CROSS-ENTROPY METHOD FOR RELIABILITY WORTH ASSESSMENT OF RENEWABLE GENERATING SYSTEMS

Reinaldo A. González-Fernández, Armando M. Leite da Silva
Federal University of Itajubá - UNIFEI
Itajubá, Brazil
reinaldo_andres@unifei.edu.br, armando@unifei.edu.br

Abstract – This work presents a new methodology to evaluate generating capacity reliability indices, with particular emphasis on the Loss of Load Cost. Based on the pseudo-chronological Monte Carlo simulation and the Cross-Entropy method, the main idea is to obtain an *optimal distortion* for the generation model in order to promote the occurrences of failure events and reduce the variance of the estimators. As a result, the computational efforts of the pseudo-chronological simulation can be greatly reduced while retaining all of its advantages. The proposed method can capture all the actual blocks of unsupplied energy per consumer class and their respective durations to accurately characterize the interruption process. In addition, many chronological aspects such as the fluctuation of generating capacities and scheduling maintenance can be easily included in the simulation model. Comparisons with the chronological and standard pseudo-chronological simulations are reported using several test systems and configurations of real power systems.

Keywords: Cross-Entropy method, generating capacity reliability, Monte Carlo simulation, rare events, reliability worth, renewable sources, risk analysis.

1 INTRODUCTION

Most reliability assessment tools present their results in terms of loss of load indices. These indices are statistical measures which provide valuable information about the probability, energy, frequency and duration of systems failures. Although these indices are very useful in operation and expansion planning problems, it is always important to evaluate their economic impact to society, i.e. to assess the interruption costs that result from a given system reliability and/or configuration.

An important index, particularly under a competitive environment, is the Loss of Load Cost (LOLC) [1] or Expected Damage Cost (ECOST) [2]. Besides providing an easy base for discussion, i.e. dollars instead of probabilities, MWh, occurrences, etc., the LOLC index can be directly included in the objective function to be minimized in a least-cost planning approach.

The LOLC index depends on the blocks of curtailed energy (MWh) and the unit interruption costs (US$/MWh) for each consumer class: residential, commercial, industrial, etc. The unit interruption costs (UC) are usually obtained through specific economic surveys [3]-[4]. According to these surveys the UC depend on many factors such as duration, frequency, time of occurrence, warning time, depth of curtailment and geographical coverage. The duration of the interruption is considered to be the dominant factor and, therefore, an accurate assessment of the LOLC index requires knowledge about the chronological evolution of system failures. As shown in [5], if the chronological aspects of the interruption process are neglected, only approximations of the LOLC index can be obtained.

The sequential Monte Carlo Simulation (MCS) is the natural tool to simulate chronological aspects. It is not only able to assess the usual reliability indices, but also their respective probability distributions. While chronological MCS-based methods [5]-[7] are more powerful to evaluate complex systems, their computational efforts are much more substantial than non-sequential methods. In order to reduce the computational burdens of sequential simulations, the pseudo-chronological MCS was proposed in [8]. The pseudo-chronological MCS retains the efficiency of non-sequential methods and is able to model chronological load curves per area or bus. However, because of its sampling strategy based on probability of occurrence, failure states are unlikely to be sampled in very reliable system configurations and, therefore, its performance would still be jeopardized when dealing with rare failure events.

This paper presents a new method to evaluate generating capacity reliability indices, with particular emphasis on the assessment of LOLC indices. Based on the pseudo-chronological MCS and the Cross-Entropy (CE) method [9]-[11], the main idea is to obtain an *optimal distortion* for the generating unit unavailabilities using the CE concepts proposed in [12]. The optimal distortion applied to the generation model will promote the occurrences of failure events and reduce the variance of the estimators, which is particularly interesting when dealing with very reliable system configurations. As a result, the computational efforts of the Pseudo-Chronological simulation can be greatly reduced while retaining all of its main advantages.

The proposed method can capture all the actual blocks of unsupplied energy per consumer class and their respective durations to accurately characterize the interruption process. In addition, many chronological aspects of the system such as the fluctuation of generating capacities, e.g., hydro and wind units [13]-[16], and scheduling maintenance can be easily included in the simulation model. Comparisons with the chronological and standard pseudo-chronological simulations are reported using the IEEE RTS-79 (Reliability Test System) [17], IEEE RTS-96 [18], modifications of this system that include renewable sources [19], and two configurations of the Brazilian South-Southeastern generating system [20].

2 RELIABILITY WORTH

2.1 Unit Interruption Cost

The economic impact of interruptions depends on the UCs (US$/kWh), which are obtained through specific economic surveys. These surveys try to capture the damages caused by interruptions in each consumer class. As stated in the Introduction, the UCs strongly depend on the duration of system failures. Figure 1, which was obtained from an Ontario Hydro survey [3], shows the UC values for residential, commercial, and industrial consumers as a function of the interruption duration. A similar survey was carried out for the Brazilian system [4] and its results are shown in Figure 2.

2.2 Interruption Cost Calculations

An interruption I can be described as a set $S_{ES(I)}$ of energy shortages related to the successive failed states which compose this interruption [8]. The total cost associated with this interruption K_I (US$) is given by

$$K_I = \sum_{j \in S_{ES(I)}} ES_j \times UC(D_j) \qquad (1)$$

where ES_j is the curtailed energy block j; D_j is the respective duration of the energy block j; and $UC(D_j)$ is the unit interruption cost (US$/MWh). Note that a curtailed energy block can consist of: (i) only one type of consumer class (e.g. 100% residential); or (ii) a combination of consumer classes (e.g. 20% residential, 30% industrial, and 50% commercial). These concepts are illustrated in Figure 3, which shows an interruption I with different curtailed energy blocks. For this particular interruption, (1) can be written as:

$$K_I = \sum_{j=1}^{6} ES_j \times UC(D_j) \qquad (2)$$

where $ES_1=PS_1 \times D_1$, PS_1=P$_1$-0, $D_1=t_{10}-t_1$; $ES_2=PS_2 \times D_2$, PS_2=P$_2$-P$_1$, $D_2=t_9-t_2$; $ES_3=PS_3 \times D_3$, PS_3=P$_3$-P$_2$, $D_1=t_9-t_3$; $ES_4=PS_4 \times D_4$, PS_4=P$_4$-P$_3$, $D_1=t_5-t_4$; $ES_5=PS_5 \times D_5$, PS_5= P$_4$-P$_3$, $D_5=t_8-t_6$; $ES_6=PS_6 \times D_6$, PS_6=P$_5$-P$_4$, $D_6=t_7-t_6$; An energy block may consist of different connected failure states. This modeling is closer to reality since interruption processes are carried out according to certain priorities or curtailment criteria. A good approximation for the LOLC index can also be obtained by evaluating the interruption cost K_I as a function of the total interruption duration and the total curtailed energy [1], [5].

3 ASSESSMENT ALGORITHMS

3.1 Chronological Monte Carlo Simulation

The sequential MCS [5]-[7] is able to reproduce the chronological evolution of the system by sampling stochastic sequences of system states. These sequences are simulated based on the stochastic modeling of each system component and the chronological load model in the same time basis [1]. The sequential MCS algorithm can estimate the system reliability indices considering the NY simulated years as given by (3):

$$\tilde{E}[G] = \frac{1}{NY} \sum_{\mathrm{k}=1}^{NY} G(y_{\mathrm{k}}) \qquad (3)$$

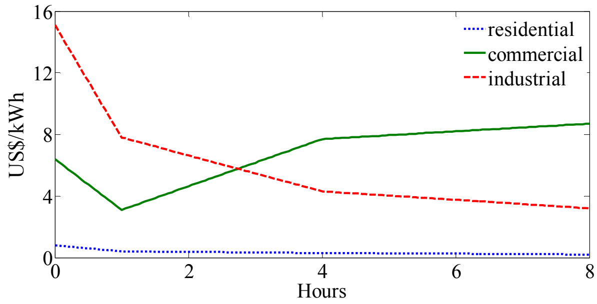

Figure 1: Unit interruption cost for Ontario Hydro.

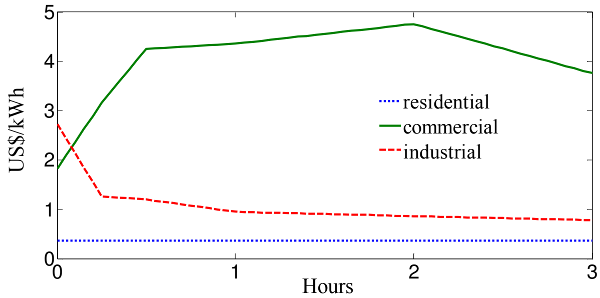

Figure 2: Unit interruption cost for the Brazilian System.

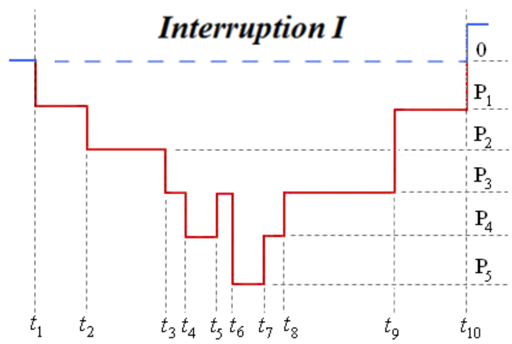

Figure 3: Graphic Representation of an interruption.

Estimates of all the basic reliability indices can be represented by (3), depending on the definition of $G(y_{\mathrm{k}})$. Considering the LOLC index, $G(y_{\mathrm{k}})$ = sum of the respective costs K_I of all the interruptions that occurred in the year y_{k}. The maximum number of simulated years and the coefficient of variation β are examples of typically used convergence criteria. The sequential MCS can easily represent any chronological aspect including the fluctuation of generating capacities and loads. It is able to assess not only the usual reliability indices, but also their respective probability distributions. In addition, non-exponential distributions can be used to represent the duration of component states. However, it requires huge computational efforts when compared to other approaches. This is especially true in composite reliability evaluation or when dealing with rare events.

3.2 Pseudo-chronological Monte Carlo Simulation

In order to reduce the computational efforts of a sequential simulation, the pseudo-chronological MCS was proposed in [8]. In the pseudo-chronological MCS, the system states are sampled according to their probability of occurrence. Once a failure state x_s has been sampled, the whole sequence of failure states that characterizes the interruption is obtained through a *forward/backward* simulation. The forward simulation is concerned with the identification of one possible *forward sequence* [8], i.e. a sequence of failure states to be experimented by the system after leaving the sampled state x_s. Under Markovian assumptions, the probability of the system arriving at x_t from x_s can be evaluated as the ratio between frequencies f_{st} and f_s^{out}. Thus,

$$P_{st} = \frac{f_{st}}{f_s^{\text{out}}} = \frac{\lambda_{st}}{\sum_{i=1}^{M_s} \lambda_{si}} \tag{4}$$

where M_s is the number of states the system can go into, after leaving state x_s. Equation (4) provides the basis for constructing the probability distribution from which the next system state x_t will be sampled from. The *forward sequence* is obtained by repeating this process until the first success state has been found.

Conversely, the backward simulation is concerned with the identification of one possible *backward sequence*, i.e. a sequence of failure states experimented by the system before arriving at sampled state x_s. The probability of the system arriving at x_s from x_r, here denoted P_{rs}, can be also evaluated as the ratio between frequencies f_{rs} and f_s^{in}. Thus,

$$P_{rs} = \frac{f_{rs}}{f_s^{\text{in}}} = \frac{P\{x = x_r\}\lambda_{rs}}{\sum_{i=1}^{M_r} P\{x = x_i\}\lambda_{is}} \tag{5}$$

where M_r is the number of states that can transit to x_s. Similar to the forward sequence, the backward sequence is conveniently constructed using (5). The whole interruption cycle is obtained by combining both forward and backward sequences. The usual loss of load indices, including the LOLC index, can now be evaluated using their respective test functions. For example, the test functions for estimating the LOLF and LOLC indices are given by

$$H_{\text{LOLF}}(\mathbf{X}_i) = \begin{cases} 0 & \text{if } \mathbf{X}_i \in \Psi_{\text{Success}} \\ 1/E[D_I] & \text{if } \mathbf{X}_i \in \Psi_{\text{Failure}} \end{cases} \tag{6}$$

$$H_{\text{LOLC}}(\mathbf{X}_i) = \begin{cases} 0 & \text{if } \mathbf{X}_i \in \Psi_{\text{Success}} \\ K_I / E[D_I] & \text{if } \mathbf{X}_i \in \Psi_{\text{Failure}} \end{cases} \tag{7}$$

where $\Psi = \Psi_{Success} \cup \Psi_{\text{Failure}}$ is the set of all possible states $\mathbf{X}_i$ (i.e. the state space), divided into two subspaces $\Psi_{Success}$ of success states and Ψ_{Failure} of failures states; $E[D_I]$ is the expected value for the total duration of the interruption I; and K_I is its associated cost.

The pseudo-chronological MCS retains the computational efficiency of non-sequential methods and the ability to model chronological load curves per area or bus. It is able to accurately capture all the actual blocks of unsupplied energy per customer class, per bus, and the respective durations which characterize the interruption process [8]. However, since it is basically a non-sequential approach, the pseudo-chronological MCS cannot assess the probability distributions of the reliability indices. Also, in very reliable systems, failure states are unlikely to be sampled and, therefore, the pseudo-chronological MCS performance would still be endangered when dealing with rare events.

4 CROSS-ENTROPY BASED ALGORITHM

4.1 Basic Concepts

Importance sampling (IS) is a well-known variance reduction technique, which is based on the idea that certain values of a random variable have greater impact, when compared to others, in the estimation process of a target quantity. If these important values are sampled more often, the variance of the estimator will be reduced. Technically, IS aims at selecting a probability density or mass function $g_{\text{opt}}(\cdot)$ different from the original, such that the sample variance is minimized [12]. The efficiency of the IS depends on obtaining this new $g_{\text{opt}}(\cdot)$, or at least, one very close to it. The obvious problem is that the optimal change of measure or new $g_{\text{opt}}(\cdot)$ is initially unknown and generally difficult to find.

The advantage of the Cross-Entropy (CE) method is that it provides a simple adaptive procedure for estimating the optimal, or close to optimal, reference parameters. This is achieved by minimizing the *distance* between the original sampling density $g(\cdot)$ and the optimal sampling density $g_{\text{opt}}(\cdot)$ iteratively. A detailed discussion of the CE Method is out of the scope of this paper. Rigorous mathematical proofs can be found in [9]-[11]. Also, readers are encouraged to refer to [12] for the fundamentals of the CE method as it is applied to power system reliability assessment.

4.2 Cross-Entropy/Pseudo-chronological MCS

An optimal CE reference parameter vector $\mathbf{v}_{\text{opt}}$ can be estimated using the same procedure proposed in [12]. Consider a system with N_C generating stations and assume that the *j-th* station (GS_j) has n_j identical and independent units, each one with a capacity C_j and unavailability u_j. An estimate for the optimal reference parameter vector can be obtained as follows:

<u>*Step 1*</u>: Define the parameters: (i) sample size N (e.g. 10 000 samples); (ii) multi-level parameter ρ (e.g. typically between 0.01 and 0.1 [9]); (iii) smoothing parameter $\alpha = 1$ (only different from 1 to avoid occurrences of zeros and ones in vector $\mathbf{v}$ [9]); and aim the distortion to the pick load, i.e. L=L_{MAX}; also define $\mathbf{u} = [u_1, u_2,\ldots, u_j,\ldots, u_{N_C}]$ and $\mathbf{n} = [n_1, n_2,\ldots, n_j,\ldots, n_{N_C}]$;

<u>*Step 2*</u>: Define $\hat{\mathbf{v}}_0 = \mathbf{u}$; also set k:=1 (iteration counter of the CE optimization process);

<u>*Step 3*</u>: Generate a random sample $\mathbf{G}_1, \mathbf{G}_2,\ldots,\mathbf{G}_i,\ldots, \mathbf{G}_N$ of generating states according to the binomial probability mass function $g(\cdot\,; \mathbf{n}, \hat{\mathbf{v}}_{k\text{-}1})$;

<u>*Step 4*</u>: Evaluate the performance function $S(\mathbf{G}_i)$= $\sum G_{ij} \cdot C_j$, which is the total available generation at state $\mathbf{G}_i$, for each sampled state and order them from the biggest to the smallest, i.e. $S_{[1]} \geq S_{[2]} \geq \ldots \geq S_{[N]}$. Note

that $S_{[j]}$ represents the *j-th order-statistic* of the sequence $S(\mathbf{G}_1), \ldots, S(\mathbf{G}_N)$;

Step 5: Let $\hat{L}_k$ be the sample ρ-quantile of the performances: $\hat{L}_k = S_{[(1-\rho)N]}$, provided this is greater than L. Otherwise, set $\hat{L}_k = L$. Evaluate the test function $H(\mathbf{G}_i)=I_{\{S(\mathbf{G}_i)<\hat{L}_k\}}$ for all $\mathbf{G}_i$: if $S(\mathbf{G}_i) < \hat{L}_k$, then $H(\mathbf{G}_i)=1$, otherwise $H(\mathbf{G}_i)=0$;

Step 6: Calculate the likelihood ratio $\mathbf{W}(\mathbf{G}_i;\mathbf{n},\mathbf{u},\hat{\mathbf{v}}_{k\text{-}1})$ for all $\mathbf{G}_i$ according to (8).

$$\mathbf{W}(\mathbf{G}_i;\mathbf{n},\mathbf{u},\hat{\mathbf{v}}_{k\text{-}1}) = \frac{\prod_{j=1}^{N_C} (1-u_j)^{G_{ij}} (u_j)^{n_j - G_{ij}}}{\prod_{j=1}^{N_C} (1-v_j)^{G_{ij}} (v_j)^{n_j - G_{ij}}}; \qquad (8)$$

Step 7: Use the same sample to evaluate each element $j = 1, 2, \ldots, N_C$ of the new reference parameter vector $\hat{\mathbf{v}}_k$ as follows:

$$\hat{v}_{k,j} = 1 - \frac{1}{n_j}\left[\frac{\sum_{i=1}^{N} I_{\{S(\mathbf{G}_i)<\hat{L}_k\}} \mathbf{W}(\mathbf{G}_i;\mathbf{n},\mathbf{u},\hat{\mathbf{v}}_{k\text{-}1}) G_{ij}}{\sum_{i=1}^{N} I_{\{S(\mathbf{G}_i)<\hat{L}_k\}} \mathbf{W}(\mathbf{G}_i;\mathbf{n},\mathbf{u},\hat{\mathbf{v}}_{k\text{-}1})}\right]; \quad (9)$$

Since the random variables involved, i.e., binomial distributions, belong to the natural exponential family (NEF), the analytical expression (9) was found by just adapting the concepts and proofs described in [9]-[11]. In case $\alpha \neq 1$, correct $\hat{v}_{k,j}$, as shown in [9]-[11];

Step 8: If $\hat{L}_k = L$, finish the CE optimization process at $k = K$ (final iteration) and consider $\hat{\mathbf{v}}_K \cong \mathbf{v}_{\text{opt}}$; otherwise, increase the iteration counter as k:=k+1, and go back to *Step 3*;

Step 9: Now, a pseudo-chronological MCS algorithm will be run based on IS techniques, using the optimal vector parameter $\hat{\mathbf{v}}_K$. Therefore, set the new iteration counter M=0; define the maximum sample size M_{MAX} and the coefficient of variation β_{MAX} (e.g. between 1 and 5%). Also, create a Bernoulli parameter vector $\mathbf{v}$ using the binomial parameter vectors $\hat{\mathbf{v}}_K$ and $\mathbf{n}$. For example, if $\hat{\mathbf{v}}_K$=[v_1, v_2, … , v_{Nc}] and $\mathbf{n}$=[n_1=3, n_2=2,…,n_{Nc}=4], then $\mathbf{v}$=[v_1, v_1, v_1, v_2, v_2, … , v_{Nc}, v_{Nc}, v_{Nc}, v_{Nc}]. Notice that $\mathbf{v}$ is a vector with dimension $1\times\sum\mathbf{n}$. In a similar way, redefine vector $\mathbf{u}$ so it becomes a Bernoulli parameter vector instead of a binomial one;

Step 10: Set M=M+1 and sample a load state $\mathbf{L}_M$ according to the load probability model;

Step 11: Sample a generation state $\mathbf{G}_M$ according to the Bernoulli probability mass function $f(\cdot\,;\mathbf{v})$;

Step 12: Evaluate the test functions H_{LOLP}, H_{EPNS}, H_{LOLF}, and H_{LOLC} [8] considering the sampled system state $\mathbf{X}_M = \{ \mathbf{G}_M ; \mathbf{L}_M \}$. Note that if $\mathbf{X}_M$ is a failure state, a *forward/backward* simulation must be carried out to evaluate H_{LOLF} and H_{LOLC};

Step 13: Evaluate the likelihood ratio for the sampled generation state $\mathbf{G}_M$ as follows:

$$\mathbf{W}(\mathbf{G}_M;\mathbf{u},\mathbf{v}) = \frac{\prod_{j=1}^{N_G} (1-u_j)^{G_{Mj}} (u_j)^{1-G_{Mj}}}{\prod_{j=1}^{N_G} (1-v_j)^{G_{Mj}} (v_j)^{1-G_{Mj}}} \qquad (10)$$

where N_G=$\sum\mathbf{n}$= total number of generating units. Equation (10) represents the compensation factor needed to ensure unbiased estimates during the MCS process;

Step 14: Evaluate the unbiased estimator for the LOLP index at iteration M as follows:

$$\text{LOLP} = \frac{1}{M}\sum_{i=1}^{M} H_{\text{LOLP}}(\mathbf{X}_M)\cdot\mathbf{W}(\mathbf{G}_M;\mathbf{u},\mathbf{v}) \qquad (11)$$

The EPNS, LOLF, and LOLC indices can be similarly estimated by using their respective test functions in (11). The other reliability indices can be estimated as: LOLE = LOLP×T, EENS = EPNS×T, and LOLD = LOLP/LOLF, where T is usually equal to 8760 hours;

Step 15: Estimate the coefficient of variations β_{LOLP}, β_{EPNS}, β_{LOLF}, and β_{LOLC} at iteration M. If all of them are less or equal to β_{MAX} or if $M \geq M_{MAX}$, stop the algorithm; otherwise, go back to *Step 10*. In order to make the MCS tracking process more efficient, the convergence can be verified in blocks of, for instance, 1000 samples.

4.3 The Φ Parameter

The Φ parameter was proposed in [12] in order to further improve the efficiency of the optimal CE parameter vector obtained for the system peak load. This parameter is very useful in systems with low load factors, since most load levels will be far away from the peak load. The Φ parameter is defined as

$$\Phi = P_{\hat{\mathbf{v}}_K}\{S(\mathbf{G}_i) < \ell\} \qquad (12)$$

If one specifies the probability Φ, an estimate $\hat{\ell}$ of ℓ can be found by sampling N (e.g. 10 000) generating states, i.e. $\mathbf{G}_1$, $\mathbf{G}_2$,…, $\mathbf{G}_N$, according to $g(\cdot;\mathbf{n},\hat{\mathbf{v}}_K)$, which is the distribution obtained by the CE approach (*Steps 1- 8*). The performance function $S(\mathbf{G}_i)$ is evaluated for each state $\mathbf{G}_i$, and the results are ordered from the smallest to the biggest: $S_{[1]} \leq S_{[2]} \leq \ldots \leq S_{[N]}$. The value $\hat{\ell}$ will be such that $\hat{\ell} = S_{[\Phi N]}$.

The implementation of this parameter is simple and very efficient from the computational point of view. Basically, during the IS based pseudo-chronological simulation (*Steps 9- 15*), *Step 10* will be repeated until a load level greater or equal to $\hat{\ell}$ is found. Note that the Φ parameter introduces a very small inaccuracy in the estimation process, since some sampled states are promptly considered as success. This inaccuracy, however, may be insignificant if the specified value of Φ is small. The value of Φ depends on the rarity of the failure events, but typical values are from 0.01 to 0.04, for a LOLP index between 10^{-3} to 10^{-5}, and from 0.05 to 0.1, for a LOLP index < 10^{-5}.

5 APPLICATION RESULTS

The proposed method will be tested using the IEEE RTS-79 (Reliability Test System) [17], IEEE RTS-96 [18], modifications of this system that include renewable sources [19], and two configurations of the Brazilian South-Southeastern generating system [20]. In all cases, the computations are performed in a MATLAB platform using an Intel Core 2 Duo 2.66 GHz.

5.1 IEEE Reliability Test System 79

This generation system consists of 32 units with total installed capacity of 3405 MW. The load is represented by an hourly curve with 8760 chronological levels, whose peak is 2850 MW. The unit interruption costs are taken from the Ontario Hydro Survey [3], which results are illustrated in Figure 1. The participation of each consumer class in a given curtailed energy block is taken from [5]. Basically, energy blocks with curtailment depths between 0 and 546 MW are 100% residential; between 546 and 1023 MW are 100% commercial; and between 1023 and 2850 MW are 100% industrial.

Table 1 presents the results obtained for this system using the chronological (Chrono), pseudo-chronological (Pseudo-Chrono), and the proposed Cross-Entropy/ pseudo-chronological MCS (CE/Pseudo-Chrono). A β_{MAX} = 5% is specified for all indices and the corresponding values are shown between brackets. All methods reached a value for the LOLP index around 1.07×10^{-3}. The Chrono and Pseudo-Chrono spent 15.2 minutes and 43.7 seconds, respectively. The CE/ Pseudo-Chrono spent only 2.2 seconds using Φ=0.05. The speed-up in relation to the Pseudo-Chrono is approximately 20, and in relation with the Chrono is around 421. This system was mainly used in order to obtain some reference values for the reliability indices and CPU times. For instance, all results shown in Table 1 are in fair agreement with the ones reported in [5].

5.2 IEEE Reliability Test System 96

In its original configuration, the IEEE RTS-96 has 96 generating units with a total installed capacity of 10 215 MW. From this total, 900 MW are hydro power units and 9315 MW are thermal units. The load is represented by 8760 chronological levels with an annual peak load of 8550 MW. The unit interruption costs are taken from Figure 1. The consumer classes participations in all curtailed energy blocks are considered to be: 21% residential, 30% commercial, and 49% industrial.

Table 2 shows the results obtained for this system using the three simulation algorithms. Considering a β_{MAX} = 5%, all methods reached a value for the LOLP index circa 1.56×10^{-5}. The Chrono and Pseudo-Chrono spent 3.48 hours and 17.9 minutes, respectively. The CE/ Pseudo-Chrono, considering Φ=0.05, spent only 10 seconds without any significant accuracy loss. The speed-up in relation to the Pseudo-Chrono is approximately 108, and in relation with the Chrono is circa 1260. In this case, since failure events are rare, larger speed-ups are obtained using the proposed approach. When dealing with very reliable system configurations, the advantages of using CE-based methods are obvious.

IEEE RTS 79	Chrono	Pseudo-Chrono	CE/Pseudo-Chrono
LOLP	1.0638×10^{-3} (2.47%)	1.0550×10^{-3} (2.43%)	1.0829×10^{-3} (3.18%)
EPNS [MW]	1.3239×10^{-1} (3.62%)	1.3432×10^{-1} (3.30%)	1.3486×10^{-1} (3.01%)
LOLF [occ./year]	2.0151×10^{0} (1.95%)	2.0105×10^{0} (3.29%)	2.0301×10^{0} (4.73%)
LOLC [US$/year]	3.5466×10^{5} (4.99%)	3.5483×10^{5} (4.98%)	3.5224×10^{5} (2.98%)
CPU Time [seconds]	914.75	43.74	2.17

Table 1: Reliability indices for the IEEE RTS-79.

IEEE RTS 96	Chrono	Pseudo-Chrono	CE/Pseudo-Chrono
LOLP	1.5534×10^{-5} (3.21%)	1.5548×10^{-5} (3.60%)	1.5855×10^{-5} (3.92%)
EPNS [MW]	2.7699×10^{-3} (4.99%)	2.8165×10^{-3} (4.99%)	2.7933×10^{-3} (3.21%)
LOLF [occ./year]	5.1509×10^{-2} (2.57%)	5.1573×10^{-2} (4.29%)	5.1078×10^{-2} (4.99%)
LOLC [US$/year]	1.1196×10^{5} (4.86%)	1.1207×10^{5} (4.52%)	1.1207×10^{5} (3.22%)
CPU Time [seconds]	12 545.13	1 075.84	9.95

Table 2: Reliability indices for the IEEE RTS-96.

5.3 IEEE Reliability Test System 96 HW

In order to cope with the power fluctuation of hydro and wind units, some modifications are introduced to the previous IEEE RTS-96. Since the original configuration does not have any wind power sources, one of the coal units of 350 MW is substituted by 1526 MW of wind power. In doing so, the total installed capacity increases to 11 391 MW, and the percentage of renewable power goes from 8.8% to 21.3%. The thermal generation subsystem has 77 units with capacities varying from 12 MW up to 400 MW, making a total of 9315 MW. The hydraulic generation subsystem has 18 units of 50 MW each, distributed among three power stations.

To simulate the capacity fluctuation of hydro units, five historical series, referring to the average monthly power capacity, are presented in [19]. These series are assumed to have the same probability of occurrence. The wind power subsystem has 763 units of 2 MW, distributed among 3 regions or areas with different wind characteristics: Area 1 (267 units), Area 2 (229 units), and Area 3 (267 units). In order to characterize wind power fluctuations, three series are used [19], for each wind area, in an hourly basis, referring to the average power produced by a wind generator. The series are classified as favorable, average, and unfavorable, with related probabilities of 0.25, 0.50, and 0.25. The load

IEEE RTS 96 HW	Chrono	Pseudo-Chrono	CE/Pseudo-Chrono
LOLP	3.9645×10^{-5} (3.33%)	4.0092×10^{-5} (3.76%)	3.8922×10^{-5} (3.59%)
EPNS [MW]	7.4567×10^{-3} (4.99%)	7.4168×10^{-3} (4.99%)	7.4497×10^{-3} (3.22%)
LOLF [occ./year]	1.2245×10^{-1} (2.70%)	1.2484×10^{-1} (4.55%)	1.1971×10^{-1} (4.99%)
LOLC [US$/year]	2.9955×10^{5} (4.88%)	3.0176×10^{5} (4.56%)	2.9794×10^{5} (3.12%)
CPU Time [seconds]	15 453.31	913.16	12.71

Table 3: Reliability indices for the IEEE RTS-96 HW.

BSS Normal	Chrono	Pseudo-Chrono	CE/Pseudo-Chrono
LOLP	3.4640×10^{-3} (2.14%)	3.4429×10^{-3} (2.88%)	3.4519×10^{-3} (4.32%)
EPNS [MW]	1.9296×10^{0} (3.46%)	1.8782×10^{0} (3.83%)	1.9522×10^{0} (4.20%)
LOLF [occ./year]	3.0036×10^{1} (1.87%)	3.0057×10^{1} (3.16%)	2.9096×10^{1} (4.99%)
LOLC [US$/year]	8.0944×10^{6} (4.73%)	8.1515×10^{6} (4.82%)	8.0248×10^{6} (4.33%)
CPU Time [seconds]	59.38	15.90	1.73

Table 4: Reliability indices for the normal Brazilian South-Southeastern system.

BSS Reinforced	Chrono	Pseudo-Chrono	CE/Pseudo-Chrono
LOLP	1.9777×10^{-5} (2.84%)	1.9052×10^{-5} (2.96%)	1.9024×10^{-5} (4.34%)
EPNS [MW]	7.1093×10^{-3} (4.09%)	7.0056×10^{-3} (4.13%)	7.1406×10^{-3} (3.46%)
LOLF [occ./year]	1.9711×10^{-1} (2.67%)	1.8747×10^{-1} (3.21%)	1.9454×10^{-1} (4.95%)
LOLC [US$/year]	2.5277×10^{4} (4.99%)	2.5086×10^{4} (5.00%)	2.5527×10^{4} (3.33%)
CPU Time [seconds]	3 519.28	2 155.12	4.13

Table 5: Reliability indices for the reinforced Brazilian South-Southeastern system.

model, the unit interruption costs and the relative participation of consumer classes in curtailed energy blocks are the same as the previous case.

As shown by Table 3, the new LOLP index achieved for all methods is approximately 3.9×10^{-5}. The Chrono algorithm spent 4.3 hours and the Pseudo-Chrono 15.2 minutes. The CE/Pseudo-Chrono spent a total of 12.7 seconds, from which 2.3 seconds were spent in obtaining the optimal distortion (*Steps 1- 8*). A Φ=0.05 was used in the CE-based method. The speed-up in relation to the Pseudo-Chrono is approximately 72, and in relation with the Chrono is around 1216. Undoubtedly, the CE-based method is a good option when compared to the chronological MCS. It is possible to observe that the combined effect of the fluctuating capacity of the hydro and wind units slightly deteriorates the reliability indices. The hydro units have their effective capacities reduced by the hydro series. The substitution of the coal unit of 350 MW by 1526 MW of wind power slightly improves the system reliability. However, the final effect was an increase in the reliability risk.

5.4 *Brazilian South-Southeastern System*

The proposed methodology will be tested using two configurations (normal and reinforced) of the Brazilian South-Southeastern (BSS) generating system planned for the 90s [12], [20]. The normal configuration consists of 67 power generation plants: 53 hydro plants and 14 thermal plants. There are 290 units with capacities varying from 15 MW up to 700 MW (ITAIPU units), totalizing an installed capacity of 42.8 GW. The reinforced configuration considers four additional ITAIPU units of 700 MW. An hourly load model with 8736 levels and peak load of 41.2 GW is used for both configurations. The unit interruption costs are taken from Figure 2 [4]. The participation of each consumer class in a given curtailed energy block is considered to be: 100% residential for curtailment depths between 0 and 1000 MW; 50% residential and 50% industrial for curtailment depths between 1000 and 1500 MW; and 20% residential, 30% industrial, and 50% commercial for curtailment depths above 1500 MW.

The reliability indices for both configurations are evaluated by the three methods. Table 4 shows the results for the normal configuration. The LOLP index is circa 3.44×10^{-3}. The Chrono spent approximately 1 minute. The Pseudo-Chrono and its CE-based version (with Φ=0.05) spent 15.9 and 1.7 seconds, respectively. The results for the reinforced configuration are shown in Table 5. The new LOLP index is approximately 1.91×10^{-5}. The performances of the Chrono, Pseudo-Chrono, and CE/ Pseudo-Chrono are 59 minutes, 36 minutes, and 4 seconds, respectively. Even if the normal BSS has more generating units than the IEEE RTS-79, it converges a lot faster since the average number of failures/year is also much larger. Notice that the performances of both Chrono and standard Pseudo-Chrono are severely affected when considering the reinforced configuration. The CPU time of the proposed CE/Pseudo-Chrono, however, was only marginally increased.

6 CONCLUSIONS

This paper presented a new methodology to assess generating capacity reliability indices, with particular emphasis on the LOLC index. Based on the pseudo-chronological MCS and the CE method, the main idea was to obtain an *optimal distortion* for the generation model using the CE concepts proposed in [12]. As a result, the occurrences of failure events were promoted and the variances of the estimators were reduced. The proposed method can capture all the actual blocks of unsupplied energy per consumer class and their respective durations. In addition, many chronological aspects such as the fluctuation of generating capacities and scheduling maintenance can be easily included in the simulation model. Comparisons with the chronological and standard pseudo-chronological MCS have demonstrated the efficiency and accuracy of the proposed approach. It reaches high speed-ups in relation to the previous approaches, especially when dealing with very reliable system configurations. Case studies were reported using the IEEE RTS-79, the IEEE RTS-96, the IEEE RTS-96HW, and two configurations of the Brazilian South-Southeastern generating system.

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