

Reliability Evaluation in Transmission Systems

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1 Introduction

In reliability evaluation of the bulk power system (generation and transmission) two kinds of analyses are used, depending on the extent and the purpose of the study: composite system analysis is used to perform a detailed study of a system or a part thereof, while a multiarea study usually encompasses a much larger system of interconnected utilities or control areas. Composite power system reliability evaluation is concerned with the total problem of assessing the ability of the generation and transmission system to supply adequate and suitable electrical energy to major system load centers. While in the multiarea reliability evaluation the transmission constraints are only indirectly considered, in the composite power system reliability internal transmission limitations are directly modeled. These reliability studies can help in better representation of generation effects in transmission system reliability analysis and optimize relative investments in generation and transmission systems, including dispersed generation.

It should be pointed out that multiarea and composite system reliability studies are both multinode and similar in many ways. The major difference is in the transmission network modeling and because of the more detailed network model, the composite system reliability model has many more nodes than the multiarea model. In addition, the type of network flow models used in these types of studies is sometimes different. Network flow model (transportation type) and DC flow methods are considered adequate for multiarea reliability evaluation but DC flow or AC flow methods are considered more appropriate for composite system reliability evaluation.

The methods used in composite system reliability evaluation could be either deterministic or probabilistic. The main principle in the deterministic methods is to maintain adequate service under most likely outages but to also accept some degradation of performance under low probability outages involving multiple generation and transmission facilities. The probabilistic methods model the factors affecting reliability more comprehensively and may be analytical, Monte Carlo simulation, or hybrid.

We first discuss the component models and then the various methods of evaluation of reliability.

2 Component Models

For performing the reliability analysis of any system, the component models need to be properly defined. The following components are considered in composite system reliability evaluation:

- Generating units
- Transmission lines
- Transformers
- Buses
- Circuit breakers

In addition, weather is an important component of this analysis and common mode failures of groups of components need to be specified.

2.1 Generating Unit Models

Generators are typically modeled as two- or three-state devices. The state transition diagram of a three-state generator is shown in Figure 1. Here, the various states are represented as follows.

- State 1: Up state with full capacity
- State 3: Down state with zero capacity
- State 2: Derated state represents a weighted average of partial capacity states

A two-state model is a special case of this model where there is no transition to state 2.

2.2 Transmission Lines

Transmission lines are assumed to be either in the up state or failed state. The failure and repair rates are further assumed to be dependent on weather. The state transition diagram of a transmission line is shown in Figure 2, where

λ = failure rate in the normal weather

λ' = failure rate in adverse weather

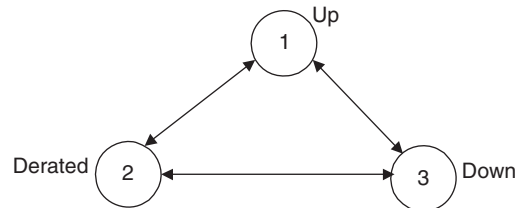


Figure 1 Three-state model of a generator

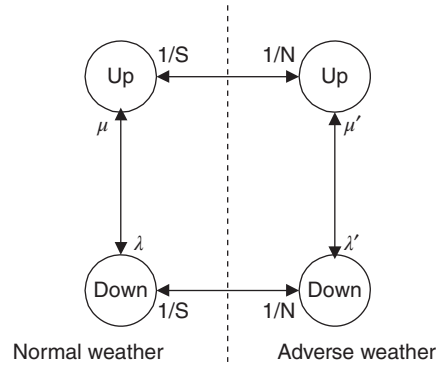


Figure 2 Weather-dependent transmission line model

μ = repair rate in the normal weather
 μ' = repair rate in the adverse weather
 N, S = mean durations of normal and adverse weather

Although weather can exist in several states it is typically assumed to exist either in the normal or the adverse state. An important issue concerning weather is its extent of coverage area. When the system is spread over a large area, at any given time, different regions may have different states of weather. An exact treatment of this effect is difficult and some simplifications are needed. One approach divides the whole area into regions. The weather in each region is characterized by mean duration of normal and adverse states. The weather changes in different regions are assumed independent. Every line is assigned to a particular region which really means that this line is predominantly affected by the weather in this region. It should be noted that for parallel transmission lines just using failure rate, which is the average of normal and adverse weather rates, can lead to error (Singh and Billinton, 1977).

2.3 Transformers and Buses

Similarly to the transmission lines, transformers and buses are treated as two-state devices but the failure rates and repair rates are assumed independent of the weather.

2.4 Circuit Breakers

A circuit breaker can have several failure modes as described below.

1. *Ground Fault.* This refers to a fault in the circuit breaker itself. For this type of fault, the circuit breaker is treated in the same manner as a transformer or a bus.
2. *Failure to Open.* The objective of a circuit breaker is to isolate the faulted component. Because of latent or hidden faults in the breaker or the associated protection system, the breaker may not open when needed. This may result in healthy components being isolated because of the operation of secondary zone protection. This failure mode is typically characterized by probability p in reliability modeling. This means

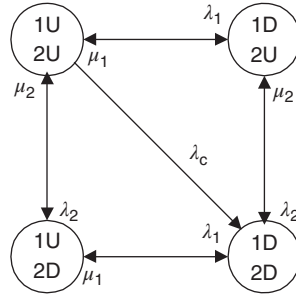


Figure 3 Representation of common mode failure

that when this breaker receives a command to open, there is a probability p that it may not respond. This could be either due to a problem in the breaker or the associated protection system.

3. *Undesired Tripping*. It is also possible that a breaker may open without a command or fault. This can be characterized as a rate and its effect will be an open line.

2.5 Common Mode Failures

A common mode outage is an event when multiple outages occur because of one external cause. An example of common mode outage is the failure of a transmission tower supporting two circuits. Although several common mode outage models have been proposed, a simple common mode outage model for two components is as follows: λ_i , μ_i , are the failure and repair rates of components i and λ_c is the common mode failure rate (Figure 3).

3 Analytical Methods for Composite System Reliability

Any reliability evaluation procedure has three facets to it – state identification, state evaluation to match the objectives, and collection into indices. The analytical methods are directly or indirectly based on some kind of contingency enumeration approach. A direct enumeration approach is described below and depicted in Figure 4. Exhaustive enumeration is, however, not possible except for a small number of components as the number of contingencies increases exponentially with the number of components. Several improvements can be made to this basic enumeration approach to improve its efficiency. Examples are as follows:

1. *Contingency Ranking and Selection*. This procedure consists of the following two steps (Mikolinnas and Wollenberg, 1981; Endrenyi, 1978):
 - (a) Ranking of branch and/or generator outages for overload conditions and voltage problems using a performance index (PI). This procedure will be briefly discussed later.
 - (b) Selection of contingencies from the ranked list using event probability or event depth cut off.
2. *State Space Truncation*. In this approach contingencies of only a certain order are considered. For example, only up to second-order contingencies may be considered.
3. *Implicit Enumeration Based on System Reliability Coherence*. If a state is identified as a failure state, it is assumed that all states resulting from this state by degradation of components are also failure states.

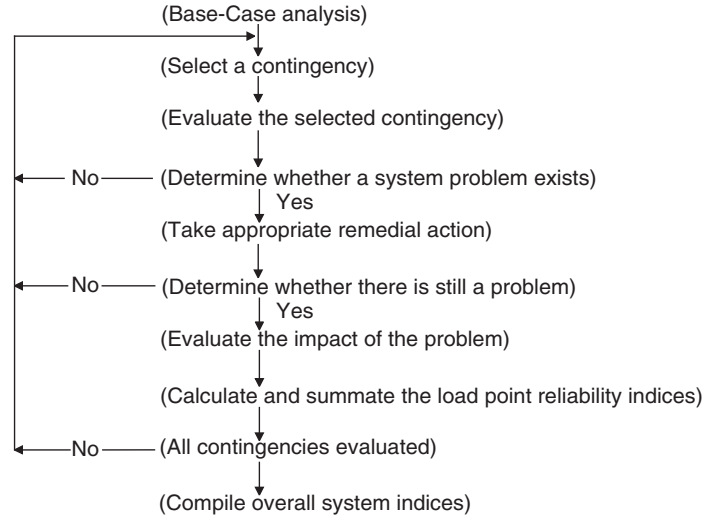


Figure 4 Contingency enumeration scheme

The use of min cut sets (Singh and Billinton, 1977; Liu and Singh, 2010) is actually an application of this principle.

4. *State Space Pruning Using State Space Decomposition*. State space decomposition is a method of recursively classifying the state space into coherent sets of functional and failure sets until all significant states have been classified. The benefit of this method is that it deals with sets of states rather than individual states. It can be made more efficient by using the method of pruning, which rapidly removes large parts of the functional states before decomposition, thereby reducing computational time and effort (Singh and Mitra, 1997).
5. *Non-overlapping Failure Regions*. Higher order outages are restricted to circuits in the same electrical neighborhood, drastically decreasing the number of contingencies to be examined.

3.1 Network Solution Methods

One difference of power system reliability evaluation from some other networks is that the state evaluation is not simple and network flow methods are needed for state evaluation. The three types of solution methods used are described below.

3.1.1 Linear Network Flow Model

Also called *transportation model* (EPRI report EL-5178, 1987), this model is based only on Kirchhoff's first law. Here, the sum of active power flows entering or leaving each bus is equal to the net injection at that bus.

$$\bar{A}F + G = D \quad (1)$$

where

$\bar{A}$ = node-branch incidence matrix

F = circuit flow vector

G = generation vector

D = demand vector

The constraints are

$$G \leq G^{\max}$$

$$F \leq F^f$$

$$-F \leq F^r$$

where

$G^{\max}$ = vector of max available generation

F^f, F^r = vectors of forward and reverse branch capacities

Although this model is generally considered adequate for multiarea reliability analysis and has been used in some commercial programs, for composite system reliability this model is not considered accurate enough.

3.1.2 DC Load Flow or Linearized Power Flow Model

This model is usually expressed by the equation

$$B\theta + G = D \quad (2)$$

where B matrix is such that

$$b_{ij} = \text{ijth element of } B$$

$$= \begin{cases} -(\text{susceptance between nodes } i \text{ and } j) & \text{if } i \neq j \\ \text{sum of susceptances connected to node } i & \text{if } i = j \end{cases}$$

θ = node voltage angle vector

and G and D are the generation and demand vectors as before.

The line flow from node i to node j is given by

$$f_{ij} = (\theta_j - \theta_i)b_{ij}$$

The constraints here are

$$G \leq G^{\max}$$

$$F \leq F^f$$

$$-F \leq F^r$$

where

F = vector of flows f_{ij}

$G^{\max}$ = vector of max available generation

F^f, F^r = vectors of forward and reverse branch capacities

The DC power flow model is generally felt to be a reasonable compromise between computational cost and accuracy for planning studies. This is often used in regions where systems are strongly meshed and do not have voltage problems.

In recent years, there has been renewed interest in development and deployment of power flow control devices as part of the “smart grid” infrastructure. These devices include high-voltage DC lines (HVDC), back-to-back AC–DC–AC ties, unified power flow controllers (UPFCs), as well as some other technologies that allow increased control of power flow over specific lines independently of the impedances of these lines.

While detailed models of these controlled lines vary in complexity, linearized power flow models can be adequately represented using the network flow model (1), because the flows on these lines are no longer dependent on their impedances. Hence for these systems the linearized power flow models can be represented as follows.

$$B\theta + \bar{A}_{\text{cont}}F_{\text{cont}} + G = D \quad (3)$$

where

$\bar{A}_{\text{cont}}$ = node-branch incidence matrix for the controllable lines only

F_{cont} = vector of real power flows on controllable lines.

3.1.3 AC Power Flow Model

The AC flow model handles both active and reactive power flow model aspects. In addition to the bounds on generator active power generation there are bounds to reactive power and constraints on voltage at buses (Bergen and Vittal, 1999).

3.2 Remedial Actions

The remedial measures are invoked after all the automatic controls as part of the network solution are exhausted.

Steps:

- Identification of failed operating constraints: line overloads, low/high bus voltages, generator reactive power output violations, area net MW export violations
- Use of linear programming to determine optimal remedial actions

DC Mode:

- Phase shifter adjustment
- Generation re-dispatch
- Interruptible load curtailment
- Critical load shedding

AC Mode:

- MW and MVAR generation adjustment
- Gen bus voltage adjustment
- Phase shifter adjustment
- Transformer tap adjustment
- Switched cap/reactor
- Load curtailment

3.3 Contingency Ranking and Selection

Contingency ranking and selection is one of the techniques that has been used in a program developed by Electric Power Research Institute. The goal of contingency selection techniques is to determine from the set of all possible contingencies the subset that will cause system failure. No contingency selection method can attain this goal perfectly; they can perhaps at best provide a subset that contains most contingencies causing system failure.

One possible approach would be to rank contingencies by first solving each contingency using DC load flow but it would be very time consuming. In a faster but less accurate method contingencies are ranked approximately by severity based on a PI. The scalar function, called *PI*, is first defined to provide a measure of system stress. Then a suitable technique is used for predicting ΔPI , that is, the change in PI when a component is outaged. The ΔPI values for contingencies are then used to rank them in the order of severity. Then AC or DC load flows are used to determine which of these ranked contingencies actually do cause problems.

When a certain specified number of consecutive contingencies do not lead to system failure, the process is stopped. The assumption here is that the remaining lower ranked contingencies will also not cause system failure. This is not a foolproof method of ranking contingencies. It is possible that some severe contingencies may be left out and also some not so severe contingencies may be ranked. Contingency ranking may be done on the basis of either overload or voltage problems. A brief discussion is provided here for contingency ranking based on overloads. A PI used for this purpose is described in EPRI report EL-2526 (1982):

$$PI = \sum_{\ell} W_{\ell} \left(\frac{P_{\ell}}{\bar{P}_{\ell}} \right)^n \quad (4)$$

where

W_{ℓ} = weighting factor for circuit ℓ

P_{ℓ} = real power flow on circuit ℓ

$\bar{P}_{\ell}$ = power rating of circuit ℓ

n = an even integer, generally 2

Several approaches for finding ΔPI have been proposed. PI can generally provide a good measure of system stress. In cases where load in one branch increases but that in others decreases, the PI may fail to recognize overloads, resulting in a masking phenomenon. Masking can be reduced by increasing the exponent n but it becomes difficult to solve ΔPI for $n > 2$.

3.3.1 PI for Generator Outages

Generator outages are ranked based on the prediction of overloads resulting from outages. The PI used is the same as that for lines. The change in PI resulting from a change in P_i , the power injection at the i th bus, is estimated by

$$\Delta PI = \frac{\partial PI}{\partial P_i} \Delta P_i \quad (5)$$

This linear predictor has been found to produce reasonably good rankings for generating unit outages. An implementation using DC power flow is shown below.

$$\frac{\partial PI}{\partial P_i} = n \hat{\theta}_i$$

where

$\hat{\theta}_i$ = i th component of vector $\hat{\boldsymbol{\theta}}$

N = number of buses

$\hat{\boldsymbol{\theta}} = \mathbf{B}^{-1}\hat{\mathbf{P}}$

$\mathbf{B} = N \times N$ system susceptance matrix (as discussed in Section 3.1.2)

$\hat{\mathbf{P}}$ = vector of length N built by adding for *every* circuit ℓ , an injection of $\hat{P}_\ell$ on the from bus and $-\hat{P}_\ell$ on the to bus of circuit ℓ where

$$\hat{P}_\ell = \frac{W_\ell B_\ell^n \theta_\ell^{n-1}}{\bar{P}_\ell^n} \quad (6)$$

In other words, $\hat{\mathbf{P}}$ is the sum of ℓ vectors each of which contains $\hat{P}_\ell$ on the from bus and $-\hat{P}_\ell$ on the to bus of circuit ℓ , and 0 at all other buses. In Equation (6), θ_ℓ denotes the angle difference between the from bus and to bus of circuit ℓ . After the base case DC flow calculation, elements of $\mathbf{B}$ and the values of θ_ℓ are available. One additional calculation is required to find $\hat{\boldsymbol{\theta}}$.

3.3.2 Contingency Selection Based on Voltage Deviations

When a circuit is outaged, two factors contribute to voltage drop – loss of charging of the outaged circuit and increased var consumption on circuits that have increased loading as a result of this outage. One of the simplest PI is

$$\text{PI} = \sum_{\ell} X_{\ell} P_{\ell}^2 \quad (7)$$

where

X_{ℓ} = reactance of circuit ℓ

A PI that has shown more success is

$$\text{PI} = \sum_{\ell} X_{\ell} \left(\frac{1}{P_{oi}^2} + \frac{1}{P_{oj}^2} \right)^{0.25} P_{\ell}^2$$

where

X_{ℓ} = reactance of circuit ℓ

P_{ℓ} = power flow on circuit ℓ

i, j = from and to buses of circuit ℓ

P_{oi}, P_{oj} = terms recognizing line charging and/or reactive sources and loads on buses i and j .

3.3.3 Contingency Evaluation

The contingencies are evaluated in the decreasing order of severity. For each single-order contingency, secondary contingencies are also ranked and evaluated. Evaluation is stopped either if a prespecified number of successes are encountered or if the contingency probability is lower than a threshold.

4 Monte Carlo Simulation

Monte Carlo simulation is one of the accepted approaches to composite power system reliability evaluation. It tries to overcome the problem of state space dimensionality by sampling. It estimates the reliability

indices by simulating the actual process and random behavior of the system. The two broad categories are random sampling or non-sequential simulation and sequential simulation. Sequential simulation is generally slower to converge than random sampling. If frequency and duration indices are not of interest, random sampling requires less data than sequential simulation. Sequential simulation, however, is suitable for considering time-correlated events and in general is more powerful, especially if dependent failures are involved.

4.1 Basic Idea of Random Sampling

Let

$$x = (x_1, x_2, \dots, x_m)$$

be a state of power system where

x_i = state of i th component

X = set of all possible states x

$P(x)$ = probability of state x

Let

$F(x)$ = test applied to verify if state x is able to satisfy the load.

The expected value of $F(x)$

$$E(F) = \sum_{x \in X} F(x)P(x) \quad (8)$$

For $E(F)$ to be loss of load probability,

$$F(x) = \begin{cases} 1 & \text{if load is curtailed in state } x \\ 0 & \text{otherwise} \end{cases}$$

Now $E(F)$ would be the true value of loss of load probability as it is computed by using the entire state space X . In random sampling, $x \in X$ are sampled from their joint distributions and then estimate of $E(F)$ is found using

$$E(F) = \frac{1}{NS} \sum_{i=1}^{NS} F(x^i) \quad (9)$$

where

NS = number of samples

x^i = i th sampled value

$F(x^i)$ = test result for i th sampled value

The variance of the estimate can be calculated as

$$V(\hat{E}(F)) = \frac{V(F)}{NS} \quad (10)$$

Since $V(F)$ is not known, its estimate can be used:

$$\hat{V}(F) = \frac{1}{NS} \sum_{i=1}^{NS} F((x^i - \hat{E}(F))^2 \quad (11)$$

As explained later, the variance of the estimate is used to calculate the coefficient of variation that can be used for testing the convergence of the simulation.

4.2 Algorithm for Sampling

The algorithm for state sampling can be formalized as

1. Set sample number $NS = 0$
2. $NS = NS + 1$, select state $x^i \in X$ by sampling from the probability distribution of $P(x)$, explained later.
3. Calculate $F(x^i)$.
4. Estimate $\hat{E}(F)$.
5. Calculate uncertainty of the estimate, explained later.
6. If uncertainty is acceptable, stop, otherwise return to step 2.

4.2.1 System State Selection (Step 2 in the Algorithm)

Assuming that components are independent, the system state can be sampled by sampling the states of components. The principle of proportionate allocation is used, that is, the states are sampled proportional to their probability. A value z is sampled from a uniform distribution in $[0, 1]$ using pseudo random number generator. The state can be found from the cumulative probability distribution by equating

$$z = P(X \leq x_i) \quad (12)$$

and the value of x_i is determined as shown in Figure 5.

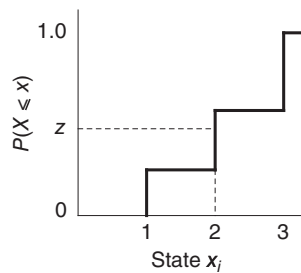


Figure 5 Finding the value of variate

4.2.2 Convergence (Step 5)

The uncertainty is typically defined using the coefficient of variation as it normalizes the standard deviation. The coefficient of variation of the estimate is defined as

$$\begin{aligned} \text{COV} &= \text{coefficient of variation of the estimator,} \\ &= \frac{\sqrt{V(\hat{E}(F))}}{\hat{E}(F)} \end{aligned} \quad (13)$$

$V(\hat{E}(F))$ = variance of the estimator of $E(F)$

$$\text{COV} = \frac{\sqrt{V(\hat{E}(F))}}{\hat{E}(F)} = \frac{\sqrt{V(F)}}{\sqrt{NS}\hat{E}(F)} \quad (14)$$

From Equation 13 we can obtain the sample size needed to reach a certain level of COV:

$$NS = \frac{V(F)}{(\text{COV} \cdot \hat{E}(F))^2} \quad (15)$$

Some interesting conclusions can be drawn from Equation 15. It can be seen that sample size is not affected by system size or complexity but by the accuracy required and the probability being estimated. The computational effort depends on the sample size (NS) and the CPU time/sample. Thus, for a given COV and the index although the number of samples is independent of the system size the CPU time is not, as the time required for state evaluation for larger systems is higher than that for smaller systems. It should also be remembered that most of the contribution to computation time comes from the state evaluation process. The other factor that contributes to the sample size is the variance. If the variance is high then the sample size is higher. This has led to using variance reduction techniques to reduce the computation time.

4.3 Variance Reduction for Computational Efficiency

There are several techniques to reduce variance to decrease the sample size. Two of these techniques are described here.

4.3.1 Control Variable Method

Let Z be a random variable (rv) that is strongly correlated with F and define

$$Y = F - \alpha(Z - E(Z)) \quad (16)$$

Then

$$E(Y) = E(F) \quad (17)$$

$$V(Y) = V(F) + \alpha^2 V(Z) - 2\alpha C(F, Z) \quad (18)$$

Now if

$$2\alpha C(F, Z) > \alpha^2 V(Z)$$

then

$$V(Y) < V(F) \quad (19)$$

where $C(F, Z)$ is the covariance between F and Z .

Equation 19 implies that if the process is made to converge on Y instead of Z , then it will converge faster. But Equation 17 ensures that the mean value that we compute through Y will be that of Z . For example Z can be loss of load probability (LOLP) due to generation alone and $E(Z)$ can be computed by a generation reliability program that is typically fast.

4.3.2 Antithetic Variable Method

The concept of antithetic variables can be explained as follows.

Let

$$F_\alpha = 1/2(F' + F'')$$

If

$$E(F') = E(F'') = E(F)$$

then

$$E(F_\alpha) = E(F)$$

$$V(F_\alpha) = 1/4[V(F') + V(F'')] + 2C(F', F'')$$

If F' and F'' are negatively correlated, $C(F', F'') < 0$, then

$$V(F_\alpha) < V(F)$$

To obtain negative correlation, use random numbers Z_i to compute $E(F')$ and $(1 - Z_i)$ to compute $E(F'')$.

4.4 Sequential Simulation

In sequential simulation, states of the system are generated sequentially by transition from one state to the next using probability distributions of component state durations and random numbers from $[0, 1]$.

Take a component i . Assume that this component is up and its duration is given by U_i (rv). If z is a random number in $[0, 1]$ then the observation of up time can be drawn by using

$$\begin{aligned} z &= P(U_i \leq U) \\ &= F_i(U) \end{aligned}$$

A component with minimum time makes a transition and causes system transition. State evaluation is done in the same manner as random sampling (Figure 6).

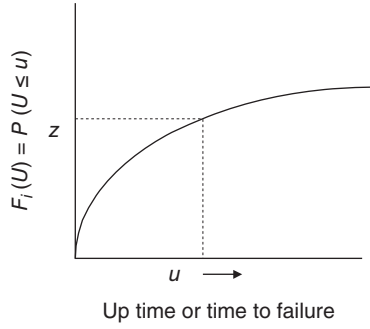


Figure 6 Finding the time to transition

The algorithm can be formulated in the following steps:

Let us assume that the n th transition has just taken place at time t_n and the time to next transition of component i is given by T_i . Thus the vector of times to component transitions is given by $\{T_i\}$ and the simulation proceeds in the following steps.

Step 1. The time to next system transition is given by

$$T = \min \{T_i\}$$

If this T corresponds to T_p , that is, the p th component, then the next transition takes place by the change of state of this component.

Step 2. The simulation time is now advanced:

$$t_{n+1} = t_n + T$$

Step 3. The residual times to component transitions are calculated by

$$T_i^r = T_i - T$$

where T_i^r is the residual time to transition of component i .

Step 4. The residual time for component p causing transition becomes 0 and the time to its next transition T_p is determined by drawing a random number.

Step 5. The time T_i is set where

$$T_{i,i \neq p} = T_i^r \text{ and } T_{i,i=p} = T_p$$

Step 6. From t_n to t_{n+1} , the status of the equipment stays fixed and the following steps are performed:

- a. The load for each node is updated to the current hour.
- b. If no node has loss of load, the simulation proceeds to the next hour; otherwise the state evaluation module is called.
- c. If after remedial action all loads are satisfied, then the simulation proceeds to the next hour. Otherwise, this is counted as loss of load hour for those nodes and the system. In addition, if in the previous hour there was no loss of load, then this is counted as one event of loss of load.
- d. Steps (a)–(c) are performed till t_{n+1} .

Step 7. The statistics are updated and the process moves to step 2.

Step 8. The simulation is continued till the convergence criterion is satisfied.

5 Cyber-Physical Considerations

In composite power system reliability evaluation, the cyber part including communication and protection failures is generally assumed to be perfectly reliable. Thus the failure of a current-carrying component such as a transmission line is assumed to result in the isolation of that component only. However, it has been recognized that protection system hidden or undetected failures are common causes of multiple, extended, or cascading outages (Singh and Patton, 1980a; Phadke and Thorp, 1996; Elizondo *et al.*, 2001; Yang *et al.*, 2006; Yu and Singh, 2004). Studies such as in Yang *et al.* (2006), Yu and Singh (2004), Singh and Patton (1980b), Billinton and Tatla (1983), Bozchalui, Sanaye-Pasand, and Fotuhi-Firuzabad (2005), and Jiang and Singh (2011) indicate that protection system failure modes have significant effect on reliability indices. Modern protection panels are equipped with multifunctional intelligent electronic devices (IEDs) that are connected to communication networks. As indicated in Lei, Singh, and Sprintson (2014) due to the variety of protection system architectures as well as the diversity of control and communication mechanisms, it is hard to explicitly model protection systems with detailed configurations simultaneously with the current-carrying components. Falahati, Fu, and Wu (2012) and Falahati and Fu (2014) attempt to study the direct and indirect cyber-physical interdependencies, introduce some mathematical terms and operations, and propose applications on small test systems including monitoring, control, and protection features. These references provide valuable information on the impact of cyber element failures on physical system reliability indices but do not provide a tractable method to deal with the cyber-physical aspects of power systems. Lei, Singh, and Sprintson (2014) and Lei and Singh (2015) propose a more systematic and scalable methodology for the overall analysis in a tractable manner with the use of *cyber-physical interface matrix (CPIM)*. The concept of CPIM provides a way of decoupling the cyber analysis from the overall reliability evaluation. In fact, cyber analysis is done outside the main simulation for composite system evaluation and then the results of analysis are interfaced through CPIM. In Lei, Singh, and Sprintson (2014) and Lei and Singh (2015), a typical substation protection system with detailed architecture is designed and analyzed as an example to illustrate the procedures of obtaining a CPIM. The steps for using a CPIM in composite power system reliability evaluation are also formulated.

6 Integration of Wind Energy

In recent years there has been considerable emphasis on installing non-hydro renewable energy sources in power systems. Of these, wind is one of the most important sources of renewable energy. The energy generated by wind depends on the wind speed and the availability of the wind turbines and thus the output of a wind farm is intermittent and a source of great uncertainty. This situation can be improved by installing a significant amount of storage. Many papers have been published for modeling and simulation methodology for reliability evaluation of composite power systems with integration of wind farm and storage. There are several factors that should be considered in evaluating the impact of integration of intermittent energy sources on the composite power system reliability.

6.1 Correlation between Load and Wind Energy Output

A certain level of correlation exists between the wind power and the load as both are correlated to the time of the day as well as seasonal variations. This influence of correlation was recognized (Singh and Gonzales, 1985; Singh and Kim, 1988) and suitable models were proposed. The use of clustering techniques for model reduction (Singh and Kim, 1988) have been later extended (Kim and Singh, 2012; Kile and Uhlen, 2012)

and proved to be effective. It has been shown (Kim and Singh, 2012) that ignoring the correlation can lead to optimistic evaluation of reliability.

6.2 Wake Effect

The wind speed entering a turbine is higher than that leaving it, since turbines generate electricity from the entering wind. In the area behind a turbine, leeward, turbulent flow occurs and this power loss is called wake effect. As a result of this effect, downstream wind turbines generate less power than the upstream ones. For a realistic evaluation of the impact of integrating wind turbines, the wake effect should be considered; otherwise the evaluation of reliability will be too optimistic. The inclusion of wake effect and its impact on reliability indices is discussed in great detail in Kim, Singh, and Sprintson (2012).

6.3 Integration of Storage

There is a growing realization that if large-scale intermittent sources of energy are to be integrated into the grid, storage will be needed. For example, California is mandating a certain amount of battery storage. The location, amount, and the level of storage should be included in the reliability modeling of composite power systems (Xu and Singh, 2014; Mitra and Vallem, 2012).

7 Conclusions

This chapter provided a summary of the objectives and methods of composite system reliability evaluation. These methods have been utilized for several applications in power system planning, such as (i) identification of transmission bottlenecks in the system under study, (ii) prioritization or optimization between investments in generation and transmission, (iii) evaluation of the impact of transmission constraints in economic and energy market analyses, and (iv) planning studies concerning integration of distributed and variable resources. In modern grid operation practices where generation and transmission assets are increasingly operated closer to their limits, the role of composite system analyses is becoming increasingly important.

Related Articles

**Evolution of Power Grids (Transmission);
Role of Energy Storage;
Cascading Failures in Power Systems;
Grid Codes in Power Systems with Significant Renewable-Based Generation;
Cybersecurity of SCADA within Substations;
Defining, Measuring, and Improving Resilience of Electric Power Systems;
Reliability Indices.**

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