned integer numbers starting from 1 in an ascending order respectively. In this dissertation, the relevant data of IEEE reliability test system is listed in Appendix.

3.5.2 System reliability indices

In this subsection, the system minimal cut-sets identified by using the proposed analytical method and the evaluation results obtained are presented.

3.5.2.1 System minimal cut-sets

Here, the minimal cut-sets are determined up to second-order. The minimal cut-sets determined are as follows: first-order minimal cut-sets of generation and transmission parts, second-order minimal cut-sets of generation and transmission parts, and second-order mixed type which consists of a generator and a transmission line. A mixed minimal cut-set is represented in the form of {generator, transmission line}. The system minimal cut-sets determined are listed in Tables 1-3. It is pointed out that distinguishing the minimal cut-sets of different orders and different types in three tables is just for the purpose of illustration. In programming, actually they are processed indistinguishably as one *table* by using the algorithm developed in Section 3.3.

Table 1: System Minimal Cut-Sets (Generation)

Type	1-Order	2-Order
Generator	None	{12,13},{12,14},{13,14},{12,22},{13,22}
		{14,22},{20,22},{21,22},{12,23},{13,23}
		{14,23},{20,23},{21,23},{22,23},{22,30}
		{23,30}{22,31},{23,31},{12,32},{13,32}
		{14,32},{20,32}{21,32}{22,32},{23,32}
		{30,32},{31,32}

Table 2: System Minimal Cut-Sets (Transmission)

Type	1-Order	2-Order
Transmission Lines	{5},{10} {11}	{1,7},{2,7},{6,7},{4,8},{3,9},{7,9}
		{12,13},{7,14},{7,15},{3,16},{7,16}
		{12,16},{15,16},{3,17},{7,17},{12,17}
		{15,17},{16,17},{7,18},{15,18},{17,18}
		{18,20},{7,21},{18,21},{20,21},{21,22}
		{7,23},{15,23},{17,23},{18,23},{19,23}
		{21,23},{1,27}{2,27},{6,27},{7,27}
		{8,27},{9,27},{14,27},{15,27},{16,27}
		{17,27}{18,27},{21,27},{23,27},{31,38}

Table 3: System Minimal Cut-Sets (Mixed)

Type	1-Order	2-Order
Mixed	N/A	{7,1},{8,1},{1,7},{2,7},{3,7},{4,7}
		{5,7},{6,7},{7,7},{8,7},{12,7},{13,7}
		{14,7},{32,7},{32,25},{32,26},{1,27}
		{2,27},{3,27},{4,27},{5,27},{6,27}
		{7,27},{8,27},{12,27},{13,27},{14,27}
		{32,27},{32,29}

3.5.2.2 System reliability indices

The system reliability indices and the computational time are listed in Table 4. The average value is the average of the upper and lower bounds. For simplicity, only the system reliability indices in normal weather are calculated. If the relevant data is available, the effects of adverse weather can be easily incorporated.

3.5.3 Nodal reliability indices

As discussed in Section 3.3, the proposed analytical method can also compute nodal reliability indices. The algorithm is the same as that computing system indices except that the nodal minimal cut-sets are used instead. For illustration, in Tables 5-7 the minimal cut-sets identified for bus 19 of the test system are listed. As mentioned in Section 3.3, the minimal cut-sets of bus 19 are the subsets of system minimal cut-sets. In Table 8, the reliability indices obtained at bus 19 are listed. The indices for all the nodes are listed in Table 9. For clarity, only the average values of p_f, f_f are computed. The computational time for system and all 20 bus indices is approximately 138 seconds as compared with the only system indices (Table 4) of 134 seconds. So, the additional computational time for the nodal indices is only about 4 seconds, about 3% of the time for the system indices. The reason, as explained earlier, is that the determination of minimal cut-sets where most CPU time is spent, is the same for the algorithms for computing system and nodal indices.

Table 4: Long-Term System Reliability Indices

Index	Upper Bound	Lower Bound	Average Value
p_f	0.1443	0.0853	0.1148
f_f (/yr)	35.04	12.264	23.652
d_f (yr)	N/A		0.0049
Computation time (s)	133.592		

Table 5: Minimal Cut-Sets of Bus19 (Generation)

Type	1-Order	2-Order
Generator	None	{12,13},{13,22}, {14,22},{20,22},{21,22}
		{12,23},{13,23},{14,23},{20,23},{21,23}
		{22,23},{22,30},{23,30}{22,31},{23,31}
		{12,32},{13,32},{14,32},{20,32}{21,32}
		{22,32},{23,32},{30,32},{31,32}

Table 6: Minimal Cut-Sets of Bus 19 (Transmission)

Type	1-Order	2-Order
Transmission Lines	{11}	{4,8},{3,9},{19,23},{7,27},{31,38}

Table 7: Minimal Cut-Sets of Bus 19 (Mixed)

Type	1-Order	2-Order
Mixed	N/A	{32,25},{32,26},{32,29}

Table 8: Reliability Indices at Bus 19 (Long-Term)

Index	Upper Bound	Lower Bound	Mean Value
p_f	0.1333	0.0815	0.1074
f_f (/yr)	30.66	12.264	21. 4506
d_f (yr)	N/A		0.005

Table 9: Long-Term Nodal Reliability Indices

Bus	p_f	f_f (/yr)	d_f (yr)
1	0.1123	22.8456	0.0049
2	0.1121	22.7399	0.0049
3	0.0923	18.0322	0.0051
4	0.1122	22.8178	0.0049
5	0.1122	22.8213	0.0049
6	0.0339	5.1403	0.0066
7	0.0002	0.1966	0.001
8	0.0998	19.6637	0.0051
9	0.0321	4.3344	0.0074
10	0.1121	22.7205	0.0049
13	0.1122	22.8087	0.0049
14	0.0398	6.9801	0.0057
15	0.091	17.6535	0.0052
16	0.1073	21.4319	0.005
18	0.0908	17.4674	0.0052
19	0.1074	21.4506	0.005
20	0.1072	21.3369	0.005
Computation time (s): 138.408			

3.5.4 Simulation results

Table 10: Simulation Results: Part 1 (Long-Term)

Iteration	*up*	*lp*	p_f	*uf*(/yr)	*lf*(/yr)	f_f (/yr)
50	0.2013	0.0787	0.14	53.9589	18.4706	36.2147
250	0.1649	0.1121	0.14	57.5648	33.4846	45.5247
500	0.164	0.124	0.144	40.0002	26.4266	33.2134
2500	0.1258	0.1094	0.1176	27.6618	22.2996	24.9807
5000	0.1245	0.1127	0.1186	27.2848	23.4432	25.364

Table 11: Simulation Results: Part 2 (Long-Term)

Iteration	p_f	f_f (/yr)	d_f (yr)	Computation time(s)
50	0.14	36.2147	0.0039	3.01
250	0.14	45.5247	0.0031	14.835
500	0.144	33.2134	0.0043	29.796
2500	0.1176	24.9807	0.0047	148.34
5000	0.1186	25.364	0.0047	294.54

The reliability indices obtained by using the simulation method are listed in Tables 10-11. Here, for clarity only the results after some number of iterations are listed. Here, the 90*th* percentile of *t*-distribution is used to compute the confidence intervals. Corresponding to the analytical results, only the reliability indices in normal weather are simulated. For simplicity, only the system reliability indices are simulated. But the proposed algorithm is also applicable to simulating the nodal indices. The abbreviations used in Table 10 are as follows:

up = upper bound of the confidence interval of p_f

lp = lower bound of the confidence interval of p_f

uf = upper bound of the confidence interval of f_f

lf = lower bound of the confidence interval of f_f

3.5.5 Comparison of results from two methods

The results of the two methods are compared in Figs. 7-8. Here, the straight lines represent the bounds and the average value of the analytical results, and the curves represent the confidence intervals and the estimates of the simulation results. Here, the legends used are as follows:

UBAM: upper bound of the analytical method

LBAM: lower bound of the analytical method

MVAM: mean value of the analytical method

UBCI: upper bound of the confidence interval

LBCI: lower bound of the confidence interval

EFP: estimate of system failure probability

EFF: estimate of system failure frequency

From the comparison, the following conclusions can be made:

1) The simulation results fall into the bounds of the analytical results, and the bounds of the analytical results is wider than the confidence intervals of the simulation results except in the beginning of the simulation.

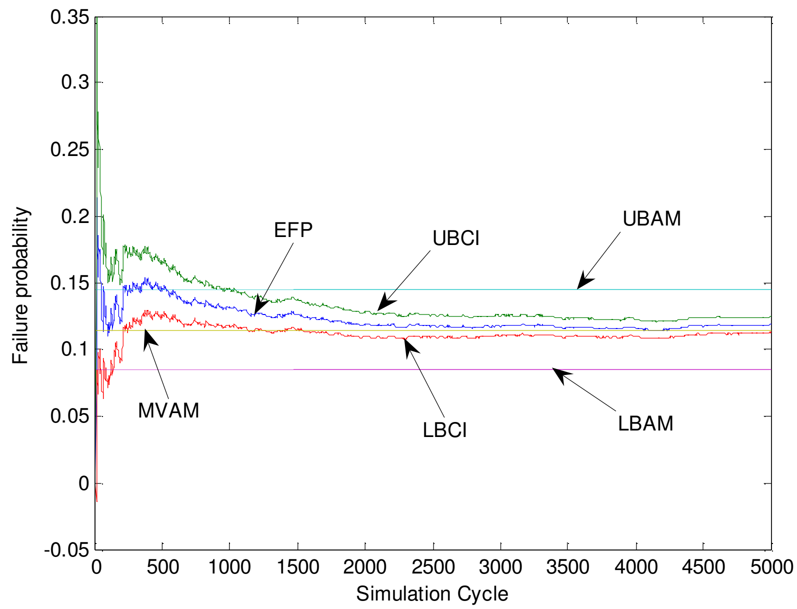

Fig. 7: Long-Term System Failure Probability

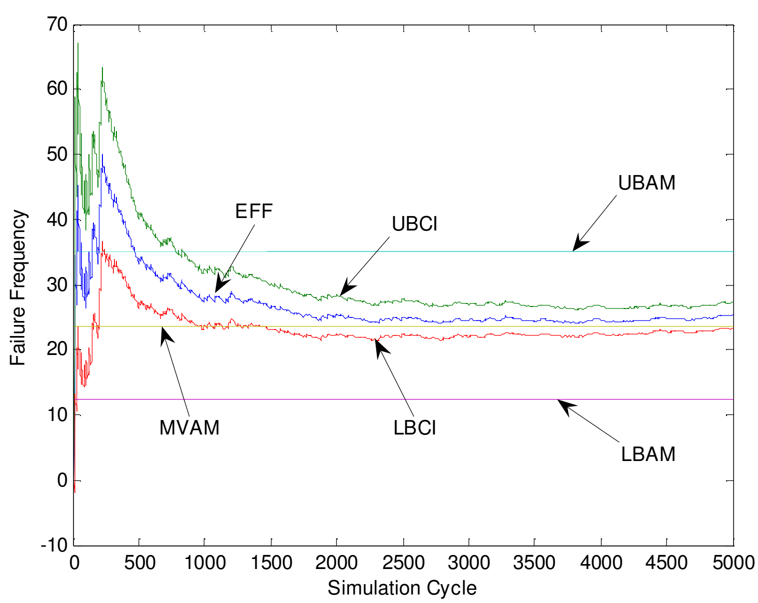

Fig. 8: Long-Term System Failure Frequency

2) The average values of the analytical results fall into the confidence intervals of the simulation results, and they are close to the estimates of the simulation, i.e. the average values of the analytical results can approximate the system reliability indices and they are comparable to the simulation results.
3) When the simulation is proceeding, the confidence intervals become narrower and the bounds of a confidence interval become parallel. Therefore, the variation tendency of the confidence intervals can be used as the termination criterion of the simulation, e.g. setting the difference of the bounds of a confidence interval being less than a small value.
4) In this dissertation, no special technique is used to accelerate the convergence of the simulation. The comparison shows that in the current case the proposed analytical method is faster and comparable results can be obtained.
5) In the current case, the computational time of the proposed analytical method is acceptable, and the additional computational burden in computing nodal reliability indices and storing corresponding data is not significant. For real-world applications, further investigation and improvements of implementation could be done. For instance, usually both analytical and simulation methods use linear optimization to analyze failure effects and this is time-consuming. Some heuristics combined with this approach can improve the performance of reliability evaluation methods.

3.6 Summary

In this chapter, an improved analytical method is proposed to evaluate the impact of adverse weather on the reliability of composite power systems. This method proposes an algorithm to identify system and nodal minimal cut-sets, and proposes an improved algorithm to compute the reliability indices of the bounds of minimal cut-sets. An algorithm for using sequential simulation to assess the effects of fluctuating weather is also developed. These two methods are applied to the modified IEEE reliability test system. The evaluation results obtained by using different methods are compared and analyzed.

From the implementation, the following conclusions are made:

1) The proposed analytical method is effective and efficient. In the current case, it is fast and the evaluation results can be comparable to those of the simulation method.
2) The proposed analytical method has the advantages of easy implementation, convenience of incorporating more system operational considerations, and easy interpretation of the obtained results.
3) The variation tendency of the confidence intervals can be used to terminate the simulation.
4) The additional computational burden in computing nodal reliability indices and storing corresponding data is not significant. The reason is that the proposed analytical method can identify system and nodal minimal cut-sets simultaneously, and this process is time-consuming compared to the calculation of reliability indices.
5) For real-world applications, further investigation and improvements of implementation could perhaps be done. For instance, some intelligent methods can be used to improve the performance of reliability evaluation techniques.

CHAPTER IV

EVALUATION OF HURRICANE IMPACT ON THE SHORT-TERM RELIABILITY OF COMPOSITE POWER SYSTEMS

In the last chapter, the impact of adverse weather on the long-term reliability of composite power systems is investigated. Typically, hurricanes only last a few days but their impact on life-line systems is drastic. Therefore, the impact of hurricanes on the short-term reliability of composite power systems needs to be investigated as their impact on the long term reliability is likely to be diluted. In this chapter, a methodology is proposed to investigate the impact of hurricanes on the short-term reliability of composite power systems. Firstly, a fuzzy inference system is combined with regional weather model [8]-[9] to assess the effect of hurricanes on the failure rates of system components. Here, different methods are used to build two types of fuzzy inference systems [12]-[14]. Then short-term minimal cut-set method is developed to compute time-specific system and nodal reliability indices [13], [17]. The proposed methodology is also applied to the modified IEEE reliability test system. The evaluation results obtained by using different methods are compared and analyzed. The implementation demonstrates that the proposed methodology is effective and efficient and is flexible in its applications [13].

This chapter is organized as follows: in Section 4.1 relevant researches about the effect of weather on the short-term reliability of power systems are reviewed; in Section 4.2 the overall evaluation scheme of the short-term reliability of composite power systems affected by hurricanes is presented; in Section 4.3 the basic concepts of fuzzy sets and fuzzy inference systems are introduced; in Section 4.4 the different methods to build different fuzzy inference systems are presented; in Section 4.5 the main steps of short-term minimal cut-set method are presented; in Section 4.6 the proposed methodology is applied to the modified IEEE reliability test system; finally, in Section 4.7 the main conclusions obtained in this chapter are summarized.

4.1 Literature Review

Many power system components, such as transmission and distribution lines, are exposed to external environment, and it can have a significant impact on the reliability parameters of system components. For instance, it is known for a long time that the failure rate of a transmission or a distribution line is a function of the weather that it is exposed to, and the failure rate of the transmission or distribution line can be much higher in adverse weather than that in normal weather [11]. Thus, one of the challenges of assessing the impact of hurricanes on the short-term reliability of composite power systems is to evaluate how hurricanes affect the reliability parameters of system components, i.e. failure and repair rates.

In [1], it was pointed out that there is rough correspondence between the severity level of hurricanes and the number of power outages. Since the failure rate of a component is close to its failure frequency, i.e. the number of outages during a period of time, the preceding observation can be interpreted that there is some functional relationship between the severity level of hurricanes and the failure rates of system components. Thus, a regression method can be used to assess the relationship between them.

In [42], the impact of vegetation on the failure rates of overhead distribution feeders was assessed by using some parametric methods and an artificial neural network. In [43], multiple linear regression was used to evaluate the impact of weather on the failure rates of transmission lines. In [44], a Bayesian network was used to assess the impact of weather on the failure rates of overhead distribution lines.

In this dissertation, a fuzzy inference system is combined with regional weather model [8]-[9] to assess the functional relationship between the severity level of hurricanes and the failure rate increment of system components. Here, different methods are used to build two types of fuzzy inference systems [12]-[14]. These methods include artificial method and data-driven methods. An advantage of the proposed approach is that these methods can be used in different situations.

After the incremental failure rates of system components are determined, the short-term reliability of composite power systems can be evaluated as follows. Firstly, the reliability indices of system components are calculated. The steady state results of Markov process are not suitable here and so the short-term indices need to be calculated.

In this chapter, a method is proposed to use the minimal cut-set approach described in the previous chapter to evaluate the short-term reliability of composite power systems affected by hurricanes. Here, both system and nodal reliability indices can be computed.

4.2 Overall Evaluation Scheme

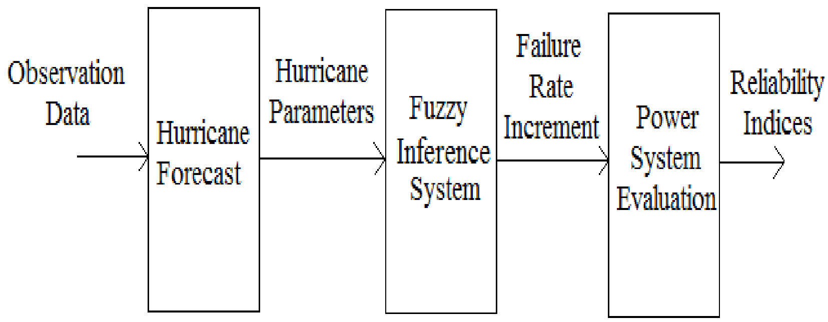

Fig. 9: Short-Term Reliability Evaluation Scheme (Independent Failures)

The overall scheme for investigating the impact of hurricanes on the short-term reliability of composite power systems is shown in Fig. 9. Generally, it consists of three steps: hurricane forecast, assessing the incremental component parameters, and system reliability evaluation. The relevant details are presented in the following subsections. Finally, the collection of required data for data-driven methods to build the fuzzy inference system is discussed.

4.2.1 Hurricane impact

A hurricane is a stormy weather which develops over large bodies of the oceans and then loses its strength after moving over land. Its main effects are strong wind and heavy rainfall when it moves over land. The movement track and strength of a hurricane can be forecast by using observation data and prediction model.

Since hurricanes develop and dissipate with time, their impact on a composite power system can be described in two aspects: *temporal* and *spatial*. *Temporal* refers to the fact that the impact of a hurricane in a given region is different at different times; *spatial* refers to the fact that that the impact of a hurricane is different in different regions at a given time. In this dissertation, the duration of a hurricane is partitioned into some small time intervals to investigate the temporal effects of hurricanes; the affected composite power system is partitioned into several regions to investigate the spatial effects of hurricanes. The temporal partition can be determined by the dissipation rate of the hurricane, and the spatial partition can be determined by the geographical conditions of the composite power system.

The severity level of hurricanes can be represented by some defined parameters. In this dissertation, wind speed and rainfall are used as two parameters of hurricanes. It is noted that in a given region, the parameters of hurricanes are assumed to be identical.

4.2.2 Fuzzy inference

In this dissertation, a fuzzy inference system is used to map the functional relationship between hurricane parameters and the increment multipliers of the failure rates (IMFR) of transmission lines, i.e. the ratios of the failure rates during hurricanes and those in normal weather. Similarly, the IMFR of transmission lines in a given region is assumed to be identical. Since a long transmission line may traverse different regions, its overall IMFR can be determined by using weighted average method which is described in detail in Section 4.5. For the purpose of comparison, in this step different methods are used to build different types of fuzzy inference systems.

4.2.3 System reliability evaluation

After the incremental failure rates of system components are obtained, short-term reliability indices can be computed by using analytical or simulation method. Here, short-term minimal cut-set method is proposed to compute system and nodal indices. Since the states of components are assumed to be independent here, firstly the reliability indices of components are computed by using the transient results of Markov process, then system and nodal indices are calculated by using the multiplication rule of probabilities.

4.2.4 Data collection and preprocessing

In this dissertation, data-driven method is also used to build the fuzzy inference system. Thus, the required data need to be collected and preprocessed. These data include hurricane parameters and the failure rates of system components affected. Usually, hurricane parameters can be collected by referring to historical meteorology records, and the average failure rates of system components can be obtained by referring to historical records of utilities, i.e. the failure rates in normal weather and during hurricanes are not distinguished. The failure rates of system components in different weathers can be obtained by using the transformation techniques like those in [43]-[44]. Basically, the relationship between failure frequency (f) and failure rate (λ) is used: $f \approx \lambda$. Here, f is the number of the failures of a system component during a period of time and it can be obtained from historical records.

Since in this dissertation the output of the fuzzy inference system is the regional IMFR of system components, the obtained failure rates need to be preprocessed. Here, the aggregated failure rates of system components during hurricanes and those in normal weather are compared to get the regional IMFR of system components.

Due to the unavailability of relevant data for confidentiality reasons, the data used in this dissertation is generated by using the fuzzy expert system in [12]. The details are given in Section 4.6.

4.3 Introduction of Fuzzy Inference Systems

4.3.1 Basic concepts of fuzzy sets

4.3.1.1 Crisp sets and fuzzy sets

The concept of fuzzy sets is the generalization of that of crisp sets, i.e. classic sets. Usually, whether an element x is a member of a crisp set A or not is classified by using the characteristic function as follows:

$$CF_A(x) = \begin{cases} 1, x \in A \\ 0, x \notin A \end{cases}, \text{ i.e. } CF_A : X \rightarrow \{0,1\} \qquad (27)$$

where,

CF	=	characteristic function
X	=	universe of discourse of x, i.e. all the possible values that x can take: discrete or continuous

However, for a fuzzy set B the degree of whether or not an element x is its member can be between 0 and 1, and this is described by using the membership function as follows:

$$MF_B : X \rightarrow [0,1] \qquad (28)$$

Apparently, the expression of membership functions is more flexible than that of characteristic functions, and this makes membership functions more descriptive of how the real world is perceived. Actually, we always encounter many objects that partially belong to a category and maybe belong to other categories at the same time. In practice, a membership function can be any function that satisfies the relationship defined in (28). It can be in triangular, trapezoidal, Gaussian, and many other forms.

4.3.1.2 Operations on fuzzy sets

Correspondingly, the operations of fuzzy sets are the generalization of those on crisp sets. For instance, the characteristic function of the intersection of two crisp sets *A* and *B* can be expressed as follows:

$$CF_{A \cap B}(x) = \min(CF_A, CF_B) \qquad \text{for } x \in X \tag{29}$$

where,

min = minimum operation

Using membership functions instead of the characteristic functions, the membership function of the intersection of two fuzzy sets *C* and *D* can be expressed as follows:

$$MF_{C \cap D}(x) = \min(MF_C, MF_D) \qquad \text{for } x \in X \tag{30}$$

Similarly, other operations on crisp sets can be extended to those on fuzzy sets. Here, it is noted that the laws of *noncontradiction* and *excluded middle* are applicable to crisp sets but not to fuzzy sets. This is described in Table 12 where usually the universe of discourse of interest is the set of real numbers. More generally, the intersection operation on fuzzy sets can be realized by using triangular norms (*t*-norms) [45]. It presents a group of operations, e.g. minimum and product operations. In the same way, the union operation on fuzzy sets can be realized by using *t*-conorms (*s*-norms), e.g. maximum and probabilistic sum operations.

Table 12: Comparison of Crisp Sets and Fuzzy Sets

Operation	Crisp Sets	Fuzzy Sets
Noncontradiction	$A \cap \overline{A} = \varnothing$	$A \cap \overline{A} \neq \varnothing$
Excluded Middle	$A \cup \overline{A} = X$	$A \cup \overline{A} \neq X$

4.3.1.3 Fuzzy relations

A relation captures the association between objects. Generally, a relation *R* defined over the Cartesian product of *X* and *Y* is a collection of selected pairs (x, y), $x \in X$, $y \in Y$. Here, the two-dimensional case is illustrated and the definition is also applicable to multi-dimensional case. Mathematically, *R* is a mapping as follows:

$$R(x, y) = \begin{cases} 1, x, y & related \\ 0, x, y & unrelated \end{cases}, \text{ i.e. } R : X \times Y \rightarrow \{0,1\} \tag{31}$$

A fuzzy relation generalizes the above concept by recognizing the partial degree of association between objects, i.e. a fuzzy relation R_F is a mapping such that:

$$R_F : X \times Y \rightarrow [0,1] \tag{32}$$

Actually, a fuzzy relation is a multi-dimensional fuzzy set or a fuzzy rule, and the aggregation of them forms a key part of a fuzzy inference system.

4.3.1.4 Cylindrical extension and projection

Cylindrical extension and projection are two important notions in fuzzy theory. Generally, they can be regarded as two operations on fuzzy sets. Cylindrical extension on a fuzzy set *A* is defined as follows:

$$MF_A : X \rightarrow [0,1] \Rightarrow MF_{Ce(A)} : X \times Y \rightarrow [0,1] \tag{33}$$

where,

$Ce(A)$	=	cylindrical extension on fuzzy set *A*

Basically, cylindrical extension is an operation which extends a low-dimensional fuzzy set to a high-dimensional one. Oppositely, projection is an operation that reduces a high-dimensional fuzzy set to a low-dimensional one. For instance, the projection of a fuzzy set *B* from space $X \times Y$ to space *X* is as follows:

$$MF_B : X \times Y \rightarrow [0,1] \Rightarrow MF_{\Pr oj_Y(B)} : X \rightarrow [0,1] \tag{34}$$

here,

$\Pr oj_Y(A)$	=	projection of fuzzy set *B* on Y

4.3.1.5 Fuzzy inference

The inference refers to the derivation of the fuzzy set *B* that if a fuzzy set *A* and a fuzzy relation *R* between them are known. Mathematically, it is as follows:

$$MF_B = \Pr oj_Y(Ce(A) \cap R) \tag{35}$$

Alternately, equality (35) can be expressed as follows:

$$MF_B = MF_A \circ R \tag{36}$$

where,

"∘" = composition operation.

The above equation is the composition rule of fuzzy inference.

4.3.2 Fuzzy inference systems

In this subsection, the basic concepts of fuzzy inference systems are introduced. Firstly, the reasoning mechanism is explained; then, the inference procedure of fuzzy inference systems is described.

4.3.2.1 Reasoning mechanism

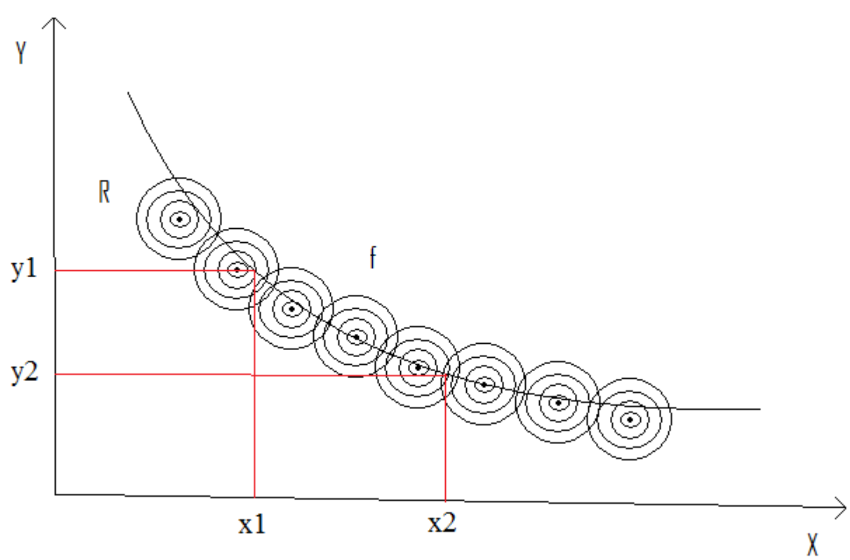

Fig. 10: Reasoning of Fuzzy Inference Systems

Actually, a fuzzy inference system is a rule-based system. Here, a fuzzy rule is actually a fuzzy relation. Thus, the reasoning process of a fuzzy inference system is just the extension of that in the last subsection, and it is as follows:

$$MF_B = \mathrm{Proj}_Y\left(Ce(A) \cap \oplus R_i\right) \qquad i \in I \tag{37}$$

here,

"$\oplus$"	=	aggregation operation
R_i	=	ith fuzzy rule
I	=	index of the set of fuzzy rules

The inference process of fuzzy inference systems is shown in Fig. 10. Here, *f* represents the functional relationship described by a set of fuzzy rules.

4.3.2.2 Fuzzy inference systems

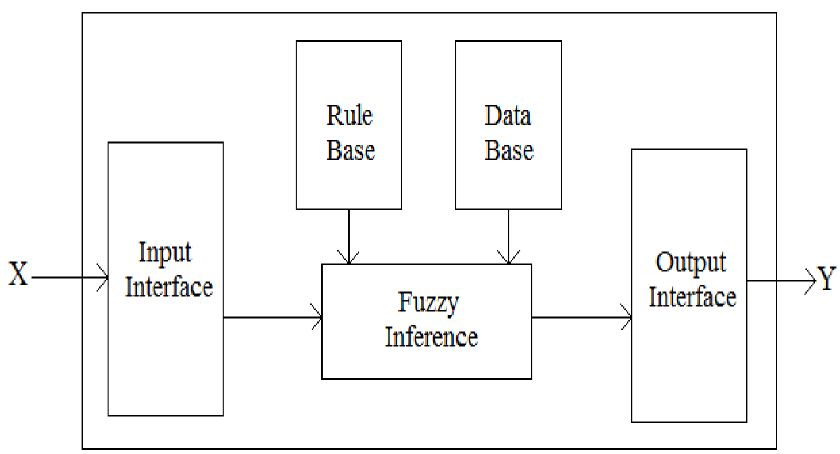

Fig. 11: Architecture of Fuzzy Inference Systems

Usually, a fuzzy inference system consists of five parts as shown in Fig. 11 [45]: input interface, rule base, data base, fuzzy inference, and output interface. Here, X and Y represent the input and output of fuzzy inference systems respectively. Generally, there are two types of fuzzy inference systems: Sugeno-type [46] and Mamdani-type [47]. Their differences are described as follows.

A. Input interface

In this dissertation, the input *X* is the time-specific regional hurricane parameters and it is a vector. Thus, it needs to be converted into the form that the fuzzy inference system can deal with by *fuzzification*, i.e. finding the corresponding membership value of the input. This is shown in Fig. 12. Here, MF represents membership function.

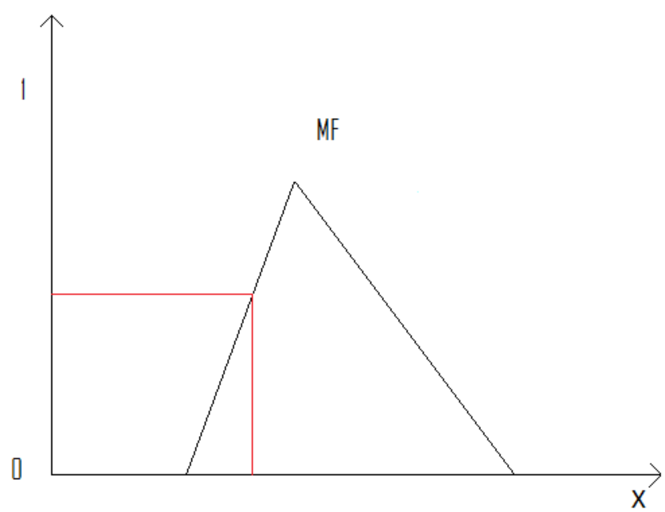

Fig. 12: Fuzzification

B. Rule base

Rule base is a set of fuzzy rules that describe the relationships between the input and output variables of fuzzy inference systems. Generally, for a Mamdani-type fuzzy inference system a fuzzy rule can be in the following form:

$$\text{If } X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } A_2 \text{ and } \cdots \text{ and } X_n \text{ is } A_n \text{ then } Y \text{ is } B$$

here,

X_i	=	ith input variable, $i \le n$
A_i	=	value of X_i, $i \le n$
Y	=	output variable
B	=	value of Y

For instance, in this dissertation a Mamdani-type fuzzy rule can be as follows:

$$\text{If } H_1 \text{ is High and } H_2 \text{ is Medium and } \cdots \text{ and } H_n \text{ is Low then IMFR is High}$$

where

H_i	=	ith hurricane parameter, $1 \le i \le n$

For a Sugeno-type fuzzy inference system, a fuzzy rule can be in the following form:

$$\text{If } X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } A_2 \text{ and } \cdots \text{ and } X_n \text{ is } A_n \text{ then } Y \text{ is } f(X_1, X_2, \cdots X_n)$$

here,

$f(X_1, X_2, \cdots X_n)$	=	linear function of X_i, $i \le n$

C. Data base

The type and parameters of the membership functions of input and output variables as well as other parameters of a fuzzy inference system are stored in data base. Generally, there are two kinds of methodologies to construct the rule base and data base of a fuzzy inference system: knowledge-based (expert systems) and data-driven [45]. In this dissertation, both methodologies are used. The relevant details are given in the next section.

D. Fuzzy inference

Inference process is the most important part of a fuzzy inference system. This is the procedure that the fuzzy inference system processes input data and implement the function of reasoning using the information in rule base and data base. Its main steps are as follows:

1) Input matching: for each rule, determine the membership value of each element of input vector.
2) Input aggregation: for each rule, compute rule activation degree, i.e. the intersection of all the membership values of the input obtained in the last step. It is noted that different *t*-norm operations can be applied to different types of fuzzy inference systems. Here, product operation is used for the Sugeno-type fuzzy inference system and minimum operation is used for the Mamdani-type fuzzy inference system.
3) Output derivation: for each rule, a *t*-norm operation is used to compute the intersection of the rule activation degree and the output. Here, product operation is used for the Sugeno-type fuzzy inference system and minimum operation is used for the Mamdani-type fuzzy inference system.
4) Output aggregation: finally, normalized weighted method is used to compute the overall output of the Sugeno-type fuzzy inference system and the details can be found in the next section; for the Mamdani-type fuzzy inference system, a *s*-norm operation can be used to compute the union of all the obtained output in the last step. Here, maximum operation is used.

E. Output interface

In this dissertation, the output of the fuzzy inference system is the time-specific regional IMFR of system components. Whereas, the output of the Mamdani-type fuzzy inference system is a fuzzy set. Thus, it needs to be converted into a numeric value by *defuzzification*. There are many defuzzification techniques available [45]. Here, centroid method is used [45]. Basically, it determines the gravity center of the aggregated membership function of the overall output and is as follows:

$$y = \frac{\int_Y y \cdot MF(y) d(y)}{\int_Y MF(y) d(y)} \tag{38}$$

where,

MF = membership function

For the Sugeno-type fuzzy inference system, the normalized weighted method can be regarded as a method of defuzzification.

4.3.2.3 Comparison of different fuzzy inference systems

From previous discussion, there are differences between the Sugeno-type and Mamdani-type fuzzy inference systems in terms of rule base, inference procedure, and difuzzification. Accordingly, different methods can be used to build them and this is described in the next section.

4.4 Building Fuzzy Inference Systems

Generally, there are two kinds of methodologies to build a fuzzy inference system: knowledge-based (expert system) and data-driven [45]. When sufficient data is available, a data-driven method can be used to build fuzzy inference system; if the data is not available or is insufficient, knowledge-based method can be used. Moreover, other intelligent methods can be used to improve the performance of fuzzy inference systems. In this section, different methods used to build the fuzzy inference system are introduced: expert system [12], fuzzy clustering methods [13], and a hybrid method which combines a neural network and a fuzzy inference system [14].

4.4.1 Fuzzy expert systems

A fuzzy inference system can be built by using artificial method, i.e. the domain expertise of experts are collected and processed to form a rule system. Actually, fuzzy expert systems are the generalization of deterministic expert systems, and they can handle the uncertainty and vagueness that traditional expert systems cannot deal with [45]. For the fuzzy inference system used in this dissertation, the domain knowledge of experts can be helpful to determine fuzzy rules and the parameters of membership functions.

4.4.2 Fuzzy clustering methods

A fuzzy inference systems can be built by using some data-driven methods too, e.g. clustering methods. In this chapter, two fuzzy clustering methods are used to build two types of fuzzy inference systems [13]: subtractive clustering [48] is used to build the Sugeno-type fuzzy inference system and fuzzy *c*-mean clustering [49] is used to build the Mamdani-type fuzzy inference system. In the end, different fuzzy clustering methods are compared.

4.4.2.1 Fuzzy clustering methods

Usually, some relationships exist among a set of variables and the corresponding data can be collected via observation. Fuzzy clustering methods group these data into different clusters. Each fuzzy cluster is represented by a cluster center and the membership degrees of the data belonging to this cluster, and it represents a fuzzy rule. At the same time the membership functions can be obtained by projecting the fuzzy clusters on the spaces of input and output variables. Thus, fuzzy clustering methods can construct the membership functions and fuzzy rules of a fuzzy inference system automatically and simultaneously, and the number of fuzzy rules obtained can be reduced compared to that of a fuzzy expert system [45].

4.4.2.2 Subtractive clustering

The basic idea of subtractive clustering is as follows [48]:

1) The potential value of each data point as a cluster center is computed based on its distances to other data points.
2) The data point with the highest potential value is chosen as the first cluster center, and the potentials of all data points (including the cluster center) are reduced according to their distances to this cluster center.
3) For other data points, the one with the highest remaining potential value is chosen as the next cluster center.
4) The above procedure goes on till the potential values of all data points fall below some threshold.

Mathematically, the main steps of subtractive clustering are as follows:

1) For a collection of data points $\{x_1, x_2, \cdots, x_n\}$, the following equation is used to compute the potential value of each data point as a cluster center:

$$P_i = \sum_{j=1}^{n} e^{-\alpha \left\| x_i - x_j \right\|^2} \tag{39}$$

where,

P_i	=	potential value of data point x_i
n	=	number of data points
α	=	$\frac{4}{r_\alpha^{\,2}}$, and r_α is a positive constant
$\left\| \cdot \right\|$	=	Euclidean distance

The above measure shows that a data point with many neighboring data points nearby will have a high potential value. The neighborhood radius is defined by r_α and the data points outside r_α have little influences on the potential of the data point. Generally, a large r_α results in fewer clusters and a small r_α results in more clusters.

2) Suppose now the *k*th cluster center has been determined, then the potential values of all data points (including the cluster centers) are in the following form:

$$P_i^{(k)} = P_i^{(k-1)} - P_k^{*} \cdot e^{-\beta \left\| x_i - x_k^{*} \right\|^2} \tag{40}$$

where,

$P_i^{(k)}$	=	potential of data point x_i, and $P_i^{(0)} = P_i$
x_k^{*}	=	*k*th cluster center
P_k^{*}	=	potential value of x_k^{*}

$\beta \quad = \quad \frac{4}{r_\beta^{\,2}}$, and r_β is a positive constant

The above equation shows that the data point near the cluster center has greatly reduced potential and therefore is unlikely to be chosen as the next cluster center. The radius of reduction neighborhood is defined by r_β and it is selected as being greater than r_α in order not to produce two close adjacent cluster centers.

3) The following equation is used to compute the membership degree of each data point belonging to the fuzzy cluster with cluster center x_k^*:

$$m_i = e^{-\alpha \left\| x_i - x_k^* \right\|^2} \tag{41}$$

where,

$m_i \quad = \quad$ membership degree of x_i.

Actually, the membership function is in the form of Gaussian function.

4) Since subtractive clustering is used to build the Sugeno-type fuzzy inference system, its output functions are determined by using linear regression [48].

4.4.2.3 Fuzzy c-mean clustering

Fuzzy *c*-mean clustering is one of the most used fuzzy clustering methods in pattern recognition [49]. Its basic idea is to assign each data point to several pre-determined cluster centers and a constrained objective function is solved to determine the optimal partition.

Mathematically, the objective function is as follows:

$$\text{Min} \quad \sum_{i=1}^{c}\sum_{k=1}^{n}(u_{ik})^m \cdot \|x_k - v_i\|^2 \tag{42}$$

$$\text{St.} \quad 0 \le u_{ik} \le 1 \tag{43}$$

$$\sum_{i=1}^{c} u_{ik} = 1 \tag{44}$$

$$0 < \sum_{k=1}^{n} u_{ik} < n \tag{45}$$

where,

c	=	number of cluster centers
n	=	number of data points
x_k	=	kth data point, $1 \le k \le n$
v_i	=	ith cluster center, $1 \le i \le c$
u_{ik}	=	membership value of x_k belonging to the ith fuzzy cluster
m	=	a constant representing fuzzification degree, and $m \ge 1$

Normally, small or big value of m leads to small or big number of cluster centers. The above formulation is a non-linear constrained optimization problem and its optimality condition is as follows:

$$v_i^* = \frac{\sum_{k=1}^{n}(u_{ik})^m \cdot x_k}{\sum_{k=1}^{n}(u_{ik})^m} \tag{46}$$

$$u_{ik}^* = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|}\right)^{\frac{2}{m-1}}} \tag{47}$$

where,

v_i^* = ith optimal cluster center

u_{ik}^* = optimal membership value of data point x_k belonging to the ith fuzzy cluster

Equations (46)-(47) show that the update of u_{ik}/v_i can only be done if the value of v_i/u_{ik} has been known. Thus, an alternate optimization algorithm can be used to solve the problem (42)-(45), and it is as follows. Here, v_i is assumed being known. Similarly, we can assume u_{ik} being known first.

1) Using (47) to compute u_{ik};
2) Using (46) to update v_i and suppose now it is $\overline{v_i}$;
3) Test if $\left\|v_i - \overline{v_i}\right\|$ is not greater than a pre-set threshold: if true, stop; otherwise, go back to step (1).

4.4.2.4 Comparison of two methods

From previous discussion, subtractive clustering and fuzzy *c*-mean clustering are compared as follows:

A. Initialization problem

For subtractive clustering, the initialization is simple and it considers each data point as a potential cluster center; for fuzzy *c*-mean clustering, this problem is more complex. There are several methods to get the initial cluster centers, e.g. randomly choosing some points, choosing cluster centers according to some modeling or choosing the results of another clustering method as cluster centers, and the chosen cluster centers can be data points or not. Here, the results of subtractive clustering are chosen as the initial cluster centers of fuzzy *c*-mean clustering.

B. Implementation procedure

The comparison of their algorithms shows that the implementation of subtractive clustering is simpler than that of fuzzy *c*-mean clustering. Since fuzzy *c*-mean clustering solves a constrained optimization problem, it has the inherent weaknesses in initialization and convergence, i.e. the sensitivity to initialization and the possibility of trapping at a saddle point, i.e. a local minimum.

C. Complementation of two methods

By contrast, subtractive clustering is a simpler method. But, these two methods can be complementary rather than competitive. For example, as mentioned earlier the results of subtractive clustering can be used as the initial cluster centers of fuzzy *c*-mean clustering. Thus, the performance of fuzzy *c*-mean clustering can be improved.

4.4.2.5 Mamdani-type membership functions

The input membership functions of Sugeno-type fuzzy inference systems are in the form of Gaussian function, whereas the membership functions of Mamdani-type fuzzy inference systems are not in any specific form. Here, the membership functions of the Mamdani-type fuzzy inference system are obtained by using the projection method and are approximated by using two-side Gaussian function [50]. It is actually a combination of two Gaussian functions, and each one represents a side of the membership function.

4.4.3 A hybrid method

After a fuzzy inference system is built, its parameters can be fine tuned by using some intelligent methods. In this chapter, a neural network is used to improve the performance of the Segeno-type fuzzy inference system. Here, adaptive neuro-fuzzy inference system (ANFIS) is used [51]. In this subsection, firstly the underlying motivation of combing fuzzy inference systems and neural networks is given. Then, the algorithm of ANFIS is introduced.

4.4.3.1 Neuro-fuzzy systems

Table 13: Comparison of Neural Networks and Fuzzy Inference Systems

	Neural Networks	Fuzzy Inference Systems
Advantages	No mathematical model	No mathematical model
	No rules required	Prior knowledge used
	Learning ability	Inference and interpretability
Disadvantages	Black box	Rules required
	No prior knowledge	No learning
	Iteration needed to determine parameters	Difficulty in tuning parameters

Neural networks and fuzzy inference systems have some common merits, e.g. no need for establishing mathematical model in advance and universal approximation feature. However, they have their own advantages. As compared in Table 13 [52], neural networks have a learning ability but it is difficult to incorporate prior knowledge into them and to interpret their processing procedure; fuzzy systems can utilize prior knowledge and it is easy to interpret their inference process, but they have no learning ability. Therefore, it is appealing to combine the merits of neural networks and fuzzy inference systems and the resultant is neuro-fuzzy systems. Here, the emphasis is to use the learning ability of neural networks to improve the performance of fuzzy inference systems.

4.4.3.2 Algorithm of ANFIS

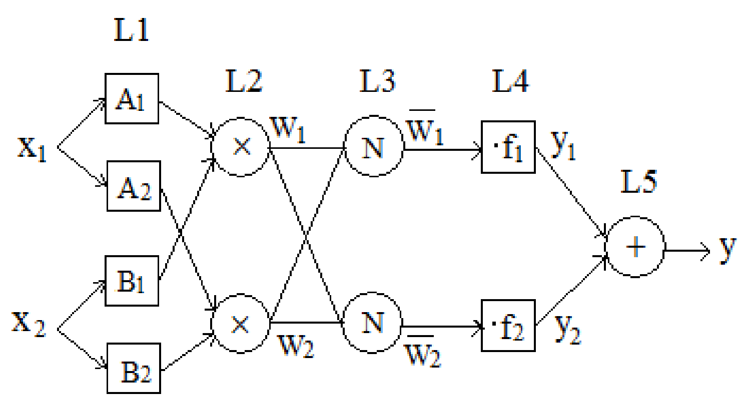

Fig. 13: Configuration of Adaptive Neuro-Fuzzy Inference System

Adaptive neuro-fuzzy inference system is a popular neuro-fuzzy system. It has the configuration of a multilayer perceptron, i.e. a feed-forward neural network that consists of an input layer, one or multiple hidden layers and an output layer. Actually, adaptive neuro-fuzzy inference system uses a multilayer perceptron to realize the functions of a Sugeno-type fuzzy inference system. In such a way, it combines the merits of neural networks and fuzzy inference systems. It has the learning feature of neural networks and retains the interpretability of fuzzy inference systems. Therefore, adaptive neuro-fuzzy inference system can use the learning ability of neural networks to improve the performance of Sugeno-type fuzzy inference systems. The schematic architecture of adaptive neuro-fuzzy inference system is shown in Fig. 13 [51]. Here, only two input variables and one output variable are shown. And,

L_i	=	layer *i, i* =1, 2, 3, 4, 5

The operating procedure of adaptive neuro-fuzzy inference system is as follows:

- Layer 1

X_i	=	*i*th input variable, *i*=1, 2
A_i, B_i	=	Gaussian-shaped linguistic labels, *i*=1, 2, and their parameters are called *antecedent parameters*.
output	=	membership value

- Layer 2

“×”	=	product operation
W_i	=	product of the membership values of X_i, *i*=1, 2, i.e. rule activation degree

- Layer 3

“*N*”	=	normalization operation
$\overline{W_i}$	=	$\frac{W_i}{\sum_{i=1}^{2} W_i}$, *i*=1, 2

- Layer 4

f_i	=	*i*th linear output function, *i*=1, 2, and its parameters are called *consequent parameters*

“$\cdot f_i$” = “multiplied by f_i”

y_i = $\overline{W_i} \cdot f_i$, $i = 1, 2$

- Layer 5

“+” = summation operation

$$y = \sum_{i=1}^{2} y_i = \sum_{i=1}^{2} \overline{W_i} \cdot f_i = \frac{\sum_{i=1}^{2} W_i \cdot f_i}{\sum_{i=1}^{2} W_i}$$

As mentioned before, adaptive neuro-fuzzy inference system has a learning ability, i.e. it can adjust its parameters to achieve the minimal error measure using the samples of input and output data. Adaptive neuro-fuzzy inference system realizes its learning ability using a hybrid algorithm: backpropagation and least squares estimation. Generally, the learning process of adaptive neuro-fuzzy inference system is as follows:

1) The input is forwarded and consequent parameters are estimated by using least squares estimation while antecedent parameters are assumed unchanged.
2) The error signal in the last step is propagated backwards and antecedent parameters are updated by using backpropagation while estimated consequent parameters are used and they are assumed unchanged.
3) The learning process stops if the error measure is below some threshold.

4.4.4 Clustering Data

In the previous subsections, the implementation of the data-driven methods depends on the availability of relevant data. Due to the unavailability of the data for confidentiality reasons, the clustering data used in this dissertation is generated by using the fuzzy expert system in [12] and the details are given in Section 4.6.

4.5 Short-Term Minimal Cut-Set Method

In this section, the short-term minimal cut-set method proposed to compute time-specific reliability indices is presented. Firstly, the short-term reliability indices used are introduced; then, the computation procedure of reliability indices is described and finally, the weighted average method used to compute the overall IMFR of transmission lines that traverse a few regions is presented.

4.5.1 Short-term reliability indices

Since hurricanes usually last only a few days, the short-term reliability indices of composite power systems should be calculated instead of the long-term ones. In the last chapter, equations (3), (6)-(7) are suitable for calculating steady state reliability indices but not the short-term ones.

In this section, the short-term reliability indices used are interval frequency and fractional duration [53], and they are defined as follows:

$$IF(t_1,t_2) = \int_{t_1}^{t_2} f_f(t)dt \tag{48}$$

$$FD(t_1,t_2) = \int_{t_1}^{t_2} p_f(t)dt \Big/ (t_2 - t_1) \tag{49}$$

where,

IF	=	interval frequency
FD	=	fractional duration
$[t_1, t_2]$	=	time duration of interest

$f_f(t)$	=	time-specific value of failure frequency
$p_f(t)$	=	time-specific value of failure probability

Actually, interval frequency is the expected number of system failures, and fractional duration is the mean value of $p_f(t)$ during $[t_1, t_2]$. In definition (48), the upper and lower bounds on $f_f(t)$ can be computed by using the following equations which are derived based on [54]:

$$f_f^u(t) = \sum_i p_t\left(\overline{C_i}\right) \cdot \sum_{j \in C_i} \lambda_j \frac{p_s^j(t)}{p_f^j(t)} \tag{50}$$

$$f_f^l(t) = \sum_i p_t\left(\overline{C_i}\right) \cdot \sum_{j \in C_i} \lambda_j \frac{p_s^j(t)}{p_f^j(t)} - \sum_{i<j} p_t\left(\overline{C_i} \cap \overline{C_j}\right) \cdot \sum_{j \in C_i \cup C_j} \lambda_j \frac{p_s^j(t)}{p_f^j(t)} \tag{51}$$

where,

$f_f^u(t)$	=	first upper bound on $f_f(t)$
$f_f^l(t)$	=	first lower bound on $f_f(t)$
$p_t\left(\overline{C_i}\right)$	=	time-specific value of the occurrence probability of minimal cut-set C_i
λ_j	=	constant failure rate of component *j*
$p_s^j(t)$	=	success probability of component *j* by time t
$p_f^j(t)$	=	failure probability of component *j* by time *t*

In this dissertation, the time-specific value $\lambda_j(t)$ of λ_j is assumed to be constant during a small time interval Δt. Thus, equations (50)-(51) can be used appropriately. Actually, when extended to steady state equations (50)-(51) are the same as (6)-(7) in Chapter III.

In definition (49), $p_f(t)$ can be computed by using (4)-(5) in Chapter III. Since the states of components are assumed to be independent with each other in this chapter, the multiplication rule of probabilities can be used to compute the time-specific failure probability of a minimal cut-set or that of a union of minimal cut-sets. Additionally, we have $p_s^j(t) = 1 - p_f^j(t)$, thus the calculation of the short-term reliability indices only depends on that of the time-specific failure probabilities of components as described in the next subsection.

4.5.2 Time-specific probabilities of components

For time-specific case, the steady state results of Markov process are not suitable to compute the reliability indices. Instead, the transient state results of Markov process should be used. Basically, a set of differential equations need to be solved. In this chapter, for the investigation of the temporal effect of a hurricane, its duration is portioned into some small time intervals. Thus, the continuous time Markov chain to model the time-specific characteristics of a system component affected by hurricanes can be approximated by using a pseudo discrete time Markov chain. Thus, only a set of linear equations need to be solved as described as follows. Suppose that the hurricane duration $[t_1, t_2]$ is partitioned into *n* equal time intervals and each one is Δt, i.e. $\Delta t = (t_2 - t_1)/n$. For component *j* in the *i*th time interval, the following equation can be derived from [23]:

$$\left[p_s^j(i) \quad p_f^j(i) \right] = \left[p_s^j(i-1) \quad p_f^j(i-1) \right] \cdot \left[I + R_j(i) \cdot \Delta t \right] \tag{52}$$

where,

$p_s^j(i)$	=	success probability of component *j* by the end of the *i*th time interval
$p_f^j(i)$	=	failure probability of component *j* by the end of the *i*th time interval
I	=	identity matrix
$R_j(i)$	=	transition rate matrix of component *j* in the *i*th time interval and is assumed to be a constant matrix

Basically, equation (52) approximates a continuous time non-Markov process by using a pseudo discrete time Markov process with an equal time step Δt and different constant transition rate matrix in each step. If the repair of a failed component is not considered, i.e. $\mu_j = 0$, the following equations are obtained:

$$R_j(i) = \begin{pmatrix} -\lambda_j(i) & \lambda_j(i) \\ 0 & 0 \end{pmatrix} \tag{53}$$

$$p_s^j(i) = p_s^j(i-1) \cdot (1 - \lambda_j(i) \cdot \Delta t) \tag{54}$$

$$p_f^j(i) = p_s^j(i-1) \cdot \lambda_j(i)\Delta t + p_f^j(i-1) \tag{55}$$

where,

μ_j	=	rapier rate of component *j*
$\lambda_j(i)$	=	failure rate of component *j* in the *i*th time interval and is assumed to be a constant

There is an interpretation of equations (54)-(55): if suppose that at the beginning of the *i*th time interval the success probability of component *j* is 1, it is well known that by the end of the *i*th time interval its failure probability is $1 - e^{-\lambda_j(i)\Delta t} \approx \lambda_j(i)\Delta t$ if $\lambda_j(i)\Delta t$ is small enough. Equations (54)-(55) can be interpreted as a modification of the preceding conclusion when the initial success probability of component *j* is $p_s^j(i-1)$. From equation (55), the time-specific failure probability of component *j* can be calculated by using the following iteration:

$$p_f^j(i) = \left(1 - p_f^j(i-1)\right)\cdot \lambda_j(i)\Delta t + p_f^j(i-1) \tag{56}$$

$$p_f^j(0) = 0 \tag{57}$$

Here, condition (57) refers to the assumption that at the beginning of the first time interval the failure probability of component *j* is 0.

4.5.3 Time-specific system and nodal indices

After the time-specific reliability indices of components are calculated (actually only those of the components belonging to some minimal cut-sets need to be computed), time-specific system and nodal reliability indices can be calculated as follows. The only difference in computing system and nodal indices is that system and nodal minimal cut-sets should be used appropriately.

1) It is pointed out that the desired reliability indices are $p_f(i)$, $IF(t_1, t_2)$ and $FD(t_1, t_2)$. Here,

   $p_f(i)$ = failure probability by the end of the *i*th time interval

2) Use equations (4)-(5) to compute the bounds on $p_f(i)$ and their average is used as its value.

3) In [53] it is pointed out that the following equation can be obtained if the repair is not considered:

$$IF(t_1,t_2) = p_f(t_1,t_2) \tag{58}$$

here,

$p_f(t_1,t_2)$ = failure probability by time t_2 assuming that the time starts at t_1

Thus, there is no extra computation for $IF(t_1,t_2)$, and its value can be obtained from the last step directly. Since no repair of failed components is considered, failure probability p_f is monotonically increasing during $[t_1,t_2]$. Thus, $IF(t_1,t_2)$ is actually the maximal value of p_f by time t_2.

4) From equation (49), the following equation can be used to compute $FD(t_1,t_2)$.

$$FD(t_1,t_2) = \frac{\sum_{i=1}^{n} p_f(i)\cdot \Delta t}{t_2 - t_1} = \frac{\sum_{i=1}^{n} p_f(i)}{n} \tag{59}$$

Thus, $FD(t_1,t_2)$ is just the mean value of the results of Step (2).

5) It is possible that utilities may arrange more repair teams and materials than they normally do to be prepared for upcoming hurricanes. When the repair of failed components is considered, an approach is to assume that the repair rate of a single component is a smaller number than that of it in normal weather, and it is a constant during the duration of hurricanes [13].

4.5.4 Weighted average method

To investigate the spatial effect of hurricanes on composite power systems, the power system is divided into different regions. If a transmission line traverses a few regions, its overall IMFR can be calculated as follows:

$$n_i = \sum_{j \in M} \frac{l_i^j}{l_i} n_i^j = \sum_{j \in M} w_i^j n_i^j \qquad (60)$$

where,

n_i	=	overall IMFR of transmission line i
M	=	index of the set of all the regions that transmission line i traverses
l_i^j	=	length of transmission line i in region j
l_i	=	overall length of transmission line i
n_i^j	=	IMFR of transmission lines i in region j
w_i^j	=	weight of transmission line i belonging to region j

4.6 Implementation

In this section, the proposed methodology investigating the impact of hurricanes on the short-term reliability of composite power systems is applied to the modified IEEE reliability test system. Firstly, the data used in this chapter is presented; then, the different types of fuzzy inference systems built by using different methods are presented; finally, evaluation results obtained by using different methods are compared and analyzed.

4.6.1 Test system

Here, the test system used is the same as that in the last chapter, and is not described in this chapter repeatedly.

4.6.2 Relevant data

4.6.2.1 Clustering data

Here, the training data for the data-driven methods is generated by using the fuzzy expert system in [12]. To verify the effectiveness of different data-driven methods, the criterion is as follows: if the results obtained are close to those in [12], the data-driven method is effective - the closer to the results in [12], more effective it is. In detail, the data is obtained as follows: for each input variable, the input data is generated from its minimal value to its maximal value with a step being $(\max - \min)/100$, here *max* and *min* represent the minimal and maximal values respectively, and the inferred output is used as the output data. Thus, 101 data points are obtained for the data-driven methods. Using these data, different types of fuzzy inference systems are built by using MATLAB [50].

4.6.2.2 Hurricane data

Table 14: Hurricane Data

Time Interval	Region 1		Region 2	
	Wind Speed (mph)	Rainfall (in)	Wind Speed (mph)	Rainfall (in)
1	80	10	70	5
2	90	15	80	10
3	100	20	90	15
4	110	25	100	20
5	120	30	110	25
6	130	35	120	30
7	140	40	130	35
8	130	35	120	30
9	120	30	110	25
10	110	25	100	20
11	100	20	90	15
12	90	15	80	10

Here, the IEEE reliability test system is partitioned into two parts and the split basically follows along its voltage levels. Specifically, the tie lines between the 230KV and 138KV parts of the IEEE reliability test system are four transmission lines [38]. The split is assumed to pass through the middle points of these lines. The hurricane parameters are listed in Table 14. Here, hurricane duration is assumed to be 48 hours, and each time interval is set as 4 hours.

Table 15: Rule Base (S-FIS)

Output		Rainfall		
		High	Medium	Low
Wind Speed	High	Output(H)		
	Medium		Output(M)	
	Low			Output(L)

4.6.3. Different fuzzy inference systems

4.6.3.1 Sugeno-type fuzzy inference system

For the Sugeno-type fuzzy inference system, the fuzzy rules are listed in Table 15. Here, *Output (H/M/L)* represents the output function. The membership functions of the input variables are shown in Figs. 14-15. It is noted that the output in Table 15 and those in Tables 16-17 are different: in Table 15 the output represents the linear function of the input variables; in Tables 16-17 the output represents membership function.

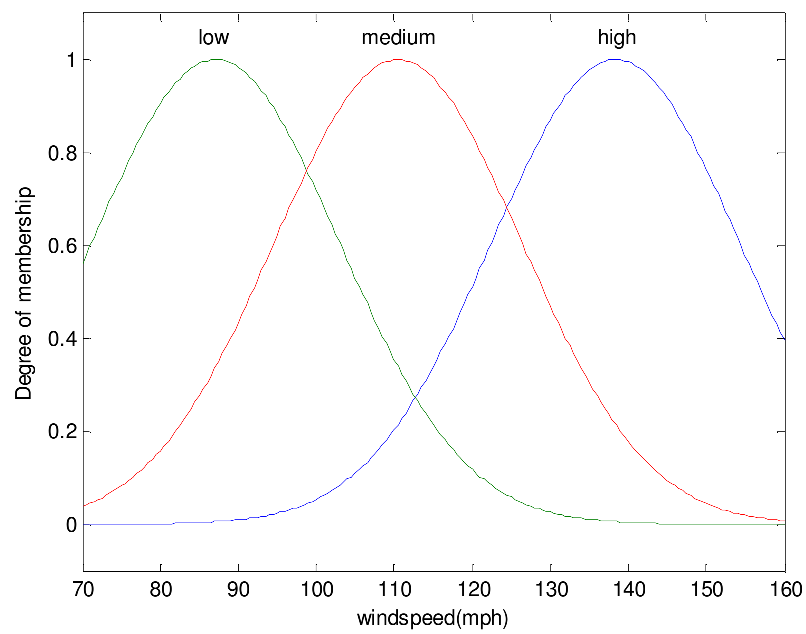

Fig. 14: Membership Function of Wind Speed (S-FIS)

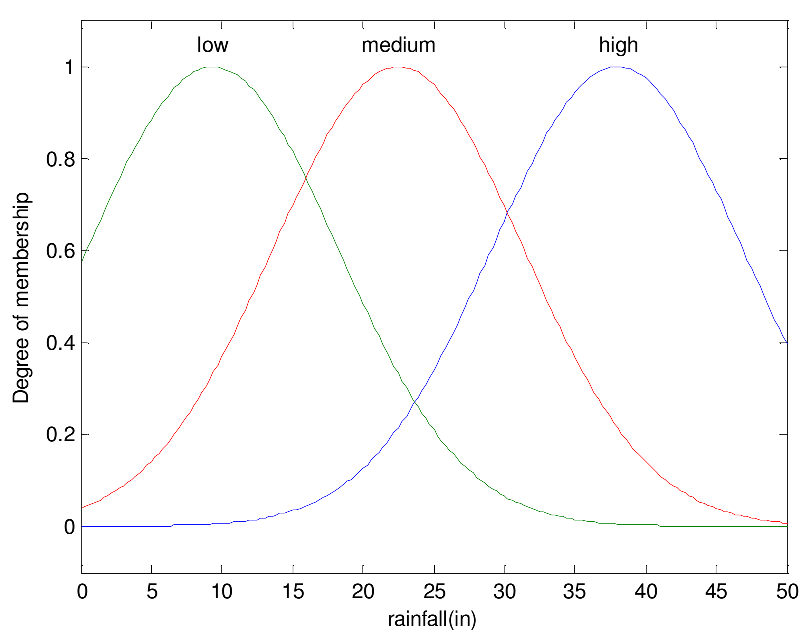

Fig. 15: Membership Function of Rainfall (S-FIS)

4.6.3.2 Mamdani-type fuzzy inference system

For the Mamdani-type fuzzy inference system, the fuzzy rules are listed in Table 16, and the membership functions of the input and output variables are shown in Figs. 16-18.

Table 16: Rule Base (M-FIS)

Output		Rainfall		
		High	Medium	Low
Wind Speed	High	High		
	Medium		Medium	
	Low			Low

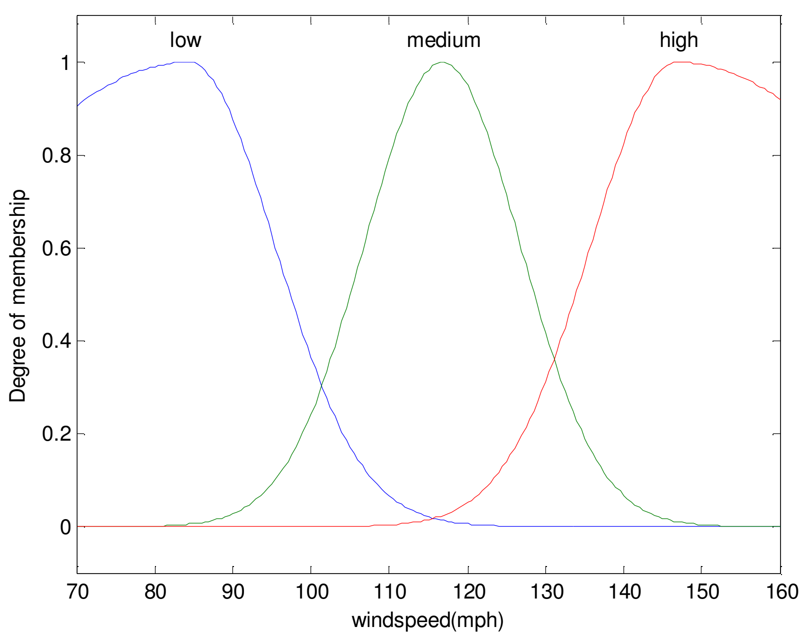

Fig. 16: Membership Function of Wind Speed (M-FIS)

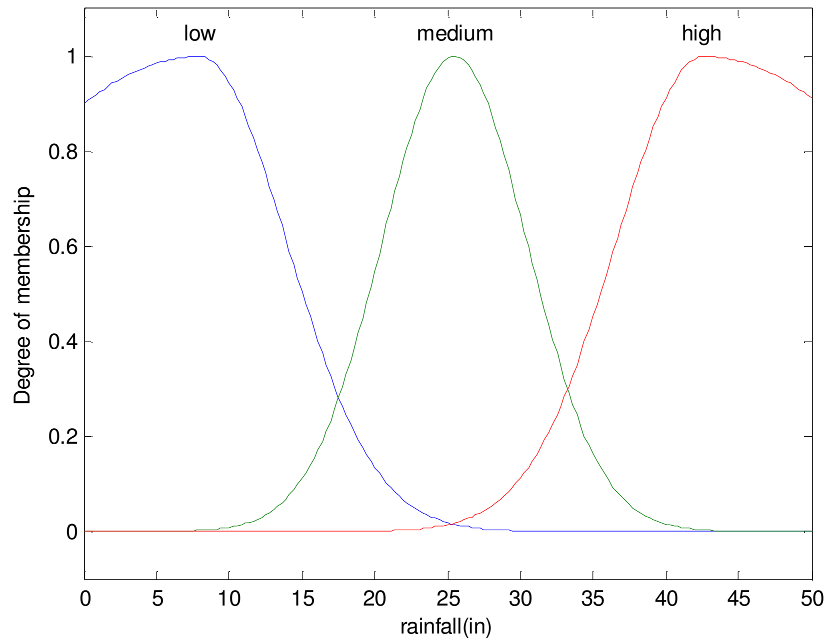

Fig. 17: Membership Function of Rainfall (M-FIS)

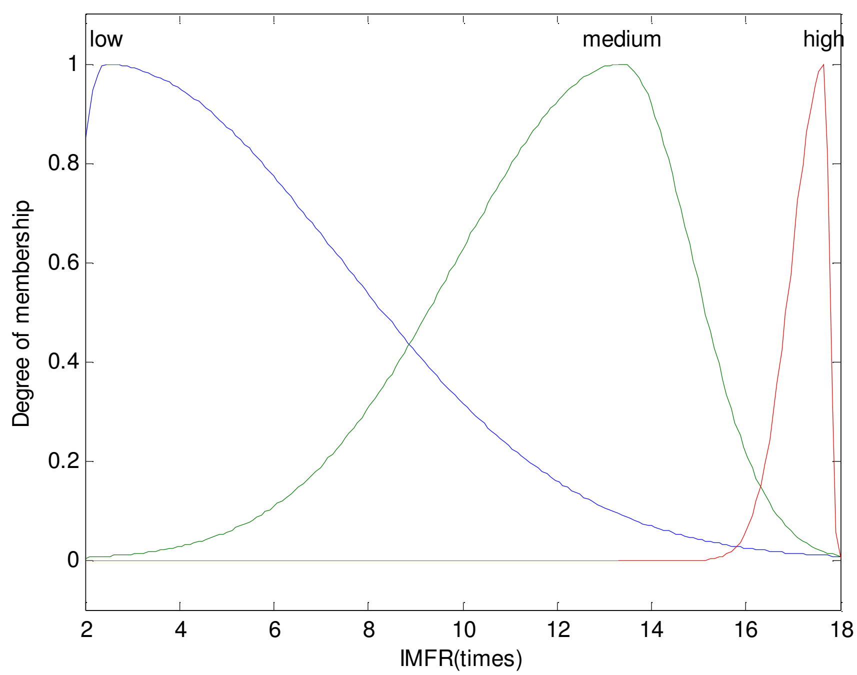

Fig. 18: Membership Function of IMFR (M-FIS)

4.6.3.3 Fuzzy expert system

For comparison, the fuzzy rules of the fuzzy expert system in [12] are listed in Table 17, and its membership functions are shown in Figs. 19-21.

Table 17: Rule Base (FES)

Output		Rainfall		
		High	Medium	Low
Wind Speed	High	High	High	Medium
	Low	Medium	Low	Low

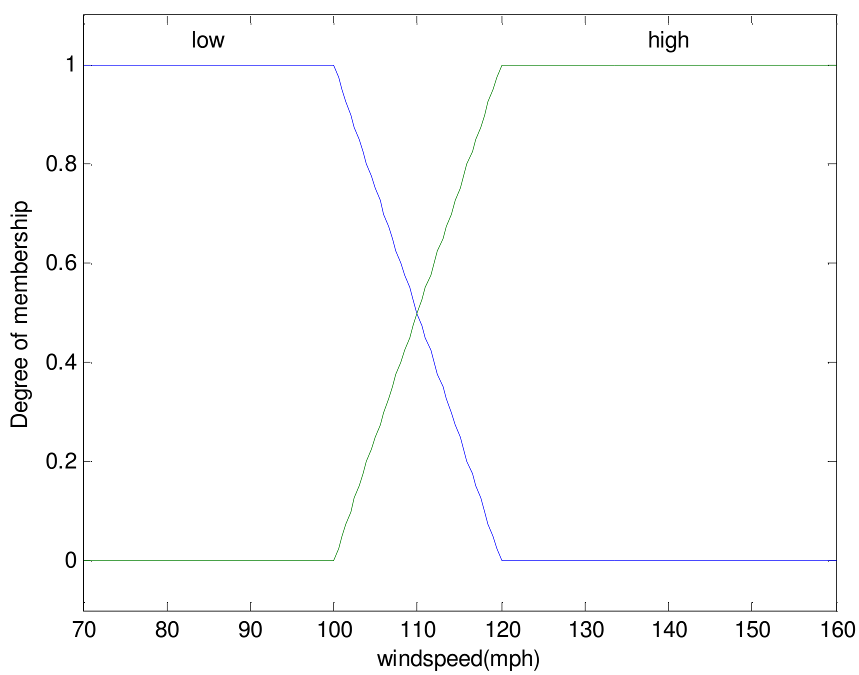

Fig. 19: Membership Function of Wind Speed (FES)

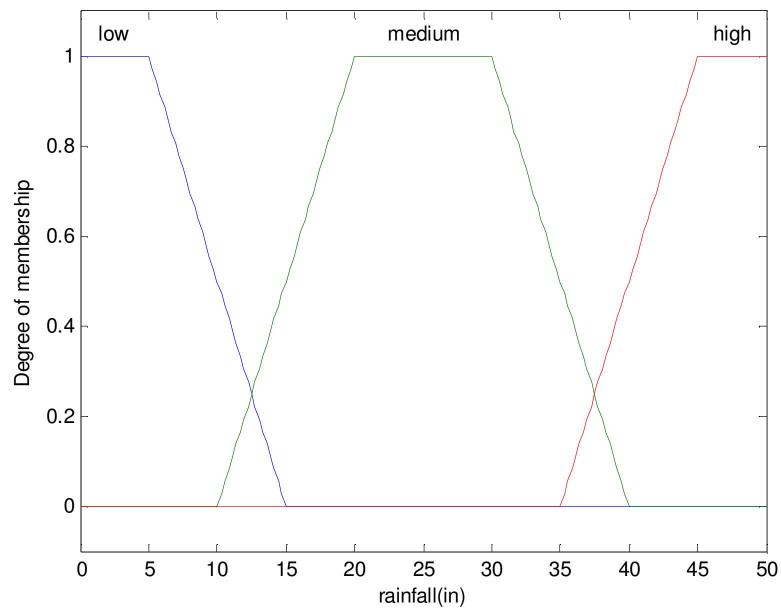

Fig. 20: Membership Function of Rainfall (FES)

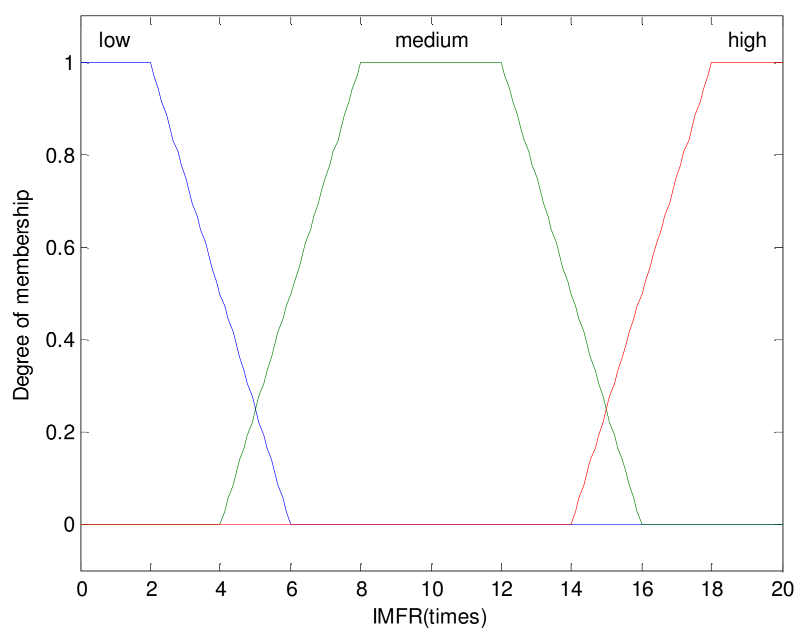

Fig. 21: Membership Function of IMFR (FES)

4.6.4 Evaluation results

The system reliability indices obtained by using different methods are listed in Table 18 and are shown in Fig. 22. Here, for simplicity no repair of failed components is considered. The legends used in Fig. 22 are as follows:

FPSF: system failure probability of Sugeno-type fuzzy inference system

FPMF: system failure probability of Mamdani-type fuzzy inference system

FPF: system failure probability of fuzzy expert system

FDSF: fractional duration of Sugeno-type fuzzy inference system

FDMF: fractional duration of Mamdani-type fuzzy inference system

FDF: fractional duration of fuzzy expert system

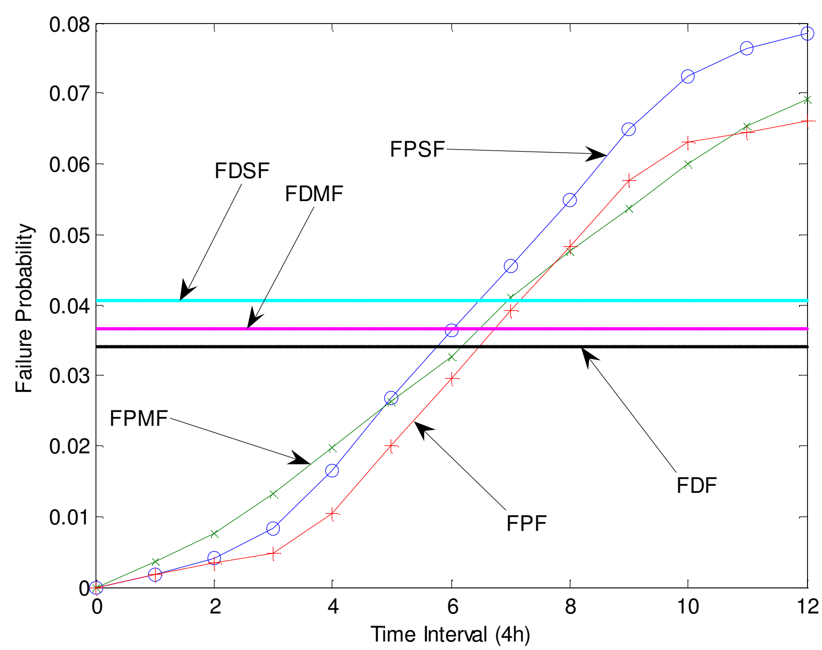

Fig. 22: Short-Term System Failure Probability (Independent Failures)

Table 18: Short-Term System Failure Probability (Independent Failures)

Time Interval	System Failure Probability		
	Sugeno-Type System	Mamdani-Type System	Fuzzy Expert System
1	0.0018	0.0036	0.0017
2	0.0041	0.0076	0.0034
3	0.0084	0.0133	0.0049
4	0.0164	0.0197	0.0104
5	0.0267	0.0262	0.0201
6	0.0363	0.0327	0.0296
7	0.0455	0.0411	0.0391
8	0.0549	0.0476	0.0484
9	0.0648	0.0538	0.0577
10	0.0723	0.06	0.063
11	0.0764	0.0654	0.0644
12	0.0785	0.0692	0.066
Interval Frequency (Maximum)	0.0785	0.0692	0.066
Fractional Duration (Mean)	0.0405	0.0367	0.0341

The nodal reliability indices obtained by using different methods are listed in Table 19. Here, for simplicity only those of two methods are listed.

4.6.5 Comparison of results from different methods

According to the obtained results, the following conclusions can be made:

1. Figs. 14-21 show that the membership functions obtained by using different methods can be much different.
2. Tables 15-17 show that fuzzy clustering methods can effectively reduce the number of the fuzzy rules of the fuzzy inference system, i.e. it can alleviate the

dimensionality problem of the artificial method.

Table 19: Short-Term Nodal Failure Probability (Independent Failures)

Node	Fractional Duration	
	Mamdani-Type System	Fuzzy Expert System
1	0.0122	0.0114
2	0.0121	0.0114
3	0.0116	0.0109
4	0.0121	0.0114
5	0.0122	0.0115
6	0.0334	0.0308
7	0.0091	0.0084
8	0.0032	0.0032
9	0.0094	0.0088
10	0.0121	0.0114
13	0.0119	0.0112
14	0.0018	0.0018
15	0.0107	0.01
16	0.0114	0.0107
18	0.0021	0.0022
19	0.0115	0.0108
20	0.0032	0.0032
System Indices (Mean)	0.0367	0.0341

3. Table 18 and Fig. 22 show that the evaluation results obtained by using different methods are different. Compared with the results of the fuzzy expert system, the Mamdani-type fuzzy inference system appears to obtain more accurate results than the Sugeno-type fuzzy inference system since the results of the former are closer to those of the fuzzy expert system. The reasons are as follows:

1) The membership functions of the input of the Sugeno-type fuzzy inference system is in the form of Gaussian function. Actually, this approximation may be over-simplification.
2) The assumption of the Sugeno-type fuzzy inference system that the input and the output variables have a linear functional relationship may be also over-simplification.

4. Table 18 and Fig. 22 also show that for time-specific case, interval index fractional duration can more clearly indicate the performance of different methods than time-specific failure probability.
5. Table 19 shows that nodal reliability indices can be much different. They can be helpful for utilities to effectively allocate recourses in preparation for upcoming hurricanes.
6. The proposed methodology is efficient. After the fuzzy inference system is built, its inference time is almost negligible.
7. In this chapter, the proposed methodology evaluates the impact of hurricanes on the short-term reliability of composite power systems. It is also applicable to simulation method as well as in other systems, e.g. distribution systems.
8. In this chapter, for simplicity the repair of failed components is not considered. But, the proposed methodology is also applicable when the repair is considered.

4.7 Summary

In this chapter, the impact of hurricanes on the short-term reliability of composite power systems is investigated. The incremental failure rates of system components are obtained by combining a fuzzy inference system and regional weather model. For the purpose of comparison, different methods are used to build different types of fuzzy inference systems. Since hurricanes only last a short period of time but their effects are drastic, time-specific system and nodal reliability indices are calculated during the duration of hurricanes.

The proposed methodology is applied to the modified IEEE reliability test system. From the implementation, the main conclusions obtained in this chapter are summarized as follows:

1) The proposed methodology is effective. It can evaluate the impact of hurricanes on the failure rate increment of system components temporally and spatially.
2) The proposed methodology is efficient. After the fuzzy inference system is built, its inference time is almost negligible.
3) The performances of different methods are different. But, different methods can be complementary rather than competitive. In practice, the requirements of efficiency and accuracy can determine the selection of suitable method.
4) For time-specific case, steady state reliability indices are not suitable anymore. Instead, short-term indices should be used such as interval frequency and fractional duration.
5) Nodal reliability indices can provide helpful information for utilities to effectively allocate recourses in preparation for upcoming hurricanes.
6) The proposed methodology is flexible in its applications. It is applicable to analytical and simulation methods, and can be applied to different systems.

7) It should be pointed out that the implementation of the proposed methodology is mainly to demonstrate the feasibility of the idea. For practical applications, relevant hurricane parameters and the failure data of system components can be used to build the fuzzy inference system.

CHAPTER V

EVALUATION OF HURRICANE IMPACT ON THE SHORT-TERM RELIABILITY OF COMPOSITE POWER SYSTEMS INCLUDING COMMON-CAUSE FAILURES

In the previous chapter, the impact of hurricanes on the short-term reliability of composite power systems is investigated and the states of components are assumed to be independent. Another impact of hurricanes on composite power systems is that they can cause simultaneous failures of multiple components. For instance, hurricanes can damage transmission towers and the transmission lines on them can collapse together. This kind of failures is called common-cause failures and it can deteriorate the reliability of composite power systems affected by hurricanes. Thus, the common-cause failures of components should be included in the investigation of hurricane impact on the short-term reliability of composite power systems.

In this chapter, the impact of hurricanes on the short-term reliability of composite power systems is investigated and both the independent and common-cause failures of components are considered. Here, two methods are proposed to achieve this goal. One of them uses a Bayesian network to alleviate the dimensionality problem of conditional probability method. Another one extends minimal cut-set method to model the common-cause failures of system components.

The proposed methods are applied to the modified IEEE reliability test system. The evaluation results obtained by using the two methods are compared and analyzed.

The implementation demonstrates that the proposed methods are effective and are flexible in their applications.

This chapter is organized as follows: in Section 5.1 relevant researches that investigated the effect of common-cause failures are reviewed; in Section 5.2 the overall scheme for investigating the impact of hurricanes on the short-term reliability of composite power systems is presented; in Section 5.3 the basic concepts of Bayesian networks are introduced; in Section 5.4 the use of noisy OR-gate model is presented; in Section 5.5 the use of pseudo repetitive temporal model to compute time-specific system reliability indices is described; in Section 5.6 the extended minimal cut-set method is presented; in Section 5.7 the proposed methods are applied to the modified IEEE reliability test system; finally, the summary concludes this chapter.

5.1 Literature Review

Common-cause failures refer to the simultaneous failures of multiple components due to a common cause. With the effect of common-cause failures considered, the states of component become dependent, and reliability evaluation becomes more complex.

Some methods for evaluating the effects of common-cause failures are listed in [10]. These methods include beta-factor model, basic-parameter model, multiple Greek letter model, binomial failure-rate model, and Markov model. But, these models are not suitable for composite power systems. These models have two disadvantages when they are applied to composite power systems. One is that their required parameters drastically increase as the number of system components increases [55]. The other is that these models usually rely on some special techniques, e.g. building fault trees or solving equations, thus they are computationally tedious when the number of system components is large [56]-[57]. In [56]-[57] some improved methods such as binary decision diagram and dynamic fault tree have been proposed.

A straightforward method for evaluating the effect of common-cause failures is conditional probability formula [19], [23], [58]. Actually, this method decomposes system state space on condition whether common-cause failures occur or not. Thus, for each decomposed state space, the failures of system components are independent, and the evaluation of common-cause failures can be simplified. However, this method has a significant drawback that the decomposition is subject to an exponential explosion when the number of common-cause failures considered increases, i.e. if the number of common-cause failures is n, the number of decompositions will be 2^n.

Hurricanes are extreme adverse weather and can cause common-cause failures in composite power systems. In [13], the impact of hurricanes on the short-term reliability of composite power systems was investigated. But, the common-cause failures of system components were not considered in [13].

In this chapter, two methods are proposed to investigate the impact of hurricanes on the short-term reliability of composite power systems, and both the independent and common-cause failures of components are considered [15]-[16].

The first proposed method is based on Bayesian networks. Basically, it uses noisy OR-gate model to alleviate the dimensionality problem of conditional probability method, and uses pseudo repetitive temporal model to calculate time-specific system reliability indices.

Compared to other methods, the proposed method has following advantages:

1) By using certain techniques [59]-[60], a complex Bayesian network can be simplified.
2) The parameters of a Bayesian network can be obtained by using some learning algorithms, e.g. Monte Carlo simulation.
3) Bayesian networks have a powerful inferring capability and the inference results may be various probabilities, such as marginal probability, joint probability, and posterior probability.
4) Bayesian networks can be applied to time-specific case by using repetitive temporal model [61].

The second proposed method extends minimal cut-set method to model the common-cause failures of system components. The basic idea is to formulate the components associated with a common-cause failure as *one* component.

Both proposed methods are applied to the modified IEEE reliability test system. The results obtained by using the two methods are compared and analyzed. The implementation demonstrates that the proposed methods are effective and are flexible in their applications.

5.2 Overall Evaluation Scheme

As shown in Fig. 23, the overall scheme for investigating the impact of hurricanes on the short-term reliability of composite power systems consists of two parts: determining the failure rate increment of system components, and evaluating the effect of common-cause failures. Here, system failure refers to any load shedding at any node of a composite power system.

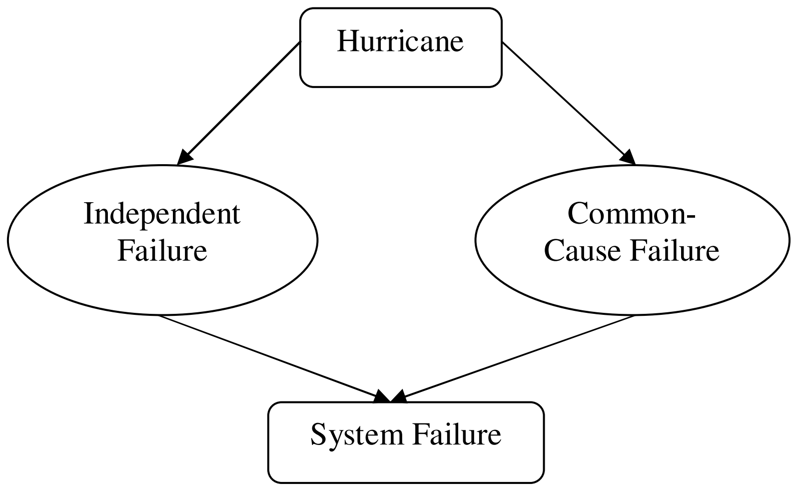

Fig. 23: Overall Short-Term Reliability Evaluation Scheme

5.2.1 Increment of failure rates

One of the impacts of hurricanes on composite power system reliability is that they can increase the failure rates of system components, and this has been investigated in the last chapter. In this chapter, this impact of hurricanes is also considered to obtain the overall reliability evaluation results. However, this chapter emphasizes on the assessment of the common-cause failures of system components, and the relevant results in the last chapter are directly used here.

5.2.2 Common-cause failures

In this chapter, the effect of common-cause failures caused by hurricanes on the short-term reliability of composite power systems is assessed. Finally, the marginal probability of system failure, and the occurrence probabilities of common-cause failures conditioning on the occurrence of system failure are calculated. The latter probability refers to the occurrence probability of a common-cause failure when system failure has been observed. This probability indicates the chance of the occurrence of a common-cause failure when system failure occurs, and can be helpful for the decision-making process of utilities. The detailed discussion is given in Section 5.4.

There are a few points to be noted as follows:

1) This chapter investigates the impact of hurricanes on the short-term reliability of composite power systems considering both the independent and common-cause failures of components. Thus, the final evaluation results are the overall reliability indices.
2) Although this chapter assesses the common-cause failures due to damaged transmission towers on which transmission lines are installed, the proposed methods are also applicable to other types of common-cause failures in other systems, e.g. that caused by a bus failure.
3) The transmission lines associated with a common-cause failure may comprise a minimal cut-set or not. This is an important issue in this chapter. The relevant details are discussed in Section 5.4. and 5.6.

4) For simplicity, the repair of failed transmission towers and system components are not considered. The reason is that usually hurricanes make such repair difficult. But, it is possible that utilities arrange more repair crew and equipments for upcoming hurricanes than they do in normal weather. When the repair is considered, [13] proposed an approach to deal with the independent failures of system components.

5.3 Introduction of Bayesian Networks

In this section, the basic concepts of Bayesian networks are introduced to facilitate the following discussion. Firstly, a simple example is given to illustrate the basic idea of Bayesian networks; then, modeling Bayesian networks and their inference are introduced; additionally, using Bayesian networks for time-specific applications, and modeling different types of random variables are introduced.

5.3.1 A simple example

Basically, a Bayesian network is a directed acyclic graph and its structure and parameters determine its functionality. The structure includes nodes and directed edges: the former represent random variables and the latter usually represent their causal relationships. The parameters are the conditional probability distributions associated with the nodes. Numerous algorithms for the inference and learning in Bayesian networks have been developed.

A simple Bayesian network is shown in Fig. 24. Here, random variable X_i, $i = 1,2,3,4$, represents an event. According to the chain rule of probabilities, the following equation is obtained:

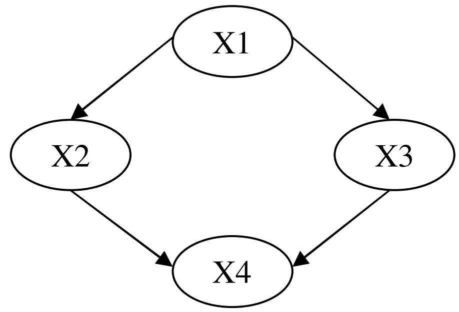

Fig. 24: A Simple Bayesian Network

$$P(X_1, X_2, X_3, X_4) = P(X_4|X_1, X_2, X_3) \cdot P(X_3|X_1, X_2) \cdot P(X_2|X_1) \cdot P(X_1) \quad (61)$$

here,

P = probability

In Fig. 24, if there is an edge from a node to another node, the node at head end is the parent of that at tail end or the node at tail end is the child of that at head end. For example, X_1 is the parent of X_2 and X_3, and they are the parents of X_4, or X_4 is the child of X_2 and X_3 and they are the children of X_1. According to the recursive factorization of above joint probability distribution [62], the following equation is obtained:

$$P(X_1, X_2, X_3, X_4) = P(X_4|X_2, X_3) \cdot P(X_3|X_1) \cdot P(X_2|X_1) \cdot P(X_1) \quad (62)$$

The above equation shows that the joint probability distribution can be expressed as the product of some conditional probability distributions, and each conditional probability distribution is in the form $P(X_i|Pa(X_i))$, $i = 1,2,3,4$.

here,

$Pa(X_i)$ = parents of random variable X_i, $i = 1,2,3,4$

In contrast, (62) is more compact than (61), and the joint probability is easy to be computed if all the conditional probabilities in (62) are known. Then, all the other probabilities, say $P(X_1, X_2, X_3)$, $P(X_2, X_3|X_1)$, or $P(X_1|X_2)$, can be computed accordingly by using variable elimination and conditional probability formula. For example, after summing out X_4 we get $P(X_1, X_2, X_3)$. Repeatedly, we can get $P(X_1, X_2)$, $P(X_1)$, and $P(X_2)$. Then, the desired conditional probabilities can be computed accordingly if the marginal probabilities are greater than zero.

$$P(X_2, X_3|X_1) = \frac{P(X_1, X_2, X_3)}{P(X_1)} \tag{63}$$

$$P(X_1|X_2) = \frac{P(X_1, X_2)}{P(X_2)} \tag{64}$$

If the marginal probabilities equal to zero, seemingly the above conditional probabilities equal to zero too.

A pivotal concept of Bayesian networks is the conditional independences of random variables. For example, (61) and (62) show that the following equations can be obtained:

$$P(X_4|X_1, X_2, X_3) = P(X_4|X_2, X_3) \tag{65}$$

$$P(X_3|X_1, X_2) = P(X_3|X_1) \tag{66}$$

The conditional independences of Bayesian networks can be equally expressed as follows with some assumptions [63]:

Global Markov property

Basically, global Markov property refers to that two sets of nodes can be separated by a set of nodes which is called a *d-separation* [62]. Actually, the Markov blanket of a node is the minimal one of all the *d*-separations, and it consists of the parents and children of a node, and the parents of the children of the node.

Local Markov property

This property refers to that a node is independent of the nodes of its non-descendants given its parents [63]. Here, the descendants of a node refer to all the nodes which are connected by the directed edges emanating from the node.

Factorization

Actually, an easily understandable factorization form of Bayesian networks, named recursive factorization, has been illustrated in the simple example. More generally, a joint probability distribution can be expressed as follows:

$$P(X_1, X_2, \cdots X_n) = \prod_{1 \le i \le n} P(X_i | B(X_i)) \tag{67}$$

here,

$B(X_i)$ = nodes before X_i according to some principle

Equally, the joint probability distribution can be expressed as follows:

$$P(X_1, X_2, \cdots X_n) = \prod_{1 \le i \le n} P(X_i | A(X_i)) \tag{68}$$

here,

$A(X_i)$ = nodes after X_i according to some principle

Summarily, a Bayesian network uniquely determines a joint probability distribution of the random variables [61]. By using recursive factorization, a joint probability distribution can be expressed as follows [61]:

$$P(X_1, X_2, \cdots X_n) = \prod_{1 \le i \le n} P(X_i | Pa(X_i)) \quad (69)$$

where

X_i	=	random variable represented by node i, $1 \le i \le n$
n	=	number of nodes
$Pa(X_i)$	=	parents of node i

For the root node which has no parents, its conditional probability is just the marginal probability.

5.3.2 Modeling Bayesian networks

For the simple example, its structure and parameters are assumed to be known in advance. For practical applications, the structure and parameters of a Bayesian network need to be determined, and this is called the modeling of Bayesian networks. Generally, there are two kinds of approaches to model a Bayesian network: artificial method (expert opinion) and data-driven method [59]-[61], [64]. Usually, a hybrid method which combines the merits of two approaches can be used. When the data-driven method is used to model a Bayesian network, it can be used to *learn* the structure and parameters.

Learning parameters

Usually, a statistical approach can be used to learn the parameters of a Bayesian network, i.e. we assume that the data belongs to some distribution but the parameters are unknown. Thus, we can use statistical methods to estimate the desired parameters. For instance, maximum likelihood estimation and Bayesian inference are two common methods. Due to the stochastic characteristics of learning the parameters of Bayesian networks, Monte Carlo simulation can be used to achieve the goal. Actually, the simulation result is the estimator that minimizes the likelihood function [65]. Statistical methods can be used to learn the parameters of a Bayesian network from complete and incomplete data, i.e. when some data is missing statistical methods can be applied as well.

Learning structure

Similarly, statistical methods can be used to learn the structure of a Bayesian network. But, learning structure is more complex than learning parameters. Usually, some search techniques have to be used to learning the structure of a Bayesian network.

In this chapter, the structure of the Bayesian network used is determined *a priori*, i.e. it is built by considering the causal relationships in composite power systems affected by hurricanes. The parameters are obtained by using random sampling. More details are given in the next section.

5.3.3 Inference in Bayesian networks

In Subsection 5.3.1, variable elimination method is used to compute the desired probabilities in a simple Bayesian network. This process is actually the inference in Bayesian networks. But for a practical Bayesian network, variable elimination method is inefficient, and more efficient algorithms have been developed. In this subsection, several common inference algorithms are introduced as follows:

Junction tree

Actually, junction tree or join tree algorithm is an improvement of variable elimination method [65]. This method eliminates factors instead of variables and uses elimination tree instead of elimination order. Here, a factor is actually a conditional probability. The core of the algorithm is message passing formulation. Compared with variable elimination method, this method can eliminate a set of variables at a time. Thus, it is more efficient than variable elimination method.

Conditioning method

Conditioning method uses conditional probability formula to decompose the original Bayesian network into some simpler ones, and suitable algorithms can be used for each small network.

Local structure exploitation

Similar to conditioning method, local structure exploitation is actually a kind of methodology rather than an algorithm. It utilizes the local structure of a Bayesian network, i.e. the specific values of some parameters, to simplify the inference. Actually, the noisy OR-gate model used in this chapter is such a method which exploits the local characteristics of a Bayesian network.

Approximate methods

The elimination method is an exact inference algorithm. For complex Bayesian networks, the computation can be expensive. Instead, some iterative methods can be used to get approximate results. The massage passing algorithm, originally designed for exact inference, can be extended to such a method. Another such method is Monte Carlo simulation. It can be used not only for learning parameters but also for approximate inference.

5.3.4 Repetitive temporal model

When the dynamics of some random variables are of interest, Bayesian networks can be applied to the time-specific case. The basic idea is to interconnect the Bayesian networks in different periods of time. When the structures of the Bayesian networks are the same and the interconnection is the same, the resultant Bayesian network is called repetitive temporal model [61]. Additionally, if the conditional probabilities in each period of time are the same, this model is called dynamic Bayesian networks.

In this chapter, in order to investigate the impact of hurricanes on the short-term reliability of composite power systems, a pseudo repetitive temporal model is proposed to calculate time-specific system reliability indices. This model is a modification of repetitive temporal model and it is different from a dynamic Bayesian network. More details are given in Section 5.5.

5.3.5 Types of random variables

Basically, a Bayesian network can deal with discrete and continuous random variables. But, when the latter is modeled, the exact inference can be impossible for an arbitrary distribution. Usually, continuous random variables can be transformed by *discretization*, and then suitable methods can be used. In this chapter, all the random variables of the Bayesian network used are binary variables which represent the occurrences or not of some events.

5.4 Noisy OR-Gate Model

In this section, the noisy OR-gate model used to investigate the impacts of hurricanes on composite power system reliability is described in detail. Firstly, the overall evaluation strategy is presented; secondly, the noisy OR-gate model used is described in detail; thirdly, the algorithm for simulating the required parameters is given; finally, the interpretation of the posterior probability of a common-cause failure is presented.

5.4.1 Overall evaluation strategy

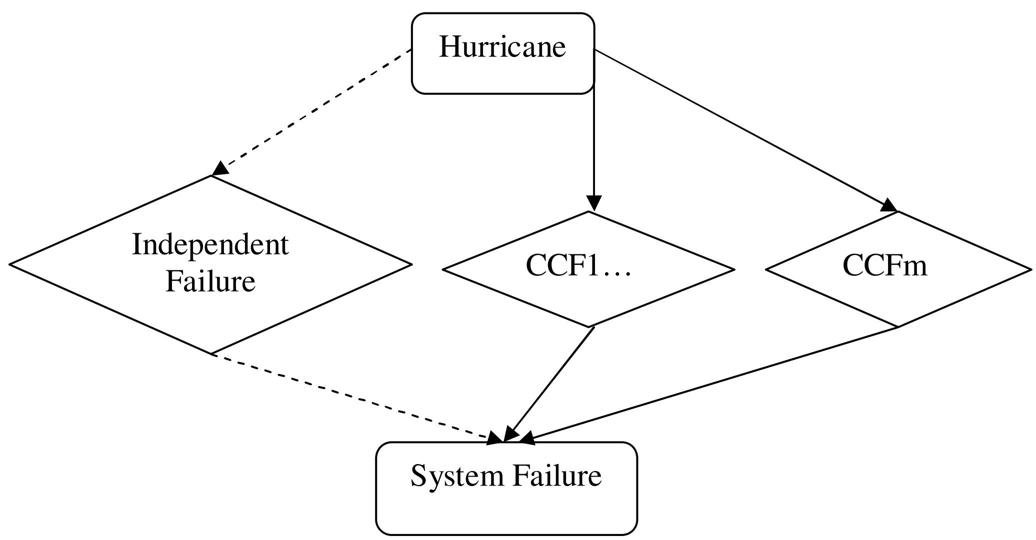

Fig. 25: Noisy OR-Gate Model

The overall evaluation strategy for the impact of hurricane on the short-term reliability of composite power systems is shown in Fig. 25. This is the Bayesian network used in this chapter. Here, CCF_i, $1 \le i \le m$, is the ith common-cause failure; m is the number of common-cause failures. In Fig. 25, the impact of hurricanes on the failure rate increment of transmission lines is indicated by a dashed line, i.e. it is implicitly incorporated in the noisy OR-gate model used. More details are given in the next subpart. After the structure of the Bayesian network used is determined, the conditional probability distributions associated with the nodes needs to be determined. They are the marginal probabilities of the hurricane, the conditional probabilities of CCF_i, $1 \le i \le m$, and those of system failure. In the following discussion, P represents a probability, and 1/0 represents the occurrence or not of an event.

5.4.1.1 Probability of hurricane

Since the dynamic impact of hurricanes on the short-term reliability of composite power systems is of interest in this chapter, i.e. the impact of hurricanes is investigated during their durations, the occurrence of a hurricane is assumed to be a sure event and the following equation is obtained:

$$P(Hurricane = 1) = 1 \Leftrightarrow P(Hurricane = 0) = 0 \tag{70}$$

5.4.1.2 Probability of common-cause failures

The conditional probability distributions of a common-cause failure are the probability of its occurrence or not given the occurrence or not of the hurricane. First of all, the following assumption is used in this chapter:

$$P(CCF_i = 1 | Hurricane = 0) = 0 \Leftrightarrow P(CCF_i = 0 | Hurricane = 0) = 1 \quad 1 \le i \le m \tag{71}$$

The above equation refers to that only the hurricane can cause common-cause failures. In reality, other kinds of common-cause failures exist in power systems, e.g. station-originated common-cause failures. For simplicity, in this chapter only the common-cause failures caused by a hurricane are considered. But, it is straightforward to model other types of common-cause failures by adding additional directed edges and nodes in Fig. 25.

Following (71), only $P(CCF_i = 1 | Hurricane = 1)$, $1 \le i \le m$, needs to be determined. Then, $P(CCF_i = 0 | Hurricane = 1)$ can be easily obtained as follows:

$$P(CCF_i = 0 | Hurricane = 1) = 1 - P(CCF_i = 1 | Hurricane = 1) \qquad 1 \le i \le m \qquad (72)$$

In [66] reliability theory was applied to the risk analysis of transmission towers, and the effects of wind and ice on their failures were considered. However, the method in [66] is not suitable for the determination of $P(CCF_i = 1 | Hurricane = 1)$, $1 \le i \le m$. The reasons are as follows:

1) The main effects of hurricanes are strong wind and heavy rainfall when they move over land.
2) The reliability indices calculated in [66] are averages over long time spans.

Thus, the time-specific failure model of transmission towers affected by hurricanes needs to be developed. This may be realized by using structural reliability analysis. For simplicity, $P(CCF_i = 1 | Hurricane = 1)$, $1 \le i \le m$, is assumed to be an *a priori* constant during the duration of hurricanes in this chapter. The relevant data is given in Section 5.7.

5.4.1.3 Probability of system failure

The conditional probability distribution of system failure is the probability of its occurrence or not given the combined occurrences or not of common-cause failures, i.e. it is in the form $P(System\_failure = 1|CCF)$ or $P(System\_failure = 0|CCF)$.

here,

CCF = combination of the occurrences or not of all common-cause failures

For instance, it can be in the form as follows:

$$CCF = \{CCF_1 = 0, \cdots CCF_i = 1, \cdots CCF_m = 1\}$$

$$\text{or } CCF = \{CCF_1 = 1, \cdots CCF_i = 0, \cdots CCF_m = 0\} \quad 1 \le i \le m$$

The number of all the combinations is 2^m. If m is large, the determination of the conditional probability distribution of system failure is tedious. To solve this problem, some techniques such as parent divorcing and temporal transformation can be used [60]. But, they are not suitable for the Bayesian network used in this chapter. Here, noisy OR-gate model is used and is described in detail in the next subsection.

5.4.2 Noisy OR-gate model

Like parent divorcing and temporal transformation, noisy OR-gate model modifies the structure of a Bayesian network by adding some auxiliary variables as well as corresponding directed edges to reduce its complexity logically when multi-causal relations are modeled. For example, a simple multi-causal Bayesian network is shown in Fig. 26. Here, Y_i, $i = 1,2,3,4$, is the *i*th event. By using noisy OR-gate model, the equivalent Bayesian network is shown in Fig. 27. Here, I_i, $i = 1,2,3$, is the *i*th inhibitor (noisy); $A_i = 1$ if and only if $\{I_i = 0\} \cap \{Y_i = 1\}$, $i = 1,2,3$; $Y_4 = 0$ if and only if $A_i = 0$, $i = 1,2,3$. Clearly, A_i, $i = 1,2,3$, comprises the input of an OR gate and Y_4 is its output. Noisy OR-gate model makes a few assumptions: causal inhibition, exception independence, and accountability [59]. Basically, these assumptions refer to the fact that the inhibitors are independent with each other and one intermediate cause is enough to make the common result happen. Given the assumptions, equations (73)-(74) are obtained:

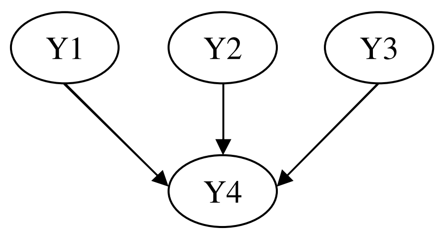

Fig. 26: A Simple Multi-Causal Bayesian Network

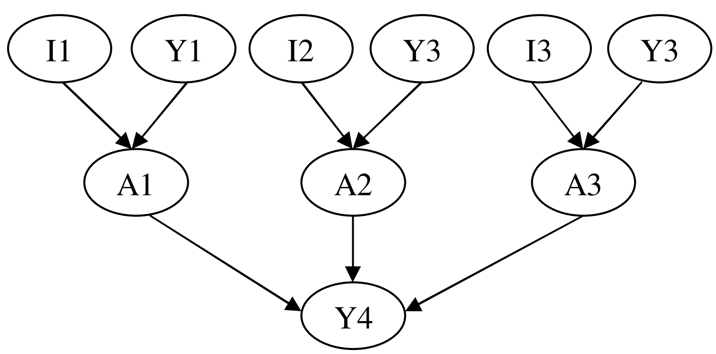

Fig. 27: Equivalent Noisy OR-Gate Model

$$P(Y_4 = 1|Y_1, Y_2, Y_3) = 1 - \prod_i (1 - P(Y_4 = 1|Y_i = 1)) \qquad i = 1,2,3 \tag{73}$$

$$P(Y_4 = 0|Y_1, Y_2, Y_3) = 1 - P(Y_4 = 1|Y_1, Y_2, Y_3) \tag{74}$$

Equation (74) shows that noisy OR-gate model only determines $P(Y_4 = 1|Y_i = 1)$, $i = 1,2,3$, instead of determining $P(Y_4 = 1|Y_1, Y_2, Y_3)$ directly. Thus, the determination of the conditional probability distribution of a multi-causal Bayesian network can be simplified. For example, $8 = 2^3$ conditional probabilities need to be determined if $P(Y_4 = 1|Y_1, Y_2, Y_3)$ is determined directly. By using noisy OR-gate model, only 3 conditional probabilities need to be determined. In other words, the conditional probabilities to be determined can be reduced from an exponential number to a linear number.

To determine the conditional probability distribution of system failure, the following equation is obtained by using noisy OR-gate model:

$$P(System\_failure = 1|CCF) = 1 - \prod_{i \in I} (1 - P(system\_failure = 1|CCF_i = 1)) \tag{75}$$

$$P(System\_failure = 0|CCF) = 1 - P(System\_failure = 1|CCF) \tag{76}$$

where,

I = set of all the common-cause failures such that $i \in I$ if and only if $CCF_i = 1$

Equation (75) shows that noisy OR-gate model can be interpreted as a series connection of common-cause failures. Thus, the Bayesian network in Fig. 25 can be interpreted as follows: system failure is the failure of a series system consisting of common-cause failures, i.e. only the occurrence of one common-cause failure is sufficient to cause the occurrence of system failure, and only when no common-cause failure occurs system failure does not occur. Presumably, equation (75) has the following implication:

$$P(System\_failure = 1 | CCF = 0) = 0 \tag{77}$$

Here, $CCF = 0$ represents that no common-cause failure occurs, i.e. $CCF_i = 0$, $1 \leq i \leq m$. In this chapter, both the independent and common-cause failures of system components are considered. Thus, equation (77) is modified as follows:

$$P(System\_failure = 1 | CCF = 0)$$

$$= P(system\_failure = 1 | independent\_failure = 1, CCF = 0) \tag{78}$$

Here, $independent\_failure = 1$ represents the occurrence of the independent failures of system components. Here, the failure rate increment of system components is considered. Equation (78) refers to that when no common-cause failure occurs, system failure is that caused by the independent failures of system components. The time-specific value of the probability in (78) has been calculated in [13], and it can be directly used here as well as in the pseudo repetitive temporal model in the next section. Accordingly, equation (75) is modified as follows:

$$P(System\_failure = 1 | CCF)$$

$$= 1 - \prod_{i \in I} \left(1 - P(system\_failure = 1 | independent\_failure = 1, CCF_i = 1)\right) \tag{79}$$

Equations (76), (79) show that the conditional probability distribution of system failure is only determined by the following probabilities:

$$P(system\_failure = 1 | independent\_failure=1, CCF_i = 1) \qquad 1 \le i \le m$$

These conditional probabilities can be obtained by using a simple simulation method. Its algorithm is described in detail in the next subsection.

5.4.3 Simulation algorithm

Simulating $P(system\_failure = 1 | independent\_failure=1, CCF_i = 1)$, $1 \le i \le m$, can be realized as follows: remove the transmission lines associated with the *i*th common-cause failure CCF_i simultaneously, then simulate the system failure only caused by the independent failures of other system components. Thus, a simple simulation method, named random sampling [24], can be used here. Basically, random sampling assumes that the states of system components are independent with each other. Thus, the simulation of system state can be realized by simulating the states of system components separately. Finally, the system state is usually checked by running an optimization routine in a composite power system. If there is any load shedding at any node, the system state is marked as *failure*; otherwise, it is marked as *success*.

When the state of a single component is simulated, the following method is used. Firstly, a random number between 0 and 1 is generated, and then it is compared with the success or failure probability of the component to determine its state. Suppose the success probability of the component is $P_S = a$, $0 \le a \le 1$, and its failure probability is $P_F = b$, $0 \le b \le 1$, such that $P_S + P_F = a + b = 1$. If the random number generated is as follows:

$$0 \le RN \le P_S \qquad (80)$$

here,

RN = random number, $0 \le RN \le 1$

Then, the state of the component is *success*. If the random number generated is as follows:

$$P_S < RN \le 1 \tag{81}$$

Then, the state of the component is *failure*. Alternately, if the random number generated is as follows:

$$0 \le RN \le P_F \tag{82}$$

Then, the state of the component is *failure*. If the random number generated is as follows:

$$P_F < RN \le 1 \tag{83}$$

Then, the state of the component is *success*.

In Chapter IV, the time-specific failure probabilities of system components have been calculated. Thus, inequalities (82)-(83) can be used to determine the state of a component. Here, the simulation results are $P(system\_failure = 1 | independent\_failure{=}1, CCF_i = 1)$, $1 \le i \le m$. The estimate of a probability is as follows:

$$\overline{P_f} = \frac{1}{N}\sum_{i=1}^{N} F_i \tag{84}$$

where,

P_f = $P(system\_failure = 1 | independent\_failure{=}1, CCF_i = 1)$, $1 \le i \le m$

$\overline{P_f}$ = estimate of P_f

N = a sufficiently large number

F_i = $\begin{cases} 1, system\_failure = 1 \\ 0, otherwise \end{cases}$, $1 \le i \le N$

In this chapter, the coefficient of variation of the estimate is used to terminate the simulation, i.e. when it is less than a preset value. The coefficient of variation of $\overline{p_f}$ is as follows:

$$COV_p = \frac{\sqrt{Var\left(\overline{p_f}\right)}}{\overline{p_f}} = \frac{\sqrt{\frac{1}{N}\overline{Var\left(p_f\right)}}}{\overline{p_f}} \tag{85}$$

where,

COV_p = coefficient of variation of $\overline{p_f}$

$Var\left(\overline{p_f}\right)$ = variance of $\overline{p_f}$

$Var\left(p_f\right)$ = variance of p_f

$\overline{Var\left(p_f\right)}$ = $\frac{1}{N}\sum_{i=1}^{N}\left(F_i - \overline{p_f}\right)^2$, estimate of $Var\left(p_f\right)$

Here, an observation can simplify the simulation: if the transmission lines associated with a common-cause failure comprise a minimal cut-set, the following equation is obtained:

$$P\left(system\_failure = 1 \middle| independent\_failure = 1, \underset{j \in J}{CCF_j} = 1 \right) = 1 \tag{86}$$

here,

J = index of a set such that $j \in J$ if and only if the transmission lines associated with the *j*th common-cause failure comprise a minimal cut-set

The relevant data is given in Section 5.7.

The algorithm of random sampling is as follows:

1) For each common-cause failure, check if the associated transmission lines comprise a minimal cut-set: if true, the relevant probability is 1; otherwise, go to the next step.
2) Set the states of the associated transmission line as *failure*.
3) Simulate the states of other system components separately. Here, the failure rate increment of system components is considered, and the time-specific probabilities of components in [13] are directly used.
4) The system state is obtained by combining all the states of components determined in Step (2) and (3).
5) Run optimization routine which is model as the same as that in Chapter III.
6) Check if there is any load shedding at any node: if yes, the system state is *failure*; if no, the system state is *success*.
7) If the system state is *failure*, update the estimate; if not, go to the next step directly.
8) Check if the convergence criterion is met: if yes, stop; if not, go back to step (3).

5.4.4 Inference results

Finally, the inference results of the Bayesian network in this chapter are marginal probability $P(system\_failure = 1)$ and posterior probability $P(CCF_i = 1 | System\_failure = 1)$, $1 \le i \le m$. The former is the probability of system failure caused by both the independent and common-cause failures of system components; the latter is the occurrence probability of a common-cause failure when system failure has been observed. It can be interpreted as an importance index [67] and it indicates the weakness of a common-cause failure. Intuitively, greater is the posterior probability, more important (weaker) is the common-cause failure. Actually, $Max(P(CCF_i = 1 | System\_failure = 1))$, $1 \le i \le m$, is called *maximum a posterior (MAP) hypothesis* [65], and the corresponding common-cause failure is the weakest one. Here, *Max* is maximum operation. The posterior probability of common-cause failures can provide utilities another perspective on the decision-making process of hurricane prevention. The detailed analysis is given in Section 5.7.

5.5 Pseudo Repetitive Temporal Model

The pseudo-repetitive temporal model used to investigate the dynamic impact of hurricanes on composite power system reliability is shown in Fig. 28. Firstly, the duration of a hurricane is partitioned into *n* equal time intervals and each one is Δt. Here, the value of Δt can be determined by the tradeoff between evaluation accuracy and computational effort. Moreover, the speed of the development and dissipation of the hurricane should be taken into account. Then, during each Δt the Bayesian network in Fig. 25 is used. For the whole duration of the hurricane, the Bayesian networks in different Δt are only connected via system failure node.

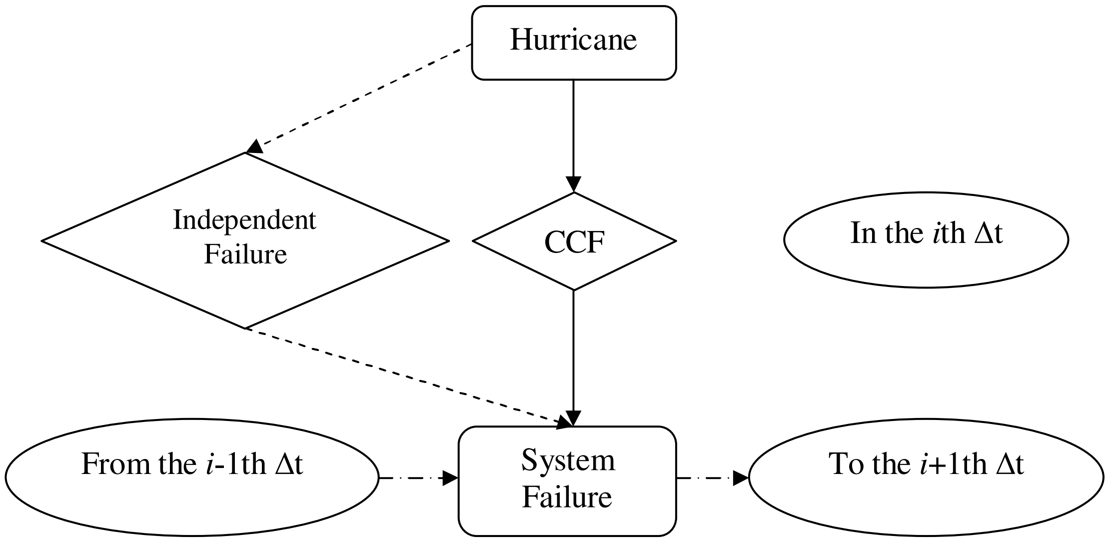

Fig. 28: Pseudo Repetitive Temporal Model

It is noted that the time-specific model used here is a modification of repetitive temporal model. Here, the Bayesian networks in different time slices are not connected by the directed edges as in repetitive temporal model. Instead, the connections between different Bayesian networks merely indicates temporal order, i.e. the Bayesian network in a time slice only affects that in the next time slice. This is similar to Markov property. This model is also different from a dynamic Bayesian network since the conditional probability distributions of system failure in different time slices can be different. The reason is that the failure rate increment of system components is considered here.

Finally, the results obtained by using pseudo repetitive temporal model are the time-specific values of the inference results in the last section. In summary, the overall procedure for the evaluation of the impact of hurricanes on composite power system reliability is as follows:

1) During each Δt, use the method in the last section to determine the conditional probability distribution of system failure.
2) Do inference in the Bayesian network to calculate the desired probabilities.
3) At the end of the last Δt, for each probability calculate its average during the duration of hurricanes. Actually, the average of the time-specific probability during a period of time is the fractional duration in the last chapter.

5.6 A Simple Analytical Method

In this section, a simple analytical method is proposed to investigate the impact of hurricanes on the short-term reliability of composite power systems. This method is an extension of the minimal cut-set method in Chapter III. Firstly, the identification of the extended minimal cut-sets is discussed; then, the computation of their probabilities is discussed.

5.6.1 Identification of extended minimal cut-sets

As mentioned before, the transmission lines associated with a common-cause failure may comprise a minimal cut-set or not. This is analyzed in detail as follows:

1) If the associated transmission lines comprise a minimal cut-set, there is no need to identify further minimal cut-sets as far as these transmission lines are concerned. In other words, these transmission lines can be regarded as a first-order minimal cut-set.
2) If the associated transmission lines do not comprise a minimal cut-set, these transmission lines can be regarded as *one* component, and further minimal cut-sets

can be identified up to the desired order by using the algorithm in Chapter III.

5.6.2 Probabilities of extended minimal cut-sets

After the additional minimal cut-sets are determined, their probabilities can be calculated as follows:

1) If the associated transmission lines comprise a minimal cut-set, the probability of the minimal cut-set can be calculated as follows:

   i. If the number of the transmission lines is greater than the desired order of minimal cut-sets, the obtained minimal cut-set is a new one, and its probability is just the occurrence probability of the common-cause failure.

   ii. If the number of the transmission lines is less than or equal to the desired order of minimal cut-sets, the obtained minimal cut-set is an existed one, and its probability can be calculated as follows:

$$P\left(\overline{C_k}\right) = P\left(\overline{C_k} \middle| CCF_{C_k} = 1\right) \cdot P\left(CCF_{C_k} = 1\right) + P\left(\overline{C_k} \middle| CCF_{C_k} = 0\right) \cdot P\left(CCF_{C_k} = 0\right) \quad (87)$$

where,

C_k	=	existed minimal cut-set k
$\overline{C_k}$	=	event that all members of C_k fail
CCF_{C_k}	=	common-cause failure that C_k associates
1/0	=	occurrence or not of CCF_{C_k}

From the above equation, the following equation is obtained.

$$P\left(\overline{C_k}\right) = 1 \cdot P\left(CCF_{C_k} = 1\right) + P\left(\overline{C_k} \middle| CCF_{C_k} = 0\right) \cdot \left(1 - P\left(CCF_{C_k} = 1\right)\right) \quad (88)$$

If $P\left(CCF_{C_k} = 1\right)$ is small, then $1 - P\left(CCF_{C_k} = 1\right) \approx 1$, and the following equation is obtained:

$$P\left(\overline{C_k}\right) \approx P\left(CCF_{C_k} = 1\right) + P\left(\overline{C_k} \middle| CCF_{C_k} = 0\right) \tag{89}$$

The above equation shows that $P\left(\overline{C_k}\right)$ can be approximated as two parts: the occurrence probability of CCF_{C_k} and the probability of $P\left(\overline{C_k}\right)$ when CCF_{C_k} does not occur. Here, the second part can be calculated by using the multiplication rule of probabilities considering the fact that now the failures of the member of C_k are independent with each other.

2) If the associated transmission lines do not comprise a minimal cut-set, these transmission lines and other components may comprise a minimal cut-set, and its probability can be calculated as the product of the occurrence probability of the common-cause failure and the probabilities of other components.
3) When the lower bounds of the reliability indices in Chapter III are computed, the above rules are also applicable to compute the probabilities of the joint events.

5.7 Implementation

In this section, the two methods proposed to evaluate the impact of hurricanes on composite power system reliability are applied to the modified IEEE reliability test system. Firstly, the relevant data is given; then, the evaluation results obtained by using different methods are presented and analyzed.

5.7.1Test system

In this chapter, the same modified IEEE reliability test system as those in the previous chapters is used as the test system.

5.7.2 Input data

5.7.2.1 Hurricane data

Here, the same time-specific regional hurricane data as that in the last chapter is used.

5.7.2.2 Data of common-cause failure

Table 20: Common-Cause Failure Data

CCF	Occurrence Probability	Associated Lines	Minimal Cut-Set?
CCF1(B)	0.05	[32,33]	No
CCF2(C)	0.025	[25,26]	No
CCF3(E)	0.025	[18,20]	Yes
CCF4(F)	0.05	[12,13]	Yes
CCF5(G)	0.05	[34,35]	No

The data of common-cause failures is listed in Table 20. In Table 12 of [38] some transmission lines exposed to common-mode failures are described. They are on a common right of way or a common transmission tower for at least some length. In this chapter only the latter case is investigated, and the common-mode failures are indicated by using the same letters as those in [38]. As mentioned before, the transmission lines associated with a common-mode failure may comprise a minimal cut-set or not. The relevant data is also listed in Table 20. The determination of the minimal cut-sets is described in detail in Chapter II.

Table 21: Short-Term Joint System Failure Probability

Time Interval	$P(system\_failure = 1)$		
	Independent Failure	Overall Effects (Bayesian Network)	Overall Effects (Analytical Method)
1	0.0036	0.1555	0.0787
2	0.0076	0.1581	0.0833
3	0.0133	0.1611	0.0901
4	0.0197	0.1651	0.0984
5	0.0262	0.1681	0.1074
6	0.0327	0.172	0.1172
7	0.0411	0.1761	0.1297
8	0.0476	0.1803	0.1407
9	0.0538	0.1841	0.1521
10	0.06	0.1867	0.164
11	0.0654	0.1922	0.1752
12	0.0692	0.1925	0.1851
Interval Frequency (Maximum)	0.0692	0.1925	0.1851
Fractional Duration (Average)	0.0367	0.1743	0.1268

5.7.3 Evaluation results

The time-specific marginal probabilities of system failure obtained by using the two proposed methods are listed in Table 21 and are shown in Fig. 29. For comparison, the result in the last chapter where only the independent failures of components are considered, is also presented here. The obtained posterior probabilities of common-cause failures are listed in Table 22 and are shown in Fig. 30. The legends used in Figs. 29 and 30 are as follows:

SP-IN: system failure probability only when independent failures considered

SP-JOINT (BN): overall system failure probability by using Bayesian networks

SP-JOINT (A): overall system failure probability by using analytical method

FD-IN: fractional duration only when independent failures considered

FD-JOINT (BN): overall fractional duration by using Bayesian networks

FD-JOINT (A): overall fractional duration by using analytical method

CCF1: Circle CCF2: “×” CCF3: “+” CCF4: “*”

CCF5: Square

Table 22: Posterior Probabilities of Common-Cause Failures

Time Interval	$P(CCF_i = 1 \mid System\_failure = 1), i = 1, \cdots, 5$				
	CCF1	CCF2	CCF3	CCF4	CCF5
1	0.0245	0.0177	0.1474	0.2948	0.0256
2	0.0266	0.0232	0.1454	0.2909	0.0316
3	0.0295	0.0311	0.1433	0.2866	0.0354
4	0.0364	0.0351	0.1405	0.281	0.0436
5	0.0386	0.0431	0.1387	0.2774	0.0455
6	0.0439	0.0467	0.1362	0.2725	0.0533
7	0.0481	0.0544	0.1339	0.2678	0.0571
8	0.0544	0.0588	0.1314	0.2628	0.0634
9	0.0563	0.061	0.1294	0.2588	0.073
10	0.0595	0.0685	0.1282	0.2564	0.0704
11	0.0699	0.0687	0.125	0.2501	0.081
12	0.072	0.0681	0.1252	0.2503	0.0785
Interval Frequency (Maximum)	0.072	0.0681	0.1252	0.2503	0.0785
Fractional Duration (Average)	0.0466	0.048	0.1354	0.2708	0.0549

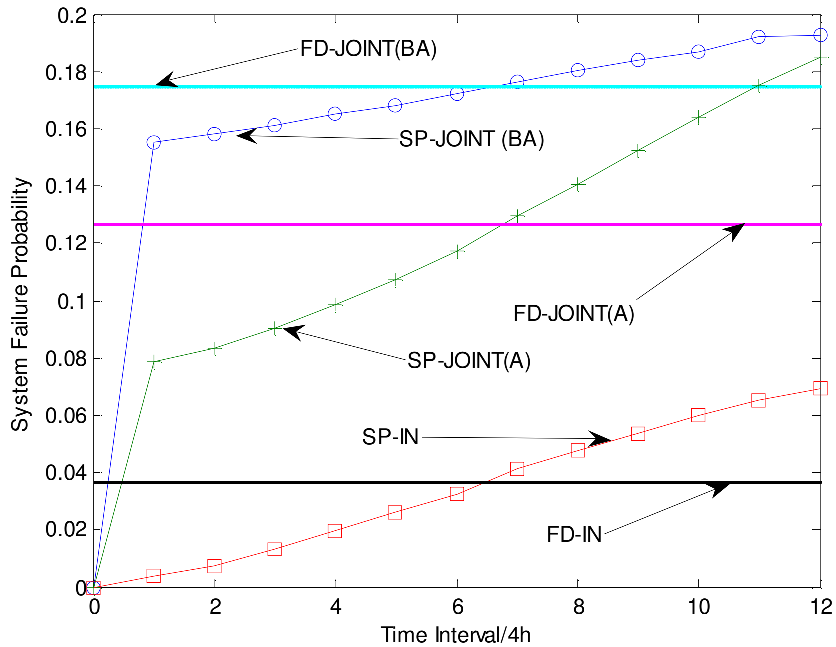

Fig. 29: Overall Short-Term System Failure Probability

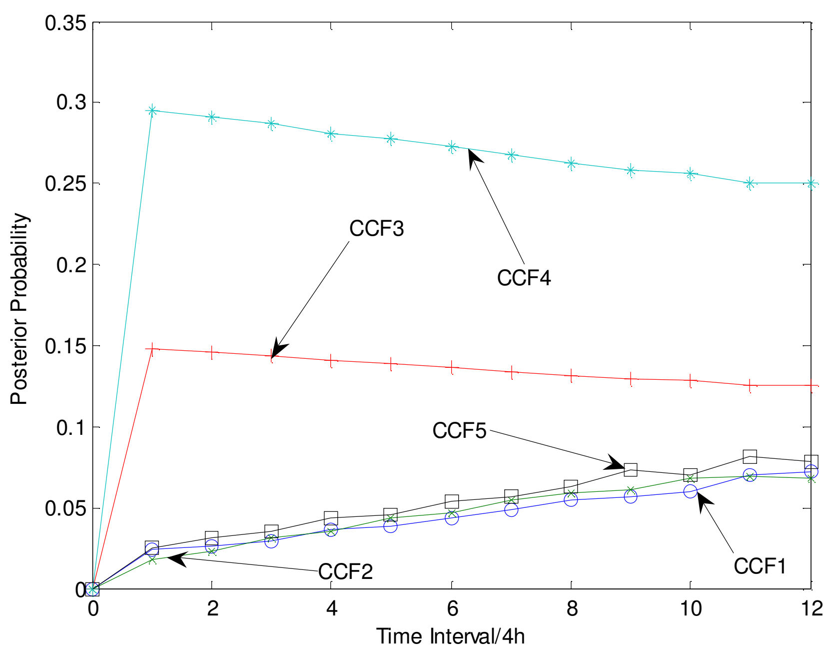

Fig. 30: Posterior Probabilities of Common-Cause Failures

5.7.4 Analysis of evaluation results

According to the above results, the following conclusions can be drawn:

1. Table 21 and Fig. 29 show that common-cause failures have a significant impact on composite power system reliability. When their effect is considered, as would be expected, the reliability of composite power systems becomes worse than that when only the independent failures of system components are considered.
2. Table 21 and Fig. 29 also show that different overall reliability indices are obtained by using different methods. The reasons are as follows:

   1) The system failure probability obtained by using the Bayesian network is greater than that obtained by using the analytical method. The reason is that the former method considers all the combinations of common-cause failures whereas only partial combinations are considered in the latter method.

   2) The discrepancy of the results of two methods decreases with time. The reasons are as follows:

      i. Initially, the probabilities of the independent failures of system components are relatively small. Thus, the contribution of common-cause failures is big. Since two methods model common-cause failures differently as mentioned, the discrepancy of their results is big.

      ii. With system reliability deteriorating, the probabilities of the independent failures of system components are increasing. Then, the contribution of common-cause failures is decreasing. Although the models of two methods are different, the discrepancy of their results is also decreasing.

3. From Table 22 and Fig. 30, the following observations can be made:

1) The posterior probabilities of CCF3 and CCF4 are greater than those of CC1, CC2, and CCF3. The reason is that the transmission lines associated with CCF3 and CCF4 comprise minimal cut-sets respectively.

2) The posterior probability of CCF3 is less than that of CCF4 as its prior probability is. Actually, the posterior probabilities of CCF3 and CCF4 will be the same if their prior probabilities are the same, i.e. CCF3 and CCF4 cannot be distinguished. Similarly, the reason is that the transmission lines associated with them comprise minimal cut-sets respectively. To differentiate CCF3 and CCF4, the load-shedding values associated with their minimal cut-sets can be used.

3) The posterior probability of CCF1 is less than that of CCF5 whereas their prior probabilities are the same.

4) The posterior probability of CCF1 is less than that of CCF2 whereas its prior probability is greater than that of CCF1.

5) Generally, the posterior probabilities of CCF3 and CCF4 decrease whereas the posterior probabilities of CCF1, CCF2, and CCF4 increase with time. The reason is as follows: initially the probability of system failure is relatively small, the impact of important (weak) common-cause failures (CCF3 and CCF4) on it is big; with system reliability deteriorating, the impact of important (weak) common-cause failures decreases whereas the impact of unimportant (strong) common-cause failures (CCF1, CCF2, and CCF4) increases, i.e. important common-cause failures and unimportant ones are becoming indistinguishable with system reliability

deteriorating.

4. For time-specific case, interval index fractional duration can more clearly indicate the characteristics of different evaluation results than time-specific failure probability.
5. For the method of using Bayesian networks, most CPU time is spent on determining the parameters. This problem has been alleviated by using linear optimization, and it can be further alleviated by using the sensitivity analysis in Bayesian networks, i.e. analyzing the sensitivity of the evaluation results to the parameters of system failure node [59]-[61], [65]. The iteration number of simulating the parameters to which the results are insensitive can be reduced.
6. For the analytical method, most computational time is spent on determining the minimal cut-sets. However, this needs to be done only once in current case where system load is constant. This is in contrast to the case when simulation method is used where it has to be implemented in each time interval.
7. In this chapter, the proposed methods evaluate the impact of hurricanes on the short-term reliability of composite power systems. They also can evaluate other types of common-cause failures, e.g. that caused by a bus failure. They also can be applied to other systems. For example, they can be applied to a substation to investigate some station-originated failures.

5.8 Summary

Common-cause failures have a significant impact on the reliability of composite power systems. In this chapter, two methods are proposed to investigate the impact of hurricanes on the short-term reliability of composite power systems. Here, both the independent and common-cause failures of system components are taken into account. One method uses Bayesian networks to alleviate the dimensionality problem of conditional probability method. The other method is a simple analytical method which extends the minimal cut-set method in previous chapters. These two methods are applied to the modified IEEE reliability test system. From the implementation, the following conclusions are summarized:

1) The proposed methods are effective. They can evaluate the impact of hurricanes on composite power system reliability. When common-cause failures are not considered, the reliability of composite power systems is overestimated.
2) The evaluation results obtained by using different methods are different. Choosing suitable method should depend on practical requirements.
3) Posterior probability has different characteristics from prior probability. In some cases, its results are counter-intuitive. It can provide a new perspective on the reliability evaluation of composite power systems, and can be a helpful vehicle for the decision-making process of utilities.
4) For time-specific case, interval index fractional duration can more clearly indicate the characteristics of different evaluation results than time-specific index.
5) The proposed methods are applicable to other types of common-cause failures in other systems.
6) The implementation of the proposed methods is mainly to demonstrate the feasibility of the ideas. Possible improvements can be investigated for practical applications,

e.g. developing the time-specific failure model of transmission towers damaged by hurricanes.

CHAPTER VI

CONCLUSIONS AND EXTENSIONS

In this chapter, the evaluation methods proposed in previous chapters are summarized. Additionally, possible extensions of them are discussed.

6.1 Summary

Adverse weather such as hurricanes has a significant impact on the reliability of composite power systems. Predicting the impact of hurricanes can help utilities for better preparedness and make appropriate restoration arrangements. In this dissertation, long-term and short-term impacts of adverse weather on the reliability of composite power systems are investigated.

In summary, the proposed methods to investigate the impact of adverse weather on composite power system reliability are as follows:

In Chapter III, the impact of adverse weather on the long-term reliability of composite power systems is investigated by using Markov cut-set method and sequential simulation. For the analytical method, an algorithm based on linear optimization is developed to identify system and nodal minimal cut-sets, and another algorithm is developed to compute the probabilities of minimal cut-sets and their unions. These algorithms are important not only for the inclusion of the impact of adverse weather but also for reliability evaluation of composite power systems. These algorithms differ from the previous cut-set methods that it can compute nodal indices and use linear optimization. Both the analytical and simulation methods are applied to the modified

IEEE reliability test system. The evaluation results obtained by using different methods are compared and analyzed. The implementation demonstrates that comparable results can be obtained by using the analytical method, and meantime it can be faster than the simulation method.

In Chapter IV, the impact of hurricanes on the short-term reliability of composite power systems is investigated where the states of components are assumed to be independent. Firstly, a fuzzy inference system is combined with regional weather model to assess the failure rate increment of components affected by hurricanes. Here, different methods are used to build two types of fuzzy inference systems: Then, short-term minimal cut-set method is proposed to compute time-specific system and nodal reliability indices. This is the first time the cut-set method is used to compute short term reliability indices for composite power systems. The proposed methodology is also applied to the modified IEEE reliability test system. The implementation demonstrates that the proposed methodology is effective and efficient and is flexible in its applications.

In Chapter V, the impact of hurricanes on the short-term reliability of composite power systems including the common-cause failures of components is investigated. Here, two methods are proposed to achieve this goal. One of them uses Bayesian networks to alleviate the dimensionality problem of conditional probability method. The other methodology is the extension of minimal cut-set method. As in Chapter IV, the time-specific reliability indices of composite power systems are calculated by using these two methods. The methods proposed also can compute nodal reliability indices.

They are also applied to the modified IEEE reliability test system. In the implementation, the results obtained by using different methods are compared and their discrepancy is analyzed.

6.2 Possible Extensions

In this section, two possible extensions of the proposed methods in this dissertation are discussed.

6.2.1 Extension to distribution systems

The proposed methods for investigating the impact of hurricanes on composite power system reliability can be extended to distribution systems in two ways as follows:

6.2.1.1 Extension of methods

When the proposed methods are applied to distribution systems, the only modification is the analysis of failure effects, i.e. determining a system state is success or failure as defined. The reason is that the configuration of a distribution system can be different from that of a transmission system. In a meshed distribution system, the identification of system states is the same as that in a transmission system, i.e. usually linear optimization is used to identify whether load shedding is needed. In a radial distribution system the analysis of failure effects becomes simpler, and network reduction method can be used. It is noted that the modification of the analysis of failure effects is applicable to both analytical and simulation methods.

6.2.1.2 Nodal reliability indices

The nodal reliability indices of transmission systems can be used in distribution systems, and more accurate evaluation results in distribution systems can be obtained.

The basic idea is to regard each node of the transmission system as a power source in the distribution system. Thus, the nodal reliability indices in the transmission system can be regarded as the reliability indices of the power sources in the distribution system. Since the reliability evaluation of power systems at hierarchical level III is too complex to be implemented directly, usually the reliability evaluation of distribution systems is implemented separately, and their power sources are assumed to be perfectly reliable. Considering the actual reliability performance of the power sources in distribution systems, more accurate evaluation results for power systems can be obtained at hierarchical level III.

6.2.2 Extension to other applications

The proposed methods in this dissertation are also applicable to other applications in power systems, e.g. operational reliability, and intermittent renewable energy.

Usually, reliability evaluation in power systems is implemented for long-term applications, e.g. planning issues [37], [68]-[69]. Additionally, the reliability parameters of system components, i.e. failure and repair rates, are assumed to be constant, and the probabilities of components are calculated by using renewal process [68].

However, the above approach is facing challenges in present power systems with some emerging applications, e.g. unit commitment considering probabilistic constraints [70], assessment of the impact of extreme weather [13], [15], and intermittent renewable energy [71]-[72]. The common characteristic of these applications is that the observation horizon is much shorter compared to that of planning. For example, electricity market is cleared say every half an hour or an hour, some extreme weather say hurricanes last only a few days, and the output of some intermittent energy sources say wind energy can fluctuate hourly. In general, there is likely to be more emphasis on reliability evaluation over short term where the proposed methods can be used.

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APPENDIX

DADA OF IEEE RELIABILITY TEST SYSTEM

Table 23: Generating Unit Reliability Data

Unit Size (MW)	Number of Units	Forced Outage Rate	Mean Time To Failure (hr)	Mean Time To repair (hr)	Scheduled Maintenance (week/yr)
12	5	0.02	2940	60	2
20	4	0.1	450	50	2
50	6	0.01	1980	20	2
76	4	0.02	1960	40	3
100	3	0.04	1200	50	3
155	4	0.04	960	40	4
197	3	0.05	950	50	4
350	1	0.08	1150	100	5
400	2	0.12	1100	150	6

Note:

$$Forced\_Outage\_Rate = \frac{Mean\_Time\_To\_\mathrm{Re}apir}{Mean\_Time\_To\_\mathrm{Re}apir + Mean\_Time\_To\_Failure}$$

Table 24: Generation Mix Data

Type	Installed Capacity (MW)	Percentage (%)
Fossil Oil	951	28
Fossil Coal	1274	37
Nuclear	800	24
Combustion Turbine	80	2
Hydro	300	9
Total	3405	100

Table 25: Generating Unit Locations

Bus	Unit 1 (MW)	Unit 2 (MW)	Unit 3 (MW)	Unit 4 (MW)	Unit 5 (MW)	Unit 6 (MW)
1	20	20	76	76		
2	20	20	76	76		
7	100	100	100			
13	197	197	197			
15	12	12	12	12	12	155
16	155					
18	400					
21	400					
22	50	50	50	50	50	50
23	155	155	350			

Table 26: Bus Load Data

Bus	Load (MW)	Percentage (%)
1	108	3.8
2	97	3.4
3	180	6.3
4	74	2.6
5	71	2.5
6	136	4.8
7	125	4.4
8	171	6
9	175	6.6
10	195	6.8
13	265	9.3
14	194	6.8
15	317	11.1
16	100	3.5
18	333	11.7
19	181	6.4
20	128	4.5
Total	2805	100

Table 27: Transmission Line Length and Forced Outage Data

Bus (From)	Bus (To)	Length (ml)	Outage Rate (/yr)	Outage Duration (hr)
1	2	3	0.24	16
1	3	55	0.51	10
1	5	22	0.33	10
2	4	33	0.39	10
2	6	50	0.48	10
3	9	31	0.38	10
3	24	0	0.02	768
4	9	27	0.36	10
5	10	23	0.34	10
6	10	16	0.33	35
7	8	16	0.3	10
8	9	43	0.44	10
8	10	43	0.44	10
9	11	0	0.2	768
9	12	0	0.2	768
10	11	0	0.2	768
10	12	0	0.2	768
11	13	33	0.4	11
11	14	29	0.39	11
12	13	33	0.4	11
12	23	67	0.52	11
13	23	60	0.49	11
14	16	27	0.38	11
15	16	12	0.33	11
15	21	34	0.41	11
15	21	34	0.41	11
15	24	38	0.41	11
16	17	18	0.35	11
16	19	16	0.34	11
17	18	10	0.32	11
17	22	73	0.54	11
18	21	18	0.35	11
18	21	18	0.35	11
19	20	27.5	0.38	11
19	20	27.5	0.38	11
20	23	15	0.34	11
20	23	15	0.34	11
21	22	47	0.45	11

Table 28: Circuits on Common Right Way or Common Structure

Right of Way Identification	Bus (From)	Bus (to)	Common Row (ml)	Common Row (ml)
A	22	21	45	
	22	17	45	
B	23	20		15
	23	20		15
C	21	18		18
	21	18		18
D	15	21	34	
	15	21	34	
E	13	11		33
	13	12		33
F	8	10		43
	8	9		43
G	20	19		27.5
	20	19		27.5

VITA

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