

Reliability Evaluation of Generation Systems via Sequential Population-Based Monte Carlo Simulation

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Abstract—This paper introduces the use of a Population-Based method (PBM) to decrease the computational effort during the state evaluation stage of the sequential Monte Carlo simulation (SMCS). The proposed methodology consists of two phases. Firstly, a list of generation states whose total capacity is inferior to the system's peak load is created using a PBM. Secondly, the generation states sampled using the SMCS are compared to those on the list. The aim is to decide whether the system's state evaluation should be performed or not. If a generation state proceeds with the evaluation, the yearly load model and the time-dependency of the generator's capacity are chronologically followed to form system states which may or may not have loss of load. Otherwise, it is assumed that no loss of load occurs throughout its duration. The proposed methodology is applied to the generation capacity reserve (GCR) assessment of configurations of the IEEE-RTS 79 and IEEE-RTS 96 power systems that include wind and hydro intermittency. Results demonstrate significant improvements in efficiency regarding the state evaluation stage, paving the way to applications in large-scale systems.

Keywords—generation capacity reliability assessment; sequential Monte Carlo simulation; Population-Based methods

I. INTRODUCTION

It is unanimous among scientists, engineers and policy-makers that renewable energy sources (RES) play an important role in sustainable power systems. Their massive integration brings new challenges to power system planning and operation different from those posed by conventional fossil fueled power plants. The high variability observed in the power produced by some types of RES, which is mainly a consequence of the intermittency of their primary energy resource, is seen as a risk to the adequacy of supply [1]. Incorporating this characteristic of RES into the generation capacity reserve (GCR) assessment framework is a twofold problem. On the one hand, it is necessary to develop complex stochastic and/or deterministic models that can accurately capture the time-dependent characteristic of RES and their integration strategies. On the other hand, obtaining the GCR indexes according to these models often requires high simulation times as a result of the cardinality and the time-dependent characteristic of the variables of the models.

Several studies on how to reduce the simulation time of the methods for power system reliability assessment can be easily

found in the literature. These works can be categorized as follows, according to the technique used: state space pruning [2], variance reduction [3, 4], Fast Fourier Transform [5], pseudo-sequential [6] and quasi-sequential [7] simulation, artificial intelligence [8, 9] and pattern recognition [10, 11], object oriented [12], parallel [13] and agent-based [14] computation. Of all techniques categories mentioned above, the most successful [15] in reducing the simulation time of the sequential Monte Carlo simulation (SMCS) is based on variance reduction, namely, importance sampling, where parameters are optimized by the Cross-Entropy method [16]. However, this technique fails to provide one of the outcomes of the SMCS, which is the probability distribution of the reliability indexes [15].

This paper presents a new methodology for reducing the simulation time of the SMCS state evaluation stage. It relies on a list to decide whether the sampled generation states should trigger the state evaluation stage. If a generation state is not on the list, it is assumed that no loss of load occurs throughout its duration. The list is created using the intelligent search mechanisms of the Population-Based method (PBM) proposed in [17]. This method provides a broad coverage of the region of the generation state space and keeps the ones that contribute the most to the GCR annual indexes. A generation state is included in the list if its capacity is insufficient to supply the peak load and if its probability is greater than or equal to a given threshold. Other generation states can also be included during the SMCS if the last system state evaluated is a failure state. This cooperation mechanism aims at reducing the probability of classifying a generation state as successful when in fact it contains at least one failure system state. The net gain in the simulation time depends on the time spent creating the list and on the time saved by using the new methodology instead of following the traditional procedure of the SMCS for evaluating system states. The highest gains will be obtained when the state evaluation stage is the most time demanding procedure.

This paper is organized as follows: Section II presents brief remarks regarding GCR assessment using PBM and SMCS. Section III introduces the proposed methodology. Section IV shows the results obtained for the configurations of the IEEE-RTS 79 [18] and IEEE-RTS 96 [19] including wind and hydro power. Finally, Section V contains conclusions, final remarks and future work.

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II. GCR ASSESSMENT VIA PBM AND SMCS

The GCR is assessed via loss of load indexes. These provide important information on loss of load events and are categorized as probability, energy, frequency and duration indexes. The GCR probability indexes [4] are the Loss of Load Probability (LOLP) and the Loss of Load Expectation (LOLE) [4]. The energy indexes [4] are the Expected Power Not Supplied (EPNS) and the Expected Energy Not Supplied (EENS). Frequency and duration indexes [4] are the Loss of Load Frequency (LOLF) and the Loss of Load Duration (LOLD), respectively. In this work, GCR annual indexes are estimated in the SMCS-based stage. Estimates of the GCR annual indexes can also be obtained using PBMs [17]. Only GCR annualized indexes are estimated in the PBM-based stage.

A. Population-Based Methods

PBMs [9, 17] provide estimates of the GCR indexes by enumerating generation states. The idea is to drive the population in a guided search for the generation states that contribute the most to the formation of the indexes. If all states contributing to a certain index can be identified, the index will be accurately calculated. PBMs attempt to find, if not the totality, the majority of those generation states so that a good approximation of the GCR indexes can be computed.

The search process is set to find the highest possible number of different high probability generation states with insufficient capacity to supply the peak load. During this process, there is neither a sense of order nor time-dependent representations.

In PBMs, the estimate of a given GCR index F is obtained using (1)

$$\tilde{F} = \sum_{x_i \in D} p(x_i) H(x_i) \quad (1)$$

where D is the set of generation states saved, $p(x_i)$ is the probability of the generation state x_i , $H(x_i)$ is the value of the test-function of the GCR index being assessed, and $D \subset U$, i.e., D is a subset of all possible generation states U . It is usual to truncate the subset containing all generation states with insufficient capacity to supply the peak load, $D_f (D \subset D_f \subset U)$. Therefore, the results provided by PBMs may underestimate the correct value of the GCR indexes.

The GCR annual indexes are estimated by confronting the generation states in the list with the annual load curve [9, 17]. PBMs are not statistical, and therefore, they do not provide an interval of confidence to the results [9, 17].

In general, the stopping criterion can be based either on a maximum number of iterations allowed or on the “stability” of a given GCR annualized index. Taking the EPNS annualized index as an example, the latter criterion is rendered as in (2)

$$\frac{\text{EPNS}_k - \text{EPNS}_{(k-N_{MAX})}}{\text{EPNS}_{(k-N_{MAX})}} \leq \varepsilon \quad (2)$$

where k is the current sample, N_{MAX} is the maximum number of iterations without “significant” improvement on the EPNS in-

dex estimate, and ε is the maximum tolerance to the improvement. Hence, there is no guarantee of accuracy.

The generation states are collected and included in a list, which is used to keep track of generation states that have already been saved and to recognize new ones. Searching the list can be a time consuming task towards the end of the search process when many generation states have already been saved. This problem can be tackled by adopting appropriate programming techniques.

The work presented in [17] has introduced innovative techniques so that the spreading of the population along the state space is promoted instead of attracting it to the best generation state. In fact, the aim with the search process is not to discover the optimum, but rather visit as many different generation states as possible. Traditionally, PBMs rely only on the evolutionary mechanisms to create the diversity required to visit new generation states. These mechanisms may cause generation states to be visited repeatedly before new generation states are discovered, especially when the search is close to the optimum. Spreading techniques applied in [17] have helped mitigate this problem in the Evolutionary Particle Swarm Optimization (EPSO) algorithm [20] by increasing the ratio of different states visited against the total number of states visited. The search phase of the proposed methodology is based on the PBM described in [17].

B. Sequential Monte Carlo Simulation

The Monte Carlo simulation [4] can be divided into three approaches according to the representation of system states: the non-sequential [6, 15], the pseudo-sequential [7] and the sequential approach [15]. The sequential approach simulates sequences of events creating a synthetic chronological “lifespan” of the system. Chronological aspects such as correlated load models, time-dependent loss of load cost or maintenance, and so forth, can be easily represented. Furthermore, it makes it possible to use non-Markovian representations to model failure/repair events and to obtain the probability distributions of the GCR indexes. Traditionally, it requires a higher computational effort comparatively to the other approaches.

In SMCS, GCR indexes are estimated using (3)

$$\tilde{E}[F] = \frac{1}{N_{YEAR}} \sum_{n=1}^{N_{YEAR}} F(y_n) \quad (3)$$

where N_{YEAR} is the number of simulated years, y_n is the sequence of system states of year n , and $F(y_n)$ is the test function used for calculating yearly indexes over the sequence y_n .

All the GCR indexes can be estimated using (3) with the appropriate test function. Contrarily to the PBM, it is a statistical method in the sense that the relative uncertainty of the estimate is given by the coefficient of variation as in (4)

$$\beta = \frac{\sqrt{V(\tilde{E}[F])}}{\tilde{E}[F]} \quad (4)$$

where $V(\tilde{E}[F])$ is the variance of the estimate.

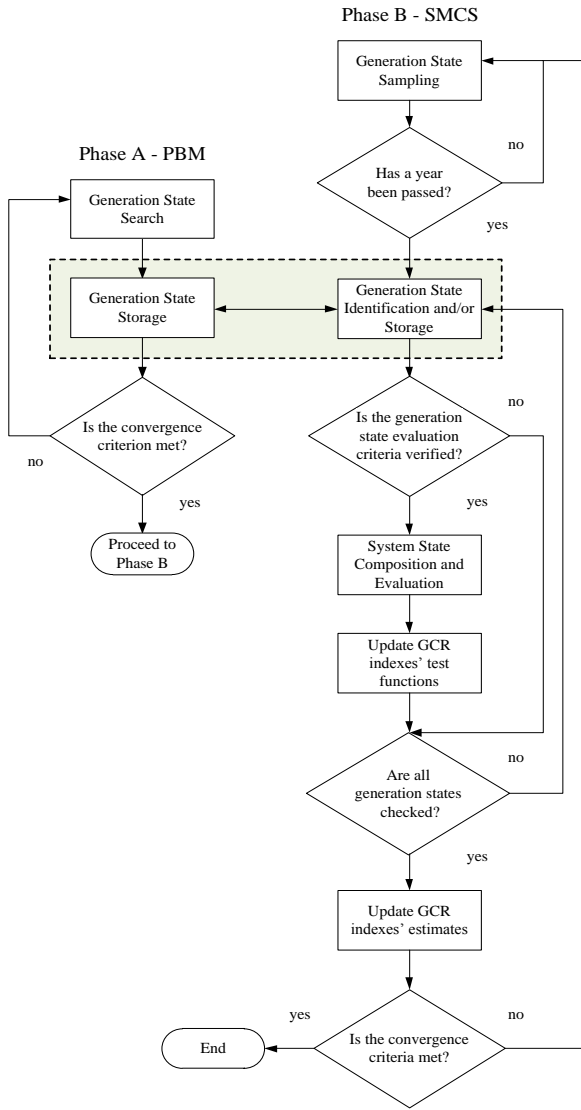


Figure 1. Flowchart of the proposed methodology.

III. PROPOSED METHODOLOGY

The proposed methodology is composed of two phases. Phase A consists of using the PBM proposed in [17] to create the list of generation states. Phase B runs a SMCS-based algorithm to calculate the GCR annual indexes. Instead of performing the traditional SMCS procedure of composition to test $G-L < 0$ to all sampled generation states, the list created in Phase A is used to identify which of them will proceed to the SMCS composition and evaluation stage. Fig. 1 illustrates the structure of the proposed methodology.

A. Models

1) Generation Units

The capacity of a generation unit when in a given state depends on the failure/repair cycle stochastic model and on the time-dependent capacity model. The first model is related to stochastic transitions between failure and repair states.

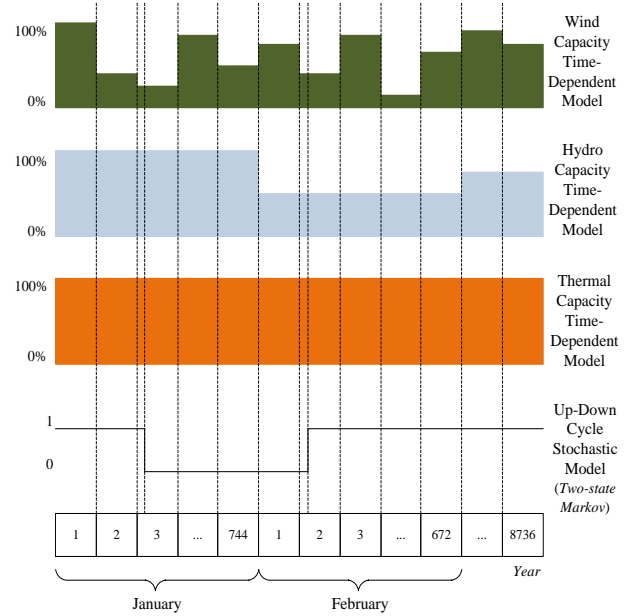


Figure 2. Representation of the time-dependent capacity model for different generation technologies and of the two-state Markov stochastic model.

The second one represents the time-dependent behavior of the generation units' capacity linked to the primary resources.

A simple illustration of these models is shown in Fig. 2, where the thermal capacity fluctuation depends only on its stochastic model, and the hydro capacity fluctuation depends not only on the stochastic model but also on the hydrological monthly fluctuation. Furthermore, the wind capacity fluctuation also depends on the stochastic model and on the wind hourly fluctuation.

a) Conventional Generation Units (Thermal)

The failure/repair cycle of conventional generation units is represented by a two-state stochastic model [7] whose transitions follow an exponential probability distribution. When in up-state, a conventional generator is able to provide its capacity. When in the down-state, the capacity value is zero.

b) Hydro Units

Similarly to conventional units, the two-state failure/repair cycle stochastic model is used to represent hydro units [7]. Capturing the time-dependency of the hydro units' capacity is a complex task since it depends on the volume of water stored in the reservoirs and on the river flow [21]. It is a well-known practice in GCR assessment studies to consider hydrological series that proportionally relate the hydro unit's capacity with the actual power available in each month. These series are based on historical data and may have probabilities associated with them. In Phase A, the time-dependency of the hydro units' capacity is accounted for by a reduction factor. This reduction factor corresponds to the average capacity obtained considering all hydrological series. In Phase B, the generation capacity of the hydro units is multiplied by the corresponding value (p.u.) of the hydrologic series to obtain the monthly capacity available. A new hydro series is selected at the beginning of each simulated year

c) Wind Farms

A multi-state Markov model [7] is used to represent the failure/repair cycle of wind farms. Its transitions follow an exponential probability distribution. Similarly to hydro units, the time-dependency of wind farms' capacity is captured via wind series. These series model a proportional relation between the total capacity of the wind farm with the power available at each hour [21]. They are also constructed based on historical data and have probabilities associated. Despite their probabilistic nature, these series are used as input parameters as the hydrological series. In Phase A, the time-dependency of the wind farms' capacity is modeled by a reduction factor. This reduction factor corresponds to the average capacity obtained considering all wind series. In Phase B, the generation capacity of the wind farm is multiplied by the corresponding value of the wind series to obtain the hourly available capacity. A new wind series is selected at the beginning of each simulated year.

2) Load Model

The system load is modeled using a chronological representation containing as many steps as hours in the year. Only peak load is considered in Phase A.

B. Coding Generation States

A generation state contains the availability of conventional and hydro units. The availability of wind generators is not included. Wind generators are often equal and have a small capacity when compared to the capacity of the wind farm. Furthermore, wind farms traditionally have capacity factors ranging between 20% and 30%. As a result, depending on the primary energy resource, wind generator failures may not significantly influence the total wind power produced when compared to the capacity variation caused by wind intermittency. The wind farms' total capacity affected by the corresponding reduction factor is considered in Phase A. In Phase B, the wind farm's generation capacity is calculated according to Section III.A.1)c).

The failure/repair cycle of all types of generation units represented in the generation state follows the two-state Markov model which can be coded as a binary vector. This type of coding can be optimized if one takes into account that some of these generation units have the same capacity and the same stochastic parameters [17], making them "equal" from the GCR assessment point of view. In this work, a generation state is a vector containing the number of "equal" generation units in the up-state. Each entry of the vector is an integer number ranging between zero and the maximum number of "equal" units. This type of coding significantly reduces the dimension of the vector especially in the case of power systems with a large number of "equal" units. The PBM used [17] in this work is designed for real spaces. To obtain a vector of integers from a vector of real numbers, a simple rounding procedure is performed. The limits of the search space are carefully chosen so that each integer within the range has an equal probability of being attained.

C. Proposed Methodology Algorithm

The proposed methodology applies the two phases described previously. Both phases are summarized as follows.

Phase A – PBM

```
Define EPSO's parameters and the position of all particles
While the maximum number of iterations is not achieved or
the EPNS annualized index tolerance criterion is not verified.
  Round the position of the particles to obtain generation
  states
  Code the generation states according to Section III.B and
  calculate their capacity and probability
  If the generation state has not enough capacity to supply the
  peak load
    Then If its probability is equal or higher than a probabil-
    ity threshold
      Then If the generation state is not contained in the list
        Then add the generation state to the list and assign its
        fitness as the product of the probability with the load
        curtailed
      Else assign the fitness and the personal best fitness of
      all particles, whose personal best position represents
      the generation state being evaluated, which is a very
      small value
    Else assign a very small value to the fitness
  Find the particle with the best fitness and set it as best par-
  ticle of the population
  Perform population reproduction using EPSO's replication
  and crossover operators [20]
  Estimate the EPNS annualized index using (1)
End While
```

Phase B – SMCS

```
While the maximum number of years to be simulated is not
achieved or the relative uncertainty of the GCR annual indexes
is higher than the tolerance
   $h = 0$ 
  While  $h \leq 8736$ 
    Sample a new generation state and obtain its duration,  $d$ 
    Code the new generation state according to Section III.B
     $h := h + d$ 
  End While
Do
  If the next generation state is contained in the list
    Then perform state evaluation
  Else If the last system state evaluated represents a failure
    Then perform state evaluation, code the generation state
    according to Section III.C, and add it to the list
  Else no failure events occur throughout the duration of the
  generation state
  Update the test functions of the GCR annual indexes
Until all sampled generation states are evaluated
Update the estimates of the GCR annual indexes and their
  relative uncertainty
End While
```

TABLE I. RESULTS OBTAINED FOR IEEE-RTS 79 AND IEEE-RTS 96

	IEEE-RTS 79		IEEE-RTS 96	
	<i>Proposed Methodology</i>	<i>Crude SMCS</i>	<i>Proposed Methodology</i>	<i>Crude SMCS</i>
LOLE (h/y)	9.530	9.550	0.1312	0.1366
EENS (MWh/y)	1,261.11	1,266.96	22.75	23.81
LOLF (occ./y)	2.026	2.089	0.05006	0.05198
System States Composed and Evaluated	8,099,648	28,883,137	11,425,175	648,547,765
Total Time (min)	0.64	1.78	20.20	114.90
Phase A Time (min)	0.036	-	0.26	-
SMCS Year Average Evaluation Time (ms)	8.65	31.14	1.95	89.84

IV. RESULTS

The proposed methodology was applied to the GCR assessment of the IEEE-RTS 79 [18], IEEE-RTS 96 [19] and IEEE-RTS 96 HW [21]. The GCR annual indexes obtained were validated by performing the same evaluations using crude SMCS. All estimates of the GCR indexes have a coefficient of variation lower than or equal to 5%. The simulations were conducted on an Intel Core 2 Duo CPU (3.16 GHz).

A. IEEE-RTS 79, IEEE-RTS 96 and IEEE-RTS 96 HW basic characteristics

The IEEE-RTS 79 [18] has 32 generation units. The installed capacity and the annual peak load are 3405 MW and 2850 MW, respectively. The annual load curve has 8736 load steps. Only 8.8% of the installed capacity is renewable consisting of 6 hydro units of 50 MW. The IEEE-RTS 96 [19] consists of three interconnected areas. Each area is an IEEE-RTS 79 system. From the point of view of the GCR assessment, the IEEE-RTS 96 can be seen as an augmentation of the IEEE-RTS 79 by a factor of 3. The IEEE-RTS 96 HW [21] is the result of modifications to the IEEE-RTS 96 with the purpose of increasing the share of renewable capacity. Hence, one coal unit of 350 MW is replaced by 1526 MW of wind capacity. With this modification, the renewable capacity share increases from 8.8% to 21.3%. The wind capacity is composed by 763 units of 2 MW (MTTF = 1914.74 h and MTTR = 80 h). These units are distributed by the three areas: 267 units in area 1, 229 in area 2, and 267 units in area 3. Wind capacity fluctuation in each of the three areas is characterized by three series. These are labeled as favorable, average and unfavorable. Their probabilities of occurring are 25%, 50% and 25%, respectively. The series can be obtained from [21]. The capacity fluctuation of each of the three groups of 6 hydro units of 50 MW is characterized by five hydro series. These series have the same probability of occurring and can be obtained from [21].

B. Discussion of Results

Tables I and II present the estimates of LOLE, EENS and LOLF for the IEEE-RTS 79, IEEE-RTS 96 and IEEE-RTS 96 HW systems.

TABLE II. RESULTS OBTAINED FOR IEEE-RTS 96 HW

	IEEE-RTS-96 HW	
	<i>Proposed Methodology</i>	<i>Crude SMCS</i>
LOLE(h/y)	0.3036	0.3553
EENS (MWh/y)	59.34	67.28
LOLF (occ./y)	0.1071	0.1267
System States Composed and Evaluated	30,078,849	643,280,417
Total Time (min)	100.32	263.11
Phase A Time (min)	0.43	-
SMCS Year Average Evaluation Time (ms)	14.83	277.83

TABLE III. METHODOLOGY STATISTICS FOR IEEE-RTS 79

Phase A	Generation states added to the list	15,150
Phase B	Generation states added to the list	61
Phase B	Generation states sampled	1,452,641
Phase B	Generation states selected for evaluation and with failure states	6,134
Phase B	Generation states not selected for evaluation and without failure states	1,014,198
Phase B	Generation states selected for evaluation and without failure states	432,294
Phase B	Generation states not selected for evaluation and with failure states	15

All estimates obtained with the proposed methodology are similar to those obtained using crude SMCS and with those published in [15]. This result proves that the proposed methodology is accurate in sorting out the generation states that contain system states with loss of load from those that do not. Moreover, the estimates of the annual indexes obtained for the IEEE-RTS 96 HW prove that not including the availability of the wind generators when coding the generation states is an appropriate hypothesis. The reduction factors of the hydro and wind units used in Phase A are also able to approximately represent their average capacity available

Tables I and II show that, by using the list, less system states have to be composed and evaluated comparatively to crude SMCS. This allows significant savings in simulation time especially when state evaluation is the most time-demanding stage of SMCS. Furthermore, the time required to run Phase A is not significant comparatively to the total simulation time in all simulations performed. When using the proposed methodology, the speedup achieved in evaluating one year of sampled generation states is 3.6 for the IEEE-RTS 79, 46.01 for the IEEE-RTS 96 and 18.73 for the IEEE-RTS 96 HW. Since the number of years simulated and the dimensions of the systems are different, the same gains are not extended to the total simulation time. In fact, the gain obtained for the IEEE-RTS 79 was 2.78, 5.69 for the IEEE-RTS 96, and 2.62 for the IEEE-RTS 96 HW.

In order to investigate the accuracy of the proposed methodology, statistics where collected during the GCR assessment of the IEEE-RTS 79 system. These statistics are presented in Table III. Firstly, it can be seen that the large majority of the

generation states in the list are collected during Phase A. The small number of states collected in Phase B proves that the most important generation states to compute the estimates of the GCR annual indexes were already saved in the list in Phase A. Secondly, by using the proposed methodology, 1,020,332 of the 1,452,641 generation states sampled were correctly identified. In other words, 70.24% of the sampled generation states were successfully detected as not containing failure states throughout its duration and/or containing at least one failure state.

The most important statistic in Table III is the small number of sampled generation states not selected for the state evaluation stage which contained at least one failure state. If this number was high, the accuracy of GCR annual indexes estimated using the proposed methodology would be severely compromised. Finally, the number of sampled generation states selected for evaluation that did not contain failure system states is noteworthy when compared to the total number of sampled generation states. In fact, 29.76% of all sampled generation states were composed and evaluated unnecessarily. If this percentage is reduced, additional gains in simulation time will be obtained without compromising the accuracy in the estimates of the GCR annual indexes.

V. CONCLUSIONS AND FUTURE WORK

This paper presented a new application of PBMs in the GCR assessment. These methods are combined with SMCS to reduce the simulation time required to obtain GCR annual indexes. The proposed methodology consists of two phases. Phase A aims at constructing a list of generation states with insufficient capacity to supply the peak load. A PBM is used to perform this task, taking advantage of the broad coverage of the generation state space. This list is subsequently used in Phase B, whose core is a SMCS, to help decide if the sampled generation states should move on to the state evaluation stage. Since real power systems are traditionally reliable, the majority of the generation states sampled will not contain system states with failure. By using the list, the additional simulation time associated with composing and evaluating those generation states is avoided.

The proposed methodology was successfully applied to the GCR assessment of three power systems that include wind and hydro intermittency: the IEEE-RTS 79, the IEEE-RTS 96 and the IEEE-RTS 96 HW systems. The results have shown significant gains in simulation time without compromising the accuracy of the GCR estimates and preserving all the advantages of the SMCS such as the possibility of estimating the GCR probability distributions. Future works includes the application of the proposed methodology to the reliability assessment of composite systems, studying the possibility of dynamically changing the size of the list to reduce search times, and analyzing the convergence process of the GCR annual indexes.

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