

Composite System Reliability Evaluation using State Space Pruning

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Abstract

This paper presents a method of computing the reliability indices of a composite generation-transmission system by performing Monte Carlo simulation selectively on those regions of the state space where loss of load states are more likely to occur. These regions are isolated by performing state space decomposition to remove coherent acceptable subspaces. It is shown that this method results in a significant reduction in the number of sampled states, thereby reducing the computational effort required to compute the system and bus indices. The method assumes a DC flow model, and is tested using the IEEE Reliability Test System. The proposed method is not intended to replace existing variance reduction techniques; in fact, such techniques may be used in conjunction with the proposed method to further improve its efficiency.

Keywords: reliability indices, composite reliability, Monte Carlo simulation, DC load flow

1 Introduction

Composite system reliability evaluation involves the determination of reliability indices of a power system, giving due consideration not only to changes in generation levels, but also to transmission line capacities and outages [1]. Many of the papers found in the literature have emphasized the calculation of system indices for composite reliability. In the deregulated environment of the future, generation, transmission, and distribution aspects may be owned by separate entities. In this situation, the bus indices will become very significant. In one sense, however, the problem will stay similar to what it is today, i.e., every network will have generated power injected at some buses, and loads tapped from some buses.

Composite reliability methods currently in use employ one of the following approaches, or combinations thereof [2, 3, 4]:

1. Contingency enumeration
2. State space decomposition
3. Monte Carlo simulation

Contingency enumeration [2, 5] consists of listing all contingencies of upto a given order, usually second, computing their probabilities, and evaluating the reliability indices from these probabilities. The limitation of this approach lies in the fact that higher order contingencies often have a non-negligible contribution in composite reliability indices. Contingency enumeration has also been applied together with contingency ranking to reduce the number of contingencies to be evaluated [6, 7, 8].

State space decomposition [9, 10, 11, 12] is an analytical method which recursively decomposes the system state space into sets of acceptable, unclassified, and loss of load states. The coherency property, which requires that an acceptable set be homogeneous to the extent that it should have no loss of load states, and that a loss of load set should likewise be devoid of acceptable states, is a necessary condition for this method. This condition restricts the flexibility of the power flow model which can be used for composite reliability analysis, because for DC and AC flow models, changes in transmission line states result in noncoherency of the state space. The only power flow model which is robust to transmission state changes is the capacity flow model, but this model suffers from the inability to accommodate Kirchhoff's voltage law. The capacity flow model has been frequently used for multi-area reliability studies, but is not considered suitable for composite system reliability. Furthermore, for a large system, the number of loss of load sets generated can become unmanageably large.

Monte Carlo simulation [13, 14] consists of randomly sampling system states, testing them for acceptability, and aggregating the contribution of loss of load states to the reliability indices till the coefficients of variation of these indices drop below prespecified tolerances. The advantages of Monte Carlo simulation in the context of composite reliability analysis are manifold: virtually any desired power flow model can be accommodated, the problem of noncoherency is circumvented,

and contingencies of all orders are sampled. Indeed, for complex systems, simulation may often be the only recourse. There is, however, an important limitation — the number of states that must be sampled before the indices stabilize is large, especially for highly reliable systems, and the more complex the power flow model used, the more time intensive is the method. Even though some variance reduction techniques have been shown to accelerate the convergence of Monte Carlo simulation [14], the need persists for methods which will alleviate the computational burden when dealing with composite systems of realistic dimensions.

This motivates the development of methods to reduce the number of samples required to achieve convergence, without compromising the accuracy of the indices. This paper describes a method which selectively samples states from those regions of the state space where the likelihood of occurrence of loss of load states is higher than in the complete state space. This is accomplished by pruning the state space by removing coherent acceptable subspaces, and performing proportional sampling over the residual subspaces. The concept is analogous to that of importance sampling [16]. An advantage of the proposed method is that it permits the use of variance reduction techniques [2, 14, 15] to further accelerate the process of simulation over the pruned state space.

2 Theoretical Justification

In this section, the concepts which constitute the proposed methodology will be discussed. The state space will be characterized, the concept of state space pruning will be described using a simplified model, the method of pruning will be described, and finally the extraction of reliability indices will be discussed.

2.1 Characterization of State Space

For any given load scenario, the available bus generations and the transmission line capacities will determine whether or not the bus loads will be satisfied. We can, therefore, define a state space as the set of all possible combinations of generation levels and transmission line capacities. The treatment of temporal load variations and planned outages of generators can be accommodated using clustering concepts [11, 12]. Since clustering will finally result in a model which uses a single load level, the proposed method will be described in this paper in terms of a model using a single load level. The method can be easily extended to include multiple load levels and planned maintenance.

In general, therefore, a system with N_b buses and N_t transmission lines will have a discrete state space of dimension $(N_b + N_t)$, each axis consisting of the generation or transmission capacity levels, zero levels included.

2.2 The Concept of State Space Pruning

Consider a hypothetical two dimensional discrete state space (FIGURE 1) over which it is desired to perform Monte Carlo simulation to obtain reliability indices. Using some device, an arbitrary number of coherent acceptable sets are identified and removed. This “pruning” results in a reduced state space,

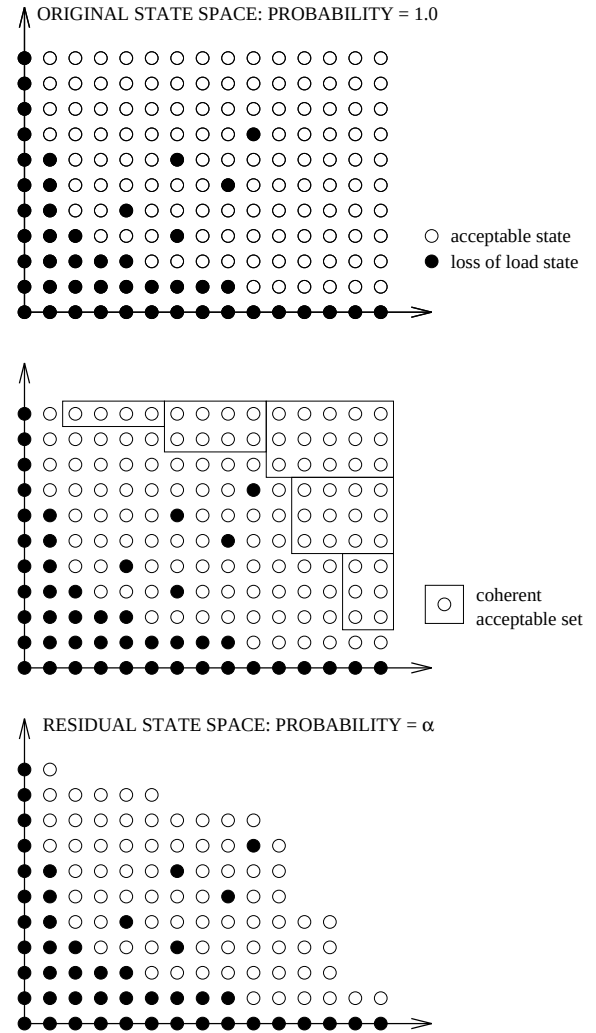


FIGURE 1: PRUNING OF STATE SPACE

wherein the loss of load states are left undisturbed, as in the original state space, but the likelihood of encountering these loss of load states in the course of Monte Carlo sampling over the residual state space is higher than the likelihood of the same in the original state space. It is reasonable to assert that simulation over the residual state space would require a smaller sample size to meet the same convergence criterion.

This assertion is justified as follows:

Consider calculating the *system Loss of Load Probability (LOLP)*, p ;

Let p be the estimate of p ;

Since failure states are binomially distributed (a sampled state can be a failure state or a success state), the distribution has mean p and variance $p(1 - p)$;

Then the coefficient of variation of p is

$$\eta = \frac{1}{p} \sqrt{\frac{p(1 - p)}{N}} \quad (1)$$

where N is the number of sampled states.

If sampling is performed over the residual state space of probability α , then the estimate of the *conditional LOLP* is

$$p' = \frac{p}{\alpha}$$

Then the coefficient of variation of p' is

$$\eta' = \frac{1}{p'} \sqrt{\frac{p'(1-p')}{N'}} = \frac{\alpha}{p} \sqrt{\frac{\frac{p}{\alpha}(1-\frac{p}{\alpha})}{N'}} \quad (2)$$

where N' is the number of states sampled from the residual state space.

Now if both the estimates p and p' are required to converge to the same tolerance, then

$$\frac{N'}{N} = \alpha \frac{1 - \frac{p}{\alpha}}{1 - p} \quad (3)$$

Note that (3) has been obtained by equating η and η' , i.e., the coefficients of variation of p and p' , which are actually estimates of different quantities. However, η and η' are the coefficients of variation within their respective state spaces over which sampling was performed, and it is therefore reasonable to equate them.

Note also how (3) indicates an approximate equality between the fraction N'/N and the residual probability α , since p is small. In other words, the reduction in sample size is almost proportional to the extent of pruning the state space.

2.3 Removal of Acceptable Subspaces

Application of the proposed method requires that acceptable subspaces be identified and pruned, and that the residual subspaces be properly organized so as to enable fair sampling. This may be accomplished by using any appropriate device. One possibility is to use suitably selected partitioning vectors which will partition the state space into acceptable and residual subspaces. Note that the term ‘subspace’ is loosely applied here, and refers to any set of points in the state space.

The method described in this paper uses the concept of partitioning vectors, and applies it in a form which is analogous to the idea of state space decomposition [9, 10, 12]. The original state space is first treated as an unclassified set (U -set); based on the maximum capacity levels available in this U -set, the system load curtailment is minimized; then the combination of the lowest capacity states which yield zero total curtailment constitutes a partition vector which will be called the u -vector. The u -vector has the property that all capacity levels between and including the u -vector and the upper boundary of the U -set will be acceptable states and will constitute an acceptable set (A -set). Using the u -vector, the original U -set is now decomposed into an A -set, and $N_b + N_t - n_1$ disjoint U -sets, where n_1 is the number of single level components in the original U -set (i.e., the maximum generation or transmission level in the U -set coincides with the corresponding minimum level). If more A -sets are desired to be removed, more of the undecomposed U -sets

may be decomposed. A large proportion of the sets generated have very low probabilities; thus their number can be kept manageable by deleting sets with very low probabilities (e.g., less than 10^{-16}).

2.4 Solving the Noncoherency Problem

The method described in section 2.3 can be applied only if the A -sets generated satisfy the coherency property. This is not a problem if a capacity flow model is used, but if a DC or AC flow model is used, then the system remains coherent for generation level changes, but not for transmission level changes, because transmission capacity changes are accompanied by line susceptance changes, which alter the flow profile, and may cause transmission capacity violations, thereby producing a failure state in an otherwise acceptable set. It is, however, not realistic to use the capacity flow model in composite reliability problems. In using DC or AC flow models, therefore, the noncoherency problem must be addressed. The proposed method addresses this problem by performing decomposition over the generation levels, holding the transmission levels at the maximum capacity states. In other words, every time the u -vector is determined, the components of the u -vector corresponding to transmission lines are set at the maximum capacity levels. It should be noted that the transmission system is generally far more reliable than the generation system, and therefore the above approach is able to prune fairly large portions of the probability space.

The implementation reported in this paper uses a DC flow model. In determining the u -vector, the transmission components are set at the maximum capacity levels; the generation components are determined by minimizing the total load curtailment, with the flows constrained by the maximum transmission capacities. The minimization model is described in detail in section 3.4.

If for a certain U -set the minimum curtailment is not zero, no A -set can be formed, and the entire U -set is set aside for Monte Carlo simulation. Otherwise when the desired level of pruning has been completed, decomposition is terminated, and the undecomposed U -sets are subjected to simulation.

2.5 Proportional Sampling on Residual Subspaces

At termination of decomposition, all the disjoint undecomposed U -sets form the residual subspaces, and these are subjected to proportional sampling for determination of the reliability indices. First, the probabilities of all the residual subspaces are computed. Then each sampled state is selected as follows.

1. a subspace is randomly selected in such a manner that the probability of that subspace being selected is proportional to the probability of the subspace
2. if a cluster model is used, a load cluster is randomly selected; otherwise the same load scenario is used
3. within the selected subspace, proportional sampling is used to select a generation level at every bus, and a trans-

mission level for every line

The generation-transmission-load scenario thus selected constitutes the sampled state, which is tested for acceptability. If the state turns out to be a failure state, then the system and bus indices are updated. This is continued till the coefficients of variation of selected indices drop below prespecified tolerances.

The indices calculated in the work reported in this paper are the *Loss of Load Expectation (LOLE)* and *Expected Unserved Energy (EUE)* for the system as well as for every bus.

Notice that the question of noncoherency does not arise in the context of simulation.

3 Model Description

This section will briefly discuss the models used in the work reported in this paper.

3.1 Generation Model

Based on the capacity states and forced outage rates of units available in a given bus, a discrete probability distribution function is constructed, for every bus, using the *Unit Addition Algorithm* [1].

3.2 Transmission Line Model

The transmission line model can be constructed for every transmission line, in the form of a discrete probability density function, or a probability distribution function, over all the capacity levels, including zero.

3.3 Load Model

The load model is constructed as a vector of size N_b , comprising the load levels at all the buses. If multiple load levels are to be accommodated, they are combined into a cluster load model [10, 12], and the vector of maximum load levels is used as the reference load state in the pruning phase.

3.4 DC Flow Model

The DC power flow model is described by the nodal equation

$$\hat{B}\theta + G = D \quad (4)$$

and the line flow equation

$$b\hat{A}\theta = F \quad (5)$$

where

N_b = number of buses

N_t = number of transmission lines

$b = N_t \times N_t$ primitive (diagonal) matrix of transmission line susceptances

$\hat{A} = N_t \times N_b$ element-node incidence matrix

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

$\theta = N_b$ -vector of bus voltage angles

$G = N_b$ -vector of bus generation levels

$D = N_b$ -vector of bus loads

$F = N_t$ -vector of transmission line flows

This model is used in the simulation and pruning phases as described below.

3.4.1 DC Flow Model in Simulation phase

To improve the computational efficiency, a sampled generation-transmission-load scenario is tested for acceptability by first using the following heuristic algorithm:

1. the available injections at all buses are calculated by subtracting the bus loads from the available generations at the buses
2. if the sum of the positive injections exceeds the sum of the negative injections, the positive injections are proportionately scaled down so that their sum equals that of the negative injections; if the sum of negative injections is larger, all the loads are proportionately curtailed so that their sum equals that of the available generations
3. once power balance is accomplished, the G vector resulting from the injections determined in step 2 are used in (4) to solve for the θ vector
4. the θ vector is substituted in (5) to obtain the line flow solution

If the line flows thus calculated satisfy the flow constraints sampled, then the heuristic is said to have found a feasible flow, and if one or more bus loads had to be curtailed, the system and bus LOLPs and EUEs are suitably updated.

If the heuristic fails to find a feasible flow, then the following linear programming model [2, 12] is solved:

$$\text{Loss of Load} = \text{Min} \sum_{i=1}^{N_b} C_i$$

subject to:

$$\begin{aligned} \hat{B}\theta + G + C &= D \\ G &\leq G^{max} \\ C &\leq D \\ b\hat{A}\theta &\leq F^{max} \\ -b\hat{A}\theta &\leq F^{max} \\ G, C &\geq 0 \\ \theta &\text{ unrestricted} \end{aligned} \quad (6)$$

where

$C = N_b$ -vector of bus load curtailments

$C_i = i$ -th element of C , i.e., unsatisfied demand at bus i

$G^{max} = N_b$ -vector of maximum available bus generation levels

$F^{max} = N_t$ -vector of flow capacities of transmission lines

The values of D , G^{max} and F^{max} are set equal to the sampled values for demand, generation, and transmission levels, during each simulation. Here the bus generation vector G is kept at

or below the sampled generation level, so as to satisfy the constraints in (6). In the pruning phase, the values of G^{max} and F^{max} are defined in a different manner, as explained later.

If (6) yields a non-zero curtailment, then the system and bus indices are suitably updated.

3.4.2 DC Flow Model in Pruning Phase

In the pruning phase, the DC flow model is used to determine the u -vector. To do this, a feasible solution must be found, subject to the constraints imposed by the upper boundaries of the current U -set, such that the bus load curtailments are all zero. If such a solution does not exist, then the entire U -set is set aside for simulation.

In attempting to find a feasible solution, first the heuristic described in section 3.4.1 is used, with one difference: in step 2, if the sum of negative injections is larger than that of positive injections, then a feasible flow with zero curtailment cannot be determined, so attempts to isolate an A -set are abandoned. Otherwise, if the heuristic works, then the generation components of the u -vector are taken as the generation levels (the G vector) obtained from scaling down the positive injections.

If the heuristic fails, then the LP model (6) is solved, with D as the load level (the reference load, if a cluster model is used), and G^{max} set at the corresponding upper bounds in the current U -set. F^{max} , in the pruning phase, is always set at the highest capacity levels of the transmission lines. The generation components of the u -vector are taken as the solution of the G vector obtained from (6), while the transmission components equal the corresponding values in F^{max} .

4 The Algorithm

1. Construction of state space:
 - (a) Build bus generation models.
 - (b) Build transmission line models.
 - (c) Build load model: single load level, or clusters.
 - (d) If single load level is used, go to step 2; else select reference load level, then modify generation models for every cluster level and interleave them to form integrated state space.
2. Pruning:
 - (a) Define entire state space as first U -set, store it in an array C_U .
 - (b) If C_U is empty, go to step 3; else pick an U -set from C_U and compute its probability p_U .
 - (c) If p_U is smaller than a prespecified threshold p_0 ¹ set the current U -set aside, in an array S_U , for simulation, and go to step 2(b); else proceed to step 2(d).

¹ p_0 is used to control the extent of pruning; a small p_0 results in a large part of the state space being pruned, while $p_0 = 1.0$ results in the entire state space being subjected to simulation.

- (d) Decompose current U -set into an A -set and $N_b + N_t - n_1$ U -sets. First try heuristic; if heuristic fails, use LP. If no A -set can be formed, store entire current U -set in array S_U ; else store all $N_b + N_t - n_1$ U -sets in C_U . Use reference load levels, if cluster loads are used. Maintain transmission line levels at maximum capacity.
- (e) Go to step 2(b).

3. Simulation:

- (a) Using proportional sampling, randomly select an U -set from S_U .
- (b) If a cluster model is used, randomly select a load level; else use specified load level as demand vector.
- (c) For all buses and transmission lines, randomly select generation and transmission levels.
- (d) Test selected scenario for acceptability. First try heuristic; if heuristic fails, use LP. If loss of load is unavoidable, update LOLE and EUE for system and affected buses.
- (e) Continue till coefficient of variation of selected index converges to prespecified tolerance.

5 Case Studies and Results

The proposed method was tested using the *Modified Reliability Test System* (MRTS) [2, 4]. The MRTS is identical in topology and component outage rates to the IEEE-RTS [17], and differs from the latter in that all the generation levels are doubled and the loads are multiplied by a factor of 1.8, while the transmission line capacities are the same. This system has been described in references [2] and [4], and is used in this work without alteration. The MRTS was preferred over the RTS for testing composite reliability techniques because it was found [2] that the transmission network of the RTS was too strong, and that transmission line capacities had little effect on the reliability indices. Indeed, when the proposed method was tested on the RTS, using a 10-cluster load model, the system indices determined were almost identical to the generation reliability indices of the RTS, as obtained from a direct convolution of the generation and load distribution functions.

The MRTS consists of 24 buses and 38 transmission lines. 10 of the buses are generator buses, there being 32 generators in all. 17 of the buses have loads connected to them. The total generation is 6810 MW, and the total load is 5130 MW. For the studies reported in this paper, only the peak load levels were used.

The performance of the method, in terms of sample size reduction and computation time, is reported in TABLE I, for five different levels of pruning. The system and bus reliability indices of the MRTS, as determined by the proposed method, are shown in TABLE II. The results obtained by sampling from the entire state space, corresponding to the first case in TABLE I,

TABLE I: VARIATION OF SAMPLE SIZE AND COMPUTATION TIME WITH PRUNING LEVEL

RESIDUAL PROBABILITY α	SAMPLE SIZE ² N'	$\frac{N'}{N}$	$\alpha \frac{1-p/\alpha}{1-p}$	COMPUTATION TIME ³ (hours)		
				Pruning time	Simulation time	Total time
1.0000	37345	1.000	1.000	0.000	54.276	54.276
0.6019	21168	0.567	0.585	0.013	31.043	31.056
0.2738	8584	0.230	0.243	0.879	12.797	13.676
0.1475	3956	0.106	0.111	5.272	6.025	11.297
0.1069	2457	0.066	0.069	14.078	3.835	17.913

and those obtained from the other four cases did not differ significantly from each other.

The data in TABLE I pertains to the sample sizes and computation times required to converge on the LOLE at bus 6, with a 2.5% tolerance on the coefficient of variation. The value of p used in column 4 corresponds to the bus 6 LOLP; the values in columns 3 and 4 are shown with the intent to demonstrate the compliance of the results with equation (3). The data in columns 5, 6 and 7 are shown graphically in FIGURE 2; this plot also shows that there is an optimal mix of pruning and simulation, since the efficiency of pruning deteriorates as the residual probability approaches the system LOLP.

TABLE II: COMPOSITE RELIABILITY INDICES OF MRTS

LOCATION	RELIABILITY INDICES	
	LOLE (h/year)	EUE (MWh/year)
system	600.001	91169.9
bus 1	1.173	20.6
bus 2	1.642	23.5
bus 3	97.811	10935.1
bus 4	75.528	1838.8
bus 5	36.357	1342.3
bus 6	360.048	22215.9
bus 7	36.357	959.1
bus 8	311.728	19766.4
bus 9	44.097	2533.9
bus 10	54.652	3578.3
bus 11	0.235	7.7
bus 12	0.235	5.0
bus 13	2.111	105.5
bus 14	270.446	21409.2
bus 15	2.346	209.2
bus 16	32.838	4392.1
bus 17	0.000	0.0
bus 18	21.110	1347.7
bus 19	7.271	407.9
bus 20	2.346	71.8
bus 21	0.000	0.0
bus 22	0.000	0.0
bus 23	0.000	0.0
bus 24	0.000	0.0

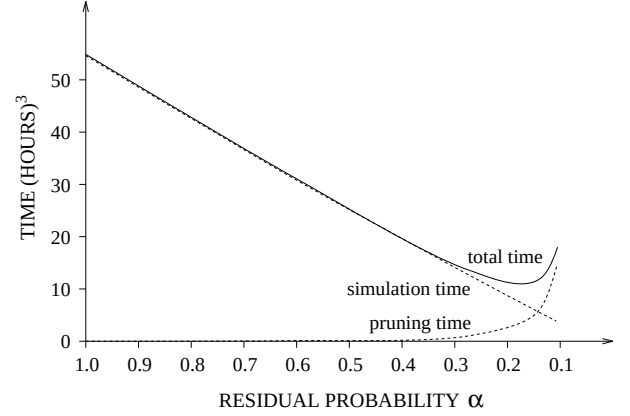


FIGURE 2: VARIATION OF COMPUTATION TIME WITH PRUNING LEVEL

6 Discussion and Conclusion

This paper has introduced the concept of pruning the state space and then performing Monte Carlo sampling on the conditional state space. Further, a technique is introduced for circumventing the problem of noncoherency during the process of pruning. This is achieved by keeping the transmission lines at their maximum capacity during pruning, but allowing them to fail during sampling. For the sake of computational efficiency, state evaluation is done in two steps, first using a heuristic to seek a feasible solution, failing which linear programming is used.

Probabilities of generation failures are much higher than those of transmission lines, and this allows a large portion of probability space to be pruned. However, as the probability of the residual state space approaches the system LOLP, pruning becomes inefficient. This can be seen from TABLE I and FIGURE 2.

The role of the heuristic versus linear programming depends on whether the system is dominated by generation or transmission. The IEEE-RTS is generation dominant, whereas the MRTS is relatively more transmission dominant. As a result, studies revealed that while computing the indices of the MRTS, the LP was invoked far more frequently than it was in the case of the RTS. That the RTS is generation dominant was evidenced by

²Converging on bus 6 LOLE, coefficient of variation 2.5%.

³CPU time on a DEC Alpha.

the fact that the composite indices obtained using a 10-cluster load model (system LOLE 9.505 h/y and EUE 1198.2 MWh/y) were almost equal to those obtained by convolving the generation model with the hourly load model (LOLE 9.394 h/y and EUE 1175.9 MWh/y) [18].

It should be noted that variance reduction techniques, such as the correlated control variable method, proposed by several authors, can be used on the pruned state space to further accelerate convergence. The purpose of this paper, however, is to demonstrate the feasibility and the usefulness of the pruning technique.

Acknowledgment

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Biographies

Chanan Singh is Professor of Electrical Engineering at Texas A&M University, Director of the Electric Power Institute, and Vice President of Associated Power Analysis Inc. Dr. Singh received the 1972 Best Paper Award of the Engineering Institute of Canada, the 1986–87 Haliburton Professorship, and the 1992–93 Dresser Professorship. Dr. Singh is a senior TEES Fellow at Texas A&M University, Fellow of the IEEE, and Advisory Editor for Microelectronics and Reliability, Pergamon Press.

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Discussion

A.M. LEITE DA SILVA (EFEI, Itajubá, Brazil), **J.C.O. MELLO** and **A.C.G. MELO** (CEPEL, Rio de Janeiro, Brazil): The discussers would like to compliment the authors for their interesting paper. The idea of reducing or pruning the state space by removing coherent acceptable subspaces is welcome.

The authors have used a DC flow and linear programming models in both pruning and simulation phases. The evaluation of frequency and duration (F&D) indices were not considered in the paper. Therefore, the obvious doubts are concerned with the extension of the proposed method to include a nonlinear AC flow model and the assessment of F&D indices. Concerning F&D indices one interesting technique which could be tried with the authors' method is the conditional probability approach, as proposed in ref. [A].

The results shown on Tables I and II were obtained considering only the peak load. Even though, the algorithm spent a total of 11 hours on a DEC Alpha, considering a coefficient of variation of 2.5% applied to bus 6 for index LOLE. This seems to be a very high figure in terms of IEEE Modified RTS. In order to better compare with previously proposed techniques, for instance as in refs. [A] and [B] which also have used DC load flow, what would be the computation time to converge the authors' algorithm considering a coefficient of variation of 5% applied to system level indices LOLE and EUE?

The computational time when multiple load levels are considered could be relatively accelerated due to the reduction on loss of load events. Did the authors apply their algorithm for multiple load levels? Finally, what is the impact of pruning on the computer memory usage?

Once again we congratulated the authors for their interesting paper.

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- [A] A.C.G. Melo, M.V.F. Pereira, A.M. Leite da Silva, "A Conditional Probability Approach to the Calculation of Frequency and Duration Indices in Composite Reliability Evaluation", IEEE Trans. PWRs, Vol. 8, pp. 1118-1125, Aug. 1993.

- [B] J.C.O. Melo, M.V.F. Pereira, A.M. Leite da Silva, "Evaluation of Reliability Worth in Composite Systems Based on Pseudo-Sequential Monte Carlo Simulation", IEEE Trans. PWRs, Vol. 9, pp. 1318-1326, Aug. 1994.

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C. Singh, J. Mitra, (Texas A & M University, College Station, TX): We thank the discussers for their insightful comments and queries. They have highlighted some important and interesting issues which were not directly addressed by the paper.

The discussers' concern regarding the applicability of the *pruning and simulation* technique to AC flow models and to the determination of F&D indices basically involves the state space coherence issue. In addressing this concern, we would first like to construct a premise, based on the following propositions.

Proposition 1: Dispatcher action precludes occurrence of those events whereby the restoration of a failed component results in deterioration of system performance.

Proposition 2: In a power system model rendered noncoherent solely by inclusion of DC or AC flow constraints, the aggregated probability of states contributing to noncoherence is negligibly small.

Proposition 1 simply means that the dispatcher can choose not to bring a repaired generator or transmission line back into service, if such restoration is deemed detrimental to system performance. We claim that proposition 1 is justifiable from an engineering standpoint, and as such does not represent an approximation or inaccuracy. However, it excludes those events whereby the degradation or failure of a component improves system performance, since these are random events beyond the dispatcher's control. Ignoring these states constitutes an approximation which, we claim via proposition 2, may be acceptable. This is in fact supported by [C]. Besides, when pruning is performed, these states always reside in the residual space, so if the indices are estimated only from sampled failure states, these states are appropriately identified as success states, and contribute no error at all.

Nevertheless, the above premise represents a mathematical imperfection, and its acceptance or otherwise is essentially a matter of engineering judgement. If, however, we choose to accept it, then we have several interesting consequences. To name a few:

1. In the *pruning and simulation* method described in the paper, we can drop the requirement of holding the transmission states at their highest capacity levels during pruning, thereby increasing the efficiency of pruning.
2. The method can be extended to include AC flow constraints as well.
3. The method described in [A] can be applied *in toto* to the *pruning and simulation* method, regardless of the flow

model used, since the method of [A] computes the F&D indices from the sampled failure states, and pruning the state space leaves *all* failure states for simulation. (We emphasize the word *all*, since we have chosen to accept proposition 1.) The only additional requirement in such an implementation would be that of scaling the calculated indices by the residual probability.

We also wish to point out that the method of [A] implicitly accepts the proposed premise.

Regarding the run time of the *pruning and simulation* method, our program took 1.32 hours to converge on system LOLE with 5% coefficient of variation. (The results thus obtained gave zero LOLEs for buses 1, 2, 11, 12, 13, 15 and 20; TABLE II shows that a more stringent convergence criterion produces nonzero indices for these buses.) We concede that our run times can be considerably reduced by using more efficient LP algorithms, since it is the LP module which accounts for the bulk of the computation time. However, the main purpose of our work was to evolve a method which accelerates the convergence of Monte Carlo simulation, and to demonstrate the relative efficiency of the technique.

We did not experiment with multiple load levels, for the

MRTS. But the use of multiple load levels would result in longer computation times than would the use of peak load levels. This is explained as follows. When multiple load levels are used to approximate the actual load distributions, the proportion of loss of load states decreases. Sampling a sufficient number of these failure states to achieve the same degree of convergence would therefore necessitate testing a larger number of samples.

Since pruning necessitates storage of information describing the residual state space, it does increase the computer memory usage. It will be evident from the algorithm given in section 4 that a larger degree of pruning increases the size requirements of arrays C_U and S_U .

We once again thank the discussers for their illuminating comments and for their interest in our paper.

Reference

- [C] A. C. G. Melo, M. V. F. Pereira, A. M. Leite da Silva, *Frequency and Duration Calculations in Composite Generation and Transmission Reliability Evaluation*, IEEE Trans. PWRs, Vol 7, No 2, pp 469–476, May 1992.

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