RELIABILITY EVALUATION OF LINE SWITCHING OPERATIONS AND INVESTIGATIONS INTO INCOMPLETE DATA ISSUES

A Dissertation

by

SHIJIA ZHAO

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

DOCTOR OF PHILOSOPHY

Chair of Committee,	Chanan Singh
Committee Members,	Garng Huang
	Alex Sprintson
	Yu Ding
Head of Department,	Miroslav M. Begovic

August 2018

Major Subject: Electrical Engineering

ABSTRACT

Research in this dissertation is mainly focused on two topics: reliability evaluation of line switching operations and the investigation into incomplete data issues observed in reliability evaluation.

A method is proposed for studying the reliability implications of line switching operations in power systems. This method is designed to explore previously overlooked areas, study objectives and study measures, in reliability evaluation of line switching operations. Line removal test is proposed to obtain simulation data of the system, and then with risk analysis and impact analysis, six reliability indices are used to evaluate reliability performance of each transmission line in the system. Weibull distribution is used to reconstruct distributions of reliability indices which provide variance analysis and worst-case scenario comparisons. Eventually, with results obtained, categorization for line switching operations is introduced to classify all transmission lines based on their reliability performance. The categories provide reliability implications of line switching operations and can be used for guidance in actual operations. This method is tested in two case studies: IEEE Reliability Test System (RTS) and IEEE 118-bus system. Both case studies validate the effectiveness of this method.

A contingency ranking (CR) method is introduced as a pre-selection method to create a hybrid reliability evaluation method. The objective is not only to speed up the simulation but also to provide analytical analysis of state space. The differences between event-based and yearly-based indices are analyzed to better understand the results of the proposed method. Two case studies on IEEE RTS and IEEE 118-bus system conclude that this method have high accuracy in identifying critical lines with a significant improvement in calculation speed.

To resolve incomplete data issues observed in reliability evaluation, mathematical conditions are derived for the probabilities obtained from the Markov model using transition rates to be identical with those obtained from the state residence times. This research provides guidance on building or recovering transition rate matrix in the absence of complete data. This research also shows equivalent transition rates with implicit assumption of exponential distribution is not affected by the probability distribution of state residence times in steady state analysis.

DEDICATION

To my parents and my family for their love and support.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Singh, and my committee members, Dr. Huang, Dr. Sprintson, Dr. Ding, and Dr. Begovic, for their guidance and support throughout the course of this research.

Thanks also go to my friends and colleagues and the department faculty and staff for making my time at Texas A&M University a great experience.

This research was made possible by NPRP grant # 7-106-2-053 from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors.

Finally, thanks to my mother and father for their encouragement and unconditional support and love throughout the course of this research.

CONTRIBUTORS AND FUNDING SOURCES

This work was supported by a dissertation committee consisting of Professor Chanan Singh and Professors Garng Huang, Alex Sprintson of the Department of Electrical and Computer Engineering and Professor Yu Ding of the Department of Industrial and System Engineering.

The analyses depicted in section 4 were conducted in part by Dr. Chanan Singh of the Department of Electrical and Computer Engineering and were published in 2016 in an article listed in the proceedings of PMAPS 2016.

All other work conducted for the dissertation was completed by the student independently.

Graduate study was supported by the NPRP grant # NPRP 7-106-2-053 from the Qatar National Research Fund (a member of Qatar Foundation).

NOMENCLATURE

CR	Contingency Ranking
EENS	Expected Energy Not Supplied
EENSP	Expected Energy Not Supplied Percentage
EFORd	Equivalent Forced Outage Rate – demand
EPNSP	Expected Power Not Supplied Percentage
HLOLE	Hourly Loss of Load Expectation
LDLE	Load Level Expectation
LOLE	Loss of Load Expectation
MCS	Monte Carlo Simulation
PI	Performance Index
RTS	Reliability Test System

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1. INTRODUCTION*

1.1 Background and Scope

System reliability has several definitions but the one most often stated in textbooks is "the probability that the system will perform its intended function for a given period of time under stated environmental conditions" [1]. However, this definition is restrictive in its scope of application. For example, for power system reliability, its intended function is to supply load at every bus while meeting all grid limits. It is more appropriate to talk of quantitative measures which evaluate the expected performance compared with reference indices. Power system reliability is usually divided into two aspects: system adequacy and system security. System adequacy focuses on the ability of system to supply load within the system with available generation, transmission and distribution facilities. System security focuses on the ability of the system to respond to disturbances in power system. Both aspects are important to utilities, vendors and regulators for planning, operation, maintenance and regulatory purposes.

Line switching operations in power systems is an important part of network topology and flow control, which includes the innovative transmission technologies as well as enhanced transmission usage. The idea of line switching operations was initially introduced as a control

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method to reduce overloads on transmission lines and improve system security [2]. By treating transmission lines as controllable assets and incorporating transmission switching into power system operations, it is possible to have a more flexible framework of power system but switching operations also increase complexity and uncertainty that make analysis of the power system more challenging. There is no doubt that integration of topology and flow controls can affect the reliability performance of power systems. To avoid degradation of reliability and effectively utilize line switching in power system operations, comprehensive reliability evaluation is essential.

Traditional approach to contingency ranking (CR) is based on using a performance index (PI) to provide a measure of system performance [3]. It has been widely used in power system security analysis. However, there have been limited research efforts on using CR method in reliability evaluation of line switching operations. There are three objectives of introducing CR method into the reliability evaluation. Firstly, compared with traditional reliability simulation, CR method is not as accurate and is subject to mis-ranking but it is computationally fast and able to provide some insights into system contingencies. So, CR method could serve as a fast and reasonably accurate "pre-selection" method before the detailed reliability simulation. Secondly, the contingencies enumerated in CR having already been analyzed, the result of CR method can serve as a dictionary for the reliability simulation, which could speed up the simulation and provide visualization tools like map of state space. Thirdly, CR method is based on the analytical analysis. Every enumerated state in CR method is based on analytical solutions, which is not affected by the randomness inherent in Monte Carlo Simulation (MCS). For this reason, the results of CR can provide a certain amount of understanding of state space of line switching operations from the analytic aspect.

Traditional contingency ranking approach is based on using a performance index (PI) to provide a measure of system performance. It is designed to calculate the difference of the PI after a certain contingency. Due to the calculation complexity, normally, the first order change is approximated as the difference of PI of the corresponding contingency. So, the traditional contingency ranking method is based on calculating the first order derivative of PI function to control variable of each enumerated contingency and rank them based on calculated PI. Several improvements and adaptations need to be performed on the traditional CR method before it can be effectively introduced into the reliability evaluation of line switching operations.

Data collection schemes for power system components like generating units and transmission lines have different levels of sophistication. Generally, it is easier to collect the data for calculation of probabilities of the different states of the unit than the transition rates. This is because for calculating the state probabilities all that is needed is the cumulative time spent in the states whereas for the transition rate calculations, details on the number of transitions between various states is needed. For this reason, a more sophisticated data gathering procedure is needed when interstate transitions data is to be collected. In terms of applications to reliability evaluation, if one is interested in the probability based indices like the Loss of Load Expectation (LOLE) or Expected Energy Not Supplied (EENS) then the data on state probabilities alone is sufficient. However, if frequency and mean duration indices are needed then Markov models using interstate transitions are required. It is observed that there are several common incomplete data issues in the reliability evaluation of power system. Thus, it is important to investigate and provide corresponding remedial actions to resolve these incomplete data issues in reliability data analysis and application.

1.2 Literature Review

Power system reliability is usually divided into two aspects: system adequacy and system security. System adequacy focuses on the ability of system to supply load within the system with available general, transmission and associated distribution facilities [4]. System security focuses on the ability of the system to respond to disturbances in power system. An emerging topic in reliability area is the cyber-attack related studies, like the vulnerability of SCADA system [5-8] and the potential cyber-attacks on substations, wind farms and load redistribution [9-13]. In order to properly evaluate the impact of cyber-attack, the communication system can no longer be considered as always reliable [14, 15]. References [16-18] illustrated the reliability evaluation considering cyber-malfunctions in substations and also developed a benchmark test system [19] and a non-sequential Monte Carlo Simulation (MCS) method [20] for cyber-physical reliability evaluation of composite power system. Various optimization methods are also utilized in reliability evaluation as well as power system analysis [21-28].

The research interest in line switching operations has been increasing over the recent years. References [29-33] discussed the economic benefits of incorporating line switching operations, N-1 reliability is studied in [34] considering the co-optimization of generation unit commitment and transmission switching, [35-37] illustrated the possible improvement of stability with topology control, especially project led by Dr. Huang which focused on the critical switching flow in optimal transmission switching as well as possible cyberattack with false data injection [38-41]. However, there are only limited research efforts on the reliability evaluation of line switching operations. It is pointed out in [42] that most studies strongly prune the cases evaluated, instead of analysis on the overall state space of line switching, only selected scenarios were evaluated to make the case. A reliability evaluation method based on Monte Carlo Simulation (MCS) is proposed in [43, 44]. The method provides insights into the overall state space of line switching operations. However, the method is based on transmission line sweeping without analytical guidance so the computation speed is rather slow. Meanwhile, another investigation in the reliability evaluation of line switching operation named “Robust Adaptive Topology Control” [30, 31, 34-36, 45-49] proposed by Dr. Kezunovic and Dr. Hedman with the objective to “add flexibility to system operations and can be used for a variety of purposes”. Compared with research presented in this dissertation, RATC is more focused on the online implementation and real-time suggestions for operators, that’s why it leverages on the robustness of the algorithm and adaptiveness to different scale of power systems. Another new idea related to line switching operation was proposed as Network Topology Optimization (NTO). It considers not only the Optimal Transmission Switching (OTS) but also the bus-bar switching [50-53]. Contrary to line switching operations, the traditional way to increase redundancy in power system is to increase transmission lines or other related facilities in power system. The idea of Transmission Expansion Planning (TEP) emerged early in the research history, however, considering the complexity of power system, this problem is large-scale, mixed-integer, nonlinear and nonconvex, but with recent development in algorithm and computing power, a mixed-integer LP approach to solve TEP was proposed in [54], [55, 56] illustrated a multi-stage TEP scheme considering not only transmission lines but also FACTS devices and phase shift transformers.

Traditional approach to contingency ranking (CR) is based on using a performance index (PI) to provide a measure of system performance [3]. It has been widely used in power system security analysis [57-60], some innovative usage of CR method has been proposed in recent years. A bi-level optimization model was introduced in [61] for the risk assessment of transmission systems, Neural network and data environment analysis was combined with contingency ranking in [62]. A margin-based framework for contingency selection was proposed in [63] for unbalanced systems. However, there have been limited research efforts on using CR method in reliability evaluation of line switching operations.

Data collection schemes for power system components like generating units and transmission lines have different levels of sophistication. Following situations can arise in data analysis and application as the previously mentioned incomplete data issues:

1) Data may be collected for both interstate transitions and probabilities but the data for interstate transitions may be inconsistent with the probability data. This will give the state probabilities derived from the Markov model different than the state probabilities derived from the probability data.
2) Because of damage to interstate data, data for some transitions may be either incomplete or missing.
3) In some situations, only probability data may be collected but the software for reliability evaluations may be based on interstate transitions and so arbitrary transition rates may need to be used. These transition rates should produce the probabilities that would be calculated from the probability data.
4) The available data for transition rates may need to be modified or adjusted to suit a model. For example in [64, 65], Equivalent Forced Outage Rate - demand (EFORd), a probability based index, is calculated from two sources. One source is state occupancy data and the other is a computer program using transition rates. These

transition rates need to be adjusted to maintain the EFORd values from two sources identical.

1.3 Research Objectives and Procedures

It is observed in section 1.2 that there are research opportunities in the reliability evaluation of line switching operations, as well as the incomplete data issues in reliability evaluation. Research in this dissertation is performed with the objective to investigate above topics and solve problems observed in this process. Other than the research depicted in this dissertation, the author also performed research studies in the area of power system modelling [66], power system protection [67] and renewable energy integration [68, 69].

The research procedure is mainly divided into 3 steps.

In the first step, a method is proposed to evaluate reliability implications of line switching operations in power systems [43, 44]. This method is designed to solve the problems observed in traditional evaluation: study objective and study measure. To expand traditional study objectives, line removal test is designed to provide comprehensive reliability evaluation through sampling of potential failure states subsequent to line switching operations. The concept of this process is similar to adequacy evaluation but the data acquisition and analysis method in simulation is different from traditional adequacy analysis, they are designed to study the impact of switching out a particular transmission line. Furthermore, the analysis of simulation data involves newly introduced study measures to explore previously overlooked areas. Impact analysis is conducted separately from risk analysis to demonstrate the impact of each failure event. Apart from traditional mean value analysis, variance is introduced to reconstruct distributions of reliability indices using the Weibull distribution, which provide worst case comparisons. This method is tested on two test systems: IEEE Reliability Test System (RTS) and IEEE 118-bus system, both case studies validate its effectiveness.

In the second step, a contingency ranking method is introduced into the reliability evaluation of line switching operations as a pre-selection method. The hybrid of CR and traditional MCS method is designed to not only speed up the simulation, but also provide analytical analysis of state space of line switching operations. To further improve the proposed hybrid method, results analysis is updated to distinguish the difference between event-based and yearly-based indices. This method is also tested with two tested system, both case studies show not only the increase of computation speed but also the accuracy in picking up critical transmission lines.

In the third step, in order to resolve incomplete data issues observed in reliability evaluation [70], mathematical conditions is derived for the probabilities obtained from the Markov model using transition rates to be identical with those obtained from the state residence times. Then these results are illustrated by giving examples how this information can be used in the various situations just discussed. This research is motivated by building useful unit models in the absence of complete data. So, the examples used are small systems to verify and illustrate unit models as unit models are the focus. This research also shows that although the transition rates derived from the data are used in a Markov model with the implicit assumption of exponential distribution of state residence times, these constant transition rates are in fact equivalent rates and so far as the steady state probabilities are concerned, these will not be affected by the probability distribution of state residence times.

1.4 Organization of the Dissertation

The rest of dissertation is organized as following, section 2 illustrates the details of method proposed for the reliability evaluation of line switching operations; section 3 depicts the introduction of CR method and the details of hybrid reliability evaluation method for line switching operations; section 4 presents the theoretical deduction and proof to resolve the incomplete data issues observed in reliability evaluation. Contributions and research conclusions are summarized in section 5, as well as the outlook of possible future research work.

2. RELIABILITY EVALUATION METHOD PROPOSED FOR LINE SWITCHING OPERATIONS*

2.1 Introduction

This research proposes a method for studying the reliability implications of line switching operations in power systems. Two case studies are conducted on RTS and IEEE 118-bus system to illustrate this method. This method is designed to explore previously overlooked areas in reliability evaluation of line switching operations. Line removal test is proposed to obtain simulation data of the system, and then with risk analysis and impact analysis, six reliability indices are used to evaluate reliability performance of each transmission line in the system. Instead of the traditionally used mean value, this method introduces variance into analysis. Weibull distribution is used to reconstruct distributions of reliability indices which provide worst case scenario comparisons in reliability evaluation. Eventually, with results obtained from the proposed reliability evaluation method, categorization for line switching operations is introduced to classify all transmission lines based on their reliability performance. The categories provide reliability implications of line switching operations and can be used for guidance in actual operations.

Line switching operations in power systems is an important part of network topology and flow control, which includes the innovative transmission technologies as well as enhanced transmission usage. The idea of line switching operations was initially introduced as a control method to reduce overloads on transmission lines and improve system security [2]. Benefits of treating transmission lines as controllable assets and incorporating transmission switching into power system operations are manifold, but switching operations also increase complexity and uncertainty that make analysis of the power system more challenging. The integration of topology and flow controls will inevitably impact the power system reliability at different levels. Comprehensive reliability evaluation of line switching operations is essential before its effective utilization.

Although research around line switching operations is an important topic in power systems, there are two overlooked areas, study objective and study measure, in recent studies. For the study objective, most papers focus on the economic benefit [29-33] or stability improvement [35-38] or N-1 reliability [34] and only a few papers choose their objective as the reliability evaluation of overall potential failure events subsequent to line switching operations. It is mentioned in [42] that most papers strongly prune the cases considered. They focus on limited number of special scenarios of line switching that does not provide understanding of impact of all possible scenarios. For the study measure, risk assessment is a useful study tool in reliability evaluation, however, from statistical point of view, risk assessment is generally limited to mean value studies and it is necessary to involve variance in reliability evaluation. So far, there are only limited works on the variance or worst case study of reliability evaluation [44]. Furthermore, risk analysis is based on the combinatorial effect of impact and associated probability, which inherently mask the information of impact study. In this research, impact analysis is conducted separately from risk assessment to reveal previously overlooked patterns.

In this research, a method is proposed to evaluate reliability implications of line switching operations in power systems. To expand traditional study objectives, line removal test is designed to provide comprehensive reliability evaluation through sampling of potential failure states subsequent to line switching operations. The concept of this process is similar to adequacy evaluation but the data acquisition and analysis method in simulation is different from traditional adequacy analysis, they are designed to study the impact of switching out a particular transmission line. Furthermore, the analysis of simulation data involves newly introduced study measures to explore previously overlooked areas. Impact analysis is conducted separately from risk analysis to demonstrate the impact of each failure event. Apart from traditional mean value analysis, variance is introduced to reconstruct distributions of reliability indices using the Weibull distribution, which provide worst case comparisons.

Following are the contributions of the proposed method:

1) Introduced an investigation process to study the failure events subsequent to a line switching. Although the process concept is similar to adequacy evaluation, but with newly introduced data analysis method, the objective is not adequacy evaluation, but to study the impact of line removal through sampling of potential failure states subsequent to line switching operations.
2) Sequential MCS is used to form an approximate state space model with probabilistic enumeration of events subsequent to a specific line removal. Different from previous work, this test intends to capture all states in state space instead of any special state.

3) Weibull distribution is used to reconstruct the distribution of reliability indices from simulation data, which provides the variance patterns and worst-case scenarios.
4) The event-based HLOLE and EENS are introduced. Different from the yearly-based indices, these indices are based on each failure event. These indices are used in impact analysis to separate failure frequency from the impact of each failure event so that the low probability, high impact events are not diluted in the analysis. This is useful in the worst-case scenario comparison and reveals patterns different from intuitive expectations.
5) Two new indices, EENSP and LDLE, are introduced for impact analysis. Since they record new information in simulation, their pattern in results analysis is different from traditional analysis and are used as supplemental consideration in line categorization.
6) Based on reliability performance of each transmission line, line categorization is proposed to provide guidance on line switching operations considering reliability implications.

The organization of this research is as follows. The proposed reliability evaluation method is described in section 2.2. In section 2.3, two case studies using the proposed method are presented. Line categorization for line switching operations is performed in both case studies. Finally, the conclusions are summarized in section 2.4.

2.2 Reliability Evaluation Method

The proposed reliability evaluation method is described in this section. Firstly, six reliability indices used to evaluate reliability performance are described. Secondly, the necessity to introduce variance into results analysis is presented and Weibull distribution is chosen to reconstruct distribution of reliability indices. Thirdly, the processes of the proposed method are described. Finally, the detailed information of the test systems is presented.

2.2.1 Reliability Indices

Six reliability indices are used in this research to compare reliability performance in line removal tests.

The first two are traditional reliability indices, HLOLE and EENS of each year in simulation, the mean values of these indices are traditionally used to evaluate reliability of systems.

Other than the two traditional yearly-based indices, event-based HLOLE and EENS are introduced to capture information of each failure event subsequent to line removal and are defined in (1)-(2).

$$Event\_based\ HLOLE = \frac{\sum_{i=1}^{N} HLOL_i}{N} \tag{1}$$

Where

$HLOL_i =$ Loss of load hours of ith load loss event

$N =$ Number of load loss events

$$Event\_based\ EENS = \frac{\sum_{i=1}^{N} ENS_i}{N} \tag{2}$$

Where

$ENS_i =$ Energy not supplied of ith load loss event

$N =$ Number of load loss events

Traditional yearly-based indices provide risk analysis which is a combined effect of impact and associated probability. Event-based indices provide impact analysis which is different from risk analysis and is designed for a probabilistic enumeration of failure events subsequent to a specific line removal. With enough simulation time, each line removal test provides an approximate state space model for the corresponding transmission lines. The distribution of impact related to specific line removal reveals patterns different from traditional analyses.

The last two indices are LDLE and EENSP. These two event-based indices are designed for impact analysis. The detailed definitions are as following:

Load Level Expectation (LDLE) is used to measure average load level at all load loss events and is defined in (3):

$$LDLE = \frac{\sum_{i=1}^{N} LDL_i}{N} \tag{3}$$

Where

LDL_i = Mean load level of ith load loss event

N = Number of load loss events

It should be noted that LDLE in this research is not a controlling condition in simulation. Instead, it is a recorded index during simulation. In MCS of this research, load level data is a given 8760h repetition for all transmission line removals, thus under the same load level diagram, LDLE evaluates whether load loss events happen at lower or higher load level.

In reliability evaluation, the behavior of LDLE is different from all other indices. Since the load conditions are the same for all transmission line removals, then reliability is worse when LDLE is lower because that indicates load loss events occurring at lower load levels, in other words, it takes lower load level to trigger load loss events, thus indicating less redundancy in the system.

Expected Energy Not Supplied Percentage (EENSP) is used to measure energy not supplied as a percentage of energy to be supplied during each load loss event and defined in (4)-(5). It should be noted that LDL_i and $HLOL_i$ are recorded during load loss events with positive values, thus the validity of (5) is preserved.

$$EENSP = \frac{\sum_{i=1}^{N} ENSP_i}{N} \tag{4}$$

$$ENSP_i = \frac{ENS_i}{LDL_i * HLOL_i} \tag{5}$$

Where

$ENSP_i =$ Energy not supplied percentage in ith load loss event

$ENS_i =$ Energy not supplied in ith load loss event

$LDL_i =$ Mean load level of ith load loss event

$HLOL_i =$ Hourly loss of load in ith load loss event

$N =$ Number of load loss events

In reliability evaluation, reliability is worse when EENSP is higher because failure impact is more severe with higher loss percentage.

2.2.2 Necessity of Variance Analysis

Traditional analyses of MCS are based on the mean value of indices obtained through simulation. They output only a mean value for the reliability indices and distribution information is overlooked in the process. It is noted in the observation of simulation data that mean value study alone may not be sufficient.

For example, consider results of two line removal tests, each forming a distribution of reliability index LDLE as shown in Figure **1**. It is observed that case 1 and case 2 have the same mean value while their variances are different.

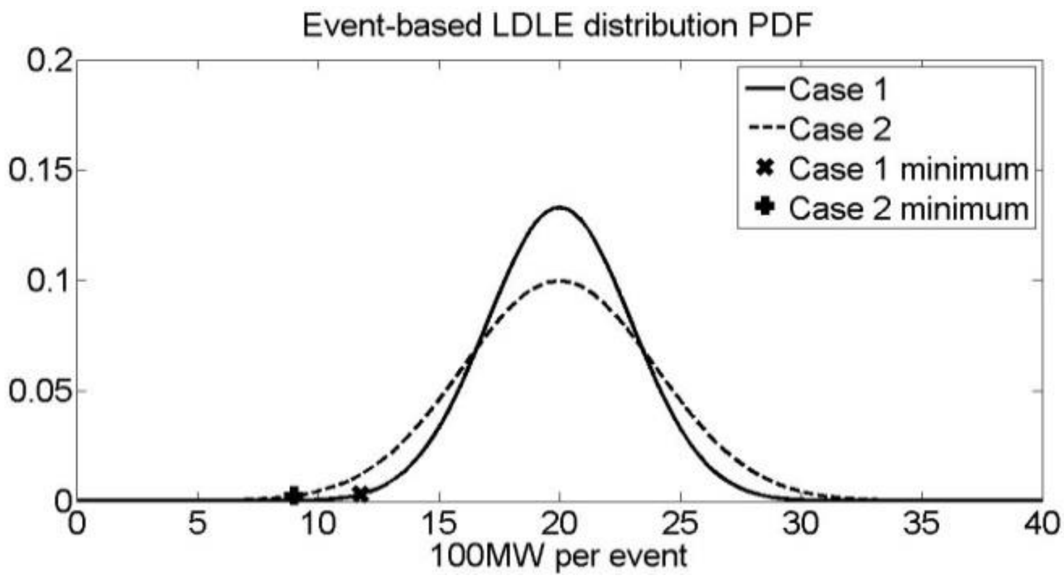

Figure 1. LDLE distribution comparison of two cases.

To consider the worst-case comparison, minimum value of LDLE is considered as the value at 0.03% of cumulative distribution probability, the mean value and minimum value of LDLE of two cases are presented in Figure 2.

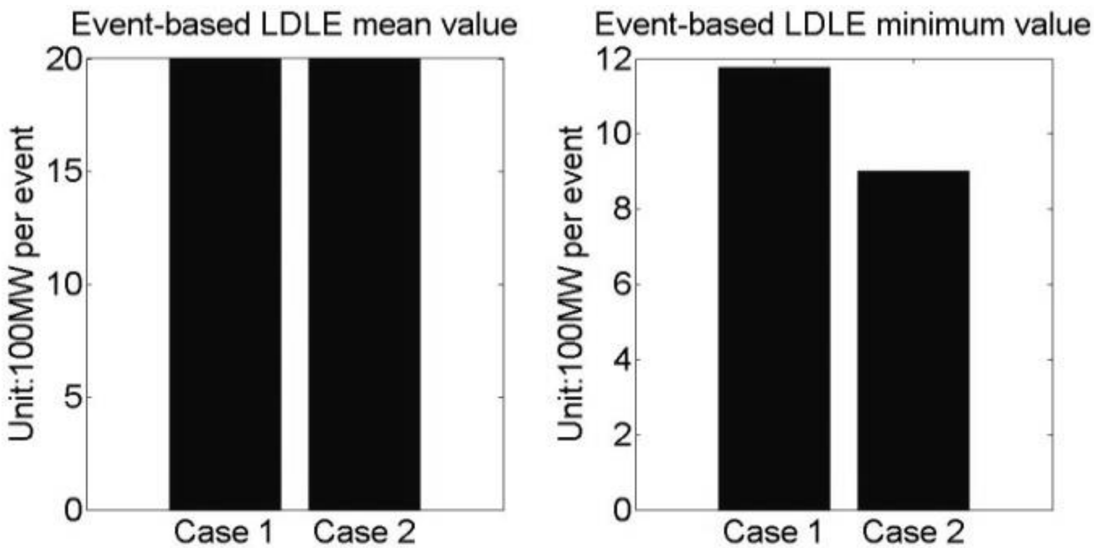

Figure 2. LDLE comparison of two cases. Reprinted from [43].

In traditional analysis, the impact of these two transmission lines would be considered the same simply because they have the same mean value in LDLE, but if we compare the distributions of these two results, their variance and worst-case scenario are completely different. Therefore, variance analysis needs to be added into reliability evaluation.

Many distributions like Gaussian Mixture Method (GMM) [71] or a combination of exponentials or gamma or Weibull are quite versatile in approximating the distributions. It is also possible to estimate variance of indices [72] without distribution reconstruction. In this research, to retrieve the distribution information overlooked in traditional analysis, Weibull distribution is used to process simulation data obtained from MCS because it can represent a wide range of data by appropriate choice of shape and scale parameters.

It should be noted that in sequential MCS as used in this research, we only record the information on failure events. The next event is determined by the system state (consisting of component states) and newly drawn random numbers for components to determine their next states. For example, consider a failure event X. After this event, the system will change its state based on the independent failures and repairs of components. The system will go through many changes of its states before the next failure state is encountered. In a reasonably reliable system, the next failure event is likely to happen after a considerable length of time. The random nature of transitions between these events will isolate these two events in terms of their correlation or dependence. So, it is reasonable to believe that failure events in this sequential simulation are independent and the distribution is thus normal. However, in actual operation, simulation data like HLOL and ENS are small non-negative values, which make the distribution a “truncated” non-negative normal distribution. So instead of normal distribution, Weibull distribution is used to reconstruct the distribution of reliability indices. As shown in Figure 3, reconstructed Weibull distribution closely captures distribution information of event-based ENS. Using the actual results of sequential MCS, it is observed that the results of sequential MCS failure events follow “truncated” normal distribution and Weibull distribution fitting closely captures the distribution information of recorded reliability indices.

In Figure 3-Figure 6, the Weibull distribution reconstruction and corresponding simulation data is provided for four event-based indices of benchmark case in IEEE 118-bus system.

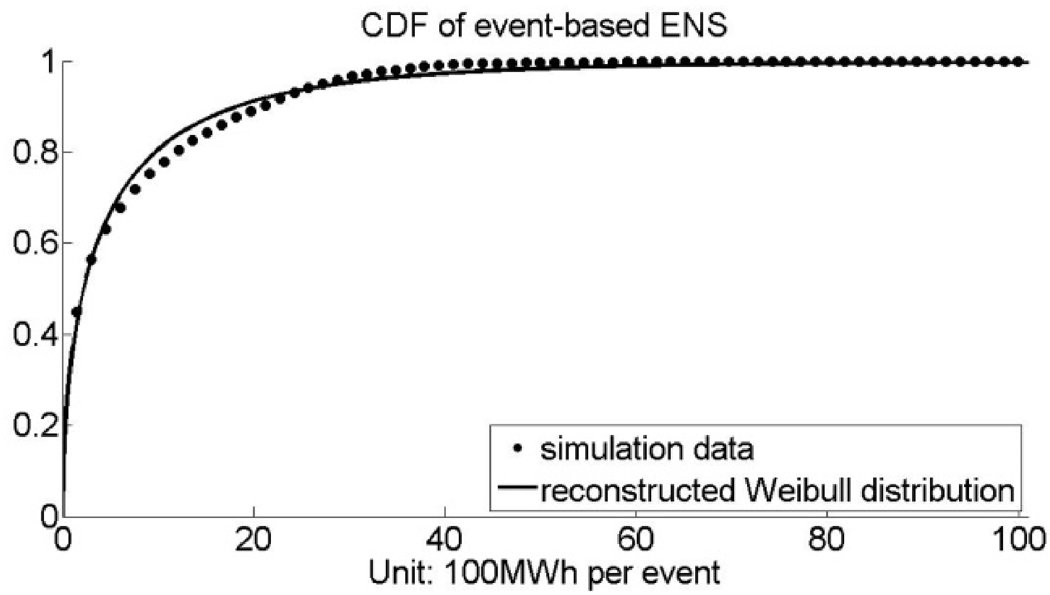

Figure 3. Reconstructed Weibull distribution based on event-based ENS.

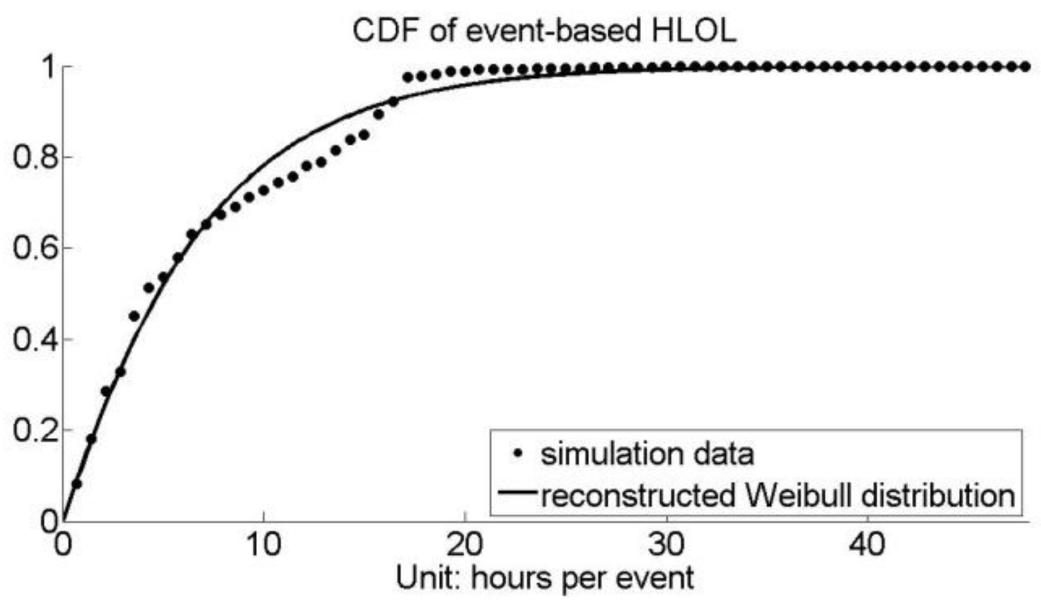

Figure 4. Reconstructed Weibull distribution based on event-based HLOL.

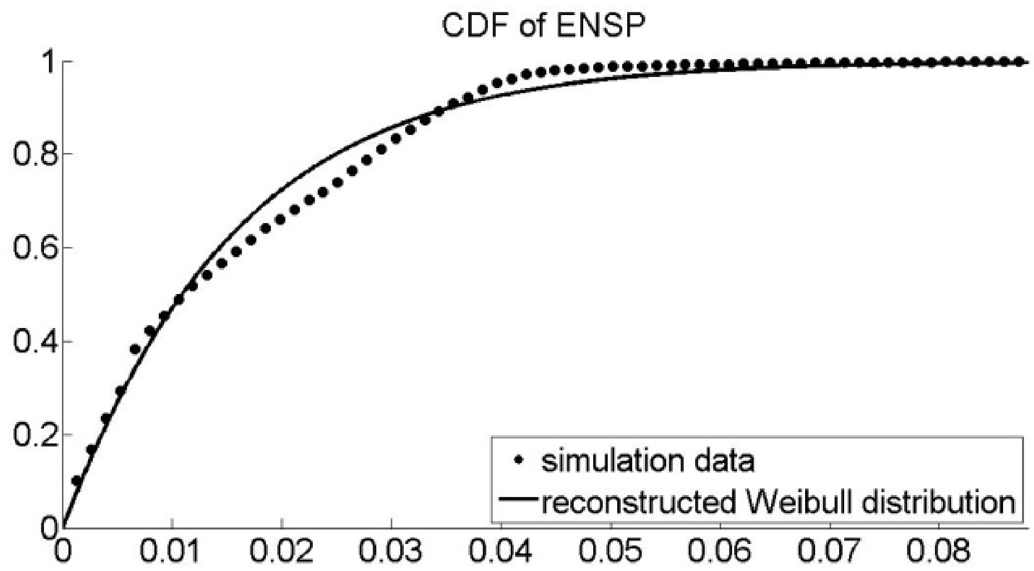

Figure 5. Reconstructed Weibull distribution based on ENSP.

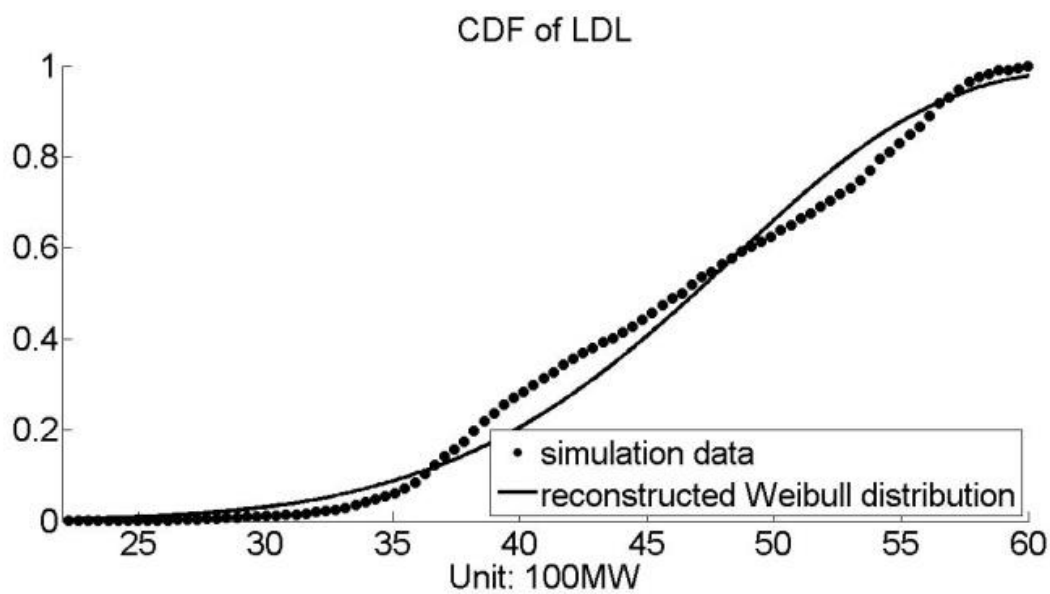

Figure 6. Reconstructed Weibull distribution based on LDL.

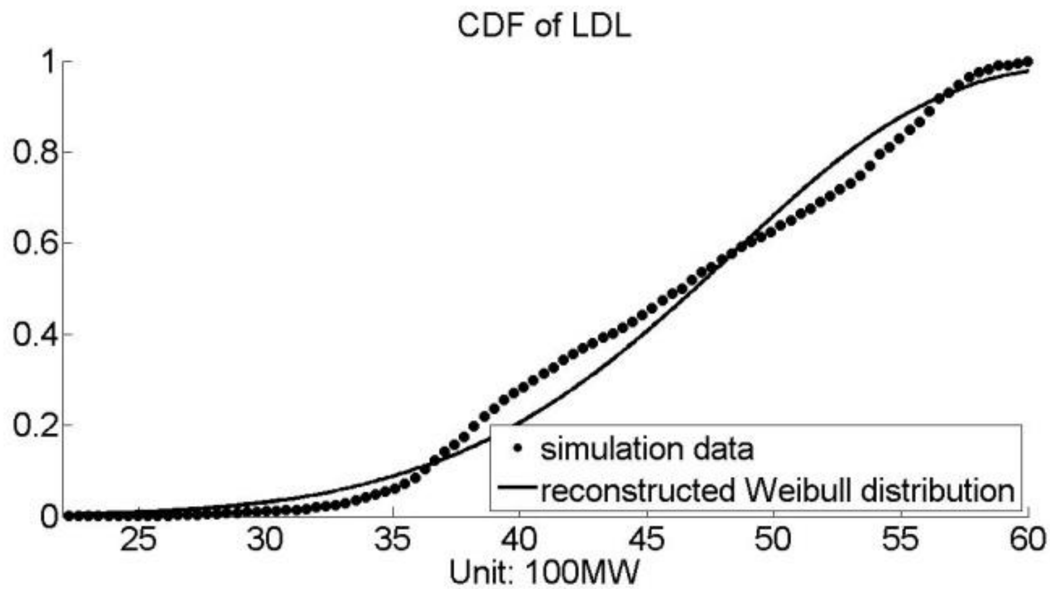

Figure 7. Reconstructed Weibull distribution based on event-based ENS of IEEE 118-bus system.

To show it works well for other transmission line removal, event-based ENS of case 38 in IEEE 118-bus system is shown in Figure 7. The Root Mean Square Error (RMSE) of these distribution fitting is presented in Table 1.

It is noted that Weibull distribution closely captures the distribution information for all reliability indices in both case studies.

Table 1 RMSE of Weibull distribution

Reliablity Indices	**Cases**	**RMSE**
Event-based ENS,	Bechmark case	0.0126
Event-based HLOL		0.0230
ENSP		0.0233
LDL		0.0392
Event-based ENS	Case 38	0.0147

2.2.3 The Procedures

In this research, sequential MCS is used to conduct line removal tests so that the time behavior of the test system after line switching is preserved and repeatedly tested in the simulation. System dynamics and transient is not considered in the current simulation. Each time when there is a state change for system component, the simulation will re-dispatch the generation and redo DC power flow to determine the system state. The model of DC power flow and transmission line flow are described in (6)-(7). If load is supplied, system is in successful state, if load is not supplied at any bus due to lack of generation or transmission congestion, system is in failure state and recorded as a load loss event. Simulation history of each failure event is preserved for newly introduced event-based indices.

$$\hat{B}\theta + G = L \tag{6}$$

$$b\hat{A}\theta = F \tag{7}$$

where

N_b is number of buses

N_t is number of transmission lines

b is N_t×N_t primitive matrix of transmission line susceptance

$\hat{A}$ is N_t×N_b element-node incidence matrix

$\hat{B}$ is $N_b \times N_b$ augmented node susceptance matrix= $\hat{A}^T b\hat{A}$

θ is N_b-vector of bus voltage angles

G is N_b-vector of bus generation levels

L is N_b-vector of bus load levels

F is N_t-vector of transmission line flows

In order to improve computation efficiency, for each sampled system state, pre-selection method from [73] is used before Linear Programming (LP). The pre-selection method is described as following.

1) The net injections at all buses are calculated by subtracting bus load from bus generation.
2) If sum of net injection is positive, the positive bus injections are proportionally scaled down so that their sum equals that of the negative injections; if the sum of net injection is negative, load of all buses are proportionally curtailed so that their sum equals that of the generation.
3) Step 2 ensures power balance and output G vector, which is used in (6) to solve θ vector and then transmission line flow solution is obtained by (7)

If the line flow solution from pre-selection method satisfies line flow constraints, then a feasible flow is found for the system state and reliability index like HLOL and ENS is recorded if load is curtailed. However, if pre-selection method fails to find a feasible flow, LP model is used in (8)

$$\textbf{Minimize}\ \sum_{i=1}^{N_b} LL_i \quad \text{(Loss of Load)} \tag{8}$$

Subject to

Power Balance: $\hat{B}\theta + G + LL = L$

Generation Limits: $G \leq G^{max}$

Flow Limits: $b\hat{A}\theta \leq F^{max}$

$$-b\hat{A}\theta \leq F^{max}$$

$$0 \leq LL \leq L$$

where

LL is N_b-vector of bus loss of load

G^{max} is N_b-vector of maximum bus generation

F^{max} is N_t-vector of transmission line flow capacity

The idea of upper and lower bounds [1] is used in this paper, the confidence level is set to 95% which means there is a 95% probability that the exact value is within the bound range of simulation results. The bounds are computed as follows:

Assume MCS results have normal distribution with real mean of m and sample size of n, and let $\bar{X}$ be the mean result of MCS, then considering t-distribution, it follows distribution in (9):

$$\text{Prob.}\left\{\bar{X} - t_{\frac{\alpha}{2}}^{n-1} * \frac{v}{n} \leq m \leq \bar{X} + t_{\frac{\alpha}{2}}^{n-1} * \frac{v}{n}\right\} = 1 - \alpha \quad (9)$$

Where

$v = \sum_{i=1}^{n} \frac{(X_i - \bar{X})^2}{n-1}$, Variance of t-distribution with (n-1) degrees of freedom

$t_{\frac{\alpha}{2}}^{n-1} =$ The $100 * \frac{\alpha}{2}$ percent point of t-distribution

$X_i =$ The ith observation in MCS

It can be concluded from previous equations that if we set confidence level to be 95%, the upper and lower bound of the real mean of simulation can be expressed using mean result, variance and sample size from MCS as shown in (10)-(11):

$$\text{Upper bound} = \bar{X} + t_{2.5}^{n-1} * \frac{v}{n} \quad (10)$$

$$\text{Lower bound} = \bar{X} - t_{2.5}^{n-1} * \frac{v}{n} \quad (11)$$

Without using bounds, several line removal results have only trivial difference compared with base case (no line removed). These trivial differences are coming from random variations which should not be considered in the final comparison, only difference beyond bound range should be considered as non-trivial difference. So, with the introduction of bound range, if there is an overlap between the bound range of specific line removal and base case, these trivial differences are eliminated by setting that line removal result values equal to base cases. In this way, transmission lines with non-trivial difference are emphasized in the result comparison.

The process of the proposed method includes several steps. The first step is to obtain simulation data with line removal tests, second step is to reconstruct distribution of simulation data using Weibull distribution and the last step is to analyze distributions and extract insights from the patterns observed.

The first step, line removal tests, is as following:

1) Conduct MCS on the original test system without any line removal and set it as a benchmark case.
2) Remove line k of the system, and conduct MCS on the test system while recording reliability indices of each failure event.
3) Increase k=k+1 and repeat step 2 until it sweeps all transmission lines in the test system.

The second step, distribution reconstruction, is as following:

1) From the simulation data of line removal test of line k, reconstruct distribution of event-based reliability indices using Weibull distribution. Maximum likelihood estimation is used to obtain scale and shape parameters. The inherent random

characteristic of MCS simulation data is represented by the upper and lower bounds with 99.7% confidence interval.

2) For the worst-case analysis, the extreme value is obtained from the inverse cumulative distribution function. The extreme point is set at 99.7% of distribution for maximum and 0.03% for minimum.
3) The upper and lower bounds of extreme value are confidence bounds of 99.7% confidence interval using a normal approximation to the distribution of estimate.
4) For yearly-based reliability indices, the impact of each failure event is combined with failure frequency to perform risk analysis. Like steps 1-2, scale and shape parameter, extreme value and corresponding upper and lower bounds are obtained.
5) Increase k=k+1 and repeat steps 1-3 until it sweeps all transmission lines in the test system.
6) Summarize reliability indices obtained for all transmission line removals and compare with benchmark case. The upper and lower bounds of obtained parameters are designed to avoid trivial difference in line removals, thus if bounds of parameter of transmission line k has overlapping region with bounds of benchmark case, the corresponding parameter is set to be the same as benchmark case.

The third step, line categorization, is as following:

1) For each reliability index, record all transmission lines showing non-trivial difference compared with benchmark case. The differences are distinguished between increase and decrease of reliability.
2) Extract insights from patterns obtained and categorize transmission lines with line categorization based on reliability performance of each transmission line.

The backbone of this procedure is the line removal test as shown in Figure 8.

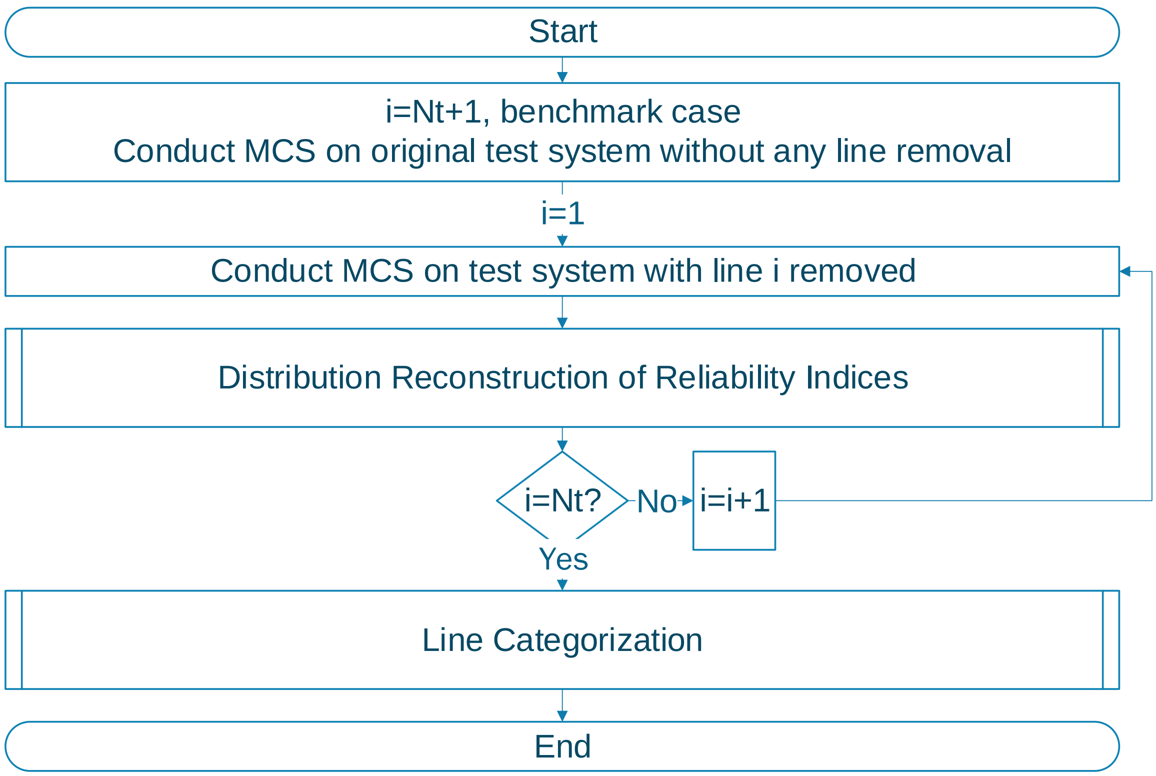

Figure 8. Procedure of line removal test.

There are two sub-processes in Figure 8 as distribution reconstruction and line categorization. These two sub-processes are illustrated in Figure 9 and Figure 10 respectively.

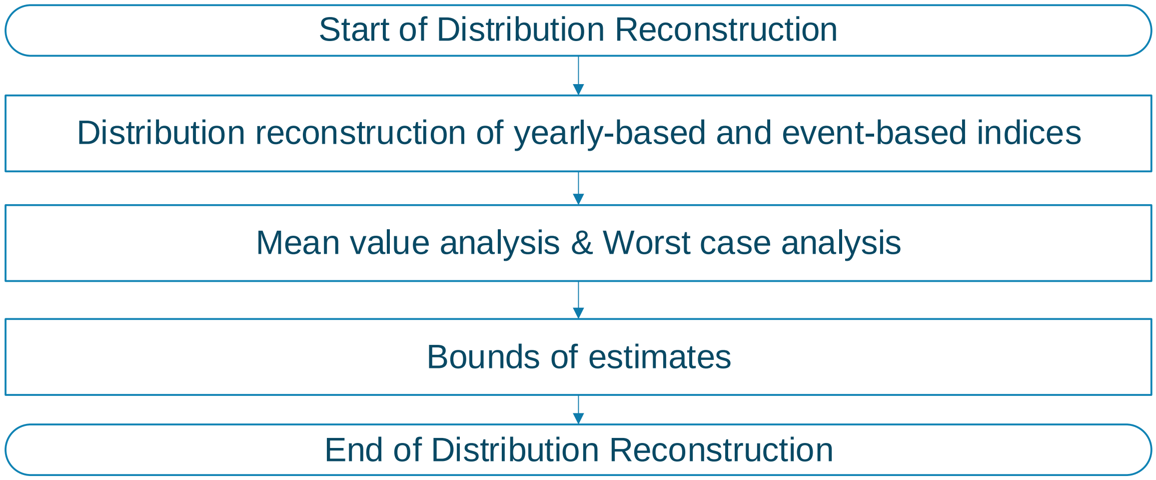

Figure 9. Procedure of distribution reconstruction.

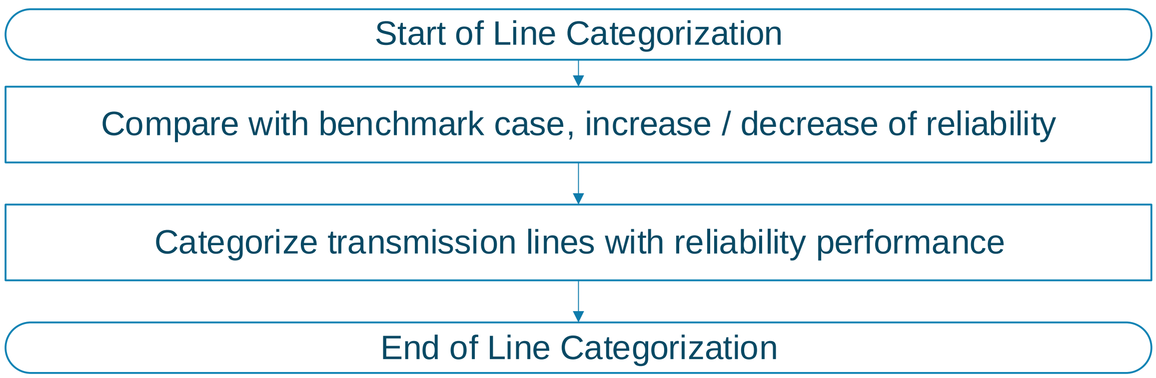

Figure 10. Procedure of line categorization.

2.2.4 Reliability Test Systems

In this research, two test systems are used to illustrate the method, one is IEEE-RTS, and another is IEEE 118-bus system.

RTS used in this research is from [74], there are 38 transmission lines in the system, with 3450MW maximum generation and 2850MW maximum load. The load diagram is obtained from [74] as an 8760h load cycle, meaning the load level will change every hour. With long enough simulation time, all possible load levels are evaluated in the simulation, corresponding to dealing with the uncertainty of load levels in actual operations. However, the load levels in replications of 8760h cycle can be changed if more information is available on the nature of uncertainty. This is not a limitation on the method but availability of data. Reliability parameters used are the same as [74] to perform case study on the original test system, however, it may provide an interesting comparison when loading coefficient of transmission lines are altered.

Since RTS only has 24 buses, in order to show the effectiveness of this method on a larger system, IEEE 118-bus system is introduced as a test system with more buses and more complicated topology, the topology and reactance data is captured from [75]. Since there is no reliability data associated with this system, corresponding parameters are chosen from RTS, for simplicity, all generators share the same failure rates and repair time and all transmission lines share same failure rates and repair time. The identical values could emphasize the impact of topology of components in the system.

There are 186 transmission lines in IEEE 118-bus system, with 7220MW maximum generation and 6000MW maximum load. The load diagram is also an 8760h load cycle and it is scaled from RTS load level.

2.3 Case Studies

Two case studies were conducted on IEEE-RTS and IEEE 118-bus system respectively. After the results analysis of these case studies, line categorization as one of the output of this method is performed for both test systems.

2.3.1 Studies on IEEE RTS

In the first case study on RTS, line removal test is performed on all 38 transmission lines of RTS. Case 39 is the benchmark case which is the original system without any line removal. Its benchmark value is represented by a straight line and the inherent random characteristic is represented by bounds of reliability indices shown as two straight lines besides benchmark value.

To compare the reliability performance of each transmission line, the mean value comparison and worst-case comparison are demonstrated for all 6 reliability indices.

Figure 11 and Figure 12 show the comparison of yearly-based HLOLE. Most transmission lines have the same performance compared with benchmark case (case 39). However, there are also transmission lines that show non-trivial differences. Considering the definition of HLOLE, these negative/positive differences are categorized as increase/decrease of reliability.

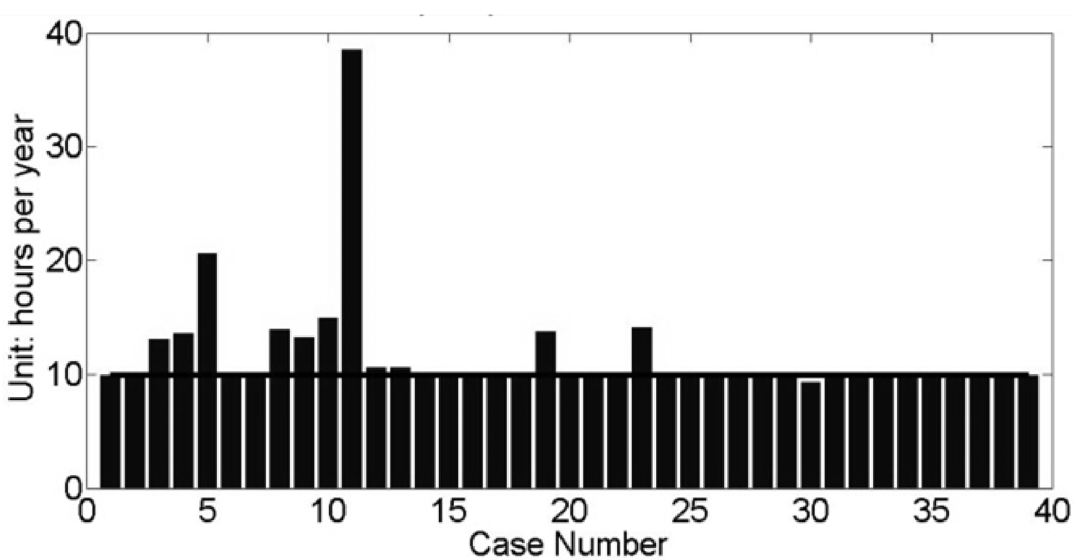

Figure 11. Yearly-based HLOLE mean value comparison of IEEE RTS.

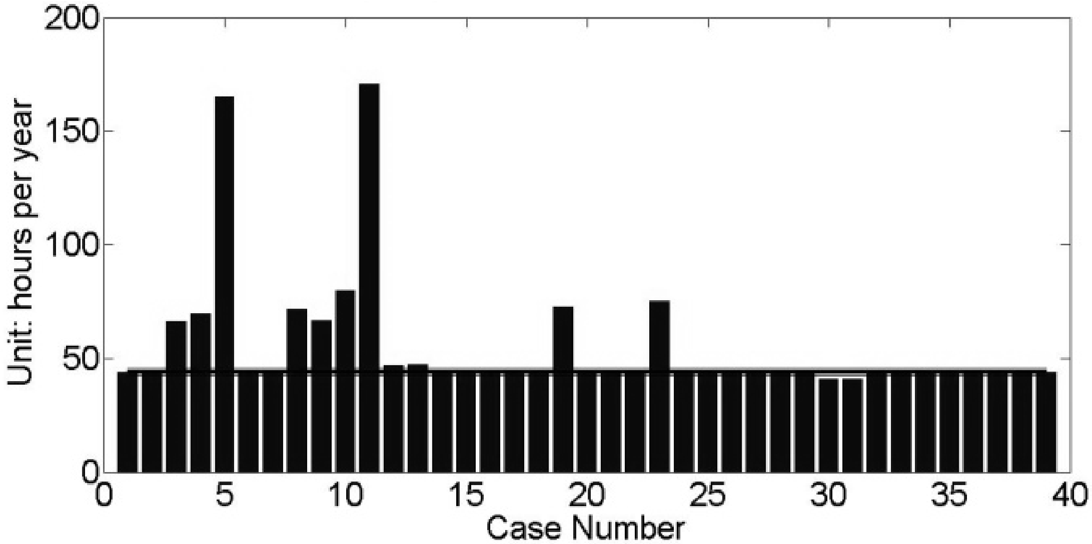

Figure 12. Yearly-based HLOLE worst case comparison of IEEE RTS.

In the comparison of yearly-based HLOLE, transmission lines with non-trivial differences are listed in Table 2. Row 1 and row 2 distinguish between increase/decrease of reliability. Column 2 and column 3 distinguish between mean value/worst case comparison.

Table 2 Transmission lines with non-trivial difference in yearly-based HLOLE in IEEE RTS

	Mean value	**Worst case**
Increase of reliability	30	30,31
Decrease of reliability	3,4,5,8,9,10,11,12,13,19,23	3,4,5,8,9,10,11,12,13,19,23

Figure 11 and Figure 12 show similar patterns because they are two aspects of comparisons of the same index, thus there are several transmission lines display the same trend of effects on reliability in both mean value comparison and worst-case comparison. Consequently, these transmission lines are listed in both column 2 and 3 in Table 2, for example, line 30 shows increase of reliability in both mean value and worst-case comparison and it is listed in both column 2 and 3, row 1.

Transmission lines show non-trivial differences in only one of the comparisons are listed and underscored in the corresponding column of the table. For example, line 31 shows increase of reliability only in worst case comparisons, so it is listed and underscored in column 3, row 1.

If there are no transmission lines in certain entry of the table, they will be marked as "N/A" showing no transmission lines fitting the criterion in comparisons.

The rest 5 reliability indices are compared in similar ways. Figure 13-Figure 22 show the mean value comparison and worst-case comparison of yearly-based EENS, event-based HLOLE, event-based EENS, event-based EENSP and event-based LDLE respectively. Table 3 list all transmission lines that display non-trivial differences in corresponding reliability index compared with benchmark case.

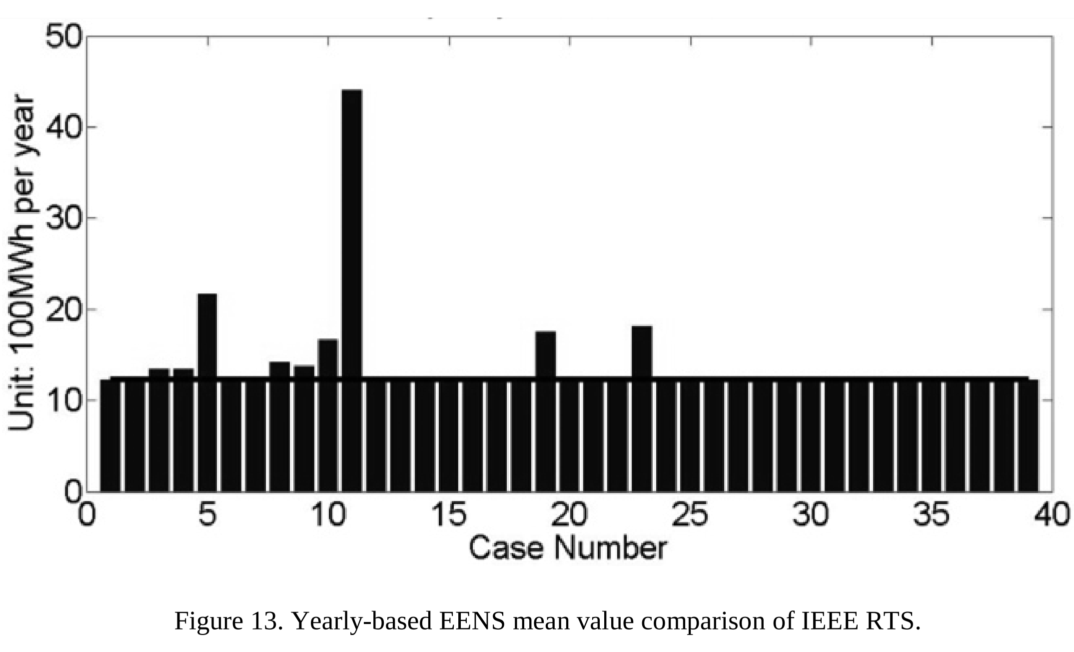

Figure 13. Yearly-based EENS mean value comparison of IEEE RTS.

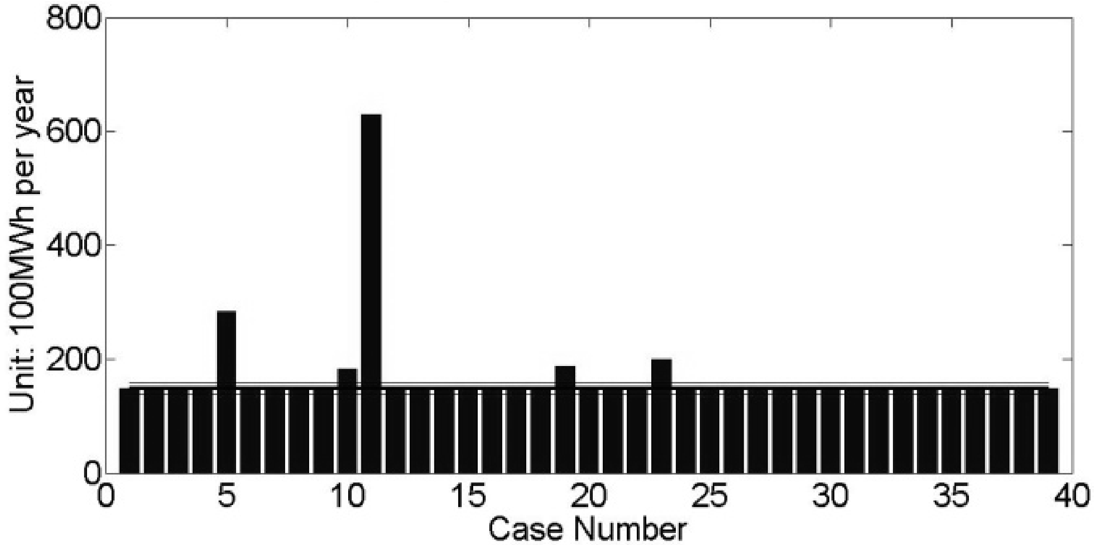

Figure 14. Yearly-based EENS worst case comparison of IEEE RTS.

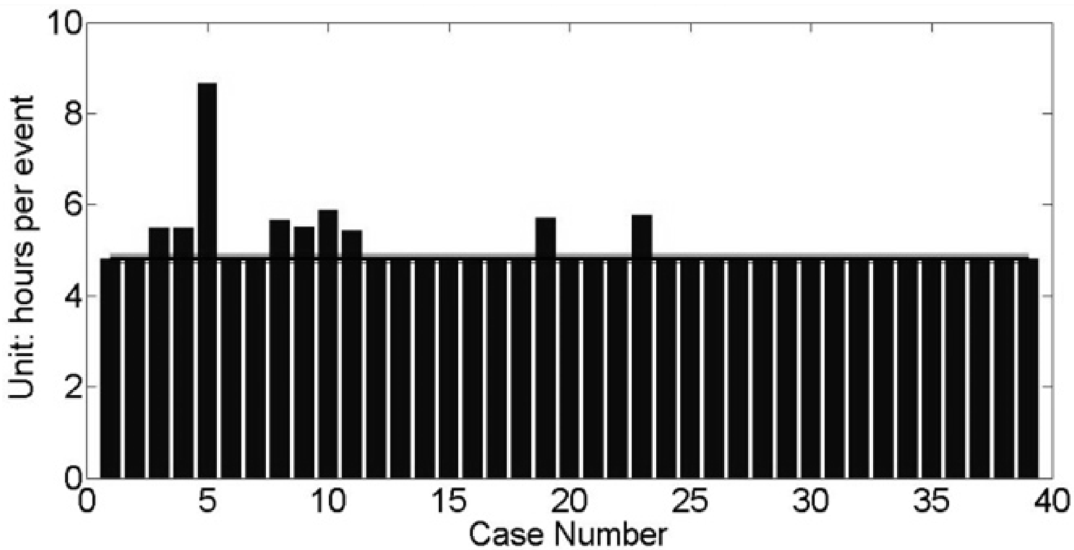

Figure 15. Event-based HLOLE mean value comparison of IEEE RTS.

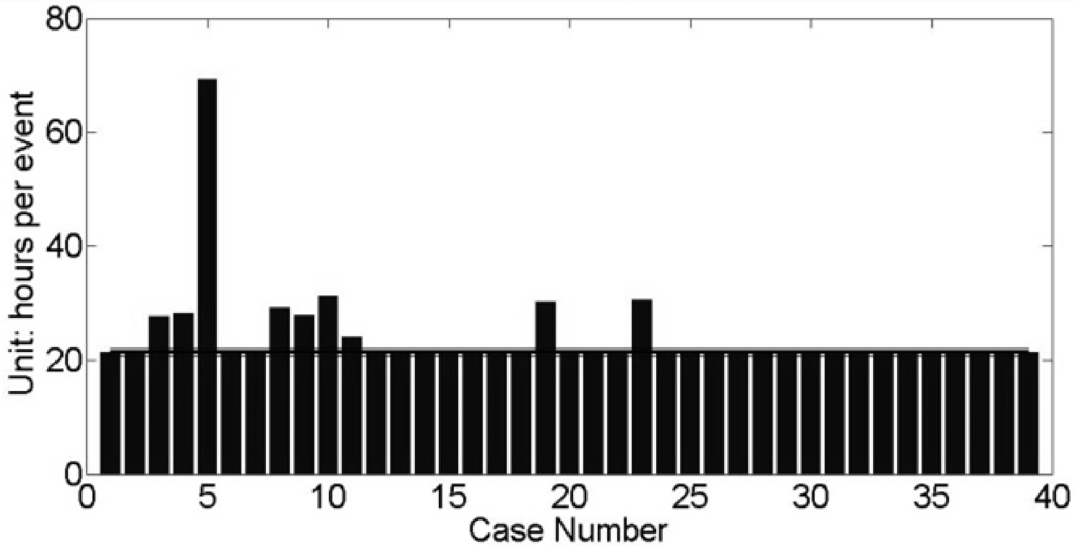

Figure 16. Event-based HLOLE worst case comparison of IEEE RTS.

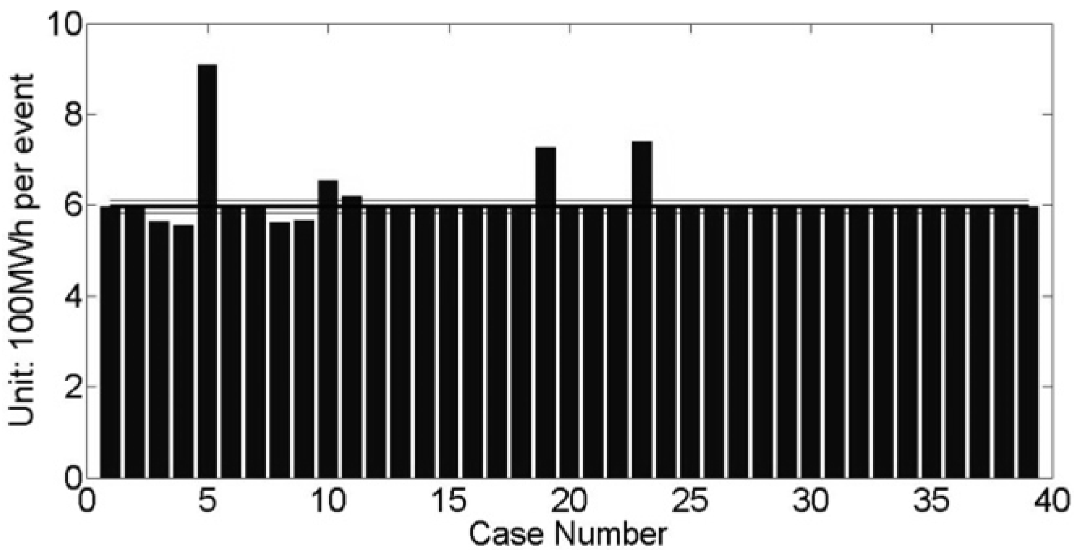

Figure 17. Event-based EENS mean value comparison of IEEE RTS.

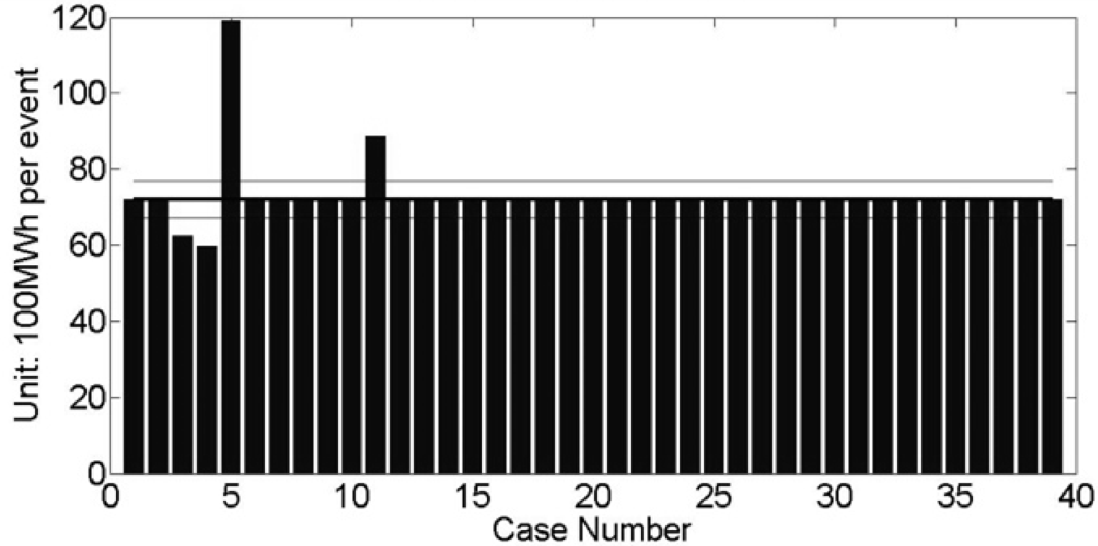

Figure 18. Event-based EENS worst case comparison of IEEE RTS.

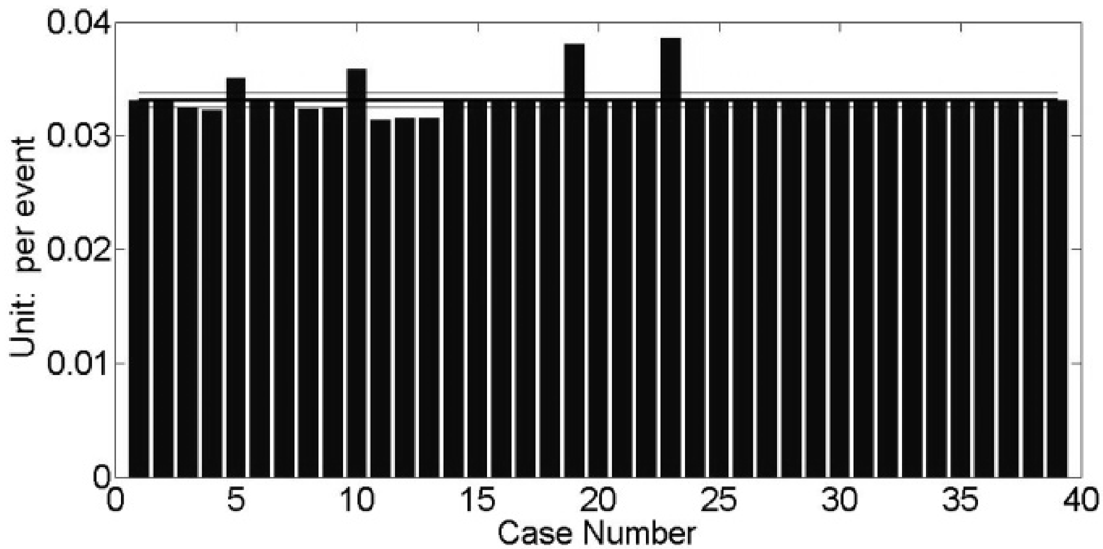

Figure 19. Event-based EENSP mean value comparison of IEEE RTS.

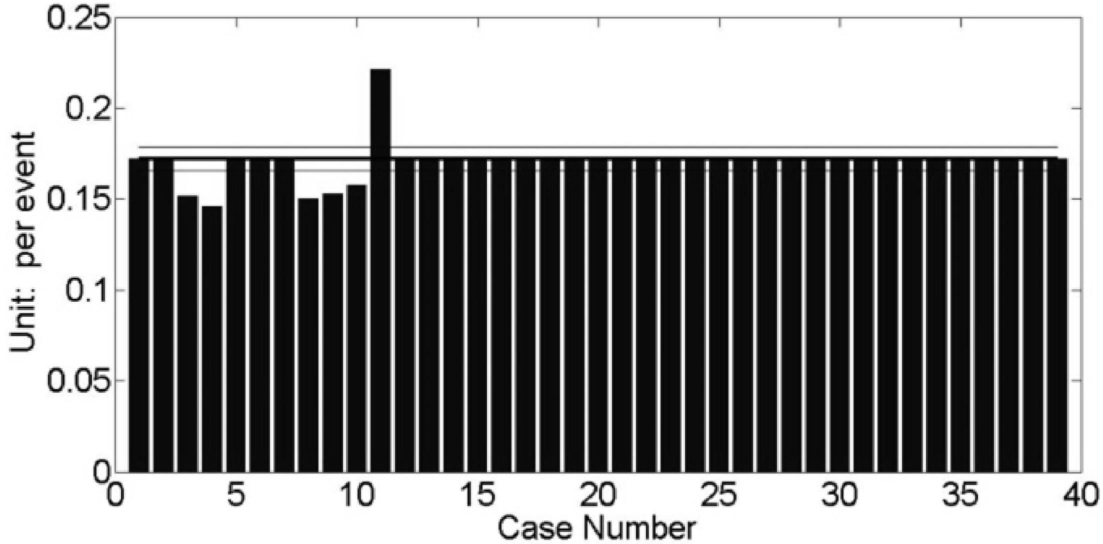

Figure 20. Event-based EENSP worst case comparison of IEEE RTS.

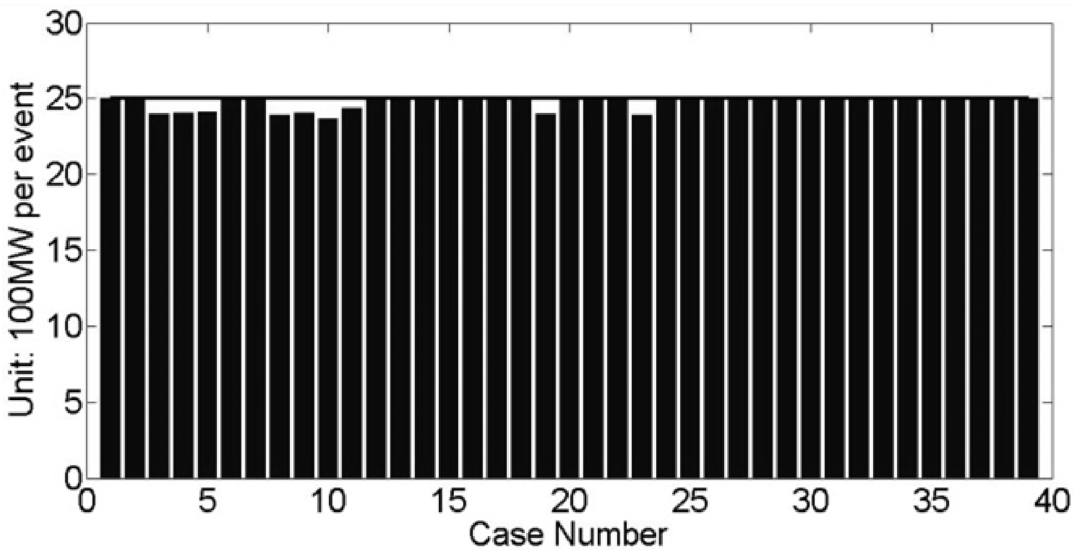

Figure 21. Event-based LDLE mean value comparison of IEEE RTS.

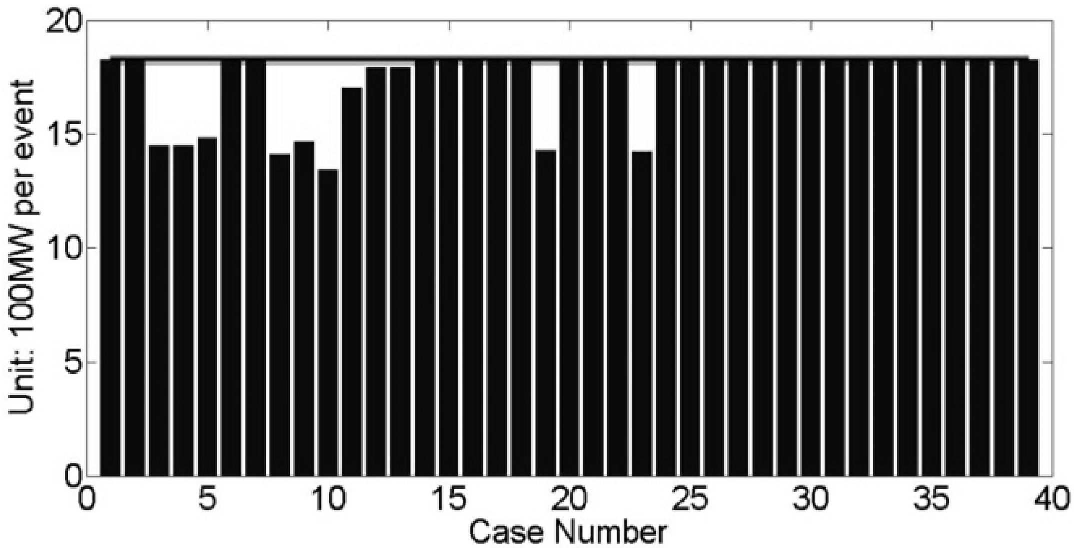

Figure 22. Event-based LDLE worst case comparison of IEEE RTS.

Table 3 Transmission lines with non-trivial difference in IEEE RTS

Yearly-based EENS		
	Mean value	**Worst case**
Increase of reliability	N/A	N/A
Decrease of reliability	3,4,5,8,9,10,11,19,23	5,10,11,19,23
Event-based HLOLE		
	Mean value	**Worst case**
Increase of reliability	N/A	N/A
Decrease of reliability	3,4,5,8,9,10,11,19,23	3,4,5,8,9,10,11,19,23
Event-based EENS		
	Mean value	**Worst case**
Increase of reliability	3,4,8,9	3,4
Decrease of reliability	5,10,11,19,23	5,11
Event-based EENSP		
	Mean value	**Worst case**
Increase of reliability	3,4,8,9,11,12,13	3,4,8,9,10
Decrease of reliability	5,10,19,23	11
Event-based LDLE		
	Mean value	**Worst case**
Increase of reliability	N/A	N/A
Decrease of reliability	3,4,5,8,9,10,11,12,13,19,23	3,4,5,8,9,10,11,12,13,19,23

2.3.2 Studies on IEEE 118-bus System

In the second case study on IEEE 118-bus system, line removal test was performed on all 186 transmission lines of 118-bus system. Case 187 is the benchmark case which is the original system without any line removal.

It should be noted that, since removal of line 184 alone directly causes system failure, its removal test and reliability indices obtained are not meaningful in comparisons and thus case 184 is masked as an empty entry in all comparisons.

The comparisons are demonstrated similarly as case study of RTS. Figure 23-Figure 34 show the mean value comparison and worst-case comparison of 6 reliability indices. Table 4 list all transmission lines that display non-trivial differences in 6 reliability indices compared with the benchmark case. “Inc.” is short for “Increase of reliability” in row 1 of corresponding sections, and “Dec.” is short for “Decrease of reliability”.

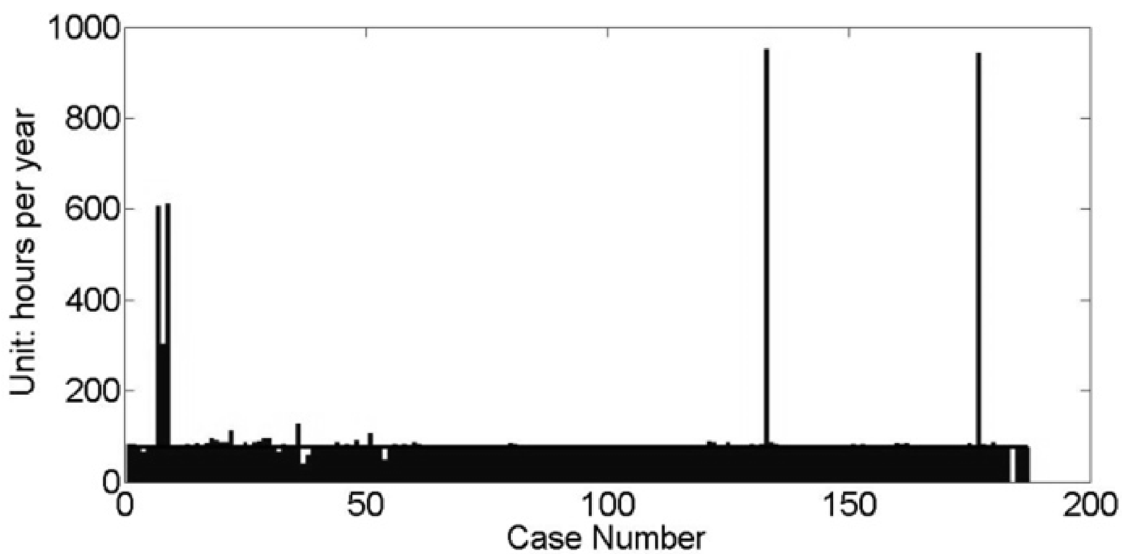

Figure 23. Yearly-based HLOLE mean value comparison of IEEE 118-bus system.

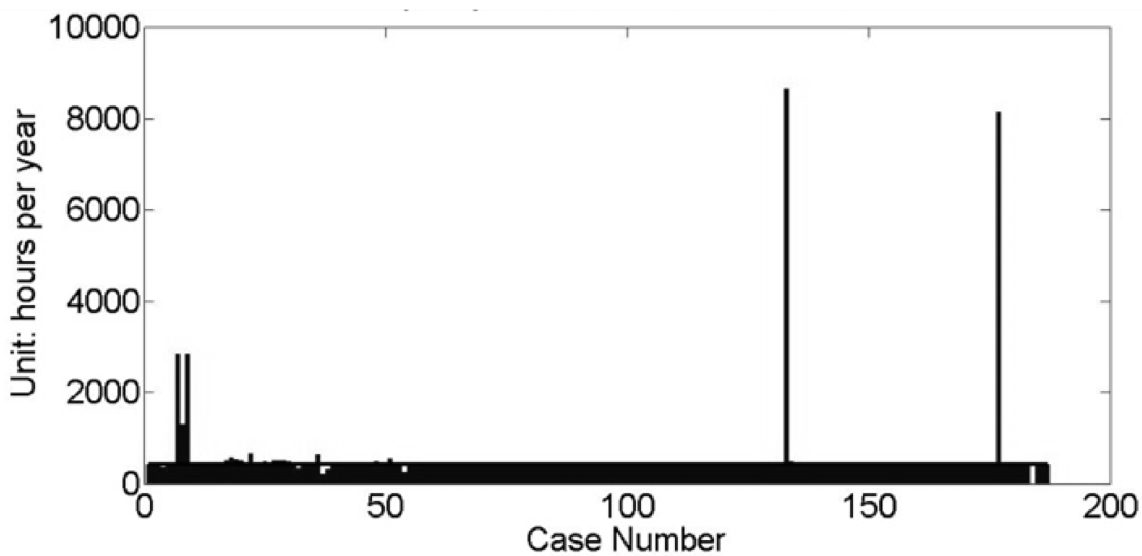

Figure 24. Yearly-based HLOLE worst case comparison of IEEE 118-bus system.

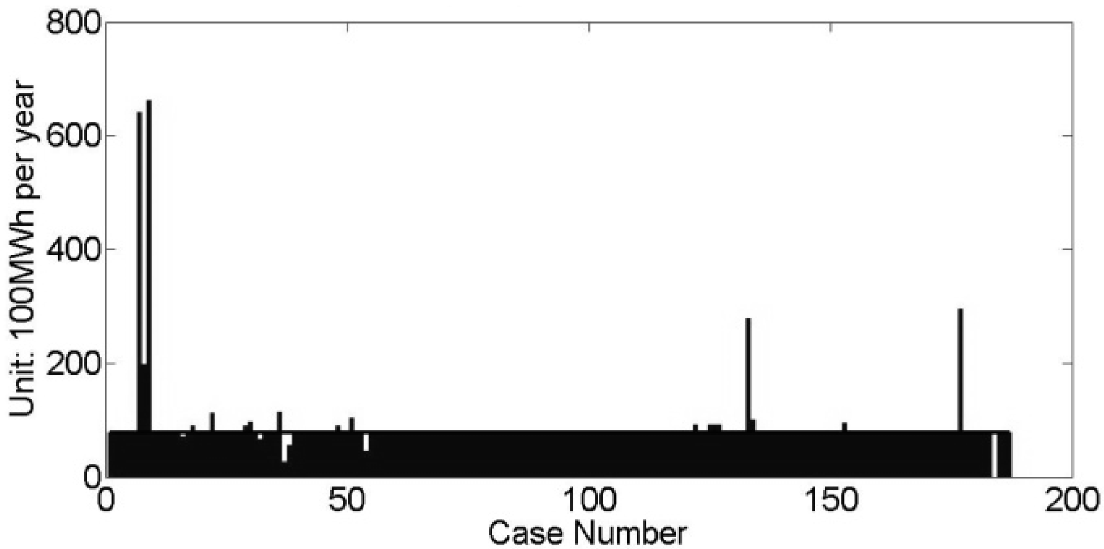

Figure 25. Yearly-based EENS mean value comparison of IEEE 118-bus system.

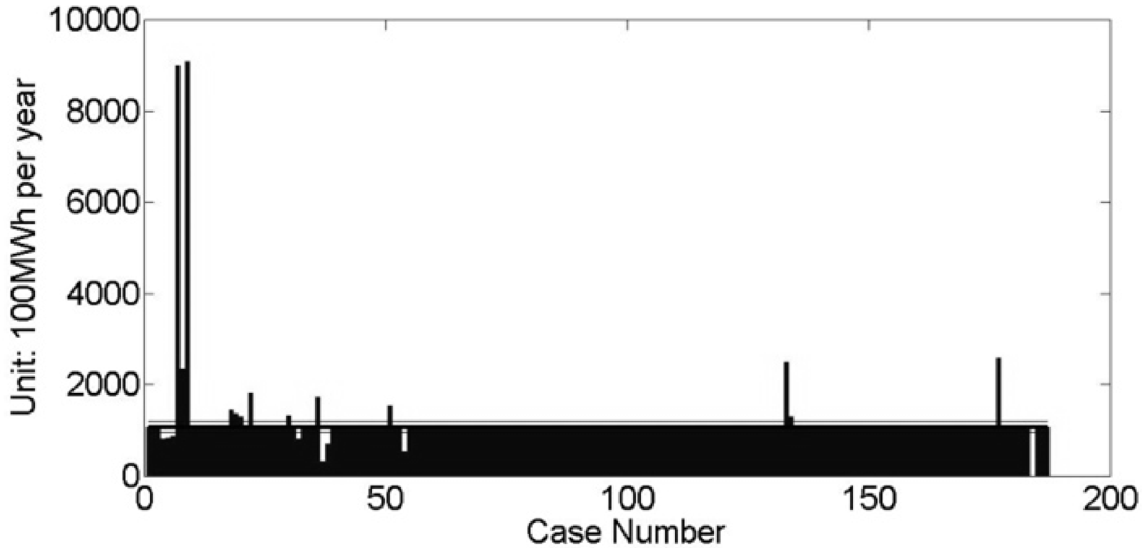

Figure 26. Yearly-based EENS worst case comparison of IEEE 118-bus system.

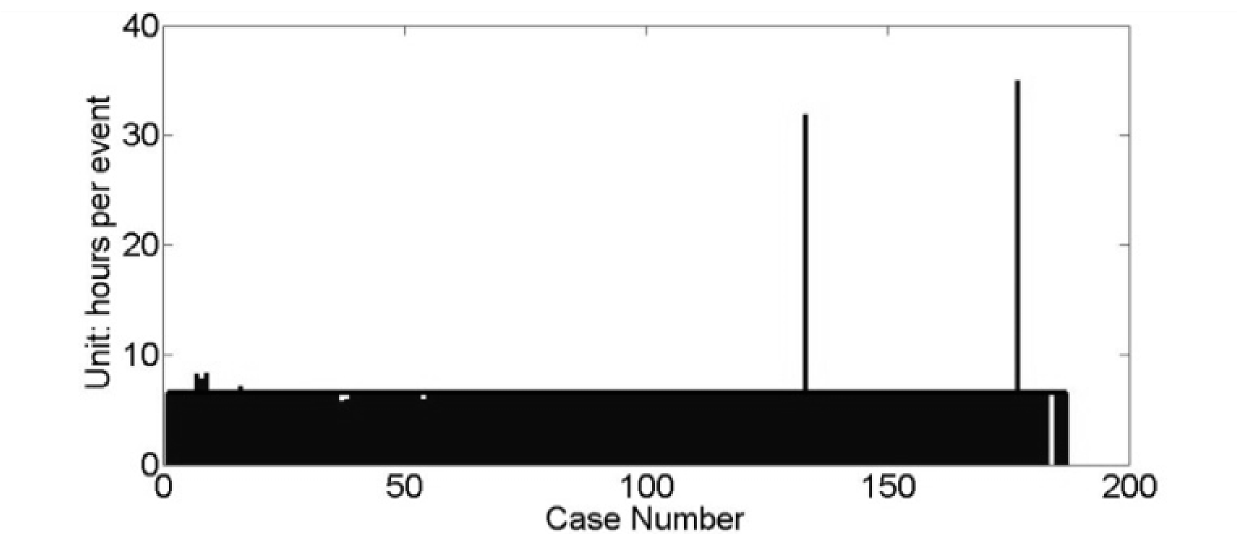

Figure 27. Event-based HLOLE mean value comparison of IEEE 118-bus system.

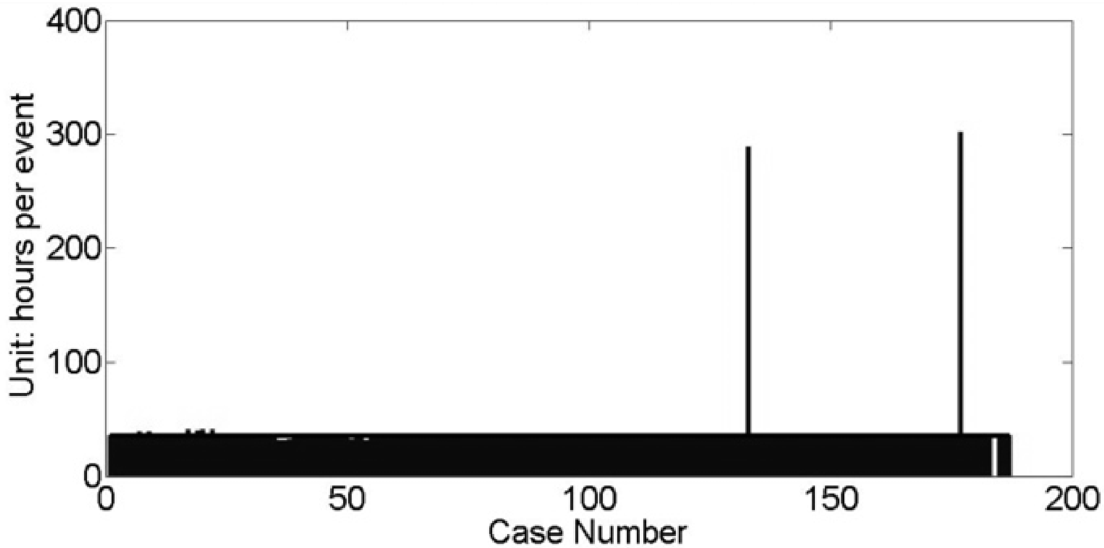

Figure 28. Event-based HLOLE worst case comparison of IEEE 118-bus system.

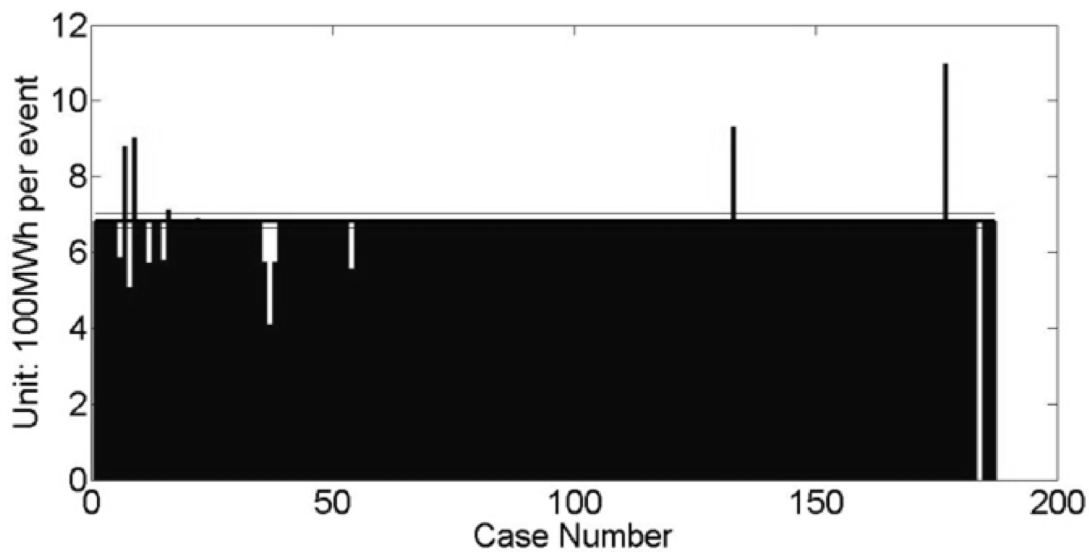

Figure 29. Event-based EENS mean value comparison of IEEE 118-bus system.

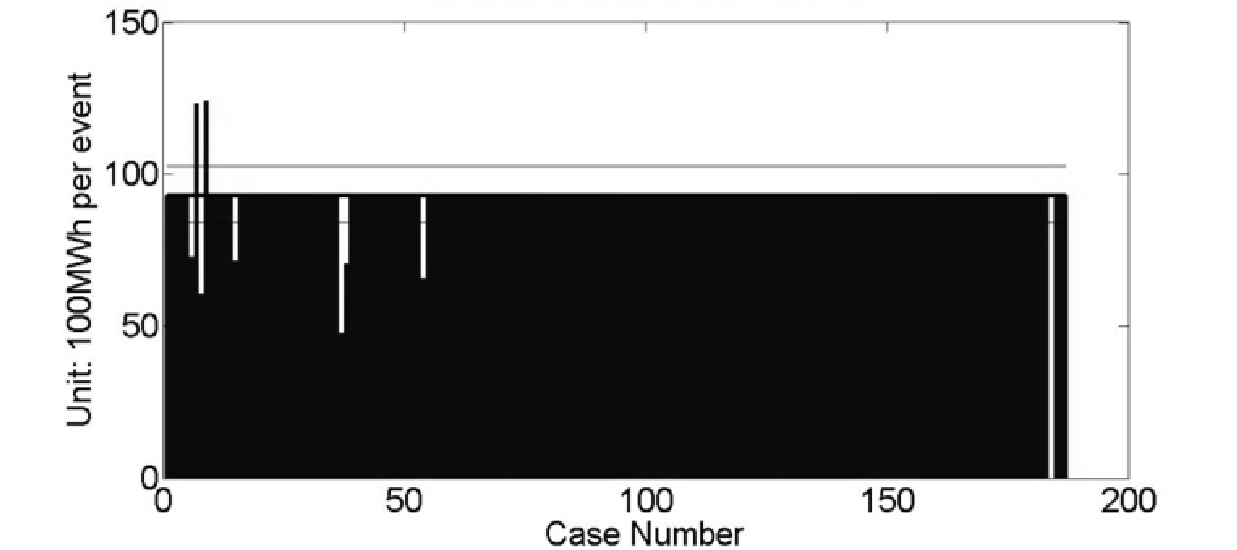

Figure 30. Event-based EENS worst case comparison of IEEE 118-bus system.

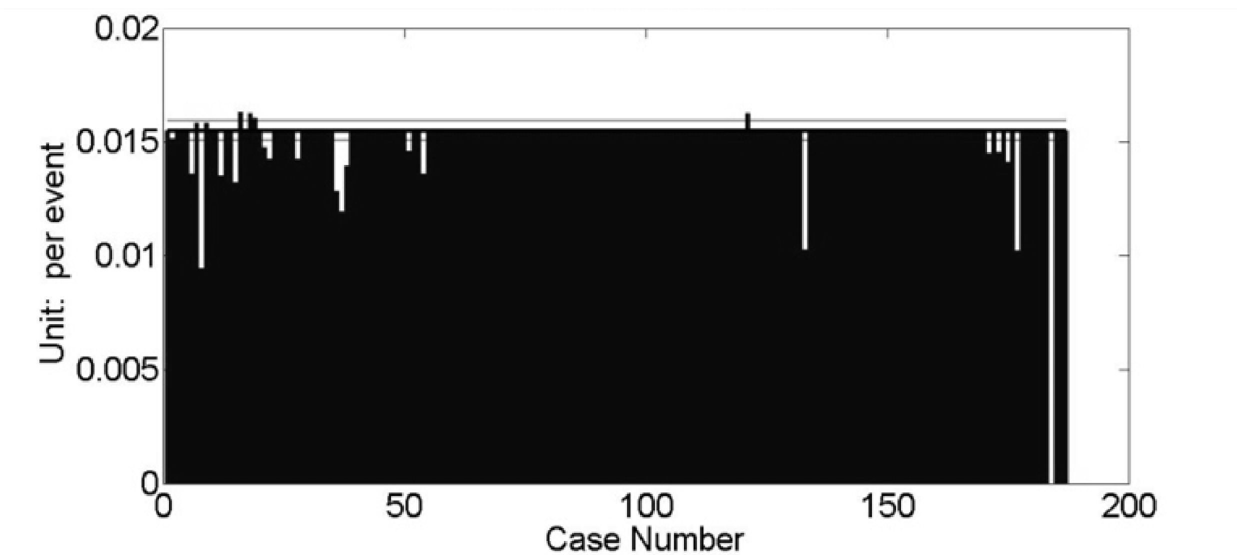

Figure 31. Event-based EENSP mean value comparison of IEEE 118-bus system.

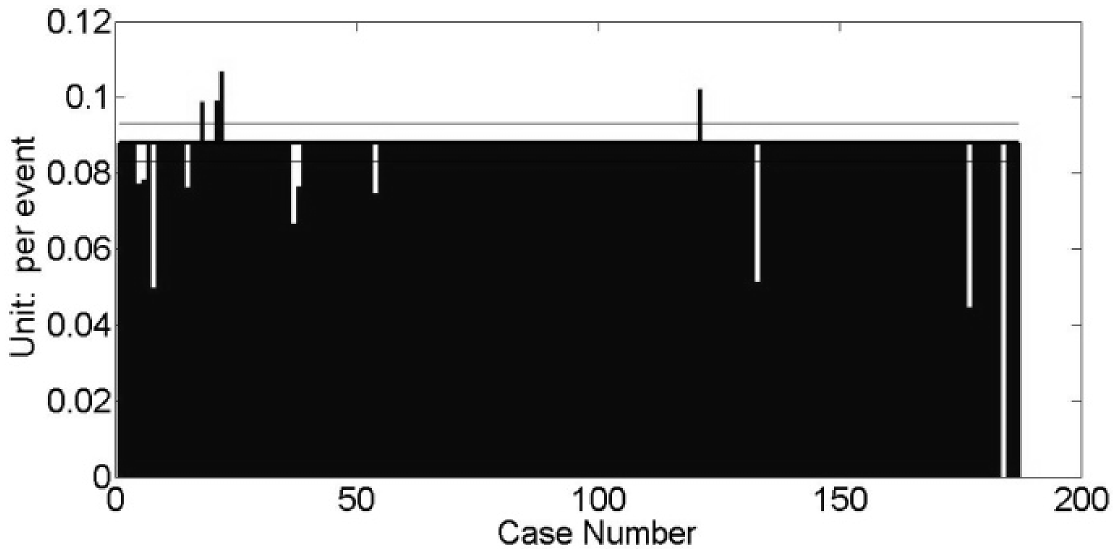

Figure 32. Event-based EENSP worst case comparison of IEEE 118-bus system.

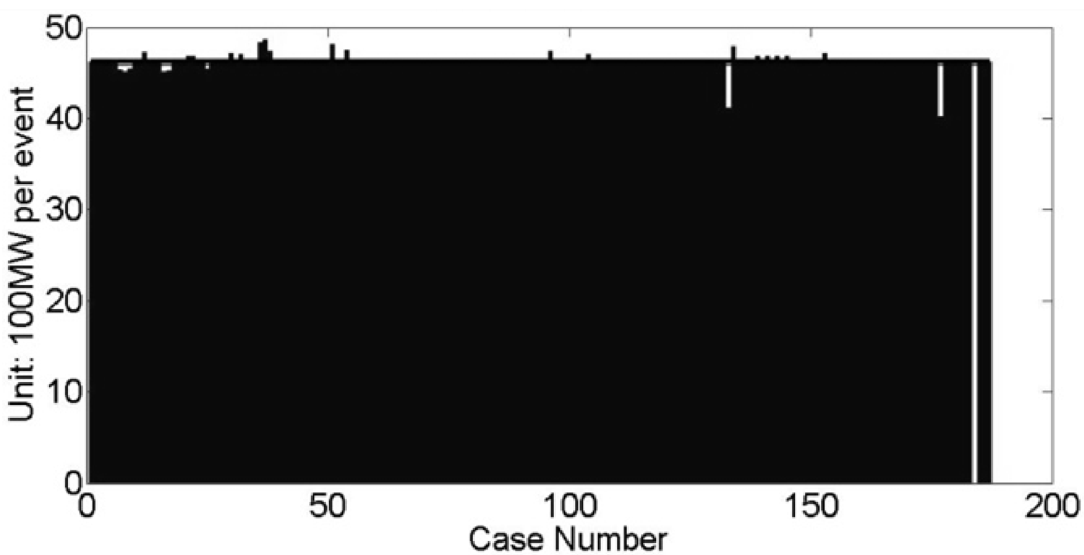

Figure 33. Event-based LDLE mean value comparison of IEEE 118-bus system.

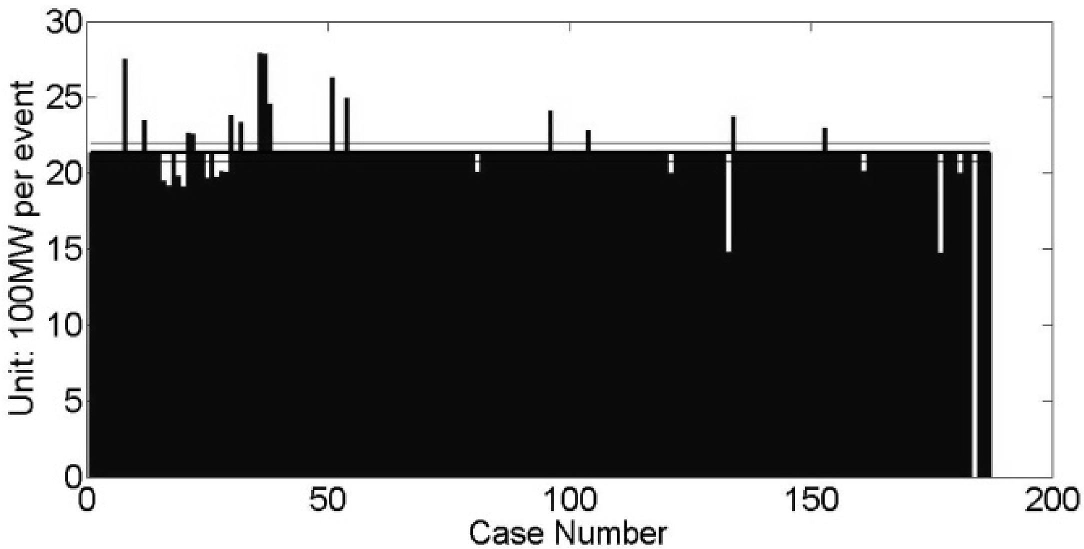

Figure 34. Event-based LDLE worst case comparison of IEEE 118-bus system.

2.3.3 Line Categorization

From the results obtained, line categorization is designed to separate transmission lines into several groups to provide actionable information.

It is obvious that event-based indices and worst-case comparison show different patterns compared with traditional yearly-based indices. Event-based indices separate the impact of each failure event from failure frequency, worst case comparison reveal different distribution of reliability indices. Therefore, all reliability indices are considered as performance inputs in the evaluation of line categorization for line switching operations.

In this research, all transmission lines are categorized into the following groups based on results of line removal tests.

1) Recommended lines: their removal improves system reliability in all six reliability indices, including risk analysis and impact analysis as well as worst case comparison. Thus, they should be considered as the first choice in line switching operations.

Table 4 Transmission lines with non-trivial difference in IEEE 118-bus system

Yearly-based HLOLE		
	Mean value	**Worst case**
Inc.	4,32,37,38,54	4,32,37,38,54
Dec.	1,2,7,8,9,13,15,17,18,19,20,21,22, 25,27,28,29,30,33,36,44,46,48,51, 56,58,60,61,80,81,121,122,125,130,132,133, 134,135,151,153,160,161,162,175,177,178,180,184 (48 lines)	7,8,9,17,18,19,20,21,22,25,27,28,29,30,36,44, 48,51,60,80,81,121,122,133,134,160,171,175, 177,180,184 (31 lines)
Yearly-based EENS		
	Mean value	**Worst case**
Inc.	16,32,37,38,54,148	4,5,6,32,37,38,54
Dec.	7,8,9,18,22,29,30,36,48,51,122, 125,126,127,133,134,153,177,184 (19 lines)	7,8,9,18,19,20,22,30, 36,51,133,134,177,184 (14 lines)
Event-based HLOLE		
	Mean value	**Worst case**
Inc.	10,37,38,54	36,37,38,51,54
Dec.	7,8,9,16,133,177,184	7,9,17,19,20,22,133,177,184
Event-based EENS		
	Mean value	**Worst case**
Inc.	6,8,12,15,36,37,38,54,148	6,8,15,37,38,54,149
Dec.	7,9,16,22,23,133,177,184	7,9,184
Event-based EENSP		
	Mean value	**Worst case**
Inc.	2,6,8,12,15,21,22,28,36,37,38, 49,51,54,133,166,171,173,175,177 (20 lines)	5,6,8,15,37,38,54,133,165,177 (10 lines)
Dec.	7,9,16,18,19,43,71,121,184	18,21,22,121,136,138,163,164,184
Event-based LDLE		
	Mean value	**Worst case**
Inc.	12,21,22,30,32,36,37,38,51,54, 96,104,134,139,141,143,145,153 (18 lines)	8,12,21,22,30,32,36,37,38, 51,54,96,104,134,153 (15 lines)
Dec.	4,7,8,9,16,17,19,20,25,27, 28,29,81,121,133,177,181,184 (18 lines)	16,17,19,20,25,27,28,29,81, 121,133,161,177,181,184 (15 lines)

2) Safe lines: their removal causes no or trivial impact to system reliability, thus they are "safe" to be considered in line switching operations.

3) Critical lines: their removal causes non-trivial reduction to system reliability in at least one of the reliability indices. Critical lines should be dealt with caution in line switching operations. In critical lines, there are further categories as following:

    a. Critical-islanding lines: their removal causes one of the buses to disconnect from the system. These lines are spotted from the topology of the system before line removal tests. Islanding of buses should be avoided in all scenarios and should not be considered in line switching operations.

    b. Critical-risky lines: Removal of critical-risky lines causes reduction of system reliability in all reliability indices. Thus, they should be avoided in line switching operations.

In the first case study on RTS, 38 transmission lines of RTS are categorized in Table 5 based on the described process. In the second case study on IEEE 118-bus system, 187 transmission lines are categorized in Table 6.

Results of line categorization are the output of the proposed method based on reliability implications. There is evidence [71, 76] on utilizing variance reduction approaches to improve convergence of MCS. The simulation and calculation presented in this research are used to describe an approach for offline use to create Table 5 and Table 6 that could serve as "look-up-table" for operators when performing line switching operations. However, in actual implementation the speed could be greatly improved by variance reduction techniques such as importance sampling [77].

Table 5 Line categorization of IEEE RTS

<table>
<tr><td>Recommended lines</td><td colspan="3">N/A</td></tr>
<tr><td>Safe Lines</td><td colspan="3">The other 29 lines (76% of all lines)</td></tr>
<tr><td rowspan="2">Critical Lines</td><td rowspan="2">3,4,5,8,9,10,11,19,23
(9 lines)</td><td>Critical-islanding</td><td>11</td></tr>
<tr><td>Critical-risky</td><td>N/A</td></tr>
</table>

Table 6 Line categorization of IEEE 118-bus system

<table>
<tr><td>Recommended lines</td><td colspan="3">37,38,54</td></tr>
<tr><td>Safe Lines</td><td colspan="3">The other 122 lines (66% of all lines)</td></tr>
<tr><td rowspan="2">Critical Lines</td><td rowspan="2">1,2,4,7,8,9,13,15,16,17,
18,19,20,21,22,23,25,27,28,29,
30,33,36,43,44,46,48,51,56,58,
60,61,71,80,81,121,122,125,126,127,
130,132,133,134,135,136,138,151,153,160,
161,162,163,164,171,175,177,178,180,181,184
(61 lines)</td><td>Critical-islanding</td><td>9,113,134,176,
177,183,184</td></tr>
<tr><td>Critical-risky</td><td>184</td></tr>
</table>

Recent researches mostly focus on special scenarios of line switching that strongly prune the cases studied, to tackle this problem, the comprehensive evaluation presented in this research considers the average impact of all events subsequent to a line switching. This includes multiple contingencies and their effect on the load loss events. So, this information is to be used by the operator before his decision on line switching. The study results are provided as a “look-up-table” of switching performance of all transmission lines in the system considering the reliability implications. The look up table provided in this study is for the operator to make a judicious decision about line switching considering what the impact might be because of line switching. Following observations are provided from Table 5 and Table 6 to effectively utilize line categorization.

1) Although there are no recommended lines found in RTS, 3 recommended lines are found in IEEE 118-bus system. It should be noted that this reliability implication is not based on any specific scenario but the average effect of subsequent events

2) In both case studies, around 70% of all transmission lines are safe lines that could be safely considered in line switching operations.
3) In both case studies, few lines are categorized as critical-risky lines, meaning most transmission lines are acceptable in at least one of six reliability indices.
4) Risk and impact analysis are based on average effect of subsequent events, this allows critical lines contributing to line switching operations under rare cases.
5) Transmission lines have different characteristics in six reliability indices. To highlight the general difference, line categorization is used to present the average impact of all indices. However, if we zoom into each reliability index, detailed information of each transmission line removal is provided for further analysis and comparison. The study results presented in this research could be used as the foundation of investigation on the optimal line switching schemes.
6) It is observed in both case studies that event-based indices display different pattern from yearly-based indices, this is because impact analysis separates impact of each failure event from failure frequency, thus provides a better understanding of state space subsequent to line removals.
7) It is observed in both case studies that worst case comparison demonstrates different behavior compared with mean value analysis, this reveals previous overlooked distribution of reliability indices.
8) In case study 2, islanding lines 113,183 display no reliability decrease in all reliability indices

2.4 Summary

A reliability evaluation method for studying the reliability implications of line switching operations in power systems is proposed and demonstrated. Two case studies are conducted on IEEE RTS and IEEE 118-bus system to illustrate this method. This method is designed to explore previously overlooked areas in reliability evaluation of line switching operations.

Line removal test is proposed to sweep all transmission lines in the system for simulation data, six reliability indices are used to conduct risk analysis and impact analysis. Instead of the traditionally used mean value analysis, variance analysis is introduced into reliability evaluation. Weibull distribution is used to reconstruct distributions of reliability indices which reveal overlooked patterns in worst case comparisons. Eventually, line categorization for line switching operations is introduced to classify all transmission lines based on their reliability performance. The categories provide reliability implications of line switching operations and can be used for guidance in actual operations.

It is observed in both case studies that a few recommended lines and critical-risky lines are found. Most (around 70%) transmission lines are safe lines that could be safely utilized in line switching operations, the rest 30% critical lines could contribute to line switching operations under rare cases yet needs to be dealt with caution.

3. HYBRID RELIABILITY EVALUATION METHOD WITH CONTINGENCY RANKING*

3.1 Introduction

Line switching operation in power systems is an important part of network topology and flow control, it utilizes novel transmission technology to improve the transmission usage. The idea was first proposed in [2] to consider transmission line as controllable assets. Using line switching in power system operations can not only reduce overflows in transmission lines but also improve system security. However, additional complexity and uncertainty are also introduced into power system analysis with line switching operations. There is no doubt that integration of topology and flow controls can affect the reliability performance of power systems. To avoid degradation of reliability and effectively utilize line switching in power system operations, comprehensive reliability evaluation is essential. To achieve this objective, a hybrid reliability evaluation method for line switching operations is proposed in this research.

The research interest in line switching operations has been increasing over the recent years, References [29-33] discussed the economic benefits of incorporating line switching operations, N-1 reliability is studied in [34] considering the co-optimization of generation unit commitment and transmission switching, [35-38] illustrated the possible improvement of stability with topology control. However, there are limited research efforts on the reliability

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evaluation of line switching operations. It is pointed out in [42] that most studies strongly prune the cases evaluated, instead of analysis on the overall state space of line switching, only selected scenarios were evaluated to make the case. A reliability evaluation method based on Monte Carlo Simulation (MCS) is proposed in [43, 44]. The method provides insights into the overall state space of line switching operations. However, the method is based on sweeping through transmission lines without analytical guidance so the computation speed is rather slow.

Traditional approach to contingency ranking (CR) is based on using a performance index (PI) to provide a measure of system performance [3]. It has been widely used in power system security analysis [57-59], some innovative usage of CR method has been proposed in recent years. A bi-level optimization model was introduced in [61] for the risk assessment of transmission systems, Neural network and data environment analysis was combined with contingency ranking in [62]. A margin-based framework for contingency selection was proposed in [63] for unbalanced systems. However, there have been limited research efforts on using CR method in reliability evaluation of line switching operations.

In this research, a contingency ranking (CR) method is introduced into the reliability evaluation of line switching operations as a pre-selection method. The hybrid of CR and traditional MCS method is designed not only to speed up the simulation, but also provide analytical analysis of state space of line switching operations. To further improve the proposed hybrid method, analysis of results is updated to distinguish between event-based and yearly-based indices. Results analysis is designed to be clearer and emphasizes the observed patterns.

Following are the contributions of this research:

1) A novel CR method with improvements to accommodate reliability evaluation is introduced as a pre-selection step of the proposed hybrid method. It not only reduces

the computation time of this method, but also provides analytical understanding of state space contrary to the inherent randomness of traditional reliability evaluation based on MCS alone.

2) A new performance index (PI), based on Expected Power Not Supplied Percentage (EPNSP) is proposed in this research to be used as an indicator in the CR pre-selection method. Its performance is superior to the traditional PI and its direct connection to load loss ensures the accurate pick-up rates of pre-selection method.
3) Two outputs are obtained from CR method: the ranking list and the newly introduced dictionary. Both are utilized in the MCS afterwards. The ranking list generated is used to guide the sequence of line removal tests and significantly reduce the number of tests required while still picking up most of the target transmission lines with non-trivial difference from benchmark case. The dictionary is used to speed up simulation and provide map of PIs for analytical analysis of state space.
4) The difference between event-based and yearly-based indices is discussed in this research to provide guidance on analysis of results. Instead of showing all the recorded results, only important results are shown to emphasize patterns observed.
5) Contrary to intuition, removal of some transmission lines is found to be beneficial to the reliability of power system. The reasons are further analyzed in section 3.3.

This research is organized as following: section 3.2 illustrates the foundation and new features of the proposed hybrid reliability evaluation method. Two case studies were conducted using the proposed method and results are presented and analyzed in Section 3.3. The conclusions are summarized in section 3.4.

3.2 Hybrid Reliability Evaluation Method

3.2.1 Foundation of the Proposed Method

The foundation of the proposed hybrid method before the introduction of CR method is illustrated in this section.

Four reliability indices are used in this research to record the reliability performance in transmission line removal tests [43]. The first two are traditional reliability indices, yearly-based HLOLE and EENS, the mean values of these indices are traditionally used to evaluate reliability of power systems. Different from yearly-based indices, event-based HLOLE and EENS are introduced to capture information of each failure event subsequent to line removal and are defined in (1)-(2).

In traditional MCS analysis, only one mean value is saved for each recorded reliability index and the distribution information is not captured and is lost. Therefore event-based indexes and worst-case comparison are introduced in the proposed method. Event-based index treats each failure event separately and equally which makes impact analysis possible and worst-case comparison is based on the reconstruction of index distribution and maximum value is taken at 99.7% of Cumulative Distribution Function (CDF) as the worst-case scenario.

Many distributions like Gaussian Mixture Method (GMM) or a combination of exponentials or gamma or Weibull are quite versatile in approximating the distributions. To reconstruct the distribution of reliability index, Weibull distribution is selected to process recorded data obtained from MCS because it can represent a wide range of distributions by appropriate choice of shape and scale parameters. To provide more details on the Weibull distribution reconstruction, actual results of sequential MCS are used to validate its accuracy and effectiveness. It is observed in Figure 3 that the results of sequential MCS failure events follow "truncated" distribution due to its non-negative characteristic and Weibull distribution fitting the data closely captures the distribution information of recorded reliability indices. The Root Mean Square Error (RMSE) of fitting these distribution is presented in Table 1 to further validate its accuracy and effectiveness in distribution reconstruction. It should be noted that extra processing is needed for yearly-based indices which is illustrated in section 3.2.7.

In order to ameliorate inherent randomness of MCS, the bounds of recorded indices are obtained according to [44]. They are then used in comparison of indices to emphasize non-trivial difference compared with the benchmark case. The definition of trivial/non-trivial difference is given as following: If bounds of indices of certain test and benchmark case have overlapping regions, then the test's indices are assumed to have trivial difference compared with benchmark case. Otherwise, the bounds have no overlapping regions, and the test is denoted having non-trivial difference compared with benchmark case.

Based on the results of the proposed method, transmission lines are categorized into 3 categories.

1) Recommended lines: their removal improves system reliability in at least one of the four reliability indexes
2) Safe lines: their removal causes none or trivial impact to system reliability, thus they are "safe" to be considered in line switching operations.
3) Critical lines: their removal causes non-trivial reduction to system reliability in at least one of the reliability indices.

It should be noted that the although the MCS based reliability evaluation method uses some concepts from [43], the hybrid reliability evaluation method proposed in this paper is a new approach using a hybrid of CR and MCS method. For example, based on the line categorization proposed in [43], most transmission lines in power system are safe lines, CR pre-selection method is introduced to provide analytical guidance and provide a ranking list of failure severity so that MCS is not based on the random line selection but targeted search for potential critical lines.

3.2.2 Objectives of Using Contingency Ranking Method

The objectives of introducing CR method into the reliability evaluation are described as following.

Firstly, compared with traditional reliability simulation, CR method is not as accurate and is subject to mis-ranking. However, it is computationally fast and able to provide some insights into system contingencies. So, CR method could serve as a fast and reasonably accurate "pre-selection" method before the detailed reliability simulation.

Secondly, the contingencies enumerated in CR having already been analyzed, the results of CR method can serve as a dictionary for the reliability simulation, which could speed up the simulation and provide visualization tools like a map of state space in the dictionary.

Thirdly, CR method is based on the analysis of enumerated states. Although its probability coverage is not close to that of MCS, every enumerated state in CR method is based on analytical solutions, which are not affected by the randomness inherent in MCS. For this reason, the results of CR can provide a certain amount of understanding of state space of line switching operations from an analytic viewpoint.

3.2.3 Improvements in Contingency Ranking Method

Traditional contingency ranking approach is based on using a performance index (PI) to provide a measure of system performance [3]. It is designed to calculate the difference of the PI after a certain contingency. Due to the calculation complexity, normally, the first order change is approximated as the difference of PI of the corresponding contingency. So, the traditional contingency ranking method is based on calculating the first order derivative of PI function to control variable of each enumerated contingency and rank them based on the calculated PI.

In this paper, several improvements and adaptations have been made on the traditional CR method before it was introduced into the reliability evaluation of line switching operations.

Firstly, traditional CR method is based on the AC power flow analysis and the difference is approximated by the first order derivative. However, in practice, DC power flow is used so that derivative of PI before/after a certain contingency can be easily computed and the difference obtained.

Secondly, traditional CR method is based on the derivative subject to single order contingency. In order to expand the probability of coverage, the idea of line removal tests in [43] is used to conduct the “second” order contingency enumeration. After a certain transmission line is removed from the system, the single order contingency enumeration is performed on the residual system and PIs of contingency are summed with their normalized probability as the weighting coefficient. In the end, each line removal test has one PI, which represents the risk of all single order contingencies of the residual system after the removal of that transmission line.

Thirdly, traditional PIs used in CR method include voltage level or line saturation level. The performance index in contingency ranking is designed to indicate what is likely to happen based on the loading conditions of the system. For example, if a line is closer to its full loading, it is more likely to be source of problem However, it does not ensure that it necessarily will. Also in ranking the reliability characteristics of the lines or generators are not considered, also the load loss level commonly used in reliability evaluation is not considered. Therefore, a new PI, Expected Power Not Supplied Percentage (EPNSP) is proposed. Compared with traditional PI, the proposed new PI has better identification rates and provides better understanding of the state space of line switching operations.

3.2.4 Mathematical Formulation of New PI

The detailed definition of line removal test is included in [43]. It should be noted that in the line removal test of i^{th} transmission line, that transmission line is considered removed.

The single order contingency added to PI calculation is to consider the states with only one of the components failed in the original system. The components considered in this research include transmission lines and generators in the system.

The formulation of Expected Power Not Supplied Percentage (EPNSP), to be used in the proposed PI, is shown in (12)

Minimize $$EPNSP = \frac{\sum_{k=1}^{N_b} LL_k}{\sum_{k=1}^{N_b} LM_k} \tag{12}$$

Subject to $\hat{B}\theta + G + LL = L$ (power balance)

$$F = b\hat{A}\theta$$

$$-F_{cap} \le F \le F_{cap} \text{(line flow limit)}$$

(other limit)

Where

θ is N_b-vector of bus voltage angles (Decision variable)

G is N_b-vector of bus generation levels (Decision variable)

N_b is number of buses

N_t is number of transmission lines

LL is N_b-vector of bus load loss with subscript indicating the bus number

LM is N_b-vector of maximum bus load with subscript indicating the bus number

b is N_t×N_t primitive matrix of transmission line susceptance

$\hat{A}$ is N_t×N_b element-node incidence matrix

$\hat{B}$ is $N_b \times N_b$ augmented node susceptance matrix= $\hat{A}^T b\hat{A}$

θ is N_b-vector of bus voltage angles

G is N_b-vector of bus generation levels

L is N_b-vector of bus load levels

F is N_t-vector of transmission line flows

F_{cap} is N_t-vector of transmission line capacity

Above formulation of EPNSP is applied to every line removal test and the calculation of PI is shown in (13).

$$PI_i = \begin{cases} \sum_{j=1}^{N_t+N_g} EPNSP_{i,j} * \frac{P_{i,j}}{\sum_{j=1}^{N_t+N_g} P_{i,j}}, 1 \le i \le N_t \\ \sum_{j=1}^{N_t+N_g+1} EPNSP_{i,j} * \frac{P_{i,j}}{\sum_{j=1}^{N_t+N_g+1} P_{i,j}}, i = N_t + 1 \end{cases} \quad (13)$$

Where

N_t = number of transmission lines

N_g = number of generators

PI_i = PI of system with ith line removed. No line is removed when $i = N_t + 1$

$EPNSP_{i,j}$ = EPNSP of system with ith line removed and jth component failed

No component is failed when $j = N_t + N_g + 1$

$P_{i,j}$ = Probability of system with ith line failed and jth component failed

It can be seen in (13) that PI is the weighted sum of EPNSP of single order contingencies considered. The weights of summation are the normalized probability of each contingency. The benchmark case is set as the last PI with the original system as no transmission line is removed.

3.2.5 Reasons for Using EPNSP as PI

The reasons for using EPNSP as PI are twofold. The PI traditionally used in CR method did not perform well in the proposed framework where EPNSP performs the best as the new possible PI related to load loss.

Traditional PI like the one based on line saturation level performs poorly in reliability evaluation because reliability evaluation is focused on the system failure states with typical indicator as load loss. However, the heuristic relationship between heavily loaded transmission lines and higher load loss probability is not theoretically proven. Moreover, since traditional PI is based on the assumption of power balance with no load loss, the failures states due to transmission line overflow can be recorded but the failure states due to generation deficiency/islanding is infeasible in the formulation of traditional PI, which leads to mis-ranking of contingencies.

The reasons of choosing EPNSP as new PIs are as following. EPNSP is chosen over EPNS because percentage is an index with no units that can be generalized to compare systems of different size. EPNSP is chosen over Expected Energy Not Supplied (EENS) because EENS also performed worse in CR method. This is because CR method is based on a “snapshot” of power system. The idea to include time is different from theoretical considerations for CR. It should also be noted that, to use CR results as “dictionary” for later simulation, the load level in problem formulation of EPNS is set to be the maximum value, this also affects the calculation of EENS.

3.2.6 Definition and Usage of Dictionary

As mentioned in section 3.2.2, the results of CR pre-selection method not only provide the ranking list of transmission lines, but also input to the dictionary to speed up the simulation. The formulation and usage of the dictionary is described as following.

The formulation of dictionary is completed while calculating PIs of single order contingencies. The first and foremost assumption in the CR method is that the load level is set at the highest and kept as a constant. The results of PI are used to categorize enumerated states. If

EPNSP of an enumerated state equals to zero, it means this state is safe with no load loss even at the highest load; If EPNSP of a state is larger than zero, the state is not safe at the highest load.

The usage of dictionary is based on the categorization of states in the formulation. It is observed in (14) that in each dictionary entry, the corresponding system topology is the same (same $\hat{B}$), thus load loss vector in dictionary is the upper bound of cases encountered in MCS.

$$LL_{MCS} = L_{MCS} - \hat{B}\theta - G \leq LM - \hat{B}\theta - G = LL_{dic} \tag{14}$$

Where

LL_{MCS} = Bus load loss vector of MCS cases that has same $\hat{B}$ matrix (same topology) with LL_{dic}

L_{MCS} = Bus load vector of MCS cases, used to calculate LL_{MCS}

LM = Maximum bus load vector, used to calculate LL_{dic}

LL_{dic} = Bus load loss vector of dictionary cases, represent upper bound under corresponding $\hat{B}$

$\hat{B} = N_b \times N_b$ augmented node susceptance matrix $= \hat{A}^T b \hat{A}$

Based on (14), it can be seen in (15) that, all cases encountered in MCS that have the same topology with safe cases marked in dictionary will definitely yield zero load loss, thus reducing computation burden of MCS.

$$LL_{MCS} \leq LL_{dic-safe} = \vec{0} \tag{15}$$

It should be noted that above statement assumes that load at each load bus is varying proportionally with the load level, which is a common assumption in reliability evaluation. If load level variation could also affect the allocation of load at each load bus, then safe state in dictionary with highest load could also have load loss at lower load level.

Dictionary output from CR method is introduced to not only speed up the simulation but also provide a better analytic understanding of the state space. The detailed performance in case study is illustrated in section 3.3 with visual display of map and combination with line removal test.

3.2.7 Difference between Event-based and Yearly-based Indices

Event-based indices are different from yearly-based indices. They treat each failure separately and disregard the time between failures as these are concerned with what happens during the event.

One important difference is that event-based indices are always positive with no zero values, however, yearly-based indices are non-negative with possible zero values. Yearly-based indices need additional procedure to consider the zero values because Weibull fitting cannot be used directly on data with zero values. In this research, the zero values are removed before Weibull fitting while saving percentage of zero values in data.

Since mean value of zero values is zero, the actual mean value of yearly-based indices is proportional to the fitting mean value with the zero-data-percentage as shown in (16)

$$AM = \frac{FM * (1 - zper) + 0 * zper}{1} = FM * (1 - zper) \tag{16}$$

Where

$AM =$ Actual mean value

$FM =$ Fitting mean value

$zper =$ Percentage of zero values in data

To acquire the extreme value of yearly-based indices, the Cumulative Distribution Function of Weibull fitting is adjusted with the zero-data-percentage, so that the extreme value of yearly-based indices at pre-set percentage of distribution are correctly calculated in (17)

$$Fper = \frac{Pper - zper}{1 - zper} \tag{17}$$

Where

$Fper =$ Percentage of CDF in fitting

$Pper =$ Pre-set percentage of CDF for extreme value

Although the state residence time of each component is assumed to follow exponential distribution, after components are combined to form a power system, distribution of reliability parameter at system level is not exponential anymore. Furthermore, it is observed in Figure 35 that distributions of event-based and yearly-based indices are also different.

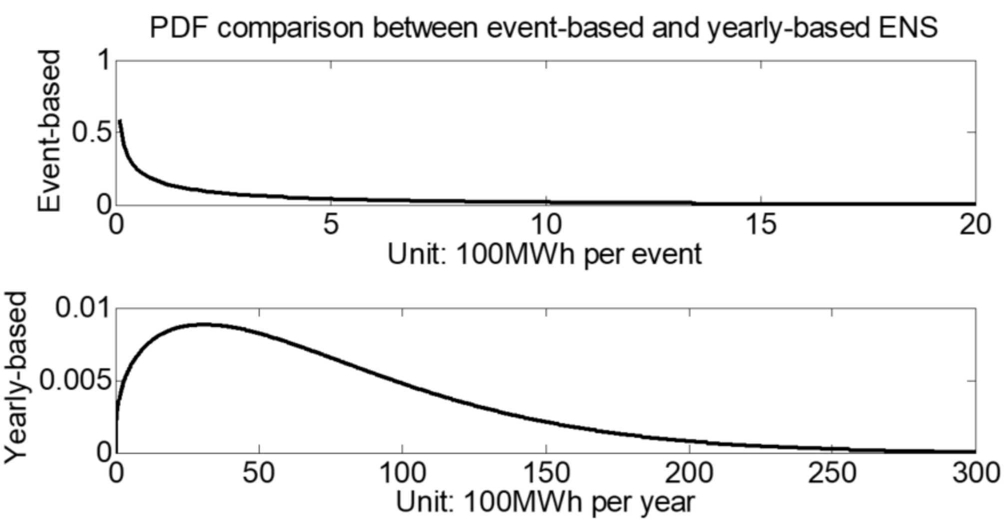

Figure 35. PDF comparison of event-based and yearly-based EENS.

Since these two indices have different physical meaning, analysis of their results is also different in the proposed hybrid reliability evaluation method. Since event-based indices disregard time between failures, the mean value of event-based indices does not represent the failure severity level like that of yearly-based indices. On the other hand, the worst-case analysis of event-based indices is comparatively valuable because the worst-case scenario for each line removal test is chosen at the same percentage of distribution. Thus, its physical meaning is the mean value of worst case scenario which is comparable between different cases.

3.2.8 Procedure of the Proposed Method

The procedure of the proposed hybrid method includes two steps. First step is using CR as a pre-selection method and second step is Monte Carlo Simulation based on the guidance from the results of CR pre-selection method.

The procedure of first step is presented in Figure 36.

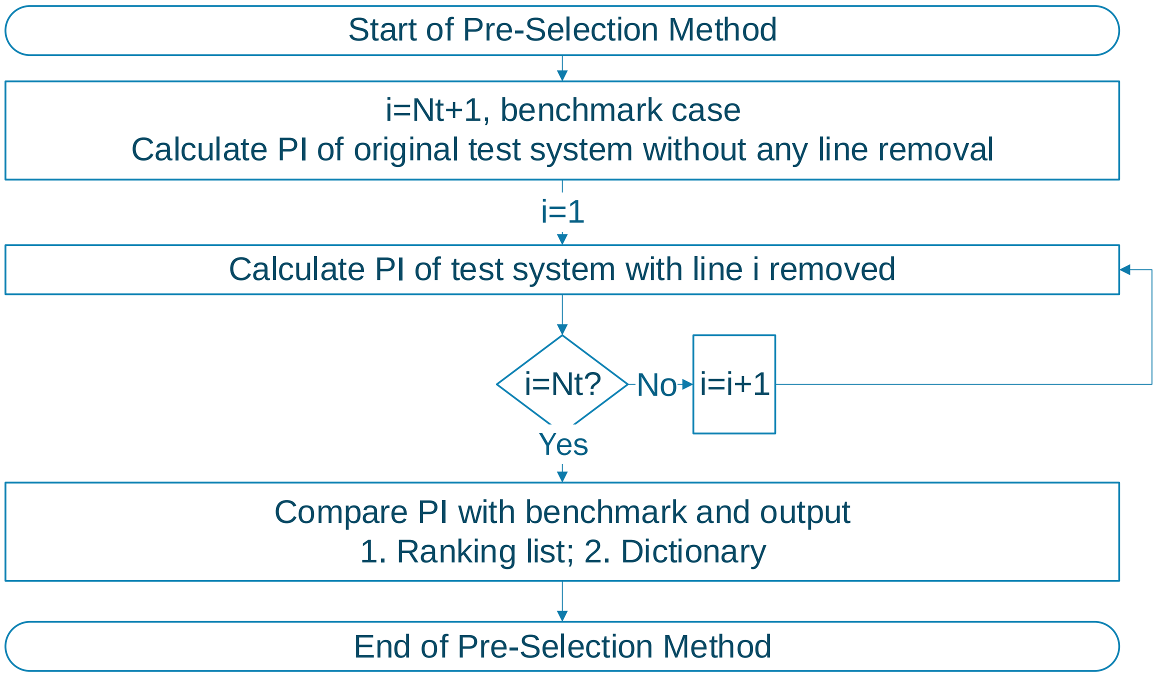

Figure 36. Procedure of using CR as pre-selection method.

It should be noted that N_t is the number of transmission lines in the system and case $N_t + 1$ is set as the benchmark case. The results of pre-selection method include two aspects. The ranking list is used to provide analytic guidance on the MCS of reliability evaluation, the dictionary of state space is used in each trial of MCS to speed up the simulation.

The procedure after pre-selection method is presented in Figure 37.

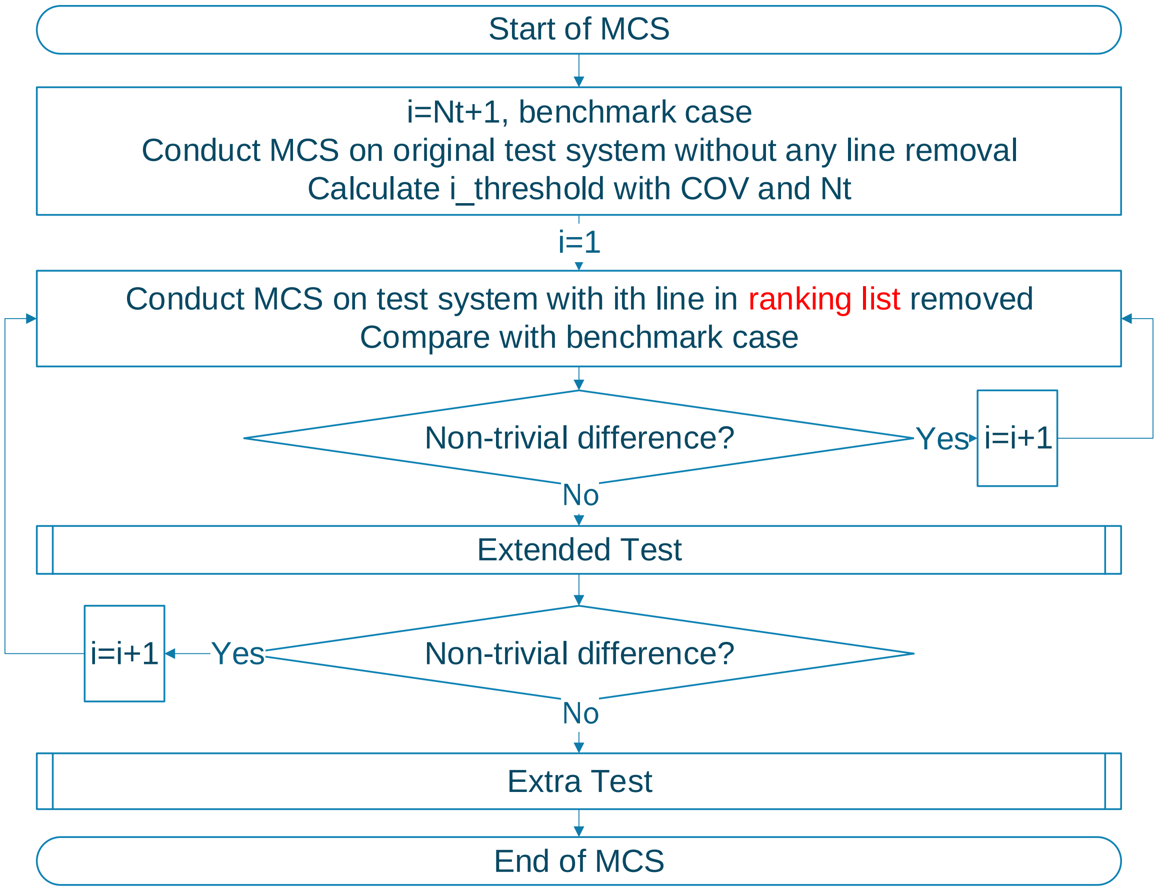

Figure 37. Procedure of MCS based on CR pre-selection method.

It should be noted that procedure of MCS is started from the first line in ranking list, so instead of a crude enumeration, the guidance of pre-selection method is used to pick most critical transmission lines. However, CR method is after all a pre-selection method that is subject to mis-ranking, so Extend Test module in Figure 37 is utilized as a "mercy" rule to extend the cut-off point in ranking list. The number of transmission lines to be tested in this module is determined by $i_{threshold}$ and calculated according to (18)

$$i_{threshold} = \lceil i_{threshold} \rceil = \lceil COV \cdot N_t \rceil \tag{18}$$

Where

$\lceil x \rceil$ = Smallest integer larger than or equal to x

COV = Coefficient of Variation of EENS

N_t = Number of transmission lines in test system

There are two different ways to exit Extended Test module. If non-trivial difference is found, then procedure exits this module and goes back to procedure of Figure 37 to find another cut-off point. However, if non-trivial difference is not found and $i_{threshold}$ is reached, procedure exits this module and moves to the Extra Test module.

Extra Test module is designed for islanding lines and recommended lines in the test system that may be overlooked in the ranking list. The detailed procedures of Extended Test and Extra Test modules are presented in Figure 38 and Figure 39 respectively.

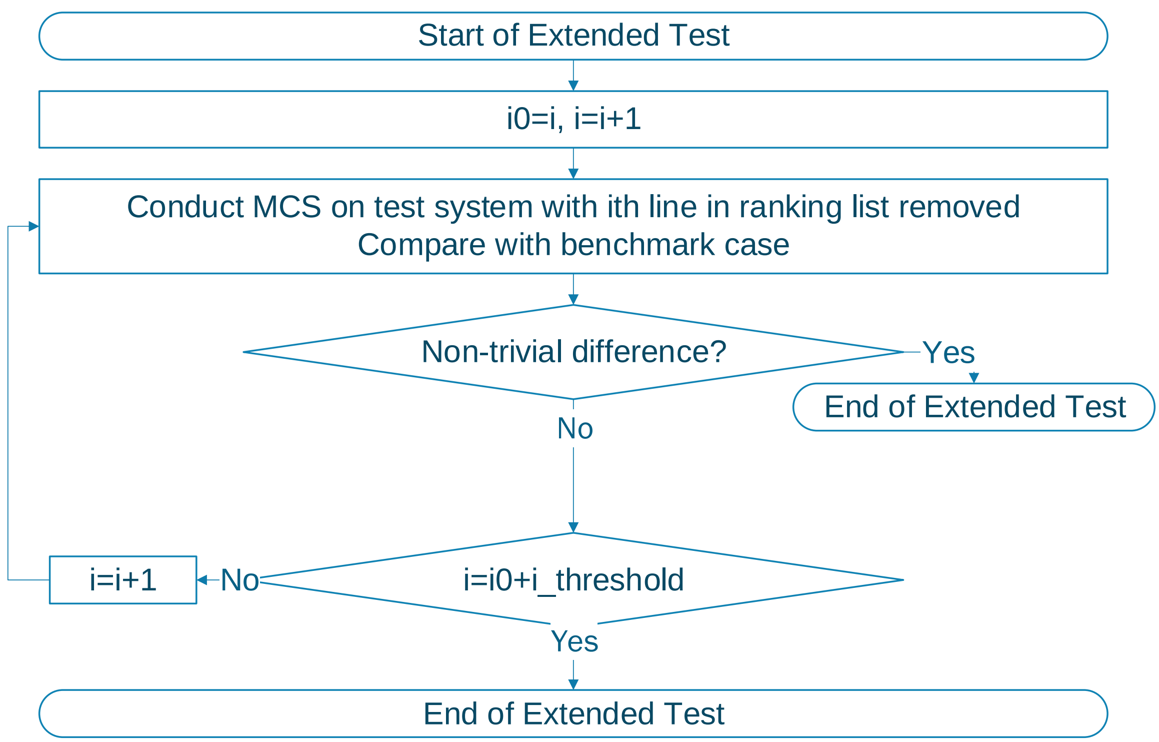

Figure 38. Procedure of Extended Test module in MCS.

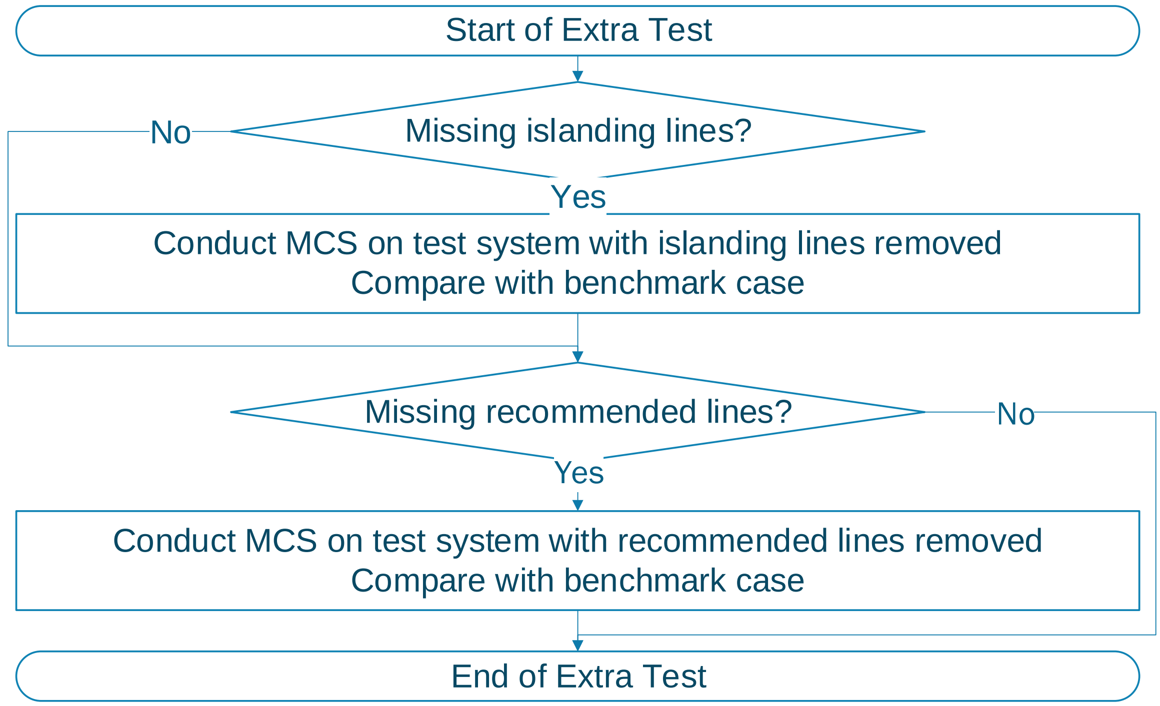

Figure 39. Procedure of Extra Test module in MCS.

After Extra Test module, MCS procedure is terminated and the rest of transmission lines are marked with non-trivial difference compared with benchmark case and categorized as safe lines in line switching operations.

3.3 Case Studies

Two case studies were conducted to test the performance of the proposed hybrid reliability evaluation method.

One is on IEEE Reliability Test System (RTS) and another is on IEEE 118-bus system. They are illustrated in section 3.3.1 and section 3.3.2 respectively.

3.3.1 Case Study I: IEEE RTS

RTS used in this research has 38 transmission lines in the system, with 3450MW maximum generation and 2850MW maximum load. Reliability parameters used are the same as in [74].The load variation pattern is obtained from [74] as an 8760 h load cycle, the load level changes every hour.

Firstly, CR pre-selection method is performed on the RTS to have the ranking list and dictionary. The benchmark case and all 38 line removal tests were finished within 1 minute on an Intel Core i5 CPU (4200M / 2.5 GHz).

The PIs of all transmission line removal tests in RTS are shown in Figure 40. Case 39 is the benchmark case with no transmission line removed. Since PI of line 11 is too high compared with other line removals, the bottom figure is representing the same comparison of PIs but in log-scale.

It can be seen from Figure 40 that the first 12 entries of ranking list of PIs is shown in Table 7.

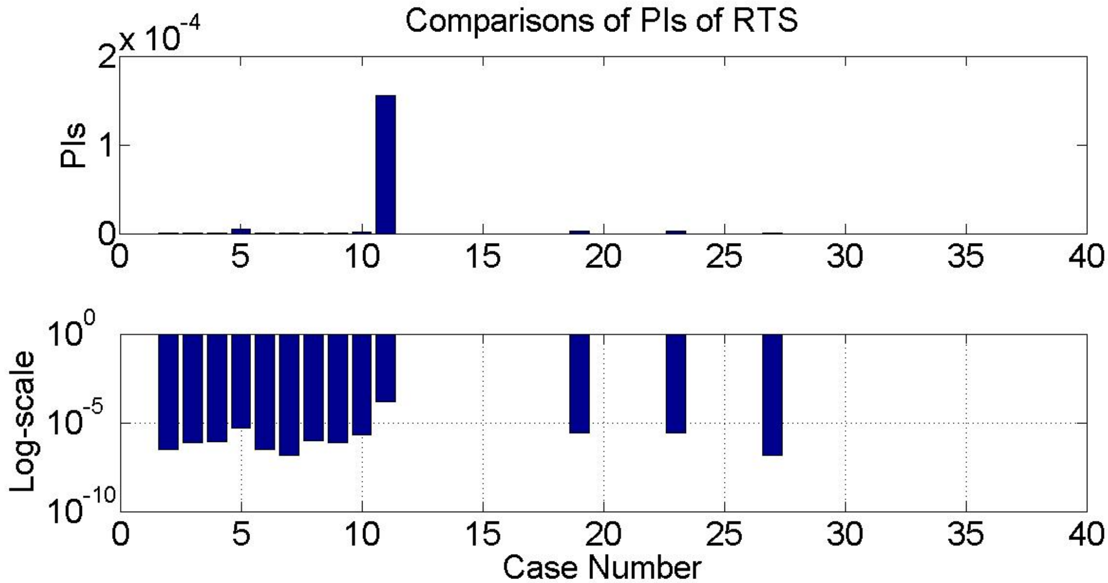

Figure 40. Comparison of PIs of IEEE RTS.

Table 7 Ranking list of case study I

Ranking Number	Transmission Line Number
1	11
2	5
3	23
4	19
5	10
6	8
7	4
8	3
9	9
10 ($\boldsymbol{i_0}$)	2
11	6
12 ($\boldsymbol{i_0 + i_{threshold}}$)	7

Secondly, MCS is performed on RTS according to the ranking list obtained from CR pre-selection method. The first 9 lines of the list all proved to have non-trivial difference in yearly-based EENS comparison with benchmark case. The 10th line, line 2, does not show non-trivial difference. Since $i_{threshold}$=2, two more lines were tested in MCS and still no non-trivial difference was observed. According to the procedure described in section 3.2.8, the MCS evaluation is terminated and the rest of transmission lines are marked as safe lines with no or trivial difference compared with benchmark case.

To prove the effectiveness of the proposed method, the rest of transmission line removal tests were conducted to validate the above statement. The yearly-based EENS comparison is shown in Figure 41. Line removal tests with trivial difference to benchmark case (case 39) are represented by the dashed line of the benchmark case to emphasize line removal tests with non-trivial difference. Based on the difference compared with benchmark case, the line categorization is shown in Table 8.

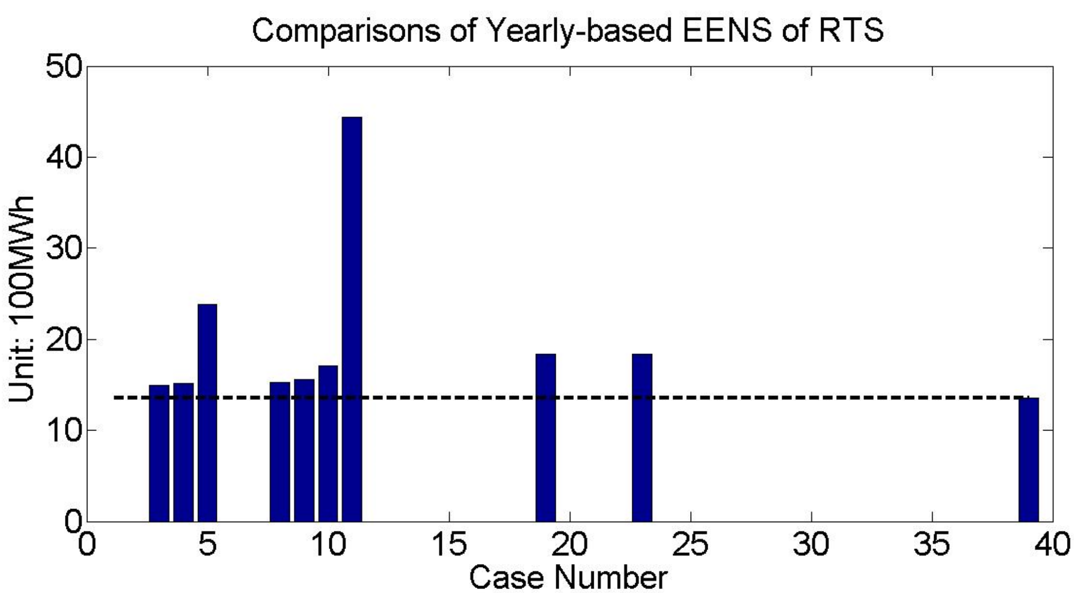

Figure 41. Comparison of yearly-based EENS of IEEE RTS.

Table 8 Transmission lines with non-trivial difference in IEEE RTS

Yearly-based EENS	
	Mean value
Increase of reliability	N/A
Decrease of reliability	3,4,5,8,9,10,11,19,23

It can be seen from Figure 41 and Table 8 that all 9 critical lines have been identified with the CR pre-selection method, the rest of transmission lines prove to have only trivial differences.

To show the effectiveness of proposed CR method over traditional CR method, the performance of hybrid method with traditional CR is also tested in this paper. Similar contingency ranking pre-selection process was conducted except this time the traditional CR method is used to generate PI difference and ranking list.

The PIs of all transmission line removal tests in RTS are shown in Figure 42 and the first 3 entries of ranking list of PIs to guide MCS are shown in Table 9.

It is observed in Figure 42 and Table 9 that traditional CR method is subject to mis-ranking in reliability evaluation. Even with the “mercy” rules described in section 3.8, it stops after the first 3 three lines while the first critical line is ranked at number 5. This shows the effectiveness of the proposed CR to traditional CR method. The comparison of benchmark method (MCS alone), hybrid method with traditional CR method and the proposed hybrid reliability evaluation method is presented in Table 10.

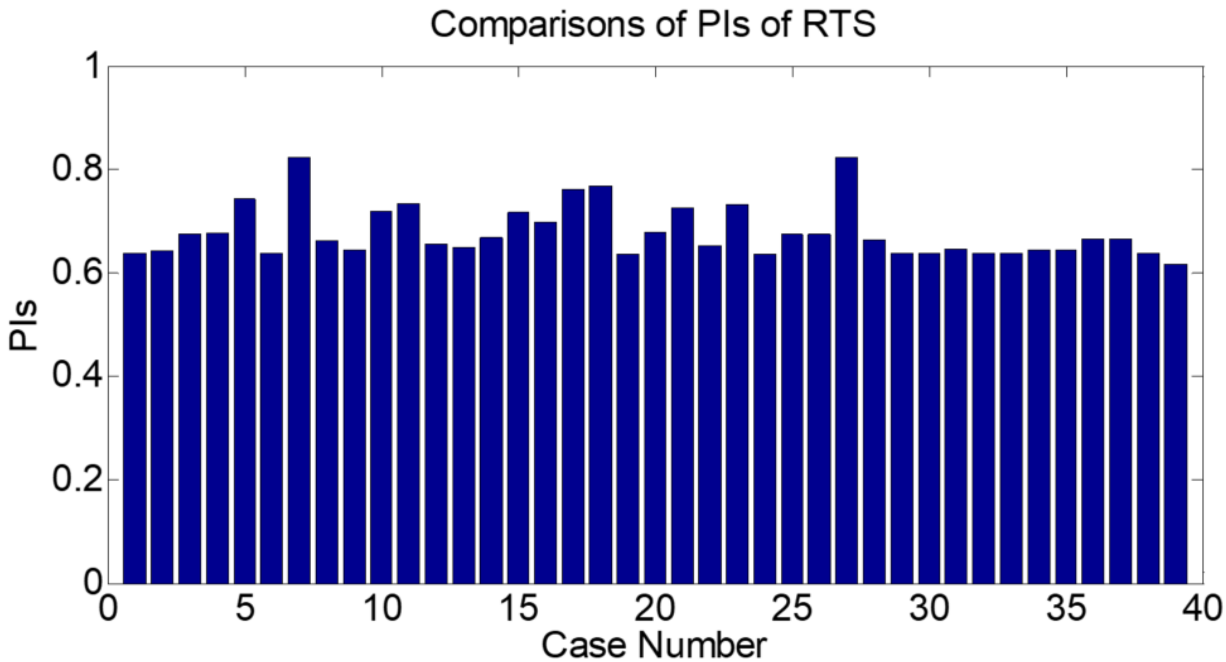

Figure 42. Comparison of PIs using traditional CR Method of RTS.

Table 9 Ranking list of case study I using traditional CR method

Ranking Number	**Transmission Line Number**
1 ($\boldsymbol{i_0}$)	7
2	27
3 ($\boldsymbol{i_0 + i_{threshold}}$)	18

Table 10 Performance of hybrid reliability evaluation method on IEEE RTS

	Benchamark MCS alone	**Hybrid Reliability Evaluation Method**	
Number of transmission line removal tests conducted	38	12	**Speed Improvement Percentage** 68.42%
Number of critical transmission lines picked up	9	9	**Pick up Percentage** 100%

In summary, as shown in Table 10, with the proposed reliability evaluation method, only 12 out of 38 transmission lines removal tests were conducted to pick up all 9 critical lines in the power system. The results validate both the accuracy in picking up critical lines and a significant increase in computational speed compared with traditional evaluation method based on MCS alone.

Only part of analysis of results is shown to validate the advantage and effectiveness of the proposed hybrid reliability method. The complete line categorization and dictionary analysis are illustrated in the following sections.

Although yearly-based EENS is used in the CR pre-selection method as benchmark, this index alone is not enough to represent the reliability performance of test system. The rest three indexes recorded in MCS are also used in line categorization and transmission lines with non-trivial difference are listed in Table 11.

Table 11 Transmission lines with non-trivial difference in IEEE RTS

Yearly-based EENS		
	Mean value	**Worst case**
Increase of reliability	N/A	N/A
Decrease of reliability	3,4,5,8,9,10,11,19,23	5,11
Yearly-based HLOLE		
	Mean value	**Worst case**
Increase of reliability	N/A	N/A
Decrease of reliability	3,4,5,8,9,10,11,19,23	5,11
Event-based EENS		
	Worst case	
Increase of reliability	N/A	
Decrease of reliability	5	
Event-based HLOLE		
	Worst case	
Increase of reliability	N/A	
Decrease of reliability	3,4,5,8,9,10,11,19,23	

Instead of showing all the results of reliability indexes, selected results are shown to emphasize patterns observed. As mentioned in section 3.2.7, yearly-based and event-based indices have different physical meanings, thus representations of these indices are different in Table 11.

The mean value comparison of yearly-based indices is used as the indicator of critical/recommended transmission lines. On the other hand, although mean value analysis of event-based analysis can represent the scatter of failures, its physical meaning alone is not comparable between different line removal tests, so the mean value comparison is not shown for event-based indices.

The worst-case comparison of both yearly-based and event-based indices are based on their corresponding distribution, only a handful of lines are showing non-trivial difference in this category, this means these transmission lines will bring serious impact to the system even compared to other critical lines, so they should be dealt with caution in the line switching operations.

Apart from line categorization, more results are provided based on the dictionary analysis, compared with original MCS, the speed up effect of dictionary is based on the probability coverage of single order contingencies enumerated in the pre-selection method. In other words, the effect is more significant when there are fewer lines in the test system (50% for RTS). It is noted that other speed up method are also utilized in modern MCS. For example, the "pre-selection" method proposed in [43, 73] is also focused on "easy" states that don't require heavy optimization. The objective of dictionary usage in function is similar to other speed up methods and the effect may be comparable with MCS using other speed up methods. Therefore, in case study I, the speed up effect of dictionary is significant compared with MCS using LP alone, but not as significant compared with MCS already using other speed up method.

However, it should be noted that the value of dictionary is not only in the increase of computational speed. Since single order contingencies are enumerated for each line removal test, visualization tools like map can be formulated from dictionary to emphasize the component with potential threats to the power system. The PI map of dictionary is shown in Figure 43.

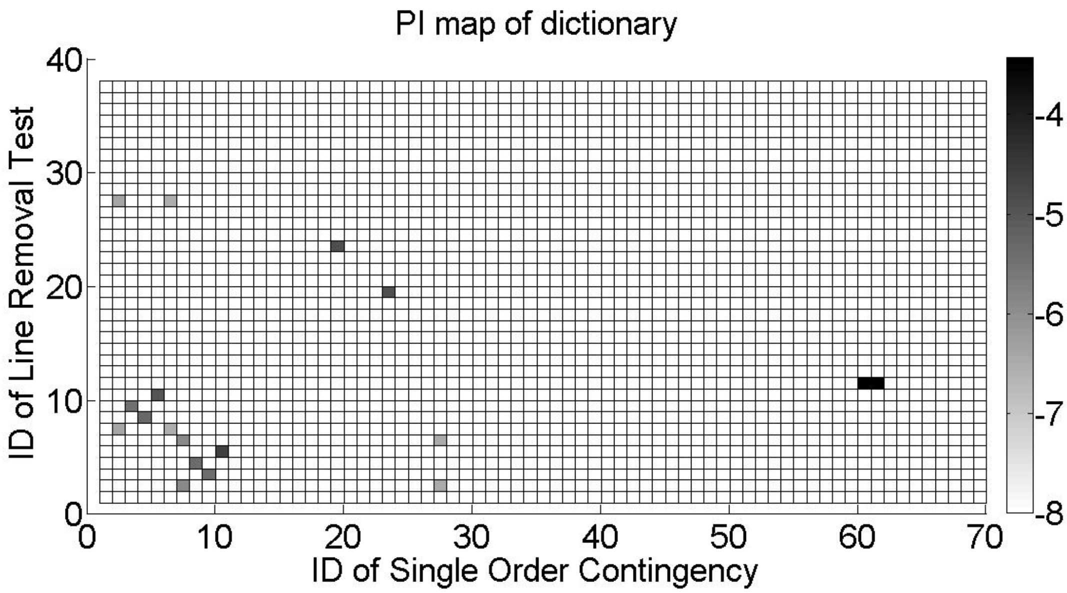

Figure 43. PI map of dictionary of IEEE RTS.

Each row in Y axis represents a specific line removal test, and each column in X axis represents the corresponding single order contingency of the residual system after line removal. The first 38 contingencies are transmission line failures and the last 32 contingencies are generator failures. So, each block represents a state in the dictionary and the black ones are the failures states. The scale of failure severity is represented by the PI value, log10-scale is used in the color bar to represent the drastic difference, darker color means higher PI value and more load loss in the system.

Another finding by digging into dictionary is the identification of “area-islanding” line combinations. It is easy to spot single islanding line when removal of such line will island part of the system. However, when it comes to the combination removal of two transmission lines, it is hard to eyeball all the correct combinations. With the help of dictionary, the line combination that causes “area-islanding” are picked up by evaluating the ranks of B ̂ matrix formulated in (12) and shown in Figure 44.

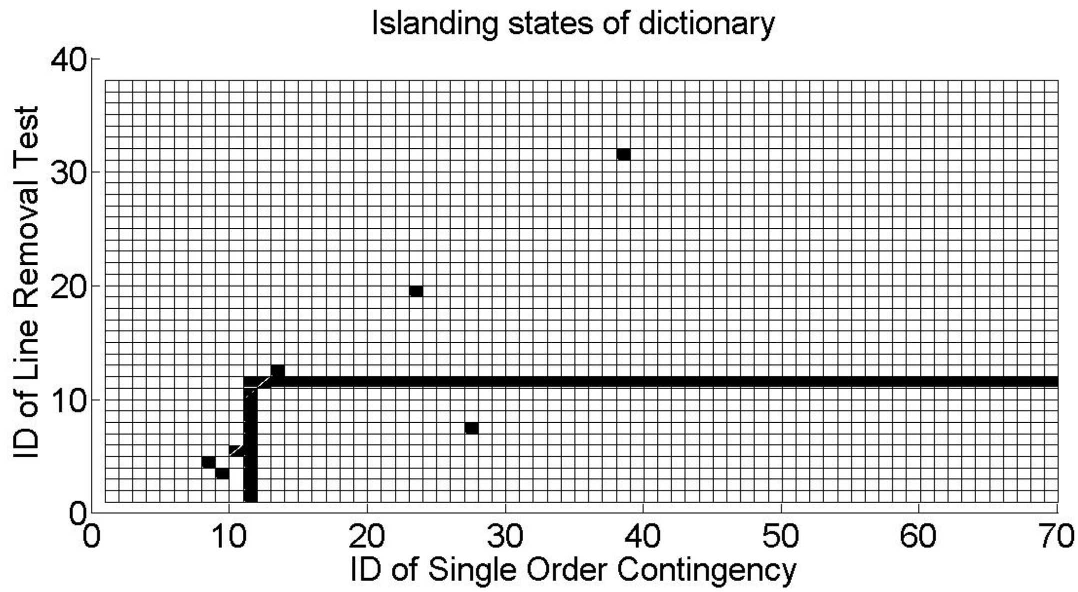

Figure 44. Islanding states of dictionary of IEEE RTS.

The black blocks represent islanding states that will island part of the system. It should be noted that states above diagonal lines are symmetrical to the ones below thus only below states are counted in the map here.

3.3.2 Case Study II: IEEE 118-bus system

To validate the effectiveness of the proposed method, IEEE 118-bus system is used for the second case study with more buses and more sophisticated topology. The topology and reactance data is obtained from [75]. The load diagram is an 8760h load cycle and it is scaled from RTS load data. There are 186 transmission lines in IEEE 118-bus system, with 7220MW maximum generation and 6000MW maximum load.

Like case study 1, the CR pre-selection method is used to formulate the ranking list and dictionary. The benchmark case and all 186 transmission line removal tests were finished within 15 minutes on the same i-5 CPU.

The differences of PIs are shown in Figure 45, Case 187 is the benchmark case with no transmission line removed. To show a clear comparison, y-axis in bottom figure is represented in log-scale. It should be noted that two lines (37,54) are showing PI lower than the benchmark case.

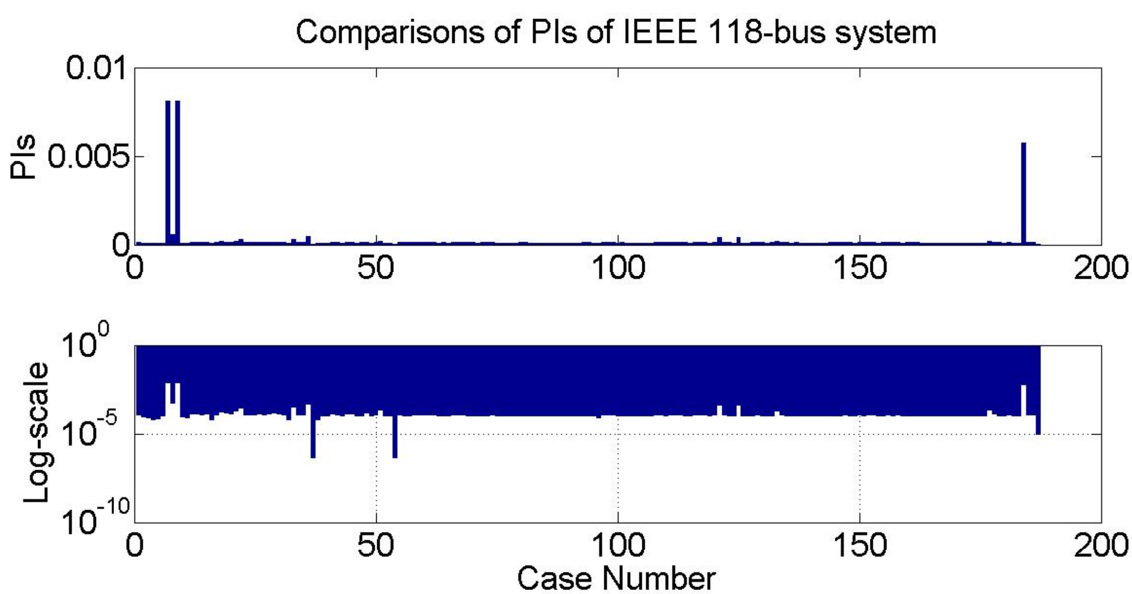

Figure 45. Comparison of PIs of IEEE 118-bus system.

According to the procedure described in section 3.2.8, MCS was conducted on the test system according to the ranking list with $i_{threshold} = 6$ so the extended test will test six more lines in the ranking list before terminating the MCS searching, hoping to find another non-trivial difference compared with the benchmark case. Once non-trivial difference is observed in extended test, the procedure will break from the extended test and enter again only when trivial difference is observed in normal procedure. In this case study, the extended test was called upon 4 times until it terminated at the 29th line in the list, and 14 lines are identified as critical lines.

Since 4 of the islanding lines (113,134,176,183) are not tested to this step, extra test is utilized to perform removal tests on these 4 transmission lines and line 134 is identified as critical line. Furthermore, since there are negative differences in the PIs compared with the benchmark case, extra test is utilized to perform line removal test in MCS starting from the end of the ranking list and move backwards. The procedure ends at 11th line, and 3 lines are marked as recommended lines.

This concludes the extra test as well as the MCS procedure of the proposed method with 44 transmission line removal tests and the rest of transmission lines are marked as safe lines with no or trivial difference compared with the benchmark case.

To prove the effectiveness of the proposed method, the rest of transmission lines were also tested in MCS. The yearly-based EENS comparison is shown in Figure 46 and based on the difference compared with benchmark case, the complete line categorization is shown in Table 12.

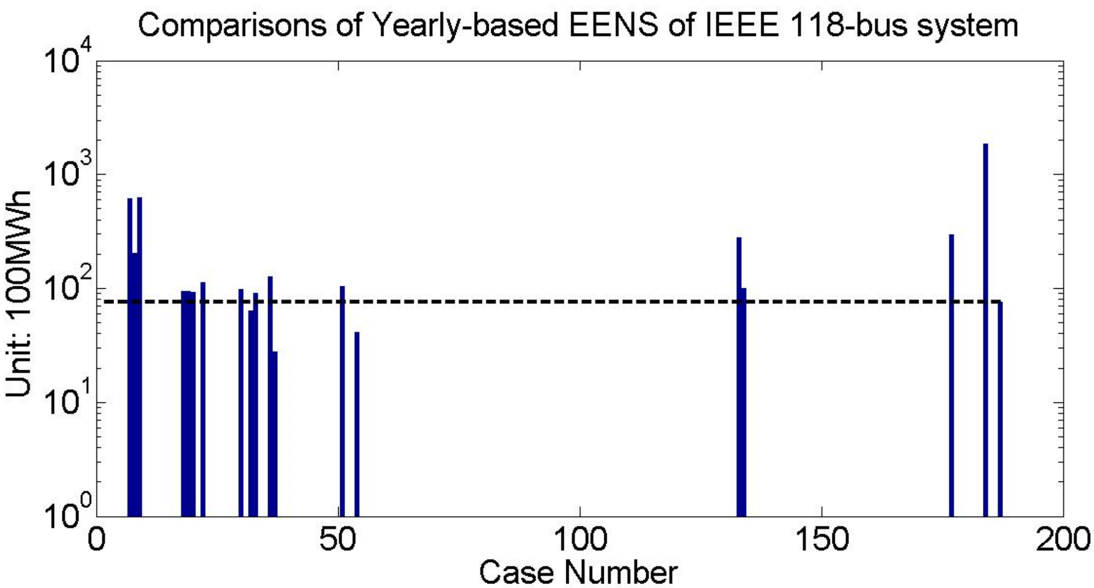

Figure 46. Comparison of yearly-based EENS of IEEE 118-bus system.

Table 12 Transmission lines with non-trivial difference in IEEE 118-bus system

Yearly-based EENS		
	Mean value	**Worst case**
Inc.	32,37,54 **(3 recommended lines)**	37
Dec.	7,8,9,18,19,20,22,30,33,36,51,133,134,177,184 **(15 critical lines)**	7,8,9,22,36,133,177,184
Yearly-based HLOLE		
	Mean value	**Worst case**
Inc.	37,54	37,54
Dec.	7,8,9,18,19,20,22,27,28,29,30,33,36,48,51,133,134,177,184	7,8,9,22,36,133,177,184
Event-based EENS		
	Worst case	
Inc.	6,8,33,37,38,54	
Dec.	7,9,184	
Event-based HLOLE		
	Worst case	
Inc.	33,36,37,38,51	
Dec.	7,9,17,19,20,22,133,177,184	

It is observed that all 15 critical lines and 3 recommended lines have been picked up with the CR pre-selection method, the rest of transmission lines prove to have only trivial differences.

Table 13 Performance of hybrid reliability evaluation method on IEEE 118-bus system

	Benchamark MCS alone	**Hybrid Reliability Evaluation Method**	
Number of transmission line removal tests conducted	186	44	**Speed Improvement Percentage**
			76.34%
Number of critical transmission lines picked up	15	15	**Pick up Percentage**
			100%
Number of recommended transmission lines picked up	3	3	**Pick up Percentage**
			100%

In summary, as shown in Table 13, with the proposed reliability evaluation method, removal test on only 44 out of 186 transmission lines were conducted to pick up all 15 critical lines and all 3 recommended lines in the power system. Similar to IEEE RTS, the results again validate both the accuracy in picking up critical lines and the significant speed increase compared with traditional evaluation method based on MCS alone.

Complete analysis of results with line categorization and dictionary analysis is illustrated in the following sections.

In line categorization, 3 recommended lines are identified in the system. Line 32, 37 and 54 are recommended lines in simulation, which means their removal will improve the system's reliability on average. It turns out that these three lines are heavily loaded and subject to overflow when other critical lines are removed. So, these recommended lines are creating transmission bottleneck in the original system, therefore their removal will redistribute the power flow and improve the overall system reliability.

Other than the recommended lines, there are some interesting findings in the worst-case comparison of event-based indices. Although line 33 is marked as a critical line, its performance in worst case comparison of event-based indices is better than the benchmark case. This means that for some critical lines with centralized failure distribution, the failure may be higher than normal cases yet failure severity of each case is centralized and even comparable to benchmark case. So, if worst case were to happen, performance may be comparable or even better than the benchmark case with no transmission line removed.

On the dictionary analysis, the PI map of IEEE 118-bus system is shown in Figure 47, islanding states are shown in Figure 48. Due to the large number of states in this case study, the grid lines are omitted in the map display to provide better presentation of state space.

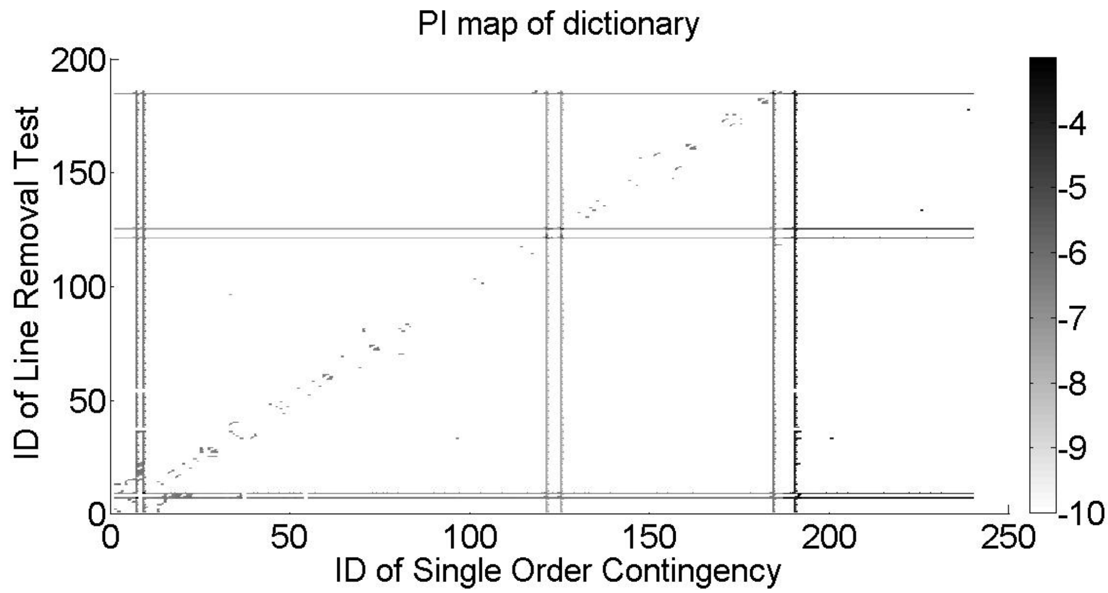

Figure 47. PI map of dictionary of IEEE 118-bus system.

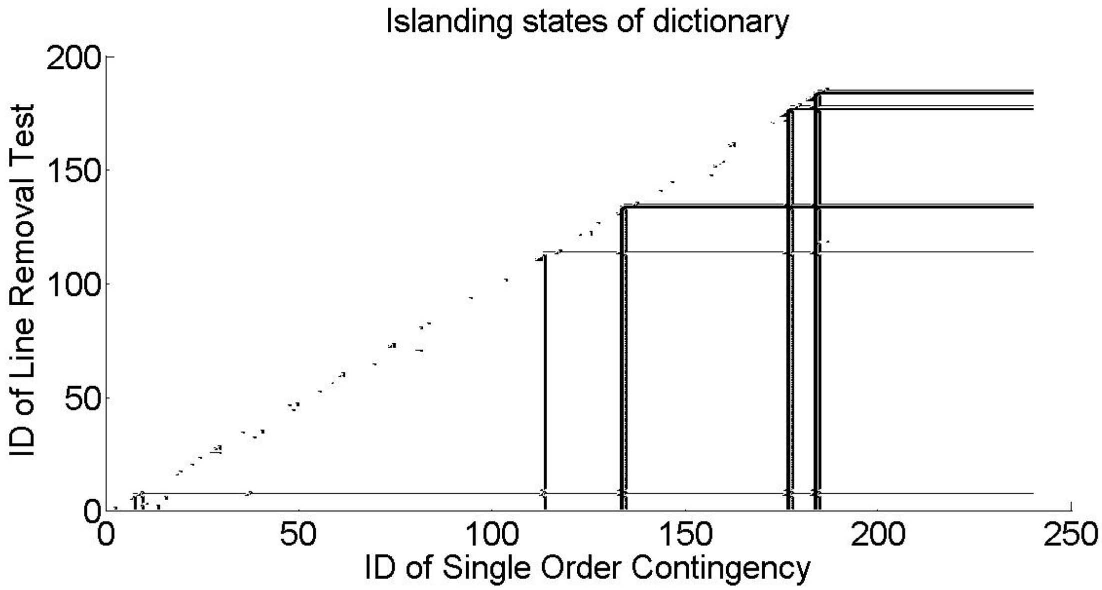

Figure 48. Islanding states of dictionary of IEEE 118-bus system.

3.4 Summary

A hybrid reliability evaluation method is proposed in this paper for line switching operations in power systems. An enhanced contingency ranking method is introduced as a pre-selection method to speed up the simulation and to provide analytical perspective of state space. Compared with the method based on MCS alone in [43], CR is introduced into hybrid evaluation method in this paper with improvements to adapt to reliability evaluation. In the overall procedure, it serves as a pre-selection method before MCS method to provide guidance on the sequence of MCS test and ameliorate inherent randomness of MCS. The proposed reliability evaluation method was tested on two systems, RTS and IEEE 118-bus system. In both case studies, the proposed CR pre-selection method picked up critical lines with reasonable accuracy and showed a significant improvement of calculation speed. Other than the ranking list, the dictionary outputs from CR pre-selection method reduced the computation burden in simulation stage and provide analytical guidance compared to the randomness inherent in MCS reliability evaluation. In the updated analysis of results, the differences between event-based and yearly-based indices are further analyzed to distinguish the distributional difference and only selected results are shown to emphasize observed patterns from proposed hybrid reliability evaluation method.

4. INVESTIGATION INTO INCOMPLETE DATA ISSUES IN RELIABILITY EVALUATION*

4.1 Introduction

Conditions for equivalence of state probabilities obtained from the data on state residence times and those from data on interstate transitions are explored in this research. The derived conditions are useful in applications under various situations. The situations illustrated in this research include when data is available only for state residence times but a state transition rate matrix needs to be developed for purposes of application. A situation is also illustrated when data on state residence times and interstate transitions is collected but inaccuracies may exist in the collection or processing of interstate data. Another condition explored is the effect of the probability distribution of state residence times on the reliability indices.

Data collection schemes for power system components like generating units and transmission lines have different levels of sophistication. Generally, it is easier to collect the data for calculation of probabilities of the different states of the unit than the transition rates. This is because for calculating the state probabilities all that is needed is the cumulative time spent in the states whereas for the transition rate calculations, details on the number of transitions between various states is needed. For this reason, a more sophisticated data gathering procedure is needed

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when interstate transitions data is to be collected. In terms of applications to reliability evaluation, if one is interested in the probability based indices like the Loss of Load Expectation (LOLE) or Expected Energy not served then the data on state probabilities alone is sufficient. However, if frequency and mean duration indices are needed then Markov models using interstate transitions are required. Following situations can arise in data analysis and application:

1) Data may be collected for both interstate transitions and probabilities but the data for interstate transitions may be inconsistent with the probability data. This will give the state probabilities derived from the Markov model different than the state probabilities derived from the probability data.
2) Because of damage to interstate data, data for some transitions may be either incomplete or missing.
3) In some situations, only probability data may be collected but the software for reliability evaluations may be based on interstate transitions and so arbitrary transition rates may need to be used. These transition rates should produce the probabilities that would be calculated from the probability data.
4) The available data for transition rates may need to be modified or adjusted to suit a model. For example in [64, 65], EFORd, a probability based index, is calculated from two sources. One source is state occupancy data and the other is a computer program using transition rates. These transition rates need to be adjusted to maintain the EFORd values from two sources identical.

This research derives the mathematical conditions that should be satisfied for the probabilities obtained from the Markov model using transition rates to be identical with those obtained from the state residence times. Then these results are illustrated by giving examples how this information can be used in the various situations just discussed. This research is motivated by building useful unit models in the absence of complete data. So, the examples used are small systems to verify and illustrate unit models as unit models are the focus.

This research also shows that although the transition rates derived from the data are used in a Markov model with the implicit assumption of exponential distribution of state residence times, these constant transition rates are in fact equivalent rates and so far as the steady state probabilities are concerned, these will not be affected by the probability distribution of state residence times.

4.2 Problem Formulation and Solution

The investigation of equivalence between interstate transition rates and state probabilities is arranged in the following four sections.

Section 4.2.1 investigates the process to build transition rate matrix consistent with probability vector; section 4.2.2 investigates an alternative scenario, which is the process to recover missing information of transition rates matrix with a given probability vector; section 4.2.3 investigates the effects of underlying distribution of residence time on equivalence conditions; the summary of analysis is given in Section 4.2.4.

4.2.1 Build Transition Rate Matrix

Using the concept of probability as the long run fraction of time spent in a state, the state probability can be calculated from the data on state residence times using (19):

$$p_i = \frac{T_i}{T}, \text{as } T \rightarrow \infty \tag{19}$$

Where

p_i = Steady state probability of being in state i

T_i = Cumulative time spent in state i

T = Total time of exposure

It should be noted that for equation (19), for computing the probability of state i all that is needed is the cumulative time spent in that state and the total exposure time. What we intend to derive are the conditions that need to be met to create or adjust transition rates that will yield the same probabilities as given by (19). It will be assumed that the data on state residence times is dependable and thus the state probabilities given by (19) are correct.

To derive this condition for equivalence, it will be useful to review how the state probabilities for a Markov Process are calculated. The equation for a Markov process [1] is given by (20):

$$P(t)R = P'(t) \tag{20}$$

Where

P(t)= Row vector of dimension n whose ith element $p_i(t)$ is the probability of state i at time t.

P'(t)= Row vector such that its i^{th} element is the derivative of $p_i(t)$

n= Number of states.

R= Transition rate matrix, nxn, such that its ijth element

λ_{ij} = Transition rate from state i to state j when $i \neq j$

- (Sum of transition rates in row i) when $i = j$

In steady state the derivatives of $p_i(t)$ become zeros and the equation (20) becomes:

$$PR = O \tag{21}$$

$P =$ Row vector of steady state probabilities p_i

$O =$ Row vector of dimension n with all zeroes

Since the n equations in (21) are not linearly independent, only n-1 equations can be used. The nth equation is supplied by the total probability equation (22)

$$\sum_{1}^{n} p_i = 1 \tag{22}$$

Equations (21) and (22) can be combined by replacing any column vector of R by 1s and changing the corresponding entry in O by a 1. These modified equations can then be solved to find the steady state probability vector P.

Now let us assume that data for state residence times and interstate transitions has been collected for a time period T.

Let us designate N_{ij} = Number of transitions from state i to j in time T

Now as $T \rightarrow \infty$, the state probabilities can be calculated using (18). The transition rate from state i to j can be calculated by

$$\lambda_{ij} = \frac{N_{ij}}{T_i} \tag{23}$$

Substituting these values in R in (21)

$$\lambda_{ij} = \frac{N_{ij}}{T_i} \text{ for } i \neq j \tag{24}$$

And

$$\lambda_{ii} = -\sum_{\forall j, j \neq i} \frac{N_{ij}}{T_i} \tag{25}$$

Once all interstate transition rates have been calculated, the state probabilities can be obtained from (21) and (22).

Now the question is: will these probabilities be the same as those obtained from (19)?

For this let us replace the i^{th} element of P as

$$p_i = \frac{T_i}{T} \tag{26}$$

Then using the probabilities derived from state residence times in (1), the i^{th} equation of (21) becomes

$$\frac{T_i}{T} * \left(- \sum_{\forall j, j \neq i} \frac{N_{ij}}{T_i} \right) + \sum_{\forall j, j \neq i} \left(\frac{N_{ji}}{T_j} * \frac{T_j}{T} \right) = 0 \tag{27}$$

That is

$$\sum_{\forall j, j \neq i} N_{ij} = \sum_{\forall j, j \neq i} N_{ji} \tag{28}$$

This gives us the condition that the vector P obtained by solving (21) and (22), using the transition rates calculated by data N_{ij}, will reproduce the probabilities obtained from the state residence times using equation (19). If this condition is not satisfied, then the probabilities obtained will not be the same as obtained by using state residence times.

4.2.2 Recovery of Transition Rate Matrix

There is also an alternate problem. Here the transition rate matrix has been properly calculated and the state probabilities are also known. Now because of some reason, some transition rates may be lost or damaged and need to be recovered.

Assume the calculation is based on a component with n states. To recover the transition rate matrix from the probability vector, the calculations can be performed as following.

The first step is the frequency enforcement, which builds the diagonal elements of transition rate matrix. This step can also be represented as a row operation of the transition rate matrix as shown in (29)

$$R \cdot \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \tag{29}$$

The second step is based on frequency balance, which indicates frequency in and out of a state is equal. This step can also be represented as column operation of the transition rate matrix as shown in (30)

$$[p_1 \quad \cdots \quad p_n] \cdot R = [0 \quad \dots \quad 0] \tag{30}$$

Matrix operations in (29) and (30) generate 2n equations and only (2n-1) equations are independent. There are two ways to utilize these equations.

First utilization is to build the transition rate matrix from the given probability vector, which is discussed previously in section 4.2.1. In this utilization, the diagonal elements are not considered as variables because they don't have physical meanings, thus the n equations of frequency enforcement would represent these diagonal elements with non-diagonal elements, just like the definition of λ_{ii} in equation (20). The n equations of frequency balance would contribute (n-1) independent equations to solve a maximum of (n-1) non-diagonal variables with unique solutions.

In this section, the second way of utilization is presented, which is to recover the missing information of transition rate matrix from probability vector. In this case, the diagonal elements can be considered as variables. Thus, the 2n equations can contribute (2n-1) independent equations to solve a maximum of (2n-1) variables with unique solutions.

4.2.3 Effects of Underlying Distribution of Residence Time

An observation can now be made regarding the effect of distribution form of state residence times on the steady state probabilities. Probabilities obtained by (19) do not depend on the type of distribution of T_i.

If condition (28) is satisfied, then the transition rate matrix will also give the same probabilities as (19). Thus, even though (21) is the equation for a Markov process, the steady state probabilities obtained will be independent of the assumption of exponential distribution. Now

$$\lambda_{ij} = \frac{N_{ij}}{T_i} = \frac{N_{ij}}{T} * \frac{T}{T_i} = \frac{N_{ij}}{T} * \frac{F_{ij}}{p_i} \tag{31}$$

That is, the transition rate obtained by dividing the frequency of transition from i to j by steady state probability will give the results independent of probability distribution. This point was also noted in [78] during the response by authors of [78] to a question by one of the discussers.

4.2.4 Summary of Analysis

The following can be stated as a result of this discussion and analysis:

1) To be able to reproduce the probabilities obtained directly from state residence times using equation (19), the condition (28) needs to be satisfied while using the interstate frequency data.
2) When building transition rate matrix, only (n-1) equations are available from (21), so if n-1 or fewer transition frequencies are missing or doubtful, these can be uniquely determined using (28). If more than n-1 are missing, then multiple solutions are possible but will yield the same probabilities so long (28) is satisfied. However, the frequency index cannot then be unique.
3) When recovering missing information in the transition rate matrix, (2n-1) missing variables can be solved with unique solutions.
4) When condition (28) is satisfied and the transition rates are obtained by (23), these equivalent transition rates will reproduce correct steady state probabilities irrespective of the underlying probability distribution of the state residence times.

4.3 Examples for Illustration

Three case studies were conducted to verify and illustrate the use of the equivalence conditions. First case study focuses on building a transition rate matrix from a probability vector in the absence of data in interstate transitions; second case study focuses on the recovery of missing information in a transition rate matrix using probability vector; third case study focuses on using sequential Monte Carlo Simulation (MCS) using transition rate matrix built from probability vector.

It should be noted that the focus of this research is on building models for units using incomplete data and not the system analysis. So, the examples selected are purposefully of small systems to verify and illustrate the concepts.

4.3.1 Case Study I

Case study I was conducted based on the example of a 3-state generator. This is one of the most frequently used models for a generating unit in system planning studies [79]. From the data collected, the times spent by the generator in three states are assumed known and given in Table 14. The probabilities of the three states can be estimated using (19) and are given in the Table 14.

Table 14 State residence time and state probability

State	**Time in hours**	**Probability**
1	40000	0.86956522
2	4000	0.08695652
3	2000	0.04347826
Total	46000	1

For example, the estimate of probability of state 2 is shown in (32),

$$\text{Probability of state 2} = \frac{4000}{40000+4000+2000} = 0.086956652 \tag{32}$$

The data on transition between various states has not been collected and so is not known. Now we want to use this data in an algorithm or software that is based on transition rates like sequential MCS, so we would like to assign transition rates such that the state probabilities are the same as in Table 14. To obtain probabilities in Table 14 using a transition rate matrix, two cases are generated for the number of interstate transitions. The matrices shown in Table 15 (case 1) and Table 16 (case 2) assign different number of interstate transitions, i.e., N_{ij}. These numbers of transitions are over the same total time as in Table 14.

Any set of arbitrary transition frequencies, so long as these satisfy the condition given by equation (28), when converted to transition rates using the state residence times in Table 14, will reproduce the probabilities in Table 14 by using these transition rates. However, it can require some effort to generate these frequencies. An easier way to generate matrices for the number of interstate transitions is to start from a reference model of a similar component with complete and correct data. For example, Table 15 is generated from a reference model of 3-state generator from [75] as a 50MW fossil fuel generator. We start from transition rates matrix from [75] as shown in (33) (unit: transitions/hour).

$$R_{reference} = \begin{bmatrix} -0.0033 & 0.00183 & 0.00147 \\ 0.00595 & -0.00757 & 0.00162 \\ 0.0124 & 0.00441 & -0.01681 \end{bmatrix} \quad (33)$$

Table 15 Number of interstate transitions of case 1

State	1	2	3	Row Sum
1	0	59	47	106
2	60	0	16	76
3	46	17	0	63
Column Sum	106	76	63	

Using equations (21) and (22), the probability vector of reference model is obtained in (34).

$$P_{reference} = [p_1 \quad p_2 \quad p_3] = [0.70055995 \quad 0.21724168 \quad 0.08219837] \quad (34)$$

Using equation (33) and (34) the interstate frequency matrix of reference model is calculated in (35) (unit: transitions/hour) and used in this case study to generate the matrix of number of interstate transitions.

$$F_{reference} = \begin{bmatrix} 0 & p_1\lambda_{12} & p_1\lambda_{13} \\ p_2\lambda_{21} & 0 & p_2\lambda_{23} \\ p_3\lambda_{31} & p_3\lambda_{32} & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0.00128202 & 0.00102982 \\ 0.00129259 & 0 & 0.00035193 \\ 0.00101926 & 0.00036249 & 0 \end{bmatrix} \quad (35)$$

Using equation (31) and states residence time in Table 14, the interstate transition matrix, Table 15, is generated in (36) with integer rounding. These interstate transitions are over the same time period as the state residence times in Table 14.

$$N = T \cdot F_{reference} = \begin{bmatrix} 0 & 58.9731 & 47.3719 \\ 59.4590 & 0 & 16.1889 \\ 46.8860 & 16.6748 & 0 \end{bmatrix} \approx \begin{bmatrix} 0 & 59 & 47 \\ 60 & 0 & 16 \\ 46 & 17 & 0 \end{bmatrix} \quad (36)$$

It should be noted that this operation is suggested only as a convenient method to generate transition frequency matrix instead of arbitrary guessing. It guarantees the matrix generated is frequency balanced, and the scale of frequency is perhaps closer to reality. But since the frequency is taken from a reference model and is not based on real data which is non-existent, any frequency result from this matrix will follow the reference model and not represent physical data of the actual component. The probability information, however, will be correct. Table 16 is generated based on Table 15 with small changes on the number of interstate transitions.

Table 16 Number of interstate transitions of case 2

State	1	2	3	Row Sum
1	0	50	40	90
2	60	0	10	70
3	30	20	0	50
Column Sum	90	70	50	

Table 15 and Table 16 both follow the relationship in (28) for frequency balance. A quick check on frequency balance of each state is that the column and row sum for the state should be equal. For example, in Table 14, the column sum for state 1 is 106, i.e., the number of times the component enters the state and the row sum is also 106, the number of times the component exits the state. Therefore, the state 1 is balanced for frequency. Similarly looking at Table 15, states 2 and 3 are also balanced.

An interstate transitions matrix can be converted to interstate transition rates matrix using (23). The interstate transition rate matrices R corresponding to Table 15 and Table 16 are shown in Table 17 and Table 18. For example, the transition rate from state 1 to 2 in Table 17 is found in (37) by dividing $N_{12} = 59$ by $T_1 = 40000$

$$\lambda_{12} = \frac{59}{40000} = 0.001475 \text{ (transition/hour)} \tag{37}$$

Table 17 Interstate transition rate matrix of case 1

State	**1**	**2**	**3**
1	-0.00265	0.001475	0.001175
2	0.015	-0.019	0.004
3	0.023	0.0085	-0.0315

Table 18 Interstate transition rate matrix of case 2

State	**1**	**2**	**3**
1	-0.00225	0.00125	0.001
2	0.015	-0.0175	0.0025
3	0.015	0.01	-0.025

The off-diagonal elements are the transition rates using (23) and the diagonal elements are obtained by the negative of row sum [1]. It should be noted that the diagonal elements are not physical transition rates but values calculated from the transition rates for calculation with equations (21) and (22).

State probabilities found using (21) and (22) for matrices in Table 17 and Table 18 are shown in Table 19 and are identical to those found using (19) in Table 14.

Table 19 State probabilities corresponding to Table 17 and Table 18

State	Probabilities Using Table 15/Table 17	Probabilities Using Table 16/Table 18
1	0.86956522	0.86956522
2	0.08695652	0.08695652
3	0.04347826	0.04347826

It should be noted that the number of interstate transitions in Table 15 and Table 16 are different but the states are frequency balanced. Under these conditions, the probabilities for both cases are identical to those obtained using (19). The frequencies were next unbalanced by changing entry N_{12} from 59 to 50 and then 40 but keeping the other entries unchanged in Table 15. The resulting frequency matrices are shown in Table 20 and Table 21.

Table 20 Number of interstate transitions of unbalanced case 1

State	1	2	3	Row Sum
1	0	50	47	97
2	60	0	16	76
3	46	17	0	63
Column Sum	106	67	63	

Table 21 Number of interstate transitions of unbalanced case 2

State	1	2	3	Row Sum
1	0	40	47	87
2	60	0	16	76
3	46	17	0	63
Column Sum	106	57	63	

In Table 20 and Table 21, the row and column sum for state two are not equal. These interstate transitions matrices were converted to the transition rate matrices and then probabilities were computed and are shown in Table 22. The probabilities now deviate from the state residence time based probabilities in Table 14, deviation increasing with the scale of frequency imbalance.

Table 22 State probabilities when frequencies are unbalanced

State	$N_{12} = 59$ Frequency Balance	$N_{12} = 50$	$N_{12} = 40$
1	0.86956522	0.88039770	0.89275477
2	0.08695652	0.07698606	0.06561234
3	0.04347826	0.04261624	0.04163290

This study is important in showing the importance of ensuring consistency between data on transition rates and probabilities. Let us say that data has been collected both for interstate transitions and state residence times. It does happen that there can be an error in counting the number of interstate transitions and the interstate frequency matrix may not be balanced. In such a case the transition rate matrix will not reproduce the state probabilities calculated directly by the state residence times. So, it is important that the interstate frequency matrix be checked for satisfying the condition of frequency balance.

4.3.2 Case Study II

The second case study is focused on recovering missing information in a transition rate matrix using the probability vector. The case study is also based on the example of a 3-state generator.

The problem is formulated as following: known information includes probability vector from Table 14 and partial information of transition rate matrix. It is assumed that the transition rate matrix had been constructed and the state probabilities calculated. Then some elements of the transition rate matrix are lost. In this example, the problem is to recover the missing 5 variables in the transition rate matrix in (39) with probability vector in (38).

$$P = [p_1 \quad p_2 \quad p_3] = [0.86956522 \quad 0.08695652 \quad 0.04347826] \tag{38}$$

$$R = \begin{bmatrix} -0.00265 & \lambda_{12} & \lambda_{13} \\ \lambda_{21} & -0.019 & \lambda_{23} \\ 0.023 & 0.0085 & \lambda_{33} \end{bmatrix} \tag{39}$$

According to equation (29) and (30), 6 equations can be derived. Firstly, equations in (40) consider the frequency enforcement with row operation.

$$\begin{cases} -0.00265 + \lambda_{12} + \lambda_{13} = 0 \\ \lambda_{21} - 0.019 + \lambda_{23} = 0 \\ 0.023 + 0.0085 + \lambda_{33} = 0 \end{cases} \tag{40}$$

Secondly, equations in (41) consider frequency balance with column operation.

$$\begin{cases} p_1 * (-0.00265) + p_2 * \lambda_{21} + p_3 * 0.023 = 0 \\ p_1 * \lambda_{12} + p_2 * (-0.019) + p_3 * 0.0085 = 0 \\ p_1 * \lambda_{13} + p_2 * \lambda_{23} + p_3 * \lambda_{33} = 0 \end{cases} \tag{41}$$

Take any 5 equations from 6 equations in (40) and (41) and they form independent equations which solve the missing 5 variables with a unique solution as shown in (42) and (43).

$$\begin{bmatrix} 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & p_2 & 0 & 0 \\ p_1 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \lambda_{12} \\ \lambda_{13} \\ \lambda_{21} \\ \lambda_{23} \\ \lambda_{33} \end{bmatrix} = \begin{bmatrix} 0.00265 \\ 0.019 \\ -0.0315 \\ p_1 * 0.00265 - p_3 * 0.023 \\ p_2 * 0.019 - p_3 * 0.0085 \end{bmatrix} \tag{42}$$

$$\begin{bmatrix} \lambda_{12} \\ \lambda_{13} \\ \lambda_{21} \\ \lambda_{23} \\ \lambda_{33} \end{bmatrix} = \begin{bmatrix} 0.001475 \\ 0.001175 \\ 0.015 \\ 0.004 \\ -0.0315 \end{bmatrix} \tag{43}$$

If solutions for the 5 missing variables in (43) are put back into the transition rate matrix, its unique solution matches the full transition rate matrix in Table 17 correctly.

This case study shows that for a component with n states, it is possible to fully recover transition rate matrix with unique solution for a maximum of (2n-1) missing variables.

4.3.3 Case Study III

The third case study is focused on Monte Carlo simulation using transition rate matrix built using the probability vector. Two scenarios were evaluated in this case study. First scenario has only 1 component as the example of a 3-state generator and the second scenario consists of 3 components.

The first scenario is based on the example of a 3-state generator with probability vector in Table 14 and transition rates matrix in Table 17. Generation capacity of state 1 is 50MW, and 25MW, 0MW for state 2 and 3 respectively. The load level is held constant at 30 MW.

To provide a reference for comparison, analytical solution for this scenario is calculated in (44) and (45). Loss of Load Probability (LOLP) is the probability of states 2 and 3 and Failure Frequency (FF) is the frequency summation between states 1-2 and 1-3.

$$LOLP = 0.13043478 \tag{44}$$

$$FF = 20.18608696(/year) \tag{45}$$

Now sequential MCS is used which needs a transition rate matrix to run. In the first MCS trial, assume the transition rate matrix built is in Table 17. The simulation time is 10000 years with coefficient of variation (COV) less than 1%. The results of first MCS trial are given in Table 23.

It can be seen in this MCS trial that since the transition rate matrix used is the same as analytical method, as expected, results of LOLP and FF are the same as analytical solutions.

Table 23 MCS results of trial 1 in scenario 1

	Analytical Solution	MCS	Error Percentage
LOLP	0.13043478	0.13042856	-0.00477 %
FF (/y)	20.18608696	20.17225009	-0.06855 %

In the second MCS trial, assume the transition rate matrix built is in Table 18. The simulation time is 10000 years with COV less than 1%. The result of second MCS trial is given in Table 24.

Table 24 MCS results of trial 2 in scenario 1 with alternative transition rate matrix

	Analytical Solution	MCS-Alternative	Error Percentage
LOLP	0.13043478	0.13041293	-0.01675 %
FF (/y)	20.18608696	17.10156702	-15.28043 %

The transition rate matrix in Table 18 is derived from the interstate transitions matrix of Table 16 but the state residence times of Table 14. So, the difference from Table 17 is in using a different set of number of interstate transitions but the same state residence times. But since the underlying interstate transitions matrix still follows frequency balance, the result of LOLP is the same as analytical solutions.

In the third MCS trial, assume the transition rate matrix is based on interstate transitions matrix Table 21, which is frequency imbalanced but the state residence times are from Table 14. The simulation time is 10000 years with COV less than 1%. The result of third MCS trial is given in Table 25.

The transition rate matrix in this case is derived from the interstate transitions matrix in which the frequencies are not balanced. So even though the state residence times are still from Table 14, we are not able to reproduce the correct LOLP.

Table 25 MCS results of trial 3 in scenario 1 with wrong transition rate matrix

	Analytical Solution	**MCS-Wrong**	**Error Percentage**
LOLP	0.13043478	0.10718643	-17.82374 %
FF (/y)	20.18608696	16.96758174	-15.94418 %

In the second scenario, MCS is used for a system with 3 components. The system consists of two generators and one transmission line to supply the load. The simple topology is shown in Fig.1. The two generators are the same as in first scenario, the transmission line is a two-state component, the reliability parameter is captured from [75] as transmission line between bus 101 and 102. Transmission capacity of up state is 100MW and 0MW for down state. The load level is constant at 80MW.

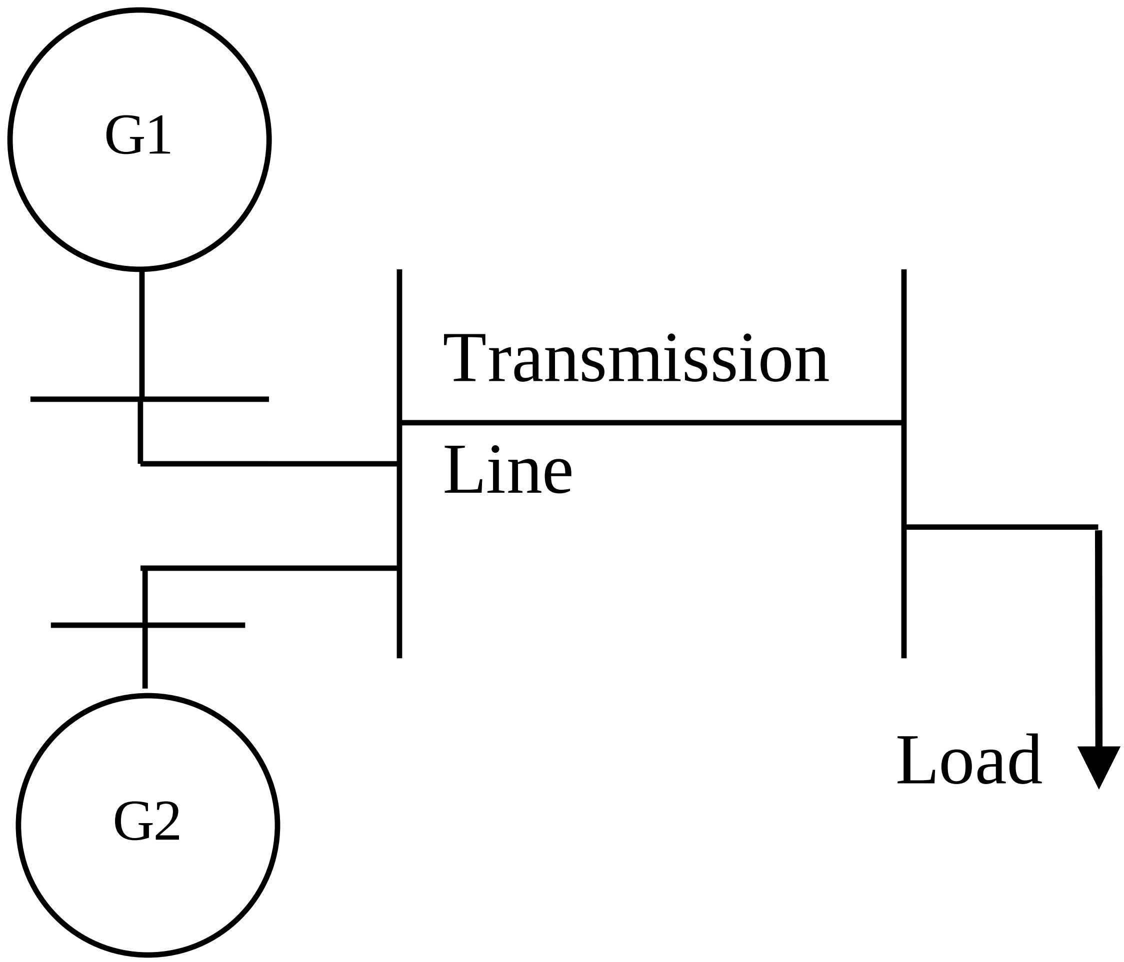

Figure 49. Topology of MCS Scenario 2. Reprinted from [70].

Analytical solution for this scenario is calculated in (46) and (47).

$$LOLP = 1 - p_1^2 p_{TL-up} = 0.34248378 \tag{46}$$

$$FF = \left((\lambda_{12} + \lambda_{13}) * 2 + \lambda_{TL}\right) * p_1^2 p_{TL-up} = 25.91928988\ (/year) \tag{47}$$

The three MCS trials were conducted similar to scenario 1. In the first trial, assume both generators have transition rates matrix as Table 17, which is the same as actual components. In the second trial (MCS-Alternative), assume both generators have transition rates matrix as Table 18, which is different from actual components but still follows frequency balance. In the third trial (MCS-Wrong), assume both generators have transition rates matrix based on Table 21 whose frequencies are unbalanced.

The simulation time is 10000 years with COV less than 1%. The result of first MCS trial is given in Table 26.

Table 26 MCS results of all 3 trials in scenario 2

	Analytical Solution	**MCS**	**Error Percentage**
LOLP	0.24418765	0.24415417	-0.01371 %
FF (/y)	35.27225086	35.29386356	0.06127 %
	Analytical Solution	**MCS-Alternative**	**Error Percentage**
LOLP	0.24418765	0.24439877	0.08646 %
FF (/y)	35.27225086	29.97158731	-15.02786 %
	Analytical Solution	**MCS-Wrong**	**Error Percentage**
LOLP	0.24418765	0.20355609	-16.63948 %
FF (/y)	35.27225086	30.54513721	-13.40179 %

It can be seen in Table 26 that the second scenario of MCS follows the same pattern as of scenario 1.

When using the exact transition rate matrix, the LOLP and FF results are the same as analytical solutions; when using alternative transition rate matrix, LOLP result is still correct but FF is different from analytical solutions; when using wrong transition rate matrix that don’t follow frequency balance, the result of LOLP and FF are different from analytical solutions.

4.4 Summary

The investigation in this research is focused on the equivalence between the state probabilities obtained directly from the data on state residence times and those obtained from transition rate matrix derived from data, real or assumed, on frequencies of interstate transitions.

A mathematical equation has been derived that sets the condition for these two calculated probabilities to be equal. The following situations have been used to illustrate the usefulness of this condition.

The first is a situation where only the data on state residence times is available but the computer algorithm is based on sequential MCS. It is shown that any arbitrary matrix of interstate frequencies will reproduce the state probabilities so long as the frequencies are balanced for each state. However, a convenient method of forming the interstate frequency matrix is also suggested.

It is also shown that if the interstate frequencies are not balanced, then the probabilities calculated will not be correct. This case is important to show that when data is collected for both state residence times and the interstate frequencies, it is important to ensure the balance of frequencies as there could be errors introduced because of data entry or data processing.

It is also shown that for an existing interstate matrix, if some elements get lost, how these can be uniquely recovered.

It is shown that if the interstate transition rates are calculated by a ratio of frequency to probability, then the equivalent transition rates will calculate correct steady state probability irrespective of the underlying probability distribution of state residence times.

5. CONCLUSIONS AND OUTLOOK*

This dissertation investigates the reliability evaluation of line switching operations in power system as well as the incomplete data issues in reliability evaluation. The major contributions, research conclusions, and outlook are summarized as follows.

5.1 Contributions and Conclusions

In section 2, a reliability evaluation method for studying the reliability implications of line switching operations in power systems is proposed and demonstrated. Two case studies are conducted on IEEE RTS and IEEE 118-bus system to illustrate this method. This method is designed to explore previously overlooked areas in reliability evaluation of line switching operations.

Line removal test is proposed to sweep all transmission lines in the system for simulation data, six reliability indices are used to conduct risk analysis and impact analysis. Instead of the traditionally used mean value analysis, variance analysis is introduced into reliability evaluation. Weibull distribution is used to reconstruct distributions of reliability indices which reveal

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overlooked patterns in worst case comparisons. Eventually, line categorization for line switching operations is introduced to classify all transmission lines based on their reliability performance. The categories provide reliability implications of line switching operations and can be used for guidance in actual operations.

It is observed in both case studies that a few recommended lines and critical-risky lines are found. Most (around 70%) transmission lines are safe lines that could be safely utilized in line switching operations, the rest 30% critical lines could contribute to line switching operations under rare cases yet needs to be dealt with caution.

The contributions of research in section 2 are listed as following:

1) The authors introduced an investigation process to study the failure events subsequent to a line switching operation. Although the concept is similar to adequacy evaluation, but with newly introduced data analysis method, the objective is not adequacy evaluation, but to study the impact of line removal through sampling of potential failure states subsequent to line switching operations.
2) Sequential MCS is used to form an approximate state space model with probabilistic enumeration of events subsequent to a specific line removal. Different from previous work, this test intends to capture all states in state space instead of any special state.
3) Weibull distribution is used to reconstruct the distribution of reliability indices from recorded simulation data. This analysis provides the variance patterns and worst-case scenarios.
4) The event-based HLOLE and EENS are introduced. Different from the yearly-based indices, these indices are based on each failure event. These indices are used in impact analysis to separate failure frequency from the impact of each failure event so

that the low probability, high impact events are not diluted in the analysis. This is useful in the worst-case scenario comparison and reveals patterns different from intuitive expectations.

5) Two new indices, EENSP and LDLE, are introduced for impact analysis. Since they record new information in simulation, their pattern in results analysis is different from traditional analysis and are used as supplemental consideration in line categorization.
6) Based on reliability performance of each transmission line, line categorization is proposed to provide guidance on line switching operations considering reliability implications.

In section 3, a hybrid reliability evaluation method is proposed for line switching operations in power system. CR method is introduced as a pre-selection method to speed up the simulation and to provide analytical analysis of state space. The proposed reliability evaluation method was tested on two systems, RTS and IEEE 118-bus system. In both case studies, CR pre-selection method picked up critical lines with reasonable accuracy and showed a significant improvement of calculation speed. Other than the ranking list, the dictionary outputs from CR pre-selection method reduces the computation burden in simulation stage and provides analytical guidance compared to the randomness inherent in MCS reliability evaluation. In the updated analysis, the differences between event-based and yearly-based indices are further analyzed to distinguish the distribution difference and only selected results are shown to emphasize observed patterns from proposed hybrid reliability evaluation method.

The contributions of research in section 3 are listed as following:

1) A novel CR method with improvements to accommodate reliability evaluation is introduced as a pre-selection step of the proposed hybrid method. It not only reduces

the computation time of this method, but also provides analytical understanding of state space contrary to the inherent randomness of traditional reliability evaluation based on MCS alone.

2) A new performance index (PI), based on Expected Power Not Supplied Percentage (EPNSP) is proposed in this research to be used as an indicator in the CR pre-selection method. Its performance is superior to the traditional PI and its direct connection to load loss ensures more accurate pick-up rates of pre-selection method.
3) Two outputs are obtained from the CR method: the ranking list and the newly introduced dictionary. Both are utilized in the MCS afterwards. The ranking list generated is used to guide the sequence of line removal tests and significantly reduce the number of tests required while still picking up most of the target transmission lines with non-trivial difference from benchmark case. The dictionary is used to speed up simulation and provide map of PIs for analytical analysis of state space.
4) The difference between event-based and yearly-based indices is discussed in this research to provide guidance on results analysis. Instead of showing all the recorded results, only important results are shown to emphasize patterns observed.
5) Contrary to intuition, removal of some transmission lines is found to be beneficial to the reliability of power system. The reasons are further analyzed in section 3.3.

In section 4, the investigation in this research is focused resolving the incomplete data issues in reliability evaluation. The first part is focused on the equivalence between the state probabilities obtained directly from the data on state residence times and those obtained from transition rate matrix derived from data, real or assumed, on frequencies of interstate transitions. A mathematical equation has been derived that sets the condition for these two calculated probabilities to be equal. The following situations have been used to illustrate the usefulness of this condition. The first is a situation where only the data on state residence times is available but the computer algorithm is based on sequential MCS. It is shown that any arbitrary matrix of interstate frequencies will reproduce the state probabilities so long as the frequencies are balanced for each state. However, a convenient method of forming the interstate frequency matrix is also suggested. It is also shown that if the interstate frequencies are not balanced, then the probabilities calculated will not be correct. This case is important to show that when data is collected for both state residence times and the interstate frequencies, it is important to ensure the balance of frequencies as there could be errors introduced because of data entry or data processing.

It is also shown that for an existing interstate matrix, if some elements get lost, how these can be uniquely recovered. It is shown that if the interstate transition rates are calculated by a ratio of frequency to probability, then the equivalent transition rates will calculate correct steady state probability irrespective of the underlying probability distribution of state residence times.

The contributions of research in section 4 are listed as following:

1) This research derives the mathematical conditions that should be satisfied for the probabilities obtained from the Markov model using transition rates to be identical with those obtained from the state residence times. Then these results are illustrated by giving examples how this information can be used in the various situations just discussed.
2) This research also provides guidance on building and recovering transition rate matrix in the absence of complete data.

3) This research also shows that although the transition rates derived from the data are used in a Markov model with the implicit assumption of exponential distribution of state residence times, these constant transition rates are in fact equivalent rates and so far as the steady state probabilities are concerned, these will not be affected by the probability distribution of state residence times.

5.2 Outlook

The outlook of future work is summarized in this section.

One extension work in reliability evaluation of line switching operations is the introduction of Network Topology Optimization. In recent years, some research has indicated the potential benefits brought by changing the power system topology through optimal transmission switching (OTS) and/or busbar switching. There is evidence showing the incorporation of busbar switching in short-term power system operation strategy could serve as a remedial action to relieve transmission line overloading and prevent load loss considering the security constraints.

Another future work is on the improvement of traditional MCS. In current research presented in this dissertation, results of line categorization are the output of the proposed method based on reliability implications. There is evidence on utilizing variance reduction approaches to improve convergence of MCS. The simulation and calculation presented in this research are used to describe an approach for offline use to create “look-up-table” for operators when performing line switching operations. However, in actual implementation the speed could be greatly improved by variance reduction techniques such as importance sampling.

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