COMPOSITE SYSTEM RELIABILITY EVALUATION AND EFFECTIVE CAPACITY EVALUATION OF TIME LIMITED ENERGY RESOURCES

A Thesis

by

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ABSTRACT

This first part of the thesis presents a study of the composite system reliability evaluation using a cross-entropy based importance sampling method to improve computational efficiency of sequential Monte Carlo simulation (MCS). The sensitivity analysis studies show how the computational performance of the method and reliability indices are affected by varying the system parameters like peak load and forced outage rates of the generators. The relationship between computation time, simulation parameters, coefficient of variance and number of system cores is also explored. The sequential Monte Carlo simulation is implemented using parallel computing techniques which reduces the computation time. A comparison study is carried out using Simple Monte Carlo method. These methods are tested on an IEEE RTS 79 test system.

The second part of the thesis presents a study of various techniques to evaluate effective capacity of time limited and energy limited energy resources. The energy limited sources are added to the generation buses in the IEEE RTS 79 test system and the effective load that it can serve to maintain the same reliability benefit is evaluated. All the capacity evaluation of the energy limited resources is studied using a composite power system model. It is observed that the effective capacity increases as the resource duration increases.

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All other work conducted for the thesis (or) dissertation was completed by the student independently.

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NOMENCLATURE

MCS	Monte Carlo Simulation
CE	Cross Entropy
COV	Coefficient of variation
IS	Importance Sampling
SMC	Simple Monte Carlo
GCR	Generation Capacity Reliability
RTS	Reliability Test System
DC	Direct current
OPF	Optimal power flow

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CHAPTER I

INTRODUCTION

Power system reliability assessment is divided into three hierarchical levels [2]. The reliability assessment at hierarchical level 2 is usually termed as composite system reliability evaluation. The composite system can be used to assess the adequacy of an existing or proposed system including both the generation and transmission. The adequacy [2] is explained as the existence of sufficient facilities (i.e., generation and transmission facilities) within the system to satisfy the consumer load demand or system operational constraints. Adequacy is therefore associated with static conditions and does not include system dynamic and transient disturbances.

Composite system reliability evaluation is important for power system planning, operation and maintenance. Various deterministic as well as probabilistic methods to evaluate the reliability indices have been proposed. The probabilistic methods are more capable of incorporating the factors that actually influence reliability.

The probabilistic methods can be implemented using analytical and Monte Carlo (MC) approaches. The analytical approaches are attractive since they give exact results but the computational time rises heavily as the size of state space increases. Pereira and Balu [27] study various analytical techniques and methodologies used for composite system reliability evaluation until early 1990s. The MC approach is based on sampling the states of the system from its probability distribution and evaluating the expectation of the required estimates such as curtailed load. The MC method is computationally more tractable than the analytical approaches because the number of samples needed to estimate the parameters is independent of the system size.

The Monte Carlo Simulation (MCS) is one of the frequently used probabilistic methods for power system reliability evaluation. The MCS methods are classified as sequential and non-sequential methods. In non – sequential MCS all the possible system states across the required period of interest is randomly sampled and are independent. In sequential MCS all the system states that are generated for the period of interest follow a sequence resulting from system changes.

Sequential MCS is of two types [20], fixed time step method and next event method. In the fixed time step method, a fixed time interval t is taken for each state depending on the characteristics of the system. The time is advanced by time interval t after each state, and whether an event has occurred is determined in each state. If no event occurs the states remain the same and if an event occurs new states are generated according to the event. In the next event method after the initial state is generated, we assume an event occurs and the time for which the system stays in the particular state is measured and after the time the new states are generated according to the previous event. This process is repeated continuously until a required convergence is achieved.

In the MCS methods it is very important to sample sufficient number of states to estimate the reliability indices with a specified level of confidence. To increase the precision of the calculated reliability indices a large quantity of samples is needed. To increase precision means to reduce the variance of the estimates of reliability indices, and the process of repeating the simulations continuously until the variance is reduced below a threshold value, is a very time -consuming process. So, various sampling techniques are used for reducing the variance.

One of the important factors in reducing the simulation time is the variance. In an attempt to improve computational efficiency various sampling methods have been implemented to reduce the variance like stratified sampling [9] [10], dagger sampling [11] [12], Latin Hypercube sampling [13],[14], Importance sampling [15] while using the MCS based methods. In this thesis a cross entropy (CE) based Importance sampling (IS) method is used. Reference [1] describes various approaches where CE method can be used.

Importance sampling modifies the distribution functions of the components of the system due to which the number of rare events or loss of load states increases. Due to the increase in the number of loss of load states in the sampled states the variance is reduced and the simulation time decreases. In importance sampling, generating the modified distribution functions of the system components is of utmost importance as the variance may not be reduced if an optimal distribution function is not generated. There is no direct procedure to generate these modified distribution functions, in this situation the cross entropy (CE) method provides an iterative procedure to generate the optimal modified distribution functions. The cross-entropy method can be implemented using both non sequential and sequential Monte Carlo simulations.

The CE method using non-sequential MCS has been implemented in generation capacity reliability (GCR) evaluation, where the system transmission constraints are ignored [3] and the method is tested using a fixed load model and a multilevel load model. A CE based sequential Monte Carlo simulation method for GCR evaluation is implemented in [4], where time dependent systems are considered and it gives a comparison between different CE based and non-CE based Monte Carlo simulation algorithms. They are tested on an IEEE RTS 96 and a modified RTS 96 system. These papers show that CE method is a computationally improved method to simple Monte Carlo methods, as it reduces the sample size and consequently the computation time.

Reference [5] implements the CE method in a composite power system model using non sequential Monte Carlo Simulation, where the indices are calculated for both single area and multi area power systems. Reference [6] implements the CE method using quasi sequential Monte Carlo methods, where renewable energy sources are integrated in the test system. The CE method has been improved in [7] by assuming the load to follow a Gaussian distribution and using a truncated Gaussian distribution for the load in the training phase instead of having a fixed load. Here a different mathematical model is used for DC OPF where instead of calculating the load curtailment, the excess load served is calculated. These are implemented on a single and multi-area reliability test systems.

A three stage CE IS method is implemented in [8] for degenerate cases. Here a third stage is employed before the normal CE algorithm to detect the degenerate parameters. A parallel cross entropy optimization method has been implemented in [16].

In this thesis we have extended the sequential Monte Carlo simulation for composite system reliability evaluation. Using the developed tools, we have explored the conditions under which importance sampling based cross entropy method is computationally advantageous over simple Monte Carlo simulations.

Time Limited Energy Resources

Traditionally energy limited generation units have been of the type of hydro units with limited storage capacity and they have been included in reliability studies either through load modification or capacity modification approach [21]. These units have been treated as an integral part of the installed capacity system supplying load and not used just in emergency situations. Their modeling in reliability studies has depended on whether they are used as base load units or peak shaving units. If they are part of peak shaving, then their order of commitment is important as they may or may not be energy limited depending on the level of load, they are called upon to serve. These units are then modelled by modification of their forced outage rates or capacity modification [22, 23].

The capacity markets such as New York Independent System Operator (NYISO) are expanding to include the time-limited energy resources in their planning and forecasting studies for power system adequacy. By calculating the effective capacities of these resources, we can understand their performance and contribution of these time-limited energy sources to maintain the power system adequacy. These resources are required by power system operators to respond to curtailment request for a minimum time. The effective capacity is the capacity value of the resources used to produce an equivalent reliability benefit. Most of the literature evaluates effective capacity using multi-area reliability systems, which does not consider transmission congestion [24][25] in sufficient detail.

Technical report [24] evaluates the effective capacity of time limited sources where these are called special case resources (SCR). Here the effective capacity as well as penetration level of the sources are studied using a GE MARS software which is a multi-area reliability program, on the New York Independent System Operator (NYISO). This program uses only the effective capacity of tie lines between the areas. The composite system reliability evaluation uses more detailed information of the transmission system.

In this thesis we have evaluated and compared the effective capacity of time limited energy resources using two different procedures in the context of composite system. To our knowledge this the first-time capacity credit is calculated using composite power system model. The CE method used for composite system reliability evaluation is used here for the reliability index calculation phase of the procedure.

CHAPTER II

COMPOSITE SYSTEM RELIABILITY EVALUATION USING SEQUENTIAL SIMULATION

The Monte Carlo simulation is implemented, in this research, as a sequential simulation instead of a non -sequential simulation. The sequential simulation steps through the year chronologically, recognizing the status of equipment is not independent of its status in adjacent hours. Equipment forced outages are modeled by taking the equipment out of service for contiguous hours, with the length of outage period being determined from the equipment's mean time to repair. Sequential simulation can model issues of concern that involve time correlations and can be used to calculate indices such as frequency and duration.

A non-sequential simulation process does not move through time chronologically, but considers each hour independent of every other hour. Because of this the model cannot accurately model issues that involve time correlations such as maintenance outages and cannot be used to calculate indices such as frequency and duration.

Importance Sampling and Cross Entropy Method

Importance Sampling is a variance reduction technique, where using a modified probability distribution function g*(X) (X is the system states) of the components of the system, the rare events (failure events in reliability evaluation) or loss of load events are sampled more frequently. An optimal choice for this modified distribution is the distribution which yields the zero-variance estimator.

As there is no direct procedure to generate the modified probability distribution function, an iteratively updated probability distribution function $f(X_i,v)$ (X_i is the system states and v is the distorted parameters) is generated by distorting the original parameters. The cross-entropy method [1] gives an adaptive iterative procedure to find the distorted parameters. In Importance sampling the modified probability distribution is chosen from the iteratively updated distribution such that the distance between the optimal probability distribution and iteratively updated probability distribution is minimum. A particular measure of distance between the two distributions is the Kullback-Leibler distance (Appendix A), which is termed as the Cross Entropy between the optimal $g^*(X)$ and $f(X_i,v)$. The Cross Entropy based approach is an accelerated Monte Carlo approach which improves the computation efficiency.

The system State X_i is generated as $[X_G,X_L,X_{load}]$, which is a vector containing generator states , transmission states and load level. The X_G and X_L are calculated using the component unavailability vector $u = [u_G,u_L]$ where u_G and u_L are sub vectors for generation and transmission. The up/down states of generator and transmission lines are determined after generating random numbers for each component and comparing with its unavailability vector. The load is randomly generated from the load curve. The reliability adequacy indices such as Loss of Load Probability (LOLP), Expected Energy not Supplied (EENS) etc. are used for reliability assessment. For a random sample X_1, X_2, …. X_N generated considering $[u_G,u_L]$ the generator and transmission line unavailabilities and probability distribution, the reliability index calculated from a Monte Carlo simulation is given by

$$E(H) = \frac{1}{N}\sum_{i=1}^{N} H(X_i) \qquad (1)$$

Where $H(X_i)$ is the test function for computing the reliability index. $H(X_i) = 1$ if there is loss of load event and $H(X_i) = 0$, otherwise.

For a system using importance sampling where rare events are sampled more often, the reliability index calculated from the samples $X_1,X_2,\ldots.X_N$ generated considering distorted unavailabilities of generators and transmission lines $[v_G,v_L]$ and probability distribution, with likelihood ratio (W) is given by

$$E(H) = \frac{1}{N}\sum_{i=1}^{N} H(X_i)W(X_i;u,v) \qquad (2)$$

Likelihood Ratio

The expression $W(X_i;u,v)$ is the likelihood ratio between the two probability distribution functions and is a correction factor introduced to avoid any biased estimates. Here the density functions $f(X_i,u)$ and $f(X_i,v)$ represent Bernoulli distribution, $W(X_i;u,v)$ is given by

$$W(X_i;u,v) = \frac{f(X_i;u)}{f(X_i;v)} = \frac{\prod_{j=1}^{Nc}(1-u_j)^{x_j}(u_j)^{(1-x_j)}}{\prod_{j=1}^{Nc}(1-v_j)^{x_j}(v_j)^{(1-x_j)}} \qquad (3)$$

$X_i=X_1,X_2,\ldots.X_N$ are random samples of generating states, u_j represents unit unavailability, v_j represents distorted unavailability. x_j represents availability of a component, with a value 1 if the component is available and 0 if not. Nc is the total number of components.

Here likelihood ratio W for the composite system is given by

$$W = W_G * W_L \tag{4}$$

$$W_G = \frac{\prod_{G=1}^{N_G} (1 - u_G)^{x_G} (u_G)^{(1-x_G)}}{\prod_{G=1}^{N_G} \left(1 - v_j\right)^{x_G} (v_G)^{(1-x_G)}} \tag{5}$$

$$W_L = \frac{\prod_{L=1}^{N_L} (1 - u_L)^{x_L} (u_L)^{(1-x_L)}}{\prod_{L=1}^{N_L} (1 - v_L)^{x_L} (v_L)^{(1-x_L)}} \tag{6}$$

W_G and W_L are the likelihood ratios of generators and transmission lines respectively. N_G, N_L are total number of generators and transmission lines. u_G, v_G, u_L, v_L are generator and transmission line original and distorted unavailabilities. x_G, x_L are the generator and transmission lines states represented by 1 if up and 0 if down.

The sequential simulation using cross entropy method uses the distorted parameters of the system generators and transmission lines.

Evaluation of Distorted Parameters for the Sequential Simulation

The initial undistorted unavailabilities of the power system components are given by $u = \frac{\lambda}{(\lambda+\mu)}$. Where λ and μ are the component failure and repair rates respectively. During the cross-entropy procedure, a distortion is applied to the unavailabilities and a new distorted unavailability parameter are generated. So, during the sequential simulation to calculate the residence time of each state the new failure and repair rates, λ* and μ* rates generated from distorted parameters are used.

The new distorted parameters [3] are given by,

$$\mu^* = \mu \qquad (7)$$

$$\lambda^* = \frac{\nu\mu *}{(1-\nu)} \qquad (8)$$

To maximize the number of failure events in a time period the distortion is applied only to the failure rate.

The cross-entropy algorithm as given in [1][3] is used to evaluate the required distorted parameters of the proposal distribution. The CE algorithm steps are given below.

Cross - Entropy algorithm

Step1: Initialize all the parameters such as N (number of samples), ρ (multi-level parameter), α (smoothing parameter), Nmax (maximum sample size) and Limiting Load or threshold load (Ld) below which the samples are considered as loss of load samples.

Step 2: Define V_0 = u, that is the initial undistorted unavailabilities of Generators and Transmission lines. Set t = 1 (iteration counter).

Step 3: Generate system states X_1, X_2, …. X_N from the initial unavailabilities according to the Bernoulli mass function.

Step 4: Evaluate the system performance function $P(X_i)$ for all X_i. A DC power flow analysis is performed and load curtailment is calculated. If any power flow violations occur then an optimization algorithm based on linear programming, described in (Appendix B), is solved. $P(X_i)$ is the sum of capacity of all the generators. If a load curtailment occurs then $P(X_i)$ is recalculated as

$$P(Xi) = L_{max} – \text{load Curtailment.} \qquad (9)$$

Step 5: Sort the calculated performance functions $P(X_i)$ in an ascending order such as P = [P_1, P_2, ….P_N], P_1<P_2<…<P_N. Then calculate the (1-ρ) th quantile of performance function P[(1-ρ)*N].

Step 6: If P[(1-ρ)*N] <Ld, set L = Ld, otherwise set L = P[(1-ρ)*N]. Then evaluate the function $H(X_i)$ for all Xi, such that $H(X_i)$ = 1 if $P(X_i)$ <L and $H(X_i)$ = 0, otherwise.

Step 7: Calculate the Likelihood ratios $W(Xi,u,v_{t-1})$, Where W = W_G*W_L. Update the new distorted parameters v_{Gt},v_{Lt}

$$v_{Gtj} = 1 - \frac{\sum_{i=1}^{N} I_{\{P(X_i)<L\}} W(X_i;u,v) X_{ij}}{\sum_{i=1}^{N} I_{\{P(X_i)<L\}} W(X_i;u,v)} \qquad (10)$$

$$v_{Ltj} = 1 - \frac{\sum_{i=1}^{N} I_{\{P(X_i)<L\}} W(X_i;u,v) X_{ij}}{\sum_{i=1}^{N} I_{\{P(X_i)<L\}} W(X_i;u,v)} \qquad (11)$$

The derivation for generating the distorted parameters v_{Gt}, v_{Lt} is given in Appendix A.

Step 8: If L=Ld, then the training phase ends and go to Step 9 or else increase the iteration counter t and go to step 3 for next iteration.

Step 9: Start the Testing Phase.

The reference [3] implements the CE based sequential simulation for Generation capacity reliability evaluation where transmission constraints are ignored. Here we have used the sequential simulation and implemented it to a composite system which includes transmission constraints. Including the transmission constraints complicates the task of evaluating the reliability indices as it requires a power flow analysis and an optimal power flow algorithm has to be run to eliminate any violations in operating limits (eg., circuit overloads) if any violations occur.

Testing phase (sequential simulation)

For the testing or evaluation phase of sequential simulation, the optimal distorted parameters are derived from the initial training phase. Here the load is taken from the hourly load curve [17] and is not distorted.

Step 1: From the distorted parameter vector v the new transition rate vectors μ^* and λ^* are generated for the generators and transmission lines. Initialize NY max (maximum simulated years ~5000)

Step 2: Generate the random sample X_1 from the new distorted transition rate vectors and the sample residence time (T_{res} (X_i)) is calculated. Initialize T_{sim} (~8736 hours), T_Down, T_WDown, T_Up, T_WUp to Zero.

Step 3: Evaluate the Current sample likelihood ratios $W(X_i;u,v)$.

Step 4: Transition to the next system states, and sample the residence time from the chronological load model and the distorted transition rate vectors. Calculate the cumulative sample times T_{res} total = $\Sigma T_{res}(X_i)$. If the total residence time after the current sample is greater than Tsim, the residence time of the current sample is reduced and same sample is used as starting sample for the next year.

Step 5: Once all the sample states and likelihood ratios for a simulation year is generated all the states are evaluated to generate each sample up time and down time. Here a parallel computing technique is used to calculate the sample up and down times to reduce the computational time. The MATLAB parallel tool box is used to reduce the computational time by evaluating all the states parallelly using the multi cores of the processor. Go to step 6 if down time or go to step 7 if up time.

Step 6: Accumulate the Down time

$$T\_Down = T\_Down + t_i; \qquad (12)$$

$$T_W Down = T_W Down + (t_i * W(X_i,u,v)); \qquad (13)$$

Step 7: Accumulate the Up time

$$T\_Up = T\_Up + t_i; \qquad (14)$$

$$T_W Up = T_W Up + (t_i * W(X_i,u,v)) \qquad (15)$$

Step 8: The LOLP index for this simulation year is evaluated using a weighted mean approach.

$$\omega(NY) = \frac{(T_W UP + T_W Down)}{T_{sim}} \qquad (16)$$

$$LOLP(NY) = \frac{(T_W Down * \omega(NY))}{(T_W Up + T_W Down)} \qquad (17)$$

Step 9: The Coefficient of Variation (β) is calculated and Compared with the β_{max}. If it falls below β_{max} or $NY > NY_{max}$ the simulation is stopped. Or else go to step 2.

Step 10: Evaluate the LOLP index

$$LOLP = \frac{\sum_{i=1}^{NY} LOLP(i)}{\sum_{i=1}^{NY} \omega\,(i)} \qquad (18)$$

Acceleration using parallel pool

Using the parallel computing capacity of any desktop or laptop for simulations helps us in improving the computation efficiency. Using Matlab for parallel computing [19], we need to first assign number of cores we need for simulation, depending on the availability of cores. Once the number of cores is specified the main Matlab creates the same number of worker Matlabs. Main Matlab divides the work and sends the data and code to the workers. The workers execute the assigned iterations and send results back to the main Matlab. Then main Matlab combines results and continues executing statements after parallel computing. This causes an extra overhead time but for a large system the parallel computing benefit is far higher than the overhead time.

For example, if the main Matlab has to evaluate 100 samples with four cores it divides the work between the workers and each worker evaluates 25 samples.

Results

IEEE RTS 79 test system

The Sequential Monte Carlo-Cross Entropy Method is illustrated using IEEE RTS 79 [16]. To show the sensitivity of computation time the parameters are varied and the change in computation time is recorded. The IEEE RTS 79 is a 24-bus system with 32 generating units and 38 transmission lines. The maximum generation capacity is 3405 MW. The load is a correlated hourly load with a peak load of 2850 MW. The load is correlated amongst the buses. All the simulations are performed on Matlab using an Intel 4 core, 3.4GHz processor.

Varying the multi core for computational efficiency

Here the number of cores or workers used for computing is varied and computational time is noted. All the computations are done at system peak load of 2850 MW until a 2% convergence is reached.

It can be observed from the Table I that as the number of cores of the computer utilized for evaluating the states increases the computational time decreases. As expected, the improvement ratios as a function of cores are about the same in CE-ISMC and SMC.

Table 1 Results with varying cores

	Number of cores	**LOLP (10^{-3})**	**Ny (years)**	**Time (Secs)**	**Ratio of improvement in time #core1/#core1,2,4**
CE-ISMC	1	1.17	182	5,753	1
	2	1.16	177	2,893	1.98
	4	1.18	181	1,987	2.89
SMC	1	1.1	6990	46,498	1
	2	1.1	6957	24,919	1.86
	4	1.1	7061	17,130	2.71

Table 2 Results with varying Coefficient of variation

	COV (β) (%)	LOLP (10^{-3})	Ny (years)	Time (Secs)	Time saving= SMC-CE-ISMC
CE-ISMC	5	1.1	26	335	2359
	2	1.1	179	1,846	15,284
	1	1.1	775	8,000	60,658
SMC	5	1.1	1077	2,694	
	2	1.1	7061	17,130	
	1	1.1	28204	68,658	

Varying coefficient of variation (COV)

The COV value is varied from 5% to 1% and the change in LOLP and computation time is observed. This simulation is implemented at a system peak load of 2850 MW using 4 cores.

It can be seen from Table 2 and Fig 1 that for COV of 5%, the CE IS reduces computation time by 2395 seconds whereas for 1% the time is reduced by 60,658 seconds. Therefore CE-IS becomes computationally more advantageous as value of COV is made tighter.

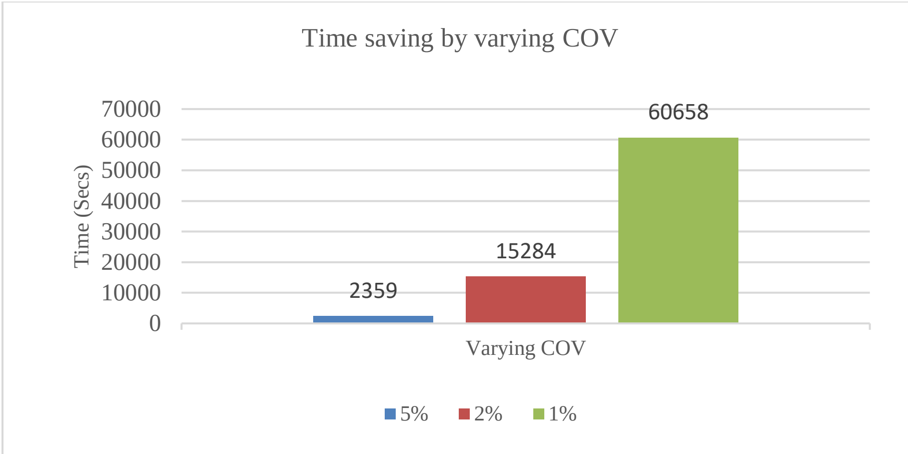

Figure 1 Time Saving by varying Coefficient of Variation

<u>Varying the system peak load</u>

In this case the system peak load is increased and decreased by 300 MW from the base peak load of 2850 MW of the chronological Load Curve.

The LOLP and the computation time is evaluated and compared with the Simple Monte Carlo Simulation. All the values are calculated for a 2% convergence using 4 cores.

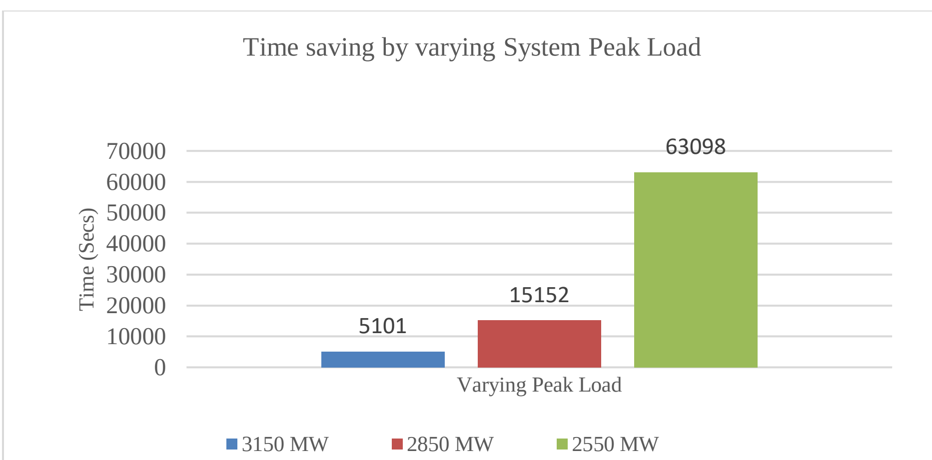

Figure 2 Time Saving by varying system peak load

Table 3 Results with varying system peak load

	LOAD (MW)	LOLP (10^{-3})	Ny (years)	Time (Secs)	Time saving= SMC-CE-ISMC
CE-ISMC	3150	5.9	163	1,637	5101
	2850	1.1	185	1,978	15152
	2550	0.14	224	2,666	63098
SMC	3150	6.0	1696	6,738	
	2850	1.1	7061	17,130	
	2550	0.14	39329	65,784	

As can be seen from the table 3 and Fig 2, the simulation requires a greater number of samples and increased computation time before converging as the load decreases. This is because the LOLP increases with higher peak load and simulation time is inversely proportional to the LOLP being estimated [20]. Therefore, the CE-IS MC becomes computationally more advantageous with higher reliability systems.

Varying the system outage rates

The component outage rates are varied and the change in LOLP and computation time are observed. The Forced outage rate is the generator probability of failure. The forced outage rate is changed uniformly for all the generating components. This is carried out at a system peak load of 2850 MW and 2% convergence criteria.

It can be observed from the Table IV and Fig 3 that increasing the forced outage rates increases the loss of load and decreases the computational time. Similar to the previous case, increased reliability leads to higher savings in computational time with the CE-IS use in MC.

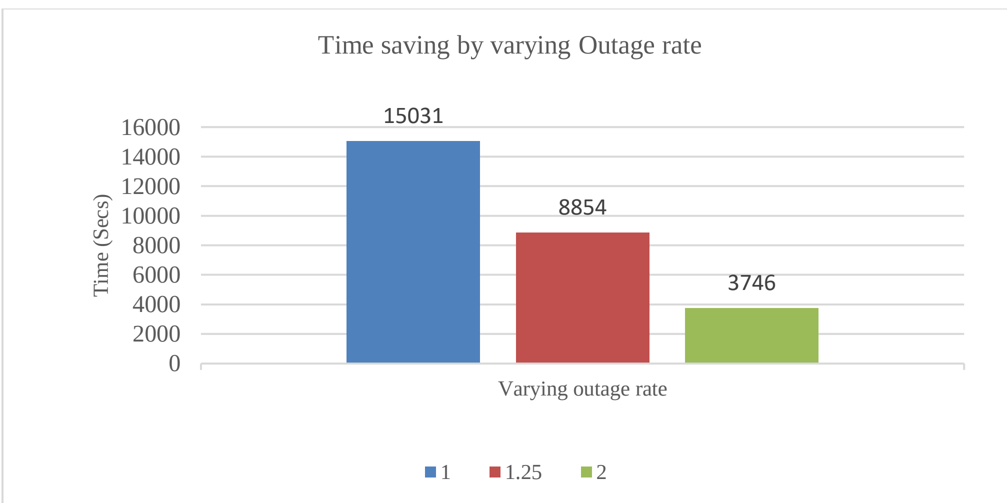

Figure 3 Time Saving by Varying Outage rate

Table 4 Results with varying Forced Outage Rates

	Outage Rate (multiplier)	LOLP (10^{-3})	NY (Years)	Time (Secs)	Time saving= SMC-CE-ISMC
CE-ISMC	1	1.1	194	2,099	15031
	1.25	2.2	156	1,808	8854
	2	9.4	85	1,058	3746
SMC	1	1.1	7061	17,130	
	1.25	2.2	3617	10,662	
	2	9.6	989	4,804	

CHAPTER III

EFFECTIVE CAPACITY EVALUATION OF TIME LIMITED AND ENERGY LIMITED RESOURCES

As by New York Independent system operator [24], energy limited resources are a resource that, due to environmental restrictions on operations, cyclical requirements, such as the need to recharge and refill, and other non-economic reasons, is unable to operate continuously on a daily basis, but is able to operate a limited number of consecutive hours each day. Examples of energy limited resources are hydro units that are subjected to recharge periods, storage systems or generators with NOx/Sox restrictions on run times.

The need for calculating effective capacity of duration limited resources has been highlighted by the plans to incorporate these in the capacity markets [24]. The Effective capacity of the time limited energy resources is the amount of perfect capacity of the resource which would provide equivalent reliability benefit. Reliability benefit is the impact the resource has on the reliability indices such as loss of load probability. So, effective capacity is the increase of load the time limited resource can serve and maintain the reliability of the system.

The time limited energy units are added at some of the buses in the composite system model. In the composite model the generation (conventional and time limited) and load at different buses are connected together using transmission lines. In the composite system the constraints imposed by the capacities and failures of transmission lines are also considered whereas in a generation planning model the constraints on transmission lines are not considered. In this chapter the Importance sampling based cross entropy method investigated in the chapter II for composite system reliability evaluation is used for the reliability index calculations.

The effective capacity of the time limited energy units can be calculated using two approaches. In one procedure, the effective load is added uniformly across the load curve. In the other procedure it is added at the peak load point of the load curve and all other hours are updated proportionally. The time duration limited units are added as discontinuous units. For example, if an energy unit has the capacity to work for 4 h it can be utilized continuously for 4 hours or used as a combination of smaller intervals totaling 4 hours within a day.

General algorithm [25][26] for the effective capacity evaluation is described in the following for these two scenarios mentioned.

Effective Capacity Evaluation

For calculating effective capacity, the reliability indices will be calculated using sequential Monte Carlo simulation including importance sampling based cross entropy method. The effective capacity of limited time energy sources is calculated as follows:

Step 1: First the reliability index without adding the limited time sources is evaluated.

Step 2: The limited time sources at the respective buses are added and the reliability index calculated. The reliability improves, i.e., the LOLP index value decreases.

Step 3: Procedure 1: To calculate the effective capacity which would provide the same reliability benefit, the load is added uniformly in steps of 50 MW in the hourly load curve.

Step 3: Procedure 2: To calculate the effective capacity which would provide same reliability benefit, the load is added uniformly in steps of 50 MW to the annual peak load in the hourly load curve. All the loads in the hourly load curve will increase proportionally to the annual peak load.

Step 4: Once the load is added the reliability index is evaluated and if the reliability index reaches the earlier value without the time limited resources the iteration is stopped. Or else go to step 3 and increase the load and reevaluate the reliability index.

Step 5: The load value at which the reliability index matches is the effective capacity of the time limited sources.

Results

Effective capacity evaluation adding load uniformly to load curve

In this case the load is added uniformly to the load curve, across all the hours. From the table 5 and figure 4 it can be observed that if the limited time resource generation capacity is less compared to the peak load, it can reach maximum effective capacity even if it works for less time. The 200 MW source reaches maximum effective capacity if it works for 12 hours whereas the 400 MW source reaches maximum capacity at 16 hours and 800 MW source at 24 hours.

In this case the generation sources are used discontinuously, as all the hours the source is available can be used whenever the loss of load occurs. All the simulations are done until the reliability index loss of load probability reaches 0.0012 and a convergence of 5%.

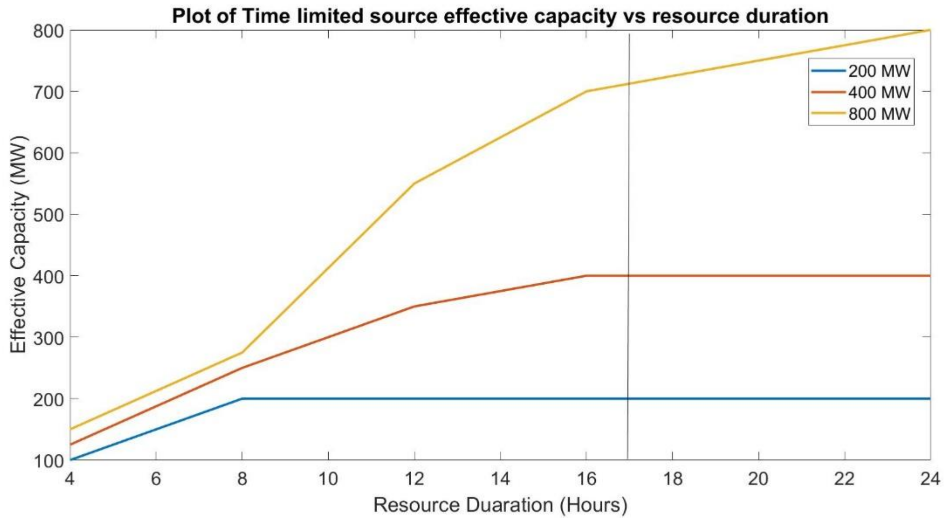

Figure 4 Plot of effective capacity vs resource duration for discontinuous time limited resource

Table 5 Effective capacity of discontinuous time limited energy sources

Resource Duration (Hours)	**Effective capacity of 200 MW Source**	**Effective capacity of 400 MW Source**	**Effective capacity of 800 MW Source**
4	100	115	160
8	150	230	260
12	200	350	500
16	200	400	700
20	200	400	755
24	200	400	800

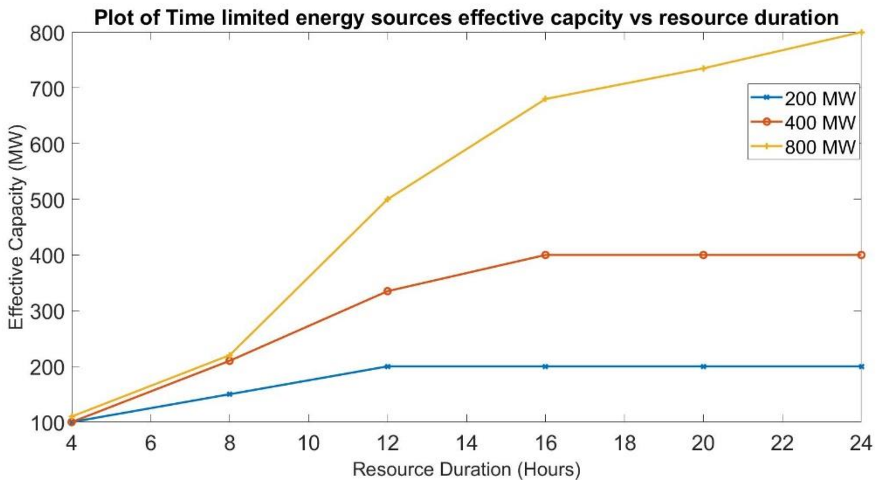

Figure 5 Plot of effective capacity vs resource duration for continuous time limited resource

Table 6 Effective capacity for continuous time limited resource

Resource Duration (Hours)	**Effective capacity of 200 MW Source (MW)**	**Effective capacity of 400 MW Source (MW)**	**Effective capacity of 800 MW Source (MW)**
4	100	100	110
8	150	210	220
12	200	335	500
16	200	400	680
20	200	400	735
24	200	400	800

In table 6 and figure 5 the limited energy source is used continuously i.e., whenever the source is used to supply the load it cannot be stopped until the time it can be used is ended. The effective capacity reaches maximum when the time limited source is a 12 hour source for 200 MW, a 16 hour source for 400 MW and a 24 hour source for 800 MW.

It can be observed from figures 4 and 5 that there is not much difference in the effective capacity calculated. As all the different energy limited sources reach their maximum effective capacity when they work for the same amount of time in both continuous and discontinuous cases.

Effective capacity evaluation adding load at peak hour

In this case the load is added at the annual peak hour and the load curve is adjusted proportionately for all hours. Here all the simulations are run until a COV of 5% is reached and loss of load probability reaches the same value as before adding time limited resources.

Table 7. Effective capacity for discontinuous time limited resource with load added at peak hour

Resource Duration	Effective capacity of 200 MW Source	Effective capacity of 400 MW Source	Effective capacity of 800 MW Source
4	135	160	160
8	200	300	315
12	220	415	645
16	220	445	900
20	220	445	900
24	220	445	900

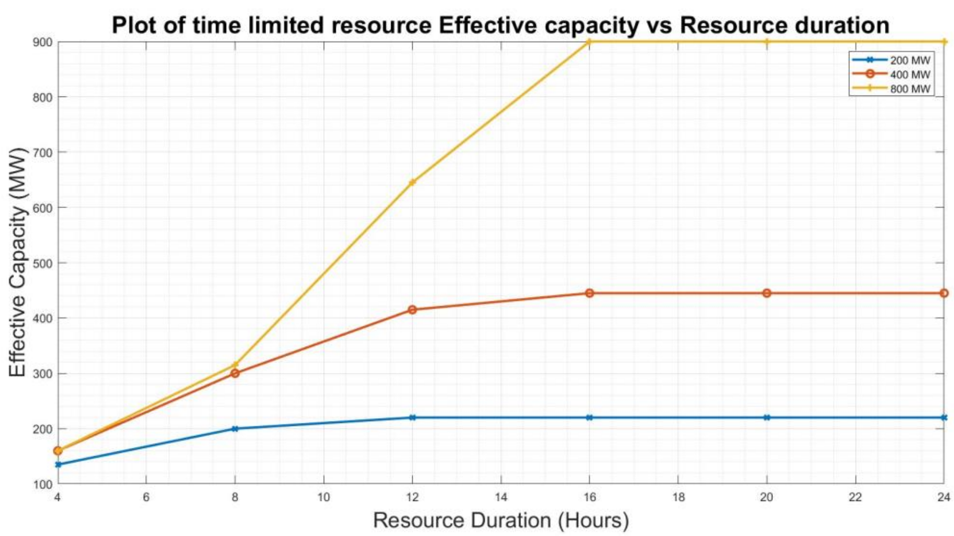

Figure 6 Plot of effective capacity vs resource duration for discontinuous time limited resources with load added at peak load.

It can be observed from table 7 and figure 6 that the effective capacity calculated can be greater than the generation capacity as the effective load added is not uniform across the load curve but at non-peak hours it is less than at the peak load. For longer resource durations the added capacity the resource additions over compensate the decrease in reliability due to load increase.

When the time limited energy sources are used continuously, it can be inferred from table 8 and figure 7 that the effective capacity evaluated is similar to that of table 7 and figure 6.

Table 8 Effective capacity for continuous time limited resource with load at peak hour

Resource Duration	**Effective capacity of 200 MW Source**	**Effective capacity of 400 MW Source**	**Effective capacity of 800 MW Source**
4	115	150	160
8	200	280	300
12	220	420	630
16	220	445	900
20	220	445	900
24	220	445	900

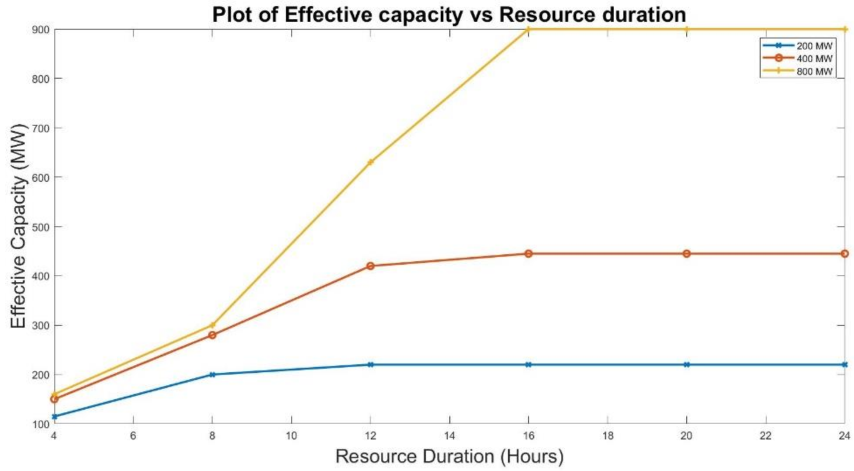

Figure 7 Plot of Effective capacity vs resource duration for continuous generation and load added to peak hour.

CHAPTER IV

CONCLUSION

Composite System Reliability Evaluation

It should be noted that the results obtained by Monte Carlo are only estimates of true values and not the true values., the estimates have a variance. The estimates approach the true values as the variance of estimates is reduced by increasing the sample size. Importance sampling helps by reducing the variance of the estimator and thus a smaller sample size is needed to get the same coefficient of variation. The coefficient of variation determines the gap between the upper and lower bounds with a given level of confidence. The smaller the coefficient of variation, the tighter are the bounds around the true values. The main advantage of using variance reduction technique of Importance sampling is the reduction in computational time. This paper has explored the conditions under which the computation time is reduced more favorably by implementation of IS and thus it becomes advantageous to use this variance reduction approach. In general, the conditions which lead to higher computation time for the straight MCS tend to favor the use of IS for relatively higher reduction of computation time by reducing the variance of estimates. The conditions which lead to higher computation time are either the ones that lead to higher reliability, i.e., lower loss of load probability or the ones where tighter bounds on estimates are needed to have higher confidence in the estimated results.

Time limited Energy Resources

It is understood from the effective capacity evaluation studies that, to properly evaluate the effective capacity of time limited and energy limited resources, it is better to add the extra load the resource can serve uniformly across the load curve i.e., all the hourly loads increases uniformly with the same amount of load across the annual load curve. If the annual load curve is changed by adding the load at the annual peak and the annual load curve is adjusted proportionately for other hours, there is a mismatch in the evaluated effective capacity. It is observed that for the time limited resources there is not much difference in the evaluated effective capacity when they are used continuously and discontinuously. This is because the contributions to reliability indexes come primarily around the peak period. It can also be seen that higher the capacity of the resource, the longer is the duration of the resource to reach maximum effective capacity.

REFERENCES

[1] Rubinstein, Reuven Y, and Dirk P Kroese. *The Cross-Entropy Method: A Unified Approach to Combinatorial Optimization, Monte-Carlo Simulation and Machine Learning*. Springer, 2004.

[2] R. Billinton and W. Li, Reliability Assessment of Electric Power Systems Using Monte Carlo Methods. New York, NY, USA: Plenum, 1994.

[3] A. M. Leite da Silva, R. A. G. Fernandez and C. Singh, "Generating Capacity Reliability Evaluation Based on Monte Carlo Simulation and Cross-Entropy Methods," in *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 129-137, Feb. 2010.

[4] R. A. Gonzalez-Fernandez and A. M. Leite da Silva, "Reliability Assessment of Time-Dependent Systems via Sequential Cross-Entropy Monte Carlo Simulation," in *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2381-2389, Nov. 2011.

[5] R. A. González-Fernández, A. M. Leite da Silva, L. C. Resende and M. T. Schilling, "Composite Systems Reliability Evaluation Based on Monte Carlo Simulation and Cross-Entropy Methods," in *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4598-4606, Nov. 2013.

[6] A. M. L. da Silva, R. A. González-Fernández, S. A. Flávio and L. A. F. Manso, "Composite reliability evaluation with renewable sources based on quasi-sequential Monte Carlo and cross entropy methods," *2014 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Durham, 2014, pp. 1-6.

[7] E. Tómasson and L. Söder, "Improved Importance Sampling for Reliability Evaluation of Composite Power Systems," in *IEEE Transactions on Power Systems*, vol. 32, no. 3, pp. 2426-2434, May 2017.

[8] C. Yan, L. G. Luca, Z. Bie, T. Ding and G. Li, "A three-stage CE-IS Monte Carlo algorithm for highly reliable composite system reliability evaluation based on screening method," *2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Beijing, 2016, pp. 1-6.

[9] A. C. G. Melo, G. C. Oliveira, M. Morozowski Fo and M. V. F. Pereira, "A hybrid algorithm for Monte Carlo/enumeration based composite reliability evaluation (power systems)," *1991 Third International Conference on Probabilistic Methods Applied to Electric Power Systems*, London, UK, 1991, pp.70-74.

[10] D. Li, L. Dong, H. Shen, B. Li and Y. Liao, "Reliability evaluation of composite generation and transmission systems based on stratified and gradual importance sampling algorithm," *2011 International Conference on Advanced Power System Automation and Protection*, Beijing, 2011, pp. 2082-2087.

[11] H. Kumamoto, K. Tanaka, K. Inoue and E. J. Henley, "Dagger-Sampling Monte Carlo for System Unavailability Evaluation," in *IEEE Transactions on Reliability*, vol. R-29, no. 2, pp. 122-125, June 1980.

[12] Sun, R.; Singh, C.; Cheng, L.; Sun, Y. Short-term reliability evaluation using control variable based dagger sampling method. Electr. Power Syst. Res. 2010, 80, 682–689

[13] Z. Shu and P. Jirutitijaroen, "Latin Hypercube Sampling Techniques for Power Systems Reliability Analysis with Renewable Energy Sources," in *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2066-2073, Nov. 2011.

[14] Z. Shu, P. Jirutitijaroen, A. M. Leite da Silva and C. Singh, "Accelerated State Evaluation and Latin Hypercube Sequential Sampling for Composite System Reliability Assessment," in *IEEE Transactions on Power Systems*, vol. 29, no.4, pp.1692-1700, July2014.

[15] D. Lieber, A. Nemirovskii and R. Y. Rubinstein, "A fast Monte Carlo method for evaluating reliability indexes," in *IEEE Transactions on Reliability*, vol. 48, no. 3, pp. 256-261, Sept. 1999.

[16] G. E. Evans, J. M. Keith and D. P. Kroese, "Parallel cross-entropy optimization," *2007 Winter Simulation Conference*, Washington, DC, 2007, pp. 2196-2202.

[17] P. M. Subcommittee, "IEEE Reliability Test System," in *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-98, no. 6, pp. 2047-2054, Nov. 1979.

[18] C. Singh and J. Mitra, "Composite system reliability evaluation using state space pruning," in *IEEE Transactions on Power Systems*, vol. 12, no. 1, pp. 471-479, Feb. 1997.

[19] MATLAB and Parallel Computing Toolbox Release 2017a, The MathWorks, Inc., Natick, Massachusetts, United States.

[20] C. Singh., P. Jirutitijaroen and J. Mitra, 2018. *Electric Power Grid Reliability Evaluation: Models and Methods*. Wiley-IEEE Press, 2019.

[21] B. Bagen., D. Huang, and C. Singh. "A new analytical technique for incorporating base loaded energy limited hydro units in reliability evaluation." *Electric Power Systems Research* 131 (2016): 218-223.

[22] Chanan Singh, "Course Notes: Electrical Power System Reliability." *https://chanansingh.engr.tamu.edu/electrical-power-system-reliability/*

[23] C. Singh, A.D Patton, GRIP: Generation Reliability Indices Program, Associated Power Analysts Inc, College Station, TX.

[24] John Adams, David Allen, Donna Pratt, "Special Case Resources: Evaluation of the Performance and Contribution to Resource Adequacy," in Technical Report New York System Operator May 2012.

[25] Hall W, Zhang B, Legnard T., "Valuing Capacity for Resources with Energy Limitations". Slide deck GE Energy Consulting, 08 January 2019.

[26] L. L. Garver, "Effective Load Carrying Capability of Generating Units," in *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-85, no. 8, pp. 910-919, Aug. 1966.

[27] M. V. F. Pereira and N. J. Balu, "Composite generation/transmission reliability evaluation," in *Proceedings of the IEEE*, vol. 80, no. 4, pp. 470-491, April 1992.

APPENDIX A

KULLBACK – LEIBLER DISTANCE

Derivation of v parameter using Kullback-Leibler Distance

This appendix provides a detailed derivation on calculating the v parameter for Importance sampling as given in [1].

With samples X_1, X_2, …X_N generated from secondary density g*(X) the reliability index is calculated using an unbiased estimator as

$$r = \frac{1}{N}\sum_{i=1}^{N} I_{\{P(X_i<L)\}} \frac{f(X_i;u)}{g(X_i)} \qquad (19)$$

The best way to estimate r is given by

$$g(X_i) = \frac{I_{\{P(X_i<L)\}} f(X_i;u)}{r} \qquad (20)$$

Using this g we will have a zero variance estimator for r and it requires only one sample. But this approach is unworkable because of the unknown parameter r which we want to estimate. So, the idea of cross entropy is to choose g from a family of densities f(.;v), i.e. to calculate the reference parameter v such that the distance between the densities g* and f(.;v) is minimum. This distance between the densities is represented by Kullback -Leibler distance or Cross Entropy.

The Kullback - Leibler distance or Cross Entropy is defined as

$$D(g^*, f) = E(ln\left(\frac{g^*(X)}{f(X;v)}\right))$$

$$= \int g^*(X)\ln(g^*(X))\,dx - \int g^*(X)\ln\big(f(X;v)\big)\,dx \qquad (21)$$

Minimizing Kullback-Leibler distance is equivalent to maximizing

$$\max \int g^{*}(X) \ln\big(f(X;v)\big)\, dx \qquad (22)$$

This can be written as:

$$Max\ D(v) = \max E\ \big(I_{\{P(X<L)\}} \ln\big(f(X,v)\big)\big) \qquad (23)$$

Using Importance Sampling and a change of measure f(.;v) we can rewrite it as

$$\text{Max D(v)} = \max E\ (I_{\{P(X)<L\}}\ W(X;u,v) \ln(f(X;v))) \qquad (24)$$

for any reference parameter v, where

$$W(X;u,v) = \frac{f(X;u)}{f(X;v)} \qquad (25)$$

The optimal solution v* can be written as

$$v^{*} = \text{argmax}\ E_{w}\ (I_{\{P(X)<L\}}\ W(X;u,v) \ln(f(X;v))) \qquad (26)$$

The D(v) is differential with respect to v, and the solution can be obtained by solving the following system of equations.

$$\frac{1}{N}\sum_{i=1}^{N} I_{\{P(X_i)<L\}} W(X_i;u,v) \nabla\, ln(\,f(X_i,v)) = 0 \qquad (27)$$

Now

$$\frac{\partial}{\partial v_j}(\ln\big(f(X_i;v)\big)) = \frac{-x_i}{v_j\big(1-v_j\big)} + \frac{1}{v_j} \qquad (28)$$

Substituting this equation in the above equation, the j_{th} equation becomes

$$\sum_{i=1}^{N} I_{\{P(X_i)<L\}} W(X_i;u,v)\Big(\frac{-X_{ij}}{v_j(1-v_j)} + \frac{1}{v_j}\Big) = 0 \qquad (29)$$

By solving the equation (29) we get

$$v_j = 1 - \frac{\sum_{i=1}^{N} I_{\{S(X_i)<L\}} W(X_i; u, v) X_{ij}}{\sum_{i=1}^{N} I_{\{S(X_i)<L\}} W(X_i; u, v)} \qquad (30)$$

APPENDIX B

DC POWER FLOW MODEL

This appendix describes the DC Power flow model used in the simulations.

The DC power flow equation and line flow equations are

$$B\theta + G = D \qquad (31)$$

$$b\hat{A}\theta = F \qquad (32)$$

where

N_b = Number of buses

N_t = Number of transmission lines

b = N_t x N_t primitive matrix of transmission line susceptances

$\hat{A}$ = N_txN_b element node incidence matrix

B = N_bxN_b augmented node susceptance matrix

θ = N_b vector 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

A computationally efficient selective approach based on DC power flow as given in [17] is first used to find a feasible flow.

This approach consists of the following steps.

Step 1: The total injection at all buses are calculated by subtracting the bus loads from available generations at buses.

Step 2: If the sum of positive injections is greater than the sum of negative injections, the positive injections are scaled down proportionately so that the sum equals that of negative injections and vice versa if net negative injections are greater than net positive injections.

Step 3: once power balance is accomplished the G vector generated from step 2 is used in DC Power flow equation (31) to calculate θ, then θ is used in line flow equation (32) to calculate the line flows.

If the line flows satisfy flow constraints a feasible flow is found and if load is curtailed then the reliability indices are updated. If the line flows do not satisfy the flow constraints a Linear Programming (LP) model is implemented to calculate the optimized line flows and load curtailment. This LP model is described as follows:

Minimize Load Curtailment = $\text{Min}\sum_{i=1}^{N} LC_i$

Subject to Constraints:

Power balance: $B\theta + G + LC = D$

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

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

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

Load Limits: $LC \leq D$

Boundaries: $G, LC \geq 0$

θ unrestricted

where

LC = N_b vector of Load curtailments

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

F^{max} = N_t vector of flow capacities of transmission levels